Artificial Intelligence

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What A.I. is and What it is Not

What A.I. Is Not

In popular media, A.I. is sometimes portrayed as a seemingly 'all-knowing' machine with super-human powers that is continually self-upgrading. This idea is called the technological singularity. In truth, not only is this not representative of A.I. today, but such an outcome is nowhere in sight. Worrying about the technological singularity (while entertaining) is about as productive as concerning oneself with the fact that in billions of years the Sun will engulf the Earth.

Successful A.I. – A Combination of Tools

A.I. as it exists today can still be exciting, but it can also sometimes be quite mundane. This is true because any successful A.I. implementation will comprise a set of solutions and tools that combine complexity and elegance with rote task automation. Those seeking to incorporate A.I. solutions are faced with a significant problem-since many different components exist but not all may be a truly valuable addition on a standalone basis.

To illustrate the point above, consider an application in one subset of Artificial Intelligence called Machine Learning. Machine Learning is a generic term for an algorithm that allows a computer to "learn." While that may sound fancy, the strict definition could be satisfied quite simply. For example, arguably the most canonical model in finance is the Capital Asset Pricing Model (CAPM), which uses linear regression to estimate the sensitivity of an asset's price to changes in the price of the broader market. Linear regression is a traditional statistical modelling technique, but if new market information (e.g., returns) were added to that model each day and the regression re-run in an automated way, then that traditional technique could be considered a machine learning approach. While obviously not a large value-add, it does meet the strict definition.

The takeaway is that artificial intelligence is a field of study with a wide spectrum of tools. A successful implementation of A.I. will use several components from that spectrum together. Classification of these components will fall into three general pillars (categories) shown in Exhibit 1 below, and in some cases will fall into multiple pillars at once:

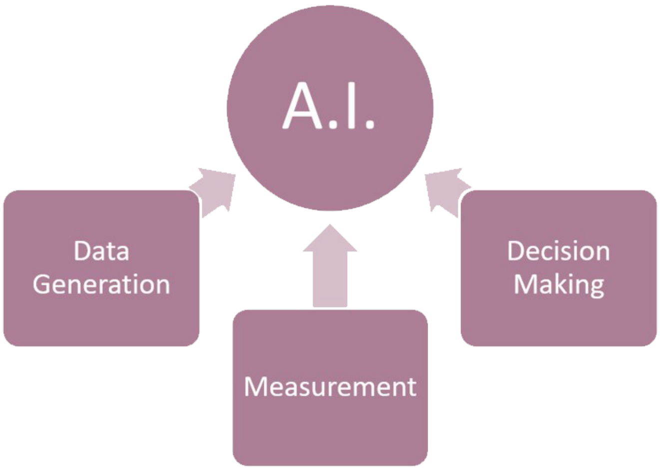

Exhibit 1

1. Data Generation – Any informed decision requires high quality data. This pillar supports getting quality-checked data into a pipeline. The process can also include generating new data; the two most common examples would be (i) data from text[1] and (ii) generation of 'hidden' layers or 'states.[2, 3]

2. Measurement – After data has been collected, some type of measurement process will take place. This pillar helps quantify how much any change or expected change will affect the world around us. While the focus is on making this quantifiable, it is important to point out that these insights can also be what may traditionally be thought of as qualitative in nature.

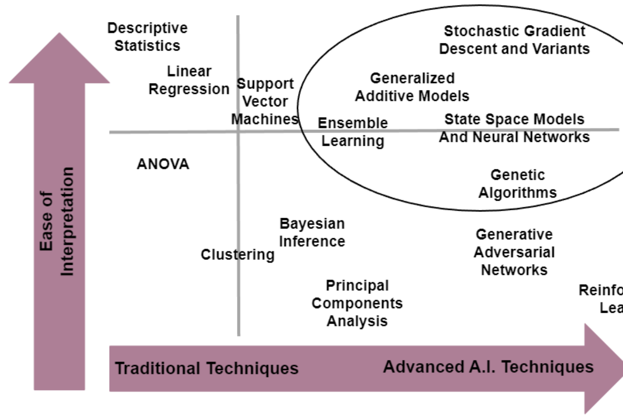

Exhibit 2

3. Decision Making – While possessing vast quantities of data and measurements is important, perhaps the most valuable impact of A.I. is the ability to make informed decisions from that information. A.I. brings the ability to simultaneously "think" about many more aspects of an investment problem than would be possible to do so in a timely fashion otherwise. Working in tandem with human insight and interpretation, the simple value-add of A.I. is the ability to take more information into account with a more holistic perspective. As a result, *a successful implementation of A.I. leads to more informed decision-making.*

What Are A.I. Tools?

The tools used in a successful implementation of A.I. can range across each of the pillars in Exhibit 2 as well as across levels of complexity from traditional techniques to the most recent advancements. Later in this paper we will discuss some of the most widely-adopted and exciting success stories in A.I.

