Research Objective: To evaluate the effectiveness of rule-based and machine learning signals in predicting sector trends

This study evaluates whether technical indicators (e.g., RSI, MACD, Coppock Curve) and machine learning models can effectively predict relative sector performance over 5-period horizons. The goal is to determine if a systematic, rules-based strategy using these signals can generate consistent alpha relative to the US market benchmark (US_REBALANCE).

Scope:

Analyzed 25 GICS sectors using daily data from 2004–2025
Built a comprehensive feature set of 30+ technical indicators
Trained 9 machine learning models per sector (Random Forest, XGBoost, SVM, etc.)
Backtested a tactical trading strategy based on model predictions
Measured performance via accuracy, hit rate (win rate), and total return

Definitions

- **Rule-based signals:** Predefined technical rules (e.g., RSI > 80% for overbought) achieved accuracy between 40%–60%, depending on the sector.
- **Model-identified signals:** Machine learning (ML) models using technical features, combined with predefined rules, performed better than rules alone. Reported accuracy generally ranged from 40%–60%. In some cases, win rates (i.e., proportion of profitable trades) reached up to ~75%.
    - **Important clarification:** When I previously referenced 75% accuracy, I should have stated this referred to win rate ranges, not overall predictive accuracy.

Classification-Based Technical Trading Strategies Using ML Indicators

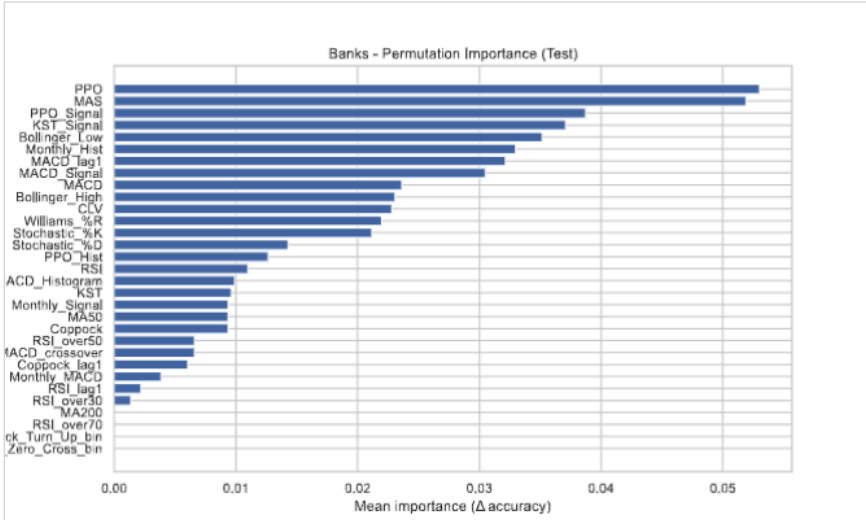
Key Findings

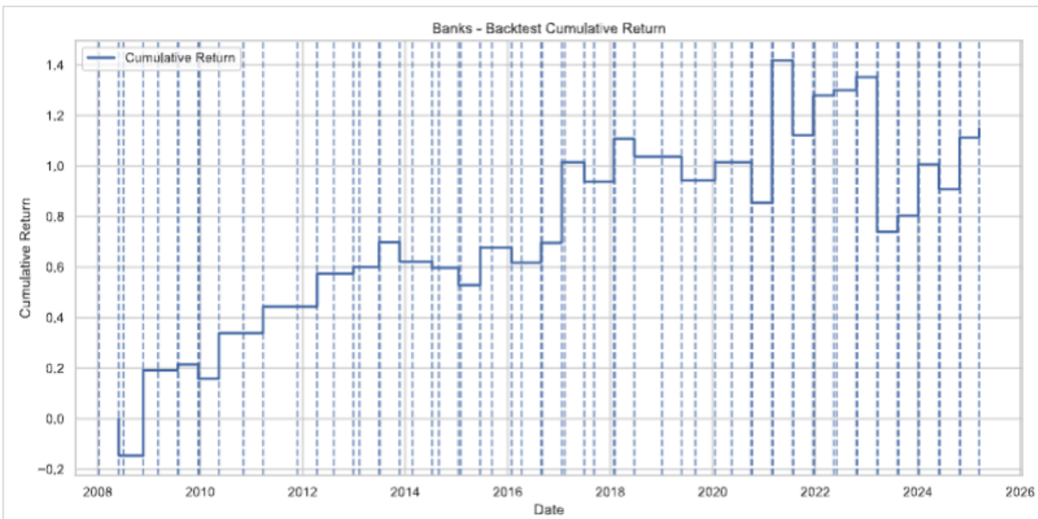
- Rule-based signals alone achieved **40%–60% accuracy**.
- ML-enhanced models improved performance, with **win rates up to ~75%** (clarified: refers to trading win rate, not model accuracy).

