

Engineering Data Products for Investment Analytics: The Role of Product Master Data and Scalable Big Data Solutions

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Abstract

This book teaches you how to create interactive, dynamic, data-driven investment dashboards. Dashboards transcend boring paper reports that are published infrequently and rarely read by their intended audience. Like a map, a dashboard dynamically illustrates the investment journey and current safety status of a portfolio, answering questions such as “Where are we now?”, “Where have we been?”, and “Where are we going?” Dashboards allow researchers, clients, and portfolio managers to seamlessly share the latest data analysis and visualizations in real-time while establishing a collaborative dialogue about enhanced portfolio performance.

The investment example developed throughout this book is quantitative in nature, and samples come from twenty years of data in various forms. The quantitative risk indicator we will examine is Value-at-Risk (VaR) defined using linear projections from a factor model. The numerical data corresponds to the portfolio-level or mean of risk projections characterized for thirteen different industry sectors over time. This information creates the dashboard, the goal of which is to tell a synthesized story regarding risk movement of the portfolio and its sectors. In addition to illustrating the dynamic aspect of risk, the dashboard also allows pattern recognition of peak VaR level along with long-term bursts. Dashboards are basically intuitive graphic representations. However, creating one does require that a researcher connects all proper display pieces interactively, uses best graphical practices, and possesses the motivation to build a surrounding technology on a programming platform to captively engage the audience's attention to explore inquiring visual analytics.

Keywords: *Engineering Data Products, Investment Analytics, Product Master Data, Scalable Solutions, Big Data, Data Engineering, Financial Data Systems, Data Architecture, Investment Platforms, Metadata Management, Data Pipelines, Data Integration, Data Governance, Cloud Computing, Real-Time Analytics, Data Quality, Financial Modeling, Distributed Systems, Data Scalability, Product Taxonomy, Machine Learning, AI-Driven Insights, Data Lakes, ETL Processes, Financial Services, Data Standardization, Investment Intelligence, Data Infrastructure, Decision Support Systems, Data Reliability.*

I. INTRODUCTION

Finance, while far from perfect, has often been cited as the most successful of social sciences. Investment professionals are masters of leveraging data into profitable action. Over centuries of real-world testing, they have concisely discovered and quantified principles that guide asset prices. They have engineered product after product toward reducing the friction of these principles — allowing capital to flow more efficiently around the globe, while politely extracting their fees for the service. The results speak for themselves: billions of people have enjoyed rising living standards in tandem with the persistent positive returns and risk pooling made possible by the global capital markets.

At a fundamental level, the task of investment professionals is to decide how to allocate capital to the set of available investment opportunities so as to maximize risk-adjusted returns. The complexity of that task, however, is extreme. Building an actionable view of any single investment opportunity requires the careful consideration of a dizzying array of inputs, from macroeconomic trends, to cyclical conditions, to industry specifics, to company fundamentals. And there is no shortage of opinions about how to evaluate those inputs. The set of inputs and the ways they come together vary widely across investment opportunities. Investment styles also allow both investors and the assets they target to vary greatly. Some are well-defined and based on easily-

computable metrics. Others focus on vague, hard to quantify concepts, deftly honed over decades into a true art. Relying on observed history alone is often not an option. Unlike scientists who can rely on the scientific method to test their theories in a controlled way, investment professionals will often not find results shaping up as theory predicts until present economic, social, and political conditions have fundamentally changed.

II. UNDERSTANDING INVESTMENT ANALYTICS

Investment analytics is the process of measuring and evaluating returns generated by an investment strategy, being usually expressed in percentage terms. Returns show the percentage change in value of the portfolio, given a specific investment horizon, without respect to the amount of money invested. Sometimes, analysts consider the performance dollar amount to determine the efficiency of a portfolio management strategy over an investment horizon. In spite of that, considering the money in excess of the invested amount could lead to poorly formulated decisions.

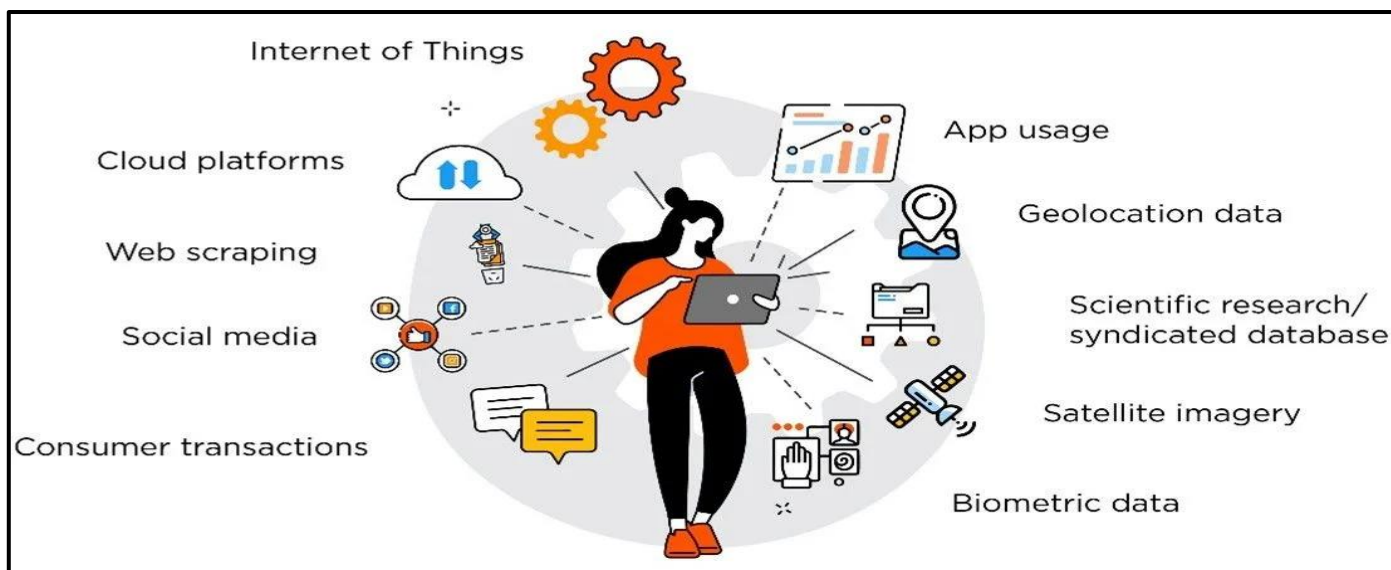


Fig 1 Alternative Data - Why Alternative Data is the Future of Investment Analytics

The primary goal of investment analytics is risk-adjusted return measurement, which usually says how much risk is exposed to the portfolio manager to achieve performance level. Risk-adjusted performance indicates to what extent risk exposure is necessary to realize different levels of return. Understanding investment performance is important for everyone who has a role in the investment process, be they investors, regulatory authorities, or those with the task of managing investment activities. Without performance measurement, it would be difficult to raise capital for funds or attract new clients to invest in investment services.

