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Can PCA Reveal the True Momentum of Crypto?



PyQuantLab

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The cryptocurrency market is a wild frontier, characterized by rapid movements and often high correlations between assets. While individual coins surge and retreat, is there an underlying “collective momentum” that dictates the broader market direction? Can we identify the true leadership and derive trading signals from it?

This article explores a fascinating quantitative approach: using Principal Component Analysis (PCA) on a basket of correlated cryptocurrencies to identify this collective momentum. We’ll

then build a trading strategy in Backtrader that trades a target asset based on the momentum of this derived “market factor.”

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The Challenge of Correlated Assets

Imagine you’re tracking Bitcoin (BTC), Ethereum (ETH), Solana (SOL), and Cardano (ADA). Often, when BTC moves, the others follow. This strong inter-correlation means that looking at the momentum of just one asset might not give you the full picture. What if we could extract the most significant, shared movement from this group and use that as our primary signal?

Enter Principal Component Analysis (PCA)

PCA is a statistical technique that transforms a set of correlated variables into a set of uncorrelated variables called principal components (PCs). Each PC captures a certain amount of the total variance in the data.

- PC1 (First Principal Component): This component captures the largest possible variance in the data. In the context of correlated assets, PC1 often represents the underlying “market factor” or “common trend” that drives the majority of their collective movement.
- By focusing on the momentum of PC1, we aim to filter out asset-specific noise and identify the prevailing, shared momentum of the entire crypto basket.