When thinking about applying A.I., specifically in an investment process, a higher bar must be set. In contrast to playing games, recognizing images, or suggesting ads, when it comes to using A.I. in the investment process, interpretability plays an important role. That is, investors will need to understand the 'why' in the process, rather than just accepting a black-box outcome.[4] Even if an A.I. algorithm resulted in a successful investment process most of the time, it is simply unacceptable to lose money with the

Technique	What Is It?	Is It Interpretable?
Reinforcement Learning	Essentially a reward is given each time the computer "wins"	Probably Not - While the computer understands what worked in the past, it doesn't necessarily understand why
Generative Adversarial Networks	The computer plays against itself	No - Works well for two-player games but not for market-based systems
Genetic Algorithms	Extended optimization	No - While good at finding extended optimal trade-offs it can't understand "why" more of X is better than Y
Ensemble Learning	Running many models comparing hypotheses	Maybe - While good at comparing different theories it often suggests multiple models and chooses the best general model which can lead to being very wrong in the non-general cases
State Space Models and Neural Networks	Input -> "finds hidden states" -> output	Maybe - Adding more "hidden layers" or "states" will make a model more predictive backward-looking, including more states, therefore needs strong rationale
Generalized Additive Models	Search through factors for model inclusion and test robustness	Yes - This is an extension of current modelling practices but can examine more possible models and incorporate robustness testing which avoids overfitting
Stochastic Gradient Descent and Variants	Extended optimization with underlying theory	Yes - Can find extended optimal trade-offs and include the underlying theory for why more X is better than Y

Exhibit 3

only explanation being that that "the A.I. said so," as this hints at the possibility of larger risks that may not be understood by the algorithm.

In Exhibit 3 we briefly cover some of the most widely-adopted techniques in recent A.I. advancements and discuss whether they meet the interpretability threshold.

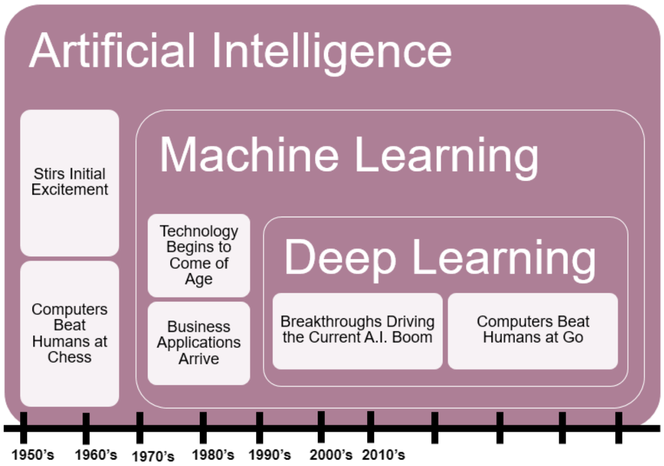

Exhibit 4

Deepening Areas of Research

Artificial Intelligence is currently a booming area of research. As was illustrated earlier, A.I. methods can represent one or more of the three pillars that can be combined for successful implementation. It is common for some methods to overlap. This is often the case as research in A.I. progresses. Exhibit 4 demonstrates how machine learning grew as a subset of research into more general artificial intelligence, and that more recently Deep Learning has grown out of that subset.

Popular Examples (Non-Finance)

Most people are probably familiar with the fact that computers beat humans at chess. DeepMind[5, 6] was able to "look-ahead" at every conceivable move out to a number of moves that is about the same as the average number of moves in a game. Combining foresight with reinforced learning based on a massive history of previous chess games played led to this success. Perhaps less well known is the game Go, in which Google's Deepmind and the AlphaGo[7] program now consistently defeats the top human players. In contrast to chess, where each possible move can be known for most games, this is not possible in the game Go. This is where a Deep Learning approach can excel, by combining large datasets, massive computing power, and cutting edge A.I. approaches.

Another interesting example is from the ImageNet Large Scale Visual Recognition Challenge, which tests a computer program's ability to recognize the contents of a photo. Exhibit 5 shows that not only are the competing teams getting better each year, but that in 2017, 29 of 38 teams were below the 5% misclassification level, which is roughly the accuracy of a human in the same competition.[8]

