

```

In [3]: import json
import requests
from bs4 import BeautifulSoup

def scrape_article_content(url):
    headers = {
        "User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit
    }
    try:
        response = requests.get(url, headers=headers)
        response.raise_for_status()
        soup = BeautifulSoup(response.text, 'html.parser')

        # Modify the following selector to match the article content structure
        content_paragraphs = soup.find_all('p')
        article_text = ' '.join([p.get_text(strip=True) for p in content_paragraphs])

        return article_text

    except requests.exceptions.RequestException as e:
        print(f"Error fetching article from {url}: {e}")
        return None

with open('/Users/tiff1101/Downloads/alpha_vantage_financial_news_week.json') as f:
    articles_data = json.load(f)

# Print the first item to verify the data structure
print("First article:", articles_data[0])

# Assuming `articles_data` is a list of article metadata with URLs
for article in articles_data:
    article_url = article['url']
    full_content = scrape_article_content(article_url)
    if full_content:
        article['full_content'] = full_content

print(articles_data[0])

```

First article: {'title': 'DATA BREACH ALERT: Edelson Lechtzin LLP Is Investigating Claims On Behalf Of PracticeSuite, Inc. Customers Whose Data May Have Been Compromised', 'url': 'https://www.benzinga.com/pressreleases/24/11/g42100443/data-breach-alert-edelson-lechtzin-llp-is-investigating-claims-on-behalf-of-practicesuite-inc-cust', 'time_published': '20241120T220956', 'authors': ['Globe Newswire'], 'summary': 'NEWTOWN, Pa., Nov. 20, 2024 (GLOBE NEWS WIRE) -- The law firm of Edelson Lechtzin LLP is investigating claims regarding data privacy violations by PracticeSuite, Inc. ("PracticeSuite") . PracticeSuite learned of suspicious activity on its computer network on or about October 11, 2024.', 'banner_image': 'https://www.benzinga.com/next-assets/images/schema-image-default.png', 'source': 'Benzinga', 'category_within_s

source': 'News', 'source_domain': 'www.benzinga.com', 'topics': [{'topic': 'Finance', 'relevance_score': '1.0'}, {'topic': 'Financial Markets', 'relevance_score': '0.108179'}], 'overall_sentiment_score': -0.026751, 'overall_sentiment_label': 'Neutral', 'ticker_sentiment': [{'ticker': 'STT', 'relevance_score': '0.082111', 'ticker_sentiment_score': '0.0', 'ticker_sentiment_label': 'Neutral'}]}

{'title': 'DATA BREACH ALERT: Edelson Lechtzin LLP Is Investigating Claims On Behalf Of PracticeSuite, Inc. Customers Whose Data May Have Been Compromised', 'url': 'https://www.benzinga.com/pressreleases/24/11/g42100443/data-breach-alert-edelson-lechtzin-llp-is-investigating-claims-on-behalf-of-practice-suite-inc-cust', 'time_published': '20241120T220956', 'authors': ['Globe Newswire'], 'summary': 'NEWTOWN, Pa., Nov. 20, 2024 (GLOBE NEWSWIRE) -- The law firm of Edelson Lechtzin LLP is investigating claims regarding data privacy violations by PracticeSuite, Inc. ("PracticeSuite"). PracticeSuite learned of suspicious activity on its computer network on or about October 11, 2024.', 'banner_image': 'https://www.benzinga.com/next-assets/images/schema-image-default.png', 'source': 'Benzinga', 'category_within_source': 'News', 'source_domain': 'www.benzinga.com', 'topics': [{'topic': 'Finance', 'relevance_score': '1.0'}, {'topic': 'Financial Markets', 'relevance_score': '0.108179'}], 'overall_sentiment_score': -0.026751, 'overall_sentiment_label': 'Neutral', 'ticker_sentiment': [{'ticker': 'STT', 'relevance_score': '0.082111', 'ticker_sentiment_score': '0.0', 'ticker_sentiment_label': 'Neutral'}], 'full_content': 'NEWTOWN, Pa., Nov. 20, 2024 (GLOBE NEWSWIRE) -- The law firm of Edelson Lechtzin LLP is investigating claims regarding data privacy violations by PracticeSuite, Inc. ("PracticeSuite"). PracticeSuite learned of suspicious activity on its computer network on or about October 11, 2024. To join this case, goHERE. About PracticeSuite, Inc. PracticeSuite, Inc., located in Tampa, Florida, is a cloud-based software company that provides comprehensive medical practice management solutions. These solutions include medical billing, electronic health records, and overall practice management services. What happened? On or about October 11, 2024, PracticeSuite discovered that an unauthorized hacker had accessed a data file on one of its servers, which contained backup records from one of PracticeSuite's clients, Texan ENT Specialists, PLLC, up to March 19, 2024. After learning about this, PracticeSuite began investigating and discovered that certain personal information had been obtained. The compromised information that the data breach has impacted includes names, Social Security numbers, account numbers, demographic information such as addresses, dates of birth, phone numbers, email addresses, and other sensitive personal health information. How can I protect my personal data? If you receive a data breach notification, you must guard against possible misuse of your personal information, including identity theft and fraud, by regularly reviewing your account statements and monitoring your credit reports for suspicious or unauthorized activity. Additionally, you should consider legal options for mitigating such risks. Edelson Lechtzin LLP is investigating a class action lawsuit to seek legal remedies for customers who may have had their sensitive personal and patient data compromised by the PracticeSuite data breach. For more information, please contact: Marc H. Edelson, Esq.EDELSON LECHTZIN LLP411 S. State Street, Suite N-300Newtown, PA 18940Phone: 844-696-7492Email:medelson@edelson-law.comWeb:www.edelson-law.com About Edelson Lechtzin LLP Edelson Lechtzin LLP is a national class action la

w firm with offices in Pennsylvania and California. In addition to cases involving data breaches, our lawyers focus on class and collective litigation in cases alleging securities and investment fraud, violations of the federal antitrust laws, employee benefit plans under ERISA, wage theft and unpaid overtime, consumer fraud, and dangerous and defective drugs and medical devices. This press release may be considered Attorney Advertising in some jurisdictions. No class has been certified in this case, so counsel does not represent you unless you retain one. You may select counsel of your choice. You may also remain an absent class member and do nothing now. Your ability to share in any potential future recovery does not depend on serving as lead plaintiff. © 2024 Benzinga.com. Benzinga does not provide investment advice. All rights reserved. Trade confidently with insights and alerts from analyst ratings, free reports and breaking news that affects the stocks you care about.

First article: {'title': 'Goldman Sachs To Spin Out Digital Assets Platform Amid Blockchain Push - Goldman Sachs Gr (NYSE:GS) ', 'url':

'<https://www.benzinga.com/markets/cryptocurrency/24/11/42047066/goldman-sachs-to-spin-out-digital-assets-platform-amid-blockchain-push>', 'time_published':

'20241118T195339', 'authors': ['Murtuza Merchant'], 'summary': 'Goldman Sachs Group Inc. NYSE: GS) is advancing its blockchain ambitions, planning to spin out its digital-assets platform into an independent company within the next 12 to 18 months.',

'banner_image': '<https://cdn.benzinga.com/files/images/story/2024/11/18/Goldman-Sachs-Accepts-Resolution.jpeg?width=1200&height=800&fit=crop>', 'source':

'Benzinga', 'category_within_source': 'News', 'source_domain': 'www.benzinga.com',

'topics': [{'topic': 'Finance', 'relevance_score': '1.0'}, {'topic': 'Blockchain',

'relevance_score': '0.838487'}, {'topic': 'Financial Markets', 'relevance_score':

'0.161647'}], 'overall_sentiment_score': 0.449601, 'overall_sentiment_label': 'Bullish',

'ticker_sentiment': [{'ticker': 'GS', 'relevance_score': '0.181819',

'ticker_sentiment_score': '0.0', 'ticker_sentiment_label': 'Neutral'}, {'ticker':

'CRYPTO:BTC', 'relevance_score': '0.269776', 'ticker_sentiment_score': '0.443827',

'ticker_sentiment_label': 'Bullish'}, {'ticker': 'CRYPTO:ETH', 'relevance_score':

'0.091509', 'ticker_sentiment_score': '0.274239', 'ticker_sentiment_label': 'Somewhat-

Bullish'}}] {'title': 'Goldman Sachs To Spin Out Digital Assets Platform Amid Blockchain

Push - Goldman Sachs Gr (NYSE:GS) ', 'url':

'<https://www.benzinga.com/markets/cryptocurrency/24/11/42047066/goldman-sachs-to-spin-out-digital-assets-platform-amid-blockchain-push>', 'time_published':

'20241118T195339', 'authors': ['Murtuza Merchant'], 'summary': 'Goldman Sachs Group Inc. NYSE: GS) is advancing its blockchain ambitions, planning to spin out its digital-assets platform into an independent company within the next 12 to 18 months.',

'banner_image': '<https://cdn.benzinga.com/files/images/story/2024/11/18/Goldman-Sachs-Accepts-Resolution.jpeg?width=1200&height=800&fit=crop>', 'source':

'Benzinga', 'category_within_source': 'News', 'source_domain': 'www.benzinga.com',
 'topics': [{ 'topic': 'Finance', 'relevance_score': '1.0'}, { 'topic': 'Blockchain',
 'relevance_score': '0.838487'}, { 'topic': 'Financial Markets', 'relevance_score':
 '0.161647'}], 'overall_sentiment_score': 0.449601, 'overall_sentiment_label': 'Bullish',
 'ticker_sentiment': [{ 'ticker': 'GS', 'relevance_score': '0.181819',
 'ticker_sentiment_score': '0.0', 'ticker_sentiment_label': 'Neutral'}, { 'ticker':
 'CRYPTO:BTC', 'relevance_score': '0.269776', 'ticker_sentiment_score': '0.443827',
 'ticker_sentiment_label': 'Bullish'}, { 'ticker': 'CRYPTO:ETH', 'relevance_score':
 '0.091509', 'ticker_sentiment_score': '0.274239', 'ticker_sentiment_label': 'Somewhat-
 Bullish'}],

'full_content': 'Goldman Sachs Group Inc.NYSE: GS) is advancing its blockchain ambitions, planning to spin out its digital-assets platform into an independent company within the next 12 to 18 months. What Happened:The platform aims to enable large financial institutions to create, trade, and settle financial instruments using blockchain technology, Bloombergreported. Mathew McDermott, Goldman's global head of Digital Assets, revealed the plans, emphasizing the importance of making the platform "industry-owned" to benefit the broader market. The move is contingent on regulatory approval. Goldman is actively engaging with potential partners to enhance the platform's capabilities and explore new commercial applications. The first strategic partner,Tradeweb Markets Inc., has already joined forces with Goldman to develop use cases, marking a significant step toward the initiative's realization. Goldman's spin-out plan reflects a broader trend of financial institutions leveraging blockchain to streamline the issuance, trading, and settlement of traditional assets like cash and bonds. Blockchain technology offers a faster, more efficient alternative to conventional systems, a proposition increasingly attractive to institutional players. Also Read:Bitcoin To 100,000'SeemsAroundTheCorner,' BullsAre'OnTheRightSideOfHistory'— Ber 93,000 has further bolstered confidence in the transformative potential of digital assets. "Despite market volatility, we see significant long-term opportunities for blockchain and Bitcoin in institutional finance," McDermott said. Goldman's optimism is evident in its investments in blockchain-backed financial products. Earlier this year, the firm partnered withDRW Capitalto allocate \$600 million across spot Bitcoin and Ethereum ETFs, signaling a strong commitment to the sector's growth. In addition to its blockchain platform, Goldman is exploring opportunities to facilitate secondary transactions in private digital-asset companies, providing liquidity for clients like family offices while allowing buyers to capitalize on private market discounts. The bank is also preparing to resume its Bitcoin-backed lending activities, highlighting its confidence in Bitcoin's role as a financial instrument. Goldman's efforts align with renewed momentum in the crypto market following Donald Trump's election victory. Investors are betting on favorable

digital asset policies under his administration, driving institutional interest and regulatory clarity. These developments will be central to discussions at Benzinga's Future of Digital Asset event on Nov. 19. Read Next: Photo: Shutterstock © 2024 Benzinga.com.

