

## Future Trend and Perspective

# Quant 4.0: Engineering Quantitative Investment with Automated, Explainable and Knowledge-driven Artificial Intelligence

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## Abstract

Quantitative investment (abbreviated as “quant” in this article) is an interdisciplinary field combining financial engineering, computer science, mathematics, statistics, etc. Quant has become one of the mainstream investment methodologies over the past decades. The development of quant has experienced three generations: Quant 1.0, trading by mathematical modeling to discover mis-priced assets in markets; Quant 2.0, an evolution of quant research workflow moving from small “strategy workshops” to large “alpha factories” with standardized and scalable pipelines; Quant 3.0, applying machine/deep learning techniques to discover complex nonlinear pricing rules. However, deep learning rely on extremely large data volume and labor-extensive designing and tuning of “black-box” neural network models. To address these limitations, in this paper, we introduce Quant 4.0 and provide an engineering perspective for next-generation quantitative investment. Compared with Quant 3.0, Quant 4.0 has three key differentiating components. First, *Automated AI* changes investment research process from traditional hand-craft modeling way to the state-of-the-art automated modeling pipeline, practicing the philosophy of “algorithm produces algorithm, model builds model, and eventually AI creates AI”. Second, *Explainable AI* develops a series of techniques in order to better understand and interpret investment decisions made by machine learning black-boxes, thus helping explain complicated, subtle and hidden risk exposures. Third, *Knowledge-driven AI* serves as a complementary to data-driven AI such as deep learning by incorporating prior knowledge like financial events and economic behaviors to improve financial decision-making, in particular for low-frequency investment such as value investment and global macro investment. Moreover, we discuss how to build a research and trading system that practices the Quant 4.0 concept. Finally, we propose ten challenging research problems for quant technology, and discuss potential solutions, research directions, and future trends.

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## 1. Introduction

Quantitative investment is an important part of wealth management (a.k.a. asset management) industry. This section contains introductory knowledge about quant, including market situation, classification and principles of strategy development, historical landmarks, and concepts of Quant1.0–Quant4.0.

### 1.1. Wealth Management and Quant

The wealth management industry is one of the largest sectors of the world’s economy. According to a global wealth report from Boston Consulting Group (BCG) [1] and the illustration in Figure 1, the volume of global financial wealth has grown from 188.6 trillion USD in 2016 to 274.4 trillion USD in 2021, almost three times as the global nominal GDP in 2021. Moreover, the company predicts this number will increase to 355 trillion USD in 2026. It is not surprising that North America, Asia, and Europe are the three biggest regional markets

of wealth management in the world, with approximately 46%, 26%, and 21% of the global market size in 2021, respectively. We also see the stable and sustainable growth of the wealth management market, both globally and regionally. Figure 2 shows an ecosystem of the wealth management industry, where investment funds as well as fund managers (a.k.a. investment managers) play core roles. They raise money from various capital providers, such as endowment foundations, fund of funds (FOF), family offices, billionaires, insurance companies, pension/sovereign funds and retail clients, and invest this money into financial markets to bet return and profit for their customers. Many types of investment instruments are liked by fund managers, such as stocks, exchange-traded funds (ETFs), bonds, futures, options, and foreign exchange [2]. Some investment funds even borrow money from depository institutions such as banks or peer-to-peer lending companies for investment and profit from the difference between investment return and loan interest. With the rapid development of digital economy, big data, and artificial intelligence, more and more new technologies are applied in the wealth management industry, leading to a branch of financial technology/engineering, called “investment engineering” [3]. Consequently, the pipeline of investment research, trading execution, and risk management is

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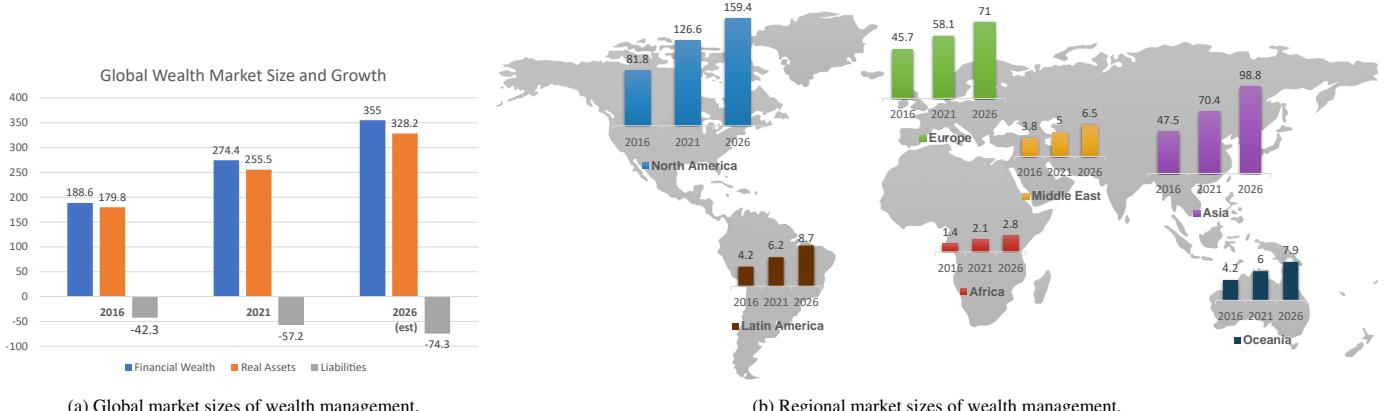


Figure 1: Global and regional market sizes of wealth management industry (unit: trillion USD). Panel (a) illustrates the volume of financial wealth, real assets and liabilities in 2016, 2021 and 2026 (estimated) in the world. Panel (b) shows the distribution of financial wealth in seven regional markets around the world in 2016, 2021 and 2026 (estimated). Data come from the report of BCG [1].

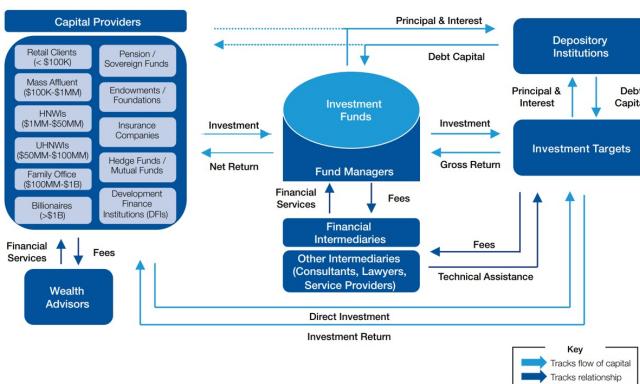


Figure 2: The asset management ecosystem [4]

becoming a systematic, automated, and intelligent process, and this philosophy has been practiced in the recent evolution of quant.

As an important family of players in financial markets and the wealth management industry, contemporary quant applies rigorous mathematical and statistical modeling techniques, machine learning techniques, and algorithmic trading techniques to discover asset pricing abnormalities in financial markets and make money from the following arbitrage or investment opportunities. Compared with traditional fundamental and technical investment, quantitative investment has a number of advantages. Firstly, the performance of quant strategies can be examined and evaluated beforehand using back-test experiments based on historical data before the beginning of real trading. Secondly, quant trading has speed superiority in bidding orders with the best price. Thirdly, it eliminates the negative effect of human emotion in decision-making. Finally, quant research has significant advantages in data analysis with much deeper, broader and diversified coverage of information about financial markets and sectors. In the past 30 years, information infrastructure and computer technology are widely applied by financial exchange markets around the world. Nowadays, massive financial data are generated and millions of orders are executed

every second, leading to the rapid growth of the quant industry. Taking the U.S. stock market as an example, over 60% of overall trading volumes comes from the orders placed by computer trading algorithms rather than human traders [5].

## 1.2. Quant Strategies

A quant strategy is a systematic function or trading methodology used for trading securities in financial markets based on predefined rules or trained models for making trading decisions. Strategies are usually the core intelligent property of a quantitative fund.

### 1.2.1. Components of Quant Strategy

A standard quant strategy contains a series of components, such as investment instrument, trading frequency, trading mode, strategy type and data type, and we introduce them one by one (see Figure 3).

- **Investment instrument** specifies which financial instruments are put in the universe by the strategy. Popular candidate instruments include stocks, ETFs, bonds, foreign exchanges, convertible bonds, and cryptocurrencies, as well as more complicated financial derivatives such as futures, options, swaps, and forwards [6]. An investment strategy could trade either a single type of instrument (e.g., a strategy for trading ETFs) or multiple types of instruments (e.g., an alpha hedging strategy that longs stocks and shorts index futures to eliminate market risks).
- **Trading frequency** specifies how to hold your asset in portfolio and how frequently to trade. Usually, high-frequency trading holds a position in several minutes or seconds, while low-frequency trading may hold an asset over several months or years. Comparing high-frequency trading and low-frequency trading, the dramatic discrepancy of holding periods result in very different consideration in strategy design. For example, asset capacity limitations and trading costs are big issues for high-frequency trading, while how to control the risk of drawdown [7] is what we should carefully think about for low-frequency trading.

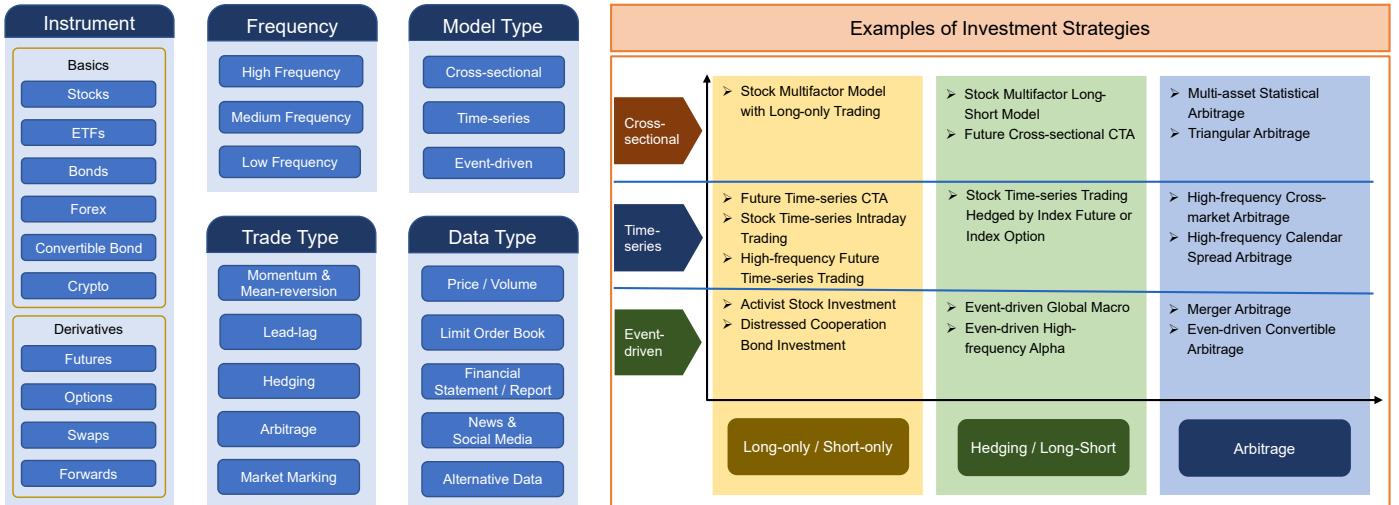


Figure 3: Classification of common strategies and investment instruments.

- Model type characterizes how to formally model the trading problem. Examples include cross-sectional trading, time-series trading, and event-driven trading [7]. Cross-sectional trading is used commonly in stock selection, where all stocks in a universe are ranked according to their scores of expected future returns predicted by a model, and portfolio managers could long stocks with the highest scores and short those with the lowest scores. Time series trading is relatively simple, where long/short trading operates only on a single instrument such as a certain stock or a certain future contract. Event-driven trading differs from time-series trading because the time intervals between events are not evenly distributed over time, while investment decisions and trading executions are triggered by the occurrence of events.
- Trade type is a series of thinking templates for us to design a strategy quickly. Examples include momentum trading [8], mean-reversion trading [9], arbitrage trading [10], hedging [11], market making [12], etc. By leveraging these strategy types, traders can explore profit chances from different aspects of financial markets. Specifically, momentum trading assumes the price trend is sustainable in the following time window and it follows this trend direction to trade. Mean-reversion trading, on the contrary, bets the price trend will move towards the opposite direction in recent future and buy opposite positions. Hedging is the purchase of one asset with the intention of reducing the risk of loss from another asset. Arbitrage is simultaneously longing and shorting the same asset in different markets or a pair of highly correlated assets in order to profit from the convergence of price discrepancy. Market making is a liquidity-providing trade that quotes both a buy and a sell price in a tradable asset held in inventory, hoping to make a profit on the bid–ask spread.
- Data type means what type of data is used in a strategy. Typical data types include quote data, limit order books [13] b, news data, financial statements, analysts’ reports, and alternative data such as sentimental data, location data, satellite

images, etc. A strategy researcher must consider what kind of data he has and what kind of data he needs in a strategy development process. For example, limit order book streams are usually used in building high-frequency trading strategies, while news data are used more commonly in event-driven strategies.

### 1.2.2. Examples of Popular Strategies

Figure 3 also list a number of popular strategies as examples. For example, stock hedging strategy based on multifactor model [14] is very popular in many main markets around the world. This strategy hedges market risk by longing the most favorable stocks and shorting the other end (in some markets prohibiting shorting, short the corresponding index future or index option instead). If we trade stocks with multifactor models in a long-only way without shorting and constrain the risk exposure between selected portfolios and certain stock indices, it is an enhanced indexing strategy, which is almost the most popular quantitative strategy in China’s stock market if measured by assets under management (AUM).

### 1.3. Fundamental Principles of Asset Management

Similar to the situation that learning law of energy conservation could help avoid the trap of perpetual motion machine, it is beneficial to learn some fundamental principles of asset management so as to get rid of some common traps in strategy development.

#### 1.3.1. Fundamental Law of Active Management

The first principle is the *fundamental law of active management* developed by Richard Grinold and Ronald Kahn [15]. This principle states that the performance of an active investment manager (or equivalently quant model) depends on the quality of investment skills and, consequently, the frequency of investment opportunities. This law can be expressed mathematically as follows:

$$IR = IC \times \sqrt{Breadth} \quad (1)$$

where  $IC$  is the information coefficient (correlation between the predicted return and true return in a future time window) evaluating investment quality,  $Breadth$  means the number of independent investment decisions in a year, and  $IR$  is the ratio of portfolio returns above the returns of a benchmark to the volatility of returns, measuring the performance of asset management. Mathematically, the fundamental law of active management can be regarded as an application of the central limit theorem in mathematical statistics [16]. When applying this law in practice, we have to notice that  $IC$  and  $Breadth$  are usually not independent. For example, given a strategy, we may increase its  $Breadth$  by relaxing the threshold of trading signals, but in this way,  $IC$  may decrease because more false-positive noise is introduced to our decisions. Therefore, a good strategy should find an optimal trade-off between these two coupled variables. Figure 4a illustrates the distribution of various popular strategies on  $IC$  and  $Breadth$ , and their corresponding  $IR$  performance.

### 1.3.2. Impossible Trinity of Investment

The second principle is the impossible trinity of asset management. Specifically, any investment strategy can not meet the following three conditions simultaneously, i.e., high return, low risk (or equivalently high stability), and high capacity. Figure 4b illustrates the impossible trinity using a radar chart with three variables return, stability and capacity. For example, high-frequency market making and calendar arbitrage strategy could reach high return and stability (low portfolio volatility), but the capacity of its AUM is usually small, typically hard to exceed several billions of USD even in global trading. On the contrary, stock fundamental strategy has high capacity up to trillions of USD, but its return and stability are not as good as those of high-frequency trading.

## 1.4. History of Quantitative Investment

The origin of quant can trace back to over a century ago when French mathematician Louis Bachelier published his Ph.D. thesis “The Theory of Speculation” in 1900 [17] and he exhibited how to use probability law and mathematical tools to study the movement of stock prices. As a pioneer exploring the application of advanced mathematics in financial markets, Bachelier’s work inspired academic research of quantitative finance despite the lack of industry application due to data scarcity at his age. Quantitative investment was first practiced by American mathematics professor Edward Thorp, who used probability theory and statistical analysis to win blackjack games, and his research was subsequently used to seek systematic and consistent returns in stock markets [18]. In this subsection, we introduce the history and landmarks in the development of quantitative finance through two routes: research landmarks in academia and evolution of quant in industry practice.

### 1.4.1. Q-Quant and P-Quant

People in academia and investment industry classify quantitative finance into two branches, which are usually referred to

as “Q-quant” and “P-quant”. These two branches are named after their differentiation in modeling based on risk-neutral measure and probability measure, respectively. Generally speaking, Q-quant studies the problem of derivative pricing and *extrapolate the present*, using a model-driven research framework where data is usually used to adjust the parameters of models. On the other hand, P-quant studies quantitative risk and portfolio management to *model the future*, using a data-driven research framework where different models are built to improve the fitting of historical data. Usually, Q-quant research is conducted in sell-side institutes such as investment banks and security companies, while P-quant is popular in buy-side institutes such as mutual funds and hedge funds. Table 1 compares the characteristics of these two types of quant.

Table 1: Comparisons of P-quant and Q-quant [19].

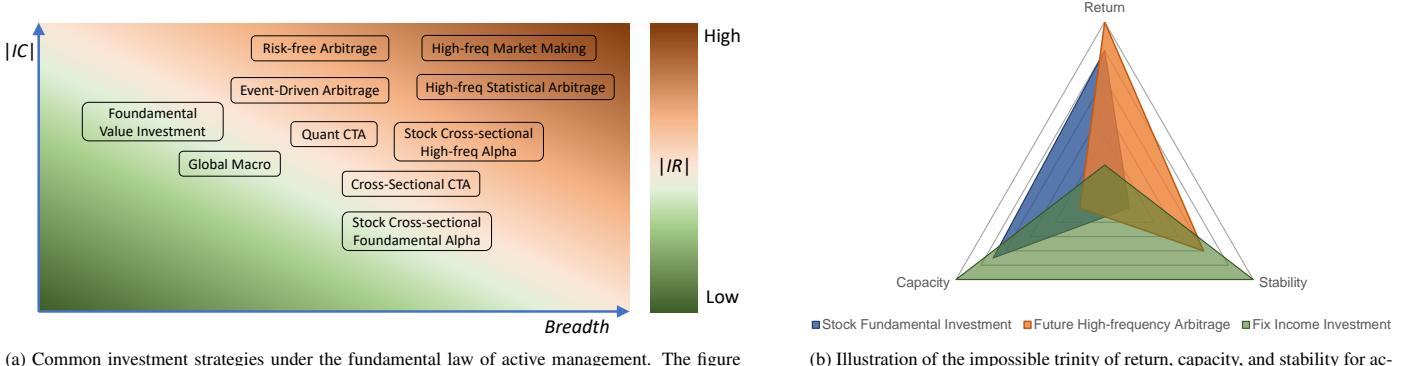
	Q-quant	P-quant
Goal	Extrapolate the present	Model the future
Scenario	Derivatives pricing	Portfolio management
Measure	Risk-neutral measure	Probability measure
Modeling	Continuous stochastic process	Discrete time series
Example	Black-Scholes model	Multifactor model
Algorithm	Ito calculus, PDEs	Statistics, Machine Learning
Challenge	Calibration	Estimation/Prediction
Business	Sell-side	Buy-side

### 1.4.2. Landmarks in Q-Quant

In 1965, Paul Samuelson, American economist and the winner of 1970 Nobel Memorial Prize in Economic Sciences, introduced stochastic process and stochastic calculus tools in analyzing financial markets and modeling the stochastic movement of stock prices [20], and in 1965, he published a paper studying the lifetime portfolio selection problem using a stochastic programming method [21]. In the same year, another American economist Robert Merton published his work about lifetime portfolio selection as well. Different from Samuelson’s work using discrete-time stochastic process, Merton’s work modeled the random uncertainty of portfolio using continuous-time stochastic calculus [22]. Almost in the same year, economists Fischer Black and Myron Scholes demonstrated that the expected return and risk of assets under management could be removed by dynamically revising a portfolio, and thus inventing the risk-neutral strategy for derivative investment [23]. They applied the theory to real market trading and published it in 1973. The risk-neutral formula was later named in honor of them and called *Black-Scholes Model* [24], a partial differential equation (PDE) tool for pricing a financial market containing derivative investment instruments. Specifically, the Black–Scholes model establishes a partial differential equation governing the price evolution of a European option call or European option put, as follows:

$$\frac{\partial V}{\partial t} + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + rS \frac{\partial V}{\partial S} - rV = 0 \quad (2)$$

where  $V$  is the price of the option as a function of stock price  $S$  and time  $t$ ,  $r$  is the risk-free interest rate, and  $\sigma$  is the volatility of the stock. This PDE has a closed-form solution called Black-Scholes Formula. Since Robert Merton was the first to publish a



(a) Common investment strategies under the fundamental law of active management. The figure illustrates the relationship between the magnitude of  $IC$  with *breadth* and the magnitude of  $IC$  for different strategies.

(b) Illustration of the impossible trinity of return, capacity, and stability for active management using three typical strategies: stock fundamental investment, future high-frequency arbitrage and fixed income investment.

Figure 4: Illustration of the principles for active investment management with specific strategies.

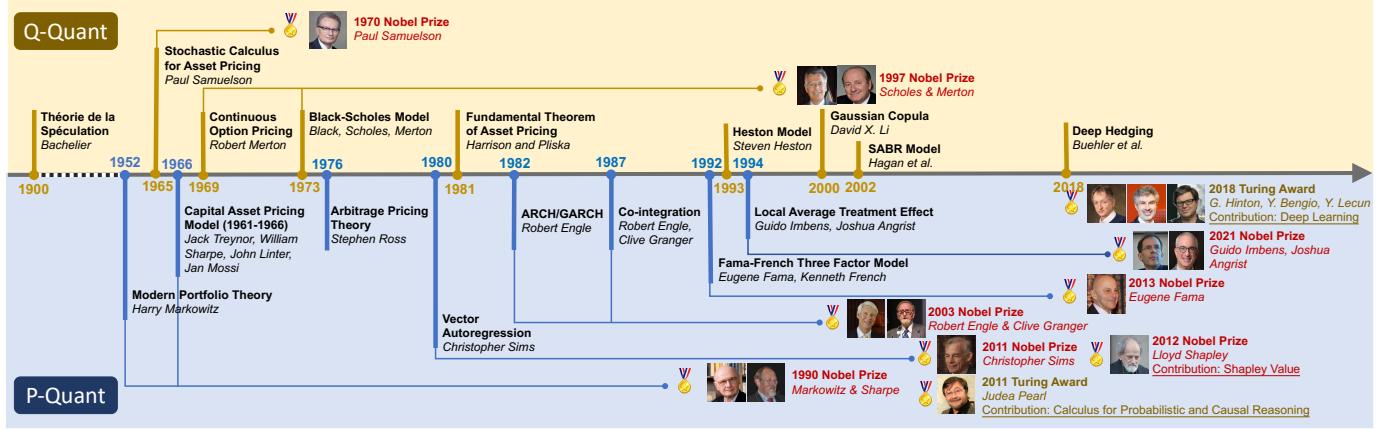


Figure 5: Main academic contributors and their works that deeply influence the development of quantitative investment. Photo credit: Wikipedia.

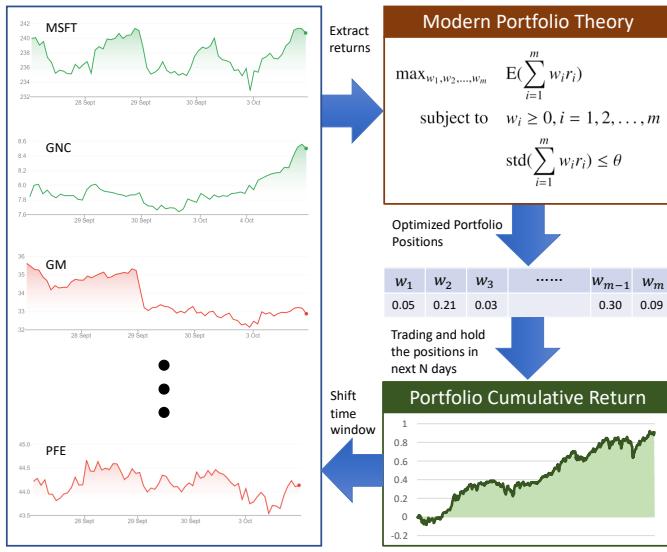
paper expanding the mathematical understanding of the options pricing model, he was usually credited with the contribution of this theory as well. Merton and Scholes received the 1997 Nobel Memorial Prize in Economic Sciences for their discovery of the risk-neutral dynamic revision. The original Black-Scholes model was extended later for deterministically variable rates and volatilities, and was extended to characterize the price of European options on instruments paying dividends, as well as American options and binary options.