➤ Key Metrics and Indicators:

Several metrics are usually used to assess the performance of a portfolio strategy, such as Total Return, Net and Gross Return, Sharpe ratio, Treynor ratio, Jensen ratio, Information Ratio, among others. In measuring the risk-adjusted performance, analysts have to compare performance with an appropriate benchmark for the investment type to determine if performance has been extraordinary or just expected. A benchmark is usually an index that measures returns on a representative group of securities and serves as a standard against which portfolio returns can be compared. However, there is controversy in the use of one single benchmark, because some analysts argue that the appropriate benchmark for every strategy is the risk-free return.

➤ Definition and Importance:

Investment analytics is a process that involves gathering, interpreting, and analyzing data about various investment classes in order to aid in decision making. Analysts constantly look for signals that may suggest or point to future changes in market or investment class behavior. While many different types of analytics exist to be applied to investment data, decision making in this particular area tends to focus mainly on data related to risk or return. Analysts generally look to see if a given investment grows quickly enough to compensate for the amount of risk present, and whether or not the behavior of an investment matches someone's expectation of that investment's behavior. However, more rigid field definitions containing the same basic components exist. General financial analytics focuses on understanding monetary-related characteristics of the business that are predicted to assist with various monetary-related activities and planning. Whereas investment analytics focuses on understanding how investments are expected to behave to help determine what potential to allocate to a given investment. Investment analytics tends to cover a broader swath of areas than just stock trading; indeed, private equity investing, the gold and precious metals investing, hedge fund investing, public equity investing, R&D investing, venture capital investing, and virtually every other type of investing have different areas of focus when

it comes to investment analytics. Nevertheless, some common categories appear in many of these fields.

- *Key Metrics and Indicators:*

Understanding your investment performance is a necessary step to improve as an investor, and it is only made possible by the multiplicity of persistent key performance indicators (KPIs) that allow investors to close the feedback loop on their decision-taking process. There are many different kinds of indicators, which give you information on how well you are doing. They can be ranked according to different characteristics: timeliness, from the latest fashion aberration to the Winner’s Curse of post-dictions using only the hindsight; and periodicity, anything from daily returns to measures that easily span five years or longer can bemoan to a huge variety of investment horizons. It is a common practice among fund managers to use extreme periods to demonstrate their prowess at either outperforming or underperforming the market average, getting the right bet at the right time.

Investors should not only look at the length of an event or trend but focus also on average outperformance or underperformance over the course of a position. They should also be wary of highly systemic events and how much of their performance is due just to that. Warning flags should be raised for too-insistent correlations over time periods that do not match the horizon of the bet taker. Likewise, prompt illusions of control over volatility may well be misleading; “When the wind blows, even the turkeys fly”. Performance is only one side of the coin, and it is always at odds with risk. Deviating as little as possible from not being insurable, we cannot forget optimization on the Risk/Reward front, along the sharp ratio, how much do we make for how much it hurts times, respecting the order of events, as we live by and die by our budget constraints, drawing down, odds of a loss getting bigger than the budget.

III. THE ROLE OF DATA IN INVESTMENT DECISIONS

Investing by its very nature involves allocating capital to earn higher returns than the risk-free rate. Muscular institutional investors aim for higher alphas; everyday investors settle for sensible betas. Macro indicators and cross-sectional return differentials are both characterized by slow information flows, which imply that fast access is important for excess returns.

Equation 1 Expected Return Estimation

$$\mathbb{E}[R_i] = \frac{1}{T} \sum_{t=1}^T R_{i,t}$$

Denotations:

- $\mathbb{E}[R_i]$: Expected return of asset i
- $R_{i,t}$: Return of asset i at time t
- T : Number of time periods

We begin this section with a review of the sources and types of investment-determining data. Whether the goal is simple or sophisticated — to choose the right hedge funds or to contrast regime-based asset allocation with a multi-factor model — investment returns causally depend on a handful of underlying non-financial data. Macroeconomic key parameters, such as inflation, risk-free interest rates, and demographic-workethic productivity, evolve slowly over decades. Financial market anomalies, such as closed-end fund discounts or contrarian strategies, fade away in a few months. Finally, the same bottom-up information that guides company decisions — on takeovers, investments, and growth — also helps frame the top-down analytical process for asset managers.

Investment analytics address essentially a prediction problem: Can states of the world be predicted from available information? In financial economics parlance, such prediction is a forecasting exercise of possibly limited forecast horizons — specifically for expected returns or expected excess returns. Alas, widely available financial data — accounting data, for example — are characterized by high micro-level noise and low cross-sectional correlation. A properly designed aggregation across many micro observations can eliminate the problem of noise relative to signal. Appropriately designed forecasting models lead to significant forecasting gains compared to including only past excess returns in the model specification — specifically over medium-term horizons of one year.

➤ *Data Sources and Types:*

Data plays a central role in investment choices and decision-making and whether intentionally or not such decisions are based on observing complex patterns in the data. The resulting financial products are society's way of processing and compensating risks so that people can lead fulfilling and satisfying lives. The types of data used to analyze financial instruments are vast and vary with the structure of the asset, the method of investment, and the view taken by the investors. The motivation for investment will often dictate the instruments and hence the types of data used. An individual wishing to save for retirement will use data from institutions that offer long-term annuities. A trader offering one-sided risks to clients will work with data from the exchanges over which he will liquidate his positions.

There are two primary sources of financial data: exchanges and information vendors. While exchanges provide objective data based purely on observed transactions and the reactions of market makers, the data from information vendors are often not based on direct observation, but are compiled from numerous third-party sources. These different information sources lead to different types of data that vary broadly, depending on the types of financial instruments being evaluated. Data types may include market data, company fundamentals, sentiment scores, newsfeed processing, alternative data sources including social media trends and online traffic, and zoning permit data, to name a few.

➤ *Data Quality and Integrity:*

Data is a critical component of the investment decision-making process, and its quality heavily influences the results of those decisions in the form of risk and return to investors. This section extends the discussion of internal and external data types to a discussion of important issues in data quality and integrity, and the underlying cause of such issues. Data analysts and data users will face little issues with data quality and integrity when they build analytical models for investments using their own proprietary internal data, proprietary external research datasets, or data from credit rating agencies for fixed income research. Many of these datasets are built from market datasets using proprietary algorithms that only the data vendor knows. However, these proprietary datasets do come with restrictions on the financial use and economic consequences of the research using these datasets.

The economic consequences of investment-related decisions are high, so it is prudent to carefully validate the data models, datasets, data processes, and data integrity checks implemented during data engineering before any data outputs are consumed. This is particularly important when internal analysts or external researchers fill in missing values, or use published FABs and market datasets. Furthermore, it is also important to not rely on the information from a single external or market dataset for research. Multisource validation of the research is an important enabling condition for building PD, LGD, and EAD for securitized lending risk management purposes or CDO structuring. It is relatively easier to perform multisource validation of the common data inputs for bottom-up analytical modelers using external market or vendor datasets as opposed to internal research datasets. These internal datasets are proprietary to the model builders and will not be publicly available or verifiable by external parties.