Benzinga does not provide investment advice. All rights reserved. Trade confidently with insights and alerts from analyst ratings, free reports and breaking news that affects the stocks you care about.{'

```
In [4]: import yfinance as yf
from datetime import datetime, timedelta

# Expanded list of stock indices from global markets
tickers = [
    '^GSPC', '^DJI', 'QQQ', '^IXIC', '^RUT', '^RUA', '^W5000', '^MID', '^VIX',
    '^FTSE', '^DAX', '^CAC40', '^N225', '^HSI', '^ASX200', '^STOXX50E', '^AEX',
    '^BSE', '^NSEI', '^KOSPI', '^TSEC', '^KLSE', '^JSE', '^BVSP', '^MXM', '^TA35',
    '^SENSEX', '^SET50', '^SSEC', '^TWSE', '^IDX', '^CSI300', '^NZ50', '^OMXS30',
    '^GDAXI', '^SPTSX', '^OSEBX', '^ATHEX', '^KSE', '^IBOV', '^TA35', '^MERV',
    '^ALLORDS', '^JKSE', '^IBOVESPA', '^IBEX35', '^TADAWUL', '^SAX'
]

# Function to calculate the binary trend (1 for increase, 0 for decrease)
def calculate_binary_trend(stock_data):
    """
    Calculates binary trends based on intraday price movement.

    Parameters:
        stock_data (DataFrame): The stock data with 'Open' and 'Close' columns.

    Returns:
        List[int]: Binary trends for each day in the data.
    """
    trends = []
    for _, row in stock_data.iterrows():
        trends.append(int(row['Close'] > row['Open']))
    return trends

def get_stock_trends(tickers, start_date, end_date):
    """
    Fetches intraday trends for a list of stock indices over a given date range.

    Parameters:
        tickers (list): List of stock indices.
        start_date (str): Start date in 'YYYY-MM-DD' format.
        end_date (str): End date in 'YYYY-MM-DD' format.

    Returns:
        dict: Dictionary of binary trends for each ticker.
        list: Flattened list of all binary trends.
    """
```

```

"""
binary_trends = {}

# Retrieve data for each ticker for the specified date range and calculate binary trends
for ticker in tickers:
    print(f"Fetching data for {ticker}...")
    try:
        stock_data = yf.download(ticker, start=start_date, end=end_date,
                                  auto_adjust=True)
        if not stock_data.empty:
            binary_trends[ticker] = calculate_binary_trend(stock_data[['Open', 'Close']])
        else:
            binary_trends[ticker] = [None] * ((datetime.strptime(end_date, '%Y-%m-%d') -
                                                datetime.strptime(start_date, '%Y-%m-%d')).days + 1)
    except Exception as e:
        print(f"Error fetching data for {ticker}: {e}")
        binary_trends[ticker] = [None] * ((datetime.strptime(end_date, '%Y-%m-%d') -
                                            datetime.strptime(start_date, '%Y-%m-%d')).days + 1)

# Flatten all binary trends into a single list (filter out None values)
binary_feature_list = [trend for trends in binary_trends.values() for trend in trends]

return binary_trends, binary_feature_list

# Set start and end dates for data retrieval
start_date = "2024-11-21"
end_date = "2024-11-24"

# Fetch binary trends
binary_trends, binary_feature_list = get_stock_trends(tickers, start_date, end_date)

# Print the binary trends for each ticker
print("Binary Trends for Each Index:")
print(binary_trends)

# Display the binary feature list
print("Binary Feature List for Classification:")
print(binary_feature_list)

```

```

[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead

```

```

trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^DAX']: YFPricesMissingError('$%ticker%: possibly delisted; no price data
found (1d 2024-11-21 -> 2024-11-24)')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^CAC40']: YFTzMissingError('$%ticker%: possibly delisted; no timezone foun

```

d')

```

Fetching data for ^GSPC...
Fetching data for ^DJI...
Fetching data for QQQ...
Fetching data for ^IXIC...
Fetching data for ^RUT...
Fetching data for ^RUA...
Fetching data for ^W5000...
Fetching data for ^MID...
Fetching data for ^VIX...
Fetching data for ^NDX...
Fetching data for ^FTSE...
Fetching data for ^DAX...
Fetching data for ^CAC40...
Fetching data for ^N225...

```

```

[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

```

1 Failed download:

```

['^ASX200']: YFTzMissingError('%ticker%: possibly delisted; no timezone foun
d')

```

```

[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

```

1 Failed download:

```

['^BEL20']: YFTzMissingError('%ticker%: possibly delisted; no timezone foun
d')

```

```

[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))

```



```
[*****100%*****] 1 of 1 completed

1 Failed download:
['^BSE']: YFTzMissingError('%ticker%: possibly delisted; no timezone found')
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.py:27: FutureWarning: Calling int on a single element Series is deprecated and will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^KOSPI']: YFTzMissingError('%ticker%: possibly delisted; no timezone found')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^TSEC']: YFTzMissingError('%ticker%: possibly delisted; no timezone found')
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.py:27: FutureWarning: Calling int on a single element Series is deprecated and will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^JSE']: YFTzMissingError('%ticker%: possibly delisted; no timezone found')
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.py:27: FutureWarning: Calling int on a single element Series is deprecated and will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.py:27: FutureWarning: Calling int on a single element Series is deprecated and will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
```

```
Fetching data for ^HSI...
Fetching data for ^ASX200...
Fetching data for ^STOXX50E...
Fetching data for ^AEX...
Fetching data for ^BEL20...
Fetching data for ^IBEX...
Fetching data for ^BSE...
Fetching data for ^NSEI...
Fetching data for ^KOSPI...
Fetching data for ^TSEC...
Fetching data for ^KLSE...
Fetching data for ^JSE...
Fetching data for ^BVSP...
Fetching data for ^MXS...
Fetching data for ^IPSA...
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^IPSA']: YFPricesMissingError('$%ticker%: possibly delisted; no price data found (1d 2024-11-21 -> 2024-11-24)')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^RTS']: YFPricesMissingError('$%ticker%: possibly delisted; no price data found (1d 2024-11-21 -> 2024-11-24)')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^TA35']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^SENSEX']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^SET50']: YFPricesMissingError('$%ticker%: possibly delisted; no price data found (1d 2024-11-21 -> 2024-11-24)')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^SSEC']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^TWSE']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed

1 Failed download:
['^IDX']: YFPricesMissingError('%ticker%: possibly delisted; no price data
found (1d 2024-11-21 -> 2024-11-24)')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^CSI300']: YFTzMissingError('%ticker%: possibly delisted; no timezone fou
nd')
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^PSI20']: YFPricesMissingError('%ticker%: possibly delisted; no price dat
a found (1d 2024-11-21 -> 2024-11-24)')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^OMXHPI']: YFPricesMissingError('%ticker%: possibly delisted; no price da
ta found (1d 2024-11-21 -> 2024-11-24)')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^OMXS30']: YFPricesMissingError('%ticker%: possibly delisted; no price da
ta found (1d 2024-11-21 -> 2024-11-24)')
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^SPTSX']: YFTzMissingError('%ticker%: possibly delisted; no timezone foun
d')
```

```
Fetching data for ^RTS...
Fetching data for ^TA35...
Fetching data for ^SENSEX...
Fetching data for ^SET50...
Fetching data for ^SSEC...
Fetching data for ^TWSE...
Fetching data for ^IDX...
Fetching data for ^CSI300...
Fetching data for ^NZ50...
Fetching data for ^PSI20...
Fetching data for ^OMXHPI...
Fetching data for ^OMXS30...
Fetching data for ^GDAXI...
Fetching data for ^SPTSX...
Fetching data for ^OSEBX...
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^OSEBX']: YFPricesMissingError('$%ticker%: possibly delisted; no price data found (1d 2024-11-21 -> 2024-11-24)')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^ATHEX']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^KSE']: YFPricesMissingError('$%ticker%: possibly delisted; no price data found (1d 2024-11-21 -> 2024-11-24)')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^IBOV']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^TAIEX']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^PX']: YFPricesMissingError('$%ticker%: possibly delisted; no price data found (1d 2024-11-21 -> 2024-11-24)')
```

```
[*****100%*****] 1 of 1 completed
```

```
1 Failed download:
```

```
['^BIST100']: YFTzMissingError('$%ticker%: possibly delisted; no timezone found')
```

```
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^ALLORDS']: YFTzMissingError('$%ticker%: possibly delisted; no timezone fo
und')
[*****100%*****] 1 of 1 completed
/var/folders/qj/lwff4ygj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.
py:27: FutureWarning: Calling int on a single element Series is deprecated a
nd will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
[*****100%*****] 1 of 1 completed

1 Failed download:
['^IBOVESPA']: YFTzMissingError('$%ticker%: possibly delisted; no timezone f
ound')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^IBEX35']: YFTzMissingError('$%ticker%: possibly delisted; no timezone fou
nd')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^TADAWUL']: YFTzMissingError('$%ticker%: possibly delisted; no timezone fo
und')
[*****100%*****] 1 of 1 completed

1 Failed download:
['^SAX']: YFPricesMissingError('$%ticker%: possibly delisted; no price data
found (1d 2024-11-21 -> 2024-11-24)')
Fetching data for ^ATHEX...
Fetching data for ^KSE...
Fetching data for ^IBOV...
Fetching data for ^TAIEX...
Fetching data for ^PX...
Fetching data for ^BIST100...
Fetching data for ^MERV...
Fetching data for ^ALLORDS...
Fetching data for ^JKSE...
Fetching data for ^IBOVESPA...
Fetching data for ^IBEX35...
Fetching data for ^TADAWUL...
Fetching data for ^SAX...
Fetching data for ^NYA...
[*****100%*****] 1 of 1 completed
```

Binary Trends for Each Index:

```
{'^GSPC': [1, 1], '^DJI': [1, 1], 'QQQ': [0, 1], '^IXIC': [0, 1], '^RUT': [1, 1], '^RUA': [1, 1], '^W5000': [1, 1], '^MID': [1, 1], '^VIX': [0, 0], '^NDX': [0, 1], '^FTSE': [1, 1], '^DAX': [None, None, None], '^CAC40': [None, None, None], '^N225': [0, 1], '^HSI': [0, 0], '^ASX200': [None, None, None], '^STOXX50E': [1, 1], '^AEX': [1, 1], '^BEL20': [None, None, None], '^IBEX': [1, 1], '^BSE': [None, None, None], '^NSEI': [0, 1], '^KOSPI': [None, None, None], '^TSEC': [None, None, None], '^KLSE': [0, 0], '^JSE': [None, None, None], '^BVSP': [0, 1], '^MXX': [1, 1], '^IPSA': [None, None, None], '^RTS': [None, None, None], '^TA35': [None, None, None], '^SENSEX': [None, None, None], '^SET50': [None, None, None], '^SSEC': [None, None, None], '^TWSE': [None, None, None], '^IDX': [None, None, None], '^CSI300': [None, None, None], '^NZ50': [1, 1], '^PSI20': [None, None, None], '^OMXHPI': [None, None, None], '^OMXS30': [None, None, None], '^GDAXI': [1, 1], '^SPTSX': [None, None, None], '^OSEBX': [None, None, None], '^ATHEX': [None, None, None], '^KSE': [None, None, None], '^IBOV': [None, None, None], '^TAIEX': [None, None, None], '^PX': [None, None, None], '^BIST100': [None, None, None], '^MERV': [0, 1], '^ALLORDS': [None, None, None], '^JKSE': [0, 1], '^IBOVESPA': [None, None, None], '^IBEX35': [None, None, None], '^TADAWUL': [None, None, None], '^SAX': [None, None, None], '^NYA': [1, 1]}
```

Binary Feature List for Classification:

```
[1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1]
```

```
/var/folders/qj/lwff4yggj6r728t_ytn73v3sw0000gn/T/ipykernel_35179/1758677038.py:27: FutureWarning: Calling int on a single element Series is deprecated and will raise a TypeError in the future. Use int(ser.iloc[0]) instead
    trends.append(int(row['Close'] > row['Open']))
```

```
In [5]: #text cleaning
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer

# Download necessary NLTK data files
nltk.download('stopwords')
nltk.download('wordnet')

# Initialize lemmatizer and stopwords
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words('english'))

def clean_text(text):
    # Remove punctuation and non-alphabetic characters
    text = re.sub(r'[^a-zA-Z\s]', '', text)
    # Convert text to lowercase
    text = text.lower()
    # Tokenize and remove stopwords, then lemmatize
    words = text.split()
    words = [lemmatizer.lemmatize(word) for word in words if word not in stop_words]
```

```

    return ' '.join(words)

# Apply text cleaning to the content in articles_data
for article in articles_data:
    article['cleaned_content'] = clean_text(article['full_content'])

```

```

[nltk_data] Downloading package stopwords to
[nltk_data]      /Users/tiff1101/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]      /Users/tiff1101/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!

