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Unified Data Engineering Pipelines for Scalable Machine Learning in the Cloud

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Abstract

We are entering a new era of data science and machine learning, where the size of data continues to grow at an unprecedented rate. Natural resources such as oil, gold, etc. have not been used solely in their raw form before. The emergence of the Internet and Social Media has given rise to the data economy. The amount of data generated every hour is beyond imagination. However, raw data is not useful until its values are mined in an automated fashion. The necessity of using previously generated data efficiently has changed traditional approaches towards machine learning pipelines. Machine learning is a dataflow calculation problem, where massive amounts of data need to be ingested, cleaned, processed, aggregated, and transformed into actionable insights with huge computational resources in a reproducible and reliable way. Data Processing Engines or Data Engineering Pipelines are the frameworks that enable the above functionalities in a resource-agnostic manner. Data Processing Engines have not been actively used for training machine learning models. The emergence of new models such as neural networks or deep learning pioneered by the rise of Cloud Computing has made it feasible to train large-scale models on a variety of problems. However, training a model is not limited just to a machine learning framework, it incorporates multiple steps that ingest relevant data for the model, clean and process data, join and import relevant features and transfer the trained model to a serving engine or application.

In principle, a data processing job is similar to a machine learning job. The dataset or data source must be specified and on that data source complex dataflow with a variety of transformations, filtering criteria, and algorithms must be executed in a computationally efficient manner to produce the data product. Dissecting a Data Processing Pipeline into individual and it-can-be-run-on-its-own jobs leaves room for execution optimizations, and the reproducibility of individual jobs shows the readability and reliability of the data pipeline. The agile methodology is the most prominent one followed for splitting up a Data Engineering Pipeline. The data science industry currently uses a wide variety of tools and frameworks across the whole workflow of training machine learning models. Each framework focuses on a design aspect of the system such as orchestration of jobs on a cluster, task management, fault-tolerance, parallel data ingestion, or large-scale training of algorithms. The frameworks chosen to implement the data processing and machine learning pipelines must communicate and operate together. This is non-trivial because of the inability to scale up or down resources on-demand and the lack of servers that expose APIs to manage resources externally. In this work, we present an integrated framework that enables the implementation of highly scalable data engineering pipelines that span the loud and a set of on-premise Data and Compute resources across multiple clouds.

Keywords: Data Processing, Data Pipelines, Machine Learning, Cloud Computing, Kubernetes, Distributed Containers, Containers, Cloud Deployments, Cloud Orchestration, Apache Hadoop, Apache Spark, Cloud Storage, HyperPreprocessing, HyperPostprocessing, CloudML.

1. Introduction

Despite numerous successful implementations of Machine Learning (ML) in various applications, many organizations are still struggling with a lack of a single platform that unifies the whole workflow of production deployments in a scalable way. This results in data stagnation due to an inability to leverage freshness and limited visibility of business intelligence. A cloud-based development paradigm for scalable ML pipelines consisting of three different stages, data transformation, model training, and prediction serving, within a single environment is proposed. For each component, highly scalable cloud-managed services are enabled to eliminate the operational burden of leveraging the cloud. Users can leverage improved productivity without worrying about the operational cost. As a proof of concept, the proposed services are integrated into a unified platform, with one successful production deployment using a

10.48047/jocaaa.2024.33.08.79

transformer-based recommendation model and held-out offline evaluation with positive feedback on its performance.

Big Data is creating a huge opportunity for ML applications in various domains from finance to healthcare. While there are many success stories of ML implementations, many organizations are still struggling with a lack of a single platform that unifies the whole workflow of production deployments in a scalable way. As a result, data in the organization stagnated as they were unable to leverage the freshness of data. Moreover, limited visibility of daily business intelligence results in a lack of detection of outliers, compliance issues, and missed opportunities to discover insights from business events.

This text contains sections, namely Related Work which mentions existing work in these areas and how cloud-managed services can help this transition, ML Pipeline Development Paradigm outlines the proposed three stages of a cloud-based ML pipeline development with high scalability, Prototype Development which discusses an implemented proof-of-concept prototype platform that includes one successful production deployment of a recommendation model and held-out offline evaluation with positive feedbacks. Finally, Future Work and Conclusion summarize the work and plans.

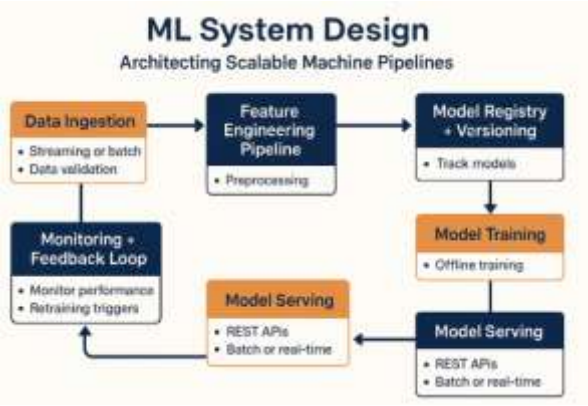

Fig 1: ML System Design — Architecting Scalable Machine Learning Pipelines.

1.1. Background and Significance

Data Engineering (DE) is a subset of Data Science, focusing on gathering, cleaning, and preprocessing data for Machine Learning (ML) tasks . DE transforms raw data into a clean version, known as a data pipeline. The DE process consists of extracting raw data from multiple sources, transforming it through data cleaning and processing, and loading it into data warehouses or databases.

Modern companies typically employ various services for data processing, analytics, and machine learning. Services like AWS S3, Kinesis, Parquet, EMR, and Redshift or their equivalents from GCP and Azure are most commonly used in the industry. Each service could be provided by a different cloud provider and come with detailed documentation.

Setting up data pipelines across multiple cloud providers or on-premises setups necessitates complex DevOps efforts. Once running, data pipelines consume data and output clean data or reports for ML tasks. However, existing cloud providers do not provide native services for MLOps, as there is an ever-growing need for AutoML solutions to automatically convert cleaned data to ML models, deployment scripts, or monitoring systems.

