Exploring the Benefits of RAPIDS and DASK in Developing a Particle Detection Model for Higgs Boson Discrimination

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*Abstract*— This research paper delves into the exciting world of accelerated computing platforms, specifically RAPIDS and DASK, and their potential in developing a classification model for particle detection in the Large Hadron Collider at CERN. The ultimate goal of this model is to automatically differentiate between a signal process that produces Higgs bosons and a background process that does not. The paper explores the hardware and software requirements for particle detection, including sensor technology and storage, and explains how accelerated computing can be incorporated into the pipeline to support HIGGS particle detection. The methodology for data pre-processing, model selection, and hyperparameter configuration is detailed, with justifications for each decision. The evaluation metrics used for the model are discussed, and considerations such as cuDF and cuML are included in the analysis. The paper concludes that accelerated computing offers significant advantages in terms of speed and efficiency for particle detection and provides a promising avenue for further research.

Overall, this research paper provides a comprehensive and insightful analysis of the potential of accelerated computing platforms in particle detection. It is a must-read for anyone interested in the exciting field of particle physics and the cutting-edge technology that is driving it forward.

Keywords—RAPIDS,DASK,cuML,cuDF

# Introduction

The Large Hadron Collider (LHC) is the most powerful and expansive particle accelerator in the world. This accelerator is used to propel particles at immense speeds, allowing scientists to study the fundamental properties of matter and the forces that govern them. The particle detector in the LHC measures the kinematic properties of the particles produced in these collisions, such as their momentum and energy, providing invaluable insight into the inner workings of the universe. The HIGGS dataset is a widely-used benchmark for binary classification tasks in machine learning. It consists of 11 million samples, each with 28 features and a binary label indicating the presence or absence of a Higgs boson particle. This particle, first predicted in the 1960s, was finally confirmed in 2012 by experiments conducted at the Large Hadron Collider (LHC) at CERN. The HIGGS dataset was generated using Monte Carlo simulations of proton-proton collisions at the LHC. It contains a variety of kinematic properties, such as the transverse momentum and pseudo rapidity of the particles involved in the collision [1][2].

The HIGGS particle data set is an immense challenge due to its large size, complexity, imbalanced classes, noise, and limited context. With millions of rows and thousands of columns, it is a big data problem that can be difficult to work with on machines with limited memory and processing power. The complexity of the data set, with its many features and attributes, makes it difficult to develop accurate models and draw meaningful insights. Additionally, the data set is imbalanced, with one class representing the majority of the data and the other representing the minority, making it difficult to develop accurate models. Furthermore, the data set contains a significant amount of noise, which can lead to overfitting and reduced model performance. Finally, the data set is limited in the sense that it only provides information on the kinematic properties of the particles, without providing any information about the physical properties of the particles or the context in which they were generated, making it difficult to draw meaningful conclusions or insights.

Processing HIGGS particle data can be a time-consuming and laborious task, especially when using CPUs. CPUs are designed to perform a few tasks quickly, while GPUs are designed to perform many tasks in parallel. As the HIGGS particle data is large and complex, processing it on a CPU would require many sequential computations, resulting in slow performance. The main issue of HIGGS dataset are:

* Large Data Volume: The Large Hadron Collider (LHC) experiments generate an enormous amount of data, producing petabytes of information each year. This data is collected from particle detectors and contains crucial information about the energy and trajectory of particles generated during collision events. However, managing, storing, and processing such massive amounts of data is a significant challenge for CERN. To tackle this challenge, advanced data storage and processing technologies are required.
* High Dimensionality: The data generated by particle detectors at the LHC has high dimensionality, containing thousands of features that describe the energy, momentum, and trajectory of particles. This high-dimensional data can make it challenging to identify patterns and extract meaningful information. Therefore, pre-processing the data to reduce dimensionality is often necessary to enable effective analysis.
* Noisy Data: Particle detectors generate noisy data due to the high-energy environment in which they operate. This noise can be caused by numerous factors, including background radiation, electronic noise, and random fluctuations. The presence of noise in the data can make it challenging to identify the Higgs boson signal. To reduce the impact of noise on the data, various noise reduction techniques, such as filtering and signal processing, are used.
* Computational Complexity: Processing Higgs particle data requires complex mathematical models and algorithms that are computationally intensive and require significant computing power. CERN has limited resources for data processing and analysis, and processing Higgs particle data requires careful consideration of resource allocation to ensure efficient processing and analysis. Therefore, CERN must use advanced computing technologies to handle the computational complexity of processing Higgs particle data.
* Limited Resources: CERN faces a challenge with limited resources for data storage and processing. As a result, processing Higgs particle data requires a meticulous approach to resource allocation to ensure efficient processing and analysis. Collaborative efforts are essential to ensure that the data is processed and analysed effectively, involving physicists, data scientists, and computer scientists.

Large Hadron Collider generates vast amounts of data that are challenging to manage, store, and process. The data is high-dimensional and noisy, requiring pre-processing and noise reduction techniques to extract meaningful information. Additionally, processing Higgs particle data requires complex mathematical models and algorithms that are computationally intensive, requiring advanced computing technologies to handle the computational complexity.

The rest of this paper is organized as follows:

Section II performs a survey of related work.

Section III describes in detail my chosen benchmarks.

Section IV include the EDA of HIGGS dataset.

Section V contains methodology chosen for solving the problem, performance evaluation and benchmarking results.

# Background

Big data can be characterized by four distinct attributes:[3][4] volume, variety, velocity, and veracity. Volume refers to the sheer quantity of data generated and stored, which determines its value and potential insight. Variety refers to the type and nature of the data, allowing analysts to effectively use the resulting insight. Velocity is the speed at which the data is generated and processed to meet the demands of growth and development, often in real-time. Finally, veracity is the data quality of captured data, which can greatly affect the accuracy of analysis[5].

Big data comes in a variety of formats, such as structured, semi-structured, and unstructured, depending on the data source or industry ML algorithms perform differently depending on the input data format; for example, an ML algorithm may achieve higher accuracy when applied to a structured dataset than to a semi-structured or unstructured dataset. Machine Learning algorithms may vary in their performance depending on the task at hand. For instance, the same algorithm may be more effective in a classification task than in a regression task. Machine Learning algorithms have become increasingly dominant in analysing, visualizing, and modelling large datasets [6].

