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Chapter 5: Integrating Machine Learning into Data Platforms

5.1. Introduction

Machine learning (ML) increasingly drives the innovation and operational efficiencies of organizations across sectors and industries. Its integration into data platforms, however, remains fragmented and poorly documented. This paper addresses two core questions. Which tools, methods, and resources optimize the ML process end to end within a data platform? Which architectural design choices can tackle the current limitations of centralized data platforms while enabling end-to-end ML in data platforms?

On data ingestion and integration, the paper explores open-source and commercial tools, standardized schemas, model packaging, serving, and operations (MLOps) within the ML lifecycle. Evidence points toward multiple, federated zones of control, supported by appropriate orchestration, data-ML workflows, and user empowerment. A recent self-service ML capability demonstrates a scalable deployment of these principles and practices. The integration of ML into data platforms is expanding, but questions about data privacy, security, bias, fairness, and accountability—and the risks these imply for ML solutions—remind practitioners that effective control must remain paramount.

5.1.1. Scope and Objective

Machine Learning (ML) has become one of the most exciting and rapidly emerging areas of research and application. In numerous organizations, ML is adding significant value and being consumed almost as a utility. As interest grows, so does the complexity of integrating ML into existing technology and business processes. In turn, the demand for integrating ML into a coherent stack across the Data, ML, and Application platforms is becoming a pressing agenda. Data Platforms, traditionally optimized for reporting and analytics workloads, are expected to exploit their built-in advantages for the broader ML

lifecycle. However, due to the unique characteristics of ML, integrating this capability is more difficult than including other workloads.

In these platforms, ML workloads interact with Data, Application, and ML platforms. A holistic perspective can help identify various design choices and trade-offs required for such an integration. Answering questions about the need to centralize or federate Data and ML platforms, the nature of orchestration needed, the role of openness and standards, and the challenges involved in integration can help form a more complete picture of how to implement ML in Data Platforms.

Equation 1: End-to-End ML Pipeline Equation

This represents how raw data becomes predictions inside a data platform:

$$y^=f\theta\big(T(Draw)\big)\hat{y} = f_\theta\backslash big(T(D_{raw})\backslash big)y = f\theta\big(T(Draw)\big)$$

Where:

- DrawD_{raw}Draw: Raw data from sources (logs, APIs, databases)
- T(·)T(\cdot)T(·): Transformation pipeline (ETL/ELT, feature engineering)
- fθf_\thetafθ: ML model with parameters θ\thetaθ
- y^\hat{y}y^: Predicted output

5.1.2. Background and Significance

Integration of machine learning models into data platforms has the potential to substantially improve decision-making processes. Numerous proven solutions and use cases exist in the industrial and academic worlds. Nevertheless, the integration process is often poorly documented. And the knowledge artefacts and tools provided by service providers, industry solutions, and practitioners are frequently inefficient, inconsistent, or scattered across multiple pieces of software. Dedicated infrastructures can certainly facilitate the integration process. However, ML integration must also be addressed at a broader level, encompassing all necessary components, tools, and methodologies. Numerous challenges remain, above and beyond the pure technical aspects. Data privacy and security must be guaranteed. The models deployed must be transparent, comprehensible, and accountable to the users.

5.2. Foundations of Data Platforms for Machine Learning

The following text maintains an academic tone, emphasizes evidence-based arguments, and presents concepts clearly within a formal structure for integrating machine learning into data platforms.

Like other data-driven applications, ML needs to assume data ingestion and integration, storage, and all other platform facilities comprise, at least, a shared service, and large organisations with ML ambitions should consider end-to-end orchestration of the ML lifecycle. Smart integration decisions, supported by suitable tools and standards, can improve a platform's usability, performance, and scalability, while also helping reduce privacy risks and bias.

Data ingestion and integration Machine learning is also a data-hungry technology, and the quality of its predictions largely depends on the quantity and quality of training data. But the ingestion of data-grain processes often needs to be meticulously planned. They should preferably cover all standardised data sources supporting analytics forecasting, taking into account all human behaviours involved in the prediction process. Supporting an on-demand ingestion service taking a pure NoStructure, as a Service (NoSaaS) approach can also create data-grain ML-oriented data sources faster, but at the cost of maintaining more copies of the same data that can present validations issues if done in an ad-hoc way.

