BRVM Super Portfolio Strategy

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Contents

1 Objective

To maximize return over a 1-month horizon using a capital of 1 million FCFA on the BRVM, leveraging momentum, value, volume, volatility, and macroeconomic context.

2 Data Prepocessing

2.1 Data Structure

To support our portfolio construction logic, we define a structured data architecture. The base unit of analysis is the stock ticker, for which we store both market and fundamental data.

2.1.1 Ticker-Based Data Dictionary

We use a dictionary-like object where each key corresponds to a ticker (e.g., `BNBC`, `BOAB`), and each value is a pandas `DataFrame` holding time-series metrics:

- **Close**: Daily closing price.
- **Volume**: Daily traded volume.
- **Return**: Daily return, computed as $r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$.
- **MA_30**: 30-day moving average.
- **Volatility_30**: 30-day rolling standard deviation.
- **PER, PB, ROE, Net_Margin**: Static or periodic fundamental indicators.

Table 1: Example of `data_dict["BNBC"]`

Date	Close	Volume	Return	MA_30	Vol_30	PER	PB	ROE	Net Margin
2024-12-01	142	3100	0.010	135	0.028	9.2	1.1	12.5	8.3%
...	...	...	...	...	...	...	...	...	...

2.1.2 Matrix Representation

For cross-sectional computations like correlation analysis, covariance, PCA, or Markowitz optimization, we reshape the data into matrix form:

- `price_df`: matrix of historical prices.
- `return_df`: matrix of computed daily returns.
- `volume_df`, `fundamentals_df`: same structure for other metrics.

This hybrid structure allows modular use: ticker-wise filtering and matrix-based optimization.

Table 2: Example of `price_df`

Date	BNBC	BOAB	PALC	...
2024-12-01	142	202	94	...
2024-12-02	143	201	92	...
...	...	...	...	...

2.2 Data Pipeline

Robust and consistent data preprocessing is critical for constructing a reliable BRVM stock portfolio. This section outlines the systematic pipeline applied before any indicator computation, stock scoring, or portfolio optimization.

2.2.1 Overview

The **Data Processing Pipeline** ensures that all raw market and fundamental data are clean, aligned, and ready for analysis. It acts as the backbone of the entire modeling framework.

2.2.2 Pipeline Steps

1. **Data Cleaning**: Remove invalid entries (e.g., null or negative prices), correct date formats, and ensure unique time stamps.
2. **Handling Missing Data**:
   - Use forward fill or backward fill for small gaps.
   - Exclude assets with excessive missingness.
3. **Resampling and Alignment**:
   - Convert all time series to a daily frequency.
   - Align time series across all assets to ensure consistent indexing.
4. **Normalization and Scaling**:
   - Normalize price series (e.g., percentage change, log-returns).
   - Standardize indicators (mean-zero, unit variance) when needed for optimization.
5. **Feature Engineering**:
   - Compute derived features such as moving averages, volatility windows, and momentum metrics.
6. **Validation**:
   - Ensure no NaNs remain in final datasets.
   - Log data statistics for auditability (e.g., average return, volatility, completeness ratio).

2.2.3 Implementation Notes

This pipeline will be wrapped inside a modular Python class (`DataProcessor`), called before scoring and optimization routines. Flexibility is ensured through parameterized configuration (e.g., missing value threshold, resampling rule).

3 Selection Criteria

3.1 Quantitative Factors

Criterion	Description	Weight
Momentum	Weekly and monthly performance	30%
Relative Valuation	Current price vs. 30-day MA	20%
Volatility	Standard deviation of returns	10%
Volume	5-day average volume	15%
Free float cap	Preference for small liquid caps	10%
Recent Earnings	Growth YoY (Revenue, Net Income)	15%

3.2 Fundamental Metrics

Metric	Interpretation	Threshold
PER	Price / Earnings	< 15
PB	Price / Book	< 1.5
ROE	Return on Equity	$> 10\%$
Net Margin	Profitability	$> 5\%$

3.3 Stock Risk Filters

Metric	Interpretation	Threshold
Liquidity	Daily turnover	$> 1\,000\,000$ FCFA
Max Drawdown (1M)	Recent downside risk	$< 10\%$
Sharpe Ratio	Risk-adjusted return	> 1
Correlation	Pairwise average in portfolio	< 0.7

3.4 Qualitative Factors

- Sector-specific impact (e.g. inflation, monetary policy)
- Country-specific macro trends (Ivory Coast, Burkina Faso, Senegal)
- Corporate events (AGMs, dividend declarations)

4 Stock Selection Methodology

4.1 Step by Step applying above criteria

The selection process follows a quantitative, systematic framework to choose stocks from the BRVM, based on both quantitative and qualitative factors, ensuring a diversified and risk-optimized portfolio.