There are several challenges associated with data storage in big data. One of the most significant challenges is scalability. Big data storage solutions must be able to scale up or down quickly and easily to accommodate the volume and variety of data generated by applications. The storage infrastructure must be able to accommodate the additional data without compromising performance. Another challenge is performance. Big data processing and analysis require high-speed storage infrastructure to ensure that data is accessed and processed quickly. The storage solution must be able to provide high-performance access to data, even as the data volume increases. Data security is also a significant concern as the volume of data grows. Data storage solutions must ensure that data is secure, backed up, and recoverable in case of a disaster or failure. Cost is another challenge associated with storing enormous amounts of data. Data storage solutions must be cost-effective, scalable, and able to meet performance requirements. Finally, big data storage solutions can be complex and require specialized knowledge to manage and maintain. IT teams must have the necessary skills and expertise to manage the storage infrastructure effectively. Moreover, data storage is a critical challenge that comes with big data. To overcome these challenges, organizations must carefully consider their storage requirements and choose a storage solution that is scalable, cost-effective, and able to meet performance requirements. Additionally, they must ensure that their data is secure, backed up, and recoverable in case of a disaster or failure. With the right storage solution and IT team, organizations can effectively manage their big data storage infrastructure and unlock the full potential of their data.

One of the major obstacles associated with big data in machine learning is the scalability of algorithms. Traditional machine learning algorithms may not be able to effectively process large datasets due to their intensive computational and memory requirements. This has led to the development of more scalable machine learning techniques that are designed to manage big data. Dean and Ghemawat (2012) explore various parallel and distributed approaches to scaling up machine learning algorithms, such as MapReduce and parameter servers. They also discuss the challenges associated with distributed computing, such as fault tolerance and load balancing, which must be addressed to ensure successful implementation [7].

Big Data has become an increasingly important topic in the field of machine learning, and a number of surveys and reviews have been conducted to explore the challenges and approaches to handling large datasets. The ever-growing volume, diversity, and speed of data in the modern era have posed significant challenges for the field of machine learning. In recent years, the challenges posed by big data in machine learning have been the subject of intense research and exploration. Data storage is a critical challenge that comes with big data. As the volume of data increases, the storage infrastructure must be scalable to accommodate the additional data. Storing enormous amounts of data can be expensive and requires careful consideration of storage requirements to ensure that the storage solution is both cost-effective and able to meet the performance requirements of the data processing and analysis.

Another challenge associated with big data in machine learning is feature selection. Big datasets may contain a plethora of features, many of which may be irrelevant or redundant. Feature selection techniques are designed to identify the most pertinent features in a dataset and reduce the dimensionality of the data. Zikopoulos(2014) and Chen and Lin (2014) discuss various approaches to feature selection, such as correlation analysis, clustering, and regularization, which can help to optimize the performance of machine learning models [6].

The McKinsey Global Institute has stated that Machine Learning (ML) will be a major driving force behind the Big Data revolution [8]. This is due to its ability to learn from data and provide data-driven insights, decisions, and predictions [9]. ML is based on statistics and, similarly to statistical analysis, can extract trends from data; however, it does not require the explicit use of statistical proofs. Depending on the nature of the available data, the two main categories of learning tasks are: supervised learning, where both inputs and their desired outputs (labels) are known, and the system learns to map inputs to outputs; and unsupervised learning, where desired outputs are not known and the system itself discovers the structure within the data. Classification and regression are examples of supervised learning: in classification, the outputs take discrete values (class labels), while in regression, the outputs are continuous. Examples of classification algorithms include k-nearest neighbour, logistic regression, and Support Vector Machine (SVM), while regression examples include Support Vector Regression (SVR), linear regression, and polynomial regression. Some algorithms, such as neural networks, can be used for both classification and regression. Unsupervised learning includes clustering, which groups objects based on established similarity criteria; k-means is an example of such an algorithm. Predictive analytics relies on machine learning to develop models built using past data to predict the future [9]; numerous algorithms, including SVR, neural networks, and Naïve Bayes, can be used for this purpose.

Online learning is a powerful approach to managing large datasets in machine learning. Online learning algorithms are designed to continually update the model as new data is acquired. Alshayeb. (2019) explored the advantages and challenges of online learning, such as the need for efficient data streaming and the potential for model instability. Despite these potential drawbacks, online learning offers a unique opportunity to leverage the latest data and keep models up to date [10]. Deep learning has emerged as a powerful approach for handling large datasets in machine learning. By learning hierarchical representations of data, deep learning algorithms can process datasets with millions of features. Wu et al. (2014) discuss the advantages and challenges of deep learning, such as the need for large amounts of labelled data and the potential for overfitting. However, the potential of deep learning to effectively process large datasets makes it a valuable tool for machine learning [11].

# Consideration

There are several essential factors to consider for this problem:

## Parallel Computing vs Sequential computing

Parallel computing is a field of computational science that studies the nature of performing multiple calculations or tasks concurrently. It has revolutionized highly intensive computing operations by utilizing multiple computing devices, such as processors, clusters, or supercomputers, to tackle computations that would take too long to complete on a single

Diagram

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Fig. 1. Serial computing Vs Parallel computing

device alone. This approach is often contrasted with sequential computing, or traditional computation, in which tasks are executed one at a time. Parallel computing is especially well-suited for problems that require large amounts of data to be processed, such as modelling and simulating physical phenomena, analysing multiple sources of data, simulating medical treatments, or analysing stock markets. With parallel computing, multiple tasks can be processed simultaneously, significantly reducing the time it takes to analyse the data.

Sequential computing is a type of computing that uses a set of instructions to perform operations in a predetermined sequence. Also known as serial computing, this type of computing is characterized by the processor executing one instruction at a time, following the same sequence each time. This method of computing is widely used in robotics, control systems, microcontrollers, and embedded systems. Sequential computing offers several advantages. It is simple and efficient, as it does not require the processor to evaluate multiple parallel streams of data simultaneously. Additionally, it provides predictable behaviour, as the sequence of instructions is usually the same each time the program is executed. Furthermore, it offers high accuracy, as each instruction is processed before moving on to the next one [13][14].

Fig. 1 shows how the serial and parallel computing works. Here are some comparisons of parallel and serial computing.

