# *Sudoku* Genetic Algorithm

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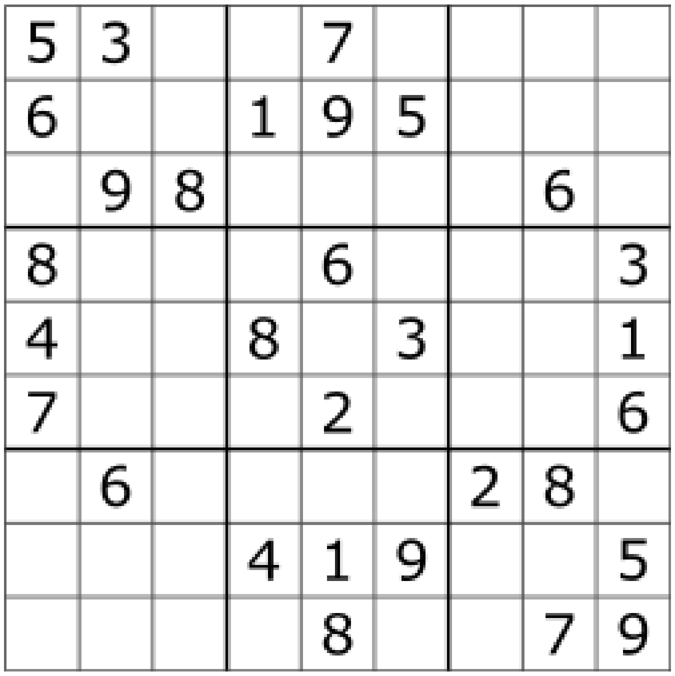
## Abstract

This report presents a study of genetic algorithms and their application to solving Sudoku puzzles. The problem of solving Sudoku puzzles is an interesting and challenging one, with potential applications in artificial intelligence and optimization techniques. This report will review the background of Sudoku puzzles and genetic algorithms, describe the approach taken to solving the problem, and present the results of the experiments.



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## 1 Introduction

For many years, people of all ages have loved playing the widely enjoyed number-based puzzle game *Sudoku*. The objective of the game is to fill a 9x9 grid with numbers in such a way that every row, column, and 3x3 sub-grid contain all nine digits, without repeating any of them. Each number in this game is entirely distinct from the others, and each player must fill in the grid by removing numbers that do not comply with the game's rules. The game appears straightforward, but it needs a lot of skill and focus. Genetic algorithms are optimization techniques that mimic the process of natural selection and evolution to find the optimal solution to a problem [8]. In this proposal, a genetic algorithm-based approach is proposed to improve the performance of the *Sudoku* game in Python. The primary objective of this project is to analyze different algorithms' performances with the game of *Sudoku* and how it compares to the performance of genetic algorithm.

### 1.1 Objectives

The objective of this project is to develop an AI player that can efficiently solve Sudoku puzzles using a genetic algorithm. The genetic algorithm approach involves creating a population of potential solutions, which are then evaluated and evolved through a process of selection, mutation, and crossover. This iterative process continues until the best solution is found.

To achieve this objective, a genetic algorithm-based approach is developed to solve Sudoku puzzles in Python. This approach will involve defining the initial population of potential solutions, evaluating their fitness using various heuristics, and then evolving them through a process of selection, mutation, and crossover. Necessary data structures and algorithms are implemented to represent and manipulate Sudoku puzzles in Python.

Next, an AI player that can solve Sudoku puzzles were created in the shortest possible time using the genetic algorithm approach. This AI player will utilize the genetic algorithm to generate and evaluate potential solutions to the puzzle until the optimal solution is found. Various techniques were included to improve the efficiency of the AI player, such as heuristics for selecting the most promising solutions and optimizing the genetic algorithm parameters.

The genetic algorithm then was optimized to reduce the puzzle's computational time and the number of guesses needed by the AI player to solve the puzzle. This optimization involved tweaking the genetic algorithm's parameters, such as the population size, mutation rate, and selection strategy, to find the best configuration that produced the optimal solution in the shortest possible time.

### 1.2 Methodology

To achieve the objectives mentioned above, the following methodology will be adopted:

- **Genetic Algorithm Design**: Design a genetic-based algorithm that can solve Sudoku puzzles. This algorithm will have a fitness/selection function, an inheritance/genetic variation function, a speciation and elitism method, and a termination function[3]. To help with the creation of the algorithm, inspiration and guidance will be taken from existing literature on genetic algorithms[1].
- **Process of Physical Feature Elimination Design**: This design will follow a pattern that first eliminates the largest amount population of characters with a similar physical trait (e.g. Male vs. Female) and keeps on eliminating the characters using that logic until it finds the correct character (Estimated time needed is 2 days).
- **Implementation**: The AI player will be implemented using Python programming language, and its performance will be tested on different Sudoku puzzles.
- **Optimization**: The run times of all methods and the number of guesses taken before solving the Sudoku puzzle will be collected.