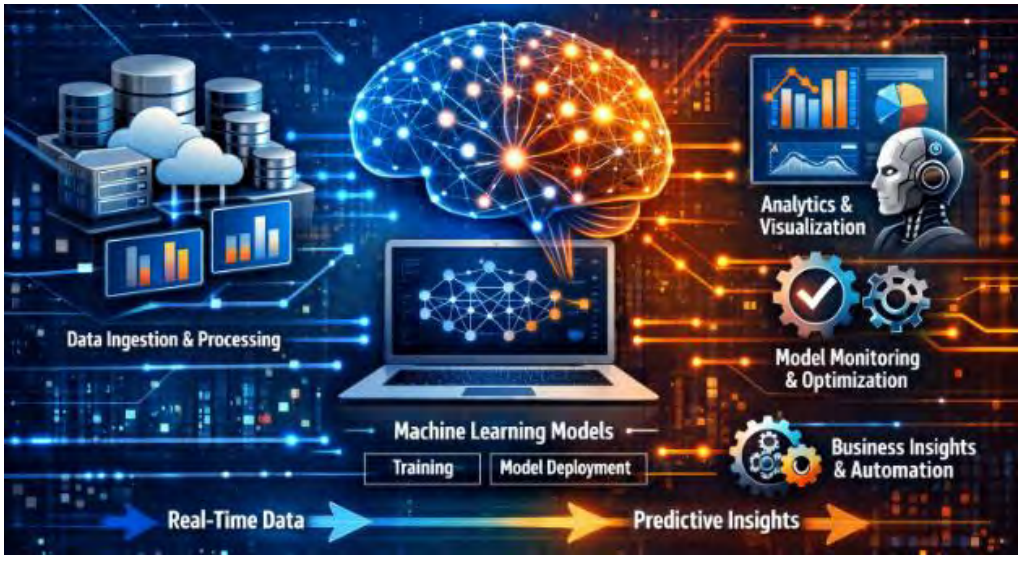

Fig 5.1: Integrating machine learning into platforms

5.2.1. Data ingestion and integration

The need to bring new types of data into data platforms and to integrate them with existing datasets for analysis is crucial throughout the lifecycle of machine learning and data science. User-generated external content on social media, product review sites, web pages, APIs and other data sources can add additional data that can help address many classes of questions. Moreover, machine learning is very often used to provide a model that produces labels, classifications or other engineered features that complement those in the existing data in a standard data platform. These engineered features are typically generated at scale, across many entities. Integrating results from ML models back into the existing data platform can create great value.

And yet, in many environments there is little or no investment in the data ingestion and integration capabilities of the data platform that are of direct relevance to machine learning. In particular, data engineering, the process of preparing data for analysis, is often the least automated, least scaled and least resourced component of the data analytics lifecycle. Too often, these steps are, at best, brittle and poorly monitored processes that rely heavily on manual work at each stage. They may be coded in the same language as the models themselves. There is typically little standardization of quality control steps on scraped data or new features.

5.2.2. Storage architectures for ML workloads

Large-scale ML training and inference workloads are typically executed in large data centers containing specialized hardware accelerators for ML, such as GPUs and TPUs. The ML-serving computation pattern is characterized by a large number of concurrent requests of a small size, resulting in high-throughput and low-latency requirements. However, unlike the data ingestion pattern, the data-serving pattern is similar to that of web-based serving workloads. Processing-intensive ML workloads are emerging in different domains, with data-centric requirements and involving the training of hundreds of thousand models, demanding not only the scalability of the data-storage architecture but also its throughput.

