(P=NP)

Methods of Organizing Data

A solution for NP-Complete problems, with examples provided for “Clique”, “Sudoku” and “The Traveling Salesman”.

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1 Introduction

BACKGROUND OF THE INVENTION

NP-completeness

In computational complexity theory, an NP-complete decision problem is one belonging to both the NP and the NP-hard complexity classes. In this context, NP stands for "nondeterministic polynomial time". The set of NP-complete problems is often denoted by NP-C or NPC.

Although any given solution to an NP-complete problem can be verified quickly (in polynomial time), there is no known efficient way to locate a solution in the first place; the most notable characteristic of NP-complete problems is that no fast solution to them is known. That is, the time required to solve the problem using any currently known algorithm increases very quickly as the size of the problem

grows. As a consequence, determining whether it is possible to solve these problems quickly, called the P versus NP problem, is one of the fundamental unsolved problems in computer science today.

The Purposed Solution to P vs NP

SUMMARY OF THE INVENTION

The present invention takes a novel approach to solving NP-Complete problems and provides steps that a computational device and software program can follow to accurately solve NP-class problems without the use of heuristics or brute force methods. The present invention (methods and computational devices) provides methods that are fast and accurate if utilized properly.

The present inventor states that the solution to solving the **"Does P=NP?"** question (and our ability to design algorithms to solve such problems efficiently) lies in a novel method presented for searching, filtering, combining and structuring data. Those skilled in the art seem to have failed to recognize the power of representing data variables as specific unique binary place values and/or their sums (collaborative variables), prior to searching or filtering selected data sets. By binary place values, the present inventor is referring to the selected place values for 1 or 0 in the binary numbering system. The numbers 1, 2, 4, 8, 16, 32, 64, etc., are all examples.

What the inventor refers to when stating **"their summations"** is the unique value that each grouping of two or more of these numbers can create when added together. For instance, if we take the number 7 and state that it must consists of **unique** binary numbers, then there is only one possible outcome. The numbers to create a 7, must be 1, 2 and 4. If we take the number 255 and state that it must consists of **unique** binary numbers, then there is also only one possible outcome. If (again) no number is allowed to repeat, then 255 must be created from 1, 2, 4, 8, 16, 32, 64 and 128.

By constraining the binary system to **unique** values (meaning that no number can be used or added more than once in any collaborative variable) a number such as 255 can store a tremendous amount of information. In the described system 255 will thus state that there are eight different numbers that are required to create the sum 255 and that the eight numbers required to fulfill its creation successfully are required to be 1, 2, 4, 8, 16, 32, 64 and 128. It can also indirectly provide us with a number of

sub-groups that will be described in more detail, in the Clique Problem example provided further on in this paper. As another example, if we are specifically looking for two-digit variables, the numbers 3, 5, 6, 7, 9 etc., will all be options, but 1, 2, 4 and 8 will not.

Note: Please remember that the number 5 MUST consist of (4 and 1) as (2, 2 and 1) are not allowed, because the 2 would be duplicated. The avoidance of duplicated variables is a key to the success of the present system as these duplicate variables seem to be one of the difficulties that make certain questions in computational complexity theory very difficult to answer.

The present invention also describes a novel method for breaking specific problems into logical groupings that the present inventor (John Archie Gillis) has defined as collaborative variables. They utilize novel binary representations/conversions, so that one can more easily and quickly determine selected and desired informational outputs. In a number of instances for the present system to work, we must organize two or more variables into larger variables (collaborative), so that we can determine logical NOT's. It seems that in many cases that finding constraints by looking at a problem as single variable data points in insufficient. This seems specifically true as will be seen in the TSP problem, as constraints or NOT's are difficult to come by unless two or more variables are joined as one. We can then utilize a system of permutations, logic and searching to find fast and accurate answers.

Numbers are organized into various groups, levels and hierarchies as will be shown in the three different NP-Complete examples provided below. In the present system the higher value of each number does not necessarily mean that it has prominence over any other number. The numbers are instead listed into values that assist with sorting specific things into selected and specific groupings.

The present invention provides a number of methods for solving NP-class problems. NP-class problems include many pattern-matching and optimization problems that are of great practical interest, such as determining the optimal arrangement of transistors on a silicon chip, developing accurate financial-forecasting models, or analyzing protein-folding behavior in a cell. Since all the NP-complete optimization problems become easy with the present methods, everything will be much more efficient. Transportation of all forms can now also be scheduled optimally to move people and

goods around quicker and cheaper. Manufacturers can improve their production to increase speed and create less waste.

Developments in vision recognition, language comprehension, translation and many other learning tasks will now become much simpler. The present inventor feels that by utilizing the systems of the present invention in numerous fields, that the invention will have profound implications for mathematics, cryptography, algorithm research, artificial intelligence, game theory, internet packet routing, multimedia processing, philosophy, economics and many other fields.

2 Clique

In computer science, the clique problem is the computational problem of finding cliques (subsets of vertices, all adjacent to each other, also called complete subgraphs) in a graph. It has several different formulations depending on which cliques, and what information about the cliques, should be found. Common formulations of the clique problem include finding a maximum clique (a clique with the largest possible number of vertices), finding a maximum weight clique in a weighted graph, listing all maximal cliques (cliques that cannot be enlarged), and solving the decision problem of testing whether a graph contains a clique larger than a given size.

The clique problem arises in the following real-world setting. Consider a social network, where the graph's vertices represent people, and the graph's edges represent mutual acquaintance. Then a clique represents a subset of people who all know each other, and algorithms for finding cliques can be used to discover these groups of mutual friends. Along with its applications in social networks, the clique problem also has many applications in bioinformatics and computational chemistry.

Most versions of the clique problem are hard. The clique decision problem is NP-complete (one of Karp's 21 NP-complete problems). The problem of finding the maximum clique is both fixed-parameter intractable and hard to approximate. And, listing all maximal cliques may require exponential time as there exist graphs with exponentially many maximal cliques. Therefore, much of the theory about the clique problem is devoted to identifying special types of graph that admit more efficient algorithms, or to establishing the computational difficulty of the general problem in various

models of computation.

To find a maximum clique, one can systematically inspect all subsets, but this sort of brute-force search is too time-consuming to be practical for networks comprising more than a few dozen vertices. Although no polynomial time algorithm is known for this problem, more efficient algorithms than the brute-force search are known. For instance, the Bron–Kerbosch algorithm can be used to list all maximal cliques in worst-case optimal time, and it is also possible to list them in polynomial time per clique.

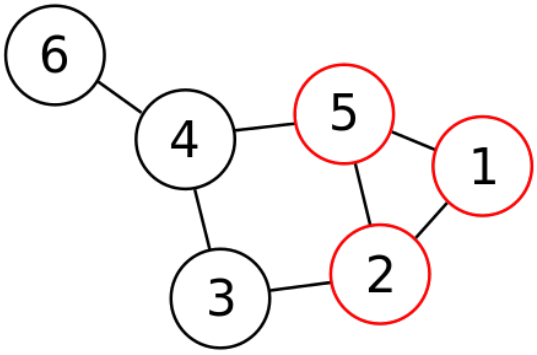
While a method for computing the solutions to NP-complete problems using a reasonable amount of time remains undiscovered, computer scientists and programmers still frequently encounter NP-complete problems. NP-complete problems are often addressed by using heuristic methods and approximation algorithms.

