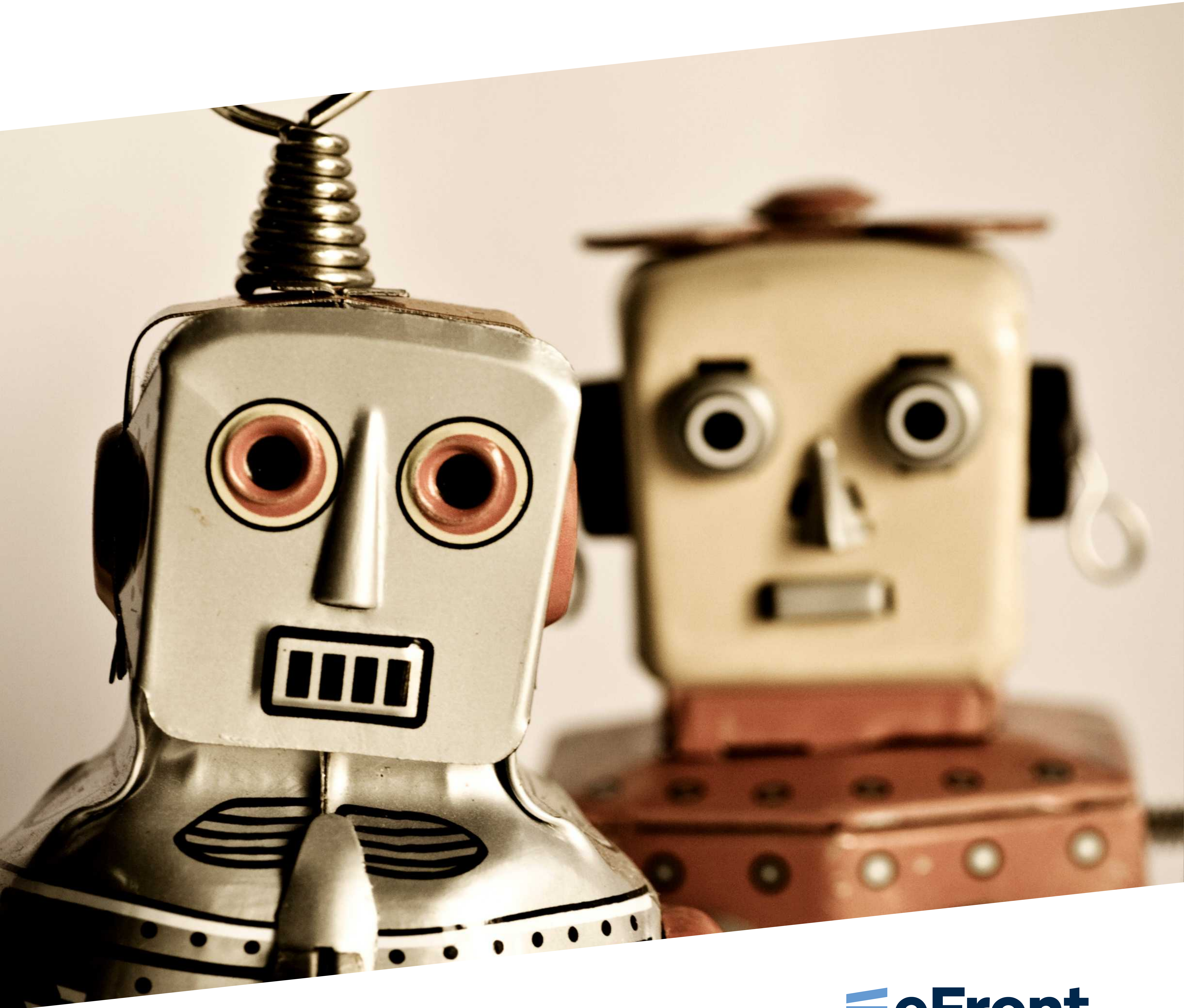
AI^2: Alternative Investments Meet Artificial Intelligence

A comprehensive overview of how the rise of AI technology may influence Alternative Investing



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Introduction

Over the years, many have tried to replicate or enhance private equity returns by the application of algorithms and computing power. They have been invariably frustrated. Unlike, say, hedge fund trading strategies, private equity and venture capital are too close to the chaotic, unstructured real world, with all its complexity and ambiguity, to be 'solvable' by armchair technicians.

But today, with the advent of ever more powerful artificial intelligence, the territory that remains unreadable to machines is shrinking, and patterns are emerging where, before, there was only noise. Venture capital investors are, of course, well aware of this potential, with AI-related investment running at around 10% of total venture investment, while enterprise investment into AI is expected to reach $232 bn by 2025, dwarfing the $12.5 bn spent today.

The profitability and investment potential into AI is not a contentious topic. But to what extent could AI disrupt and enhance the actual process of investing in alternatives itself?

We believe the scope for added value is significant, and growing quickly, both in terms of delegated investments and direct investment into high potential companies. This paper outlines some of the areas of investing into alternative investments (AI) where we think the application of artificial intelligence (AI) already makes sense and where it will become increasingly relevant in the future.

We call it "AI squared".

Contents

ABOUT AI

Artificial intelligence promises to perform tasks that traditionally have required human intelligence, such as *learning, reasoning, recognizing things and understanding natural human languages.*

There are six main Artificial intelligence applications

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Expert systems

An interactive and reliable computer-based decision-making system which relies on the body of knowledge of experts in the task domain and heuristics to solve complex decision-making problems. This knowledge-base is combined with a problem-solving model, typically structured as a set of IF-THEN rules. These systems are capable of advising, diagnosing, and deriving a solution and interpreting inputs, but they cannot produce accurate output that is based on inadequate knowledge base or refine their own knowledge.

