Studies in Classical Behavioural Economics:

A Thesis Proposal

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Abstract

I propose to investigate the computable foundations of decision making along the lines of Classical Behavioural Economics. First, decision makers will be represented as Information Processing Systems underpinned by bounded rationality and satisficing as in the theory of Human Problem Solving proposed by Herbert Simon. The game of Go, which has a finite and large search space, provides a rich paradigm for analyzing how boundedly rational individuals use “heuristics” (algorithm) to solve highly complex problems. Hence, I will use Go to study different aspects of human problem solving, via simulations. Second, I will make a case for posing human decision problems as Diophantine decision problems, as opposed to optimization problems (as in Modern Behavioral Economics) and viewing full rationality as a special case of bounded rationality. Finally, the role of Near Decomposability, a recurring theme in Simon’s works, and its relevance in modeling human behavior and learning will be explored.

1 Introduction

I propose to investigate and (re)construct the Computable Foundation of Behavioral Economics along the lines of Classical Behavioral Economics (henceforth CBE). CBE can be distinguished from Modern Behavioral Economics (henceforth MBE) by its central themes, theories and ap-
The motivation for choosing the CBE approach is due to its computationally un-derpinned cognitive science which ought to be taken into account when building economic models. CBE incorporates cognitive and evolutionary evidences and suggests a more realistic structure of decision making. In addition, the notions of CBE have desired properties which are inherently algorithmic, and enhance building behavioral models which are computable. Another reason for opting for a computable model is my interest on the debates in the Philosophy of Mind on Gödel’s Dichotomy\textsuperscript{2}.

**Modern Behavioral Economics** The birth of Behavioral Economics can be traced back to the 1950s, when the Allais paradox (Allais, 1953) appeared as a critique of the axioms of expected utility theory, postulated by Von Neumann and Morgensten in 1944 (von Neumann and Morgenstern, 1947). Axioms of rational behavior led to various inconsistencies, and economists started to look for ways to rationalize them and find alternative theories. Behavioral economists opted for psychological, cognitive, and social factors to explain behavior in different contexts of decision making. There are several branches of modern behavioral economics, such as behavioral finance, behavioral game theory, computational behavioral economics and neuroeconomics.

As in Neo-Classical Economics, MBE assumes the agents possess the preference orders over the entire choice set. It further assumes that the preference order can be revealed by choices which are made by the economic agents. To rationalize inconsistent choices, MBE models the behavior by introducing contextual attributes - i.e. framing - or considering different levels of intelligence, or introducing psychological and social factors, such as guilt-aversion and altruism, respectively. Although various behavioral interpretations are provided, the eco-

\textsuperscript{1}The distinction of the two branches of Behavioral Economics was first made in Velupillai (2010b)

\textsuperscript{2}Gödel’s Dichotomy can be stated as: “Either...the human mind infinitely surpasses the powers of any finite machine, or else there exist absolutely unsolvable diophantine problems”(Gödel’s statement as quoted in Feferman (2009). Also refer to Shapiro (2003))
nomic agents are still assumed to be able and willing to choose the best choice out the different subsets.

**Classical Behavioral Economics** There is another framework, formalized and pioneered by Herbert Simon, that introduced the concept of Bounded Rationality and Satisficing (Simon, 1955, 1956). In CBE, there is no predetermined preference ordering over a given choice set of a problem for an economic agent. Instead, the agent is given methods to explore the entire space and discover(generate) new elements and procedures; and one owns only partial orders over choices. Besides, the elements tend to be compared qualitatively rather than quantitatively in many cases. Though the agents will gradually know more elements in the set, he(she) has limited attention because of computational constraints on cognitive faculties; therefore the focus is only on a subset of the choices that he(she) explores. That is to say, human reasoning is bounded by his(her) limited cognitive capacity. Satisficing agents will stop searching when there is at least one desired solution discovered by him(her) in the subset he(she) pays attention to. Furthermore, based on the nature of human thinking, Simon also suggested to view/model decision making in a step-by-step manner. In other words, though the human mind can receive information from different sources simultaneously, it only processes them sequentially.