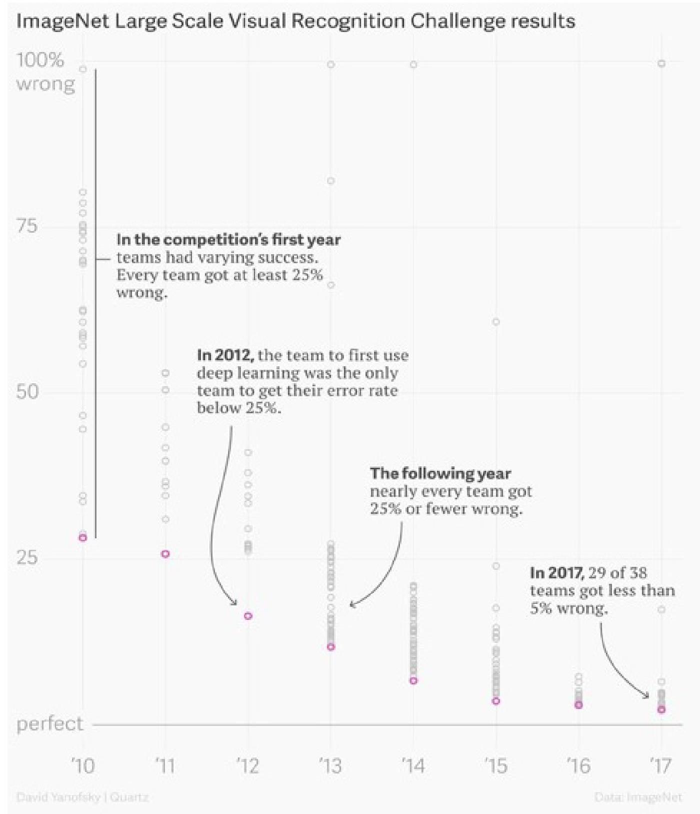

Exhibit 5

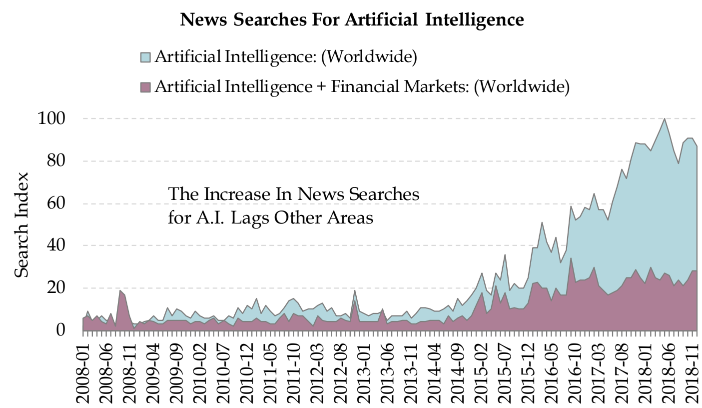

Exhibit 6

Adoption in Finance and Economics

Turning our attention to finance and economics, the examples tend to be less well known. In general, when comparing the penetration of A.I. into finance and economics with other fields, the sector has arguably lagged. There are a few metrics[9, 10] that support this finding, but one simple measure is just comparing the amount[11] of news searches that are focused on A.I. by industry category, as seen in Exhibit 6. We show this chart as a proxy for level of interest around A.I. in the financial sector relative to other sectors.

While it is hard to know exactly why artificial intelligence adoption and interest in finance and economics has lagged other areas, it is likely that the higher bar for interpretation is at

Artificial Intelligence Driven Hedge Funds vs. Hedge Fund Universe

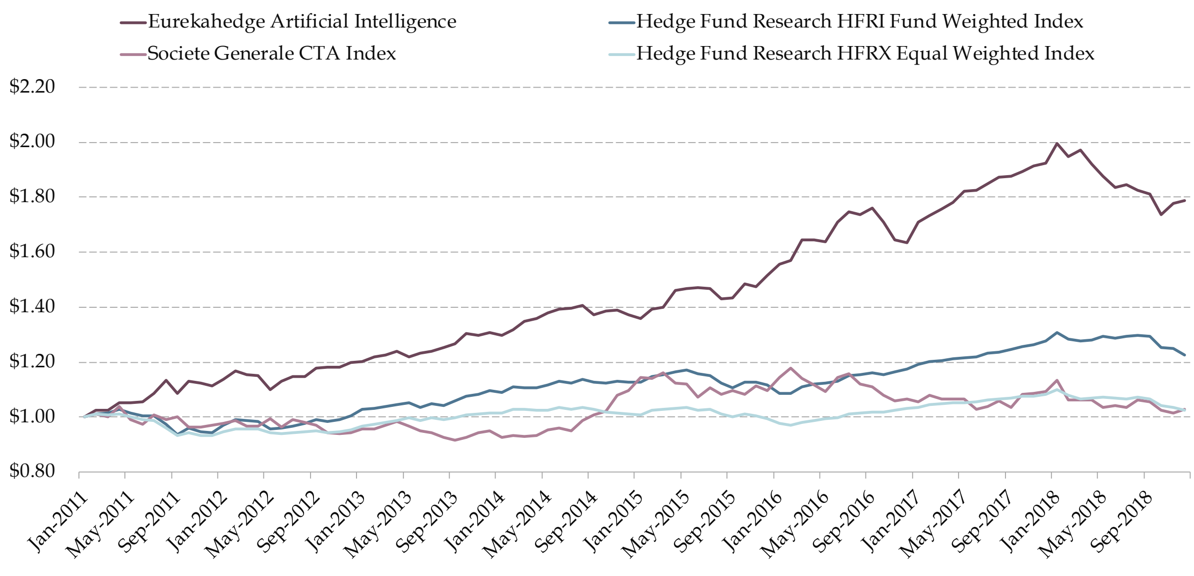

Exhibit 7

least one important contributing factor. That said, as Exhibit 7 indicates, interest has grown in the past three years as this barrier is being gradually overcome. Despite lagging other sectors, A.I. adoption is widespread across finance and investing. A 2017 survey showed that 30% of financial services companies are already incorporating A.I. at the enterprise level and 52% are currently making 'substantial investments'.[12] In the next section, we highlight some more specific examples of current uses and their impact.

