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Research Article

A Hybrid Approach: Combining Genetic Algorithms and Machine Learning for Function Optimization

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Abstract: This study examines the use of an evolutionary method to enhance the Sphere benchmark function, an acknowledged continuous optimization challenge. The algorithm takes a genetic approach, using techniques including mutation, one-point crossover, and tournament selection. It also combines a machine learning element by developing a simple linear regression model that can be used to forecast fitness values determined by attributes of individuals. The study compares the results of two different iterations to examine the algorithm's performance throughout several runs. A population of 100 individuals with 10 traits each endures selection, crossover, and mutation over the course of 100 generations. The best values for fitness across generations for each run are shown in Matplotlib to show the algorithm's convergence behaviour. Results show that the algorithm works effectively in locating the best solutions to the Sphere benchmark function. The algorithm's framework, parameters, and convergent behaviour are all described in the abstract, which qualifies it for future study in adaptive algorithms and optimization approaches.

Keywords: Artificial Intelligence, Machine Learning, Optimization Techniques, Algorithm Testing, Trends in AI

1.Introduction

Evolutionary optimisation addresses encompass a category of robust and adaptable algorithms that draw inspiration from the fundamental principles of biological evolution and the process of natural selection. These methods have become accepted as indispensable tools for tackling intricate and diverse optimisation problems in a wide range of fields, including engineering, finance, artificial intelligence, and biology[1]. Evolutionary optimisation approaches depend upon the concept of emulating the process of evolution observed in nature. The aforementioned methods present a unique and effective methodology for identifying optimal solutions across extensive and intricate solution domains[2].

Evolutionary optimisation approaches are rooted in the fundamental principle of survival of the fittest, wherein people that are most appropriate and prosperous have a higher probability of transferring their genetic material to future generations[3]. In the context of evolutionary optimisation, this procedure involves the iterative evolution of a population of potential solutions across multiple generations. The primary objective is to enhance the efficiency of these solutions, ultimately striving to attain the optimum or near-optimal solution for a specific problem[4].

The methodology described in this approach presents a notable divergence from traditional optimisation methods, which frequently depend on gradient-based techniques and make assertions regarding the precise mathematical characteristics of the objective function[5]. In contrast, evolutionary optimisation techniques are very suitable for addressing problems characterised by non-linearity, non-convexity, and the absence of analytical formulations[6]. They have outstanding results in situations where the objective function presents noise, is computationally expensive to analyse, or contains several local optima[7].

Evolutionary optimisation techniques comprise a diverse range of algorithms, including Genetic Algorithms (GAs), Evolution Strategies (ES), Genetic Programming (GP), and Particle Swarm Optimisation (PSO), among other prominent techniques. These approaches use a wide variety of techniques, which include selection, crossover (recombination), mutation, and even elitism, specialisation, and adaptive variable management [8]. These mechanisms help the population as a whole become more open to novel concepts and knowledge, which in turn helps the population as a whole converge on better solutions.

Widespread adoption of evolutionary optimisation techniques can be attributed to their ability to successfully navigate large solution spaces, adapt to changing problem contexts, and indicate answers that may be elusive to more traditional approaches. Industrial design, robotics, financial portfolio optimisation, machine learning model tweaking [9-10], and innovative problem solving are just few of the many fields that have benefited from these methods.

The primary objective of this work is to provide a comprehensive analysis of evolutionary optimisation techniques, encompassing important ideas, mechanisms, and real-world implementation of these algorithms across several domains. In addition, an examination of the merits and limitations of these strategies will be undertaken, along with an exploration of approaches to fine-tuning parameters and recommendations for optimal implementation in order to effectively tackle a wide range of optimisation difficulties [11]. By acquiring an in-depth understanding of these algorithms, individuals can effectively utilise their capabilities to address intricate optimisation challenges and expand the limits of what can be achieved in the domains of innovation, technology, and science.