```

```

In [6]: from sklearn.feature_extraction.text import TfidfVectorizer

# Extract cleaned content from articles for TF-IDF transformation
corpus = [article['cleaned_content'] for article in articles_data]

# Initialize TF-IDF Vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=1000) # Adjust max_features
tfidf_matrix = tfidf_vectorizer.fit_transform(corpus)

# Convert the TF-IDF matrix to a DataFrame for better handling
import pandas as pd
tfidf_df = pd.DataFrame(tfidf_matrix.toarray(), columns=tfidf_vectorizer.get

```

```

In [7]: from transformers import BertTokenizer, BertModel
import torch

# Initialize BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')

def get_bert_embeddings(text):
    # Tokenize and convert to tensor
    inputs = tokenizer(text, return_tensors='pt', truncation=True, padding=True)
    with torch.no_grad():
        outputs = model(**inputs)
    # Use the mean of the last hidden state as the sentence embedding
    embeddings = torch.mean(outputs.last_hidden_state, dim=1)
    return embeddings.squeeze().numpy()

# Apply BERT embeddings to the cleaned content
for article in articles_data:
    article['bert_embedding'] = get_bert_embeddings(article['cleaned_content'])

```

```

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/tqdm/auto.py:21: TqdmW
arning: IProgress not found. Please update jupyter and ipywidgets. See http
s://ipywidgets.readthedocs.io/en/stable/user_install.html
    from .autonotebook import tqdm as notebook_tqdm

```

```
In [8]: print(article['cleaned_content'])
```

founded motley fool financial service company dedicated making world smarter happier richer motley fool reach million people every month premium investing solution free guidance market analysis foolcom personal finance education top rated podcasts nonprofit motley fool foundation founded motley fool financial service company dedicated making world smarter happier richer motley fool reach million people every month premium investing solution free guidance market analysis foolcom personal finance education top rated podcasts nonprofit motley fool foundation you're reading free article opinion may differ motley fool premium investing service become motley fool member today to get instant access to analyst recommendation in depth research investing resources and more learn you're reading free article opinion may differ motley fool premium investing service become motley fool member today to get instant access to analyst recommendation in depth research investing resource more learn glbe earnings call period ending september image source motley fool global online lbeq earnings call nov 11 et operator welcome global third quarter earnings announcement conference call call simultaneously webcast company website investor relation section news event opening remark introduction turn call erica mannion sapphire investor relation please go ahead erica mannion investor relation thank good morning today global amir schlachet cofounder chief executive officer ofer koren chief financial officer nir debbie cofounder president amir begin review business result third quarter ofer review financial result third quarter followed company outlook fourth quarter full year open call question certain statement make today may constitute forward looking statement information within meaning section security act section e security exchange act safe harbor provision u private security litigation reform act relate current expectation view future event forward looking statement subject risk uncertainty assumption beyond control addition forward looking statement reflect current view respect future event guarantee future performance actual outcome may differ materially information contained forward looking statement result number factor including set forth section titled risk factor prospectus filed sec september document filed furnished sec statement reflect management current expectation regarding future event operating performance speak date call put undue reliance forward looking statement although believe expectation reflected forward looking statement reasonable cannot guarantee future result level activity performance event circumstance reflected forward looking statement achieved occur except required applicable law make obligation update revise publicly forward looking statement whether result new information future event otherwise date statement made reflect occurrence unanticipated event please refer press release dated november additional information addition certain metric discuss today nongaap metric presentation financial information intended considered isolation substitute superior financial information prepared presented accordance gaap use nongaap financial measure financial operating decisionmaking mean evaluate period to period comparison believe measure provide useful information operating result enhance overall understanding past financial performance future prospect allow greater transparency respect key metric used management financial operating decisionmaking information nongaap financial measure please see reconciliation table provided press release dated november throughout call provide number key performance indicators

or used management often used competitor industry key performance indicator discussed detail press release dated november turn call amir cofounder ceo a mir schlachetcofounder chief executive officer thank erica welcome everyone q earnings call delivered strong third quarter thanks growing contribution new merchant launch within quarter well growth existing merchant q saw gmv revenue growth accelerating respectively well top range guidance strong topline growth accompanied continued efficiency measure cost control yielding adjusted ebitda growth rate almost midpoint guidance range given successful launch new merchant trading well positive consumer sentiment september expect growth continue accelerating q rate year year raising full year guidance accordingly expect annual gmv full year grow revenue grow adjusted ebitda grow almost year year moreover strong performance across board combined new merchant booking alltime high strengthen conviction ability hit mark gmv growth beyond financial metric would also like give update strategic poster main initiative know globales mission power better global ecommerce clear leader global ecommerce service nevertheless invest adding new feature new functionality time continuously transform way merchant shopper across world engage one another example q went live new clickandcollect option bopis buy online pick store enabling relevant merchant enhance multichannel reach global level merchant using bopis utilize physical store different country around world local fulfillment hub global ecommerce well convenient pickup location shopper thereby enabling better shopper experience efficient global stock utilization rise physical store footprint first u merchant utilize capability saw around ecommerce sale canada managed incountry branded store first month offering option shopper operational side started beta testing several additional direct injection lane outbound inbound several new consolidated return lane strive provide merchant bestinclass logistics offering around globe enhancing efficiency offering better diverse set option shopper duty tax front comprehensive duty drawback platform support additional option standard shipping mail granted early access several merchant new global duty drawback program gddp new program enables merchant provide better customer service simplified transparent hasslefree duty tax refund process leveling global shopper experience domestic one last least continue invest aibased capability evolving landscape large language model llm enables u make incredible leap service efficiency example q rolled new iteration ai product classification tool leverage cuttingedge llm generate precise mapping product merchant catalog respective harmonized customer code h code crucial prerequisite accurate duty tax calculation well shipping import restriction management compared previous system utilize firstgeneration machine learning algorithm new llmbased tool yield increased accuracy ability learn improve time constantly bettering performance platform continues evolve merchant sign go live u mentioned earlier third quarter continued onboard many new merchant across different market vertical north america went live leading fashion brand fastgrowing plussize fashion brand torrid emerging elevated basic twin brand nuuds tone iconic footwear brand dr marten name vertical went live raycon fastgrowing consumer electronics brand watchmaker fossil cosmetic brand jones road beauty vitamin brand dr berg quarter also completed successful migration several brand old borderfree platform onto globales including llbean land end oscar de la renta enjoy benefit trading cuttingedge platform service also went live many new brand across uk europe including significant launch sport vertical two top premier league bu

ndesliga football club manchester united bayern munich deepening penetration track record within vertical also went live many brand across various vertical including german ski lifestyle brand bogner british clothing brand trapstar london swiss sciencebased sportswear brand xbionic swedish horse riding brand equestrian stockholm fastgrowing swedish swimwear brand bright ukbased land rover spare part site lr part polish clubwear brand misbhv danish handbag brand vee collective many many others asia pacific continued exhibit fast growth q gaining share activity apacbased brand choose go global via platform example would leading australian fashion brand dissh brand offs site japan hong kong japanese preowned fashion seller ragtag hong kongbased leather brand cafune korean sport gear brand dimito q also saw several addition growing portfolio luxury brand notably web store derek rose luxury fashion designer margaret howell uk longchamp paco rabanne france famous watch jewelry brand chopard switzerland biggest news merchant front recent launch harrod probably world iconic luxury department store last list planned large merchant launched planned launch year integration scayle platform chosen harrod support online sale delivered fully localized toposoftheline shopping experience every harrod customer around globe including domestic customer uk well time traditional holiday sale extremely excited supporting online business harrod much look forward growing together coming year apart launch new merchant always also continue expand activity existing brand brand group part landandexpand motion quarter added remaining lane victoria secret thereby completing phased launch planned also went live disney australia new zealand added support market assoulines apac store france went live luxury eyewear brand vuarnet expanding list brand work within lvmh group also went live swiss design fashion brand strellson second brand go live u three brand form holy fashion group well iconic swimmer brand billabong third brand go live liberated brand group new merchant booking year alltime high continue see strong demand service across geography vertical serve moving additional element road map continue develop roll new capability shopify managed market continues grow planned generate great value thousand merchant using among new feature released past quarter order editing provides merchant ability add international order prior fulfillment support several new alternative payment method upgrade automated catalog analysis algorithm allowing merchant sell product market q also expanded strategic partnership digital transformation leader transcosmos following successful joint work japan extended partnership transcosmos also cover south korea work together support international online growth korean client finally im happy announce planned recently launched demand generation offering based revamped borderfreecom brand discovery portal hundred merchant already signed launch displaying product portal tapping fastgrowing mass international shopper wear world starting fashion journey borderfreecom launch supported outofhome medium campaign online campaign across multiple channel shopper cashback reward offering many participating merchant already signed well still early inning already see increased level engagement activity portal believe time demand generation offering spearheaded borderfreecom grow provide value merchant hand offer take quarterly figure detail present updated guidance remainder year offer korechief financial officer thank amir thanks joining u today earnings call pleased performance third quarter q experienced accelerated growth combined healthy margin strong growth driven contribution new merchant successfully onboarded launched planned improvement consumer sentiment

