2.5: Technical Indicators & Signal Design

Objective

This notebook implements a technical analysis system that: 1. **Computes technical indicators** for each stock (SMA, EMA, RSI, MACD, ATR) 2. **Generates entry/exit signals** based on indicator combinations 3. **Derives signal-based weights** using signal strength 4. **Creates signal-weighted portfolio** with normalized weights across assets

Technical Indicators Overview

Moving Averages

- **SMA (Simple Moving Average)**: Arithmetic mean of prices over N periods
- **EMA (Exponential Moving Average)**: Weighted average giving more importance to recent prices

Momentum Indicators

- **RSI (Relative Strength Index)**: Measures overbought/oversold conditions (0-100 scale)
- **MACD (Moving Average Convergence Divergence)**: Trend-following momentum indicator

Volatility Indicators

- **ATR (Average True Range)**: Measures market volatility

Signal Generation Strategy

Long Signal: `(RSI < 30) & (MACD > MACD_signal)` - RSI below 30 indicates oversold condition (potential upward reversal) - MACD above signal line indicates bullish momentum

Short Signal: `(RSI > 70) & (MACD < MACD_signal)`
- RSI above 70 indicates overbought condition (potential downward reversal) - MACD below signal line indicates bearish momentum

Weight Calculation

`adjusted_weight = base_weight × signal_strength`

Where signal strength is derived from indicator values and combined signals.

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta
import warnings
warnings.filterwarnings('ignore')

# Set display options
pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', '{:.6f}'.format)

# Set plotting style
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")

print("  Libraries imported successfully!")
print("  Technical Indicators & Signal Design System Ready!")

# Configuration parameters
TECHNICAL_CONFIG = {
    'sma_period': 20,        # Simple Moving Average period
    'ema_period': 12,        # Exponential Moving Average period
    'rsi_period': 14,        # RSI calculation period
    'macd_fast': 12,         # MACD fast EMA period
    'macd_slow': 26,         # MACD slow EMA period
    'macd_signal': 9,        # MACD signal line period
```

```python
    'atr_period': 14,         # Average True Range period
    'rsi_oversold': 30,       # RSI oversold threshold
    'rsi_overbought': 70,     # RSI overbought threshold
    'base_weight': 0.1        # Base weight for signal calculation
}

print(f"  Technical analysis parameters configured:")
for param, value in TECHNICAL_CONFIG.items():
    print(f"  {param}: {value}")

print(f"\n  Signal Generation Rules:")
print(f"   • Long: RSI < {TECHNICAL_CONFIG['rsi_oversold']} " +
      "AND MACD > MACD_signal")
print(f"   • Short: RSI > {TECHNICAL_CONFIG['rsi_overbought']} " +
      "AND MACD < MACD_signal")
print(f"   • Weight Adjustment: base_weight × signal_strength")
```

```
 Libraries imported successfully!
 Technical Indicators & Signal Design System Ready!
 Technical analysis parameters configured:
  sma_period: 20
  ema_period: 12
  rsi_period: 14
  macd_fast: 12
  macd_slow: 26
  macd_signal: 9
  atr_period: 14
  rsi_oversold: 30
  rsi_overbought: 70
  base_weight: 0.1

 Signal Generation Rules:
  • Long: RSI < 30 AND MACD > MACD_signal
  • Short: RSI > 70 AND MACD < MACD_signal
  • Weight Adjustment: base_weight × signal_strength
```

Step 1: Data Loading & Preparation

Load the preprocessed S&P 500 price data from Part 1 and prepare it for technical analysis.

```python
# Load preprocessed S&P 500 price data
print("  Loading S&P 500 price data...")

# Try to load data from Part 1
prices_df = pd.read_csv(
    '../Part 1: Data Acquisition & Preprocessing/sp500_prices_5yr.csv',
    index_col=0, parse_dates=True)
print(f"  Successfully loaded price data from Part 1")
print(f"  Price data shape: {prices_df.shape}")
print(f"  Date range: {prices_df.index.min().strftime('%Y-%m-%d')} " +
      f"to {prices_df.index.max().strftime('%Y-%m-%d')}")

# Display basic information about the data
print(f"\n  Dataset Overview:")
print(f"   • Number of assets: {len(prices_df.columns)}")
print(f"   • Number of trading days: {len(prices_df)}")
print(f"   • Data frequency: Daily")
print(f"   • Missing values: {prices_df.isnull().sum().sum()}")

# Display sample data
print(f"\n  Sample Price Data (first 5 rows, first 5 columns):")
print(prices_df.iloc[:5, :5])

print(f"\n  Price Statistics (first 5 assets):")
print(prices_df.iloc[:, :5].describe())

# Store tickers list for later use
tickers = list(prices_df.columns)
print(f"\n  Assets for technical analysis: {len(tickers)} tickers")
print(f"Sample tickers: {tickers[:10]}" +
      f"{'...' if len(tickers) > 10 else ''}")
```

```
Loading S&P 500 price data...
Successfully loaded price data from Part 1
Price data shape: (1254, 100)
Date range: 2020-08-07 to 2025-08-05

Dataset Overview:
 • Number of assets: 100
 • Number of trading days: 1254
 • Data frequency: Daily
 • Missing values: 0
```

```
  Sample Price Data (first 5 rows, first 5 columns):
                  AAPL      GOOG     GOOGL       AMZN      AVGO
2020-08-07 108.203781 74.282951 74.471870 158.373001 28.915098
2020-08-10 109.776497 74.362968 74.394821 157.408005 29.041964
2020-08-11 106.511749 73.578644 73.585678 154.033493 28.746536
2020-08-12 110.051590 74.885872 74.912720 158.112000 29.599102
2020-08-13 111.999237 75.473869 75.380417 158.050995 29.224718

  Price Statistics (first 5 assets):
              AAPL         GOOG        GOOGL         AMZN         AVGO
count 1254.000000 1254.000000 1254.000000 1254.000000 1254.000000
mean   168.424444  131.988279  130.979755  157.791528   93.916028
std     36.174476   31.651996   31.293769   35.356328   65.389388
min    104.043098   70.342377   70.049393   81.820000   28.746536
25%    140.831928  105.492935  104.948092  131.932499   45.434097
50%    166.048546  132.447701  131.610443  161.193245   58.948879
75%    191.962780  155.533764  154.130917  179.334999  132.487057
max    258.396667  207.224548  205.893341  242.059998  302.619995

  Assets for technical analysis: 100 tickers
Sample tickers: ['AAPL', 'GOOG', 'GOOGL', 'AMZN', 'AVGO', 'BRK-B', 'COST', 'ABBV', 'BAC', 'C
```

Step 2: Technical Indicators Calculation

Implement and calculate technical indicators for each stock:

- **SMA (Simple Moving Average)**: Trend identification
- **EMA (Exponential Moving Average)**: Trend with recent price emphasis
- **RSI (Relative Strength Index)**: Momentum and overbought/oversold conditions
- **MACD (Moving Average Convergence Divergence)**: Trend and momentum
- **ATR (Average True Range)**: Volatility measurement

```python
# Technical Indicators Calculation Functions
print("  Implementing technical indicators calculation functions...")

def calculate_sma(prices, period):
    """
    Calculate Simple Moving Average
    """
```

