hull_mini_project_12_19

December 19, 2023

[ ]:
```python
import yfinance as yf
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pandas.tseries.offsets import BDay
from datetime import datetime
```

[ ]:
```python
# Ticker symbol for S&P 500 index
ticker_symbol = '^GSPC'

# Fetch historical data
sp500_data = yf.download(ticker_symbol, start='1900-01-01', end='2023-12-31')

# Display the fetched data
print(sp500_data)
```

```
[*********************100%%**********************]  1 of 1 completed
                   Open         High          Low        Close    Adj Close  \
Date
1927-12-30    17.660000    17.660000    17.660000    17.660000    17.660000
1928-01-03    17.760000    17.760000    17.760000    17.760000    17.760000
1928-01-04    17.719999    17.719999    17.719999    17.719999    17.719999
1928-01-05    17.549999    17.549999    17.549999    17.549999    17.549999
1928-01-06    17.660000    17.660000    17.660000    17.660000    17.660000
…                   …            …            …            …            …
2023-12-13  4646.200195  4709.689941  4643.229980  4707.089844  4707.089844
2023-12-14  4721.040039  4738.569824  4694.339844  4719.549805  4719.549805
2023-12-15  4714.229980  4725.529785  4704.689941  4719.189941  4719.189941
2023-12-18  4725.580078  4749.520020  4725.580078  4740.560059  4740.560059
2023-12-19  4743.720215  4764.189941  4743.720215  4758.640137  4758.640137

                Volume
Date
1927-12-30           0
1928-01-03           0
1928-01-04           0
1928-01-05           0
```

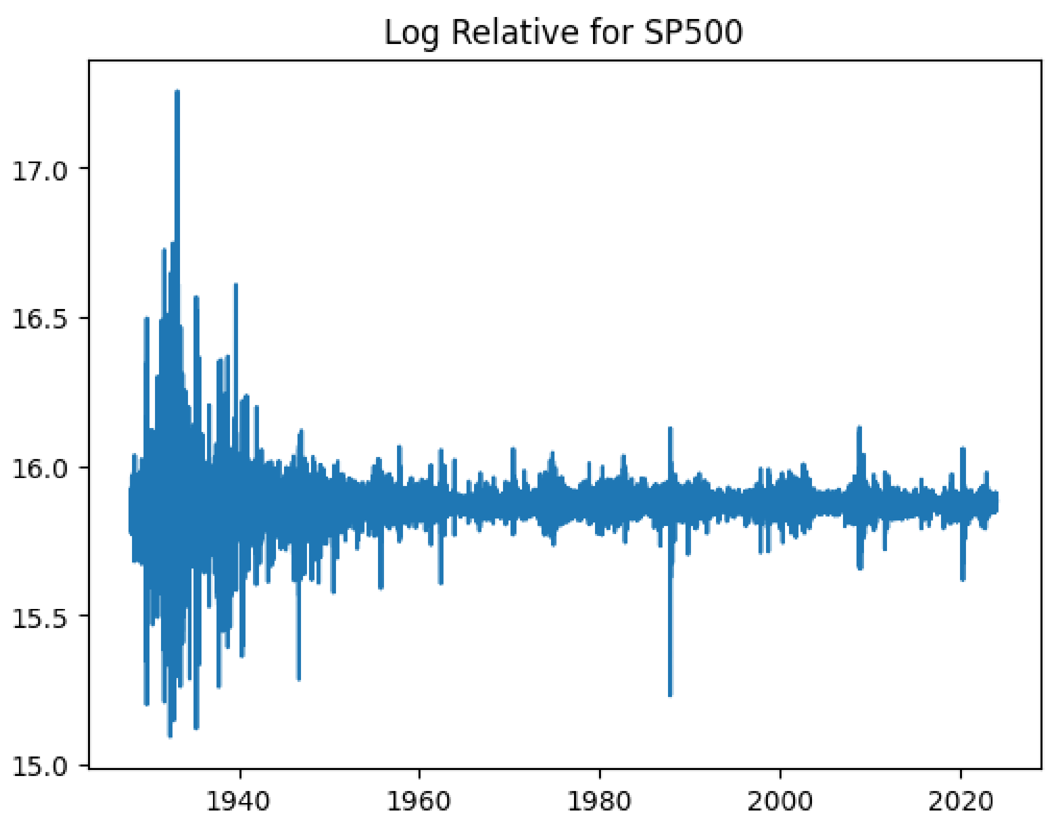
```
1928-01-06           0
…                  …
2023-12-13  5063650000
2023-12-14  6314040000
2023-12-15  8218980000
2023-12-18  4060340000
2023-12-19  1033582000

[24108 rows x 6 columns]

                   Open         High          Low        Close    Adj Close  \
Date
1927-12-30    17.660000    17.660000    17.660000    17.660000    17.660000
1928-01-03    17.760000    17.760000    17.760000    17.760000    17.760000
1928-01-04    17.719999    17.719999    17.719999    17.719999    17.719999
1928-01-05    17.549999    17.549999    17.549999    17.549999    17.549999
1928-01-06    17.660000    17.660000    17.660000    17.660000    17.660000
…                   …           …           …           …           …
2023-12-13  4646.200195  4709.689941  4643.229980  4707.089844  4707.089844
2023-12-14  4721.040039  4738.569824  4694.339844  4719.549805  4719.549805
2023-12-15  4714.229980  4725.529785  4704.689941  4719.189941  4719.189941
2023-12-18  4725.580078  4749.520020  4725.580078  4740.560059  4740.560059
2023-12-19  4743.720215  4764.189941  4743.720215  4758.640137  4758.640137

                Volume
Date
1927-12-30           0
1928-01-03           0
1928-01-04           0
1928-01-05           0
1928-01-06           0
…                  …
2023-12-13  5063650000
2023-12-14  6314040000
2023-12-15  8218980000
2023-12-18  4060340000
2023-12-19  1033582000

[24108 rows x 6 columns]
```

