Bollinger Bands Strategy

September 29, 2024

Functions (IGNORE)

[ ]:
```
# import packages that will be used for analysis
import random
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
```

Get Stock Data

[ ]:
```
import yfinance as yf
missing_data_tickers = [] # use this as a list of tickers with missing data

def get_data_from_start_to_end(ticker, start_date, end_date):
    global missing_data_tickers  # Use the global list to accumulate missing␣
 ↪tickers
    try:
        stock_data = yf.download(ticker, start=start_date, end=end_date)
        if stock_data.empty:
            missing_data_tickers.append(ticker)
            raise ValueError(f"Stock data for ticker {ticker} during the period␣
 ↪from {start_date} to {end_date} was not found.")
        return stock_data
    except Exception as e:
        print(f"An error occurred for ticker {ticker}: {e}")
        missing_data_tickers.append(ticker)
        return None
```

[ ]:
```
# for a variety of periods load in different list of tickers
def download_stock_data_for_periods(tickers, periods):
    all_data = {}

    for period, (start_date, end_date) in periods.items():
        period_data = {}
        for ticker in tickers:
            data = get_data_from_start_to_end(ticker, start_date, end_date)
            if data is not None:
```

```
                period_data[ticker] = data
        all_data[period] = period_data

    return all_data
```

[ ]:
```
import pandas as pd

# Get the adjusted close prices
adj_close_sector_etf = {}

# Create adjusted close price only listing of sector ETFs
def get_adjusted_closed_price(nested_dict, tickers, periods):
    for period in periods:
        stock_price_df = pd.DataFrame()  # Create a new DataFrame for each␣
 ↪period
        for ticker in tickers:
            stock_price_df[ticker] = nested_dict[period][ticker]['Adj Close']

        adj_close_sector_etf[period] = stock_price_df  # Store the complete␣
 ↪DataFrame for the period

    return adj_close_sector_etf
```

Stochastic Modeling

[ ]:
```
def stochastic_modeling(nested_dict, tickers,␣
 ↪periods,num_samples,investment_period):
    # Store the returns in a nested dictionary
    nested_dict_returns = {period: {ticker: [] for ticker in tickers} for␣
 ↪period in periods}

    # Go through each economic time period
    for period in periods:
        max_index = len(nested_dict[period]) - investment_period  # Ensure␣
 ↪there's enough data to calculate ROI

        # Generate random samples from the valid range
        random_dates = random.choices(range(max_index), k=num_samples)

        for ticker in tickers:
            for date_idx in random_dates:
                start_price = nested_dict[period][ticker].iloc[date_idx]
                end_price = nested_dict[period][ticker].iloc[date_idx +␣
 ↪investment_period]

                # Get the return by the Holding Period Return
                roi = (((end_price - start_price) / start_price) * 100)
```

```
                nested_dict_returns[period][ticker].append(roi)

    return nested_dict_returns  # Return the nested dictionary with returns
```

```
[ ]: def stochastic_roi(tickers,periods,return_rates_list,analysis_type):
         df = pd.DataFrame(index=tickers,columns=periods)
         for period in periods:
             for ticker in tickers:
                 data = pd.Series(return_rates_list[period][ticker])
                 if analysis_type=='Mean':
                     df.at[ticker,period] = data.mean()
                 elif analysis_type=='Median':
                     df.at[ticker,period] = data.median()
                 elif analysis_type=='Std':
                     df.at[ticker,period] = data.std()
                 elif analysis_type=='Variance':
                     df.at[ticker,period] = data.var()

         return df
```

Bollinger Bands

```
[ ]: # create bollinger bands
     import scipy.stats as stats
     def add_bollinger_data(data,window,conf_int):
             z_score = stats.norm.ppf(1 - (1 - conf_int) / 2) # create a zscore from␣
       ↪the mean

             data['middle_band'] = data['Adj Close'].rolling(window).mean()
             data['upper_band'] = data['middle_band'] + z_score * data['Adj Close'].
       ↪rolling(window).std()
             data['lower_band'] = data['middle_band'] - z_score * data['Adj Close'].
       ↪rolling(window).std()

             data['Signal'] = None

             data['Signal'] = np.where(data['Adj Close'] < data['lower_band'], 'Buy',
                                    np.where(data['Adj Close'] > data['upper_band'],␣
       ↪'Sell', np.nan))

             return data
```

```
[ ]: # create bollinger data for multiple time period and multiple tickers
     def␣
       ↪bollinger_data_multiple_periods_tickers(periods,tickers,data,window,confidence_period):
       ↪
```

```
    # for each ticker in economic time periods
    for period in periods:
            for ticker in tickers:
                    try:
                        ␣
↪add_bollinger_data(data[period][ticker],window,confidence_period)
                    except KeyError:
                        print(f'Data for {ticker} does not exist during␣
↪{period}')
```

[ ]:

```
# create a function that plots the bollinger bands and actions
def plot_with_boll_bands(bollinger_data):
    """
    bollinger_data: holds the signals and bollinger data
    """
    buy_data = []
    sell_data = []

    for index, row in bollinger_data.iterrows():
        if row['Signal']=='Buy':
            buy_data.append(row['Adj Close'])
        else:
            buy_data.append(np.nan)

        if row['Signal'] == 'Sell':
            sell_data.append(row['Adj Close'])

        else:
            sell_data.append(np.nan)

    bollinger_data['Buy Data'] = buy_data
    bollinger_data['Sell Data'] = sell_data

    plt.figure(figsize=(12,8))

    plt.plot(bollinger_data.index,bollinger_data['Adj␣
↪Close'],color='grey',label='Adjusted Close Price')
    plt.plot(bollinger_data.
↪index,bollinger_data['lower_band'],color='green',label='Lower␣
↪Band',linestyle='-')
    plt.plot(bollinger_data.
↪index,bollinger_data['upper_band'],color='red',label='Upper␣
↪Band',linestyle='-')
    plt.scatter(bollinger_data.index,bollinger_data['Buy␣
↪Data'],marker='o',color='green',label='Buy Signal')
    plt.scatter(bollinger_data.index,bollinger_data['Sell␣
↪Data'],marker='o',color='red',label='Sell Signal')
```

```
    #plt.plot(investment_tracking_df['Date'],investment_tracking_df['Investment␣
↪Value'])
    # goal is to make a subplot which shows both the investment and bollinger␣
↪bands

    plt.xlabel('Date')
    plt.xticks(rotation=60)
    plt.ylabel('Price')
    plt.legend()
    plt.show()
```

[ ]:
```
def collect_signals(nested_dict, periods, tickers):
    # Initialize an empty dictionary to hold DataFrames for each period
    bb_nested_dict = {}

    for period in periods:
        # Create a DataFrame for each period with the tickers as columns
        signals_period = pd.DataFrame(columns=tickers)

        # Loop through each ticker and extract the 'Signal'
        for ticker in tickers:
            signals_period[ticker] = nested_dict[period][ticker]['Signal']

        # Store the DataFrame in the dictionary using the period as the key
        bb_nested_dict[period] = signals_period

    # Return the dictionary containing DataFrames for each period
    return bb_nested_dict
```

Plot data

[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Function to plot percentage-based histogram
def plot_percentage_histogram(data, title, xlabel, ylabel, bins=10,␣
↪color='skyblue'):
    """
    Plots a percentage-based histogram for the given data.

    Parameters:
    data (array-like): Data to plot the histogram for.
    title (str): Title of the plot.
    xlabel (str): Label for the x-axis.
    ylabel (str): Label for the y-axis.
    bins (int): Number of bins for the histogram.
```

```
    color (str): Color for the histogram bars.
    """
    # Set modern aesthetic
    sns.set_style("whitegrid")

    # Create the histogram
    plt.figure(figsize=(10, 6))
    plt.hist(data, bins=bins, color=color, edgecolor='black',
             weights=np.ones_like(data) / len(data))

    # Convert y-axis to percentages
    plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda y, _: f'{y*100:
↪.0f}%'))

    # Add titles and labels with improved font sizes
    plt.title(title, fontsize=16, fontweight='bold')
    plt.xlabel(xlabel, fontsize=14)
    plt.ylabel(ylabel, fontsize=14)

    # Add gridlines for better readability
    plt.grid(True, which='both', linestyle='--', linewidth=0.7, alpha=0.7)

    # Adjust layout for better spacing
    plt.tight_layout()

    # Show the plot
    plt.show()
```

[ ]:
```
import matplotlib.pyplot as plt

def plot_sector_investment_changes(sector_allocation, title):

    sector_df = sector_allocation.apply(pd.Series)
    """
    Plots a stacked area chart to track how the investment in different sectors␣
↪changes over time.