Due to the data explosion of modern services, Cloud Historical Data would be at terascale in a few years. After ingesting huge data, a given subset is usually processed with data pipelines. Existing cloud providers typically provide a series of launch setups to improve developer experience. However, analyzing historic data using either profiling, reporting, or visualizing takes at least a few minutes to tens of minutes after a huge dataset is processed. Often, the whole data setup would be required for processing and analysis.

2. Understanding Data Engineering

With the increasing diversification and complexity of data sources, building an efficient Data Pipeline has become crucial for improving work efficiency and solving complex problems, and how to optimize data flow through automated machine learning methods by integrating AutoML with Data Pipeline. As the most complete and pivotal step in the machine learning process, data preprocessing accounts for 70% of the work. In addition, with the rapid growth of the data scale, especially in the cloud, the need to manage massive data transfers and operations has emerged. However, the workflow of ML data preprocessing currently remains complex and not sufficiently automated. In this talk, we leverage a new type of data and operator-level AutoML technology to help automate this task. We propose a systematic framework that can simultaneously optimize both data and operator using heuristic methods and a heuristic termination condition. Additionally, the framework can be easily integrated with any existing AutoML solution for model optimization. First, we dig into the background and main issues to tackle. Second, a solution architecture is

10.48047/jocaaa.2024.33.08.79

proposed. Finally, an experimental evaluation on both quantitative and qualitative sides is provided. The rise of deep learning in conjunction with affordable GPUs leads to a set of industries and applications such as automatic driving and smart city, which generate huge volumes of visual and sensor data. The pipeline that transfers these data to computational units, transforms the raw data, and feeds them into predictive models is often complicated in terms of scale, number of steps, and variety of processing functions. In this case, the ambition for generating new model-centric learning and reasoning functions was superseded by the data engineering community's effort to provide unified general-purpose data engineering pipelines. This work aims to present the formulation of the general case of the data engineering pipeline, describe representative pipelines from data-centric and learning-centric perspectives, and provide a sketch of a data engineering workflow automation algorithm. Pipeline engineering concerns systematic, tractable, reusable, and easy-to-deploy general-purpose compositions, termed pipelines, of an agnostic set of preprocessing steps and simple prediction functions modeling statistical relations among observables formatted as time series of tensors. Model engineers can choose classes of known precognitive and predictive modules from a library and interconnect them into pipelines that ingest data and format, essentially designing a neural network. In parallel, pipeline learning concerns expediting data discovery, transformation and selection, monitoring and automating pipeline execution, and fault recovery.

Equ 1: Data Ingestion Throughput.

$$T_{\text{ingest}} = \frac{D_{\text{total}}}{t_{\text{ingest}}}$$

Where:

- T_{ingest} = data ingestion throughput (e.g., MB/s)
- D_{total} = total data ingested
- t_{ingest} = time taken for ingestion

2.1. Definition and Importance

The spread of Machine Learning (ML) applications has increased the need to reliably ingest, process, and manage massive amounts of data over extended time horizons. With data proliferating and ML pipelines becoming more complex, cloud Data Engineering (DE) pipelines to support the full-fledged ML lifecycle have become crucial. However, the design and implementation of scalable DE pipelines is currently still a manual, time-consuming, and error-prone process requiring specialized knowledge. This work develops techniques to automatically generate Dataflow jobs that reliably ingest and process data for training Kafka pipelines with fault-tolerant Kafka systems as input to capture a realistic scenario. Given the user-provided Data Ingestion (DI) specifications with source data and freshness requirements, the generation is formulated as an optimization problem with the complex objective of optimizing pipeline accuracy and scalability. If the performance requirement can not be guaranteed, an incomplete output can still be generated. A hierarchical solution approach is developed to first generate an initial holistic solution by means of a Mixed-Integer Programming formulation and then to refine it to a faster local-search heuristics for larger input sizes. High-order transformations are directly compiled into job queries to leverage the optimizer's planning and optimization capabilities. To automatically schedule and batch streaming jobs across heterogeneous processing domains, a three-phase framework is presented. In the first phase, job configuration and resource properties are inferred from the provided job specification, transformation graph, and execution environment. In the second phase, the inference results are merged with the cost models to produce an intermediate representation of the scheduling problem. Finally, a Mixed-Integer Nonlinear Programming formulation is designed to generate a batch scheduling form. The efficacy of the above technique is validated with experiments and presented with Apache Beam and Flink as an industrial context. They have participated in running, validating, and debugging demo-optimized data processing and ML pipelines on Google Cloud Spanner, Dataflow, and CloudML.

2.2. Key Components of Data Engineering

With the widespread use of big data, artificial intelligence (AI), and machine learning (ML), data engineering has emerged as a new work area, gaining importance in industry. Creating data for modeling and extracting insights from the data is critical for organizations, especially enterprises, to train, validate, and deploy their machine-learning models. The workflow of data engineering spans large and complex processes of gathering, cleaning, labeling, evolving, and monitoring data for ML in production settings. Traditionally, data engineering has been a lot of work, performed by software engineers and data scientists specializing in data processing, web scraping, version control, building databases, setting up pipelines and dashboards, etc. With the increasingly complex diversity of data sources, the mining of rich information concealed in the data is gaining significance, requiring more technical depth in data engineering. Since 2012, with the tremendous growth of available data and the advent of machine learning solutions

10.48047/jocaaa.2024.33.08.79

to process and probe into the data, there has been a sea change in how the data is leveraged by industries, leading to the adoption of associated frameworks and systems. Data teams are increasingly proposed to perform data-related jobs spanning many roles and responsibilities in data-centric organizations. This paper focuses on the key components used in the data engineering pipelines of successful case studies. Fragmentation and isolation of enterprise systems lead to the scattering of data in many silos. Data extraction connects source systems to destination systems where the created data resides. Data ingestion helps move initiated data from endpoint connections through workflow management systems to cloud databases and data lakes. Data transformation computes a dataset from one or more datasets, while data formatting renames or reshapes the dataset. Since the target data governance frameworks are often different from those of the systems storing the data, data integration helps move datasets between data governance frameworks. Data monitoring tracks data-generating systems and how well they produce data by configuring sensors and dashboards to visualize the data flow. Data labeling creates ML datasets from source datasets containing the same data via user data-labeling interfaces, client SLC adjustments, and bulk API calls to labeling model down-deployment.