Cloud computing offers a new type of on-demand, pay-as-you-go, and large-scale computing services through the Internet. Computation and storage resources are abstracted into virtualization layers and are very convenient and low-cost to use. The evolution of CPU architecture and the scale of large data centers enable cloud computing to provide highly parallelized data services with extreme high throughput. Cloud storage plays an important role in high-speed data ingestion and in serving-side processes. Cloud vendors are able to satisfy the storage requirement for large model training and supervision using object storage or file systems. However, the traditional block-storage

solution does not scale out easily, resulting in a bottleneck in training for both data preprocessing and model serving. These requirements open up a new area of research related to data-storage architecture for model training and serving.

5.3. Machine Learning Lifecycle in Data Platforms

As for all data-driven use cases, the data requirements for machine learning should be defined clearly and early. Machine learning models are only as good as the data used to train them. The amount of data required depends on the choice of algorithm, the arbitrary nature of the problem being solved, and the degree of data preprocessing. For example, natural language processing (NLP) use cases require many terabytes of text data, while classifying handwritten digits can be solved with only a few thousand annotated samples. Such requirement definitions can be aided by reference templates from historical projects or domain experts.

Feature engineering is the process of transforming raw data into an intermediate format suitable for ML algorithms through a sequence of transformations (such as data wrangling, dimensionality reduction, and featuring extraction). This often requires significant domain knowledge, and will become easier with the availability of a comprehensive data catalogue, data quality measures, and a feature store alongside features from similar problems solved in the past. Data and ML engineers should collaborate closely and start the feature engineering as early as possible, preferably even before the data collection begins.

Feature stores are emerging as a new class of component in data platforms, designed specifically to store and manage features on-par with, or as a layer above, classic data producers and consumers. They maintain features in a catalogue, ensuring discoverability, describe and enforce data quality measures, and provide both batch and online serving capabilities. Feature stores can be populated primarily from data producers but also from data pipelines, ML pipelines, notebooks, and ad-hoc queries, in batch or streaming mode.

Equation 2: Training Optimization Objective

This defines how models learn from data within the platform:

$$\theta *= ar\ g\ m\ i\ n\ \theta\ L(f\theta(X), y)\theta^* = \arg\min_{\theta} \quad \mathcal{L}\backslash big(f_{\theta}(X), y\backslash big)\theta * = arg\theta minL(f\theta(X), y)$$

Where:

- XXX: Feature matrix stored in the data platform

- yyy: Ground truth labels
- L\mathcal{L}L: Loss function (e.g., MSE, cross-entropy)
- θ∗\theta^*θ∗: Optimal model parameters

5.3.1. Problem formulation and data requirements

The first step in the ML lifecycle involves framing a business problem as an ML problem and determining the data requirements. An underlying factor driving data platform adoption of ML is that data scientists increasingly seek to understand what data are available for analysis and to explore these data. A problem formulation often requires balancing the cost and feasibility of collecting ground truth with the expected value of the ML solution. Understanding these requirements enables interaction between data engineers and data scientists through a data platform governance process.

A frequently cited problem is securing sufficient labeled data for supervised learning solutions. Such data requirements may be supported through approaches such as crowd-sourcing, leveraging related-labeling, semi-label or self-supervised learning, and transfer learning techniques. Data platforms supporting these workflows must remain aware of the data needs of models that support ML-based features. Issues of acquisition and ground-truth labeling are especially relevant in autonomous programs that attempt to generate ML feature stores without strict human oversights.

5.3.2. Feature engineering and feature stores

Feature engineering affects a model's performance but is often treated as an unstructured task or informal workflow component. A deep understanding of the domain problem can help identify suitable transformations to enhance prediction quality, e.g. creating lag variables, encoding categorical levels, etc. Performing feature engineering in a formalized manner through collaboration reduces inconsistency when creating ML models for future scoring. Feature stores represent a recent advance to automate and centralize such transformations, enabling reusability, controllability, and consistency. They also help standardize data preparation, expose derived data and features for direct consumption in both inference-mode ML pipelines and ad-hoc analyses.

Feature engineering refers to the creation of new variables or features based on existing variables in the dataset. The goal in this context is to enhance a model's predictive capability without introducing confounding factors.The process is one of the most important aspects of modeling for supervised learning. The experience and intuition of the analyst are often critical, and it is not unusual for new features to substantially improve prediction capability. However, there is usually no formalized process for

feature engineering, and no record is kept of the transformations applied, which makes deploying the same logic for scoring new observations challenging.