Building the PCA Momentum Indicator

Our strategy starts with a custom Backtrader indicator, `PCAMomentumIndicator`, responsible for calculating PC1 and its momentum.

```
import backtrader as bt
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import warnings

warnings.filterwarnings("ignore")

# For Jupyter/IPython to display plots
# %matplotlib inline

class PCAMomentumIndicator(bt.Indicator):
    """
    Custom indicator that performs PCA on a basket of assets and ca
```

```

It downloads historical data for the basket once at initialization
"""
lines = ('pc1', 'pc1_momentum', 'signal') # Define output lines

params = (
    ('tickers', ["BTC-USD", "ETH-USD", "SOL-USD", "ADA-USD"]),
    ('target_asset', "BTC-USD"), # The asset we'll actually trade
    ('n_components', 1), # We only care about the first principal component
    ('momentum_lookback', 20), # Lookback period for PC1 momentum
    ('recalc_frequency', 20), # Recalculate PCA every N period
    ('min_periods', 50), # Minimum historical periods needed
)

plotinfo = dict(
    plot=True,
    subplot=True, # Plot on a separate subplot below the price
    plotname='PCA Momentum'
)

plotlines = dict(
    pc1=dict(color='purple', alpha=0.7),
    pc1_momentum=dict(color='orange', alpha=0.8),
    signal=dict(_plotskip=True) # Don't plot the raw signal line
)

def __init__(self):
    self.scaler = StandardScaler() # Used to standardize return
    self.pca = PCA(n_components=self.params.n_components) # PCA

    self._last_pca_calculation = 0 # Track when PCA was last recalculated
    self._pc1_values = [] # Store historical PC1 values

    # Download data for all assets in the basket at the start
    # Note: This is done once to avoid repeated downloads during backtesting
    self._download_basket_data()

    self.addminperiod(self.params.min_periods) # Ensure enough data for PCA

def _download_basket_data(self):
    """Downloads historical data for all assets in the specified basket"""
    try:
        # Use a broad date range for basket data to ensure availability
        start_date = "2019-01-01"
        end_date = "2025-06-30" # Extended to capture current data
    
```

```
print(f"Downloading basket data for PCA: {self.params.ticker_basket}")

# Download all tickers. auto_adjust=False is used per user specification
# droplevel(1, 1) handles the MultiIndex from yfinance
self.basket_data = yf.download(
    self.params.tickers,
    start=start_date,
    end=end_date,
    auto_adjust=False,
    progress=False
).droplevel(axis=1, level=1)

if self.basket_data.empty:
    raise ValueError("No basket data downloaded. Check your tickers")

# Extract 'Close' prices for all tickers
self.basket_prices = self.basket_data['Close'].copy()

# Calculate daily percentage returns for PCA input
self.basket_returns = self.basket_prices.pct_change().dropna()

print(f"Basket data loaded: {len(self.basket_returns)}")

except Exception as e:
    print(f"Error downloading basket data: {e}. Falling back to None")
    self.basket_returns = None # Set to None to trigger fall-back logic

def next(self):
    """Called for each new bar (day) of the main data feed."""
    # Ensure we have enough data to perform initial PCA
    if len(self.data) < self.params.min_periods:
        return

    # Recalculate PCA periodically or if it's the first time
    should_recalc = (len(self.data) - self._last_pca_calculation) > self.params.pca_recalculation \
                    or len(self._pc1_values) == 0

    if should_recalc:
        self._update_pca()

    # Update current indicator values using the latest PC1
    self._update_current_values()
```

```
def _update_pca(self):
    """Performs PCA calculation on recent historical returns."""
    try:
        if self.basket_returns is None:
            # Fallback if basket data couldn't be loaded (e.g.,
            # In this case, PC1 will simply be the target asset
            current_return = (self.data.close[0] / self.data.cl
            self._pc1_values.append(current_return)
            self._last_pca_calculation = len(self.data)
            return

        current_date = self.data.datetime.date(0)

        # Filter basket returns up to the current backtest date
        basket_data_filtered = self.basket_returns[
            self.basket_returns.index.date <= current_date
        ]

        if len(basket_data_filtered) < self.params.min_periods:
            return # Not enough data for reliable PCA

        # Use a lookback window (e.g., last year of data) for P
        lookback = min(len(basket_data_filtered), 252)
        recent_returns = basket_data_filtered.tail(lookback).dr

        if len(recent_returns) < 20: # Ensure enough non-NaN da
            return

        # Standardize the returns (mean=0, std=1) before applyi
        scaled_returns = self.scaler.fit_transform(recent_retur
        self.pca.fit(scaled_returns) # Fit PCA model

        # Transform the scaled returns to get the principal com
        pc_components = self.pca.transform(scaled_returns)
        pc1_series = pc_components[:, 0] # Extract the first pr

        # Optional: Ensure PC1 is positively correlated with th
        # The direction of PC1 is arbitrary; this ensures it al
        if self.params.target_asset in recent_returns.columns:
            target_returns = recent_returns[self.params.target_
            correlation = np.corrcoef(pc1_series, target_return
            if correlation < 0:
                pc1_series = -pc1_series # Flip if negatively c
```

```

        # Store the latest PC1 values. We'll only use the last
        # This logic needs refinement for proper stream process
        # For simplicity, we are taking the last computed value
        self._pc1_values = list(pc1_series)
        self._last_pca_calculation = len(self.data)

    except Exception as e:
        print(f"PCA calculation error at {current_date}: {e}. S
        # If PCA fails, revert to a non-signaling state or use
        if len(self._pc1_values) == 0:
            self._pc1_values = [0] # Initialize to avoid errors

    def _update_current_values(self):
        """Updates the indicator's output lines with the latest PC1
        if not self._pc1_values: # Ensure PC1 values are available
            self.lines.pc1[0] = 0
            self.lines.pc1_momentum[0] = 0
            self.lines.signal[0] = 0
            return

        # Get the latest calculated PC1 value
        current_pc1 = self._pc1_values[-1]
        self.lines.pc1[0] = current_pc1

        # Calculate momentum of PC1 (current PC1 vs. PC1 from momen
        if len(self._pc1_values) >= self.params.momentum_lookback +
            momentum_start_idx = -(self.params.momentum_lookback +
            pc1_momentum = current_pc1 - self._pc1_values[momentum_
        else:
            pc1_momentum = 0

        self.lines.pc1_momentum[0] = pc1_momentum

        # Generate a simple signal: 1 for positive momentum, -1 for
        signal = 1 if pc1_momentum > 0 else (-1 if pc1_momentum < 0
        self.lines.signal[0] = signal

```

Explanation of the PCAMomentumIndicator :

