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AN EXAMINATION ON THE LEGALITY AND VALIDITY OF EXPERT SYSTEMS BUILDING CONTRACTS IN THE FINANCIAL SECTOR

Shannon Mc Girk, Embry-Riddle Aeronautical University

Cindy Greenman, PhD, CFE, Embry-Riddle Aeronautical University

Abstract

In the past three years, the technology of Expert Systems, underneath the broader field of Artificial Intelligence (AI), has taken on a new role in the use of contracts in the financial sector. JP Morgan Chase is currently using Expert Systems to build algorithms that evaluate credit and underwrite risk. It is possible that in the future these systems could evolve to be used to draw up unilateral contracts for investors and clients. The validity and enforceability of unilateral contracts is a matter of law in both Federal and State statutes. Currently neither Federal nor State lawmakers have passed regulations specific to Artificial Intelligence. As financial institutions seek to use Expert Systems to increase the efficiency of their business, the questions should be asked about the validity of the contracts. Normally Expert Systems undergo constant review to ensure false positives and negatives are not categorized as such. The United States Court System has no precedent for a false positive contract going to trial for a breach committed by either party. Herein lies a thought experiment on the background of such a contract when Expert Systems are in use not only with J.P. Morgan and Chase, but other financial institutions as well, and how navigating through the court system would work possibly when the document in question is a contract written by Expert Systems and executed by the parties with no oversight by an attorney.

Keywords: Artificial intelligence, expert systems, finance, AI and financial sector, AI and the law, machine learning.

INTRODUCTION

The growing ability of Expert System's ability to reason and automate the generation of contracts in a cost-effective manner has led to the financial, legal, intelligence, and other fields utilizing Expert Systems more and more. To understand the possible ramifications, it is first necessary to understand the following areas: 1) how Artificial Intelligence works; 2) the current legal definition and framework for a contract; 3) how the areas of law and contracts intersect with Artificial Intelligence and 4) how the potential utilization of AI by the financial sector. Once this information is understood, it is then important to determine the probability and nature of future issues outlined in the thought experiment. In order to put safeguards in place to protect both the financial institutions and the consumer from damages, we must first understand the background and evolution of possible issues.

Machine learning under the umbrella of Expert Systems is a broad term that can mean multiple things depending of the mood of the media. For the purposes of this paper, it is used as the field over Adversary L earning Style Systems. Alpha Zero uses an adversary style to learn the game of

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Go and the accompanying 3,000 years of tradition and game play by playing against a similar alpha machine. Neither machine had anything, but the basic rules of Go programmed into the algorithm, but through playing each other, Alpha Zero learned enough to beat the previous Google Deep Learning Go champion in 40 days as well as the current human world champion. This is known as the nueralneural network system of deep learning using the adversarial method.

Currently, the legal world is being disrupted by the outsourcing of traditional junior legal work and by the use of Correctional Offender Management Profiling for Alternative Sanction (COMPAS) for making sentencing easier. Electronic discovery systems are becoming more and more prevalent as the technology gets better and better and less expensive for smaller firms to buy and use. Most courts around the United States accept cases and documents that are electronically submitted to them. Of course, Expert Systems are not able to work on the more complex cases, but for something as simple as data entry into a program that then produces as will or contract, an attorney is not needed. This has currently ballooned into outsourcing of the work that junior attorneys used to produce. Without that preliminary experience, these attorneys cannot be expected to practice law in the same way that their more experienced colleagues.

When court districts began using the COMPAS algorithms to judge how likely a defendant was to reoffend, recidivism rates skyrocketed (Larson). The algorithms for COMPAS are based on personal characteristics to assess how high of a risk somebody poses whether through bail or through reoffences later on. As of right now, people, even experts in computer science, have very little understanding of how the underlying logic behind algorithms such as COMPAS and other similar ones. If judges do not understand how the logic works and the potential biases when working with algorithms, then they cannot be expected to administer the law to its full effect.

Hypothetically, the year is 2050 and Expert Systems have been used for contracts for a while. As the software gets better, there is less oversight to continue to cut costs and increase revenue. The contracts continue to be approved based on the data entry from years ago. The Courts have developed a system that allows for electronic filings from anywhere and take the computer's IP address at the time of signing along with a holograph signature that carries the penalty of perjury if misused as e-signatures. Then an investment firm is sued by a client as the algorithm that uses deep learning to make trades loses nearly 90 percent of the client's assets. Under current US law, the investment firm nor the algorithm would be found at fault for the losses of the client's losses. Who is at fault here? The algorithm was bought by the investment firm to make these trades using a reinforcement deep learning mechanism much like Alpha Zero, it 'taught' itself how to optimize portfolios without human data input. This again can be achieved through an Adversary Learning Style. Stock markets and humans are inherently illogical, though, and learning about them and then evolving the trades to exist in a continual optimization format.

EXPERT SYSTEMS LEADING TO ADVERSARIAL LEARNING SYSTEMS

Beginning in the 1980s, Expert Systems began to be narrowed down as the definition emerged as "An intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution. The knowledge necessary to perform at such a level, plus the inference procedures used, can be thought of as a model of the expertise of the best practitioners in that field." (Feigenbaum, 1980) Each system is built on an ecosystem of facts and heuristics using the facts to set the parameters and boundaries while heuristics provide the "Mostly private, little-discussed rules of good judgment (rules of plausible reasoning, rules of good guessing) that characterize expert-level decision making in the field." (Feigenbaum, 1980) In 1987, Google filed a patent for the basic expert system detailed as "The knowledge system includes a knowledge base in an easily understood English-like language expressing facts, rules, and meta-facts for specifying how the rules are to be applied to solve a specific problem. The tool includes interactive knowledge base debugging, question generation, legal response checking, explanation, certainty factors, and the use of variables. The knowledge base language permits recursion and is extensible. Preferably,

control during a consultation is goal directed in depth-first fashion as specified by rule order." (Hardy et al, US Patent Office).

Presently, there are four different classifications of Expert Systems: Rules-based, Frame-Based, Fuzzy Logic-Based, and The Expert System based on Neural Network Each classification starting with Rules-Based Expert Systems builds the foundation for the evolution after it. Each of the following classifications builds its expertise and way of "logic" based on the one before that. Having this type of gradual evolution of technology made it easier for people to understand how the machine 'thought' and how the inference engines gathered from the knowledge bases that A goes to B goes to C.

