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Architecture and Framework for Machine Learning as a Service

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Abstract – **Machine learning is becoming part of every domain, from social media network to autonomous driving. Because of different activities humans are generating indirectly trillions of bytes of data every day in their lives; Different sources like Websites, Social media, Mobile applications, System logs, Sensors, Supermarket purchases, Mobile, and Web application usage are generating huge amount of data in every day.The companies and organizations collect this extensive amount of data for data mining in order to extract valuable information, finding similar patterns in the data, and estimating customer behavior; with this information from data companies generate new income and possibly to expand their markets. However, current trending machine learning frameworks are containing limited services and features.This paper proposes an architecture and framework to create a flexible and scalable system. It includes model creation, validation, training, testing, and serving.**

Keywords–. **Social media, bytes of data every, creation, validation, training, testing, and serving.**

I. INTRODUCTION

The acclivitous technologies like big data, the internet of things, cloud computing, and artificial intelligence are changing the way we live in the uprising of these technologies which can shrink the gap between human and machine relations.

Because research replaces old technologies with new innovations and this innovation influences new markets and markets impact economic growth.

In the current market scenario, machine learning is one of the main innovative fields, it simply analyzing big data, and directs market growth along with increasing new revenue streams. Machine learning is able to predict future trends and interests based on current and historical data.

Data is continuously generating from different sources (ex.social media) with proper preparation, which data requires to process. There are different machine learning algorithms existing for processing this huge amount of data and generating trends from it.

Machine learning boosts the benefits of cloud computing services, because cloud service provides advantages of adaptability and flexibility.

The impact of Artificial Intelligence in every field, is growing rapidly in every possible dimension. This possibility is opening doors to new opportunities to implement a lot of research challenges. Increasing performance in computing technologies and processing units capable to handle huge amounts of workloads for machine learning systems. But the available ecosystems for cloud computing services have limited infrastructure.

To handle the large scale of machine learning tasks, it required proper infrastructure because most of the large scale applications work on a distributed environment.

Most of the large scale companies and industries build their own infrastructure otherwise integrate with the third party services in their infrastructure, but small and medium companies have difficulties investing large amounts of money to build their owno infrastructure. Hence machine learning as a service platform reduces cost and adds a lot of advantages over third party services. This proposed service becomes easily adaptable to the requirements of the user as for needs.

II. RELATED WORK

There are different kinds of cloud services available such as private, public, and hybrid cloud, based on user requirements. Cloud computing[3] is the most confusing term in the last decade even though we are using it in services like Gmail, for mobile applications and digital applications. The Cloud services help us for reducing capital expenditure, for example, instead of buying a DVD player and movie DVDs for watching movies simply login to amazon prime or NetFlix and watch movies with minimal expenses. This service is possible to access anywhere in the world where Cloud provides

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greater scale of performance because vendors focus on their infrastructure regularly based on evolving hardware and infrastructure(ex. CPU or GPU) availability. We need to focus on our business, IoT, and big data applications. But Public cloud contains backup, Flexibility, Scalability, and disaster recovery capabilities.

There are different kinds of platforms available for machine learning based on user needs and requirements has shown in figure 1.

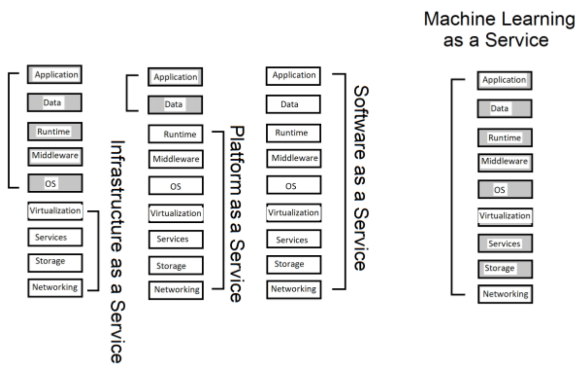

Fig.1.different type of platforms.

