📊 Multi-Source Market Intelligence System:

This notebook builds an end-to-end data analysis pipeline using:

- Market price data (API)
- News headlines (GDELT)
- Sentiment-based feature engineering
- Time-series analysis and insights

In [300…

```
!pip install pandas numpy requests matplotlib seaborn vaderSentiment
```

```
Requirement already satisfied: pandas in /opt/anaconda3/envs/Assignments/l
ib/python3.13/site-packages (2.3.3)
Requirement already satisfied: numpy in /opt/anaconda3/envs/Assignments/li
b/python3.13/site-packages (2.3.2)
Requirement already satisfied: requests in /opt/anaconda3/envs/Assignment
s/lib/python3.13/site-packages (2.32.5)
Requirement already satisfied: matplotlib in /opt/anaconda3/envs/Assignmen
ts/lib/python3.13/site-packages (3.10.6)
Requirement already satisfied: seaborn in /opt/anaconda3/envs/Assignments/
lib/python3.13/site-packages (0.13.2)
Requirement already satisfied: vaderSentiment in /opt/anaconda3/envs/Assig
nments/lib/python3.13/site-packages (3.3.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /opt/anaconda3/en
vs/Assignments/lib/python3.13/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/anaconda3/envs/Assignm
ents/lib/python3.13/site-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /opt/anaconda3/envs/Assig
nments/lib/python3.13/site-packages (from pandas) (2025.2)
Requirement already satisfied: charset_normalizer<4,>=2 in /opt/anaconda3/
envs/Assignments/lib/python3.13/site-packages (from requests) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /opt/anaconda3/envs/Assignm
ents/lib/python3.13/site-packages (from requests) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /opt/anaconda3/envs/A
ssignments/lib/python3.13/site-packages (from requests) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in /opt/anaconda3/envs/A
ssignments/lib/python3.13/site-packages (from requests) (2025.10.5)
Requirement already satisfied: contourpy>=1.0.1 in /opt/anaconda3/envs/Ass
ignments/lib/python3.13/site-packages (from matplotlib) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /opt/anaconda3/envs/Assignm
ents/lib/python3.13/site-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /opt/anaconda3/envs/As
signments/lib/python3.13/site-packages (from matplotlib) (4.59.2)
Requirement already satisfied: kiwisolver>=1.3.1 in /opt/anaconda3/envs/As
signments/lib/python3.13/site-packages (from matplotlib) (1.4.9)
Requirement already satisfied: packaging>=20.0 in /opt/anaconda3/envs/Assi
gnments/lib/python3.13/site-packages (from matplotlib) (25.0)
Requirement already satisfied: pillow>=8 in /opt/anaconda3/envs/Assignment
s/lib/python3.13/site-packages (from matplotlib) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /opt/anaconda3/envs/Ass
ignments/lib/python3.13/site-packages (from matplotlib) (3.2.3)
Requirement already satisfied: six>=1.5 in /opt/anaconda3/envs/Assignment
s/lib/python3.13/site-packages (from python-dateutil>=2.8.2->pandas) (1.1
7.0)
```

In [301…

```python
import requests #lets python talk to the internet
import pandas as pd
import numpy as np

import urllib.parse

import matplotlib.pyplot as plt
import seaborn as sns

from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer #Imp
# rule-based sentiment analyzer: dosen't train model but uses predefined
```

🔷 STEP 1: ENVIRONMENT SETUP & LIBRARY IMPORTS

In [302…
```
pd.set_option("Display.max_columns", None) #Show all columns while displa
pd.set_option("Display.float_format","{:.4f}".format) #Format floating nu

plt.style.use("seaborn-v0_8") #Pre-defined ploting theme
sns.set_context("talk") #Sclaes plot elements (paper = small, notebook =

print("Environment Setup Complete!")
```

```
Environment Setup Complete!
```

🔷 STEP 2: FETCH MARKET DATA (CoinGecko API)

In this step, we fetch historical cryptocurrency market data. This data will serve as the backbone for our time-series analysis.

In [303…
```
url = "https://api.coingecko.com/api/v3/coins/bitcoin/market_chart"

params = {
    "vs_currency": "usd", #Prices in USD
    "days": 180, #Last 180 days
    "interval": "daily" #daily data
}

response = requests.get(url, params = params) #API request

response.status_code #Anything other than 200 stop and debug
```

Out[303…
```
200
```

In [304…
```
data = response.json() #Formats our response to JSON

data.keys() #Return keys of our data
```

Out[304…
```
dict_keys(['prices', 'market_caps', 'total_volumes'])
```

In [305…
```
prices = data["prices"]
print(prices[:5]) #[timestamp, value] -> time and bitcoin price at that t
```

```
[[1752364800000, 117418.95745007684], [1752451200000, 119117.55666327637],
[1752537600000, 119833.67446712355], [1752624000000, 117678.19493404306],
[1752710400000, 118748.1627367753]]
```

In [306…
```
price_df = pd.DataFrame(prices, columns=["timestamp","price"]) #converts
price_df.head()
```

Out[306…

	timestamp	price
0	1752364800000	117418.9575
1	1752451200000	119117.5567
2	1752537600000	119833.6745
3	1752624000000	117678.1949
4	1752710400000	118748.1627

In [307…
```
#Convert timestamp to date
price_df["date"] = pd.to_datetime(price_df["timestamp"], unit="ms").dt.da
price_df = price_df[["date","price"]]
price_df.head()
```

Out[307…

	date	price
0	2025-07-13	117418.9575
1	2025-07-14	119117.5567
2	2025-07-15	119833.6745
3	2025-07-16	117678.1949
4	2025-07-17	118748.1627

In [308…
```
price_df.shape
price_df.info()
price_df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181 entries, 0 to 180
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    181 non-null    object
 1   price   181 non-null    float64
dtypes: float64(1), object(1)
memory usage: 3.0+ KB
```