Rules-based Expert Systems produce answers based on what the rules dictate. The rules are often programmed in the form of 'IF-THEN' statements. These rules are derived from information input by a human expert and provide a program that contains a logical methodology for reasoning of the rules from the knowledge base. "The rule can then be used to perform operations on data to inference in order to reach appropriate conclusion. These inferences are essentially a computer program that provides a methodology for reasoning about information in the rule base or knowledge base, and for formulating conclusions." (Liao) They can be used for many things including "Production planning, system development, knowledge verification/validation, knowledge base maintenance, scheduling strategy, management fraud assessment, knowledge acquisition, knowledge representation, communication system fault diagnosis," (Liao). The main purpose of Rules-Based Expert Systems can be categorizing data to make management and maintenance easier. This categorization is limited by the amount of knowledge in the data base and the logic of the IF-THEN statements for the inference engine. When a data point does not fit neatly into an IF-THEN definition, then it is more likely to be categorized wrongly and therefore, needs to be compensated by a larger database of knowledge and better boundaries in the inference engine, both of which are addressed below.

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Frame-Based Expert Systems connect the inference engine of a rules-based system to a large external database of knowledge. Frames are comprised of a names, slots or attributes of the frames and/or facets. Each of these can be organized into a taxonomy that describes the groups and classes of objects. These lack encapsulation properties and yet, enable the taxonomy to work without being bound by strict rules. "(Rattanaprateep, Chittayasothorn) In the most basic sense, frames enable the rules-based system to be open ended about the boundaries of knowledge although they cannot handle the uncertainty that Fuzzy Logic Expert Systems can.

Fuzzy Logic Expert Systems developed to handle the uncertainty that comes when a knowledge base is finite and contains unknown conclusions that could potentially be drawn form the knowledge base. The fuzzy set simulate the process of normal human reasoning by allowing the computer to behave less precisely than conventional computers. Information is inherently association with uncertainty in the Knowledge Frontiers. Through type-1 fuzzy sets, the uncertainty in problem solving from information deficiencies from the information and data sets being presented as fragmentary, unreliable, vague, contradictory, or otherwise unusable for normal logic sets. (Melin, Castillo)

The Fuzzy Logic is still characterized by IF-THEN rules, then extrapolated to the output processor when circumstances are too uncertain to determine exact sets of minimum and maximum. This leads to the Fuzzifier, the Rules, the Inference, Type Reducer, then the Output. These systems make it useful for pattern recognition of images especially which can then be further developed to categorize different and more complex objects such as high frequency trades. High Frequency Trades occur so quickly in the investment sector that people cannot possibly review and approve all of them. Using Support Vector Machines (SVM) boundaries plus fuzzy logic algorithms could enable machines to review the trades and then categorized them as 'good' and 'bad' accordingly. In the use of SVM, the Fuzzy Logic classifier presents as a support for determining the vectors for maximization of boundaries and generates the combined results to quantify the uncertainties of the boundaries of the knowledge base. "The type-2 fuzzy model takes SVMs accuracies and distances of data examples to the SVMs hyper planes from phase I and produces outputs to indicate whether data examples belong to positive or negative class.

Currently, the legal profession utilizes computing power for contracts through expert systems which are formed from the Knowledge Base, the Inference Engine, and the User Interface with human data input. The knowledge base is the foundation that the Expert System is based upon. With the knowledge base, all the expertise that has been input into the system is used to evaluate and build new models. The key is having good information to use in the foundation to build models and have good inference and analysis during the creation of the product - here contracts (O' Riordan). This is referred to as Accepted Wisdom and contains the Nature of Expertise. The first Expert Systems explored the behaviors of problem solving in any depth. As the neural networks imitate how the human brain trains itself to solve problems: "The first-generation stems like DENDRAL and MACSYMA focused solely on performance, while second generation systems began to explore behaviors like explanation and knowledge acquisition. Of these, performance is still the best understood;" (Davis). The knowledge base needs to be exact about what is not known as the types of problems attacked with Artificial Intelligence do not necessarily have complete laws and theories, but theories at best and guesses at worst. The knowledge base is first categorized and programmed for a base to learn from then incrementally builds on that knowledge base according to observation, categorization, and the solving of problems.

From the knowledge, the Inference Engine is free to work. The original purpose of the inference engine was to examine the Knowledge Base and from there provide insight. The Inference Engine has developed in recent years to be able to expand the knowledge base. This expansion is based on interpretation of new data streams and observance of data.

The User Interface is the bridge between the computer's model and formation of model and the client. This is currently a combination of the user inputting the data as well as the product produced. A good example in of the current use of the user interface combined with a knowledge base and inference engine in a simple rules-based system in the legal field is the use of Hot Docx. Hot Docx will use macros based on the predetermined parameters on the State and County specifications. The macros will then produce any legal document based on the inputs and the data added to the knowledge base. Beyond this current example of the User Interface helping the legal profession, Google’s patent applications were showing systems built on those three fundamental parts as early as 1989. The three fields (Knowledge Base, Inference Engine, and User Interface) described above are shown explicitly in Google’s patent application for the Basic Expert System Tool, which then laid the foundation for Alpha Go.

In building an Expert System, we start with the Accepted Wisdom as the foundation and the tools for rules based on ‘compiled experience’. By providing exposures to numerous examples (for example, Google’s Alpha Go machine winning against the Go world champion by observing and playing games to learn the game), the systems learn the basis of the rules for the contract and ‘play’ the game accordingly. The logic then goes, “If A and B then C? If the strongest argument we can make is of the sort, previously, when A and B held, C was also found to be true, then the inference is justifiably characterizable as an association that grew from accumulated empirical observations (Davis) The above inference shows a linear logic pattern familiar to most: if A equals B, and B equals C, then A equals C. The difference comes to whether or not inferences are being built using associations that grew from empirical observation or from an understanding of the underlying structures and functions. This is the associative logic from observations that the algorithms must make to ‘learn’ how to repeat those same observations when handling enormous streams of data. Structure and causality logic through if ‘A and B are true because of these rules, then C must true as it also follows these rules.

Alpha Go machines use the deep learning technique, a subset of machine learning, that is defined as “A family of processes by which a computer program is able to refine its own internal models to improve its ability to process a set of information.” (Solum) As a computer or algorithm is able to refine its own internal processes (similar to what the human brain does as it ‘trims’ off excess neurons during growth and processes the day’s information during sleep) Fachechi, 2018) it can be said to have the ability to develop original ways of thinking or ‘processing’ that be said to be humanlike. In refining how it grades and corrects itself, the unsupervised AI can exhibit emergent behavior that no human specifically coded for (Moussa, Windle; 2018). The most common way to refine the AI code is through Generative Adversarial Networks. For example, when Alpha Zero learned the game of Go in 40 days, it did so from playing against itself.