3. Machine Learning Fundamentals

The real-world data is dispersed across numerous heterogeneous data sources and is usually messy and unstructured. Data engineers build data pipelines to convert raw data to desired data that is easy to use. In this process, data engineers need to choose efficient data processing algorithms and design workflows to optimize data flow. However, data pipelines are typically designed manually by data engineers. Machine learning provides heuristic solutions to automate the design of data pipelines.

Currently, data-cleaning algorithms are viewed as the second class of algorithms that are justified by efforts to establish good theoretical frameworks. Traditional wisdom has proved effective in cleaning data from closed sources. Unfortunately, real-world data, especially those from open sources, is generally messy, unstructured, and goes through rapid changes. Consequently, the incumbent data cleaning algorithms are often ineffective or inapplicable and cannot be easily scaled to the huge volume of cheap data. This leads to increasing demands for scalable data engineering solutions.

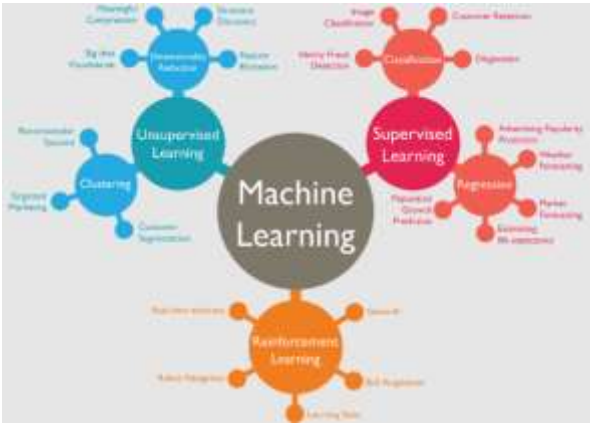

Fig 2: Fundamentals of Machine Learning.

Recent advances in machine learning (ML) provide heuristic solutions to learn new scalable data cleaning algorithms from human-intelligible cleaning actions specified over noisy data. However, to generalize beyond the scenarios seen in the training data, it is vital to design the analogs of "good features". Some of the traditional theoretical paradigms on data and noise impart useful insights on task layout and selection. Nevertheless, thorough studies on generic features as far as data structure and data noise do not seem to exist. The proposed data structure features only exploit spatial domain characteristics while ignoring frequency domain ones. Some promising engineering features, including the amplitude and frequency domain histograms, can be used to evaluate data generalization performance. Though simple and easy to compute, they may be fault-prone on noise-targeted tasks as well. These two continuously used approaches can restrict generalization on simple but critical tasks. It is worth investigating more adaptive and robust frequency domain features invariant to data formats and distribution changes.

3.1. Overview of Machine Learning

Machine Learning (ML) describes a wide array of algorithms to analyze data. Common tasks of ML algorithms include prediction, classification, and ranking. Most ML algorithms are iterative in that they optimize parameters via repeated update steps over available data. An ML task usually has a workflow composed of the following high-level steps (though they can appear in any order and some can be skipped): Feature extraction is the process of converting raw data into data columns that the ML algorithm can understand. In the estimation step, an ML algorithm is trained on available data. The trained model is evaluated in a monitoring step. The trained model can either be used in a prediction step with new data or put into a new iterative

10.48047/jocaaa.2024.33.08.79

workflow, e.g., retraining on new data or feature extraction on new data.

Most cloud solutions for ML do not allow customizing the plugins in the high-level ML workflow within the cloud environment. For example, on Google Cloud's Prediction API or Amazon EC2, a user can submit a trained ML model to be hosted, but cannot customize data preprocessing or retraining in the cloud. Similarly, SQL-ML can only be applied to a database that supports user-defined functions but not stored procedures. Cloud solutions support customizing coded algorithms and data storage, and thus allow for automatic retrieval and concatenation of heuristic features across tables. To trigger on low-level events, some cloud solutions provide event synchronizations. For example, Amazon S3 can generate an event when a new object is available for processing or a new object with a certain prefix is available for batch processing. This is useful for lower-processing-event ML algorithms, but researchers want to push data to trained ML models on batch processing.

ML research is either pure research with no clear early-stage impact or highly integrative research where seldom new methods are proposed. As an integrative data engineering research, researchers observed usage of on-cloud relational storage and automated cloud-based tasks such as ETL and ML. With the design of DE and the HDSyntax specification, researchers expect the final consensus in the future. A detailed review of cloud ML solutions, covering cloud management providers, batch-processing trigger support, and filter capacity, can provide proper research usage criteria on a cloud provider.

3.2. Types of Machine Learning Algorithms

Machine learning can be classified as supervised and unsupervised learning. In supervised learning, which is the most necessary kind of machine learning, the computers learn an objective that portrays an input to an output hinged on training input-output pairs. The task of supervised learning is usually viewed as a regression instead of classification, where the class labels take real values. The task of supervised learning would be linear if a linear objective function can represent the relationship between inputs of higher dimension and scalar outputs. The class labels are assigned to new data samples by approximating a model that can predict the score of the class label from their input features. Without fitting, a classification scenario ought to declare the most precise way for the segmenting boundary. Different class labels drawn by inputs accumulate in separate clusters with a segmenting boundary in between where no class label exists.