IV. PRODUCT MASTER DATA

The investment analytics ecosystem is significantly different from Corporate Business Intelligence. Corporate Business Intelligence is concerned with a specific firm, its products, and its clients. It focuses on the firm's profitability and the most productive investments to meet its strategic goals. Investment analytics are concerned with manifold products of manifold firms and their loan or lease or debt clients. Investment data products are the raw material for investment analytics. The major objective of analytics in this domain is to address issues of risk management and risk return tradeoff, and the main audience for such investments data products is internal – risk and quantitative research departments of banks and other financial firms. However, external stakeholders – institutional investors, governmental supervisory departments – are also increasingly demanding contributions from investment data products.

Investment analytics depend importantly on definitions of loan or lease or debt products. Product definitions determine the breakups of portfolios into which

loan or lease or debt balances are grouped, for analytics purposes, and are associated with interest calculations for the product, risk category for the loan or lease or debt account, credit loss calculations for the overall portfolio, and so on. For such purposes, loan or lease or debt products are classified on the basis of many characteristics: loan type; loan purpose; collateral of the loan or lease or debt account; type of deal or type of client; loan features; product priority; product brand. A small number of additional characteristics identify the product in loan or lease or debt or other data sets.

Although analysts have kept publishing adjustment files for portfolio breakdowns and attributes, the robustness of investment analytics has lagged the advances in other sectors in terms of data sharing and product definitions. Credit loss adjustment factors, the main building blocks of data products, reflect loss models that are static – vary by product, and in sensitivity to economic conditions. For investment data products, analyst generalization and temporal stability of loss modeling is confirmed by empirical exercises. It is safe to say that analysts have focused more on the valuations of adjustable-rate mortgages and mortgage servicers than on the economics of mortgage product classes.

➤ *Definition and Components:*

Have you ever wondered what a product master data and what components are needed to make it useful for investment data analytics? Well, not in many words, master data, also called reference data or dimensional data, describe products such as stocks, bonds, indexes, funds, commodity futures or options, and foreign exchange. Moreover, the product master data gives meaning and context to transactional data warehouses and enterprise systems, integrating and centralizing repeated transactions that occur in various parts of the organization. The data are used in reports or processes to answer questions such as, given the current market capitalization of company A, how does it compare to recent history? At a given height, what is the historical yield of U.S. Treasury securities? What is the flow of equity invested in hedge fund B, considering the cumulative net asset value and the latest release of shares outstanding? What is the VIX spread of options on index C, given its strike price and expiration date?

However, product master data and more specifically, the data components allow your investment data warehouse or data mart to classify transactional data with additional attributes that are required in investment analytics. These classifications are used to optimize the data processing and query execution, allowing you to make the best use of the system resources and cut costs. The components are used to build either hierarchical or parallel classifications linked to a product, and define the attribute relation with transactional data such as transactional currency, transactional pricing source, or partner currency. It is crucial to approach these components with great care because they drive the quality and the efficiency of transactional data processing.

➤ *Impact on Investment Analytics:*

Investment research and analytics generates vast amounts of metadata, which ideally should all be engaged

with the same normalized schema, to maximize consistency and utility.



Fig 2 Mapping the Impact Investing Industry

In fact, product metadata from the enterprise schema will be used as the core metadata basis for all content across Research, Client Serving, Sales, and BackOffice as higher efficiency and better automation opportunities are identified and pursued. This is no simple matter as both the schema and the structure of the datasets are highly heterogeneous, and heavily modified by each data feeds' Owners and Content Managers, who might not easily agree to any changes. Yet a normalized set of core metadata has distinct advantages for Research Value and Metadata Quality in Investment Analytics, particularly for Management Information and Interactive Intelligence. The latter are being continuously refreshed with ad and cross-hoc machine learning and Artificial Intelligence.

The basic challenge is that some Product Master data is shared across analytic queries and some is completely query-specific. How does a data warehouse balance both objectives? Design cannot rely on both aspects being similar for different parts of the schema because that is exceedingly unlikely for any sufficiently complex data warehouse. Instead, design takes a hybrid approach that incorporates generalization, specialization, and abstraction. Where possible, it uses generalization to share the same structure across different PDMs, with additional specialization-dependent tables appended where necessary or helpful. Furthermore, it hides the underlying specialization-dependent tables from users and applications, topside, presenting a streamlined version of the shared structure. Only applications, like batch jobs and contributory tools, that need to reference specialized PDMs directly use the extra abstraction tables.

V. BIG DATA SOLUTIONS IN FINANCE

Investment firms face the challenge of building proprietary analytical tools to gain an edge over a highly competitive landscape. Investment analytics is

increasingly reliant on big data techniques that allow analyzing training sets that are rich in data yet scarce in labels. A combination of powerful expressive computing resources, big data technologies paired with flexible coding paradigms can help build such tools.

This chapter discusses potential tools or solutions to address the investment analytics challenge. Part of the tooling discussion is limited to considerations emerging from big data technologies that are becoming increasingly popular. Often, these tools are designed for data science problems, where the solution philosophy emphasizes flexible experimentation. We focus on technologies that support rapid experimentation in model building and iteration. These technologies allow building exploratory models that can process hundreds of features, and explore detailed historical data over many years, while being agnostic about suitability and availability of labeled data.

During the early 2000s, academic and commercial users of big data had very different perspectives on big data products. In research universities, there was a great deal of thought about problems for which big data analysis was especially likely to yield success, and incentives to deliver proofs of technology or physics, rather than proofs of concept about how big data enabled business innovation. Commercial users had little choice but to produce returns driven by big data capabilities; consequently, the most successful big data startups often focused on the B2C market.

➤ *Overview of Big Data Technologies:*

Financial companies have strategies to improve trading performance using advance order transactional data at high frequency. To avoid transaction costs, forcing close a position to be hedge against market fluctuation is rejected. In addition, a close microsecond delay for investment decision yields considerable profit loss. The

performance problem needs large number of investment transaction records to be analyzed to improve investment performance which is the idea of the big data technologies. The Financial Industry has many big volume data on trading market available. Predicting movements constitute an important area of finance, it is difficult to assess if predictive directional models are more useful than random directional guesses, having minimal level of directional prediction accuracy that is better than chance.

The area of big data technology offers tools that fit to the stated objectives. Components and alternatives have become mainstream products and are widely used by companies, but they are now being adopted for enterprise usage. Transactional and operational data in enterprise settings also needs fast query response time on small volume period data. The objectives for process monitoring to provide alerts with large scale caching directly query the original detailed source data. By architectural design, it is possible to have a solution that can achieve both enterprise and web objectives. We argue the design for hybrid solutions is force upon information management domain by use cases of funding, hands-free efficiency, and programmatic insights. By architectural design, scalable data organization is implemented using techniques from database, data warehouse, distributed hash, and big data frame. The importance of basis data services is then discussed, the role of cloud based, workflow service, ontologies, sophisticated models for prediction is expressed briefly, and other operational services are also described.

➤ *Scalability and Performance:*

There is a plethora of very efficient, open-source big data technologies developed by web companies that can be utilized in finance for engineering more scalable data products. We classify the available and emerging big data solutions into programming models, storage systems, execution platforms, and distributed computation. The other options that allow users to simply scale up easily with optimal parallelism include high-performance data analytics libraries such as Python-based DataFrame libraries.