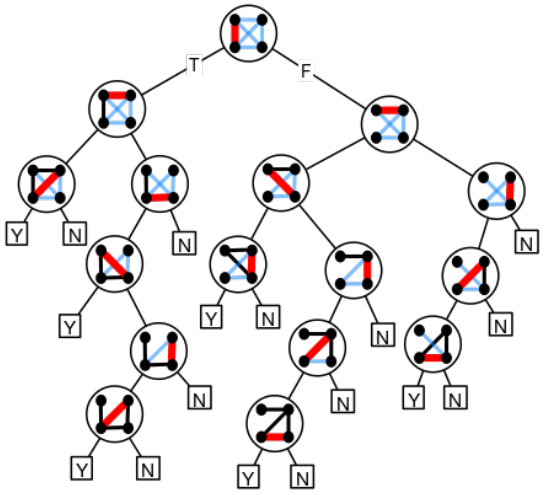
Description

The first example described in this paper provides a novel approach to solving the clique problem. Modern computing systems need to (generally) work on a Turing machine. A Turing machine is a mathematical model of computation that defines an abstract machine, which manipulates symbols on a strip of tape according to a table of rules. Despite the model's simplicity, given any computer algorithm, a Turing machine capable of simulating that algorithm's logic can be constructed.

The ability to compute solutions for problems such as clique (and many others) has been deemed the holy grail of computational complexity theory and is one of the Millennium Prize Problems. The Millennium Prize Problems are seven problems in mathematics that were stated by the Clay Mathematics Institute in 2000 for which a solution to any individual problem would award the solver $1,000,000.

The present inventor states that a solution lies in how we input the data, how the data is represented, the questions that we ask the computational device and the conversion back to the data's original state for the input/output.

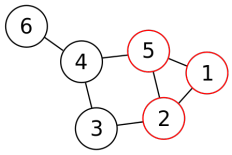




Present methods of working with graphs as seen above, seem to be one of the problems as to why finding items, such as a largest clique, or clique(s) of a fixed size is a real problem for computational devices.

I will use a social network to explain how the present system provides a better method for communicating with computational devices for the purpose of solving difficult problems such as clique. A system must be employed that will allow a computer to sort and search for a requested output. Some algorithms for certain questions and inputs (particularly NP-Class problems) can in many instances (with many variables) take longer than the age of the universe to run. This is not acceptable.

Our first example is clique.



Mathematicians generally order elements of clique in an ordered progression 1, 2, 3, 4, 5, 6, etc., but herein lies the problem when trying to find specific size cliques or groups within the larger structure. The present invention matches a binary place valued number to the variables, which in this example are integers (or names) prior to computation.

As an example;

A (or John) becomes 1

B (or Sue) becomes 2

C (or Bob) becomes 4

D (or Jenn) becomes 8

E (or Colin) becomes 16

F (or Maggy) becomes 32

G (or Jim) becomes 64

H (or Kelly) becomes 128

TABLE 1

CLIQUE	H (or Kelly)	G (or Jim)	F (or Maggy)	E (or Colin)	D (or Jenn)	C (or Bob)	B (or Sue)	A (or John)	
	128	64	32	16	8	4	2	1	
A (or John)	1	1	1	1	1	1	1	1	**255**
B (or Sue)	1	1	1	1	1	1	1	1	**255**
C (or Bob)	0	0	1	1	1	1	1	1	**63**
D (or Jenn)	0	0	1	1	1	1	1	1	**63**
E (or Colin)	0	0	0	1	1	1	1	1	**31**
F (or Maggy)	0	0	1	0	1	1	1	1	**47**
G (or Jim)	0	1	0	0	0	0	1	1	**67**
H (or Kelly)	1	0	0	0	0	0	1	1	**131**

After computation (as will be explained in detail) the conversion to binary is reversed, so that we can see the resulting answer. By doing this we provide means for a more efficient, faster and complete search effort. Brute force will no longer be required.

In the provided example of Table 1; John has been assigned the binary variable 1 and Sue 2. John and Sue are then further assigned the number 255. 255 shows their relationship to themselves, each other and everybody else in the data set.

By following this logic, we can also see that IF an individual is assigned a number 254, 253, 251, 247, 239, 223, 191 or 127, then they will be friends with six people, themselves and enemies with one. We can see this clearly in the binary representations. 11111110, 1111101, 11111011, 11110111, 11101111, 11011111, 10111111, 01111111. These binary numbers represent both themselves and all their friendships within the data set. A high or low number doesn't mean that you have more or less friends,

but it instead tells us exactly who your friends are. This is useful for sorting and filtering purposes for requested outputs.

The present method provides a means for more efficiently finding specific groupings of people within a larger grouping. This difficulty of sorting groups into sub-groups that are all friends is again referred to as the clique problem. Although it is a bit confusing, we must sort the binary numbers into nine specific groupings or levels for our system to work. (If the data set for input is larger or smaller then 8 people we obviously need to adjust the numbers to fit the sizes to be input. If ten people are to be sorted into various groups for example, we will use numbers ranging from 0-512. For example; 1, 2, 4, 8, 16, 32, 64, 128, 256, and 512. Each individual is assigned one of these binary numbers.

We then create a grid which assigns a 1 for friendships and a 0 for enemies/non-friends. We can then create a binary representation of each individual's relationship to every other individual, which provides us with all the possible friend permutations, both large and small. Essentially an additional number is assigned to each person that includes their position in the group! We can then use these numbers to sort our data into whatever sized clique(s) that we desire. It also becomes easy to find the largest clique, by simply sorting numbers rather than resorting to a brute force methodology.

To provide an example;
What if we wanted to find if/how many clique(s) of 5 friends exist in a group of 8 people?
We will begin by searching our list for numbers with five ones. 31, 47, 55, 59, 61 and 62 are all examples of binary numbers with five ones. We then look for duplicates. In the below example, there are no duplicates for a person with 4 friends + themselves (5) as a friend.

What we find is that any binary number that shares the same five ones, must also be included in our 5 clique. Thus if a 63, 191 or 255 happen to be in our list (which they are), then they will be part of the 5 clique too! See TABLE 2.

TABLE 2

255	1111 1111	**191**	1011 1111	**63**	0011 1111	**31**	0001 1111
						47	0010 1111
						55	0011 0111
						59	0011 1011
						61	0011 1101
						62	0011 1110

Notice that 47 and 31 are the only binary numbers with five ones in our Table 1 example. We can now easily see that they are both sub-groups of 63 (six ones wherein 5 are shared) and 255 (eight ones wherein 5 are shared), which are also found in our Table 1 list, thus we have two cliques of five. *Note: Five is also the largest size clique.*

1) 47 Maggy, 63 Jenn, 63 Bob, 255 Sue, and 255 John, and

2) 31 Colin, 63 Jenn, 63 Bob, 255 Sue, and 255 John

are both our two largest cliques and consist of 5 friends.

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TABLE 3

				15				
				23				
				27				
				29				
				30				
				39				
				43				
				45				
				46				
				51				
				53				
				54				
				57				
				58				
			31	60	7			
			47	71	11			
			55	75	13			
			59	77	14			
			61	78	19			
			62	83	21			
			79	85	22			
			87	86	25			
			91	89	26			
			93	90	28			
			94	92	35			
			103	99	37			
			107	101	38			
			109	102	41			
			110	105	42			
			115	106	44			
			117	108	49			
			118	113	50			
			121	114	52			
			122	116	56			
			124	120	67			
			143	135	69			
			151	139	70			
			155	141	73			
			157	141	74			
			158	147	76			
			167	149	81			
			171	150	82			
		63	173	153	84	3		
		95	174	154	88	5		
		111	179	156	97	6		
		119	181	163	98	9		
		123	182	165	100	10		
		125	185	166	104	12		
		126	186	169	112	17		
		159	188	170	131	18		
		175	199	172	133	20		
		183	203	177	134	24		
		187	205	178	137	33		
		189	206	180	138	34		
		190	211	184	140	36		
		207	213	195	145	40		
		215	214	197	146	48		
		219	217	198	148	65		
		221	218	201	152	66		
		222	220	202	161	68		
		231	227	204	162	72		
		235	229	209	164	80		
	127	237	230	210	168	96	1	
	191	238	233	212	176	129	2	
	223	243	234	216	193	130	4	
	239	245	236	225	194	132	8	
	247	246	241	226	196	136	16	
	251	249	242	228	200	144	32	
	253	250	244	232	208	160	64	
255	254	252	248	240	224	192	128	0

As per the TABLE 3, the **first** column with the number 255 will be classified as a Level 1 number. This means that any individual with this number will belong to every clique, be friends with everybody and if they share this number with another they will all have the same exact number of friends, be friends with themselves and each other. It also means that they will belong to any grouping of smaller cliques as well. If we are to look for groupings or cliques of three for example, anyone with the number 255 will need to be automatically included.