[ ]:
```
#LOG RELATIVE - currently not used
log_today = np.log(sp500_data['Close'])
log_yesterday =np.log(sp500_data['Close'].shift(1))
sqrt_252 = np.sqrt(252)
log_data = (log_today/log_yesterday)*sqrt_252
log_data
```

[ ]: Date
```
1927-12-30          NaN
1928-01-03    15.905726
1928-01-04    15.862066
1928-01-05    15.821274
1928-01-06    15.909128
                 …
2023-12-13    15.899999
2023-12-14    15.879470
2023-12-15    15.874365
2023-12-18    15.882986
2023-12-19    15.881647
Name: Close, Length: 24108, dtype: float64
```

[ ]:
```python
plt.plot(log_data)
plt.title('Log Relative for SP500')
```

[ ]: Text(0.5, 1.0, 'Log Relative for SP500')



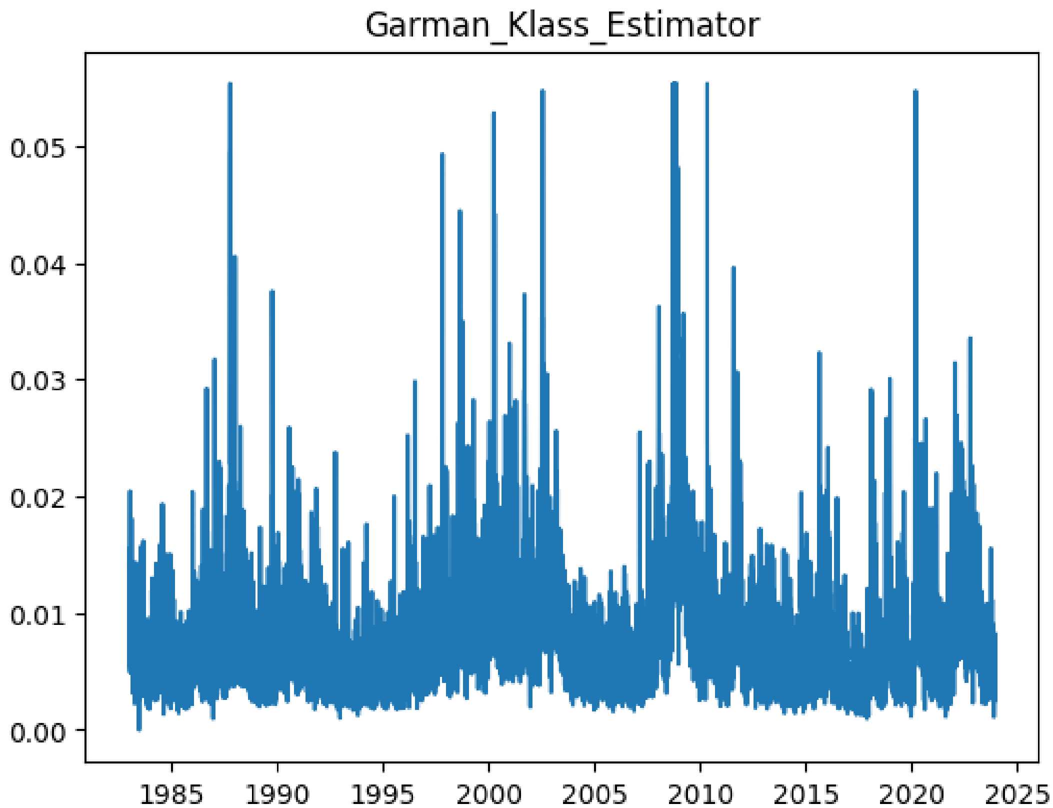
[ ]:
```python
#CALCULATE GARMAN KLASS FOR EACH DAY
```

```
# Download S&P 500 data from Yahoo Finance
sp500 = yf.download('^GSPC', start='1983-01-01', end='2023-12-31')

# Calculate Garman-Klass estimator for each day
def calculate_gk_estimator(high, low, open_price, close):
    log_hl = np.log(high / low)
    log_co = np.log(close / open_price)
    log_co_square = log_co ** 2
    return np.sqrt((1 / (2)) * np.sum(log_hl ** 2 - (2 * np.log(2) - 1) *␣
 ↪log_co_square))

# Create an empty list to store daily estimators
gk_estimators = []

# Iterate through the dataset day by day
for i in range(len(sp500)):
    high = sp500['High'].iloc[i]
    low = sp500['Low'].iloc[i]
    open_price = sp500['Open'].iloc[i]
    close = sp500['Close'].iloc[i]

    # Calculate the Garman-Klass estimator for the current day
    gk_est = calculate_gk_estimator(high, low, open_price, close)
    gk_estimators.append(gk_est)

# Add the daily estimators to the DataFrame
sp500['Garman_Klass_Estimator'] = gk_estimators

#Cap Extreme Vols
percentile_999 = sp500['Garman_Klass_Estimator'].quantile(0.999)