Out[308…

	price
count	181.0000
mean	106233.7453
std	12039.7923
min	84682.6243
25%	92036.7255
50%	110708.6696
75%	115970.5849
max	124773.5082

In [309…
```
price_df.isnull().sum()
```

Out[309…
```
date     0
price    0
dtype: int64
```

In [310…
```
price_df.duplicated().sum()
```

Out[310…
```
np.int64(0)
```

In [311…
```
price_df["date"].min(), price_df["date"].max()
```

Out[311… (datetime.date(2025, 7, 13), datetime.date(2026, 1, 8))

In [312…
```
price_df["price"] = price_df["price"].interpolate()
price_df = price_df.drop_duplicates()
price_df.isnull().sum()
```

Out[312…
```
date     0
price    0
dtype: int64
```

🔷 STEP 3: NEWS DATA COLLECTION (GDELT)

In [313…
```
news_url = "https://api.gdeltproject.org/api/v2/doc/doc"

query = "(bitcoin OR cryptocurrency OR crypto market)" #News articles may
start_date = "20250701000000"   # YYYYMMDDHHMMSS
end_date   = "20260101000000"

news_params = {
    "query": query,
    "mode": "ArtList", #Return list of articles
    "format": "JSON",
    "maxrecords": 250, #Max articles per call
    "startdatetime": start_date,
    "enddatetime": end_date
}
```

In [314…
```
url = news_url + "?" + urllib.parse.urlencode(news_params) #to see what w
url
```

Out[314…
```
'https://api.gdeltproject.org/api/v2/doc/doc?query=%28bitcoin+OR+cryptocurrency+OR+crypto+market%29&mode=ArtList&format=JSON&maxrecords=250&startdatetime=20250701000000&enddatetime=20260101000000'
```

In [315…
```
news_response = requests.get(url)

news_response.status_code
```

Out[315… 200

In [316…
```
news_data = news_response.json()

news_data.keys()
```

Out[316… dict_keys(['articles'])

In [317…
```
articles = news_data["articles"]

len(articles) #how many news articles we fetched in this API
```

Out[317… 250

In [318…
```
news_df = pd.DataFrame(articles)

news_df.head()
```

Out[318...

	url
0	https://finance.yahoo.com/news/buy-bitcoin-whi...
1	https://www.theguardian.com/technology/2025/de...
2	https://finance.yahoo.com/news/bitcoin-ethereu...
3	https://charter97.org/en/news/2025/11/6/661980/ https://qnt91x.c97.org/en/news/2025
4	https://finance.yahoo.com/news/2-best-cryptocu...

In [319...

```python
news_df = news_df[["seendate","title","domain"]]
```

In [320...

```python
news_df["date"] = pd.to_datetime(news_df["seendate"]).dt.date
news_df = news_df.drop(columns=["seendate"])

news_df.head()
```

Out[320...

	title	domain	date
0	Should You Buy Bitcoin While It Under $100 , 0...	finance.yahoo.com	2025-12-07
1	Cryptocurrency slump erases 2025 financial gai...	theguardian.com	2025-12-29
2	Bitcoin , Ethereum , Dogecoin Trade Flat , Whi...	finance.yahoo.com	2025-12-24
3	Trump : Were Turning The U . S . Into A Bitcoi...	charter97.org	2025-11-06
4	The 2 Best Cryptocurrencies to Buy With $100 R...	finance.yahoo.com	2025-12-20

In [321...

```python
news_df.shape
news_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   title   250 non-null    object
 1   domain  250 non-null    object
 2   date    250 non-null    object
dtypes: object(3)
memory usage: 6.0+ KB
```

In [322...

```python
news_df.isnull().sum()
```

Out[322…
```
title     0
domain    0
date      0
dtype: int64
```

In [323…
```
(news_df["title"].str.strip() == "").sum() #check for empty or blank titl
```

Out[323…
```
np.int64(0)
```

In [324…
```
news_df.duplicated(subset = ["title","date"]).sum()
```

Out[324…
```
np.int64(29)
```

In [325…
```
news_df["date"].min(),news_df["date"].max()
```

Out[325…
```
(datetime.date(2025, 10, 3), datetime.date(2026, 1, 1))
```

In [326…
```
news_df = news_df.reset_index(drop = True) #reset the index of dataFrame
```

🔷 STEP 4: SENTIMENT FEATURE ENGINEERING (VADER)

In this step, we convert news headlines into numeric sentiment scores using a rule-based sentiment analyzer. These scores will later be aggregated and aligned with market data.

In [327…
```
analyzer = SentimentIntensityAnalyzer()
```

In [328…
```
sample_text = news_df.loc[0,"title"]
sample_text
```

Out[328…
```
'Should You Buy Bitcoin While It Under $100 , 000 ? '
```

In [329…
```
analyzer.polarity_scores(sample_text)
# neg = negative, neu = neutral, pos = positive, compound = overall senti
#Compound: >=  +0.05 positive
#          <=  -0.05 negative
#      between neutral
```

Out[329…
```
{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

In [330…
```
news_df["sentiment_dict"] = news_df["title"].apply(
    lambda x: analyzer.polarity_scores(x)
)
```

In [331…
```
news_df.head()
```

Out [331...

	title	domain	date	sentiment_dict
0	Should You Buy Bitcoin While It Under $100 , 0...	finance.yahoo.com	2025-12-07	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...
1	Cryptocurrency slump erases 2025 financial gai...	theguardian.com	2025-12-29	{'neg': 0.0, 'neu': 0.468, 'pos': 0.532, 'comp...
2	Bitcoin , Ethereum , Dogecoin Trade Flat , Whi...	finance.yahoo.com	2025-12-24	{'neg': 0.0, 'neu': 0.891, 'pos': 0.109, 'comp...
3	Trump : Were Turning The U . S . Into A Bitcoi...	charter97.org	2025-11-06	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...
4	The 2 Best Cryptocurrencies to Buy With $100 R...	finance.yahoo.com	2025-12-20	{'neg': 0.0, 'neu': 0.682, 'pos': 0.318, 'comp...

In [332...