ent september id like point addition gaap result ill also discussing certain nongaap result gaap financial result along reconciliation gaap nongaap result found earnings release gmv continued grow rapidly q generated billion gmv increase year year midpoint guidance quarter strong gmv growth fueled positive consumer sentiment september trading volume generated new merchant launched upper side expectation q generated total revenue million year year service fee revenue million fulfillment service revenue million quarter characterized balanced growth service fee take rate slightly decreased q due loss ted baker account provided demand generation service high service fee take rate fulfillment service take rate increased compared q driven favorable mix nong aap gross profit outpaced topline growth q nongaap gross profit million year year representing nongaap gross margin compared period last year driven operational efficiency gaap gross profit million representing margin moving operational expense continue invest development enhancement platform rd expense q excluding stockbased compensation million revenue compared million revenue period last year total rd spend q million also continued invest sale marketing continue see strong pipeline ahead sale marketing expense excluding shopifyrelated amortization expense stockbased compensation acquisitionrelated intangible amortization million revenue compared million revenue period last year shopify warrantrelated amortization expense million total sale marketing expense quarter million general administrative expense excluding stockbased compensation acquisitionrelated contingent consideration million revenue compared million revenue period last year total ga spend q million adjusted ebitda totaled million representing adjusted ebitda margin increase million margin period last year net loss million compared net loss million yearago period net loss driven mainly amortization expense related shopify warrant transactionrelated intangible believe despite impact item mentioned close gaap breakeven q thanks growth peak trading period amortization expense related shopify warrant expected decrease significantly april end december believe track turn gaap profitable mid making firstever gaap profitable year switching gear turning balance sheet cash flow statement continue generate cash quarter cash flow generated operating activity million compared million year ago ended quarter million cash cash equivalent including shortterm deposit marketable security moving financial outlook introducing guidance q raising fullyear guidance q expecting gmv range billion billion midpoint range represents growth rate versus q expect q revenue range million million midpoint range represents growth rate versus q adjusted ebitda expecting profit range million million midpoint range represents growth rate versus q full year raising guidance anticipate gmv range billion billion representing annual growth middle point range revenue expected range million million representing growth rate midpoint range adjusted ebitda expecting profit million million representing growth rate midpoint range conclusion opportunity u immense continue enable merchant around globe unlock potential global directtoconsumer business remain focused execution believe continue grow rapidly generating growing free cash flow year ahead amir nir happy answer question might operator operator thank operator instruction first question come william nance goldman sachs line open william nanceanalyst hey guy nice result morning appreciate taking question great hear commentary profitability outlook wondering note ebitda margin coming strong wondering could talk around outlook free cash flow conversion ebitda think historically youve elevated free cash flow conversion four

th quarter dip first quarter wondering could speak seasonality there still something expect thank offer korenchief financial officer sure thank offer yes mentioned seasonality cash flow free cash flow particular typically q q quite standard due peak season q positive working capital typically around q strong quarter q way around typically slowest quarter term cash flow generally speaking look full year put aside seasonality free cash flow tends slightly adjusted ebitda level expect strong q term free cash flow william nanceanalyst great thats great hear fullyear number helpful announced product enhancement buy online pick store thats kind operationally intensive get product rolled im wondering could talk kind client reception product enhancement youre thinking pricing pricing power next couple year thank nir debbicofounder president hi nir thank question continue invest product enhance solution amir mentioned bopis weve seen great traction first large enterprise client rolled shop canada shop canada aiming provide service many enterprise client global network physical retail order enable global multichannel great customer experience also field lot product enhancement optimize cost trade merchant duty drawback globale duty drawback program recently released market intend continue build capability inherently increase slightly take rate example duty drawback new service merchant adopt basically outofpocket money save money reclaim duty expense return however take cut yes able increase take rate however merchant see increase fee contrary save cost create efficiency place happy enjoy extra margin general dont expect foreseeable future increase price understand merchant going difficult time interest rate cost medium buying etc trying make efficient trade trying utilizing pricing power william nanceanalyst thats great hear pricing value appreciate taking question amir schlachetco founder chief executive officer thanks lot operator next question come andrew bauch well fargo line open andrew bauchanalyst hey guy thanks taking question wanted hit demand gen platform hundred merchant said pipeline give u sense big merchant anticipate activity level would could reconfirm believe youve mentioned past demand gen would gross margin uplift maybe could kind put way dollar frame opportunity nir debbicofounder president hi andrew thank nir mentioned yes weve recently launched borderfreecom cornerstone demand generation initiative partner brand still sorry still early inning excited longer term potential contribution brand coming year grows start adopt believe coming year affect effect also ability generate additional take think short term coming quarter focus would penetration product making sure create value brand seeing increase traffic couple hundred brand came already registered midsize largest joined already think gain traction able demonstrate value bring merchant see client coming stage dont think impact take rate top line believe building coming quarter see adoption rate value create might start see traction andrew bauchanalyst great followup would want talk managed market last time spoke believe mentioned tracking ahead plan guess kind think product perspective also tracking ahead plan think could mean far adoption managed market year ahead amir schlachetcofounder chief executive officer yes hi amir said managed market indeed tracking well go adding new feature new capability thanks continuing gain traction within shopify merchant base expect trend continue next year product gradually improves expect merchant adoption curve improve well andrew bauchanalyst great thank amir amir schlachetcofounder chief executive officer thanks andrew operator next question come koji ikeda bank america line open koji ikedaanalyst yes hey guy thanks taking question want

d ask question gmv guide fourth quarter kind looking midpoint guide implies gmv adding million sequentially thats pretty big absolute number year year look q last year sequential net add gmv million know growth wanted kind dig little bit definitely hear launch good news seeing transaction trend quarter date thats giving confidence guide ofer korenchief financial officer yes thank koji ofer basically seen two driver behind basically build confidence around q guide first one mentioned merchant successful merchant launch throughout second half year obviously call many name including larger one victoria secret harrod manchester united others basically launched plan mentioned theyre trading well theyre trading higher side expectation definitely one strong driver second one improved consumer sentiment first unlike first half surprisingly stable second half continues volatile term consumer sentiment saw mentioned previous quarter softness july deep going august however september picked nicely continued october beginning november know control may may continue volatile havent incorporated highest number seen past month two also much encouraged compared saw august also driving growth operator next question come scott berg needham line open scott berganalyst hi everyone really nice quarter guess two well start booking revenue growth year date dont know going firmer near think composition booking looked like year date know get net revenue retention fourth quarter number shifted landed really large company last year know launch went well launch larger typical didnt know youre seeing customer year try land really big market versus historical cadence might little bit small strong expansion activity time nir debbico founder president yes hi scott nir happy yeartodate result booking record level booking seen great momentum market large enterprise enterprise signing going live victoria secret actually gave u global ecommerce outside specific distribution market local distribution market go harrod took global market also domestic market uk part multilocal strategy seen also manchester united weve taken global expansion also local market part multilocal strategy see positive effect large merchant actually launching virtually almost everything give global ecommerce even though domestic ecommerce part think see robust pipeline also looking optimistic advanced stage funnel see conversion lead deal staying strong quite optimistic going continue also going scott berganalyst helpful thank ofer kind noted ga expense quarter quarter seasonal nature much weve seen historically anything led im really trying think modeling q next year might lower rate sustainably going forward ofer korenchief financial officer yes oneoff expense related timing really oneoffs q basically look q andor maybe something middle two quarter representing pace going forward obviously growing expect expense grow time base think look midpoint quarter operator next question come samad samana jefferies line open samad samanaanalyst hi good morning thanks taking question maybe first going back borderfreecom guess think youre embedding q expectation launch anything think maybe take rate implication youre thinking fourth quarter next year ofer korenchief financial officer hi samad thanks question ofer q embedding mainly expense related borderfreecom launched product expense associated dont expect see revenue yet nir mentioned currently main objective create value merchant create confidence service would say short term going least first half next year nothing significant top line expense related service already embedded q guide samad samanaanalyst great know mentioned booking prior question well guess comment harrod last major launch year imply large merchant youve booked point well wait go live guess

s case think maybe seasonality youre thinking based golives looking like similar first half nir debbicofounder president yeah understood robust pipeline already signed advanced stage project motion would launch year dont think would see material change timing versus weve seen expect would say couple decent merchant launch first half dont think q would see significant contribution havent year new merchant think q would start see rise operator next question come james faucette morgan stanley line open james faucetteanalyst great thank much wanted ask quickly take rate little bit clarification mentioned ted baker one driver service fee take rate decel strip would service fee stable maybe slightly versus last quarter similarly fulfillment alluded broadband aov increase last quarter compressing fulfillment take rate factor quarter think trajectory near medium term offer korenchief financial officer hi james offer thank question term service fee take rate yes mentioned main impact ted baker account basically put aside quite stable quarter expect see stability side going forward term fulfillment take rate always much volatile service fee different parameter impacting aov mix multi local forth quarter positive mix positive impact actually expected expectation met reality reality met expectation term aov actually slightly decreased q havent seen trend q continuing look forward try think fulfillment take rate would think q take rate bit lower embedded guidance would good base next year quarter slightly higher see ongoing take rate operator next question come chris zhang ubs line open chris zhangubs analyst hey good morning thanks taking question question whats embedded q guidance term merchant launch told youve talked completing last merchant launch year also number smaller merchant midsized merchant assume better visibility part spotify managed market wondered whats rampup pattern throughout fourth quarter last year since turnkey solution based understanding lot easier turn expect continued onboarding new shopify managed market merchant throughout rest fourth quarter even holiday shopping season offer korenchief financial officer yes thank question offer think generally speaking every year see less significant launch calendar typically around october sometimes see going november smaller merchant also onboarding launching generally speaking larger merchant decentsized merchant wouldnt go october everybody preparing peak season peak behind u typically everybody go holiday season see launch december nothing significant would impact result typically start seeing merchant getting back work sort prioritizing project midjanuary beginning february typically see additional launch coming toward end q q would standard cadence seeing well operator next question come brian peterson raymond james line open unknown speaker analyst hi thanks taking question john brian wanted ask sale cycle enterprise customer realize customer journey going different there certainly seasonality holiday wondering could speak timing sale cycle trended versus earlier year attracted larger larger brand platform maybe helping pace sale cycle quick followup nir debbicofounder president hi nir thank question enterprise client think last two year three year see improvement sale cycle timing come multiple factor u gaining much experience onboarding launching enterprise merchant getting would say clarification financial stability etc much quicker due positioning publicly traded company stable company generates cash every quarter going multiple factor sharpened year see additional potential improvement dont think material difference take sell enterprise large enterprise client sale cycle typically run around six month launching would realm three month four month depending phase depending co

mplexity ask client enterprise client would launch impact already sale funne
l said earlier already signed early advanced stage back see converting launc
hing throughout year unknown speaker analyst great thanks thats really good
color maybe followup earlier commentary managed market wondering could share
update youve added feature youre seeing maybe merchant size changing also co
lor pace merchandise managed market thank amir schlachetcofounder chief exec
utive officer yes sure amir yes expected see gradual increase pace somewhat
also size number slightly larger merchant joining gradual process dependent
collection various feature applicable various merchant dont expect kind majo
r stepups continuous gradual improvement roll feature operator next question
come patrick walravens citizen jmp line open patrick walravensanalyst great
thank congratulation yeah amir think possible impact would business end gett
ing higher tariff potential universal tariff united state amir schlachetcofo
under chief executive officer yes hi pat good question think two side positi
on one hand obviously higher tariff make harder u shopper buy outoftheus mer
chant sell believe long extremely high unreasonable tariff impact probably g
rander scale detrimental let say type good price point mainly deal hand impo
rtant remember business helping merchant overcome trade barrier way addition
al trade barrier case form tariff actually make offering valuable merchant w
ant serve u biggest ecommerce market world take prior example like introduct
ion brexit rule market historically weve seen change like brexit good busine
ss yes uk merchant took hit hand made service much valuable european merchan
t selling uk everyone overcome additional export import challenge depending
side look general thats assumption going forward patrick walravensanalyst aw
esome thank operator operator instruction next question come maddie schrage
keybanc capital market line open maddie schragekeybanc capital market analys
t hey guy wanted go back demand generation portion wondering expense guy inc
urring right going recurring expense kind onetime expense baked guidance sec
ond question geo callouts obviously u seems strong goal additional geo penet
ration thanks ofer korenchief financial officer hi maddie ofer thanks questi
on regarding expense related demand gen theyre onetime expense obviously hig
her expense around launch ongoing expense promoting product traffic borderfr
eecom expense going forward term second question nir debbicofounder presiden
t yes clear expect going forward rate investment demand generation create ma
terial difference level spend sale marketing see today ofer korenchief finan
cial officer regarding second part question mentioned seen better consumer s
entiment around globe call europe continent saw highest rise time would ment
ion really year year look ladenburg base pretty low seen good trade europe d
estination market low base europe least currently well term trading maddie s
chragekeybanc capital market analyst great thanks question operator next que
stion come mark zgutowicz benchmark line open mark zgutowiczanalyst thank ap
ology asked im jumping another earnings call term shopify managed market im
curious target roughly million million year curious gmV contribution coming
lower versus higher end range maybe talk related gmV pickup expect see perha
ps next year perhaps there copromotion shopify ofer korenchief financial off
icer yes thank question think looking year top range broad range within rang
e mentioned already mentioned call going pretty well planned regarding going
forward expect see continuous add merchant coming dont expect see step chang
e expect offering continue grow operator question time turn call amir closin
g remark amir schlachetcofounder chief executive officer thank everyone join

