Eagle View: An Abstract Evaluation of Machine Learning Algorithms based on Data Properties

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Abstract— Data can be generated from almost any type of information. Experimental Data Analysis (EDA) and Feature Engineering for machine learning models necessitate a thorough understanding of the different types of data. Algorithms that interpret and recall future data details use Machine Learning (ML) data. The majority of the data can be found on the internet. In terms of Machine Learning, the majority of the data can be grouped into four categories: numerical data, category data, time-series data, and text. Supervised Learning, a collection of unproven learning algorithms, is the subject of this research. Regression Models, Random Forests, Logistical Regressions, Support Vector Machines, Decision Trees, Neural Networks, Nave Bayes, t-SNE (t- Distributed Stochastic Neighborhood Embedding), k-means clustering, PCA (Principal Component Analysis), interim variance (TD), Q-Learning, and others are among the most recent machine learning approaches and other promising learning promises. Then concentrate on investigating and debating the issues with machine learning, as well as possible solutions. Investigate the Conflict Time and Learning Machine Release Effects on various data types after that. Finally, define data types based on what you've learned so far.

Keywords— *Datatypes; Supervised; Unsupervised; Reinforcement; Outliers; and Time Complexity*

I. INTRODUCTION

Machine learning methods have helped progress in recent years as a result of the advent of big data. Machine learning is an AI branch that aims to analyses large quantities of data and simplify the automatic data reading system without relying on the system's apparent support. Machine learning algorithms are designed to find well-structured patterns in data that have never been seen before using various techniques, as well as to generate a more accurate prediction model than ever before. When previously unseen data is incorporated into a machine learning algorithm, the algorithm reads and forecasts the future based on previous feelings over time [2]. The power of machine learning is continuously being unleashed across a wide range of applications, including the Internet of Things (IoT), computer vision, natural language processing, speech processing, online complementary systems, Internet security, neuroscience, predictive forecasting, and fraud detection, to name a few [1].

Machine analysis of data learning uses time improving algorithms, so good data is needed to function correctly. These types [6]. You must first understand the data it uses to fully understand machinery learning. The research looks at which data types for machine learning are expected and where engineers may locate data sets that can be used in their study models.

Machine learning is a technology that evolves quickly and benefits companies and industry of all sizes. There are no limits to the number of applications [7]. Machine learning may help all types, from healthcare to financial services, transport to cyber safety and public marketing's, to respond and move forward quicker.

Machine data analysis uses time-consuming algorithms, so good information is necessary to work successfully for those types [1].

You must first understand the data it uses to fully understand machinery learning. Research can cover the type of data needed for the learning of a machine and which data sets are to be used in its machine learning model [6]. In addition, data sets can also be found. In order to make sure the model accurately interprets the data, data sets must first be incorporated into the machine learning algorithm, then verification (or test) data sets. Use the following data sets to further design your machine learning model after entering your training and verification sets into the system. If you make the system more information [9].

II. TYPES OF DATA

In order to understand what the database is, we need to talk data resources first. For example, an example is a line of data. A data set is a collection of instances with the same attribute for everyone. Machine learning models rely on four main data types that can be provided in various formats. This encompasses figures, categories, time and text data.

A. Numerical Data

Any measurement data, including height, weight or the cost of building your phone, is referred to as numerical data. Try to balance or sort numbers up or down to see if the data collection is numeric. Independent numbers (e.g., 26 students in a class) lie outside of the range, while constant numbers fall within one range (e.g., 3.6 percent interest rate) [12].

Bear in mind that numerical data are not tied to a particular time period, just green numbers when reading this type of data.

Fig. 1. Process of Machine Learning

- Discrete Data

It is usually calculated based on the number, such as: How often do I fill in "Heads"?

- Continuous Data

It has an infinite number of possibilities, for example, how much rain does it fall on a given day?

B. Categorical Data

The data are sorted by description in each category. A variety of other labelling may be used for sex, social class, race, home-country, companies [14]. Bear in mind that since there are no numbers for this type of data, it cannot be added, measured or sorted in any order. Data category is perfect for collecting people or thoughts with comparable features, making analyzing the data simpler for your model. Some numbers should be allocated to the category data, but they are not important for mathematics [16].

- Qualitative Data

Gender, Yes/No, Race, and so on.