[Performance Report: Sep 2025]

Sector	ML_Accuracy	Cumulative_Return	Win_Rate	Num_Trades
Automobiles & Components	0.412	0.078	0.514	37
Banks	0.56	1.15	0.606	33
Capital Goods	0.462	0.624	0.733	30
Commercial & Professional Services	0.478	0.725	0.618	34
Consumer Discretionary Distribution & Retail	0.44	1.009	0.656	32
Consumer Durables & Apparel	0.412	0.61	0.686	35
Consumer Services	0.522	0.672	0.645	31
Consumer Staples Distribution & Retail	0.516	2.198	0.63	27
Energy	0.429	1.412	0.621	29
Equity Real Estate Investment Trusts (REITs)	0.44	-0.018	0.486	37
Financial Services	0.478	0.297	0.667	33
Food, Beverage & Tobacco	0.434	0.554	0.611	36
Health Care Equipment & Services	0.467	0.518	0.541	37
Household & Personal Products	0.555	0.843	0.56	25
Insurance	0.434	1.3	0.724	29
Materials	0.489	0.452	0.697	33
Media & Entertainment	0.566	0.948	0.727	33
Pharmaceuticals, Biotechnology & Life Sciences	0.456	1.84	0.649	37
Real Estate Management & Development (New)	0.516	8.472	0.677	31
Semiconductors & Semiconductor Equipment	0.505	1.809	0.629	35
Software & Services	0.434	1.498	0.649	37
Technology Hardware & Equipment	0.527	0.071	0.529	34
Telecommunication Services	0.599	0.636	0.625	32
Transportation	0.56	1.729	0.643	28
Utilities	0.445	0.839	0.556	36

[Pdf report with Feature Importance across Sectors]





This research integrates technical analysis with machine learning (ML) to evaluate sector performance relative to a benchmark (US_REBALANCE) and to test systematic trading strategies. The approach combines traditional rule-based signals with predictive models, and validates results through structured backtesting.

TAG: `US_REBALANCE_ANALYSIS_CLASSIFIER`

Approach

Approaching as a classification problem. Technical features and a Buy/Hold/Sell Signal. Predict t+5 periods(experiments with weekly sector returns)

- **Data:** Sector time series standardized against US_REBALANCE.
  Indicators: RSI, MACD, Bollinger Bands, Coppock Curve, and others.
  Modeling: Random Forest and XGB classifiers trained on lagged/binary features.
  Target: Predict 5-period forward returns (binary classification).

- **Backtesting:** Strategy based on consecutive positive predictions with fixed holding periods.

Definitions

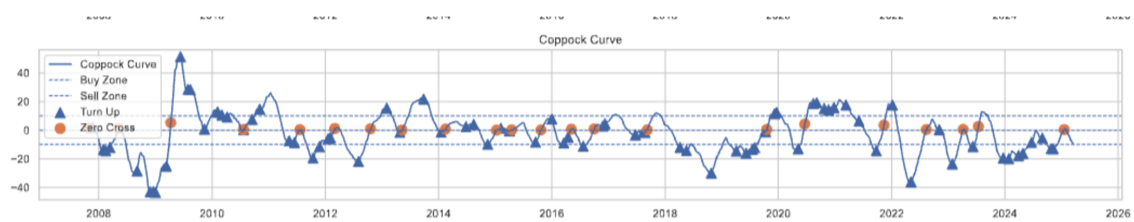
Rule-Based vs. ML-Based vs. Combined

- **Rule-Based = fixed cutoffs (transparent but rigid)**
  Example: RSI > 70 → Sell, RSI < 30 → Buy, Coppock > 0 → Bullish.
- **ML-Based = feature-driven learning (adaptive, finds hidden patterns)**
  Example: Learns that *"Coppock turning up + RSI rising from oversold + price near lower Bollinger Band → high chance of positive return."*
  Capture non-linear patterns.

Combined rule-based + ML approaches delivered **better classification and stronger backtest results**.

