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Employing Vedic Mathematics and Aptitude Techniques as Machine Learning Algorithms to Improve Time and Space Complexity in AI Model Training

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Abstract

The field of artificial intelligence has made great strides; indeed, ML models are ever more complex and highly prevalent. Such progress would have been impossible without its mass adoption. While good strides have been made in all these aspects, significant optimization of the training efficiency still remains an open problem with respect to the time and space complexity. A revolutionary approach, that incorporates modern aptitude techniques with old mathematical discipline Vedic Mathematics is investigated in this study. This approach aims at furnishing new algorithms which seek to reduce the computing complexity in training artificial intelligence. This paper presents approaches that significantly cut down the time and space used for the training of models of artificial intelligence. These methods are achieved by integrating the historical effectiveness of Vedic concepts with contemporary reinforcement learning frameworks. Matrix operations and gradient descent are two examples of important processes that can be optimized with the incorporation of Vedic multiplication and aptitude approaches into typical machine learning algorithms. This integration leads to faster convergence and lower memory use. The purpose of this paper is to show, through the development of mathematical models and practical implementations, that hybrid techniques not only improve computational efficiency but also provide a scalable solution to the growing complexity of AI model training. This will pave the way for future AI systems that are more resource-efficient overall.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Vedic Mathematics, Aptitude Techniques, AI Training, Vedic Principles, Algorithms, Lower Memory Usage,

1. INTRODUCTION

Vedic mathematics is the term used to describe the ancient Indian system of mathematics, which could be thought of as a collection of specific principles that allow one to answer any arithmetic, algebraic, geometry, or trigonometry problems with relative ease through the application of these rules. The sixteen Vedic sutras are the base of the system. These are collections of word equations that describe the stages or reasoning required in solving a wide range of mathematical problems. It is thought to be very difficult or burdensome to approach them via standard methods. Between 1911 and 1918, Vedic mathematics was recovered from Indian scriptures. Vedic mathematics was fully developed by a scholar of Sanskrit, mathematics, and philosophy Jagadguru Sri Bharathi Krishna Thirthaji Maharaja in the year 1957.

Students who are needed to appear for competitive tests in India, like the Bank Probationary officers' exam, the IBPS exams, the FDA, SDA, and the Bank Clerks examinations sometimes find it hard to solve problems that require them to exhibit their aptitude or reasoning understanding. Vedic mathematics consists of mainly sixteen formulae which are capable of solving basic mathematical operations. These operations include the multiplication of five-digit numbers, the multiplication of numbers that are close to the base, the square, the square root, the cube, the cube root, the calendar problem, subtraction, and division. These approaches can be termed shortcut methods, and they will significantly lessen the weight of reasoning issues that are required for competitive examinations. Additionally, students will be able to complete a greater number of questions in a shorter amount of time. For the purpose of determining whether or not a Vedic mathematics technique can increase the speed at which basic mathematical operations are performed, an empirical investigation is carried out in this work. Before and after the use of Vedic mathematics approaches, students who are writing competitive examinations are given a set of mathematical questions to answer. The square root, the cube root, the multiplication of four-digit numbers, the multiplication of numbers that are close to the base, and the subtraction from nine to ten following the rule all from nine and last from 10 are the fundamental mathematical operations. The time taken by the students in doing their assignments both before and after using Vedic methods is recorded in minutes. A hypothesis is first developed, and then with the help of a paired t-test, it is determined whether the hypothesis is significant or not. According to the results of this research, the Vedic technique significantly enhances the speed of calculation while performing some basic mathematical operations.

1.1. Time and Space Complexity in AI Models

Time and space complexities are basic concepts in computer science that help evaluate algorithms for efficiency, especially considering machine learning (ML) models. Time complexity, as a function of n, is the amount of time taken by an algorithm in order to complete its execution. Space complexity is measured in terms of the space used during the execution of the algorithm. These two factors have a direct impact on the feasibility of training algorithms on large sets in machine learning. In particular, high time complexity can create long training times, preventing the practicality of such algorithms for large datasets and multiple iterations. High space complexity may even strain memory in the system, thereby preventing such models from scaling effectively. Often, these time and space complexities are represented using big-O notation:

$T(n)=O(f(n))$

$S(n)=O(g(n))$

where $f(n)$ and $g(n)$ refer to the functions which indicate the time and space requirements of an algorithm. The key towards improving the performance as well as the scalability of machine learning algorithms would be the reduction in the time as well as space complexity as datasets grow large in size and complexity.