Feature stores are a relatively new approach for operationalizing feature engineering and have become increasingly common in organizations adopting a data-centric approach to machine learning. They allow data scientists to share domain knowledge by codifying and centralizing transformation routines to create model features. The rationale behind this is that, since feature engineering is a vital step for the success of supervised learning, deploying the transformation logic in a stable manner for reuse should increase productivity and contribute to greater consistency across models.

5.4. System Architectures for Integrated ML

Two alternative approaches for integrating ML into standard data platform architectures can be considered: a centralized approach and a federated approach. In the centralized approach, the history of data ingestion, storage, ML model execution, and ML pipeline execution are managed and optimized by a single component of the data platform. The traditional Medallion architecture allows a certain specialization of the storage layer, directing the data towards either Delta tables for optimized low-cost company-wide analysis or ML data lakes optimized for ML workloads. A more specific architecture that incorporates this aspect for ML is the central Data Science platform architecture described by Lin et al. (2019), where the history of data eases the execution of ML processes by centralizing the collection and transformation of operational models.

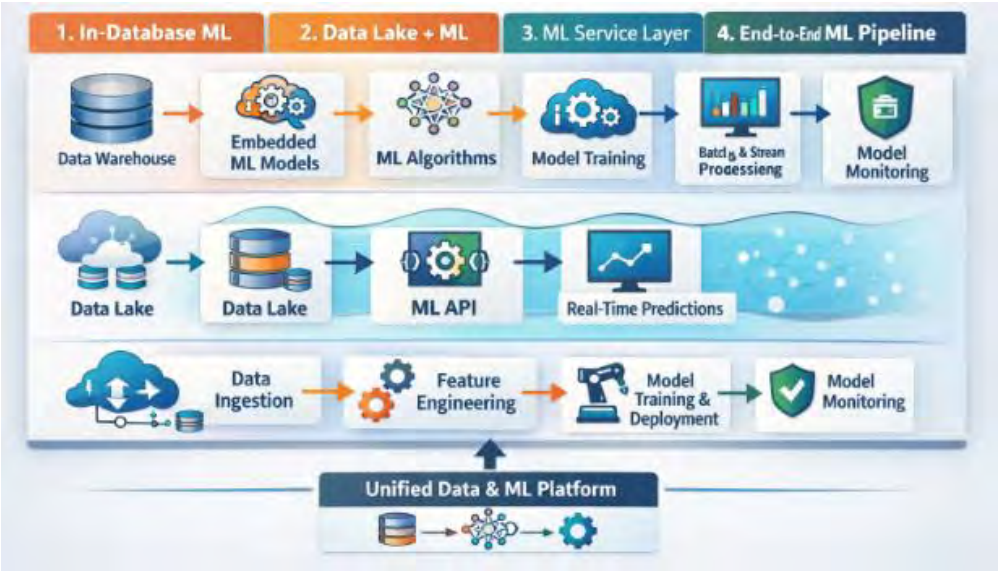

Fig 4.2: System architectures for integrated ML

Under a federated architecture, independent components are preserved and optimized according to their specificity. ML can be treated as another burden on the normal execution of the data platform but requires the execution of ML processes in its context. This is the case in the Data Wine Architecture presented by Marques et al. (2020), where the specifics of Knowledge Discovery in Databases (KDD) are preserved with Data Mining components that interact with the other components in a forced manner as part of the process execution in DM execution. The DataOps principles described by Woodie (2020b,c) and the ML-Oriented DABs (Bennett et al., 2020) provide similar lines of thought, where component interactivity is the focus to preserve their specificity while allowing the interaction required by KDD activities. The open-source ML orchestration tool Apache Airflow is an example of a tool used to operate in this perspective. A different ML-related orchestration tool is the MLflow, which can be classified as a MLOps tool.

