Quantitative Trading Strategies

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Outline

A Brief History

Learning Tips

Smart Beta Strategy

Asset Allocation Strategy

AI-driven Strategy

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Academia

- Modern Portfolio Theory (MPT), Markowitz (1952, 1959)
- M&M Theorem, Modigliani and Miller (1958)
- CAPM, Sharpe (1964)
- Efficient Captial Market, Fama (1970)
- B-S Option Pricing Model, Black and Scholes (1973)
- Arbitrage Pricing Pheory (APT), Ross (1976)
- B-L Gobal Portfolio Optimization Model, Black and Litterman (1992)
- FF3, Fama & French (1993)
- FF5, Fama & French (2015)

Industry: $\mathbb{P}$ vs. $\mathbb{Q}$

	Risk/portfolio management	**Derivatives pricing**
Goal	model the future	extrapolate the present
Environment	real probability $\mathbb{P}$	risk-neutral probability $\mathbb{Q}$
Processes	discrete-time series	continuous-time martingales
Dimension	large	low
Tools	multivariate statistics	Ito calculus, PDE's
Challenges	estimation	calibration
Business	buy-side	sell-side

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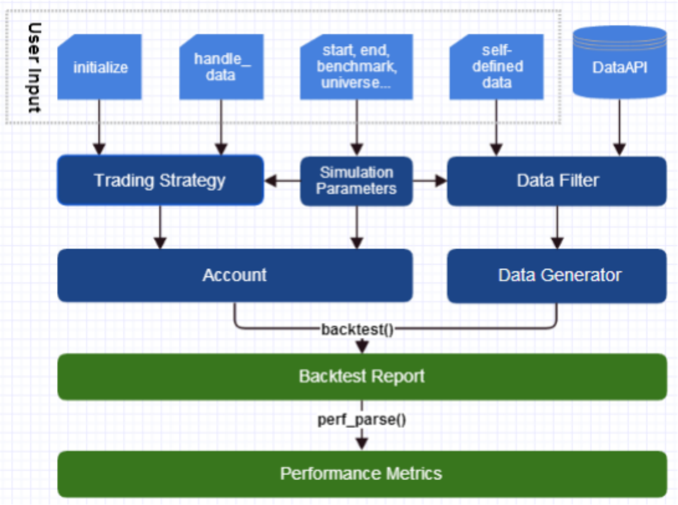
Learning Tips

- Quantconnect: Alternative for Quantopian
- Quantiacs
- Blueshift

Pipeline



User Input
initialize
handle_ data
start, end, benchmark, universe...
self-defined data
DataAPI
Trading Strategy
Simulation Parameters
Data Filter
Account
Data Generator
backtest()
Backtest Report
perf_parse()
Performance Metrics

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Smart Beta

Along with the concept of factor/style investing, Smart Beta becomes a hop topic in the last few years.

Definition (Smart Beta Strategies)

Smart beta strategies are designed to add value by systematically selecting, weighting, and rebalancing portfolio holdings on the basis of factors or characteristics other than market capitalization.

Why is it so disruptive to the business of traditional active management?

- simple and rule-based
- transparent
- lower fees

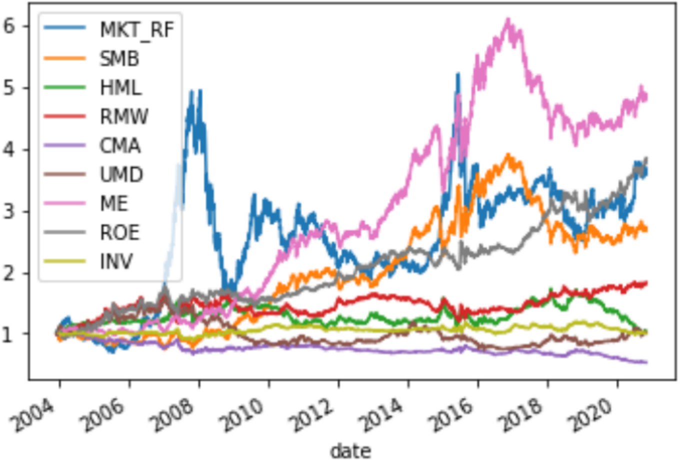
Smart Beta Model

$$E(R^e) = \alpha + \beta' \lambda$$

where

$$\lambda : \text{risk premium}$$
$$\beta : \text{risk exposure}$$
$$\alpha : \text{pricing error}$$

Performance of classic factors in China's market (2004/01-2020/10)