    Parameters:
    sector_df (pd.DataFrame): DataFrame where columns represent sectors and␣
↪index represents dates.
    title (str): The title of the plot (optional).
    """
    # Create the plot
    plt.figure(figsize=(12, 6))
    plt.stackplot(sector_df.index, sector_df.T, labels=sector_df.columns)

    # Add title and labels
```

```
    plt.title(title)
    plt.xlabel('Date')
    plt.ylabel('Allocation Amount')
    plt.legend(loc='upper left')

    # Rotate x-ticks for better readability
    plt.xticks(rotation=45)
    plt.grid()

    # Display the plot
    plt.tight_layout()
    plt.show()

    return sector_df
```

Stock Investment History

[ ]:
```
import pandas as pd
import numpy as np
from datetime import timedelta
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

def portfolio_investment(bb_signals_nd, adj_close_nd, periods_date,␣
↪periods_list, tickers, n_sample, initial_investment, percent_to_buy,␣
↪percent_to_sell):
    # Track actions day by day for the entire portfolio
    portfolio_tracker = {period: pd.DataFrame(columns=['Date', 'Account␣
↪Balance', 'Portfolio Value', 'Total Value', 'Profit', 'Sector Allocation'])␣
↪for period in periods_list}

    # Portfolio summary - nested dictionary for each period and ticker
    portfolio_summary = {period: {ticker: pd.DataFrame() for ticker in tickers}␣
↪for period in periods_list}

    # Set data to be accessed
    adj_close_data = adj_close_nd
    bollinger_band_data = bb_signals_nd

    all_data = {
        'Stock Tracker': portfolio_summary,
        'Portfolio Tracker': portfolio_tracker,
        'Adjusted Close Price': adj_close_nd,
        'Bollinger Band Signal': bollinger_band_data
    }

    # Loop through each economic period
```

```
    for period in periods_list:
        # Create the date range for the current period
        date_range = pd.date_range(start=pd.
↪to_datetime(periods_date[period][0]), end=pd.
↪to_datetime(periods_date[period][1]) - timedelta(days=90))
        # Get random dates for stochastic modeling
        start_dates = np.random.choice(date_range, size=n_sample, replace=False)

        # Loop through sampled start dates
        for start_date in start_dates:
            time_stamp = pd.to_datetime(start_date)

            # Initialize balance for portfolio investment
            account_balance = initial_investment
            shares_number = {ticker: 0 for ticker in tickers}  # Initialize␣
↪share count for each ticker

            # Extract the adjusted close and signal data for time period
            adj_close_period = adj_close_data[period].loc[time_stamp:time_stamp␣
↪+ timedelta(days=90)]
            bb_signals_period = bollinger_band_data[period].loc[time_stamp:
↪time_stamp + timedelta(days=90)]

            # Iterate over each row in the Bollinger Band signals (day by day)
            for row_idx, row in bb_signals_period.iterrows():
                daily_balance_change = 0
                portfolio_value = 0

                # Initialize tracking for each ticker
                for col_idx, signal in enumerate(row):
                    ticker = tickers[col_idx]  # Correctly get ticker for each␣
↪column
                    adj_close_price = adj_close_period.loc[row_idx, ticker]  #␣
↪Get corresponding adjusted close price

                    # Initialize stock tracker for current ticker
                    stock_tracker = all_data['Stock Tracker'][period][ticker]

                    # Handle Buy action
                    if signal == 'Buy':
                        amount_to_buy = percent_to_buy * account_balance
                        if account_balance >= amount_to_buy:
                            # Calculate shares to buy
                            shares_to_buy = amount_to_buy / adj_close_price
                            shares_number[ticker] += shares_to_buy
```

```
                            # Track investment for the current period
                            stock_tracker = stock_tracker.append({
                                'Date': row_idx,
                                'Share Price': adj_close_price,
                                'Signal': 'Buy',
                                'Buy/Sell Amount ($)': amount_to_buy,
                                'Buy/Sell Number of Shares': shares_to_buy,
                                'Shares ($) Ownership': shares_number[ticker] *␣
↪adj_close_price,  # Update based on current price
                                'Shares Ownership': shares_number[ticker]
                            }, ignore_index=True)

                            # Update account balance after buying
                            account_balance -= amount_to_buy

                    # Handle Sell action
                    elif signal == 'Sell':
                        if shares_number[ticker] > 0:  # Ensure we have shares␣
↪to sell
                            amount_to_sell = percent_to_sell *␣
↪(shares_number[ticker] * adj_close_price)
                            shares_to_sell = amount_to_sell / adj_close_price
                            if shares_number[ticker] >= shares_to_sell:
                                shares_number[ticker] -= shares_to_sell

                                # Track the sell action
                                stock_tracker = stock_tracker.append({
                                    'Date': row_idx,
                                    'Share Price': adj_close_price,
                                    'Signal': 'Sell',
                                    'Buy/Sell Amount ($)': amount_to_sell,
                                    'Buy/Sell Number of Shares': shares_to_sell,
                                    'Shares ($) Ownership':␣
↪shares_number[ticker] * adj_close_price,  # Update based on current price
                                    'Shares Ownership': shares_number[ticker]
                                }, ignore_index=True)

                                # Update account balance after selling
                                account_balance += amount_to_sell

                    # Handle Hold action (no action taken)
                    else:
                        # Track the hold state
                        stock_tracker = stock_tracker.append({
                            'Date': row_idx,
                            'Share Price': adj_close_price,
                            'Signal': 'Hold',
```

```
                            'Buy/Sell Amount ($)': 0,
                            'Buy/Sell Number of Shares': 0,
                            'Shares ($) Ownership': shares_number[ticker] *␣
↪adj_close_price,  # Update based on current price
                            'Shares Ownership': shares_number[ticker]
                        }, ignore_index=True)

                        # Save the updated tracker back to portfolio summary
                        all_data['Stock Tracker'][period][ticker] = stock_tracker.
↪copy()

                # Calculate total portfolio value for all tickers for the day
                portfolio_value = sum(shares_number[ticker] * adj_close_period.
↪loc[row_idx, ticker] for ticker in tickers)

                # Total value (account balance + portfolio value)
                total_value = account_balance + portfolio_value

                # Calculate profit (difference from initial investment)
                profit = total_value - initial_investment

                # Calculate percentage allocation of each ticker to total␣
↪portfolio value
                sector_allocation = {ticker: (shares_number[ticker] *␣
↪adj_close_period.loc[row_idx, ticker]) / portfolio_value * 100 if␣
↪portfolio_value > 0 else 0 for ticker in tickers}

                # Track portfolio changes for the current day
                portfolio_tracker[period] = portfolio_tracker[period].append({
                    'Date': row_idx,
                    'Account Balance': account_balance,
                    'Portfolio Value': portfolio_value,
                    'Total Value': total_value,
                    'Profit': profit,
                    'Sector Allocation': sector_allocation
                }, ignore_index=True)

            # Update the portfolio tracker for the period
            all_data['Portfolio Tracker'][period] = portfolio_tracker[period]

    # Return the complete portfolio summary for all periods and tickers
    return all_data
```

[ ]:
```
def stochastic_roi(tickers,periods,return_rates_list,analysis_type):
    df = pd.DataFrame(index=tickers,columns=periods)
    for period in periods:
        for ticker in tickers:
```

```
            data = pd.Series(return_rates_list[period][ticker])
            if analysis_type=='Mean':
                df.at[ticker,period] = data.mean()
            elif analysis_type=='Median':
                df.at[ticker,period] = data.median()
            elif analysis_type=='Std':
                df.at[ticker,period] = data.std()
            elif analysis_type=='Variance':
                df.at[ticker,period] = data.var()

    return df
```

[ ]:
```
def calculate_stock_roi(bb_signals_nd, adj_close_nd, periods_date,␣
↪periods_list, tickers, n_sample, initial_investment, percent_to_buy,␣
↪percent_to_sell):
    # Initialize a nested dictionary to store ROI percentages for each period␣
↪and ticker
    roi_results = {period: {ticker: [] for ticker in tickers} for period in␣
↪periods_list}

    # Loop through each economic period
    for period in periods_list:
        # Create the date range for the current period
        date_range = pd.date_range(start=pd.
↪to_datetime(periods_date[period][0]), end=pd.
↪to_datetime(periods_date[period][1]) - timedelta(days=90))