Machine learning (ML)

Method of data analysis that automates analytical model-building and enables the systems to automatically learn and adapt the specification of predictive models without being explicitly programmed. The ML methods include: a) supervised learning, b) unsupervised learning, c) reinforcement learning and d) deep learning.

Natural language processing (NLP)

Techniques aimed at enabling computers to understand human language and analyse unstructured natural language data. Typical tasks include translations, text mining, sentiment analysis and question answering.

Computer vision

Sub-field which works on developing techniques that enable computers to understand digital images and videos. It is a multidisciplinary field of study, relying on general learning algorithms that seeks to automate the tasks that human visual system does.

Automated speech recognition (ASR)

Systems developed to identify and process human voice. Most commonly, this function is to transform speech to text. It is a different technology from natural language processing, as NLP is concerned with the meaning of words and ASR with the meaning of sounds, just as the computer vision is focused on the meaning of images.

AI Planning

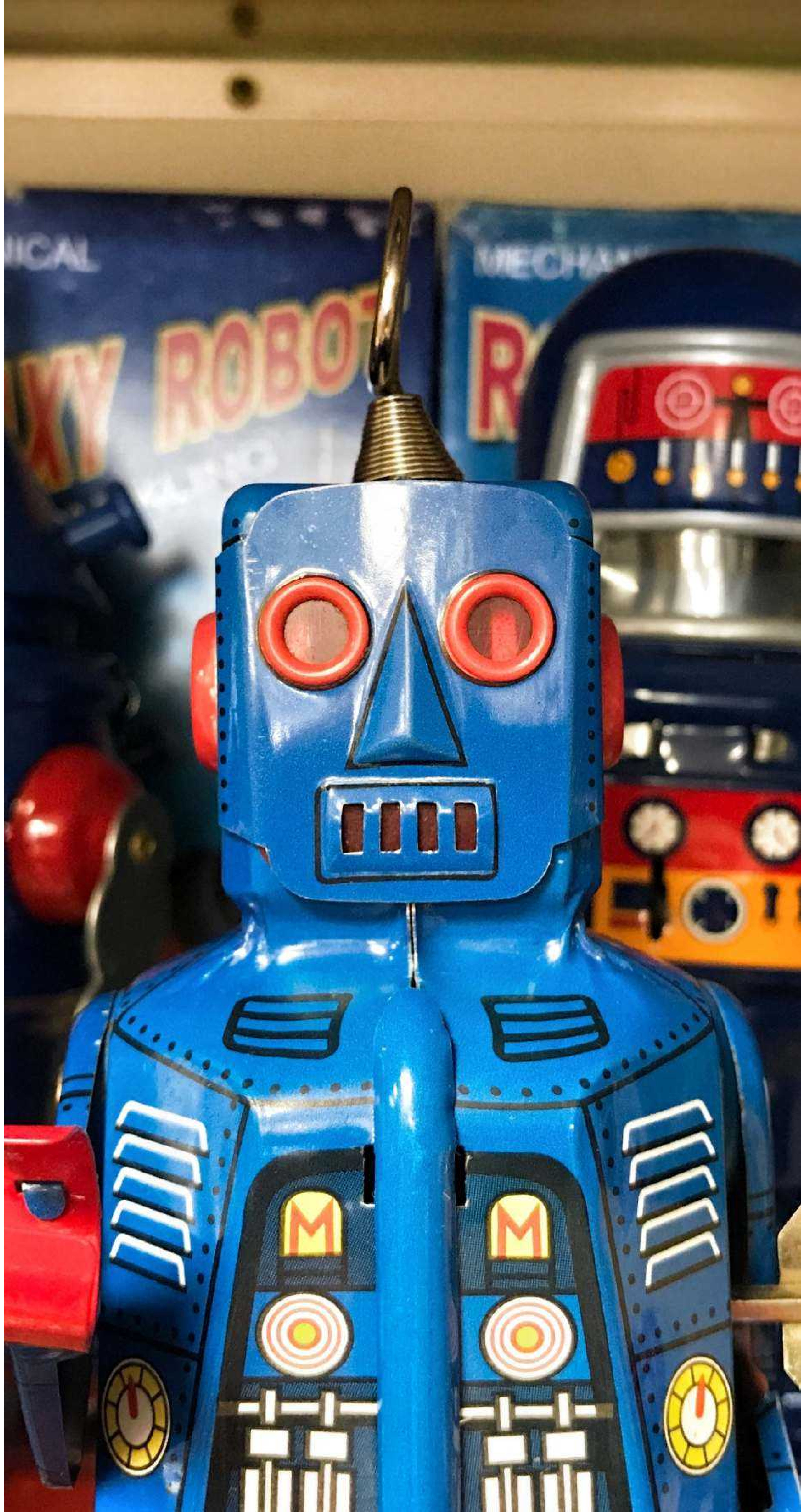
Branch of AI which involves the optimal choice of procedural course of action or strategies for a predefined system (autonomous robots or unmanned vehicles) to reach its goal. Planning involves the defining the actions and models, reasoning about the effects of actions, and techniques for efficiently searching the space of possible plans.

AI CAN CONVERT INFORMATION INTO KNOWLEDGE

Finding an edge in financial markets is often about exploiting information asymmetries. The lack of data underlying the models of decision-making is a key challenge, and opportunity lies in the huge amount of information available in repositories of documents, news, social media posts, as well as from sensor data analytics.

Information that leads to an investment action is often provided in a format that is not readable by a machine. Even when it is available in digital format, for a machine to understand the hidden meaning, technology is employed to derive the semantics. Computers are then equipped to further analyze the informational content and establish the model that predicts future performance of investment.