Numerous algorithms, such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), Random Forests (RF), Bagging techniques, Boosting techniques, and Artificial Neural Networks (ANN), can be utilized for supervised learning. The most efficient and widely used supervised learning algorithms are KNN, SVM, Large Margin Nearest Neighbor (LMNN), and Extended Nearest Neighbor (ENN). Though a huge amount of literature has been studied on supervised learning algorithms, the comparative study of the selected algorithms on different sizes of datasets and the manipulation of data separately is still an open area to research. The main contribution of this paper is to implement the selected supervised learning algorithms on eleven different datasets to observe the variation of accuracies for each of the algorithms on all datasets. Furthermore, during the implementation of these algorithms on four datasets, which are either large in size or complex or both, iteration-wise accuracies on the entire datasets are determined to fulfill the main motivation of the study. Analyzing the accuracy of the above-mentioned four algorithms will give us a brief idea about the relationship between the machine learning algorithms and the data dimensionality.

Tabular data is one of the most widely used data types across various industries, including financial services, health care, research, retail, logistics, and climate science. It contains heterogeneous features, meaning a table can be a mixture of different types of data: text, numerical, and categorical. Tables have intricate inter-dependencies between columns and intra-dependencies within the column. The data stored in tables serves as an essential source of information for decision-making. As computational power and internet connectivity increase, the data stored by companies grow exponentially, leading to challenges in maintaining and operating vast databases. A line of research has started to apply various learning techniques to support database tasks for these large and complex tables. The learning on tabular data can be split into two phases: (1) The Classical Learning Phase that consists of models such as SVMs, linear and logistic regression, and tree-based methods, which are best suited for small-size tables and limited to classification and regression tasks; (2) The Modern Machine Learning Phase that includes models that use deep learning for learning latent space representation of table entities.

4. The Role of Cloud Computing in Data Engineering

Cloud Computing has revolutionized Data Engineering. The enormous on-demand computational and storage resources

10.48047/jocaaa.2024.33.08.79

scale with the Data Engineer's needs and provide these seamless or cost-efficient. Clouds offer a wide variety of services to cover Data engineers' needs. Such a tremendous offering around cloud computing brings flexibility and efficiency to Data Engineers' tasks such as data processing, preparation, archiving, monitoring, anomaly detection, troubleshooting, etc. Different services are provided for these separate tasks, but they do have similarities and differing implementations. Regardless of the cloud provider, businesses nowadays rely on multiple cloud providers. The motivation for multi-clouds ranges from budgeting and pricing, compliance with regulations and standards, proprietary information and data protection, and business continuity. The tendency for multiple clouds requires expertise to appropriately manage the disparate data processing engines in separate clouds. Data Engineers should frequently switch among different consoles to utilize services that could do parts of a task, which is frustrating. This also brings another challenge of orchestrating the data processing engines across different clouds. These afflicted us to develop a unified data pipeline, namely HyP, with which both data migration and processing engines in different clouds can be utilized in one place without switching among consoles.

A variety of resources and services reliably speed up the data processing in the cloud. Data Engineers can leverage tools that provide flexible scheduling and orchestrating solutions, but all these tools seem to share the same limitations. These tools rely on cloud services, meaning that an appropriate instance of an expensive continuous running service should be allocated to manage workloads. In addition, they typically support transferring and processing data in one cloud only. Some cloud-agnostic efforts try to maintain an orchestrating layer that keeps the transfer/processing work private to the cloud implementation. But they all get inefficient by executing scripts on arbitrary machines in a discretionary way, resulting in the challenge of data movement. They are also hard to customize to tightly integrate with cloud services to automatically select cost-efficient instances for the required services. With several examples, a vision for a fine-grained unified cloud data engineering pipeline architecture is provided which indexes all available resources, conducts efficient scheduling and data migration, and orchestrates workloads across different clouds as a whole. This is built upon the premise that the cloud providers open all their internal APIs and assign an instance to execute each service at a low cost. This architecture is implemented and demonstrated. Finally, the future directions of research are discussed.

4.1. Benefits of Cloud Computing

Having computing resources on-demand brings flexibility to data engineering pipelines. If there is not enough computing capacity for an ML task, it is possible to add resources. This prevents the abandonment of tasks due to crude underestimation of the required resources. Cloud infrastructures provide more opportunities for reducing maintenance costs of on-premise clusters and using best-suited hardware acceleration not necessarily owned by the organization. Moving redundant on-premise data storage systems to the cloud significantly decreases backup and recovery time. Moreover, moving web applications to the cloud opens opportunities to auto-scale resources based on real-time workload. Typically, more extensive data (or more complex ML tasks) means higher resource demand. On-premise clusters are limited in their potential growth (negative scalability). Cloud services are designed with the opposite approach (positive scalability): if a needed resource cannot be allocated, the job just cannot be executed. The analogy can be drawn to the limits of water pipes (on-premise) vs. rivers (cloud). Using cloud services enables dynamic storage to compute ratios and large data processing directly based on the cloud data. If the data does not fit into one instance, it must be processed across multiple ones. However, it could have been the goal from the start to discard data that is only temporarily needed. For workloads executed on large supercomputers, additional clearance resources are needed. Similarly, large CPU allocations should be monitored and released if possible while still providing sufficient performance for the most demanding tasks. Water reservoir comparison applies: if the desired allocation cannot be granted, it must be filled or produced at the cost of expensive time and checks. The goal when switching to a uniform architecture is to achieve the highest possible performance at a reasonable cost. To analyze costs, it is necessary to gather usage statistics along with resource consumption and cloud bill indications and compare those with on-premise prices.

Equ 2: Pipeline Latency.

$$L_{\text{pipeline}} = \sum_{i=1}^{n} l_i$$

Where:

- L_{pipeline} = total pipeline latency
- l_i = latency at stage i
- n = number of stages in the pipeline

4.2. Popular Cloud Platforms

Big Tech Cloud Platforms are widely adopted by industries

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generalizing the exploration of cloud computing in data science. They have a mature service ecosystem for data engineers and scientists to build data science pipelines. However, there are gaps in architectures and methodologies to systematically evaluate Big Tech platforms for data science workflows. The proposed cloud platforms' comparative review framework uses a comprehensive set of evaluation criteria for data science. The proposed framework can quantify subjective judgments from users, can handle dynamic and uncertain data, and can be easily implemented with popular libraries. The framework is validated by cloud platforms' comparative evaluations. The comparative review of Big Tech cloud platforms validates the proposed framework and reveals their pros and cons for data science pipelines. The platforms are recommended for possible use based on users' criteria of dual weightings.