Other than the path-breaking research program of bounded rationality in economic decision making, Simon was also one of the founders of Artificial Intelligence. The seeds of artificial intelligence were also sown in the middle of 50s, when he encountered Polya (1945) through Allen Newell, who was a young cognitive scientist. After reading about the concept of “heuristics”, they wondered how thoughts are represented and processed in the mind. The birth and rapid development of digital computers influenced them and they devoted themselves to simulating thoughts symbolically with computers. The idea originated while trying to understand the process of human problem solving using cognitive psychology. In their view, human minds can think and learn by manipulating symbols from initial states to target states.
Spirit of Herbert Simon  I consider that Herbert Simon was a quintessential problem solver. He had broad interests in the hard sciences and fascination with applying mathematics to the social sciences. Being a genuine multi-disciplinarian, Simon regarded himself as a scientist in many disciplines. In my understanding, Simon practiced problem solving throughout his professional and intellectual life. When curiosities about some phenomena arose in his mind, he searched for solutions and most of the time moved across different disciplines. Either by corresponding and collaborating with academic friends or by himself, he made profound contributions in each sphere he investigated. On the journey of solving one problem, he discovered subproblems unexpectedly. Eventually, he had been traveling around different science-mazes (Simon’s metaphor) to the extent that even he could not anticipate. He ended up as a scholar having both depth and broadness. For him, problem solving is not merely solving equations or puzzles. Rather it is the process of identifying alternative methods or subproblems, knowing the possible directions of finding methods, and deciding where attention ought to be employed. It is the core of his view of organizations, economics and his life. He won numerous prizes and honors for his fundamental contributions – Turing Award in 1975 and Nobel Prize in Economic Science in 1978 – to mention a few.

Near Decomposability  In addition to bounded rationality and satisficing, Simon uncovered an interesting property, which became a recurring theme in his works, observed in many entities. In 1951, when Simon read Goodwin (1947), it inspired him to think about dynamic systems in both economic and mathematical senses. Later, the concept of Near Decomposability appeared in his papers and he applied it to diverse problems, such as identifying causality, counterfactuals, aggregation, organizational behavior, evolution of organisms, human and machine thinking. The role of “near decomposability” will be mentioned in later chapters in a detailed manner.

Motivated by Simon’s special role in economics, and his influential contributions, I pro-
pose to incorporate the notions of Bounded Rationality, satisficing, sequential decision making and heuristics, into modeling problem solvers (economic agents). I will study problem situations in the game of Go, and thereby extending Herbert Simon’s paradigm of Chess. The game of Go, which has a finite and large search space, provides a rich paradigm for analyzing how human beings solve highly complex problems. The research principle and procedure can be structured as follows.

First, I will formalize the behavior of problem solvers according to Simon’s illustration. Second, I will define the problem space of Go and its task environments for players. Third, in order to investigate the behavior of the problem solver in an algorithmic way, I will build an algorithmic problem solver who can solve problems corresponding to the first step. Fourth, I have to translate the well-defined problem in a formal way that the algorithmic problem solver can understand.

After constructing the above, I will investigate the following questions:

1. How decisions are generated by the problem solvers, when they are facing a huge search space?
2. How do problem solvers interact with different task environments?
3. What are the learning patterns we can observe from the behaviors of the algorithmic problem solver?

In the second stage, I will explore the following two aspects:

1. I will exploit the role of Nearly Decomposable Matrices in Simon’s work, and apply it by introducing them to the above framework.
2. I propose to study the relationship between optimization (the best) and satisficing (good enough) rigorously. Subsequently, I will attempt to make a case for posing optimization
problems to problem solvers (economic agents), and replace it with Diophantine Decision Problems. Hence, I can examine the properties of its solution in a more general manner.

2 Foundations of Classical Behavioural Economics

In this and the next chapters, I will summarize the seemingly isolated, but intrinsically connected concepts and materials in the integrated framework of Computable Foundation of Behavioral Economics. In this chapter, I will focus on Simon’s profound and influential contributions to Bounded Rationality, Human Problem Solving, and Near Decomposability. In the next chapter, the focus will be shifted to the computable and mathematical foundations of the first two ideas mentioned above. Subsequently, the methodology of this research program will be set up as the applications of these concepts and strengthening the linkages between them through the demonstration of the paradigm of Go.