As a pioneering work in risk-neutral theory, Black-Scholes model has many limitations, one of which is the assumption that the underlying volatility is constant over the life of the derivative, and is unaffected by the changes in the price level of the underlying security. This assumption usually contradicts the phenomenon of the smile and skew shapes of implied volatility surfaces. A possible solution is to relax the constant volatility assumption. By characterizing the volatility of the underlying price using stochastic process, it is possible to model derivatives more accurately in practice, and this idea leads to a series of works about stochastic volatility, such as the Heston model [25] and the SABR model [26]. As a commonly used stochastic volatility model, the Heston model assumes the variation of the volatility process varies as a square root of the variance itself, and it exhibits a reversion trend towards the long-term mean

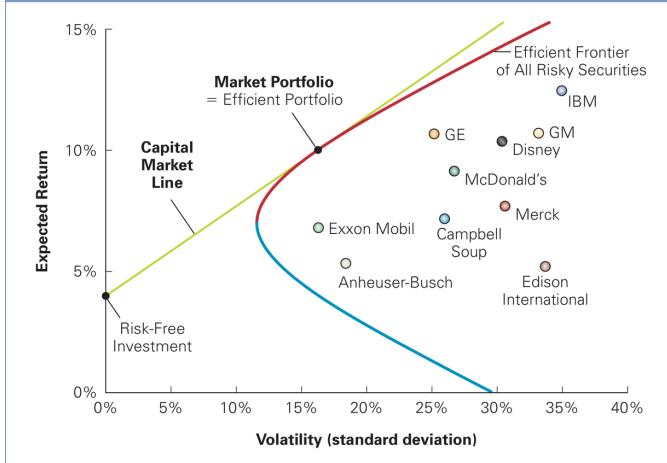
of variance. Another popular stochastic volatility model is the SABR model, commonly used in interest rate derivative markets. This model uses stochastic differential equations to describe a single forward (such as a LIBOR forward rate, a forward swap rate, or a forward stock price) as well as its volatility, and has the ability to reproduce the effect of volatility smile. In recent years, deep learning and reinforcement learning techniques are applied to integrate with risk neural Q-quant modeling and a concept *learning to trade* was introduced by Hans Buehler [27], who proposed the deep hedging model, a framework for hedging a portfolio of derivatives in the presence of market frictions such as transaction costs, market impact, liquidity constraints or risk limits and for modeling the volatility stochastic process using deep reinforcement learning and market simulation. It does not use the Greeks anymore and naturally captures co-movements of relevant market parameters.

In addition to derivative pricing models, market efficiency theory and risk modeling theory are also very important in Q-quant, both in academia and industry. In 1980s, Harrison and Pliska established the fundamental theorem of asset pricing [28], which provides a series of necessary and sufficient conditions for an efficient market to be arbitrage free as well as complete. In 2000, David X. Li introduced the statistical model Gaussian copula [29] to evaluate the value-at-risk (VaR) of derivative

pricing and portfolio optimization, especially the collateralized debt obligations (CDO). Gaussian copula quickly became a tool for financial institutions to correlate associations between multiple financial securities since it is relatively simple in modeling even for those assets too complex to price previously, such as mortgages.



(a) Illustration of Markowitz' portfolio optimization theory.



(b) Illustration of efficient frontier first formulated by Harry Markowitz. Figure cited from [30].

Figure 6: Portfolio optimization

#### 1.4.3. Landmarks in P-Quant

Q-quant plays an extremely important role in quantitative finance. In this article, however, we stand on a buy-side point of view and focus on asset prediction and portfolio optimization problems, and thus all discussions about quantitative investment in the following content assume a P-quant statement unless otherwise specified. The origin of P-quant started from the establishment of modern portfolio theory introduced by Harry Markowitz. The theory was initialized in his Ph.D. thesis "Portfolio Selection" and later published in Journal of Finance in 1952 [31], and an extension published in his book *Portfolio Selection: Efficient Diversification of Investments* [32] in 1959.

According to the old adage "Don't put all your eggs in one basket", Markowitz came up with the concept of efficient frontier of asset investment in financial market and formalized it mathematically as a quadratic optimization problem by maximizing the expected return of the portfolio given its risk (usually measured by the variance of the assets in a portfolio) at a certain level. Figure 6 illustrates the application of Markowitz's theory for allocating the best positions for assets in portfolio and illustrates the concept of efficient frontier.

Based on the modern portfolio theory, the Capital Asset Pricing Model (CAPM) was later introduced by Jack Treynor (1961, 1962) [33], William F. Sharpe (1964) [34], John Lintner (1965) [35] and Jan Mossin (1966) [36] independently. CAPM aims to describe the relationship between systematic risk from the market and expected return for assets.

$$E(R_p) - R_f = \alpha + \beta \cdot (E(R_m) - R_f) \quad (3)$$

where  $E(R_p)$  is the expect return of portfolio,  $R_f$  is the risk-free return,  $E(R_m)$  is the expected return of market. Specifically, CAPM decomposes asset return and risk into two separate parts, alpha and beta. Alpha measures the performance of a portfolio compared to a benchmark index (e.g., S&P500 index), while beta measures the variance of the portfolio in relation to a benchmark index, characterizing the risk from market volatility. One of the main contributors to CAPM, William Sharpe, shared the 1990 Nobel Prize with Harry Markowitz. A following important step in quantitative finance is the establishment of arbitrage pricing theory (APT) by MIT economist Stephen Ross in 1976 [37]. APT improved its predecessor CAPM by further introducing the multifactor model framework to build the relationship between asset price and various macroeconomic risk variables. Under the multifactor model framework, Nobel Prize-winning economist Eugene Fama proposed the famous Fama–French Three-Factor Model with his colleague Kenneth French at the University of Chicago in 1992 [14].

$$E(R_p) - R_f = \beta_0 + \beta_1 \cdot (E(R_m) - R_f) + \beta_2 \cdot SMB + \beta_3 \cdot HML \quad (4)$$

This model establishes the relationship between the expected portfolio return (up to subtracting a risk-free return)  $E(r_p) - r_f$  with respect to three systematic risk factors: expected market return  $E(R_m) - R_f$ , size  $SMB$  (the spread between small capitalization stocks and large capitalization stocks), book-to-market values  $HML$  (the spread between high book-to-market companies and low book-to-market companies). The three-factor model was then extended to Fama and French Five Factor Model in 2015 [38], by adding two more factors: profitability (return spread of the most profitable firms minus the least profitable) and investment aggressiveness (the return spread of firms that invest conservatively minus aggressively).

Parallel with the progress of multifactor models, a number of significant research about time-series analysis appears in 1980s. In 1980, Nobel Prize winner Christopher Sims introduced the Vector Autoregression (VAR) model into economics and finance. As an extension of single sequence autoregressive (AR) model and autoregressive-moving-average (ARMA)

model commonly used in time-series analysis, VAR characterizes the autoregressive properties over time across multiple times series and it assumes constant variance of error terms in the regression formula. In 1982, Robert Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model and extend it to Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to characterize the pattern of financial volatility in the market by specifying stochastic variance in the model. In 1987, he introduced co-integration method with Clive Granger (inventor of Granger Causality for modeling lead-lag patterns among multiple time series) for testing the significance of mean-reversing patterns in financial time series, and co-integration test has been widely used in discovering promising asset pairs for statistical arbitrage strategies. Both Engle and Granger received the 2003 Nobel Prize for their contribution to time series analysis which has been widely applied in quantitative finance for market forecasting and investment research. In 2018, three pioneers in deep learning techniques, Yoshua Bengio, Geoffrey Hinton and Yann LeCun, are granted the Turing Award. Nowadays, deep learning has been widely used by academic researchers in finance and quant researchers in financial institutions to build complex nonlinear models in order to learn the relationship between financial signals and expected returns and to predict asset prices, and its powerful ability in fitting big data significantly improves the performance of market prediction and portfolio management.

Although accurately predicting the future trend of asset price is a very important task in P-Quant, how to explain the effect of model prediction and interpret how a model is really working seems more important for quant researchers since “know how” is more crucial than “know what” in risk management for portfolio managers. Causal effect analysis [39] and factor importance analysis are two core tasks in quant model interpretation. Clive Granger invented the Granger Causality Test in 1969 [40] for determining whether one time series is useful in forecasting another. The original Granger causality test does not account for latent confounding effects and does not capture instantaneous and non-linear causal relationships, though several extensions have been proposed to address these issues. Although there is an argument about whether Granger causality test can evaluate “real” causality in terms of statistics, this method has been widely applied in quant research such as searching and evaluating pairs of stocks with significant lead-lag effect and trading with corresponding strategies. In 1994, Guido Imbens and Joshua Angrist introduced the local average treatment effect (LATE) model to characterize the statistical causal effect in economics, finance and social sciences, and they shared the 2021 Nobel Prize in economics. Another important contributor in causal inference is the Turing Award winner Judea Pearl, who invented the causal diagram (Bayesian network) and it can be used to mine the causal effect among factors and returns in multifactor model. On the other hand, in the area of factor importance analysis, Shapley Value has become an important criterion for measuring the contribution of single feature in a complex nonlinear machine learning model. In fact, it is interesting that this criterion was invented originally to measure the contribution of individual player/agent in a cooperative gaming

process when it was first proposed by Lloyd Shapely, a Nobel Prize winner and a pioneer in game theory research.

#### 1.4.4. Development of Quant in Industry

The blooming era of quantitative investment funds started from 1990s, along with the emergence of the Internet and the development of electronic trading in exchanges. Here we briefly introduce the evolution of quant operating models and classify them into three generations, denoted as Quant 1.0–3.0, and summarize their characteristics in Figure 7.

- Quant 1.0 appeared in the early age of quantitative investment but it is still the most popular quant operating model in contemporary market. The features of Quant 1.0 includes: 1) Small but elite team, typically led by an experienced portfolio manager and composed of a few genius researchers and traders with strong mathematics, physics or computer science background; 2) applying or even inventing mathematical and statistical tools to analyze financial market analysis and discover mispriced assets for trading; 3) trading signals and trading strategies are usually simple, understandable and interpretable to reduce the risk of in-sample over-fitting in modeling. This operating model has high efficiency in quant trading but low robustness in management. Especially, the success of a Quant 1.0 team relies too much on particular genius researchers or traders, and such a team may decline or even bankrupt rapidly with the departure of genius. In addition, such a small “strategy workshop” limits the research efficiency on complex investment strategies such as quantitative stock alpha strategy which depends on diversified financial data types, extremely large data volume, and complex modeling techniques such as super large deep learning model.
- Quant 2.0 changes quant operating model from small *genius’ workshop* to an industrialized and standardized *alpha factory*. In this model, hundreds or even thousands of investment researchers work on the same pipeline to mine effective alpha factors [41] out of the plethora of financial data, using standardized evaluation criteria, standardized back-test processes and standardized parameter configurations. These alpha mining researchers are rewarded by submitting qualified alpha factors which usually have high back-test returns, high Sharpe ratio, reasonable turnover rate and low correlation with existing factors in the alpha database. Traditionally, each alpha factor is a mathematical expression characterizing some pattern or profile of stocks, or some relationship between stocks, although more and more complicated machine learning factors are mined as well. Typical alpha factors include momentum factors, mean-reversion factors, event-driven factors, volume-price dispersion factors, growth factors, etc. Many alpha factors submitted by alpha researchers are combined into statistical models or machine learning models by portfolio managers to find the optimal asset positions after appropriate risk neutralization, expecting to obtain a stable and promising excess return in the market. However, large-scale team work results in huge costs for

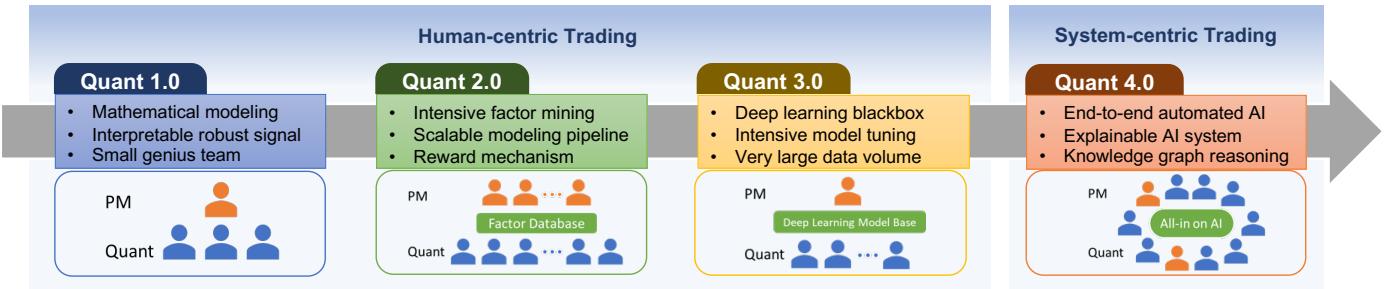


Figure 7: The development history of quantitative investment in industry, from Quant 1.0 to Quant 4.0.

human resources, and the situation gets more and more serious with the team growing larger and larger. Specifically, we could expect the number of discovered effective alphas follows an approximately linear trend with the team size (actually in practice, discovering new effective alphas is more and more difficult when the size of accumulated factors is already large), but the portfolio return grows significantly lower than the expand of alpha volume and team size, and this results in the profit margin getting smaller and smaller. This phenomenon is caused by a number of reasons such as the limitation of strategy market capacity, the growing difficulty in discovering new effective alphas, and even the limitation of human intelligence in searching all possibilities in strategy space.

- **Quant 3.0** emerges with the rapid development of deep learning techniques which have exhibited success in many domain areas such as computer vision and natural language processing. Different from Quant 2.0 which puts more research efforts and human labor into mining sophisticated alpha factors, Quant 3.0 pays more attention to deep learning modeling. With relatively simpler factors, deep learning still has the potential to learn a prediction model performing as well as a Quant 2.0 model, by leveraging its powerful end-to-end learning ability and its flexible model fitting ability. In Quant 3.0, the cost of human labor of alpha mining is at least partially replaced by the cost of computing power, especially for the expensive GPU servers. But generally speaking, it is a more efficient way for quant research in the long run.

### 1.5. Quant 4.0: Why and What

#### 1.5.1. Limitations of Quant 3.0

Although Quant 3.0 has demonstrated its success in some strategy scenarios such as high-frequency stock and future trading, it has three primary limitations.

1. Traditionally, building a “good” deep neural network is time-consuming and labor-intensive, because of the heavy work in network architecture design and model hyperparameter tuning, as well as the tedious work in model deployment and maintenance in trading ends.
2. It is a challenge to read understandable messages from a model encoded by deep learning black box, making it very unfriendly to investors and researchers who care much about the mechanism of financial markets and expect to know the source of profit and loss.

3. The good performance of deep learning relies heavily on extremely large volumes of data, and thus only high-frequency trading (or at least medium cross-sectional alpha trading with large breadth) belongs to the strategy pool that deep learning favorites. This phenomenon prevents deep learning techniques from application in low-frequency investment scenarios such as value investing, fundamental CTA and global macro.

New research and new techniques are needed to address these limitations, and this leads to our proposal for Quant 4.0 in this article.

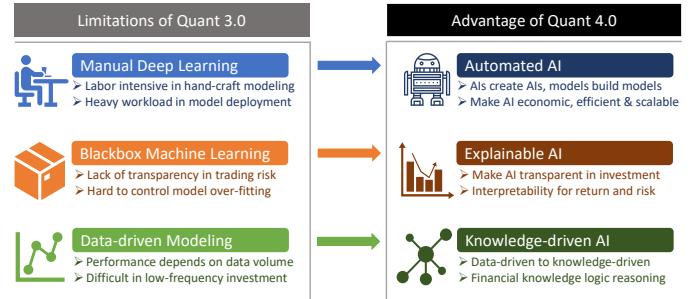


Figure 8: The three key components of Quant 4.0.

#### 1.5.2. What is Quant 4.0?

We believe the limitations of Quant 3.0 are very likely to be solved or at least partially solved in the future with the quick development of the artificial intelligence (AI) technology frontier. Quant 4.0, the next-generation quant technology, is practicing the philosophy of “end-to-end going all-in on AI” and “AI creates AI” by incorporating the state-of-the-art automated AI, explainable AI and knowledge-driven AI and plotting a new picture for quant industry.

- **Automated AI** aims to build end-to-end automation for quant research and trading, in order to significantly reduce the cost of labor and time for quant research including data preprocessing, feature engineering, model construction and model deployment, and to dramatically improve R&D’s efficiency and sustainability. In particular, we introduce state-of-the-art AutoML [42] techniques to automate every module in the whole strategy development pipeline. In this way, we propose to change traditional hand-craft modeling to an automated modeling workflow in an “algorithm produces algo-

rithm, model builds model” manner, and eventually move towards a technical philosophy of “AI creates AI”. Besides AI automation, another important task is to make AI more transparent, which is essentially important for investment risk management.

- Explainable AI, usually abbreviated as XAI in machine learning area, attempts to open the black box encapsulating deep learning models. Pure black-box modeling is unsafe for quant research because people can not calibrate the risk accurately. It is difficult to know, for example, where returns come from and whether they rely on certain market styles, and what the reason for a specific drawdown is, under black-box modeling. More and more new techniques in the field of XAI could be applied in quant to enhance the transparency of machine learning modeling, and thus we recommend quant researchers to pay more attention to XAI. We have to notice that improving model explainability has costs. Figure 9 shows an impossible trinity of versatility, accuracy and explainability, and tells us that we have to sacrifice at least one apex in the triangle to obtain the benefit from the other two. For example, physical law  $E = mc^2$  establishes an explainable and accurate relationship among energy, mass and speed of light, but this formula can be only applied in specific domains of physics and sacrifices versatility. Imagining that we provide more prior knowledge or domain experience in a model, it is equivalent to reducing the versatility to protect the performance of accuracy and explainability simultaneously.

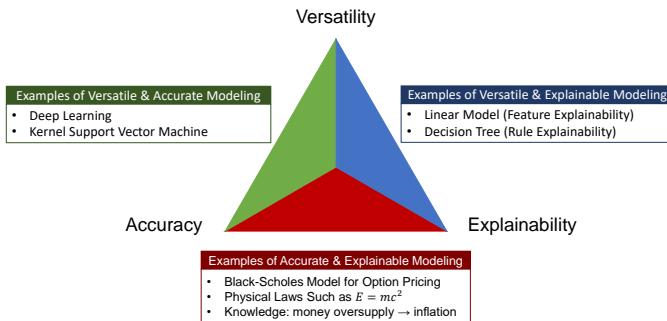


Figure 9: Impossible trinity of versatility, accuracy and explainability in modeling.

- Knowledge-driven AI differs from the data-driven AI which heavily depends on large volumes of data samples and thus is appropriate for investment strategies with large breadth such as high-frequency trading or stock cross-sectional trading. It is an important complement to data-driven AI techniques such as deep learning (illustrated in Figure 10 using Bayes’ theorem). In this paper, we introduce knowledge graph which represents knowledge with a network structure composed of entities and relations, and stores knowledge with semantic triples. A knowledge graph of financial behaviors and events could be analyzed and inferred for investment decisions using symbolic reasoning and neural reasoning techniques. This implies potential applications to those invest-

ment scenarios with low trading frequency but intensive fundamental information in collection and analysis, including value investing and global macro investment.

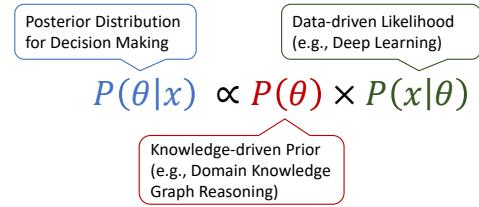


Figure 10: Complementary function of data-driven AI and knowledge-driven AI in decision making.

## 2. Automated AI for Quant 4.0

Automated AI for Quant 4.0 covers the automation of the full quant pipeline. In this section, we will first give an overview of the pipeline and then introduce how to upgrade it to an automated AI pipeline.

### 2.1. Automating Quant Research Pipeline

#### 2.1.1. Traditional Quant Pipeline

Over decades of development, quant research has formed a standard workflow as shown in Figure 11 (blue part). This workflow consists of a number of modules, including data preprocessing, factor mining, modeling, portfolio optimization, order execution, and risk analysis.

- Data preprocessing is usually the first step in quant research. Original raw data may have many issues. Firstly, financial data usually have missing records, more or less. For example, in technical analysis, you may not receive price data at some time points due to packet loss during communication, or you may miss the price data on some trading days because of stock suspension. Similarly, in fundamental analysis, you may miss part of financial statement data since they are not reported on time. Although conventional statistical data imputation methods could be used to estimate and fill in missing records, we must avoid using future information in the imputation process. Secondly, financial data contain extreme values and outliers which may come from misrecording, data storage issues, data transfer issues, or extreme markets, and these outliers may lead to risky biases in investment decisions. Outliers could be eliminated by data winsorization methods [43] which limit extreme values in a certain percentile range, but we have to notice that some outliers are actually strong signals for quant trading rather than noise, and must differentiate the two during data preprocessing. Thirdly, many financial data, such as news event data, have low data coverage and irregular updating frequency. We must align these types of data with high coverage and regular frequency such as quotes data for the convenience of downstream factor mining and modeling tasks. Fourthly, different data features have quite different scales in value range and thus some “large” features may dominate “small” features in modeling.

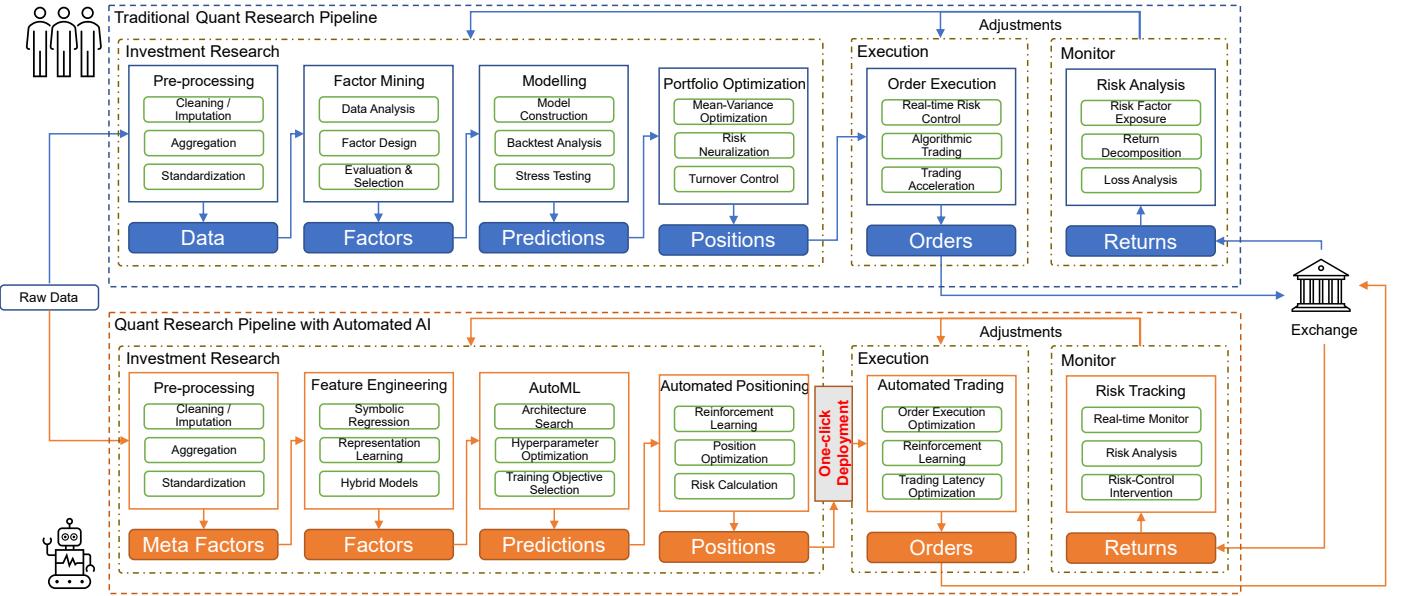


Figure 11: A prototypical workflow of quantitative investment with comparisons between the current quantitative investment system (manual, upper blue part) and AI investment engineering (automated, lower orange part).

Therefore, data standardization methods are used to normalize the range of features. We have to take care of the way to standardize the data in order to reduce information loss.

- Factor mining is a task of feature engineering [44], which uses financial and economic domain knowledge to design, search, or extract factors (features for downstream modeling) from raw data. Usually, a larger factor value indicates a more significant trading signal. The motivation of factor mining is to find those signals from raw data for market prediction and improve the quality of downstream modeling tasks. Traditionally, financial factors could be represented as either algebraic formulas or rule-based expressions. Let's take a simple stock alpha factor as an example.

$$\text{factor} = -\text{ts\_corr}(\text{rank}(close), \text{rank}(volume), 50) \quad (5)$$

where the `ts_corr()` function computes the correlation of daily close price and volume along time using the data from the previous 50 trading days, representing how similar the trend of `close` time series and `volume` time series are. The `rank()` function maps the values in a cross-section to their orders and normalizes them to the range of  $[-1, +1]$  evenly according to their descending order, in order to remove the effect of extreme values. This factor prefers to select those stocks when their price and volume move in opposite directions, and the idea behind it is based on the assumption that a price trend can not sustain without the support of volume growth. Traditionally, factor mining is a labor-intensive job. Most quant researchers can only discover a limited number of “good” factors in a year. Different financial institutions have different definitions or criteria for a “good” factor, but most of them consider a few common aspects, such as return, Sharpe ratio, maximum drawdown, turnover rate, and correlation with other factors [41], and moreover, some institutions require

the factors must be meaningful, understandable and explainable in economics.