```
news_df["sentiment_neg"] = news_df["sentiment_dict"].apply(lambda x: x["n
news_df["sentiment_neu"] = news_df["sentiment_dict"].apply(lambda x: x["n
news_df["sentiment_pos"] = news_df["sentiment_dict"].apply(lambda x: x["p
news_df["sentiment_compound"] = news_df["sentiment_dict"].apply(lambda x:

news_df = news_df.drop(columns=["sentiment_dict"])
```

In [333...

```
news_df.head()
```

Out [333...

	title	domain	date	sentiment_neg	sentiment_neu	senti
0	Should You Buy Bitcoin While It Under $100 , 0...	finance.yahoo.com	2025-12-07	0.0000	1.0000	
1	Cryptocurrency slump erases 2025 financial gai...	theguardian.com	2025-12-29	0.0000	0.4680	
2	Bitcoin , Ethereum , Dogecoin Trade Flat , Whi...	finance.yahoo.com	2025-12-24	0.0000	0.8910	
3	Trump : Were Turning The U . S . Into A Bitcoi...	charter97.org	2025-11-06	0.0000	1.0000	
4	The 2 Best Cryptocurrencies to Buy With $100 R...	finance.yahoo.com	2025-12-20	0.0000	0.6820	

🔷 STEP 5: DAILY SENTIMENT AGGREGATION

As our market price data has price per day whereas news consists of various articles every day so we need to aggregate the articles per day in our news dataFrame

In [334...

```
news_df["date"].value_counts().head()
```

Out [334…
```
date
2025-12-01    21
2025-11-24    11
2025-12-02     9
2025-12-29     8
2025-11-01     8
Name: count, dtype: int64
```

In [335…
```
daily_sentiment = (
    news_df.groupby("date").agg(
        avg_compound=("sentiment_compound", "mean"),
        avg_positive=("sentiment_pos", "mean"),
        avg_negative=("sentiment_neg", "mean"),
        avg_neutral=("sentiment_neu", "mean"),
        article_count=("sentiment_compound", "count") #News volume
    )
    .reset_index() #Converts date to back to column
)

daily_sentiment.head()
```

Out [335…

	date	avg_compound	avg_positive	avg_negative	avg_neutral	article_count
0	2025-10-03	0.1327	0.1123	0.0313	0.8564	7
1	2025-10-04	0.2533	0.1202	0.0000	0.8798	4
2	2025-10-05	-0.0512	0.0000	0.0454	0.9546	5
3	2025-10-06	0.1346	0.1295	0.0580	0.8125	2
4	2025-10-08	0.1027	0.1360	0.1170	0.7480	1

🔷 STEP 5: MERGING MARKET DATA WITH DAILY SENTIMENT

In this step, we merge daily market price data with aggregated daily news sentiment to create a unified analysis-ready dataset.

In [336…
```
price_df.head()
```

Out [336…

	date	price
0	2025-07-13	117418.9575
1	2025-07-14	119117.5567
2	2025-07-15	119833.6745
3	2025-07-16	117678.1949
4	2025-07-17	118748.1627

In [337…

```
daily_sentiment.head()
```

Out[337…

	date	avg_compound	avg_positive	avg_negative	avg_neutral	article_count
0	2025-10-03	0.1327	0.1123	0.0313	0.8564	7
1	2025-10-04	0.2533	0.1202	0.0000	0.8798	4
2	2025-10-05	-0.0512	0.0000	0.0454	0.9546	5
3	2025-10-06	0.1346	0.1295	0.0580	0.8125	2
4	2025-10-08	0.1027	0.1360	0.1170	0.7480	1

In [338…

```
#Merging on date column
final_df = price_df.merge(daily_sentiment, on = "date", how = "left")

# Why left? : keep all market date and attach sentiment only if available

final_df.head()
```

Out[338…

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral	a
0	2025-07-13	117418.9575	NaN	NaN	NaN	NaN	
1	2025-07-14	119117.5567	NaN	NaN	NaN	NaN	
2	2025-07-15	119833.6745	NaN	NaN	NaN	NaN	
3	2025-07-16	117678.1949	NaN	NaN	NaN	NaN	
4	2025-07-17	118748.1627	NaN	NaN	NaN	NaN	

In [339…

```
final_df.tail()
```

Out[339…

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral
176	2026-01-05	91373.2159	NaN	NaN	NaN	NaN
177	2026-01-06	93926.7956	NaN	NaN	NaN	NaN
178	2026-01-07	93666.8639	NaN	NaN	NaN	NaN
179	2026-01-08	91257.1554	NaN	NaN	NaN	NaN
180	2026-01-08	89788.8330	NaN	NaN	NaN	NaN

In [340…

```
final_df.isnull().sum() #sentiment are null as there is no relevant news
```

Out[340…

```
date               0
price              0
avg_compound     108
avg_positive     108
avg_negative     108
avg_neutral      108
article_count    108
dtype: int64
```

In [341…

