Algorithmic Trading and Backtesting

Paragon National Group

Overview

Quantitative trading uses mathematical models and automated models to make trading decisions. It often involves a combination of multiple fields including

1. Mathematics (e.g. options pricing, portfolio optimization, numerical analysis)
2. Statistics (e.g. relative value, stat arb)
3. Computer science (e.g. algorithms, parallel computing, networks, etc, etc)
4. Data processing (data cleaning, data pipelines, storage)
5. Finance/Economics (e.g. fundamental analysis, accounting, macro-economic indicators)

Quantitative Trading

Key elements of a algorithmic trading strategy:

- Source of profit
- Regular securities trading
- Processing data flow
- Risk management

Each of these can be very rich and complex problems to solve in quantitative finance!

Profit

Above all, we want a quantitative trading strategy to be profitable. The key question is where can we find sources of profit in secondary markets that are able to source returns systematically.

Sources of profit

- Providing services
  - Liquidity
  - Insurance/risk underwriting
- Market Inefficiencies
  - Pure arbitrage
  - Statistical arbitrage
  - Fundamental analysis

Regular trading

Quantitative trading strategies require continual processing of new information, dynamic hedging, and enter/exiting new attractive/unattractive positions as part of re-balancing.

This is in contrast to event-driven traders or stock-pickers who will only make a few large trades in hopes that those specific trades will be extremely profitable.

The advantages of regular trading activity is the ability to make multiple independent bets over time as similar scenarios arise over history. This allows for the realization of steadier profits.

Data processing

Quantitative trading strategies deal with the continual processing and analysis of data that is streamed from the market.

The steps to the data cycle are generally as follows

1. Receive and parse useful information from data stream
2. Run models on returns and risks
3. Rebalance positions to an ideal portfolio to optimize risk-adjusted returns

The trading system is dynamic and responds to information from seemingly random events.

Risk management

Trading strategies will often involve trading across numerous amounts of asset classes and securities at the same time. In addition to this, they may apply some amount of leverage to the positions using derivatives and/or margin. Due to this, it is important to take into account position sizing and risk exposures.

Above all, the strategy should never blow up.

Example: Value (and Momentum) Factor Portfolio (Asness et al, 2012)

What is value? Value is the idea that some securities are cheap and some securities are expensive.

How do we determine what is a cheap security and what is an expensive security? For the purposes of this paper, we use the common signal of lagged book value of equity to market value of equity used in Fama and French (1992)

$$BE/ME$$

Example: Value (and Momentum) Factor Portfolio (Asness et al, 2012)

Source of profit: Value signal (BE/ME)

Investment universe: Highest market-cap stocks that cumulatively account for 90% of the total market cap of the entire stock market. Corresponds to 354 firms up to the 676 largest names which are pretty liquid.

Data: Stock universe returns from CRSP and book value from Compustat.

Value Factor Portfolio

For the factor portfolio construction, we would use the following algorithm as our strategy:

1. Rank each security by its value signal weighting
2. Demean the ranks to produce a dollar-neutral weighting portfolio
3. Multiply by a scalar factor c_t to normalize for our dollar notional

Thus the dollar weighting for stock i at time t with signal S_{it} is

$$w_{it} = c_t(\mathsf{rank}(S_{it}) - \sum_i \mathsf{rank}(S_{it})/N)$$

Value Market-Cap Weighted Portfolios

For the market-cap weighted portfolio construction, we consider the following pseudo-algorithm to be our systematic strategy:

1. Rank each security by value signal
2. Sort into three equal groups - high, middle, low
3. For each group, we form a subportfolio with returns weighted by their beginning-of-month market cap

Question: What are the advantages/disadvantages to using each of the portfolios (market-cap vs factor portfolio) on our strategy analysis?

Value MC Portfolio Results

		Value Portfolios				
		P1	P2	P3	P3–P1	Factor
U.S. stocks	Mean	9.5%	10.6%	13.2%	3.7%	3.9%
01/1972 to	(t-stat)	(3.31)	(4.33)	(5.19)	(1.83)	(1.66)
07/2011	Stdev	17.9%	15.4%	15.9%	12.8%	14.8%
	Sharpe	0.53	0.69	0.83	0.29	0.26
	Alpha	−1.7%	0.8%	3.6%	5.3%	5.8%
	(t-stat)	(−1.59)	(1.02)	(3.17)	(2.66)	(2.49)

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

- Can we look for a better signal for value?

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

- Can we look for a better signal for value?
- How can we combine different signals?

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

- Can we look for a better signal for value?
- How can we combine different signals?
- How can we apply this to different asset class for diversification?

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

- Can we look for a better signal for value?
- How can we combine different signals?
- How can we apply this to different asset class for diversification?
- How might we come up with a better portfolio construction methodology?

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

- Can we look for a better signal for value?
- How can we combine different signals?
- How can we apply this to different asset class for diversification?
- How might we come up with a better portfolio construction methodology?
- How does the incorporation of transaction costs and liquidity to our rebalancing affect our performance?

