Artificial Intelligence and Value Investing

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Machines today can drive your car, pilot your airplane, transcribe your emails, vacuum your floors, search for your spouse, educate your children, power your home, and organize your factory. The trends in technology and artificial intelligence (AI) over the last 50 years will continue, and machines will only expand in power, intelligence, and scope. The question remains: Can they allocate capital? In particular, can they do so in the classic style of a value investor like Benjamin Graham or Warren Buffett?

Yes. This kind of AI differs from the algorithmic trading currently in vogue in financial markets. Most algorithms today are based on large-sample analysis that uses machine learning techniques from AI to process information on thousands of securities, using millions of data points as input. These algorithms usually do not take concentrated positions, nor do they hold these positions for very long. For machines to buy and hold over long horizons, they will require a more radical and advanced form of AI that is now emerging.

This article provides speculation on what this kind of intelligence looks like and how exactly it may come to be. It seeks to connect two broad and disparate areas: the sprawling domain of AI and the more old-fashioned style of value investing. The crux of the analysis rests on computers and their ability to reason, not just use statistical techniques.[1] The push for a viable technology that can mimic and even replace the human value investor will have long-term consequences for both AI itself and the efficiency of capital markets. I will begin by discussing the modus operandi of AI. I will then discuss and recast value investing in terms of this method. Finally, I will mine the AI scientific literature for the most relevant bodies of knowledge that can help implement value investing.

A SKETCH OF AI

Most are familiar with programming languages. One layer of abstraction above the programming language is the *algorithm*, a set of instructions given to a machine written in *pseudocode*, a shorthand that expresses the main ideas in mathematical logic. Algorithms can be expressed in multiple languages (e.g., C++, Python, and Java) because the language serves to implement the fundamental ideas from the algorithm. There is an even higher level of abstraction above the algorithm: the representation of the problem. Every algorithm must work within a representation, but there may be several ways to represent each problem (Lin [1965]).

For example, consider the classic 8-puzzle in Exhibit 1. The user manipulates a 3×3 grid by moving tiles into a single

EXHIBIT 1

The 8-Puzzle

Start State

7	2	4
5		6
8	3	1

Goal State

	1	2
3	4	5
6	7	8

empty space (Slocum and Sonneveld [2006]). One way to represent this puzzle is to represent the location of each tile, but an even better representation is to represent the location of the hole. The representation that the analyst employs will determine which algorithm to write.

The core of AI is the agent, which is similar to the rational agent that populates models of academic economics, such as in game theory and general equilibrium (Osborne and Rubinstein [1994]; Mas-Colell, Whinston, and Green [1995]). The agent behaves according to the actions available and takes the state of the world as an input. The agent can transition to new states and obtain new information on its environment (or even develop new actions). Much of successful AI is efficiently representing the problem and the agent's strategies, actions, and preferences.

The first problem of the artificial agent is defining the *state space*. The state space captures a representation of the world as it pertains to the problem at hand. The next step is to define the *action set* of the agent. This is how the agent moves between each state. Finally, the analyst must define a *goal test*, conditions that solve the problem. The *transition model* determines how actions move the agent into a different state. For example, in the game of chess, the state space is the position of the pieces at any given time. The action spaces are the legal moves available to any player given the current board state. The transition model constitutes the rules of the game.

For our purposes, the three domains that are most useful in AI will be searching, learning, and reasoning (Russell and Norvig [2010]). These are the three main (although not only) categories that are leading research in AI (Segaran [2007]).

REPRESENTING THE VALUE INVESTOR

To apply these ideas to AI, we must first meditate on the activities of a value investor. I focus analysis on the discretionary investor who holds a concentrated portfolio over long horizons in the style of Benjamin Graham or Warren Buffett. This investor does not trade frequently and seeks to purchase undervalued securities at a margin of safety that will deliver abnormal returns over long horizons. This analysis may also apply to discretionary growth investors, but it will not fit the short-term traders who trade in and out of stocks at high volume. I focus on the equity markets as a case study. All of the analysis in this article may apply to the discretionary bond investor.[2]

Consider the value investor. This investor seeks to purchase securities at favorable prices, hold them for long periods, and sell them after appreciation. The portfolio of securities is small (e.g., fewer than 20), and much of the work goes into selecting the right security at the right price. We can represent the state as a vector (s, t, p, b, e), where s is the security, t is the time, p is the current market price, b is the purchase (buy) price, and e is the sales (exit) price. For value investors like Warren Buffett, this exit price does not need to be defined.[3] The action of the investor at any given state is to buy, sell, or hold. Buy and sell refer to transactions on the security, and hold refers to doing nothing. Because stock prices constantly change, the state changes even when the investor takes no action.