```
final_df.info()
final_df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181 entries, 0 to 180
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           181 non-null    object 
 1   price          181 non-null    float64
 2   avg_compound   73 non-null     float64
 3   avg_positive   73 non-null     float64
 4   avg_negative   73 non-null     float64
 5   avg_neutral    73 non-null     float64
 6   article_count  73 non-null     float64
dtypes: float64(6), object(1)
memory usage: 10.0+ KB
```

Out[341…

	price	avg_compound	avg_positive	avg_negative	avg_neutral	artic
count	181.0000	73.0000	73.0000	73.0000	73.0000	
mean	106233.7453	0.0422	0.0718	0.0610	0.8672	
std	12039.7923	0.2467	0.0740	0.0671	0.0792	
min	84682.6243	-0.6249	0.0000	0.0000	0.6985	
25%	92036.7255	-0.0705	0.0000	0.0000	0.8160	
50%	110708.6696	0.0169	0.0557	0.0510	0.8690	
75%	115970.5849	0.2001	0.1117	0.0920	0.9187	
max	124773.5082	0.5973	0.3015	0.2856	1.0000	

🔷 STEP 6: HANDLING MISSING SENTIMENT VALUES

After merging market and sentiment data, some days contain missing sentiment values due to the absence of news articles. These are handled explicitly to preserve semantic meaning.

In [342…

```
final_df[final_df["avg_compound"].isnull()].head()
```

Out [342...

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral	a
0	2025-07-13	117418.9575	NaN	NaN	NaN	NaN	
1	2025-07-14	119117.5567	NaN	NaN	NaN	NaN	
2	2025-07-15	119833.6745	NaN	NaN	NaN	NaN	
3	2025-07-16	117678.1949	NaN	NaN	NaN	NaN	
4	2025-07-17	118748.1627	NaN	NaN	NaN	NaN	

In [343...

```
#Instead of dropping missing values from sentiment, we can replace null w
final_df["avg_compound"] = final_df["avg_compound"].fillna(0)
final_df["avg_positive"] = final_df["avg_positive"].fillna(0)
final_df["avg_negative"] = final_df["avg_negative"].fillna(0)
final_df["avg_neutral"] = final_df["avg_neutral"].fillna(0)
final_df["article_count"] = final_df["article_count"].fillna(0)
```

In [344...

```
final_df.isnull().sum()
```

Out [344...

```
date             0
price            0
avg_compound     0
avg_positive     0
avg_negative     0
avg_neutral      0
article_count    0
dtype: int64
```

In [345...

```
final_df.head()
```

Out [345...

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral	a
0	2025-07-13	117418.9575	0.0000	0.0000	0.0000	0.0000	
1	2025-07-14	119117.5567	0.0000	0.0000	0.0000	0.0000	
2	2025-07-15	119833.6745	0.0000	0.0000	0.0000	0.0000	
3	2025-07-16	117678.1949	0.0000	0.0000	0.0000	0.0000	
4	2025-07-17	118748.1627	0.0000	0.0000	0.0000	0.0000	

In [346...

```
final_df.tail()
```

Out [346...

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral
176	2026-01-05	91373.2159	0.0000	0.0000	0.0000	0.0000
177	2026-01-06	93926.7956	0.0000	0.0000	0.0000	0.0000
178	2026-01-07	93666.8639	0.0000	0.0000	0.0000	0.0000
179	2026-01-08	91257.1554	0.0000	0.0000	0.0000	0.0000
180	2026-01-08	89788.8330	0.0000	0.0000	0.0000	0.0000

🔷 STEP 7: CREATING SENTIMENT REGIMES

In this step, we categorize daily sentiment scores into interpretable sentiment regimes (Positive, Neutral, Negative) to enable regime-based analysis. A regime is a state or condition of the system.

In [347...

```
# creating a new column to explicitly defin type of sentiment on the basi
def classify_sentiment(score):
    if score >= 0.05:
        return "Positive"
    elif score <= -0.05:
        return "Negative"
    else:
        return "Neutral"
```

In [348...

```
final_df["sentiment_regime"] = final_df["avg_compound"].apply(classify_se
final_df.head()
```

Out [348...

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral	a
0	2025-07-13	117418.9575	0.0000	0.0000	0.0000	0.0000	
1	2025-07-14	119117.5567	0.0000	0.0000	0.0000	0.0000	
2	2025-07-15	119833.6745	0.0000	0.0000	0.0000	0.0000	
3	2025-07-16	117678.1949	0.0000	0.0000	0.0000	0.0000	
4	2025-07-17	118748.1627	0.0000	0.0000	0.0000	0.0000	

In [349...

```
final_df["sentiment_regime"].value_counts()
```

Out [349…
```
sentiment_regime
Neutral     127
Positive     31
Negative     23
Name: count, dtype: int64
```

🔷 STEP 8: PRICE RETURNS & VOLATILITY FEATURE ENGINEERING

In this step, we transform raw price data into daily returns and volatility measures to enable meaningful market analysis.

- returns → how much price changes
- volatility → how unstable price is

In [350…
```
final_df = final_df.sort_values("date").reset_index(drop = True)
```

In [351…
```
final_df["daily_return"] = final_df["price"].pct_change()

# Percentage Change
# pct = (price[t] − price[t−1])/ price[t−1]

final_df[["date","price","daily_return"]].head()
# first day return is NaN as there is no previous day
```

Out [351…

	date	price	daily_return
0	2025-07-13	117418.9575	NaN
1	2025-07-14	119117.5567	0.0145
2	2025-07-15	119833.6745	0.0060
3	2025-07-16	117678.1949	-0.0180
4	2025-07-17	118748.1627	0.0091

In [352…
```
# Create rolling volatility (7−day)
final_df["volatility_7d"] = (final_df["daily_return"].rolling(window=7).s

# What is Volatility: Markets often react to negative news with volatilit
# Higher volatility → more uncertainty && Lower volatility → stability

final_df["volatility_14d"] = (final_df["daily_return"].rolling(window=14)

final_df["volatility_30d"] = (final_df["daily_return"].rolling(window=30)
```

In [353…
```
final_df.head(31)