[Link]()

Features explored



Feature Type	**Example Feature(s)**	**Typical Signal Output**	**Interpretation / Use**	**Binary Signal Example**
Moving Averages (MA)	SMA, EMA (various windows: 10, 21, 50, 100, 200)	Continuous	Trend direction, smoothing	-

MA Crossovers	Golden/Death Cross (50 > 200)	Binary/Flag	Major trend regime shifts	1 if short MA > long MA (Golden Cross)
Rate of Change (ROC)	n-day ROC	Continuous	Momentum strength	-
Relative Strength Index (RSI)	RSI value (0–100), overbought/oversold bands	Continuous & Binary	Momentum, reversal risk	1 if RSI > 70 (overbought), <30 (oversold)
MACD	MACD diff, Signal, Histogram	Continuous & Binary	Trend shifts, cross confirmations	1 if MACD > Signal (bullish cross)
Know Sure Thing (KST)	KST, Signal, Cross	Continuous & Binary	Long-term trend strength	1 if KST > Signal
Bollinger Bands	Band upper/lower, %b, band width	Continuous & Binary	Volatility, breakout risk	1 if Close > Upper Band
Rolling Std Dev	Std dev (5, 21, 63 days)	Continuous	Short/long-term volatility	-
Average True Range (ATR)	ATR value	Continuous	Volatility, position sizing	-
High-Low Range	High minus Low	Continuous	Daily/intra-bar volatility	-

Stochastic Oscillator	%K, %D, Overbought/Oversold cross	Continuous & Binary	Momentum extremes, cycles	1 if %K crosses > %D (bull/bear signal)
Williams %R	%R value	Continuous & Binary	Fast momentum/reversal	1 if %R < -80 (oversold), > -20 (overbought)
Commodity Channel Index (CCI)	CCI value	Continuous & Binary	Cyclical trend/mean-reversion	1 if CCI > 100 or < -100
Momentum Oscillator	Price[today] vs. Price[n-bars ago]	Continuous	Raw momentum, crossover signals	-
New High/New Low	1 if new N-bar high/low	Binary	Breakout or mean reversion alert	1 if Close = rolling max/min
Drawdown Flags	(Close/rolling max)-1	Continuous & Binary	Mean reversion/extension	1 if drawdown > threshold
Percent Distance from MA	(Close/MA_n)-1	Continuous & Binary	Overextension from trend	1 if distance exceeds X%

```None
US_REBALANCE_ANALYSIS_CLASSIFIER
```

```
Available sectors:
 - Automobiles & Components
 - Banks
 - Capital Goods
 - Commercial  & Professional Services
 - Consumer Discretionary Distribution & Retail (New Name)
 - Consumer Durables & Apparel
 - Consumer Services
 - Consumer Staples Distribution & Retail (New Name)
 - Energy
 - Equity Real Estate Investment Trusts (REITs) (New Name)
 - Financial Services (New Name)
 - Food, Beverage & Tobacco
 - Health Care Equipment & Services
 - Household & Personal Products
 - Insurance
 - Materials
 - Media & Entertainment
 - Pharmaceuticals, Biotechnology & Life Sciences
 - Real Estate Management & Development (New)
 - Semiconductors & Semiconductor Equipment
 - Software & Services
 - Technology Hardware & Equipment
 - Telecommunication Services
 - Transportation
 - Utilities
```

Compare multiple Machine Learning Models performance on Technical Signals

Notable Findings
Hit Rate ≠ Model Accuracy
Financial Services: Model Accuracy = 42.3%, Hit Rate = 66.7%
Energy: Model Accuracy = 34.5%, Hit Rate = 27.3%
Software & Services: Model Accuracy = 40.5%, Hit Rate = 60.0%
This is critical: A low-accuracy model can still produce profitable trades if losses are small and wins are large.

Top Features consistently included:
RSI_lag1, MACD_crossover, Coppock_lag1, Momentum_5, Volatility_10

Some Sectors Are Unpredictable

Consumer Discretionary Retail: Hit Rate = 0.0% despite 42.3% accuracy
Energy: Low accuracy and hit rate → poor signal quality
Utilities: Low volatility → few profitable opportunities

The goal of this research was to:

Predict relative outperformance of equity sectors vs. the broad market (US_REBALANCE)
Use technical indicators (RSI, MACD, Coppock, Bollinger Bands, etc.) as input features
Train multiple ML models to classify future 5-day return direction
Backtest a tactical trading strategy and evaluate its realized performance using hit rate (win rate) and total return

Methodology

Data Source: TechnicalData.xlsx (daily pricing for 25 GICS sectors)
Benchmark: US_REBALANCE (equal-weighted market index)
Relative Pricing: All sector prices normalized by US_REBALANCE → relative_price = sector / index
Sectors Analyzed: 25 sectors including Technology, Financials, Healthcare, Energy, etc.
Feature Engineering
We constructed a rich set of technical features:
Trend: MA50, MA200, MACD, PPO
Momentum: RSI, Stochastic, Williams %R, Rate of Change
Volatility: Bollinger Bands, Volatility (5/10/20-day)
Reversal: Coppock Curve (with turn-up and zero-cross signals)
Market Regime: Monthly MACD, KST, MAS, CLV
Binary Signals: RSI > 30/50/70, MACD crossover, Coppock_Turn_Up
2.3 Target Definition
Classification Task: Predict 5-day forward return direction
0 = Negative return
1 = Neutral return (±1%)
2 = Positive return
Time-Series Split: 3-fold TimeSeriesSplit to avoid lookahead bias