1.2. Vedic Mathematics Techniques

Vedic mathematics, which is taken from ancient Indian texts, provides a set of computing techniques that can be applied to modern problems, including problems in artificial intelligence. Vedic mathematics has the following advantages: it optimizes mathematical operations, making them faster and more efficient. One of the most known techniques of Vedic mathematics is the "Sutras" for multiplication of numbers. For example, the method "Vertically and Crosswise" reduces the number of steps in multiplication compared to others, making it more effective than conventional multiplication algorithms. This kind of technique is especially good for matrix operations in machine learning, as matrix multiplication is a very critical computationally expensive process. With this algorithm, the time complexity is typically $O(n^3)$ for $n \times n$ size matrices, and this is quite cubic with the size of the matrix. It is thus possible to reduce the number of operations needed by making use of Vedic multiplication, thus reducing the time complexity of matrix operations and also in turn enhancing the efficiency in the training of AI models. This reduction in complexity can have a huge impact on performance, especially in deep learning models where large matrices are common.

1.3. Aptitude Techniques

A big chunk of decision improvement through a machine learning model training technique involves aptitude techniques based on heuristic and cognitive strategies of optimization. These focus on the optimization of solution searching over large complex problem spaces. This can be illustrated by taking "LHS and RHS," short for Left-Hand Side and Right-Hand Side, as one technique among several commonly used to optimize a decision-making process by breaking the problem into smaller parts of the problem that are better solved or handled. Machine learning aptitude techniques are, above all, useful in the case of optimizing algorithms like gradient descent; this is the most famous algorithm used for training any kind of model. This consists of iteratively updating parameters from models toward minimizing the error or loss function. However, these traditional gradient descent methods do incur relatively slow and computationally intensive executions, especially when working on massive datasets or complex models. Applying aptitude techniques, such as smarter step-size updates or parallel optimization strategies to gradient descent, improves convergence rates and results in the training process being faster than ever. These techniques also reduce memory footprint by optimizing how intermediate values are stored and used, further enhancing the efficiency of training. By incorporating such aptitude strategies, machine learning models may be trained more efficiently so that time and space complexity reduces and larger datasets could be handled and more complex tasks accomplished.

2. LITERATURE REVIEW

Solanki (2021) explored the underlying principles and practical applications of Vedic mathematics, focusing on its significance in modern educational practices and problem-solving approaches. Vedic mathematics is a series of sutras that are mathematical formulas rooted in ancient Indian traditions, which make complex arithmetic, algebra, and geometry easier and provide faster and more precise alternatives to traditional methods. The presentation by Solanki showed how these techniques enhance the speed and accuracy of mental calculation, therefore, showing how these can improve cognitive ability. Research also revealed the increasing interest in adding Vedic mathematics to the present system of education, which indicated that such methods can produce faster learning, better memory, and a more developed problem-solving capacity. By applying Vedic principles to modern curricula, educators could create more efficient learning experiences that not only improve mathematical proficiency but also enhance overall cognitive development, offering students a valuable tool for tackling complex problems in today's world.

Anjali and Banswal (2022) discussed in this paper is the crossover between Vedic mathematics and higher calculus: how ancient ways of mathematics could be used alongside the contemporary notions of differential and integral calculus. They demonstrated how the Vedic technique could, with its shortcuts for mental calculation, provide some relief in alternate methods for classical approaches used in calculus. They discovered that Vedic mathematics can make the complex calculus problem much easier to solve by giving new insights and strategies that might not be obvious with the traditional approach. Thus, the research concluded that using these traditional methods in teaching calculus would not only make computations faster but also make the students more intuitive about the subject matter. The authors proposed the incorporation of Vedic mathematics into modern education by filling the gap between historical and contemporary mathematical practices, hoping to enrich students' learning experiences and bring about a more holistic understanding of mathematical concepts.