Within Python, there is also a library built to scale from a single laptop to a large cluster that uses parallel computing using task scheduling. These technologies provide both MAP and pipeline primitive support out-of-the-box and make it easier to engineer scalable solutions. By scaling horizontally, it is easier to provide for concurrent, on-demand access to the resulting products which have instant serving latency. As a result, engineering scalable data products providing concurrent, instant access to the data analytics is much easier using the above parallel data computing and in-memory data solutions.

The main contribution of this chapter is to provide practical guidelines to engineer analysis layers that provide the desired level of scalability—providing concurrent access at the required latency—transactional, real-time, or near-real-time. We do this by exploring

features such as data size and dimensionality, workload dimensions, storage cost, data replication, partitioning, and distribution and the rules of thumb to select the right options. We then review the data engineering rules of thumb with a case study to summarize our guidelines.

VI. ENGINEERING DATA PRODUCTS

Some of the most significant breakthroughs in investment management over the past 30 years have come from the development of data products for investment analytics. Investment managers have adopted and built countless variations of the following product types in their quest for performance. Price and market data products enable market access for valuation and risk analysis. Financial model validation products provide a multistakeholder foundation to substantiate model outputs for performance attribution and risk. Market research synthesis products enable interaction and engagement among disruptive energy transition participants to re-envision the future of energy. Publishing document products support knowledge transfer by capturing the tacit knowledge of experienced investment analysts as first-draft copies of institutional investment analytics. Document security and anterior product controls enable sensitive information management for collaborative in-house investment product review. Verbal visualization products provide a systematic approach for building and observing market beliefs through a multistakeholder lens. Sector-specific analytic worksheet products exemplify the advantages of niche solutions to derivative and investment strategy development. Primer paper products summarize investment strategies and their respective anticipated behaviors in times of market stress.

Investment managers are also expected to provide a certain degree of transparency to their clients, which requires additional investments in data-rich analytics and the associated engineering, publishing, and infrastructure control processes. The challenge of engineering investment analytics products to support investment decision making is transforming the investment management process into an increasingly collaborative enterprise. This chapter describes the design principles and development frameworks for engineering these products in a way that is expeditious while allowing flexibility and scale so that the cost can be absorbed by investment analytics product users.

➤ *Design Principles:*

Summary of the section This section distills our experiences creating investment analytics into design principles. These principles will assist practitioners delivering analytics using data products. As engineers, our role is to translate business needs into engineering requirements, working with the flexibility and resources afforded by modern software engineering processes. The need for flexibility in investment analytics comes from evolving modeling choices, source data changes, business need shifts, and user skill level differentials. Users should expect to have their requirements thought through clearly in advance, and not have to worry about requesting model

changes or new datasets every four weeks. As engineers, we should be information-ready for all these changes. The engineering-oriented design principles in this section address this tension, maintaining engineering discipline while allowing analysts and users flexibility. These principles will assist users and business personnel producing the initial product specification. Strict adherence will provide a roadmap for our engineering teams to follow, but they are not a replacement for experienced engineering judgment when translating business requests into engineering deliverables and development timelines. As lessons-learned, we will illustrate design principles failures in the original implementation of our data products, poor investor foresight to users, and our internal engineering infrastructure. Engineering data products for investment analytics represents a special case. The analytics are often used by workers whose detailed understanding of model mechanics and structure exceeds that of the engineers. These skilled users and knowledge workers are the models' more obvious and immediate consumers. The work performed on models using the data products is creative in nature. Data products for analysts in other technical fields differ only in subject matters, but work follows more structured product organizations.

➤ *Development Frameworks*

Over the past few decades there has been an explosion of new technologies, programming frameworks, and tools employed in turn by software engineering departments of all kinds. It is not possible to capture the whole development paradigm, given the range of technical stacks, resources, and expertise present in engineering data products for investment analytics. However, here we provide a brief overview of how software engineers approach the problem generating software infrastructure from existing and newly developed analytic products, what stacks they typically use, and how they structure their approach. In so doing we cover desktop and server frameworks, data gathering, and analytical tools, user-friendly development tools, financial and business analytic packages, exploratory data analysis, visualization tools, and code version control.

Equation 2 Agile Velocity Estimation

$$V = \frac{\sum_{i=1}^n \text{StoryPoints}_i}{n}$$

- *V*: Average velocity (story points per sprint)
- *n*: Number of completed sprints

For the investment management industry, the preferred languages for data product development are R and python. The complete software engineering tool stack of frameworks, utility libraries, platforms, visualization and exploratory tools, and development environments for coding in these languages are increasingly derived from

the preference of a few large commercial vendors or cloud services providers. The utility software tool stack comprises packages that extend the built-in functionality of R and python to provide capabilities beyond general programming and for analyzing, visualizing, and other lower-level functions needed to code up a higher-level analytic data product. Utility tools and packages allow coders to access services, functions, and analysis tools through simplified interfaces. The data product developers start with installing the packages and modules to provide functionality for the coding stage of development. Users, who are one-time or occasional consumers of the implementation, must interact with potentially complex products, engaging in data and analytical trade-offs.

VII. DATA INTEGRATION STRATEGIES

Investment analytics within capital markets is a collaborative field that encompasses diverse teams with differing tasks and technologies. For every action, there is a leader who is responsible, and stakeholders who have an interest in the action being successful. For example, when a user buys mutual fund securities through their broker, it is the broker's operations team responsible for reconciling the transaction with the transfer agent, who will also be processing the transaction using nightly processes. Because our design principles dictate that we never introduce friction to our users, we make few requirements of our partners other than to publish trade data to an open format so that our processes could ingest the data without manual intervention.

Data integration occurs when an organization extracts data from various source systems, transforms that data into a usable format and loads it into a target database, data warehouse or analytics platform. A traditional approach to data integration relies on processes that move data in batch overnight. Although modeling and reporting against near real-time data isn't new, it hasn't always been easily implemented. Our original view of data integration was that every user could select the data they wanted whenever they wanted it. The scalability of data integration with traditional processes is limited by the need for request/response round trip communications to the sources of every data source and by the cost of storage, which mandates that little, if any, data redundancy be allowed for optimizing read latencies. Ultimately, the combination of low storage costs and a cloud data warehouse capable of near instantaneously updating data from multiple external sources made a solution easier to deliver, and more cost effective for our user partners than the traditional approach.

➤ *ETL Processes:*

The integration of internal and external financial data, obtained from the information systems depicted in the preceding chapters, can be performed following either a centralized or decentralized architecture. In a centralized architecture, the data integration and storage operations take place in a centralized repository, designed for structured, high-quality data. This version of a "single source of truth" design pattern allows access to convenient

tables, views or data product interfaces, while abstracting analysts and researchers from the complexity inexpensive, "frontier" data often holds. In a decentralized architecture, each end user or desk carries out its own data integration and storage specifications and decisions, functioning off of its fragmented set of ad hoc extracts and tables. A decentralized architecture lowers the burden on the infrastructure management teams typically in charge of capacity-planning these systems, allowing each desk to adapt idiosyncratic demands. However, ad hoc extracts lead to fragmented and poorly-sized data products, which are difficult to update regularly and which lose their coherence over time. We discuss batch and real-time methods for distributing and routinely refreshing data products below.