This has lead from the aching need for humans and for human logic to drive the conversation to a scenario where human logic might harm the algorithm's process so it is deemed unnecessary and avoided. There are differences between the degrees of how much Expert Systems need human input. Alpha Go and other deep learning machines have traditionally been supervised. Supervised learning requires human input. This input can be through either observation of past events and how the rules would play out in different scenarios, through direct human input of the rules surrounding the knowledge points through programming, or a combination of both. "These approaches work best with quantitative results such as a hormone level or the number of healthy versus diseased individuals". (Bzdok, Krzywinski, Altman).

Active learning methods use the existing classifiers and then improves those classifiers. Retraining the model at every step enables the model to use the classifies more carefully and at a higher level. Combining this with batch mode ups the time efficiency of it as well. The "Active learning methods aim to use the existing classifier in some way so as to decide which unlabeled items are best to label in order to improve the existing classifier the most. The majority of popular approaches are based on heuristics such as choosing the item whose label the model is most uncertain about, choosing the item whose addition will cause the model to be least uncertain about other items, or choosing the item that is most 'different' compared to other unlabeled items according to some similarity function….Though these heuristics work well, they are motivated in the context where instances to label are selected oneat a time, re-training the model at every step. On the other hand, it is often more appropriate and efficient to send data for labeling in batch mode, i.e. requesting that asset of instances be labeled by people. The heuristics mentioned above can be extended to the batch setting by taking the best items according to the heuristic's metric of selection; however, this can lead to substantially suboptimal performance and produce sets with overly redundant items." (Hoi et al) Active learning methods do not always translate or evolve into batch modes. For the sake of expediency in learning, the machine is often programmed to allow for that possibility. This is due to the amount of information available for the machine to process and learn from.

Batch Mode Active Learning conceptualizes of deciding the size and the most appropriate images from the video. These algorithms can easily be categorized by SVM, statistical approaches, queries by committee, and information theoretic approaches. Once the active batches have trained the algorithms through the processing of data, the now unsupervised deep learning machine can use the algorithm to make insights that it wouldn't have otherwise. Again, using the Alpha Go Zero Algorithm, Google refines this program from the previous versions as "First and foremost, it is trained solely by self-play reinforcement learning, starting from random play, without any supervision or use of human data. Second, it uses only the black and white stones from the board as input features. Third, it uses a single neural network, rather than separate policy and value networks. Finally, it uses a simpler tree search that relies upon this single neural network to evaluate positions and sample moves, without performing any Monte Carlo rollouts.

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To achieve these results [of beating the previous versions], we introduce a new reinforcement learning algorithm that incorporates look ahead search inside the training look, resulting in rapid improvement and precise and stable learning" (Silver et al).

It appears that potentially Batch Modes will be able to feed data into expert system algorithms such as Alpha Go Zero without human input. When that can occur, it is unknown how that logic will develop and progress. In the transition from supervised to unsupervised machine learning, most machines especially SVM and kNN algorithms are semi-supervised at the most advanced levels. The dynamics of the specific batch that is learning reveals whether it is supervised, semi-supervised, or unsupervised. "The batch size and selection criteria are integrated into a single optimization formulation; whose solution yields the desired batch size and the specific samples for query. The frameworks were validated on the face recognition application using two challenging biometric data sets" (Shayok). If a batch can self-select its sample size and type, then the algorithm is considered semi-supervise. Again, Alpha Zero managed through self-play master chess, shogi and Go. "Alpha Zero: a more generic version of the Alpha Go Zero algorithm that accommodates, without special-casing, to a broader class of game rules. We apply Alpha Zero to the games of chess and shogi as well as Go, using the same algorithm and network architecture for all three games. Our results demonstrate that a general-purpose reinforcement learning algorithm can learn, tabula rasa – without domain-specific human knowledge or data, as evidenced by the same algorithm succeeding in multiple domains – superhuman performance across multiple challenging games." (Silver et al) Through the emphasis placed on the neural networks of the algorithm and the dynamic batch modes of the learning inputs themselves, Google has the beginning of unsupervised machine learning.

UNILATERAL CONTRACTS VS. BILATERAL CONTRACTS

Contract definitions taken from Black's Law dictionary are: "A covenant or agreement between two or more persons, with a lawful consideration or cause." (Jacob) and/or "A deliberate engagement between competent parties, upon a legal consideration, to do or abstain from doing, some acts" (Blacks). Both of these are used interchangeably in the current legal field, but the difference between 'persons' and 'competent parties will become increasingly important as artificial intelligence develops. Blackstone's commentaries have provided multiple ways in which contracts may be used in daily life from securing a debt to building a business. The most contact a person will have with contracts, though, outside of a law office or a bank, is with the 'Term of Agreement' for software that they must accept in order to access different websites and applications.

Common Law classifies the differences between bilateral and unilateral contracts as such: "the bilateral contract of a promise for a promise, and the unilateral contract of a promise for an act. In the case of bilateral contracts one promise is held to be consideration for the other, the agreement, therefore, becoming effective currently when the promises are exchanged. In the case of a unilateral contract, however, the promise does not become binding until the act has been completely performed. A promisor may therefore withdraw his promise at any time before completion of the act, even though he knows that the promisee has already entered upon the performance and has nearly completed it." (Kessler) Most contracts are unilateral such as in

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signing a rent agreement, the property management agrees to let the signer live at the property (the act) in exchange for rent being paid every month plus general upkeep (the promise). When the act is completed – the tenants move in – the rent every month or the promise now required. If the tenants were not allowed to move in, then the rent every month would not be required. Courts are involved with unilateral contracts once the promise is withdrawn. From Yale Law Review, 1916: "Let us suppose that B starts to walk across the Brooklyn Bridge and has gone about one-half of the way across. At that moment A overtakes B and says to him, "I withdraw my offer." Has B then any rights against A? Again, let us suppose that after A has said "I withdraw my offer," B continues to walk across the Brooklyn Bridge and completes the act of crossing. Under these circumstances, has B any rights against A?" (Wormser, 1916)

Contracts require five steps to be considered legally valid:

1. The Offer – in which one party promises either an action or a promise in exchange for an action, example being that I will pay such and such amount of money for a car

2. Acceptance – in which the other party says yes to the offer.

3. Consideration – Was this given due diligence by all parties? For example, in buying a home, was an inspection done, appliances either left or take with the seller, are utilities hooked up?