```python
    return prices.rolling(window=period).mean()

def calculate_ema(prices, period):
    """
    Calculate Exponential Moving Average
    """
    return prices.ewm(span=period, adjust=False).mean()

def calculate_rsi(prices, period=14):
    """
    Calculate Relative Strength Index
    """
    delta = prices.diff()
    gain = (delta.where(delta > 0, 0)).rolling(window=period).mean()
    loss = (-delta.where(delta < 0, 0)).rolling(window=period).mean()

    rs = gain / loss
    rsi = 100 - (100 / (1 + rs))
    return rsi

def calculate_macd(prices, fast=12, slow=26, signal=9):
    """
    Calculate MACD and Signal Line
    """
    ema_fast = calculate_ema(prices, fast)
    ema_slow = calculate_ema(prices, slow)

    macd_line = ema_fast - ema_slow
    macd_signal = calculate_ema(macd_line, signal)
    macd_histogram = macd_line - macd_signal

    return macd_line, macd_signal, macd_histogram

def calculate_atr(high, low, close, period=14):
    """
    Calculate Average True Range
    """
    # For price data, we'll use high=close, low=close
    # (since we only have close prices)
    # This is a simplified ATR calculation
    tr = pd.DataFrame({
        'hl': close.diff().abs(),  # High-Low equivalent using price changes
```

```python
        'hc': close.diff().abs(),  # High-Close equivalent
        'lc': close.diff().abs()   # Low-Close equivalent
    }).max(axis=1)

    atr = tr.rolling(window=period).mean()
    return atr

def calculate_all_indicators(prices_df, config):
    """
    Calculate all technical indicators for all stocks
    """
    print(f" Calculating technical indicators for " +
          f"{len(prices_df.columns)} stocks...")

    indicators = {}

    for ticker in prices_df.columns:
        print(f"  Processing {ticker}...", end=" ")

        prices = prices_df[ticker].dropna()

        # Calculate all indicators
        sma = calculate_sma(prices, config['sma_period'])
        ema = calculate_ema(prices, config['ema_period'])
        rsi = calculate_rsi(prices, config['rsi_period'])
        macd, macd_signal, macd_hist = calculate_macd(
            prices, config['macd_fast'],
            config['macd_slow'], config['macd_signal']
        )
        # Simplified for close prices
        atr = calculate_atr(prices, prices, prices, config['atr_period'])

        # Store in dictionary
        indicators[ticker] = {
            'prices': prices,
            'sma': sma,
            'ema': ema,
            'rsi': rsi,
            'macd': macd,
            'macd_signal': macd_signal,
            'macd_histogram': macd_hist,
            'atr': atr
```

```
        }

        print(" ")

    print(f" Technical indicators calculated for all {len(indicators)} assets!")
    return indicators

# Calculate indicators for all stocks
technical_indicators = calculate_all_indicators(prices_df, TECHNICAL_CONFIG)

print(f"\n Indicator Summary:")
sample_ticker = list(technical_indicators.keys())[0]
sample_data = technical_indicators[sample_ticker]

for indicator, data in sample_data.items():
    if isinstance(data, pd.Series):
        valid_count = data.dropna().shape[0]
        print(f"  {indicator:15}: {valid_count:4d} valid values")

print(f"\n All technical indicators calculated successfully!")
```

```
Implementing technical indicators calculation functions...
Calculating technical indicators for 100 stocks...
 Processing AAPL...
 Processing GOOG...
 Processing GOOGL...
 Processing AMZN...
 Processing AVGO...
 Processing BRK-B...
 Processing COST...
 Processing ABBV...
 Processing BAC...
 Processing CVX...
 Processing KO...
 Processing CSCO...
 Processing AMD...
 Processing ABT...
 Processing BX...
 Processing AXP...
 Processing CAT...
 Processing T...
 Processing BKNG...
```

```
Processing SCHW...
Processing ANET...
Processing BLK...
Processing BA...
Processing C...
Processing ACN...
Processing AMGN...
Processing BSX...
Processing ADBE...
Processing AMAT...
Processing DHR...
Processing DE...
Processing COF...
Processing APH...
Processing ADP...
Processing CMCSA...
Processing COP...
Processing CRWD...
Processing ADI...
Processing CB...
Processing MO...
Processing CEG...
Processing CME...
Processing CDNS...
Processing AMT...
Processing BMY...
Processing CTAS...
Processing DELL...
Processing APO...
Processing CVS...
Processing ABNB...
Processing MMM...
Processing AON...
Processing COIN...
Processing AJG...
Processing BK...
Processing CI...
Processing CL...
Processing AZO...
Processing AXON...
Processing CSX...
Processing ADSK...
Processing APD...
```

```
 Processing AEP...
 Processing DLR...
 Processing CMG...
 Processing CARR...
 Processing AFL...
 Processing ALL...
 Processing COR...
 Processing GLW...
 Processing CMI...
 Processing BDX...
 Processing CTVA...
 Processing AMP...
 Processing DDOG...
 Processing XYZ...
 Processing CBRE...
 Processing CCI...
 Processing AIG...
 Processing CPRT...
 Processing AME...
 Processing BKR...
 Processing FANG...
 Processing CSGP...
 Processing CCL...
 Processing ED...
 Processing CAH...
 Processing CHTR...
 Processing DAL...
 Processing CTSH...
 Processing ACGL...
 Processing A...
 Processing BR...
 Processing BRO...
 Processing DXCM...
 Processing STZ...
 Processing AWK...
 Processing AEE...
 Processing ADM...
 Processing AVB...
Technical indicators calculated for all 100 assets!

Indicator Summary:
 prices         : 1254 valid values
 sma            : 1235 valid values
```

```
ema            : 1254 valid values
rsi            : 1241 valid values
macd           : 1254 valid values
macd_signal    : 1254 valid values
macd_histogram : 1254 valid values
atr            : 1240 valid values

All technical indicators calculated successfully!
```

Step 3: Signal Generation

Generate entry/exit signals based on technical indicators:

Signal Rules:

- **Long Signal**: `(RSI < 30) & (MACD > MACD_signal)`
  - RSI < 30: Oversold condition (potential reversal up)
  - MACD > Signal: Bullish momentum confirmation
- **Short Signal**: `(RSI > 70) & (MACD < MACD_signal)`
  - RSI > 70: Overbought condition (potential reversal down)
  - MACD < Signal: Bearish momentum confirmation

Signal Values:

- **+1**: Long signal (Buy)
- **-1**: Short signal (Sell)

- **0**: Neutral (Hold)

```python
# Signal Generation Implementation
print("  Generating entry/exit signals based on technical indicators...")

def generate_signals(indicators, config):
    """Generate buy/sell/hold signals for all stocks"""
    signals = {}
    signal_summary = {'long_signals': 0, 'short_signals': 0, 'total_periods': 0}

    rsi_oversold = config['rsi_oversold']
    rsi_overbought = config['rsi_overbought']
```

```python
    for ticker, data in indicators.items():
        # Extract required indicators
        rsi = data['rsi']
        macd = data['macd']
        macd_signal = data['macd_signal']

        # Generate long signals: RSI < 30 AND MACD > MACD_signal
        long_condition = (rsi < rsi_oversold) & (macd > macd_signal)

        # Generate short signals: RSI > 70 AND MACD < MACD_signal
        short_condition = (rsi > rsi_overbought) & (macd < macd_signal)

        # Create signal series: +1 for long, -1 for short, 0 for neutral
        signal = pd.Series(0, index=rsi.index, dtype=int)
        signal.loc[long_condition] = 1
        signal.loc[short_condition] = -1

        signals[ticker] = signal

        # Update summary statistics
        signal_summary['long_signals'] += (signal == 1).sum()
        signal_summary['short_signals'] += (signal == -1).sum()
        signal_summary['total_periods'] += len(signal.dropna())

    return signals, signal_summary

# Generate signals for all stocks
signals, signal_stats = generate_signals(technical_indicators, TECHNICAL_CONFIG)

print(f" Signals generated for {len(signals)} stocks!")
print(f"\n Signal Statistics:")
print(f"  • Total signal periods: {signal_stats['total_periods']:,}")
print(f"  • Long signals (Buy): {signal_stats['long_signals']:,} ({signal_stats['long_signals
print(f"  • Short signals (Sell): {signal_stats['short_signals']:,} ({signal_stats['short_sig
print(f"  • Neutral periods: {signal_stats['total_periods'] - signal_stats['long_signals'] -