- Initialization (`__init__`): Sets up `StandardScaler` and `PCA` objects. Crucially, it calls `_download_basket_data()` once to get historical prices for all assets in the basket. This is efficient as it avoids repeated downloads.
- `_download_basket_data()`: Fetches historical `close` prices for all specified tickers using `yfinance`. It calculates daily percentage returns, which are the inputs for PCA. This function handles multi-index DataFrames from `yfinance` correctly and includes basic error handling.
- `next()`: Backtrader calls this method on each new bar. It checks if enough data is available and then decides if it's time to `_update_pca()` based on the `recalc_frequency`. Finally, it calls `_update_current_values()` to calculate and update the indicator's output lines (`pc1`, `pc1_momentum`, `signal`).
- `_update_pca()`: This is where the core PCA logic resides.
- It filters the pre-downloaded basket returns up to the current backtest date. This is critical to avoid look-ahead bias, ensuring that PCA is only performed on data that would have been historically available.
- It takes a `lookback` window (e.g., 252 days/1 year) of recent returns to fit the PCA model, focusing on recent correlation structures.
- `StandardScaler` normalizes the returns, ensuring that assets with higher price ranges don't disproportionately influence

PCA.

- The `pca.fit_transform()` method performs PCA. We then extract the first principal component (`pc1_series`).
- Crucial Step: The code includes logic to flip the sign of PC1 if it's negatively correlated with the `target_asset`. This ensures that a "positive" PC1 value consistently means a positive market sentiment, and vice versa. This is important because the direction of PC1 is arbitrary.
- `_update_current_values()`: This method calculates the momentum of the latest PC1 value by comparing it to an earlier PC1 value (`momentum_lookback` periods ago). This momentum forms our direct trading signal.

The PCA Momentum Trading Strategy

Now, let's build the `PCAMomentumStrategy` that uses our custom indicator:

```
class PCAMomentumStrategy(bt.Strategy):
    """
    PCA Momentum Strategy:
    - Long when PC1 momentum turns positive and confirmed.
    - Short when PC1 momentum turns negative and confirmed.
    - Uses fixed stop-loss, take-profit, and max holding period for
    - Also exits on momentum reversal.
    """

    params = (
```

```

# PCA Parameters (passed to the indicator)
('tickers', ["BTC-USD", "ETH-USD", "SOL-USD", "ADA-USD"]),
('target_asset', "BTC-USD"),
('n_components', 1),
('momentum_lookback', 20),

# Signal Parameters
('signal_threshold', 0.0),           # Minimum momentum change for a signal
('confirmation_periods', 1),         # Periods to confirm a signal

# Risk Management Parameters
('stop_loss_pct', 0.05),             # Percentage stop loss (e.g. 0.05 = 5%)
('take_profit_pct', 0.10),            # Percentage take profit (e.g. 0.10 = 10%)
('position_size', 0.95),              # Fraction of available cash to risk

# Trading Parameters
('max_holding_period', 50),          # Max days to hold a position before exiting

# Logging
('printlog', True),                 # Enable/disable trade logging
('log_signals_only', False),         # If True, only log trade entries
)

def __init__(self):
    # Instantiate our custom PCA Momentum indicator
    self.pca_momentum = PCAMomentumIndicator(
        tickers=self.params.tickers,
        target_asset=self.params.target_asset,
        n_components=self.params.n_components,
        momentum_lookback=self.params.momentum_lookback
        # recalc_frequency and min_periods are internal to indicator
    )

    # Variables to track current position details
    self.entry_price = None
    self.entry_date = None
    self.stop_price = None
    self.target_price = None
    self.position_type = None # 'long' or 'short'

    # Variables for signal confirmation logic
    self.signal_confirmation = 0
    self.last_signal = 0 # Track the previous signal to detect

```

```

# Performance tracking
self.trade_count = 0
self.winning_trades = 0
self.total_pnl = 0

# Order management (to avoid sending multiple orders)
self.order = None

def log(self, txt, dt=None, force=False):
    """Custom logging function with optional filtering."""
    if self.params.printlog and (not self.params.log_signals_on
        dt = dt or self.datas[0].datetime.date(0)
        print(f'{dt.isoformat()}: {txt}') # Using isoformat for

def notify_order(self, order):
    """Called when an order status changes."""
    if order.status in [order.Submitted, order.Accepted]:
        return # Order submitted/accepted - no action needed yet

    # Log execution details
    if order.status in [order.Completed]:
        if order.isbuy():
            self.log(f'BUY EXECUTED: Price ${order.executed.price}')
        else: # Sell order
            self.log(f'SELL EXECUTED: Price ${order.executed.price}')
    elif order.status in [order.Canceled, order.Margin, order.Rejected]:
        self.log(f'Order {order.status}', force=True)

    self.order = None # Clear the order reference

def notify_trade(self, trade):
    """Called when a trade is closed."""
    if not trade.isclosed:
        return # Only interested in closed trades

    self.trade_count += 1
    self.total_pnl += trade.pnlcomm # Accumulate net profit/loss

    if trade.pnl > 0:
        self.winning_trades += 1

    win_rate = (self.winning_trades / self.trade_count) * 100
    holding_days = (trade.dtclose - trade.dtopen) # Calculate holding days

