Combined Part1 Step3 and Part2 Code

April 29, 2025

0.1 Step 3: Replication

[2]:
```
import yfinance as yf
import pandas as pd
import numpy as np
import datetime
import os
```

[3]:
```
from datetime import date
```

[4]:
```
pip install pandas_ta
```

```
Requirement already satisfied: pandas_ta in c:\users\drmus\anaconda3\lib\site-
packages (0.3.14b0)
Requirement already satisfied: pandas in c:\users\drmus\anaconda3\lib\site-
packages (from pandas_ta) (2.2.2)
Requirement already satisfied: numpy>=1.26.0 in
c:\users\drmus\anaconda3\lib\site-packages (from pandas->pandas_ta) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\drmus\anaconda3\lib\site-packages (from pandas->pandas_ta)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
c:\users\drmus\anaconda3\lib\site-packages (from pandas->pandas_ta) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in
c:\users\drmus\anaconda3\lib\site-packages (from pandas->pandas_ta) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\drmus\anaconda3\lib\site-
packages (from python-dateutil>=2.8.2->pandas->pandas_ta) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[5]:
```
import pandas_ta as ta
```

1 Selected fund: ECH

[7]:
```
#Download data for period. Dates set according to comment re SMA on under '2.6␣
 ↪Data Cleaning'
#ECH is the iShares MSCI Chile ETF and IVV is the comparative S&P500 iShares ETF

tickers = ['ECH', 'IVV']
```

```
start = datetime.date(2009,1,1)
end = datetime.date(2020,1,1)
```

[8]:
```
# In order to minimize Yahoo Finance calls, a Pandas DataFrame is saved␣
 ↪externally to CSV file:
if os.path.exists("tickers.csv"):
    ticker_data = pd.read_csv("tickers.csv", parse_dates=True, index_col=0)
else:
    ticker_data = yf.download(tickers, start, end, auto_adjust = False)['Adj␣
 ↪Close']

    #save for future use
    ticker_data.to_csv("tickers.csv")
```

[9]:
```
# In order to minimize Yahoo Finance calls, a Pandas DataFrame is saved␣
 ↪externally to CSV file:
if os.path.exists("ech.csv"):
    ech_data = pd.read_csv("ech.csv", parse_dates=True, index_col=0)
else:
    ech_data = yf.download("ECH", start, end, multiple_index_value = False)

    #save for future use
    ech_data.to_csv("ech.csv")
```

[10]:
```
ech_data.head()
```

[10]:

Date	Close	High	Low	Open	Volume
2009-01-02	20.624191	20.624191	20.046578	20.046578	45600
2009-01-05	20.590204	20.807660	20.488273	20.807660	56600
2009-01-06	21.303732	21.487209	21.065891	21.460027	113900
2009-01-07	21.059095	21.650300	20.970755	21.650300	9400
2009-01-08	21.249367	21.249367	20.997935	21.004730	14600

[11]:
```
ticker_data.head()
```

[11]:

Date	ECH	IVV
2009-01-02	20.624191	68.957314
2009-01-05	20.590204	68.779854
2009-01-06	21.303732	69.216072
2009-01-07	21.059095	67.182709
2009-01-08	21.249367	67.478500

[12]:
```
# Implement class label Gamma as per Sec 2.1 of the paper

ticker_data['Gamma_ech'] = ticker_data['ECH']-ticker_data['ECH'].shift(1)
```

```
ticker_data.iloc[0,2] = 0
ticker_data['GE'] = ticker_data['Gamma_ech'].apply(lambda x: '1' if x > 0 else␣
 ↪'-1')
ticker_data.head()
```

[12]:

Date	ECH	IVV	Gamma_ech	GE
2009-01-02	20.624191	68.957314	0.000000	-1
2009-01-05	20.590204	68.779854	-0.033987	-1
2009-01-06	21.303732	69.216072	0.713528	1
2009-01-07	21.059095	67.182709	-0.244637	-1
2009-01-08	21.249367	67.478500	0.190271	1

[13]:
```
#To gain insight into the DataFrame used in the research paper, we implement␣
 ↪the two most prominent TA library technical indicators to expand dataset

ech_data.ta.indicators()
```

```
Pandas TA - Technical Analysis Indicators - v0.3.14b0
Total Indicators & Utilities: 205
Abbreviations:
    aberration, above, above_value, accbands, ad, adosc, adx, alma, amat, ao,
aobv, apo, aroon, atr, bbands, below, below_value, bias, bop, brar, cci,
cdl_pattern, cdl_z, cfo, cg, chop, cksp, cmf, cmo, coppock, cross, cross_value,
cti, decay, decreasing, dema, dm, donchian, dpo, ebsw, efi, ema, entropy, eom,
er, eri, fisher, fwma, ha, hilo, hl2, hlc3, hma, hwc, hwma, ichimoku,
increasing, inertia, jma, kama, kc, kdj, kst, kurtosis, kvo, linreg, log_return,
long_run, macd, mad, massi, mcgd, median, mfi, midpoint, midprice, mom, natr,
nvi, obv, ohlc4, pdist, percent_return, pgo, ppo, psar, psl, pvi, pvo, pvol,
pvr, pvt, pwma, qqe, qstick, quantile, rma, roc, rsi, rsx, rvgi, rvi, short_run,
sinwma, skew, slope, sma, smi, squeeze, squeeze_pro, ssf, stc, stdev, stoch,
stochrsi, supertrend, swma, t3, td_seq, tema, thermo, tos_stdevall, trima, trix,
true_range, tsi, tsignals, ttm_trend, ui, uo, variance, vhf, vidya, vortex, vp,
vwap, vwma, wcp, willr, wma, xsignals, zlma, zscore