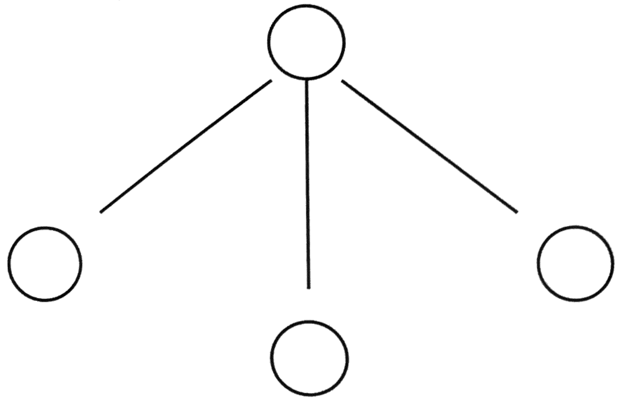
To visualize this, consider the decision tree in Exhibit 2, where each node pertains to a state of the world. For the sake of exposition, I will consider only the case in which the investor seeks to purchase one stock. For example, the state in Exhibit 2 could be (Apple, March 25, 2016 at 2:00 p.m., \$90, \$80, \$150). The investor's choices are to buy Apple, sell Apple if he or she already owns it, or hold it and do nothing. Each of these actions leads to a new state that refers to Apple's price at 2:15 p.m. on the same day.

A goal state for the investor would be a sufficiently high return on capital. Define return as $R = \frac{e-b}{b}$, the excess of exit price over purchase price as a proportion to the purchase price. An investor with a threshold return of $R*$ will take action when the return on that stock exceeds the threshold ($R > R*$). In that case, the investor has achieved his or her goal and can move on to another opportunity to deploy capital.

EXHIBIT 2

The State Space and Tree

(AAPL, 3/25/16 @ 2 pm, $90, $80, $150)



(AAPL, 3/25/16 @ 2:15 pm, $89, $80, $150)

This is the beginning of a model that can provide some high-level architecture for designing an AI-inspired approach to value investing. The details of this point rest on implementation. We now turn to alternative approaches within AI given this high-level scheme.

SEARCH

Representing the value investor as a tree leads to the problem of search.[4] Much of the early work in AI lies within search algorithms on trees, as in Exhibit 2. These trees can be finite or infinite. The most common algorithms provide different ways of navigating a game tree to locate a solution that satisfies the goal state. Common solutions are breadth-first search and depth-first search (Dijkstra [1959]). More-advanced algorithms provide heuristics that simplify the search problem (Dechter and Pearl [1985]; Hart, Nilsson, and Raphael [1968]).

For value investing, the search problem has both quantitative and qualitative aspects. The quantitative dimension is fairly straightforward: The value investor cares about purchasing stocks at a price below their intrinsic value. This is hard to know with certainty, so investors rely on common ratios or multiples. This is the approach Benjamin Graham [2005] proposes in *The Intelligent Investor.* These are similar to the heuristics used in AI because they are shortcuts that help narrow the search universe to find the stock that would satisfy the goal test.

For a simple example of a heuristic, return to the game of chess. For any given board position, there are up to 35 possible moves from each side. Therefore, chess has a branching factor of 35: The tree can expand into 35 possible ways at any given node.[5] Each move itself creates a different path of the game. After any possible move, there is a subtree from that point onward.

Exploring each subtree is infeasible even with current computing technology. As such, researchers have developed heuristics that approximate the value of these subtrees (Newell and Ernst [1965]; Mitchell [1982]). Some moves are probabilistically superior to others because they are more likely to end in wins than losses. A heuristic would provide some rules of thumb that would assist in pruning the tree by eliminating suboptimal moves. Thus, sacrificing a queen with no strategic or material benefit would count as a simple heuristic. There are many possible such heuristics, and much of the details on how computers win against world champions in chess rely on the implementation of heuristics and how the machine accesses prior databases of games.[6]

Value investors also use heuristics. A value investor seeks to buy a stock at a discount when its intrinsic value exceeds its current market price. Evaluating the goal test for an investor requires the passage of time because the truth behind the stock is revealed years later when the investor sells the stock at either a gain or a loss. However, the investor must decide now whether to buy and cannot walk down the game tree into the future to make that decision. A heuristic that most value investors agree on is simple financial multiples or ratios.