Prerequisites for viable use of Artificial Intelligence in finance include the economic foundation, technological development and data availability.



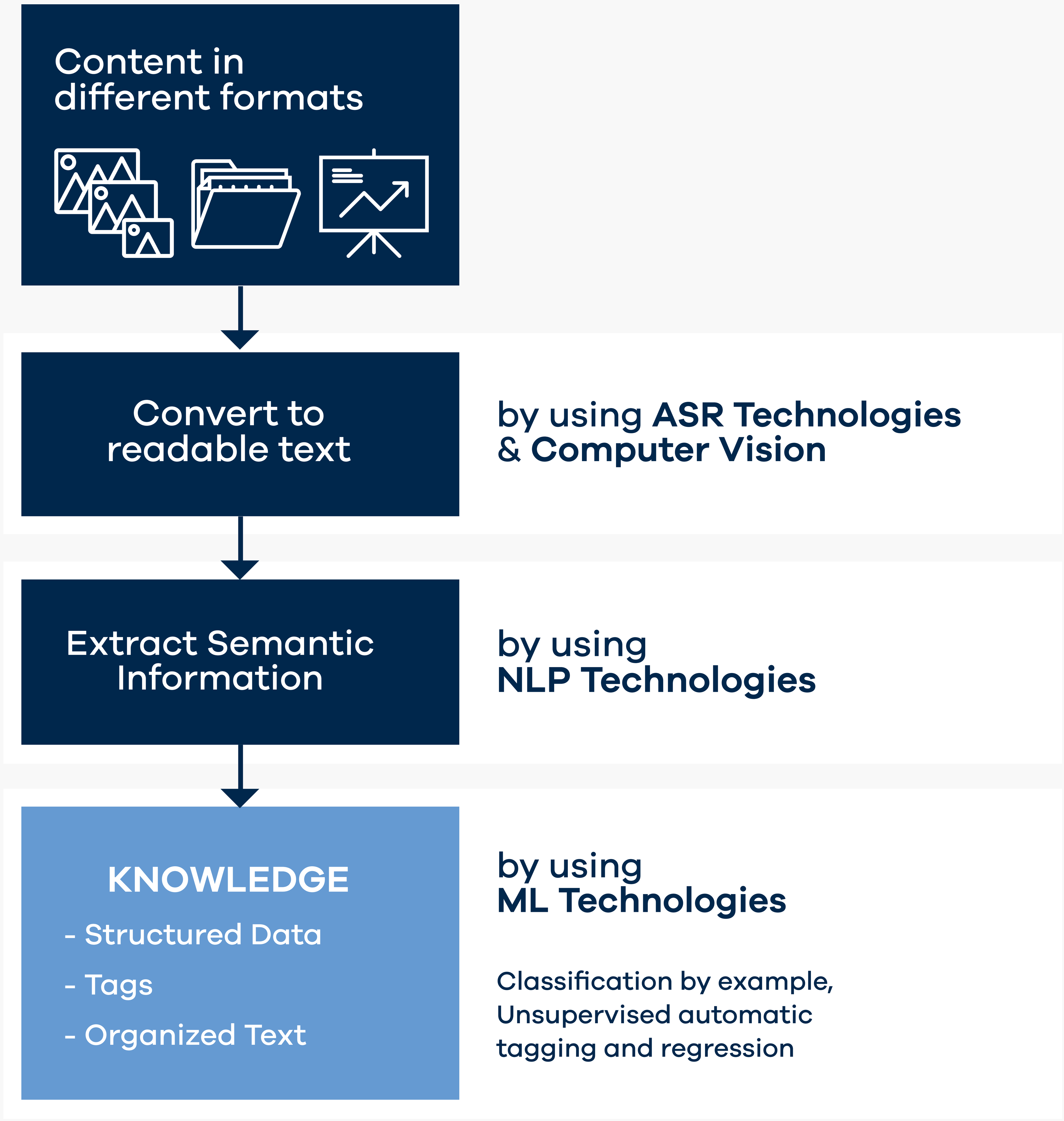
The first step is in bringing complex and diverse data sources, that are often rich in content, such as (scanned) documents, emails, videos and social media content into a readable text. This is enabled using some specific Artificial Intelligence functions such as Computer Vision and Automated Speech Recognition (ASR), as depicted in Figure 1.

The next two steps constitute Cognitive Search methodology. Initially, Natural Language Processing (NLP) technology is employed to identify the meaning of the content and extract semantic information. The last step leverages Machine Learning algorithms to classify information, discover patterns and relationships between different types of information and make predictions of future or out-of-sample values. Machine Learning technology is also used to improve the relevance of search results.

Forrester, research and advisory firm, defined Cognitive Search as "indexing, natural language processing, and machine-learning technologies combined to create an increasingly relevant corpus of knowledge from all sources of unstructured and structured data that use naturalistic or concealed query interfaces to deliver knowledge to people via text, speech, visualizations, and/or sensory feedback."

Figure 1: AI applications that transform rich multimedia content into structured and organized text.