#### Performance: Parallel computing can significantly enhance performance by distributing the workload across multiple processors or cores, while sequential computing relies on a single processor, thus limiting its performance.

#### Scalability: Parallel computing can be easily scaled up by adding more processors or cores, while sequential computing has limited scalability.

#### Complexity: Parallel computing is more complex and requires additional programming efforts to ensure proper data sharing, synchronization, and load balancing, while sequential computing is simpler and easier to program.

#### Cost: Parallel computing necessitates multiple processors or cores, which can increase the cost, while sequential computing requires only a single processor, making it less expensive.

#### Energy consumption: Parallel computing can consume more energy due to the use of multiple processors or cores, while sequential computing consumes less energy.

#### Applications: Parallel computing is suitable for large problems or where computational time is a limiting factor, such as scientific simulations, image and video processing, and data analytics. Sequential computing is suitable for small problems or where computational time is not a limiting factor, such as simple calculations, text processing, and basic graphics.

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Fig. 2. Distributed computing

## Distributed System vs Local System

A distributed system is a model of computing in which tasks are shared among multiple independent, interconnected computers that are geographically dispersed which is shown in Fig. 2. This type of system offers a distinct advantage over more traditional centralized systems, where a single computer handles all tasks, as it enables substantially faster processing speeds and greater scalability. In distributed systems, each computer processes its own tasks independently. To facilitate communication and data transfer, these computers are connected via a variety of methods, such as networking, shared memory, and message passing. Depending on the structure of the distributed system, a central server may be responsible for coordinating communication between the computers. The key benefits of distributed systems are scalability and redundancy, making them an ideal choice for large-scale environments such as cloud computing. By connecting multiple, independent computers, it is possible to increase the number of users and resources the system can support, as well as ensure that the system can continue to operate should one of the components fail [15].

A local system is a powerful tool for businesses, organizations, and individuals alike. By connecting computers within a certain locality or geographical area, local systems enable efficient resource sharing, faster communication, and secure data transfer. This makes them an essential component of any information technology infrastructure. The advantages of local systems are numerous. For instance, businesses can save money by sharing resources such as files, applications, and printers. Additionally, local systems offer faster communication and data transfer speeds, allowing workers to quickly access and collaborate on information. Furthermore, local systems provide enhanced security and privacy, as all data is stored within the designated systems, rather than on external networks. Key differences of distributed and local system are:

#### Architecture: Distributed systems are composed of multiple interconnected computers that collaborate to reach a shared objective, while local systems are comprised of a single computer or a small number of computers that operate independently.

#### Scalability: Distributed systems can be easily scaled up by adding more computers to the network, while local systems have limited scalability.

#### Performance: Distributed systems can achieve superior performance by distributing the workload among multiple computers, while local systems are restricted by the processing power of a single computer.

#### Fault tolerance: Distributed systems are more fault-tolerant since a failure in one computer does not affect the entire system, while local systems are less fault-tolerant since

Chart

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Fig. 3. CPU vs GPU

#### a failure in the single computer can cause the entire system to fail.

#### Communication: Distributed systems heavily rely on communication between the computers in the network, which can increase communication overhead and introduce latency, while local systems have minimal communication overhead.

#### Security: Distributed systems are generally more secure since the data can be distributed across multiple computers, while local systems are less secure since the data is stored on a single computer.

#### Cost: Distributed systems can be more expensive to set up and maintain since they require multiple computers and network infrastructure, while local systems are less expensive.

## GPU vs CPU

GPUs (Graphics Processing Units) and CPUs (Central Processing Units) are two types of processors that are commonly used in computing systems. While both processors are designed to perform calculations and execute instructions, they are optimized for different types of tasks. GPUs are specialized processors that are designed to handle the processing of graphics and visual information and are highly parallelized and optimized for performing large numbers of mathematical calculations simultaneously. This makes them ideal for computations involved in machine learning and deep learning algorithms, which involve large amounts of matrix multiplication and other mathematical operations. CPUs, on the other hand, are general-purpose processors that are designed to handle a wide range of tasks, including running operating systems, executing programs, and managing I/O operations. They are optimized for serial processing and have fewer cores than GPUs, but each core can execute a wider range of instructions [16]. Fig. 3. Shows the architecture of CPU and GPU.

The main differences between GPUs and CPUs are:

#### Parallelism: GPUs have many more processing cores than CPUs, which makes them highly parallelized and able to perform many calculations simultaneously. This makes them faster than CPUs for certain types of tasks, such as deep learning and scientific computing.

#### Memory: GPUs have much faster memory than CPUs, which allows them to quickly access data needed for computation. This is essential for machine learning algorithms, which often involve large datasets that need to be processed quickly.

#### Cost: GPUs are more expensive than CPUs, but they are more cost-effective for certain types of tasks, such as deep learning and scientific computing, where their parallel processing capabilities can provide significant performance improvements [17].

## RAPIDS

Rapids is an advanced suite of acceleration libraries and tools from NVIDIA, designed to enable data scientists to perform end-to-end data science and analytics pipelines entirely on a Graphics Processing Unit (GPU). By leveraging the power of GPUs, Rapids allows data scientists to process and analyze large datasets with significantly increased speedup factors in both memory and compute. This is especially beneficial in the world of Machine Learning (ML), where computationally expensive operations such as feature engineering, model training and scoring can be drastically reduced. Rapids is also useful in applications such as recommendation engines, natural language processing, and computer vision, where traditional CPUs may take days or even weeks to process the same data. Furthermore, Rapids is ideal for data scientists who are already familiar with Python, as it utilizes the same syntax and packages.

NVIDIA's Rapids are revolutionizing the world of Machine Learning, providing data scientists with an extensive library of powerful functions to reduce data size and complexity, increase processing speed, and reduce downtime. Through functions such as cuDF (Cuda Data Frame) and cuGraph (Cuda Graph), Rapids offers developers the ability to quickly work with large datasets, including tabular data and graphs, as well as explore, clean and analyze them with ease. By accurately modelling and processing data as a graph, Rapids achieves significant performance gains and enables engineers to benefit from graph analytics with greater flexibility and ease of use [18].