On a more tactical note, there are two practical steps behind the data integration and storage phase of the ETL process alluded to by the acronym: which data to extract from which data source and how to store the combined data. Batch frequency, data quality, infrastructure support and costs, as well as reconciliation and redundancy choices and considerations, will feed into these critical specifications. Batch ETL processes are generally run once a day or a week, using a well-documented ETL orchestration framework. Analysts or researchers write scripts or notebooks to extract data daily or weekly into temporary tables, whose data is finally copied in bulk into the main integrated architecture storage tables by the ETL orchestration engine.

➤ *Real-time Data Processing:*

The process of real-time data processing is a continuing challenge for the architecture of streaming data application modules for investment domains. At a basic level, data is collected into data brokers, translated into a library-accessible object hierarchy that represent required services, and adapted into necessary data formats for any downstream applications. The goal is for these services to be available from a potentially large number of primary research data sources, often just a few milliseconds after they are triggered. A macroeconomic policy time-series

service would be triggered by the release of a macroeconomic report, like the inflation rate for the consumer price index. An example of a market news event service would be a corporate earnings report or acquisition announcement. Other examples of investment triggers that require specialized services would be a cease-trade order occurring on a stock, the asset price hitting its lower bound, or a big alarm about a stock issued by an analyst.

As a general observation about the event environment, a great goal is to have as many of the events as possible with events being fired together in time. Investment applications have a shared interest to reduce the processing time needed to publish investment triggers service. Also with a moderate increase in latency and overhead, investment service producers may try to increase the number of services to be published by reducing the reprocessing of previously-completed event services, while adjusting the parameters that drive service events. Since the service producers can depend on the availability of these centralized brokers, there will be times when one service is producing many separate events and other services are producing very little in the individual trading days.

VIII. DATA VISUALIZATION TECHNIQUES

The examples in this chapter are straightforward. There are many visualization options available, and creating them is often no more difficult than calling the right function on a data structure. Data visualization is possibly the only domain in engineering data products where there are no expensive prerequisite investments in technology or knowledge. Everyone can do it. As a result, the field is littered with examples of bad visualizations. Choosing the right plot is essential to making an effective point and avoiding needless confusion or misunderstanding. Selecting the wrong plot can strengthen the opposite of the intent or end up oversimplifying situations. There are many interesting areas concerning our common visual language.

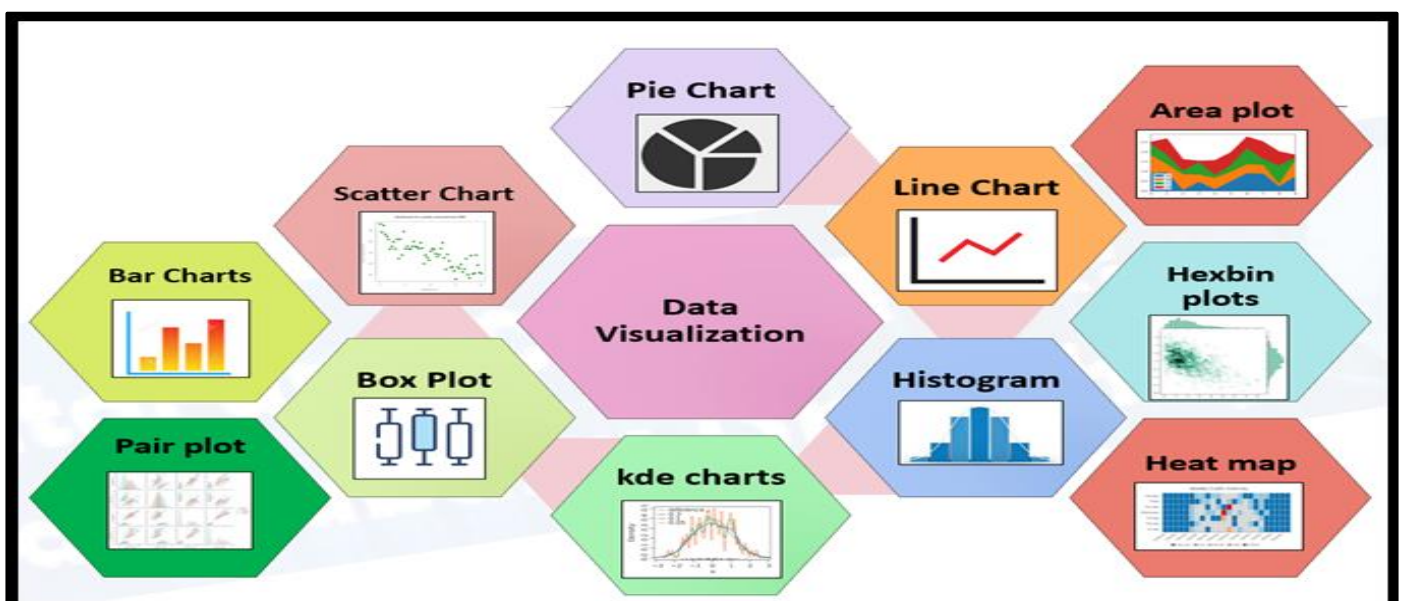


Fig 3 Effective Data Visualization Techniques in Data Science Using Python

A good starting point to getting Chief Technology Officers and data analysts to agree on the point at hand is to avoid too much enterprising freedom. The linear grouping of dots conveying what looks like a linear function might not be the best way of communicating a logistic function. In an enterprise where a lot of individual users do plotting to explore, going with the basic plotting defaults is often a good idea. The automatic color coding applied by the plotting function is usually a cool way of conveying the concept of many special interest groups. When working closely with a single data analyst, it's a good idea to help her choose the plot that displays the intuition you both have and that guides your exploration. The point of the exercise is allowing analysts to better explore the intentions and puzzling details of your dataset.

➤ *Tools and Technologies:*

Data visualization is presented as a category of direct manipulation technologies that aim to enable insight, discovery, inference, and understanding by increasing the accuracy and speed of visual inference. The development and use of these visualization technologies are discussed, culminating in a schematic framework for data visualization. On the distinction between data analysis and data visualization, it is claimed that only a small part of data analysis necessitates the use of visualization technologies. In particular, processes such as forming and testing specific hypotheses related to data contents and structure, exploring the structure of high dimensional data, assessing and enhancing the quality of data, and the visual discovery of general patterns require data visualization. The spectrum of data visualization processes is presented as a bridge from conventional data analysis to user-directed visual exploration. Following the belief that as an extension of ourselves, data visualization technologies enable people to rediscover their senses and enhance their exploration and understanding of the natural, social, and economic worlds that surround and involve them.

Among the used tools and technologies, we have chosen a multi-years effort on a JavaScript library for producing dynamic, interactive data visualizations in web browsers. This library makes use of the widely implemented standards. It is free to download and use, although it is not an IDE tool and requires several skills while enabling great flexibility and innovation for your Engineering Data Products. What this library enables is a tool to build Data Visualization Engineering Data Products, and hence, it complements a number of other tools and technologies. What makes it so unique and powerful is the fact that it is a general-purpose technology. It is intended for visualization enthusiasts and computer programmers. It is often considered a very low-level library, in the sense that so many tasks need to be coded up by the developer.