2.1 Bounded Rationality

The idea of bounded rationality was first proposed by Herbert A. Simon in the paper called “the Behavioral Model of Rational Choice” which was published in 1953. It was further polished and republished with a similar title as Simon (1955) and was phrased as “limited rationality”. Simon further described human behavior as “intendedly rational” in (Simon, 1957). The book “Models of Man” collected the papers which he published in early to mid 50s. It is where the phrase Bounded Rationality appeared for the first time, in the introduction of Part IV. The phrase was, then, much maligned in its uses and misuses compared to the original definition and formalizations by Simon. Subsequently, bounded rationality became one of the bases of MBE. On the contrary, in Simon’s advocacy, human beings can solve their problems relying on heuristics and intuition without a given model in mind. Therefore, there seems to be a mismatch between the contemporary interpretation of bounded rationality and its original definitions.
In Simon’s definition, bounded(limited) rationality is composed, gradually, of different notions, such as limited attention, limited capacity of computation, satisficing, and sequential decision making (naturally dynamic) (Simon, 1955, 1956). That is to say, it is not evident and admissible to assume that human beings are able to exhaust all the information and make the best choice out of it. A short story which was written by Simon - *The Apple: A Story of a Maze*, can describe the dynamics of non-maximizing agents adequately (Simon, 1991). The story says that our knowledge and interpretation of the world we are living in are associated with our experience and memory. Gradually, our tastes and understanding are constructed. Therefore, the pursuit for stability in taste and knowledge also rely on what has been constructed. The unhappiness or satisfaction which are subsequent to our aspiration depend on whether the desires are satisfied in terms of our anticipation. The aspiration level expands with satisfaction and shrinks with disappointment. Nonetheless, the memory that is stored in our mind prevents our aspiration level from becoming null. Thus, we are in the loop of unhappiness and satisfaction.

### 2.2 Human Problem Solving

The same properties in bounded rationality have been encoded implicitly into the *information processing system* which was proposed in Simon et al. (1958) and analyzed thoroughly with detailed recording and interview with human subjects in Newell and Simon (1972). IPSs have shown that they are capable of solving problems algorithmically, such as cryptarithmetic, logic, and chess games. In their conclusion, it is suggested that task environments of greater complexity and openness ought to be studied. Therefore, I plan to use the board game Go as the paradigm for studying human problem solving.

The notions of Simon’s bounded rationality are used in simulating (representing) human problem solving. Problem solving is the practicing of searching for paths from initial states
to the target states. The methods that a problem solver uses are strongly associated with his or her memory and experience. The accumulated knowledge in the memory will form the heuristics to guide the problem solver him(her)self. Identically, that is the intuition which comes out automatically to lead the problem solver when he or she faces a huge number of possible choices. For example, as a student who is learning geometry, heuristic may guide him(her) to refer to the Pythagorean theorem when a problem related to triangles are presented.

Practically, the idea of human problem solving has been postulated and structured with the evidences of cognitive science and published in Newell and Simon (1972). I will summarize the theory of human problem solving briefly here and the theory will be applied by replacing the chess problem which has been studied with the more complex example, the game of Go.

2.2.1 Theory of Human Problem Solving

Literally, we need a problem and the problem solver to achieve problem solving, and the problem should be presented, recognized and understood. A problem is faced when one wants to do something about a particular task but does not know what series of actions can be done to implement it immediately. The three main factors that make problems as problems are the huge size of possible solutions, the dispersion of actual solutions and the high cost of search. The problem space contains a set of elements which represent knowledge, a set of operators which generate new knowledge from existing knowledge, an initial state of knowledge, a problem which is specified by a set of desired states, and the total knowledge available to problem solvers. The problem can be further formulated (represented) by set-predicate formulations and search formulation.

**Set Representation** In the former representation, the set of elements contains symbolic objects which are all possible solutions. Precisely, the set can be generated by a certain enumerative procedure according to set theory. Thus, the problem solver will not be given the entire set,
rather, is given a process to generate elements out of the set. A formal definition of problem will then be finding a subset which has the desired properties out of a given set.

**Search Representation** In search representation, solutions as elements of a set, have the format of sequences. For instance, a proof of a theory contains a sequence of steps and chess representations contain continuations for some players.

**Task Environment** Task environment describes the attributes that are associated with the problem that problem solvers encounter. It consists of external and internal representations, where the former is the format in which the problem is exactly presented and the latter stands for the subjective representation the player applies. Accordingly, not only the presentation of the current problem, but also the ability and intelligence of the problem solver should be considered. This is because players with diverse abilities may perceive the problem differently.

**Factorization** The decomposition of the problem into subproblems has been mentioned in both representations, especially it is more relevant in search representation than in set representation. The factorability is the property used to examine how players can simplify a difficult problem into subproblems. The idea can be linked to another profound contribution of Simon - Near decomposability.