ing u call today conclude would like take opportunity thank amazing globale staff member worked tirelessly past month onboard new merchant support exist ing merchant make necessary preparation ensure fully ready serve global client allimportant peak trading period would also like thank ongoing support shared belief vision transform world global directtoconsumer ecommerce head holiday period behalf u globale would like wish happy successful holiday season much look forward updating call continue exciting rapid path capture immense opportunity lie ahead u next time goodbye take care operator operator sign off duration minute erica mannioninvestor relation amir schlachetcofounder chief executive officer ofer korenchief financial officer william nanceanalyst nanceanalyst nir debbicofounder president andrew bauchanalyst koji ikedaa nalyst scott berganalyst samad samanaanalyst james faucetteanalyst chris zhangubs analyst unknown speaker analyst patrick walravensanalyst pat walravens analyst maddie schragekeybanc capital market analyst mark zgutowiczanalyst globe analysis earnings call transcript article transcript conference call produced motley fool strive foolish best may error omission inaccuracy transcript article motley fool assume responsibility use content strongly encourage research including listening call reading company sec filing please see our terms conditionsfor additional detail including obligatory capitalized disclaimer liability motley fool position recommends globale online motley fool disclosure policy stock mentioned average return recommendation since inception cost basis return based previous market day close related article invest better motley fool get stock recommendation portfolio guidance motley fool premium service making world smarter happier richer motley fool right reserved market data powered byxigniteandpolygonio motley fool service around globe free tool affiliate friend

```
In [9]: #part 2
import pandas as pd
import numpy as np
import re
from sklearn.feature_extraction.text import TfidfVectorizer
from transformers import BertTokenizer, BertModel
import torch
from sklearn.preprocessing import StandardScaler

# Assuming articles_data is already loaded and contains 'cleaned_content'
# Extract cleaned content from articles for TF-IDF transformation
corpus = [article['cleaned_content'] for article in articles_data]
print("Corpus prepared for transformation.")

### Preprocess the Corpus (if needed)
def preprocess_text(text):
    """
    Preprocesses the text data by removing special characters, lowercasing,
    """
    text = re.sub(r'\W', ' ', text) # Remove special characters and punctuation
    text = text.lower() # Convert to lowercase
    text = re.sub(r'\s+', ' ', text) # Replace multiple spaces with a single space
```



```

    text = text.strip() # Remove trailing spaces
    return text

# Apply preprocessing (uncomment if corpus needs further processing)
# corpus = [preprocess_text(text) for text in corpus]
# print("Text preprocessing completed.")

### Convert Text to Numerical Features

# Option 1: Using TF-IDF Vectorization
tfidf_vectorizer = TfidfVectorizer(max_features=500, stop_words='english')
tfidf_features = tfidf_vectorizer.fit_transform(corpus).toarray()
tfidf_feature_names = tfidf_vectorizer.get_feature_names_out()

# Add TF-IDF features to articles_data
for i, article in enumerate(articles_data):
    article['tfidf_features'] = tfidf_features[i].tolist() # Convert each row to list

print("TF-IDF feature extraction completed.")

# Option 2: Using BERT Embeddings (advanced NLP technique)
# Initialize BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
bert_model = BertModel.from_pretrained('bert-base-uncased')

def get_bert_embeddings(text):
    """
    Generates BERT embeddings for a given text.
    """
    with torch.no_grad(): # Disable gradient calculation for faster processing
        inputs = tokenizer(text, return_tensors='pt', truncation=True, padding='max_length')
        outputs = bert_model(**inputs)
        # Pooling method: Using the mean of the last hidden state for sentence representation
        return outputs.last_hidden_state.mean(dim=1).squeeze().numpy()

# Apply BERT embeddings in batches to optimize for large datasets
bert_features = [get_bert_embeddings(text) for text in corpus]

# Add BERT features to articles_data
for i, article in enumerate(articles_data):
    article['bert_features'] = bert_features[i].tolist() # Convert numpy array to list

print("BERT embedding extraction completed.")

import requests

# # Example API call (use your actual API key and modify parameters as needed)
# def get_stock_price(symbol, date):
#     api_key = 'G9EC8UT11P0EG92N'
#     url = f'https://www.alphavantage.co/query?function=TIME_SERIES_DAILY_A'

```

```

#     response = requests.get(url)
#     data = response.json()

#     # Extract stock price for the given date
#     try:
#         return data['Time Series (Daily)'][date]['5. adjusted close']
#     except KeyError:
#         return None

# # Merge stock prices with article data
# for article in articles_data:

#     try:
#         raw_date = article['time_published'].split('T')[0] # Extract the
#         formatted_date = datetime.strptime(raw_date, '%Y%m%d').strftime('%Y-%m-%d')
#         article['formatted_date'] = formatted_date
#         article['stock_price'] = get_stock_price('^GSPC', formatted_date)
#     except ValueError as e:
#         print(f"Error processing date for article {article}: {e}")

```

Corpus prepared for transformation.

TF-IDF feature extraction completed.

BERT embedding extraction completed.

```

In [10]: #LDA Topic Modeling
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
articles_df = pd.DataFrame(articles_data)
# Vectorize the text
count_vect = CountVectorizer(max_df=0.95, min_df=2, stop_words='english')
dtm = count_vect.fit_transform(articles_df['cleaned_content'])

# Apply LDA
lda = LatentDirichletAllocation(n_components=5, random_state=42)
lda.fit(dtm)

# Print top words per topic
for idx, topic in enumerate(lda.components_):
    print(f"Topic {idx + 1}:")
    print([count_vect.get_feature_names_out()[i] for i in topic.argsort()[-1]

```

Topic 1:
 ['free', 'price', 'etf', 'rank', 'data', 'company', 'report', 'zacks', 'share', 'stock']

Topic 2:
 ['fashion', 'growth', 'experience', 'walmart', 'quarter', 'market', 'november', 'analyst', 'share', 'th']

Topic 3:
 ['trading', 'benzinga', 'buy', 'stock', 'target', 'rating', 'analyst', 'price', 'trade', 'option']

Topic 4:
 ['service', 'market', 'new', 'merchant', 'best', 'business', 'question', 'brand', 'quarter', 'year']

Topic 5:
 ['global', 'statement', 'transaction', 'investor', 'stock', 'share', 'million', 'market', 'financial', 'company']

```
In [11]: from wordcloud import WordCloud
import matplotlib.pyplot as plt

# Assume `lda` is your trained LDA model and `count_vect` is your CountVectorizer
# Create a word cloud for each topic
def plot_topic_wordclouds(lda_model, feature_names, num_words=10):
    """
    Generate and display word clouds for each topic in the LDA model.

    Parameters:
        lda_model: Trained LDA model
        feature_names: List of feature names from CountVectorizer
        num_words: Number of words to include in the word cloud
    """
    num_topics = lda_model.n_components
    plt.figure(figsize=(15, 10))

    for topic_idx, topic in enumerate(lda_model.components_):
        # Get the top words for the topic
        top_words = {feature_names[i]: topic[i] for i in topic.argsort()[-num_words:]}

        # Generate the word cloud
        wordcloud = WordCloud(
            background_color='white',
            width=800,
            height=400,
            max_words=num_words,
            colormap='viridis'
        ).generate_from_frequencies(top_words)

        # Plot the word cloud
        plt.subplot((num_topics + 2) // 3, 3, topic_idx + 1) # Adjust subplot
        plt.imshow(wordcloud, interpolation='bilinear')
        plt.axis('off')
```

```
plt.title(f"Topic {topic_idx + 1}", fontsize=14)

plt.tight_layout()
plt.show()

# Use feature names from the CountVectorizer
feature_names = count_vect.get_feature_names_out()

# Call the function to plot word clouds
plot_topic_wordclouds(lda, feature_names, num_words=10)
```



```
In [12]: import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.ensemble import RandomForestClassifier
import torch
import torch.nn as nn
import joblib

# Assuming articles_data is your original data and binary_feature_list contains
# Convert articles_data to a DataFrame
articles_df = pd.DataFrame(articles_data)

# Ensure binary_feature_list has the correct length
if len(binary_feature_list) != len(articles_df):
    raise ValueError("The length of binary_feature_list does not match the r

# Add the binary_feature_list to the DataFrame as a new column
articles_df['binary_trend'] = binary_feature_list

# Drop rows with missing values in the 'binary_trend' or 'overall_sentiment_
```

```

articles_df.dropna(subset=['binary_trend', 'overall_sentiment_score'], inplace=True)

# Extract features from TF-IDF and/or BERT embeddings
tfidf_features = np.array(articles_df['tfidf_features'].tolist())
bert_features = np.array(articles_df['bert_features'].tolist())

# Add overall_sentiment_score as a feature
sentiment_scores = articles_df['overall_sentiment_score'].values.reshape(-1, 1)

# Combine TF-IDF, BERT features, and sentiment scores
X = np.hstack([tfidf_features, bert_features, sentiment_scores])

# Use the binary trends as the target variable
y = articles_df['binary_trend']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Save the trained Random Forest model
joblib.dump(rf_model, "/Users/tiff1101/Downloads/trained_rf_classifier_model.joblib")

# Make predictions using the Random Forest model
y_pred_rf = rf_model.predict(X_test)

# Evaluate the model's performance
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print(f"Random Forest Accuracy: {accuracy_rf}")
print(f"Classification Report:\n{classification_report(y_test, y_pred_rf)}")

# Prepare data for LSTM (reshaping to [samples, time steps, features])
X_train_lstm = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
X_test_lstm = X_test.reshape(X_test.shape[0], 1, X_test.shape[1])

# Define LSTM model class
class StockPredictorLSTM(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(StockPredictorLSTM, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        _, (hn, _) = self.lstm(x)
        out = self.fc(hn[-1])
        return self.sigmoid(out)

```

```

# Model parameters
input_size = X_train.shape[1]
hidden_size = 50
output_size = 1 # For binary classification

# Initialize LSTM model, loss function, and optimizer
model = StockPredictorLSTM(input_size, hidden_size, output_size)
criterion = nn.BCELoss() # Binary Cross-Entropy Loss for classification
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)

# Train the LSTM model
epochs = 10
for epoch in range(epochs):
    model.train()
    X_train_tensor = torch.tensor(X_train_lstm, dtype=torch.float32)
    y_train_tensor = torch.tensor(y_train.values, dtype=torch.float32).view(-1)

    optimizer.zero_grad()
    outputs = model(X_train_tensor)
    loss = criterion(outputs, y_train_tensor)
    loss.backward()
    optimizer.step()

    print(f"Epoch {epoch+1}/{epochs}, Loss: {loss.item()}")

# Save the trained LSTM model
torch.save(model.state_dict(), "/Users/tiff1101/Downloads/trained_lstm_class")

# Evaluate the LSTM model
model.eval()
with torch.no_grad():
    X_test_tensor = torch.tensor(X_test_lstm, dtype=torch.float32)
    y_test_tensor = torch.tensor(y_test.values, dtype=torch.float32).view(-1)
    y_pred_lstm = model(X_test_tensor)
    y_pred_lstm_binary = (y_pred_lstm.numpy() > 0.5).astype(int)
    accuracy_lstm = accuracy_score(y_test, y_pred_lstm_binary)
    print(f"LSTM Accuracy: {accuracy_lstm}")
    print(f"Classification Report:\n{classification_report(y_test, y_pred_lstm_binary)}")