Further directions

The signal and portfolio construction used was pretty basic. The following questions can be potential areas for improvement on the initial portfolio. (Asness does address many of these in his paper)

- Can we look for a better signal for value?
- How can we combine different signals?
- How can we apply this to different asset class for diversification?
- How might we come up with a better portfolio construction methodology?
- How does the incorporation of transaction costs and liquidity to our rebalancing affect our performance?

These are general questions that are of interest to a quant and are often significant areas of research for systematic strategies.

Why Backtest

As shown in our example, quantitative strategy goes through a period of analysis against historical data. The reasons for this are to

- Develop a sense of risks and rewards in potential trading scenarios
- Optimize strategy parameters to increase expectancy
- Create a case to invest in the strategy for investors (or for ourselves)

Return Metrics

We may be interested in many different metrics in our analysis. Some common ones include (but are not limited to):

- Average return per trade
- Strategy return: size each trade up by a reasonable amount and sum across all trades over time
- Backtested returns: use assumptions about trade size and cost models as well as setting risk limits. Also include capital requirements

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

- Sharpe/Information ratio with benchmark r_b.

$$\frac{E[r - r_b]}{\sqrt{E[(r - r_b)^2]}}$$

  Examples of benchmarks can be the risk-free-rate, market return, or factor returns

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

- Sharpe/Information ratio with benchmark r_b.

  $$\frac{E[r - r_b]}{\sqrt{E[(r - r_b)^2]}}$$

  Examples of benchmarks can be the risk-free-rate, market return, or factor returns
- Largest single-period drawdown

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

- Sharpe/Information ratio with benchmark r_b.

  $$\frac{E[r - r_b]}{\sqrt{E[(r - r_b)^2]}}$$

  Examples of benchmarks can be the risk-free-rate, market return, or factor returns
- Largest single-period drawdown
- Maximum drawdown

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

- Sharpe/Information ratio with benchmark r_b.

  $$\frac{E[r - r_b]}{\sqrt{E[(r - r_b)^2]}}$$

  Examples of benchmarks can be the risk-free-rate, market return, or factor returns
- Largest single-period drawdown
- Maximum drawdown
- Downside beta: defined by

  $$r \sim \beta \cdot r^M + c$$

  conditioned on the set where $r^M < 0$

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

- Sharpe/Information ratio with benchmark r_b.

  $$\frac{E[r - r_b]}{\sqrt{E[(r - r_b)^2]}}$$

  Examples of benchmarks can be the risk-free-rate, market return, or factor returns
- Largest single-period drawdown
- Maximum drawdown
- Downside beta: defined by

  $$r \sim \beta \cdot r^M + c$$

  conditioned on the set where $r^M < 0$
- Stress moments

Strategy Metrics

Once we have the strategy return series, we may be interested in other risk/reward metrics:

- Sharpe/Information ratio with benchmark r_b.

  $$\frac{E[r - r_b]}{\sqrt{E[(r - r_b)^2]}}$$

  Examples of benchmarks can be the risk-free-rate, market return, or factor returns
- Largest single-period drawdown
- Maximum drawdown
- Downside beta: defined by

  $$r \sim \beta \cdot r^M + c$$

  conditioned on the set where $r^M < 0$
- Stress moments
- Other moments of returns: skew, kurtosis, etc

Benchmarks

The choice of benchmark for our strategy is used to determine how much additional reward that an investor can get from our strategy compared to either a simpler method (like buying an index) or a comparative strategy.

Some common benchmarks include:

Benchmarks

The choice of benchmark for our strategy is used to determine how much additional reward that an investor can get from our strategy compared to either a simpler method (like buying an index) or a comparative strategy.

Some common benchmarks include:

- Buy-and-hold market/other index

Benchmarks

The choice of benchmark for our strategy is used to determine how much additional reward that an investor can get from our strategy compared to either a simpler method (like buying an index) or a comparative strategy.

Some common benchmarks include:

- Buy-and-hold market/other index
- ETFs

Benchmarks

The choice of benchmark for our strategy is used to determine how much additional reward that an investor can get from our strategy compared to either a simpler method (like buying an index) or a comparative strategy.

Some common benchmarks include:

- Buy-and-hold market/other index
- ETFs
- Fama-French-Carhart Factors

Benchmarks

The choice of benchmark for our strategy is used to determine how much additional reward that an investor can get from our strategy compared to either a simpler method (like buying an index) or a comparative strategy.

Some common benchmarks include:

- Buy-and-hold market/other index
- ETFs
- Fama-French-Carhart Factors
- Barra factors

Benchmarks

The choice of benchmark for our strategy is used to determine how much additional reward that an investor can get from our strategy compared to either a simpler method (like buying an index) or a comparative strategy.

Some common benchmarks include:

- Buy-and-hold market/other index
- ETFs
- Fama-French-Carhart Factors
- Barra factors
- Some similar strategy

Return Attributions

Once we have our return series from our strategy, it is useful to decompose the returns series into our benchmarks, which would attribute some amount of P&L to each systematic or common factor.