Step 1: Data Collection

The first step involves gathering relevant data for all BRVM-listed stocks:

- **Daily prices** (last 60-90 days)
- **Volumes** (5-day average turnover in FCFA)
- **Market cap** and **free float** data
- **Fundamental data:** PER, PB, ROE, and net margin (from the latest earnings reports)
- **Corporate news:** Dividends, Annual General Meetings (AGMs), mergers, acquisitions, and other relevant corporate events
- **Macro-economic data:** Inflation rates, monetary policy, and trends specific to Ivory Coast, Burkina Faso, and Senegal

Step 2: Compute Key Metrics

The following metrics are calculated for each stock to capture essential features:

- **Momentum:** Performance over the past 7 and 30 days (% change in price)
- **Relative Valuation:** Price compared to the 30-day moving average
- **Volatility:** Standard deviation of daily returns over the past 20 days
- **Volume:** 5-day average volume turnover in FCFA
- **Free Float Capitalization:** Free float × stock price
- **Earnings Growth:** YoY revenue and net income growth
- **Fundamentals:** Price-to-earnings ratio (PER), Price-to-book ratio (PB), Return on Equity (ROE), Net margin
- **Risk:** Maximum drawdown (30-day) and Sharpe ratio
- **Correlation:** Pearson correlation with other stocks in the potential portfolio

Step 3: Apply Hard Constraints (Filters)

The following filters eliminate stocks that do not meet certain criteria:

- **Liquidity filter:** Remove stocks with daily turnover less than 1,000,000 FCFA
- **Valuation filter:** Exclude stocks with PER greater than 15 or PB greater than 1.5
- **Profitability filter:** Remove stocks with ROE less than 10% or net margin below 5%
- **Risk filter:** Exclude stocks with a drawdown exceeding 10% in the last 30 days
- **Correlation filter:** Eliminate stocks that have a correlation greater than 0.7 with other stocks in the short-list

Step 4: Score the Remaining Stocks

Each stock is scored based on its performance across the metrics. The score for each stock is calculated as a weighted sum of the following normalized metrics:

$$\text{Total Score} = 0.30 \cdot S_{\text{momentum}} + 0.20 \cdot S_{\text{valuation}} + 0.10 \cdot S_{\text{volatility}} + 0.15 \cdot S_{\text{volume}} + 0.10 \cdot S_{\text{free float}} + 0.15 \cdot S_{\text{earnings}}$$

where:

- Each metric (S_{metric}) is normalized (via min-max or z-score transformation) to a range between 0 and 1.
- Qualitative factors such as **corporate catalysts** (dividends, AGMs) are assigned a binary bonus (0.1 or 0.2) based on presence or significance.

Step 5: Rank and Select Stocks

Once the scores are computed, stocks are ranked based on their **Total Score**. The top-ranked stocks are selected for inclusion in the portfolio. To avoid concentration risk, ensure the selected stocks have **low pairwise correlation** ($\rho < 0.7$).

Final Selection:

- Top N stocks (e.g., 5-10 stocks) are chosen based on score ranking.
- Ensure **diversification** by selecting stocks that have low correlation with each other.

4.2 Optional Enhancements

- Dividend/AGM calendar monitoring
- Country risk scoring (macro indicators)
- Market sentiment (Twitter, forums)
- Insider trading volume detection
- Technical analysis (RSI, MACD)

4.3 Backtesting

- Test over past 12 months
- Metrics: win rate, avg return, drawdown, risk/reward
- Based on historical daily BRVM data

5 Portfolio Optimization : Sharpe Ratio

Once the stocks selected, we can proceed to allocation. To enhance risk-adjusted returns, portfolio construction must account for correlation between asset returns. The following procedure outlines the practical implementation of a mean-variance optimization framework on BRVM data:

5.1 Data Collection

- Retrieve daily closing prices of selected BRVM stocks over the past 6 to 12 months.
- Convert prices into daily log returns:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

  where $P_{i,t}$ is the price of stock i on day t.