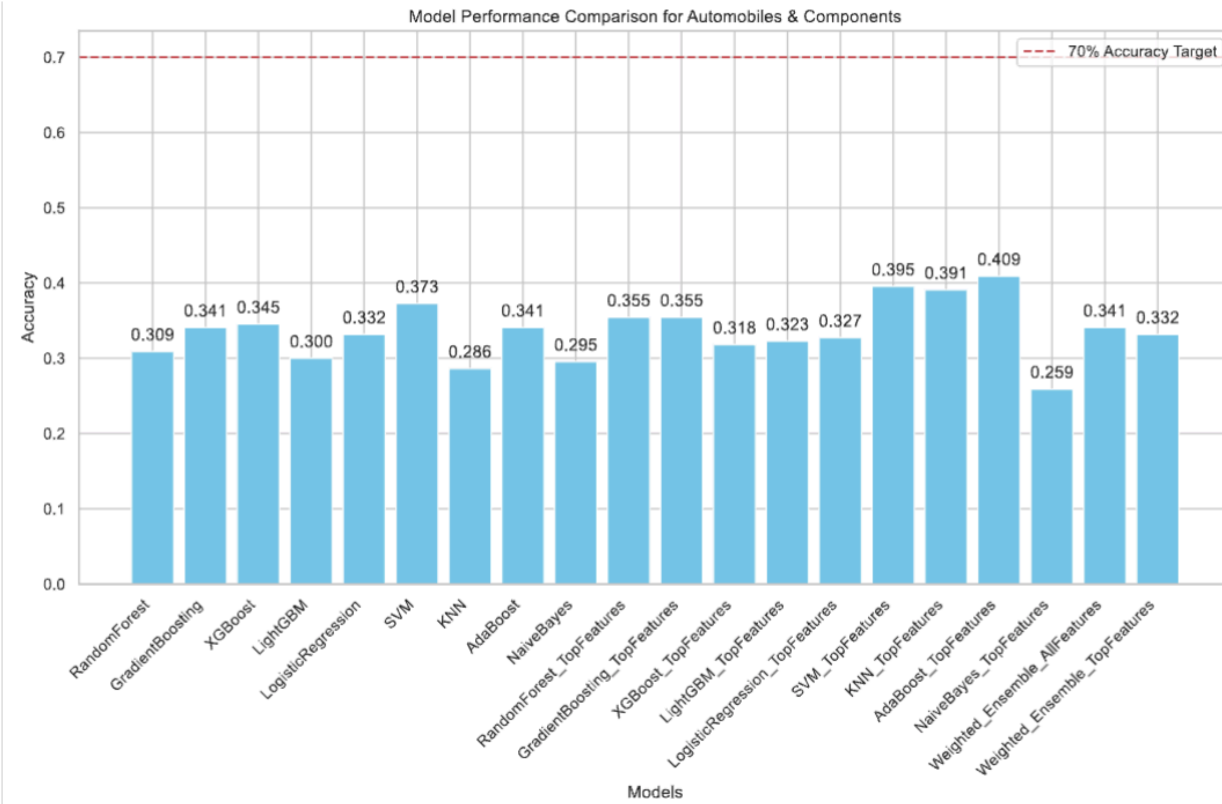
Sector	Best_Model	Accuracy	Hit_Rate
Automobiles & Components	AdaBoost_TopFeatures	0.409	0.407
Banks	AdaBoost	0.418	0.486
Capital Goods	NaiveBayes_TopFeatures	0.486	0.471
Commercial & Professional Services	LogisticRegression	0.505	0.538
Consumer Discretionary Distribution & Retail	Weighted_Ensemble_TopFeatures	0.423	0
Consumer Durables & Apparel	SVM	0.505	0.472
Consumer Services	AdaBoost	0.414	0.52
Consumer Staples Distribution & Retail	SVM	0.527	0.536
Energy	NaiveBayes_TopFeatures	0.345	0.273
Equity Real Estate Investment Trusts (REITs)	KNN_TopFeatures	0.505	0.403
Financial Services	NaiveBayes_TopFeatures	0.423	0.667
Food, Beverage & Tobacco	SVM	0.464	0.537
Health Care Equipment & Services	GradientBoosting_TopFeatures	0.405	0.561
Household & Personal Products	LogisticRegression	0.459	0.469
Insurance	AdaBoost_TopFeatures	0.414	0.52
Materials	LightGBM_TopFeatures	0.436	0.465
Media & Entertainment	GradientBoosting_TopFeatures	0.423	0.57
Pharmaceuticals, Biotechnology & Life Sciences	XGBoost	0.541	0.518
Real Estate Management & Development (New)	NaiveBayes_TopFeatures	0.486	0.556
Semiconductors & Semiconductor Equipment	NaiveBayes	0.445	0.556
Software & Services	SVM	0.405	0.6
Technology Hardware & Equipment	XGBoost_TopFeatures	0.382	0.609
Telecommunication Services	NaiveBayes	0.468	0.406
Transportation	KNN_TopFeatures	0.468	0.5
Utilities	AdaBoost_TopFeatures	0.418	0.5