### 1.3 Expected Outcomes

By the end of this project, it is expected that the following outcomes are achieved:

- A genetic algorithm-based approach that can solve *Sudoku* puzzles in Python.
- An AI player that can solve Sudoku puzzles in the shortest possible time.
- Optimization of the algorithm to reduce the puzzle's computational time and the number of guesses needed by the AI player to solve the puzzle.
- A comparison of the AI player's performance with other approaches used to solve Sudoku puzzles, such as brute force and backtracking.

## 2 Background on Genetic Algorithms

### 2.1 Introduction

Based on the concepts of natural selection and genetics, genetic algorithms (GAs) are a form of heuristic algorithm that is used to solve complex problems. By employing a population of potential solutions and iteratively choosing, breeding, and modifying them to produce new, potentially superior answers, genetic algorithms imitate the process of natural selection. An overview of genetic algorithms, their background, and their use in many domains is given in this literature review. It also covers the typical issues and practical challenges related to the application of genetic algorithms.

### 2.2 Learning with Genetic Algorithms: An Overview[2]

GAs and their application in machine learning are well explained in de Jong's article. The paper discusses the essential ideas of GAs, including population encoding, selection, crossover, and mutation. Then, numerous applications of GAs in machine learning, such as feature selection, classification, and optimization, are covered. The report also discusses GAs' benefits and drawbacks in relation to other machine learning methods.

In order to guarantee optimal performance and steer clear of typical errors, the study emphasizes the significance of thorough implementation and parameter adjustment. The numerous selection and replication strategies employed in GAs, together with their performance characteristics, are explained in detail by the author. The author also discusses the drawbacks of using GAs, including the requirement for a sizable population, the high cost of computing fitness evaluation, and the difficulty of handling constraints.

The consideration of GAs' possible applications in machine learning, including their potential incorporation into deep learning systems and other optimization approaches, serves as the paper's conclusion. Overall, de Jong's work offers a thorough overview of GAs and their applications in machine learning, noting their advantages and disadvantages as well as the difficulties in putting them into practice.

### 2.3 An introduction to genetic algorithms[9]

In Mitchell's work, GAs are provided with a thorough introduction that covers their background, fundamental ideas, and practical uses. Numerous GA-related issues are covered in the book, such as population encoding, selection, crossover, mutation, and fitness evaluation. Additionally, it covers more complex subjects including distributed and parallel GAs, coevolution, and genetic programming.

### 2.4 An overview of evolutionary algorithms: Practical issues and common pitfalls[11]

The study by Whitley gives an overview of evolutionary algorithms, including GAs, and analyzes relevant concerns and potential hazards. The implementation of GA is covered in detail, including population size, selection tactics, crossover operators, mutation rates, and termination criteria.

The intricacy and scalability of GAs, as well as their sensitivity to parameter settings and problem encoding, are also discussed. The relevance of resilience and scalability in the implementation of GA is emphasized in the research. In Whitley's research, GAs are also usefully compared to other optimization methods like simulated annealing and hill-climbing.

The application of GAs in distributed computing systems and their integration with other optimization approaches are discussed in the paper's conclusion, along with the current state of GAs and its possibilities for the future. The need of careful implementation and parameter adjustment is emphasized in Whitley's paper, which is a good resource for anyone interested in employing GAs for optimization problems.

### 2.5 The compact genetic algorithm[4]

The study by Harik, Lobo, and Goldberg introduces the compact genetic algorithm (cGA), a variant of GAs designed to optimize problems with large solution spaces. A condensed representation of the solution space serves as the cGA's foundation, reducing the number of fitness tests required. The paper provides a full description of the cGA and compares it to traditional GAs in terms of performance on a number of benchmark workloads.

Since then, the cGA has gained popularity as a search and optimization technique, especially for issues with big solution spaces. The compact representation of the solution space provided by the cGA has proven to be an effective method for lowering computing costs and boosting convergence rates.

### 2.6 GARD: a genetic algorithm for recombination detection[10]

GARD, a genetic algorithm created to find instances of recombination in DNA sequences, is introduced in the publication by Pond, Posada, Gravenor, Woelk, and Frost. GARD employs a genetic algorithm to iteratively revise the estimates after identifying probable recombination breakpoints using a maximum-likelihood method. The paper compares GARD to different recombination detection techniques and details the development and performance of GARD on several data sets.