1. Infrastructure as a service (IaaS):
Infrastructure as a service is the rapid computing service and manages over the internet, it also can modify as per the demand and the customer requirements. IaaS can scale up and down based on user business bandwidth. Iaas contains advantages like scalability and portability. But the Challenges for using IaaS are over-dependency, customization, virtualization, and user privacy. In this case the vendor handles servers, storage, virtualization, and networking. Here, user is responsible for handling applications, operating systems, middleware, data, and runtime. Some popular providers of IaaS vendors are Google Compute Engine (GCE)[37], Microsoft Azure[38], Amazon Web Services (AWS)[39], Linode[40], Rackspace[41], DigitalOcean[42] and CloudSigma[43].

2. Platform as a service (PaaS):
Platform as a service is one of the fastest-growing services in the public domain. PaaS is growing rapidly from time to time in the public cloud services, because, it provides an effective life cycle management for machine learning models. The advantages of using PaaS infrastructure are Cost Effective, Flexibility, and Time Savings. There are some challenges for customers may lock in a program, they no longer required, compatibility issues, and vendor dependency. There are different phases involved in providing platform services. Paas take organizations is the next level based on user response and demand. In PaaS, vendor provides services for networking, storage, servers, virtualization, operating system, middleware, and runtime; the user is responsible for handling data and application. Some of the applications of PaaS vendors are Google Cloud ML Engine[35], IBM Watson Studio[36], Microsoft Azure ML Services[44], Amazon SageMaker[45], C3 – AI suite[46], DataRobot[47], Deep Cognition[48], Dataiku[49] major platforms are available in the cloud.

3. Software as a Service(SaaS):
Software as a service most commonly used word in the software industry but in Artificial Intelligence and in machine learning it is still in the initial phase. Industries are capable of revolutionizing technologies from time to time. Machine learning has the possibility to increase efficiency for every business. The advantages of using SaaS are Accessibility, Operational Management, Data Storage, and flexibility. User does not need to concentrate on installing, managing, updating infrastructure but user can spend most of the time on priorities. Challenges involved for SaaS are very limited Customization, snd user has no control over service. Vendor provides almost everything to the user as a service. Some of the applications of SaaS vendors are EnsoData[50], Excelion[51], RCM Brain[52], CognitiveScale [53], and Neurala [54] which are major platforms.

The IaaS, PaaS, and SaaS stacks are able to implement and deliver results based on community requirements but they contain challenges like privacy issues and less control on infrastructure. In such a situation machine learning as a service(MaaS) provides complete infrastructures for service.

Big companies have enough resources to fund in their infrastructure to spot their options based on their necessity and requirement[25] but small and middle scale companies contain limited options for their business and have difficulties to choose right platform, because third parties conceivably change their cost and availability for services based on their market demands and business growth from time to time. But these small and middle scale companies can build their own infrastructure with machine learning as a service(MaaS) platform. If users utilize their own platforms in a cloud or normal database, it can reduce cost and increases proficiency. This proposed platform gives complete control of infrastructure and provides a lot of flexibility to the user.

3 Implementation Process: When, we are applying machine learning to our business, it requires solid architecture to cover significant business concerns like privacy, security, and risk of model failure.

In the market, most of the architectures available are from commercial vendors. All vendor-specific architectures provide vendor-specific solutions[16] to the business process. It is very better to choose architecture, more flexible and best suits our business requirements in the long run. This machine learning as a service architecture is an open architecture for machine learning models and based on business process and requirements. And it is possible to build our own architecture as shown in figure 2, which will provide more security and privacy in the long run.

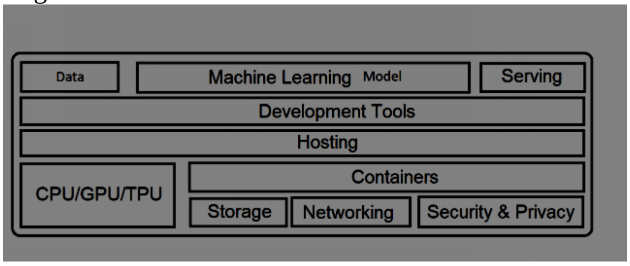

Fig.2.Architecture building blocks for machine learning as a service

In this architecture concentrated on low level and high-level solutions to the machine learning as a service.