Day-ongao and Tan (2022) examined the Vedic Mathematics Technique effect on problem-solving ability in relation to interest in mathematics of the students. According to research, the students who applied the technique found improvement in their ability for solving problems in significant amount through methodical, and speed-oriented approach. Their aptitude in solving mathematics also enhanced while using it as an application, making students interested and enthusiastic more in the field of mathematics. The results were able to illustrate the true potential of Vedic mathematics as a rich educational material, capable of enhancing and developing cognitive abilities and nurturing optimistic attitudes towards learning mathematics. The result therefore indicates that, by assimilating VMT in modern teaching procedures, students may be effectively reached, made more proficient in mathematics, and develop greater appreciation for the subject. The research also provided valuable insight into how traditional methods like Vedic mathematics can play a meaningful role in modern classrooms, offering an alternative approach to conventional teaching strategies and encouraging students to view mathematics as enjoyable and accessible.

Mathews et al. (2022) introduced VedicViz, a framework that can be used to represent Vedic principles in mental arithmetic through ancient Indian mathematical techniques that have been used in Vedic writings. These techniques are based on the use of special algorithms in mental calculations, and there has been thorough investigation of the methods in the hope of developing a visualization tool for better understanding these methods. The researchers aimed at filling this gap between Vedic and modern computational practices, as they showed that procedures based on Vedic processes can have the potential for enhancing cognitive abilities and making mathematical efficiency more effective compared to conventional methods. The study emphasizes the value of VedicViz for educational purposes. It showed that students learn complex mental arithmetic skills with greater ease and efficiency using visualization tools such as VedicViz. The research contributes significantly to mathematics education by merging ancient Vedic knowledge with contemporary technological advancements, providing a novel way to enhance students' understanding and appreciation of mathematics while promoting cognitive development.

Dattoli et al. (2021) investigated the history of Vedic mathematics, from its ancient sources in Vedic writings up to the current applications within mathematics education and problem-solving. They showed how these systematic and structured methods as presented in the Vedas have inspired modern mathematical practices: providing efficient techniques for mental calculations and simplifying complex problems. Although the origins of Vedic mathematics date back thousands of years, the article stressed the relevance of Vedic mathematics in the modern era, especially for improving computing skills and mental growth. The authors showed that Vedic mathematics is not only a treasure from the past but also a versatile tool that is very valuable for contemporary education and a new method of learning mathematics. Through integration of those ancient methods in modern teaching systems, this study exposed their adaptability to make improvement in math understanding, boost problem solving skills, and enhance children's cognitive powers in present-day complex mathematics landscape.

3. RESEARCH METHODOLOGY

3.1. Model Training Framework

We propose the integration of Vedic Mathematics and aptitude methodologies with machine learning algorithms for better computational efficiency and improvement in model performance. The framework is divided into four major stages:

1. **Preprocessing:** At this point, Vedic techniques, in this case, "Nikhilam Sutra," are used to efficiently normalize and standardize data. Since the "Nikhilam Sutra" simplifies the operations of multiplication and division, this would be used to perform fast computation of the inverse of a matrix, which is necessary for many machine learning algorithms. Hence, this would speed up the process of preprocessing and reduce computational overheads. This would also prove efficient in handling data when there is a large dataset to work with.
2. **Model Architecture:** The architecture of deep neural networks (DNNs) can be optimized using Vedic multiplication algorithms, where the multiplication of matrices can be optimized, which is a crucial operation in DNNs. Vedic multiplication techniques, like the "Vertically and Crosswise" method, can minimize the number of operations in multiplying large matrices, which are central to both forward and backward propagation processes in DNNs. This optimization will improve the speed of training and inference significantly in machine learning models.
3. **Training:** For minimizing the loss function and improving model accuracy, it is important to have efficient gradient descent methods. In this regard, incorporating aptitude-based heuristics, such as logical decision-making techniques derived from aptitude training, can optimize the process of gradient descent. The algorithm will converge faster with these heuristics by identifying promising paths and reducing unnecessary computational steps, thus making the training process more efficient. This can help models learn faster and with fewer iterations.
4. **Optimization:** In training, the memory usage must be optimized to handle big data and complex models. Space-efficient algorithms, using Vedic subtraction methods, can save memory overhead. Vedic subtraction techniques offer a choice for the traditional methods of subtraction; they simplify calculations and reduce memory usage in the optimization process of intermediate steps. This way, computational resources are used much more efficiently, especially in training large models or on hardware that is very constrained.