The two most common ratios are price to earnings and price to book, which are computed from stock market and accounting data. These are heuristics because they are not perfect measures of whether a stock is undervalued. Instead, they are approximations that provide assistance to the investor to make decisions today. Other value investors have defined their own set of heuristics. For example, Benjamin Graham writes in *The Intelligent Investor* that he seeks stocks that have net current assets per share below 67% of the purchase price, common during periods of steep market declines. Other disciples of the Benjamin Graham approach, like Charles Brandes, have developed a four-point test for a value stock that relaxes some of the Graham metrics and supplements with others (Brandes [1998]). Value investors are already using heuristics, and the first step is simple: to embed these heuristics inside an AI representation.

As Buffett once noted, though, the quantitative analysis of a stock is straightforward relative to the qualitative analysis (Ferraro [2009]). Inspection of Buffett's stock selection over his lifetime reveals that many of his selections would not qualify as deep value stocks but, rather, have features of growth stocks. For example, when Buffett bought Disney and Coca Cola in 1966 and 1988, respectively, both were enjoying price-to-book ratios well above 1.0, the classic threshold for a value investor. A heuristic that incorporates qualitative metrics must use more than the existing heuristics employed by value investors. This is where AI can shine.

Observing market price is easy, but measuring intrinsic value is the challenge. To make this qualitative assessment precise, the investor needs to define the features, or qualities, of the company that have high intrinsic value. These can include characteristics such as the business model, competitive advantage, strong management, or good governance (Ashworth [2016]). In the first step, the investor needs to describe these in verbal terms. For example, suppose that high-value companies have managers with long horizons, large ownership stakes, deep industry experience, and arm's length relationships with their boards of directors.

The second step is for the investor to define and identify quantitative measures of these attributes. In my example, they would be the length of the vesting cycle of stock options or restricted stock, the ownership stake in the company measured through proportionate share from stock option holdings, the manager's years of experience in the industry in which the firm operates, and the number of independent directors on the board. These measures are all available from public datasets. Much of the academic accounting and finance literature seeks to correlate these attributes with long-term abnormal stock performance.

The next step would be to increase the size of the input data into the AI system. To continue my example, suppose managers who give conservative forecasts or discuss their firm in conservative language are more likely to represent a value company than a growth company. As such, reading both the level of the earnings forecast from management guidance during the conference calls and the text from the conference call itself could provide a qualitative assessment of whether the company qualifies as a value stock. Again, this area has already begun to appear in academic research and is one of the most active areas of research today, called *textual mining* (Belsky [2012]).

The final step would be to include an ever-expanding amount of data into the valuation of the manager or the firm. These data, up until now, have been relatively structured in that they take a numerical and are easily readable by a machine. But the undiscovered country lies in unstructured data: namely, natural language, social media, and data on human productivity and output. In fact, 80% of business-relevant information originates in unstructured form (Grimes [2008]). Indeed, the analysis of unstructured data is where AI methods can excel because it requires the facility of computers to process huge amounts of data that are unknowable by any single human (Marsland [2009]).

As a simple taste of what the future will bring, observe the dramatic improvements in sensor technology, which have exploded the volume of data coming from wireless sensors. For example, new cars today feed huge amounts of information on the performance of the vehicle to enable features like adaptive cruise control (Thrun et al. [2006]). These sensors will only increase in scope and decrease in cost, thereby increasing the amount of data available for analysis. The Internet of Things revolution will catapult cheap sensors into all facets of everyday life so that human productivity is measurable and quantifiable. These changes can already be seen in the way a Fitbit or Nike Fuelband can quantify aspects of a person's fitness or health (Watson [2014]).

As an example, consider a sales manager at a company. Today, the manager's compensation depends on his or her sales calculated on an annually or quarterly basis, but these are output measures only. Once human productivity becomes cheaper to measure, input measures can also be incorporated into compensation. Imagine measuring his or her productivity by the number of emails sent to follow up on leads or the number of meetings or phone calls with prospective clients. Some companies, such as Shuttle Express, Inc., have already began to increase the rate at which they monitor employees (Katz [2015]). In the long term, third-party companies will distribute highly aggregated metrics on firms or industries with respect to the productivity of their employees. The astute value investor could then use these data to help assess the quality of the company's sales force and provide a better estimate of intrinsic value.