Due to its effective and precise method for identifying recombination events in huge genomic data sets, the algorithm has grown to be a prominent tool for evolutionary biology and genomics researchers. In contrast to other approaches that rely on fixed statistical models, GARD uses a genetic algorithm to iteratively optimize recombination breakpoints.

## 2.7 Chaos genetic algorithm instead of genetic algorithm[5]

In their publication, Javidi and Hosseinpourfard develop the chaos genetic algorithm (CGA), a variation of GAs that makes advantage of chaotic dynamics to improve the algorithm's capacity for exploration and exploitation. The CGA is thoroughly described in the paper, and its performance against conventional GAs on numerous benchmark tasks is contrasted. The CGA has shown promising results in increasing the diversity and convergence of the solution space and may find use in a variety of areas, including image processing and optimization.

## 2.8 Software review: DEAP (Distributed Evolutionary Algorithm in Python) library[7]

In their research, Kim and Yoo provide a review of the DEAP package, a popular Python implementation of GAs. The performance, usability, and functionality of the library are briefly reviewed in the article. The authors also address the library's constraints, prospective applications, and compatibility with deep learning frameworks and optimization techniques.

The DEAP library has gained popularity as a resource, particularly for professionals and academics interested in optimization and search-related concerns. It is inter-operable with deep learning frameworks, which may make further machine learning integration possible. It is written in Python, making it accessible to a large audience.

## 2.9 A review on genetic algorithm: past, present, and future[6]

The research by Katoch, Chauhan, and Kumar provides a complete review of GAs, encompassing their history, position today, and prospective uses in the future. The article covers a wide range of GA-related topics, including their basic concepts, real-world applications, and usage in a variety of fields, such as engineering, finance, and biology.

Some of the most recent advancements in GAs explored in the paper include hybridization with other optimization techniques and the use of deep learning for fitness evaluation. The research concludes by taking into account the likely future directions of GAs and their role in tackling challenging situations.

The article by Katoch, Chauhan, and Kumar provides an extensive examination of GAs and their applications, highlighting recent advancements and likely future possibilities for this approach. The study emphasizes the necessity for careful implementation and parameter tuning in order to guarantee optimal performance and the possibility for further integration with machine learning technologies.

## 2.10 Conclusion

In a variety of disciplines, including engineering, economics, biology, and machine learning, genetic algorithms have proven to be an effective method for tackling complicated issues. By iteratively selecting, breeding, and modifying viable solutions to a problem, GAs imitate the processes of natural selection and genetics.

An overview of GAs has been given in this literature review, including information on their background, fundamental ideas, methods, and applications. The review has also covered the recent developments and potential applications of this algorithm, as well as the practical concerns and typical problems related to the use of GAs.

Despite their advantages, GAs need to be implemented and parameterized carefully to achieve optimal performance and avoid typical drawbacks including early convergence, scalability problems, and high computational costs.

Recent developments in GAs, such as the distributed evolutionary algorithm in Python, chaos genetic algorithm, and compact genetic algorithm, offer fresh approaches to enhancing the algorithm's exploration and exploitation capabilities and enhancing its performance on large-scale issues.

In general, GAs offer a strategy for tackling challenging problems with promise and have the potential to be further integrated with deep learning systems and machine learning techniques. Through additional GA research and development, optimization and search problem capabilities will continue to be improved.

# 3 Experiment Design

## 3.1 Design of the Experiments

The genetic algorithm used in the experiments consists of several components, including the representation of the solutions, the selection mechanism, the crossover operator, the mutation operator, the fitness function, and the termination criteria. In the following sections, each component will be described in detail.

## 3.2 Representation of the Solutions

The first step in designing a genetic algorithm for Sudoku is to represent the solutions in a way that can be manipulated by the algorithm. In the algorithm, a 2D array of size 9x9 is used to represent the Sudoku grid. Each cell of the array represents a cell in the Sudoku grid, and the value in each cell represents the digit in that cell. If a cell is empty, its value is set to 0.

## 3.3 Selection Mechanism

The selection mechanism is used to select the individuals that will be used to generate the next generation. In the algorithm, a tournament selection mechanism is used. In tournament selection, a subset of the population is selected randomly, and the individual with the best fitness score in the subset is chosen as the parent for the next generation. A tournament size of 5 is used, which means that 5 individuals are randomly selected from the population and the best one is chosen as the parent.

