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CERN Finance Club

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Contents

 Introduce quantitative trading and backtesting from a theoretical point of view

 Show how to implement in Python a backtesting environment for simple trading strategies

Quantitative trading

Also called systematic trading or algorithmic trading

- Creates a set of rules to generate trade signals and risk management of positions with minimal manager intervention
- Attempts to identify statistically significant and repeatable market behaviour that can be exploited to generate profits
- Low-frequency (weekly, daily) through to highfrequency (seconds, milliseconds...)

Quantitative trading system

- Four major components of a quantitative trading system:
 - 1) Strategy identification
 - 2) Strategy backtesting
 - 3) Execution system
 - 4) Risk management

Focus on first two, last two won't be covered here

Strategy identification

- Research strategies in blogs, forums, journals, etc. For example:
 - Journal of Investment Strategies
 - Quantpedia.com
 - Many more (GIYF)
- Many of these strategies are either not profitable anymore or only slightly profitable (they get "crowded" or "arbitraged away")
- Key to making them highly profitable is to build on them, e.g. adapt them to new market conditions or optimise their parameters

Strategy identification

- ► Two main categories of strategies:
 - Trend-following: Trades on momentum, i.e. on the basis of the slow diffusion of information
 - Mean reversion: trades on the deviation of a stationary time series (price or spread) from its expected value
- Range of trading frequencies
 - Low frequency trading (LFT): days-years
 - High frequency trading (HFT): intraday
 - Ultra high frequency trading (UHFT): secondsmilliseconds
- High frequency trading requires detailed knowledge of market microstructure (how the order book and exchange work)

Backtesting

Once a strategy is identified, need to test its performance using historical data as well as out-of-sample data

<u>Data</u>

- Many types: fundamental, OHLC, sentiment, news
- Many frequencies: intraday, daily
- Many instruments: equities, futures
- Many sources: many are expensive, but there are a few good free sources, e.g. Yahoo Finance, Quandl
- Qualities of good data:
 - Clean and accurate (no erroneous entries)
 - Free of survivorship bias (see next slide)
 - Adjusted for stock splits and dividends

Backtesting

<u>Biases</u>

 Biases tend to inflate performance. A backtest is likely an upper bound on the actual performance

Optimisation bias

- Over fitting the data as a result of too many free parameters
- Strategy will fail with real data

Lookahead bias

- Introduction of future information into past data
- e.g. using the day's high/low, calculating a parameter using data that would not have been available at the time

Survivorship bias

- Using only instruments which exist at present
- Companies that went bankrupt would have made your performance worse

Backtesting

Transaction costs

 Backtest performance is inflated if transaction costs are not modelled appropriately

Commissions/fees

- ► A commission is paid to the broker for every transaction
- Bid-ask spread is also important, especially for illiquid instruments

Slippage

- Price difference between time of trade signal and time of order fill
- Depends on the volatility of the asset and the latency between the trading system, the broker and the exchange
- Especially important for HFT

Market impact

- Placing large orders can "move the market" against you
- May want to break the transaction into smaller chunks

Execution and risk management

The last two components of a quantitative trading system would entail a whole other talk. Very briefly:

Execution system

- Generates trades in real time
- Provides an interface to the broker (e.g. via an API)

Risk management

- Decides how to act on trade signals
- Controls leverage
- Assigns capital to trades or strategies as optimally as possible

Analysing performance

Some common measures of performance

Compounded growth rate

Usually annualised, gives the average annual return

$$CAGR = \left(\frac{Ending Value}{Beginning Value}\right)^{\left(\frac{1}{\# of years}\right)} - 1$$

Volatility

- Usually annualised, given by the standard deviation of annual returns
- Measure of risk

Sharpe ratio

$$S = rac{\mathbb{E}(R_a - R_b)}{\sqrt{\mathrm{Var}(R_a - R_b)}}$$

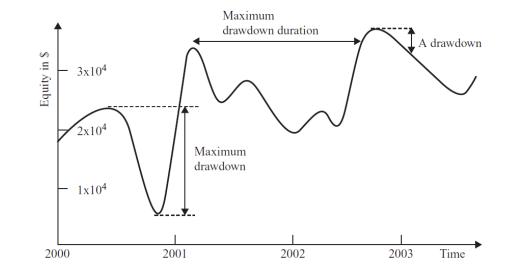
- Measure of reward/risk ratio
- Usually annualised and measured with respect to a benchmark b (e.g. risk-free rate or S&P500)