4. Legality – Is the contract legal? Would it hold up in court as a contract? If the judge would recognize this as a contract, then that does answer the question of whether or not it is legal.

5. Capacity – Do both parties have the mental capacity to understand the terms and conditions as they are applied in this situation?

The tradition of US common law requires court precedence to resolve legal issues. In the US, court precedence has established the solution to these two questions as if there is no enrichment for A and therefore no recovery for B. This solution follows the facts and decision held of Offord v. Davies. Following the court case of Hawkins v. McGee (146 A. 641, 84 N.H. 114 (N.H. 1929), unilateral contracts have grown in proliferation in the use of American contract law. The most common and modern example is the Terms of Agreement for many different software. By hitting the "I agree" button, the user effectively signs a unilateral contract saying that they will abide by certain rules to use the software. They do not have to follow these rules, but they are a condition of using the software [e.g. a promise exchanged for an action, use of the software in exchange for abiding by the rules and regulations].

In 2019, the standard questions for a contract when combined with technology lies in "To ensure the validity of a contract, the parties thereto must have the contractual capacity, i.e. the legal ability to enter into a contractual relationship. Therefore, the attribution of computer acts to a person raises an important issue: can a computer-which cannot be considered as a legal or natural person-, accept an offer and create a contract? In other words, who are the contracting parties? Are they seller (A), buyer (B) or buyer (B's) computer?" (Billah 2008) (Begheri, Hassan, Mansour) Signatures are still not accepted as electronic unless explicitly stated to be so on websites such as Docusign. The states within the US vary on what constitutes an electronic signature for documents, but the response from different courts range from defining what makes an acceptable electronic signature.

Courts like the US Bankruptcy Court in the Eastern District of California ruled 2016 tha

although certain signatures follow ruling LBR 9004-1(c)

> Facsimile or Electronically Produced Signature. Unless otherwise provided in a case, the clerk may accept documents for filing that bear a facsimile or electronically produced signature as the equivalent of an original signature, provided the filing party and clerk comply strictly with the court's electronic filing procedures described in LBR 5005-4 for the safeguarding of documents with original signatures….The electronic filing or lodging of a document by a Filer through the CM/ECF, ePOC, LOU or other system, constitutes a signature on that document by such Filer and shall subject the Filer to the same consequences as if the Filer had signed such document by hand, including sanctions under FRBP 9011 and liability for perjury. When a password is required to electronically file or lodge a document, the Filer whose password is used to effectuate such filing shall be deemed to be a Filer of the document. If required by the Court Manual, an electronically-filed document shall include in the signature block an /s/ followed by the name of the Filer; provided, however, that failure to do so will not invalidate the signature deemed made by the Filer….Whenever a holographic signature is required, the Filer must maintain the executed original of any filed document for a period of five years after the closing of the case or adversary proceeding in which the document is filed, and must make the executed original available for review upon request of the court or other parties (Re: Mayfield, US Bankruptcy Court, 2016).

that if the original 'wet' signature is not produced on paper when the court has asked for it, then

the electronic signature is not valid .

WHERE EXPERT SYSTEMS AND THE LEGAL SYSTEM MEET

Today the legal field uses Expert System to compose a contract or similar document. This is useful and is seen mostly as a timesaver in that an attorney does not have to redraft a 10,000-word document from scratch for every contract, filing, or motion. Any attorney with this software can input the information from the client and their preferred strategy quicker. Faster and more accurate document turnover means more clients and more billable hours for attorneys. This process is benign because the attorney is reviewing each document and making the necessary changes to be the best fit for that matter to avoid litigation for damages by negligence.

All the above is assuming that an attorney is available to review the document to be eligible as a legally binding document in the United States. An example of contracts being done well with the help of artificial intelligence is in the Defense Logistics Agency (DLA). The only person that can bind the United States Government to an agreement is a contracting officer under the employee of the DLA as they alone have the full faith and credit of the United States behind them. Since they have started using their program since the 1990s, they have been able to streamline their contract process as well as expand their supply chain. Contracting Officers still have the final say over every contract though, and their staff and legal teams are the ones reviewing and passing the approved (in Expert Systems terms, those classified as 'good') contracts on for review by the Contracting Officer before signing. The final review of the contracts by the only people able to bind the authority and backing of the United States Government is how the Expert System is checked and balanced so to speak.

Going back to our basics, the steps of a contract to be considered complete are still 1) Offer, 2) Acceptance, 3) Consideration, 4) Legality, and 5) Capacity. Anyone can offer anything, and anyone can accept anything with due consideration. Consideration is to stop and look at the content of the contract and of signatures and to make sure everything is valid — and- if it is signed electronically from the buyer's or seller's algorithm, then the court may or may not accept dependent on the jurisdiction. That is uncertain enough that most attorneys would not want to hinge their case on that consideration. is it still valid? Saying essentially that someone did, in fact, read and understand the Terms of Use for Software's. From there the question of legality and capacity arise. Revisiting the Turing Tests and Chinese Room Tests, if a robot is fooling fools the questioner and is producing a language that is perceived to be Chinese, then a robot could be considered a person with thought and comprehension. are they understanding the rules and using their capacity to formulate answers or parroting back what they have learned?

The Defense Logistics Agency works as it does because of the human behind it. If there were no supervision, no way of arguing that this person is a competent person with full legal capacity making these decisions and not a computer, we then must explore the topic of legal personhood and its intersection with deep learning algorithms and artificial intelligences. Solum argues in 1992 that, "If AIs behaved the right way and if cognitive science confirmed that the underlying processes producing these behaviors were relatively like the processes of the human mind, we would have very good reason to treat AIs as persons." In a future where persons interact with AIs on a regular basis, and as AI grows more autonomous in in its intelligence, society will have to redefine our concept of person (Solum).

Solum used his essay for exploring the borders of how legal personhood can be defined and how that not only applies to artificial intelligence but also for immigrants and abortion. Machines have been responding appropriately though that in the last 10 years, from users having to decipher misshapen letters and numbers on hard to read backgrounds to identifying pictures two or three times before being authenticated. With Turing's Test and the Chinese Room thought experiments using pattern recognitions and human based patterns of logic through direct and indirect confrontation of what 'thinking' and 'intelligence. "After a round of play is completed, the questioner guesses which of the two players is the human", Turing suggested we postpone a direct answer to the question whether machines can think; he proposed that we ask instead whether an artifact could fool a series of questioners as often as the human was able to convince them of the truth, about half the time. The advantage of Turing's test is that it avoids direct

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confrontation with the difficult questions about what is "thinking" or "intelligence". Turing thought that he had devised a test that was so difficult that anything that could pass the test would necessarily qualify as intelligent.