Descriptive Statistics

	MKT_RF	SMB	HML	RMW	CMA	UMD	ME	ROE	INV
count	202	202	202	202	202	202	202	202	202
mean	0.92	0.64	0.06	0.32	-0.28	0.04	0.86	0.73	0.02
std	7.98	4.81	3.89	3.46	2.35	4	4.18	3.47	2.06
min	-25.14	-20.10	-14.76	-8.72	-11.69	-13.23	-19.46	-9.42	-9.63
25%	-3.45	-2.30	-1.94	-1.48	-1.80	-2.30	-1.55	-1.38	-1.10
50%	1.04	0.40	0.05	0.08	-0.45	0.03	0.87	0.71	-0.15
75%	4.87	3.64	2.07	1.95	1.17	2.54	3.51	2.74	1.26
max	28.58	19.36	19.30	16.45	5.69	13.14	18.27	15.24	6.66
t-stat	1.65	1.90	0.22	1.32	-1.70	0.16	2.94	2.97	0.16

How to combine?

- Reasearch: e.g. Altman's Z-score (1968)

$$\begin{aligned} Z_{score} =& 1.2 \cdot \frac{\text{Working capital}}{\text{Total assets}} + 1.4 \cdot \frac{\text{Retained Earnings}}{\text{Total assets}} + 3.3 \cdot \frac{\text{EBIT}}{\text{Total assets}} \\ & + 0.6 \cdot \frac{\text{Market value of equity}}{\text{Book value of total liabilities}} + 0.999 \cdot \frac{\text{Sales}}{\text{Total assets}} \end{aligned}$$

- IC: $\text{corr}(\beta_{-1}, R^e)$
- IR: $\frac{Mean_{IC}}{Std_{IC}}$

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Asset Allocation

- 1952, Markowitz's Mean-Variance optimization (MVO)
  Improvement: incoporating macro data to estimate expected return and CVaR as alternative risk measrue
- 1990, Fischer Black & Robert Litterman, Goldman Sachs, B-L Model
- 1996, Ray Dalio, Bridgewater, All Weather Strategy
  55% fixed income, 30% stocks and 15% real assets
- 2005 Edward Qian, PanAgora, Risk Parity Model

Risk Parity Model

The risk contribution for each asset i is given by

$$RC_i = w_i \frac{\partial \sigma_p}{\partial w_i} = w_i \frac{(\sum w)_i}{\sqrt{w' \Sigma w}}$$

Solution

$$\underset{w}{\operatorname{argmin}} \sum_{i=1}^{n} \left(\frac{\sqrt{w' \Sigma w}}{n} - RC_i \right)^2$$

Black-Litterman Model

First, consider the implied excess equilibrium return

$$\Pi = \delta\Sigma \cdot w_{mkt}$$

where

$$\begin{aligned} \delta &: \text{risk aversion coefficient} \\ \Sigma &: \text{covariance matrix of excess returns} \\ w_{mkt} &: \text{market capitalization weight} \end{aligned}$$

Black-Litterman Model (cont'd)

Then compute the posterior expected return

$$E(R) = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}Q]$$

where

τ : scalar

P : view matrix

Q : view vector

Ω : diagonal covariance matrix with entries of the uncertainty within each view

Black-Litterman Model (cont'd)

After that, compute the posterior covariance matrix

$$\Sigma_p = \Sigma + (\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}$$

Finally, plugging updated expected return and covariance matrix back in MVO.

Market Timing/GTAA

Summary of Risky Assets

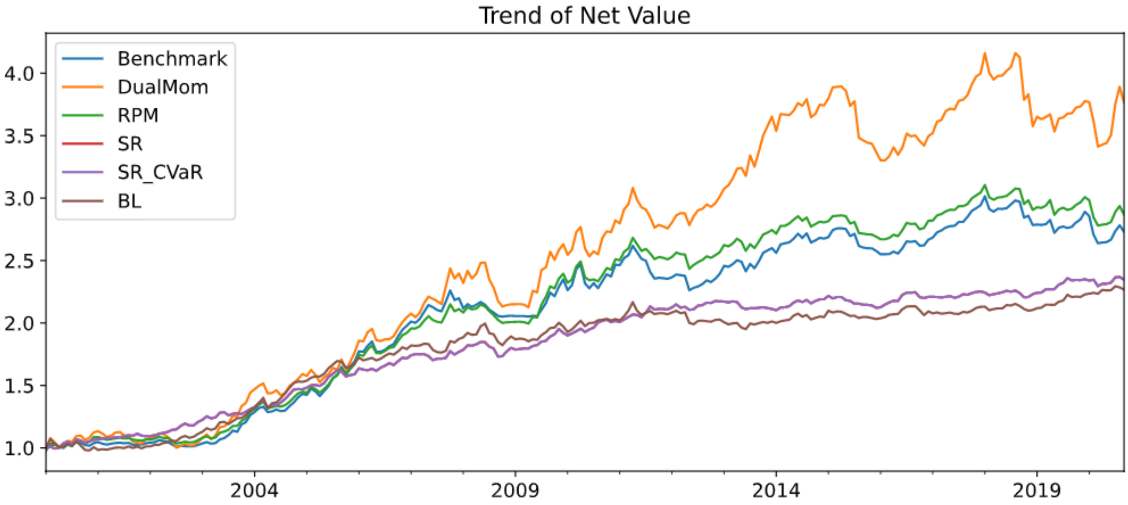
- U.S. Equity: 10
- Global ex U.S. Equity: 19
- Fixed Income: 6
- Real Assets: 7