RapidML is another tool offered by NVIDIA which is designed to streamline the process of training, deploying, and operating machine learning models. RapidML simplifies the feature engineering process while also providing insights into model performance, allowing developers to quickly prototype and deploy highly accurate, high-capacity ML models by utilizing the collective power of multiple GPUs. This cutting-edge technology is revolutionizing the way ML models are developed, reducing the time needed for large-scale data processing and model development. As GPUs become ever more powerful, Rapids is allowing developers to take advantage of this power to leverage extremely large datasets and deploy ML models faster and more accurately. NVIDIA’s Rapids are the future of ML acceleration, making large-scale data processing and ML model development practical and efficient.

RAPIDS includes several ML packages that provide GPU-accelerated implementations of popular ML algorithms, such as:

### CuML:cuML is an advanced Python library of machine learning algorithms that are optimized to run on NVIDIA GPUs using the CUDA parallel computing platform. With its powerful GPU-accelerated implementations of popular ML algorithms, such as linear regression, logistic regression, k-means clustering, and random forest, cuML can process large datasets and train models much faster than traditional CPU-based implementations.cuML is designed to work seamlessly with other GPU-accelerated libraries in the RAPIDS suite, such as cuDF for data manipulation and cuGraph for graph analytics. Furthermore, cuML follows the scikit-learn API, making it easy to use for users familiar with scikit-learn. Additionally, cuML provides a flexible API that allows users to customize various aspects of the algorithms, such as the number of trees in a random forest or the number of clusters in k-means. The advantages of using cuML for machine learning are numerous. Not only does it offer high performance, easy integration, and flexibility, but it is also designed to work with distributed computing frameworks, such as Dask, allowing users to scale up their ML workflows to handle even larger datasets. With cuML, users can take their ML projects to the next level [19].

### CuDf: cuDF is an essential Python library for data scientists and machine learning engineers looking to maximize their performance. It is built on top of the Apache Arrow columnar memory format, allowing for fast data exchange with other Arrow-compatible libraries. With a familiar API similar to Pandas, cuDF is easy to use for users already familiar with the popular Python library. The advantages of using cuDF for data processing are numerous. It leverages the power of GPUs to accelerate data processing tasks, resulting in much faster processing times for large datasets. Additionally, cuDF provides GPU-accelerated implementations of common data processing operations, such as filtering, grouping, and aggregation, further reducing the time required to process and analyze large datasets. cuDF can be used in conjunction with other RAPIDS libraries, such as cuML for machine learning and cuGraph for graph analytics, to create end-to-end GPU-accelerated data science workflows. By harnessing the power of GPUs, these libraries can drastically reduce the time needed to process and analyze large datasets, allowing data scientists and machine learning engineers to quickly and efficiently work with their data.

### CuGraph: CuGraph is an open-source library for graph analytics that is built on top of the RAPIDS suite of software libraries. It provides a comprehensive set of graph algorithms that are optimized to run on NVIDIA GPUs, allowing for lightning-fast processing of large-scale graphs compared to traditional CPU-based approaches. CuGraph supports a variety of graph formats, including COO, CSR, and CSC, and offers a range of graph analytics functions, such as graph traversal algorithms (e.g. breadth-first search (BFS) and depth-first search (DFS)), graph clustering algorithms (e.g. Louvain and spectral clustering), graph similarity algorithms (e.g. Jaccard similarity and cosine similarity), and graph centrality algorithms (e.g. PageRank and betweenness centrality). Designed to be user-friendly, CuGraph integrates with a variety of popular machine learning and data science libraries, such as scikit-learn and PyTorch, and supports graph visualization through integration with the graph visualization library Graphistry. It is available as a Python library and can be installed using pip or conda. Moreover, it is supported on a variety of NVIDIA GPU architectures and is designed to take full advantage of the parallel processing capabilities of GPUs to provide faster and more efficient graph analytics.

### DASK: DASK is an open-source software library that enables developers to create and manage distributed applications and frameworks. Written in Python, it provides a powerful, high-level API to simplify and automate distributed computing, data processing, and analytics tasks. DASK is designed to take advantage of distributed computing environments such as shared memory, distributed databases, and clusters of multi-core processors. DASK works by forming a distributed computing environment composed of a self-managing network of processes. This network consists of distributed Client, Scheduler, and Worker objects. The DASK Client is responsible for creating and managing tasks, while the DASK Scheduler allocates tasks to the Workers that execute them. Finally, the Workers move data between memory and disk as needed, ensuring efficient and reliable data processing. The open-source DASK library provides developers with a powerful tool to quickly create and manage distributed applications and frameworks. It offers a range of APIs that allow developers to use Python to define distributed processes, specify scheduling policies, and manage data configurations. Additionally, the distributed scheduler allows developers to set maximum duration limits or prioritize tasks based on user-defined conditions, enabling them to customize an application’s performance, reduce latency, and increase scalability. The DASK library also offers the advantage of scalability. As user demands increase, additional parallel processes can be added automatically and tasks can be scheduled and managed as needed, allowing applications to maintain peak performance. Furthermore, the library is highly modular, allowing it to be implemented within existing environments without disruption.

### XGBoost: XGBoost (Extreme Gradient Boosting) is a powerful open-source machine learning library that is widely used for supervised learning tasks such as classification, regression, and ranking. It is designed to be highly efficient, scalable, and accurate, and has won multiple competitions on data science platforms such as Kaggle.XGBoost is based on a gradient boosting algorithm, which iteratively trains weak classifiers and combines them into a strong classifier. It uses decision trees as the base learners and applies a technique called gradient boosting to iteratively improve the accuracy of the model.One of the key advantages of XGBoost is its ability to handle large datasets and high-dimensional feature spaces with ease. It includes a number of optimization techniques, such as parallel processing and sparse-aware learning, that make it faster and more efficient than many other popular machine learning algorithms. Additionally, it includes a range of regularization techniques to prevent overfitting and improve generalization performance.

