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Cloud Computing and AI in Analysis of Worksite

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Abstract: These days, almost every corporate sector is interested in expanding their operations via the use of artificial intelligence. In addition to this, businesses now have access to tools like artificial intelligence and data analytics, which allow them to get a deeper understanding of the people who make up their target market and automate the production of products in response to the requirements of customers. In exchange, each of these factors contributes to a rise in a company's profitability, which in turn provides the business with an advantage over its rivals. In most cases, salary is the most important factor to consider. But in order for businesses to generate this profit in the past, they had to invest a significant amount of capital into artificial intelligence over a protracted period of time. Artificial intelligence machines were expensive, as were programmers with experience in AI; this latter group was especially harder to come by when there was a lack of meaningful data. In contrast to big organizations, small and medium-sized firms found this challenge to be a serious obstacle to overcome. A third-party AI platform enables today's organizations to begin enjoying the benefits of artificial intelligence and data analysis at a considerably smaller initial investment, all while adapting to the special needs of their individual clientele. SMEs that don't want to construct and test their own AI systems could profit from AI-as-a-Service, which can be accessible through the internet and then utilized in their company. They are able to focus on their primary business without having to become an authority on statistics and apprenticeships, and yet gain the value addition that comes from using artificial intelligence.

Keywords: Artificial intelligence, Cloud computing, Worksite, Data analysis.

1. Introduction

Training on various aspects of computers is a topic that is often covered in the sector of contemporary technology (Kanda, Kanno and Katsukawa, 2019). It is being put to use in an increasing number of business processes, some of which were previously less logical or relied on solutions that were hard-coded. A large amount of data is required for an algorithm to work properly, and a number of companies have proactively obtained data and are looking for ways to exploit it for applications related to machine learning (Teo and Ling, 2009). One subfield of artificial intelligence (AI) is referred to as machine learning (ML), and its goal is to give computers and other machines the ability to teach themselves new skills by recognizing patterns in data and gaining knowledge through experience. The study of algorithms as well as the development of computer programs that are capable of accessing and using data for the purpose of self-training are covered in this course. However, it might be difficult for individuals working in AI to apply the techniques of machine learning to extraordinarily large amounts of data (decision tree, logistic regression, linear regression, SVM, KNN, etc.). Because traditional libraries are unable to accommodate the processing of huge amounts of data, novel and inventive ways have become necessary (Ahmed and Muqeem Ahmed, 2018). In addition, the implementation of artificial intelligence technology and other technologies into a company's infrastructure was far out of reach for small and medium-sized firms. Machine learning systems become capable of being updated and expanded when combined with cloud computing. The term "intelligent cloud" refers to the integration of AI with cloud computing (Talia, 2012). Although computing, networking, and storage are the most common uses for the cloud, the capabilities of both the cloud and AI algorithms may be significantly increased by using cloud machine learning. The process of machine learning is inherently laborious; however, the paradigm of cloud computing makes it possible to significantly accelerate the execution of AI activities. Additionally, traditional statistical programs such as R, Octave, and Python have moved to the cloud.

1.1. Challenges

The development of AI faces a number of obstacles (Yang et al., 2021), some of which have been mentioned in this article. The information and ability that are in little supply and not easily accessible are really necessary. The installation of specialized hardware and its subsequent use will result in increased costs being incurred for the labor force as well as the infrastructure. In addition, problems arise with open-source learning systems like CNTK, MX Net, and Tensor Flow when additional machines are required (Chen et al., 2019). Today, the majority of cloud providers, such as Amazon Web Services (AWS), Google, and Microsoft, provide support for three distinct types of predictions.

This is used for a variety of purposes, the primary ones being the prevention of fraud, the provision of suggestions, and the processing of your request. During the process of category prediction, this method of predicting a dataset is used, and the dataset in question is assigned to a certain category on the basis of the information that was acquired from it. For instance, insurance companies will use forecast categories to classify the many sorts of claims that may be filed. This approach of value prediction finds patterns in the cumulative data by applying learning models to display the statistical analysis of all potential outcomes. This is done within the context of value prediction. The estimated number of units is used by industries to predict the total quantity of an item that will ultimately be accessible (for example, next month). In response to this, they will adjust their manufacturing schedules.