        # Get random dates for stochastic modeling
        start_dates = np.random.choice(date_range, size=n_sample, replace=True)

        # Loop through sampled start dates
        for start_date in start_dates:
            time_stamp = pd.to_datetime(start_date)

            # Initialize variables
            account_balance = initial_investment
            shares_number = {ticker: 0 for ticker in tickers}  # Initialize␣
↪share count for each ticker
            shares_value = {ticker: 0 for ticker in tickers}   # Initialize␣
↪share value for each ticker

            # Extract the adjusted close and signal data for time period
            adj_close_period = adj_close_nd[period].loc[time_stamp:time_stamp +␣
↪timedelta(days=90)]
            bb_signals_period = bb_signals_nd[period].loc[time_stamp:time_stamp␣
↪+ timedelta(days=90)]
```

```python
        # Iterate over each row in the Bollinger Band signals (day by day)
        for row_idx, row in bb_signals_period.iterrows():
            for col_idx, signal in enumerate(row):
                ticker = tickers[col_idx]  # Correctly get ticker for each column
                adj_close_price = adj_close_period.loc[row_idx, ticker]  # Get corresponding adjusted close price

                # Handle Buy action
                if signal == 'Buy':
                    amount_to_buy = percent_to_buy * account_balance
                    if account_balance >= amount_to_buy:
                        shares_to_buy = amount_to_buy / adj_close_price
                        shares_number[ticker] += shares_to_buy
                        account_balance -= amount_to_buy

                # Handle Sell action
                elif signal == 'Sell':
                    if shares_number[ticker] > 0:
                        shares_value[ticker] = shares_number[ticker] * adj_close_price
                        amount_to_sell = percent_to_sell * shares_value[ticker]
                        if shares_value[ticker] >= amount_to_sell:
                            shares_to_sell = amount_to_sell / adj_close_price
                            shares_number[ticker] -= shares_to_sell
                            account_balance += amount_to_sell

        # Calculate total portfolio value at the end of the period
        portfolio_value = sum(shares_number[ticker] * adj_close_period.iloc[-1][ticker] for ticker in tickers)
        total_value = account_balance + portfolio_value

        # Calculate the profit relative to the initial investment
        profit = total_value - initial_investment

        # Calculate ROI for each stock as a percentage of the initial investment
        for ticker in tickers:
            if shares_number[ticker] > 0:  # Only consider tickers with shares owned
                roi_dollar_value = shares_value[ticker] - (initial_investment * (percent_to_buy * shares_number[ticker]))
```

```
                else:
                    roi_dollar_value = 0

                # Store ROI in the results dictionary
                roi_results[period][ticker].append(roi_dollar_value)

    return roi_results
```

1 Chapter 2: Bollinger Bands

Bollinger Bands investing is a popular technical analysis tool created by John Bollinger in the 1980's. They measure market volatility and utilize moving averages to understand whether a stock is overbought or oversold which signals a buy or sell signal. It consists of the following parameters: - Middle band: The 20 day moving average - Upper band: The 20 day moving average plus 2 standard deviations of the current moving average - Lower band: The 20 day moving average minus 2 standard deviations of the current moving average

1.1 Bollinger Bands Strategy using Sector ETF's

Sector ETFs are the accumulation of a variety of stocks within one of the 11 GICS Sectors (see documentation). They are meant to be a representation of a sector's overall movement. This will allow for a better understanding of which sectors perform best over time. To add further complexity, different economic time periods will be used to evaluate the changing success of an investment based on macroeconomic environments. For example some stocks out perform benchmarks during a recession due to their defensive nature such as the Health Care ETF (XLV).

Chapter 1's investigation into buy and hold strategies gave a good background into what can be expected of stock performance. This is going to be used as a bench mark to compare the success of the Bollinger Bands.

1.2 Sector ETF and Time Period Setup

[ ]:
```
# create time periods for where this takes place
economic_cycle_periods = {

    "trough": ("2008-10-01", "2009-06-01"),
    "expansion": ("2012-01-01", "2015-01-01"),
    "peak": ("2019-06-01", "2020-02-01"),
    "contraction": ("2007-12-01", "2008-10-01"),
    'all_data': ('2005-01-01','2024-06-01')
}

economic_cycle_periods_list =␣
 ↪['trough','expansion','peak','contraction','all_data']
```

[ ]:
```
# create etf tickers for sectors
sector_etf_tickers = [
    'XLB', # materials sector
```

```python
    'XLI', # industrials sector
    'XLF', # financials
    'XLK', # information technology
    'XLY', # consumer discretionary
    'XLP', # consumer staples
    'XLE', # energy
    'XLV', # healthcare
    'VOX', # communication services
    'XLU', # utilities
    'IYR' # real estate
    ]
```

[ ]:
```python
# save nested dictionary data as a variable to be accessed.
sector_etf_data =
 ↪download_stock_data_for_periods(sector_etf_tickers,economic_cycle_periods)
```

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

1.3 Bollinger Bands Introduction

Bollinger bands require the use of the adjusted close price to create an upper and lower bound from the moving average. Working within the 'sector_etf_data' nested dictionary, the upper, middle and lower bound can be added as columns to the dataframe. This can then create a signal for each day which is going to be combined into one dataframe dependent on the macroeconomic cycle of investment.

[ ]:
```
# use 20 day moving average
# use a 95% confidence interval (2 standard deviations)
for ticker in sector_etf_tickers:
    
 ↪bollinger_data_multiple_periods_tickers(economic_cycle_periods_list,sector_etf_tickers,sect
 ↪95)
```

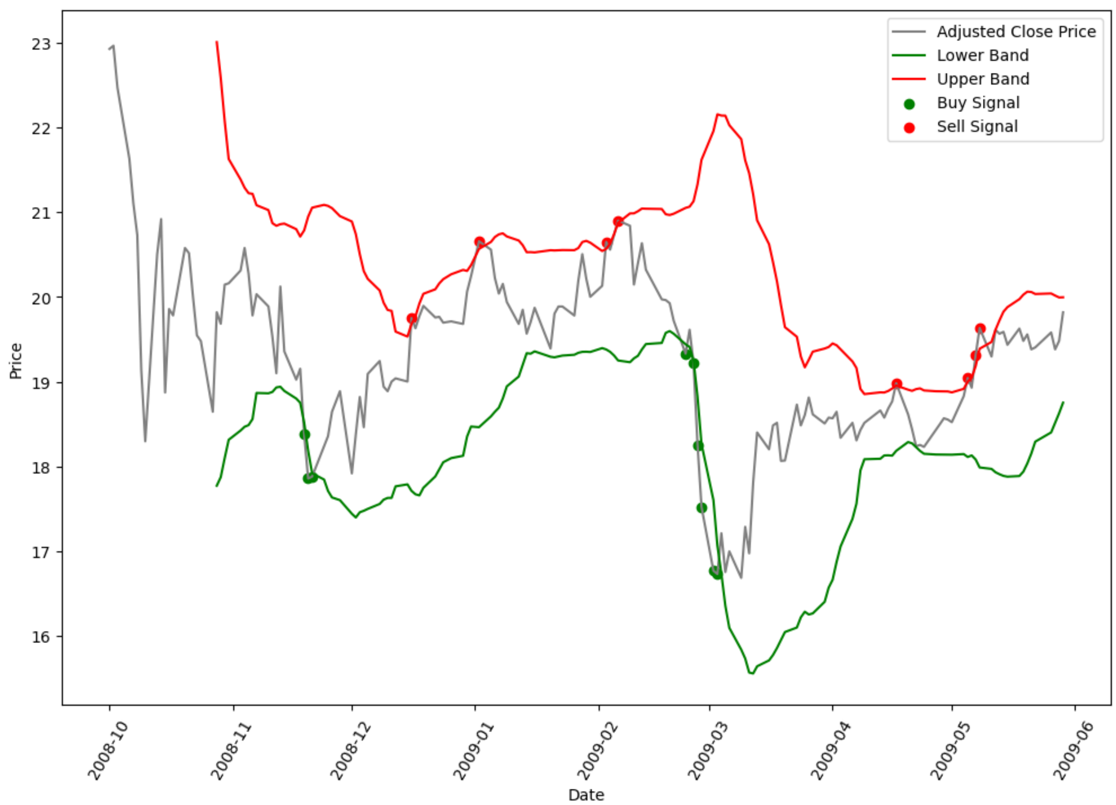
[ ]:
```
# show an example of XLV healthcare sector during a trough
sector_etf_data['trough']['XLV']
```

[ ]:
```
                 Open       High        Low      Close  Adj Close   Volume  \
Date
2008-10-01  30.100000  30.480000  30.100000  30.250000  22.927486  6053600
2008-10-02  30.250000  30.590000  29.930000  30.299999  22.965378  6353400
2008-10-03  30.600000  30.600000  29.650000  29.650000  22.472727  6814400
2008-10-06  29.400000  29.879999  27.410000  28.540001  21.631422  8545000
```