The **second** column will be classified as Level 2 numbers. There are 8 of them (127, 191, 223, 239, 247, 251, 253, 254). This means that anybody with one of these numbers is friends with six people, themselves and non-friends or enemies with one. Each specific number actually tells us exactly whom their friends and enemies are.

The **third** column will be classified as Level 3 numbers. There are 28 of them (63-252).
The **fourth** column will be classified as Level 4 numbers. There are 56 of them (31-248).
The **fifth** column will be classified as Level 5 numbers. There are 70 of them (15-240).
The **sixth** column will be classified as Level 6 numbers. There are 56 of them (7-224).
The **seventh** column will be classified as Level 7 numbers. There are 28 of them (3-192).
The **eighth** column will be classified as Level 8 numbers. There are 8 of them (8-128).
The **ninth** column will be classified as a Level 9 number. There is 1 of them (0).

We have broken our numbers down into a variety of levels. Searching out various cliques gets more and more complicated as we get closer and closer to a 50/50% distribution. For example, if everyone were to have 4 different friends and four different enemies, then we would be at our maximum complexity with 70 numbers at the level 5. Level 4, 3, 2 and 1 could be complicated, but we can alternatively look for enemies rather that friends if needed, which may simplify these levels. As an example; 3 or 0000 0011 will be a sub-level number to any binary digit with two ones at the end 0000 00**11.** Some examples are 7 (0000 01**11**), 67 (0100 00**11**), 15 (0000 11**11**), 127 (0111 11**11**), 256 (1111 11**11**) and many more!

An individual that has only four friends occur would be in LEVEL 5. Any LEVEL 1 individuals would obviously be friends with the exact same four people, because logically LEVEL 1 individuals

are friends with everybody. Again this would hold true for the other levels as well, but becomes slightly more complex.

TABLE 4

LEVEL 1	LEVEL 2	LEVEL 3		LEVEL 4			LEVEL 5				LEVEL 6			LEVEL 7		LEVEL 8	LEVEL 9
255	127	63	237	31	124	211	15	85	149	204	7	67	140	3	96	1	0
	191	95	238	47	143	213	23	86	150	209	11	69	145	5	129	2	
	223	111	243	55	151	214	27	89	153	210	13	70	146	6	130	4	
	239	119	245	59	155	217	29	90	154	212	14	73	148	9	132	8	
	247	123	246	61	157	218	30	92	156	216	19	74	152	10	136	16	
	251	125	249	62	158	220	39	99	163	225	21	76	161	12	144	32	
	253	126	250	79	167	227	43	101	165	226	22	81	162	17	160	64	
	254	159	252	87	171	229	45	102	166	228	25	82	164	18	192	128	
		175		91	173	230	46	105	169	232	26	84	168	20			
		183		93	174	233	51	106	170	240	28	88	176	24			
		187		94	179	234	53	108	172		35	97	193	33			
		189		103	181	236	54	113	177		37	98	194	34			
		190		107	182	241	57	114	178		38	100	196	36			
		207		109	185	242	58	116	180		41	104	200	40			
		215		110	186	244	60	120	184		42	112	208	48			
		219		115	188	248	71	135	195		44	131	224	65			
		221		117	199		75	139	197		49	133		66			
		222		118	203		77	141	198		50	134		68			
		231		121	205		78	141	201		52	137		72			
		235		122	206		83	147	202		56	138		80			

TABLE 1

CLIQUE	H (or Kelly)	G (or Jim)	F (or Maggy)	E (or Colin)	D (or Jenn)	C (or Bob)	B (or Sue)	A (or John)	
	128	64	32	16	8	4	2	1	
A (or John)	1	1	1	1	1	1	1	1	**255**
B (or Sue)	1	1	1	1	1	1	1	1	**255**
C (or Bob)	0	0	1	1	1	1	1	1	**63**
D (or Jenn)	0	0	1	1	1	1	1	1	**63**
E (or Colin)	0	0	0	1	1	1	1	1	**31**
F (or Maggy)	0	0	1	0	1	1	1	1	**47**
G (or Jim)	0	1	0	0	0	0	1	1	**67**
H (or Kelly)	1	0	0	0	0	0	1	1	**131**

In our above example we can see that John and Sue have the most friends in common and are actually friends with everybody in the data set because their numbers are 255. They thus are friends with themselves and each other and also share six other friends. They have no enemies and thus it is very simple to see and visualize. The largest "clique" in this scenario wherein everybody is friends with each other would be the clique of 5 friends consisting of John, Sue, Bob, Jenn and Colin. Colin's number is 31 which is a LEVEL 4 number. We can see in the figure below that 31 falls into the sub-set class of 63, (191) and 255 and so by default 31 is friends with all 63 numbered people and both 31 and 63 fall into sub-set classes of 255 (as ALL numbers do), and so 31, 63 and 255 numbers for which

there are five, make up the largest clique of friends that are all friends with each other. The diagram below shows how these numbers all share five 1's. In this simplified scenario they are the five 1's justified furthest to the right.

TABLE 2A

255	1111 1111	**191**	1011 1111	**63**	0011 1111	**31**	0001 1111
						47	0010 1111
						55	0011 0111
						59	0011 1011
						61	0011 1101
						62	0011 1110

…go to next page.

TABLE 2B (sample of the full tree table)

255	1111 1111	**127**	0111 1111	**63**	0011 1111	**31**	0001	1111
						47	0010	1111
						55	0011	0111
						59	0011	1011
						61	0011	1101
						62	0011	1110
				95	0101 1111	**31**	0001	1111
						79	0100	1111
						87	0101	0111
						91	0101	1011
						93	0101	1101
						94	0101	1110
				111	0110 1111	**47**	0010	1111
						79	0100	1111
						103	0110	0111
						107	0110	1011
						109	0110	1101
						110	0110	1110
				119	0111 0111	**55**	0011	0111
						87	0101	0111
						103	0110	0111
						115	0111	0011
						117	0111	0101
						118	0111	0110
				123	0111 1011	**59**	0011	1011
						91	0101	1011
						107	0110	1011
						115	0111	0011
						121	0111	1001
						122	0111	1010
				125	0111 1101	**61**	0011	1101
						93	0101	1101
						109	0110	1101
						117	0111	0101
						121	0111	1001
						124	0111	1100
				126	0111 1110	**62**	0011	1110
						94	0101	1110
						110	0110	1110
						118	0111	0110
						122	0111	1010
						124	0111	1100
		191	1011 1111	**63**	0011 1111	**31**	0001	1111
						47	0010	1111
						55	0011	0111
						59	0011	1011
						61	0011	1101
						62	0011	1110
				159	1001 1111	**31**	0001	1111
						143	1000	1111
						151	1001	0111
						155	1001	1011
						157	1001	1101
						158	1001	1110

Table 2B shows how our data system will work. For example, if one or more higher level numbers are found in a request/search, but there is also a lower level number that shares ALL the same 1's of the higher level then we will also want the computer system to include the lower level number(s) in the clique. There are a number of ways to approach this, but we demonstrate a small portion of an example reference table in Table 2B. Table 2A also provides an example showing how 31, 47, 55, 59, 61 and 62 (Level 4 numbers) would all have 4 out of 5 friends in common with 63 (a Level 3 number).