# Replace values above the 99.9th percentile with the percentile value in the␣
 ↪DataFrame
sp500.loc[sp500['Garman_Klass_Estimator'] > percentile_999,␣
 ↪'Garman_Klass_Estimator'] = percentile_999


# Displaying the DataFrame with the Garman-Klass estimator for each day
print(sp500[['Open', 'High', 'Low', 'Close', 'Garman_Klass_Estimator']])
plt.plot(sp500['Garman_Klass_Estimator'])
plt.title('Garman_Klass_Estimator')
```

```
[*********************100%%**********************]  1 of 1 completed
                  Open        High         Low       Close  \
Date
1983-01-03  140.649994  141.330002  138.199997  138.339996
1983-01-04  138.330002  141.360001  138.080002  141.360001
1983-01-05  141.350006  142.600006  141.149994  141.960007
```

```
1983-01-06   142.009995   145.770004   142.009995   145.270004
1983-01-07   145.270004   146.460007   145.149994   145.179993
…                 …            …            …            …
2023-12-13  4646.200195  4709.689941  4643.229980  4707.089844
2023-12-14  4721.040039  4738.569824  4694.339844  4719.549805
2023-12-15  4714.229980  4725.529785  4704.689941  4719.189941
2023-12-18  4725.580078  4749.520020  4725.580078  4740.560059
2023-12-19  4743.720215  4764.189941  4743.720215  4761.950195

            Garman_Klass_Estimator
Date
1983-01-03                0.014065
1983-01-04                0.013598
1983-01-05                0.006975
1983-01-06                0.015555
1983-01-07                0.006347
…                             …
2023-12-13                0.008261
2023-12-14                0.006630
2023-12-15                0.003091
2023-12-18                0.003291
2023-12-19                0.002535

[10327 rows x 5 columns]
```

[ ]: Text(0.5, 1.0, 'Garman_Klass_Estimator')