```
2008-10-07  28.719999  28.780001  27.389999  27.850000  21.108452  5060200
…                …          …          …          …          …        …
2009-05-22  25.280001  25.400000  25.070000  25.290001  19.404514  3655700
2009-05-26  25.190001  25.660000  24.889999  25.520000  19.580986  4412900
2009-05-27  25.549999  25.600000  25.219999  25.260000  19.381500  4591100
2009-05-28  25.209999  25.590000  25.139999  25.389999  19.481243  5720000
2009-05-29  25.360001  25.840000  25.290001  25.830000  19.818851  6549200

            middle_band  upper_band  lower_band Signal
Date
2008-10-01          NaN         NaN         NaN    nan
2008-10-02          NaN         NaN         NaN    nan
2008-10-03          NaN         NaN         NaN    nan
2008-10-06          NaN         NaN         NaN    nan
2008-10-07          NaN         NaN         NaN    nan
…                    …          …          …     …
2009-05-22    19.163588   20.034958   18.292217    nan
2009-05-26    19.221133   20.041095   18.401172    nan
2009-05-27    19.265252   20.016430   18.514075    nan
2009-05-28    19.310905   19.994301   18.627510    nan
2009-05-29    19.374206   19.996141   18.752271    nan

[166 rows x 10 columns]
```

[ ]:

```python
# show the same example but with bollinger bands plotted for XLV during trough
plot_with_boll_bands(sector_etf_data['trough']['XLV'])
```



1.4 Stochastic Modeling for Bollinger Bands

Stochastic modeling is going to be slightly different. There needs to be 2 dataframes associated with the investment. There needs to a signal dataframe and the adjusted close price dataframe. The signal dataframe is the different tickers signal for each day meanwhile the adjusted close price is the dataframe with the closing adjusted price for each ticker. When there is a signal to buy or sell you need to get the adjusted close price data from the other dataframe in order to update the investment.

[ ]:
```
# get the adjusted close price dataframe
sector_etf_closed_price =␣
 ↪get_adjusted_closed_price(sector_etf_data,sector_etf_tickers,economic_cycle_periods_list)
```

[ ]:
```
# load in the dataframe for the trough time period
sector_etf_closed_price['trough']
```

[ ]:
```
                  XLB        XLI        XLF        XLK        XLY        XLP  \
Date
2008-10-01  23.119270  21.858334  12.413445  15.649678  22.589607  18.009497
2008-10-02  21.458338  20.549889  11.794876  15.037062  21.771828  17.782763
2008-10-03  21.247194  20.222775  11.278399  14.822246  21.010748  17.640251
2008-10-06  20.198568  19.692122  10.689856  14.002766  20.419697  17.128462
```

```
2008-10-07  19.156967  19.037899   9.560816  13.286716  19.108042  16.584293
…                …          …          …          …          …          …
2009-05-22  18.848715  16.073534   7.178291  13.618083  18.520390  15.070188
2009-05-26  19.300220  16.658958   7.412233  13.971807  19.143747  15.260777
2009-05-27  18.576378  16.117987   7.190603  13.835135  18.725441  14.873021
2009-05-28  18.906042  16.273613   7.393766  14.036111  18.651619  15.030753
2009-05-29  19.472227  16.666374   7.529204  14.188856  18.963306  15.195066

                  XLE        XLV        VOX        XLU        IYR
Date
2008-10-01  37.393242  22.927486  36.648045  18.666508  34.011742
2008-10-02  35.261116  22.965378  35.561878  18.395731  31.759169
2008-10-03  34.840698  22.472727  35.039402  18.119318  30.064146
2008-10-06  32.966827  21.631422  33.396400  17.233656  29.512159
2008-10-07  31.159039  21.108452  31.966496  16.528513  27.019825
…                …          …          …          …          …
2009-05-22  29.497372  19.404514  33.037407  14.918161  18.541616
2009-05-26  30.122391  19.580986  34.221874  15.351323  19.500559
2009-05-27  29.794701  19.381500  33.881413  15.039441  18.851515
2009-05-28  30.783810  19.481243  34.314072  15.351323  19.208204
2009-05-29  31.360291  19.818851  34.512653  15.461059  19.734447

[166 rows x 11 columns]
```

[ ]:
```python
# get the signals for tickers
bb_signals = collect_signals(sector_etf_data,economic_cycle_periods_list,sector_etf_tickers)
```

[ ]:
```python
# get the bollinger band signals for trough
# nan represent no purchase or sell (hold)
bb_signals['trough']
```

[ ]:
```
            XLB  XLI  XLF  XLK  XLY  XLP  XLE  XLV  VOX  XLU  IYR
Date
2008-10-01  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2008-10-02  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2008-10-03  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2008-10-06  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2008-10-07  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
…             …    …    …    …    …    …    …    …    …    …    …
2009-05-22  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2009-05-26  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2009-05-27  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2009-05-28  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan
2009-05-29  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan  nan

[166 rows x 11 columns]
```

[ ]:
```python
# ensure that the dataframe has buy and sell signals
for ticker in sector_etf_tickers:
    print(bb_signals['trough'][ticker].value_counts())
```

```
nan     158
Sell      5
Buy       3
Name: XLB, dtype: int64
nan     150
Buy       8
Sell      8
Name: XLI, dtype: int64
nan     148
Buy      13
Sell      5
Name: XLF, dtype: int64
nan     156
Sell      8
Buy       2
Name: XLK, dtype: int64
nan     153
Sell      7
Buy       6
Name: XLY, dtype: int64
nan     153
Buy       7
Sell      6
Name: XLP, dtype: int64
nan     151
Sell      9
Buy       6
Name: XLE, dtype: int64
nan     149
Buy       9
Sell      8
Name: XLV, dtype: int64
nan     153
Buy       7
Sell      6
Name: VOX, dtype: int64
nan     154
Buy       6
Sell      6
Name: XLU, dtype: int64
nan     153
Buy       9
Sell      4
Name: IYR, dtype: int64
```

1.4.1 Investment

The following is a portfolio investment example of using sector etfs during different economic time periods. It follows the following methodology.

A random start date is collected from the date ranges of the given period the investment will last for 90 days. The function will go through each day and each ticker and make an investment based on the available balance or will make an appropriate sale based on the amount of stocks owned.

The history of these purchases are saved in 'Stock Tracker' meanwhile the overall portfolio is saved as 'Portfolio Tracker' which includes the sector allocation throughout the investment as well profit, account balance and portfolio value.

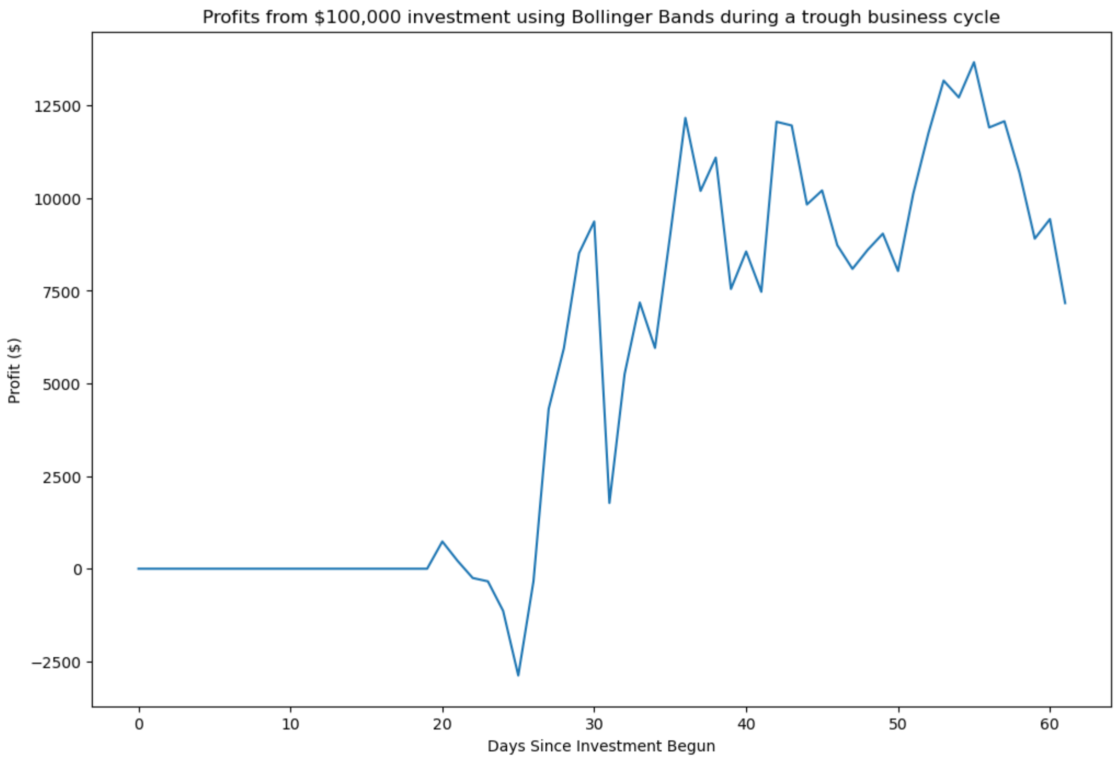
[ ]:
```
# investment 5% of balance to purchasing stocks
# sell 25% of current holding when a sell signal occurs
bb_portfolio_investment =␣
 ↪portfolio_investment(bb_signals,adj_close_sector_etf,economic_cycle_periods,economic_cycle_
 ↪05,0.25)
```

[ ]:
```
# an example of portfolio tracking during a trough time period
bb_portfolio_investment['Portfolio Tracker']['trough']
```

[ ]:
```
          Date Account Balance  Portfolio Value    Total Value        Profit  \
0   2008-10-16          100000         0.000000  100000.000000      0.000000
1   2008-10-17          100000         0.000000  100000.000000      0.000000
2   2008-10-20          100000         0.000000  100000.000000      0.000000
3   2008-10-21          100000         0.000000  100000.000000      0.000000
4   2008-10-22          100000         0.000000  100000.000000      0.000000
..         …               …                …             …             …
57  2009-01-08    63317.554835     48758.426591  112075.981426  12075.981426
58  2009-01-09    63317.554835     47364.459355  110682.014191  10682.014191
59  2009-01-12    57144.093239     51764.064399  108908.157638   8908.157638
60  2009-01-13    57144.093239     52290.996431  109435.089670   9435.089670
61  2009-01-14    51572.544148     55596.554900  107169.099048   7169.099048