Realizing that certain numbers such as 1, 2, 4 or 128 will likely not be included in a clique, (unless we are looking for cliques of 1), it is still important to include them in the process as their inclusion will be required to eliminate any letters/people that are only friends with themselves. As an example, if a woman named Gertrud signed up to Facebook, but decided to not become friends with anybody before she abandoned the platform then she would show up as a LEVEL 8 number. LEVEL 8 numbers are not compatible with anybody except for themselves and thus will not belong to a clique. LEVEL 9 numbers (which can't really exist as they are 0), don't even like themselves, so it is quite a sad state of affairs for them and these poor people may need to seek counselling.

In an alternative embodiment of the present invention we may find it more beneficial to flip all the zeros to ones and ones to zeros. If the majority of people were to have very few friends we may find numbering the NOT FRIENDS as 1 a more economical method of organization rather than numbering the WE ARE FRIENDS method. Again, if the distribution is relatively equal, then it will not matter much as to how we organize the 0's and 1's.

https://jamesmccaffrey.wordpress.com/2011/06/24/the-maximum-clique-problem/

"It turns out that finding the maximum clique for graphs of even moderate size is one of the most challenging problems in computer science. The problem is NP-complete which means, roughly, that every possible answer must be examined. Suppose we have a graph with six nodes. First we'd try to see if all six nodes form a clique. There is Choose (6,6) = 1 way to do this. Next we'd examine all groups of five nodes at a time; Choose (6,5) = 6 ways. And so on, checking Choose (6,4) = 15, Choose (6,3) = 20, Choose (6,2) = 15, and Choose (6,1) = 6 possible solutions for a total of 63 checks. (For the maximum clique problem we can stop when we find the largest clique so let's assume that on average we'd have to go through about one-half of the checks).

The total number of checks increases very quickly as the size of the graph, n, increases. For n = 10 there are 1,023 total combinations. For n = 20 there are 1,048,575 combinations. But for n = 1,000 there are 10,715,086,071,862,673,209,484,250,490,600,018,105,614,048,117,055,336,074,437,503,883,703,510,511,249,361,224,931,983,788,156,958,581,275,946,729,175,531,468,251,871,452,856,923,140,435,984,577,574,698,574,803,934,567,774,824,230,985,421,074,605,062,371,141,877,954,182,153,046,474,983,581,941,267,398,767,559,165,543,946,077,062,914,571,196,477,686,542,167,660,429,831,652,624,386,837,205,668,069,375 combinations. Even if you could perform one trillion checks per second it would take you 3.4 x 10^281 years which is insanely longer than the estimated age of the universe (about 1.0 x 10^10 = 14 billion years)."

- James McCaffrey

Note:
In appendix A, I will provide a strategy for using smaller numbers for our methods as working with very large numbers can be difficult for computers with limited resources.

2 SUDOKU

Sudoku is a logic-based, combinatorial number-placement puzzle. The objective is to fill a 9×9 grid with digits so that each column, each row, and each of the nine 3×3 sub grids that compose the grid (also called "boxes", "blocks", or "regions") contains all of the digits from 1 to 9. The puzzle setter provides a partially completed grid, which for a well-posed puzzle has a single solution.

Completed games are always a type of Latin square with an additional constraint on the contents of individual regions. For example, the same single integer may not appear twice in the same row, column, or any of the nine 3×3 sub regions of the 9x9 playing board.

French newspapers featured variations of the puzzles in the 19th century, and the puzzle has appeared since 1979 in puzzle books under the name Number Place. However, the modern Sudoku only started to become mainstream in 1986 by the Japanese puzzle company Nikoli, under the name Sudoku, meaning "single number". It first appeared in a US newspaper and then The Times (London) in 2004,

from the efforts of Wayne Gould, who devised a computer program to rapidly produce distinct puzzles.

In computational complexity theory, the Cook–Levin theorem, also known as Cook's theorem, states that the Boolean satisfiability problem is NP-complete. That is, any problem in NP can be reduced in polynomial time by a deterministic Turing machine to the problem of determining whether a Boolean formula is satisfiable. The theorem is named after Stephen Cook and Leonid Levin.

An important consequence of this theorem is that if there exists a deterministic polynomial time algorithm for solving a problem that can be reduced to Boolean satisfiability, then every NP problem can be solved by a deterministic polynomial time algorithm. The question of whether such an algorithm exists to solve a problem that has been reduced to Boolean satisfiability in deterministic polynomial time is thus equivalent to the P versus NP problem, which is widely considered the most important unsolved (until the publication of this paper) problem in theoretical computer science.

We will now provide an example of Sudoku, but this is in no way meant to limit the present methods to this or any single problem. Any NP-Complete problem may be addressed with variations of the present invention as can be seen in the Cook-Levine papers or the proof based on the one given by Garey and Johnson[8]. Every NP problem can be reduced to an instance of a SAT problem by a polynomial-time many-one reduction.

First we will take an example of a standard 9x9 Sudoku puzzle.

TABLE 5

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

Transposing our clique solving process for Sudoku will require that we transform the Sudoku numbers into binary values. Sudoku numbers 1-2-3-4-5-6-7-8-9 will now become 1-2-4-8-16-32-64-128-256. This will better allow for yes/no answers for our collaborative variables and simplify our solving process. The present method will SEEM QUITE COMPLICATED, but the process will be much more efficient then presently available methods of brute force or single variable constraint programming.

Why?

Because rather than having 81 individual variables, that need to be considered, we have created a system wherein two sets of 27 variables (54 variables in total) can be used instead. In a 16x16 grid with 256 variables, the present system will only require two sets of 64 variables (128 in total). As chart 1 below shows, traditional methods grow extremely rapidly, wherein the present method (although the variables DO grow), the variables grow at a much smaller rate! The variables of the present invention in the 100x100 grid have only one-fifth the variables of traditional constraint methods.

CHART 1

Grid Size	Traditional Number of Variables	Variables of the present invention		Sum
9x9	81	27	27	54
16x16	256	64	64	128
25x25	625	125	125	250
36x36	1296	216	216	432
49x49	2401	343	343	686
100x100	10000	1000	1000	2000

As we will see in the upcoming explanation of how to solve TSP we will be using what I call collaborative constraints for Sudoku. If we now focus on A1 we will notice that it will be provided with constraining elements from A2 and A3 (the horizontal constraints) and also constraints from A4 and A7 (the 3x3 constraint). Any numbers (or collaborative sum) in any of these areas will affect the available options for numbers which can be input into A1. If A1 already has a number in its area, this will also limit available options.

It is essential that we keep in mind that A1, A4 and A7 share the same 3x3 block as D1, D2 and D3. This is one of the elements that will allow our logic to work. They share a commonality, but also are provided with differing constraints. This holds true for all the other 3x3 blocks as well. For example, B2, B5 and B8 share many constraints with E4, E5 and E6, but each also have unique ones that make our system function.

Thus, if we create a number of logic statements, we can solve the Sudoku. For example, in the Sudoku example provided in Table 5, **IF** E1 is a three-variable number (which it is) and **IF** I know that F2, B2 and B9 all contain a variable that contains an identical value (which it does), (32 in binary and 6 in Sudoku), **THEN** B4 and E3 must contain that same number. (For visualization purposes **B4Z is equal to E3Y**).