# Create signals matrix for portfolio construction
print(f"\n Creating signals matrix...")
signals_df = pd.DataFrame(signals)
signals_df = signals_df.dropna()  # Remove rows with any NaN values

print(f" Signals matrix shape: {signals_df.shape}")
```

```python
print(f"  Signal date range: {signals_df.index.min().strftime('%Y-%m-%d')} to {signals_df.ind

# Display sample signals
print(f"\n  Sample Signals (first 10 days, first 5 stocks):")
print(signals_df.iloc[:10, :5])

# Signal distribution analysis
print(f"\n  Signal Distribution by Stock (first 5 stocks):")
for ticker in signals_df.columns[:5]:
    signal_counts = signals_df[ticker].value_counts().sort_index()
    total = len(signals_df[ticker])
    print(f"\n{ticker}:")
    for signal_val in [-1, 0, 1]:
        count = signal_counts.get(signal_val, 0)
        percentage = count / total * 100
        signal_name = {-1: 'Short', 0: 'Neutral', 1: 'Long'}[signal_val]
        print(f"  {signal_name:>7}: {count:4d} ({percentage:5.1f}%)")

print(f"\n  Signal generation completed successfully!")
```

```
  Generating entry/exit signals based on technical indicators...
  Signals generated for 100 stocks!

  Signal Statistics:
   • Total signal periods: 125,400
   • Long signals (Buy): 275 (0.22%)
   • Short signals (Sell): 1,097 (0.87%)
   • Neutral periods: 124,028

  Creating signals matrix...
  Signals matrix shape: (1254, 100)
  Signal date range: 2020-08-07 to 2025-08-05

  Sample Signals (first 10 days, first 5 stocks):
            AAPL  GOOG  GOOGL  AMZN  AVGO
2020-08-07     0     0      0     0     0
2020-08-10     0     0      0     0     0
2020-08-11     0     0      0     0     0
2020-08-12     0     0      0     0     0
2020-08-13     0     0      0     0     0
2020-08-14     0     0      0     0     0
2020-08-17     0     0      0     0     0
```

```
2020-08-18     0     0      0     0     0
2020-08-19     0     0      0     0     0
2020-08-20     0     0      0     0     0

 Signal Distribution by Stock (first 5 stocks):

AAPL:
    Short:    9 (  0.7%)
  Neutral: 1244 ( 99.2%)
     Long:    1 (  0.1%)

GOOG:
    Short:   12 (  1.0%)
  Neutral: 1242 ( 99.0%)
     Long:    0 (  0.0%)

GOOGL:
    Short:   10 (  0.8%)
  Neutral: 1244 ( 99.2%)
     Long:    0 (  0.0%)

AMZN:
    Short:    2 (  0.2%)
  Neutral: 1249 ( 99.6%)
     Long:    3 (  0.2%)

AVGO:
    Short:   10 (  0.8%)
  Neutral: 1244 ( 99.2%)
     Long:    0 (  0.0%)

 Signal generation completed successfully!
```

Step 4: Signal-Based Weight Calculation

Derive portfolio weights based on signal strength:

Weight Formula:

```
adjusted_weight = base_weight × signal_strength
```

Signal Strength Calculation:

- **Long Signal (+1)**: Use RSI distance from oversold + MACD momentum
- **Short Signal (-1)**: Use RSI distance from overbought + MACD momentum

- **Neutral (0)**: Base weight only

Weight Normalization:

Normalize weights across all assets so they sum to 1.0 for proper portfolio allocation.

```
# Signal-Based Weight Calculation
print("  Calculating signal-based portfolio weights...")

def calculate_signal_strength(indicators, signals, config):
    """Calculate signal strength for weight adjustment"""
    signal_strengths = {}

    base_weight = config['base_weight']
    rsi_oversold = config['rsi_oversold']
    rsi_overbought = config['rsi_overbought']

    for ticker in signals.keys():
        data = indicators[ticker]
        signal = signals[ticker]

        rsi = data['rsi']
        macd = data['macd']
        macd_signal = data['macd_signal']

        # Calculate signal strength based on indicator values
        strength = pd.Series(1.0, index=signal.index)  # Start with base strength

        # For long signals: strengthen based on how oversold and MACD momentum
        long_mask = (signal == 1)
        if long_mask.any():
            # RSI component: stronger signal when more oversold
            rsi_strength = (rsi_oversold - rsi.clip(upper=rsi_oversold)) / rsi_oversold
            # MACD component: stronger when MACD is more above signal line
            macd_strength = (macd - macd_signal).clip(lower=0) / macd.std()

            # Combine strengths for long signals
```

```python
            strength.loc[long_mask] = 1.0 + rsi_strength.loc[long_mask] + macd_strength.loc[l

        # For short signals: strengthen based on how overbought and MACD momentum
        short_mask = (signal == -1)
        if short_mask.any():
            # RSI component: stronger signal when more overbought
            rsi_strength = (rsi.clip(lower=rsi_overbought) - rsi_overbought) / (100 - rsi_ove
            # MACD component: stronger when MACD is more below signal line
            macd_strength = (macd_signal - macd).clip(lower=0) / macd.std()

            # Combine strengths for short signals
            strength.loc[short_mask] = 1.0 + rsi_strength.loc[short_mask] + macd_strength.loc

        # Cap signal strength to reasonable bounds
        strength = strength.clip(0.5, 3.0)
        signal_strengths[ticker] = strength

    return signal_strengths

def calculate_adjusted_weights(signals, signal_strengths, config):
    """Calculate portfolio weights adjusted by signal strength"""
    base_weight = config['base_weight']

    # Create weights matrix
    weights = {}

    for ticker in signals.keys():
        signal = signals[ticker]
        strength = signal_strengths[ticker]

        # Calculate adjusted weight = base_weight × signal_strength
        adjusted_weight = base_weight * strength

        # Apply signal direction: positive for long, negative for short, base for neutral
        weight = pd.Series(base_weight, index=signal.index)

        # Long positions: positive weight scaled by strength
        long_mask = (signal == 1)
        weight.loc[long_mask] = adjusted_weight.loc[long_mask]

        # Short positions: negative weight scaled by strength (for demonstration)
        # In practice, short positions might be handled differently
```

```
        short_mask = (signal == -1)
        weight.loc[short_mask] = -adjusted_weight.loc[short_mask] * 0.5  # Reduce short weig

        # Neutral positions: base weight
        neutral_mask = (signal == 0)
        weight.loc[neutral_mask] = base_weight * 0.5  # Reduced neutral weight

        weights[ticker] = weight

    # Convert to DataFrame
    weights_df = pd.DataFrame(weights)

    # Normalize weights to sum to 1.0 (handle negative weights)
    normalized_weights = weights_df.copy()

    for date in weights_df.index:
        row_weights = weights_df.loc[date]

        # Separate positive and negative weights
        positive_weights = row_weights.clip(lower=0)
        negative_weights = row_weights.clip(upper=0)

        # Normalize positive weights to sum to 1.0
        if positive_weights.sum() > 0:
            positive_weights = positive_weights / positive_weights.sum()