# daily_return start at second day
# volatility start at 8th day with rolling volatility for the first 7 day
```

Out [353…

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral
0	2025-07-13	117418.9575	0.0000	0.0000	0.0000	0.0000
1	2025-07-14	119117.5567	0.0000	0.0000	0.0000	0.0000
2	2025-07-15	119833.6745	0.0000	0.0000	0.0000	0.0000
3	2025-07-16	117678.1949	0.0000	0.0000	0.0000	0.0000
4	2025-07-17	118748.1627	0.0000	0.0000	0.0000	0.0000
5	2025-07-18	119445.3652	0.0000	0.0000	0.0000	0.0000
6	2025-07-19	117988.9466	0.0000	0.0000	0.0000	0.0000
7	2025-07-20	117901.6266	0.0000	0.0000	0.0000	0.0000
8	2025-07-21	117256.9208	0.0000	0.0000	0.0000	0.0000
9	2025-07-22	117482.4698	0.0000	0.0000	0.0000	0.0000
10	2025-07-23	119955.7957	0.0000	0.0000	0.0000	0.0000
11	2025-07-24	118629.0559	0.0000	0.0000	0.0000	0.0000
12	2025-07-25	118354.4352	0.0000	0.0000	0.0000	0.0000
13	2025-07-26	117540.8084	0.0000	0.0000	0.0000	0.0000
14	2025-07-27	117959.5423	0.0000	0.0000	0.0000	0.0000
15	2025-07-28	119418.9141	0.0000	0.0000	0.0000	0.0000
16	2025-07-29	118003.3020	0.0000	0.0000	0.0000	0.0000
17	2025-07-30	117853.3089	0.0000	0.0000	0.0000	0.0000
18	2025-07-31	117833.2409	0.0000	0.0000	0.0000	0.0000
19	2025-08-01	115700.0024	0.0000	0.0000	0.0000	0.0000
20	2025-08-02	113234.6051	0.0000	0.0000	0.0000	0.0000

	date	price	avg_compound	avg_positive	avg_negative	avg_neutral
21	2025-08-03	112554.9023	0.0000	0.0000	0.0000	0.0000
22	2025-08-04	114199.1097	0.0000	0.0000	0.0000	0.0000
23	2025-08-05	115138.6861	0.0000	0.0000	0.0000	0.0000
24	2025-08-06	114128.3541	0.0000	0.0000	0.0000	0.0000
25	2025-08-07	115022.0958	0.0000	0.0000	0.0000	0.0000
26	2025-08-08	117463.4745	0.0000	0.0000	0.0000	0.0000
27	2025-08-09	116688.3666	0.0000	0.0000	0.0000	0.0000
28	2025-08-10	116510.0839	0.0000	0.0000	0.0000	0.0000
29	2025-08-11	119266.9252	0.0000	0.0000	0.0000	0.0000
30	2025-08-12	118773.7996	0.0000	0.0000	0.0000	0.0000

🔷 STEP 9: EXPLORATORY DATA ANALYSIS (EDA)

In [354…

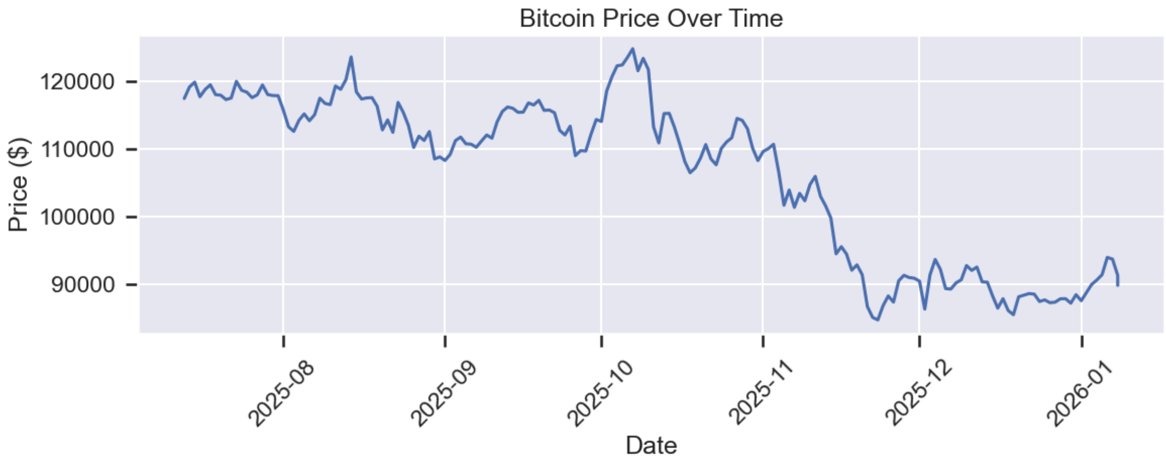
```
# A. Price Trend over Time
plt.figure(figsize = (12,5))

plt.plot(final_df["date"],final_df["price"])

plt.title("Bitcoin Price Over Time")
plt.xlabel("Date")
plt.ylabel("Price ($)")

plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```



Analysis:

- The price shows clear periods of upward and downward movement.
- The market is non-stationary (it trends over time).
- This confirms why analyzing returns instead of raw prices is necessary.