**2.2.2 Information Processing System**

The information processing system which can deal with problem solving can be characterized as follows. An IPS is a serial, adaptive, and deterministic system which receives input and generates output. It is composed of internal building blocks such as long term memory (LTM), short term memory (STM) and external memory (EM). LTM and STM share identical patterns and are distinguished by their size. LTM can contain all the symbolic objects without limitation, while STM contains only five to seven symbols. The fact of sequential decision making is
inherent in IPS; moreover, how a problem solver reads from LTM to STM relies on heuristic search.

**Heuristics** Heuristic is a method of “Rule of Thumb” that serves as a guide in searching. Intuitively, it is an ability and process to refer to one’s own memory and experience and lead oneself to focus on appropriate subsets of knowledge. Without external help, one can learn and discover new knowledge by him(her)self.

When an IPS receives information from the task environment, it generates the goals and the methods for the achievement of the goals will be generated by heuristic search. If heuristics cannot achieve a satisfactory job, then either the heuristic method will be reprogrammed or the representation, namely, the internal representation in the task environment, will be reformulated. In short, IPS and task environment are interdependent, and the process of change is learning.

### 2.3 Near-Decomposability, Evolution and Emergence

Near-decomposability, which is a mathematical property, allows one to decompose a system into subsystems in the short run without considering certain links between variables, had been emphasized by Simon throughout his main contributions.

**From Richard Goodwin to Herbert Simon** In partial equilibrium analysis in Economics, it is assumed, *ceteris paribus*, one can analyze a particular sector at a time neglecting other sectors. This assumption contravenes to the fact that (almost) all economic sectors do interact. In other words, when one sector changes and the change affects the other sectors as well; naturally, it is not admissible to state that the other sectors can remain unchanged. When sectors are interdependent, the analysis becomes intractable. One noticeable observation is that the interactions between two sectors are not necessarily symmetric (Goodwin, 1947). For example, sector
A affects sector B strongly, while the feedback from sector B to sector A is relatively weak. This asymmetric interaction is called ‘unilateral coupling’ and is related to the idea of ‘causal’ ordering which is investigated in Simon (1952, 1953); Simon and Rescher (1966). Nearly decomposable systems play the role of reducing the difficulty and complication of analyzing coupled interdependent systems.

In an economic system, for example, there are several sectors; there are, further, several mechanisms in each sector. If in a particular sector, the interdependence is nearly decomposable, then in the short term, the weak feedbacks from one mechanism to the other can be ignored. Then one can study the mechanisms with different causal orderings in this sector independently. The same story applies to the whole system. If the system is nearly decomposable, then in the short term, one can study the group of sectors independently. Decomposability is a terminology in matrix algebra, which will be presented as following: A square matrix $A$ is said to be decomposable if there exists a permutation matrix $P$ such that

$$PAP^T = \begin{bmatrix} B & 0 \\ C & D \end{bmatrix}$$

(1)

Otherwise $A$ is indecomposable. Equation 1 has the Jordan Canonical Form. In general interpretation, decomposability means that one can find a permutation that appears as ascending or descending causal order among mechanisms - i.e. Jordan canonical form. As long as such permutations exist, one can start to study the mechanisms with order zero and then feed in the pre-determined variables in to order 1 mechanisms, and then order 2, order 3, till the highest order. Near decomposability refers to the situation that there might be very weak feedbacks from higher order to lower order. As mentioned above, the effect can be neglected in the short term. Moreover, if the null matrix we try to obtain by the operation mentioned above has the elements which are non-zero but very close to zero (go to zero in the limit), we can say the matrix $A$ is nearly decomposable.
Decomposable Systems and Causal Ordering  Causal ordering is asymmetric or unidirectional. On the contrary, an equation states the relation between independent variables and dependent variables presenting only functional relationships. The functional relationship remains by inverting the equation; however, causal relation cannot be inverted. Furthermore contraposition does not necessarily hold for causal relation. Simon claimed that the causal relations can be identified under some conditions - decomposability. Decomposability requires the structure to be self-contained - the number of variables is equal to the number of equations. Self-containment is the necessary condition for unique solutions within the structure as a whole. For a structure to be decomposable, it should further have a minimal self-contained structure. A minimal self-contained structure is itself self-contained and includes no more self-contained structures inside.

Intuitively, the variables in the minimal self-contained system (order zero) can be determined separately without being affected by variables outside of this subsystem. Subsequently, the determined variables can be treated as exogenous for the derivation of a system of next order. In mathematical representation, decomposable systems are those systems which can be rearranged in Jordan canonical form.