Return Attributions

Once we have our return series from our strategy, it is useful to decompose the returns series into our benchmarks, which would attribute some amount of P&L to each systematic or common factor.

A simple, but useful technique is just using a cross-sectional linear regression:

$$r \sim \alpha + \beta_1 F_1 + \beta_2 F_2 + \dots$$

where F_k represents each of our factors. Typical factors include F-F-C, volatility, liquidity, credit risk, inflation/interest rate changes.

Return Attributions

Once we have our return series from our strategy, it is useful to decompose the returns series into our benchmarks, which would attribute some amount of P&L to each systematic or common factor.

A simple, but useful technique is just using a cross-sectional linear regression:

$$r \sim \alpha + \beta_1 F_1 + \beta_2 F_2 + \dots$$

where F_k represents each of our factors. Typical factors include F-F-C, volatility, liquidity, credit risk, inflation/interest rate changes.

The βs can be used to analyze how much of our P&L is explained by each factor. The residual alpha α is considered to be our strategy novelty compared to our benchmarks.

Return Attributions

Once we have our return series from our strategy, it is useful to decompose the returns series into our benchmarks, which would attribute some amount of P&L to each systematic or common factor.

A simple, but useful technique is just using a cross-sectional linear regression:

$$r \sim \alpha + \beta_1 F_1 + \beta_2 F_2 + \dots$$

where F_k represents each of our factors. Typical factors include F-F-C, volatility, liquidity, credit risk, inflation/interest rate changes.

The βs can be used to analyze how much of our P&L is explained by each factor. The residual alpha α is considered to be our strategy novelty compared to our benchmarks.

In practice, the amount of α is a limited and very hard to find, due to transaction costs and adverse selection.

Backtest Prerequisites: Asset Prices

Asset Prices: In order to generate accurate P&L metrics for our backtest, we need accurate asset prices.

For US equities, futures, and FX, i.e. electronically traded assets, this data is relatively easy to get.

For international products and products that are primarily traded OTC such as exotic options and corporate bonds, this data can be difficult to obtain.

Slippage and Trading Costs

Whenever you place a trade, there is a difference between the price that you intend to transact at and the price that you actually transact at. This is called **slippage** and is generally a function of the size of your order and the trading speed, market liquidity, commissions, bid-ask spread, and/or volatility.

A good first-order approximation is the square-root law for transaction cost assumptions which is a linear function of the square-root of the size of your trade N:

$$c \sim c_0 + c_1 \cdot \sqrt{N}$$

where c_0 represents your fixed costs (such as commissions, fees, rebates) and c_1 scales your slippage.

For those interested in further exploration of the theory and practice of optimal execution, Almgren and Chriss, 2001 is a seminal paper in this area

Financing

Typically, quantitative strategies will use some amount of leverage in order to increase returns. This also comes with the cost of increasing risk.

In order to access leverage, one needs to fund their positions by borrowing money from a prime broker (typically large commercial banks i.e. Goldman Sachs, Morgan Stanley, BofA).

The rate at which they will borrow money is usually referenced from a rate such as SOFR. Excess capital can also receive interest, but less than the borrowing rate.

Available Assets

Q: Consider that we have a trading strategy that we want to backtest on equities data over the past 20 years. We choose our asset universe to be the current top 500 assets ranked by market cap so that there is sufficient liquidity to transact. What may be some issues caused by this approach?

Available Assets

Q: Consider that we have a trading strategy that we want to backtest on equities data over the past 20 years. We choose our asset universe to be the current top 500 assets ranked by market cap so that there is sufficient liquidity to transact. What may be some issues caused by this approach?

Surivivorship bias! By only including current highest market-cap stocks, it does not include companies that defaulted or fell out of the top 500 assets.

It is crucial to make sure that the assets that you use are actually available and are included at each time during the backtest.

Expanding the asset universe will usually allow more opportunities to gain returns or deploy more capital.

System Assumptions

Typically, trading signals are based of point prices at a specific time. However unless one is transacting at a very small amount, it is unfeasible to be able to transact exactly at that price.

For example, if a trading strategy signal fires using the close price of the asset each day, then one would only actually be able to transact at the beginning of the next day.

For a higher frequency strategy in electronic markets, it may be reasonable to incur a lag of 1 second to a few minutes in order to attain your position. For OTC markets, this can even be several days.

Hedging

A quantitative strategy will want to hedge out some amount of risks. For an equity long-short strategy, this may be market risk in order to be market-neutral. For options, this may be delta and other volatility-related Greeks.

Equities Considerations

Many of our trading strategies will involve equities data as that is the most readily available. Some considerations to take into account:

- Mergers/spinoffs
- Dividends/stock splits - usually want to use dividend and split adjusted data.
- High benchmark sensitivity. Most of equity strategy returns can be described by the market factor or Fama-French factors. It is pretty difficult to find non-noise alphas.