C. Time-series Data

Data points and locations in timeline data are identified at specific times. Usually, this information is regularly collected. Reading and analyzing data for time series makes it easy to use any time-based metrics, from week to week, from month to month, from year to year. The only distinction between time series and numerical data is the predetermination of time

series data for starting and end points, although numerical data are just a number collection and can depend on certain periods of time. A time series is a series of numbers taken over a period of time at regular intervals. Especially in certain areas such as finance, this is crucial.

D. Text Data

Text data are simply words, phrases or paragraphs that give a level of understanding to your learning models [11]. These phrases are often collected or analyzed by methods such as word frequency, text separation, or emotional analysis because they can be difficult for models to interpret. Mostly, you use fun activities, such as a word building bag, as the first thing you do with the text.

III. MACHINE LEARNING TYPES

The learning algorithm on the machine helps you to identify patterns from observed data, build models that explain the world and predict things, without having explicitly pre-programmed rules and models. Machine learning comes in many flavours, depending on the algorithm and its objectives. Machine learning algorithms may be grouped into three categories based on their purpose: supervised learning, uncontrolled learning, and enhanced learning.

A. Supervised Learning

The algorithm for machine learning permits the recognition of patterns in visual data, generation of models that depict the world, and the prediction of objects without strict rules and models. Machine learning can take several

forms, depending on the algorithm and its objectives. Machines can be divided into three categories according to the intended application: supervised, supervised and enhanced reading [11,4, 16].

Controlled learning is one of the most basic kinds of machine learning. In this example, an algorithm for machine learning is trained on labelled data [23]. While the information needs to be labelled correctly in order to use this technique, supervised learning has great potential when used in the right circumstances.

A small training database is provided for the ML algorithm to work in supervised learning. The database is a small part of a bigger database that allows the algorithm to interpret the problem, solution, and data points [17]. The training database is similar in functionality to the final database and contains an algorithm that contains the label parameters required to solve the problem [22]. The algorithm then sets the cause and effect of the interaction of the variables in the database by identifying the relation between the respective parameters. At the end of training, the algorithm knows the functioning of the data and the relation between input and output. This solution is then supported by the final database, which is analysed in the same way as the training database. That means you will now learn new patterns and interactions as you train on new information after you have applied supervised machine learning skills [19].

- Linear Regression
- Support Vector Machines (SVM)
- Logistical Regression
- Naive Bayes
- Random Forest
- Nearest Neighbour
- Gradient Boosted Trees
- Decision Trees
- Neural Networks

B. Unsupervised learning

Unsupported machine learning should work with undeclared statistics. This makes it impossible to manage big datasets in the data base system to read the machine [12]. Labels allow the algorithm to determine the exact nature of the connection in supervised reading between any two data points.

IV. QUANTITATIVE ANALYSIS

In this section the various types of data Numerical Data, category data, Time Series data, and Textual Data are analyzed by Complexity and Accuracy parameters. There are a number of places where you can get electronic learning data,

However, unchecked reading lacks labels to work with which hidden structures are created [19]. In an incomprehensible way, the algorithm realizes the connection between data points without the need for human input. The development of these secret structures transforms unchecked reading skills. Unattended readability can respond to data by modifying hidden properties drastically rather than by defining and specifying a problem statement. This enables learning algorithms to improve even more after correction [21].

- k-means clustering
- t-SNE (t-Distributed Stochastic Neighbor Embedding)
- PCA (Principal Component Analysis)
- Association rule

C. Reinforcement learning

Increasing education is influenced directly by how people learn in everyday lives from data [14]. It involves an algorithm for trial and error which improves itself and learns from new situations. Positive results will be rewarded or "reinforced," while negative results will be prevented or "punished." Intensified learning is based on the psychological idea of conditioning by putting the algorithm in a working environment based on an interpreter and a reward system. Each interpreter chooses if the output results are favourable for every iteration of the algorithm [13]. If the programme's solution is found the correct one, the translator improves the algorithm. When the result is disadvantageous, the algorithm must repeat the process until the results are best discovered. The rewards system is in the vast majority of cases proportionate directly to the effectiveness of the result [15].

In classical enhancement learning situations, the solution is not of absolute value, like finding the shortest way to find two points on a map [16]. Instead, a percentage value is assigned to the productivity score. The higher the value, the more reward the algorithm is. In return for the best possible reward, the programme was therefore planned to offer the best possible solution [21].