5.4.1. Centralized versus federated architectures

Integration of machine learning (ML) into data platforms can be realized with either a centralized or federated operating model. A centralized design enables data scientists and ML engineers to leverage the data platform for the complete ML workflow, from problem formulation and data requirements through model research and retraining. A dedicated team, typically centered in the data engineering department, is responsible for ML-related data integration, ingestion, feature engineering, and serving. While this design can minimize friction and maximize the reusability of ML components for multiple data science use cases, it can also create a bottleneck that constrains ML adoption and time to production. A federated operating model, therefore, is frequently adopted. In a federated architecture, the central data platform provides the connectivity and manages ingestion, integration, and storage of underlying datasets. Ideally, data scientists in the business unit use the data platform primarily for ML model research and development. Feature engineering, particularly for temporal datasets, resides locally.

The federated architecture requires data scientists to have deep understanding of the data platform's architectures and pipelines to maximize the reuse and sharing of underlying datasets. Centralized collaboration improves by using open feature specification formats and data catalogs with clear lineage. An organization-wide ML orchestration layer or workflow management system facilitates the scheduling of both research and production jobs. Proper orchestration and well-designed scheduling policies ease maintenance burdens by automating shared infrastructure support tasks. The combined effect accelerates overall business unit ML adoption by minimizing the cost of ML production work without the overhead of a bottlenecked need for localized model support.

5.4.2. Orchestration and workflow management

Appliance-level orchestration decouples single-appliance processes (e.g. ETL or ML pipelines) into modular, potentially-distributed workflows. As a solution-oriented approach, the indigenous domain offers multiple appliance implementations for a common use-case. The appliance-level interfaces are oriented towards delivery and fulfillment. Thus, data supply and ML model serving processes can be curated as modular flows that orchestrate the underlying appliance processes. Data supply processes provide curated and enriched data feed as a service to ML model serving processes, which in turn serve ML model inference APIs (and corresponding persistence if required). Such an arrangement naturally enables the use of event-driven pipeline orchestration patterns without any additional custom effort. Multi-tenant flows that provide data/fiduciary services to users outside the institution, and cross-data-domain observability are organically supported.

Domain-specific `workflow-as-code´ engines offer a high-level description of the workflow's topology, lifecycle, scheduling, and sink. The engine executes a small set of fine-grained network appliance-management primitives to instantiate and orchestrate the specified workflow. The specialization in ML domain reduces noise and allows users to directly reason in terms of ML-dedicated abstractions without getting bogged down in general-purpose airflow administration. Other widely-used domain language constructs include multi-stage pipelines that enable transfer-learning-style sharing of large models across ML workflows, and multi-root DAGs that model processes that combine templated observations with model inference. Non-standard plug-ins for event-driven flow and cloud-persistent model-serving deployment constitute the dorsal process of the framework.

5.5. Tools, Standards, and Interoperability

Open formats and models play an important role in enabling interoperability across the technology ecosystem. First, they allow diverse tools addressing different aspects of the ML lifecycle to work together. Second, they alleviate the vendor lock-in danger that arises from closed proprietary systems. Both of these benefits stem from access to industry-standard open specifications. Because these specifications are independent from any vendor, they also act as a language for integration among different platforms.Data model definitions that describe shape and semantics of data read and written by various tools help to achieve full interoperability.

The machine learning model packaging format (MLmodel) serves this purpose for ML models. Act-ML describes a standard way to define, serialize, and exchange ML models. While still experimental, it has been adopted by ML servers like Tensorflow

Serving.Packed models trained with these frameworks and formalized in ONNX or Act-ML can be served by different servers without requiring platform-specific adaptations. Similar language-agnostic operating procedures for storage, transport, and serving of ML models can be captured in a machine learning operational practice (MLOps) model.