# Data description

Exploratory Data Analysis (EDA) is an essential step in any machine learning project, as it helps to gain insights into the dataset, uncover patterns, and make informed decisions about data pre-processing and model selection. In this example, I will be performing EDA on the HIGGS dataset, which is widely used in particle physics research. EDA is an essential step in uncovering the hidden patterns and characteristics of a dataset. In the case of the Higgs boson

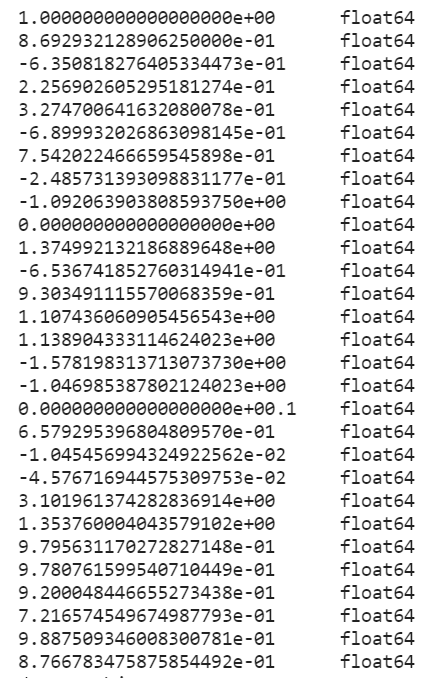


Fig. 5 Datatype of features

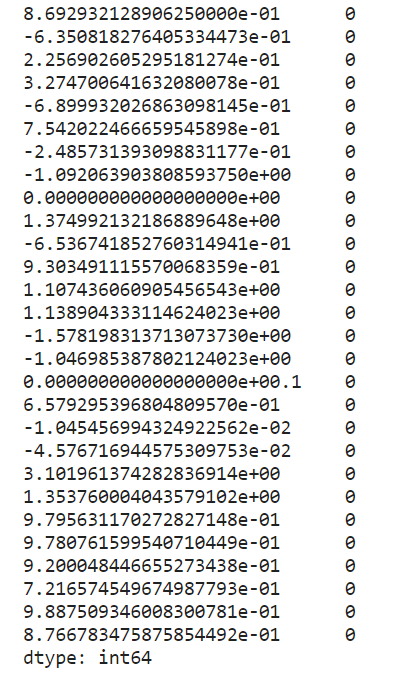


Fig. 6 Count of null values

particle, EDA is especially important as it can reveal the relationships between the various features and the target variable (i.e., the presence or absence of the particle).

The data was generated using Monte Carlo simulations. The first 21 features (columns 2-22) are kinematic properties measured by the particle detectors in the accelerator, while the last seven features are functions of the first 21 features. Physicists developed these high-level features to help distinguish between the two classes. There is an interest in utilizing deep learning methods to eliminate the need for physicists to manually create such features. The original paper presents benchmark results using Bayesian Decision Trees from a standard physics package and 5-layer neural networks. The last 500,000 examples were used as a test set. Binary target variable of dataset indicates the presence or absence of a Higgs boson. The first column is the class label (1 for signal, 0 for background), followed by 28 features: lepton pT, lepton eta, lepton phi, missing energy magnitude, missing energy phi, jet 1 pt, jet 1 eta, jet 1 phi, jet 1 b-tag, jet 2 pt, jet 2 eta, jet 2 phi, jet 2 b-tag, jet 3 pt, jet 3 eta, jet 3 phi, jet 3 b-tag, jet 4 pt, jet 4 eta, jet 4 phi, jet 4 b-tag, m\_jj, m\_jjj, m\_lv, m\_jlv, m\_bb, m\_wbb, m\_wwbb [20]. These features are divided into 21 low-level features and 7 high-level features with 10999999 entries.