- Modeling is a task to build statistical or machine learning models using factors and to predict market trends, asset price movements, best trading times, or most/least valuable assets. Usually, prediction models are evaluated through back-test experiments which simulate the prediction and trading process using historical data. Choices of models must consider a number of factors, such as prediction accuracy, model explainability, model robustness, and computational complexity, and find the best tradeoff according to the ultimate goal. In particular, we must notice that most statistical or machine learning models are not specifically developed for financial time series, and we have to adjust the application of these models in quant modeling. Firstly, financial time series prediction must avoid using future information, and thus we prefer forward-validation [45] (splitting the time series into training, validation, and test blocks over time) rather than cross-validation in model hyperparameter optimization. Secondly, financial time series are usually significantly nonstationary, far from the *independent and identically distributed* (i.i.d.) assumption required by many machine learning models. Therefore, data transformation is needed to make the data distribution closer to i.i.d. and if possible, look more like a normal distribution. Thirdly, market style moves over time and it results in the shift of financial time-series distribution. Therefore, periodic model retraining is necessary for keeping the model adapted to market style variation.
- Portfolio optimization aims to find the optimal asset allocation to expect high return and low risk simultaneously. While prediction models tell us what or when to buy/sell, portfolio optimization specifies how much to buy/sell. A typical portfolio optimizer attempts to solve a constrained con-

vx quadratic programming problem which is extended from Markowitz’s efficient frontier theory.

$$\begin{aligned} & \max_{w_t} w_t^T r_t \\ \text{subject to } & w_t^T \Sigma w_t \leq C_1 \\ & |w_t - w_{t-1}| \leq C_2 \\ & 0 \leq w_{i,t} \leq C_3 \leq 1, \text{ for } i = 1, 2, \dots, n \end{aligned}$$

where  $r_t = (r_{1,t}, r_{2,t}, \dots, r_{n,t})^T$  is the returns of  $n$  assets (e.g., stocks) at time  $t$ , and  $w_t = (w_{1,t}, w_{2,t}, \dots, w_{n,t})^T$  is the corresponding position weights (percentages of capital allocation).  $C_1, C_2, C_3$  are positive constraint bounds.  $\Sigma$  is the volatility matrix of the  $n$  asset returns at time  $t$ . The target function tries to maximize the portfolio return and control the upper bound of risk and turnover rate (to reduce transaction cost). The key in this optimization problem is how to estimate the volatility matrix  $\Sigma$  whose estimation is usually unstable if historical data is not long enough, and in this case dimension reduction tricks such as regularization and factorization can be helpful to improve estimation robustness.

- Order execution is a task that buys or sells orders with optimal prices and minimal market impact. Usually buying (or selling) a big order at one time will push the price of the target asset in a harmful direction (market impact by this big order), and therefore increase the trading cost. A widely used solution is order splitting, which divides a big order into a number of small orders to reduce market impact. Algorithmic trading provides a series of mathematical tools for order splitting, from the simplest time-weighted average price (TWAP) and volume-weighted average price (VWAP) to the complicated reinforcement learning methods [46] in which optimal order flow is modeled as a (partially observable) Markov decision process.
- Risk analysis is an indispensable task for quant research and quant trading. We must discover and understand every possible risk exposure in order to better control unnecessary and harmful risks in quant research and trading [47]. In the monitor module, risks are measured in real-time and these messages and analysis are sent back to help quant researcher improve their strategies. The most popular risk model in stock trading is the BARRA model [48] which decomposes portfolio volatility into the exposures of a number of predefined risk factors, including style factors (size, growth, liquidity, etc.) and industry factors. However, the BARRA model could explain only about 30% of total volatility, leaving the risk hidden in the remaining 70% part still unknown.

### 2.1.2. Automated AI Quant Pipeline

The automated pipeline of Quant 4.0 is shown in Figure 11 (orange part), where modules in the pipeline are automated by applying state-of-the-art AI technology. In the following part of this section, we will concentrate on three core modules in the automated pipeline.

1. Automated factor mining (§2.2) applies automated feature engineering techniques to search and evaluate significant fi-

nancial factors generated from meta factors. We will introduce popular search algorithms and demonstrate how to design the algorithmic workflow.

2. Automated modeling (§2.3) applies AutoML techniques to discover optimal deep learning models, automatically selecting the most appropriate models and the optimal model structures, and tuning the best hyperparameters;
3. One-click deployment (§2.4) builds an automated workflow to deploy trained large models on trading servers with limited computing power. It executes model compression, task scheduling, and model parallelization automatically, saving a lot of labor and time for tedious “dirty” work.

## 2.2. Automating Factor Mining

Feature engineering for quant refers to the process of extracting financial factors from original data, on which effective pattern recognition is difficult due to their intrinsic noisiness [49, 50, 51]. Traditionally, financial factors with significant “alpha” are explored and developed by quant researchers manually, they rely on professional domain expertise and comprehensive knowledge of financial markets. Although some financial institutions started using random search or generic programming algorithms, these techniques are mainly used as small-scale auxiliary tools to help improve the productivity of quant researchers. In Quant 4.0, We propose to automate the factor mining process by formulating feature engineering as a search problem and utilize corresponding algorithms to generate factors with satisfactory backtest performance at scale. In particular, according to their expression form, we classify factors as 1) symbolic [52] factors which are symbolic equations or symbolic rules, and 2) machine learning factors which are expressed by neural networks, and we will elaborate on the details in the following part of §2.2.

### 2.2.1. Symbolic Factors

Symbolic factor mining can be regarded as a special case of symbolic regression [56]. Traditional symbolic regression algorithms usually generate a large number of symbolic expressions from given operands and operators and select the symbolic expressions that maximize the predefined objective function. Figure 12 shows a framework for automated symbolic factor mining, which consists of four core parts: operand space, operator space, search algorithm, and evaluation criterion.

- Operand Space defines which meta factors could be used for factor mining. Meta factors are fundamental components for factor construction. Typical meta factors include basic price and volume information, sector categorizations, basic features extracted from limit/order books, common technical indices, basic statistics from financial analysts, important signals from financial reports, announcements and other research reports from public companies, sentiment signals from investor emotions [57, 58], etc.
- Operator space defines which operators could be used in the factor mining process. For example, in cross-sectional stock

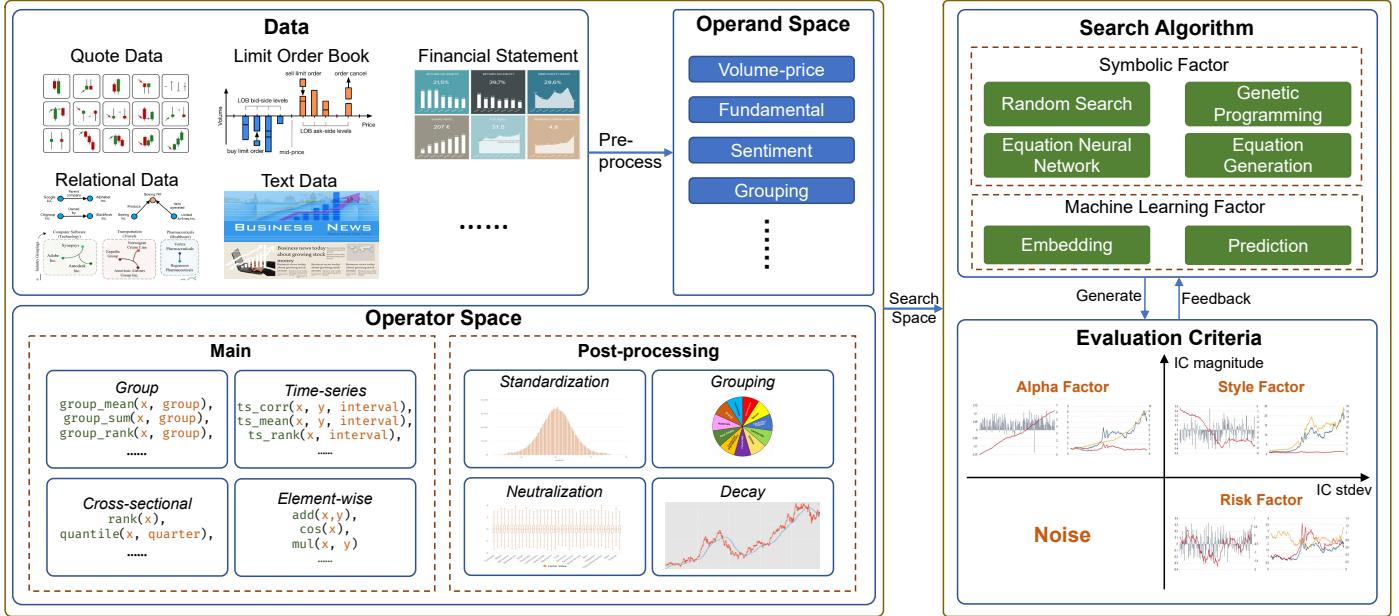


Figure 12: An example factor mining pipeline. The search space is defined by operators and meta-factors, where meta-factors are extracted from raw data in various forms. The search space is explored by search algorithms that are discrete or continuous. The evaluation module provides feedback to search algorithms based on certain criteria that serve as guidance for the next search iteration. Part of this figure is cited from [53, 54, 55].

selection, the operators could be classified as main operators for constructing symbolic factors and post-processing operators for standardizing the factors for different trading environments. Main operators could be classified further as element-wise operators such as  $\sqrt()$  and  $\log()$ , time-series operators such as  $ts\_rank()$  and  $ts\_mean()$  which compute the rank order and mean along each stock respectively, cross-sectional operators such as  $rank()$  and  $quantile()$  which compute the rank and quantile along the cross-section at a specific trading time, and group operators such as  $group\_rank()$  which compute rank order in each group (e.g., industry or sector) respectively. Post-processing operators are used to “fine-tune” the generated factors. Typical post-processing operators are standardization operators such as winsorization for outlier clipping [43] and normalization for unifying data range, neutralization operators for risk balancing, grouping operators for restricting the universe of stock selection, and decay operators for controlling turnover rate so as to reduce transaction cost.

- Search algorithms aim to search and find effective or qualified factors as efficiently as possible. A simple way to generate new factors is the Monte Carlo (MC) algorithm which randomly picks the elements in the operand and operator spaces and generates a symbolic expression tree recursively. Unfortunately, the search time may grow exponentially with the length and complexity of the generated formula, and push us to consider more efficient alternatives. The first option is Markov-chain Monte Carlo (MCMC) algorithm [59], which generates factors in sampling with importance way from a posterior distribution [60], and thus it is more efficient than MC. The second option is genetic programming [61], which is a special evolutionary algorithm for sampling and optimiz-

ing tree-type data. The third option is about gradient-based methods such as neural networks, which approximate the discrete symbolic formulas with continuous nonlinear functions and search along the gradient direction, significantly more efficient than random search.

- Evaluation criteria measure the quality of factors found by search algorithms. The performance of the generated factors is evaluated using backtest experiments. Typical evaluation criteria include information coefficient (IC), information ratio based on information coefficient (ICIR), as well as annualized return, maximum drawdown, Sharpe ratio, and turnover rate. In addition, it is very important to keep information diverse among factors by filtering out redundant factors which highly correlated with other factors.

Due to their importance in factor mining, we introduce about two types of search algorithms in detail.

- Genetic programming (GP) [64] (Figure 13), an extension of genetic algorithm [65], is a metaheuristic algorithm for searching tree-structured symbolic factor expressions. In an algorithmic loop, GP starts from a number of initial factors, and it uses an evolutionary mechanism to produce the next generation of factors, aiming to improve factor performance measured by the fitness function. There are two types of evolutionary mechanism in GP: *mutation* which replace a node randomly with another operand of an operator, and *crossover* where two trees swap their subtrees randomly. In each iteration, all factors are evaluated using IC or alternatives and only the best-performing factors are kept. This process is repeated until convergence.
- Neural symbolic regression utilizes gradient information to accelerate the search process. Neural networks are used to

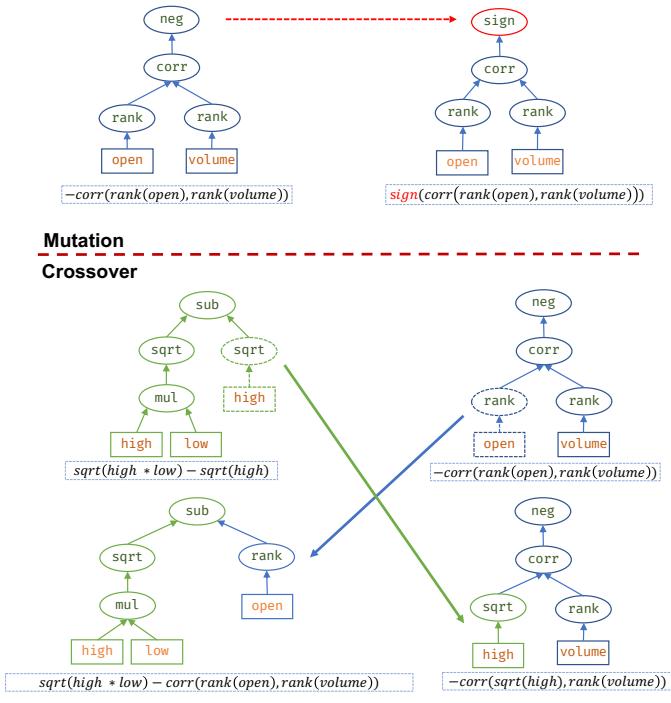
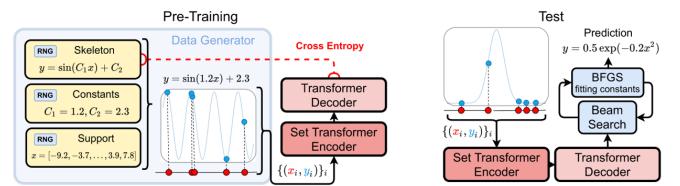


Figure 13: Illustrations of two evolutionary mechanism used in genetic programming.

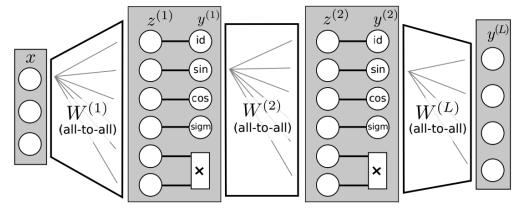
learn a continuous and nonlinear function to approximate those discrete symbolic expressions and use this function to generate new formulas. We introduce two works about neural symbolic regression. The first paper [62] (Figure 14a) builds a transformer generative model from a number of existing symbolic expressions. In the training stage, a special transformer model (called set transformer [66]) encodes the formulas in the training set into embedded vectors, and they are delivered to a transformer decoder to update symbolic expressions in an autoregressive way using beam search, and this process is repeated until convergence. The generative model is trained by minimizing the cross-entropy loss between the generated expression and the original one. In the test stage, the trained model is used to generate new symbolic expressions. The second paper [63] (Figure 14b), designed a new neural network specifically for expressing symbolic formulas. In particular, the activation functions in this network are replaced with symbolic operators such as  $\sin(\cdot)$  and  $\sqrt{(\cdot)}$ . This special neural network has the flexibility to generate almost all formula expressions need to use in factor mining.

### 2.2.2. Machine Learning Factors

Symbolic factors have their advantages in simplicity and understandability, and are thus widely used in practice. However, their representation ability is limited by the richness of operands and operators. Machine learning factors, on the other hand, have more flexibility in representation to fit more complicated nonlinear relationships [67], and thus they have the chance to perform better in market prediction. In particular, mining machine learning factors [68, 69, 70, 71] is a process to fit neural networks, where gradients provide the optimal direc-



(a) Neural symbolic regression in a sequence generation manner [62].



(b) Neural symbolic regression that directly uses the neural network as symbolic expressions [63].

Figure 14: Illustrations of neural symbolic regression algorithms.

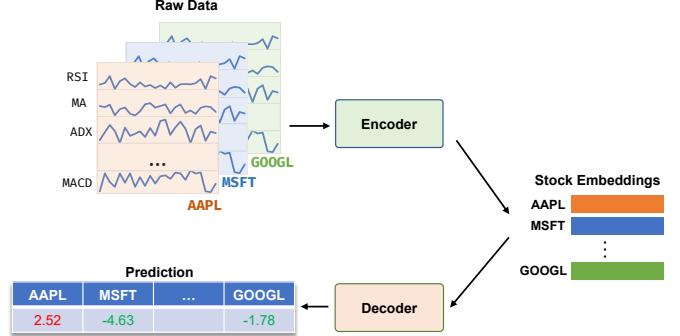


Figure 15: Illustration of the encoder-decoder architecture used in stock prediction. Both embeddings and predictions can be used as factors.

tion for fast search of solutions. As shown in Figure 15, most deep neural networks for stock prediction follows the encoder-decoder architecture [72], where the encoder maps meta factors to a latent vector representation and the decoder transforms this embedding to some outcome such as future return [73]. In fact, not only the final outcome, but also the embedding itself could be used as a (high-dimensional) machine learning factor [74], and further applied to various downstream tasks.

Machine learning factors have some limitations as well. Firstly, they are usually hard to interpret and understand because of the black-box nature of machine learning. Secondly, gradient search used by neural networks may be stuck at some local optima and result in model instability problems. Finally, neural networks may suffer more serious overfitting due to their flexibility, and this situation gets worse in quant because data are extremely noisy.

### 2.3. Automated Modeling

The automation of statistical machine learning such as SVM, decision tree and boosting has been extensively researched. A simple and direct automation method is the brute-force enumeration of all possible configurations, each including the choice

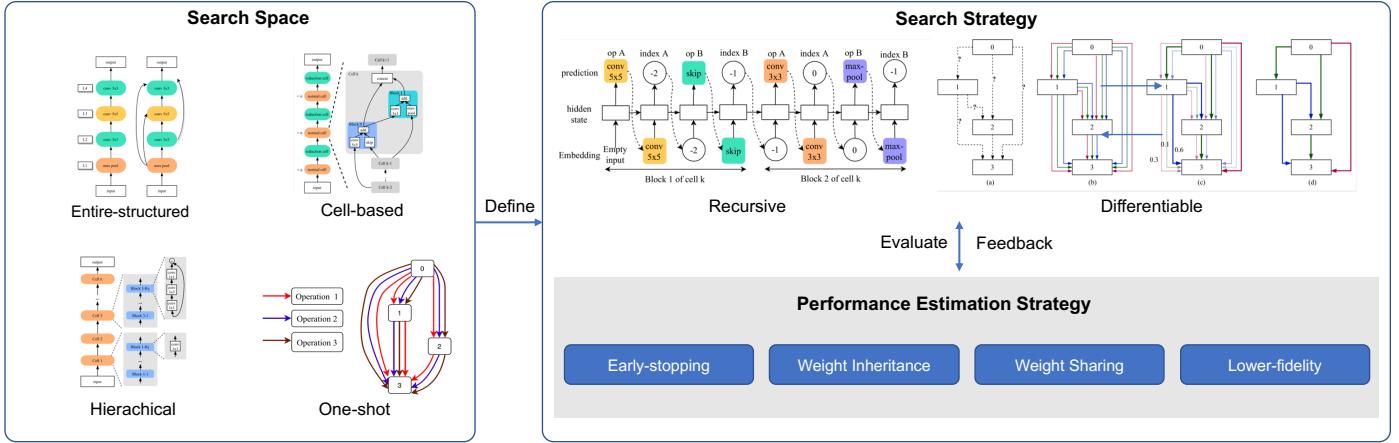


Figure 16: The automated modeling pipeline for architecture search. The structure of this figure is adapted from [75]. Illustrations of search spaces and search strategies are cited from [42, 76].

of machine learning algorithms and the corresponding hyperparameters (Figure 17).

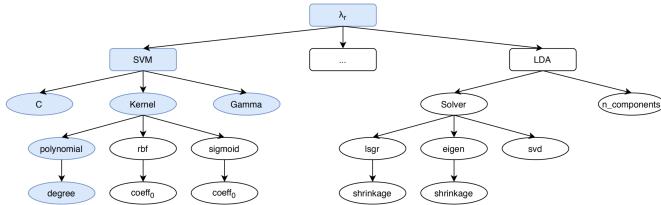


Figure 17: Illustration of early-stage automated machine learning based on brute-force search of algorithms and hyperparameters. Figure is cited from [77].

In this article, we focus on the state-of-the-art deep learning automation problem, which is more complex due to the end-to-end property and network architecture issue in modeling. The configuration of a deep learning model consists of three parts: architecture, hyperparameters, and objectives, and they jointly determine the final performance of the models. Traditionally, these configurations are tuned manually. In Quant 4.0, they are searched and optimized using various AutoML algorithms. A standard AutoML system needs to answer the following three questions: what to search (i.e., search space §2.3.1), how to search (i.e., search algorithm §2.3.2), and why to search (i.e., performance evaluation §2.3.3).

### 2.3.1. Search Space

Search space is designed for the three configuration settings that need to be optimized in an automatic way.

- **Architecture** configures a network structure. For example, the architecture of a multi-layer perceptron is specified by the number of hidden layers and the number of neurons at each layer. The architecture of a convolution neural network needs to consider more configurations such as the number of convolution kernels as well as their strides and receptive fields. The architecture of large-scale models such as Transformer is composed of a number of predefined blocks (e.g. self-attention blocks, residual blocks) linked together.

As discussed above, architecture is complex and may have a hierarchical structure at different scales. Accordingly, the search space can be defined at various granularities, ranging from low-level operators such as convolutions and attentions to high-level modules such as LSTM cells. Early search algorithms run on the finest granularity and optimize the low-level structure of the neural network [78, 79]. Such a search process is flexible in network structure but inefficient in incorporating prior knowledge and abstraction. One solution is to assume a hierarchical structure in network architecture. Specifically, at a high level, the network is designed to be a graph of cells (a.k.a. blocks/motifs [42, 80]), each of which is a subnetwork. Many cells share the same internal structure at a low level in order to reduce the computational cost. Cell-based search algorithms [81, 82] need to find both high-level structures between cells as well as low-level structures within the cells.

- **Hyperparameter** controls the overall training process. For example, learning rates determines the step size moving towards a minimum of a loss function. A smaller learning rate is more accurate in solution but slower in convergence. The batch size determines the number of samples involved in a batch for gradient estimation, which also has an influence on training efficiency and stability. The search space for hyperparameters is simpler than that for architecture since most hyperparameters are continuous (e.g., learning rate) or approximately continuous values (e.g., batch size).
- **Objective** specifies the loss functions and labels used for training models. The loss function is the key component of machine learning models since it provides a goal towards which a model should be trained. Besides classic loss functions such as mean square loss and cross-entropy loss, new loss functions specifically designed for quant tasks can be also selected. Labels define the “ground-truth” target the model aims to fit. For example, either price raise/fall or future returns in different holding time windows can be considered in the search space.

### 2.3.2. Search Algorithm

Given the search space, we could use search algorithms to find the best model configuration. Table 2 lists various types of search algorithms and their corresponding tasks: network architecture search (NAS) [75], hyperparameter optimization (HPO) [83] and training objective selection (TOS).

Table 2: Search algorithms and their applicable search targets.

Algorithm \ Target	NAS	HPO	TOS	References
Grid/Random Search		✓	✓	[84, 85]
Evolutionary Algorithm	✓	✓	✓	[86, 87, 88, 89, 90]
Reinforcement Learning	✓	✓		[91, 81, 82, 92]
Bayesian Optimization	✓	✓		[93, 94, 95, 96]
Gradient-based Method	✓	✓		[97, 98, 99, 100, 101]

- Grid search is a brute-force algorithm that searches on a grid of configurations and evaluates all of them. It is a good choice when the search space is small due to ease of implementation and parallelization [84]. However, most NAS and HPO problems in deep learning have extremely large search spaces and grid search can not scale well for them. Moreover, grid search is used more popular in HPO and TOS than in NAS whose search space is difficult for grid layout except enumerating all possibilities.
- Random search generates a number of candidate configurations using some stochastic sampling mechanisms, such as Monte Carlo or MCMC. It is very straightforward to implement and parallelize (mainly for independent sampling mechanisms such as Monte Carlo sampling or importance sampling). Random search is very flexible and can be used for NAS, HPO, and TOS. Although random search is usually faster than grid search [84], it is still difficult to handle high-dimensional search space as the number of potential configurations grows exponentially with the number of hyperparameters.
- Evolutionary algorithm is an extension of random search. It utilizes evolution mechanisms to improve model configurations iteratively. It encodes the architecture of network networks as a population and performs the evolution steps on them to improve the model iteratively. Specifically, the models are first encoded according to their underlying computation graph. Then, a set of pre-defined evolutionary operators are applied to the encoded models, including architectural modifications such as inserting or deleting several operations and adding skipping connections, as well as hyperparameter-related operations such as learning rate adjustment. At each iteration, the best-performing models are selected via tournaments and combined via mutation and crossover operations to form the next generation. Evolutionary algorithms inherently support weight inheriting among generations, which helps accelerate the convergence in training and increase the searching efficiency.
- Reinforcement learning models the architecture search problem as a Markov decision process. In each step, an RNN controller chooses an action to sample a new architecture and the corresponding deep neural network model is trained. Then the performance of the model evaluated on the validation set is used as a reward which is forwarded to compute the policy gradient and update the RNN controller. This loop is iterated until convergence. The reinforcement learning framework is very universal for most optimization problems and it could be used for NAS, HPO, and TOS.

troller chooses an action to sample a new architecture and the corresponding deep neural network model is trained. Then the performance of the model evaluated on the validation set is used as a reward which is forwarded to compute the policy gradient and update the RNN controller. This loop is iterated until convergence. The reinforcement learning framework is very universal for most optimization problems and it could be used for NAS, HPO, and TOS.

• Bayesian optimization explores the search space more efficiently by leveraging surrogate models to approximate the objective function that couldn't be expressed explicitly. Specifically, for a black-box objective function for HPO, Bayesian optimization initializes a prior distribution using a surrogate function such as Gaussian process or tree-structured Parzen estimator. Then it samples new data points from the prior distribution (with importance) and calculates their values using the underlying objective function. Given these new samples and prior, the posterior function can be calculated and is used as an updated surrogate function to replace the original prior function. This process is repeated until the optimal solution is found. Traditionally, Bayesian optimization is used for continuous search tasks such as HPO, but recent works have extended it to NAS tasks as well.