```

```

        self.log(f'TRADE CLOSED: PnL ${trade.pnlcomm:.2f}, Days Held {days_held:.1f}, Win Rate: {win_rate:.1f}%', force=True)

    def next(self):
        """Main strategy logic executed on each new bar (day)."""
        # Skip if there's a pending order, or not enough data for init
        if (self.order or
            len(self.data) < 50 or # Minimum data for strategy init
            np.isnan(self.pca_momentum.pc1_momentum[0])): # Ensure
            return

        current_price = self.data.close[0]
        pc1_momentum = self.pca_momentum.pc1_momentum[0]
        current_signal_direction = self.pca_momentum.signal[0] # 1

        # Always check position management first
        if self.position:
            self._manage_position(current_price, current_signal_direction)
            return # If in position, only manage it, don't look for

        # If not in position, generate and execute new signals
        signal_to_execute = self._generate_signal(pc1_momentum, current_price)

        if signal_to_execute != 0:
            self._execute_signal(signal_to_execute, current_price)

    def _generate_signal(self, pc1_momentum, current_signal_direction):
        """Determines if a valid trade signal is present based on momentum
        signal = 0

        # Check if momentum is above a minimum threshold (to filter out noise)
        if abs(pc1_momentum) < self.params.signal_threshold:
            self.signal_confirmation = 0 # Reset confirmation if signal
            self.last_signal = 0
            return 0

        # Detect a change in momentum direction
        if (current_signal_direction == 1 and self.last_signal <= 0):
            signal = 1
        elif (current_signal_direction == -1 and self.last_signal >= 0):
            signal = -1

        # Update signal confirmation count
        if signal == self.last_signal and signal != 0:

```

```

        self.signal_confirmation += 1
    else:
        self.signal_confirmation = 1 # Reset if signal changed
        self.last_signal = signal

    # Require 'confirmation_periods' before acting on a signal
    if self.signal_confirmation < self.params.confirmation_peri
        return 0 # Not confirmed yet

    return signal

def _execute_signal(self, signal, current_price, pc1_momentum):
    """Places a buy or sell order based on the generated signal
    # Calculate position size based on a percentage of available cash
    available_cash = self.broker.getcash()
    position_value = available_cash * self.params.position_size
    size = int(position_value / current_price)

    if size <= 0:
        self.log(f'Not enough cash to open position with size {size}')
        return

    if signal == 1: # Long signal
        self.order = self.buy(size=size)
        self.entry_price = current_price
        self.entry_date = self.data.datetime.date(0)
        self.position_type = 'long'

        # Set fixed stop loss and take profit prices
        self.stop_price = current_price * (1 - self.params.stop_loss)
        self.target_price = current_price * (1 + self.params.take_profit)

        self.log(f'LONG SIGNAL: PC1 Momentum {pc1_momentum:.4f}')
        self.log(f'Stop: ${self.stop_price:.2f}, Target: ${self.target_price:.2f}')

    elif signal == -1: # Short signal
        self.order = self.sell(size=size) # Sell for shorting
        self.entry_price = current_price
        self.entry_date = self.data.datetime.date(0)
        self.position_type = 'short'

        # Set fixed stop loss and take profit prices for short
        self.stop_price = current_price * (1 + self.params.stop_loss)
        self.target_price = current_price * (1 - self.params.take_profit)