These ideas are speculative because they are based on data that do not yet exist. If current trends are any indication, though, the measurement of economic output will only increase, thus increasing the amount of available data. As technology marches on, the cost of acquiring new measures of corporate and human performance will plummet, and it will be imperative for successful investors to assemble, aggregate, process, and make decisions over this ever-expanding trove of data. In this sense, the search problem of the value investor will be the core problem, and advances in AI technology on search techniques will assist the value investor in better measuring intrinsic value.

The search algorithms discussed in this section were based on human guidance. These are the handful of metrics that successful value investors have used to access quality in companies. The promise of AI is to develop new heuristics and methods that no human could ever devise. To do so, the machine must learn from the data, and this brings us to our next key intellectual pillar of AI.

LEARNING

The second main cluster of approaches in AI are related to learning (Mitchell [1997]). Machine learning has exploded as a field in the last decade and has many applications to financial markets. For example, hedge funds like Two Sigma Investments and Renaissance Technologies are reputed to have used machine learning techniques to screen and select diverse portfolios of stocks for years (Vardi [2016]). How can this body of knowledge be useful to concentrated value investing? It is important to first consider the main forms of learning. The two broad categories are supervised and unsupervised learning.

Supervised Learning

The classical and original form of machine learning took place under human supervision. A human classifies a set of input–output pairs according to a hypothesis. Once the machine has learned based on the training set, it then proceeds to classify untrained data based on its initial training.

Consider visual recognition from photographs. Imagine 10,000 photographs of the jungle, and a human has identified 100 photos that contain a tiger. The training set is the 100 photos that the computer knows contain a tiger. The computer then searches the remaining 9,900 photos and tries to classify them as {tiger, no tiger}.[7] To apply this to value investing, a necessary input would be a relevant training set (i.e., data on a successful value investor and both the investor's stock picks and the universe from which he or she selected these stocks). Each stock could be classified as buy, hold, or sell. Once the analyst has trained the machine over this training set, the machine would rely on its initial training to classify future stocks.

One problem with this approach is that it may suffer from insufficient data. If the only input is the universe of stocks and the only output is the actual stock selected, there is a wide chasm between input and output and much can be lost. The machine will have difficulty crossing the chasm, especially because training sets will be small; most value investors hold concentrated portfolios over a long horizon, so the actual output set is small. To improve training and machine learning, the analyst should supply more intermediate data that are used in the decision-making process of the value investor.

For example, most investors employ something of a pyramid-like decision process, narrowing the universe of stocks over time. For example, quantitative filters may sort the full universe of stocks down to a cluster of potential investments. The investor may further narrow this cluster based on his or her own expertise or interest. At the penultimate stage, the investor does a deep dive into the company's financials to research one or two investments that are candidates for a major position. If the analyst can supply data about this sequential decision process over time, the machine could use this richer data structure to improve on its own learning.

An open question is whether the machine would need to represent the sequential narrowing process explicitly. This is where the field of AI has differing opinions. There are those who believe all that matters is the final output, regardless of the specific approach or method used. Those in this group, often called *scruffies*, are willing to use any manner of statistical or mathematical tools, even if they have little resemblance to the actual decision process at hand.[8]

Another approach is to represent the decision process explicitly through data structures and algorithms that bear a faithful similarity to the actual human process. Adherents of this view, often called *neats* for their taste in neat analytical models, draw on explicit mathematical and logical axioms and work from first principles aiming to understand key truths through any given problem.

Both approaches are needed, and the best algorithm will benefit from a combination of both approaches. A more structured representation would take each round of the decision process as an input into some explicit data structure, and the machine would learn from its datasets how to refine every step. This of course requires larger inputs, and it would require an investor to hand over not just final stock picks but even intermediate picks. It is likely that every value investor goes through something of a sequential elimination process just described, and each could furnish such details if he or she had sufficient financial incentive.