Google Cloud Platform and Amazon Web Services are the best choices for ML model training and deployment, whilst Azure is a better option for batch ETL, ELT, and data preparation/cleaning. The proposed framework can be improved by adding non-functional criteria, and platform services, increasing technology platform options, and utilizing outer evaluation methods in the automatic report generation. The cloud platforms comparative review framework provides insights for users, cloud platforms to help increase competitive advantage or enhance services, etc. Many data scientists and engineers would wish to leverage the benefits of cloud computing in their workflows. Hence, a comparative review of cloud platforms can help identify important avenues for future research. Commercial cloud platforms such as Alibaba Cloud, Snowflake, and IBM Cloud, and open-source platforms such as Asahi Linux Cloud and Apache Beam, to name a few. User-specific criteria for cloud platform selection and options for multi-cloud architecture.

5. Designing Unified Data Pipelines

With the rapidly increasing number and diversification of data sources, the rapidly growing amount of data, and the increasing complexity of data, building an efficient Data Pipeline (Pipelines for short) for Machine Learning has become a problem of vital importance to improve work efficiency. Intelligently handling the data flow of Machine Learning occurred via the application of Data Pipeline has been brought into focus recently. As a nascent research direction, there are still many unexplored tracks, which motivate us to delve deeper into it. Recently, as AutoML has been innovative in providing intelligent model solutions in Machine Learning and its related fields, it is worth investigating whether similar AutoML strategies could also be adapted to the same end within Data Pipelines.

Pipelines are a system that facilitates the building and creation of Machine Learning Data and Model Pipelines. The Pipeline mechanism provides flexible and extensible pipeline components and aims to separate intricate details from end-users so that users only need to "plug and play" the predefined components to construct their workflows. It is common practice to connect several components so that the output of one component will be passed as the input of the next component. Pipelines are often created or constructed from the low-level pipeline API to connect predefined components. An efficient Data Pipeline can save more computing resources, reduce computing time, and improve the overall performance of Machine Learning. Quality Data Pipelines are often complex and costly, requiring Machine Learning engineers considerable amounts of time and effort to be built and created.

5.1. Architecture of Data Pipelines

The design of data pipelines should support various tasks, such as data preprocessing and feature engineering, in addition to data extraction and transfer between datasets. Moreover, the pipeline architecture should facilitate global variable sharing and collaboration among pipeline components. Adapting scalable models to new datasets requires a single architecture at scale. The architecture must consider common characteristics that cross modalities, such as edge-oriented design and input processing speed. Unlike traditional machine learning, which focuses solely on model design, this work considers the pipelines as a whole. A new unified architecture has been designed with modular and flexible ingredients for operators and pipelines. Based on this architecture, two implementations of data pipelines have been developed on Ray: the tensor-based multi-tasks that compute heterogeneous data among multiple datasets on data slices, and the graph-based removal-based modality designers that build operator connections to construct the data graph on the prepared tensors.

Data pipelines are essential for the development of scalable machine learning (ML) systems with complex data ingestion, processing, and extraction workflows. Machine learning tasks obtained an upload rise of technologies and application scenarios, while traditional on-premise computing platforms could hardly accommodate the rapidly growing scale of popular ML models. Cloud-based systems present standalone options for organizations to easily overview the computing resources they purchased and handle workloads in a flexible, elastic manner. However, it remains a challenge to wield the unprecedented scale efficiently when the algorithm model increases using cloud

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systems as the backends. In addition, evolving heterogeneous datasets poses a big challenge to adjust previously trained ML models. Meanwhile, differentiable data pipelines arise as brand new options to integrate ML into data systems to dramatically improve data quality/architecture-based search.

Fig 3:Designing Data Pipelines.

5.2. Data Ingestion Techniques

Scalable data ingestion is necessary for large-scale data-intensive applications such as Internet of Things (IoT) applications, social media analytics, healthcare, and various machine learning (ML) and deep learning (DL) applications. Developing a data ingestion pipeline that can scale out to data at a petabyte (PB) scale is often an important requirement for cloud-based data analytics. Ingesting a very large amount of data into a cloud-based data analytics platform has many unique challenges related to a lack of infrastructure, unpredictable and extensive geographical data sources, and cloud data transport costs. These challenges may affect data arrival rates, network bandwidth, and temporal and spatial data consistency. Existing data ingestion techniques may not be scalable in the cloud environment because they were mainly developed for relatively small systems in an a priori predictable and controlled environment. In addition, they do not provide integration with data storage and analytics, while cloud-based platforms provide comprehensive services to support data management and analytics.

Data ingestion may involve much more complex operations than the ones supported by standard data storage engines. Examples of such operations include predictive tasks using ML and DL models, spatial data enrichment using Geographic Information System (GIS) algorithms, and Natural language processing (NLP) tasks on text data. Although data storage engines may provide the basic ingredients to build a complex data ingestion pipeline, they offer little help in terms of implementing the required algorithms efficiently or debugging, monitoring, and integrating them. Existing data ingestion frameworks can rarely cater to such requirements. Data ingestion is often a strict one-time operation that needs to account for little structural or operational changes in the future. Data ingestion pipelines may also serialize and store the corresponding operations/queries for later repeats. Existing models for offering ingestible outputs are often based on properties of off-the-shelf data storage systems, such as the output being a sorted list of items. However, accurate realizations of such properties are generally far less clear in the context of distributed systems, especially for those based on MapReduce-like architectures and large-scale NoSQL systems.

5.3. Data Transformation Processes

Data transformation processes preprocess input data, resulting in data being inserted into a Configured Data Store. A data transformation may be a complex composition of simpler processes. Each data store defined as a Data Store Cliff-Hanger is referenced in the definition of a data transformation so that the data may be retrieved in a format suitable for processing. The transformation between data stores may refer to another Pipe, whose process may be specified instead of the process being defined inline. Each transformation's action processes input data to produce output data.