Every good architecture is based on fundamental, business requirements and limitations. Applying machine learning as a service required an overview on complete machine learning stack[32] and machine learning as a service should integrate with our business flow.

In order to build suitable MaaS architecture required knowledge on complete business process, machine learning models development, maintenance, network security, and privacy. For building machine learning models required to choose the right development tools that suits and supports business requirements.

3.1 Hosting:

To run the machine learning applications required a suitable hosting platform. Depending upon business size and machine learning type(ex: realtime) it required that hosting infrastructure should be chosen. In machine learning as a service possible to create our hosting service based on our business fundamentals because it supports business extendability and it is easy to update our hosting service without effecting our primary application.

3.2 Containers:

Containers like LXD(Linux)[55] FreeBSD(Unix)[56], docker[57], and Kubernetes[58] increase application flexibility and provide a consistent environment for machine learning in order to increase model accuracy, efficiency, and performance.

3.3 Processing units:

Machine learning required suitable computer resources for model training and data processing. Based on our machine learning application size, we have to choose a suitable processer(For example real-time applications required a high-speed processor to handle application in milliseconds). Based on our business and machine learning pipeline size have to choose proper processor. Some of the suitable processors are CPU(central processing unit), GPU(graphics processing unit), and TPU(Tensor processing unit) in our application.

3.4 Storage:

Machine learning requires huge amounts of data storage to build and run machine learning pipeline. In each new pipeline cycle, new data adds to the system and it requires enough storage area. Considering several factors like machine learning model lifetime and business size suitable infrastructure storage type should be chosen.

3.5 Networking:

networking is a blueprint for complete communication in the architecture because it provides a foundation for framework design, building, and deploying services. Standard network infrastructure is required for building long-lasting machine learning as a service architecture.

3.6 Security and privacy:

There are a lot of risks(ex: user data privacy) associated, when machine learning application is deployed on the world‘s public platform. Most of the machine learning application should reside on a huge trust zone in order to provide high security to the data and required enough care for operating and maintaining machine learning applications.

3.7 machine-learning as a service framework:

Machine learning as a service flexible to any kind of application and this approach focuses on predictive analysis. Predominantly, here concentrated complete overview for the machine learning as a service framework.

The machine learning framework contains building blocks[28, 31, 34] for data preparation, data validation, model training, testing, and deployment. Most of the machine learning frameworks contain APIs for required programming languages. For example, TensorFlow offers APIs for model training.

Most factors required to consider in order to choose a suitable machine learning framework that produces security, privacy, stability, performance, features, flexibility, and transparency.

There are lot of programming languages suitable for machine learning applications but some languages are better ensembles for creating machine learning algorithms. They are statistical computing programming language R, general-purpose, and high-level programming language python.

For creating a machine learning framework which suits to our business context is a difficult task. Initially, we have to determine the problem required to solve, collecting suitable raw data, selecting a suitable machine learning

models and later finding suitable solution to a defined problem.
Here, Collecting suitable data for machine learning is a primary task in machine learning life cycle because data is not just a heart but also oil for the machine learning process.

Data comes from different sources for example general bills, medical records, electronic records, images, text, audio and video, log files, weblogs, app logs, sensor logs, chat logs and etc. Using all kinds of data and preparing for the machine learning model is a complex task. Building the best machine learning model for any business requires almost 70% of the time to spend on preparing data for machine learning training.

Here, machine learning as a service covers end to end machine learning life cycle. This framework contains different modules like central module, data processing unit, data serving unit, and data storage unit.

Our approach is to build a framework that handles user interactions with machine learning tools. This framework contains well-defined APIs and using those APIs possible to access services from any remote location if we operate it on cloud platform.