Candle Patterns:
    2crows, 3blackcrows, 3inside, 3linestrike, 3outside, 3starsinsouth,
3whitesoldiers, abandonedbaby, advanceblock, belthold, breakaway,
closingmarubozu, concealbabyswall, counterattack, darkcloudcover, doji,
dojistar, dragonflydoji, engulfing, eveningdojistar, eveningstar,
gapsidesidewhite, gravestonedoji, hammer, hangingman, harami, haramicross,
highwave, hikkake, hikkakemod, homingpigeon, identical3crows, inneck, inside,
invertedhammer, kicking, kickingbylength, ladderbottom, longleggeddoji,
longline, marubozu, matchinglow, mathold, morningdojistar, morningstar, onneck,
piercing, rickshawman, risefall3methods, separatinglines, shootingstar,
shortline, spinningtop, stalledpattern, sticksandwich, takuri, tasukigap,
thrusting, tristar, unique3river, upsidegap2crows, xsidegap3methods
```

[14]:
```
help(ta.obv)
```

```
Help on function obv in module pandas_ta.volume.obv:

obv(close, volume, talib=None, offset=None, **kwargs)
    On Balance Volume (OBV)

    On Balance Volume is a cumulative indicator to measure buying and selling
    pressure.

    Sources:
        https://www.tradingview.com/wiki/On_Balance_Volume_(OBV)
        https://www.tradingtechnologies.com/help/x-study/technical-indicator-
definitions/on-balance-volume-obv/
        https://www.motivewave.com/studies/on_balance_volume.htm

    Calculation:
        signed_volume = signed_series(close, initial=1) * volume
        obv = signed_volume.cumsum()

    Args:
        close (pd.Series): Series of 'close's
        volume (pd.Series): Series of 'volume's
        talib (bool): If TA Lib is installed and talib is True, Returns the TA
Lib
            version. Default: True
        offset (int): How many periods to offset the result. Default: 0

    Kwargs:
        fillna (value, optional): pd.DataFrame.fillna(value)
        fill_method (value, optional): Type of fill method

    Returns:
        pd.Series: New feature generated.
```

[15]:
```
ech_obv = ech_data.ta.obv()
```

[16]:
```
ech_data = ech_data.join(ech_obv)
```

[17]:
```
ech_data.head()
```

[17]:

Date	Close	High	Low	Open	Volume	OBV
2009-01-02	20.624191	20.624191	20.046578	20.046578	45600	45600.0
2009-01-05	20.590204	20.807660	20.488273	20.807660	56600	-11000.0
2009-01-06	21.303732	21.487209	21.065891	21.460027	113900	102900.0
2009-01-07	21.059095	21.650300	20.970755	21.650300	9400	93500.0

```
2009-01-08  21.249367  21.249367  20.997935  21.004730   14600  108100.0
```

[18]:
```
#Next we add the Bollinger Band Percent indicator
help(ta.bbands)
```

```
Help on function bbands in module pandas_ta.volatility.bbands:

bbands(close, length=None, std=None, ddof=0, mamode=None, talib=None,
offset=None, **kwargs)
    Bollinger Bands (BBANDS)

    A popular volatility indicator by John Bollinger.

    Sources:
        https://www.tradingview.com/wiki/Bollinger_Bands_(BB)

    Calculation:
        Default Inputs:
            length=5, std=2, mamode="sma", ddof=0
        EMA = Exponential Moving Average
        SMA = Simple Moving Average
        STDEV = Standard Deviation
        stdev = STDEV(close, length, ddof)
        if "ema":
            MID = EMA(close, length)
        else:
            MID = SMA(close, length)

        LOWER = MID - std * stdev
        UPPER = MID + std * stdev

        BANDWIDTH = 100 * (UPPER - LOWER) / MID
        PERCENT = (close - LOWER) / (UPPER - LOWER)

    Args:
        close (pd.Series): Series of 'close's
        length (int): The short period. Default: 5
        std (int): The long period. Default: 2
        ddof (int): Degrees of Freedom to use. Default: 0
        mamode (str): See ```help(ta.ma)```. Default: 'sma'
        talib (bool): If TA Lib is installed and talib is True, Returns the TA
Lib
            version. Default: True
        offset (int): How many periods to offset the result. Default: 0

    Kwargs:
        fillna (value, optional): pd.DataFrame.fillna(value)
        fill_method (value, optional): Type of fill method
```