Unsupervised Learning

A more recent approach to machine learning skips the initial step of human supervision, and the computer learns on its own (Bishop [2007]). This requires even larger datasets because there is no structure in the problem at all. The machine tries different approaches and receives feedback from the system regarding which ones work and which ones fail. This is called *reinforcement learning* because the system itself provides reinforcement feedback to the machine. For example, a machine learning to play chess would try different moves, and with enough simulations of the game, it would receive feedback on which moves probabilistically are more profitable. Rather than relying on a human to inform the computer that losing a queen is a poor move, the computer simulates games in which it loses its queens and learns that, statistically, these games are harder to win. For such a strategy to work with value investing, the computer would be required to simulate stock selection and would receive market feedback on those stocks. This is more challenging than the chess example because chess is deterministic (nonrandom), whereas the stock market has uncertainty and risk at every point. A computer can simulate different moves in chess and, therefore, populate an entire game tree; it cannot do so with the stock market without making strong assumptions that themselves may violate the fundamental randomness of markets.

As such, an alternative strategy is to mine past data using historical stock prices as the ultimate output. To do this, the investor would need to back test the algorithm on the last 50 years of stock data. This approach is possible, although I do not believe it to be of high value given the long horizons and low turnover of successful value investors.

The third approach is to use unsupervised learning to improve search heuristics. Recall that the search problem is to find stocks of high intrinsic value and low price. Estimating intrinsic value requires the investor to screen large amounts of information, both qualitative and quantitative, to deliver an assessment.

A reinforcement learning approach would not just simulate specific selections of stocks, but rather would simulate different attributes that may or may not lead to a better assessment of intrinsic value. For example, rather than relying on a structured model that says long-term compensation and independent directors lead to better performance, the machine would traverse the universe of corporate attributes to discover which ones lead to high abnormal returns.

In this sense, unsupervised learning pertains not to the selection of the securities per se, but rather to the selection of the *attributes* that then lead to the selection of the securities.[9]

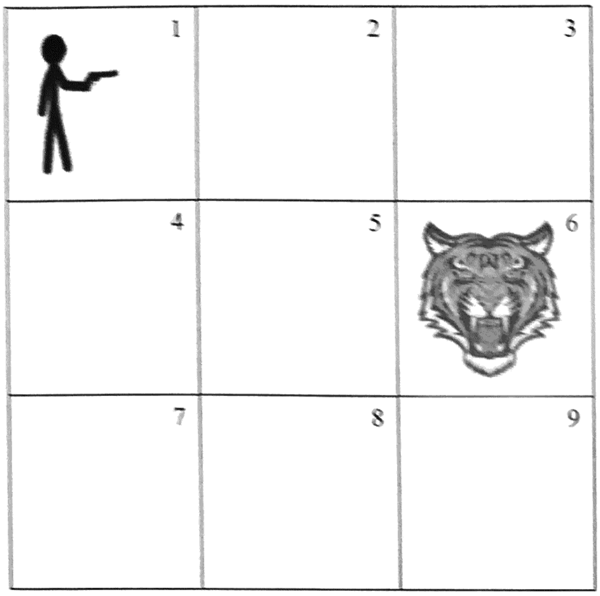
REASONING

Approaches thus far may seem unconventional, but they have already gained traction in industry. The truly revolutionary work in AI concerns reasoning (Minker [2000]). Getting a computer to reason logically has been a goal of computer science for decades. This approach takes a different path than the searching and learning algorithms discussed. Now, a computer and machine seek to make logical statements and inference using the same principles of logic that underlie philosophy and abstract mathematics (Davis [1990, 2005]).

Consider the following examples that can illustrate elemental reasoning. A hunter seeks to locate a tiger hiding in a cave.[10] The man cannot see in the dark cave but can smell the tiger from a distance. He has a rifle with one bullet and seeks to minimize his travel inside the cave so that he kills the tiger. This can be represented as a 3×3 grid, as shown in Exhibit 3. Each square in the grid corresponds to a location in the cave, and the man starts at Square 1. He can move up or down, but not diagonally, one square at a time. The tiger sits in Square 6, but the man cannot see the tiger. Instead, he can smell the tiger in any adjacent square (again, up or down, but not diagonal). From the starting position, the man smells nothing, so he knows for sure that the tiger is not in Squares 2 or 4. Therefore, he moves into Square 2 with certainty that he will not be eaten. Again, he smells nothing and infers that the tiger is not in Squares 1, 3, or 5. If it were, he would have smelled the tiger while

EXHIBIT 3

A Reasoning Game



standing in Square 2. Of course, he already knows there is no tiger in Square 1 because he started there.