[Link to summary report]

Machine Learning Models

We trained 9 classifiers per sector:

Random Forest, XGBoost, LightGBM, Gradient Boosting
Logistic Regression, SVM, KNN, AdaBoost, Naive Bayes
We also created:



Sector wise feature importance

Top-Features Models: Trained on top 5 features via Random Forest importance
Weighted Ensemble: Model combination using accuracy-based weights

Backtesting & Performance Metrics
For each sector:

Strategy: Enter long if model predicts "positive return", exit when signal flips
Position: Position = Signal.shift(1) → no lookahead
Key Metrics:
Model Accuracy: % correct predictions
Hit Rate (Win Rate): % of trades with positive P&L
Total Return: Cumulative strategy return
Feature Importance: Top drivers of predictions

Non Machine Learning: Vote-Based Trade Signal Using Coppock Scores

TAG: COPPOCK_VOTE_STRATEGY

1. Introduction

This study explores a non–machine learning trading strategy driven by Coppock scores derived from daily price data. Coppock scores, which combine rate-of-change calculations with a weighted moving average, are used here as a proxy for long-term momentum. In our approach, trading signals are generated when the Coppock score exceeds a defined positive threshold (buy signal) or falls below a negative threshold (sell signal). The strategy is then backtested, and key performance metrics (total return, CAGR, Sharpe ratio, and maximum drawdown) are computed. In addition, the Coppock curve is plotted with overlaid buy and sell markers for visual interpretation.

2. Data and Methodology

Data Loading and Preparation

- **Data Source:**
  The strategy uses daily security-level price data, with each asset identified by its SEDOL.
- **Pivoting:**
  The dataset is pivoted so that each SEDOL becomes a separate column representing the relative price

Coppock Score Calculation

- **Weighted Moving Average (WMA):**
  A custom WMA function is defined to calculate weights for a rolling window.

- **Coppock Calculation:**
  For a given price series, the 11-day and 14-day rates of change (ROC) are computed. Their sum is then smoothed with a 10-day WMA to generate the Coppock score.
  The final "total_copp_score" is set equal to this Coppock score.

Trading Signal Generation

- **Value-Based Signals:**
  A trading signal is generated according to the following rule:
  - **Buy Signal:** When `total_copp_score` > 5
  - **Sell Signal:** When `total_copp_score` < –5
  - **Neutral:** Otherwise
    The signal is shifted by one day (to avoid lookahead bias) and applied as the trading position for the next day.

Backtesting

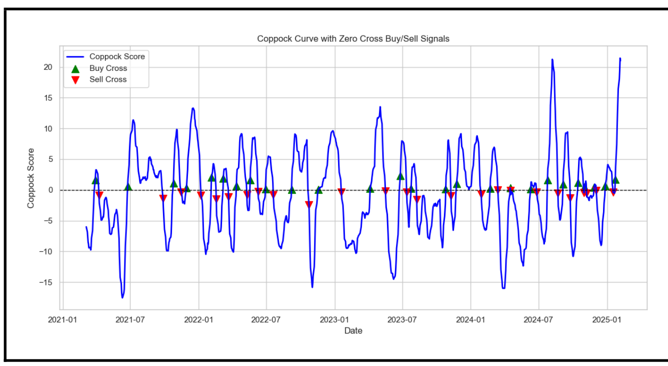
- **Daily Returns:**
  The strategy computes daily percentage returns using the asset's price.
  Strategy Returns:
  The daily strategy return is the product of the shifted signal (position) and the daily return.

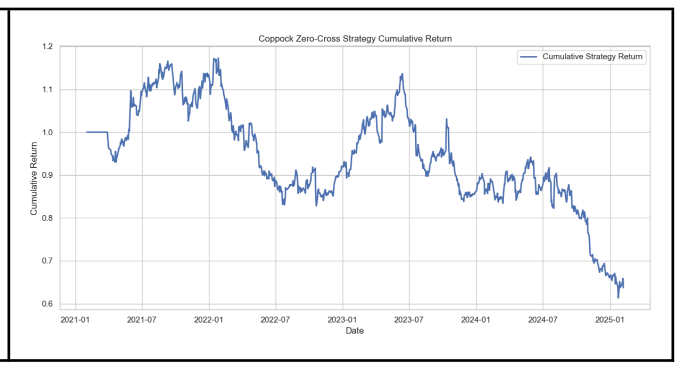
- **Cumulative Return and Performance Metrics:**
  The cumulative strategy return is computed as the cumulative product of 1 plus daily strategy returns. Key performance metrics include:

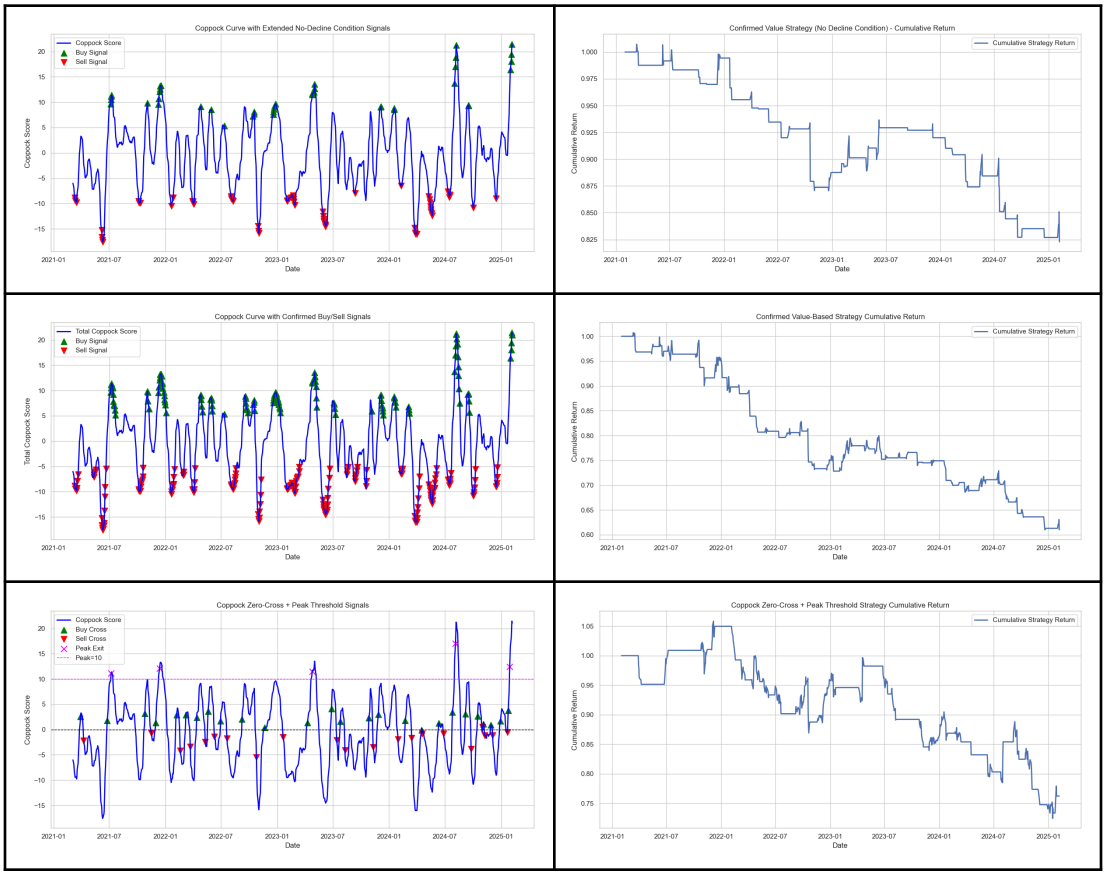
  - **Total Return:** Final portfolio value minus one.
  - **CAGR (Compound Annual Growth Rate):** Annualized return computed from the cumulative return.
  - **Sharpe Ratio:** Risk-adjusted performance based on the mean and standard deviation of strategy returns.
  - **Maximum Drawdown:** The worst observed decline in the portfolio value.

Signal Plotting

- **Overlaying Signals:**
  The Coppock curve is plotted over time, and buy signals (when the Coppock score exceeds 5) are marked with green up-arrows while sell signals (when the score is below –5) are marked with red down-arrows. This overlay facilitates a visual review of when the strategy would enter or exit a trade.