Does A.I. Impact My Investments Today?

Evidence suggests that A.I. in the investment process does impact investment performance. This is true because the adoption of A.I. in capital markets is now wide enough that it is having an observable impact on manager performance. The fundamental improvements that A.I. can bring to the table are quite clear. *Any investor who can more easily compare broader and deeper perspectives should benefit from improved insights and outcomes.*[13]

While A.I. is still relatively new, it already appears to be producing superior performance in some segments of the market.[14] For example, the chart below compares the Eurekahedge A.I. hedge fund index[15] with the broader hedge fund universe and a Commodity Trading Advisor (CTA) index.[16] The composite of A.I.-driven hedge funds has outperformed the broader hedge fund universe since the inception of the Eurekahedge index.

While not shown in Exhibit 7, the A.I.-driven hedge fund subset has also outperformed for each available rolling three-year period. The extent to which each of these hedge funds incorporates A.I. into their process - and the value it adds - varies. For example, The Man Group uses artificial intelligence in one of its largest funds and that process contributed roughly half of the profits for that fund in 2015.[17]

Beyond hedge funds, A.I. impacts investment outcomes across a myriad of organizations and in different ways. A comprehensive list is beyond the scope of this paper, but a quick list of examples can be found in Exhibit 8 (a larger list can be found in the appendix).

How much value A.I. can add remains open for debate, and incorporating A.I. is no guarantee of success. To be clear, incorporating A.I. into an investment process does not mean that less emphasis should be put on human-led fundamental insights. It is also likely that as an A.I. technique spreads, the additional value add it is able to produce in a competitive environment will diminish. That said, as this space continues to evolve, it will put more pressure on other investors to keep up. Successfully implementing A.I. carries its own risks and must be done with care, but those that do not attempt to incorporate the benefits that A.I. bring to their investment process run a risk of falling behind.

Company	A.I. Use Today
BlackRock[18]	"Integrated into [the] investment process" across "nearly everything we do"
BarclayHedge	56% rate of adoption for institutional analytics in 2018[19]
Government Pension Investment Fund - Japan	Active Manager analysis[20]
Natixis	Uses machine learning for robustness checking of stress-test models[21]
Securities Exchange Commission	Word detection for regulatory compliance[22]
Ontario Teachers Pension Plan	A.I. is a blanket theme [across] investment, risk, and enablement[23]

Exhibit 8

Implementing A.I. in the Investment Process

A Slow, Steady, and Sweeping Approach

Artificial Intelligence has momentum, widespread adoption, and investment backing supported by extremely promising results. For these reasons, it looks as though the technology is poised to be transformational in many respects. Due to its transformational nature, incorporating A.I. requires a more extensive approach than other investment innovations have in the past. To make clear why this is the case, Exhibit 9 contrasts the impact of A.I. with the famous Fama-French three factor model[24] at the time each was introduced into the market.

Fama-French Enhancements	A.I. Enhancements
Showed combining the value and size factors with the market factor for U.S. equities could explain roughly 90% of their returns. This led to investors hiring specialized value / growth and small cap equity managers in an attempt to "harvest" more of the fundamental factors that were driving returns.	A.I. has shown its ability to make improvements by searching across every known factor to get the best from existing best practices and by adding its own insights through new data/ factor creation. Not only has this been shown to work across different markets but also throughout the investment process.
-	-
Enhancements from Fama-French were focused on a single market and two specific factors.	Enhancements from A.I. are applied across every market, every factor, and many applications.

Exhibit 9

In short, what this contrast highlights is that A.I. potentially has much more far-reaching implications. Following this rationale, while hiring a manager utilizing A.I. may add value, this will fall short of realizing the full potential of A.I. for an institutional investor. This is true for two simple reasons:

1. As we alluded to when comparing A.I. managers to the broader hedge fund manager universe, history has shown that the market is a quick learner and other market participants will soon incorporate A.I. into their investment process. In 2015, 47% of new hedge funds used technology including A.I. and machine learning; in 2018 that grew to 70% of the new entrants into this market.[25] While adoption rates vary, this is true across the institutional investment industry. For example, a 2018 survey by Greenwich Associates found that 56% of institutional investors were incorporating A.I. integration planning into their investment process.[26]
2. Most investors limit the size of the allocation they are willing to make to a single manager in order to avoid over-concentration of risk. The implication is that any investment made via a single A.I. manager will add a relatively small amount of value at the total fund level. In contrast, the total potential the investor has if they incorporate A.I. into the investment process across their entire portfolio is substantial.