[ ]:
```
#ADD TRADING_DAY COLUMN
# Add a column labeling each trading day from 1 to 252
sp500['Year'] = sp500.index.year

# Calculate the total number of trading days in each year
total_trading_days = sp500.groupby('Year').size()

# Add a column labeling each trading day from 1 to 252 and divide by the total␣
↪trading days in that year
sp500['Trading_Day'] = sp500.groupby('Year').cumcount() + 1

# Get today's date
current_date = datetime.now()

# Define the start and end dates for the current year
start_date = pd.Timestamp(datetime(current_date.year, 1, 1))  # January 1st of␣
↪the current year
end_date = pd.Timestamp(datetime(current_date.year, 12, 31))  # December 31st␣
↪of the current year
```

```
# Generate a date range from today until the end of the year (excluding␣
↪weekends and holidays)
date_range = pd.date_range(start=current_date, end=end_date, freq=BDay())

# Calculate the remaining trading days in the year
remaining_trading_days = len(date_range)

# Create a function to divide Trading_Day by the total trading days of its year
def calculate_trading_day_ratio(row):
    year = row['Year']
    if year < current_date.year:
        return row['Trading_Day'] / total_trading_days[year]
    else:
        return row['Trading_Day'] /␣
↪(total_trading_days[year]+remaining_trading_days)

# Apply the function to create Trading_Day_Ratio column
sp500['Trading_Day_Ratio'] = sp500.apply(calculate_trading_day_ratio, axis=1)
```

[ ]:
```
#ADD QUARTER END COLUMN
sp500['Quarter_End'] = sp500.index - pd.offsets.BQuarterEnd()
#quarter_ends = sp500.groupby(sp500['Quarter_End'].dt.to_period('Q'))['Date'].
↪max()

# Calculate the difference between 'Date' and 'Quarter_End' in days
sp500['Days_After_Quarter_End'] = (sp500.index - sp500['Quarter_End']).dt.days

# Create 'Seasonal_Trading' column based on the condition (25-31 days after␣
↪Quarter End)
sp500['Seasonal_Trading'] = 0  # Initialize with 0
sp500.loc[(sp500['Days_After_Quarter_End'] >= 25) &␣
↪(sp500['Days_After_Quarter_End'] <= 31), 'Seasonal_Trading'] = 1
```

[ ]:
```
#HAR MODEL
import statsmodels.api as sm

# Calculating different volatility measures
sp500['yesterday_volatility'] = sp500['Garman_Klass_Estimator'].shift(1)
sp500['avg_2_5_day_volatility'] = sp500['Garman_Klass_Estimator'].shift(6).
↪rolling(window=5).mean()
sp500['avg_6_21_day_volatility'] = sp500['Garman_Klass_Estimator'].shift(21).
↪rolling(window=16).mean()

# Dropping NaN values resulting from rolling means
data = sp500.dropna()

# Creating the HAR model
```

```python
X = data[['yesterday_volatility', 'avg_2_5_day_volatility',␣
 ↪'avg_6_21_day_volatility', 'Trading_Day_Ratio', 'Seasonal_Trading']]
X = sm.add_constant(X)  # Adding a constant coefficient
y = data['Garman_Klass_Estimator']

# Fitting the model
model = sm.OLS(y, X).fit()

# Printing the model summary
print(model.summary())
```

```
                              OLS Regression Results
================================================================================
==
Dep. Variable:     Garman_Klass_Estimator   R-squared:
0.499
Model:                                OLS   Adj. R-squared:
0.499
Method:                     Least Squares   F-statistic:
2052.
Date:                    Tue, 19 Dec 2023   Prob (F-statistic):
0.00
Time:                            14:36:19   Log-Likelihood:
42369.
No. Observations:                   10291   AIC:
-8.473e+04
Df Residuals:                       10285   BIC:
-8.468e+04
Df Model:                               5
Covariance Type:                nonrobust
================================================================================
===========
                              coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
const                       0.0011      0.000     10.045      0.000       0.001
0.001
yesterday_volatility        0.4150      0.009     45.453      0.000       0.397
0.433
avg_2_5_day_volatility      0.3687      0.012     29.995      0.000       0.345
0.393
avg_6_21_day_volatility     0.1037      0.012      8.808      0.000       0.081
0.127
Trading_Day_Ratio          -0.0004      0.000     -3.291      0.001      -0.001
-0.000
Seasonal_Trading         9.168e-05      0.000      0.635      0.526      -0.000
0.000
```

```
==============================================================================
Omnibus:                     4931.619   Durbin-Watson:                   2.198
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            64816.544
Skew:                           1.965   Prob(JB):                         0.00
Kurtosis:                      14.650   Cond. No.                         433.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```