2. Literature review

2.1. Learning in AI

AI algorithms can be roughly split into three categories: supervised learning, unsupervised learning and reinforcement learning (Sarker, 2021).

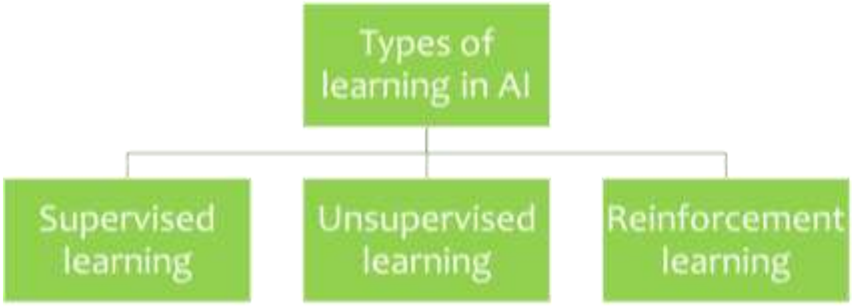

Figure 1 Types of learning

2.1.1. Supervised learning

Teaching a machine to behave in a manner that is analogous to the training data is an example of supervised learning in action. When using supervised learning, training data is made up of inputs and outputs that have been paired with one another before being stored (Voyant et al., 2017). The issue of determining if a picture contains a cat or a dog, which was discussed previously, is an example of supervised learning. In this kind of problem, the input is a picture, and the output is a Boolean value that correlates to the image's quality and indicates whether or not the image is of high quality. Classification is the process of instructing a computer to pick, from a set of predetermined labels or classes, the one that is most likely to correctly classify each piece of incoming data (Kaur and Singh, 2017). Regression is the other subcategory that falls under the umbrella of supervised learning. Issues are considered to be regression problems if they require the computer to be taught to infer or predict a continuous value based on the input data. Predicting the pay of a job based on its description is an example of a problem that falls within the category of regression (Shamim, 2022).

2.1.2. Unsupervised learning

Because there are no known output values corresponding to the input data, a value that was produced by an unsupervised learning approach is not employed in the training of the model (Camps-Valls, 2008). Unsupervised learning techniques are often put to use in the fields of clustering, dimensionality reduction, and anomaly detection, amongst others. Data clustering algorithms organize the data into categories or subcategories that the algorithms have determined for themselves. The basic objective of dimensionality reduction approaches is to bring high-dimensional data sets down to a lower dimensional count than they originally had (Shen, Zhou and Zhou, 2005). Anomaly detection algorithms look for data abnormalities and outliers. These algorithms may be used in instances of fraudulent credit card usage or when there is a breakdown in the system.

2.1.3. Reinforcement learning

Reinforcement learning is a kind of machine learning that is used when a computer learns how to choose the appropriate action depending on its environment (Asada et al., 1996). A computer is necessary for the process of reward-based learning because it must calculate which behavior will result in the biggest numerical reward. The reward for successful completion of a task may not be immediate in the case of reinforcement learning, in contrast to supervised learning. When it comes to reinforcement learning, as opposed to supervised learning, the appropriate actions for the environment circumstances of the data set are unknown, and only the final reward is taken into consideration. After then, the computer has to try out a variety of different policies in order to locate the one that performs the best in each specific circumstance. Examples of algorithms that fall under this category include the well-known "reinforcement learning" algorithms, such as AlphaGo. It is possible to teach a computer algorithm how to play go by using reinforcement learning, which involves rewarding the system when it is successful and penalizing it when it is unsuccessful. This either validates or reduces the judgments that the algorithm made during the course of the game.