Now, suppose he moves down to Square 5. Because the tiger is in Square 6, he smells the tiger. However, smelling a tiger in Square 5 means the tiger could be in any of Squares 2, 4, 6, or 8. Of course, the tiger is not in Square 2 (because he was just there), but it is also not in Square 4. If it were in Square 4, he would have smelled it in Square 1. Therefore, the tiger must be in Squares 6 or 8. Suppose he moves left to Square 4. He smells nothing because there is no tiger in Squares 1, 5, or 7. When he moves down to Square 7, he again smells nothing and concludes that the tiger must not be in Square 8. If it were in Square 8, he would have smelled it in Square 7. Therefore, by the process of elimination, the tiger must be in Square 6 because he smelled it in Square 5 but not in Square 7. The man returns to Square 5 and shoots the tiger in Square 6.[11]

This simple example from a child's puzzle illustrates some of the intuitions and layers of logic that a computer could conceive, construct, and execute. The problem is well defined; therefore, building a data structure and algorithm is straightforward for such a setting. As with much of AI, however, this simple example can illustrate some techniques that may apply more broadly in real-life settings.

The core idea is to use information to reason, to take actions, and to infer the state of the world (Hwang and Schubert [1993]). The example given indicates a level of reasoning that is common in everyday human life but still foreign to machines. Investing in a stock market involves layers of uncertainty and information that is asymmetric. Yet, there are still parallels. A computer could begin to reason about managerial attributes and corporate quality based on what is and what is not disclosed in its financials. For example, during an economic downturn, one would expect cutbacks in research and development expenses. If no such cutbacks are forthcoming, this may reveal that the firm is more insulated from macroeconomic events, leading to a higher intrinsic value during times of distress. This is an example of how reasoning and inference can be employed through machines to draw conclusions about a company's quality.

LOOKING FORWARD

Logic-based AI may still be a few years away, but there is no doubt that it is in our future. However, making this future a reality will require several steps along parallel tracks. These steps need not be coordinated or happen at the same time, but they do need to happen. First, the value investing community will need to acknowledge that the application of AI to their field is inevitable and embrace rather than fight this secular trend. Rather than see this as a war between man and machine, the discretionary investing community needs to acknowledge that computation can assist in the kind of reasoning traditionally done by humans, thus enlarging the scope of analysis. Investors will need to adjust their analysis, knowing that they will now have a very powerful tool, an AI engine, to use along with their own minds.

First, investors need to think hard about the mental process through which they make their investments. Successful investors have already done this, as many of the best investors have written books and given speeches about their investment process. Others have spoken at length about specific investments, which reveals this investment process to outsiders. This first step must come from the investing community if AI is to have a legitimate application to value investing. Investors will need to meditate on the kinds of data sources they bring to bear on their investment choices and how exactly they interpret those data. Investing is ultimately a process of reducing down an enormous set of financial information into qualitative statements about price and quality. If a few value investors were to write down in narrative form how this process takes place, that could provide the initial material for computer science to step in and build a more specific AI model tailored to value investing.

On the technology side, computer science as a field will need to continue its steady march toward logic-based AI. This shows no signs of abating, but the research is still in its early stages. Although existing methods of AI (such as machine learning) have leaned heavily on statistics, logic-based AI will lean more heavily on pure mathematics and philosophical logic. This is an entirely different branch of knowledge and currently will require greater inroads into cross-disciplinary research. Beyond this, computer scientists will need to communicate extensively with value investors to build a custom AI engine for investing. They will need to take the narrative descriptions documented by the value investors and program their engine to replicate this kind of reasoning on a large scale. Although this may seem daunting, the Wumpus World is an example of one successful case. In that children's game, the rules provide enough structure for a computer algorithm to work through. A similar but more elaborate process will need to occur for an investing example.

Investors who have documented their data sources for a variety of successful investments will serve as the guiding light for the AI engine. This corpus of knowledge will be hardcoded into an AI algorithm, and the algorithm will essentially replicate the human reasoning process through formal rules and explicit procedures written in software. As the engine applies this technique to actual investing, early results will be mixed, and there will be many misclassification errors (successful investments incorrectly classified as poor, and poor investments classified as successful). However, as data improve and as more reasoning methods are hardcoded into software, results will also improve.