TABLE 6

A1	A2	A3
A4	A5	A6
A7	A8	A9
B1	B2	B3
B4	B5	B6
B7	B8	B9
C1	C2	C3
C4	C5	C6
C7	C8	C9

D1	D2	D3	D4	D5	D6	A3	D8	D9
E1	E2	E3	E4	E5	E6	E7	E8	E9
F1	F2	F3	F4	F5	F6	F7	F8	F9

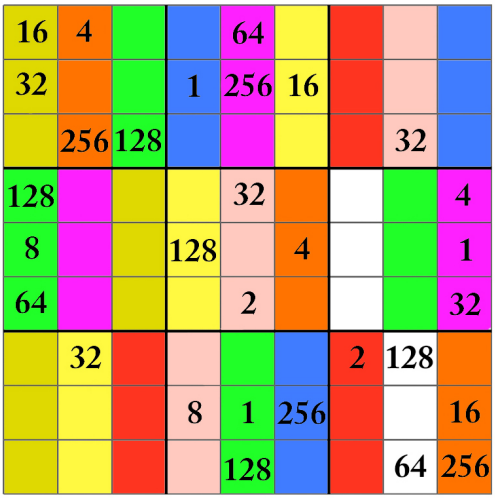
TABLE 7 (not really necessary)

Table 7 shows further breakdown into xyz zones, but realistically we may not require these in the preferred embodiment as for example, if we were to say that A1 and D1 shared a number, the only possible place that they can share that number is in the top space of D1 or furthest left of A1. No other location is possible.

After we name our independent sections we turn the Sudoku numbers 1-2-3-4-5-6-7-8-9 into binary place values 1-2-4-8-16-32-64-128-256. This will make everything much easier for a computational device to comprehend. An essential part and novel aspect of the present solution that has been missing from the art is the ability to assist a computational device with fully understanding what variables do NOT need to be looked at during a searching effort. This will hold true in our next example (TSP) as well. The searching effort seems to be what takes up the computational devices time. The more possibilities that can be eliminated from the searching efforts the faster the output or answers will be found.

TABLE 8

16	4			64				
32			1	256	16			
	256	128					32	
128				32				4
8			128		4			1
64				2				32
	32					2	128	
			8	1	256			16
				128			64	256



We will need to list what I will call our number levels for Sudoku. There are three variations. Level 1 numbers are single variables and will include 1, 2, 4, 8, 32, 64, 128, and 256. Once the Sudoku has been solved by our algorithm three of these unique numbers will add up to a larger collaborative variable (Level 3 number) and will reside in one of the 3x1 or 1x3 sections (i.e. A1, A2, D1, D2, etc.). Level 2 numbers are collaborative variables and will be the sum of any two different level one numbers. Again, Level 3 numbers are also collaborative variables and will be the sum of any three different level 1 numbers. This strategy better provides a computer with the ability to answer yes or no questions, as is a requirement in Boolean logic. For example, if A1=7 then we will logically know that A1 consists of a 4, 2 and a 1. By utilizing a binary number system, we allow only the one possibility, no matter what the numbers. This also tells us that the sum of A2 and A3 must be 249.

This is not the case when we use 1-9 numbering. If for example, we were to use 1-9 integer values and A1 equaled 15. This would not really tell us ANYTHING! The 15 in this scenario could be comprised of 456, 951, 942, 861, 852, 834, 762, or 753. By Utilizing binary digits rather than 1-9 integers we can dramatically reduce the time required to find a solution to the Sudoku via faster and better method of constraint programming that have not prior to the present invention been utilized.

Level 1 (one variable numbers) = 1, 2, 4, 8, 16, 32, 64, 128, or 256

Level 2 (two variable numbers) = Any one of --- 3, 5, 6, 9, 10, 12, 17, 18, 20, 24, 33, 34, 36, 40, 48, 65, 66, 68, 72, 80, 96, 129, 130, 132, 136, 144, 160, 192, 256, 257, 258, 260, 264, 272, 288, 320, or 384

Level 3 (three variable numbers) = Any one of --- 7, 11, 13, 14, 19, 21, 22, 25, 26, 28, 35, 37, 38, 41, 42, 44, 49, 50, 52, 56, 67, 69, 70, 73, 74, 76, 81, 82, 84, 88, 97, 98, 100, 104, 112, 131, 133, 134, 137, 138, 140, 145, 146, 148, 152, 161, 162, 164, 168, 176, 193, 194, 196, 200, 208, 224, 259, 261, 262, 265, 266, 268, 273, 274, 276, 280, 289, 290, 292, 296, 304, 321, 322,, 324, 328, 336, 352, 385, 386, 388, 392, 400, 416, or 448

We can now simply run a program with a number of logic steps again and again until the Sudoku is fully solved. It can be modelled as a much simpler and faster constraint satisfaction problem that would likely use many less lines of code.

Here are some examples of logic steps that may be applied **recursively** as numbers get filled in and the constraints increase. This type of program should be effective at solving any Sudoku that would be input into it without the requirement of backtracking or brute force methods.

- **IF** A1 and A2 both = a Level 3 (3 variables added) number **AND IF** A3 = a Level 2 number **THEN** the one empty box (the x, y **or** z) of A3 must = 256 minus the sum of A1, A2 and A3. A3 must then be modified from a Level 2 number to a Level 3 number and the new addition placed in the one empty x, y or z space that is available. The full horizontal line would now in this scenario be complete.
- **IF** E1 contains a Level 3 (3 variables added) number **AND IF** (F2 **OR** D2) AND (B2 **AND** B9) contain the same Level 1 number **THEN** E3 and B4 should share that number *(in the only place they can, which is the z location).*
- We can also be more specific and even use the xyz variables if desired. **IF** (D3 and E1) and (C3 and C8) contain the sum 128 (a Level 1 variable), or the sum 129, 130, 132, 136, 144, 160, 192, or 384 (a Level 2) or 131, 133, 134, 137, 138, 140, 145, 146, 148, 152, 161, 162, 164, 168, 176, 193, 194, 196, 200, 208, 224, 385, 386, 388, 392, 400, 416 or 448 (a Level 3), **THEN** C4(Y) is 128 (8 in Sudoku).
- We can also make generalized family systems. For example, **IF** B3 and B5 contain a same number (such as binary 4) or contain a higher level number that includes binary 4, (by binary necessity to acquire its sum such as 5 (4,1) or 13 (1, 8, 4), **AND** (E1 and E3) contain Level 3

numbers **THEN** E2(Z) should be filled with that number. The (example 4) number is then converted to the Sudoku number 3. *(Note: the pictured examples, do not provide this example).*

- MANY more logic operators can be created and will guarantee a solution to even the most complicated Sudoku. Brute force methods will no longer be required to solve these types of problems, but they may be used in collaboration. We can design a complete system utilizing only a portion of all possible logic operators. The simpler the Sudoku, the less operators that will likely be required.

The key to the Sudoku solution seems to be in breaking the puzzle down into a variety of smaller units, each of which share two unique logic systems. By logic systems I am referring to our 3x1 units which each belong to both a 9x1 horizontal and a 3x3 group **and** our 1x3 units which belong to 1x9 vertical and 3x3 groups. When logic operators make these two groups talk to each other, every blank in a satisfiable Sudoku can easily be found. Each Sudoku number is assigned a binary digit (1, 2, 4, 8, 16, 32, 64, 128 or 256). We can apply the logic operators recursively (again and again as more blank spaces are filled with numbers) to fill in the puzzle. Once it is complete and everything is satisfied logically, we can convert our numbers back to 1-9 and our puzzle is solved in polynomial time.

This method can also be utilized for larger puzzles, we simple need to increase our numbers. A 16x16 Sudoku would require 1x4 and 4x4 logic groupings and our binary numbers would go to 65536.

Note:
A similar approach can be used to solve the "Eight Queens Puzzle". If the chess board has an even length (i.e. 8x8) it is easy to visualize, but if it is an odd length (i.e. 9x9), we need to adjust the strategy wherein we have two 5x5's with some crossover between each sub-group…but that's for another paper.