2.2. Cloud computing

According to the National Institute of Standards and Technology (NIST), "cloud computing is a concept that permits the ubiquitous, functional, on-demand network access to the common pool of programmable computer resources (Klymash et al., 2016)." Cloud computing refers to the sharing of data and computing resources over the internet. The phrase "computing in the cloud" may refer to a variety of different things. Computing on a grid and in clusters are two more analogies that are often used. The term "grid computing" refers to an infrastructure for scientific computing that makes use of several computers located in different locations to achieve a desired result more quickly than a single computer could. Cluster computing, which is analogous to grid computing, connects together a number of distinct computers to create a single, more effective processing unit. Grid computing is another term for this kind of computing. When compared to a grid, the computers that make up a cluster are reliant on each other both in terms of their programming and their physical location. However, the goal of grid computing and cloud computing is the same: to create "invisible" user power by optimizing efficiency for large-scale operations. The cloud computing model, on the other hand, aims to offer a more general computing solution that can handle any form of on-demand activity. Cloud computing allows for the delivery of computers as a network by providing clients with resources and paying them depending on how much they actually utilize those resources.

2.2.1. Infrastructure as a service

This abbreviation refers to application programming interfaces that are based on the Internet and provide consumers high-level access to the network infrastructure that supports the website of a service provider (Verma, 2021). These services may be accessed via the use of the internet if desired. Because of the existence of cloud operating system hypervisor pools, it is now possible to scale virtual machines and services to meet the requirements of individual clients. The underlying technology provided by the Linux kernel is used in order to isolating, securing, and managing the data that has been containerized. It is essential to use Linux c groups and namespaces in your programming. When compared to virtualization, it is superior since it does not need the installation of a hypervisor (Pahl, 2015). In addition to these additional benefits, dynamic loading assists in solving the issue of overprovisioning and makes it possible to conduct sales depending on the amount of resource use. Cloud service companies who provide IaaS make a wide range of computers that are stored in data centers accessible on demand. Customers have the option of using either the Internet or carrier clouds in order to achieve widespread connection. Users of the cloud network are responsible for uploading files such as photos and software to the network so that their programs may be run. Under this paradigm, the cloud user is responsible for installing updates and performing maintenance on the apps and operating system. The pricing accurately reflects both the value that is provided by the service and the amount of value that is consumed by it.

2.2.2. Platform as a service

The end user is the one who is responsible for installing licensed programming languages, libraries, and resources on the cloud infrastructure. The customer is not influenced in any way by or under the control of the cloud infrastructure on which the network is formed. Using PaaS, applications may be built and evaluated in a live environment before being released to users. The firm is responsible for the creation of a standardized software toolset as well as payment networks. Cloud providers often

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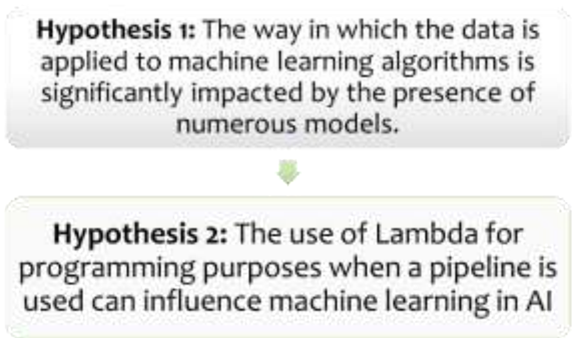
supply the operating system, the programming environment, the database, and the web server when it comes to PaaS models. Cloud computing allows application developers to construct and run their programs while the cloud provider is responsible for maintaining the underlying hardware and software. PaaS distribution techniques for data are used by specialized data processing and integration service providers as well. These strategies are utilized by particular applications.

2.2.3. Software as a service

The user gets access to the software that the corporation provides, which is housed on a network similar to a cloud. Applications are available for a wide variety of user devices, in addition to a software interface or a thin client interface (for example, web-based basic email). Users get access to a variety of software programs and databases when the SaaS paradigm is used. There will be a cloud provider that is responsible for managing the underlying infrastructure and the operating systems that run applications. This kind of subscription-based software, which is also known as SaaS (software as a service), requires payment either on a per-use or monthly basis, depending on the pricing model chosen. Through the use of the SaaS model of cloud computing, cloud companies have the ability to create and maintain cloud software, and cloud customers have access to cloud company data. The software and cloud services that are offered by the service provider should not be subject to any control whatsoever. Keeping the software updated and providing maintenance for it on your own cloud computers is now a thing of the past.