➤ *Best Practices:*

“Data visualization is really about seeing the unseen.” Turning raw data into compelling visuals can really contribute to the “a-ha” moment, or the moment of clarity and insight.

These days there are both desktop and cloud-based tools that allow a multi-disciplinary audience to visualize data in the way they want. For example, a researcher may use an analytical tool and implement a complex statistical technique to visualize data during the exploratory analysis phase. Then if the visualization needs to be presented to a wider audience, she may use a Data Visualization tool or a programming language installed with visualization libraries. Collaborative and cloud-based visualization tools are the best options for team members with non-technical backgrounds.

The decision to use a desktop or cloud-based environment can be driven by multiple factors such as number of users, cost of the tool, confidentiality of the data, creativity and design trends, size of job market and the quality of job applicants, and availability of computer languages for creating visual analysis. But regardless of the tool or technology, the following best practices can help create better data visualizations: Keep it simple, less is more – to ensure designs transfer clearly from concept to visual as these ideas are frequently not the same – it’s critical to simplify. Subjectivity and individual style – each audience has its own viewpoint about what they find attractive and aesthetic. Questioning your design is important. Be visual – visual cues are critical in communicating a design. Visuals should be able to evoke the required emotions. Emotion – go beyond usability; create a spark. Are you making your audience happy, sad, emotional? Have fun with it. Be honest – your visualization could create controversy. Design should be about intent, and designers should create with the objective of honesty.

IX. CASE STUDIES IN INVESTMENT ANALYTICS

Decision-makers in organizations are frequently faced with challenges. These can be attributed to sources of uncertainty, known as risk or problems that are vexing given a lack of convincing options for solutions.

Equation 3 Capital Asset Pricing Model (CAPM)

$$\mathbb{E}[R_i] = R_f + \beta_i(\mathbb{E}[R_m] - R_f)$$

- $\mathbb{E}[R_i]$: Expected return of asset i
- R_f : Risk-free rate
- β_i : Asset i 's sensitivity to market
- $\mathbb{E}[R_m]$: Expected return of the market

For a solution to be implementable and implemented, it needs to be convincing. Determining which available options are most likely to succeed should therefore be a priority. There are many scenarios in which decisions are characterized by risk. This is certainly true in finance, starting with the uncertain outcomes of every

speculative investment. Importantly, outcomes are uncertain but the risk associated with poor outcomes are known.

Given these factors, it is unsurprising that risk plays a key role from inception to final judgment in finance theory. Finance has a rich history of implementation of analytical tools stemming from pioneering work in the mid-1950s to early 1970s, and onto the pricing of derivative assets in the early 1970s, the pricing of risky assets in the early 1990s, and the modeling of risky asset price dynamics. Couple this with the long history of investor trading, and it is natural that the earliest engineering efforts in building data products was in the area of investment analytics. This chapter will share some observations and examples from the development of successful analytics data products.

➤ *Successful Implementations:*

Here we discuss several successful implementations of engineering data products for investment analytics. Although there are several large technology-centric firms available with investment platforms for analytic products, we focus only on those firms that have outsourced their infrastructure and developed products for the financial and investment analytics domain. We provide a high-level overview of the dimension of these investments in infrastructure and products to motivate the reader's interest.

An investment process platform serves to integrate global team-wide assignment collaboration, performance assessment, and risk analysis capabilities with fixed-income investment strategies. As a part of the long-term plan, with a committed team of data scientists and analysts, efforts are made to improve models and reduce friction between the improvements being made in data quality and production. The increasing focus by technology firms on marketing and research was foreshadowed almost a decade ago, when an analytical video portal for quantitative topics was launched. Although it is free, high-quality investment analytics, especially in data and information management, quantitative modeling, and high-capacity parallel optimizations in the space of high-dimensional IV, are provided, with managed funds dedicated to large institutional clients. These investment offerings have been recognized to deliver superior returns, especially vis-à-vis the average hedge fund performance.

➤ *Lessons Learned:*

The two experiences described in the previous section were successful implementations. The first and most important lesson learned is that dedication to the principle of “understanding the business” leads to successful implementations of engineering data products. In the case of the first experience, the data model chosen supported the business goal of identifying and forecasting asset level credit events in the hotel-lending business. In the case of the second experience, the comparative decision framework of portfolios of funds was parallel to the proprietary hedging strategy of managing asset portfolios, where the worth of a hedge portfolio was

compared to the worth of asset portfolios. Creating engineering data products that directly support business decision making is the only way to go. Therefore, collaboration with senior investment professionals, both in the area of defining desired outputs and helping iterate through the technical issues with prototypes, is essential.

The second lesson learned is that investment professionals are very pragmatic. Investment professionals are not enamored by the latest technology fads. Their main goal is to make the best possible decisions based on high-quality data output. If that means revising an existing model to incorporate the desired data and then generating the desired output from an engineering data product, nobody looks down on that model. It simply supports business decision making, which is the main goal. As technology permeates all aspects of life, investing is becoming more quantitatively oriented, requiring more data-driven decision making. The tools of classic applied econometrics, such as time series models, recursive quadratic programming with analytical solutions, and non-linear data transformations using digital filters, are being increasingly used by a younger generation of investment professionals.

X. CHALLENGES IN DATA ENGINEERING

Although the time-to-market for building data products has shrunk, data engineering continues to be riddled with challenges. From data governance to compliance and regulations, this chapter delves deeper into these challenges and how the companies are addressing these issues.

You can find it in the news more often than not. From crusades to preserve sensitive data, to sell side bans on the usage of certain data sets in our industry, to just plain incompetence about what data you can use and what you cannot. The consistent lack of data governance, particularly concerning alternative data sources is a concern. Treating all data sources with respect and have adherence to defined data governance standards across the board is expected of most technology companies these days. Especially in an industry like financial services where data is core to delivering analytics for sound decision making, the lack of governance has been surprising. It is understood that there are no explicit rules. At least ones that everyone understands. In some cases, there aren't even implicit rules that guard against maltreatment of data. Introducing disorganized data sources into the world literally requires a leap of faith.

Still, the proverbial wild west nature of alternative data sources is expected to change in the coming years, and companies are beginning to put processes into place to prevent the abuse of sensitive data. This includes setting explicit rules that not only preserve the data's sanctity, but also educate the data consumers. These rules will attempt to share the responsibility of ensuring the rights of the attributor, data sources and consumers, as well as the fact that reputational risk is a consideration.