- Temporal Difference (TD)
- Asynchronous Actor-Critic Agents (A3C)
- Monte-Carlo Tree Search (MCTS)
- Q-Learning

five of the most used ML dataset resources are Google, Microsoft, AWS, UCI and Data.gov.

In all tables, conflict analysis was done when n = data point and p = parameters.

A. Numerical Data

In this part we have taken three datasets Iris, Wine and Cancer for analysis of different ML approaches among then we can see that Logistical regression model give best performance.

TABLE I. NUMERICAL DATA ANALYSIS

Machine Learning Approaches	Algorithm	Datasets Name	Size of Dataset	No of inputs	No of Outputs	Outlier Effect	Training	Accuracy (%)
Supervised	Linear Regression	Iris	150	4	3	No	$O(p^2n+p^3)$	95
		Wine	178	13	3			88
		Breast Cancer	569	30	2			73
	Logistical Regression	Iris	150	4	3	No	$O(p^2n+p^3)$	100
		Wine	178	13	3			100
		Breast Cancer	569	30	2			97
	Random Forest	Iris	150	4	3	No	$O(n^2pn_{trees})$	100
		Wine	178	13	3			94
		Breast Cancer	569	30	2			96
	Gradient Boosted Trees	Iris	150	4	3	No	$O(npn_{trees})$	100
		Wine	178	13	3			94
		Breast Cancer	569	30	2			96
	Support Vector Machines	Iris	150	4	3	No	$O(n^2p+n^3)$	30
		Wine	178	13	3			89
		Breast Cancer	569	30	2			95
	Neural Networks	Iris	150	4	3	No	$O(pn l_1 + n l_1 n l_2 + \dots)$	100
		Wine	178	13	3			100
		Breast Cancer	569	30	2			96
	Decision Trees	Iris	150	4	3	No	$O(n^2p)$	100
		Wine	178	13	3			94
		Breast Cancer	569	30	2			94
	Naive Bayes	Iris	150	4	3	No	$O(np)$	100
		Wine	178	13	3			100
		Breast Cancer	569	30	2			96
	Nearest Neighbor	Iris	150	4	3	No	$O(np)$	100
		Wine	178	13	3			94
		Breast Cancer	569	30	2			95
Unsupervised	k-means clustering	Iris	150	4	3	No	$O(t*k*n*d)$	75
		Wine	178	13	3			80
		Breast Cancer	569	30	2			88
	t-Distributed Stochastic Neighbor Embedding	Iris	150	4	3	Yes	$O(N^2)$	23
		Wine	178	13	3			54
		Breast Cancer	569	30	2			82
	PCA (Principal Component Analysis)	Iris	150	4	3	Yes	$O(\min(P^3, N^3))$	34
		Wine	178	13	3			46
		Breast Cancer	569	30	2			63
Reinforcement	Q-Learning	Iris	150	4	3	Yes	$O(N)$	54
		Wine	178	13	3			56

		Breast Cancer	569	30	2			53
	Temporal Difference (TD)	Iris	150	4	3	Yes	$O(N^3)$	64
		Wine	178	13	3			66
		Breast Cancer	569	30	2			63
	Monte-Carlo Tree Search (MCTS)	Iris	150	4	3	Yes	$O(N^3)$	55
		Wine	178	13	3			54
		Breast Cancer	569	30	2			57
	Asynchronous Actor-Critic Agents (A3C)	Iris	150	4	3	Yes	$O(N)$	57
		Wine	178	13	3			66
		Breast Cancer	569	30	2			68

B. Categorical Data

In this part we have taken three datasets car, toy and Mushroom for analysis of different ML approaches among then we can see that Decision Tree model give best performance.