Source: eFront

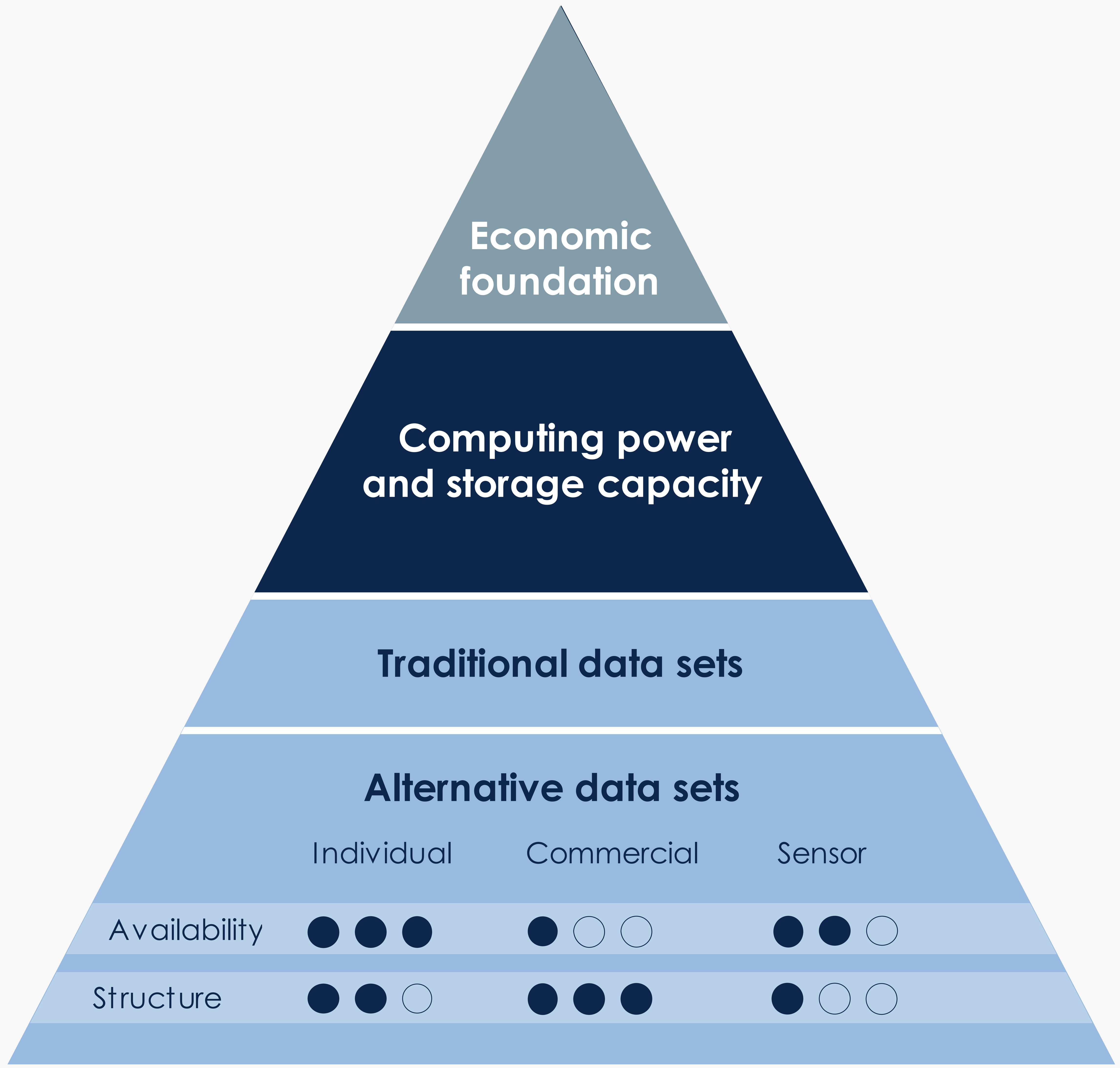


The first prerequisite for employing AI is the possibility to define a meaningful economic model that addresses the investment-related task properly. Disregarding the economic foundation when developing a model can lead to inconsistent results.

The second set of prerequisites is related to technology and includes the emergence of parallel computing and remote access to shared capacity of data storage (Cloud computing, e.g.). This technological advancement allows large-scale data analysis that is a necessary condition for Machine Learning applications.

Traditional data sets are sourced by companies or statistical offices and include information such as historical stock prices, financial statements and prospectus data, CPI and economic growth rates, etc. Alternative data sets are sourced outside of companies and include three types of data. Individual data sets include content generated by individuals that is available on the Web (social media, customer reviews, etc.). This type of data is typically readable by a machine but requires NLP technology for a computer to understand the meaning of the content. Commercial datasets, such as supermarket scanner data or banking records, are not publicly available but are well structured for sophisticated analysis. Sensor generated data (satellite images, IoT collected information, etc.) are expensive to acquire and are available in non-readable format.