```
    Returns:
        pd.DataFrame: lower, mid, upper, bandwidth, and percent columns.
```

[19]:
```
ech_bbp = ech_data.ta.bbands()
```

[20]:
```
ech_bbp.head()
```

[20]:

Date	BBL_5_2.0	BBM_5_2.0	BBU_5_2.0	BBB_5_2.0	BBP_5_2.0
2009-01-02	NaN	NaN	NaN	NaN	NaN
2009-01-05	NaN	NaN	NaN	NaN	NaN
2009-01-06	NaN	NaN	NaN	NaN	NaN
2009-01-07	NaN	NaN	NaN	NaN	NaN
2009-01-08	20.357976	20.965318	21.572659	5.793773	0.733846

[21]:
```
ech_data = ech_data.join(ech_bbp)
ech_data.head()
```

[21]:

Date	Close	High	Low	Open	Volume	OBV	\
2009-01-02	20.624191	20.624191	20.046578	20.046578	45600	45600.0	
2009-01-05	20.590204	20.807660	20.488273	20.807660	56600	-11000.0	
2009-01-06	21.303732	21.487209	21.065891	21.460027	113900	102900.0	
2009-01-07	21.059095	21.650300	20.970755	21.650300	9400	93500.0	
2009-01-08	21.249367	21.249367	20.997935	21.004730	14600	108100.0	

Date	BBL_5_2.0	BBM_5_2.0	BBU_5_2.0	BBB_5_2.0	BBP_5_2.0
2009-01-02	NaN	NaN	NaN	NaN	NaN
2009-01-05	NaN	NaN	NaN	NaN	NaN
2009-01-06	NaN	NaN	NaN	NaN	NaN
2009-01-07	NaN	NaN	NaN	NaN	NaN
2009-01-08	20.357976	20.965318	21.572659	5.793773	0.733846

At present I have two DataFrames. One with detailed information regarding ECH ETF and one with Adjusted Closes between ECH and IVV (S&P500 proxy). From the paper it would appear that the complete DataFrame contains 216 features. That would be 6 from Yahoo Finance and 210 from the Pandas TA library. Knowing that only 5 features are needed, we would need to proceed on the basis above and add the existing DataFrame. As per the notes in of Part 1 step 2, some of the features indicators have not been identified and I will choose to rather proceed with the analysis.

In the next section we are require to pick and implement a metric. According to the notes Lasso is difficult to implement so we will start with that.

[23]:
```
from sklearn.linear_model import Lasso
```

[24]:
```
from sklearn.model_selection import train_test_split
```

[25]:
```
#Create deepCopy of ech_data DataFrame
ech_df = ech_data.copy()
```

[26]:
```
ech_df.head()
```

[26]:

Date	Close	High	Low	Open	Volume	OBV	\
2009-01-02	20.624191	20.624191	20.046578	20.046578	45600	45600.0	
2009-01-05	20.590204	20.807660	20.488273	20.807660	56600	-11000.0	
2009-01-06	21.303732	21.487209	21.065891	21.460027	113900	102900.0	
2009-01-07	21.059095	21.650300	20.970755	21.650300	9400	93500.0	
2009-01-08	21.249367	21.249367	20.997935	21.004730	14600	108100.0	

Date	BBL_5_2.0	BBM_5_2.0	BBU_5_2.0	BBB_5_2.0	BBP_5_2.0
2009-01-02	NaN	NaN	NaN	NaN	NaN
2009-01-05	NaN	NaN	NaN	NaN	NaN
2009-01-06	NaN	NaN	NaN	NaN	NaN
2009-01-07	NaN	NaN	NaN	NaN	NaN
2009-01-08	20.357976	20.965318	21.572659	5.793773	0.733846

[27]:
```
#Clean data require all the NaN rows to be dropped
ech_df.drop(ech_df.index[:4], inplace= True)
```

[28]:
```
ech_df.head()
```

[28]:

Date	Close	High	Low	Open	Volume	OBV	\
2009-01-08	21.249367	21.249367	20.997935	21.004730	14600	108100.0	
2009-01-09	21.677477	21.806591	21.466818	21.480410	30800	138900.0	
2009-01-12	21.990068	21.990068	21.426046	21.813385	44900	183800.0	
2009-01-13	21.745438	21.745438	21.188211	21.188211	58500	125300.0	
2009-01-14	21.065891	22.146368	20.556233	22.132777	52700	72600.0	

Date	BBL_5_2.0	BBM_5_2.0	BBU_5_2.0	BBB_5_2.0	BBP_5_2.0
2009-01-08	20.357976	20.965318	21.572659	5.793773	0.733846
2009-01-09	20.466045	21.175975	21.885905	6.705050	0.853205
2009-01-12	20.787997	21.455948	22.123898	6.226250	0.899821
2009-01-13	20.863518	21.544289	22.225060	6.319733	0.647736
2009-01-14	20.868741	21.545648	22.222555	6.283466	0.145626

[29]:
```
#Let 'X' be the feature matrix
X = ech_df.drop('Close', axis=1)
```

[30]:
```
#Let 'Y' be the target matrix
y = ech_df['Close']
```

[31]:
```
#Implement 10-fold split of data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.1)
```

[32]:
```
#Training the Lasso model

lasso=Lasso(alpha=0.25,max_iter=3000)
lasso.fit(X_train,y_train)
```

[32]:
```
Lasso(alpha=0.25, max_iter=3000)
```

[33]:
```
#Evaluate Lasso
from sklearn.metrics import mean_squared_error