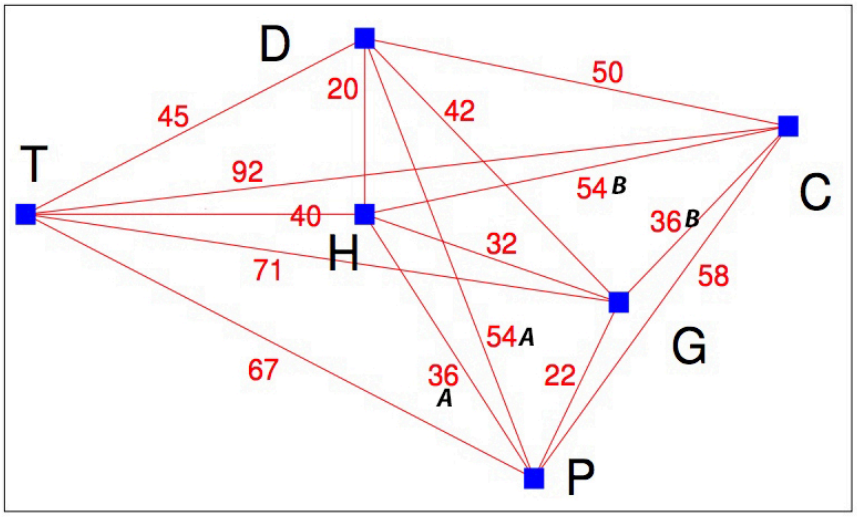
3 THE TRAVELING SALESMAN

The travelling salesman problem (TSP) asks the following question: "Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city and returns to the origin city?" It is an NP-hard problem in combinatorial optimization, important in operations research and theoretical computer science.

The problem was first formulated in 1930 and is one of the most intensively studied problems in optimization. It is used as a benchmark for many optimization methods. Even though the problem is computationally difficult, a large number of heuristics and exact algorithms are known, so that some instances with tens of thousands of cities can be solved completely and even problems with millions of cities can be approximated within a small fraction of 1%.

The TSP has several applications even in its purest formulation, such as planning, logistics, and the manufacture of microchips. Slightly modified, it appears as a sub-problem in many areas, such as DNA sequencing. In these applications, the concept city represents, for example, customers, soldering points, or DNA fragments, and the concept distance represents travelling times or cost, or a similarity measure between DNA fragments. The TSP also appears in astronomy, as astronomers observing many sources will want to minimize the time spent moving the telescope between the sources. In many applications, additional constraints such as limited resources or time windows may be imposed.

TABLE 9



Note:

The above TSP example is from:

http://people.ku.edu/~jlmartin/courses/math105-F11/Lectures/chapter6-part3.pdf

Sabrina has the following list of errands and needs to find the shortest route:

(H) Home (The start and finish of her route).

(P) Pet store

(G) Greenhouse

(C) Cleaners

(D) Drugstore

(T) Target Store

The present invention can attack the TSP in a variety of ways! I will describe a couple of examples out of many possibilities with the present system. I begin by making sure that if there is a distance that is the same as another distance, that I can distinguish them. I do this by adding A or B etc., to the number. In the example provided we will see 36A and 36B and 54A and 54B. This is a critical step.

Each unique value is then assigned a binary number based on its size. The shortest path element receives the smallest binary number and vice versa. In the example provided we see that length 20 (the shortest) is linked to binary digit 1 and that length 92 (the longest) is linked to binary digit 16384.

We then need to create a situation wherein we can produce a number of logical "NOT" scenarios. To do this (in this example) we will use two or more variables together (collaborative variable). For example, 22 and 32 are connected at G and thus can become a single larger variable with a number of NOT's. We can also call this HGP as these are the nodes that they are connected to. HPG can also double as PGH. We know that H stands for HOME and thus it will be the beginning and the end point of the journey. This tells us that in the necessary six-point journey (travel to each place once from home and also end at home via the shortest route), that we will require two different collaborative variables from TABLE 10 and one from TABLE 11. All three will work together to create our shortest path(s). (Not in the present example, but in some instances there could potentially be two different shortest paths of the same length).

Using this logic, we can start taking notes of our logical NOT's. Looking at our first collaborative variable we can see that it is comprised of nodes HGP (32 & 22). Of course HGP reversed is also PGH (22 & 32). Being the same, neither can include 36A in its path from or to home because it would

make the person on the journey visit the same place twice, which is not allowed in the TSP problem. If we look at the G node in this first collaborative variable, we can see that 32 and 22 are already used and 71, 36B and 42 can NOT be used because G has to go to P and H and thus these values are scratched or deleted as possibilities. Any value from P (22 already being used), is also scratched (67, 36A, 54A and 58), because logic states that we will need to use a number from Table 11 (with no H) for our middle collaborative variable and because any number from Table 10 would want to go straight home in two steps, which is NOT allowed.

TABLE 10

			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1		
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20		
H	G	P	1				1		1	1		1			1	1	1	6	17825
H	P	G	1				1		1	1		1		1		1	1	10	17825
H	G	C			1			1		1		1	1	1	1		1	20	4777
H	D	G	1		1	1	1				1	1		1			1	65	23592
H	G	D	1		1	1	1				1	1		1	1			68	23592
H	D	T				1	1			1			1	1	1	1	1	129	3102
H	T	D				1	1			1		1	1	1	1	1		160	3102
H	D	C		1	1				1			1		1	1	1	1	257	12334
H	D	P	1	1			1	1				1	1		1		1	513	25652
H	P	D	1	1			1	1				1	1	1	1			520	25652
H	C	G			1		1	1		1		1	1	1			1	1040	4777
H	C	D		1	1		1		1			1		1	1			1280	12334
H	P	C		1						1	1	1		1	1		1	2056	8421
H	C	P		1		1	1			1	1	1			1		1	3072	8421
H	P	T			1		1		1		1		1	1	1		1	4104	1365
H	T	P			1		1		1		1	1	1		1		1	4128	1365
H	G	T		1		1	1	1	1					1	1		1	8196	3849
H	T	G		1		1	1	1	1			1		1			1	8224	3849
H	T	C	1					1			1	1		1	1	1	1	16416	591
H	C	T	1				1	1			1			1	1	1	1	17408	591

We know that the green number 6 (the top number of the 2nd column from the right) of TABLE 10 must be 4 and 2 as binary numbers 4 and 2 are the only ones that will work to make 6. We also know that the white numbers are the ONLY compatible areas where the last two numbers for the journey can be found. TABLE 10 needs to provide both the first two and last two steps of the journey, due to the fact that the journey is six steps long. The middle two steps (two collaborative or added variables) will be provided from TABLE 11. In the present example we see that 6 and 129 are compatible and add up to **135.** 6 (a green number composed of two binary numbers 4 and 2) is a sub-group of 3102 (a white number composed of six binary numbers that also includes 4 and 2) and thus there is no conflict. They are compatible. Perhaps we can call them friends, like in the clique problem.

A computer program can easily determine this by consulting a list or program with the necessary elements. We can for example provide the software program with a list of compatible numbers. Rather than brute force however, the computer can simply look at the one number sums provided by our system to do its sorting, which will be much more efficient. Although it may seem like (and it is) a lot of work when dealing with only 6 travel points, we must remember that our system does not get much more complicated as we begin to add new data points, whereas the presently used brute force method gets exponentially more difficult. For a small number of cities, the present methods may seem slower than brute force, but as the number of cities or data points grows larger, our methods become dramatically better and faster than other available methods.

For example:

6 = 4, 2

7 = 4, 2, 1

14 = 4, 2, 8

22 = 4, 2, 16

15 = 4, 2, 8, 1

31 = 4, 2, 1, 8, 16

3102 = 4, 2, 2048, 1024, 16, 8

…all belong to a family of binary numbers that contain 4 and 2. This will dramatically assist a computing device with its sorting and searching methods.