The result of a transformation may be written as an action statement using data store decision suffix syntax. The same is true for PyMantis transformations. Data transformation devices and process representations defined as classes will yield parameterized objects. Each represented transformation may apply one or more methods to data written in standard Python data structures. Some applied methods require Formulas to select only a subset of a Data Frame column, and others may select a Data Frame column for transformation. Default data store cliffhangers give access to data in the persistent store Data Barn of a Pipe File or Data Path object. Alternatively, a standard connection may be accessed, enabling the writing and processing of any statements or commands.

In Service-Oriented Process Orchestration and Automation, big data streams formed from various kinds of sources are transformed so that they can be combined based on some serial dependency. Stream transformation processes refer to data deletion or oblivion processes. Such processes involve discarding, hiding, switching to another, more precise representation, sampling, and other transformations similar to those used in stream data mining. Stream processes defined in a data encoding favorable form minimize information loss natively without encoding. On another hand, standard processes are applied to data directly in its

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representation with smaller fidelity to support a broader application range at the cost of losing more information. All processes are designed for continuous data transformations.

6. Scalability Challenges in Machine Learning

Machine learning has entered the mainstream and modifies strong control over a range of industries such as health care, transport and logistics, and content recommendation. Within these industries, machine learning is used to build smart applications that help make better predictions or discover new insights from collected data. These tasks typically involve building a data processing pipeline that consists of several stages. The input data is ingested from one or multiple data sources, pre-processed or transformed to clean and enhance the data set, and finally built upon taken in by the training stage. Once a trained model is available, it may be deployed to serve predictions on new incoming data. This output from the training stage might be used to retrain the model, which indicates a loop back to the second stage in the pipeline.

Machine learning tasks are strongly compute- and data-intensive, resulting in substantial requirements on performance and throughput. On the one hand, a growing amount of data is being collected; on the other hand, operational time constraints are often tight. For example, in video-based security control applications, frames in video streams must be processed milliseconds within of their recording. Another example can be found in recommender systems, where incoming visitor actions must be processed within seconds, or else they become irrelevant. Such data sets may naturally span Terabytes to Petabytes and hence exceed the limit of one machine's memory storage. As a result, there is a growing need for a scalable data processing architecture to meet these performance demands that rely on clouds. Commercial cloud services nowadays offer an abundance of low-cost elastic computing resources scalable to thousands of machines. However, the adaptability of existing processing engines has not matured, and the adoption of any new architecture to supplement the existing framework is costly due to development effort and knowledge collapse. In addition, there exists a paramount need to have guidance on how to best use these current cloud resources from a more abstract resource view. Design decisions in the architectures and implementations of processing engines have a paramount effect on performance, thus spelling the difference between real-time prediction and tremendous delays, or between viable solutions and plummeting operational costs.

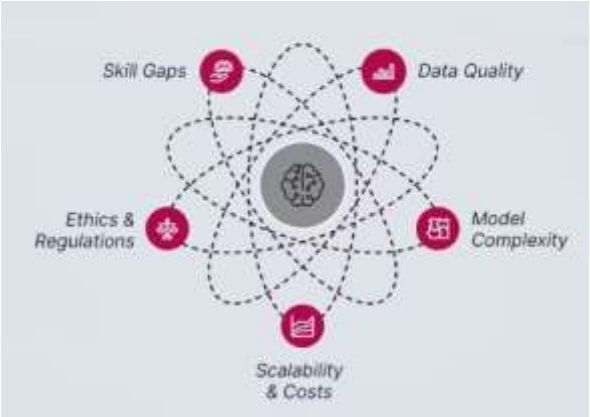

Fig 4: Scalability Challenges in Machine Learning.

6.1. Handling Large Datasets

The need to process and analyze large amounts of data is growing exponentially. Existing services of cloud providers do not cover this need with the proposed research. Architectures of popular deep learning cloud services offered by cloud providers are discussed and compared against the proposed one. A hybrid implementation of the architecture that integrates AWS and Ceres Service Providers has been tested against AWS alone. Experiments on a clinical data processing task show that the hybrid implementation outperforms the Google Cloud Platform and it is more cost-effective. Future work will include work on better allocation and task scheduling strategies and system optimization.

Deep Learning (DL) based models have outperformed manual feature-engineered algorithms in various domains. The amount of labeled data required for training production-ready models - such as surveillance events detection models, safety protocols monitoring models, social networks with very large Machine Learning (ML) forecasts, government data analysis with prediction capabilities, and so on - achieves a terabyte-scale. The unlabelled data for executing those models - such as videos from smart cameras, images from drones, and text analysis from social platforms - reaches a petabyte scale. Such computational resources are on-demand and available on the cloud. Modern Deep Learning frameworks are well-positioned for training and deploying models on multicore machines with multiple GPUs or TPUs.

Training models on terascale data often take weeks or months to converge. DL frameworks recently introduced synchronous and asynchronous distributed training methods to achieve speedup with respect to the number of nodes. With respect to the number of nodes in a distributed cluster,

10.48047/jocaaa.2024.33.08.79

this approach achieves 10–20× speedup. Even when such speedup is achieved, problems such as provisioning, orchestrating, fault-tolerance, distribution data management, task planning, and execution arise. In the case of execution of Big Data workloads, synchronous parallel processing systems have been introduced. The common approaches used in data engineering jobs are the Mappers and the Workers. In every iteration, every node processes a part of the whole data and stores the results in a distributed file system. Task-parallel frameworks provide fine-grained task management when writing a cloud application but lack native deep-learning support.