#Making predictions
y_hat = lasso.predict(X_test)

#Calculate the Mean Squared error (MSE)
mse = mean_squared_error(y_test, y_hat)

print("The Mean Square Error, indicating error regression loss is ",mse)
```

```
The Mean Square Error, indicating error regression loss is  0.1370192615856335
```

[67]:
```
#Implement sci-kit learn MLP

from sklearn.neural_network import MLPClassifier
```

No classification of individual of data has been performed. From reading the sci-kit learn documentation, it would appear that the classifier function does this automatically. In addition, some of the parameters are not addressed in the paper by Sagaceta-Mejia et al. and we experiment with different parameters in an attempt to recreate some of the outcomes achieved in the aforementioned paper.

[76]:
```
hidden_layer_sizes=int((X.shape[1])+len(np.unique(y)))/2
```

[78]:
```
#Solver parameter used is lbfgs - quasi-Newtonian (p.5)

hidden_layer_sizes=int((X.shape[1])+len(np.unique(y)))/2

ech_clf = MLPClassifier(hidden_layer_sizes=hidden_layer_sizes,␣
 ↪activation='logistic', solver='lbfgs', batch_size='auto',
                        learning_rate='adaptive', learning_rate_init=0.03,␣
 ↪max_iter=5000, momentum=0.2, random_state=np.random.get_state()[1][0],␣
 ↪early_stopping=False)
```

[121]:
```
print(ech_clf)
```

```
MLPClassifier(activation='logistic', hidden_layer_sizes=1266.5,
```

```
                learning_rate='adaptive', learning_rate_init=0.03, max_iter=5000,
                momentum=0.2, random_state=2752397761, solver='lbfgs')
```

[125]:
```
from sklearn.metrics import classification_report
y_true = ech_df['Close']
y_pred = y_hat
target_names = ['class 0', 'class 1', 'class 2']
print(classification_report(y_true, y_pred, labels=[1, 2, 3]))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[125], line 5
      3 y_pred = y_hat
      4 target_names = ['class 0', 'class 1', 'class 2']
----> 5 print(classification_report(y_true, y_pred, labels=[1, 2, 3]))

File ~\anaconda3\Lib\site-packages\sklearn\utils\_param_validation.py:213, in␣
 ↪validate_params.<locals>.decorator.<locals>.wrapper(*args, **kwargs)
    207 try:
    208     with config_context(
    209         skip_parameter_validation=(
    210             prefer_skip_nested_validation or global_skip_validation
    211         )
    212     ):
--> 213         return func(*args, **kwargs)
    214 except InvalidParameterError as e:
    215     # When the function is just a wrapper around an estimator, we allow
    216     # the function to delegate validation to the estimator, but we␣
 ↪replace
    217     # the name of the estimator by the name of the function in the erro
    218     # message to avoid confusion.
    219     msg = re.sub(
    220         r"parameter of \w+ must be",
    221         f"parameter of {func.__qualname__} must be",
    222         str(e),
    223     )

File ~\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:2626, in␣
 ↪classification_report(y_true, y_pred, labels, target_names, sample_weight,␣
 ↪digits, output_dict, zero_division)
   2491 @validate_params(
   2492     {
   2493         "y_true": ["array-like", "sparse matrix"],
   (…)
   2517     zero_division="warn",
   2518 ):
   2519     """Build a text report showing the main classification metrics.
   2520
```

```
   2521     Read more in the :ref:`User Guide <classification_report>`.
   (…)
   2623     <BLANKLINE>
   2624     """
-> 2626     y_type, y_true, y_pred = _check_targets(y_true, y_pred)
   2628     if labels is None:
   2629         labels = unique_labels(y_true, y_pred)

File ~\anaconda3\Lib\site-packages\sklearn\metrics\_classification.py:103, in␣
 ↪_check_targets(y_true, y_pred)
     76 """Check that y_true and y_pred belong to the same classification task.
     77
     78 This converts multiclass or binary types to a common shape, and raises
   (…)
    100 y_pred : array or indicator matrix
    101 """
    102 xp, _ = get_namespace(y_true, y_pred)
--> 103 check_consistent_length(y_true, y_pred)
    104 type_true = type_of_target(y_true, input_name="y_true")
    105 type_pred = type_of_target(y_pred, input_name="y_pred")

File ~\anaconda3\Lib\site-packages\sklearn\utils\validation.py:457, in␣
 ↪check_consistent_length(*arrays)
    455 uniques = np.unique(lengths)
    456 if len(uniques) > 1:
--> 457     raise ValueError(
    458         "Found input variables with inconsistent numbers of samples: %r
    459         % [int(l) for l in lengths]
    460     )