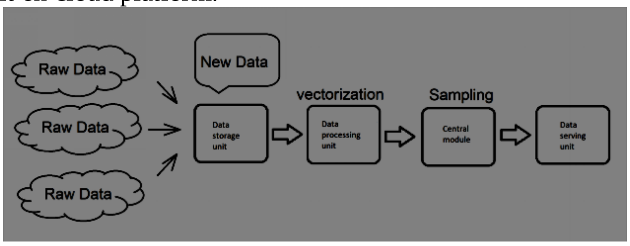

Fig.3. Framework for machine learnig as a service.

In this framework machine learning as a service data processing unit is responsible for handling data. It receives data from the data storage unit and sends it to the central module. The central module is responsible for training and testing data, later it deploys prepared data to the data serving unit. The serving unit, serves the prepared analytics from previous phases. These modules packed together to form a solid architecture for machine learning as a service as shown in figure 3.

An ML workflow contains the relevant data, preparing, validating and cleaning later training, testing, deploying, serving, and monitoring the model.

3.7.1 Data storage unit: In data storage unit user data, validating, training, testing as well as other data assets are stored.

3.7.2 Data processing unit: It receives historical raw data and currently produced data from different sources and merges together and forwards it to the central module.
For example, we can use apache spark to distribute data processing tasks on very large data sets.

3.7.3 Central module: It is responsible for data processing, here we build and validate raw data; after validating raw data, process it into training and testing sets. With those sets, we build predictive models.

3.7.4 data serving unit: This unit is responsible for deploying predictive analysis results to the user. We can use apache Kafka for model examination and monitoring because Apache Kafka is used for distributed streaming platforms and to publish a stream of records.

This system contains a flexible interface between all the modules in the framework.

4. Implementing Machine learning as a service on the eCommerce platform:
ML is useful for e-commerce platform in many ways. It finds wide applicability in predicting supply and demand for recommendation systems in e-commerce applications.
The goal is to build a ML model for eCommerce fashion clothing application using machine learning as a service.

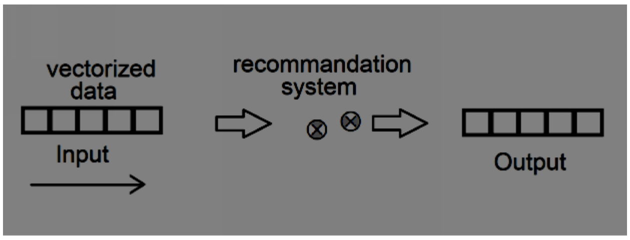

Fig.4. Building a recommendation system for E-commerce application.

Recommendation system plays a powerful role when it comes to offering a much more powerful and personalized experience to users. User likes when companies able to recognize their thoughts. Using ML we can create different user recommendations based on user sessions on our application. For example, new customers can see only unique products first; we can recommend old customers to best offer products based on their interests. short term user interest patterns become long term success for the recommendation systems. Sequential user logs are useful to derive patterns in user behavior and useful to predict users next interest. For attracting customers and promoting products, ML plays a major role in the current market scenario.

We can represent our recommendation system problem at a more traditional formalism[8] level. Let say X be a set of application users and Y be a set of recommendable items to the user. In contradistinction to matrix completion complications, predicting values for each $y \in Y$ and for each $x \in X$ but in determining an ordered list of items O of length L for each user, where each segment of $o \in O$ resembling to a segment of $y \in Y$.

literally after each succession O is a segment of the set of all permutations up to length L of the powerset of Y,

i.e., $O \in SL(P(Y))$.

final set of possible lists as O*. Let u be a function that returns a utility score of a given succession O of a user x, i.e., u: $X \times O^* \rightarrow R$.

The recommendaton system problem then consists of determining the sequence

$lx' \in O^*$

that magnifies the score for the user, i.e.,

$$\forall x \in X, l'x = \arg\max_{o \in O^*} u(x, o)$$

For example recommendation system is learning from utility function u from a given user data. Suppose our user data is a data set of T consisting of a segment of user actions, where each user action $A \in T$ has the number of characteristics. Here data set D is user log files and where each user action contains log file and each log file contains its own identification number. Here u function is not just for utility scores for individual items but it is for a complete ordered list of items.