                                       Sector Allocation
0   {'XLB': 0, 'XLI': 0, 'XLF': 0, 'XLK': 0, 'XLY'…
1   {'XLB': 0, 'XLI': 0, 'XLF': 0, 'XLK': 0, 'XLY'…
2   {'XLB': 0, 'XLI': 0, 'XLF': 0, 'XLK': 0, 'XLY'…
3   {'XLB': 0, 'XLI': 0, 'XLF': 0, 'XLK': 0, 'XLY'…
4   {'XLB': 0, 'XLI': 0, 'XLF': 0, 'XLK': 0, 'XLY'…
..                                                …
57  {'XLB': 9.180357482392292, 'XLI': 6.1339852351…
58  {'XLB': 9.221392092765004, 'XLI': 6.1762600903…
59  {'XLB': 8.086970305500293, 'XLI': 5.5272450144…
60  {'XLB': 8.048420189296804, 'XLI': 5.3776275847…
61  {'XLB': 7.287156412808842, 'XLI': 4.8698939816…

[62 rows x 6 columns]
```

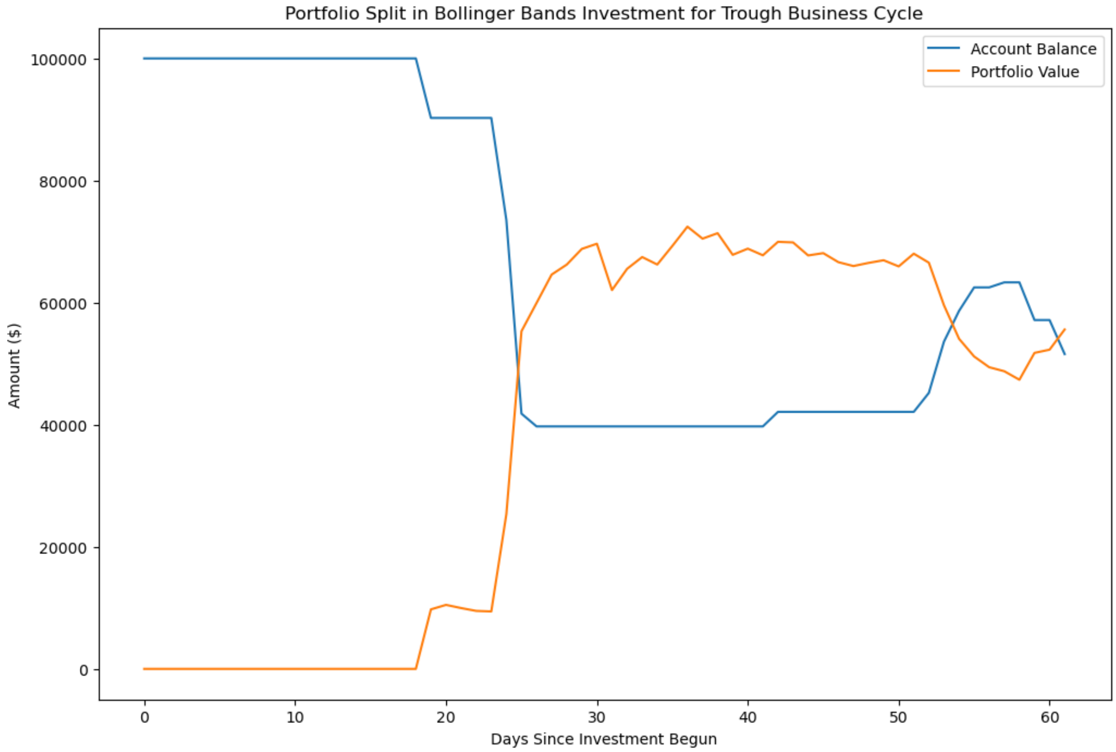
[ ]:
```
# display how the portfolio grew over time
plt.figure(figsize=(12,8))
plt.plot(bb_portfolio_investment['Portfolio Tracker']['trough']['Profit'])
plt.xlabel('Days Since Investment Begun')
plt.ylabel('Profit ($)')
plt.title('Profits from $100,000 investment using Bollinger Bands during a␣
↪trough business cycle')
```

[ ]:
```
Text(0.5, 1.0, 'Profits from $100,000 investment using Bollinger Bands during a
trough business cycle')
```

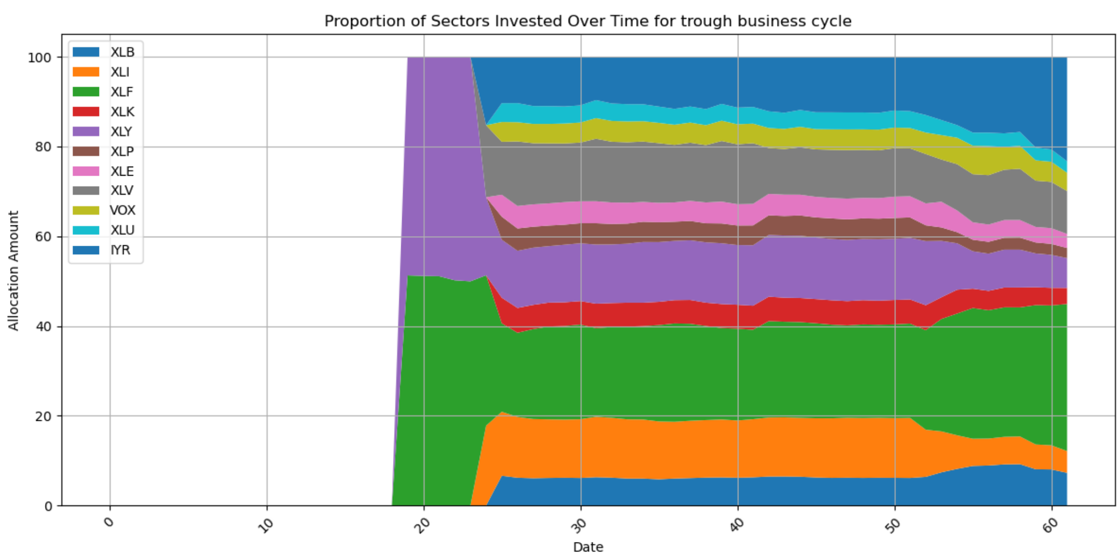


[ ]:
```
# create a plot of how account balance and portfolio value changes
plt.figure(figsize=(12,8))
plt.plot(bb_portfolio_investment['Portfolio Tracker']['trough']['Account␣
↪Balance'],label='Account Balance')
plt.plot(bb_portfolio_investment['Portfolio Tracker']['trough']['Portfolio␣
↪Value'],label='Portfolio Value')
plt.xlabel('Days Since Investment Begun')
plt.ylabel('Amount ($)')
plt.title('Portfolio Split in Bollinger Bands Investment for Trough Business␣
↪Cycle')
plt.legend()
```

[ ]: <matplotlib.legend.Legend at 0x7f99f346a880>