```

Random Forest Accuracy: 0.6

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.67	0.86	0.75	7
accuracy			0.60	10
macro avg	0.33	0.43	0.38	10
weighted avg	0.47	0.60	0.53	10

Epoch 1/10, Loss: 0.6986969709396362
 Epoch 2/10, Loss: 0.6650489568710327
 Epoch 3/10, Loss: 0.6381494998931885
 Epoch 4/10, Loss: 0.6174789667129517
 Epoch 5/10, Loss: 0.6022161245346069
 Epoch 6/10, Loss: 0.5914400219917297
 Epoch 7/10, Loss: 0.5842071175575256
 Epoch 8/10, Loss: 0.5796263217926025
 Epoch 9/10, Loss: 0.5769017934799194
 Epoch 10/10, Loss: 0.5753427743911743

LSTM Accuracy: 0.7

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.70	1.00	0.82	7
accuracy			0.70	10
macro avg	0.35	0.50	0.41	10
weighted avg	0.49	0.70	0.58	10

```
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
In [13]: #support vector machine
import pandas as pd
```

```

import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.svm import SVC
import joblib

# Assuming articles_data is your original data and binary_feature_list contains
# Convert articles_data to a DataFrame
articles_df = pd.DataFrame(articles_data)

# Ensure binary_feature_list has the correct length
if len(binary_feature_list) != len(articles_df):
    raise ValueError("The length of binary_feature_list does not match the length of articles_df")

# Add the binary_feature_list to the DataFrame as a new column
articles_df['binary_trend'] = binary_feature_list

# Drop rows with missing values in the 'binary_trend' or 'overall_sentiment_score' columns
articles_df.dropna(subset=['binary_trend', 'overall_sentiment_score'], inplace=True)

# Extract features from TF-IDF and/or BERT embeddings
tfidf_features = np.array(articles_df['tfidf_features'].tolist())
bert_features = np.array(articles_df['bert_features'].tolist())

# Add overall_sentiment_score as a feature
sentiment_scores = articles_df['overall_sentiment_score'].values.reshape(-1, 1)

# Combine TF-IDF, BERT features, and sentiment scores
X = np.hstack([tfidf_features, bert_features, sentiment_scores])

# Use the binary trends as the target variable
y = articles_df['binary_trend']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a Support Vector Machine Classifier with RBF kernel
svm_model = SVC(kernel='rbf', probability=True, random_state=42)
svm_model.fit(X_train, y_train)

# Save the trained SVM model
joblib.dump(svm_model, "/Users/tiff1101/Downloads/trained_svm_classifier_model.joblib")

# Make predictions using the SVM model
y_pred_svm = svm_model.predict(X_test)

# Evaluate the model's performance
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print(f"SVM Accuracy: {accuracy_svm}")
print(f"Classification Report:\n{classification_report(y_test, y_pred_svm)}")

```



```
# For confidence/probability scores of predictions
y_pred_prob_svm = svm_model.predict_proba(X_test)[: , 1] # Probability for c
print("Prediction Probabilities for Class 1:")
print(y_pred_prob_svm)
#fine tuning later
```

SVM Accuracy: 0.7

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.70	1.00	0.82	7
accuracy			0.70	10
macro avg	0.35	0.50	0.41	10
weighted avg	0.49	0.70	0.58	10

Prediction Probabilities for Class 1:

```
[0.73143276 0.77904661 0.7688115 0.69297022 0.71724597 0.79211234
 0.65718464 0.64383917 0.70209638 0.05726466]
```

```
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_class
ification.py:1531: UndefinedMetricWarning: Precision is ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_class
ification.py:1531: UndefinedMetricWarning: Precision is ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_class
ification.py:1531: UndefinedMetricWarning: Precision is ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
In [14]: #feedforward neural network
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import to_categorical

# Assuming articles_data is your original data and binary_feature_list conta
```

```

# Convert articles_data to a DataFrame
articles_df = pd.DataFrame(articles_data)

# Ensure binary_feature_list has the correct length
if len(binary_feature_list) != len(articles_df):
    raise ValueError("The length of binary_feature_list does not match the r

# Add the binary_feature_list to the DataFrame as a new column
articles_df['binary_trend'] = binary_feature_list

# Drop rows with missing values in the 'binary_trend' or 'overall_sentiment_
articles_df.dropna(subset=['binary_trend', 'overall_sentiment_score'], inplace=

# Extract features from TF-IDF and/or BERT embeddings
tfidf_features = np.array(articles_df['tfidf_features'].tolist())
bert_features = np.array(articles_df['bert_features'].tolist())

# Add overall_sentiment_score as a feature
sentiment_scores = articles_df['overall_sentiment_score'].values.reshape(-1,

# Combine TF-IDF, BERT features, and sentiment scores
X = np.hstack([tfidf_features, bert_features, sentiment_scores])

# Use the binary trends as the target variable
y = articles_df['binary_trend']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran

# Standardize the feature data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Convert target variable to categorical (one-hot encoding)
y_train_categorical = to_categorical(y_train, num_classes=2)
y_test_categorical = to_categorical(y_test, num_classes=2)

# Build the Feedforward Neural Network
model = Sequential([
    Dense(128, input_dim=X_train.shape[1], activation='relu'), # Input layer
    Dropout(0.3), # Dropout for regularization
    Dense(64, activation='relu'), # Hidden layer
    Dropout(0.3),
    Dense(32, activation='relu'), # Hidden layer
    Dense(2, activation='softmax') # Output layer (binary classification)
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.001),

```

```
        loss='categorical_crossentropy',
        metrics=['accuracy'])

# Print model summary
model.summary()

# Define early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_

# Train the model
history = model.fit(X_train, y_train_categorical,
                    validation_split=0.2,
                    epochs=50,
                    batch_size=16,
                    callbacks=[early_stopping],
                    verbose=1)

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test_categorical, verbose=0)
print(f"Neural Network Accuracy: {accuracy:.4f}")

# Make predictions
y_pred_nn = model.predict(X_test)
y_pred_classes = np.argmax(y_pred_nn, axis=1)

# Evaluate predictions
print(f"Classification Report:\n{classification_report(y_test, y_pred_classes)}")

# Save the trained model
model.save('/Users/tiff1101/Downloads/trained_dense_nn_with_sentiment.h5')

# Optional: Visualize training history
import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
#number of layers and nodes
```

```
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
```

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"


Layer (type)	Output Shape	Par
dense (Dense)	(None, 128)	162
dropout (Dropout)	(None, 128)	
dense_1 (Dense)	(None, 64)	8
dropout_1 (Dropout)	(None, 64)	
dense_2 (Dense)	(None, 32)	2
dense_3 (Dense)	(None, 2)	

Total params: 172,962 (675.63 KB)


Trainable params: 172,962 (675.63 KB)

Non-trainable params: 0 (0.00 B)


Epoch 1/50

2/2  1s 70ms/step - accuracy: 0.6458 - loss: 1.4508 - val_accuracy: 0.8750 - val_loss: 0.4889


Epoch 2/50

2/2  0s 10ms/step - accuracy: 0.6875 - loss: 0.7286 - val_accuracy: 0.8750 - val_loss: 0.5888


Epoch 3/50

2/2  0s 10ms/step - accuracy: 0.7083 - loss: 0.3620 - val_accuracy: 0.8750 - val_loss: 0.6359


Epoch 4/50

2/2  0s 9ms/step - accuracy: 0.7917 - loss: 0.4834 - val_accuracy: 0.8750 - val_loss: 0.6812

Epoch 5/50

2/2  0s 10ms/step - accuracy: 0.8333 - loss: 0.3209 - val_accuracy: 0.7500 - val_loss: 0.7380

Epoch 6/50

2/2  0s 10ms/step - accuracy: 0.9167 - loss: 0.2989 - val_accuracy: 0.7500 - val_loss: 0.7853

Neural Network Accuracy: 0.7000

1/1  0s 19ms/step

```
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

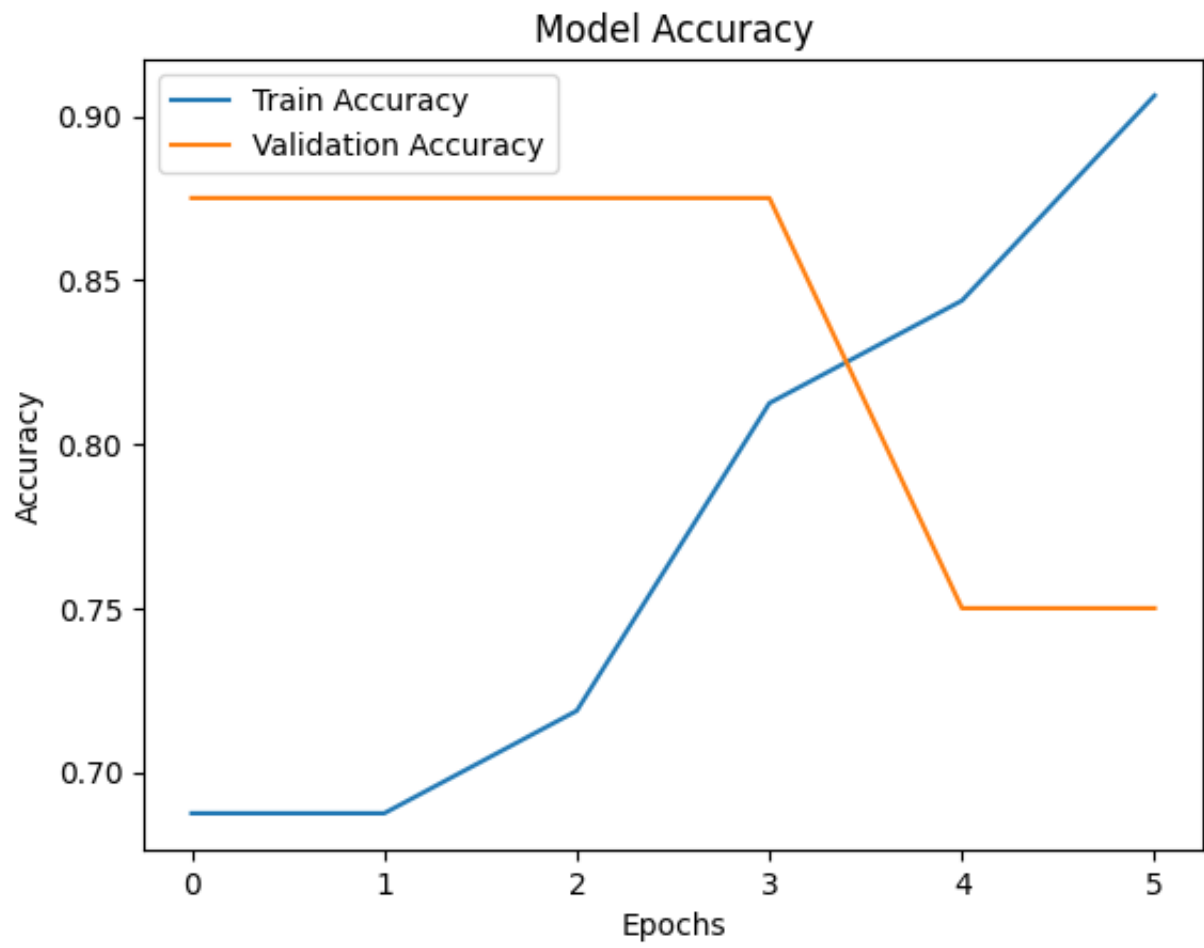
```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