For institutional investors seeking to integrate A.I. into their investment process, Nicole Musicco[27] of Ontario Teachers' Pension Plan offers a helpful structure for thinking about implementation, by breaking it into three sections based on where the technology aids their process: (i) Investment, (ii) Risk, and (iii) Enablement. Of these three areas, it is our view that 'Enablement' has the most sweeping reach and therefore impact across the investment process. As the word suggests, it enables the investment team to get more out of their investment process from end-to-end.

Manager Selection and Implementation

When choosing between investment managers that use A.I. as part of their strategy, the selection process and due diligence is the same as selecting any fundamental manager. In short, an A.I. manager should meet all of the criteria that an investment with any other manager would be subject to, with a few additional areas to focus on:

1. While an investor need not be an A.I. algorithm specialist, they should understand how the manager implements A.I. insights into their investment process and, more importantly, why they implement each step with the tools they have chosen.
2. An investor should seek a manager that is benefiting from the major areas where A.I. has brought improvements: (i) Data Generation, (ii) Measurement, and (iii) Decision Making.
3. As complexity is a risk in its own right, the bar for interpretability in all of the previous points is high. A.I. benefits from fundamental improvements in information usage and perspective, but that in no way indicates that an investor should accept a black box approach or process that they cannot understand.

Total Portfolio Implementation

The selection of a manager utilizing A.I. is a good way to take a small step into the realm of A.I., but most of the value-add that A.I. can bring to an institutional investor cuts across multiple aspects of the investment process. For this reason, the greatest amount of value added is likely to result from an adoption that is less dependent on manager selection or a specific asset class, but rather a broad implementation that can encompass the entire investment process of the organization. Exhibit 10 (on the next page) is a high level 'roadmap' that breaks this process into three stages.

Beginning at the bottom, the foundation of incorporating A.I. into the investment process is good data. Of course, this is true for any investment process, but building an infrastructure with the needs and goals of A.I. in mind should lead to a more flexible, holistic, and insightful system. As this is already best practice for institutional investors, it may be that little additional work is needed here, but a review of data infrastructure is still a good first step.

Building on that foundation, the natural place to begin using A.I. tools is within risk management. A.I. can search across more risks than were previously possible and be utilized as a simple extension to the current process. Risk review combines quantitative and qualitative insight and already has a strong focus on interpretation which make it a natural place to begin incorporating A.I. insights into the day-to-day operations of the investment process. This step also allows close integration with the people currently involved in the process so that an