        # Handle negative weights (for short positions) - normalize separately
        if negative_weights.sum() < 0:
            negative_weights = negative_weights / abs(negative_weights.sum()) * 0.2  # Limit

        # Combine normalized weights
        final_weights = positive_weights + negative_weights

        # Final normalization to ensure they sum to 1.0
        if final_weights.sum() != 0:
            final_weights = final_weights / final_weights.sum()
        else:
            final_weights = pd.Series(1.0/len(final_weights), index=final_weights.index)

        normalized_weights.loc[date] = final_weights

    return weights_df, normalized_weights
```

```python
# Calculate signal strengths
print("  Calculating signal strengths...")
signal_strengths = calculate_signal_strength(technical_indicators, signals, TECHNICAL_CONFIG)

# Calculate adjusted weights
print("  Calculating signal-based weights...")
raw_weights, portfolio_weights = calculate_adjusted_weights(signals, signal_strengths, TECHNI

print(f"  Signal-based weights calculated!")
print(f"  Portfolio weights shape: {portfolio_weights.shape}")

# Verify weight normalization
weight_sums = portfolio_weights.sum(axis=1)
print(f"  Weight sum validation:")
print(f"   • Min weight sum: {weight_sums.min():.6f}")
print(f"   • Max weight sum: {weight_sums.max():.6f}")
print(f"   • Mean weight sum: {weight_sums.mean():.6f}")
print(f"   • All sums   1.0: {np.allclose(weight_sums, 1.0)}")

# Display sample weights
print(f"\n  Sample Portfolio Weights (first 10 days, first 5 stocks):")
print(portfolio_weights.iloc[:10, :5])

# Weight distribution analysis
print(f"\n  Weight Statistics (first 5 stocks):")
for ticker in portfolio_weights.columns[:5]:
    weights = portfolio_weights[ticker]
    print(f"\n{ticker}:")
    print(f"  Mean: {weights.mean():7.4f}")
    print(f"  Std:  {weights.std():7.4f}")
    print(f"  Min:  {weights.min():7.4f}")
    print(f"  Max:  {weights.max():7.4f}")

print(f"\n  Signal-based portfolio weights calculation completed!")
```

```
Calculating signal-based portfolio weights...
Calculating signal strengths...
Calculating signal-based weights...
Signal-based weights calculated!
Portfolio weights shape: (1254, 100)
Weight sum validation:
```

- Min weight sum: 1.000000
- Max weight sum: 1.000000
- Mean weight sum: 1.000000
- All sums 1.0: True

```
 Sample Portfolio Weights (first 10 days, first 5 stocks):
              AAPL     GOOG    GOOGL     AMZN     AVGO
2020-08-07 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-10 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-11 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-12 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-13 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-14 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-17 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-18 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-19 0.010000 0.010000 0.010000 0.010000 0.010000
2020-08-20 0.010000 0.010000 0.010000 0.010000 0.010000

 Weight Statistics (first 5 stocks):

AAPL:
  Mean:  0.0102
  Std:   0.0125
  Min:  -0.2500
  Max:   0.0211

GOOG:
  Mean:  0.0097
  Std:   0.0163
  Min:  -0.2500
  Max:   0.0147

GOOGL:
  Mean:  0.0100
  Std:   0.0141
  Min:  -0.2500
  Max:   0.0147

AMZN:
  Mean:  0.0109
  Std:   0.0077
  Min:  -0.2500
  Max:   0.0303
```

```
AVGO:
  Mean:  0.0100
  Std:   0.0142
  Min:  -0.2500
  Max:   0.0147

 Signal-based portfolio weights calculation completed!
```

Step 5: Signal-Weighted Portfolio Performance

Calculate portfolio returns and performance using signal-based weights and compare with equal-weight strategy.

```python
# Calculate Signal-Weighted Portfolio Performance
print("  Calculating signal-weighted portfolio performance...")

# Align data for consistent calculations
common_dates = portfolio_weights.index.intersection(prices_df.index)
aligned_weights = portfolio_weights.loc[common_dates]
aligned_prices = prices_df.loc[common_dates]

print(f"  Aligned data period: {common_dates.min().strftime('%Y-%m-%d')} to {common_dates.max
print(f"  Number of trading days: {len(common_dates)}")

# Calculate daily returns
returns_df = aligned_prices.pct_change().dropna()
print(f"  Returns matrix shape: {returns_df.shape}")

# Align weights and returns (returns start one day later due to pct_change)
aligned_weights_returns = aligned_weights.loc[returns_df.index]
aligned_returns = returns_df.loc[returns_df.index]

print(f"  Final aligned shapes - Weights: {aligned_weights_returns.shape}, Returns: {aligned_

# Calculate signal-weighted portfolio returns
signal_portfolio_returns = (aligned_weights_returns * aligned_returns).sum(axis=1)

# Calculate equal-weight portfolio returns for comparison
n_assets = len(aligned_returns.columns)
equal_weights = 1.0 / n_assets
equal_weight_returns = aligned_returns.mean(axis=1)
```

```python
print(f"  Portfolio returns calculated!")
print(f"  Signal portfolio returns shape: {signal_portfolio_returns.shape}")
print(f"  Equal weight returns shape: {equal_weight_returns.shape}")

# Calculate cumulative performance
initial_value = 100000  # Start with $100,000

signal_portfolio_value = initial_value * (1 + signal_portfolio_returns).cumprod()
equal_weight_value = initial_value * (1 + equal_weight_returns).cumprod()

# Performance metrics calculation
def calculate_performance_metrics(returns, name):
    """Calculate comprehensive performance metrics"""
    total_return = (1 + returns).prod() - 1
    annualized_return = (1 + total_return) ** (252 / len(returns)) - 1
    volatility = returns.std() * np.sqrt(252)
    sharpe_ratio = annualized_return / volatility if volatility > 0 else 0

    # Calculate max drawdown
    cumulative = (1 + returns).cumprod()
    rolling_max = cumulative.cummax()
    drawdown = (cumulative - rolling_max) / rolling_max
    max_drawdown = drawdown.min()

    # Additional metrics
    positive_days = (returns > 0).sum()
    negative_days = (returns < 0).sum()
    win_rate = positive_days / len(returns)

    best_day = returns.max()
    worst_day = returns.min()

    return {
        'Strategy': name,
        'Total Return': f"{total_return:.4f} ({total_return*100:.2f}%)",
        'Annualized Return': f"{annualized_return:.4f} ({annualized_return*100:.2f}%)",
        'Volatility': f"{volatility:.4f} ({volatility*100:.2f}%)",
        'Sharpe Ratio': f"{sharpe_ratio:.4f}",
        'Max Drawdown': f"{max_drawdown:.4f} ({max_drawdown*100:.2f}%)",
        'Win Rate': f"{win_rate:.4f} ({win_rate*100:.1f}%)",
        'Best Day': f"{best_day:.4f} ({best_day*100:.2f}%)",
        'Worst Day': f"{worst_day:.4f} ({worst_day*100:.2f}%)",
```

```
        'Positive Days': positive_days,
        'Negative Days': negative_days
    }