Strategy

- Define signal: $Signal_t = \dfrac{MAMOM_t(12)}{Vol_t(12)} = \dfrac{\dfrac{P_t}{MA_t(13)} - 1}{Std_t(12)}$

  where $MA_t(13) = Mean(P_t, P_{t-1}, \ldots, P_{t-12})$
- Portfolio Sort: select top n(15) cross-sectional assets
- Risk control (thereshold: 0): remove assets whose signal < 0

Market Timing/GTAA (2000/1-2020/9)



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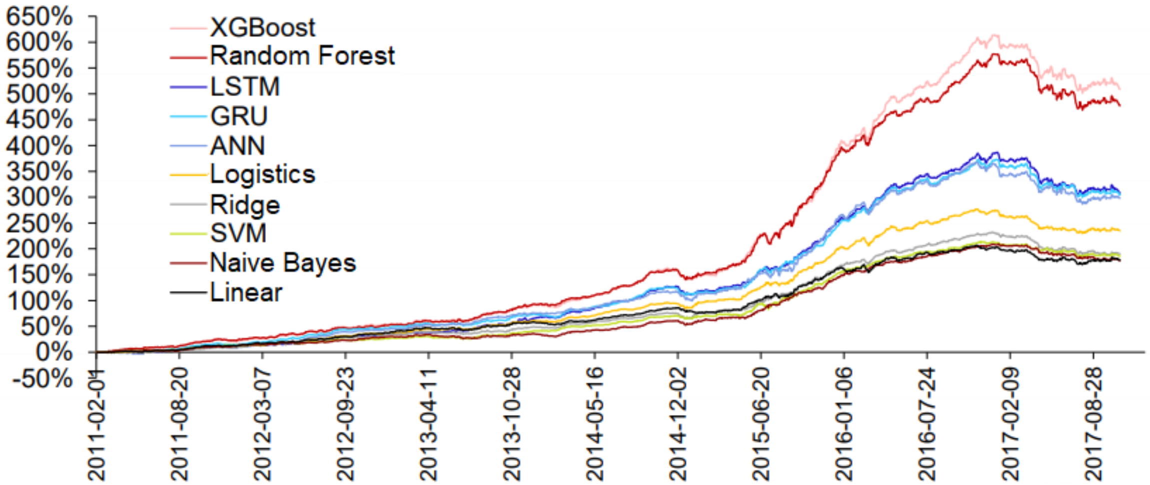
AI-driven

- Stock Selection
- Qlib
- FinRL

Research from HTSC



Feature Selection

Total Factors: 72

- Valuation factors: 5
- Size factors: 2
- Growth factors: 8
- Quality factors: 2
- Size factors: 8
- Leverage factors: 2
- Risk factors: 6
- Liquidity factors: 6
- Technical indicators: 15
- Momentum factors: 9
- Earnings Expectation: 9

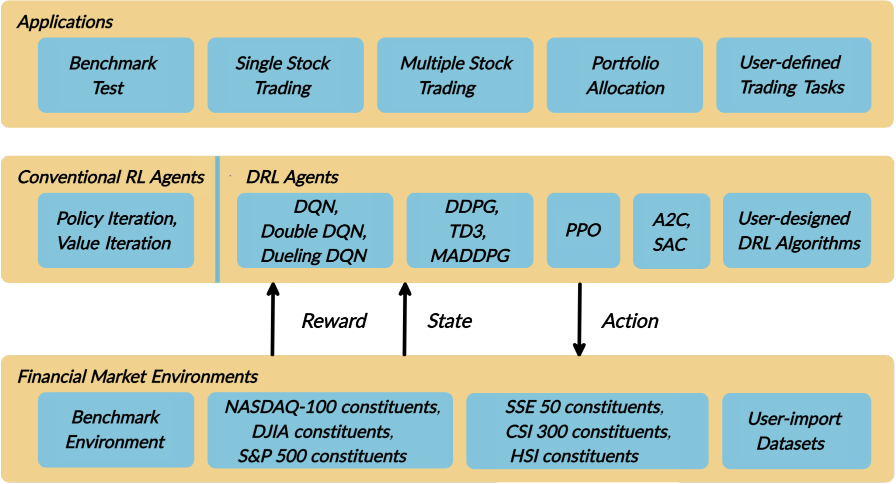
Data Cleaning

- Winsorization: MAD
- Normalization: Z-Score
- Neutralization: Cap + Style(Industry)