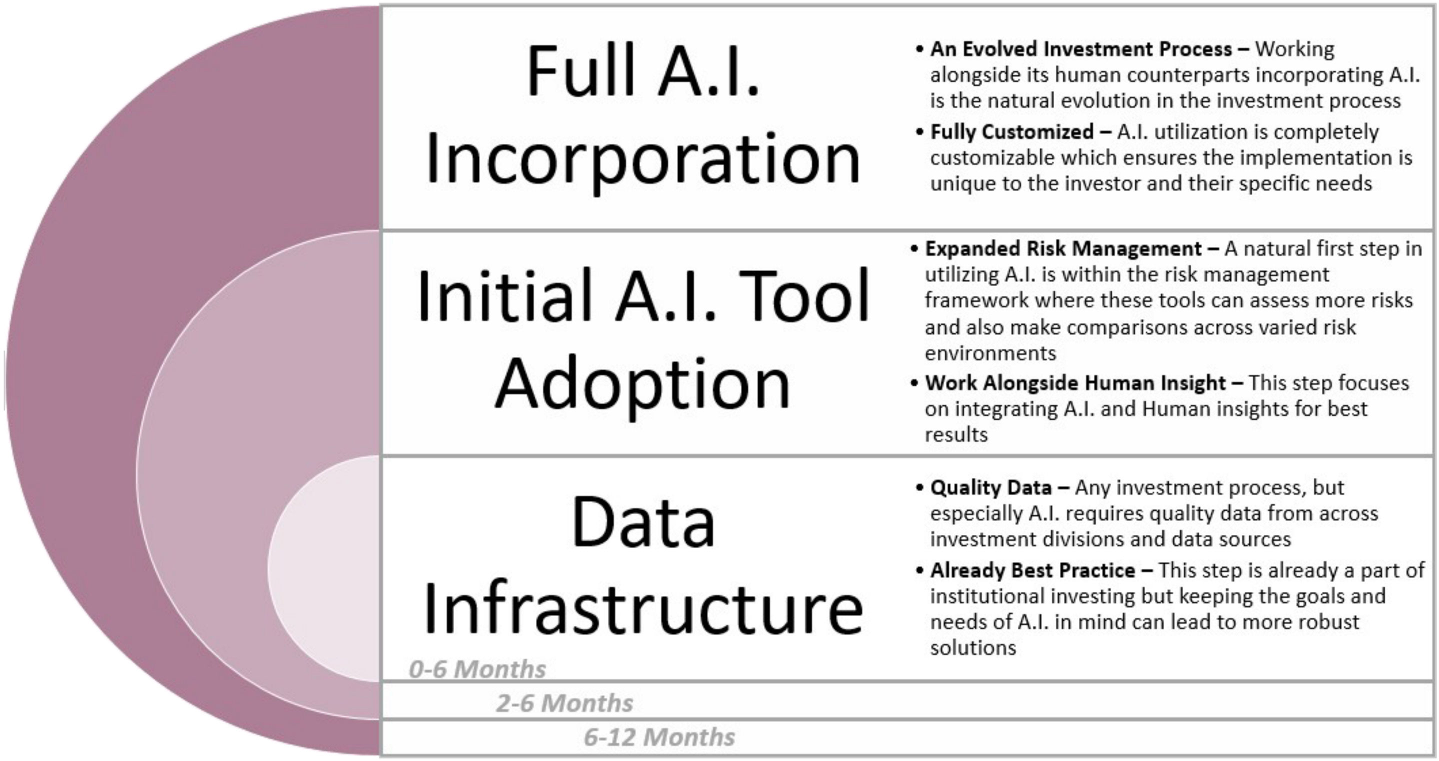

Exhibit 10

integrated solution can be crafted that achieves the most from all available resources.

Finally, now that the data infrastructure is in place and the tools have been tested and integrated into the risk management process, A.I. can be more fully incorporated into the investment process. Similar to integration with risk management, the A.I. tools will combine qualitative and quantitative information and work closely with the human team and their insights. Luckily, most of the tools used in the risk management process can be repurposed to investment monitoring, scenario analysis, portfolio optimization, as well as many other core functions.

Any investor should only invest in areas or use tools in their process that they understand and feel comfortable with, and this remains true with artificial intelligence. For this reason, it is best practice to gradually adopt A.I. technologies – but to start doing so as soon as possible. Eventually this could (and arguably should) lead to incorporating machine learning into the asset allocation and risk management process. Keeping a steady pace of evolution with an understanding of the potential value added is the best way to harness the power of A.I.

The Human and A.I. Interaction Spectrum

A successful implementation of A.I. represents an extension of current and well-understood processes while keeping a human intimately involved in the process. Exhibit 11 shows how investors can move towards artificial intelligence coordination with the human team in steps. The path(s) suggested effectively boils down to continuous refinement of the investment process using best practices.

Type	Description	Potential Problems	Process Synopsis	Time of Use	Example First Step
Fundamental	Human Intelligence Only	Limited Ability to Use/ Process All Information	Consistent but Susceptible to Human Folly (Greed/Fear/ Emotion)	Since the Advent of Markets	NA
Guided Learning	A Combination of Human Intelligence and Artificial Intelligence	Requires Close Integration of Both Intelligence Types So One Cannot Dominate the Other	Humans Guide Machines to Learn Based on Models/ Insights Driven by Humans	Since the 1950s, Successful Across All Fields	Utilizing Generalized Additive Approach to Risk Analysis
Unsupervised Learning	Artificial Intelligence without Human Intervention	Highly Correlated Market Information Finds False Positives	Machines Learn and Guide Human Understanding Relying on a Human-Level Check for Reasonability and Bias	Since the 2010s, Successful Examples but Not Yet Fully Adopted in Finance and Economics	Expanded Risk Management and Optimization with Stochastic Gradient Descent

Exhibit 11

Common Concerns

When thinking about implementing A.I. within the investment process or considering investing in a fund manager that utilizes the technology, there are several concerns that are common. While we surely cannot address every potential concern, we can address the most common broad categories that these concerns fall into.

Reliance on Historical Data

The largest problem with any backward-looking analysis is that it can only rely on historical data. That is, it is taken from what happened, and not what could have happened. This is a potential problem because the period from which the data was drawn may or may not reflect the environment(s) that will transpire in the future.

The concern with A.I. is to what extent it is subject to the same challenges. There is no evidence to support that machine-led algorithms are more susceptible to this issue than a human team. That said, our recommendation as laid out above is to pair A.I. with human interaction, to create a best of both worlds approach, as each has its own advantages.

Overfitting

We touch on overfitting a few times above as this is a legitimate risk. That said, newer A.I. methods have the power to perform robustness checks in a much more rigorous way than human teams could in a timely fashion. Again, using a combination of machine and human-led insight should be beneficial in mitigating this concern.

Not Intuitive

A.I. is undeniably complex, and the vast majority of people are not going to be as comfortable with it as they are with traditional techniques with which they have more experience. Any approach that resembles a "black box" deserves to be met with skepticism.