6 and 160 are also compatible, which add up to **166**. 10 and 129 are compatible and add up to **139**. 10 and 160 are also compatible and add up to **170**. We will need to find their compatibility with Table 11 before we can make a determination of which will be the shortest path however.

TABLE 11

			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1	
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20	
C	G	P		1								1	1		1	1		18
D	G	P		1							1		1		1	1		66
D	G	C		1							1		1		1	1		80
T	D	G						1	1	1	1						1	192
D	C	G	1			1	1		1				1					272
C	D	G						1	1	1	1						1	320
T	D	C						1	1	1	1						1	384
D	P	G			1	1		1						1		1		514
T	D	P						1	1	1	1						1	640
C	D	P						1	1	1	1						1	768
C	P	G			1	1		1						1		1		2050
G	C	P	1			1	1		1				1					2064
D	C	P	1			1	1		1				1					2304
D	P	C			1	1		1						1		1		2560
T	P	G			1	1		1						1		1		4098
G	D	P			1			1		1	1						1	4160
D	T	P	1	1	1					1		1						4224
T	P	D			1	1		1						1		1		4608
T	P	C			1	1		1						1		1		6144
T	G	P		1							1		1		1	1		8194
T	G	C		1							1		1		1	1		8208
T	G	D		1							1		1		1	1		8256
D	T	G	1	1	1					1		1						8320
G	T	P	1	1	1					1		1						12288
T	C	G	1			1	1		1				1					16400
D	T	C	1	1	1					1		1						16512
T	C	D	1			1	1		1				1					16640
T	C	P	1			1	1		1				1					18432
C	T	P	1	1	1					1		1						20480
C	T	G	1	1	1					1		1						24576

We can then look at TABLE 11 to determine our shortest path!

TABLE 12 (example with more constraints/NOT's)

			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1	
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20	
C	G	P		1		1	1			1	1	1	1	1	1	1		18
D	G	P		1				1			1		1	1	1	1	1	66
D	G	C	1	1		1	1		1		1		1		1	1	1	80
T	D	G	1	1	1			1	1	1	1	1			1		1	192
D	C	G	1		1	1	1		1		1		1		1		1	272
C	D	G			1		1	1	1	1	1		1		1		1	320
e	t	c.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.	etc.
			...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

TABLE 13

			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1		
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20		
H	G	P		1	1	1		1			1		1	1	1	1		6	32+22+
H	D	T	1	1	1			1	1	1	1	1					1	129	45+20+
T	C	P	1			1	1		1				1					18432	92+58=
																		18567	**269**
			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1		
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20		
H	G	P		1	1	1		1			1		1	1	1	1		6	32+22+
H	T	D	1	1	1			1	1	1	1	1					1	160	45+40+
D	C	P	1			1	1		1				1					2304	58+54=
																		2470	**261**
			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1		
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20		
H	P	G		1	1	1	1	1					1	1	1	1		10	36+22+
H	D	T	1	1	1			1	1	1	1	1					1	129	45+20+
T	C	G	1			1	1		1				1					16400	92+36=
																		16539	**251**
			16384	8192	4096	2048	1024	512	256	128	64	32	16	8	4	2	1		
			92	71	67	58	54B	54A	50	45	42	40	36B	36A	32	22	20		
H	P	G		1	1	1	1	1					1	1	1	1		10	36+22+
H	T	D	1	1	1			1	1	1	1	1					1	160	45+40+
D	C	G	1			1	1		1				1					272	50+36=
																		442	**229**

In this example of the TSP, the example provided states that the traveler must begin at Home (H) and end at Home (H). This information actually provides us with information that allows us to make a number of logical assumptions straight away. If we did not know the starting and ending points we would have needed 60 groupings (HTD, HPG, etc.), but because we have this information we only required 50. For example, we know that we will never see a T**H**D or a C**H**G or the like, because H can never be in the middle, no matter what the situation. This eliminated its permutation as a possibility that the computational device will no longer need to check.

In an alternative embodiment to the examples just explained above in Tables 10-13 and to demonstrate why the present system, method and computing device that utilizes such a system is far superior than present day systems, (and to keep it simple), I will provide an alternative example wherein we do not

know our starting point. As described below we can see that the standard brute force method would require checking 120 different paths for 6 cities.

http://www.businessinsider.com/p-vs-np-millennium-prize-problems-2014-9

"If we have a Traveling Salesman Problem with five cities, we have $4 \times 3 \times 2 \times 1 = 24$ paths to look at. If we have six cities, we have $5 \times 4 \times 3 \times 2 \times 1 = 120$ paths.
As we can already see with these small numbers of cities, the number of paths grows extremely quickly as we add more cities. While it's still easy to take a given path and find its length, the sheer number of possible paths makes our brute-force approach untenable. By the time we have 30 cities, the number of possible paths is about a 9 followed by 30 zeros. A computer that could check a trillion paths per second would take about 280 billion years to check every path, about 20 times the current age of the universe.

There are algorithms for the Traveling Salesman Problem that are much more efficient than this brute-force approach, but they all either provide some kind of approximate "good enough" solution that might not be the actual shortest path, or still have the number of needed calculations grow exponentially with the number of cities, taking an unacceptably long time for large numbers of cities. There is no efficient, polynomial time algorithm known for the problem."

---Andy Kiersz

The present invention initially cuts this in half thus requiring only 60 variables to be analyzed, sorted and ordered into paths that satisfy the needed constraints of the TSP problem. For these small numbers the brute force system is likely better and faster, but as these numbers grow we can see how the present system becomes dramatically superior.

TABLE 14

Number of Cities	Brute Force Paths to Check	Varibles in the present system				
6	120	5 x	4 x	3	EQUALS	60
7	720	6 x	5 x	4	EQUALS	120
8	5,040	7 x	6 x	5	EQUALS	210
9	40,320	8 x	7 x	6	EQUALS	336
10	362,880	9 x	8 x	7	EQUALS	504
11	3,628,800	10 x	9 x	8	EQUALS	720
12	39,916,800	11 x	10 x	9	EQUALS	990
13	479,001,600	12 x	11 x	10	EQUALS	1320
14	6,227,020,800	13 x	12 x	11	EQUALS	1716
15	87,178,291,200	14 x	13 x	12	EQUALS	2184
16	1,307,674,368,000	15 x	14 x	13	EQUALS	2730
17	20,922,789,888,000	16 x	15 x	14	EQUALS	3360
18	355,687,428,096,000	17 x	16 x	15	EQUALS	4080
19	6,402,373,705,728,000	18 x	17 x	16	EQUALS	4896
20	121,645,100,408,832,000	19 x	18 x	17	EQUALS	5814
etc…	etc…	etc…				
30	8,841,761,993,739,700,000,000,000,000,000	30 x	29x	28	EQUALS	24,360

Whereas the numbers in the brute force approach get exponentially larger, our numbers actually get comparatively smaller. As the example in the chart above shows; for 6 cities we require 120 groupings, but for 7, we only require 210 and so on, which is less than double. The number of variables does obviously grow, but in smaller and smaller ratios. Here is the pattern from 6 cities. From 6 to 7 cities we 2x our number. From 7 cities to 8 cities we 1.75x our number and from 8 to 9 we 1.6x, etc. Notice how the ratios get smaller and smaller! How awesome is that!