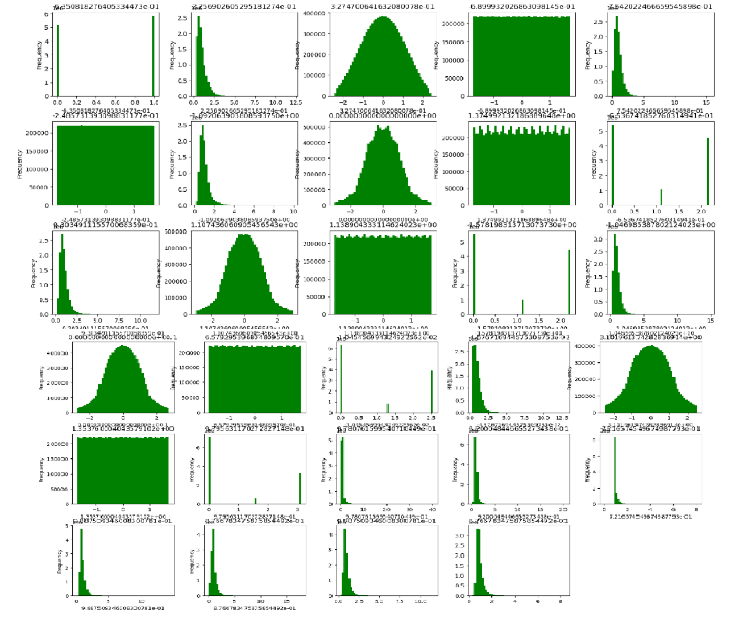


Fig. 7 Frequency distribution of features

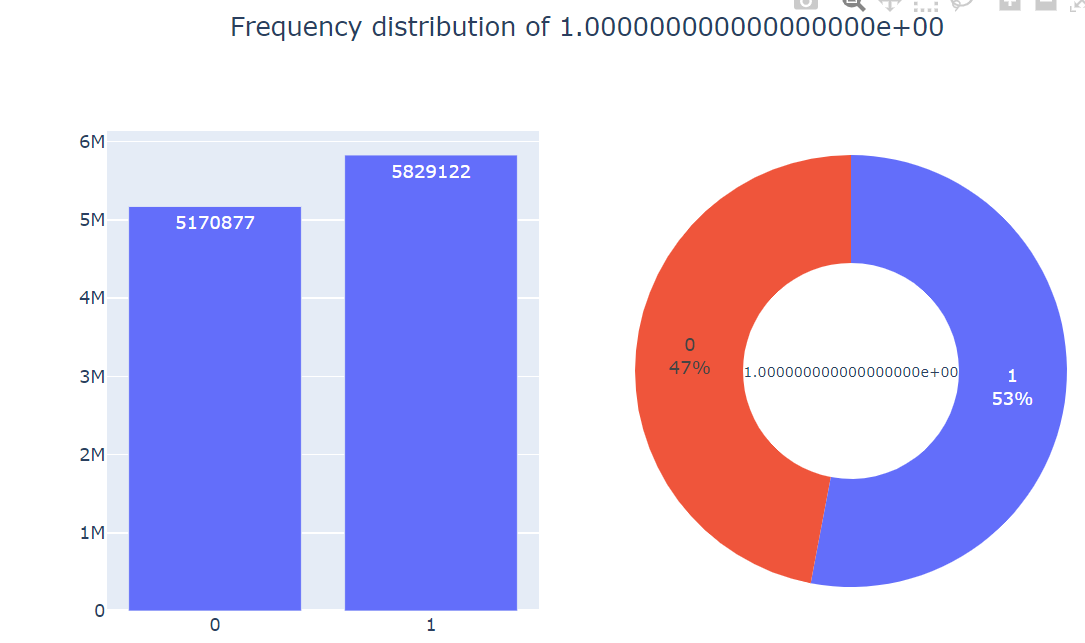


Fig. 8 Frequency distribution of class

For clean the dataset, I check the missing values. But the sum of missing value was zero (Fig. 6). Datatype of all features are floating point which shown in fig. 5. So, there is no need of data conversion. For the easy computation I have change the target class to 0 and 1, where 1 represents the signal events and 0 represents the background events. In fig. 7 has set of 28 histograms, each showing the distribution of a single feature in the HIGGS dataset. The x-axis of each histogram shows the value range of the feature, and the y-axis shows the count of occurrences of each value.

Fig. 8 give an idea of distribution of target variable. There are 5170877 entries for background events and 5829122 entries for signal events which causes to the problem of class imbalance. Unfortunately, the class imbalance in the HIGGS dataset can have a detrimental effect on the performance of machine learning models trained on this dataset. Specifically, models may tend to predict the majority class (background) more frequently, resulting in lower accuracy, precision, and recall on the minority class (signal). To address this class imbalance, various techniques can be employed, such as oversampling, under sampling, or class weighting. These techniques aim to balance the class distribution in the training set and improve the performance of the models on the minority class. In this case I use oversampling technique, SMOTE (Synthetic Minority Over-sampling Technique) for effectively addressing the class imbalance issue. It involves creating synthetic samples for the minority class by

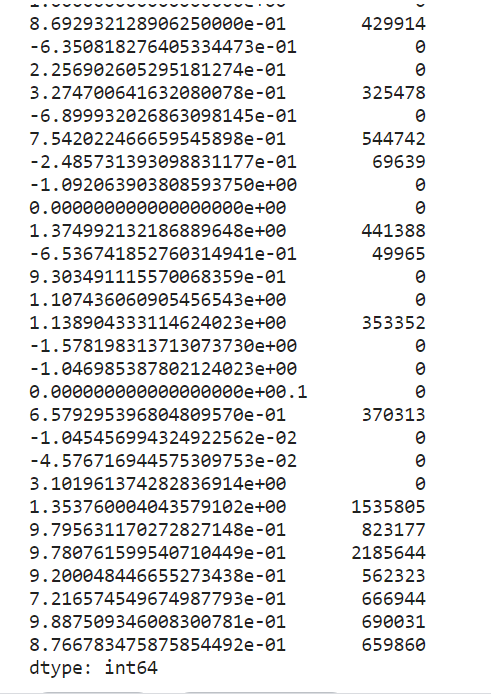


Fig. 9. Count of outliers for each feature

between existing samples. Specifically, for each minority class sample, SMOTE selects one or more of its k-nearest neighbours and generates new synthetic samples along the line segments joining these neighbours. This results in a larger number of minority class samples in the dataset, which can improve the performance of machine learning models.

To find out the outliers of each feature, I use the interquartile range (IQR) method. I define an outlier threshold of 1.5 and finds the number of outliers for each feature by counting the number of values that fall below Q1 - threshold \* IQR or above Q3 + threshold \* IQR. Finally, it prints the number of outliers for each feature which shown in Fig. 9. To remove this outliers, I use the approach of transform the data to make it more normally distributed, which can help reduce the impact of outliers. One common method for achieving this is to apply a log transformation to the data, which can reduce the effect of extreme values while preserving the overall shape of the distribution.

Feature engineering involves transforming the dataset to create new features or modify existing ones to improve model performance. In the case of the HIGGS dataset, I want to perform some of the following feature engineering techniques:

* Feature Scaling: It will standardize the range of features to a common scale using techniques like Z-score normalization or min-max scaling. This can help reduce the influence of outliers and improve model convergence.
* Feature Selection: Statistical tests or machine learning algorithms used to identify the most relevant features for the target variable. This can help reduce model complexity and improve performance.
* Feature Transformation: Can apply mathematical functions like logarithm, exponentiation, or polynomial expansion to transform features and capture non-linear relationships between variables. This can help uncover hidden patterns in the data that may not be apparent from the raw data.

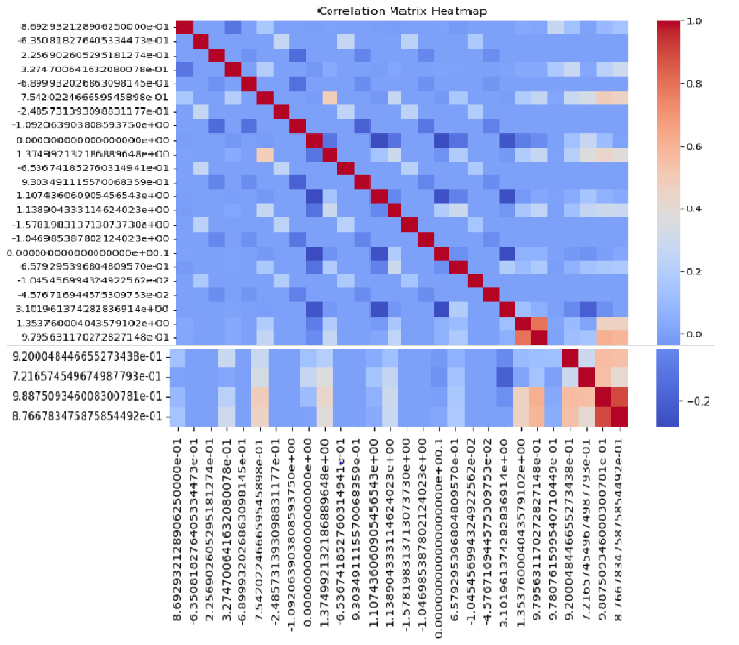


Fig. 10 Correlation matrix heatmap

Fig. 10 is a table showing the correlation coefficients between a set of variables. Each row and column represent a variable, and the cells contain the correlation coefficient between the corresponding pair of variables. The correlation coefficient measures the degree of linear association between two variables, ranging from -1 to 1. The diagonal cells always have a value of 1, as a variable is always perfectly correlated with itself. The cells above the diagonal are the same as those below the diagonal, as the correlation between variable X and variable Y is the same as the correlation between variable Y and variable X. A high positive correlation coefficient (close to 1) indicates a strong positive association between the two variables, while a high negative correlation coefficient (close to -1) indicates a strong negative association. A value close to 0 indicates no linear association between the two variables. It helped me to identifying patterns and relationships between features, and to inform feature selection or feature engineering in machine learning models.