These Inputs below must fit with each of the other six dimensions of the contract algorithm. For this construction specific model, the algorithm relies on six categories of classification: Project Scale, Nature of the Structure, Client, Time Constraint, Materials Source, and the design of works. The algorithm must correctly identify True or False for every single one of the subcategories under the main heading to produce a readable contract. Thus far, machine learning algorithms have only been able to handle up to three dimensions – the categories – with any type of accuracy . Shown in Figure 5 in the appendix.

With the four basic types of Expert Systems (Rules Based, Frame Based, Fuzzy Logic Based, and Neural Networks) before the transition into Deep Learning, there were the beginnings of legal theory research. Rules based systems are heavily used, as mentioned in the introduction, with outsourcing junior legal work and theory.

For humans, the judge follows precedents set by past cases in US Common Law with other cases as needed regarding pertinence to jurisdiction and within the bounds of rulings passed by legislature on the books.

FINANCIAL MANAGEMENT

The design of financial management services for portfolio selection and design of financial products hold the most potential for Expert Systems utilization. Second to that is Interpretation and Predictive actions. All these types of functions use models to learn and grow from in addition to human input. The current federal regulations for investments in the banking industry include the Sarbanes-Oxley act of 2002 and the Dodd Frank Act of 2010. These two acts detail the definition of good faith that corporations must have when conducting business on the investment floor and protect the consumers as much as they are able to (Dodd-Frank. SOX). While the Sarbanes-Oxley act focuses more on the accounting side and Dodd-Frank focuses on investments, both of these acts are designed to protect the current financial status quo and while be instrumental on the building contractual regulations around artificial intelligence much as the Dodd-Frank Act is based on the Glass-Steagall Act of 1933. These acts all provide regulations on what constitutes good banking and trade practices to all prevent specific events (the Great Depression, the Enron Scandal, and the Mortgage and Banking Crises of 2008) from happening again. These acts are also all based on US precedent of how stock market dips and crashes seem to occur. Similar types of regulation should happen subjecting the financial industry regarding their usage of artificial intelligence.

Designed portfolios as a part of financial management uses the rules of probability and statistics to combine stocks for the most risk resilient portfolio with the greatest returns. Expert Systems can readily follow the previous models and analyze the risk of different combinations of portfolios and based different recommendations on that. Regarding Predictive Actions, Expert Systems can recommend the best course of action based on models of the past and planning around that. Currently, Expert System algorithms are being experimented with to conduct Portfolio Optimization in the stock market. While these new models lead to different uncertainties, these uncertainties are similar to those resolved by AlphaZero and can be integrated accordingly.

Interpretation of the results and of the components leads to the unveiling of the black box of reasoning. The interpretation of the previous contract models releases the Expert System to create and expand on those models. Expanding on the previous models allows new contracts to be created for Predictive and Design results with minimal or perhaps no supervision. It is the lack of supervision and sense of ease that this produces may have disastrous consequences if the models are wrong or a false positive or false negative are let through or rejected respectively. These then follow eight portfolio optimization strategies shown in Figure 6 in the appendix. “1. SAA, which solves the sample average approxi- mation problem (MV-SAA).

2. PBR (*rank*-1), which solves the rank-1 approx- imation problem (mv-PBR-1). The RHS of the PBR constraint, U, is calibrated using the out-of-sample performance-based k-fold cross-validation algorithm (OOS-PBCV), which we explain in detail in Section 5.4.

3. PBR (PSD), which solves the convex quadratic approximation problem (mv-PBR-2). The RHS of the PBR constraint, ^{2} U, calibrated using OOS-PBCV.

4. NS, which solves problem (MV-SAA) with the no short-selling constraint $w \geq 0$, as in Jagannathan and Ma (2003).

5. L1 regularization, which solves the SAA problem (MV-SAA) with the extra constraint $\|w\|_1 \leq U$, where U is also calibrated using OOS-PBCV.

6. L2 regularization, which solves the SAA prob- lem (MV-SAA) with the extra constraint $\|w\|_2 \leq U$, where U is also calibrated using OOS-PBCV.

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equally dividing up the total wealth (i.e., investing in a portfolio w with $w_i = 1/p$ for $i = 1,\ldots,p$) performs

very well relative to a number of benchmarks for the data- driven mean-variance problem. We include

this as a benchmark." (Ban, El Karoui, and Lim)

These strategies resulted in the calibration method for the restraints as to maximize performance without rendering the problem too large to have no effect and too small to be infeasible. For these optimization techniques, these models handle uncertainty well. The PBR comments on the mean separation and yield through the Sharpe Ratio. "From the perspective of an investor looking at the results of Table 2, the takeaway is clear: Focus on a small number of assets (the Fama–French (FF) 5 industry portfolio) and optimize using the PBR method on both the objective and mean constraints to achieve the highest Sharpe ratio." (Ban, El Karoui, and Lim)

For a simple example regarding contracts themselves, the European union has rules and regulations already in place for a contract being with someone of unknown or legal capacity. This authentication is usually based upon;

Something they know (e.g. password or PIN);

Something they have (e.g. magnetic card or smart card); or

Something they are (e.g. voiceprint, fingerprint, etc.).

From the United Kingdom, legal scholars are already deciding that it is unjustified that contracts be considered legal when formed with minors as they pressed the [AGREE] tab. Under English law, minors that make contracts are voidable extremely easily as those are not considered valid contracts. If the minor buys illegal goods or reneges on payment, then the seller has almost no recourse as the contract is not valid and they had no way of verifying the other party (Bagheri, Hassan, Mansour).

In short, if a minor clicks on the [AGREE] button to follow the terms of service in the website licensing, then the contract is not valid under current precedent. The age of majority is eighteen and it is at that moment that you are considered a real person in the eyes of the court system and able to duly consider and uphold contracts. The companies must follow through but do not have legal recourse if the action is not fulfilled from the minor's side. The same examines the thoughts of legal personhood when it comes to fulfilling the contract agreements of highspeed trades and investments. If a computer extends an offer through a contract, then a human accepts it, the question remains if the Court can consider that valid. Then same works in reverse for the question of what would have to be considered if a human offers to sell and computer accepted the contract in the terms specified.