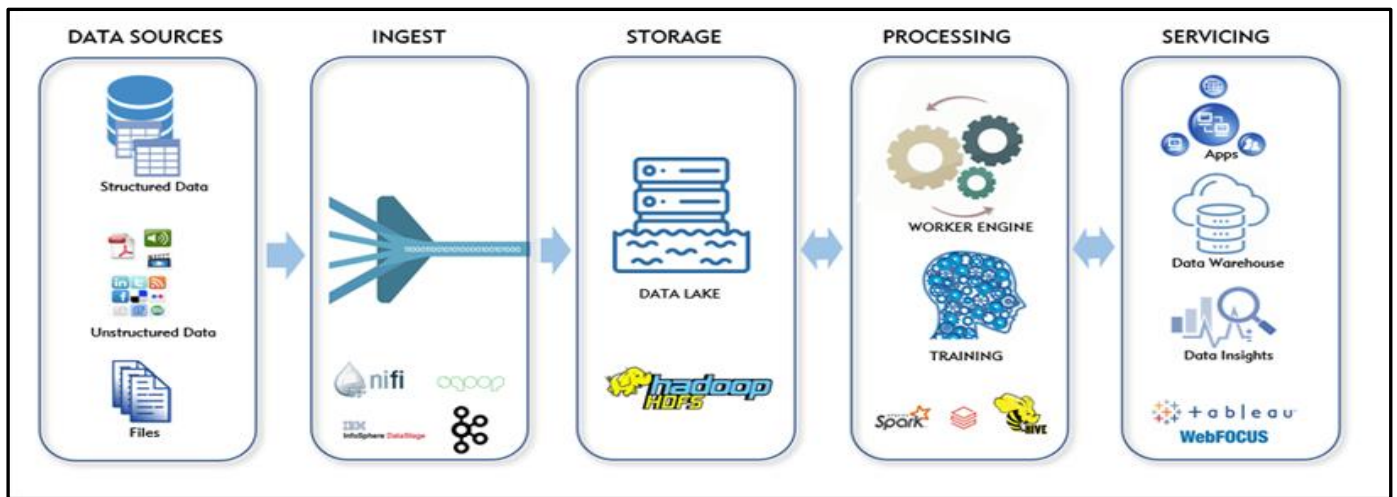


Fig 4 Big Data Analytics

➤ *Data Governance:*

Both big data and small data need appropriate data governance to ensure connectivity, control, accuracy, quality and security. Without data governance, finance organizations may experience issues with data integrity or with data explainability. This happens in quantitative finance a lot, due to black box models that leverage neural networks.

Data governance is also particularly important for sharing data in between interdisciplinary teams or networked economically connected organizations. In effect, shared data governance frameworks that include preconditioned data availability sharing agreements enables organizations to get ready to a “the more, the better” logic, encouraging synergies across the shared data pond while reducing data ponding syndromes. Besides property rights on data, a key feature in a shared data governance framework is dynamic expressed ability in showing data provenance to build trust into the data that is being shared. Indeed, sharing data provenance on data ensures transactions and connects stakeholders towards property rights on data; allows data users to ask questions on both the knowledge about data; and finally, ensures delivered results are trusted, easily understood, and auditable. Quantum finance enables achievements on dynamic expressed ability in showing data provenance while future research strives to improve onto it.

➤ *Compliance and Regulations:*

Compliance and regulation creation are also needed when a data product impacts too many people or organizations; in the area of investment analytics, these two factors go hand in hand. Implementing these regulations in a data product is hard and requires extreme granularity. As much as there are violations of market making regulations or regulations regarding asset flowing in and out of funds, there are few data products tracking market makers’ conversations or funds’ conversations with their advisors. There are algorithms highlighting periods with more divergent conversations and periods with more convergent conversations, but these algorithms are heavily errored.

In a complementary vein, regulation design also faces challenges. First, a large by-pass market where much deposit is and the impact of decisions and conversations, especially if bilateral, is visible boils down to no regulation or warning shots without fat fines, driving costs up. If authorities’ scope is limited to Registered Investment Advisors and Registered Investment Companies, deposit fleeing to Less-Audited Entities and Unregistered Pool Operators is a worrying precedent when having large deposit in Registered Investment Advisors and Registered Investment Companies. The same applies when Registered Investment Advisors keep such deposit in funds, especially Exchange Traded Funds, run by Less-Audited Entities, or when pension funds delegate asset allocation decisions to Companies and hire External General Partners while ex post shortfalls are closed at taxpayers’ expense. Would allocating business abroad with such remedies prevent long-run sanctions?

XI. FUTURE TRENDS IN INVESTMENT ANALYTICS

Investment analytics is specific to investments and does not refer to general analytics. It includes predicting future equity prices as well as macro environments, credit defaults, changes in yield curves, estimating asset expected returns, computing risk sensitivities for assets in the investment space, conducting asset valuations, and risk management. For the most part, there hasn’t been much innovation in investment analytics. Traditional approaches are based on familiar statistical and financial models, and relatively few people working in investment analytics are trained in machine learning or AI methods.

However, we may now see a new era. We are confident that the domains of investment analytics can benefit from many of the additional supervised and unsupervised statistical learning methodologies that we have explored many times, and that the new big and fast data flows can be mined to find new, large, and exploitable factors for the investment analytics domain. A case in point is the interest in Natural Language Processing on prediction models fed with sentiment data from news and social platforms. This trend is starting to gain momentum in the overall speed-challenge context.

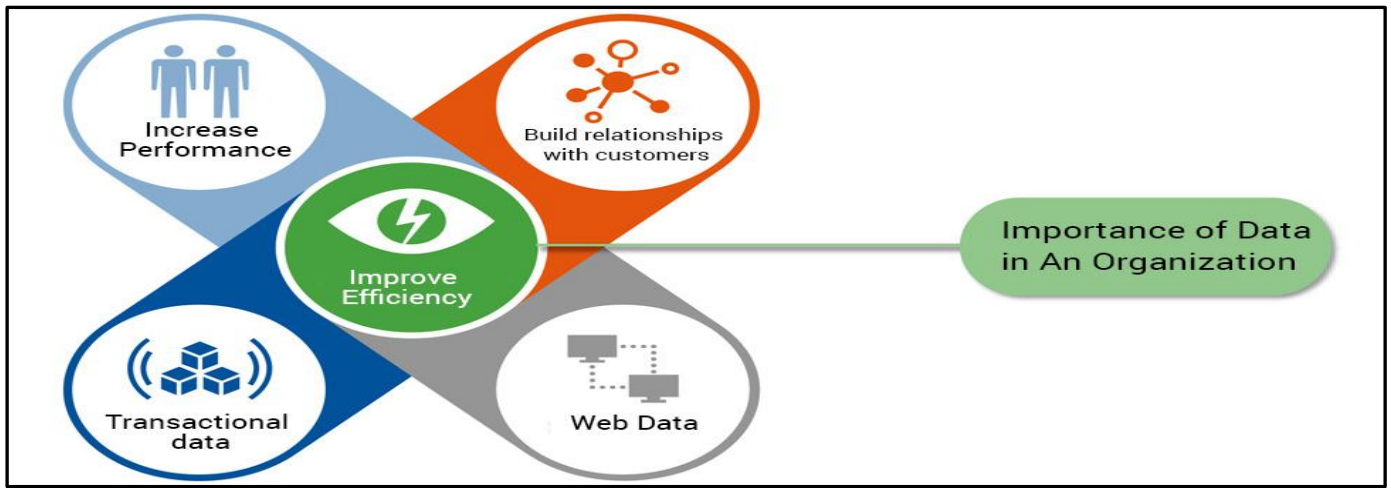


Fig 5 Embrace Tomorrow's Data Analytics

It's not that investment professionals have completely ignored machine learning, AI, or Natural Language Processing methods; they haven't. In exchange, we are now seeing firms use many efficient tools found in the Python ecosystem. Interactive brokers now offer data analysis wrappers, as well as research platforms, and firms also offer UIs for data scientists to write and visualize Python trading strategies. That said, we believe investment and macro analytics remain important problems still awaiting the application of machine learning methods and AI techniques.