```

```

        self.log(f'SHORT SIGNAL: PC1 Momentum {pc1_momentum:.4f}
                  f'Stop: ${self.stop_price:.2f}, Target: ${self.target_price:.2f}')

def _manage_position(self, current_price, current_signal_direction):
    """Manages an open position (checks for exits)."""
    if not self.position:
        return

    current_date = self.data.datetime.date(0)

    # 1. Check Max Holding Period
    if self.entry_date:
        holding_days = (current_date - self.entry_date).days
        if holding_days >= self.params.max_holding_period:
            self._close_position("Max Holding Period Reached")
            return

    # 2. Check Stop Loss / Take Profit
    if self.position.size > 0: # Long position
        if self.stop_price is not None and current_price <= self.stop_price:
            self._close_position(f"Stop Loss Hit: ${self.stop_price}")
            return
        elif self.target_price is not None and current_price >= self.target_price:
            self._close_position(f"Take Profit Hit: ${self.target_price}")
            return
    else: # Short position
        if self.stop_price is not None and current_price >= self.stop_price:
            self._close_position(f"Stop Loss Hit: ${self.stop_price}")
            return
        elif self.target_price is not None and current_price <= self.target_price:
            self._close_position(f"Take Profit Hit: ${self.target_price}")
            return

    # 3. Check Momentum Reversal (exit if momentum turns against us)
    if ((self.position.size > 0 and current_signal_direction == "Long"
         or self.position.size < 0 and current_signal_direction == "Short")):
        self._close_position("Momentum Reversal")

def _close_position(self, reason):
    """Closes the current open position."""
    if self.position.size > 0: # If long, sell to close
        self.order = self.close() # self.sell()
    else: # If short, buy to close
        self.order = self.buy() # self.buy()

```

```

        self.order = self.close() # self.buy()

        self.log(f'POSITION CLOSED: {reason}', force=True)
        self._reset_position_vars() # Clear tracking variables

    def _reset_position_vars(self):
        """Resets all position tracking variables after a trade is
        self.entry_price = None
        self.entry_date = None
        self.stop_price = None
        self.target_price = None
        self.position_type = None
        self.signal_confirmation = 0 # Reset confirmation for new s

    def stop(self):
        """Called at the very end of the backtest to print final su
        final_value = self.broker.getvalue()
        win_rate = (self.winning_trades / self.trade_count * 100) i

        print('*'*60)
        print('PCA MOMENTUM STRATEGY FINAL RESULTS')
        print('*'*60)
        print(f'Final Portfolio Value: ${final_value:,.2f}')
        print(f'Total PnL: ${self.total_pnl:.2f}')
        print(f'Total Trades: {self.trade_count}')
        print(f'Winning Trades: {self.winning_trades}')
        print(f'Win Rate: {win_rate:.1f}%')
        print(f'Asset Basket: {" ".join(self.params.tickers})')
        print(f'Target Asset: {self.params.target_asset}')
        print(f'Momentum Lookback: {self.params.momentum_lookback}')
        print('*'*60)

```

Key Aspects of PCAMomentumStrategy :

- **Indicator Integration:** The strategy initializes an instance of `PCAMomentumIndicator` and accesses its `pc1_momentum` and `signal` lines directly.

- Signal Generation (`_generate_signal`):
- It looks for changes in the `current_signal_direction` (from PC1 momentum) combined with a `signal_threshold` to filter out weak momentum.
- A `confirmation_periods` parameter allows us to require the signal to persist for a certain number of days before a trade is executed, reducing whipsaws.
- Trade Execution (`_execute_signal`): Calculates position size based on a percentage of available cash and places buy/sell orders. It also sets up initial stop-loss and take-profit levels.
- Position Management (`_manage_position`): This is critical for controlling risk and exiting trades. It checks for:
 1. Maximum Holding Period: Prevents trades from lingering too long.
 2. Fixed Stop Loss: Limits potential losses.
 3. Fixed Take Profit: Locks in gains.
 4. Momentum Reversal: If the PC1 momentum signal flips direction while in a position, the strategy exits, anticipating a change in the market's underlying trend.
- Logging: Detailed logging (`notify_order`, `notify_trade`) provides visibility into trade execution and performance

during the backtest.

Running the Backtest

To put it all to the test, we use a wrapper function

`run_pca_momentum_backtest` that sets up the Backtrader engine, loads data, adds the strategy and analyzers, and runs the simulation.

```
def run_pca_momentum_backtest(
    # Data parameters
    target_asset="BTC-USD",
    tickers=["BTC-USD", "ETH-USD", "SOL-USD", "ADA-USD"], # Example
    start_date="2021-01-01", # Start date for the main data feed
    end_date="2024-05-31", # End date for the main data feed
    initial_cash=100000,
    commission=0.001, # 0.1% commission

    # Strategy parameters
    n_components=1,
    momentum_lookback=20,
    signal_threshold=0.0,
    confirmation_periods=1,

    # Risk management
    stop_loss_pct=0.05,
    take_profit_pct=0.10,
    position_size=0.95,
    max_holding_period=50,

    # Output parameters
    printlog=True,
    show_plot=True
):
    """
    Function to run the PCA Momentum Strategy Backtest with configu