THE THOUGHT EXPERIMENT

In the original scenario of an investment firm is being sued by a client as the algorithm that uses deep learning to make trades loses nearly 90 percent of the client's assets. The court would probable conduct validity tests if the contracts were not already reviewed by an attorney to see if the standards for capacity and due consideration were met. If they were met, then the court would have to decide whether the algorithm itself can be categorized under the definition of legal personhood. If it does not, then the programmer or the corporation that utilized the algorithm would be liable for whatever loss resulted from the breach of contract. If it does meet the standard definition of legal personhood, then it is an attorney's favorite answer: it depends.

For an algorithm to meet the standard of legal personhood, it must be seen as a discrete entity from the original programmer. Alpha Zero could potentially qualify as a discrete entity as it learned how to play the game Go by essentially playing against itself. Human data input is still tremendously necessary for most unsupervised machine learning systems that utilize neural networks. The guideline for an algorithm being discrete then could potentially hinge on how much human input it had initially and how much it managed to 'evolve' in later updates independent of that data and on pure observation by the algorithms.

If a computer can determine the best way to draw up a contract through observation and then does so, that does under current precedent count as 'writing' a contract. The key argument is 'Is the algorithm able to clearly defend the contractual agreements and logic in Court?' If not, then it did not truly write a contract only copied it and cannot be considered liable for the contract, the company or programmer that owns it must be considered liable. If it is able to prove that there is a logic behind the ways that the contract was drawn and explain it the methods clearly, then it could be ruled that as the algorithm drew up the contract, it is responsible for the contract if the contract caused the breach.

If a computer can be judged to have truly written a contract, then the resulting breach can turn one of two ways. It could hold the company that owns the algorithm liable or it could hold the specific programmer liable. If the court held the company liable, there is precedent, and the judge would proceed as normal. If the court hold the specific programmer liable, then it is the same. There is a third option though. Under this third option, the algorithm would have developed to a point unrecognizable to the original code and have taught itself the different variables, the court would then have to look at possibilities of Respondeat Superior in that a party is responsible for the acts of its agents — in this case, the investment firm is responsible for the algorithm's losses.

Under the legal validity test, if the algorithm wrote the contract, but it was signed by two human parties or representatives, then the courts would more than likely treat it as another breach of contract case. If the algorithm drew up and signed the contract on behalf of a corporation, again the court must consider redefining legal personhood. The house has introduced a bill classifying artificial intelligence as a separate part of computing and the open sharing of data and the potential for the workforce. (H.R.4652) The current definition of legal personhood is "A person is any being whom the law regards as capable of rights and duties". The court could follow in the example of San Mateo County v. Southern Pacific Railroad that not only should corporations be considered people, but so should algorithms given the capacity to understand the law. The whole concept of duty of care, duty of competency, and fiduciary duties need to be evolved under this new test of legal validity.