Figure 2: Prerequisites for viable use in finance

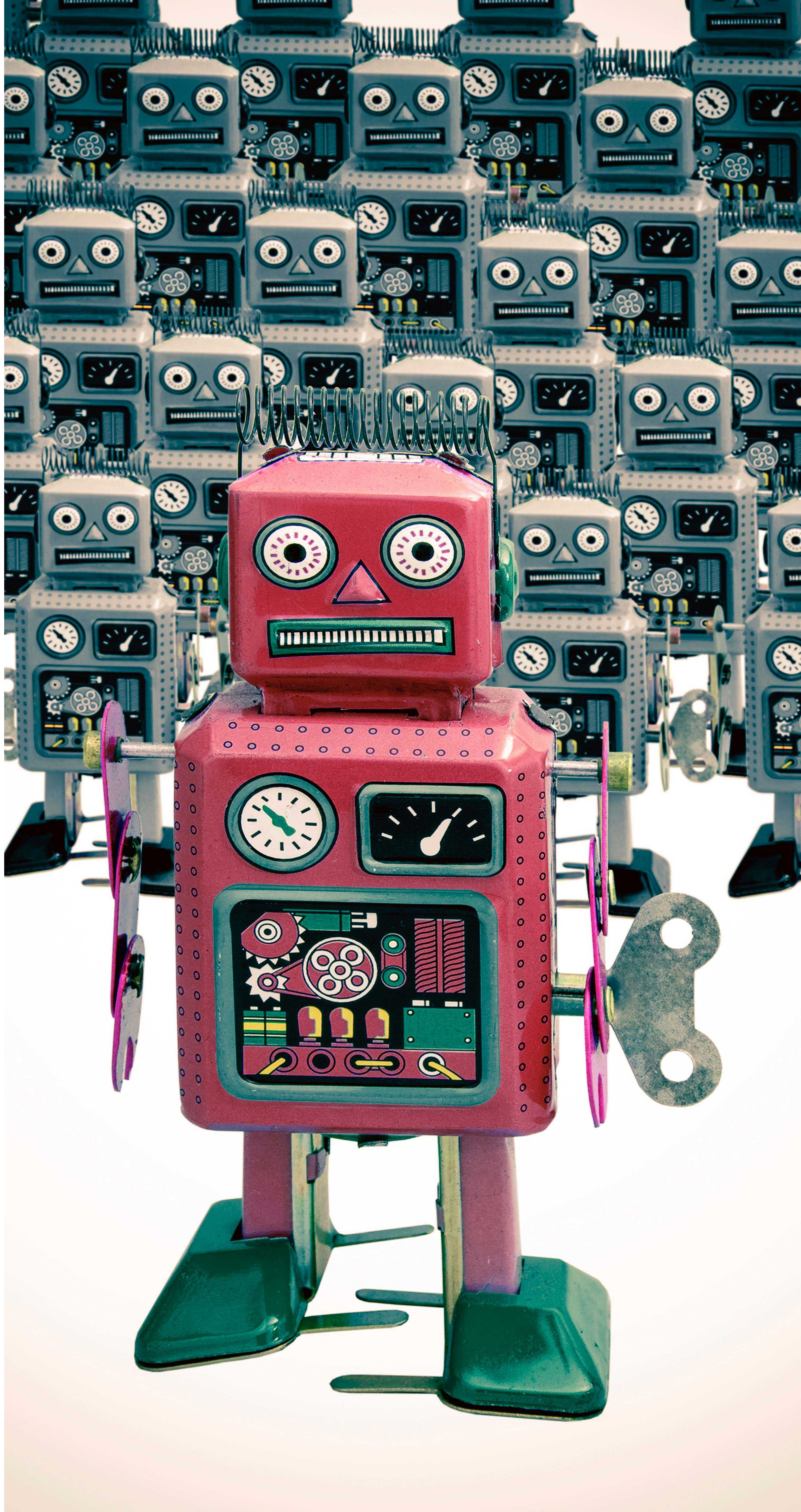


Source: eFront

AI IN TODAY'S FINANCE INDUSTRY

AI is being rapidly rolled out in those parts of the finance industry with large datasets or that are heavily process driven. Credit scoring, risk assessments and fraudulent credit card activity detection are the industry's low-hanging fruit.

After that, things get more complex. The algorithmic trading segment of alternative investments, which relies on pattern and behaviour recognition, sounds like obvious AI territory. Even though hedge funds with quantitative strategies manage almost one trillion dollars in equities globally (Hedge Funds Research, 2019), they make up only slightly more than 1% of total equity markets worldwide. So, there is still a long way to go and what is less understood is how AI can empower investing into less liquid alternative asset classes.



Personal Finance

Savings and Credit

(e.g. deposits, savings accounts)

Investments

(e.g. RE, mutual funds, pension plans)

The traditional credit scoring model uses simple rules to measure the credit-worthiness of an applicant. It relies on the set of information regarding the age, marital status, income, occupation and the credit bureau score of the applicant. Given that the credit bureau score takes into account the amount currently owed, this model may face the debt overhang problem, where some credit-worthy applicant ends up being rejected.

AI-based credit scoring model is a self-learning model that leverages personal online generated data, as well as the legitimate underutilized third-party data to decide whether to extend or deny credit to a person.

Besides the increase in speed of lending decision making, the greatest benefit is in increasing the efficiency of the lending business through better forecasting of applicant's creditworthiness.

Corporate Finance

Investment Decisions

(e.g. projects, acquisitions)

Capital Financing

(e.g. capital structure policy, capex funding)

Dividend Payout Policy

Financial Markets

Traditional

- Public Equity
- Bonds
- Money Markets

Alternative

- Private Equity
- Real Assets
- Hedge Funds
- Commodities
- Structured Products

Active management of mutual funds' positions in public equity requires fundamental analysis of individual stocks. Predicting the long-term performance of a stock, by identifying key drivers of the company's core business profitability supports the successful stock selection. Machine Learning-based models drill down into a variety of data sources to identify significant factors that predict future performance.

Brokerage companies issue research reports that leverage ML and big data to help investors gain better insights. Sentiment analysis is performed on traditional data sources such as SEC filings and historical price evolution, but also various stock related information found in alternative sources.

ETFs are growing rapidly in number, size, and scope. This led to the emergence of different solutions that leverage big data and textual analysis to help investors navigate the thousands of available ETFs based on investors' preferences.

Hedge funds with relative value investment strategy critically rely on speed in data analysis to find the difference in pricing of assets that have identical payoffs, to act on time.

In their search for Alpha, hedge funds analyze data from multiple alternative sources, including consumer transaction data, news wires, media coverage, and Twitter. Running the sentiment analysis on these data sets informs trading broad equity markets or individual securities.