Analysing performance

Some common measures of performance

Drawdown

- A period of time in which equity is below the highest peak so far
- Can calculate maximum drawdown and maximum drawdown duration



Alpha, Beta

- Fit a straight line (security characteristic line) to strategy returns against the returns of a benchmark (e.g. S&P or "the market")
- Beta is the gradient the variance/correlation with respect to the market i.e. gives a measure of systematic risk (want beta ~ 0)
- Alpha is the intercept the excess return over the market, i.e. a measure of performance (want large positive alpha)

Python backtester

- Let's put this into practice with Python
- My backtesting code:
 - www.github.com/Xtian9/QuantCode *
 - Disclaimer: Very simple and incomplete
 - Feel free to use it or contribute!
- Makes use of pandas, numpy, and matplotlib
- Employs vectorised calculations as opposed to an 'eventloop' (so less realistic as a simulation, but handy for doing quick research)

* Inspired by: <u>www.quantstart.com</u> <u>www.github.com/quantopian/pyfolio</u>

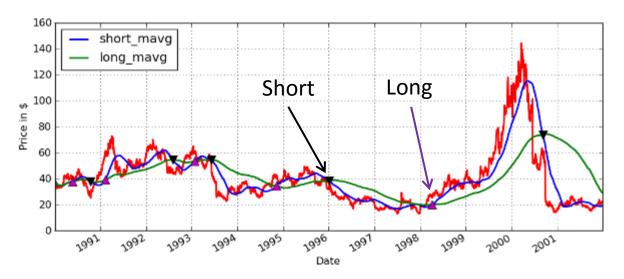
Python backtester

Components of the backtester

- Data handler
 - Downloads OHLC data from Quandl
- Strategy
 - Generates signals for each day
 - +1 long, -1 short, 0 cash (no position)
- Portfolio
 - Generates/rebalances positions
 - ▶ e.g. assign equal dollar weights to all assets
 - Computes returns (potentially for risk management)
- Analyser
 - Analyses the performance of the backtest
 - ▶ e.g. equity curve, Sharpe ratio, etc.
- Still missing: transaction costs, risk manager...

Moving average crossover

- Let's look at a "hello world" example strategy
 - Moving average crossover
 - This is a momentum strategy
- Strategy rules:
 - Create two simple moving averages (SMA) of a price series with different lookback periods, e.g. 9 days and 200 days
 - If the short MA exceeds the long MA then "go long"
 - If the long MA exceeds the short MA then "go short"



Config file

```
backtests/macross/macross_cfg.py
```

Choose trading parameters: tickers, dates, frequency, window lengths

```
symbols = ['AAPL']
qcodes = ['GOOG/NASDAQ_'+s for s in symbols]
date_start, date_end = "2010-01-01", "2015-12-31"
frequency = "daily"
datas = ['Close']
short_window = 9
long window = 200
```

Initialise strategy, portfolio, analyser and backtest classes

Run the backtest!

```
backtest.run()
```

Data handler

The DataHandler class fetches data from Quandl and returns a pandas DataFrame of prices, e.g.

	AREX	WLL	SPY
Date			
2012-01-03	31.23	49.20	127.49
2012-01-04	31.27	50.25	127.63
2012-01-05	31.92	51.83	128.10
2012-01-06	32.04	51.84	127.82
2012-01-09	32.39	52.10	127.99
2012-12-24	24.56	42.49	142.35
2012-12-26	24.73	43.04	141.75
2012-12-27	24.32	42.57	141.56
2012-12-28	24.07	41.67	140.03
2012-12-31	25.01	43.37	142.41

The Backtest class then creates empty signals and weights DataFrames that need to be filled by the Strategy and Portfoflio classes, respectively

Strategy class

strategies/macross.py

Create a MovingAverageCrossoverStrategy that inherits from Strategy

```
class MovingAverageCrossoverStrategy(Strategy):
```