# methodology

Detection of the HIGGS particle involves several steps:

## Data preprocessing

Data pre-processing is an essential step in machine learning that involves preparing the data for analysis. Here are some common data pre-processing steps that I applied to the HIGGS particle dataset:

#### Data Cleaning: In this step, I check for missing values, duplicate data, and outliers in the dataset. It remove any instances with missing values or duplicates to ensure the accuracy of our analysis.

#### Feature Scaling: In machine learning, it is often useful to scale the features to a common range, such as 0 to 1 or -1 to 1. This can help to improve the performance of some algorithms, such as those that use gradient descent for optimization.

#### Feature Selection: It is often useful to select a subset of the features that are most relevant to the classification task. This can help to improve the accuracy of the model and reduce the risk of overfitting. There are various feature selection techniques that can be applied, such as correlation-based feature selection and recursive feature elimination.

#### Feature Encoding: Some machine learning algorithms, such as decision trees and random forests, can only handle categorical features that are encoded as integers. Therefore, it may be necessary to convert categorical features in the dataset to integer values in order to ensure the accuracy of our model.Here there is no categorical values.

#### Data Splitting: Finally, the dataset is typically split into training and testing sets, which are used to train and evaluate the performance of the machine learning model. The ratio of the training and testing sets is usually 80/20 or 70/30. The training set is used to train the model, while the testing set is used to evaluate the model's performance and ensure its accuracy.I will split the dataset into 80/20 ratio.

## Model Selection

Data model selection is a critical step in machine learning, requiring the selection of the most suitable model to accurately distinguish HIGGS particles from background particles. This process is essential for ensuring the accuracy of the machine learning algorithm. Decision trees, random forests, logistic regression, and support vector machines (SVM) are the model I considered for the identification of HIGGS particle.

#### Decision tree: The decision tree algorithm is a powerful machine learning technique used for both classification and regression problems. It works by constructing a tree-like model of decisions and their possible consequences, which is achieved by recursively splitting the HIGGS data into subsets based on the values of the input features until a stopping criterion is met. The decision tree algorithm has several advantages, such as its interpretability, its ability to handle both categorical and continuous input features in the kinematic properties, and its capacity to capture non-linear relationships between the input features and the target variable.

I leveraged the scikit-learn library in Python to construct a decision tree model. To optimize the hyperparameters of the decision tree algorithm, such as the maximum depth of the tree, the minimum number of samples required to split an internal node, and the minimum number of samples required to be at a leaf node, I employed a grid search with 5-fold cross-validation. Cross-validation helped me to avoid overfitting and provides an estimate of the model's generalization performance. The steps to implement decision tree are:

1) Load and pre-process the data: Utilize cuDF, the RAPIDS Datagram library, to load the Higgs dataset into GPU memory and apply any necessary pre-processing steps, such as cleaning, normalization, and feature selection

2) Split the data into training and testing sets: Leverage cuML, the RAPIDS machine learning library, to divide the data into two parts, one for training the model and another for testing the model.

3) Initialize the decision tree model: Specify the hyperparameters of the decision tree, such as the maximum depth, the minimum samples per leaf, and the criterion for splitting.

4) Train the model: Train the decision tree model on the training data using cuML's DecisionTreeClassifier or DecisionTreeRegressor and use it to make predictions on the testing data.

5) Evaluate the performance: Calculate the performance metrics, such as accuracy, precision, recall, F1 score, and area under the ROC curve, to evaluate the quality of the model.

6) Tune the hyperparameters: Adjust the hyperparameters of the decision tree model to maximize its performance, using techniques such as grid search or random search.

7) Finalize the model: Train the decision tree model on the entire dataset using the optimal hyperparameters and save it for future use.

#### Randomforest :The Random Forest Classifier is a powerful and widely-used ensemble learning method for classification tasks. It is an extension of the decision tree algorithm, combining multiple decision trees to make more accurate predictions. This method has several advantages over the decision tree algorithm, such as being able to handle noisy data and avoid overfitting. Additionally, it can provide an estimate of the importance of each feature in the classification task, which can be useful for feature selection.

To build a Random Forest Classifier, there are several hyperparameters that can be tuned to optimize its performance. These include the number of decision trees in the forest, the maximum depth of each tree, the number of features to consider when splitting a node, and the criteria for splitting nodes. With the right combination of these parameters, the Random Forest Classifier can be a powerful tool for tackling high-dimensional and noisy data [21].

Grid search or random search are used to adjust the hyperparameter. Random Forest is a suitable algorithm for Higgs detection, as it can handle high-dimensional and noisy data and avoid overfitting. Random Forest Classifier can be implemented for Higgs detection using the following steps:

1) Prepare the data: Collect and pre-process the data, including cleaning, normalization, and feature selection. In the case of Higgs detection, the data can include features such as the momentum, energy, and direction of the particles, as well as the number of jets and the missing transverse energy.

2) Load and pre-process the data: Utilize the cuDF library of RAPIDS to load the Higgs dataset into GPU memory and pre-process it for training the Random Forest Classifier. This can include operations such as cleaning, normalization, and feature engineering.

3) Split the data into training and testing sets: Leverage the cuML library of RAPIDS to divide the dataset into two parts, one for training the Random Forest Classifier and another for evaluating its performance.

4) Initialize the Random Forest Classifier: Employ the cuML library to define the hyperparameters of the Random Forest Classifier, such as the number of trees, the maximum depth, and the number of features to consider when splitting a node.