5.2 Correlation and Covariance

- Compute the empirical correlation matrix ρ_{ij} between all pairs of stock returns.
- Compute the covariance matrix Σ, where each element is:

$$\Sigma_{ij} = \sigma_i \sigma_j \rho_{ij}$$

  with σ_i the standard deviation of asset i's return.

5.3 Expected Return Estimation

- Estimate expected returns for each stock using historical average return:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}$$

  or incorporate analyst forecasts or fundamental signals (momentum, earnings growth).

5.4 Optimization

- Solve the following optimization problem:

$$\max_{w} \quad \frac{w^\top \mu}{\sqrt{w^\top \Sigma w}} \quad \text{(Sharpe Ratio)}$$

- Subject to:

$$\sum_i w_i = 1 \quad \text{(fully invested)}$$

$$0 \leq w_i \leq w_{\max} \quad \text{(position limits)}$$

- Use numerical solvers (e.g. ‘scipy.optimize‘) to obtain optimal weights w^*.

5.5 Tangency Portfolio (Maximum Sharpe)

Objective:

$$\max_{w} \quad \frac{w^\top \mu - r_f}{\sqrt{w^\top \Sigma w}}$$

Solution (no constraints):

$$w^*_{\text{Tangency}} = \frac{\Sigma^{-1}(\mu - r_f \mathbf{1})}{\mathbf{1}^\top \Sigma^{-1}(\mu - r_f \mathbf{1})}$$

This portfolio maximizes the Sharpe ratio:

$$\text{Sharpe}(w) = \frac{w^\top \mu - r_f}{\sqrt{w^\top \Sigma w}}$$

5.6 Interpretation and Allocation

- Allocate FCFA capital based on weights: $\text{Capital}_i = w_i \times 1{,}000{,}000$
- Round to nearest integer shares using current stock prices.
- Rebalance weekly or monthly depending on volatility and transaction costs.

6 Markowitz Mean-Variance Model

An alternative to Sharpe ratio maximization is the classical Markowitz formulation, which aims to minimize portfolio risk subject to a target return level. This is particularly useful when investors have a clear return objective and want to control risk exposure.

6.1 Define Target Return

- Let R_{target} be the minimum acceptable expected return for the portfolio.
- It can be set manually (e.g., 2% monthly) or derived from past market returns.

6.2 Problem Formulation

Let:

- $w \in R^n$: vector of portfolio weights
- $\mu \in R^n$: vector of expected returns
- $\Sigma \in R^{n \times n}$: covariance matrix of returns
- $\mathbf{1} \in R^n$: vector of ones
- $r_f \in R$: risk-free rate

6.3 Minimum Variance Portfolio (MVP)

Solve the Optimization Problem

- Objective:

$$\min_{w} \quad w^\top \Sigma w$$

- Subject to:

$$\begin{cases} w^\top \mu \geq R_{\text{target}} & \text{(minimum return)} \\ \sum_{i=1}^{n} w_i = 1 & \text{(fully invested)} \\ 0 \leq w_i \leq w_{\max} & \text{(position limits)} \end{cases}$$

- Use convex optimization solvers (e.g. ‘cvxpy‘ in Python) to find optimal weights w^*.

Solution:

$$w^*_{\text{MVP}} = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}^\top \Sigma^{-1}\mathbf{1}}$$

6.4 Practical Notes

- When reliable estimates for μ are not available, MVP is preferred.
- In practice, we may impose constraints such as $w_i \geq 0$ (no short selling), or cap exposure to a single stock.
- Regularization may be applied to improve robustness if Σ is ill-conditioned.

6.5 Capital Allocation

- Allocate budget proportionally to the weights: $\text{Capital}_i = w_i \cdot 1{,}000{,}000$.
- Use current market prices to determine number of shares to buy per stock.
- Rebalance as new data becomes available or when price deviates from optimal allocation.

6.6 Advantages

- Clear control over return expectation and risk.
- Enables construction of the entire **efficient frontier** by varying R_{target}.
- Flexible: constraints can be adapted to liquidity, sector exposure, or regulatory limits.