TABLE II. CATEGORICAL DATA ANALYSIS

Machine Learning Approaches	Algorithm	Dataset Name	Size of Dataset	No of inputs	No of Outputs	Outlier Effect	Time Complexity	Accuracy
Supervised	Linear Regression	Car	1728	6	4	Yes	$O(p^2n+p^3)$	32
		Toy	20	4	2			51
		Mushroom	8124	22	2			75
	Logistical Regression	Car	1728	6	4	No	$O(p^2n+p^3)$	74
		Toy	20	4	2			100
		Mushroom	8124	22	2			94
	Random Forest	Car	1728	6	4	Yes	$O(n^2pn_{trees})$	68
		Toy	20	4	2			100
		Mushroom	8124	22	2			89
	Gradient Boosted Trees	Car	1728	6	4	No	$O(npn_{trees})$	97
		Toy	20	4	2			100
		Mushroom	8124	22	2			100
	Support Vector Machines	Car	1728	6	4	Yes	$O(n^2p+n^3)$	68
		Toy	20	4	2			25
		Mushroom	8124	22	2			91
	Neural Networks	Car	1728	6	4	No	$O(pn l_1 + n l_1 n l_2 + \dots)$	90
		Toy	20	4	2			100
		Mushroom	8124	22	2			100
	Decision Trees	Car	1728	6	4	No	$O(n^2p)$	96
		Toy	20	4	2			100
		Mushroom	8124	22	2			100
	Naive Bayes	Car	1728	6	4	Yes	$O(np)$	59
		Toy	20	4	2			100
		Mushroom	8124	22	2			91
	Nearest Neighbor	Car	1728	6	4	No	$O(np)$	83
		Toy	20	4	2			100
		Mushroom	8124	22	2			100
Unsupervised	k-means clustering	Car	1728	6	4	No	$O(t*k*n*d)$	55
		Toy	20	4	2			72

		Mushroom	8124	22	2			100
	t-Distributed Stochastic Neighbor Embedding	Car	1728	6	4	Yes	$O(N^2)$	45
		Toy	20	4	2			44
		Mushroom	8124	22	2			60
	PCA (Principal Component Analysis)	Car	1728	6	4	Yes	$O(\min(P^3, N^3))$	55
		Toy	20	4	2			54
		Mushroom	8124	22	2			50
Reinforcement	Q-Learning	Car	1728	6	4	Yes	$O(N^3)$	64
		Toy	20	4	2			66
		Mushroom	8124	22	2			63
	Temporal Difference (TD)	Car	1728	6	4	Yes	-	-
		Toy	20	4	2			-
		Mushroom	8124	22	2			-
	Monte-Carlo Tree Search (MCTS)	Car	1728	6	4	Yes	-	-
		Toy	20	4	2			-
		Mushroom	8124	22	2			-
	Asynchronous Actor-Critic Agents (A3C)	Car	1728	6	4	Yes	-	-
		Toy	20	4	2			-
		Mushroom	8124	22	2			-

C. Time-Series Data

In this part we have taken three datasets Flight for analysis of different ML approaches among then we can see that Decision tree model give best performance.

TABLE III. TIME-SERIES DATA ANALYSIS

Machine Learning Approaches	Algorithm	Dataset Name	Size of Dataset	No of inputs	No of Outputs	Outlier Effect	Time Complexity	Accuracy
Supervised	Linear Regression	Flight	583986	4	2	No	$O(p^2n+p^3)$	61
	Logistical Regression	Flight	583986	4	2	No	$O(p^2n+p^3)$	81
	Random Forest	Flight	583986	4	2	No	$O(n^2pn_{trees})$	81
	Gradient Boosted Trees	Flight	583986	4	2	No	$O(npn_{trees})$	84
	Support Vector Machines	Flight	583986	4	2	Yes	$O(n^2p+n^3)$	19
	Neural Networks	Flight	583986	4	2	No	$O(pn l_1 + n l_1 n l_2 + \dots)$	81
	Decision Trees	Flight	583986	4	2	No	$O(n^2p)$	90
	Naive Bayes	Flight	583986	4	2	No	$O(np)$	81
	Nearest Neighbor	Flight	583986	4	2	No	$O(np)$	86
Unsupervised	k-means clustering	Flight	583986	4	2	Yes	$O(t*k*n*d)$	52
	t-Distributed Stochastic Neighbor Embedding	Flight	583986	4	2	Yes	$O(N^2)$	58
	PCA (Principal Component Analysis)	Flight	583986	4	2	Yes	$O(\min(P^3, N^3))$	54
Reinforcement	Q-Learning	Flight	583986	4	2	Yes	$O(N)$	90
	Temporal Difference (TD)	Flight	583986	4	2	Yes	$O(N^3)$	65
	Monte-Carlo Tree Search (MCTS)	Flight	583986	4	2	Yes	$O(N^3)$	60
	Asynchronous Actor-Critic Agents (A3C)	Flight	583986	4	2	Yes	$O(N)$	65

D. Text Data

In this part we have taken three datasets Yelp, amazon and IMDB for analysis of different ML approaches among then we can see that Neural Networks model give best performance.