• Gradient-based methods is very efficient when the gradient of the objective function exists. However, for NAS, the search space is discrete and couldn't define a gradient directly. One solution is to “soften” the architecture and define an over-parameterized “super-architecture” which covers all possible candidates and is differentiable. A typical gradient-based NAS method is DARTS [97] which constructs an over-parameterized network where all types of candidate operations are present on the computation graph. The resulting value is the weighted sum of the results of all the operations, where the weights are the softmax values of a parameterized probability vector. Both model parameters and architectural parameters are trained via a bi-level optimization problem. In the inference process, the architecture and hyperparameters with the highest probability are selected. DARTS is substantially faster than random research and reinforcement learning in NAS and HPO tasks.

### 2.3.3. Accelerating Evaluation

The computational cost of automated model search comes from two parts: search algorithm and model evaluation, and the latter is usually the bottleneck of the computation because it is very time-consuming to train a deep neural network until convergence under a given configuration. Several methods are introduced in previous research to address this issue. Firstly, the training process of neural networks can be early-stopped before convergence to reduce the computational time for evaluation [81]. Secondly, the model can select fewer samples to accelerate the training process [94]. Thirdly, warm-start model training can be used to leverage the information from existing selected models [102] or inherit the information from an over-parameterized “parent” model [103, 97, 98] to accelerate the search loop.

## 2.4. Automated One-click Deployment

Model deployment is the task of transferring the developed model from offline research to online trading. It is not only simply transferring code and data, but also synchronizing data and factor dependency, adapting trading server and system, debugging model inference, testing computing latency, etc. In the following part, we focus on one important problem in model deployment: how to accelerate deep learning inference for high-frequency trading and algorithmic trading scenarios. We propose an automated one-click deployment solution utilizing techniques such as model compilation [104] and model compression [105, 106] to realize inference acceleration [104, 105, 106]. The former makes the inference faster without changing the model itself, and the latter seeks smaller and lighter alternative models to save inference time.

### 2.4.1. Acceleration by Model Compilation

At the development stage, deep learning models' functionality is the top priority for the underlying framework which implements the computations. Hence, at this stage, the framework strictly maps all the operations to the computation graph. However, such direct mapping introduces large room for optimization at the deployment stage where the computations are fixed. Therefore, the model's computation can be greatly simplified and adapted to hardware features without hurting its original semantics. Such optimization is one of the major topics in deep learning compilers [107, 108, 109], which can be categorized as *front-end optimizations* and *back-end optimizations*, which work on high-level and low-level intermediate representations (IRs) for deep learning models respectively. Following the summary in [104], we will briefly introduce relevant optimization techniques.

Front-end optimization, as illustrated in Figure 18a, focuses on simplifying the structure of the computation graphs. For example, algebraic simplification techniques such as constant folding [110] and strength reduction [111] convert expensive operations into cheaper ones via transformation or merging. Common subexpression extraction (CSE) [112] techniques identify repeated nodes in the computation graph and merge them into one node to avoid duplicate computations.

Back-end optimization, as illustrated in Figure 18b, is performed with an emphasis on the features of hardware architectures, such as locality and memory latency. For example, pre-fetching techniques [113] load data from main memory to GPU before they are needed, and speed up fetch operations. Loop-based optimizations [114] reorder, fuse and unroll operations inside loops to enhance locality among neighboring instructions. Memory latency hiding [115] techniques aim to increase instruction throughput so as to mitigate the problem of high latency in accessing memory. Parallelization techniques such as loop splitting [116], automatic vectorization [117] and loop skewing [118, 119], can also be applied to maximize the parallelism provided by modern processors.

### 2.4.2. Acceleration by Model Compression

Model compression aims to reduce model size for inference acceleration while minimizing drops in performance. In this

way, the compressed model can be regarded as an approximation of the original model. Generally speaking, model compression can be performed at both micro- and macro-level, where the former focuses on the precision of individual model parameters and the latter focuses on simplifying the overall model structure.

At the micro-level, pruning and quantization techniques can be applied to reduce both the number of parameters and the bit size of the individual parameters. Model pruning [120], as shown in Figure 19a, removes unimportant connections and neurons in neural networks that have little influence on the activation of the neural. The identification of candidate parameters is usually based on their weights, where those with smaller weights are considered for pruning. Model quantization [121], as shown in Figure 19b, converts the parameters from floating-point numbers to low-bit representations. Specifically, a codebook is constructed to store the approximated values of the original parameters according to the distribution of all parameter values. The parameters are then quantized according to the codebook and thus the bit size for the parameters is reduced. Due to the inevitable performance drop induced by precision reduction, the compressed model is usually re-trained to approach its original performance.

At the macro-level, the model can be significantly compressed into a smaller model with simpler architectures via knowledge distillation [122] and low-rank factorization [123, 124]. Knowledge distillation (Figure 19c) compresses a model by transferring useful knowledge from the original large model (called the teacher model) to a small and simple model (called the student model) with minimal knowledge loss. Low-rank factorization techniques (Figure 19d) assume the sparsity of model parameters and then split the parameter matrix of the original neural networks into products of low-rank matrices [123], and thus reduce the model complexity.

## 3. Explainable AI for Quant 4.0

XAI [126, 127], as an attractive research direction for decades, is critical to the trustworthiness and robustness of AI models. In the case of quant, improvement in the explainability of AI can make the decision process more transparent and easy to analyze, providing useful insights to researchers and investors and discovering potential risk exposures. In this section, we will discuss how to leverage XAI in Quant 4.0. §3.1 introduces common XAI techniques and §3.2 connects these techniques to real quant scenarios.

### 3.1. Overview of Explainable AI

XAI is an emerging interdisciplinary research area covering machine/deep/reinforcement learning, statistics, game theory and visualization. Here we focus on three types of XAI: model-intrinsic explanation [128], model-agnostic explanation [129], and causal explanation. [130].

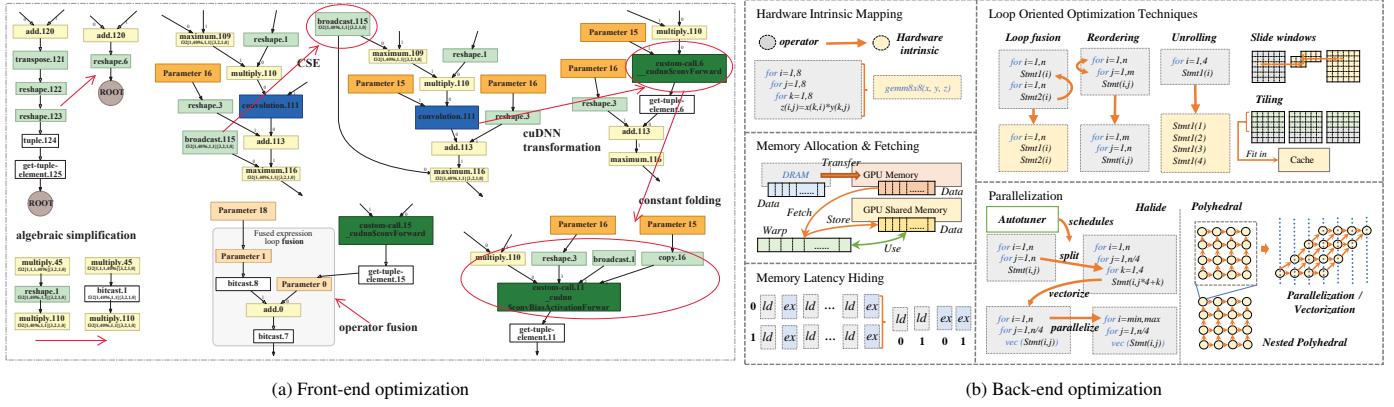


Figure 18: Deep learning compiler optimization techniques. Figure from [104]

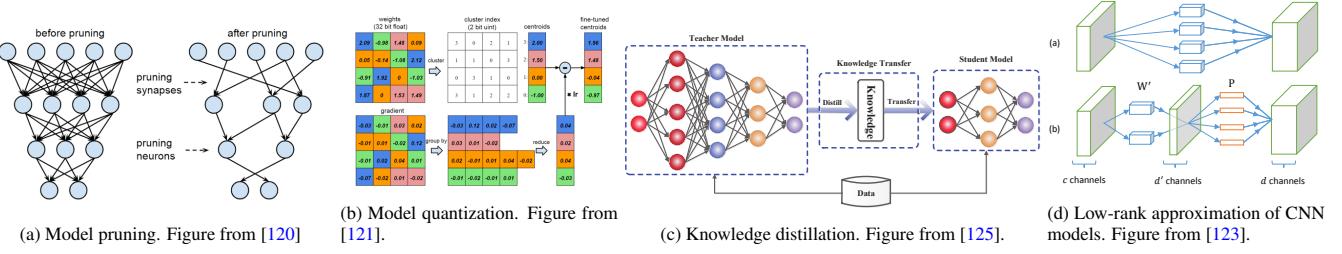


Figure 19: Model compression techniques

### 3.1.1. Model-intrinsic Explanation in XAI

Risk control and management is the top priority of financial industry. When AI models are deployed in real-world applications, their decision process is usually required to be transparent by regulatory authorities for the safety of transactions. Moreover, model-intrinsic explainability is the requirement of many large financial institutions such as banks and insurance companies.

A machine learning model is intrinsically explainable if its internal structure or mechanisms can be easily explained. Some machine learning algorithms such as linear models and decision trees are inherently explainable, as many other algorithms such as deep neural networks and kernel learning methods (SVM, Gaussian process, etc.) are black-boxes with poor explainabilities. Figure 20 illustrates many popular machine learning methods arranging along their general performance and explainability. We can see The increase in model-intrinsic explainability usually leads to the decrease in model's prediction performance, and therefore the selection of machine learning algorithms is essentially a trade-off between explainability and performance. We briefly introduce a few typical machine learning methods in terms of explainability and predictive performances and discuss their applicable scenarios.

- **Linear Models**, such as linear regression, logistic regression, linear discriminant analysis, linear SVM and addition model, is a family of methods where features or transformation of a group of features are in an additive form and thus the performance of final prediction can be easily deposed to the effects from individual features or feature groups. Therefore, linear models are intrinsically understandable and explainable. For

example, linear regression explicitly encodes the importance of each feature in their corresponding regression coefficients (assuming every feature is normalized to eliminate the effect from scales and units). Although linear models are easy to explain, they are suffering the poor prediction performance since they couldn't encode complicated nonlinear relationships between prediction outputs and features.

- **Rule-based Learning** is another type of easy-to-explain methods. Different from a linear model which fits a linear decision boundary, a rule-based learning method fits a stepwise decision boundary characterized by decision rules combining a number of logical expressions. Examples of rule-based learning include decision tree [134] and symbolic regression, as well as ensemble models such as random forest [135] and boosting [136, 137, 138]. Rule-based learning models are intrinsically explainable decision rules are close to the logical thinking process of human being. However, to better fit the training data and improve prediction performance, the decision rule is usually complicated, and it reduces the explainability and increases the risk of overfitting.
- **Ensemble Learning** combines multiple machine learning algorithms to achieve better decision performance than single models. Typical examples of ensemble learning include random forest and boosted trees that combine multiple tree models and make predictions based on the aggregation of individual decisions. Although there is controversy, in this article, we classify mixtures of experts (MoE) [139] as an ensemble method as well. MoE combines multiple expert networks in parallel in a layer and decides which expert (or experts) par-

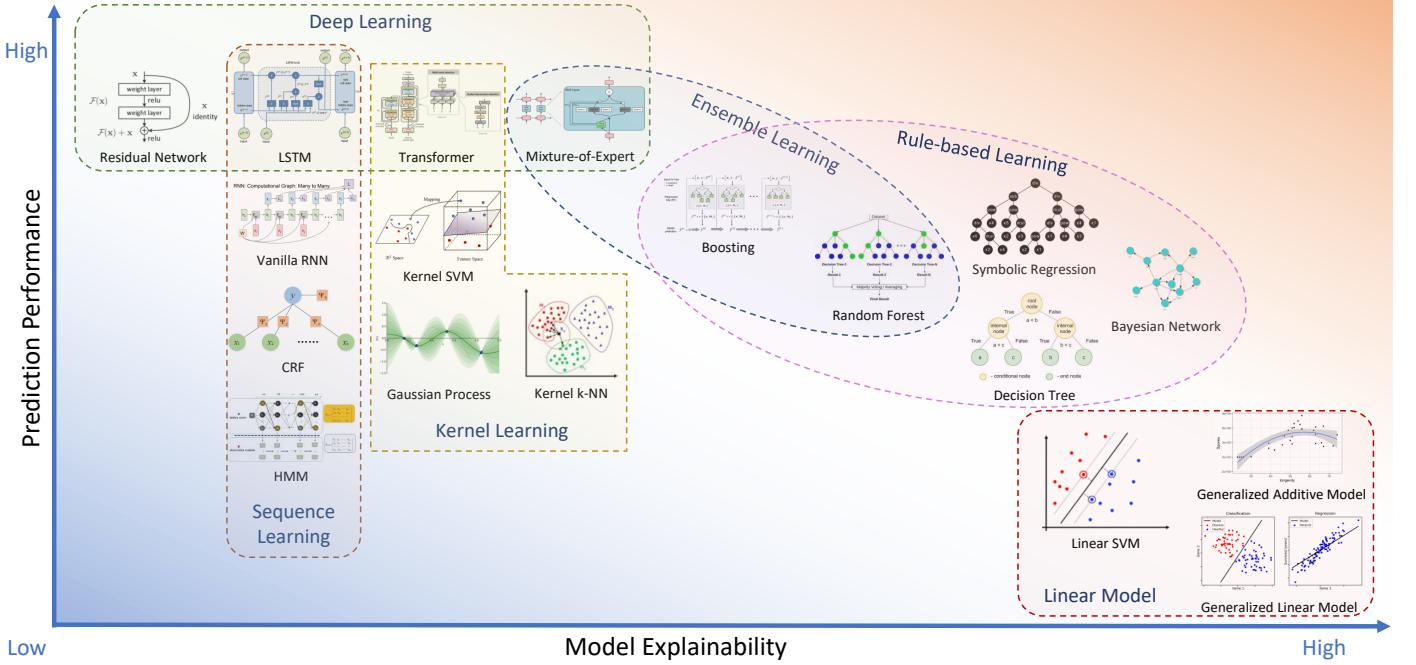


Figure 20: Comparison of popular machine learning algorithms according to prediction performance and model explainability. Part of this figure is cited from [131, 132, 133].

ticipates in the decision of a specific data point via a gating mechanism. Compared with other machine learning methods, ensemble learning provides high-level explainability by demonstrating the relative importance of single models or experts.

- Kernel Learning, also known as kernel method or kernel machine, is a family of nonparametric learning methods which make predictions by computing the similarity between samples. The similarity is characterized by a kernel function, which is a special inner product defined in a high-dimensional Hilbert space where original data samples are mapped [140]. For example, kernel SVM [141] transforms original positive/negative samples into another space where they can be easily separated using a linear decision boundary. In principle, kernel functions can be of arbitrary forms that satisfying the Mercer’s condition [142], and they determine the nonlinear relationships between inputs and outputs. Moreover, the idea of kernel functions is extended to the self-attention mechanism [143] used in neural networks such as Transformer [144]. Traditionally, we think the kernel trick improves the performance of models but weakens their explainability. From another point of view, however, the definition of kernel itself encodes the prior insight of users and could help understand the model.
- Sequence Learning refers to a family of machine learning methods that work with sequential data such as time series or sentences. They are widely used in speech recognition, languages understanding, DNA sequence analysis, and stock price prediction. Sequence learning methods characterize the underlying structure hidden in sequential data and discover implicit patterns. For example, hidden Markov model

(HMM) [145] assumes that the underlying structure is a homogeneous Markov chain determined by a transition matrix (or transition kernel for continuous state space) and assumes the observed sequence is randomly generated from this chain through emission probabilities. The transition probabilities and emission probabilities are estimated during model training. Although HMM is generally a blackbox model, its transition probability matrix provides some insight about autoregressive structure in prediction. Conditional random field (CRF) [146] extends the first-order Markov assumption of HMM and characterizes longer range time dependency using graphical model for probability modeling, and this extra flexibility usually brings better prediction performance for CRF. Recurrent neural networks (RNN) such as LSTM [147] and GRU [148] exhibit better performance in sequence prediction, but harder to explain their internal mechanism.

- Deep Learning usually has superior prediction performance [149] but its shortage in explainability is clear. Some special operators in deep neural networks such as convolution and attention provide partial and local explain about their mechanisms. For example, the attention layer in a Transformer neural network characterizes the relative importance of each position in a sequence with respect to other positions.

The model-intrinsic explainability for machine learning is always a contradiction with its prediction ability. However, before the appearance of brandnew machine learning model satisfying both high prediction accuracy and high explainability, we could rebuild and improve current machine learning methods. We could either starting from a explainable model such as linear or rule model and improves its prediction performance by incorporating more local nonlinear structures with better pre-

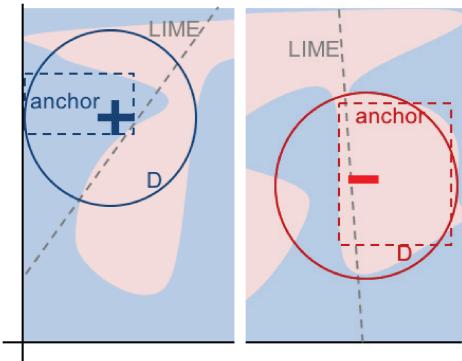


Figure 21: Illustration of LIME [151] and Anchors [152]. Figure cited from [152].

dictive power. For example, starting from a decision tree model, we could replace the decision rule in each node with a neural network decision module, and thus improve the model flexibility. As another example, starting from a deep learning network, we could also improve its partial explainability by incorporating a special layer identifying which important feature interacts more frequently.

### 3.1.2. Model-agnostic Explanation in XAI

To address the contradiction between performance and explainability, a suboptimal solution is to weaken the requirement and shift from model-intrinsic explanation to model-agnostic explanation. Following the idea in [150], model-agnostic XAI can be categorized as global methods (explanation applied to all samples) and local methods (explanation applied to part of samples). We elaborate these two concepts in the following content.

Global methods explain the characteristics of features with respect to all samples. These characteristics include the importance of features, the importance of feature sets, the interactive effect of features, and other high-order effects of features. There are various types of methods for estimating global feature importance.

- Feature marginalization methods estimate the importance of a specific feature or a specific feature set by marginalizing all other features in the model. Specifically, the importance of the first feature is calculated by integrating out all other features, and similarly we calculate the second feature, the third feature etc. For example, partial dependence plot (PDP) [136] computes the marginalized model function w.r.t. the features of interest, and it visualizes the corresponding feature importance. Accumulated local effect (ALE) plot [153] provides an unbiased estimate of marginal effects by considering the correlation between features with conditional distributions.
- Feature leave-one-out methods evaluate the importance of concerned features by comparing the difference of the model performance before and after leaving these features out of data. Specifically, the feature of a model can be left out by shuffling its values in samples [135, 154]. Leave-one-out methods can be extended to evaluate the interactive effects

of features as well. For example, based on the partial dependence function, H-statistic [155] is proposed to test for the interaction between features. Other alternative techniques for evaluating and visualizing feature interactions have also been proposed in [156, 157]. Besides, we can also perform functional decomposition [156] on the original model to explore interactions between all possible sets of features.

- Feature surrogate methods interpret the model by learning a globally explainable surrogate model [158] that approximates the original model.

Local methods explains the feature importance at sample level, i.e., how important a feature is for specific samples. Similar to partial dependence plot, we can draw the individual conditional expectation (ICE) plot [159] for each sample that illustrates the effect of the concerned features when the values of other features are fixed at specific values. To interpret a black-box machine learning model at a specific sample, we can learn a surrogate model in the vicinity of a data sample to explain the original model locally. Typical examples includes LIME [151] and Anchors Method [152]. In LIME (Figure 21), LASSO regression is used as the surrogate model to fit the samples randomly generated by perturbing the original samples around the specified one. In this way, the selected samples by this local LASSO model contribute most to the fitness of the specified sample. Analogous to LIME, anchors method learns the local surrogate model using a decision tree algorithm and interpret the original model at this local area using decision rules. Other local XAI methods include

### 3.1.3. Causal Explanation in XAI

Most statistical learning algorithms are intended to capture the correlations between input features and outcomes, which do not necessarily indicate the underlying causal relationships. In this way, models are prone to spurious correlations that lead to performance drop in face of distribution shift in data. This is especially the case in financial markets where the data are highly noisy and non-stationary, which makes it hard for models to avoid spurious correlations and keep stable performances across time. Therefore, causal explanations are needed in the financial context for explaining to human stakeholders the actual relationships that have been captured by models through training and used in inference. In the following, we will introduce several causality-related techniques that are widely used in econometrics and finance: Granger causality [40, 160], treatment effect estimation [161] and structural causal model [162].

Granger causality, as a weakened form of general causality, indicates that the lagged values of a time series is useful in forecasting another time series. Intuitively, a time series  $X$  is considered to be the Granger causality of another time series  $Y$  if taking the previous values of  $X$  leads to better predictions of  $Y$  than forecasting based solely on the historical values of  $Y$ . Granger causality indicates causal relationships between random variables evolving over time, but is determined based solely on statistics and ignores many other potential problems such as latent confounding effects. Statistical hypothesis tests can be conducted to examine the existence of Granger causal-

ity. For example, we can define the null hypothesis as two time series having no Granger causality and see if it can be rejected. We can also hypothesize the existence of Granger causality and check out its significance.

Treatment effect estimation techniques aim to measure the average treatment effect of treatment variables (i.e. model inputs) on outcomes (i.e. model outputs). To estimate the actual treatment effect, all the confounding effects need to be eliminated. Hence, treatment effect estimation can be regarded as estimating the actual causal effects between variables. Randomized controlled trials (RCTs) [163] can be adopted to eliminate confounding effects by setting variables other than treatment variables totally at random. Besides, propensity score [164] can be utilized to balance confounding effects between the treatment group and the control group. In practice, the propensity score is first estimated from data and then used for propensity score matching [165] or inverse propensity weighting [166]. The former matches each sample in the treated group with samples in the control group that have the same propensity score, and the latter adjusts the observed treatment effects with inverse propensity score for fair comparisons. Besides, instrumental variables [167] can also be applied to eliminate confounding effects by replacing the original treatment variables and error terms with instrumental variables that are correlated with treatment variables and have no correlation with the error terms.

A more thorough causal explanation can be expressed as structural causal model (SCM) [168]. An SCM is essentially a directed graph where the nodes represent variables of concern and the edges represent their causal relationships in between. A causal edge pointing from variable  $X$  to variable  $Y$  indicates that  $X$  is a cause of  $Y$ . Conditional probability distributions are usually associated with causal edges that quantify the actual causal effects between variables. And inference can be conducted based on the causal structure and conditional distributions to estimate the actual outcomes under specific conditions. In practice, problems related to SCM [169] can be categorized as *causal discovery* [170] which aim to find the structure of the causal diagram, and *causal inference* [171] which aim to quantitatively estimate the causal effects associated with given causal structures. In practice, structural causal model decouples the causal relationship among variables, such that under the same number of controlled experiments, SCM can handle more complicated causal relations involving more variables. The power of scale is the key factor that tells SCM from ATE.

### 3.2. XAI Scenarios in Quant 4.0

The XAI methods introduced in §3.1 can be applied to various scenarios in quantitative investment to provide insightful explanations. Practically, as financial data taken by deep learning models as inputs have three orthogonal dimensions, i.e. stock, time and factors, applications of XAI techniques can be categorized along these three dimensions, as shown in Figure 22. In the remainder of this part, taking the task of cross-sectional stock selection as an example, we will elaborate on prospective scenarios for XAI in quantitative investment from these dimensions respectively.

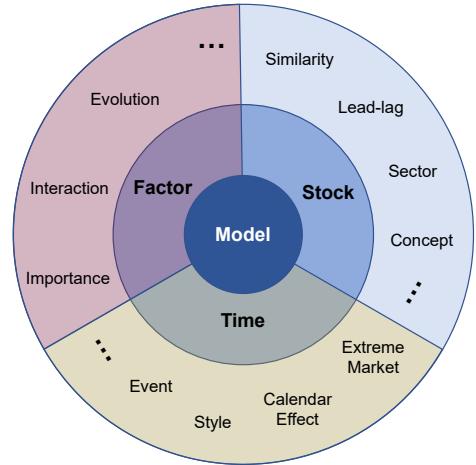


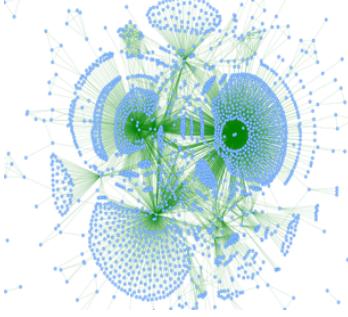
Figure 22: XAI from data dimensions.

#### 3.2.1. Stock

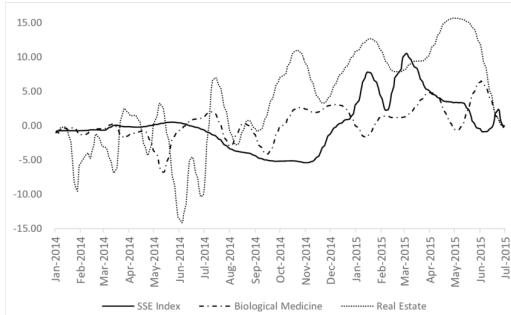
XAI along the stock dimension focuses on revealing the latent relationships among stocks that have potential influences on their future trends. These relations can be either pairwise or group-wise, explicit or implicit. In the following, we will introduce several specific problems along this dimension.