7 Portfolio Management Rules

7.1 Position Sizing

- Target per position: 100k to 200k FCFA
- Max 5–7 positions
- Max 25% exposure on a single stock

7.2 Entry Conditions

- Price below 30-day MA
- Momentum signal detected
- Volume increase

7.3 Exit Conditions

- Target gain: +10% to +20%
- Soft stop-loss: -5% to -7%
- Time-based exit: after 1 month

7.4 Monitoring

- Daily price, volume, and performance scraping
- Signal generation based on composite score
- Alert system for buy/sell decisions

7.5 Trading Signals

Signal Type	Condition	Action
Buy	$Score > 70\%$, $price < MA30$, vol up	Buy
Sell	$Loss > 5\%$, $score < 50\%$	Sell
Reinforce	$Score > 80\%$ after slight pullback	Add position
Target hit	$Gain > 15\%$	Take profit

8 Portfolio Risk Management

8.1 Sensitivity Analysis

Sensitivity analysis evaluates the portfolio's response to marginal changes in key parameters (e.g., asset returns, volatilities) rather than full-blown scenarios.

8.1.1 Procedure

1. Define Perturbations Examples:

- **Return Increase:** +1% on individual asset returns
- **Volatility Spike:** +10% on standard deviation
- **Correlation Shift:** Apply ±5

Listing 1: Perturbing Returns

```
sensitive_returns = original_returns.copy()
sensitive_returns["PALC"] += 0.01
```

3. Observe Impact on Allocation or Risk We measure:

- Change in optimal weights (if using Markowitz)
- Impact on Sharpe ratio
- Risk concentration shifts

4. Decision Making

- Identify fragile allocations (assets overly sensitive)
- Add robustness constraints (e.g., max exposure, volatility cap)
- Enable dynamic rebalancing under drift

8.1.2 Sensitivity Analysis (Extended)

To assess how fragile the portfolio is to changes in market or model parameters, we systematically perturb inputs and observe outputs.

Extended Parameters

- **Asset Return Shift:** ±1% on one or multiple assets
- **Volatility Spike:** +10% on individual asset volatility
- **Correlation Drift:** shift correlations ±5%
- **Risk-Free Rate:** impact on Sharpe and asset attractiveness
- **Liquidity Shock:** remove low volume stocks, observe reallocation
- **Dividend Cut or Surprise:** manually adjust returns to reflect dividend scenarios
- **Earnings Surprise:** apply unexpected earnings results to forward returns
- **Regulatory/Macroeconomic Constraint:** simulate price cap/floor or market closure

Result Interpretation

Compare for each perturbation:

- Portfolio return drift
- Change in optimal allocation (if using optimization)
- Changes in Sharpe, beta, or drawdown risk
- Identification of fragile vs. robust positions

8.2 Backtesting Module

The backtesting module allows for evaluating the historical performance of a strategy based on the selected stocks and the computed portfolio allocation.

8.2.1 Objectives

- Validate the effectiveness of the stock selection and allocation strategy.
- Quantify risk-adjusted performance using historical BRVM data.
- Support decision-making through empirical performance metrics.

8.2.2 Input

- Historical prices of selected stocks (at least 6 months of daily/weekly data).
- Weights computed from the Markowitz optimizer.
- Frequency of rebalancing (weekly or monthly).

8.2.3 Process

1. Compute portfolio returns using:

$$R_t^{\text{port}} = \sum_{i=1}^{N} w_i \cdot R_{i,t}$$

   where w_i are the weights and $R_{i,t}$ the returns of stock i at time t.

2. Compute performance metrics:
   - Cumulative return: $\prod_t (1 + R_t^{\text{port}}) - 1$
   - Annualized volatility: $\sigma_{\text{ann}} = \sigma_{\text{daily}} \cdot \sqrt{252}$
   - Maximum drawdown: $\max_t \left(\frac{\text{Peak}_t - \text{Trough}_t}{\text{Peak}_t} \right)$
   - Sharpe Ratio: $\frac{\mu - r_f}{\sigma}$

3. Optionally compare with benchmark (e.g. BRVM10).

8.2.4 Output

- Equity curve plot
- Performance metrics table
- Highlight of best/worst performing periods

8.2.5 Dependencies

This module relies on market data and portfolio allocation modules.

8.3 Stress Testing

To assess the portfolio's robustness under adverse macroeconomic or sectoral events, we simulate predefined shock scenarios and measure their impact on portfolio performance.