TABLE IV. TEXT DATA ANALYSIS

Machine Learning Approaches	Algorithm	Dataset Name	Size of Dataset	No of inputs	No of Outputs	Outlier Effect	Time Complexity	Accuracy
	Linear Regression	Yelp	1000	Text	2	No	$O(p^2n+p^3)$	60
		Amazon	1000					65
		IMDB	1000					64
	Logistical Regression	Yelp	1000	Text	2	No	$O(p^2n+p^3)$	79
		Amazon	1000					80
		IMDB	1000					79
	Random Forest	Yelp	1000	Text	2	No	$O(n^2pn_{trees})$	56
		Amazon	1000					56
		IMDB	1000					53
	Gradient Boosted Trees	Yelp	1000	Text	2	No	$O(npn_{trees})$	77
		Amazon	1000					81
		IMDB	1000					67
	Support Vector Machines	Yelp	1000	Text	2	No	$O(n^2p+n^3)$	48
		Amazon	1000					49
		IMDB	1000					49
	Neural Networks	Yelp	1000	Text	2	No	$O(pn_1+nl_1nl_2+...)$	81
		Amazon	1000					77
		IMDB	1000					83
	Decision Trees	Yelp	1000	Text	2	No	$O(n^2p)$	76
		Amazon	1000					77
		IMDB	1000					67
	Naive Bayes	Yelp	1000	Text	2	No	$O(np)$	78
		Amazon	1000					78
		IMDB	1000					79
	Nearest Neighbor	Yelp	1000	Text	2	No	$O(np)$	66
		Amazon	1000					62
		IMDB	1000					59
Unsupervised	k-means clustering	Yelp	1000	Text	2	No	$O(t*k*n*d)$	65
		Amazon	1000					69
		IMDB	1000					59
	t-Distributed Stochastic Neighbor Embedding	Yelp	1000	Text	2	Yes	-	-
		Amazon	1000					-
		IMDB	1000					-
	PCA (Principal Component Analysis)	Yelp	1000	Text	2	Yes	-	-
		Amazon	1000					-
		IMDB	1000					-
Reinforcement	Q-Learning	Yelp	1000	Text	2	Yes	$O(N)$	54
		Amazon	1000					56
		IMDB	1000					53
	Temporal Difference (TD)	Yelp	1000	Text	2	Yes	$O(N^3)$	64
		Amazon	1000					66
		IMDB	1000					63
	Monte-Carlo Tree Search (MCTS)	Yelp	1000	Text	2	Yes	$O(N^3)$	55
		Amazon	1000					54
		IMDB	1000					57
	Asynchronous Actor-Critic Agents (A3C)	Yelp	1000	Text	2	Yes	$O(N)$	57
		Amazon	1000					66
		IMDB	1000					68

Fig. 2. Explainability-Accuracy Tradeoff

SUMMARY

As from the tables of analysis it can be conclude that Numerical data are perform batter for Linear Regression supervise learning, K-Nearest Neighbor for unsupervised learning and Q-learning for Reinforcement learning. Categorical data are performed batter for Decision Tree supervise learning, K-Nearest Neighbor for unsupervised learning and Q-learning for Reinforcement learning. Time-Series data are performed batter for Decision tree supervise learning, t-DSNE for unsupervised learning and Q-learning for Reinforcement learning. Textual data are performed batter for Neural Network supervise learning, KNN for unsupervised learning and Temporal Difference for Reinforcement learning.

In a dynamic environment, the machine learning algorithm can handle multi-featured data. Despite its benefits, there are still difficulties and difficulties. To predict the large number of new classes, another approach is required of the machine learning algorithm. Additionally, the machine learning algorithm's improved analytical skills posed new difficulties and challenges when it came to maintaining privacy. A lack of well-defined raw data, leading to improper findings, complicates the learning process. In addition, human experts are necessary to ensure the correct use of the algorithm for machine learning. Interpreting the results is a big challenge in the machine learning algorithm.

Machine learning technology reveals secret learning details among a slew of big data bullets. However, problems such as large-size distribution of computers, distribution, versatility and data streaming are plaguing it. Data duplication also has an important impact on algorithms for machine learning. In many situations it is impossible to classify large quantities of dynamic data. The big problem with algorithms for machine learning is they are susceptible to errors. Machine learning techniques are now different. The learning algorithm takes accurate data for future forecasts. Finding a range of time consuming and resource-intensive concerns requires a massive amount of data.

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