Appendix

Figure 1 – Showing the basic setup for all expert systems starting in the 1980s

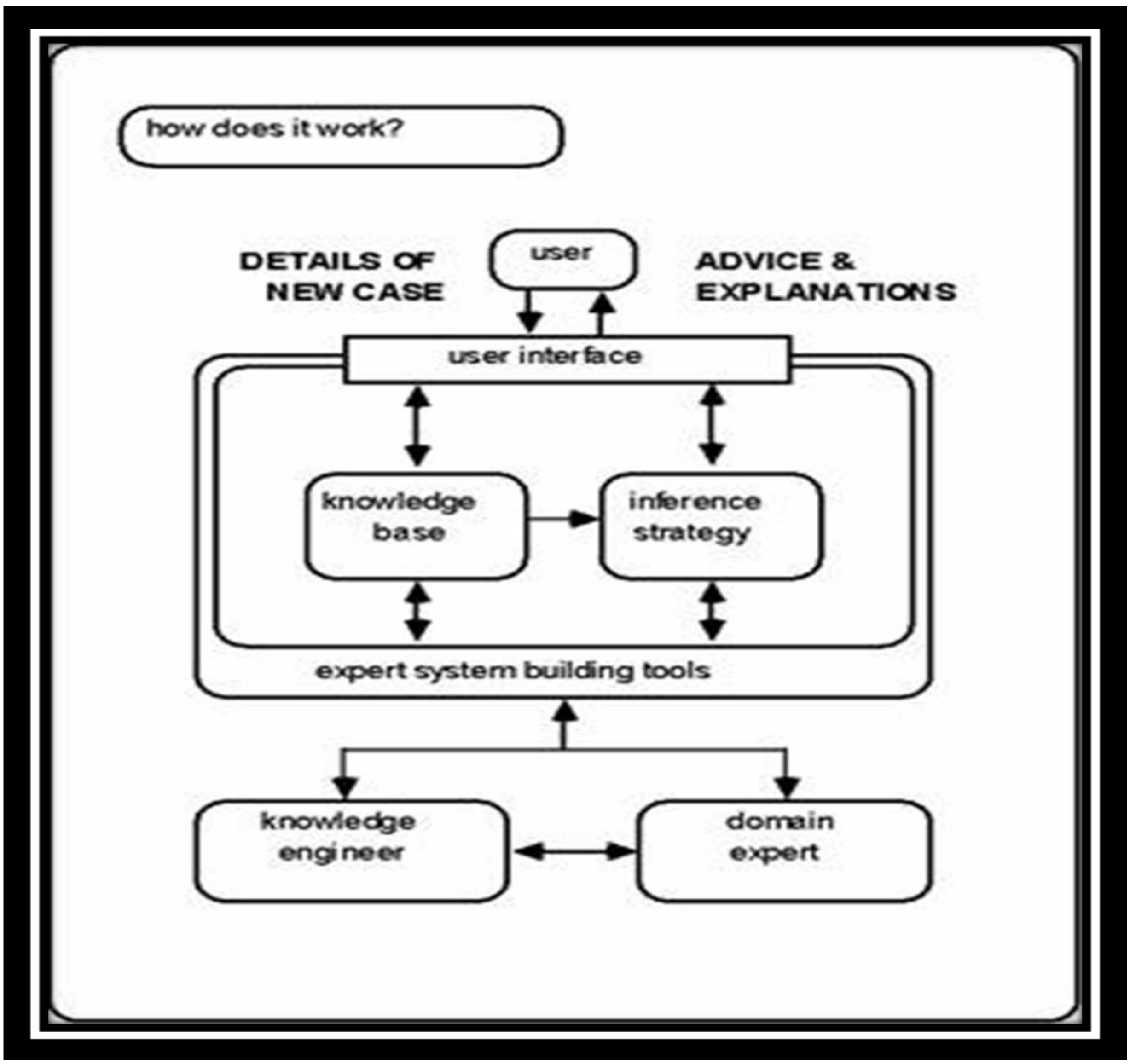

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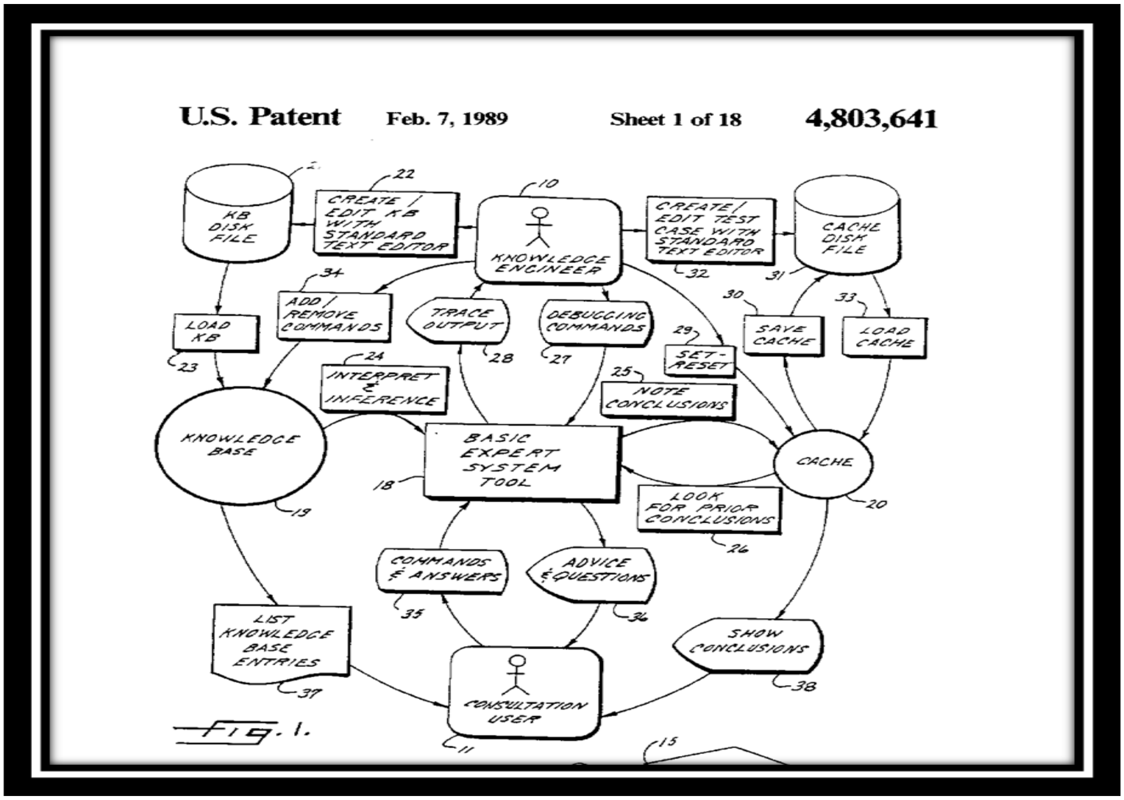
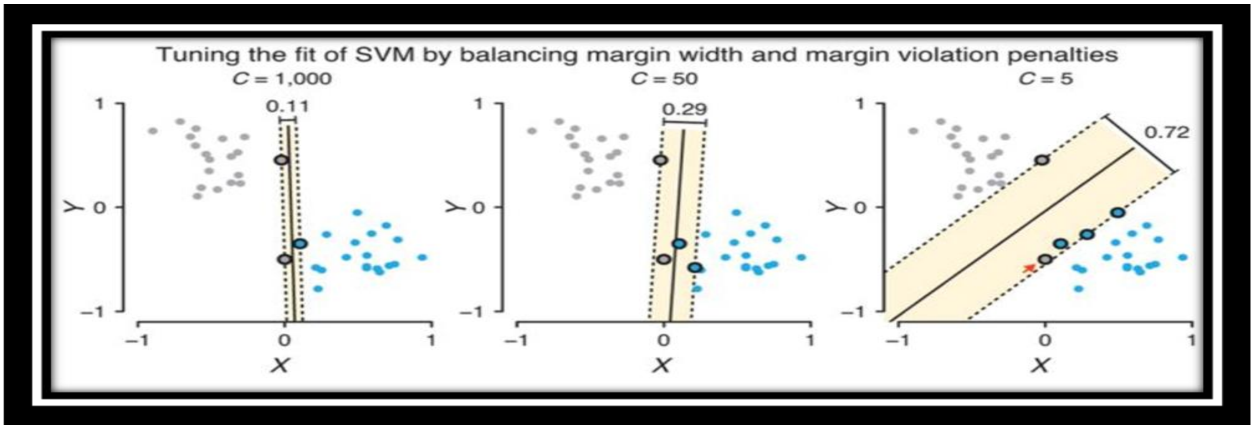
Figure 2 – Googles Patent application one of the first Expert Systems showing clearly the Knowledge Base, the User Interface, and the Inference Engine for a rules based system.



(4,803,641; 1989)

Figure 3 – Where the size of C affects the margin impact on the minimization. If C is large, the line is then place to reduce the sum of violation penalties whereas if C is small, errors have less impact and the demarcation is place with a focus on maximizing the margin.