This paper emphasizes interpretability in large part to address this concern. Tackling this concern should be the major focus of the first integration step when applying A.I. to the investment process.

Conclusion

In this paper we have shown several examples of A.I.'s use. We have laid out the tools used by A.I. and suggest that a successful implementation will include a wide spectrum of tools across data generation, measurement, and decision making.

In implementing this technology, a slow and steady approach that is well understood and is an extension of current processes is the best practice. It includes a process whereby A.I. works closely with human team members for a combined result that gets the most from all available resources. We have presented a broad 'roadmap' for implementation and laid out how this is closely aligned with best practices.

While implementing a new technology is often a risk, in this case not implementing A.I. also represents a risk, namely of falling behind. At the end of the day, while A.I. may sound intimidating, fanciful, or overwhelming, the advantages it brings are fundamental.

1. A.I. automates mundane tasks, which improves efficiency of current resources.
2. A.I. broadens the scope of considered risks and opportunities.
3. A.I. deepens the analytical level that those risks and opportunities can be evaluated in a timely fashion.
4. A.I. provides a more holistic perspective across operations and the interaction between the myriad risks and opportunities an institutional investor must evaluate.
5. A.I. works alongside, not in replacement of, human insight, the latter of which crafts a "best of both worlds" solution.

The impact of Artificial Intelligence is already upon us. The transformational nature of this technology suggests that while hiring a manager that utilizes A.I. may be a good small step to take advantage of the changing landscape, the bulk of the potential value added comes from incorporating these tools into the investment process at the portfolio level.

Appendix

Example List of Managers Using A.I.

Company	A.I. Use Today
Cerebellum Capital	Equity market neutral strategy utilizing Machine Learning.
Trinnacle	Equity market neutral strategy utilizing A.I. and Machine Learning.
FORT	Machine Learning in trend selection and memory.
AlphaSimplex	Machine Learning in trend selection and memory.
Lynx	Machine Learning in trend selection and memory.
P/E Investments	Automated Bayesian analysis for dynamic allocation between models and states.
AQR	Large investments into A.I. through data and human resources. Full application not specified.
D.E. Shaw	Large investments into A.I. through data and human resources. Full application not specified.
Two Sigma	Large investments into A.I. through data and human resources. Full application not specified.

Eurekahedge A.I. Hedge Fund Index	
Total Constituents (historic)	29
Live	16
Actively Reporting Constituents	14
Average Fund Size (live)	U.S. $60 million
Range of Fund Size (live)	U.S. $547 million

http://www.eurekahedge.com/Indices/IndexView/Eurekahedge/683/Eurekahedge_AI_Hedge_fund_Index

Endnotes

1. This includes another subfield of Artificial Intelligence call Natural Language Processing (NLP).
2. Common to neural nets or state-space modelling, this activity finds hidden or underlying states or processes that are not directly observable.
3. For example, Economic Regime Management describes 'states' when forecast surprises (positive or negative) are more likely as well as when uncertainty is higher than normal. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2663609
4. For example, a computer could describe what has worked best in the past via a "best fit" model without understanding "why" that is the case. Whereas an A.I. approach may use a preference-based objective, which means everything is a trade-off. Therefore, it "understands" it is willing to trade some units of X for some units of Y to meet those preferences. The result may (and likely will) look different than a best fit model.
5. http://www.chessgames.com/chessstats.html
6. https://www.wired.com/2016/03/googles-ai-viewed-move-no-human-understand/
7. https://deepmind.com/research/alphago/
8. https://qz.com/1034972/the-data-that-changed-the-direction-of-ai-research-and-possibly-the-world/
9. https://www.cnbc.com/2017/06/06/machine-learning-transforms-investment-strategies-for-asset-managers.html
10. https://www.mckinsey.com/mgi_notes-from-ai-frontier_discussion-paper.ashx
11. Google's search index is a normalized value for number of searches for time period and location meaning that 100 indicates the largest search amount for the topics shown. Data and definitions are available here: https://trends.google.com/trends/explore?date=all_2008&gprop=news&q=%2Fm%2F0mkz,Artificial%20intelligence%20%2B%20Financial%20Markets
12. https://www.pwc.com/us/en/financial-services/research-institute/assets/pwc-fsi-top-issues-2018.pdf
13. It should be noted that details of implementation and execution will have important implications for outcomes.
14. This finding was confirmed in a separate research piece based on Preqin Data: https://www.wired.com/2016/01/the-rise-of-the-artificially-intelligent-hedge-fund/
15. The Eurekahedge AI Hedge Fund Index is an equally-weighted index of 13 constituent funds. The index is designed to provide a broad measure of the performance of underlying hedge fund managers who utilize artificial intelligence and machine learning theory in their trading processes.
16. Proxied by the Société Générale CTA index.
17. https://www.bloomberg.com/news/features/2017-09-27/the-massive-hedge-fund-betting-on-ai
18. https://www.blackrockblog.com/2017/08/03/artificial-intelligence-evolution/
19. https://www.barclayhedge.com/about-us/
20. https://www.top1000funds.com/2018/10/ai-to-transform-gpif-manager-selection/
21. https://www.risk.net/risk-management/4646956/model-risk-managers-eye-benefits-of-machine-learning
22. https://www.sec.gov/news/speech/bauguess-big-data-ai
23. http://www.milkeninstitute.org/videos/view/how-will-technology-trends-impact-your-portfolio
24. https://rady.ucsd.edu/faculty/directory/valkanov/pub/classes/mfe/docs/fama_french_jfe_1993.pdf
25. https://www.opalesque.com/666981/of_new_hedge_funds_to_use_computer698.html
26. https://www.institutionalinvestor.com/article/b18ts4fwfg53c0/Asset-Managers-Plan-to-Boost-AI-Spending-a-Greenwich-Survey-Shows
27. http://www.milkeninstitute.org/videos/view/how-will-technology-trends-impact-your-portfolio