```
[ ]: # create a plot of different sectors invested in over time
plot_sector_investment_changes(bb_portfolio_investment['Portfolio␣
↪Tracker']['trough']['Sector Allocation'],'Proportion of Sectors Invested␣
↪Over Time for trough business cycle')
```



```
[ ]:          XLB       XLI        XLF       XLK       XLY       XLP       XLE  \
    0   0.000000  0.000000   0.000000  0.000000  0.000000  0.000000  0.000000
    1   0.000000  0.000000   0.000000  0.000000  0.000000  0.000000  0.000000
    2   0.000000  0.000000   0.000000  0.000000  0.000000  0.000000  0.000000
    3   0.000000  0.000000   0.000000  0.000000  0.000000  0.000000  0.000000
    4   0.000000  0.000000   0.000000  0.000000  0.000000  0.000000  0.000000
    ..       …         …          …         …         …         …         …
    57  9.180357  6.133985  28.849075  4.405801  8.445196  2.646891  3.946161
    58  9.221392  6.176260  28.752960  4.435628  8.426847  2.678212  3.925894
    59  8.086970  5.527245  31.036839  3.985549  7.527465  2.451648  3.450421
    60  8.048420  5.377628  31.144962  3.927300  7.355618  2.441709  3.501189
    61  7.287156  4.869894  32.743413  3.582013  6.647436  2.245942  3.135557

              XLV       VOX       XLU        IYR
    0    0.000000  0.000000  0.000000   0.000000
    1    0.000000  0.000000  0.000000   0.000000
    2    0.000000  0.000000  0.000000   0.000000
    3    0.000000  0.000000  0.000000   0.000000
    4    0.000000  0.000000  0.000000   0.000000
    ..        …         …         …          …
    57  11.212487  5.074879  3.026211  17.078956
    58  11.420192  5.099609  3.090828  16.772177
    59  10.313691  4.527483  2.829100  20.263588
    60  10.296784  4.495083  2.747641  20.663666
    61   9.546917  4.079563  2.552587  23.309523

    [62 rows x 11 columns]
```

```
[ ]: # look at the investment history of 'XLV' healthcare sector during trough
     bb_portfolio_investment['Stock Tracker']['trough']['XLV']
```

```
[ ]:          Date  Share Price Signal  Buy/Sell Amount ($)  \
    0   2008-10-16    19.857855   Hold                  0.0
    1   2008-10-17    19.782064   Hold                  0.0
    2   2008-10-20    20.577896   Hold                  0.0
    3   2008-10-21    20.517260   Hold                  0.0
    4   2008-10-22    20.009439   Hold                  0.0
    ..         …           …    …                   …
    57  2009-01-08    20.154236   Hold                  0.0
    58  2009-01-09    19.940714   Hold                  0.0
    59  2009-01-12    19.681456   Hold                  0.0
    60  2009-01-13    19.849211   Hold                  0.0
    61  2009-01-14    19.567068   Hold                  0.0

        Buy/Sell Number of Shares  Shares ($) Ownership  Shares Ownership
```

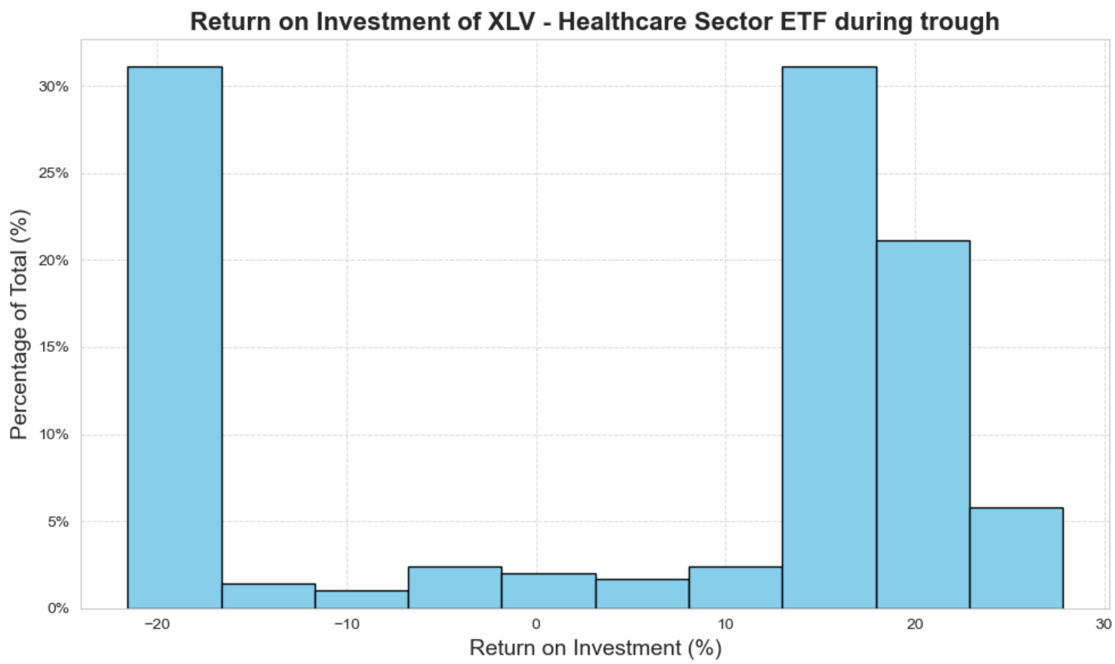
```
0                         0.0           0.000000       0.000000
1                         0.0           0.000000       0.000000
2                         0.0           0.000000       0.000000
3                         0.0           0.000000       0.000000
4                         0.0           0.000000       0.000000
..                        …             …              …
57                        0.0        5467.032073     271.259705
58                        0.0        5409.112170     271.259705
59                        0.0        5338.785848     271.259705
60                        0.0        5384.291054     271.259705
61                        0.0        5307.757125     271.259705

[62 rows x 7 columns]
```

1.4.2 Stochastic Modeling

The above only concentrated on a single set of investment dates, to get the average returns to understand how bollinger bands actually perform, it is neccessary to rereun the simulation thousands of times so that the effects of standard deviation are reduced.

[ ]:
```
bb_average_return = 
↪calculate_stock_roi(bb_signals,adj_close_sector_etf,economic_cycle_periods,economic_cycle_p
↪01,0.01)
```

[ ]:
```
# plot the histogram of the XLV healthcare during a trough
plot_percentage_histogram(
    data=bb_average_return['trough']['XLV'],
    title=f'Return on Investment of XLV - Healthcare Sector ETF during trough',
    xlabel='Return on Investment (%)',
        ylabel='Percentage of Total (%)'
)
```



[ ]:
```
# get the mean of each stock during each time period
stochastic_roi(sector_etf_tickers,economic_cycle_periods_list,bb_average_return,'Mean')
```

[ ]:

	trough	expansion	peak	contraction	all_data
XLB	-0.029593	2.584798	9.766264	10.791603	5.011131
XLI	2.900527	6.880604	13.383887	-14.406917	5.238759
XLF	-75.873412	-4.87829	7.946941	-28.523522	-4.438995
XLK	0.70924	4.937032	10.747122	-1.858801	2.751356
XLY	6.080887	7.859396	28.881756	4.779034	7.028195
XLP	-13.225207	3.095084	-1.50145	5.373152	3.765144
XLE	11.838581	9.826588	20.193686	6.99281	7.697522
XLV	4.412475	7.589642	3.688581	6.600993	6.718807
VOX	15.755505	11.741018	7.54455	4.193492	6.543275
XLU	-8.564124	4.683457	7.7972	-1.271964	4.778562
IYR	-11.240265	2.92462	2.324256	3.944548	5.234082

[ ]:
```
# get the mean return over the time period
stochastic_roi(sector_etf_tickers,economic_cycle_periods_list,bb_average_return,'Mean').
↪mean()
```

[ ]:
```
trough         -6.112308
expansion       5.203995
peak           10.070254
contraction    -0.307779
all_data        4.575258
```