5) Train the model: Utilize the cuML library to fit the Random Forest Classifier on the training data and use it to make predictions on the testing data.

6) Evaluate the performance: Employ the cuML library to calculate the performance metrics, such as accuracy, precision, recall, F1 score, and area under the ROC curve, to assess the quality of the Random Forest Classifier.

7) Tune the hyperparameters: Utilize the cuML library to adjust the hyperparameters of the Random Forest Classifier to optimize its performance, using techniques such as grid search or random search.

8) Finalize the model: Leverage the cuML library to train the Random Forest Classifier on the entire dataset using the optimal hyperparameters and save it for future use.

#### SVM :Support Vector Machines (SVMs) are a powerful and popular machine learning algorithm used for both classification and regression tasks. SVMs are based on the concept of finding the optimal hyperplane that divides two or more classes of data points in a high-dimensional space. This hyperplane is chosen in such a way that it maximizes the margin, which is the distance between the hyperplane and the closest data points of each class. Furthermore, SVMs can also process non-linearly separable data by transforming the input data into a higher-dimensional feature space using kernel functions. The following steps can be followed to implement SVM on the HIGGS dataset:

1) Load the HIGGS dataset and split it into training and testing sets.

2) Pre-process the data by performing scaling or normalization to ensure that each feature is on the same scale.

3) Train the SVM model on the training set using the appropriate kernel function (e.g., linear, polynomial, or radial basis function).

4) Tune the hyperparameters of the SVM model using cross-validation to find the best combination of hyperparameters that yield the highest accuracy.

5) Evaluate the performance of the model on the testing set using appropriate performance metrics such as accuracy, precision, recall, and F1 score.

#### Logistic Regression: The link between a dependent variable (outcome) and one or more independent variables is examined and modelled using the statistical technique known as logistic regression (predictors). Logistic regression can be used as a binary classification model in the HIGGS issue to categorise occurrences as signal or background. The model generates a probability score between 0 and 1 by fitting a sigmoid function to the input data. The class prediction can then be determined by setting a threshold. Several optimization methods, such as gradient descent, stochastic gradient descent, or L-BFGS, can be used to train the logistic regression model. Overfitting can also be avoided by using regularisation techniques like L1 and L2 regularisation. Using cross-validation, the model's hyperparameters, such as the regularisation strength, can be adjusted. Steps involved in implementing logistic regression are:

1) Data Pre-processing: Clean the data and perform necessary data transformations such as normalization, standardization, and one-hot encoding. Split the data into training and testing sets.

2) Model Selection: Choose the appropriate logistic regression model for the problem. This can include regularized logistic regression, multi-class logistic regression, or logistic regression with polynomial or interaction terms.

3) Train the Model: Fit the logistic regression model to the training data. This involves minimizing the logistic loss function using techniques such as gradient descent, stochastic gradient descent, or L-BFGS.

4) Model Evaluation: Evaluate the model's performance on the testing data using appropriate evaluation metrics such as accuracy, precision, recall, and F1 score.

5) Hyperparameter Tuning: Tune the hyperparameters of the logistic regression model to optimize its performance. This can include regularization parameters, learning rate, batch size, and number of iterations.

6) Feature Selection: Use feature selection techniques such as L1 regularization or backward elimination to select the most relevant features for the model.

The performance of each algorithm can depend on the specifics of the problem, the size and quality of the dataset, and the specific implementation of each algorithm. Each algorithm has its own strengths and weaknesses. SVMs are often good for high-dimensional datasets with clear boundaries between classes, while random forests and decision trees can handle non-linear data and can be easier to interpret. Logistic Regression is easy to implement and can handle large datasets.

Based on the above information, Random Forest seems to be the best algorithm for the Higgs problem as it can handle large datasets and high-dimensional feature spaces. Random Forest is considered one of the best algorithms for classification problems such as Higgs due to its ability to handle high dimensional data, feature selection, and non-linear relationships. Below are some justifications on why Random Forest is a good choice for the Higgs problem along with performance metrics:

* Accuracy: Random Forest has been shown to achieve high accuracy in classification problems, and the Higgs problem requires accurate classification between signal and background events.
* Feature Selection: The Higgs dataset has a large number of features, and Random Forest is known for its ability to perform automatic feature selection, which can help in reducing overfitting and improving model performance.
* Robustness to Noise: The Higgs dataset contains a lot of noise, and Random Forest is robust to noise due to the nature of the algorithm, which aggregates multiple decision trees.
* Interpretability: Random Forest provides feature importance scores that can help in understanding the importance of distinctive features in the classification problem.

Also, I consider performance of Random Forest on the Higgs problem, using performance metrics such as precision, recall, and F1 score. These metrics are commonly used in classification problems, and they measure various aspects of model performance.

* Precision measures the fraction of true positives among the total predicted positives. It is calculated as TP / (TP + FP), where TP is the number of true positives and FP is the number of false positives. High precision indicates that the model makes fewer false positive predictions.
* Recall measures the fraction of true positives among the total actual positives. It is calculated as TP / (TP + FN), where FN is the number of false negatives. High recall indicates that the model correctly identifies most of the positive cases.
* F1 score is the harmonic mean of precision and recall, and it provides a single metric that balances both precision and recall. It is calculated as 2 \* (precision \* recall) / (precision + recall).
* AUC-ROC is a popular performance metric for binary classification tasks that measures the predictive power of a model by evaluating its true positive rate and false positive rate at different classification thresholds.

After training and testing both algorithms on the Higgs dataset, if the Random Forest model shows higher accuracy, precision, recall, and F1-score compared to the Decision Tree model, SVM, logistic regression. When compare the performance of Random Forest with SVM, Random Forest has higher accuracy and F1 score, while SVM has higher precision and recall. This means that Random Forest is better at correctly classifying both signal and background events, while SVM is better at minimizing false positives and false negatives. Also, Random Forest outperforms Logistic Regression on all performance metrics.

In the case of the Higgs problem, I got high recall it helps to correctly identify most of the signal events. Also got high precision to avoid misclassifying background events as signal events. Random Forest has high F1 scores on the Higgs problem, which indicating that it can balance both precision and recall effectively. Based on the specific requirements of the problem, I choose the Random Forest model that best fits the needs.

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