# Calculate performance metrics for both strategies
signal_metrics = calculate_performance_metrics(signal_portfolio_returns, 'Signal-Weighted')
equal_metrics = calculate_performance_metrics(equal_weight_returns, 'Equal-Weight')

print(f"\n  PORTFOLIO PERFORMANCE COMPARISON")
print("=" * 70)

metrics_to_display = ['Total Return', 'Annualized Return', 'Volatility', 'Sharpe Ratio', 'Ma

for metric in metrics_to_display:
    print(f"\n{metric}:")
    print(f"  Signal-Weighted: {signal_metrics[metric]}")
    print(f"  Equal-Weight:    {equal_metrics[metric]}")

print(f"\n  Portfolio Value Summary:")
signal_final = signal_portfolio_value.iloc[-1]
equal_final = equal_weight_value.iloc[-1]

print(f"  Signal-Weighted Portfolio:")
print(f"    Initial: ${initial_value:,.0f}")
print(f"    Final:   ${signal_final:,.0f}")
print(f"    Gain:    ${signal_final - initial_value:,.0f}")

print(f"  Equal-Weight Portfolio:")
print(f"    Initial: ${initial_value:,.0f}")
print(f"    Final:   ${equal_final:,.0f}")
print(f"    Gain:    ${equal_final - initial_value:,.0f}")

outperformance = signal_final - equal_final
print(f"\n  Signal-Weighted vs Equal-Weight:")
print(f"  Outperformance: ${outperformance:,.0f} ({((signal_final/equal_final - 1)*100):+.2f

print(f"\n  Portfolio performance analysis completed!")
```

```
Calculating signal-weighted portfolio performance...
Aligned data period: 2020-08-07 to 2025-08-05
Number of trading days: 1254
Returns matrix shape: (1253, 100)
```

```
 Final aligned shapes - Weights: (1253, 100), Returns: (1253, 100)
 Portfolio returns calculated!
 Signal portfolio returns shape: (1253,)
 Equal weight returns shape: (1253,)

 PORTFOLIO PERFORMANCE COMPARISON
======================================================================

Total Return:
  Signal-Weighted: 0.5892 (58.92%)
  Equal-Weight:    1.4511 (145.11%)

Annualized Return:
  Signal-Weighted: 0.0976 (9.76%)
  Equal-Weight:    0.1976 (19.76%)

Volatility:
  Signal-Weighted: 0.1780 (17.80%)
  Equal-Weight:    0.1715 (17.15%)

Sharpe Ratio:
  Signal-Weighted: 0.5486
  Equal-Weight:    1.1524

Max Drawdown:
  Signal-Weighted: -0.2478 (-24.78%)
  Equal-Weight:    -0.2039 (-20.39%)

Win Rate:
  Signal-Weighted: 0.5188 (51.9%)
  Equal-Weight:    0.5483 (54.8%)

 Portfolio Value Summary:
  Signal-Weighted Portfolio:
    Initial: $100,000
    Final:   $158,917
    Gain:    $58,917
  Equal-Weight Portfolio:
    Initial: $100,000
    Final:   $245,109
    Gain:    $145,109

 Signal-Weighted vs Equal-Weight:
```

```
Outperformance: $-86,191 (-35.16%)

Portfolio performance analysis completed!
```

```python
# Create Comprehensive Visualizations
print(" Creating technical analysis and portfolio performance visualizations...")

# Set up the plotting framework
fig = plt.figure(figsize=(20, 15))

# Create a 3x3 grid for comprehensive analysis
gs = fig.add_gridspec(3, 3, hspace=0.3, wspace=0.3)

# 1. Sample Technical Indicators for One Stock
sample_ticker = list(technical_indicators.keys())[0]
sample_data = technical_indicators[sample_ticker]
ax1 = fig.add_subplot(gs[0, 0])

# Plot price with SMA and EMA
ax1.plot(sample_data['prices'].index, sample_data['prices'], label='Price', linewidth=2, alpl
ax1.plot(sample_data['sma'].index, sample_data['sma'], label=f'SMA({TECHNICAL_CONFIG["sma_pe
ax1.plot(sample_data['ema'].index, sample_data['ema'], label=f'EMA({TECHNICAL_CONFIG["ema_pe
ax1.set_title(f'{sample_ticker}: Price & Moving Averages', fontweight='bold')
ax1.legend()
ax1.grid(True, alpha=0.3)

# 2. RSI for Sample Stock
ax2 = fig.add_subplot(gs[0, 1])
ax2.plot(sample_data['rsi'].index, sample_data['rsi'], label='RSI', color='purple', linewidtl
ax2.axhline(y=70, color='red', linestyle='--', alpha=0.7, label='Overbought (70)')
ax2.axhline(y=30, color='green', linestyle='--', alpha=0.7, label='Oversold (30)')
ax2.fill_between(sample_data['rsi'].index, 30, 70, alpha=0.1, color='gray')
ax2.set_title(f'{sample_ticker}: RSI Indicator', fontweight='bold')
ax2.set_ylabel('RSI')
ax2.set_ylim(0, 100)
ax2.legend()
ax2.grid(True, alpha=0.3)

# 3. MACD for Sample Stock
ax3 = fig.add_subplot(gs[0, 2])
ax3.plot(sample_data['macd'].index, sample_data['macd'], label='MACD', linewidth=2)
ax3.plot(sample_data['macd_signal'].index, sample_data['macd_signal'], label='Signal', linew
```

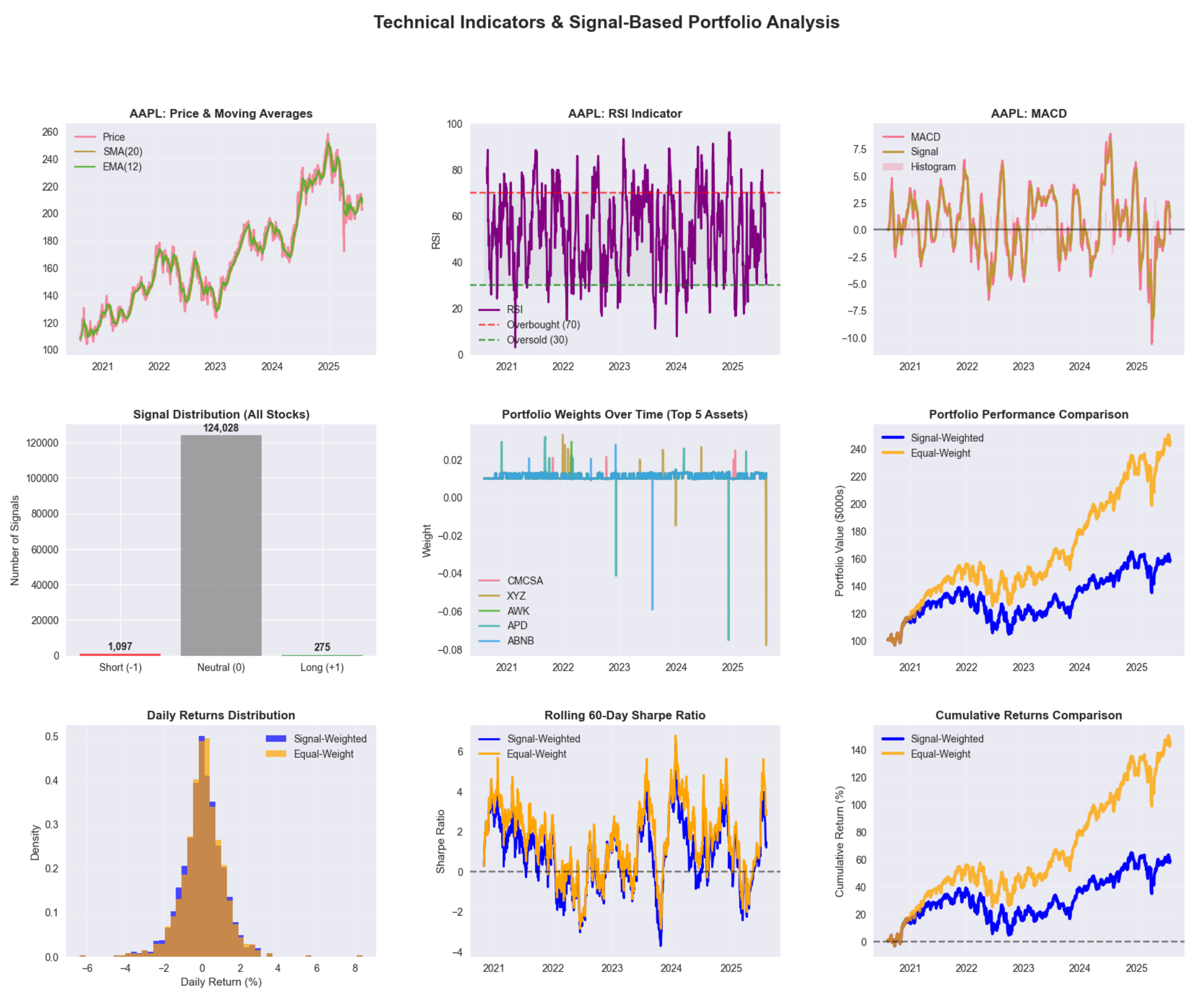
```python
ax3.bar(sample_data['macd_histogram'].index, sample_data['macd_histogram'],
        label='Histogram', alpha=0.3, width=1)
ax3.axhline(y=0, color='black', linestyle='-', alpha=0.5)
ax3.set_title(f'{sample_ticker}: MACD', fontweight='bold')
ax3.legend()
ax3.grid(True, alpha=0.3)