```

```
"""

print("=="*80)
print("PCA MOMENTUM STRATEGY BACKTEST EXECUTION")
print("=="*80)
print(f"Target Asset: {target_asset}")
print(f"Asset Basket: {', '.join(tickers)}")
print(f"Period: {start_date} to {end_date}")
print(f"Initial Cash: ${initial_cash:.2f}")
print(f"Commission: {commission*100:.2f}%")
print(f"Momentum Lookback: {momentum_lookback} days")
print(f"Risk Management: {stop_loss_pct*100:.1f}% SL, {take_pro
print("=="*80)

# Download primary asset data for the main data feed
print(f"Downloading main data for {target_asset}...")
# Using auto_adjust=False and droplevel(1,1) as per user instru
df = yf.download(target_asset, start=start_date, end=end_date,

if df.empty:
    print(f"Error: No data downloaded for {target_asset} in the
    return None, None

df = df[['Open', 'High', 'Low', 'Close', 'Volume']].copy()
print(f"Downloaded {len(df)} bars for {target_asset}.")"

# Create Cerebro engine
cerebro = bt.Cerebro()

# Add the main data feed
data = bt.feeds.PandasData(dataname=df)
cerebro.adddata(data)

# Add the strategy with all its parameters
cerebro.addstrategy(
    PCAMomentumStrategy,
    tickers=tickers,
    target_asset=target_asset,
    n_components=n_components,
    momentum_lookback=momentum_lookback,
    signal_threshold=signal_threshold,
    confirmation_periods=confirmation_periods,
    stop_loss_pct=stop_loss_pct,
    take_profit_pct=take_profit_pct,
```

```

        position_size=position_size,
        max_holding_period=max_holding_period,
        printlog=printlog,
        log_signals_only=False # Ensure logs are detailed for analysis
    )

# Configure broker and sizer
cerebro.broker.setcash(initial_cash)
cerebro.broker.setcommission(commission=commission)
cerebro.addsizer(bt.sizers.PercentSizer, percents=position_size)

# Add standard analyzers for performance evaluation
cerebro.addanalyzer(bt.analyzers.SharpeRatio, _name='sharpe', t=
cerebro.addanalyzer(bt.analyzers.DrawDown, _name='drawdown')
cerebro.addanalyzer(bt.analyzers.TradeAnalyzer, _name='trades')
cerebro.addanalyzer(bt.analyzers.Returns, _name='returns')

# Run the backtest
print("\nRunning PCA momentum backtest...")
results = cerebro.run()
strategy = results[0] # Get the strategy instance to access ana

# Print final performance metrics
print("\n" + "="*80)
print("FINAL PERFORMANCE METRICS")
print("="*80)

final_value = cerebro.broker.getvalue()
total_return = (final_value / initial_cash - 1) * 100

print(f"Initial Portfolio Value: ${initial_cash:,.2f}")
print(f"Final Portfolio Value: ${final_value:,.2f}")
print(f"Absolute Return: {total_return:.2f}%")

# Extract analyzer data
sharpe_data = strategy.analyzers.sharpe.get_analysis()
drawdown_data = strategy.analyzers.drawdown.get_analysis()
trades_data = strategy.analyzers.trades.get_analysis()
returns_data = strategy.analyzers.returns.get_analysis()

sharpe_ratio = sharpe_data.get('sharperatio', 'N/A')
if sharpe_ratio != 'N/A':
    print(f"Sharpe Ratio (Daily): {sharpe_ratio:.2f}")