*Instrument similarity.* Financial instruments are not independent of each other. Instead, they are ubiquitously correlated with each other in many aspects (as shown in Figure 23a), and correlated instruments are expected to share common properties. In this sense, utilizing the relationships between financial instruments can bring advantages to our analysis and prediction over traditional methods which treat financial instruments individually. Besides, we can attain a better understanding of the relationship between stocks and the semantic meanings captured by the model via analysis of similarities between financial instruments in the embedding space. However, the challenge in analyzing the similarities between financial instruments lies in determining an appropriate similarity metric, which is expected to be effective enough to benefit the final predictions and also flexible enough to express arbitrary semantic information. This problem is closely related to metric learning [174, 175] and graph structure learning [176] from the perspective of AI. Specifically, a good similarity metric between the embeddings of pairs of financial instruments is first needed. Then, a graph structure can be constructed by computing an adjusted adjacency matrix based on the pairwise similarity, which can be utilized for data mining and visualized to provide further explanations.

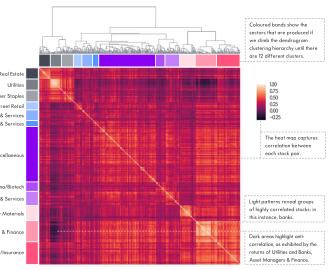
*Lead-lag effect.* Lead-lag effect describes the situation where the trend of a leading variable is followed by those of the lagging variables. In financial markets, lead-lag effects [177] widely exist and can be regarded as effective trading signals. Following lead-lag effects, investors can observe the trends (i.e. price going up/down) of the leading instruments and take corresponding positions on the lagging instruments before the same trends duplicate. Therefore, if investors can precisely identify lead-lag



(a) Stock similarity graph computed via return correlation.



(b) Lead-lag effect in Chinese stock market. Figure from [172].



(c) Stock correlation matrix. Potential clustering can be visualized from this matrix. Figure from [173].

Figure 23: XAI in stock.

effects [178, 179] from market trends, they will win an advantage over other market participants. However, it is not a trivial job to correctly identify lead-lag effects, since duplicated trends appear frequently in financial markets but only few of them are actually caused by lead-lag effects. Identification of lead-lag effects needs to be conducted from the perspective of causality, where causal explanations are required to demonstrate a reasonable causal chain that leads to the lead-lag effect. Intuitively, lead-lag effects can be verified by counterfactual explanations [180]: What will the trends of the lagging instruments be if the trend of the leading instrument didn't go in this way? Nevertheless, counterfactual reasoning is usually infeasible in real-world financial markets since they are complex and hard to simulate.

*Sector trends.* Sectors are categorizations of financial instruments that are defined according to certain criteria such as industry and market capitalization. In this way, financial instruments in the same sector share certain common properties, such as industry, business, or products. It is therefore apparent that the trends of individual financial instruments are influenced by the trends of the sectors they belong to. Meanwhile, analyzing the trend of sectors is relatively simpler than analyzing individual stocks since the influencing factors of sector trends are more explicit and intuitive. Hence, proper credit attribution of sectors' influence on individual financial instruments is crucial in providing insights for investors regarding their running portfolios. Towards achieving such explanations, we propose to treat sector membership of financial instruments as categorical features, where the problem of sector attribution be reduced to computing the importance of membership features. By evaluating the importance of membership features individually using feature importance methods (§3.1.2), we can better understand sector contributions. Besides, investors can also gain insight into the sensitivity of sectors to different types of features by evaluating feature interactions between sector memberships and other ordinary features.

*Concept mining.* In addition to sectors that are explicitly defined by human analysts, there are also many latent concepts [181] that implicitly cluster financial instruments and affect their trends implicitly, as shown in Figure 23c. Similar to the influence of sectors, financial instruments in the same latent concept tend to share common properties. In this way, effective

latent concept mining will provide investors with extra information for making decisions, thus bringing comparative advantages over other market participants who share the same pieces of public information. From a machine learning perspective, the problem of concept mining can be regarded as a clustering problem. Similar to instrument similarity, financial instruments can be first embedded into a latent space and then clustered based on distance metrics in the latent space. Further visualizations can also be applied to provide more intuitive explanations.

### 3.2.2. Time

XAI along the time dimension focuses on explaining market trends that are observable across time. Such trends can be periodical, occasional or sudden, which correspond to different behavior patterns of market participants. In this part, we will introduce several typical temporal market trends that are suitable for XAI methods to give deeper insights.

*Extreme market.* In financial markets, there are occasionally extreme conditions where nearly all instruments on the market experience severe price drops and historical experiences do not apply at all (Figure 24a). Under such extreme markets, it is hard for quantitative investment strategies to gain excess returns since all instrument prices will be dropping collectively and there will be little room for arbitrage. Therefore, during an extreme market, it is important to identify those instruments that are less affected by market trends than other instruments, in order to earn excess returns. To accomplish such identification, instrument returns at that time period need to be properly decomposed into market trends and specific returns, which can be regarded as explaining the source of return from these two perspectives. An intuitive way to achieve the decomposition is via feature importance, where features are categorized as market trend indicators and instrument-specific ones. If the importance of market features significantly outweighs that of specific features for a specific instrument, it can be regarded as being dominated by the extreme market and should be avoided in a portfolio.

*Calendar effect.* In financial markets, there are usually anomalies that are related to calendars at different scales, such as days in a week, months in a year, and event-related periods such

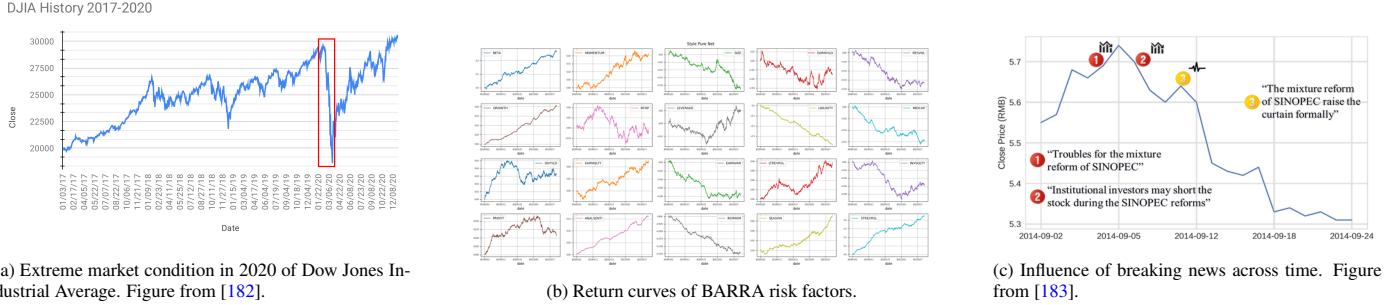


Figure 24: XAI in time.

as the U.S. presidential cycle. Such anomalies are known as calendar effects [184], which have a great influence on market trends. Calendar effects are caused by the collective anticipation of market participants towards the future and bring inevitable influence to market trends. Investors need to identify the ongoing calendar effects on the market in order not to go against them and thus experience great losses. To achieve this, we need good explanations about market trends in terms of calendar effects. Calendar effects can be effectively examined by computing the importance of calendar-related factors, such as categorical features representing weekdays, days in the month, months in a year, etc. For a model that accurately predicts market trends, if it has a heavy reliance on these calendar-related factors, it can be regarded as capturing the underlying calendar effects which have a great influence on market trends. Model-agnostic feature importance methods such as Shapley value and permutation importance can be applied to this problem. Besides, we can also use intrinsically explainable models such as linear regression and decision trees to directly check if calendar factors have larger weights.

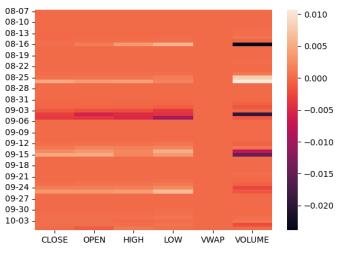
*Style transition.* Style refers to the intrinsic feature of financial instruments such as capital size, volatility, growth, liquidity, etc. In contrast to sectors, style factors are numerical variables assigned to each stock that represents the extent to which the stock exposes to this style, while sectors are categorical variables indicating the membership of each stock in the sector. It is widely acknowledged in quantitative investment that there are explicit preferences on styles in financial markets, which changes constantly over time (Figure 24b). For example, at the beginning of a market cycle, small-cap stocks may be preferred by investors due to their potential for future growth, for which we can make profits by longing them. A month later the situation may change and big-cap stocks would possibly take over due to their stability. In this way, portfolios focusing on small-cap stocks may experience losses. Hence, if market trends can be precisely explained in terms of style transition, investors can have a better understanding of the source of our portfolio returns and make use of such transitions accordingly to earn more profits. To explain the contribution of styles to portfolio returns, traditional models such as BARRA [48] compute every financial instrument’s exposure to styles via temporal regression and the return of each style via cross-sectional regression. The return of each individual financial instrument can then be

explained as the dot product of their style exposure vector and the style return vector. Portfolio returns can be explained as a linear combination of the returns of each financial instrument in the portfolio. However, such a decomposition of portfolio returns considers only linear relationships and overlooks non-linear relationships. Therefore, feature importance methods for non-linear models such as deep neural networks can be applied. Since financial instruments’ style exposures can be used as input features for deep learning models, we can calculate the feature importance of style factors using model-agnostic XAI techniques. Since market styles are fast-changing, feature importance for style factors needs to be computed at each timestep. The trend of style factor importance can then reflect the style transitions on the market.

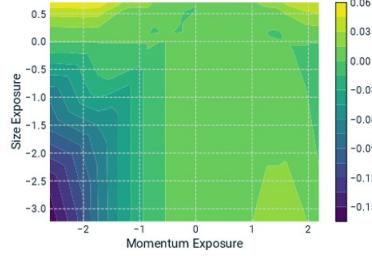
*Event influence.* Black swan events such as breaking news (Figure 24c) that happen suddenly have a great influence on the opinions of market participants and can cause great market impact. After the event outbreak, market conditions usually experience sharp changes for the following period of time. As for investors, they need to have a good comprehension of the potential effects of such events on market trends, in order to avoid severe losses caused by negative events and also capture chances for profit in face of positive events. An event is associated with information from two perspectives: the timestamp of its occurrence and its specific contents which can be converted into factors using event embedding techniques. Hence, the effect of an event can be computed as the importance of its embedded contents w.r.t. the market trends after its timestamp. Additionally, causal explanations can also be applied to further explain the actual causal effect the event brings to the market. Moreover, a thorough causal chain can be reasoned over all potential market effects, which involves knowledge-driven AI techniques which we will discuss in §4.

### 3.2.3. Factor

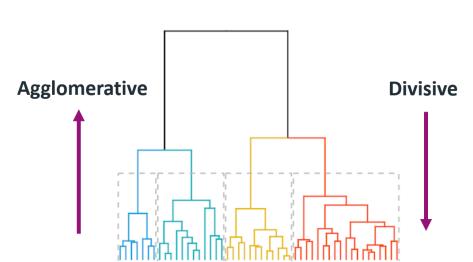
XAI along the factor dimension focuses on explaining the contribution of factors to portfolio returns, which can be evaluated in terms of both individual factors and interactions among multiple factors. In the following, we will introduce several factor explainability problems that are commonly encountered in quant.



(a) Feature importance for basic volume-price factors



(b) Interaction between size and momentum factors.  
Figure is cited from [185].



(c) Hierarchical clustering. Figure is cited from [186].

Figure 25: XAI in factors.

**Factor type.** Factors can be categorized into various types according to different criteria. In terms of data sources, factors can be categorized as volume-price factors, sentiment factors, fundamental factors, etc. In terms of financial properties they represent, factors can be categorized as momentum factors, mean reversion factors, lead-lag factors, etc. In terms of the time scale of the original data from which the factors are computed, factors can be categorized as tick-level factors, minute-level factors, day-level factors, etc. Different financial instruments at different time points may have varying sensitivities to different factors, which reflects the dynamic nature of financial markets. If we can accurately explain the performance of our portfolio by precisely evaluating the contribution of each factor to each of the financial instruments at each time point, we can have a better understanding of the underlying mechanism of the investment strategy produced by AI. Explaining the contribution of different types of factors can be regarded as a typical feature importance problem, where both model-intrinsic and model-agnostic feature importance methods introduced in §3.1 can be applied to such explanations. For example, in Figure 25a, the contribution to the model prediction of each individual factor at different times is illustrated in a heatmap. Furthermore, causal explanations can be applied to further explore the actual causal relationships between different types of factors and portfolio returns.

**Factor interaction.** When combining factors using deep learning models, chances are that the combination of several factors achieves strong portfolio performance while each of the individual components performs poorly. Such synergistic effect among factors reflects certain intriguing patterns captured by models that are not noticed in the factor mining stage, and identifying such synergy can help us better understand the effectiveness of our models. Technically, this problem can be related to a feature crossing (or feature interaction), where relevant methods can be applied. For example, in Figure 25b, the landscape of model prediction with respect to the value of two factors (exposure to size and momentum style factors) is illustrated in a contour map. And it can be seen from the map that model prediction decreases as both factor values drop.

**Factor evolution.** Since factors are intended to convey investment ideas from certain perspectives, it is important to reveal

the ideas behind factors in investment research, in order to enhance the diversity of factors and provide researchers with a better understanding of factors’ mechanisms. Borrowing the idea from bioinformatics, we propose to depict the semantic similarity among factors in terms of their underlying investment ideas via factor evolution graphs. Leveraging relevant techniques such as hierarchical clustering [187], a factor evolution graph demonstrates factor relations by arranging factors with higher similarities in lower-order neighborhoods (lower-level subtrees in the example of Figure 25c).

#### 4. Knowledge-driven AI for Quant 4.0

As discussed in §1.5, knowledge-driven AI is an important complement to data-driven AI, especially in situations such as value investing where information from data is insufficient for making credible and reasonable investment decisions. In this section, we introduce how knowledge-driven AI can be integrated into the whole picture of Quant 4.0. Specifically, this section is intended to answer two generic questions: 1) how to build a practical knowledge-based AI system, and 2) how can this knowledge-based AI system favor quant.

To answer the first question, we will first introduce what a typical knowledge-based system [188] consists of. Generally speaking, a knowledge-based system consists of two parts: a knowledge base that stores all the knowledge information, and an inference engine that generates new knowledge based on existing information [189]. These two components correspond to the problem of knowledge representation and reasoning, which is one of the major research directions in artificial intelligence. Particularly, in our proposal of Quant 4.0, we propose to adopt knowledge graph [190] as the knowledge base due to its inherent fitness to the demand of quant. Besides, knowledge reasoning techniques based on knowledge graphs have also been extensively studied in academia [191] and applied in industry [192] with proven effectiveness.

To answer the second question, we will demonstrate how knowledge graph techniques can be applied to quant from the perspective of knowledge representation and reasoning. Specifically, we will elaborate on how investment-related information can be extracted from different sources and modeled as a financial knowledge graph. We will also introduce some prospective

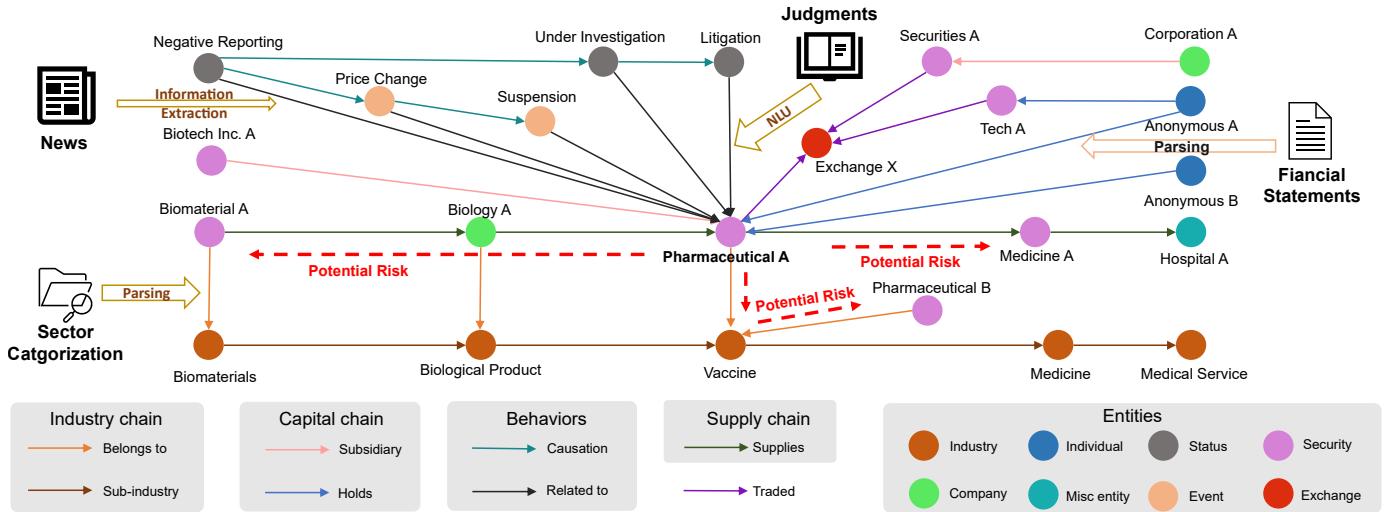


Figure 26: An example of financial knowledge graph that contains behavioral information. All the financial entities and events are fictitious and only for illustration purposes.

application scenarios where knowledge graph reasoning brings extra benefits for investment.

Figure 26 demonstrates an idealized knowledge graph system for quant. In this system, various types of financial entities including listed companies, securities, industry sectors, individuals, events, and financial relations such as supply chain, capital chain, and behavioral relations are modeled in the knowledge graph. Structured information constituting the knowledge graph is collected from various data sources such as news, judgments, financial statements, and categorizations, and extracted using advanced techniques in AI such as natural language understanding and information extraction. On top of this, reasoning techniques based on the knowledge graph can favor quant with additional analytical capabilities other than those provided by data-driven AI. For example, in this knowledge graph, when negative events happen to the listed company (*Pharmaceutical A*) potential risk on its stock will be recognized and further propagated in various ways to related companies via paths on the graph.

In the remainder of this section, we will elaborate on how this proposed system can be implemented with related knowledge-driven AI techniques. Specifically, we will introduce knowledge representation and reasoning techniques for knowledge graph in §4.1 and §4.2 respectively, in order to justify our technology selection. Besides, we will also elaborate on the second question for this section in §4.3 by demonstrating the usage scenarios of knowledge-based systems in quant that we have conceived in terms of both knowledge graph construction and reasoning.

#### 4.1. Knowledge Representation

The goal of knowledge representation is to encode human knowledge into computer-compatible forms, which is the basis of knowledge-driven AI since it determines the modeling of the knowledge base and the corresponding reasoning methods that operate upon it. In our technology roadmap towards

knowledge-driven AI for quant, we propose to utilize knowledge graph techniques for the underlying knowledge base. In what follows, we will elaborate on the technology selection for knowledge representation in Quant 4.0 by answering two questions: Why do we choose knowledge graph as the knowledge base (§4.1.1) and how do we actually build a knowledge base in the form of knowledge graph (§4.1.2).

##### 4.1.1. Knowledge Base Techniques

To demonstrate the advantage of knowledge graph, we will first introduce the history of related techniques (Figure 27), following corresponding literature reviews [194].

As the earliest prototype of knowledge graph, the idea of semantic network [195] originates from ancient philosophers centuries ago and was first implemented in 1956 [196]. A semantic network is essentially a graph structure where the nodes represent related concepts and the edges represent semantic relations between nodes. It can also be formalized as a set of semantic triples [197], which is critical for its standardization in RDF [198] and the wide adoption that follows. Typical usage scenarios of semantic networks include natural language processing tasks such as semantic parsing [199], where an unstructured text is parsed into a semantic network via entity recognition and relation extraction.

Logic-based knowledge representation techniques such as propositional logic [200], descriptive logic [201] and first-order logic [202], surged in the following decades can become the mainstream technique of that time. As an early example, the general problem solver (GPS) was proposed in 1959 [203] which formalizes problems as Horn clauses and applies formal logic methods to solve them. However, GPS is unable to solve any real-world problems due to the growing complexities caused by the curse of dimensionality. Such limitation leads to further research on expert systems [204] with a focus on solving practical problems with specific structures. Meanwhile, frame languages [205] were also studied as knowledge repre-

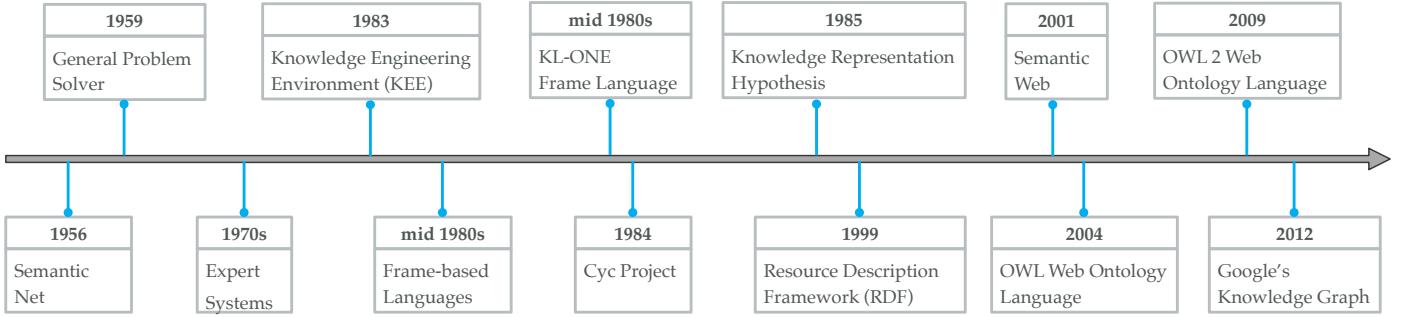


Figure 27: Knowledge base history. Figure cited from [193].

sentation techniques. Frame languages have good modeling of real-world objects by defining their classes and inheritance relationships, similar to the abstraction in object-oriented programming. Frame languages and logic rules were further combined to form stronger knowledge-based systems. Successful examples include the Knowledge Engineering Environment [206], KL-ONE framing language [207] and the Cyc project [208].

With the emergence of the Internet in 1990s, knowledge base techniques were adapted to meet the demand of increasing data scale and growing data exchange happening on the Internet. Various standards such as resource description framework (RDF) [209] and web ontology language (OWL) [210] were proposed to handle these challenges, which can be included in the family of Semantic Web [211]. As the size of the Internet continues to grow and the corresponding data scale keeps expanding, semantic web technologies started to face engineering challenges in practice. In response to these issues, knowledge graph technologies based on graph databases have been actively developed in recent years, aiming at storing and manipulating large-scale knowledge data in a more efficient way. Nowadays, knowledge graph has become the mainstream methodology for knowledge-based systems in data-driven scenarios.

It can be seen from the evolution of knowledge base techniques that their development is in pace with that of data technologies. Under the context of Quant 4.0, knowledge graph is specifically suitable for the scenario of quant from the following aspects:

- **Large-scale data:** Quant usually involves data on large scales. Meanwhile, knowledge graph involves suitable technologies such as graph database for efficient storage, management, query and storage of large-scale knowledge data.
- **Complex relationship:** The relations between financial entities are highly complex and interleaving. Knowledge graph models such relations with graph structures and provides an intuitive view of them.

#### 4.1.2. Knowledge Graph Essentials

Now that we have discussed the necessity of using knowledge graph, let's now take a deeper look at how to build a knowledge graph. To build a knowledge graph, we should first make clear all necessary components of a knowledge graph. Besides, given the specifications of components, we should also

know how to attain the information that can be used to fill up this framework, which corresponds to the problem of knowledge acquisition.

**Knowledge graph components.** As introduced in [212], a knowledge graph typically consists of three parts. To build a knowledge graph, we need to first build its schema which specifies all entity and relation types involved in the knowledge graph. Such metadata of the knowledge graph is called its *ontology*. Given the ontology, we then need to determine all specific entities that will appear in the knowledge graph. Such information is stored and organized in a *controlled vocabulary* which describes the names of entities belonging to each of the types specified in the ontology. After the domain of discourse is determined, we can then store the knowledge in the form of links on the knowledge graph, which can be alternatively expressed as semantic triples. Following the definition in RDF, we call such information *resources* that represent the actual knowledge information. In what follows, we will introduce these three components in detail.

- **Ontology** [213] specifies the types and semantic meanings of the entities and relations in a knowledge graph. As the schema of a knowledge base, an ontology defines the properties of different types of entities and how they relate to each other and is usually encoded with formal ontology languages such as OWL and RDF. In the example of Figure 26, the ontology specifies the eight types of financial entities and the various types of relationships between them. The ontology can further define detailed properties for entities and relations such as timestamps, the original data from which a relation is extracted, etc. An appropriate ontology is important for the quality of a knowledge graph, for which ontology engineering [214] has drawn much attention and grown as a new field of study. [215, 216, 217].
- **Controlled vocabulary** [218] contains names that are allowed to be associated with each type of entity or relation in the knowledge graph. With controlled vocabularies, entities and relations in knowledge graphs can be instantiated and identified with unique names. For example, we can instantiate two security entities in the knowledge graph illustrated in Figure 26 with names being “*Biomaterial A*” and “*Pharmaceutical A*” respectively. In this way, entities can also be more effi-

ciently retrieved with queries on their names. However, different from vocabulary in natural language, a controlled vocabulary is restricted to contain only the pre-selected names determined by the design of the knowledge base. Therefore, the formality of the knowledge base is guaranteed, which paves the way for knowledge reasoning in downstream applications. Moreover, problems caused by ambiguities such as homonymy, synonymy, and polysemy can be effectively addressed by controlled vocabularies where every name exactly corresponds to a unit of information in the knowledge graph. For example, in financial knowledge graphs, a listed company can be simultaneously represented by a company entity and a security entity with the same name. While both entities share the same name, they can be distinguished in the controlled vocabulary where the names belong to different categories.