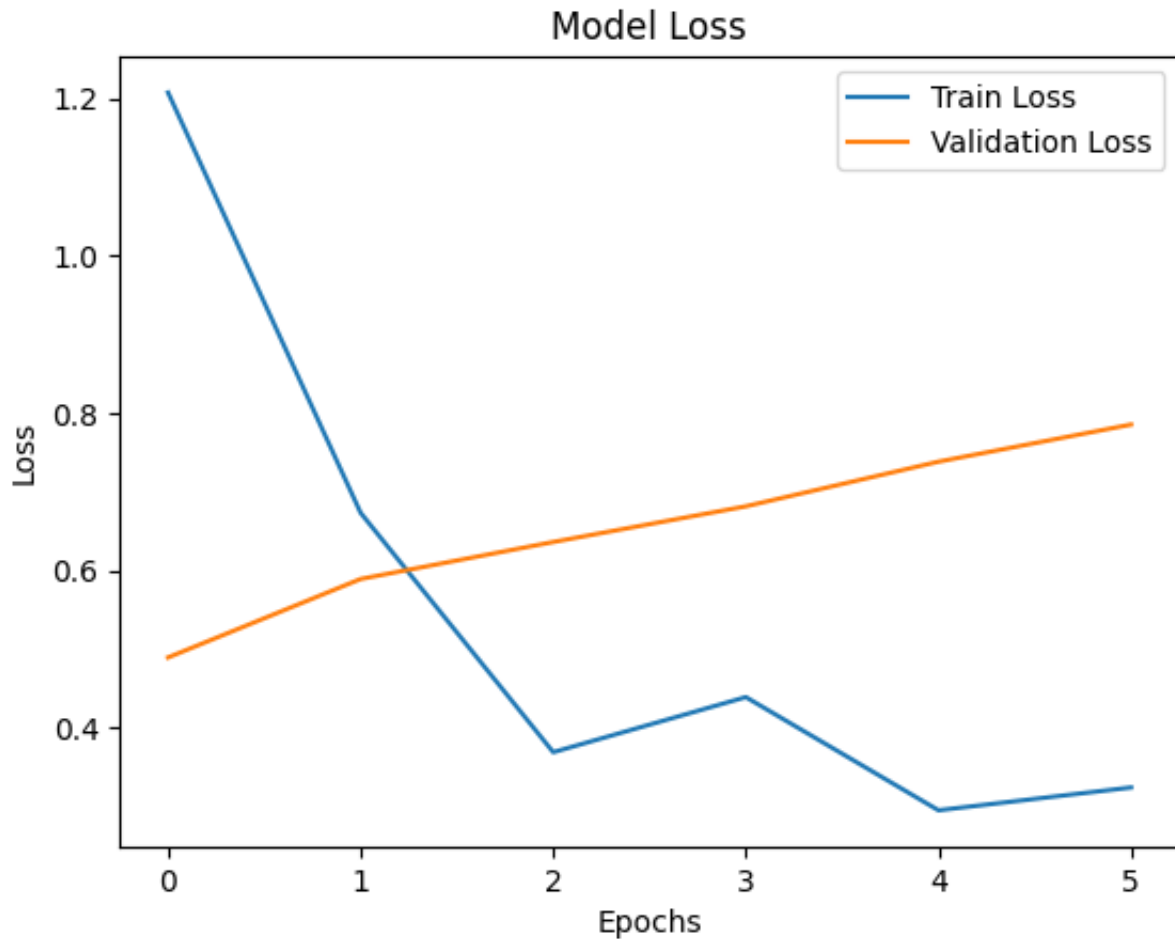
```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.
```

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.70	1.00	0.82	7
accuracy			0.70	10
macro avg	0.35	0.50	0.41	10
weighted avg	0.49	0.70	0.58	10





In [15]: *#naive bayes*

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import accuracy_score, classification_report
from sklearn.naive_bayes import MultinomialNB
import joblib

# Assuming articles_data is your original data and binary_feature_list contains
# Convert articles_data to a DataFrame
articles_df = pd.DataFrame(articles_data)

# Ensure binary_feature_list has the correct length
if len(binary_feature_list) != len(articles_df):
    raise ValueError("The length of binary_feature_list does not match the r

# Add the binary_feature_list to the DataFrame as a new column
articles_df['binary_trend'] = binary_feature_list

# Drop rows with missing values in the 'binary_trend' or 'overall_sentiment_
```

```

articles_df.dropna(subset=['binary_trend', 'overall_sentiment_score'], inplace=True)

# Preprocess text data (assuming articles_data has a 'cleaned_content' column)
corpus = articles_df['cleaned_content'].tolist()

# Extract features using TF-IDF
tfidf_vectorizer = TfidfVectorizer(max_features=1000, stop_words='english')
X_tfidf = tfidf_vectorizer.fit_transform(corpus).toarray()

# Normalize sentiment scores to be non-negative
sentiment_scores = articles_df['overall_sentiment_score'].values
min_sentiment_score = sentiment_scores.min()
sentiment_scores_normalized = sentiment_scores - min_sentiment_score # Shift to non-negative
sentiment_scores_normalized = sentiment_scores_normalized.reshape(-1, 1)

# Combine TF-IDF features and normalized sentiment scores
X = np.hstack([X_tfidf, sentiment_scores_normalized])

# Use the binary trends as the target variable
y = articles_df['binary_trend']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a Naive Bayes Classifier
nb_model = MultinomialNB()
nb_model.fit(X_train, y_train)

# Save the trained Naive Bayes model
joblib.dump(nb_model, "/Users/tiff1101/Downloads/trained_nb_classifier_model.pkl")

# Make predictions using the Naive Bayes model
y_pred_nb = nb_model.predict(X_test)

# Evaluate the model's performance
accuracy_nb = accuracy_score(y_test, y_pred_nb)
print(f"Naive Bayes Accuracy: {accuracy_nb}")
print(f"Classification Report:\n{classification_report(y_test, y_pred_nb)}")

# Save TF-IDF vectorizer for future use
joblib.dump(tfidf_vectorizer, "/Users/tiff1101/Downloads/tfidf_vectorizer.pkl")

# Feature analysis
feature_names = tfidf_vectorizer.get_feature_names_out()
top_n = min(20, len(feature_names)) # Ensure we don't request more features than available
class_labels = nb_model.classes_

print("\nTop features for each class:")
for i, class_label in enumerate(class_labels):
    # Extract the top features for the current class
    top_features = feature_names[top_n * i : top_n * (i + 1)]
    print(f"Class: {class_label}")
    print(top_features)

```



```

top_features_idx = np.argsort(nb_model.feature_log_prob_[i])[-top_n:]
top_features = [(feature_names[j], nb_model.feature_log_prob_[i][j]) for
top_features = sorted(top_features, key=lambda x: x[1], reverse=True)
print(f"Class {class_label}:")
for feature, weight in top_features:
    print(f"    {feature}: {weight:.4f}")

```

Naive Bayes Accuracy: 0.7

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.70	1.00	0.82	7
accuracy			0.70	10
macro avg	0.35	0.50	0.41	10
weighted avg	0.49	0.70	0.58	10

Top features for each class:

Class 0:

option: -6.2374
 bank: -6.2914
 trade: -6.3940
 price: -6.4075
 kinder: -6.4398
 target: -6.4400
 parcel: -6.4673
 archegos: -6.4727
 ftc: -6.4820
 analyst: -6.4842
 astra: -6.4895
 best: -6.4938
 pbms: -6.5266
 morgan: -6.5303
 institution: -6.5337
 rating: -6.5505
 hope: -6.5615
 financial: -6.5640
 lab: -6.5668

Class 1:

option: -5.8631
 price: -6.0442
 share: -6.1116
 trade: -6.1888
 company: -6.1971
 stock: -6.2122
 analyst: -6.2432
 rating: -6.3423
 market: -6.3426

```
trump: -6.3490
allbirds: -6.3542
investor: -6.3579
target: -6.3763
buy: -6.3965
better: -6.3988
trading: -6.4307
data: -6.4405
technology: -6.4409
million: -6.4588
```

```
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_class
ification.py:1531: UndefinedMetricWarning: Precision is ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_class
ification.py:1531: UndefinedMetricWarning: Precision is ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_class
ification.py:1531: UndefinedMetricWarning: Precision is ill-defined and bein
g set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
In [16]: #transformer-based NLP model (BERT)
import pandas as pd
import numpy as np
from transformers import BertTokenizer, BertForSequenceClassification
from transformers import AdamW
from torch.utils.data import Dataset, DataLoader
import torch
import torch.nn as nn
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.ensemble import RandomForestClassifier

# Step 1: Dataset Preparation
# Assuming `articles_data` contains your articles and `binary_feature_list`
articles_df = pd.DataFrame(articles_data)

# Ensure binary_feature_list matches the articles
if len(binary_feature_list) != len(articles_df):
    raise ValueError("The length of binary_feature_list does not match the r

# Add the binary_feature_list to the DataFrame
articles_df['binary_trend'] = binary_feature_list

# Drop rows with missing values in text or target
```

```

articles_df.dropna(subset=['cleaned_content', 'binary_trend'], inplace=True)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    articles_df['cleaned_content'], articles_df['binary_trend'], test_size=0.2
)

# Step 2: Custom Dataset for PyTorch
class StockPredictionDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_len):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __len__(self):
        return len(self.texts)

    def __getitem__(self, idx):
        text = str(self.texts.iloc[idx])
        label = self.labels.iloc[idx]

        encoding = self.tokenizer(
            text,
            max_length=self.max_len,
            padding="max_length",
            truncation=True,
            return_tensors="pt"
        )

        return {
            'input_ids': encoding['input_ids'].squeeze(0),
            'attention_mask': encoding['attention_mask'].squeeze(0),
            'label': torch.tensor(label, dtype=torch.long)
        }

# Step 3: Tokenizer and Dataset Preparation
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
max_len = 128

train_dataset = StockPredictionDataset(X_train, y_train, tokenizer, max_len)
test_dataset = StockPredictionDataset(X_test, y_test, tokenizer, max_len)

train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16)

# Step 4: Model Initialization
model = BertForSequenceClassification.from_pretrained('bert-base-uncased', r
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

```

```
# Step 5: Optimizer and Loss Function
optimizer = AdamW(model.parameters(), lr=2e-5)
criterion = nn.CrossEntropyLoss()

# Step 6: Training Loop
epochs = 3
for epoch in range(epochs):
    model.train()
    total_loss = 0

    for batch in train_loader:
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['label'].to(device)

        optimizer.zero_grad()

        outputs = model(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        logits = outputs.logits

        total_loss += loss.item()
        loss.backward()
        optimizer.step()

    avg_loss = total_loss / len(train_loader)
    print(f"Epoch {epoch + 1}/{epochs}, Loss: {avg_loss:.4f}")

# Step 7: Evaluation
model.eval()
y_pred = []
y_true = []

with torch.no_grad():
    for batch in test_loader:
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['label'].to(device)

        outputs = model(input_ids, attention_mask=attention_mask)
        logits = outputs.logits
        predictions = torch.argmax(logits, dim=1)

        y_pred.extend(predictions.cpu().numpy())
        y_true.extend(labels.cpu().numpy())

# Evaluation Metrics
accuracy = accuracy_score(y_true, y_pred)
print(f"Accuracy: {accuracy}")
```

```

print("Classification Report:")
print(classification_report(y_true, y_pred))

# Save the trained model
model.save_pretrained("/Users/tiff1101/Downloads/bert_stock_classifier/")
tokenizer.save_pretrained("/Users/tiff1101/Downloads/bert_stock_classifier/")

```

Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are newly initialized: ['classifier.bias', 'classifier.weight']

You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/transformers/optimization.py:591: FutureWarning: This implementation of AdamW is deprecated and will be removed in a future version. Use the PyTorch implementation torch.optim.AdamW instead, or set `no_deprecation_warning=True` to disable this warning