Later, the AI engine will learn to reason on its own in ways that do not easily replicate what humans do. After incorporating much of the early intuitions and simple logic of human-based reasoning, the software will obtain a level of complexity that no human mind can fathom and will make inferences and decisions in ways that are unknowable (and possibly incomprehensible) to human investors. If the AI engine successfully establishes its goal tests and a clear metric of success (relatively easy in the black and white world of profit and loss), then the computer can essentially back-solve and improve itself over time.

This process is similar to how machine learning has progressed. In the early phases, machine learning algorithms drew upon a training set based on human classification; in later, more mature versions of machine learning, algorithms were able to learn without a comprehensive training set. In those latter cases (reinforcement learning), the computer would experiment and simulate different actions while improving performance (in a precise, statistical sense). Indeed, the success of AI in games like chess and Go is a shining example of this process. Once these two parallel developments occur, they will propel both AI and value investing forward. Some of these steps forward will come from university researchers, and others will come from the investing and technology communities. Today, these communities have been largely separated, and much of the current applications of AI to investing come from within finance, rather than from within technology. With the next iteration, I believe there needs to be a closer alignment between the two fields, with innovations coming as much from technology as from finance. Regardless, I see this future as inevitable and am hopeful for both communities. This process will push technology forward to make markets more efficient. As always, the early movers in this space will reap the highest returns.

CONCLUSION

At the end of the day, value investing is about rationality in the face of irrational sentiment and mass investor psychology (Brandes [1998]). It is precisely the irrationality of human investors that drives prices away from fundamental value. Therefore, computers that can reason ever more faithfully than any human would have a natural advantage in such an environment. These ideas of machine reasoning are in their earliest stage of development but will have the most market impact on value investing in the long term.

The strong form of the efficient markets hypothesis states that market prices will impound *all* available information. Even the most fervent supporters of efficient markets do not believe that markets today are strongly efficient. Nonetheless, the continual advancement of technology in computation brings more data to bear on the investing problem. Sophisticated investors can make use of this information that is not yet impounded into price.

There are enormous gains from moving forward in this direction. It is smart investors who make the market efficient; they identify opportunities where value and price differ, and their trades close this gap. Artificial intelligence is the primary theoretical apparatus necessary for processing the ever-exploding amounts of data emerging from human and corporate behavior. Making sense of all these data, and reasoning through them, will remain the biggest challenge for 21st-century investing. In this article, I hoped to capture some of the spirit of this challenge and to outline the existing areas within AI that could be profitably deployed for a value investor. This is just the beginning.

ENDNOTES

I'd like to thank Brian Bruce and Dylan Shell for inspiration and comments.

[1]I refer to computers and technology equivalently as machines. *Computer* remains an outdated term because machines today take the form of smartphones, cloud services, desktop computers, mainframes, and so forth.

[2]However, bonds themselves have a richer mathematical structure than equities and lend themselves to quantitative analysis that permeates existing algorithmic trading. I focus on equities because of their more qualitative component relative to bonds. Of course, these are arbitrary distinctions, and a worthwhile agenda would be to apply AI to bond investing as well.

[3]This is part of what made Warren Buffett so successful. He stated that, "If you instead focus on the prospective price change of a contemplated purchase, you are speculating" (Farrell [2014]).

[4]The tree is an example of a directed acyclic graph. It is a graph because it contains nodes and links between nodes. It is directed because the links can move in one direction as time moves forward, and it is acyclic because there are no cycles. Nodes cannot link back to each other because time only moves forward.

[5]Although large, this is still smaller than the game of Go, which has a branching factor of 270.

[6]This technology was used by IBM to create Watson, the supercomputer that competed on the Jeopardy game show. See Ferrucci et al. [2010].

[7]This is how the iPhoto software on the Apple Macintosh works. The program asks you to classify photos and identify people by name in a handful of photos, and the computer then learns from this training and seeks to classify by itself on the larger untrained dataset.

[8]Google's algorithm recently beat the highest-ranking professional Go player. The research behind the specific methods used in Google's algorithms show that it was an alphabet soup of assorted AI techniques pooled together that dominated the human opponent. This is an example of a scruffy approach.

[9]Critics of this approach call this *data mining* because it lacks theory and instead runs large-scale statistical analysis to determine economic outcomes.

[10]This is a variation of the Wumpus World Puzzle in elementary logic.

[11]Of course, this is not the shortest path. Had he moved to Square 3 from Square 2, he would have smelled the tiger from Square 3 and identified it in Square 6, but that occurs because Square 3 is on the edge.

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