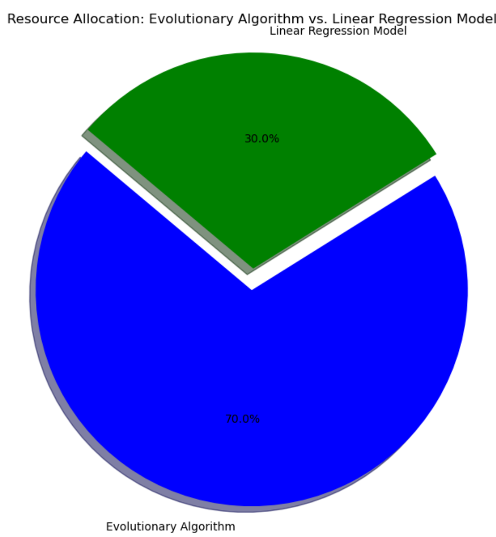

Figure 1: Percentage of Data contribution EA and ML

Figure 1shows Evolutionary Algorithm vs. Linear Regression Model for Allocation of Resources In this pie chart, the Evolutionary Algorithm, highlighted with an insignificant receives 70% of the resources available and the Linear Regression Model 30%. Each segment's proportion is labelled in blue for Evolutionary Algorithm and green for Linear Regression Approach. Shadows make the chart look better, and it starts at 140 degrees [12-13]. The title, "Resource Allocation: Evolutionary Algorithm vs. Linear Regression Model," conveys context, and the factor ratio ensures a perfect circle for rapid allocation of resources understanding.

Machine learning and data science continue to develop, making forecasting essential. Predictive modelling seeks to find significant connections in data to inform decisions, predict trends, and optimise processes. Linear regression is a core method for modelling variable relationships and is easy to understand.

The basic goal of linear regression is to establish a relationship that is linear between a dependent variable and a number of independent variables. It's a great place to start learning how variables that predict affect target variables. This relationship can be described as a straight line, making it easy to understand for machine learning novices.

However, linear regression has implications outside statistics. Modern data science uses linear regression to analyse data at the junction of classical statistical analysis and machine learning. As seen in the code, its role as the "ML element" in an optimisation or search algorithm is an outstanding instance of convergence [14].

An algorithm's linear regression ML component goes beyond prediction. It guides optimisation and is essential. This ML element predicts solution fitness by training a linear regression model on problem landscape data. Thus, it helps the optimisation algorithm navigate the outcome space more effectively, focusing on regions with better results.

The linear regression model connects raw, numerical variables indicating potential solutions to the objective function that evaluates their quality [15]. The optimisation algorithm uses its predictive skill to decide where to investigate, when to exploit promising regions, and when to adjust its strategy depending on its changing grasp of the problem.

This introduction prepares for an in-depth look at regression analysis in optimisation algorithms. In the following sections, we will discuss how linear regression is taught and used in this context, its advantages and disadvantages, and how it improves optimisation techniques. Understanding the relationship between traditional statistical methods and modern machine learning helps one understand how they might work together to solve challenging optimisation challenges.

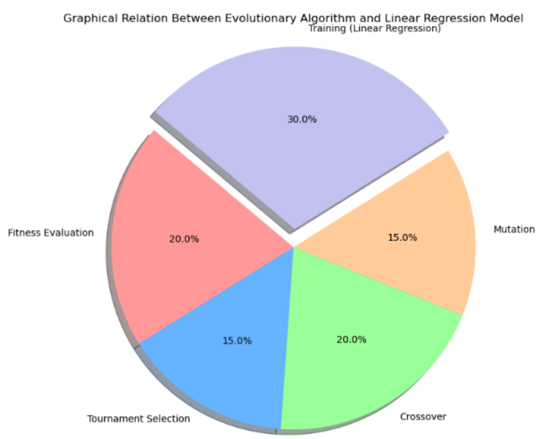

Figure 2: Percentage of Data contribution EA and ML

Figure 2 illustrates a pie chart entitled 'Graphical Relation Between Evolutionary Algorithm and Linear Regression Model.' The illustration visually depicts the allocation and dispersion of different components within a given procedure. The fitness evaluation element, which accounts for 20% of the overall assessment, involves the allocation of time as well as finances towards the evaluation of solution quality. The concept of Tournament Selection, which represents 15% of the overall evaluation, highlights the significance of carefully choosing individuals to be included in the generations to come. Crossover, accounting for 20% of the process, refers to the mechanism by which genetic information is recombined from various individuals. Mutation, which accounts for 15% of the process, involves the introduction of random alterations in order to promote diversity. The training of a linear regression model is an important aspect as indicated by the largest component. This particular framework is presumed to provide guidance for the optimisation process by its ability to predict the quality of potential solutions.