```
dtype: float64
```

[ ]:
```
stochastic_roi(sector_etf_tickers,economic_cycle_periods_list,bb_average_return,'Std')
```

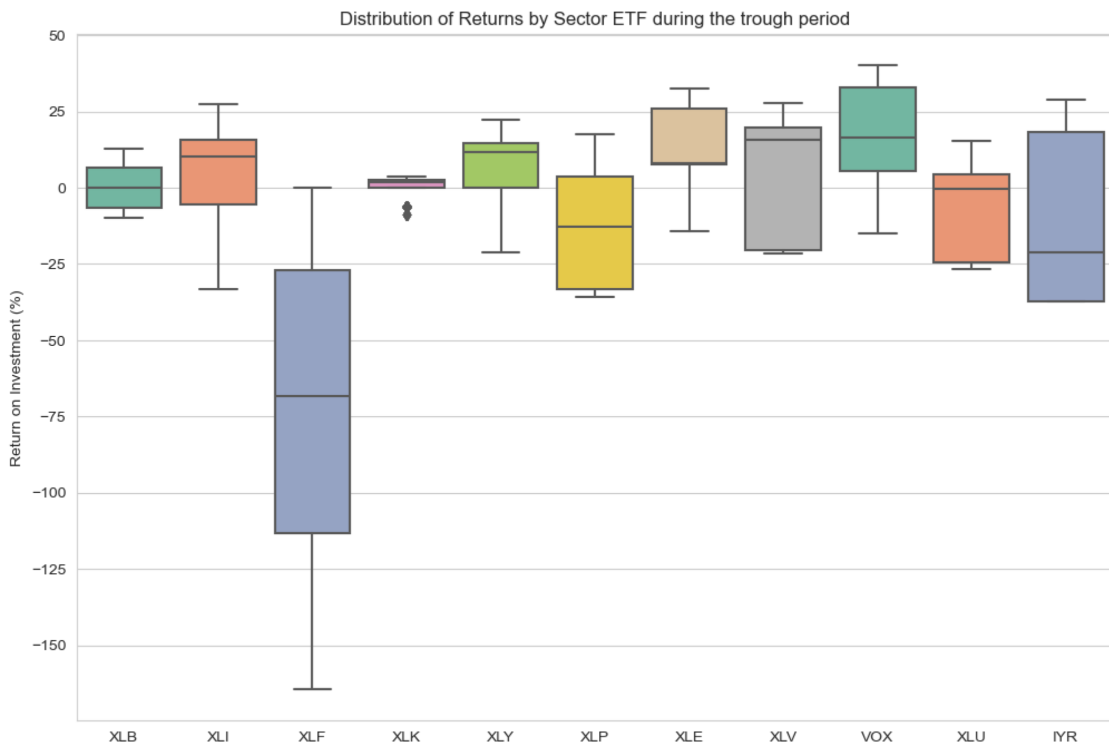
[ ]:

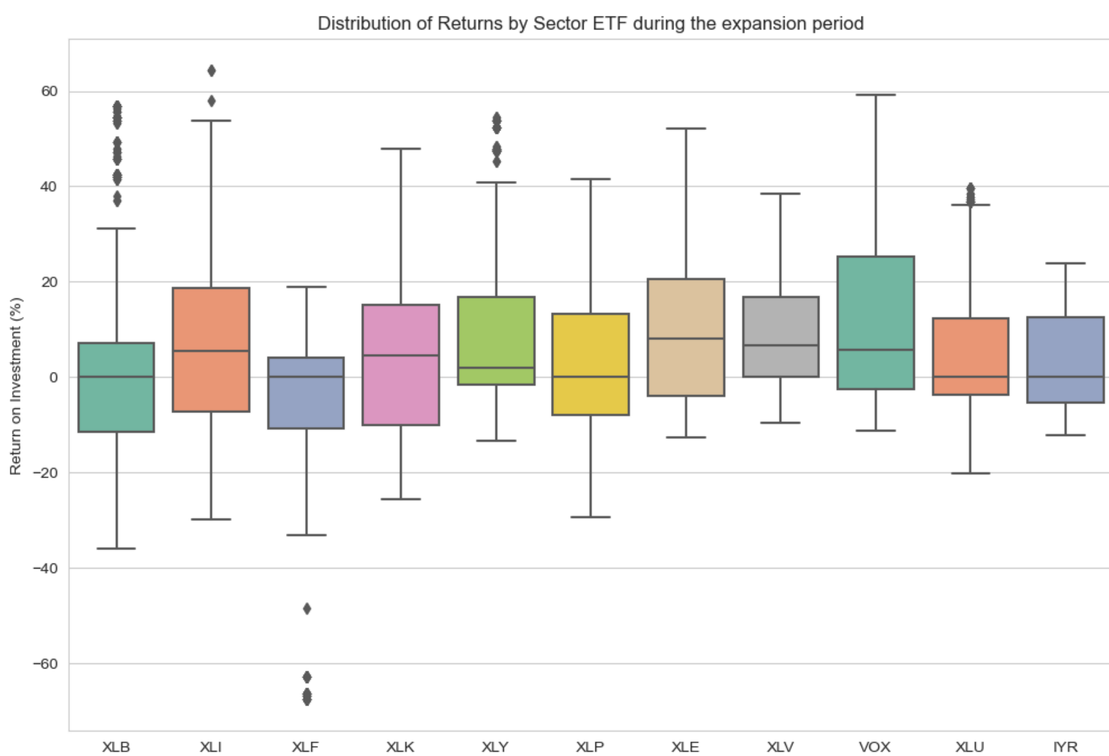
	trough	expansion	peak	contraction	all_data
XLB	7.757045	20.560357	12.013905	16.998527	18.53284
XLI	20.177943	19.615171	6.944931	5.046014	16.266796
XLF	53.341583	17.017648	12.74696	15.795665	22.465392
XLK	3.278351	17.527584	7.623107	11.040627	16.749205
XLY	14.022198	15.384349	16.16122	12.203071	16.923245
XLP	19.221933	15.841657	1.704614	11.617518	15.708927
XLE	15.529311	16.477789	17.80293	14.6185	18.602655
XLV	18.077671	11.449254	7.17092	19.149459	16.305374
VOX	18.490643	18.382685	7.987251	12.321447	15.122937
XLU	15.697912	15.597007	15.287067	14.898975	15.225878
IYR	24.105419	9.210013	13.593508	11.739586	15.337536

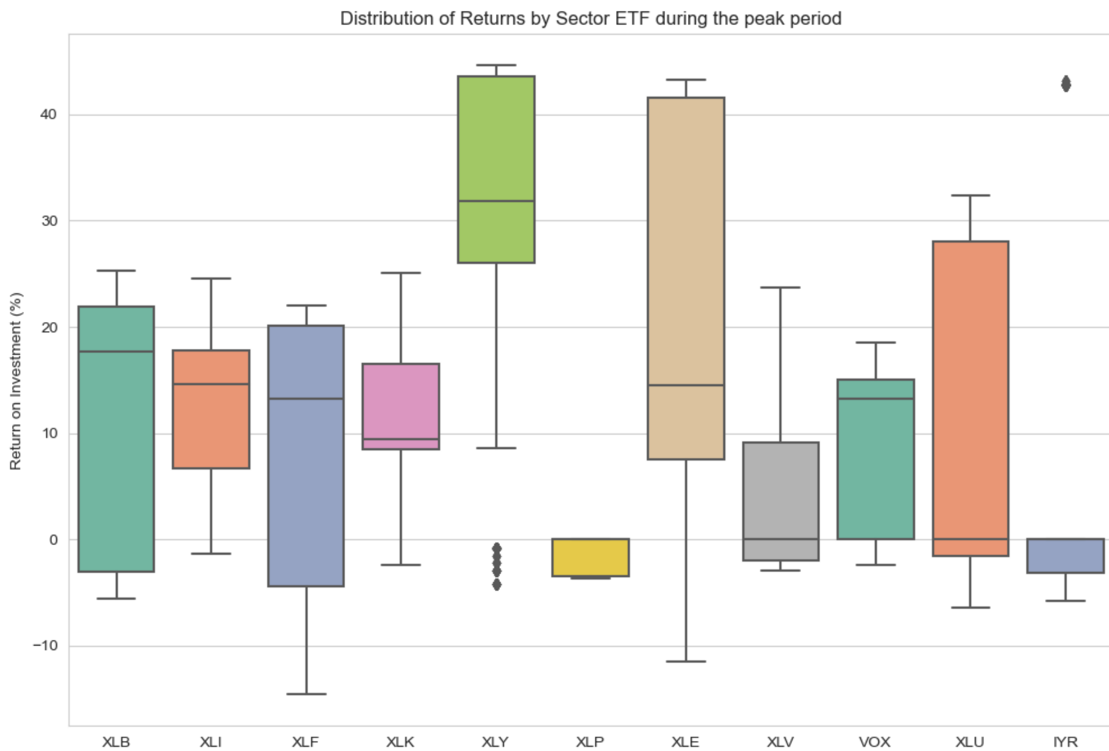
[ ]:
```
stochastic_roi(sector_etf_tickers,economic_cycle_periods_list,bb_average_return,'Std').
↪mean()
```

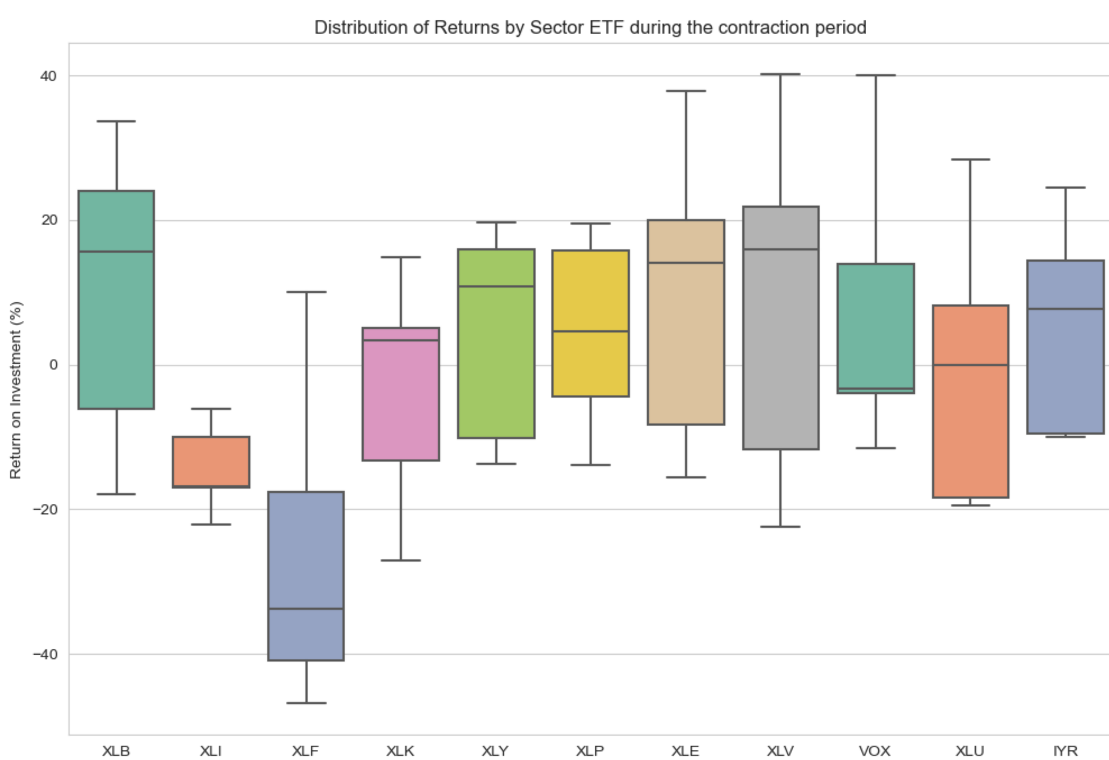
[ ]:
```
trough         19.063637
expansion      16.096683
peak           10.821492
contraction    13.220854
all_data       17.021890
dtype: float64
```

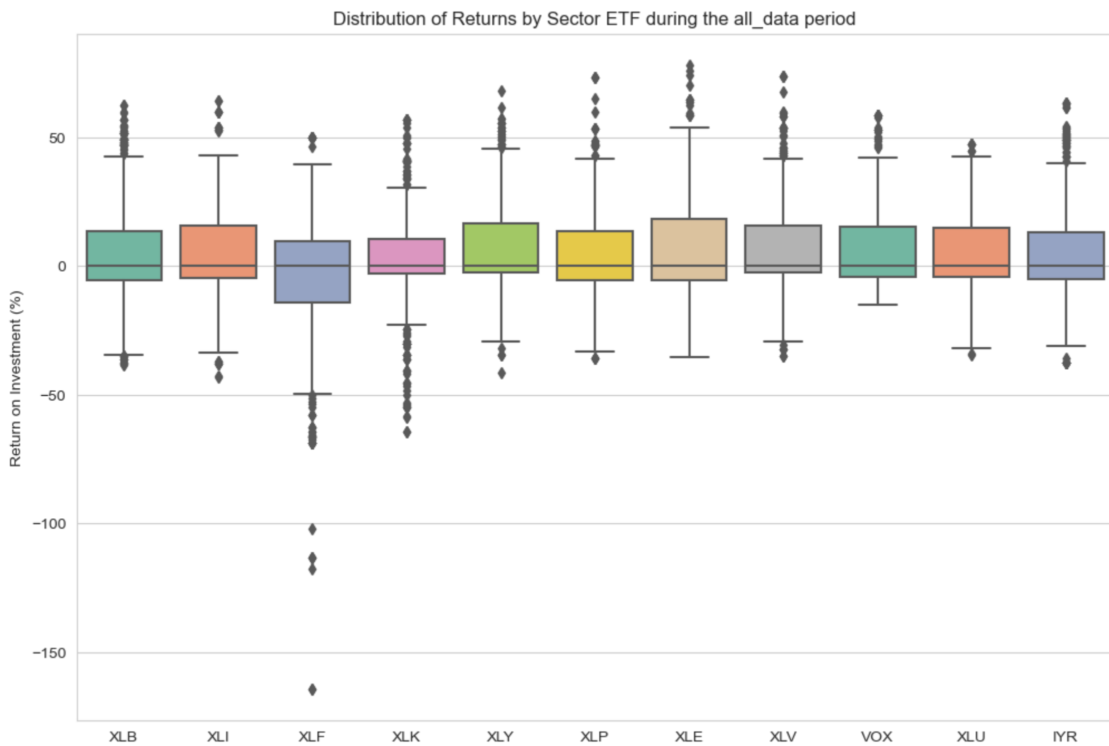
[ ]:
```
# create a boxplot of the above information for visualization
for period in economic_cycle_periods_list:
        # Boxplot of returns for each sector during the trough
        plt.figure(figsize=(12,8))
        sns.boxplot(data=[bb_average_return[period][ticker] for ticker in␣
↪sector_etf_tickers], palette='Set2')
        plt.xticks(range(len(sector_etf_tickers)), sector_etf_tickers)
        plt.title(f'Distribution of Returns by Sector ETF during the {period}␣
↪period')
        plt.ylabel('Return on Investment (%)')
        plt.show()
```


Distribution of Returns by Sector ETF during the trough period
Return on Investment (%)
50
25
0
−25
−50
−75
−100
−125
−150
XLB
XLI
XLF
XLK
XLY
XLP
XLE
XLV
VOX
XLU
IYR


Distribution of Returns by Sector ETF during the expansion period
Return on Investment (%)
60
40
20
0
−20
−40
−60
XLB
XLI
XLF
XLK
XLY
XLP
XLE
XLV
VOX
XLU
IYR


Distribution of Returns by Sector ETF during the peak period
Return on Investment (%)
40
30
20
10
0
−10
XLB
XLI
XLF
XLK
XLY
XLP
XLE
XLV
VOX
XLU
IYR


Distribution of Returns by Sector ETF during the contraction period
Return on Investment (%)
40
20
0
−20
−40
XLB
XLI
XLF
XLK
XLY
XLP
XLE
XLV
VOX
XLU
IYR


Distribution of Returns by Sector ETF during the all_data period
Return on Investment (%)
50
0
−50
−100
−150
XLB
XLI
XLF
XLK
XLY
XLP
XLE
XLV
VOX
XLU
IYR

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[ ]:
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