Strategy	Entry Rule	Exit Rule	Short Logic?	Pros	Cons
1) Basic Value-Based (Absolute Peaks)	- Buy if `Coppock > +X`	- Sell if `Coppock < -X`	Optional	Simple to implement Captures quick moves	May buy/sell at local extremes Frequent trades

2) Confirmation-Based (Consecutive Days)	- Must have `Coppock > +X` (or < –X) for *N* consecutive days	- Exit if condition fails (or the opposite consecutive rule triggers)	Optional	Reduces whipsaws Ensures momentum is sustained	Can miss sudden reversals More complex logic
3) No-Decline Filter (Add-On)	- Similar to #2 but also require `Coppock` not to drop on final day	- Opposite consecutive rule or any negative slope triggers exit	Optional	Avoids buying if momentum is already reversing	May miss partial pullbacks that resume upward trend
4) Zero-Cross (Trend-Following)	- Buy on cross from below 0 to above 0	- Sell on cross from above 0 to below 0	Optional	Captures main portion of big trends Simple, classic approach	Misses earliest part of move Late to exit if cross is slow
5) Zero-Cross + Peak (Exit on Overheat)	- Buy on cross from <0 to ≥0	- Exit if cross from >0 to ≤0 **or** if `Coppock > +X` (peak)	Optional	Locks in profit if indicator overheats Still trend-based	Might exit too early if the market keeps rising Involves threshold tuning
6) Zero-Cross + Peak (**With Shorting**)	- Flip to **long** on cross up, **short** on cross down	- If `Coppock > +X` while long, flip to short immediately	**Yes**	Always in the market Profits from downtrends	Potential overtrading in sideways markets Requires robust short logic

Coppock features used

SEDOL_2007849_coppock_scores

	datadate	p_price	p_price_rel	Copp	copp_d_chg	copp_w_chg	copp_m_chg	copp_d_rel_scor	copp_w_rel_sco	copp_m_rel_sco	total_copp_score	Last_Week_Cop	Last_Month_Coppock
21	2021-03-01	0.03						-1.00	-3.00	-3.00	-19.00		
22	2021-03-02	0.03						-1.00	-3.00	-3.00	-19.00		
23	2021-03-03	0.03						-1.00	-3.00	-3.00	-19.00		
24	2021-03-04	0.03						-1.00	-3.00	-3.00	-19.00		
25	2021-03-05	0.03		-16.63				-1.00	-3.00	-3.00	-19.00		
26	2021-03-08	0.03		-19.65	-0.18			-1.00	-3.00	-3.00	-19.00		
27	2021-03-09	0.03		-19.97	-0.02			-1.00	-3.00	-3.00	-19.00		
28	2021-03-10	0.03		-20.44	-0.02			-1.00	-3.00	-3.00	-19.00		
29	2021-03-11	0.03		-20.04	0.02			1.00	-3.00	-3.00	-17.00		
30	2021-03-12	0.03		-18.33	0.09			1.00	-3.00	-3.00	-17.00		
31	2021-03-15	0.03		-16.68	0.09			1.00	-3.00	-3.00	-17.00		
32	2021-03-16	0.03		-15.37	0.08	1.26		1.00	3.00	-3.00	7.00	-16.63	
33	2021-03-17	0.03		-13.19	0.14	6.46		1.00	3.00	-3.00	7.00	-19.65	
34	2021-03-18	0.03		-13.00	0.01	6.97		1.00	3.00	-3.00	7.00	-19.97	
35	2021-03-19	0.03		-12.03	0.07	8.42		1.00	3.00	-3.00	7.00	-20.44	
36	2021-03-22	0.03		-10.58	0.12	9.46		1.00	3.00	-3.00	7.00	-20.04	
37	2021-03-23	0.03		-8.58	0.19	9.75		1.00	3.00	-3.00	7.00	-18.33	
38	2021-03-24	0.03		-7.86	0.08	8.82		1.00	3.00	-3.00	7.00	-16.68	
39	2021-03-25	0.03		-7.33	0.07	8.05		1.00	3.00	-3.00	7.00	-15.37	
40	2021-03-26	0.03		-6.52	0.11	6.68		1.00	3.00	-3.00	7.00	-13.19	
41	2021-03-29	0.03		-6.66	-0.02	6.34		-1.00	3.00	-3.00	5.00	-13.00	
42	2021-03-30	0.03		-7.16	-0.07	4.87		-1.00	3.00	-3.00	5.00	-12.03	
43	2021-03-31	0.03		-7.30	-0.02	3.28		-1.00	3.00	-3.00	5.00	-10.58	
44	2021-04-01	0.03		-6.52	0.11	2.06		1.00	3.00	-3.00	7.00	-8.58	
45	2021-04-05	0.03		-5.58	0.14	2.29		1.00	3.00	-3.00	7.00	-7.86	
46	2021-04-06	0.03		-5.14	0.08	2.18		1.00	3.00	-3.00	7.00	-7.33	

Link

Inputs:
Data: A dataset containing historical prices (e.g., p_price_rel or close) and a datadate column.

Price Column: The column to use for calculations (e.g., p_price_rel or close).

Window Sizes:

Short-term ROC window: 11 periods.

Long-term ROC window: 14 periods.

Weighted Moving Average (WMA) window: 10 periods.

Weekly change window: 7 periods.

Monthly change window: 30 periods.