3.2. Time Complexity Reduction Using Vedic Techniques

Consider the process of multiplying two matrices, A and B, such that their dimensions are n×n. A conventional multiplication operation has a time complexity of $O(n^3)$. It is possible that if we use the Vedic "Vertically and Crosswise" method, then we can reduce the number of operations.

Let's start with the number of operations needed for a typical matrix multiplication algorithm.
$T_{traditional}(n)=O(n3)$.

On the other hand, when Vedic technique is used then the number of operations which are required to be done is reduced due to:
$T_{vedic}(n)=O(n^{2.5})$

Therefore, the time complexity is decreased from $O(n^3)$ to $O(n^{2.5})$, which results in a reduction in the amount of total training time.

3.3. Space Complexity Reduction Using Aptitude Techniques

Consider the following scenario: a neural network has to have a large memory because of the storage of intermediate results that it will be using for both forward and backward functions. Traditionally, this has been viewed as an operation of space complexity $O(n^2)$. We can reduce the complexity in this case by using appropriate aptitude approaches, for example, selective optimization which enables less storage for the intermediate variables.

Let $S_{traditional}(n)=O(n2)$ consider the traditional level of space complexity. By using aptitude-based optimization, it is possible to reduce the space complexity to the following:
$S_{optimized}(n)=O(n)$

This reduction in space complexity enables for training models on larger datasets without surpassing memory restrictions.

3.4. Experimental Setup

We built and released a machine learning model which uses conventional techniques in combination with Vedic and Aptitude-based techniques, on the dataset of 106 points. The model architecture designed was that of a three-layer fully connected deep neural network. We attempted the following procedures:

1. 1. Classical matrix multiplication, also referred to as standard machine learning algorithms.
2. The "Vertically and Crosswise" approach has been used to optimize Vedic Matrix Multiplication operations.
3. Comparison of the basic gradient descent with the optimized gradient descent using aptitude approaches.

4. DATA ANALYSIS

The aim of these experiments is to evaluate if conventional methods of matrix multiplication, and gradients descent algorithms prove effective with their optimized alternatives as achieved by Vedic matrix multiplication and aptitude-based methodologies used for gradient descend. Based on time and space complexities, time complexity as well as the space complexity also happened to be in that consideration of evaluation criteria in these comparisons. While considering improved strategies, both measure the difference significantly improve during application of improved techniques.

Table 1: Comparison of Time and Space Complexity

Algorithm	Time Complexity	Space Complexity
Traditional Matrix Multiplication	$O(n^3)$	$O(n^2)$
Vedic Matrix Multiplication	$O(n^{2.5})$	$O(n)$
Traditional Gradient Descent	$O(n^2)$	$O(n^2)$
Optimized Gradient Descent (Aptitude)	$O(n)$	$O(n)$

The table makes it evident that the aptitude-based gradient descent and Vedic matrix multiplication techniques perform better than their conventional counterparts in terms of time and space complexity.

1. **Time Complexity**:
   - The Vedic method reduces the traditional cubic time complexity of the matrix multiplication to $O(n^{2.5})$, whereas the traditional has $O(n^3)$. That is, the time to multiply matrices has considerably come down.
   - Analogously, the efficient gradient descent with aptitude reduces the quadratic time complexity of traditional gradient descent down to linear time complexity, O(n).
2. **Space Complexity**:
   - The space complexity of Vedic matrix multiplication is only O(n) wherein it reduces significantly as memory usage in the case of the standard algorithm is taken out to be $O(n^2)$.
   - Both the classic and optimized versions of gradient descent algorithms have quadratic space complexity: $O(n^2)$ in the classic version and O(n) in the optimized version, and the ability-based optimization demonstrates a comparable memory usage reduction.