Making predictions in real-time recommendations using ML requires a huge amount of time and high-end computing resources required. Because the fastest real-time recommendation prediction system should take the shortest time to make useful predictions against user interest. For example displaying suitable predictive advertisements to the user, involves plenty of predictive models within milliseconds.

Here input features like user gender and age, purchasing history and number of clicks per day, how much time users spend his time on the page, what are the user buying preferences, all of this information required for model building and training. For better latency, we have to update Historical features and input data on regular intervals, and each feature should be built and predict separately in a model. For data processing we can choose apache-spark; For asynchronous, real-time log data processing we can use apache storm. All these resources managed with git or svn for regular code reviews and for updates. All important attributes need to be stored, processed and computed.

Most of the preferred algorithams for recommendation systems are decision tree, Bayesian, Matrix factorization-based, Neighbor-based, Neural Network, Rule Learning, Ensemble, Gradient descent-based, Kernel methods, Clustering, Associative classification, Bandit, Lazy learning, Regularization methods and Topic Independent Scoring Algorithm.

The goal of this recommendation system is to recommend suitable items to the user based on user interest.

Out of above all algorithms decision tree algorithm is chosen for recommendation systems because of its relative intelligibility and in order to generate probabilities of recommendation system. Initially we have to collect raw data from our fashion clothing application.

In this section we explain about machine learning as a service for recommendation systems using the decision tree algorithm.

4.1 Data storage unit :

The log data is automatically produced by systems for activities and action takes place on it. This log data is in the form of a file. Examples of different log files are server logs, audit log files, transaction logs, message logs, Syslog, server Log File, daemon Logs, and swift Logs. These generated log files from different users collected using log collectors and stores this data in the data storage unit and later sends it to the data processing unit.

4.2 Data processing unit:

This collected log data should be accurate and informative because the type of received data affects the overall model performance. Here each log record has its own information about user activity. In order to handle log data, it is required huge experience because log data is complex and it's presentation directly affects hyperparameters and expected end results. Here knowledge discovery plays a huge role in driving useful information from log files

In the data cleaning process removing unrelated and corrupted data that can affect the accuracy of the process. After cleaning data, it should be represented in the vectorization form because quires could execute on them.

Cleaned data should be processed for data integration, data validation data transformation(example normalization) later pattern analysis grasp the relevant information from the data for finding variables behavior in the data.

After cleaning and preparing data, we should select suitable variables like user gender, age, marital status, profession, education, average time on the application, past buying data, user interested brands and price range etc.

4.3 Central Module:

In this module various steps will take place such as finding hyperparameters for the model, finalizing algorithm, later training, testing, and model deployment.

Initially analyze the vectorized data and finding patterns in the data. Now, the next step is to choose a suitable algorithm for data analysis.

c5.0 decision tree classification model is used for recommendation systems because it contains better efficiency, more accurate, and less overfitting problems.

Easy to handle missing values in the fashion clothing recommendation application data set.
Using c5.0 classification to train and test our model using available data.
Applying c5.0 decision tree classifier to find out the interests that are similar clothes that the user ordered earlier from the application. Using collaborative filtering [21] on the user to find out the similar users that they have similar interests comparted to the targeted users and find out both parties interested in cloths and shortlisted clothes to recommend targeted users. Using the upper confidence limit recommended those clothes to user on descending order.

4.4 The serving unit

Once machine learning models are trained, tested, and validated. Making these models available to those, who need them. Served models need to be monitored for their performance because model degradation should be detected immediately.

IV. CONCLUSION

Machine learning has the ability to transform the global economy using technological innovation and scientific research. Preparing, Developing maintaining and operating machine learning as a service is a challenging task. This paper presented architecture and framework for machine learning as a service and it helps to get a comprehensive overview of MlaaS. There is a lot of research required in this domain in order to reduce complexity, increase flexibility and security to the users.

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