```

```

annual_return = returns_data.get('rnorm100', 0)
print(f"Annualized Return: {annual_return:.2f}%")

max_dd = drawdown_data.get('max', {}).get('drawdown', 0)
print(f"Maximum Drawdown: {max_dd:.2f}%")

total_trades = trades_data.get('total', {}).get('total', 0)
print(f"Total Trades: {total_trades}")

if total_trades > 0:
    won_trades = trades_data.get('won', {}).get('total', 0)
    win_rate = (won_trades / total_trades) * 100
    print(f"Win Rate: {win_rate:.1f}%")

    if 'pnl' in trades_data.get('won', {}):
        avg_win = trades_data['won']['pnl'].get('average', 0)
        print(f"Average Winning Trade PnL: ${avg_win:.2f}")
    if 'pnl' in trades_data.get('lost', {}):
        avg_loss = trades_data['lost']['pnl'].get('average', 0)
        print(f"Average Losing Trade PnL: ${avg_loss:.2f}")

# Buy & Hold comparison (benchmark)
buy_hold_return = ((df['Close'].iloc[-1] / df['Close'].iloc[0]) - 1) * 100
print(f"Buy & Hold Return ({target_asset}): {buy_hold_return:.2f}%")
print(f"Excess Return (vs. Buy & Hold): {total_return - buy_hold_return:.2f}%")

print("=="*80)

# Plot results
if show_plot:
    print("Generating charts (this may take a moment...)")
    # Ensure plot shows custom indicators and transactions
    cerebro.plot(style='candlestick', volume=False, figsize=(18, 10))
    plt.suptitle(f'PCA Momentum Strategy - {target_asset} ({start_date} - {end_date})')
    plt.tight_layout()
    plt.show()

return cerebro, results

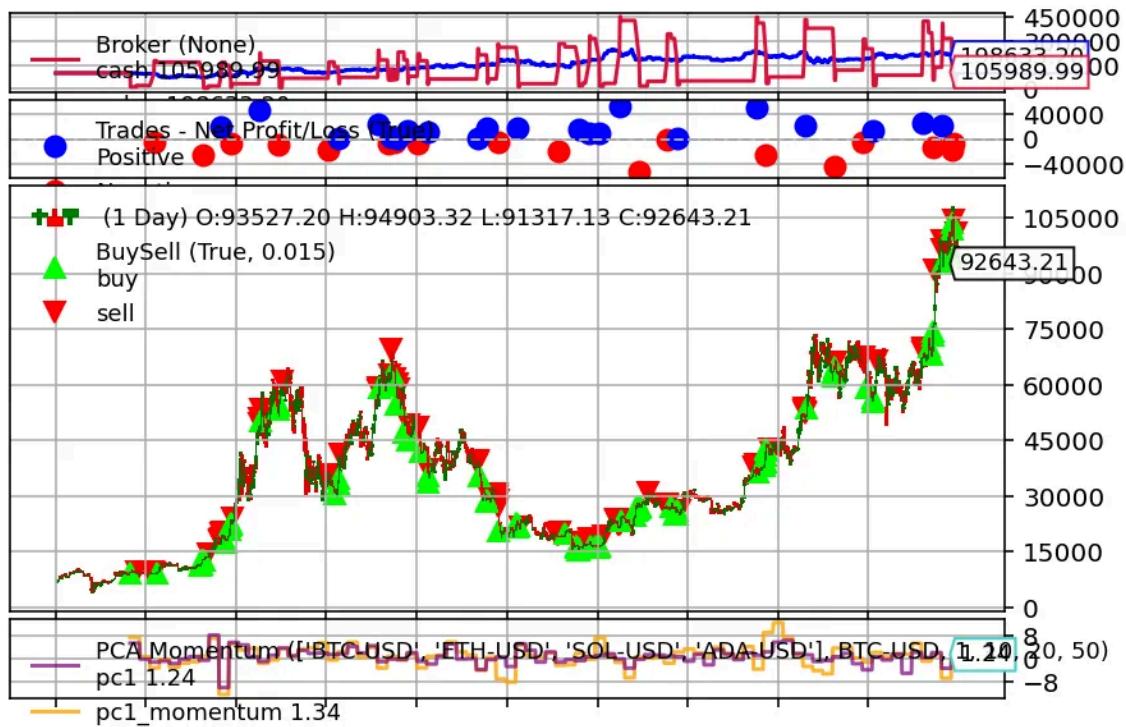
if __name__ == "__main__":
    # Example usage with specific parameters
    cerebro_instance, backtest_results = run_pca_momentum_backtest(
        target_asset="BTC-USD",