- Resources are the instantiated relations between entities in the graph. They serve as the main body of a knowledge graph. Essentially, resources can be expressed as semantic triples in the knowledge base that stands for factual knowledge. A semantic triple consists of a subject, a predicate, and an object. The subject is the resource itself. The predicate describes the relation between the subject and the object. And the object is the property of the relation, which can be either another entity in the knowledge graph or a specific value. Originating from Semantic Web, resources are usually described and exchanged in standardized forms such as RDF, where they are described in formal languages and can be parsed by dedicated programs. Besides, resources can be stored in graph databases that are specifically designed for graph-structured data at scale. The mature engineering framework based on graph databases supports the wide adoption of knowledge graph in the big data era.

*Knowledge Acquisition.* In knowledge base construction, after the ontology has been defined, the knowledge base needs to be filled up with knowledge information in terms of facts and rules. For knowledge graph, these contents need to be imported into the database in the form of semantic triples. However, knowledge information in its original form does not have such well-defined formats in the wild. And it usually costs a lot of human effort to manually extract such structural information from the raw data. Hence, knowledge acquisition techniques need to be applied in order to automatically generate the factual triples that fit into the ontology. As summarized in [193], knowledge can be acquired both internally (based on existing knowledge bases) and externally (based on external data). To infer new knowledge based on existing data, knowledge graph completion techniques [219, 220] can be applied to reason over current knowledge bases and compute the plausibility of new facts. To extract new knowledge from external data, information extraction [221] techniques can be applied to parse and comprehend data of various modalities. In what follows, we will elaborate on these two types of knowledge acquisition techniques.

- Knowledge graph completion aims to fill up the missing links in a knowledge graph based on existing information. Specif-

ically, given an incomplete semantic triple where one of the three components (subject, predicate, or object) is missing, knowledge graph completion is intended to find the missing component in the triple based on the current knowledge graph. In this sense, the problem of knowledge graph completion is closely related to knowledge graph reasoning, where the related techniques can be applied. Specifically, the missing component can be either directly inferred via binary operations between the embeddings of the two given components or reasoned over multi-hop semantic paths. A detailed discussion of reasoning techniques is left for §4.2.

- Information extraction aims to extract from unstructured data (usually texts) semantic information that is structural. Such information can be represented as semantic triples in the case of knowledge acquisition. This task can be further decomposed into two steps: 1) recognizing entities from the text (i.e. entity recognition) and 2) extracting relations between the recognized entities (i.e. relation extraction). And these two sub-tasks have been extensively studied in natural language processing [222, 223]. For entity recognition, entities can be directly recognized from texts using either hand-crafted features or neural networks. Semantic role labeling [224] can also be performed to identify the role of entities in semantic triples. Moreover, the task is also related to entity disambiguation (i.e. entity linking [225]) where entity tokens in the text need to be aligned to entities in the knowledge graph. For relation extraction, various machine learning methods have been proposed and achieved satisfactory performance. Neural networks can be directly applied to pairs of entities to predict the semantic relations in between [226]. Besides, attention mechanisms can also be utilized to capture the semantic information between words [227]. Additionally, graph neural networks can also be applied to encode the parsed structure of natural languages such as dependency trees [228]. Furthermore, instead of inferring the semantic relations between given entities, relation extraction can be carried out jointly with entity recognition in an end-to-end manner [229].

## 4.2. Knowledge Reasoning

Reasoning refers to generating new knowledge (e.g. inferring new facts, extracting new rules) based on existing information in the knowledge base. Depending on the form of the new knowledge inferred, reasoning can be categorized as deductive reasoning and inductive reasoning, where the former tries to generate new facts based on existing ones and given rules, and the latter tries to extract general rules from specific facts. For example, a deductive reasoner may make predictions on the future trend of an individual stock based on some generalized principles of stock prediction, which may be summarized by an inductive reasoner from the history of over a thousand stocks on the market for the last 20 years. Both deductive and inductive reasoning can be conducted in various ways, including symbolic reasoning, neural reasoning, and neurosymbolic reasoning. Symbolic reasoning utilizes symbolic logic operations to deduce the truth value of facts or induce rules from

facts. Neural reasoning maps knowledge into the embedding space and converts the reasoning process into numerical operations. Neurosymbolic reasoning, as the name suggests, combines symbolic and neural reasoning methods for better reasoning capabilities. In what follows, we will introduce these different types of reasoning methodologies in detail.

#### 4.2.1. Symbolic Reasoning

Intuitively, symbolic reasoning can be conducted in a deterministic way by deriving the expected results using logic rules. However, as the real world is complex and uncertain, symbolic reasoning can also be conducted in a probabilistic way where the rules become “soft” and the distribution of the outcome is derived instead of a precise result. In the remainder of this part, we will introduce both types of symbolic reasoning methods respectively.

*Deterministic Reasoning.* There are two commonly adapted ways to conduct deterministic symbolic reasoning [230]: forward chaining and backward chaining [231]. These two ways of reasoning differ from each other in the order of reasoning. Forward chaining starts from the given facts and looks for appropriate rules where new propositions can be derived from these facts. The search process is conducted iteratively until the expected answer is derived. Backward chaining, on the other hand, starts from the rules where the expected result serves as the outcome, and traces all the way back to see if the root causes can be fulfilled by the given facts. In comparison, forward chaining is suitable for finding answers to user queries, while backward chaining is good at verifying a given statement or assumption.

*Probabilistic Reasoning.* Probabilistic reasoning models the plausibility of facts as a probability distribution based on the causing variables. Therefore, logic rules are represented in a softer way, which allows more flexibility in the reasoning process. Various methods have been proposed for probabilistic reasoning. For example, probabilistic logic programming [232] models a logic program as a computation graph similar to Bayesian networks. Markov logic programming [233] proposes a first-order knowledge base where each rule is assigned as scalar weight. In this way, the joint distribution of all the observed and hidden facts is modeled as the normalized exponential weighted sum of the grounds of each rule. Other probabilistic reasoning techniques such as stochastic logic programming [234] and TensorLog [235].

As the traditional knowledge reasoning methodology, symbolic reasoning has the advantage of being direct and explainable. It also provides accurate reasoning results by explicitly modeling the knowledge. However, symbolic reasoning needs to be conducted on curated knowledge bases that require human effort for its construction. Besides, it is prone to noisy data in the knowledge base. Moreover, the inference efficiency of symbolic reasoning methods is also quite low since most methods are search-based. These disadvantages of symbolic reasoning render it unsuitable for big data applications today.

#### 4.2.2. Neural Reasoning

On account of the limitations of symbolic reasoning discussed above, neural reasoning methods are developed to increase reasoning flexibility. For neural reasoning methods, entities and relations in the knowledge graph are implicitly represented as embedding vectors. In this way, the need for curated knowledge rules to perform inference is bypassed. Besides, the search-based symbolic reasoning process can be mostly replaced by direct numerical operations on embedding vectors, which significantly reduces the computation complexity.

Neural reasoning methods typically work in two stages. Firstly, entities and relations are mapped to an embedding space. Then the plausibility of facts can be computed by scoring functions, where embedding of the corresponding semantic triple components are taken as arguments. Optionally, the interactions between entities and relations can also be modeled by encoding models, where more complex operations and learnable parameters can be integrated to increase expressivity. In the remainder of this part, we will elaborate on the embedding space, scoring function and encoding model for neural reasoning following the survey in [193].

*Embedding Space.* Most frequently, entities and relations can be embedded into a high-dimensional Euclidean space. In this way, relations are usually modeled as translation vectors [236] or projection matrices [237, 238] that transform entity embeddings. In addition to Euclidean space, other types of embedding spaces have also been adopted to make up for the shortcomings of Euclidean space. Specifically, complex vector space can be adopted to capture symmetry information [239] and model relations as rotation operations [240]. Gaussian distribution space can be adopted [241, 242] to model entities as high-dimensional Gaussian distributions. Manifold space can also be used as the embedding space [243, 244] for better algebraic and geometric properties.

*Scoring Function.* The scoring function evaluates the plausibility of a fact based on the embeddings of its components. Scoring functions can be categorized as distance-based and similarity-based, where smaller function values indicate greater plausibility for the former and the opposite situation works for the latter.

- Distance-based scoring functions measure the distance in the embedding space between the subject and the object embeddings that are transformed by the relation. For the distance metric, it can be either simple norms such as  $L_1$  and  $L_2$  norms in the Euclidean space [236], or more complex metrics such as divergence between distributions [241].
- Similarity-based scoring functions measures the similarity between subject and object embeddings with respect to the specific relation. For Euclidean embedding space, scoring functions can be either linear functions, where the cosine similarity between transformed embedding vectors is computed, or bilinear functions where the relation is represented as a matrix.

*Encoding Model.* In addition to scoring functions, the interaction among entities and relations can also be implicitly modeled by various encoding models containing learnable parameters. In this way, embeddings of entities and relations are taken as input to the encoding model. Various types of models can be applied to model interactions from different perspectives. For example, linear models [238] can be applied to directly capture interactions. Convolutional neural networks [245] can be applied to capture spatial relations in embeddings. Recurrent neural networks [246] can be applied to model relational paths involving multiple semantic triples. Moreover, graph neural networks [247] can be applied to model structural features of the knowledge graph.

#### 4.2.3. Neurosymbolic Reasoning

Symbolic reasoning has the advantage of being direct and accurate, while neural reasoning has the advantage of being expressive. The advantage of both sides can be combined in neurosymbolic reasoning techniques to achieve better performance. For example, in pLogicNet [248] that is based on Markov logic network, neural methods are used to infer the plausibility of the hidden facts and symbolic reasoning is used to combine both the observed and hidden facts to infer the queried facts. The whole system is optimized via the variational expectation maximization algorithm, where the E-step corresponds to estimating the plausibility of hidden facts and the M-step corresponds to maximizing the likelihood of the given facts. Generally speaking, neurosymbolic reasoning techniques utilize neural methods as the frontend to handle the data-driven part of the problem, and utilize symbolic reasoning as the backend inference engine to compute fact plausibility. Hence, the key challenge for neurosymbolic reasoning is to design a good interface between neural and symbolic methods for both sides to work well.

### 4.3. Knowledge Application in Quant 4.0

Now that we have introduced related techniques for knowledge-based AI from the perspective of knowledge representation and reasoning. In this part, we will demonstrate how knowledge-based AI can be integrated into the whole picture of Quant 4.0. Following the discussion above, our discussion will be conducted from the perspective of financial knowledge graph construction and applications for reasoning on knowledge graph respectively.

#### 4.3.1. Building a Financial Knowledge Graph

*Ontology.* The ontology of a financial knowledge graph is designed to cover the information from 3 aspects: 1). the fundamental information of financial entities, 2). financial events happening between financial entities, and 3) the causal relationships between entities and events. An example of the knowledge graph is shown in Figure 26. Correspondingly, the entities can be divided into the following categories:

- Financial entities corresponding to financial instruments and the underlying economic entities. Common financial instruments include securities, bonds, derivatives, etc. The under-

lying economic entities include companies, commodities, individuals, etc.

- Categories that reflect the fundamental information about financial entities. Examples include sectors, industries, markets and exchanges, regions and countries, currencies, etc.
- Behaviors representing the events happening to financial entities, such as punishments, illegal actions, litigation states, holding changes, personnel changes, etc. In this way, financial events can be represented as the links from behavior nodes to the related financial entities.

Similarly, relations can be divided into the following categories:

- Event relations connecting behavior nodes and financial entities. For example, in Figure 26, a “related to” relation connects the event of “negative reporting” and the corresponding financial entity “Pharmaceutical A” to indicate a negative reporting happening to the publicly traded company “Pharmaceutical A”. These relations are usually associated with timestamps indicating the specific time point that the events happen.
- States such as subsidiaries, belongs, holds. These relations usually hold for a time interval and are thus associated with timestamps indicating their beginning and ending times. For example, in Figure 26, the industrial chain and capital chain relationships are different types of states that describe the sector categorization and capital relationships between entities.
- Causalities between events. For example, in Figure 26 the negative reporting leads to the price change and further investigation on “Pharmaceutical A”, which further leads to suspension in trading and litigation. Causal relations are usually inferred from existing knowledge and serve as important auxiliary information in downstream reasoning tasks.

*Acquisition.* The knowledge that constitutes the financial knowledge graph can be acquired from the following sources:

- Market data such as the volume and price information. On the one hand, market quotes indicating financial behaviors such as reductions in shareholding can be directly converted as factual triples. On the other hand, market events such as anomalous price movement need to be first recognized, and then converted into semantic triples.
- Databases such as e-commerce data and the registration information database for industrial and commercial enterprises. These databases can be queried to extract factual relationships about the fundamental situations of the companies such as the subsidiary relationships between companies and the holding relationships from individuals to companies.
- Announcements and reports contain the major financial behaviors of public companies. Facts such as rises in revenue can be extracted by parsing the tables.

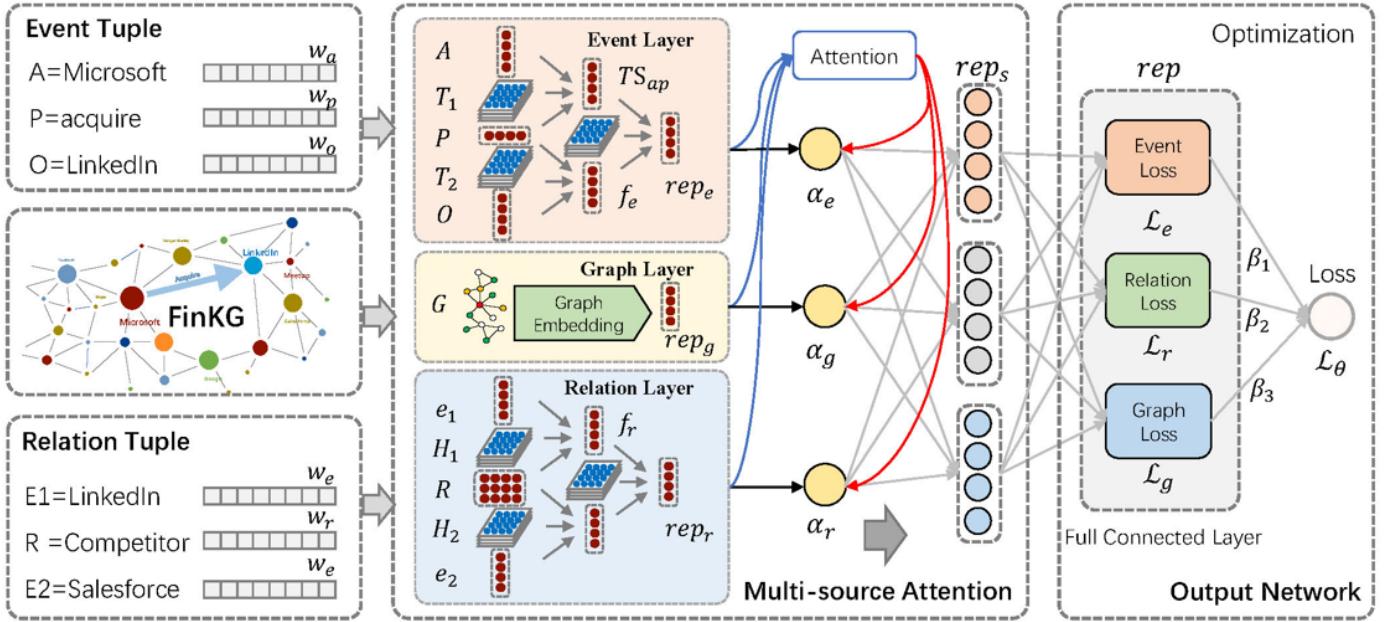


Figure 28: Knowledge graph reasoning for stock prediction. Figure is cited from [191].

- News contains most of the events that can be parsed through NLP techniques such as information extraction.

#### 4.3.2. Applications for Reasoning on Knowledge Graphs

After the knowledge graph has been constructed, reasoning techniques can be applied to provide meaningful insights for quant. On the one hand, knowledge representations can be directly incorporated into existing factors as external information, which can be combined with other factors in deep learning models for better predictions. For example, as shown in 28, neural reasoning methods are applied to generate embeddings for entities and relations with rich semantics. These embeddings can be fed into predicting models as auxiliary information. On the other hand, reasoning results can be directly used as investment suggestions. For example, we can construct knowledge-based factors corresponding to logic chains (i.e. paths on knowledge graph) that imitate the decision-making process of human investors. Then, values of these factors can be computed as the plausibility of the final outcome, which can be utilized as effective trading signals.

Moreover, in terms of specific usage scenarios, we also envision several possible applications where knowledge reasoning could be favorable:

*Event-driven Investment.* Every event that happens in financial markets and other related entities will have an inevitable influence on the market, regardless of their scale of impact. Hence, by tracking the influence of all the events on financial entities we can achieve event-driven investment. Specifically, an event can be converted into a fact happening on the knowledge graph. Reasoning can then be performed to predict all possible effects this event will have on related financial entities using forward chaining. Moreover, we can also apply backward chaining to only predict possible effects on the financial entities that we are

interested in. Meanwhile, the influence of events can be either positive or negative. For positive effects, we can use them as effective trading signals for investing in certain assets. For negative effects, we can achieve real-time risk monitoring that reacts quickly to potential risks related to our portfolio as soon as the related event happens.

*Investment Decision Visualization.* Knowledge-driven AI enables the visualization of the rationale for an investment decision by providing the reasoning chains. In this way, each trading decision can be directly attributed to a specific chain of evidence, which significantly boosts the interpretability and robustness of investment decisions made by AI, which makes AI investment more practical.

*Market Condition Attribution.* Financial markets usually experience different types of conditions (e.g., rise, fall), and each condition can be very different in its causes. In quant, it is often the case that we want to find out what the underlying reasons for current market conditions are, in order to guide our future investment decision. Under the framework of knowledge-driven AI, this problem can be regarded as a rule-learning problem, where the given facts are the market quotes and other relevant events, and the goal is to learn rules that leads to the current market condition.

## 5. Building Quant 4.0: Engineering & Architecture

Sections 2, 3 and 4 introduce the three components of Quant 4.0 for the algorithmic perspective. In this section, we “retrospect” Quant 4.0 from a system point of view and study how to put all these components together in one system. Figure 29 illustrates the architecture of a proposed Quant 4.0 system

framework, including the offline system for quant research and the online system for quant trading.

### 5.1. System for Offline Research

Quant 4.0 offline quant research system aims to improve the efficiency of quant research. It contains several layers (hardware layer, raw data layer, meta factor layer, factor layer, and model layer) and modules (high-performance computing clusters, data system, cache system, data preprocessing, automated factor mining, knowledge-based system, large-scale data analytics, AutoML, and risk simulation).

#### 5.1.1. Hardware Platform Architecture

The underlying hardware platform for offline research is a high-performance computing cluster, consisting of many computing nodes that are mounted with shared storage [256] and interconnected by high-bandwidth network [257]. The combination of multiple nodes aggregates the computing power distributed in various single nodes to support large-scale quant computing tasks. However, communication bottleneck usually serves as one of the constraints for scaling up computing power [258]. To address this problem, the network topology of the cluster adopts a hierarchical structure, where neighboring computing nodes are connected via lower-level switches to increase the overall throughput of the cluster.

#### 5.1.2. Design of Data System

The data layer for Quant 4.0 system is to collect a tremendous amount of financial data and provide data management and query service for applications in upper layers. Since financial data are heterogeneous and multimodal, different types of database systems are involved in this layer to manage different types of data. Examples include SQL database [259], time-series database [260, 261], NoSQL database [262] and graph database [263].

- SQL database stores and manages data following the relational model proposed in [259], where data are stored in tables that represent relations among attributes. Most traditional financial data such as quote data and financial statements can be represented in this type and are suitable for SQL databases.
- Graph database [264] is designed to store and manage graph-structured data composed of nodes and edges. Such graph structures widely exist in financial data since financial entities are connected with each other through various relationships such as money flow and supply chain relations. Such links may indicate some latent patterns that are shared in neighborhoods. Graph database can be used to store and manage economic graphs, financial knowledge graphs and financial behavior graphs.
- NoSQL database [262] is used for storing non-tabular data such as key-value pair, document, and wide-column. It is appropriate to manage financial text data and image data, such as financial report text, news text, social media text, satellite and drone images etc.

- Time series database [261] is a special database type designed for quickly accessing, computing and managing time series data. Such kind of database engines is optimized to accelerate time series data processing, e.g., computing stock stream data collected in real-time, and computing time-series factors for high-frequency trading etc.

Moreover, the large volume of financial data requires a highly efficient distributed storage system to accelerate data access. To further improve the read/write speed for high-frequency tick data (limit order book etc), in-memory database [265] could be used as data cache to store the most frequently read data. It saves the data transfer time between hard disk and memory.

In addition to layer-specific components, the data layer, meta factor layer, and factor layer share a large-scale data processing platform which provides a complete solution and a convenient model for various data-driven tasks. The key components of this platform include a distributed file system that provides convenient and reliable data access on distributed storage systems, and a distributed computing engine that provides simple yet efficient programming interfaces for parallel computing on a large number of computing nodes. Specifically, distributed file systems such as HDFS [253] adopts the architecture consisting of name nodes and data nodes, where data replication is performed on multiple data nodes for fault tolerance. On the other hand, distributed computing engines such as MapReduce [266] and its open-source implement including Hadoop [267] and Spark [249, 250] provide programming models for parallel computing tasks. By abstracting parallel computing tasks into a set of primitive operations (e.g. map and reduce in MapReduce and transformation in Spark), the programming tool is ease to use by developers and is generic enough to handle many common parallel programming tasks.

#### 5.1.3. Factor Mining System

Raw data have different formats, but factor mining requires unified input format. Therefore, corresponding to the workflow in Figure 12, the meta factor layer is involved to preprocess raw data with various modalities into meta factors with unified formats and appropriate values.

The factor layer builds automated factor mining engine and automated factor mining pipeline. The factor mining algorithms have been introduced in §2.2.1. Here we introduce how to implement factor mining at scale from a system point of view. In particular, we concern how to improve the system efficiency to discover more “good” factors per unit time.

- Factor mining system needs a parallelization architecture to improve computational efficiency.
- Syntactic validity of factors should be checked in real time during the factor generation process to reduce the CPU time wasted by invalid factors.
- Diversity of factors should be controlled in real time during factor generation process in order to reduce the CPU time consumption for redundant factors.

The whole system is backed by some key techniques in distributed execution and computing acceleration. Distributed execution tools such as message queues and distributed caches

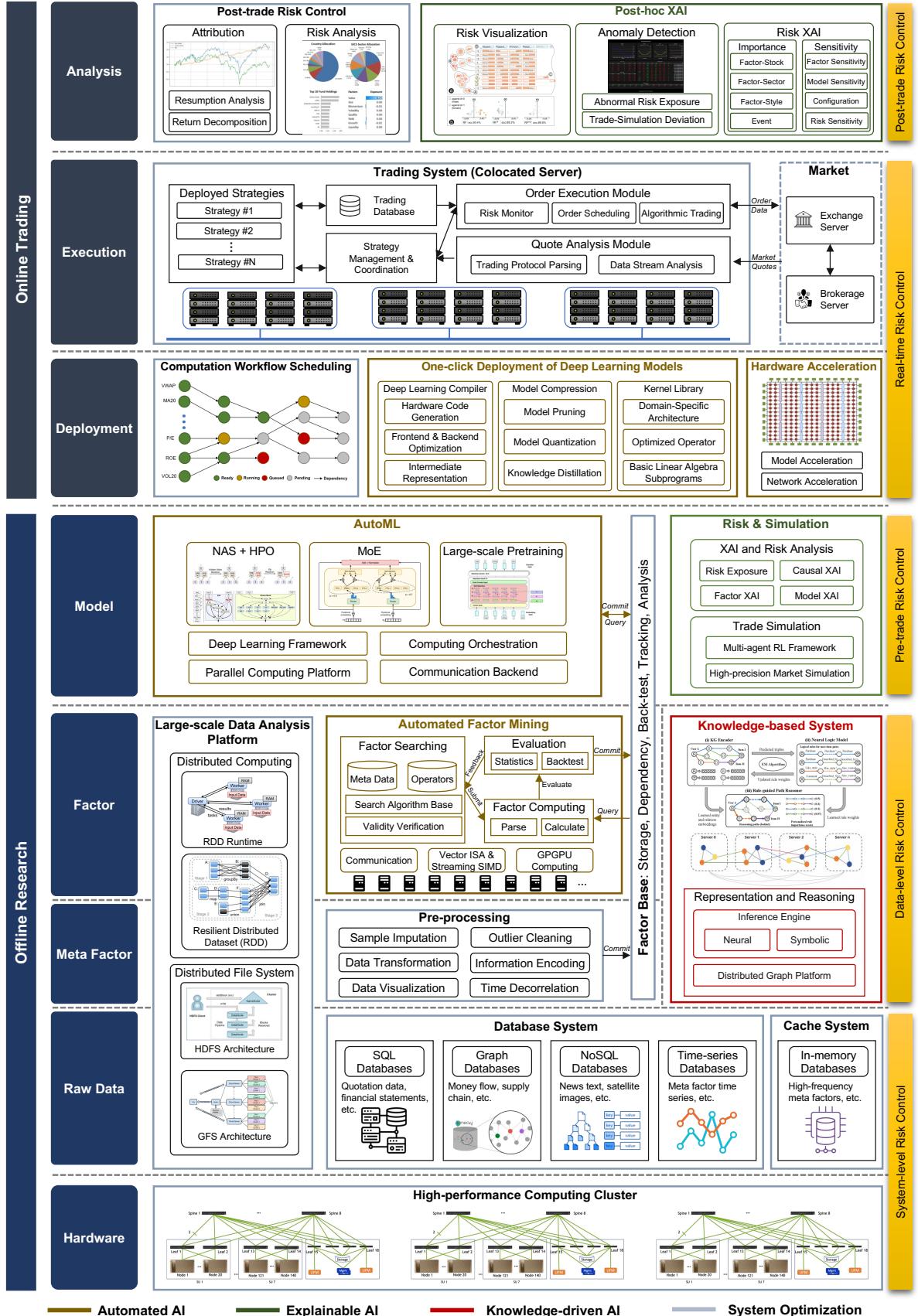


Figure 29: Architecture of an example Quant 4.0 engineering platform for investment research and trading. Part of this figure is cited from [249, 250, 251, 252, 253, 254, 89, 255].

enable asynchronous parallel execution on multiple nodes, thus guaranteeing system scalability. Computing acceleration techniques such as vector and streaming SIMD instructions on CPU and massive parallel computing on general-purpose graphics processing unit (GPGPU) [268] significantly improve the computation efficiency for data frame operations and thus increasing the productivity of the whole system.