In [355…

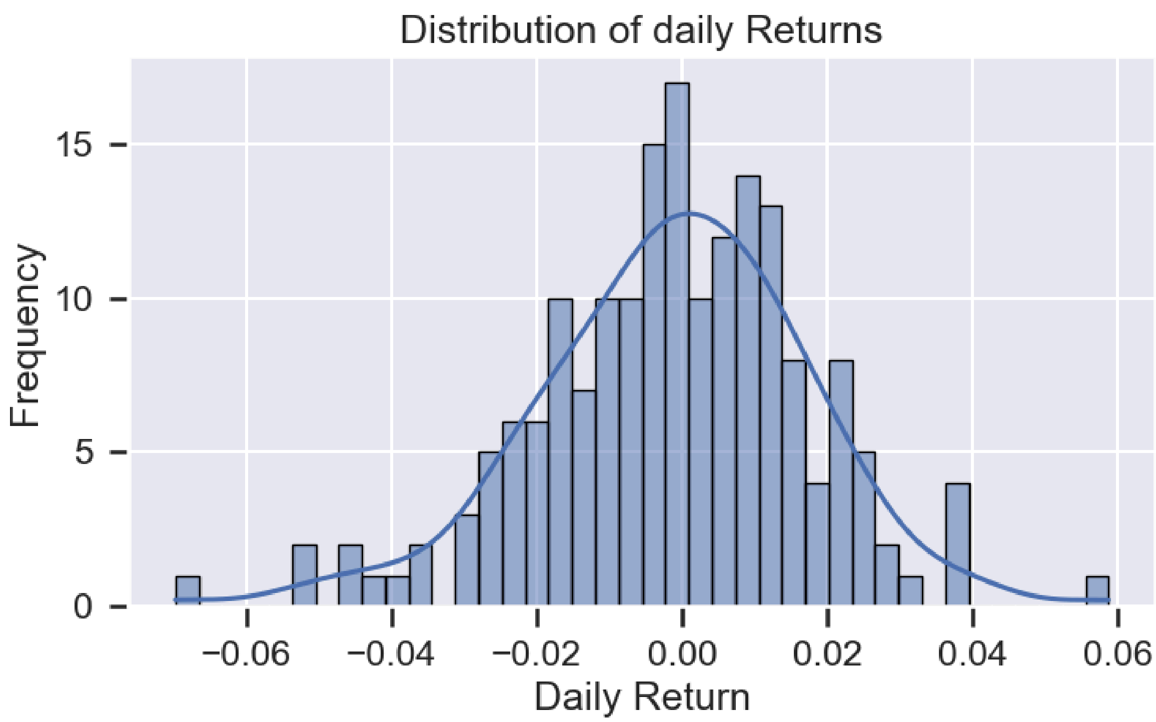
```
# B. Daily Returns distribution

plt.figure(figsize = (8,5))

sns.histplot(final_df["daily_return"].dropna(), bins=40, kde=True)

plt.title("Distribution of daily Returns")
plt.xlabel("Daily Return")
plt.ylabel("Frequency")

plt.tight_layout()
plt.show()
```



Analysis:

- Returns are centered around zero (price did not change), Most daily changes are small, A few extreme values exist on both sides.
- The market usually moves moderately but occasionally experiences large shocks.
- This is typical of financial markets and indicates risk concentration in extreme events.

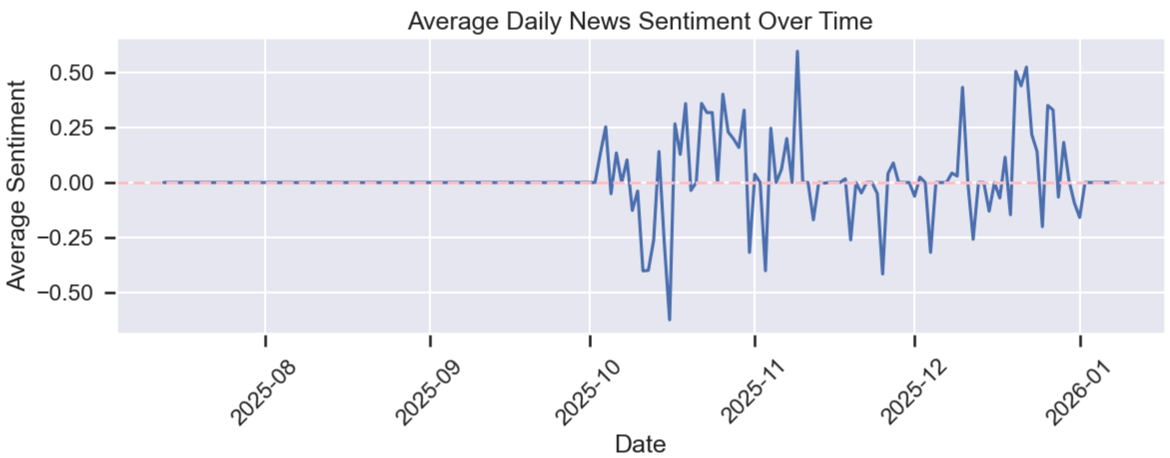
In [356…
```
# C. Sentiment Over Time
plt.figure(figsize = (12,5))

plt.plot(final_df["date"], final_df["avg_compound"])
plt.axhline(0, linestyle = "--", color ="pink")

plt.title("Average Daily News Sentiment Over Time")
plt.xlabel("Date")
plt.ylabel("Average Sentiment")

plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```



Analysis:

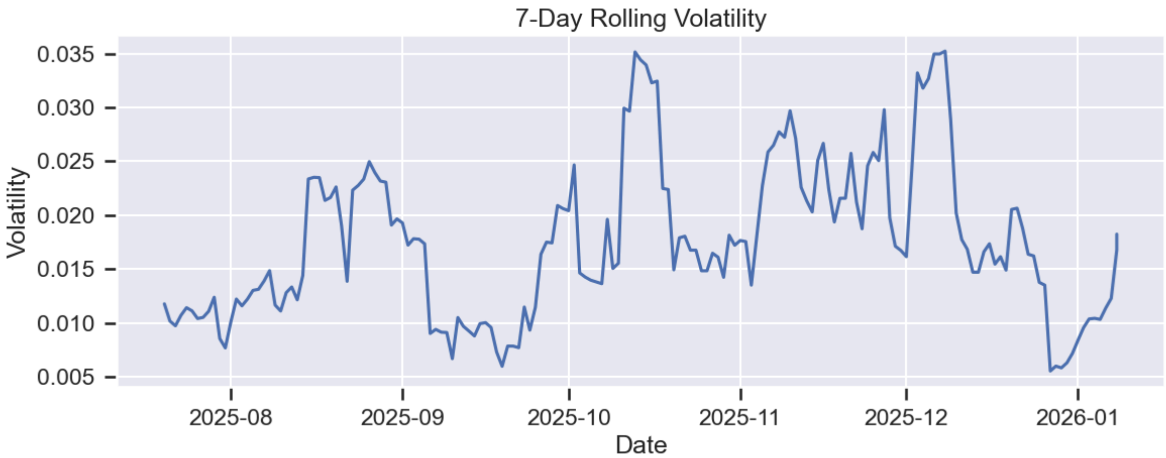
- News sentiment is event-driven, not continuous.
- Major events strongly influence sentiment on specific days.

In [357…
```
# D. Volatility Over Time
plt.figure(figsize=(12,5))