ValueError: Found input variables with inconsistent numbers of samples: [2764,␣
 ↪277]
```

[84]:
```
from sklearn.model_selection import StratifiedKFold
```

[86]:
```
#Cross-validate knn on training sample with 10 as number of folds
cv_generator = StratifiedKFold(n_splits=10, shuffle=False)
```

Unable to perform cross-validation and or integration with previous classifier result

1.1 Part 2: Evaluating One Particular Type of Alternative Data (Social Media Data)

1.1.1 No. 5: Importing and Structuring Reddit Data into Useful Data Structures

[134]:
```
!pip install praw
import praw
import pandas as pd
from datetime import datetime

# Reddit API credentials
reddit = praw.Reddit(client_id='p7UMF3D4H3VFZ-Xe2E3FrA',
                     client_secret='jQQR4I7IDTOo3hg7CA5ty-oGVvmFIw',
                     user_agent='DataBot by u/Deep_Engineering_773')

# Define subreddits and limits
subreddits = ['investing', 'stocks', 'wallstreetbets']
post_limit = 500
comment_limit = 50

# Collect posts and comments
all_posts = []

for subreddit_name in subreddits:
    subreddit = reddit.subreddit(subreddit_name)

    # Get top posts
    for post in subreddit.top(time_filter='month', limit=post_limit):
        post_data = {
            'id': post.id,
            'title': post.title,
            'text': post.selftext,
            'created_utc': datetime.fromtimestamp(post.created_utc),
            'score': post.score,
            'upvote_ratio': post.upvote_ratio,
            'num_comments': post.num_comments,
            'author': str(post.author),
            'subreddit': subreddit_name,
            'url': post.url,
            'is_post': True
        }
        all_posts.append(post_data)

        # Get comments for each post
        post.comments.replace_more(limit=0)  # Skip "load more comments" links
        for comment in post.comments.list()[:comment_limit]:
            comment_data = {
                'id': comment.id,
```

```
                'text': comment.body,
                'created_utc': datetime.fromtimestamp(comment.created_utc),
                'score': comment.score,
                'author': str(comment.author),
                'subreddit': subreddit_name,
                'parent_id': comment.parent_id,
                'is_post': False
            }
            all_posts.append(comment_data)

# Convert to DataFrame
df_reddit = pd.DataFrame(all_posts)

# Save to CSV
df_reddit.to_csv('finance_reddit_data.csv', index=False)
```

```
Requirement already satisfied: praw in c:\users\drmus\anaconda3\lib\site-
packages (7.8.1)
Requirement already satisfied: prawcore<3,>=2.4 in
c:\users\drmus\anaconda3\lib\site-packages (from praw) (2.4.0)
Requirement already satisfied: update_checker>=0.18 in
c:\users\drmus\anaconda3\lib\site-packages (from praw) (0.18.0)
Requirement already satisfied: websocket-client>=0.54.0 in
c:\users\drmus\anaconda3\lib\site-packages (from praw) (1.8.0)
Requirement already satisfied: requests<3.0,>=2.6.0 in
c:\users\drmus\anaconda3\lib\site-packages (from prawcore<3,>=2.4->praw)
(2.32.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
c:\users\drmus\anaconda3\lib\site-packages (from
requests<3.0,>=2.6.0->prawcore<3,>=2.4->praw) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
c:\users\drmus\anaconda3\lib\site-packages (from
requests<3.0,>=2.6.0->prawcore<3,>=2.4->praw) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in
c:\users\drmus\anaconda3\lib\site-packages (from
requests<3.0,>=2.6.0->prawcore<3,>=2.4->praw) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
c:\users\drmus\anaconda3\lib\site-packages (from
requests<3.0,>=2.6.0->prawcore<3,>=2.4->praw) (2025.1.31)
```

1.1.2 Data Processing and Cleaning

[141]:
```
nltk.download('punkt_tab')
```

```
[nltk_data] Downloading package punkt_tab to
[nltk_data]     C:\Users\drmus\AppData\Roaming\nltk_data…
[nltk_data]   Unzipping tokenizers\punkt_tab.zip.
```

[141]: True

[143]:
```
!pip install nltk
import pandas as pd
import numpy as np
import re
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer

# Download necessary NLTK resources
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('omw-1.4')  # For lemmatization

# Load data
df = pd.read_csv('finance_reddit_data.csv')

# Print column names to check what's available
print("Available columns:", df.columns.tolist())

# Text cleaning function
def clean_text(text):
    if isinstance(text, str):
        # Remove URLs
        text = re.sub(r'http\S+', '', text)
        # Remove mentions
        text = re.sub(r'@\w+', '', text)
        # Remove hashtags but keep the text
        text = re.sub(r'#(\w+)', r'\1', text)
        # Remove special characters
        text = re.sub(r'[^\w\s]', '', text)
        # Convert to lowercase
        text = text.lower()
        # Remove numbers
        text = re.sub(r'\d+', '', text)
        return text.strip()
    return ''

# Apply cleaning
df['clean_text'] = df['text'].apply(clean_text)

# Tokenization and stopword removal
stop_words = set(stopwords.words('english'))
lemmatizer = WordNetLemmatizer()
```

```
def tokenize_and_lemmatize(text):
    if isinstance(text, str):
        tokens = word_tokenize(text)
        tokens = [lemmatizer.lemmatize(token) for token in tokens if token not␣
 ↪in stop_words and len(token) > 2]
        return tokens
    return []

df['tokens'] = df['clean_text'].apply(tokenize_and_lemmatize)