2.3. Hypothesis development



2.4. Conceptual model

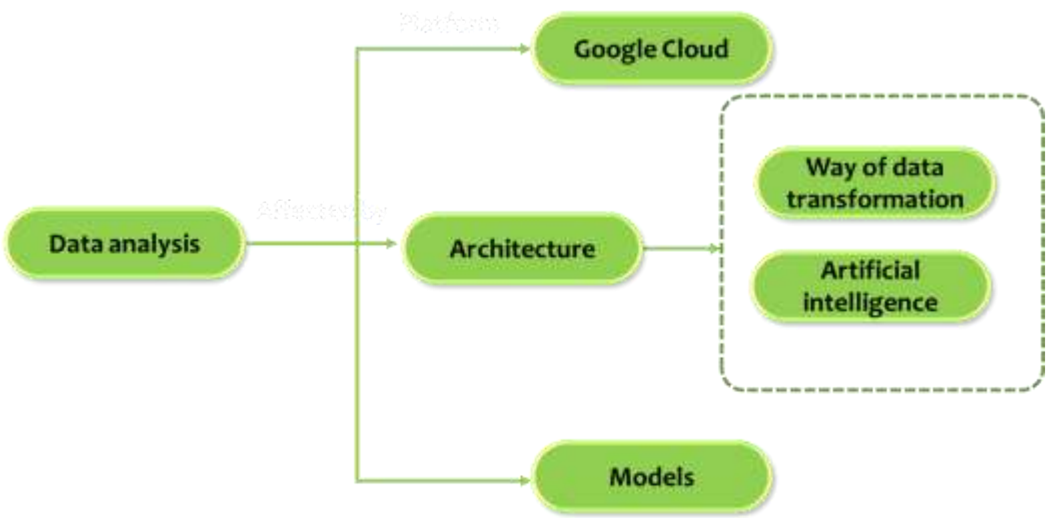


Figure 2 Conceptual model

3. Methodology

Bayesian networks, which are graphic models that define both a random collection of variables and their interconnectedness using DAG, may be used in this investigation. Bayesian networks are also known as beliefs networks or direct graphics. Bayesian networks have these other names. The network may be used to calculate the probability of exhibiting certain illness signs. There are algorithms that are both effective and low-cost accessible.

3.1. Evaluation approach

Both the MSS and the MSS (MAE). Because the limiting mean squared error can be calculated with every model, it is included into each and every one of them. The value of the Model's loss was determined to be that amount based on the mean squared error. An absolute mean error is preferable to a mean square error for determining the effectiveness of a process since the latter is more prone to being affected by outliers. If you are searching for a method that is more accurate, you should choose an absolute mean error. A significant error was made in the criteria that were used to choose which pattern should be utilized. The data pertaining to training makes up seventy percent of the total, while the data pertaining to evaluation makes up thirty percent. Each row has a unique collection of data due to the fact that the data has been arbitrarily split up into two distinct forms for each worksite. When using the split worksite method, every single data row is included into each individual worksite. The comparison list contains about one-third of the total data levels and one-third of the total occupations. The second division, also known as the blind division, is carried out in a haphazard manner using a total of thirty percent of the total number of sample rows. While operating in the blind region, it is more likely that an issue with interpolation may arise as opposed to an extrapolation problem. It is used to extrapolate data from the actual usage of data from the work sites in order to calculate the completion time of an unknown worksite and to decide on the appropriate machine learning model for that worksite. This may be accomplished by using it. Evaluating models for both divisions is necessary since the precision of the parameters acquired from the baskets might provide information about the consistency of the groups.

3.2. Prerequisite for the framework of applications that run on the cloud

When beginning the process of designing an application architecture to run on the cloud, one of the first steps that must be taken is to include all AI models. In order to avoid having an architecture that supports many platforms, each model should be validated on a single platform. The second criterion is the alteration of the data. It is not possible to do conversions inside the database because we want to ensure that it is used only for operational reasons. In addition to a complete data transformation strategy, you might also make use of an integrated data transformation service. It is essential to make use of the model that was investigated during training in order to come up with accurate post-training predictions. The Architecture outlined in this research would work properly if it were put into production. This serves as a proof of concept. Alternately, the Model might be imported into a different piece of software and utilized to generate predictions inside that environment. Having said that, it is clear that an integrated solution is superior than a single solution.