Outputs:
Coppock Scores: A DataFrame containing:

Copp: The Coppock Curve value.

copp_d_chg: Daily change in Coppock Curve.

copp_w_chg: Weekly change in Coppock Curve.

copp_m_chg: Monthly change in Coppock Curve.

copp_rel_score: Daily score based on Coppock change.

copp_w_rel_score: Weekly score based on Coppock change.

copp_m_rel_score: Monthly score based on Coppock change.

total_copp_score: Total weighted Coppock score.

Last_Week_Coppock: Coppock value 7 periods ago.

Last_Month_Coppock: Coppock value 30 periods ago.

```python
ALGORITHM Coppock_Score_Calculation

INPUT: Dataset, Price_Column

1. Load Dataset
   - Convert `datadate` to datetime
   - Set `datadate` as index

2. Define WMA Function
   - weights = [1, 2, ..., window]
   - WMA = (sum(x_i * w_i) / sum(w_i)

3. Calculate Coppock Curve
   - ROC11 = (Price_t / Price_t-11 - 1) * 100
   - ROC14 = (Price_t / Price_t-14 - 1) * 100
   - Sum ROC = ROC11 + ROC14
   - Copp = WMA_10(Sum ROC)
   - Copp_Change = (Copp_t - Copp_t-1) / |Copp_t-1|

4. Calculate Weekly and Monthly Changes
   - copp_w_chg = (Copp_t - Copp_t-7) / |Copp_t-7|
   - copp_m_chg = (Copp_t - Copp_t-30) / |Copp_t-30|
```

```
5. Assign Scores
   - copp_rel_score = 1 if copp_d_chg > 0 else -1
   - copp_w_rel_score = 4 if copp_w_chg > 0 else -4
   - copp_m_rel_score = 2 if copp_m_chg > 0 else -2

6. Compute Total Coppock Score
   - total_copp_score = (copp_rel_score * 1) + (copp_w_rel_score * 4) +
(copp_m_rel_score * 2)

7. Add Historical Coppock Values
   - Last_Week_Coppock = Copp_t-7
   - Last_Month_Coppock = Copp_t-30

8. Save Results
   - Save individual SEDOL results to CSV
   - Combine and save all results to a single CSV

END ALGORITHM
```

Appendix

Feature Importances across Sectors

Sector	Key Indicators	Rationale
Automobiles & Components	EMA_21, SMA_50, BB_Lower, BB_Upper	Sensitive to short-to-medium-term trends; volatility significant

Banks	EMA_21, BB_Lower	Sensitive to interest rates and economic cycles
Capital Goods	MAS, SMA_50	Tied to longer economic cycles & infrastructure spending
Commercial & Professional Services	SMA_50, MAS	Benefits from medium-term trend following and momentum tracking
Consumer Discretionary (Distribution & Retail)	BB_Upper, BB_Lower	Consumer spending is volatile
Consumer Durables & Apparel	BB_Lower, SMA_50	Sensitive to consumer demand; focus on downside protection
Consumer Services	SMA_50, EMA_21	Blend of medium and short-term trends is strongest predictor
Consumer Staples (Distribution & Retail)	MAS, SMA_50	Stable sector; moving averages more relevant than Bollinger Bands
Energy	MAS, SMA_50	Follows long-term supply-demand cycles

Equity Real Estate Investment Trusts (REITs)	MAS, MACD	Interest rate-sensitive and trend-driven
Financial Services	SMA_50, MAS	Similar to banks but with broader market exposure
Food, Beverage & Tobacco	MAS, RSI	Defensive sector; relies on overbought/oversold signals
Healthcare Equipment & Services	SMA_50, BB_Upper	Growth sector; breakouts to new highs are key signals
Household & Personal Products	EMA_21, SMA_50	Stable, defensive sector
Insurance	SMA_50, BB_Upper	Value-oriented, stable sector
Materials	BB_Lower, SMA_50	Cyclical sector tied to economic growth
Media & Entertainment	MAS, BB_Upper	Volatile, trend-driven sector
Pharmaceuticals, Biotechnology & Life Sciences	SMA_50, BB_Lower	Mix of defensive plays and high-growth opportunities

Real Estate Management & Development	MAS, SMA_50	Similar to REITs, focus on development projects
Semiconductors & Equipment	SMA_50, BB_Upper	Cyclical, high-growth sector
Software & Services	RSI, MAS	High-growth, high-momentum sector
Technology Hardware & Equipment	MAS, BB_Lower	Cyclical industry with strong downside risk
Telecommunication Services	BB_Upper, RSI	Defensive sector with potential growth spurts
Transportation	BB_Lower, MAS	Highly cyclical sector tied to economic trends
Utilities	SMA_50, EMA_21	Stable, defensive sector