TABLE 15

Cities	Variables	x factors
6	60	2.0000
7	120	1.7500
8	210	1.6000
9	336	1.5000
10	504	1.4286
11	720	1.3750

12	990	1.3333
13	1320	1.3000
14	1716	1.2727
15	2184	1.2500
16	2730	1.2308
17	3360	1.2143
18	4080	1.2000
19	4896	1.1875
		etc…

For the TSP problem we will need to check a number of the satisfied lower numbers as the smallest number may not be the shortest path. A low number is likely to be one of the satisfied lower paths, but recognize from the example provided that the second shortest path was actually the third lowest number.

As soon as one of our low numbered satisfied paths add up to a number lower than higher numbered potential paths (or potential partial paths), we then know that we can eliminate the upper numbers from our search! This can literally save billions of years of searching! For example; As 442 gave us a nice short path that was satisfied, then any number above this need not be investigated any further for our shortest path query. Only seven numbers were smaller than 442 in our example. Twenty-three partial paths were longer that our completely satisfied full path. Thus we can exclude these from the search, which is awesome because the computer can save an enormous amount of time.

Sorting the partial paths from smallest to largest was the key this success! The other essential and novel element of the present invention is that rather than trying to determine the shortest path by analyzing the system via its individual parts, (for which in this example there are 15), we instead combine two or more single elements, which then provide us with a number of impossible options for each selected path. This creates a NOT in logic terms, that we would not have had access to, if dealing with our variables individually. The system is made larger, but this seems like a necessity to create the necessary constrained environment.

50 partial paths (or collaborative variables), each with two variables (connected to three letters) are required if the start and end points are known. 60 partial paths are required if no starting and ending point are known. Our Sudoku example also benefited from this strategy.

SOME OTHER NP-COMPLETE PROBLEMS

Karp's 21 problems are shown below, many with their original names. The nesting indicates the direction of the reductions used. For example, Knapsack was shown to be NP-complete by reducing Exact cover to Knapsack. The methods of the present invention can be modified and transposed to solve all of these problems (and many more) in a much shorter time than is presently available.

Satisfiability: The Boolean satisfiability problem for formulas in conjunctive normal form (often referred to as SAT)

0–1 integer programming (A variation in which only the restrictions must be satisfied, with no optimization)

Clique (see also independent set problem)

Set packing

Vertex cover

Set covering

Feedback node set

Feedback arc set

Directed Hamilton circuit (Karp's name, now usually called Directed Hamiltonian cycle)

Undirected Hamilton circuit (Karp's name, now usually called Undirected Hamiltonian cycle)

Satisfiability with at most 3 literals per clause (equivalent to 3-SAT)

Chromatic number (also called the Graph Coloring Problem)

Clique cover

Exact cover

Hitting set

Steiner tree

3-dimensional matching

Knapsack (Karp's definition of Knapsack is closer to Subset sum)

Job sequencing

Partition

Factoring

Max cut

…and many more

https://en.wikipedia.org/wiki/List_of_NP-complete_problems

Appendix A

In an alternative embodiment it may be beneficial to try and limit the size of the numbers to be sorted. Computers with limited resources often have difficulty working with extremely large numbers. Naturally there are super computers that would have less difficulty with these tasks. We can do this by applying a variety of logic operators to smaller binary sets of numbers matched with an additional variable, which in this case in a color grouping. We end up trading simplicity for smaller numbers.

TABLE 16

RED	D (or Jenn)	C (or Bob)	B (or Sue)	A (or John)	
	8	4	2	1	
A (or John)	1	1	1	1	15
B (or Sue)	1	1	1	1	15
C (or Bob)	1	1	1	1	15
D (or Jenn)	1	1	1	1	15

GREEN	F (or Maggy)	E (or Colin)	D (or Jenn)	C (or Bob)	
	8	4	2	1	
C (or Bob)	1	1	1	1	15
D (or Jenn)	1	1	1	1	15
E (or Colin)	0	1	1	1	7
F (or Maggy)	1	0	1	1	11

BLUE	F (or Maggy)	E (or Colin)	B (or Sue)	A (or John)	
	8	4	2	1	
A (or John)	1	1	1	1	15
B (or Sue)	1	1	1	1	15
E (or Colin)	0	1	1	1	7
F (or Maggy)	1	0	1	1	11

YELLOW	D (or Kelly)	C (or Jim)	B (or Sue)	A (or John)	
	8	4	2	1	
A (or John)	1	1	1	1	15
B (or Sue)	1	1	1	1	15
G (or Jim)	0	1	1	1	7
H (or Kelly)	1	0	1	1	11

ORANGE	H (or Kelly)	G (or Jim)	F (or Maggy)	E (or Colin)	
	8	4	2	1	
E (or Colin)	0	0	0	1	1
F (or Maggy)	0	0	1	0	2
G (or Jim)	0	1	0	0	4
H (or Kelly)	1	0	0	0	8

WHITE	H (or Kelly)	G (or Jim)	D (or Jenn)	C (or Bob)	
	8	4	2	1	
C (or Bob)	0	0	1	1	3
D (or Jenn)	0	0	1	1	3
G (or Jim)	0	1	0	0	4
H (or Kelly)	1	0	0	0	8

Then we sort.

TABLE 17

ORANGE	1	E (or Colin)
ORANGE	2	F (or Maggy)
WHITE	3	C (or Bob)
WHITE	3	D (or Jenn)
ORANGE	4	G (or Jim)
WHITE	4	G (or Jim)
BLUE	7	E (or Colin)
GREEN	7	E (or Colin)
YELLOW	7	G (or Jim)
ORANGE	8	H (or Kelly)
WHITE	8	H (or Kelly)
BLUE	11	F (or Maggy)
GREEN	11	F (or Maggy)
YELLOW	11	H (or Kelly)
RED	15	A (or John)
RED	15	B (or Sue)
RED	15	C (or Bob)
RED	15	D (or Jenn)
BLUE	15	A (or John)
BLUE	15	B (or Sue)
GREEN	15	C (or Bob)
GREEN	15	D (or Jenn)
YELLOW	15	A (or John)
YELLOW	15	B (or Sue)

This method gets a little tricky as many factors need to be taken into consideration, but can be repeated in numerous levels as the systems get larger. We can see that the numbers 15 create a four clique of red, blue, green and yellow. To look for a larger clique than 4x4 we see that Blue and Green contain John, Sue, Bob and Jenn, but so does 11 with Maggy (Blue & Green). 7 Colin also has two colors Blue and Green. A somewhat more complicated logic is required here and the color groups become an actual variable.

We can also use our collaborative variables here as A&B, B&C and C&A, could all be smaller variables that would show that AB&C are all friends. In this instance A&B would be a binary number such as 1, 2, 4, 8, etc. This could be repeated on a number of levels and in a variety of ways.

Although features and elements are described above in particular combinations, one of ordinary skill in the art will appreciate that each feature or element may be used alone or in any combination with the other features and elements. In addition, the methods described herein may be implemented in a computer program, software, or firmware incorporated in a computer-readable medium for execution by a computer or processor. Examples of computer-readable media include electronic signals (transmitted over wired or wireless connections) and computer-readable storage media. Examples of computer- readable storage media include, but are not limited to, a read only memory (ROM), a random access memory (RAM), a register, cache memory, semiconductor memory devices, magnetic media such as internal hard disks and removable disks, magneto-optical media, optical media such as CD-ROM disks, and digital versatile disks (DVDs). Examples of computing systems are personal computers, laptop computers, super computers, tablets, data transfer systems and smart phones.

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About the Author

John Archie Gillis is from Halifax, NS, Canada. This is the first rough draft of his paper. He hopes to publish the completed version in a peer-reviewed journal at some point in time to try and win one of the Clay Mathematics Institutes Million-Dollar Millennium Prizes. This paper purposes to finally solve one of the six remaining Clay Mathematics open math problems, called the P versus NP problem. He also hopes to secure financing to complete the patenting process for his methods (PCT application), as soon as possible.

Thanks for reading!

John Archie Gillis