- def __init__(self, short_window=None, long_window=None):
 super(MovingAverageCrossoverStrategy, self).__init__()
 self.short_window = short_window
 self.long_window = long_window
- Implement a generate_signals method that fills in the signals DataFrame

```
def generate_signals(self):
    super(MovingAverageCrossoverStrategy, self).generate_signal
    mavg_short = pd.rolling_mean(self.prices, self.short_window)
    mavg_long = pd.rolling_mean(self.prices, self.long_window)
    self.signals[mavg_short > mavg_long] = 1
    self.signals[mavg_long > mavg_short] = -1
```

Portfolio class

portfolios/equalweights.py

Create a EqualWeightsPortfolio that inherits from Portfolio

class EqualWeightsPortfolio(Portfolio):

```
def __init__(self):
    super(EqualWeightsPortfolio, self).__init__()
```

Implement a generate_positions method that fills in the weights DataFrame

```
def generate_positions(self):
    super(EqualWeightsPortfolio, self).generate_positions()
    nassets = len(self.weights.columns)
    self.weights.loc[:,:] = 1. / nassets
```

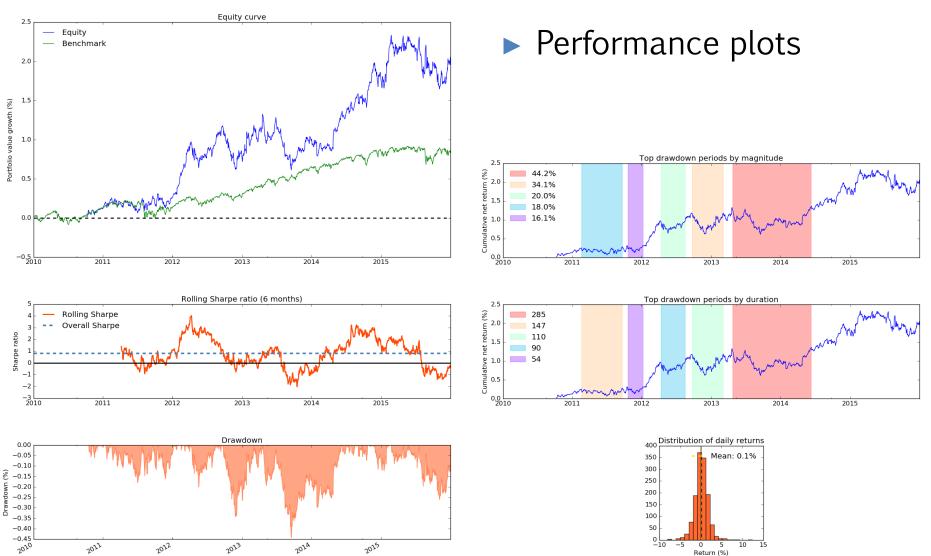
If weights sum to 1, total return of portfolio is the weighted average of the assets' returns

Analyser class

- analysers/performance.py
- Generic Analyser that computes performance measures like Sharpe ratio, drawdown etc. and makes performance plots like equity curve etc.
- Can also create and add additional Analyser sub-classes to the backtest

Start date: 2010-01-01 End date: 2015-12-31			
Symbols: ['AAPL']			
APR Volatility Total return Total return bmark Alpha Beta Sharpe ratio Information ratio Max DD Max DD duration	24.79% 26.33% 205.20% 82.94% 0.00 0.43 0.79 0.48 44.23% 285		

Analyser class



Return (%)

Outlook

- Would like to expand on this to build a more sophisticated quantitative trading system with many improvements:
 - Event-driven backtesting
 - Realistic handling of transaction costs
 - Risk management framework
 - ► GUI?
 - Real time execution
- As well as doing actual quant research
- Would anyone like to work on this together?
 - We could set up a *quant trading* or *quant research* arm within the club

Bibliography

- Michael H. Moore <u>www.quantstart.com</u>
- Ernest P. Chan

Quantitative Trading: How to Build Your Own Algorithmic Trading Business

Ernest P. Chan

Algorithmic Trading: Winning Strategies and Their Rationale