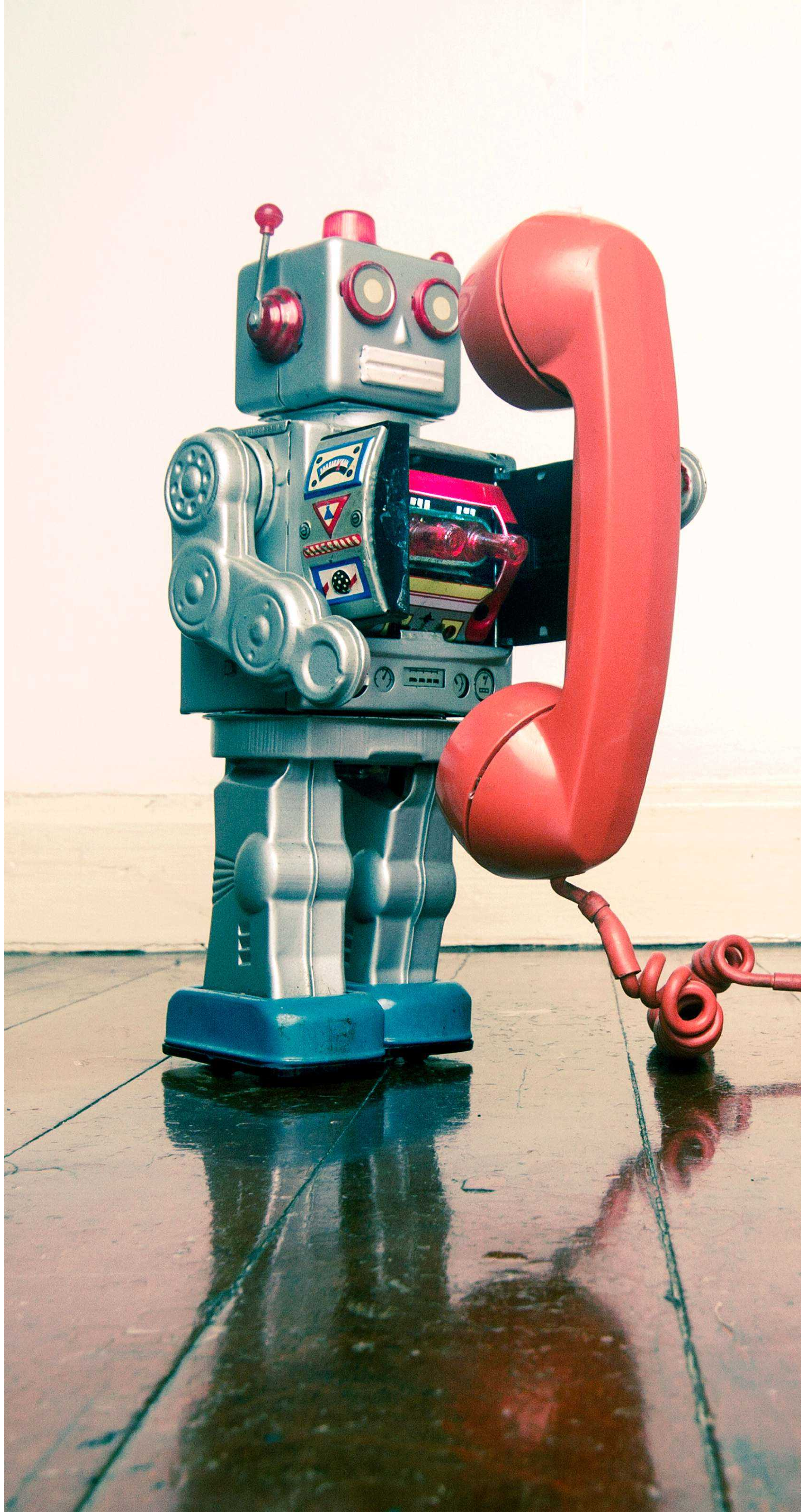
Machine Learning allows high-frequency trading funds to learn about security supply and demand from the order flows almost instantly.

CAN PRIVATE MARKETS BENEFIT FROM AI?

If AI is not fully utilized with highly transparent commodity and listed trading markets, how can it make a difference in private markets, which are notorious for their opacity and incomplete data sets?

Private market investment making decisions can also benefit from alternative data sources. Selecting a manager of private market funds or finding an investment opportunity to deploy capital are extraordinarily data-centric activities.

This section explores the extent to which prerequisites for successful employment of AI apps are met in different private market investment activities.



To assess the potential of AI disrupting the process of investing into alternatives, we divide activities into Direct or Indirect investment.

For each private equity investment activity, the score (from 1 to 5) that measures the potential of the use of artificial intelligence is assigned across two dimensions (Tables 1 and 2). The first dimension of artificial intelligence potential is related to the possibility of reducing the real-life complexity of a task to a parsimonious model, as well as the extent to which human interaction may not be necessary to perform the same task.

The second dimension applies to the current availability and accessibility of information/data that informs the model defined in the first dimension. These scores represent the assessment of the current situation, so this could quickly become out-of-date, as AI technology matures and as more data becomes available. As much, as the speed of technological advancement is orthogonal to the alternative investment industry, the data availability is internally generated, especially given the push for more transparency (ILPA, INREV templates and other initiatives).

Below is an assessment of the viability of AI applications to various activities related to alternative fund indirect investment and direct investment.

5 = highest potential / highest data availability
1 = lowest potential / lowest data availability

Table 1: The potential of the use of AI in different investment activities within the scope of indirect investing in alternatives.

AI MODEL DEFINITION \ DATA AVAILABILITY	1	2	3	4	5
5			Manager selection	Cash flow forecasting and liquidity	
4			Compliance requirement assessment		Reporting data collection
3			Open fund rising and secondary market opportunities screening	Private market program definition	
2		Negotiation	Operations management (capital calls, etc.)	Position tracking, performance benchmarking and risk monitoring	
1					

Source: eFront

Table 2: The potential of the use of AI in different investment activities within the scope of direct investing in alternatives.