Meta factor layer, factor layer, and model layer are connected to the factor base, which is an integrated platform for the storage, computation, dependency management, backtest, tracking, and analysis of all factors (the output of models are also factors). Factors generated in these layers are committed to the factor base in various forms. Specifically, meta factors pre-processed from raw data are directly committed to the factor base in data frames, with appropriate descriptions about their data sources and pre-processing methods. Factors generated via automated factor mining are committed to the factor base in the form of symbolic expressions where the operands are other factors in the factor base. The model outputs generated in the model layer can also be regarded as special machine learning factors, which can be committed to the factor base together with specifications of input factors, model architectures, hyperparameters and training descriptions, etc.

#### 5.1.4. Knowledge-based System

In parallel with the factor mining system, a knowledge-based system is also involved in the overall architecture to provide knowledge-driven AI practice. As discussed in §4, the knowledge-based system consists of two modules: a knowledge base for knowledge representation and an inference engine for knowledge reasoning. Specifically, a distributed graph computing platform is used as the knowledge base to store large financial behavior graph and the inference engine is built upon for downstream financial knowledge reasoning and decision making.

Compared with traditional small knowledge bases, financial behavior knowledge graph in Quant 4.0 has the potential to grow up to a scale with billions of nodes and edges, and thus it requires a flexible and scalable architecture [269, 270] to store and manage large-scale dynamic graph data. Therefore, we need a distributed graph computing and management platform, which partitions the whole knowledge graph into a number of subgraphs distributed in different nodes of a computing cluster. Due to the sparse nature of knowledge graph, this partition is specifically arranged to maximize data locality, where graph nodes located in the same partition are more densely connected than those located in different partitions [271]. For the inference engine, both knowledge graph embedding and rule-based symbolic reasoning algorithms can be implemented on this platform.

#### 5.1.5. Modeling System

The model layer is in charge of automatic generation of machine learning models and the corresponding risk evaluation and backtest simulation procedures before they are deployed into real-world environments. Therefore, this layer involves

two major components: an AutoML module and a pre-trade risk analysis and simulation module.

The AutoML module implements automated model generation algorithms upon large-scale distributed deep learning systems. The bottom layer of its technology stack consists of parallel computing platforms such as CUDA [272], and communication backends such as message passing interface (MPI) [273] that provide standard interfaces for communications between computing nodes in a distributed system. In the second layer of the technology stack, deep learning frameworks such as PyTorch [274] provide basic interfaces for training and inference of deep neural networks via hardware-accelerated linear algebra operations and automatic differentiation engines. In addition, computing orchestration systems such as pathways [275] combine low-level communication primitives with deep learning framework functionalities to implement higher-level parallelisms such as model parallelism and pipeline parallelism, which is further wrapped as standard interfaces for upper-level programs. The top layer of the technology stack consists of implementations of model generation algorithms such as neural architecture search and hyperparameter optimization (NAS+HPO) [276], mixture of experts (MoE) [254] and large-scale pretraining [277, 278].

The risk and simulation module identifies and analyzes the potential risk exposures of the models before they are deployed to real-world trading environments. This module implements explainable AI techniques applied to analyzing factor, model, and causality to reveal nonlinear risk exposures that are more complex than ordinary risk exposures explained by the BARRA model. In addition, market simulator [279] is used to test the performance of trading strategies with higher precision than backtest, whose results may be biased by historical data. Specifically, the simulation environment system [279] can be built using multi-agent reinforcement learning [280, 281] where agents imitate the behavior of various market participants in real world [282].

### 5.2. System for Online Trading

The online trading system focuses on deploying investment strategies for real trading and executing post-trade analysis, and its major goal is to achieve low trading latency and high execution efficiency. The trading system consists of three modules: deployment, trading and analysis, and we introduce their functions in the following part.

#### 5.2.1. Model Deployment

The deployment layer aims to implement the philosophy of technology “one-click deployment”. It involves a computation scheduling module, an automated deployment module, and an optional hardware acceleration module. The computation scheduling module arranges a reasonable and efficient computation order for factors based on their intrinsic data dependencies which form a directed acyclic graph (DAG) over factors. In the computation scheduling system, each factor starts its computation if and only if all its preceding factors on the DAG have

finished their computation. Computation scheduling is a tedious work and it should be automated by system due to the following reasons.

- We must synchronize offline factor dependencies with online factor dependencies and keep their consistency in real time.
- The number of factors may grow up quickly. Imagine what happens when you accumulate millions of factors? It is a nightmare for any quant researcher to deploy so many factors by hand.
- Adding, deleting and updating factors is the daily job of factor maintenance, which relies on correctly managing factor dependencies.

From the algorithmic point of view, the problem of computation scheduling can be regarded as topological sorting on the dependency DAG. In practice, the scheduler is designed to coordinate system components and schedule their executions according to the computation order on DAG. In common implementations [283] of such scheduling systems, asynchronous scheduling is adopted to improve the overall execution efficiency. In this way, the pending steps can start their execution immediately after the previous steps finish.

The automated deployment module aims to deploy deep learning models trained from offline research to online trading. It implements the algorithmic techniques discussed in 2.4. In addition to deep learning compilers and model compression engines, this module also involves optimized hardware kernel libraries, which provide implementations of common data processing and modeling functions that are highly optimized based on hardware features. Popular examples of such libraries include cuDNN [284] and MKL [285]. Functions in kernel libraries typically include basic linear algebra subprograms (BLAS) [286] that are standard interfaces for scientific computing, and some optimized operators for deep learning such as 3 convolution. The implementations are specifically optimized based on domain-specific architectures [287] on devices (e.g. Tensor Core [288]) to maximize the potential of hardware in use.

The hardware acceleration module aims to improve the computation efficiency of data processing and model inference using special hardware technology such as field-programmable gate array (FPGA) acceleration. Strategy components such as network protocol stack or machine learning models implemented on FPGA with customized logic can bypass redundant logics that are inevitable on generic hardware, thus achieving lower latency and winning an advantage for traders over other market participants. However, to deploy strategies on specific hardware, it usually takes a huge amount of development effort to complete strategy migration with satisfactory speed. Therefore, high-level synthesis techniques [289, 290, 291] are developed to address this problem. They directly generates register transfer languages for high-level representations in which strategies are originally implemented.

### 5.2.2. Trading Execution

The execution layer converts trading decisions to actual orders that are executed in exchanges, and its goal is to reduce the trading latency as much as possible in order to capture the fleet-

ing trading chances in the market. The latency can be decomposed into two parts: transmission latency is the delay of signal communication between trading servers and market servers (exchange server or brokerage server), and computation latency is the delay between quotes receiving and order sending. To reduce transmission latency, the trading system is usually deployed on servers that are colocated with market servers (such as racks and cabinets provided by brokers). To reduce computation latency, a trading system must be optimized in full strategy pipeline from data collection to order execution through various software and hardware acceleration techniques.

### 5.2.3. Trading Analysis

The analysis layer monitors the execution of investment strategies and performs analysis for further adjustments. It involves a post-trade risk control module responsible for ordinary performance monitor and a post-hoc XAI module for explaining strategy behavior from the perspective of AI. The post-trade risk control module performs return and risk attribution, aiming to analyze strategy's performance and revealing intrinsic risk structure hidden by machine learning blackboxes. Furthermore, the post-hoc XAI module provides in-depth analysis and explanation of investment strategies. It provides thorough risk analysis by analyzing all strategy components in terms of importance and sensitivity, and visualizes risk results.

### Remarks:

Risk control is one of the core tasks of quantitative investment and is also the primary consideration in system design. In our proposed engineering framework, the idea of risk control runs throughout the whole architecture. Specifically, system-level risk control is reflected in hardware and raw data layers, where the reliability and stability of the underlying hardware and raw data are the top priority. Data-level risk control is reflected in meta factor and factor layers, where quality control and management of factors and knowledge are emphasized. Pre-trade risk control is reflected in the model layer, where model robustness and explainability are required. Real-time risk control is reflected in deployment and execution layers, where the system's trading behavior is confined within constrained areas to avoid unexpected situations. Post-trade risk control is reflected in the analysis layer, where detailed analysis is conducted to provide comprehensive and reasonable insights into strategy performance.

## 6. Discussion on 10 Challenges in Quant Technology

We have summarized 10 challenges in the development of next-generation quant technology. These challenges range from computing and data infrastructure, investment modeling, risk modeling, market simulation and cognitive AI technology, and they provide new research directions for researchers interested in AI technology and quant. We believe some problems might be solved in the next couple of years with the rapid development of AI technology, while others may remain challenging for a long time.

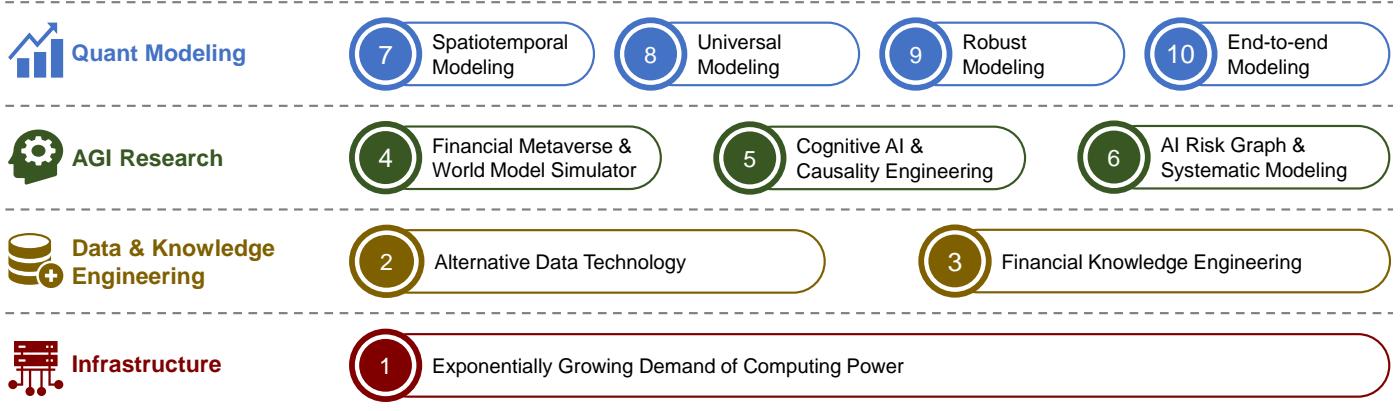


Figure 30: The 10 challenges in quantitative investment technology.

### 6.1. Exponentially Growing Demand of Computing Power



Figure 31: Growth of model sizes (measured by number of parameters) from 2018 to 2022. Figure is cited from [292].

With the rapid development of GPU technology and parallel computing technology, AI models have been scaling up year by year. The number of parameters in deep learning models has grown exponentially from 94 million (ELMo in 2018 [293]) to over 500 billion (Megatron in 2022 [292]) (Figure 31). The rapid growth in model size not only improves models' performances, but also leads to a paradigm shift which is deeply affecting the technical roadmap of AI research. Accordingly, as an important domain going all-in on AI, Quant 4.0 heavily relies on ultra large-scale computing power and related engineering technology.

#### 6.1.1. Quant 4.0 and Supercomputers

Investment Research of Quant 4.0 requires super-computing infrastructure as a fundamental support for large-scale factor mining, large-scale modeling, back-test and evaluation. One important idea behind Quant 4.0 is to “replace human power with computing power” in quant research. We have to notice

that Quant 4.0 has much more demand on computing power than what we could usually image ever before, because of the following reasons:

- Large-scale automated factor mining requires large distributed computing clusters with either homogeneous CPU parallelization or heterogeneous CPU-GPU parallelization. Even on a relatively simple homogeneously structured computing cluster, a high-frequency alpha factor mining task needs millions of CPU cores in order to achieve enough efficiency, performance and diversity in intensive factor search and evaluation. In particular, as more and more factors are discovered and accumulated, it will take longer and longer computing time (or equivalently computing power) to find a new qualified factor which not only performs well but also weakly correlated with existing factors discovered before. The same computation power problem happens similarly for heterogeneous clusters.
- Large-scale deep learning is necessary in Quant 4.0 research as some billion-parameter-level or even trillion-parameter-level deep learning models with large data volume do exhibit superior performance in many AI scenarios [294]. More and more large models are applied to quant tasks such as market prediction, portfolio position computing, risk forecasting and real trading by hedge funds and other institutional investors. However, the training process of large deep learning model requires extremely high computing power. For example, given a scenario of cross-sectional alpha model on 4000+ stocks and hundreds of daily factors of 10 years' history, a Transformer-type deep neural network with about ten billion parameters needs about 1-5 days to finish a single training/validation cycle on a cluster with 100 Nvidia A-100 GPUs, without counting the additional computational cost due to rolling training, model ensemble and autoML.

- Rolling training, i.e., iteratively retraining the same model with data sampled from a time window shifting towards the future, is a characteristic of quant modeling since the patterns of financial market and the patterns of investment instruments vary over time. In fact, financial time series are

strongly non-stationary, and thus data features exhibit different distributions in different market styles and different time periods, and the performance of a model usually decays over time without retraining on recently incremented data. This phenomenon means a one-time model training on data like what people do in many other AI scenarios such as natural language process and image recognition doesn't work well in quant research. Therefore, rolling training is widely adopted in quant research for back-test simulation, paper trading and real trading. Imaging an experiment rolling training once a week, a ten years' back-test process retrain the model  $10 \times 50 = 500$  times, significantly increasing the computational cost.

- Model ensemble [295] is a common way to improve performance and robustness of a quant strategy and reduce the risk of portfolio asset loss. Moreover, ensemble of diversified or uncorrelated models could usually improve strategy performance and asset return. However, the computational cost increases linearly with the number of models combined in a strategy, and computer power becomes an important foundation for strategy stability and risk management.
- NAS and HPO are another two modules in quant pipeline heavily consuming computing power. Both of them are formalized as search-and-optimization problems in the network architecture space and the hyper-parameter space, respectively, and the computational cost is nonnegligible even if more and more fast algorithms are developed to improve the search efficiency.
- Feature selection (or feature importance computation) plays an important role in improving model performance and enhancing model explainability. Unfortunately, feature selection algorithms for deep learning are usually computationally intensive as well due to complicated feature interactive effects in the model, and they require sufficient computing power to identify significant factors within affordable time.

#### 6.1.2. Solving Computing Power Dilemma

Learning large model is very expensive. Figure 32 compares a number of deep learning models on code generation tasks in three aspects: parameter size, sample (token) size and estimated cost. We can see that GPT-3 model has about 170 billion parameters and costs about 2 million USD to complete the computation, which is obviously too expensive to be afforded for most financial institutions. Given the expensive and limited computing power, what are the solutions to this dilemma? We attempt to provide a few suggestions and research directions.

- Research of faster algorithms is the most direct and most significant way to reduce computational cost. However, it is a difficult problem to reduce the computational complexities of deep neural network algorithms, NAS/HPO algorithms and feature selection algorithms without losing their performance and it needs the joint effort of researchers from multiple relevant areas including but not limited to applied mathematics, theoretical computer science and machine learning.

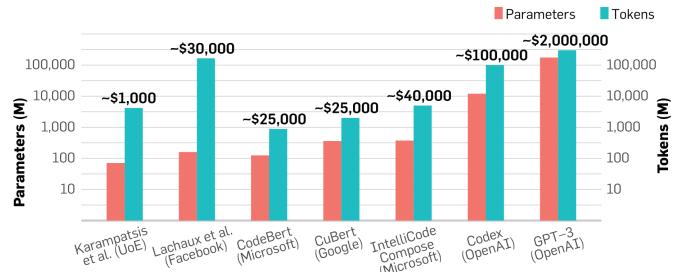


Figure 32: Comparison of large-scale deep learning pretraining models for code generation from model parameter size, data (token) size and estimated training cost. Figure is cited from [296].

- Online learning [297] and incremental learning [298] are machine learning techniques where data are acquired sequentially along time and the model is updated once new data are received without retraining the model on all data, as opposed to batch learning techniques such as traditional deep learning which train a model using the entire training data set at once. The computation time can be saved by model updating rather than model retraining.
- Pretraining-finetuning paradigm could help save overall computation time as well. Specifically, in the pretraining stage, we build a general but computationally intensive deep learning model and in the finetuning stage, we adapt it to various domains, scenarios and tasks in trading. After the computationally expensive pretraining process has been finished, the following finetuning tasks cost significantly less computation power and can be repeatedly performed.
- Model diversification reduces model similarity and reduces information redundancy in model representation, thus decreasing the number of required models in the ensemble. New algorithms are required to improve the diversity of a new model compared with existing ones in model bases. In particular, we need new techniques to enforce the model diversity before or during the training process directly.
- Utilizing informative low-frequency data is a way to enhance computational efficiency without too much effort on engineering techniques or algorithmic tricks. Many types of low-frequency data such as various alternative data, fundamental data and event data are informative for investment decisions, complementing data with relatively high frequency including quote data and limit order book data. Due to the sparsity and small size nature of these low-frequency data, and moreover, easy to compute for modeling.
- Sharing computing power and large model is a potential business/operating model to avoid overlapping investment in computing and modeling infrastructure and to dilute the cost across the whole quant investment industry. Although cloud computing service is an option for computing power sharing, it is not designed specifically for quant investment. In particular, almost all architectures and software systems of cloud computing clusters are not optimized towards the computational demand of quant. Therefore, this industry needs its

own professional quant computing sharing mechanism, platform and service. A similar sharing mechanism could be applied to large models as well. As a business model, financial institutes such as hedge funds and mutual funds could buy licenses for the usage of supercomputers and pretrained large models, just like buying financial data.

## 6.2. Alternative Data Technology

In principle, any data about economic activities have the potential to be used for investment and might be considered by quant researchers. Alternative data, a concept opposite to conventional financial data such as financial statements, stock quotes and limit order books, provides a much broader space for quant research. Although the concept of alternative data has appeared for a decade and is getting more and more popular in quant industry, it is still in the early stages of industry application because of a few reasons. Firstly, many alternative data sets such as news and research reports have very narrow coverage and low breadth since a news event usually only relates to a limited number of stocks, and you couldn't expect a public company has news or significant events every day. Secondly, some alternative data such as satellite images are too expensive for small funds, and relevant satellite image detection and recognition techniques are not well-established due to limited labeled data and expensive labeling costs. Thirdly, processing and cleaning raw alternative data is a time-consuming “dirty work”, and some informative alternative data can not be supplied legally and sustainably. In this subsection, we briefly introduce some examples of alternative data and the corresponding processing techniques, and discuss the difficulties in data acquisition and data aggregation.

### 6.2.1. Examples of Alternative Data

We list a few types of alternative data as examples and simply discuss the technical difficulties and opportunities for extracting informative signals from them. To avoid repetition, those alternative data already introduced in §4, such as supply chain data, are omitted here.

- Text data from news and social media are one of the most popular alternative data used by investment institutions. The key is to extract traders' sentiment signals correlated with future market trends. Natural language processing techniques such as opinion mining, sentiment modeling and trend tracking could be used to build useful alpha signals or factors.
- Satellite image data have been used by hedge funds and other institutional investors for many purposes. For example, investors could use satellite images to estimate how busy the parking lots of retailers are, providing investment signals for longing or shorting the retailers' stocks. Currently most satellite images are read and analyzed by human, but we believe computer vision techniques such as image recognition and object detection have huge application potential in the future when main technical issues (e.g., cheap labeled data) are solved.
- Merchandise sales data from e-commerce track sale records of consumer products companies from their online channels

and estimate their actual income before an upcoming financial statement is reported. This kind of data is usually fragmented and so correct data aggregation is important. In addition, we have to follow relevant data protection laws to make sure the data legitimacy.

- Logistic and inventory data track transportation and logistic activities of a company to estimate their sales performance which might be helpful for predicting the corresponding stocks.
- Credit card or e-payment transaction data is another angle to learn the operation and sales performance of a company or an industry, providing a possible fine-grained analysis through the information of micro-economic activities. Data legitimacy and data sensitivity are the main concerns before using them.
- Geolocation data collect foot-traffic information by GPS or cellphone locators. For example, an investor could use foot-track data for pair-trading arbitrage of Adidas and Nike by analyzing their geolocation activities in different retail shops and predicting spreads between the stock prices of these two companies.

### 6.2.2. Problems in Data Acquisition

Traditionally, hedge funds and other institutional investors acquire data from third-party data providers or data vendors. With the rapid accumulation of internet data, more and more hedge funds started data collection from websites using web crawlers. However, collecting data by web crawling is suffering unprecedented restrictions because more and more websites are attempting to protect their data using protocol securities and anti-crawler techniques. In addition, many informative data sets such as transaction data are distributed in various banks, e-payment institutes and credit card companies, and few of them allow users to take data out of their own servers considering intellectual property protection, data security and privacy protection. Here we provide a few possible ideas to collect and utilize more protected data legally.

- Certificate techniques for data asset ownership are the foundation for data owners who are willing to share their data and obtain legal income from data users. Decentralized data management techniques such as blockchain techniques provide a potential solution for this mechanism design problem.
- Data encryption techniques [299], including data storage encryption, data transfer encryption and data computation encryption, provide technical solutions for protecting the interest of data owners and data users (e.g., investors), and potentially encourage the willing of data exchange and data sharing.
- Federated learning [300, 301] is a machine learning technique for modeling data sources distributed across multiple decentralized servers each only holding a part of the whole data samples and it realizes information fusion without exchanging those local data. Federated learning techniques have the potential to help investors improve their quant models without spending too much time dealing with data security and privacy issues with massive data owners.

### 6.2.3. Problems in Data Aggregation

Data aggregation is important for quant to find alpha signals across different types of data. However, data structures of alternative data are diverse and heterogeneous, resulting in difficulties in data aggregation, especially when integrating with traditional financial data.

- Heterogeneity in frequency is a characteristic of many alternative data types such as news data and geolocation data, since they are collected irregularly. Therefore, it's important to align time-series signals occurring at unaligned time points across different instruments and different data types. A series of problems naturally arise. For example, how to build prediction models on these irregular and sparse data samples? How to better estimate and impute missing information in alternative data? All these data processing problems need to be further explored. For example, it is worthwhile to consider whether data embedding techniques learning “good” representations in lower-dimensional latent spaces help fuse heterogeneous data.
- Differentiating signals from noise is a difficult problem for the extraction of alpha signals from alternative data and should be carefully examined during data processing. Due to limited sample sizes and irregular sample timestamps, identifying true signals out of false positive patterns is more complicated than ever before. Therefore, it is demanding to develop new robustness techniques and significance test techniques to help evaluate the truth of signals and the significance of patterns.

## 6.3. Financial Knowledge Engineering

As we have introduced in §4, knowledge-driven AI will play an important role in future quantitative finance. Researching new knowledge representation methods, building complete and reliable knowledge bases and developing new knowledge reasoning and decision algorithms are crucial problems in knowledge engineering for financial investment.

### 6.3.1. Difficulties in Knowledge Engineering

Financial knowledge engineering is an engineering pipeline and research area for constructing effective AI knowledge systems covering knowledge acquisition, knowledge representation, knowledge management, knowledge reasoning, risk analysis and investment decision-making. Given the limitations of popular knowledge techniques, it is necessary for researchers to explore more efficient and more sophisticated methods to better represent and leverage different types of knowledge such as declarative knowledge [302], structured knowledge [303], procedural knowledge [304] etc. In particular, exploring and researching particular knowledge representation techniques for quant and other financial applications are valuable for contributing to the development of investment industry and for finding a broader investment field for quant. Before the wide application of knowledge engineering in quant, a number of technical difficulties need to be solved in the future.

- More sophisticated knowledge representation methods are extremely demanding for building an effective financial knowledge engineering in the future. In particular, we need better data structure and model structure to encode knowledge relevant to all types of economic and financial theories and practical activities.
- More advanced knowledge management system is the requirement of financial knowledge engineering. It requires more research on how to build an automatic and self-updating pipeline of knowledge acquisition, knowledge update, knowledge aggregation and knowledge correction, and on how to implement a reliable and scalable knowledge management system.
- Next-generation knowledge reasoning algorithms should be more explainable, providing more reliable analysis and prediction results. We encourage machine learning researchers to pay more attention to this area, which is part of next-generation AI core techniques.