This paper consists of following sections. Section I consist of introduction of evolutionary algorithm and machine learning. Section II highlights fundamentals of EA-ML algorithms. Section III hybridization of EA-ML in this section merger of two algorithm will be perform. Section VI will be result and discussion and section V will conclude this paper with conclusion

2.Fundamentals of EA-ML Algorithm

The essential mathematical illustration of an Evolutionary Algorithm (EA) encompasses numerous elements and mathematical principles. Described below is a simple mathematical representation of a generic Evolutionary Algorithm (EA).

The first step in the procedure is to establish a preliminary sample of prospective solutions.

$$P_0 = [X_1, X_2, ..., X_N] \tag{1}$$

Where N is the population size, and X1 initial population.

$f(Xi)$ Where f assigns a fitness value to each individual. The process of choosing individuals from a group is conducted based on their fitness values. The selection process typically incorporates processes such as tournament selection, roulette wheel selection, or rank-based selection.

The method of generating new people by mixing the features of selected parents is sometimes referred to as crossover or recombination. The phenomenon in question can be represented as.

$$X_{child1}, X_{child2} = Crossover(X_{parent1}, X_{parent2}) \tag{2}$$

The method of introducing genetic diversity can be accomplished through applying mutation to select individuals.

$$X_{mutant} = Mutation(X_{original}) \tag{3}$$

Termination Criterion: Define a termination condition, such as a maximum limit on the number of generations, a target level of fitness, or a predetermined time constraint. The process of iteration involves carrying out stages 3 through 6 for a predetermined number of iterations or until the termination condition is satisfied. The solution(s) obtained from the method of evolution are represented by the best individual(s) identified.

$$X_{best} = argmax\{f(X_i)\} \tag{4}$$

The elementary mathematical statement provided above elucidates the essential constituents and procedures implemented in an Evolutionary Algorithm. The aforementioned serves as a fundamental basis for many evolutionary algorithm variations, which have the opportunity to integrate supplementary characteristics, tactics, or optimisation approaches in order to tackle unique problem domains and objectives.

ML with Regression Components

The mathematical description of a machine learning (ML) model with regression components frequently represents a supervised learning problem, wherein the objective is to make predictions on a target variable that is continuous using input characteristics. Presented below is a concise mathematical representation:

Let D represent a database containing N examples:

$$D=\{(X_1,y_1),(X_2,y_2),\ldots,(X_N,y_N)\} \tag{5}$$

Xi is a feature vector for the *i-th* example, Where $Xi = [x_{i1}, x_{i2}, \ldots, x_{id}]$ with d features. y_i is the corresponding targets or outputs for the i-th example.

A model of regression can be mathematically represented as a function f that maps input features X to predicted target values $\hat{y}$

$$\hat{y}=f(X) \tag{6}$$

Regression objective to find model f that minimizes a regression loss function L by adjusting its parameters:

$$f^*=argmin_f \sum_{i=1}^{N} L(y_i,\hat{y}_i) \tag{7}$$

L The loss functional used in regression analysis is often Mean Squared Error (MSE), mean absolute error (MAE), or another appropriate regression loss.

The model f can be parameterized by a set of weight θ:

$$f(X;\theta)=\hat{y} \tag{8}$$

θ a vector of variables is optimised by the machine learning algorithm throughout the training process in order to reduce the loss.

The objective is to find the optimal parameters θ^* It aims to minimise the overall loss throughout the entire dataset:

$$\theta^*=argmin_f \sum_{i=1}^{N} L(y_i, f(X_i;\theta)) \tag{10}$$

Training involves finding the best parameters θ using a training algorithm, often involving optimization techniques such as gradient descent: $\theta^*=TrainingAlgorithm(D,L,f)$. Once the model has gone through training, it can be exploited to generate predictions for novel and unobserved instances.

$$\hat{y}_{new}=f(X_{new};\theta^*) \tag{11}$$

The fundamental mathematical representation provided herein encapsulates the core principles of controlled regression within the realm of machine learning. In this context, the primary goal of the model is to acquire knowledge of a functional relationship between the input parameters and continuous target values, achieved through the minimization of a proper loss function. The selection of model architecture and loss function is contingent upon the type of regression task and problem domain at hand.