(Bzdok, Krzywindski, Altman)

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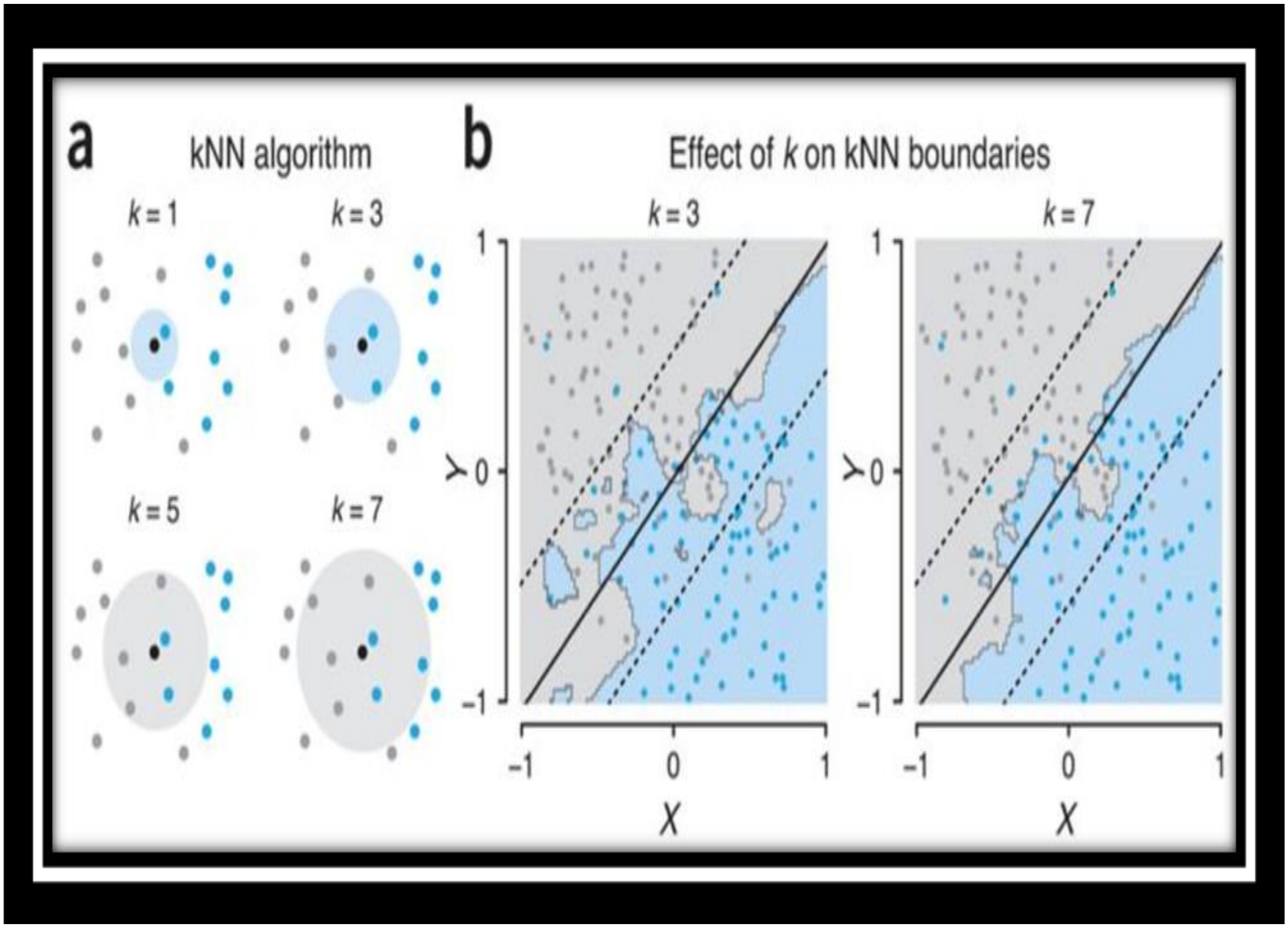
Figure 4

– A) kNN assigns a class to an unclassified point (black) based on a majority vote of the k nearest neighbors.

B) For k = 3, the kNN boundaries are relatively rough, yielding a 15 percent misclassification rate.



(Bzdok, Krzywindski, Altman)

Figure 5 – This table shows the different inputs required before this algorithm can produce a contract. Each of these produces a different subset of outputs depending on which of the inputs are changed.

Table 1 Input variables and terms

IV_1: scale of the project
- TIV_{11}: very very small
- TIV_{12}: very small
- TIV_{13}: small
- TIV_{14}: quite small
- TIV_{15}: medium
- TIV_{16}: quite large
- TIV_{17}: large
- TIV_{18}: very large
- TIV_{19}: very very large

IV_2: nature of work
- TIV_{21}: new substructure works
- TIV_{22}: new superstructure works, including specialist subcontractors
- TIV_{23}: new works for interior design and fitting out
- TIV_{24}: maintenance works

IV_3: nature of client
- TIV_{31}: government department
- TIV_{32}: quasigovernment organization formed by government ordinances
- TIV_{33}: non-profit making organization
- TIV_{34}: business company
- TIV_{35}: private client

IV_4: time constraint (including design, pre-contract preparation and contract duration)
- TIV_{41}: very slack
- TIV_{42}: slack
- TIV_{43}: normal
- TIV_{44}: tight
- TIV_{45}: very tight

IV_5: source of materials
- TIV_{51}: conventional
- TIV_{52}: innovative
- TIV_{53}: factory prefabrication or mass production in a repetitive manner

IV_6: design of works
- TIV_{61}: those originated by the client
- TIV_{62}: those originated by the consultant
- TIV_{63}: those originated by the contractor

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Figure 6 – These are the optimization techniques that serve optimization well. Using these steps, the optimization of the algorithms that would potentially draw up contracts would look something like below.

"1. SAA, solves the sample average approximation problem (MV-SAA).

2. PBR (rank-1), which solves the rank-1 approximation problem (mv-PBR-1). The RHS of the PBR constraint, U, is calibrated using the out-of-sample performance-based k-fold cross-validation algorithm (OOS-PBCV), which we explain in detail in Section 5.4.

3. PBR (PSD), which solves the convex quadratic approximation problem (mv-PBR-2). The RHS of the PBR constraint, 2 U, calibrated using OOS-PBCV.

4. NS, which solves problem (MV-SAA) with the no short-selling constraint w ≥ 0, as in Jagannathan and Ma (2003).

5. L1 regularization, which solves the SAA problem (MV-SAA) with the extra constraint ‖w‖1 ≤ U, where U is also calibrated using OOS-PBCV.

6. L2 regularization, which solves the SAA problem (MV-SAA) with the extra constraint ‖w‖2 ≤ U, where U is also calibrated using OOS-PBCV.

7. Minimum variance, which solves the above (SAA, PBR (rank-1), PBR (PSD), NS, L1, and L2) for the global minimum variance problem, which is (MV-true) with- out the mean return constraint. We do this because the difficulty in estimating the mean return is a well- known problem (Merton 1980), and some more recent works in the Markowitz literature have shown that removing the mean constraint altogether can yield bet- ter results (e.g., Jagannathan and Ma 2003).

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(Ban, El Karoui, and Lim)

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