```
warnings.warn(
```

Epoch 1/3, Loss: 0.5954

Epoch 2/3, Loss: 0.5366

Epoch 3/3, Loss: 0.5039

Accuracy: 0.7

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.70	1.00	0.82	7
accuracy			0.70	10
macro avg	0.35	0.50	0.41	10
weighted avg	0.49	0.70	0.58	10

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
Out[16]: ('/Users/tiff1101/Downloads/bert_stock_classifier/tokenizer_config.json',
'/Users/tiff1101/Downloads/bert_stock_classifier/special_tokens_map.json',
'/Users/tiff1101/Downloads/bert_stock_classifier/vocab.txt',
'/Users/tiff1101/Downloads/bert_stock_classifier/added_tokens.json')
```

```
In [17]: #ensemble method/model stacking
import pandas as pd
import numpy as np
from sklearn.ensemble import StackingClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
import joblib

# Step 1: Data Preparation
# Assuming 'articles_data' contains your articles and 'binary_feature_list'
articles_df = pd.DataFrame(articles_data)

# Ensure binary_feature_list matches the number of articles
if len(binary_feature_list) != len(articles_df):
    raise ValueError("The length of binary_feature_list does not match the number of articles")

# Add the binary_feature_list to the DataFrame
articles_df['binary_trend'] = binary_feature_list

# Drop rows with missing values in required columns
articles_df.dropna(subset=['tfidf_features', 'bert_features', 'overall_sentiment_score'], inplace=True)

# Step 2: Feature Extraction
# Extract features from TF-IDF and BERT embeddings
tfidf_features = np.array(articles_df['tfidf_features'].tolist())
bert_features = np.array(articles_df['bert_features'].tolist())

# Add overall sentiment score as a feature
sentiment_scores = articles_df['overall_sentiment_score'].values.reshape(-1, 1)

# Combine all features into a single feature matrix
X = np.hstack([tfidf_features, bert_features, sentiment_scores])

# Target variable
y = articles_df['binary_trend']

# Step 3: Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 4: Define Base Models
# Define individual models to be used in stacking
base_models = [
    LogisticRegression(),
    RandomForestClassifier(),
    GradientBoostingClassifier(),
    SVC()
]
```

```

    ('random_forest', RandomForestClassifier(n_estimators=100, random_state=
    ('gradient_boosting', GradientBoostingClassifier(n_estimators=100, rando
    ('svc', SVC(kernel='rbf', probability=True, random_state=42))
]

# Step 5: Define the Meta Model
# Logistic Regression as the meta-classifier
meta_model = LogisticRegression()

# Step 6: Create the Stacking Ensemble
stacking_model = StackingClassifier(
    estimators=base_models,
    final_estimator=meta_model,
    cv=5, # 5-fold cross-validation for training the meta-model
    stack_method='predict_proba' # Use probabilities from base models
)

# Step 7: Train the Stacking Model
stacking_model.fit(X_train, y_train)

# Step 8: Evaluate the Stacking Model
y_pred = stacking_model.predict(X_test)

# Accuracy and Classification Report
accuracy = accuracy_score(y_test, y_pred)
print(f"Stacking Ensemble Accuracy: {accuracy}")
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Step 9: Save the Stacking Model
joblib.dump(stacking_model, "/Users/tiff1101/Downloads/trained_stacking_class

# Step 10: Feature Importance (Optional)
# Extract feature importances from Random Forest (if applicable)
for name, model in stacking_model.named_estimators_.items():
    if hasattr(model, "feature_importances_"):
        print(f"Feature importances for {name}:")
        print(model.feature_importances_)

# Step 11: Load and Predict (Example)
# To load the model later and make predictions:
loaded_model = joblib.load("/Users/tiff1101/Downloads/trained_stacking_class
y_loaded_pred = loaded_model.predict(X_test)
print(f"Loaded Model Accuracy: {accuracy_score(y_test, y_loaded_pred)}")

```

Stacking Ensemble Accuracy: 0.7

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	3
1	0.70	1.00	0.82	7
accuracy			0.70	10
macro avg	0.35	0.50	0.41	10
weighted avg	0.49	0.70	0.58	10

Feature importances for random_forest:

[0. 0. 0. ... 0. 0. 0.01426744]

Feature importances for gradient_boosting:

[2.49206264e-07 0.00000000e+00 0.00000000e+00 ... 0.00000000e+00
0.00000000e+00 0.00000000e+00]

Loaded Model Accuracy: 0.7

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

/opt/anaconda3/envs/myenv/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

```
In [18]: #Visualizations
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import nltk
from nltk.corpus import stopwords
from nltk import FreqDist
from nltk.util import bigrams
import pandas as pd
import networkx as nx
from collections import Counter

articles_df = pd.DataFrame(articles_data)

# Download NLTK stopwords
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
```



```

# Ensure you have a `cleaned_content` and `overall_sentiment_score` column i
if 'cleaned_content' not in articles_df.columns or 'overall_sentiment_score'
    raise ValueError("The DataFrame must contain 'cleaned_content' and 'over

# Step 1: Sentiment Bar Chart
def plot_sentiment_bar_chart(df):
    """a
    Plots a bar chart of sentiment scores.
    """
    plt.figure(figsize=(8, 6))
    sns.histplot(df['overall_sentiment_score'], bins=20, kde=False, color='b
    plt.title('Distribution of Sentiment Scores')
    plt.xlabel('Sentiment Score')
    plt.ylabel('Frequency')
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.show()

plot_sentiment_bar_chart(articles_df)

# Step 2: Directed Bigram Network Graph
def plot_directed_bigram_network(df, top_n=20, min_count=2):
    """
    Plots a directed bigram network from the cleaned text with control over

    Parameters:
        df (DataFrame): The dataframe containing the cleaned text data.
        top_n (int): The maximum number of bigrams to include in the network
        min_count (int): Minimum frequency of bigrams to include.
    """
    # Preprocess text and extract bigrams
    all_words = ' '.join(df['cleaned_content']).lower().split()
    filtered_words = [word for word in all_words if word not in stop_words a
    bigram_list = list(bigrams(filtered_words))

    # Count bigrams
    bigram_counts = Counter(bigram_list)

    # Select top N bigrams by frequency
    bigram_df = pd.DataFrame(bigram_counts.items(), columns=['bigram', 'count
    bigram_df = bigram_df[bigram_df['count'] >= min_count].sort_values(by='c

    # Create a directed graph
    directed_bigram_graph = nx.DiGraph()
    for bigram, count in bigram_df.itertuples(index=False): # Use itertuple
        word1, word2 = bigram # Unpack the bigram tuple
        directed_bigram_graph.add_edge(word1, word2, weight=count)

    # Draw the directed graph

```

```

plt.figure(figsize=(10, 8))
pos = nx.spring_layout(directed_bigram_graph, k=0.5)
nx.draw_networkx(
    directed_bigram_graph, pos, with_labels=True,
    node_size=700, font_size=10,
    edge_color='gray', arrows=True, arrowsize=20
)
plt.title(f"Directed Bigram Network Graph (Top {top_n} Bigrams)")
plt.show()

# Example usage
plot_directed_bigram_network(articles_df, top_n=15, min_count=3)

# Step 3: Word Cloud
def plot_word_cloud(df):
    """
    Plots a word cloud from the cleaned text.
    """
    text = ' '.join(df['cleaned_content'])
    wordcloud = WordCloud(stopwords=stop_words, background_color='white', wi

    plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title("Word Cloud of Article Content")
    plt.show()

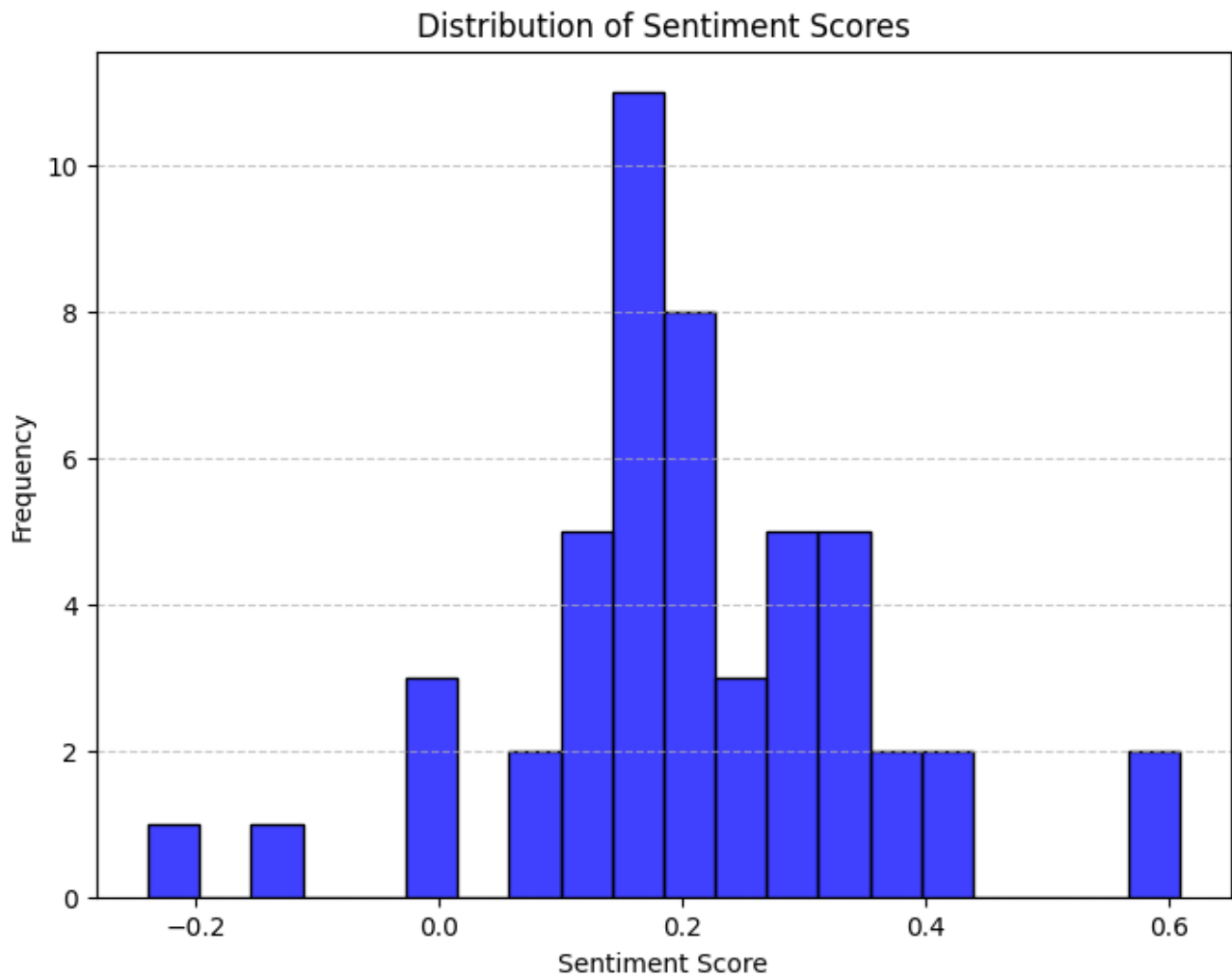
plot_word_cloud(articles_df)

```

```

[nltk_data] Downloading package stopwords to
[nltk_data]      /Users/tiff1101/nltk_data...
[nltk_data] Package stopwords is already up-to-date!

```



price target reserved right open interest care stock affect news breaking report free rating analyst alert insight provide investment motley fool