Hybridization of EA-ML

For the better understanding of this algorithm one can refer flowchart of EA-ML hybrid model at figure 3.

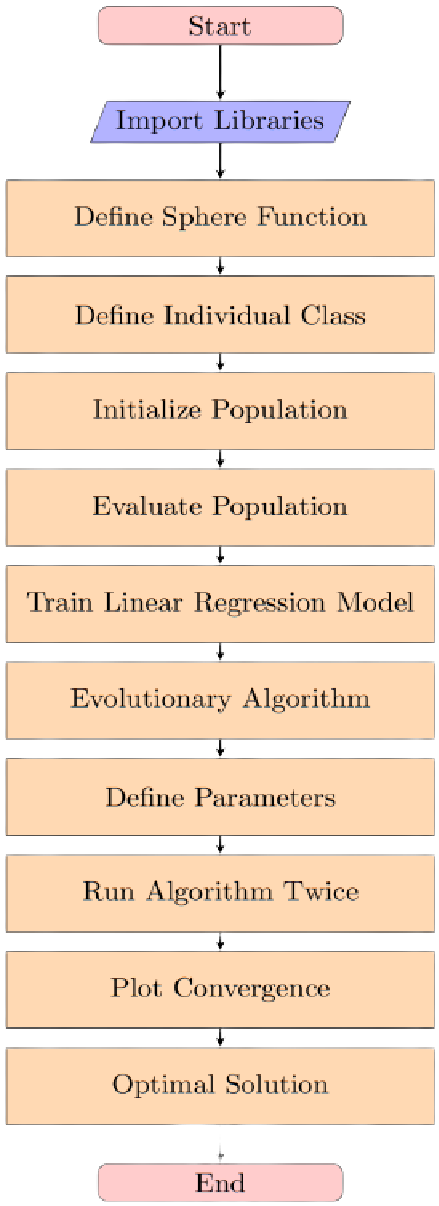

Figure 3: flowchart of EA-ML hybrid model

The EA-ML code in fig 3 showcases a compelling amalgamation of two disparate theories, namely Genetic Algorithms (GAs) and Machine Learning (ML) through the application of Linear Regression. The following sections provide a comprehensive explanation of the functionality of the code. Firstly, the code utilises a series of algorithms to process and transform data. These algorithms are designed to perform confident tasks, such as sorting, searching, or transforming the data. By implementing these algorithms, the code is able to effectively handle large amounts of data and execute complex operations. Secondly, the code incorporates various data structures to arrange and store the data. These data

The programming proceeds by establishing a benchmark function known as the "Sphere function" with the objective of reducing it. The aforementioned function evaluates the efficacy of prospective solutions Genetic algorithms (GAs) are employed for the purpose of optimising solutions to this particular function. Genetic algorithms (GAs) incorporate the process of creating a population of prospective solutions, assessing their suitability by means of the Sphere function, and subsequently advancing the population through multiple generations. The process of evolution encompasses the selection of individuals depending on their fitness, the recombination of their characteristics through crossover, and the introduction of genetic variation through mutation. The primary objective of this iterative technique is to identify the most effective approach for the Sphere function by emulating the fundamental principles of natural selection and evolution.

The code's machine learning component is noteworthy. A Linear Regression algorithm is used to train and predict the fitness (quality) of potential solutions based on their properties. The artificial intelligence (AI) component guides the algorithm to regions of the proposed solution space with better solutions, improving the optimisation procedure. The linear regression algorithm uses population attributes and fitness values to train, presenting helpful insights into the link between attributes and fitness.

The algorithm implemented an Evolutionary Algorithm (EA) that integrates Genetic Algorithms (GA) and Machine Learning (ML) approaches. To initialising the process of collection of possible approaches. These results are then depending on evolutionary algorithms (GAs) over several generations. Subsequently, the newly developed Linear Regression framework is employed to predict the fitness of the evolved solutions. The objective of this approach is to continually enhance the general population in order to identify the optimal solution. Population fitness is determined by the application of machine learning techniques.