3.3. Choosing the platform

Because Azure does not have native support for XGBoost, master learning operations on Azure need a little bit more overhead than they do on other cloud platforms. The fundamentally available options on each platform aren't all that dissimilar to one another. The data have been changed on all platforms, however there is currently no documentation accessible from Google Cloud. Describes a straightforward procedure for the collection of data for a SQL database. AWS includes the machine learning architecture, delivering the most controlled and relevant tools to suit needs. Azure and AWS both give very comparable techniques of translating data into a CSV file that can be used for machine learning applications in the SQL data base. Data that is now being used is copied from another site before being transmitted to AWS, where it has already been processed.

3.4. Transmission of data

All cloud platforms are competent of doing master learning work; however, Azure requires a little bit more overhead since it does not have native support for XGBoost. The platforms' respective offerings are, in essence, not that far apart. The data have been changed on all platforms, however there is currently no information accessible from Google Cloud. Describes a straightforward procedure for the collection of data for a SQL database. AWS includes the AI architecture, delivering the most controlled and relevant tools to suit needs. Azure and AWS both give very comparable techniques of translating data into a CSV file that can be used for AI applications in the SQL data base. Data that is now being used is copied from another site before being transmitted to AWS, where it has already been processed.

A vast variety of features, each of which is optimized for a certain part of the system, are available (CPU, memory, storage). AWS S3 connections are used in the process of configuring input and output data configuration. This is also the location where data for training, testing, and model storage as well as other prospective data are maintained. Altering model configurations, train models, and other things may be done with the use of hyper parameters. Sage Maker models are examples of machine learning models that are constructed via the use of training data. Sage Maker endpoints in S3 have the ability to get access to the through Model, which can subsequently be consumed by other applications or downloaded by them. Endpoints make use of templates, and wrapper instances are developed for each of these endpoints. It is possible to get the predictions for the input model via the use of an HTTP interface. Using Sage Maker notebooks, training may be constructed in an interactive manner, models can be executed and delivered using Sage Maker notebooks, and so on. Although they are not required for this study, notebooks are used in the process of designing training tasks and endpoints; nevertheless, the specifics of this process are not elaborated upon. It is feasible to make use of AWS Lambda in order to organize and carry out activities for the purposes of teaching and research inside the AWS platform. Due to the fact that this is only a proof of concept, the method of machine learning is only partially used in this investigation. Lambda, on the other hand, may be used for reasons related to programming when a pipeline is used. In order to put the concepts presented in the paper's approach into action, one may utilize one of the following algorithms: Scikit-learn, Tensor Flow, or XG-Boost. The Scikit-learn technique could need an additional script in order to accommodate a hyper parameter.

4. Expected outcome

Tensor Flow makes use of a library and a script made available by Scikit-learn, in addition to a script made available by the library itself, in order to build a model of a neural network. Tensor Flow, a library developed by Google, is very important to deep learning analysis. Machine learning is essential to the operation of every Google product, including search, translation, captioning, and recommendation services. Users of Google, for instance, may reap the benefits of AI-enhanced experiences that are both more efficient and intelligent. Google will provide a suggestion for the next word once you have typed a keyword into a search box and given it some information about what you are looking for. Tensors are used in a broad variety of Tensor Flow’s built-in operations. All of the different data formats may be "tensorized," or represented in the same n-dimensional vector or matrix at the same time. It is possible to establish that each given value on a tensor has the same data type and takes the same shape. The data shape might be either a matrix or an array dimension.

5. Conclusion

This project's objective is to complete the delivery of a cloud service environment that includes an integrated learning pipeline leading from a functional apprenticeship to an operational data base. A secondary goal needs to be established for this project. The first thing that has to be done is to put different types of models to the test in order to see how machine learning can make use of the data. The second problem is with how the structure of the pipeline operates on the cloud. The pipeline is composed of Glue, which is a tool for the transformation and transmission of data that is utilized by Amazon Web Services, and Sage Maker, which is a platform for multi-framework and model machine learning. Glue takes operational database data, extracts it, and stores it as CSV files so that Sage Maker's system models may be used.

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