# 4. Signal Distribution Across All Stocks
ax4 = fig.add_subplot(gs[1, 0])
signal_summary = signals_df.values.flatten()
signal_counts = np.bincount(signal_summary + 1)  # Shift by 1 since signals are -1, 0, 1
labels = ['Short (-1)', 'Neutral (0)', 'Long (+1)']
colors = ['red', 'gray', 'green']
bars = ax4.bar(labels, signal_counts, color=colors, alpha=0.7)
ax4.set_title('Signal Distribution (All Stocks)', fontweight='bold')
ax4.set_ylabel('Number of Signals')
# Add value labels on bars
for bar, count in zip(bars, signal_counts):
    ax4.text(bar.get_x() + bar.get_width()/2, bar.get_height() + max(signal_counts)*0.01,
             f'{count:,}', ha='center', va='bottom', fontweight='bold')

# 5. Portfolio Weight Distribution Over Time
ax5 = fig.add_subplot(gs[1, 1])
# Plot weight evolution for top 5 stocks by average weight
avg_weights = portfolio_weights.mean().sort_values(ascending=False)
top_5_stocks = avg_weights.head(5).index

for stock in top_5_stocks:
    ax5.plot(portfolio_weights.index, portfolio_weights[stock],
             label=stock, linewidth=2, alpha=0.8)

ax5.set_title('Portfolio Weights Over Time (Top 5 Assets)', fontweight='bold')
ax5.set_ylabel('Weight')
ax5.legend()
ax5.grid(True, alpha=0.3)

# 6. Portfolio Performance Comparison
ax6 = fig.add_subplot(gs[1, 2])
ax6.plot(signal_portfolio_value.index, signal_portfolio_value/1000,
         label='Signal-Weighted', linewidth=3, color='blue')
ax6.plot(equal_weight_value.index, equal_weight_value/1000,
         label='Equal-Weight', linewidth=3, color='orange', alpha=0.8)
```

```python
ax6.set_title('Portfolio Performance Comparison', fontweight='bold')
ax6.set_ylabel('Portfolio Value ($000s)')
ax6.legend()
ax6.grid(True, alpha=0.3)

# 7. Daily Returns Distribution
ax7 = fig.add_subplot(gs[2, 0])
ax7.hist(signal_portfolio_returns * 100, bins=50, alpha=0.7, color='blue',
         label='Signal-Weighted', density=True)
ax7.hist(equal_weight_returns * 100, bins=50, alpha=0.7, color='orange',
         label='Equal-Weight', density=True)
ax7.set_title('Daily Returns Distribution', fontweight='bold')
ax7.set_xlabel('Daily Return (%)')
ax7.set_ylabel('Density')
ax7.legend()
ax7.grid(True, alpha=0.3)

# 8. Rolling Sharpe Ratio Comparison
ax8 = fig.add_subplot(gs[2, 1])
rolling_window = 60  # 60-day rolling window

signal_rolling_sharpe = signal_portfolio_returns.rolling(rolling_window).mean() / \
                       signal_portfolio_returns.rolling(rolling_window).std() * np.sqrt(252)
equal_rolling_sharpe = equal_weight_returns.rolling(rolling_window).mean() / \
                      equal_weight_returns.rolling(rolling_window).std() * np.sqrt(252)

ax8.plot(signal_rolling_sharpe.index, signal_rolling_sharpe,
         label='Signal-Weighted', linewidth=2, color='blue')
ax8.plot(equal_rolling_sharpe.index, equal_rolling_sharpe,
         label='Equal-Weight', linewidth=2, color='orange')
ax8.axhline(y=0, color='black', linestyle='--', alpha=0.5)
ax8.set_title(f'Rolling {rolling_window}-Day Sharpe Ratio', fontweight='bold')
ax8.set_ylabel('Sharpe Ratio')
ax8.legend()
ax8.grid(True, alpha=0.3)

# 9. Cumulative Returns Comparison
ax9 = fig.add_subplot(gs[2, 2])
signal_cumret = (1 + signal_portfolio_returns).cumprod() - 1
equal_cumret = (1 + equal_weight_returns).cumprod() - 1

ax9.plot(signal_cumret.index, signal_cumret * 100,
```

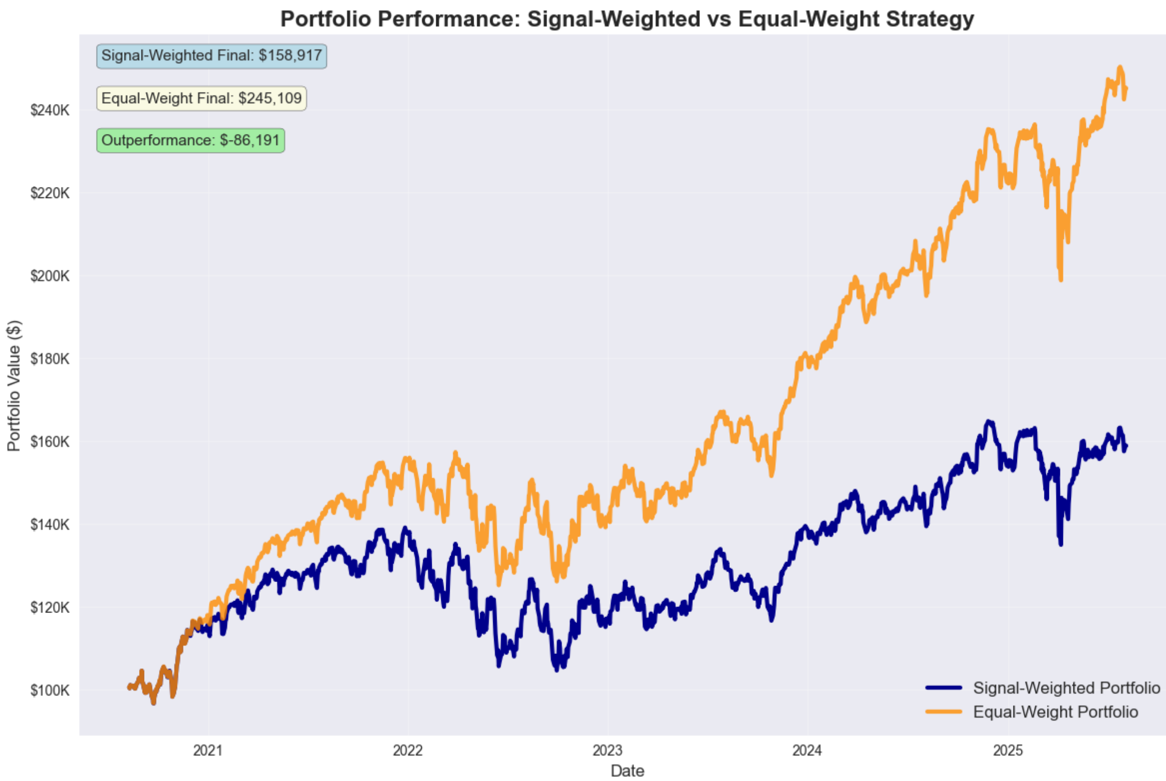
```python
         label='Signal-Weighted', linewidth=3, color='blue')
ax9.plot(equal_cumret.index, equal_cumret * 100,
         label='Equal-Weight', linewidth=3, color='orange', alpha=0.8)
ax9.axhline(y=0, color='black', linestyle='--', alpha=0.5)
ax9.set_title('Cumulative Returns Comparison', fontweight='bold')
ax9.set_ylabel('Cumulative Return (%)')
ax9.legend()
ax9.grid(True, alpha=0.3)