# Create additional features
df['text_length'] = df['text'].apply(lambda x: len(x) if isinstance(x, str)␣
 ↪else 0)
df['word_count'] = df['clean_text'].apply(lambda x: len(x.split()) if␣
 ↪isinstance(x, str) else 0)

# Extract hashtags and mentions from the original text
def extract_hashtags(text):
    if isinstance(text, str):
        return re.findall(r'#(\w+)', text)
    return []

def extract_mentions(text):
    if isinstance(text, str):
        return re.findall(r'@(\w+)', text)
    return []

# Create hashtags and mentions columns if they don't exist
df['extracted_hashtags'] = df['text'].apply(extract_hashtags)
df['extracted_mentions'] = df['text'].apply(extract_mentions)

# Now create count features
df['hashtag_count'] = df['extracted_hashtags'].apply(len)
df['mention_count'] = df['extracted_mentions'].apply(len)

# Convert timestamp to datetime if the column exists
if 'created_at' in df.columns:
    df['created_at'] = pd.to_datetime(df['created_at'])
    df['day_of_week'] = df['created_at'].dt.day_name()
    df['hour_of_day'] = df['created_at'].dt.hour
else:
    # Use current timestamp as fallback
    from datetime import datetime
    df['timestamp'] = datetime.now()
    df['day_of_week'] = df['timestamp'].dt.day_name()
    df['hour_of_day'] = df['timestamp'].dt.hour
```

```
# Save processed data
df.to_csv('processed_finance_reddit_data.csv', index=False)
print("Processing complete! Data saved to 'processed_finance_reddit_data.csv'")
```

```
Requirement already satisfied: nltk in c:\users\drmus\anaconda3\lib\site-
packages (3.9.1)
Requirement already satisfied: click in c:\users\drmus\anaconda3\lib\site-
packages (from nltk) (8.1.7)
Requirement already satisfied: joblib in c:\users\drmus\anaconda3\lib\site-
packages (from nltk) (1.4.2)
Requirement already satisfied: regex>=2021.8.3 in
c:\users\drmus\anaconda3\lib\site-packages (from nltk) (2024.9.11)
Requirement already satisfied: tqdm in c:\users\drmus\anaconda3\lib\site-
packages (from nltk) (4.66.5)
Requirement already satisfied: colorama in c:\users\drmus\anaconda3\lib\site-
packages (from click->nltk) (0.4.6)
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\drmus\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\drmus\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\drmus\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\drmus\AppData\Roaming\nltk_data…
[nltk_data]   Package omw-1.4 is already up-to-date!
```

```
Available columns: ['id', 'title', 'text', 'created_utc', 'score',
'upvote_ratio', 'num_comments', 'author', 'subreddit', 'url', 'is_post',
'parent_id']
Processing complete! Data saved to 'processed_finance_reddit_data.csv'
```

1.1.3 No. 6: Exploratory Data Analysis

1.1.4 Sentiment Analysis

[147]:
```
!pip install textblob

# Import necessary libraries
from textblob import TextBlob
import nltk
from nltk.sentiment import SentimentIntensityAnalyzer
import pandas as pd