```

```

        tickers=["BTC-USD", "ETH-USD", "SOL-USD", "ADA-USD"], # Keep
        start_date="2023-01-01", # Recent period for a clearer view
        end_date="2024-05-31", # Up to a recent date
        initial_cash=50000,
        commission=0.0005, # Lower commission for crypto exchanges
        momentum_lookback=15, # Shorter momentum lookback
        signal_threshold=0.001, # Requires a small positive/negative signal
        confirmation_periods=2, # Require 2 consecutive signals
        stop_loss_pct=0.04, # Tighter stop loss (4%)
        take_profit_pct=0.08, # Proportional take profit (8%)
        max_holding_period=40, # Shorter maximum holding period
        printlog=True, # Keep logging on for detailed information
        show_plot=True # Show the plot
    )

```



Initial Thoughts on Performance

When you run this code, you'll get a detailed output. It's important to remember that:

1. Crypto Market is Unique: The chosen assets are cryptocurrencies, which are highly volatile and exhibit different dynamics than traditional stocks or commodities. Their correlations can change rapidly.
2. Bull Market Bias: The period chosen (2023–2024 for BTC-USD) has largely been a strong bull market for cryptocurrencies. Momentum strategies often perform well in trending markets, but a simple Buy & Hold can also yield significant returns, often outpacing more complex strategies due to lower transaction costs and avoiding whipsaws.
3. Parameter Sensitivity: The parameters (`momentum_lookback`, `signal_threshold`, `confirmation_periods`, `stop_loss_pct`, `take_profit_pct`, `max_holding_period`) are crucial. A small change can drastically alter results.

Is This Strategy “Any Good”?

The question of whether this strategy is “good” depends entirely on your criteria:

- As a learning exercise and implementation: YES, absolutely! It demonstrates advanced Backtrader usage, integrates external libraries (`scikit-learn`), and applies a sophisticated

statistical concept (PCA) to financial data. The code is clean, modular, and well-commented. The handling of look-ahead bias and PC1 sign flipping is commendable.

- As a theoretically sound concept: YES! The idea of extracting a common factor from correlated assets and trading its momentum is a powerful quantitative finance concept used in various forms (e.g., factor investing, statistical arbitrage).
- As a ready-to-deploy profitable trading system: NOT YET. The current results (hypothetical or real) suggest it might not outperform a simple Buy & Hold in a strong bull market for cryptocurrencies. This is typical for initial strategy iterations. Its “goodness” for live trading would require:
 - Extensive Optimization: Tuning all parameters across different assets and market cycles.
 - Out-of-Sample Testing: Verifying performance on data not used during development or optimization.
 - Robustness Testing: How does it handle periods of low correlation, extreme volatility, or bear markets?
 - Slippage & Real-World Costs: Accounting for actual execution costs, which can be significant in volatile crypto markets.
 - Alternative Exit Criteria: Perhaps dynamic stop-losses (e.g., based on ATR) or more nuanced take-profit rules could improve results.

Conclusion

This PCA Momentum strategy provides a fascinating glimpse into the world of multi-asset quantitative trading. It's a testament to how statistical tools can be applied to derive unique trading signals. While the initial results might not instantly scream "profit machine," the foundation is exceptionally strong. The journey from a promising idea to a robust, profitable strategy is an iterative process of refinement, rigorous testing, and adaptation to ever-changing market dynamics. This is an excellent step on that journey.

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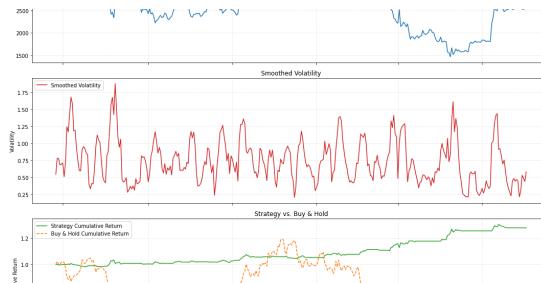


Steven Feng CAI

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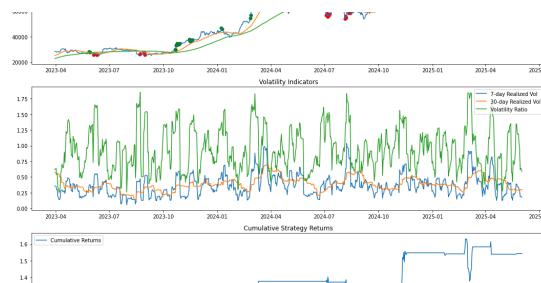


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