Authors Bios'

Timur Kaya Yontar, *PhD*
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Dr. Yontar joined Meketa Investment Group in 2015 and has been in the financial services industry for eight years. A Senior Vice President of the firm, Dr. Yontar serves as a consultant for a variety of clients on their endowments, foundations, and pension plans. His areas of expertise include investment policy design, modeling of asset and risk allocations, derivatives-based strategies, and analysis of manager and fund performance.

Prior to joining the firm, Dr. Yontar was Managing Director, Investments and Derivatives, at Cambridge Associates. While there, he advised endowment, foundation, and high-net-worth private clients on asset allocation and manager selection, while also serving as a research specialist on portfolio construction, risk management, and derivatives.

Prior to this, he led the analytic services department at Upromise where he was responsible for marketing strategy analysis, reporting, and research. Previously, he was a management consultant, serving as a project and team leader at Monitor Group and as an analyst at Dean & Company.

Dr. Yontar graduated from Harvard University with a PhD and MA in Political Science, and a BA, magna cum laude, in Government. He serves as the Treasurer for the Harvard Band Foundation, where he is responsible for supervising endowment investments and capital grants.

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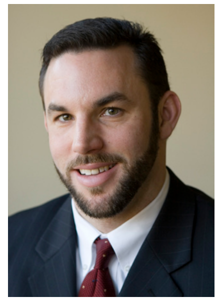
Mr. Obregon joined Meketa Investment Group in 2014. A Research Analyst for the firm, his responsibilities include asset allocation, risk management, and macro-economic research, and investment manager research. Mr. Obregon works directly with the public markets manager research team and the Director of Research to develop and communicate research and guidance to our consultants and clients.

Prior to joining Meketa Investment Group, Mr. Obregon was employed by Agrega Partners in Caracas, Venezuela, a financial and strategic consulting firm. In addition, he served as an Analyst for Core Global Management, an actuarial consulting firm in Caracas.

He received a Master of Finance from the MIT Sloan School of Management, and a Bachelor of Science degree, cum laude, in Applied Mathematics from the Universidad Metropolitana in Caracas, Venezuela. Mr. Obregon holds the Chartered Financial Analyst designation, and is a member of the CFA Institute. He also holds the Chartered Alternative Investment Analyst (CAIA) designation and is a Member of the CAIA Association®.



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Mr. Benham joined Meketa Investment Group in 1999. As Director of Research, Mr. Benham oversees all research projects, including white papers and the firm's annual asset study. Mr. Benham leads the design of the firm's portfolio construction initiatives and he is key in constructing customized investment programs. Mr. Benham is a member of the firm's Board of Directors and chairs the firm's Investment Policy and Strategic Asset Allocation/Risk Management committees. Additionally, he is a member of the Private Markets Investment Committee.

Mr. Benham received an undergraduate degree in Finance from Bentley College. He holds the Chartered Financial Analyst designation, and he is a member of the CFA Institute and the Boston Security Analysts Society. Mr. Benham also holds the Chartered Alternative Investment Analyst (CAIA) designation and is a Member of the CAIA Association®. Prior to joining Meketa Investment Group, Mr. Benham was employed at State Street Bank, performing operations analysis and developing process improvements.

Mr. Benham has served as a frequent speaker at industry events, including: the International Foundation of Employee Benefit Plans Annual Conference, the NCPERS Annual Conference, the Investment Forum for Endowments, Foundations and Pension Funds, the Endowment and Foundation Forum, the Made in America Conference, the Institutional Investor Public Funds Roundtable, the Boston Security Analysts Society Asset Allocation Seminar, the Institutional Investor Global Real Assets Forum, the Institutional Investor Infrastructure Investment Forum, the SuperReturn Latin America conference, the Institutional Real Estate VIP conference, and the Investing in Infrastructure Assets Europe and Americas conferences.