8.3.1 Step-by-Step Methodology

1. Define Scenarios Common market shocks include:

- **Sector Crash:** e.g., *-20% drop in banking sector* (BOAB, ETIT, ECOC).
- **Currency Depreciation:** *-10% on importers*, *+10% on exporters*.
- **Interest Rate Spike:** simulated as increased volatility and lower valuation.

2. Modify Historical Returns We inject shocks directly into return data:

Listing 2: Injecting a Sector Crash

```
stressed_returns = historical_returns.copy()
stressed_returns.loc["2024-09-01":"2024-09-07", ["BOAB", "ETIT", "ECOC"]] -=
```

3. Recompute Portfolio Metrics We rerun the backtest on the stressed data:

Listing 3: Evaluating Impact

```
baseline = backtest(weights, original_returns)
stress_test = backtest(weights, stressed_returns)
```

4. Compare Key KPIs

- Cumulative Return
- Volatility
- Sharpe Ratio
- Maximum Drawdown

5. Use Results Stress results help adjust the strategy:

- Reallocation
- Defensive assets
- Liquidity buffer

8.4 Monte Carlo Simulation

Monte Carlo simulations allow us to model the portfolio's behavior under a wide range of randomly generated market scenarios, accounting for randomness in returns, volatilities, and correlations.

8.4.1 Step-by-Step Methodology

1. Estimate Statistical Properties Compute the mean return vector μ and covariance matrix Σ from historical returns:

$$\mu_i = E[r_i], \quad \Sigma_{ij} = \text{Cov}(r_i, r_j)$$

2. Generate Random Scenarios Use Cholesky decomposition to simulate correlated returns:

Listing 4: Simulating Returns

```
L = np.linalg.cholesky(Sigma)
simulated_returns = mu + L @ np.random.randn(n_assets, n_simulations)
```

3. Simulate Portfolio Paths Generate multiple portfolio value paths over T time steps:

$$V_t = V_0 \times \prod_{i=1}^{t} (1 + r_i^{\text{sim}})$$

4. Analyze the Distribution From the simulated paths, extract:

- Expected Return
- VaR (Value-at-Risk)
- CVaR (Conditional VaR)
- Drawdown distributions

5. Decision Use Simulations support:

- Worst-case scenario planning
- Dynamic hedging strategies
- Confidence bounds for performance

9 Annex: Quantitative Factors Formulas

Momentum

- **Weekly Momentum:**

$$M_{1w}(i) = \frac{P_i(t) - P_i(t-5)}{P_i(t-5)}$$

- **Monthly Momentum:**

$$M_{1m}(i) = \frac{P_i(t) - P_i(t-20)}{P_i(t-20)}$$

Relative Valuation

- **Deviation from 30-day Moving Average:**

$$R_i = \frac{P_i(t) - \mathrm{MA}_{30}(i)}{\mathrm{MA}_{30}(i)}$$

where $\mathrm{MA}_{30}(i) = \frac{1}{30}\sum_{k=1}^{30} P_i(t-k)$

Volatility

- **Standard Deviation of Daily Returns:**

$$\sigma_i = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}\left(r_i(k) - \bar{r}_i\right)^2}$$

where $r_i(k) = \frac{P_i(k) - P_i(k-1)}{P_i(k-1)}$

Volume

- **5-day Average Volume:**

$$V_{5d}(i) = \frac{1}{5}\sum_{k=1}^{5} V_i(t-k)$$

Free Float Market Capitalization

- **Free Float Cap:**

$$\mathrm{FFC}_i = \mathrm{Price}_i \times \text{Shares Outstanding}_i \times \text{Free Float }\%_i$$

Recent Earnings Growth

- **Revenue Growth:**

$$G_{\mathrm{Revenue}}(i) = \frac{\mathrm{Revenue}_i^{\mathrm{latest}} - \mathrm{Revenue}_i^{\mathrm{prev}}}{\mathrm{Revenue}_i^{\mathrm{prev}}}$$

- **Net Income Growth:**

$$G_{\mathrm{NI}}(i) = \frac{\mathrm{NI}_i^{\mathrm{latest}} - \mathrm{NI}_i^{\mathrm{prev}}}{\mathrm{NI}_i^{\mathrm{prev}}}$$

10 Annex: Code Structure Diagrams