# Download VADER lexicon
```

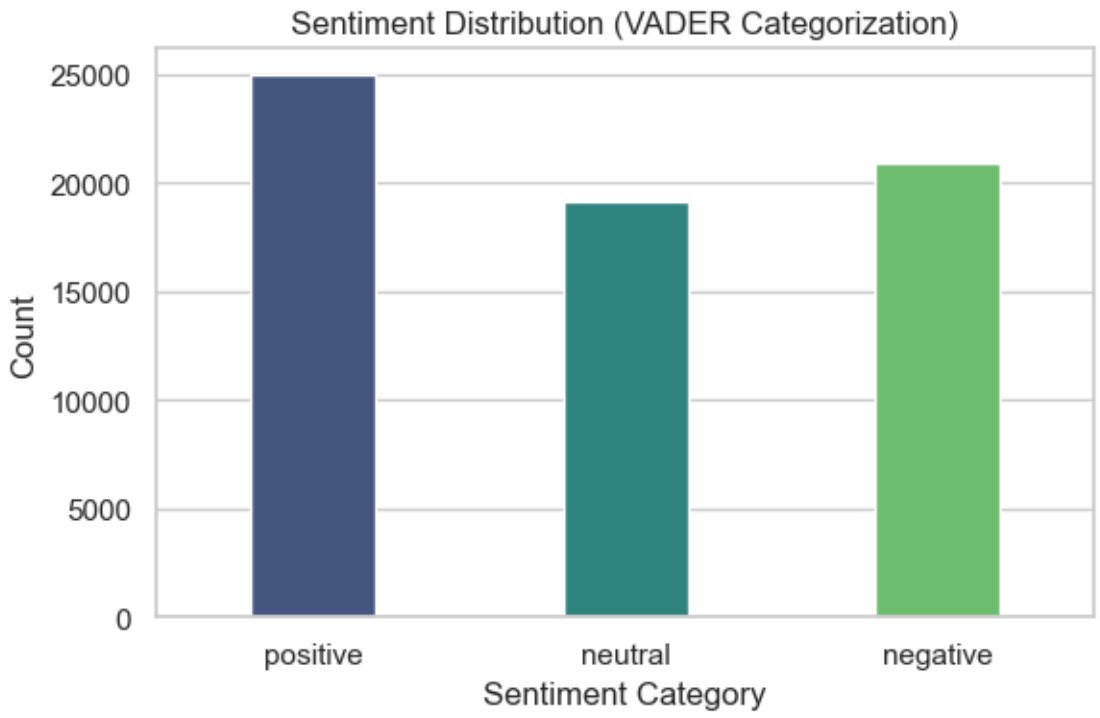
```
nltk.download('vader_lexicon')

# Load the previously processed data
try:
    df = pd.read_csv('processed_finance_reddit_data.csv')
    print(f"Successfully loaded data with {len(df)} rows")
except FileNotFoundError:
    print("Error: Could not find processed_finance_reddit_data.csv")
    # If the file doesn't exist, you might want to load your original data
    # and perform the preprocessing steps first
    # df = pd.read_csv('finance_reddit_data.csv')
    # ... preprocessing code here ...

# Initialize sentiment analyzer
sia = SentimentIntensityAnalyzer()

# TextBlob sentiment
def get_textblob_sentiment(text):
    if isinstance(text, str):
        try:
            return TextBlob(text).sentiment.polarity
        except:
            print(f"Error processing text with TextBlob: {text[:50]}...")
            return 0
    return 0

# VADER sentiment
def get_vader_sentiment(text):
    if isinstance(text, str):
        try:
            return sia.polarity_scores(text)
        except:
            print(f"Error processing text with VADER: {text[:50]}...")
            return {'neg': 0, 'neu': 0, 'pos': 0, 'compound': 0}
    return {'neg': 0, 'neu': 0, 'pos': 0, 'compound': 0}

# Apply sentiment analysis with error handling
print("Calculating TextBlob sentiment...")
df['textblob_sentiment'] = df['clean_text'].apply(get_textblob_sentiment)

print("Calculating VADER sentiment...")
df['vader_sentiment'] = df['clean_text'].apply(get_vader_sentiment)
df['vader_compound'] = df['vader_sentiment'].apply(lambda x: x['compound'])

# Categorize sentiment
def categorize_sentiment(score):
    if score > 0.05:
```

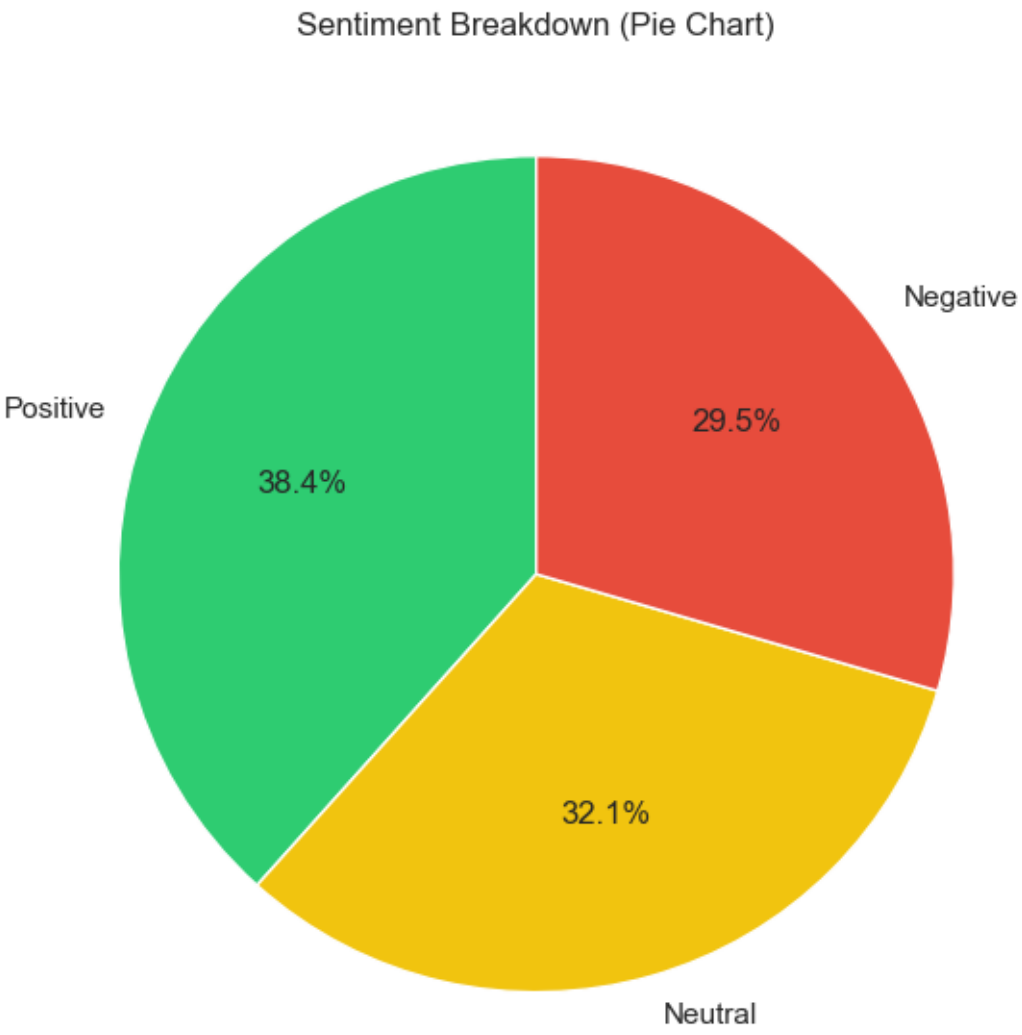
```
        return 'positive'
    elif score < -0.05:
        return 'negative'
    else:
        return 'neutral'