Equ 3: Distributed Processing Speedup.

$$S_p = \frac{T_1}{T_p}$$

Where:

- S_p = speedup from parallelization
- T_1 = processing time on one machine
- T_p = processing time on p machines

6.2. Performance Optimization Techniques

Distributed systems like the data-processing pipeline (DPP) and data flow graph (DFG) have been widely used to leverage the power of cloud resources to meet the rapid growth of ML jobs (or workflows). Distributing either the DPP or DFG can create a variety of source tasks or task-star topologies on single or networked server clusters. In addition, distributed DPPs are versatile and can be used with any DL libraries, even if they do not support graph partitioning. This section focuses on performance optimization techniques for DPPs and DFGs in cloud DDL and cloud ML platforms.

There are a variety of workloads that can be offloaded to cloud systems using a distributed DPP. Each DPP can be composed of segPA-mers, long DPPs that mix both in-database and out-of-database preprocessing tasks and distributed DPPs that duplicate DPPs using an A/B operation. All of these workloads could incur heavy overheads and, given that in-database computation is substantially more efficient than data movement through network links, the need for performance optimizations arises. Long DPPs can be broken down into segments, ie, a chain of pre-run DPPs, in response to data skew, data sampling, or to ensure better resource allocation and burst-mode analysis. Single DPPs can also be composed into a DAG-shaped structure and executed in a step-wise manner on multi-sourcing servers with a copy operation (a strong feature of a pipelined-distributed DPP).

A dynamic execution planner is in charge of resource allocation, task scheduling, and task assignment. Besides pre-defined topology, it also maintains a set of execution plans that could switch to a better-performing alternative given a certain set of job statistics. Importantly, the resource allocation scope for large-scale data-parallel DDL also needs an effective paradigm; all DDL models in cloud systems usually share the same resources with other workloads in clouds, and, in particular, new shuffling and redundant node elimination metrics need to be introduced. Another family of workloads, callabDGD, can be input-bound DDL jobs running on distributed DPPs that ingest DFF from cloud storage. A dynamic scheduler based on a backed-off exponential window is proposed that mitigates over-scheduling when the workload arrival rate is very high. Additionally, misbalanced was found, which enables routing policies to balance DFF chunks. A dynamic execution planner adapts task scheduling and resource allocation using real-time job stats to optimize execution plans and reduce redundancy. For input-bound DDL workloads like callabDGD, backed-off exponential scheduling, and disbalanced-aware routing improve efficiency under high load and shared-resource constraints.

7. Integrating Machine Learning into Data Pipelines

Machine learning (ML) applications often consume multiple data sources that go through various transformations before they can be used. In addition to training models and serving predictions, a complete ML solution should address Data Pipeline management by automating the extraction, transformation, and loading of data. However, current systems for Data Pipeline generation or orchestration only accommodate basic and static workflows. This paper introduces a unified framework for implementing a class of sequential ML tasks added with Data Pipeline generation and orchestration automatically. These steps can be integrated with existing model training and prediction processing, allowing users to focus on high-level design and implementation. It employs astute learning, AutoML, and Data Pipeline training techniques to find Intellectual Data Pipelines for users. The pipeline structure is expressed in a domain-specific language and stored as a directed acyclic

10.48047/jocaaa.2024.33.08.79

graph. The gradients provided by the trained ML model and predictions made on raw data can be used for refining a partially built Data Pipeline.

A typical Data Pipeline refers to the data processes mainly involving extraction, transformation, and loading (ETL) of data. A typical Data Pipeline is composed of a chain of components, each of which is a method or operator to perform some basic data processing tasks in the Data Pipeline. Modern Data Pipelines often report sophisticated and complex behaviors, covering a diverse range of patterns and a wide array of tasks. New features and data sources are steadily added, and fault tolerance, monitoring, and alerts are required mainly. Data Pipelines provide interfaces for users to provide data sources. OLAP service is a kind of typical Data pipeline that stores data in tables. During Data Pipeline construction, base tables are usually augmented over which additional views are created. These views are also dependent on other views, leading to complex component dependency.

Fig 5: Integrating Machine Learning into Data Pipelines.

7.1. Model Training and Evaluation

This section describes the model training and evaluation components of the data pipeline. The Distributed Processing and Scheduling component is responsible for querying and scheduling cloud resources with the distributed file system, on which all datasets created in the pipeline are saved. The data processing step can be run in parallel over multiple compute resources, which share the same input and output files. This enables rapid scaling of the processing tasks. Once processing tasks are prepared, they can be submitted to the cluster with an infinite submit queue size. No performance degradation occurs even if more tasks than available resources are submitted for execution. Once processing on the cluster is finished, the output files are automatically downloaded back and uploaded to the cloud storage.

The Distributed Model Training component schedules distributed training tasks to the cloud computing resources. Once the training task is submitted, the trainer gets invoked on the training service. It takes care of downloading the output files, starting training, and uploading the snapshot and results back to cloud storage. It also trains a model using a fully functional training script. While the synchronous version of distributed training is implemented, the framework can easily be extended to support asynchronous training with the necessary training logic. The raw parameter server deployment is realized as a highly available database-less application to manage the aggregation of gradients across resources.

The Model Evaluation component evaluates the performance of a machine learning model on one or more datasets created previously in the pipeline. An unspecified number of evaluation tasks can be created, which run in parallel on the cloud computing resources, each performing a different evaluation script on a set of input models and datasets. Once an evaluation task is finished, the metrics results are saved on cloud storage for future use. The hyperparameter optimization is accomplished via a sophisticated hyperparameter optimization strategy. The idea is to divide the search space and evaluate the Learners covering the space locally with the sub-optimal hyperparameter values being passed to the next iterations. At the end of the process, the evaluations of all Learners from different iterations are combined, and the best-performing hyperparameter configuration indicating the optimal training task is selected.

7.2. Deployment Strategies

In this section, various strategies for deploying scalable data engineering pipelines for machine learning in the cloud are presented. In this context, the priority is that Cloud Data Engineering Pipelines can be run in a fundamentally scalable way once the respective infrastructure settings and user-defined algorithms seem to be established. Secondly, Cloud Data Engineering Pipelines need to be able to communicate with the respective surrounding services worldwide via Internet standard protocols.