The near decomposability allows us to investigate the subsystems independently without considering their feedback to each other in the short run. Hence, decomposability in the static case becomes a special case of equilibrium in a dynamic system. In the long run, the feedback can be accumulated to a considerable level. The linkage or causal relation between subsystems needs to be considered. In order to study the long run behavior of a system, we need to aggregate subsystems. Moreover, for a dynamic system to be stable, all the real part of the eigenvalues should be negative. The mathematical conditions of aggregation of nearly decomposable systems were introduced rigorously in Simon and Iwasaki (1988)
Near Decomposability in Mind and Evolution  Similar to the discussion in solving problems of economic systems, Simon considered thinking by a mind and evolution of organisms as finding solutions and the process of solving it. First of all, both mind and organism have hierarchical structures (Simon, 1962, 1996). If the structure is nearly decomposable, we can investigate the system with a certain degree of isolation. The speed of convergence - finding solutions- *within* any subsystem is faster than *between* subsystems. Therefore, if the system is nearly decomposable, only certain outputs of subsystem will influence other subsystems. Furthermore, only the aggregation of subsystems at the same hierarchical level can affect other levels. In Simon (2002), it is concluded that the organisms with nearly decomposable structure, no matter how complex they are, will evolve faster than the organisms with indecomposable structures. Again, if evolution is the process of finding solutions, the organisms with nearly independent components will need less time for finding solutions than the ones without nearly independent components. Intuitively speaking, the search space of organisms with strong interacting components is larger than the organisms with weak interacting components and evolution is analogous to finding a solution.

3  Computable Behavioural Economics

In this chapter, I will summarize the issues which are critical to computable Classical Behavioral Economics. To be more precise, I will explore the tools and concepts of computability theory which are relevant for inclusion in studying and formalizing Classical Behavioral Economics.

3.1  Playing Games: Chess & Go

Like Chess, Go is the kind of game in which one can learn in a few hours and spend a lifetime perfecting it. The two games have been studied in different disciplines, i.e., combinatorial game theory in mathematical theory and computer Chess(Go) in computer science. In combinatorial
game theory\(^3\), perfect information is assumed; theorists are looking for the best strategies for a player who faces an ideal opponent. On the other hand, in computer science, programs are designed as players and compiled with hardware. The ability of programs are usually tested through the competition with human players.

The relatively closed task environment and the well-defined goal(s) make Chess suitable for studying in problem solving, while more complex and open problems ought to be analyzed (Newell and Simon, 1972). Go is a good example to go beyond Chess, as to be the next stage of study; particularly because its task environment is much more complex\(^4\) and slightly more open\(^5\) than chess. As a result of the nature of the explosive complexity characterizing these games, the players cannot evaluate all possible moves and select the optimal moves in any reasonable time framework. On the contrary, with the intention to win the game, one needs intuition, perception and a sharp analytical mind. This is where the concept of bounded rationality comes into individual decision making.

**Computer Chess** Newell, Shaw and Simon developed a chess problem (NSS) in 1958, which was one of the pioneering programs. This program incorporated the features that were considered in earlier programs, such as the concept of dead position and move generators. Although this program was not as successful as those chess programs with super-computing power (like Deep Blue of IBM) in terms of performance, its methods can be replicated and extended in this research program.

\(^3\)Both Chess and Go are proved to belong to some classes of solvable problems in computational complexity theory; for example, Chess belongs to EXPTIME-complete and Go belongs to PAPACE-hard or EXPTIME-complete depending on the rules that are restricted (Demaine, 2001)

\(^4\)The board sizes are 8 × 8 and 19 × 19 for Chess and Go respectively; the approximated state-spaces and game-tree size are \(10^{43}\) and \(10^{120}\) for Chess, respectively (Shannon, 1950); they are \(10^{120}\) and \(10^{360}\) for Go, respectively (Müller, 2002).

\(^5\)Unlike chess, the game of go can be terminated anytime with the agreement of both players.
3.2 Diophantine Decision Problems

The negative answer to Hilbert’s tenth problem (Matiyasevich, 1994) indicates that the solvability of any specific Diophantine equation need to be studied separately. For example, there are methods for knowing whether there is solution for relatively simple Diophantine Equations, such as the Diophantine Equation with one or two level-one variables, i.e., $ax = b$ and $ax + by = c$. Thus, to know whether a Diophantine equation has a solution, one has to seek for the method (algorithm) separately according to the format of it. If the answer to the above question is positive, one may continue to seek for the method (algorithm) to solve it.