plt.plot(final_df["date"],final_df["volatility_7d"])

plt.title("7-Day Rolling Volatility")
plt.xlabel("Date")
plt.ylabel("Volatility")

plt.tight_layout()
plt.show()
```



Analysis:

- Volatility clusters in certain periods, Calm periods are followed by spikes in volatility.
- Market uncertainty is not constant.
- Risk tends to increase during specific periods rather than randomly, This suggests external factors (like news) may influence instability.

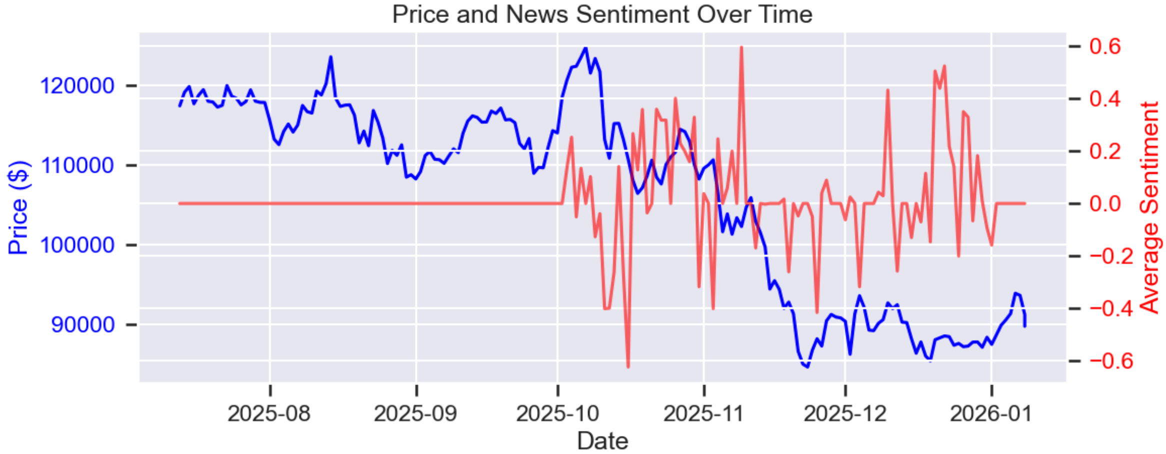
In [358…

```
# E. Price vs Sentiment
fig, ax1 = plt.subplots(figsize=(12,5))

ax1.plot(final_df["date"], final_df["price"], color = "blue")
ax1.set_xlabel("Date")
ax1.set_ylabel("Price ($)", color= "blue")
ax1.tick_params(axis="y", labelcolor="blue")

ax2 = ax1.twinx()
ax2.plot(final_df["date"], final_df["avg_compound"], color = "red", alpha
ax2.set_ylabel("Average Sentiment", color= "red")
ax2.tick_params(axis="y", labelcolor="red")

plt.title("Price and News Sentiment Over Time")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Analysis:

- Some sentiment spikes align with price movements. In other cases, price moves without strong sentiment change.
- News sentiment is not the sole driver of price.
- This supports a descriptive, not causal interpretation.

In [359…

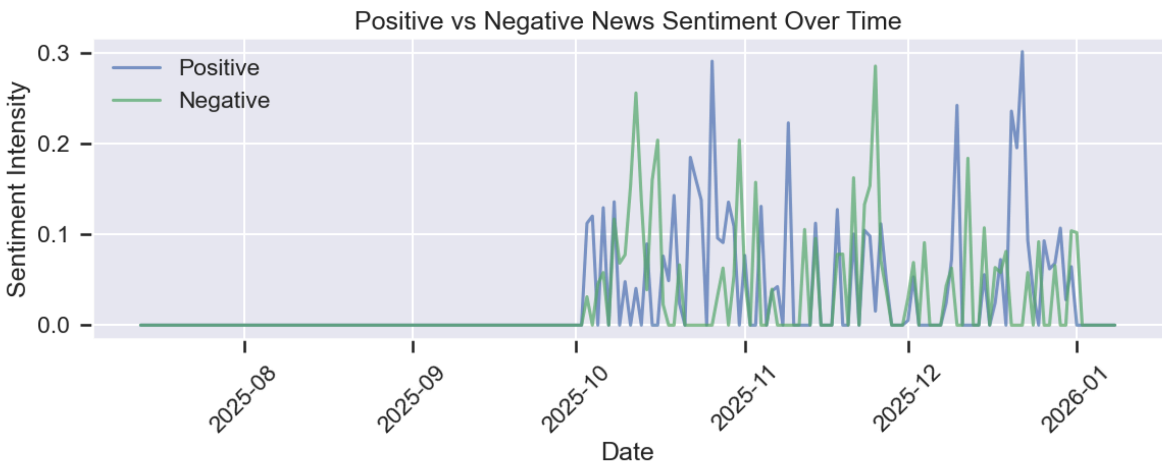
```
# F. Positive vs Negative Sentiment
plt.figure(figsize=(12,5))

plt.plot(final_df["date"],final_df["avg_positive"], label="Positive", alp
plt.plot(final_df["date"],final_df["avg_negative"], label="Negative", alp

plt.title("Positive vs Negative News Sentiment Over Time")
plt.xlabel("Date")
plt.ylabel("Sentiment Intensity")

plt.legend()
plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```



Analysis:

- Positive and negative sentiment vary independently.
- Positive sentiment does not always dominate even during price increases.
- Compound sentiment can hide sentiment imbalance.
- Negative tone often appears stronger and more volatile.
- Separating sentiment components provides deeper insight than using a single score.

🧠 Conclusion

News sentiment does not consistently predict returns, but negative sentiment regimes are associated with higher market volatility, indicating increased risk during adverse news cycles.

🔷 STEP 10: COMPARING RETURNS & VOLATILITY ACROSS SENTIMENT REGIMES

compare returns and volatility across Positive, Neutral, and Negative sentiment regimes.

In [360…