AI MODEL DEFINITION \ DATA AVAILABILITY	1	2	3	4	5
5			Deal sourcing and due diligence		
4				Investor reporting	
3				Fund administration and operations management	Investment strategy definition
2		Value creation and exit strategy preparation		Portfolio company data collection and monitoring	
1					

Source: eFront

AI's VALUE CREATION POTENTIAL IN SELECTED EXAMPLES

As AI evolves, the potential for it to disrupt and enhance fundamental aspects of private market investment is rising. According to a recent EY survey, at this stage, 74% of private equity managers do not expect to use AI*. At the same time, only 40% of hedge fund managers still hold that expectation. This can be explained by the greater amount of data generated by the public markets that support automation of front office decision-making models. For the very same reason, construction of the overall portfolio of an LP that includes both public securities and private market holdings represents an activity with one of the highest AI potential scores.

We select the activities of manager selection, cash-flow forecasting and deal sourcing to discuss the use of these advanced technologies.

** EY – "Global Alternative Fund and Investor Survey" (2018)*

Manager selection

Deciding to invest with a manager requires making predictions about its future performance. This can be achieved by identifying all the relevant drivers of value creation, not only at the management company level, but also by correctly attributing the sources of performance at the investment professional and individual deal level.

For example, thorough investigation of past performance can identify the proprietary acquisition as a deal source, improving the core business operations (expanding sales force, supporting product line development, etc.) as a value creation approach and selling to a strategic buyer as three drivers that maximize the performance of an acquisition in the biotech industry. For an investor that has predefined in her private market portfolio program that additional exposure in the biotech industry is an upgrade to the existing risk-return profile of the overall portfolio, the right approach is to look for the managers that have historically been successful in the proprietary sourcing of deals, in improving the portfolio company's top line and in arranging the exits with strategic buyers.

Predictive analytics rely critically on the array and granularity of investment and performance data. AI can prove to be instrumental in automation of all the relevant information gathering process, as well as in establishing the factor specification of the most accurate regression model for future performance prediction. It enables limited partners to rapidly scan unstructured data and leverage Cognitive Search technology to turn it into structured dataset at the lower costs and increased efficiency. Furthermore, investors will be able to reconcile manager's stated track records and information provided during the fundraising process with information available on digital networks and from third-party data providers, to provide further perspective on investment performance and deal attributions.

Reporting data collection

Every quarter, each investor with a position in a fund specialized in alternative investments receives a quarterly reporting package, consisting of the set of fund's financial statements, capital account summary which provides information on cash flows exchanged between the fund and the investor over the past quarter, as well as the core quarterly report document which updates the investor with information on the management company, major events in the fund and, most importantly, the portfolio investment schedule.

Similar to the information gathering and digitizing processes, within the manager selection scope of operations, reporting data collection leverages artificial intelligence applications such as Computer Vision and Natural Language Processing to bring the quarterly reporting documents from various formats into a text that is readable by a machine. Automatic tagging of datapoints (on GP company, a particular fund, investment professional and portfolio asset) can turn the collection of hundreds of documents received every quarter into an organized data warehouse ready to be analysed and to produce knowledge.

Machine learning models can detect inconsistencies in data and identify the indicators that represent early notifications of portfolio companies' and manged assets' inflections, etc. In this way, position monitoring becomes more effective and the spared time can be spent on negotiations and analysing the established governance over the portfolio asset.

Deal sourcing including due diligence

The processes of fund managers identifying new investment opportunities and performing target company due-diligence relies critically on acquiring large sets of information that are not readily available. AI based platforms can automatically collect unstructured data from company websites, various open web sources, social media and the third-party intelligence providers (Bloomberg, Capital IQ, etc.).