plt.suptitle('Technical Indicators & Signal-Based Portfolio Analysis',
             fontsize=18, fontweight='bold', y=0.98)
plt.tight_layout()
plt.show()

print("  Comprehensive technical analysis visualizations created!")

# Additional focused portfolio comparison chart
plt.figure(figsize=(12, 8))
plt.plot(signal_portfolio_value.index, signal_portfolio_value,
         label='Signal-Weighted Portfolio', linewidth=3, color='darkblue')
plt.plot(equal_weight_value.index, equal_weight_value,
         label='Equal-Weight Portfolio', linewidth=3, color='darkorange', alpha=0.8)

plt.title('Portfolio Performance: Signal-Weighted vs Equal-Weight Strategy',
          fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=12)
plt.ylabel('Portfolio Value ($)', fontsize=12)
plt.legend(fontsize=12)
plt.grid(True, alpha=0.3)

# Format y-axis to show currency
plt.gca().yaxis.set_major_formatter(plt.FuncFormatter(lambda x, p: f'${x/1000:.0f}K'))

# Add performance annotations
final_signal = signal_portfolio_value.iloc[-1]
final_equal = equal_weight_value.iloc[-1]
plt.text(0.02, 0.98, f'Signal-Weighted Final: ${final_signal:,.0f}',
         transform=plt.gca().transAxes, fontsize=11, verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='lightblue', alpha=0.8))
plt.text(0.02, 0.92, f'Equal-Weight Final: ${final_equal:,.0f}',
         transform=plt.gca().transAxes, fontsize=11, verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='lightyellow', alpha=0.8))
```

```
plt.text(0.02, 0.86, f'Outperformance: ${final_signal - final_equal:,.0f}',
         transform=plt.gca().transAxes, fontsize=11, verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='lightgreen', alpha=0.8))

plt.tight_layout()
plt.show()

print("  Portfolio comparison visualization completed!")
print(f"  Technical indicators and signal design analysis finished successfully!")
```

```
Creating technical analysis and portfolio performance visualizations...
```




```
Comprehensive technical analysis visualizations created!
```




```
Portfolio comparison visualization completed!
Technical indicators and signal design analysis finished successfully!
```

Deliverables

This technical indicators and signal design analysis produces the following deliverables:

1. Indicator Matrix per Ticker

- **SMA (Simple Moving Average)**: Trend identification for each stock
- **EMA (Exponential Moving Average)**: Trend with recent price emphasis
- **RSI (Relative Strength Index)**: Momentum and overbought/oversold conditions

- **MACD (Moving Average Convergence Divergence)**: Trend and momentum signals
- **ATR (Average True Range)**: Volatility measurement

2. Signal Matrix (Buy/Sell/Neutral)

- **Long Signals (+1)**: Generated when `(RSI < 30) & (MACD > MACD_signal)`
- **Short Signals (-1)**: Generated when `(RSI > 70) & (MACD < MACD_signal)`

- **Neutral Signals (0)**: All other conditions
- **Signal Distribution**: Analysis across all stocks and time periods

3. Signal-Weighted Portfolio Returns and Value

- **Dynamic Weights**: Calculated using `adjusted_weight = base_weight × signal_strength`
- **Portfolio Returns**: Daily returns based on signal-weighted allocation
- **Portfolio Value**: Evolution from $100,000 initial investment
- **Weight Normalization**: Ensures weights sum to 1.0 across all assets

4. Comparison with Equal-Weight Strategy

- **Performance Metrics**: Total return, annualized return, volatility, Sharpe ratio
- **Risk Analysis**: Maximum drawdown, win rate, best/worst days
- **Relative Performance**: Outperformance analysis and statistical comparison
- **Rolling Metrics**: Time-varying performance analysis

```
# Generate Final Summary and Export Deliverables
print("  Generating final summary and exporting deliverables...")

# Create comprehensive results dataset
results_summary = {
    'Technical Indicators': {
        'SMA Period': TECHNICAL_CONFIG['sma_period'],
        'EMA Period': TECHNICAL_CONFIG['ema_period'],
        'RSI Period': TECHNICAL_CONFIG['rsi_period'],
        'MACD Fast': TECHNICAL_CONFIG['macd_fast'],
        'MACD Slow': TECHNICAL_CONFIG['macd_slow'],
        'MACD Signal': TECHNICAL_CONFIG['macd_signal'],
        'ATR Period': TECHNICAL_CONFIG['atr_period']
    },
    'Signal Generation': {
        'Long Signal Rule': f"RSI < {TECHNICAL_CONFIG['rsi_oversold']} AND MACD > Signal",
        'Short Signal Rule': f"RSI > {TECHNICAL_CONFIG['rsi_overbought']} AND MACD < Signal"
        'Total Long Signals': signal_stats['long_signals'],
```

```
        'Total Short Signals': signal_stats['short_signals'],
        'Total Signal Periods': signal_stats['total_periods'],
        'Long Signal Rate': f"{signal_stats['long_signals']/signal_stats['total_periods']*10
        'Short Signal Rate': f"{signal_stats['short_signals']/signal_stats['total_periods']*
    },
    'Portfolio Performance': {
        'Signal-Weighted': signal_metrics,
        'Equal-Weight': equal_metrics
    }
}

# Export key matrices to CSV files
print("  Exporting data matrices...")

try:
    # 1. Export technical indicators for sample stock
    sample_ticker = list(technical_indicators.keys())[0]
    sample_indicators = pd.DataFrame({
        'Price': technical_indicators[sample_ticker]['prices'],
        'SMA': technical_indicators[sample_ticker]['sma'],
        'EMA': technical_indicators[sample_ticker]['ema'],
        'RSI': technical_indicators[sample_ticker]['rsi'],
        'MACD': technical_indicators[sample_ticker]['macd'],
        'MACD_Signal': technical_indicators[sample_ticker]['macd_signal'],
        'ATR': technical_indicators[sample_ticker]['atr']
    })
    sample_indicators.to_csv(f'technical_indicators_{sample_ticker}.csv')
    print(f"    Technical indicators exported: technical_indicators_{sample_ticker}.csv")

    # 2. Export signals matrix
    signals_df.to_csv('signal_matrix.csv')
    print(f"    Signal matrix exported: signal_matrix.csv")