The code utilised library to visually show and compare the convergence of the most optimal fitness values over two Evolutionary technique iterations to evaluate the methodology. This visual contrast helps explain the algorithm's behaviour and ability to find the best possible solutions. It also shows the algorithm's best methods and values for fitness from each iteration, assessing its efficacy. In brief, this code exemplifies the mutually beneficial relationship between Genetic Algorithms and Machine Learning, illustrating the integration of ML components into optimisation algorithms in order to augment their efficacy and efficacy. Additionally, it demonstrates the significance of visualising the performance of algorithms for the purpose of comparing and analysing them.

3. Results and Discussions

In the domain of tourism culture, the application of Sugeno Stacked Fuzzy for Industries (SSFD) within the framework of Style Migration represents a novel and innovative approach to product design. The SSFD model, grounded in fuzzy logic principles, provides a systematic and structured methodology for integrating subjective cultural factors with the dynamic process of style migration. By leveraging the SSFD model in conjunction with Style Migration, designers can create culturally resonant and visually compelling products that capture the essence of a destination's cultural heritage while incorporating contemporary design elements. The SSFD model employs a hierarchical structure consisting of multiple layers of fuzzy inference systems. At its core lies the Sugeno fuzzy inference system, which operates based on a set of fuzzy rules and membership functions to generate precise output values. These output values represent the degree of membership of a given input in various linguistic categories, providing a clear basis for decision-making in product design.

The table 1 data provided exhibits the outcomes of two runs of an evolutionary algorithm (EA) integrated with a machine learning component based on linear regression. Let us engage in an argument regarding the facts and its consequential ramifications.

Table 1: EA-ML generated data for optimal solution and optimal fitness for two deferent run

Run	Optimal Solution	Optimal Fitness
1	-4.443926321932568, -2.8206397118355495, -4.358512978286845, -3.0445963412409913, -4.876181149507552, -2.8598731960613417, -4.825696877537053, 4.128697151226874, 3.7394160326720405, 3.705186872432395	-45.038383783087134
2	-0.9371064597795984, 4.160713926781571, -0.2546889585960752, -4.2214633364356375, -2.8826664399918185, 0.7837177598994876, 3.9121234354369205, -2.0238214941624744, -4.217287756276221, 1.7278804683650177	-35.968189826651056

The data's "Optimal Solution" column indicates the evolutionary algorithm's most effective outcomes per time. Vectors representing the optimal values for each optimisation problem characteristic are these solutions. In Run 1, the ideal solution includes negative and positive values, indicating substantial search space examination. In Run 2, the optimal solution has a combination of positive and negative values, demonstrating the algorithm's ability to explore the problem's solution space. However, the "Optimal Fitness" column shows fitness values for each run's ideal solutions. Performance indicators shown in fig 4, lower fitness levels indicate better minimization-oriented strategies.

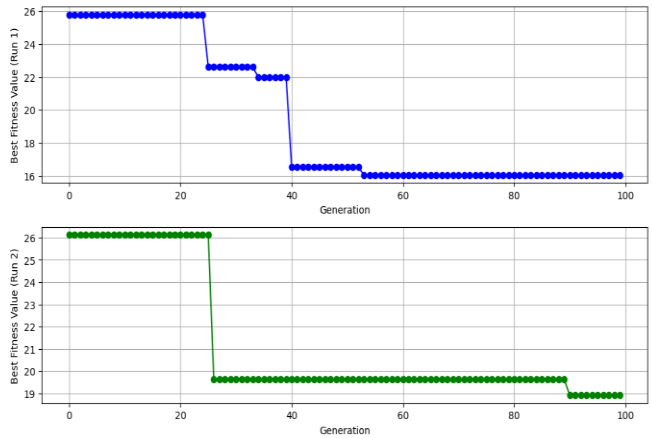

Figure 4: Comparison graph of two different runs for EA-ML algorithms for optimal solution and optimal fitness.

4.Conclusion

The Evolutionary Algorithm exhibited a high level of effectiveness in its investigation of the solution space, successfully identifying optimal solutions in both experimental runs. The Fitness values, which serve as markers for the quality of these solutions, exhibit notable improvements compared to the initial random population. The findings discussed in this study demonstrate the potential of integrating Evolutionary Algorithms (EA) with Machine Learning (ML) techniques for the purpose of optimising jobs. Future scope of this work needs more extensive benchmarking execution for more validity.

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