➤ *Machine Learning Applications:*

Artificial intelligence (AI), particularly machine learning (ML), has become an important trend in investment analytics. The shift towards automation in technology continues to enhance the efficiency and effectiveness of investment analytics. Recent developments in the combination of AI technologies such as transfer learning and other deep neural networks, pre-trained Transformer architectures, reinforcement learning combined with neural networks, advanced unsupervised learning, generative adversarial networks, realized volatility prediction using combined symbolic representation, ensemble modeling, random forest and gradient boosting trees, and self-supervised learning are designed and intended to solve problems faster and at

larger scales. The importance of AI in investment analytics is driven by the availability of large amounts of relevant historical data, continuous deployment of advanced AI algorithms from the generalized fields of information modelling and data analytics as well as computer vision applications, and intelligent speech processing capabilities. Advancements in hardware technology through specialized computational processing chips, graphics processing units (GPUs) and tensor processing units (TPUs), accelerated parallel computing frameworks, and next-generation quantum computing solutions will also empower the importance of AI in investment analytics. Practical applications of machine learning and data analytics technologies have demonstrated concrete solutions to a variety of investment problems across multiple investment functions, including project selecting and monitoring, revenue generation, and managing directional and market timing risks. These applications have highlighted the increasing acceptance of machine learning technologies by institutional investors.

➤ *AI in Investment Strategies:*

Algorithmic trading has its origins 40–50 years ago. The “fair game” and “efficient capital markets” theorems state that investors cannot earn excess returns on average by using any public information, because any anomalies will be arbitrated away.

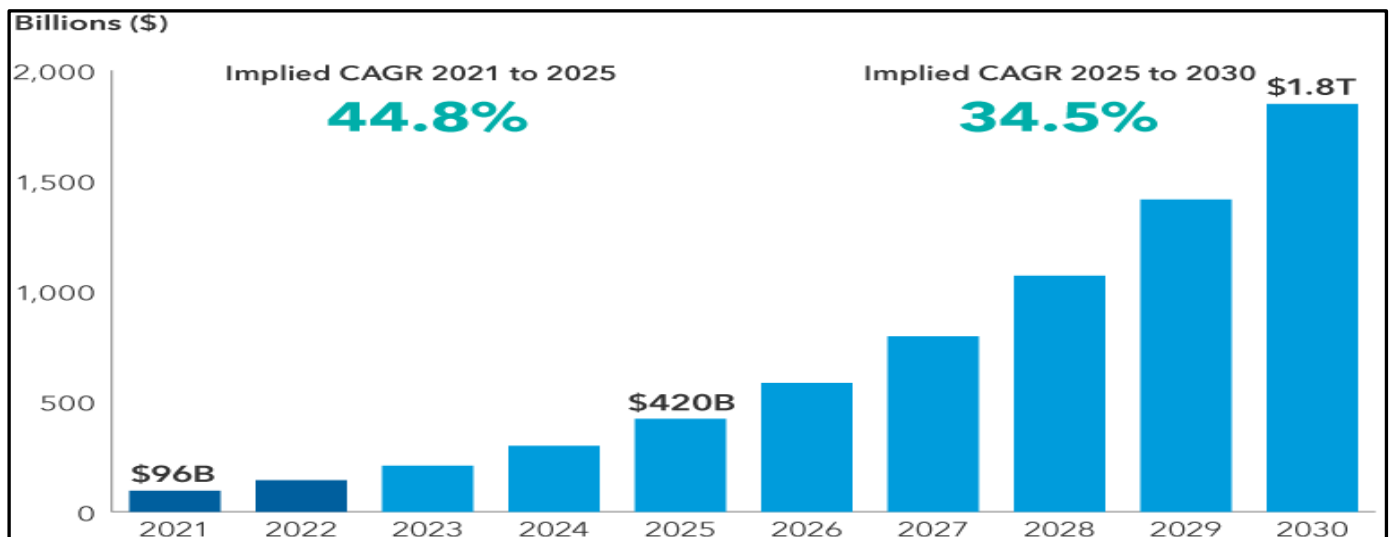


Fig 6 Global investing and the AI opportunity

Nevertheless, these results ignore the transaction costs, which are necessary to incorporate into the analysis if we want to model the real world. Since the costs of computing and executing trades have plummeted, some anomalies have resisted exploitation for decades and can be arbitrated on only with large trading volumes. Natural applications of AI are in market making and arbitrage. Automated market making by banks was initiated in the early 1990s using floor-based rapid execution systems relying on telephone communications systems. More recently, electronic limit order books have made it possible to develop algorithms capable of replenishing quotes as soon as a trade is executed. Arbitrage activities have also been executed automatically by banks for about 25 years. In the case of statistical arbitrage, the model attempts to take advantage of converging patterns of prices.

AI allows the development of new trading strategies to capitalize on anomalies in the financial markets with greater precision than currently existing more traditional algorithms, leading to lower transaction costs and better liquidity and ticket sizes. A trading strategy can take in as inputs multiple information: the level of the S&P index, the level of volatility, the differences between the price of the ETF and the price of the underlying, macroeconomic data, the characteristics of options on the ETF and the underlying, and the amount of volume traded on the ETF. The model enables different trading dynamics depending on the state of the world. For example, it could propose buying the ETF and shorting specific components of the basket in May and September at particular market levels when the market is volatile and buy at other levels on average during the rest of the year.

XII. CONCLUSION

We have described a roadmap for building engineering data products for investment analytics, emphasizing the potential for scalable automation of investment functions driven by data products. Specifically, we advocate a minimalistic design of engineering data products for investment analytics, supported by software engines for transparency, auditability, and verification of data pipelines, algorithmic performance measurements, and investment delivery. This roadmap realizes the academic and informatics foundation of financial data science, helping to overcome the chronological dislocation between real data obtainment and the delivery of its analytic utility using heuristics that inform predictive and prescriptive analytics.

By delivering transparency and auditability in algorithm training, it allows us to mitigate the shortcomings of deep reinforcement learning for investment portfolio decision-support and investment strategy automation or algorithzation. We infer algorithmic domain knowledge in the training process, addressing the primary consideration of any learning process: that of generalization beyond the training dataset. This allows for more adaptive, metacognitive, domain-aware trading algorithms, thereby avoiding the usual shortcomings of deep learning, including overspecialization,

unexplainability, and misapplication. Portfolio strategies and impractical algorithzation approaches usually violate asset pricing normalizations, which allow capital market equilibrium in theory and reality. Finally, detailed and excessive performance measurement allows for latency investigation in momentum switches and supports training and validation discussion.

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