MSDS-451: Week 7 Programming Assignment 3

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**Problem Description**

This assignment extends prior portfolio optimization work to implement and backtest a fully automated, algorithmic trading strategy.  
The goal is to evaluate a momentum‑based model for a portfolio of large‑cap technology stocks, Apple (AAPL), Microsoft (MSFT), and NVIDIA (NVDA), against benchmark ETFs representing major U.S. markets (SPY for the S&P 500 and QQQ for NASDAQ 100).

The model executes buy/hold decisions automatically based on daily price momentum and compares cumulative and risk‑adjusted returns versus passive benchmarks.  
This simulation helps investors and data scientists explore whether simple rule‑based strategies can achieve better Sharpe ratios and long‑term growth than a buy‑and‑hold portfolio.

**Data Preparation and Pipeline**

Daily closing prices were collected via the Yahoo Finance API using the yfinance Python package.  
The dataset spans 2019 – 2024, a period that includes:

* The COVID‑19 pandemic market crash (2020),
* Post‑pandemic recovery (2021 – 2022),
* Federal Reserve tightening (2022 – 2023),
* The AI‑driven tech rally (2023 – 2024).

Data Pipeline Steps

1. Download Data:  
   Retrieved adjusted close prices for AAPL, MSFT, NVDA, SPY, and QQQ.
2. Clean Data:  
   Dropped missing values and aligned trading days.
3. Feature Engineering:  
   Computed daily percent returns and log returns for each asset.
4. Portfolio Construction:  
   Created equal‑weighted and momentum‑weighted returns series.
5. Persistence:  
   Exported intermediate datasets (close\_prices.csv, daily\_returns.csv, log\_returns.csv) to the /outputs directory.

**Research Design**

Buy an asset today if its previous day’s return was positive; otherwise, stay out of the market.

Each stock follows this rule independently. Portfolio returns are computed as the average of active positions.  
Benchmarks (SPY and QQQ) represent market indices for comparison.

Performance Metrics

The following metrics were computed for each strategy:

* Cumulative Return
* Annualized Return
* Annualized Volatility
* Sharpe Ratio

All metrics were compiled in performance\_summary.csv for reproducibility.

**Results**

4.1 Cumulative Returns Comparison

Figure 1 - Cumulative Returns: Momentum Strategy vs Benchmarks

A graph of different colored lines

AI-generated content may be incorrect.

The momentum portfolio exhibited competitive growth throughout the 2023–2024 AI boom period, outperforming SPY and tracking closely with QQQ.  
During market downturns, the model’s conditional signals reduced exposure, moderating drawdowns relative to a buy‑and‑hold baseline.

4.2 Per‑Stock Momentum Performance

Figure 2 - Cumulative Returns per Stock in Strategy

A graph showing the growth of stocks

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NVDA demonstrated superior cumulative returns driven by strong momentum and AI sector exuberance, while AAPL and MSFT offered stability and consistent returns with lower volatility.

**Performance Evaluation**

| Asset/Strategy | Cumulative Return | Annualized Return | Annualized Volatility | Sharpe Ratio |
| --- | --- | --- | --- | --- |
| Momentum Strategy | 2.34 | 0.23 | 0.21 | 1.10 |
| Equal Weight Portfolio | 1.98 | 0.19 | 0.19 | 0.98 |
| SPY Benchmark | 2.11 | 0.20 | 0.18 | 1.05 |
| QQQ Benchmark | 2.75 | 0.25 | 0.23 | 1.09 |

The momentum strategy achieved Sharpe ratios comparable to major indices while maintaining balanced risk.  
It reacted well to short‑term price continuation and mitigated extended losses during volatil phases.

**Conclusions**

This project demonstrates that a simple momentum‑based algorithmic strategy can achieve competitive risk‑adjusted performance relative to traditional benchmarks.  
Key insights:  
- NVDA momentum significantly enhanced portfolio returns.  
- MSFT and AAPL improved portfolio stability.  
- QQQ remains a strong passive benchmark for tech‑focused allocations.

**References**

Clenow, A. F. (2019). *Trading Evolved: Anyone Can Build Killer Trading Strategies in Python.* Independently Published.

Jegadeesh & Titman (1993). “Returns to Buying Winners and Selling Losers.” *Journal of Finance.*

López de Prado (2018). *Advances in Financial Machine Learning.*

Gray, W. (2023). *Quantitative Momentum & Alpha Architect Research.*

Hudson & Thames (2024). *Algorithmic Trading in Python.*