2010/1-2020/5

Algorithm (lb: Months)	**Annualized Return**	**Benchmark (CSI300)**	**Excess Return**	**Sharpe Ratio**	**Max Draw-down**
LSTM(36)	27.11%	5.51%	21.60%	0.99	-20.44%
XGBoost(12)	18.42%	2.25%	16.17%	0.69	-35.82%
LR(36)	19.63%	5.51%	14.12%	0.75	-20.93%
SVM(12)	20.89%	2.25%	18.64%	0.77	-37.73%
GaussianNB(12)	13.82%	2.25%	11.57%	0.58	-32.57%
RF(12)	17.44%	2.25%	15.19%	0.66	-31.57%

FinRL

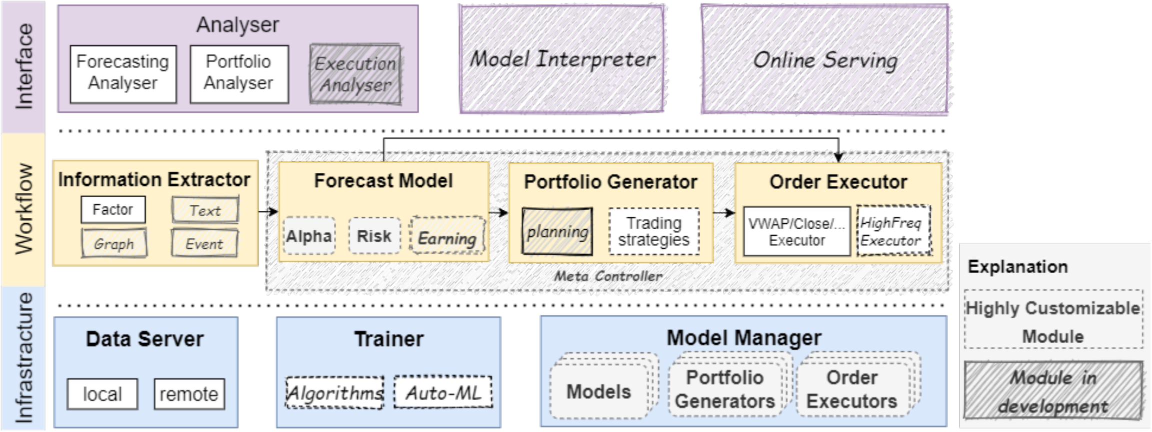


Applications
Benchmark Test
Single Stock Trading
Multiple Stock Trading
Portfolio Allocation
User-defined Trading Tasks
Conventional RL Agents
Policy Iteration, Value Iteration
DRL Agents
DQN, Double DQN, Dueling DQN
DDPG, TD3, MADDPG
PPO
A2C, SAC
User-designed DRL Algorithms
Reward
State
Action
Financial Market Environments
Benchmark Environment
NASDAQ-100 constituents, DJIA constituents, S&P 500 constituents
SSE 50 constituents, CSI 300 constituents, HSI constituents
User-import Datasets

FinRL

TD3 (Portfolio Allocation)
DDPG (Portfolio Allocation)
TD3 (Multiple Stock)
DDPG (Multiple Stock)
DJIA
Min-Variance
Cumulative Return
0.4
0.3
0.2
0.1
0
−0.1
−0.2
Jan 2
2019
Mar 13
May 22
Jul 31
Oct 9
Dec 18
Feb 26
2020
May 6
Jul 15
Sep 23

Qlib



Interface
Workflow
Infrastructure
Analyser
Forecasting Analyser
Portfolio Analyser
Execution Analyser
Model Interpreter
Online Serving
Information Extractor
Factor
Text
Graph
Event
Forecast Model
Alpha
Risk
Earning
Portfolio Generator
planning
Trading strategies
Order Executor
VWAP/Close/... Executor
HighFreq Executor
Meta Controller
Data Server
local
remote
Trainer
Algorithms
Auto-ML
Model Manager
Models
Portfolio Generators
Order Executors
Explanation
Highly Customizable Module
Module in development

Figure： Qlib built-in AI Model （qlib.contrib.model）

Category	**Model**
Linear	Linear （parameter: "ols", "nnls", "ridge" or "lasso"）
Boosting	LightGBM
	Catboost
	XGBoost
Time series based NN	GRU
	LSTM
	ALSTM
	SFM
	TFT
GNN	GATs
Other NN	MLP
	DNN