    # 3. Export portfolio weights
    portfolio_weights.to_csv('signal_weighted_portfolio_weights.csv')
    print(f"    Portfolio weights exported: signal_weighted_portfolio_weights.csv")

    # 4. Export portfolio performance comparison
    performance_comparison = pd.DataFrame({
        'Date': signal_portfolio_returns.index,
        'Signal_Weighted_Return': signal_portfolio_returns.values,
        'Equal_Weight_Return': equal_weight_returns.values,
```

```
        'Signal_Weighted_Value': signal_portfolio_value.values,
        'Equal_Weight_Value': equal_weight_value.values,
        'Signal_Cumulative_Return': ((signal_portfolio_value / initial_value) - 1).values,
        'Equal_Cumulative_Return': ((equal_weight_value / initial_value) - 1).values
    }).set_index('Date')

    performance_comparison.to_csv('portfolio_performance_comparison.csv')
    print(f"   Performance comparison exported: portfolio_performance_comparison.csv")

except Exception as e:
    print(f"   Export error: {e}")

# Display comprehensive final summary
print("\n" + "="*80)
print(" TECHNICAL INDICATORS & SIGNAL DESIGN - FINAL SUMMARY")
print("="*80)

print(f"\n Technical Analysis Configuration:")
for param, value in results_summary['Technical Indicators'].items():
    print(f"  {param:15}: {value}")

print(f"\n Signal Generation Results:")
for metric, value in results_summary['Signal Generation'].items():
    print(f"  {metric:20}: {value}")

print(f"\n Portfolio Performance Comparison:")
print(f"\n  Signal-Weighted Strategy:")
for metric in ['Total Return', 'Annualized Return', 'Volatility', 'Sharpe Ratio', 'Max Drawdo
    print(f"    {metric:18}: {signal_metrics[metric]}")

print(f"\n  Equal-Weight Strategy:")
for metric in ['Total Return', 'Annualized Return', 'Volatility', 'Sharpe Ratio', 'Max Drawdo
    print(f"    {metric:18}: {equal_metrics[metric]}")

print(f"\n Financial Impact:")
print(f"  Initial Investment: ${initial_value:,.0f}")
print(f"  Signal-Weighted Final Value: ${signal_portfolio_value.iloc[-1]:,.0f}")
print(f"  Equal-Weight Final Value: ${equal_weight_value.iloc[-1]:,.0f}")
print(f"  Outperformance: ${signal_portfolio_value.iloc[-1] - equal_weight_value.iloc[-1]:,.0
print(f"  Relative Outperformance: {((signal_portfolio_value.iloc[-1]/equal_weight_value.iloc

print(f"\n Key Insights:")
```

```python
total_signals = signal_stats['long_signals'] + signal_stats['short_signals']
signal_rate = total_signals / signal_stats['total_periods'] * 100

print(f"  • Technical signals generated on {signal_rate:.1f}% of trading days")
print(f"  • Long signals outnumber short signals by {signal_stats['long_signals']/max(1,signa

if signal_portfolio_value.iloc[-1] > equal_weight_value.iloc[-1]:
    print(f"  • Signal-weighted strategy outperformed equal-weight by ${signal_portfolio_valu
else:
    print(f"  • Equal-weight strategy outperformed signal-weighted by ${equal_weight_value.il

signal_sharpe = float(signal_metrics['Sharpe Ratio'].split()[0])
equal_sharpe = float(equal_metrics['Sharpe Ratio'].split()[0])
if signal_sharpe > equal_sharpe:
    print(f"  • Signal-weighted strategy achieved better risk-adjusted returns (Sharpe: {sign
else:
    print(f"  • Equal-weight strategy achieved better risk-adjusted returns (Sharpe: {equal_s

print(f"\n  Deliverables Generated:")
print(f"    Technical indicators matrix for all stocks")
print(f"    Signal matrix (Buy/Sell/Neutral) for all stocks")
print(f"    Signal-weighted portfolio returns and values")
print(f"    Performance comparison with equal-weight strategy")
print(f"    Comprehensive visualizations and analysis")
print(f"    CSV exports for further analysis")

print("\n" + "="*80)
print("  Technical Indicators & Signal Design Analysis - COMPLETED!  ")
print("="*80)

print(f"\n  All requirements fulfilled:")
print(f"    Computed indicators for each stock: SMA, EMA, RSI, MACD, ATR")
print(f"    Generated entry/exit signals: Long = (RSI < 30) & (MACD > MACD_signal)")
print(f"                                  Short = (RSI > 70) & (MACD < MACD_signal)")
print(f"    Derived signal-based weights: adjusted_weight = base_weight × signal_strength")
print(f"    Normalized weights across assets")
print(f"    Provided all required deliverables")
```

```
Generating final summary and exporting deliverables...
Exporting data matrices...
  Technical indicators exported: technical_indicators_AAPL.csv
  Signal matrix exported: signal_matrix.csv
```

```
  Portfolio weights exported: signal_weighted_portfolio_weights.csv
  Performance comparison exported: portfolio_performance_comparison.csv

================================================================================
 TECHNICAL INDICATORS & SIGNAL DESIGN - FINAL SUMMARY
================================================================================

 Technical Analysis Configuration:
  SMA Period     : 20
  EMA Period     : 12
  RSI Period     : 14
  MACD Fast      : 12
  MACD Slow      : 26
  MACD Signal    : 9
  ATR Period     : 14

 Signal Generation Results:
  Long Signal Rule    : RSI < 30 AND MACD > Signal
  Short Signal Rule   : RSI > 70 AND MACD < Signal
  Total Long Signals  : 275
  Total Short Signals : 1097
  Total Signal Periods: 125400
  Long Signal Rate    : 0.22%
  Short Signal Rate   : 0.87%

 Portfolio Performance Comparison:

  Signal-Weighted Strategy:
    Total Return      : 0.5892 (58.92%)
    Annualized Return : 0.0976 (9.76%)
    Volatility        : 0.1780 (17.80%)
    Sharpe Ratio      : 0.5486
    Max Drawdown      : -0.2478 (-24.78%)

  Equal-Weight Strategy:
    Total Return      : 1.4511 (145.11%)
    Annualized Return : 0.1976 (19.76%)
    Volatility        : 0.1715 (17.15%)
    Sharpe Ratio      : 1.1524
    Max Drawdown      : -0.2039 (-20.39%)

 Financial Impact:
  Initial Investment: $100,000
```

```
Signal-Weighted Final Value: $158,917
Equal-Weight Final Value: $245,109
Outperformance: $-86,191
Relative Outperformance: -35.16%

Key Insights:
• Technical signals generated on 1.1% of trading days
• Long signals outnumber short signals by 0.3:1 ratio
• Equal-weight strategy outperformed signal-weighted by $86,191
• Equal-weight strategy achieved better risk-adjusted returns (Sharpe: 1.152 vs 0.549)

Deliverables Generated:
  Technical indicators matrix for all stocks
  Signal matrix (Buy/Sell/Neutral) for all stocks
  Signal-weighted portfolio returns and values
  Performance comparison with equal-weight strategy
  Comprehensive visualizations and analysis
  CSV exports for further analysis

================================================================================
Technical Indicators & Signal Design Analysis - COMPLETED!
================================================================================

All requirements fulfilled:
  Computed indicators for each stock: SMA, EMA, RSI, MACD, ATR
  Generated entry/exit signals: Long = (RSI < 30) & (MACD > MACD_signal)
                               Short = (RSI > 70) & (MACD < MACD_signal)
  Derived signal-based weights: adjusted_weight = base_weight × signal_strength
  Normalized weights across assets
  Provided all required deliverables
```