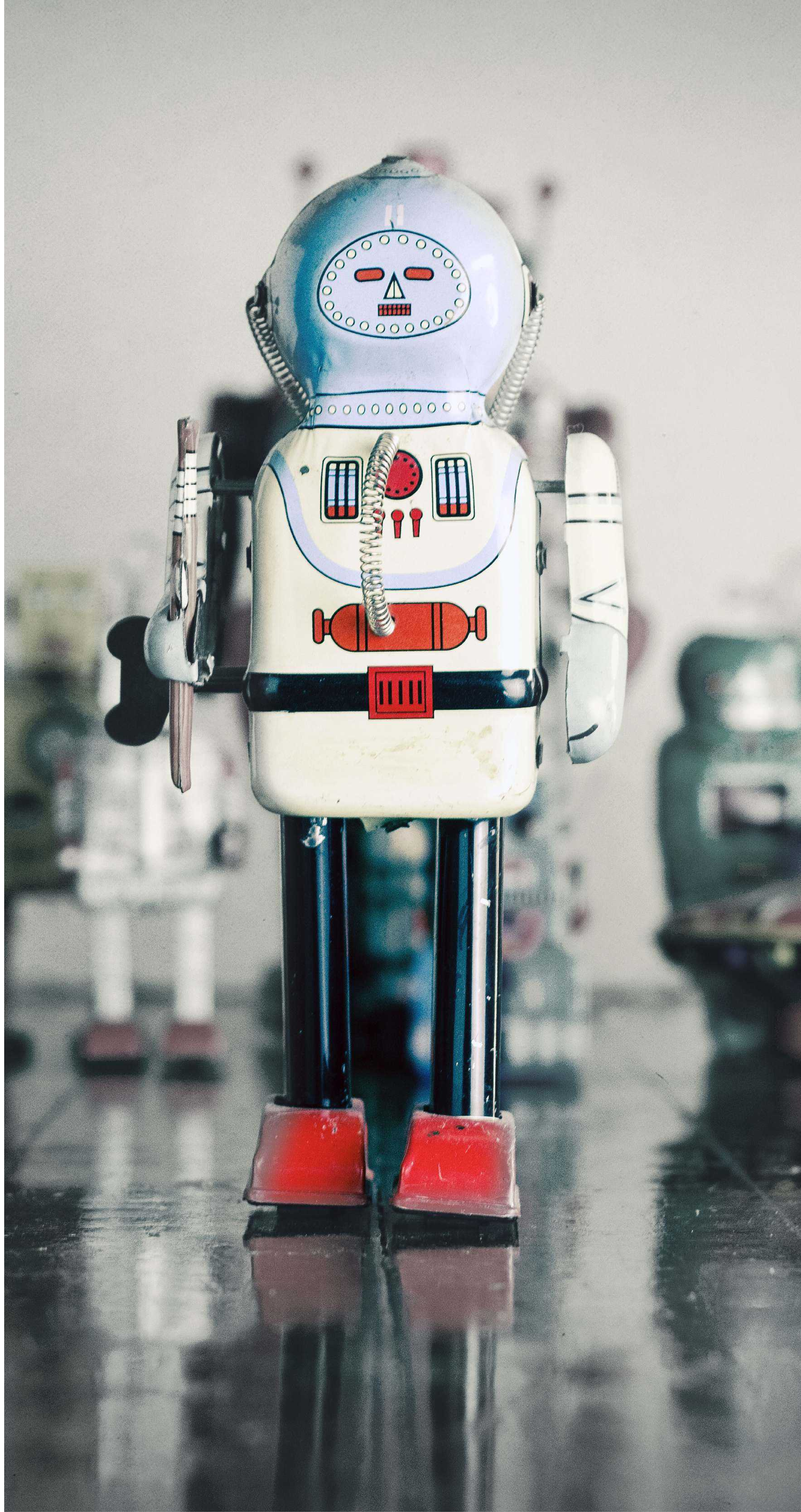
By leveraging Cognitive Search and ML technologies that transform unstructured data into organized knowledge, an alternative investment managing company can scale up the volume of transactions. Employing textual analysis algorithms enables fund managers to perform sentiment analysis of the company's customer reviews or various legal documents and contracts with clients and suppliers.

Professionals using such a platform can look at various aspects of an investment more quickly and in greater detail than those dependent purely on human analysis. A vast number of documents available in datarooms during the due-diligence period can be quickly processed and analysed, which saves human productive time, to be employed in other activities such as building the investment strategy and the value creation approach.

PIONEERING THE USE OF AI IN AI

The examples of potential applications of AI technologies in the realm of alternative investments are numerous and we have only touched the tip of the iceberg. As the technologies evolve in real time, the potential for employing AI in alternative investing will be ever increasing.

eFront is contributing to this trend by helping its clients, both those that invest directly and indirectly, by providing analytical and predictive machine learning based models that inform investor's decisions or by assisting in automation of the process of data gathering and consolidation.



Data search and consolidation (Robotic process automation)

Recognizing the need to increase the amount of data typically available to alternative investments professionals in order to drive more sophisticated analytics and asset and portfolio management practices into the alternative asset classes, in 2015 eFront pioneered a software and data feed service called eFront Data Intelligence, collecting detailed information about managers, funds and underlying assets, including cash flows. In order to be able to scale these operations and deliver growing datasets with the highest possible accuracy and timeliness, eFront has introduced Robotic Process Automation technologies (leveraging the Computer Vision technology) that are now well established and enable the capture of thousands of data points automatically every quarter, mainly from GP's electronic reports and documents.

Over time, eFront has fine-tuned its process and capabilities to reduce exceptions and maximize the level of automation. At the moment, eFront estimates that the data collection of about 80% of the GP documents it analyses every quarter can be automated through AI, and when this is done, 95% of the associated workload is reduced, and this is done within minutes compared to hours otherwise.

There is a non-negligible cost to introduce AI, which is associated with the set-up, configuration and continuous improvement of those AI technologies, which typically makes them inaccessible to most alternative investors – unless they leverage the platforms already built by services providers. This tangible example illustrates the interest of leveraging AI technologies to address some of the typical hurdles of alternative investing, in this case the lack of availability of granular and digital data.

Advanced/predictive analytics

Once the data availability challenge is addressed through AI, this clears the way for more sophisticated analytics to be performed, leveraging this information as well as publicly available information. Conventional analytics can already come a long way and bring a first level of disruption to the AI industry, considering its relative lack of maturity, especially compared to public market practices. This is the value-proposition of eFront Insight, the analytical platform developed both for LPs and GPs that enables them to perform advanced analyses, using the datasets that AI had previously made available at a large scale.

Beyond this, the potential for AI to add another layer of insight through predictive analytics is great, and eFront is currently piloting AI technologies to add even more advanced features into its Insight platform, such as the set of tools and models that inform the decision of manager selection.

About eFront

eFront is the leading pioneer of alternative investment technology, focused on enabling alternative investment professionals to achieve superior performance. With more than 850 Limited Partner, General Partner, and Asset Servicer clients in 48 countries, eFront services clients worldwide across all major alternative asset classes. The eFront solution suite is truly unique in that it completely covers the needs of all alternative investment professionals end-to-end, from fundraising and portfolio construction to investment management and reporting.

In 2019, eFront was acquired by BlackRock and since then operates as a specialized business unit within BlackRock Solutions, alongside Aladdin Institutional and Aladdin Wealth.

eFront Insight

eFront Insight is a sophisticated web-based analytical platform dedicated to alternative investments and combining granular, high quality investment data reported by General Partners, leading market benchmarks and other relevant sources in order to generate unique insights and facilitate investment decision making. eFront Insight is available to both General Partners to digitize data exchanges with investors and to Limited Partners to enhance decision making.

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