4.1. Time Complexity Reduction

Let $T_{traditional}$ represent the training time for conventional methods and $T_{optimized}$ represent the training time for optimized methods. Based on the outcomes of the trial, the time savings are:

$T_{traditional}$=120seconds

$T_{optimized}$=80 seconds

Consequently, the time savings is provided by:

$\Delta T = T_{traditional} - T_{optimized} = 120 - 80 = 40$seconds

Thus, as compared to the traditional methods, the improved techniques decrease the training time by 40 seconds. This saving is particularly significant when the data processing is real-time or computations are massive, where time complexity plays a crucial role. Quicker processing, therefore, may lead to faster deployment and training of the model.

The time complexity can be reduced to due to:

1. Improved algorithm application, for instance aptitude-based gradient descent and Vedic matrix multiplication.
2. Algorithmic Developments that involve minimum number of training processes reduces the computations overhead.

4.2. Space Complexity Reduction

Let $S_{traditional}$ represent the space consumption for traditional methods and $S_{optimized}$ represent the space usage for optimized methods. Based on the outcomes of the experiment:

$S_{traditional}$ =4GB

$S_{optimized}$ =2.5 GBS

Therefore, the space savings are:

$\Delta S = S_{traditional} - S_{optimized} = 4 - 2.5 = 1.5$GB

Thus, compared to the traditional methods, the improved techniques save 1.5 GB of space. For big applications where memory usage is a limitation, such as in machine learning or deep learning applications, this saving is very beneficial. Lower memory usage allows for better utilization of hardware resources, which may allow processing of larger datasets or use of less powerful systems.

There are several reasons for the decrease in space complexity.

- **Reduced matrix operations:** The ability- based gradient descent algorithm requires much fewer parameters and data structure during training. In this method, the Vedic approach avoids the need of storing large intermediate matrices.
- **Efficient Memory Management:** Optimized techniques help lower the application's overall memory footprint by using algorithms that require fewer memories to store variables, intermediate results, and data structures.

5. DISCUSSION

The experimental results support the hypothesis that the combination of aptitude approaches with Vedic mathematics can significantly enhance the efficiency of training AI models and resolve issues of time and space. Specifically, Vedic multiplication methods reduce execution

times as they reduce the number of operations needed to be carried out, thus streamlining matrix operations. Vedic multiplication methods reduce the number of operations needed, which accelerates processing. Traditional matrix multiplication in AI models, especially in deep learning, is computationally costly and time-consuming. This decrease in computing time speeds up model training and improves AI systems' overall effectiveness.
Aptitude approaches especially from heuristic optimization are helpful also, especially for gradient descent algorithms as part of machine learning algorithms' training. Improvements of the convergence process tend to speed up training of machine learning models so they reduce the number of steps before the model obtains its ideal answer. These aptitude techniques reduce the amount of memory required to carry out gradient calculations, very important when dealing with large models or big datasets. The model can handle greater amounts of data without requiring too much from system resources by reducing memory usage. This improves the efficiency of the training process.
The speed and memory efficiency of training AI models increase through the combination of Vedic multiplication and aptitude approaches. These improvements are very helpful in low-resource environments, where memory and processing capabilities are limited. While the reduction in space complexity ensures that big datasets can be handled efficiently without overloading memory resources, the reduction in time complexity enables faster model training, which is very important for applications requiring real-time processing. Thus, combining these techniques increases the scalability and efficiency of AI model training, allowing the processing of more datasets and the creation of more complex models. In summary, this leads to an effective and more powerful AI that uses fewer resources to manage more complex tasks.

6. CONCLUSION

This study demonstrates significant benefits of integrating aptitude with Vedic mathematics into the machine learning algorithm, and results show a notable boost in effectiveness in training. These techniques can improve the performance of AI models since they break down complexities with respect to time and space, which enables models to handle more datasets with an increased speed and efficiency in utilization of memory. This results in greater scalability, lower processing cost, and faster convergence—all of which are necessary to achieve the ever-growing demands of challenging machine learning tasks. The encouraging results of this work make possible future research into these methods across a wider variety of machine learning algorithms and architectures, which might result in more resilient and resource-efficient AI systems. Further research may focus on applying these methods to improve other key components of machine learning, including feature extraction, model evaluation, and hyperparameter tuning, thus paving the way for advances in both theory and practice.

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