The linkage between the problems faced by economic agents and Diophantine Decision Problem can be uncovered by the suggestion of treating optimization problem, which is conventionally given to economic agents, as a special case of satisficing problems, made in Velupillai (2010b) and remarked and emphasized in Velupillai (2010a). More generally, it is a view that Olympian rationality (a phrase coined in Simon (1983), p.19) is a special case of Simon’s bounded rationality. The idea is demonstrated by applying mathematical and computability foundations rigorously, for example, the proof that a process of rational choice can be formally represented by an appropriately encoded Turing Machine in Velupillai (2000).

In Velupillai (2010a), the idea was further strengthened by including the notion that Simon’s satisficing concept can be formally captured by the Satisfiability Problems (SAT) in computational complexity theory. Solving a SAT can be translated into solving an integer linear programming problem, thus, can be translated into solving a linear Diophantine equation. Since the latter two are formally equivalent in the sense that they can share the same method of solution; if we can replace optimization problems with Diophantine Decision Problems, then it will be as if we are solving a Diophantine Equation.
3.3 Methodology

I plan to represent the problems in the game of Go into the Problem Solving framework. In the short run, I expect to investigate how problem solvers can solve highly complex problems and how and what they learn form the process of solving it. Firstly, I will construct the problem space according to the theory of Human problem solving and the literature of Computer Go, such as Müller (2002), which surveyed the studies of Go in computer science and mathematics. As the literature suggests, board games, such as, Chess, Checkers, Go and so on, are represented and analyzed in Combinatorial Game Theory. Hence, I will explore the current possible representations of Go and investigate their compatibilities with Information Processing Systems. Especially, in order to reduce the difficulty and complexity at the first state, I will start building the problems with a $9 \times 9$ Go board, which is also a standard size for beginners in Go.

Secondly, I will design IPSs, which will correspond to the problems they will tackle, conceptually. Essentially, I will incorporate the notions, such as satisficing, sequential search, heuristic search, which are enveloped in Bounded Rationality into the IPSs. Thirdly, I will translate IPS into algorithmic programs in order for a computer to implement simulations. I intend to choose Turing Machines due to mainly two reasons. First, problems which are presented to problem solvers differ in complexity and boundaries separating them. The upper bound of them is Turing computability. Any problem requiring more than that is irrelevant and beyond human rationality (Simon’s letter to Velupillai, reprinted in Velupillai (2010b)). Second, IPSs which are conceptual programs (pseudo codes) are intrinsically compatible with Turing Machines. IPS has the format of steps; in each step, a problem solver is dealing with at least one decision problem, and it will have to move to other steps depending on the order and the answers of those decision problems. The stopping rules and outputs are designed within the steps.
3.3.1 Near Decomposability

Like in a Chess game, the ultimate goal of the problem (checkmate your opponent) may be achieved by several subgoals, such as capturing some pieces, defending your pieces, or occupying certain areas, etc. I consider that near decomposability can be applied by analyzing the interdependencies among these subproblems and their relations with the ultimate goal. I aim to study this property in the paradigm of Go, or in the framework of board games, extensively.

The same principle can be applied to Information Processing Systems. By viewing an IPS as a dynamic system which contains interacting subsystems, near decomposability can be included to investigate the evolving (learning) aspect of problem solving.

4 Tentative Conclusions - New Tools for Algorithmic Behavioral Economics

4.1 From Go to more Complex Problem

Due to the complexity and huge search spaces in games such as Chess and Go, they can serve as good examples to investigate human decision making. After the decision making procedure of these games are formalized, the difficulty of solving them can be discussed in the sense of Computational complexity. Thus the framework can be further carried on to more complex (again, in the sense of computational complexity) problems in real economic life.

4.2 Diophantine Decision Problem

By replacing the “optimization problem” with Diophantine Decision Problems, I wish to discuss that some of the problems are solvable and some of them are absolutely unsolvable. Regardless of the solvability of the (optimization) problem, human problem solvers in fact seek the satisfying solutions of the problem. As a result, I will be able to discuss the generality of
satisfiability problems and speciality of optimizing problems.

4.3 Near Decomposability

According to the role and property of near decomposability in different entities, I anticipate to observe the positive relation of learning rate and near decomposability in thinking, through its evolutionary interpretation. Besides, I also expect to observe that if a problem is nearly decomposable and the problem solver is capable of decomposing it, then the problem can be solved faster.

References


——— (1957), *Models of Man*, JOHN WILEY & SONS, INC.