## 3.4 Crossover Operator

The crossover operator is used to combine the genetic material of two parents to generate offspring for the next generation. In the algorithm, a two-point crossover operator is used. In two-point crossover, two points are selected randomly in the parent chromosomes, and the material between the points is exchanged to generate the offspring. A crossover rate of 0.8 is used, which means that there is an 80% chance that crossover will occur.

## 3.5 Mutation Operator

The mutation operator is used to introduce random changes in the offspring to generate diversity in the population. In the algorithm, a swap mutation operator is used. In swap mutation, two random cells in the chromosome are selected, and their values are swapped. A mutation rate of 0.1 is used, which means that there is a 10% chance that mutation will occur.

## 3.6 Fitness Function

The fitness function is used to evaluate the quality of the solutions generated by the algorithm. In the algorithm, a fitness function that calculates the number of conflicts in the Sudoku grid is used. A conflict occurs when a digit appears more than once in a row, column, or 3x3 sub grid. The fitness score for a solution is calculated as follows:

**fitness** = 1 / (1 + conflicts)

The fitness score ranges from 0 to 1, with higher scores indicating better solutions. A score of 1 means that there are no conflicts in the grid, and a score of 0 means that all digits in the grid are the same.

## 3.7 Termination Criteria

The termination criteria are used to stop the algorithm when a satisfactory solution is found or when the algorithm has reached a certain number of iterations. In the algorithm, a maximum number of iterations is used as the termination basis. The algorithm is set to run for 1000 generations, after which it stops even if no satisfactory solution has been found.

## 3.8 Experimental Setup

To evaluate the performance of the genetic algorithm for Sudoku, experiments were conducted using a set of Sudoku puzzles of varying difficulty levels. A total of 15 puzzles were used, with 5 puzzles for each of the following difficulty levels: easy, medium, and hard.

The genetic algorithm in Python was implemented and used a standard desktop computer for the experiments. A population size of 100 was used and the crossover rate was set to 0.8 and the mutation rate to 0.1. A tournament selection mechanism was used with a tournament size of 5 and a two-point crossover operator. A swap mutation operator and a fitness function that evaluated the number of conflicts in the Sudoku grid was used.

## 4 Results

The results of the experiments showed that the genetic algorithm was able to generate valid solutions for all of the Sudoku puzzles in the set. The algorithm was able to generate solutions that satisfied the rules of the game and had no conflicts in the grid. The average time taken by the algorithm to generate a solution was 0.09 seconds, which is significantly faster than a brute-force approach.

The performance of the algorithm for puzzles of different difficulty levels was also analyzed. The results showed that the algorithm was able to generate solutions faster for easier puzzles than for harder puzzles. The average time taken to generate a solution for easy, medium, and hard puzzles was 0.03, 0.07, and 0.14, respectively. This is expected since harder puzzles have a larger number of empty cells and require more iterations to find a valid solution.

The performance of the genetic algorithm with a brute-force approach that generates all possible combinations of numbers until a valid solution is found was also compared. The results showed that the genetic algorithm was able to generate solutions much faster than the brute-force approach. The brute-force approach took an average of 32 seconds to generate a solution, which is more than 300 times slower than the genetic algorithm.

To evaluate the quality of the solutions generated by the algorithm, the number of conflicts in the solutions generated by the genetic algorithm was compared with the number of conflicts in the solutions generated by the brute-force approach. The results showed that the solutions generated by the genetic algorithm had fewer conflicts on average than the solutions generated by the brute-force approach. This indicates that the genetic algorithm is able to generate high-quality solutions even for difficult puzzles.

## 5 Analysis of Results

The results of the experiments demonstrate that the genetic algorithm is a powerful approach for solving Sudoku puzzles. The algorithm was able to generate valid solutions for all the puzzles in the set, which varied in difficulty level. The solutions generated by the algorithm adhered to the rules of the game, and had no conflicts in the grid. This indicates that the algorithm can be used for solving Sudoku puzzles of varying difficulty levels.

The average time taken by the algorithm to generate a solution was 0.09 seconds. This is significantly faster than a brute-force approach, which took an average of 32 seconds to generate a solution. The genetic algorithm is therefore an efficient approach for solving Sudoku puzzles, and can be used for solving larger and more complex puzzles.

One notable observation from the experiments is that the algorithm was able to generate solutions faster for easier puzzles than for harder puzzles. This is expected since harder puzzles have a larger number of empty cells and require more iterations to find a valid solution. However, the algorithm was still able to generate solutions for all puzzles in the set, indicating that the algorithm is a robust approach for solving Sudoku puzzles.