### 6.3.2. Knowledge Engineering vs Large Model

Large-scale pretraining models have been widely used in many AI fields especially in natural language processing and computer vision and in multi-modal pattern recognition tasks. For example, large model GPT-3 [305] has about 175 billion parameters, and it could be imagined as a knowledge “crystal ball” for natural language generation and natural language reasoning. In this respect, large pretraining models play a similar role as knowledge engineering, and both of them could provide decision support and content generation function for downstream tasks. So whether large model is a good substitute for knowledge engineering? In our opinion, it is not true. Knowledge engineering has its particular advantage in explicit knowledge representation and knowledge logical reasoning, making the decision process transparent and understandable. Moreover, as the memory module in knowledge engineering, knowledge base has its advantage in flexibility, storing and managing all types of popular data structures including entities, facts and even rules. As a matter of fact, these two technology roadmaps are complementary to each other and have the potential to be integrated into a unified framework to improve the final performance of investment decisions.

## 6.4. Financial Metaverse & World Model Simulator

In quant research, it is very important to understand the underlying logic and micro-structure of financial markets. For example, we would like to know how the market will react to specific news about a financial statement fraud event, or how much a big order affects the asset price in the market. Unfortunately, empirical studies using historical data usually result in biased conclusions because they do not provide experimental access to all relevant information. In particular, even if certain extreme market events have never happened in history, it doesn't mean they will not happen in the future. What will happen if our trading strategy meets these assumed extreme events? Back-test experiments based on historical data can't answer this question, but we expect that financial metaverse can do it. Financial metaverse aims to build a simulated financial market

parallel to real-world financial markets and use it as an experimental environment to simulate situations other than what have happened in real markets.

#### 6.4.1. Financial Metaverse Market Simulator

Daniel Friedman, UCSC Economics Professor, expressed his view that simulation of markets provides a powerful tool to analyze not only individual participant behavior, but also overall market reactions that emerge from the interaction of individual agents [279]. Financial metaverse should be able to support various kinds of research experiments (about traders' behavior and market phenomenon) that are difficult to complete using historical data or trading experiments in real markets. Such a simulator could be used in a number of different scenarios. We list a number of examples as follows.

- Accurately estimating the market impact of a big order at certain market conditions and certain time point
- Analysis of trader behaviors reacting to a particular market event
- Understand the impact of a certain type of traders in markets
- High-precision simulation of transaction cost
- Running treatment-control random experiments to test causal effect to answer “what if” questions against particular historical dates

Besides the above applications, financial metaverse can also be applied to accurately justify causal effects of economic factors. This motivation is achieved by designing and conducting randomized experiments in this simulated market. Moreover, financial metaverse can also provide a fundamental experimental platform for causality engineering discussed in §6.5. Although financial metaverse is of great value for quant research and financial market research, there are many technical difficulties we have to face.

- There is no way to collect fine-grained data identifiable to individual traders, with which market simulation will become much easier.
- The data we have are lack information about the motivation and intent of every trader.
- A simulator can not enumerate and involve all possible factors affecting a market.
- Current computing power can not support high-precision simulation with a large number of trading agents in financial metaverse.

#### 6.4.2. World Model for Simulation

A technical problem of financial metaverse is the complexity of the simulation environment from which agents in the same reinforcement learning system are hard to learn, and it makes traditional reinforcement learning algorithms hard to learn millions of weights of a large model. Usually a financial metaverse requires at least thousands of agents, each of which is modeled by a large neural network and plays a specific group of traders with some typical style, to participate in simulated market trading and it aims to recurrent the real-market by a reinforcement learning simulation as precise as possible. This

makes regular computing power incapable of completing such accurate simulations. World model [306] provides a potential solution for this difficulty in financial metaverse. It is inspired by the function of human brain which develops a mental model of the world by learning an abstract representation of complex information flushing into the brain. In a world model, the dimension of outputs from the simulator (environment) is reduced using unsupervised learning such as variational autoencoder (VAE). We can use this abstraction to train small network controllers which let the training algorithm search on a small space for credit assignment task, and thus the computation can be accelerated. Figure 33 illustrates the structure of a world model for computer vision problems. The cognition abstrac-

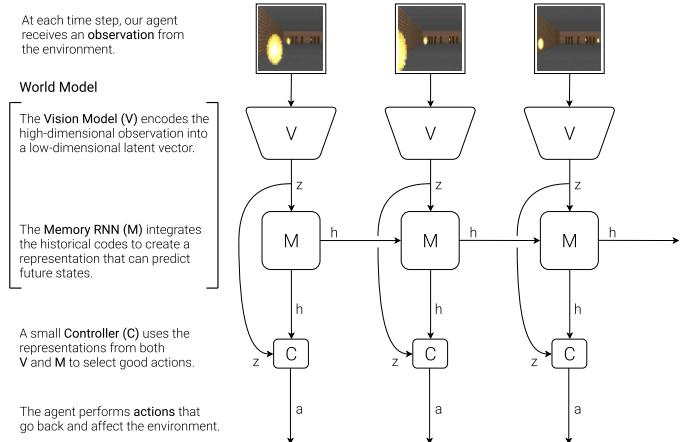


Figure 33: An example of world model architecture. Figure is cited from [306].

tion idea in world model could be used in financial metaverse to solve the simulation computation problem for financial markets.

#### 6.5. Cognitive AI & Causality Engineering

Cognitive AI has been regarded as the future direction of artificial general intelligence (AGI) [307] by many domain experts. In this subsection, we discuss its advantages and technical challenges in investment application, and we propose a new concept *causality engineering* as a potential solution for causal machine learning in AGI.

##### 6.5.1. Cognitive AI for Investment

In 2011, Israeli-American psychologist and economist Daniel Kahneman published his book *Thinking, Fast and Slow* [308], introducing two modes of thought for the first time. Specifically, system 1 thinking, driven by instinct and experiences, is a near-instantaneous process and happens automatically, intuitively, and with little effort. On the other hand, system 2 thinking, driven by comprehensive logical reasoning, is slower, more conscious, more deliberative, and requires more effort. Contemporary mainstream AI technology such as deep learning and reinforcement learning is running on a fast track approaching system 1 thinking, and we refer to it as *perceptive AI*. On the contrary, cognitive AI techniques aim to simulate system 2 thinking of human, providing more sophisticated, more

logical and more understandable AI solutions. Many pioneering researchers have proposed their opinions and/or solutions for cognitive AI. For example, Gary Marcus proposes “a hybrid, knowledge-driven, cognitive-model-based approach” towards robust artificial intelligence [309]. Yoshua Bengio identifies system 2 deep learning as being able to “understand, reason and generalize beyond training distributions” [310] and proposes corresponding techniques such as causal machine learning and generative flow networks [311] to achieve this goal. Figure 34 illustrates the concepts of system 1 and system 2,

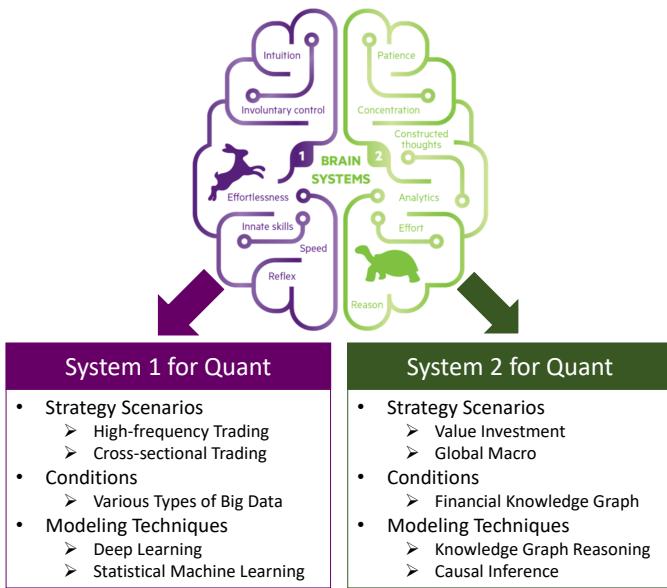


Figure 34: Comparison of System 1 and System 2 in AI technology for quant research.

and explains their appropriate scenarios and tasks for investment decisions. Different from perceptive AI mainly applied in high-frequency and high-breadth trading tasks, cognitive AI gives quant opportunities to touch those high-capacity but low-frequency investment strategies, including value investing which buys/sells securities that appear underpriced/overpriced through multi-dimensional fundamental analysis and usually holds the position over months or even over years, as well as global macro investment which selects assets and establishes portfolio based on the interpretation and prediction of large-scale events related to national economies (interest rate trends, CPIs growth, GDPs growth, unemployment rates, policies, etc.), and international relations (inter-governmental relations, international trade, cross-border payments, etc.) to decide long/short positions in various equity, fixed income, currency, commodities, and futures markets.

### 6.5.2. Causality Engineering

Causal inference [171] and causal machine learning [312, 313] have been regarded as one potential technical route towards AGI [310]. For investment tasks, understanding the true causal relationships among numerous factors is extremely challenging, due to the difficulty in enumerating all possible confounding variables that affect the future trend in one single ex-

periment and give us a misleading conclusion. Therefore, we propose a potential solution through causality engineering, a proposed concept which aims to build and maintain a large-scale causal diagram database storing and managing all known/inferred causal effect relationships and potential confounding variables [314] and causal variables. Different from regular alpha factor bases, a causal diagram database collects as many economic factors and computes their intrinsic conditional probability of causality between each other. Moreover, causality engineering will develop a series of algorithmic tools for different purposes, including testing the statistical significance of causal pairs, testing the effect of potential confounders, and searching significant causal pairs or causal clauses. Leveraging causality engineering, we expect that most main confounding factors disturbing the correct justification of true causal effect factors could be discovered in experiments and could be eliminated correctly using appropriate statistical methods.

## 6.6. AI Risk Graph & Systematic Modeling

The rapid growth of various types of financial big data brings us opportunities to model and analyze financial risk systematically, ranging from macroeconomy to micro-market. We propose the concept of *AI risk graph*, a special financial knowledge graph for recording, computing, analyzing and forecasting financial risks at different hierarchical dimensions, including country, district, industry, sector, etc.

### 6.6.1. Risk Graph for Systematic Modeling

An AI risk graph should be able to represent the causal dependency of different types of risk among public companies, private companies, banks, important individuals and many other economic entities, and represent risk transfer between various entities. Such a graph could be used to systematically model various types of risks at different levels by computing the conditional probability of risk for a specified object (public company, sector, industry, etc) at certain conditions (time, market environment, debt leverage, etc). Various statistical graphical models and machine learning algorithms could be applied to estimate risk conditional probability. Moreover, AI risk graph could help decompose observed risk value in a more scientific and more intuitive way in order to improve the interpretability of risk analysis and risk management.

### 6.6.2. Complex Risk Measure for Investment

Classic risk management techniques such as BARRA [48] risk factor analysis model are used in measuring the overall risk associated with securities relative to the market risks. Specifically, the model decomposes the overall risk into a number of exposures from different risk factors with a linearly additive interpretation. However, the limitation of linear risk modeling is obvious, in particular when the prediction model is built with highly nonlinear machine learning sample fitting. How to characterize, measure, and evaluate nonlinear risk is an important research topic in quant. In particular in nonlinear modeling scenarios.

- How to define a reasonable and practically useful nonlinear risk measure?

- How to make sure the nonlinear risk by definition exists and is identifiable?
- How to tell the difference between risk and noise in an extreme market?
- What proportion of overall risk could be explained by linear and nonlinear risk?

## 6.7. Spatiotemporal Modeling

The data structure for stock modeling is typically a tensor with three orthogonal axes: time, stock, and factor. Traditionally, stock strategies are developed either along the time axis (called time-series modeling or temporal modeling) or along the stock axis (called cross-sectional modeling or spatial modeling). These two modeling types have significant differences in strategy development. Specifically, cross-sectional modeling only compares relative strengths of investment signals within the same cross-section at some time point, and the signal strengths of the same stock at different time points are usually not comparable. Cross-sectional modeling has its advantage in neutralizing market risk automatically by longing top stocks and shorting bottom stocks ranked by cross-sectional trading signals. On the other hand, time-series modeling treats each stock individually, and the trading signals of different stocks at the same time point are not comparable.

### 6.7.1. Unifying Cross-section & Time-series

A technically difficult but practically feasible idea is to merge cross-sectional modeling and time-series modeling in a unified framework, in order to absorb the advantages from both sides. For this aim, we attempt to provide a few tips on how to build a unified model and what potential difficulties may exist.

- A unified model needs to update stock cross-sections in a very high frequency (in seconds, for example) in order to match the prediction paces of time-series modeling.
- A unified model should be very selective in longing and shorting stock positions at each trading point in order to reduce the turnover rate of strategy so as reduce transaction costs.
- The model should provide a hyperparameter for users to tune the balance between neutralization (alpha-oriented strategy) and absolute return (beta-oriented strategy), according to the design of the portfolio style and the demand of customers.

### 6.7.2. Spatiotemporal Graph for Quant

Although a unified model aims to combine the advantage of cross-sectional modeling and time-series modeling, the relationships (or interactions) among stocks are hard to be incorporated in it. Spatiotemporal graph modeling could help complement this part of the information. In particular, a spatiotemporal graph [315, 316] can be embedded as a vector of latent factors using graph convolution or graph attention representation learning techniques, the latent vector could be concatenated with the factor vector used in unified modeling to improve the prediction performance.

## 6.8. Universal Modeling

As data volume and computing power is growing rapidly, large-scale pretrained model has become one of the mainstream AI paradigms in practice. Successful examples such as BERT [317], GPT-3 [305], CLIP [318], Codex [319] and DALL-E [320] have demonstrated the effectiveness of large-scale pretrained models on a number of application domains such as machine translation, multi-modal understanding, creative content generation and so on. Many successful pretraining models have exhibited their universal power to help improve many downstream tasks with different tasks and data sources. We expect this phenomenon could be reproduced in quant applications.

### 6.8.1. Pretraining-Finetuning Paradigm

The pretraining-finetuning paradigm in AI has demonstrated its success in natural language processing [305] and computer vision [321, 322]. By pretraining a large model on as much data in a self-supervised manner, one can obtain a model extracting the common information across various tasks and use it to achieve superior performances on a series of downstream tasks, compared to task-specific training. We think the pretraining-finetuning paradigm may be transferred to quant scenarios due to a number of reasons.

- Many finance prediction tasks have sufficiently large volumes of data with diversified types and this helps train a large-scale neural network pretraining model during the pretraining stage.
- Many different quant prediction tasks may share the same pattern and information in modeling, especially for high-frequency trading where trading decisions mainly depends on market trends and traders' behaviors in the market. A general pre-training model could learn common patterns across different markets and even across different types of instruments, and these common patterns may help improve the downstream prediction tasks.
- Pretraining-finetuning improves the automation of the modeling process and saves computational cost since we only need to maintain and update a pretrained main model which is a large neural network and adapt it to solve different downstream tasks by finetuning the main model.

### 6.8.2. Challenge in Quant Pretraining

The pretraining-finetuning paradigm has to face a number of difficulties if it is applied to quant.

- Investment data have extremely low signal-to-noise ratio, and make the pretraining process difficult to converge to a satisfying solution.
- The design of the quant pretraining process must be careful to avoid using future information. Therefore, the masks in self-supervised pretraining or labels in supervised pretraining can be allocated only on the right-hand side like what GPT-3 does.
- Pretraining should retain both flexibility and versatility. Specifically, we should figure out how to define appropriate labels or how to set appropriate masking structures.

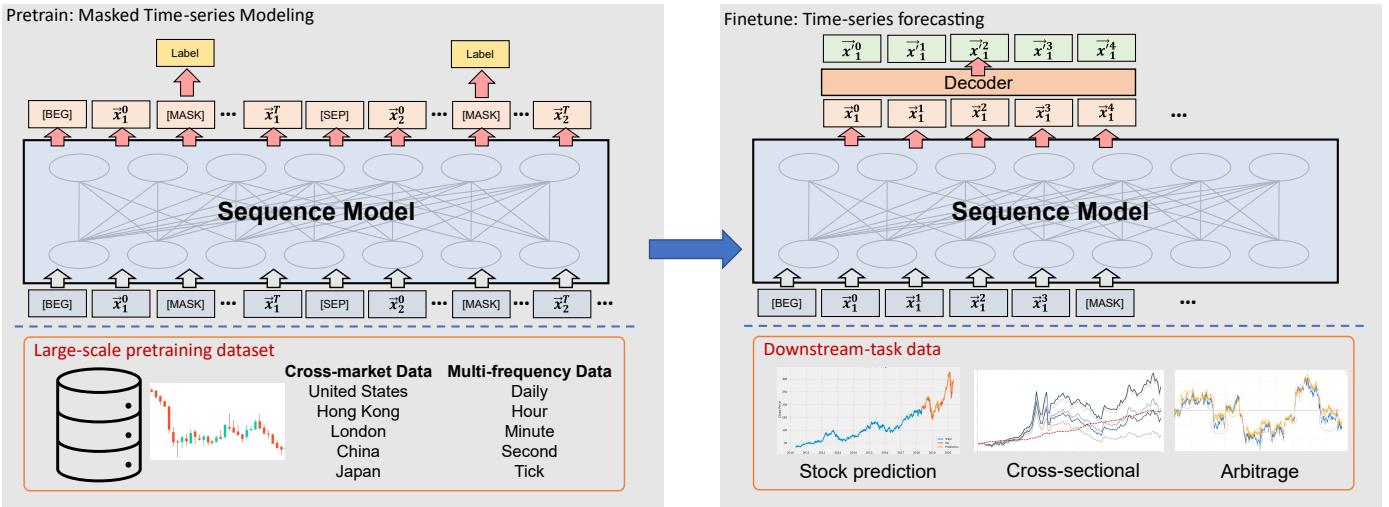


Figure 35: Pretrain-finetune paradigm. Figure is adapted from [317, 323].

### 6.9. Robust Modeling

Data noise is the biggest issue in quant modeling. It leads to three problems that negatively affect the robustness and correctness of our model.

1. The signal-to-noise ratio in financial data is extremely low. For example, empirically, the information coefficient of an effective stock cross-sectional alpha model for daily trading lies around the level of 0.1, indicating a signal-to-noise ratio at 10% level, and thus the low signal-to-noise ratio makes it more difficult for machine learning algorithms to tell true patterns out of false positive noise when the sample size is not sufficiently large.
2. It is difficult to correctly and robustly model the distribution of data with heavy noise. For example, the performance of many machine learning models is sensitive to model configurations as well as model hyperparameters when they are trained on very noisy financial data. This makes models very sensitive to sample outliers, time-series change points and the option of parameters, and thus increases the risk of overfitting.
3. The noisy financial data do not follow an independent and identical distribution (i.i.d.) condition which is considered as the underlying assumption of most machine learning algorithms. Since market style is constantly changing as a consequence of an enormous number of factors, it is hard to find a model that persistently generates effective trading signals forever. Such noisy nature of financial data hinders the effectiveness of transferring existing algorithms directly, requiring both theoretical and practical innovations in the study of AI technology.

To address these problems, we suggest researchers considering the following directions in the future.

- Causal effect modeling [169] can be applied to explore the causal effect between factors and financial decisions. By removing the interference from confounding variables, we have the chance to approximate the causal effect by esti-

mating an underlying stable relationship between input factors and output decisions, and reduce the uncertainty of the model. Moreover, causal effect learning techniques could be applied to machine learning modeling in order to improve their out-of-distribution generalization.

- Continual learning techniques [298] aim to cumulatively acquire new information from data without forgetting the knowledge obtained from previous tasks. They could be used to improve out-of-distribution generalization [324] and thus increase model robustness through iteratively retraining with accumulated data over time and frequently updating the prediction model.
- Model ensemble technique is useful in many scenarios to improve prediction stability by combining multiple single models, especially when single models have sufficiently differentiable outputs. Classic ensemble methods include bootstrap aggregating (bagging) [325], boosting [326, 327], stacking [328, 329], Bayesian model averaging [330], etc.
- Model diversification for ensemble expands the diversity of single models prepared to be combined, and the robustness of the ensemble model could benefit from diversification among single models. Various techniques could be applied to increase model diversity and discrepancy, such as model randomization (bootstrap, permutation, dropout [331], etc.), model neutralization, model decorrelation, mixture-of-experts [139], etc.
- Incorporating diversified data from different sources and different patterns helps improve model robustness as well. For example, models trained from fundamental data extracted from financial statements usually complement well with models trained from stock prices and volumes, and a combination of the two types of models may help improve stability.

### 6.10. End-to-end Modeling

As we have introduced in §2.1, the traditional quant research pipeline consists of a number of steps (as shown in the

blue blocks in Figure 36), and each step has its own optimization direction. For example, the factor mining module searches “good” factors aiming to find effective alpha signals with significant single-factor IC or back-test profit-and-loss ratio. The modeling module trains machine learning models aiming to minimize some sort of loss functions that measure the difference between labels and prediction outcomes. The portfolio optimization module allocates assets with optimal positions aiming to maximize some sort of value-at-risk (VaR) target. And the trading execution module computes the optimal order size in real-time aiming to minimize the market impact and reduce transaction costs. We can see the optimization goals of these steps are somewhat different from each other. For example, a “good” factor with high IC doesn’t necessarily contribute positively to the final model output in a complicated nonlinear relationship. Therefore, it is natural to consider if there exists an end-to-end model taking meta factors as input and trading orders as output, and if its performance has an advantage compared with traditional separate modeling.

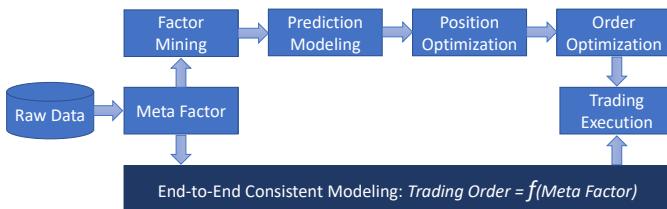


Figure 36: Comparison of traditional quant research pipeline and end-to-end consistent modeling.

#### 6.10.1. End-to-end Consistent Optimization

It is a difficult task to build a consistently optimal model due to technical reasons. Firstly, end-to-end modeling is usually hard to be formulated as a typical supervised learning problem because there is no clear label definition for the whole pipeline. In particular, the steps of portfolio optimization and algorithmic trading are dynamic optimization problems relevant to Markov time dependency which are difficult to be incorporated into a supervised learning framework. Secondly, trading decisions in the order execution step are as frequent as a few seconds, while meta factors are usually updated every couple of minutes or days, and therefore it is difficult to construct “ $(x, y)$  pairs” of samples for machine learning models. Thirdly, the noisy financial data make it difficult to train machine learning models difficult, and in particular, it is easy to be stuck at some local optimum during the training process, making the model sensitive to disturbance, noise and outliers. Finally, the computational cost of an end-to-end model is extremely high, which redirects to the challenge of computing power discussed in §6.1.

The opportunity for solutions to consistent modeling relies on the development of new machine learning paradigms satisfying the following requirements.

1. The machine learning model should have a hierarchical structure supporting data and decisions at various time granularities including millisecond-level, second-level, minute-level, day-level, week-level, or even month-level.

2. The computational complexity should be controlled to finish the computation in an affordable time.
3. The optimization direction of the model should depend on predefined labels if available, and should depend on the effect of trading executions measured by typical evaluation criterion for quant.

Based upon the above analysis, we would recommend researchers interested in the problem to think from an existing baseline model under the reinforcement learning framework [73, 74], and pay more attention to fusing data, factors, decisions and executions in multiple time granularities.

#### 6.10.2. Learning Unstructured Data

Another problem in end-to-end learning is how to model unstructured data automatically. Many raw financial data are unstructured in format, says, they are impossible or inappropriate to be formatted as matrices, tensors, or data frames. Examples include order volume distributions on various bid/ask prices from limit order book data, interactions or causal relationships from economic behavior and event data, and investor emotion from news text data. How to effectively train a deep learning quant model end-to-end with a mixture of structured and unstructured financial data is still an open problem to us. New representation learning techniques (especially new information extraction and embedding methods) for unstructured data are needed for future investment research.

## 7. Conclusion and Perspective

In this article, we proposed the concept of Quant 4.0 which describes what the next-generation quant looks like. We think AI technology will become the core of quant research in the future. In particular, we claim that Automated AI, explainable AI, and knowledge-driven AI are three key components in Quant 4.0, and we think the development of these research areas will not only drive the evolution of quant research but also promote the progress of next-generation AI technology. We emphasize the importance of engineering in Quant 4.0. All three key components can not be implemented at scale without excellent system architecture and powerful computation infrastructure. Furthermore, we summarize 10 main challenges in quant technology, including one challenge about infrastructure, two challenges about financial data, three challenges about AGI technology and quant application, and four challenges about AI quant modeling.

We must emphasize that Quant 4.0 is a dynamic concept and it will evolve and improve itself with the emergence of more and more new technology in the future. We encourage all researchers from related research areas to pay more attention to this interdisciplinary field which may become one of the demands driving the development of next-generation AI technology. To be honest, there is still a long way to go before achieving an ideal Quant 4.0 level since a lot of technical challenges in both artificial intelligence and quant engineering need to be solved. However, the rapid growth of AI technology in the past

decade always moves beyond our expectations and brings us exciting progress, brand-new ideas, and more importantly, more confidence to explore this direction. Finally, we hope this perspective article could provide some insights to both academia and industry and encourage more researchers to study and contribute to this interdisciplinary field.

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