df['sentiment_category'] = df['vader_compound'].apply(categorize_sentiment)

# Add sentiment distribution
sentiment_counts = df['sentiment_category'].value_counts()
print("\nSentiment Distribution:")
print(sentiment_counts)
print(f"Positive: {sentiment_counts.get('positive', 0) / len(df):.2%}")
print(f"Neutral: {sentiment_counts.get('neutral', 0) / len(df):.2%}")
print(f"Negative: {sentiment_counts.get('negative', 0) / len(df):.2%}")

# Calculate sentiment averages
print("\nAverage Sentiment Scores:")
print(f"TextBlob Average: {df['textblob_sentiment'].mean():.4f}")
print(f"VADER Compound Average: {df['vader_compound'].mean():.4f}")

# Save sentiment data
df.to_csv('sentiment_finance_reddit_data.csv', index=False)
print(f"\nData saved to 'sentiment_finance_reddit_data.csv' with {len(df)}␣
 ↪rows")

import matplotlib.pyplot as plt
import seaborn as sns

# Ensure visual style
sns.set(style="whitegrid")

# Create figure
plt.figure(figsize=(6, 4))

# --- Bar Chart ---
sns.countplot(
    x='sentiment_category',
    data=df,
    palette='viridis',
    order=['positive', 'neutral', 'negative'],
    width=0.4
)

plt.title('Sentiment Distribution (VADER Categorization)')
plt.xlabel('Sentiment Category')
plt.ylabel('Count')
```

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

# --- Pie Chart of Sentiment Distribution ---
plt.figure(figsize=(6, 6))
df['sentiment_category'].value_counts().plot.pie(
    autopct='%1.1f%%',
    startangle=90,
    colors=['#2ecc71','#f1c40f','#e74c3c'],
    labels=['Positive','Neutral','Negative']
)
plt.title('Sentiment Breakdown (Pie Chart)')
plt.ylabel('')
plt.tight_layout()
plt.show()
```

```
Collecting textblob
  Downloading textblob-0.19.0-py3-none-any.whl.metadata (4.4 kB)
Requirement already satisfied: nltk>=3.9 in c:\users\drmus\anaconda3\lib\site-
packages (from textblob) (3.9.1)
Requirement already satisfied: click in c:\users\drmus\anaconda3\lib\site-
packages (from nltk>=3.9->textblob) (8.1.7)
Requirement already satisfied: joblib in c:\users\drmus\anaconda3\lib\site-
packages (from nltk>=3.9->textblob) (1.4.2)
Requirement already satisfied: regex>=2021.8.3 in
c:\users\drmus\anaconda3\lib\site-packages (from nltk>=3.9->textblob)
(2024.9.11)
Requirement already satisfied: tqdm in c:\users\drmus\anaconda3\lib\site-
packages (from nltk>=3.9->textblob) (4.66.5)
Requirement already satisfied: colorama in c:\users\drmus\anaconda3\lib\site-
packages (from click->nltk>=3.9->textblob) (0.4.6)
Downloading textblob-0.19.0-py3-none-any.whl (624 kB)
   ---------------------------------------- 0.0/624.3 kB ? eta -:--:--
   ---------------------------------- ------ 524.3/624.3 kB 8.5 MB/s eta 0:00:01
   ---------------------------------------- 624.3/624.3 kB 2.3 MB/s eta 0:00:00
Installing collected packages: textblob
Successfully installed textblob-0.19.0

[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\drmus\AppData\Roaming\nltk_data…

Successfully loaded data with 64980 rows
Calculating TextBlob sentiment…
Calculating VADER sentiment…

Sentiment Distribution:
sentiment_category
positive    24925
negative    20884
```

```
neutral     19171
Name: count, dtype: int64
Positive: 38.36%
Neutral: 29.50%
Negative: 32.14%

Average Sentiment Scores:
TextBlob Average: 0.0550
VADER Compound Average: 0.0356

Data saved to 'sentiment_finance_reddit_data.csv' with 64980 rows

C:\Users\drmus\AppData\Local\Temp\ipykernel_14216\3663532248.py:92:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(
```




Sentiment Breakdown (Pie Chart)
Negative
29.5%
Positive
38.4%
32.1%
Neutral