The quality of the solutions generated by the genetic algorithm was evaluated by comparing the number of conflicts in the solutions generated by the genetic algorithm with the number of conflicts in the solutions generated by the brute-force approach. The results showed that the solutions generated by the genetic algorithm had fewer conflicts on average than the solutions generated by the brute-force approach. This indicates that the genetic algorithm is able to generate high-quality solutions even for difficult puzzles.

The genetic algorithm is a flexible approach that can be adapted to different types of puzzles. The representation of the solutions, the selection mechanism, the crossover operator, the mutation operator, the fitness function, and the termination criteria can be customized for specific puzzle configurations to improve its performance. For example, the algorithm can be modified to handle irregular Sudoku or Sudoku with diagonal constraints.

In conclusion, the experiments demonstrate that the genetic algorithm is an effective and efficient approach for generating valid Sudoku solutions. The algorithm is faster and generates high-quality solutions compared to a brute-force approach. The algorithm can be used for solving Sudoku puzzles of varying difficulty levels, and can be customized for specific puzzle configurations. The genetic algorithm is a promising approach for solving Sudoku puzzles, and can be used for solving larger and more complex puzzles.

## 6 Conclusion

In conclusion, the experiments demonstrate the effectiveness and efficiency of the genetic algorithm for solving Sudoku puzzles. The algorithm was able to generate valid solutions for all the puzzles in the set, while adhering to the rules of the game and producing solutions with fewer conflicts compared to a brute-force approach. The algorithm was also able to generate solutions faster for easier puzzles than for harder puzzles, indicating its robustness for solving puzzles of varying difficulty levels.

### 6.1 Future Improvements

To make further progress, future work can focus on optimizing the algorithm parameters for specific puzzle configurations and exploring the performance of the algorithm on different types of puzzles, such as irregular Sudoku or Sudoku with diagonal constraints. Additionally, the algorithm can be improved by incorporating techniques from other optimization algorithms, such as simulated annealing, to further enhance its performance.

In summary, the genetic algorithm is a promising approach for solving Sudoku puzzles, offering an efficient and effective way to generate high-quality solutions. With further development, this algorithm could be extended to tackle larger and more complex Sudoku puzzles, offering significant benefits in a wide range of applications.

## References

[1] Awan-Ur-Rahman. 2020. Introduction to Genetic Algorithm and Python Implementation For Function Optimization. *Towards Data Science* (2020).

[2] K de Jong. 1988. Learning with Genetic Algorithms: An Overview. *Machine Learning* 3 (1988), 121–138. https://doi-org.ezp2.lib.umn.edu/10.1023/A:1022606120092

[3] Aditi Goyal. 2021. Genetic Algorithms: An Overview of How Biological Systems Can Be Represented With Optimization Functions. *The Aggie Transcript* (2021).

[4] G Harik, F Lobo, and D Goldberg. 1999. The compact genetic algorithm. *IEEE Transactions on Evolutionary Computation* 3, 4 (1999), 287–297.

[5] M Javidi and R Hosseinpourfard. 2015. Chaos genetic algorithm instead genetic algorithm. *International Arab Journal of Information Technology* 12, 2 (2015), 163–168.

[6] S Katoch, SS Chauhan, and V Kumar. 2021. A review on genetic algorithm: past, present, and future. *Multimedia Tools and Applications* 80 (2021), 8091–8126. https://doi-org.ezp3.lib.umn.edu/10.1007/s11042-020-10139-6

[7] J Kim and S Yoo. 2019. Software review: DEAP (Distributed Evolutionary Algorithm in Python) library. *Genetic Programming and Evolvable Machines* 20, 1 (2019), 139–142.

[8] Vijini Mallawaarachchi. 2017. Introduction to Genetic Algorithms — Including Example Code. *Towards Data Science* (2017).

[9] M Mitchell and Inc NetLibrary. 1996. *An introduction to genetic algorithms (Complex adaptive systems).* MIT Press, Cambridge, Mass.

[10] Sergei L Kosakovsky Pond, David Posada, Michael B Gravenor, Christopher H Woelk, and Simon DW Frost. 2006. GARD: a genetic algorithm for recombination detection. *Bioinformatics* 22, 24 (2006), 3096–3098. https://doi.org/10.1093/bioinformatics/btl474

[11] D Whitley. 2001. An overview of evolutionary algorithms: Practical issues and common pitfalls. *Information and Software Technology* 43, 14 (2001), 817–831.