The high-level architecture consists of a Cloud Data Engineering Pipeline executed in a Kubernetes cluster hosted by a cloud provider and exposed to an outer HTTP load balancer (LB). The Data Engineering Pipeline Kubernetes Services (SVCs) representing individual processing function heads or entry points, labeled SP1-5, need to be stateless since all SVC instances associated on the same level act in a cluster. A fully consistent setup of Data Engineering Pipeline SVCs is not locally manageable. Concerning Data Engineering deadlines, routes to input SVCs and the routing to output SVCs trained models' inference time independent of the input content must be deployable.

10.48047/jocaaa.2024.33.08.79

Once deployed, a Data Engineering Pipeline should not be changed frequently. If new SVCs are added, existing ones need to be modified, or the scaling of SVC replicas needs to be altered. In production use, a container build of a CBDM Data Engineering Pipeline is rarely changed. Complex and often arduous deployment procedures are likely required. Once a Data Engineering Pipeline is running, infrastructure code only requires minor amendments, e.g., increasing deployed SVC replicas, changing metadata references, etc. The main focus must lie on user-defined algorithms if Data Engineering Pipelines are composed merely of external services. These considerations indicate that separating the deployment stage into building and run-time is reasonable. The former is mainly concerned with the structure and the respective dependencies of the environment; the latter is primarily about executing the environment description designed during deployment.

8. Conclusion

In this paper, we discussed various aspects of utilizing cloud solutions for building scalable, production-ready Machine Learning pipelines, particularly focusing on the potential of AutoML methods. We presented various considerations for selecting cloud providers. AutoML solutions greatly lower the expert knowledge barrier of ML, however, currently present solutions only run locally on computers with limited memory and CPU resources. To move the analysis to the cloud, they should be translated into clear and comprehensible cloud infrastructure definitions. Transformer-based architectures have led to new ways of leveraging large amounts of unstructured data in the form of multilingual web data for Answering open-ended questions with domain knowledge. A pipeline was created that crawls, stores, processes, and factors multi-source data to answer questions in near real-time. However, this data-heavy approach optimally needs to process research paper full-text HTML which may grow to terabyte-scale. A cloud-first design is presented for a scalable data pipeline that automates downloading, processing, and pushing to a search index. Providers lock users in after paths toward solutions have been adopted, or their TOS compromises client confidentiality. End-to-end visual data preparation is challenged by vendor TOS too. However, interoperability opens vendor ecosystems to innovation, composition, and reuse. A pragmatic approach to building interoperable interfaces is presented. The suggestions are made to extend the REPL and the TOS to enhance adoption and usability. Adopting and extending emerging interoperability standards with the paradigm added would further facilitate innovation. Cloud solutions facilitate running scalable, production-ready Machine Learning pipelines, especially emphasizing exploiting AutoML. The potential of various AutoML suppliers presents meaningful cloud provider considerations. AutoML greatly lowers the expert knowledge barrier of Machine Learning. However currently only provides a local solution for analysis. Proposals include building a cloud location-agnostic alternative. Research requests in general require knowledge of the data. Similarly, a new inversive direction for finding or predicting data of interest is presented. An open question in constructing Quality Measures for Graph Properties addressing the above need is proposed. AutoML lowers the expert knowledge barrier of Machine Learning. However currently provided solutions only run locally, hindering usage and increasing marketability for small companies. Suggest implementing a cloud-based alternative, ensuring a similar level of flexibility with an additional cloud provider agnostic wrapper to tender and monitor cloud infrastructures, independent from vendor lock-ins.

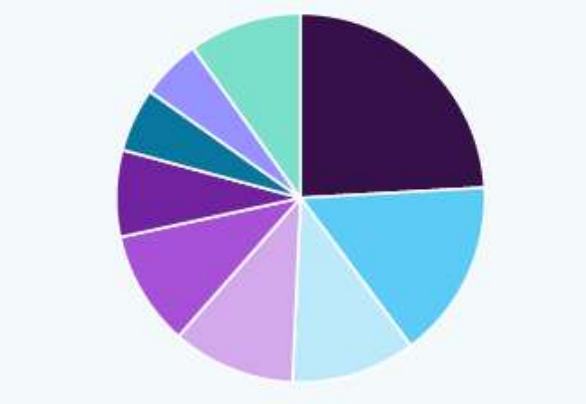

Fig 6: Unified Data Engineering Pipelines for Scalable Machine Learning in the Cloud.

8.1. Future Trends

Deep Learning (DL) models are increasingly being used to automate different stages of data pipelines. Approaches that tackle this task automatically can be broadly categorized into data-centric, model-centric, and training resource-centric paradigms. Data engineering solely relies on new data and computational resources to ensure robustness. The creation of massively diverse datasets, a suitable validation set, and a well-distributed training set is a never-ending task for users. Current practices of creating them often lead to overconfidence issues in the model under-discussed data distribution. In the Data-Centric AI paradigm, actively seeking new data is viewed as a building block to improve model robustness. Models that generalize well on unseen data trivialize the need for neural architecture search, hyperparameter tuning, or synthetic data augmentation.

10.48047/jocaaa.2024.33.08.79

On the other extreme of this control spectrum are Resource Management Engines that control the cloud resources available for parallel DL workloads. When data or compute scale to hundreds of terabytes or thousands of nodes, learning a good weight initialization is not enough for fast convergence. Instead,d schedulers have to explicitly consider data and model parallelism, stragglers, slow nodes, and contention on network, storage, or even CPU. Comprehensive resource managers with online pro-active news, fine-grained per-task subscriptions, and complex filtering have been developed for latency-critical workloads. Yet these engines are not effective for DL workloads where a giant Dedicated Scheduling Layer needs to be designed and incorporated into the resource placement, and orchestration chain. On the contrary, the recent focus is on enhancing the data perspective of the existing DL stacks. Hybrid memories, such as combining the use of node local disk and cloud, have been proposed. Nevertheless, current frameworks still lack sufficient low-latency storage systems where multiple clients can independently write and read with antiproportional throughput.

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