```python
# A. Average Daily Return by Sentiment Regime
regime_returns = (
    final_df.groupby("sentiment_regime")["daily_return"].mean()
)

regime_returns

# Average direction of market movement
# Whether negative days tend to have worse returns
# Whether positive days outperform neutral days
```

Out[360…

```
sentiment_regime
Negative   -0.0017
Neutral    -0.0014
Positive   -0.0007
Name: daily_return, dtype: float64
```

Analysis:

- Average daily returns differ slightly across sentiment regimes.
- Positive sentiment days tend to have marginally higher returns.
- Negative sentiment days often show weaker or negative average returns.
- News sentiment has some association with market direction, but the effect is modest.
- Sentiment alone is not a strong predictor of daily returns.

In [361…

```python
# B. Return Volatility by Sentiment Regime
regime_volatility = (
    final_df.groupby("sentiment_regime")["daily_return"].std()
)

regime_volatility

# Risk is often more important than return
# Negative news may increase uncertainty
# Volatility reveals stress, not direction
```

Out[361…

```
sentiment_regime
Negative    0.0230
Neutral     0.0181
Positive    0.0187
Name: daily_return, dtype: float64
```

Analysis:

- Volatility measures how much and how often prices move up and down.
- High volatility → prices change a lot, Low volatility → prices change a little
- Volatility is noticeably higher during negative sentiment regimes.
- Negative news environments are associated with greater market uncertainty.
- Sentiment impacts risk more than return direction.

In [362…
```
# C. Rolling Volatility Comparison (7-Day)
regime_vol_7d = (
    final_df
    .groupby("sentiment_regime")["volatility_7d"]
    .mean()
)
regime_vol_7d

# Sustained risk levels across regimes
# Whether bad sentiment leads to prolonged instability
```

Out[362…
```
sentiment_regime
Negative    0.0201
Neutral     0.0166
Positive    0.0189
Name: volatility_7d, dtype: float64
```

Analysis:

- Rolling volatility remains elevated during negative sentiment periods.
- Negative sentiment has a persistent effect on market risk, not just a one-day impact.

In [363…
```
regime_summary = pd.DataFrame({
    "avg_daily_return": regime_returns,
    "return_volatility": regime_volatility,
    "avg_7d_volatility": regime_vol_7d
})

regime_summary
```

Out[363…

sentiment_regime	avg_daily_return	return_volatility	avg_7d_volatility
Negative	-0.0017	0.0230	0.0201
Neutral	-0.0014	0.0181	0.0166
Positive	-0.0007	0.0187	0.0189

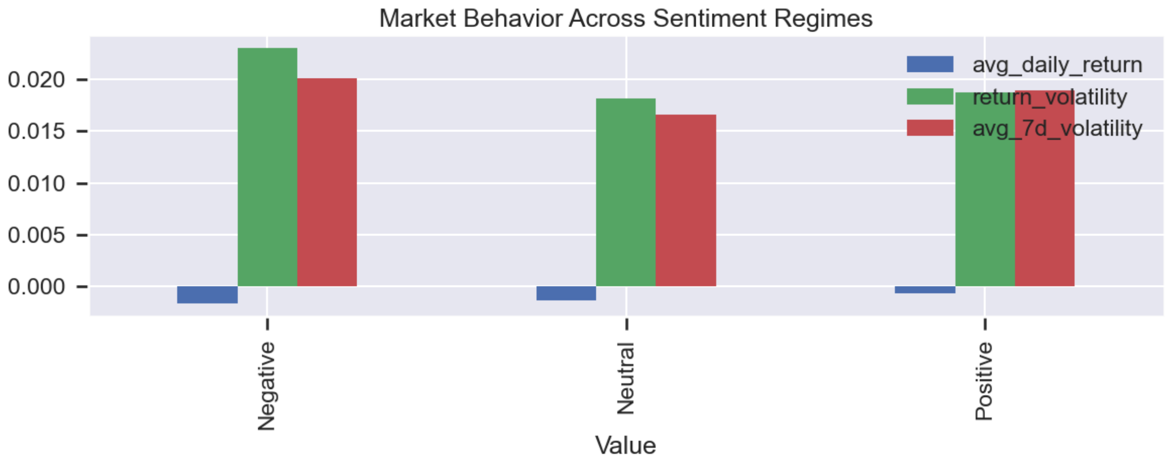
Analysis:

- Negative sentiment regimes combine lower returns with higher volatility.
- Positive regimes show slightly better stability.
- Market behavior clearly differs by sentiment regime.
- Regime-based analysis provides clearer insight than looking at averages alone.

In [364…
```
regime_summary.plot(kind = "bar", figsize = (12,5))

plt.title("Market Behavior Across Sentiment Regimes")
plt.xlabel("Value")

plt.tight_layout()
plt.show()
```



🧠 Conclusion

Negative sentiment regimes are associated with higher market volatility, while returns vary only modestly across sentiment states, suggesting sentiment affects risk more than direction.