Equation 3: Data-Driven Decision Function

This represents how predictions drive business decisions:

$$a*= ar\ g\ m\ a\ x\ a\ E[R(\ a\mid y\cdot C\ )]a^* = \arg\max_a \quad \mathbb{E}[R(\ a\mid \hat{y}, C\ )]a* = argamaxE[R(\ a\mid y, C\ )]$$

Where:

- aaa: Possible actions (recommendation, alert, pricing decision)
- RRR: Reward or utility function
- y^\\hat{y}y^: Model prediction
- CCC: Context (user behavior, environment, metadata)
- a∗a^*a∗: Optimal action

5.5.1. Open formats and data models

Extensible and interoperable formats are crucial for the long-term preservation and reuse of data, models, and workflows across platforms and domains. Open formats optimize the reuse of machine-learning artifacts such as training data, features, models, and serving infrastructures. Standards such as TensorFlow's TFX Data Validation and Model Analysis define open formats for feature data and modeling metadata. However, recent research indicates a lack of an international standard for encoding all relevant information required to achieve transparency in machine-learning models. SPOT, a linked-data-based semantic format that semantically links various machine-learning artifacts, addresses this issue. SPOT captures relationships among model components, models and their associated training data, model users, institutions, and geographical information embodied in machine learning.

Machine-learning pipelines consist of artifacts spanning various stages. Ingesting data from diverse repositories during the training phase and leveraging other platforms for the serving phase are practical requirements. SPOT provides essential metadata in an easily reusable manner, enabling these types of integration. For example, the trained models and evaluation reports are accessible via links in SPOT metadata, fostering integration among different repositories. SPOT metadata are specified using machine-readable ontologies, facilitating consumption by machines. As a result, SPOT metadata

enable data integration across various machine-learning repositories, while also serving as a complete provenance trail for any given ML pipeline.

5.5.2. Model packaging, serving, and MLOps practices

Open standards for model packaging ease their sharing and reuse, which are particularly important when multiple teams are contributing to the same problem. The best-known initiative in this area is the Open Neural Network Exchange (ONNX), which has gained considerable traction in the machine-learning community in the context of computer vision. ONNX models can be exported from popular deep-learning frameworks, such as TensorFlow and PyTorch, to an open format for inter-framework interoperability. Other recent frameworks, such as MLflow, TFX, and Seldon, have also bridged the packaging and serving domains. MLflow Model serves models in various languages and frameworks; TensorFlow Extended (TFX) provides a production-scale solution for TensorFlow; and Seldon Core deploys machine-learning models on Kubernetes.

ML models must be served with care, especially when deployed in production for online inference. Although models may initially be packaged and served in a single instance, scalability becomes a key consideration as customer and user bases grow. The leading cloud platforms (e.g., Amazon, Microsoft, Google, and IBM) provide managed services to deploy scalable machine-learning models. These services are built on docked containers and Kubernetes. The general principle is to tune the scaling of multiple container instances and the underlying Kubernetes infrastructure (e.g., by provisioning additional nodes) during stress tests, with monitoring tools observing forecast traffic patterns to scale down when demand contracts. However, businesses that prefer not to rely on external platforms or those with more specific requirements implement these solutions themselves with open-source alternatives, such as Seldon or Kubeflow.

The practice of MLOps is growing in recognition and practice, particularly in the context of large enterprises that deploy many ML models across diverse businesses, geographies, and Customer interactions. MLOps is still a nascent discipline, lacking commonly agreed-upon definitions of roles and responsibilities. Commonly blamed reasons for the slow adoption of MLOps include the lack of appropriate skills and the limited number of vendors offering fully integrated solutions. As for any other IT discipline, organizations must invest in people and processes for successful adoption and scaling of MLOps. Those organizations adopting aspects of MLOps early in their ML journey are typically rewarded through faster deployments of models and a greater number of ML applications.

5.6. Challenges and Risk Mitigation

Standardized approaches and proven technologies can help mitigate many of the challenges and risks associated with integrating machine learning into data platforms. The adoption of an open-model paradigm makes it easier to deploy and manage serving instances in production. Using data-sharing agreements to set boundaries on acceptable use reduces the risk of privacy violations. Automated workflows and model monitoring can expose model failure modes and reduce the likelihood and impact of such failure modes. These are well-known best practices that help ensure enterprise accountability in any application domain, and it is important that organizations that integrate machine learning into their data platforms adopt them.

Despite ongoing advances in fairness-aware machine-learning research, there remains no definitive standard for assessing the fairness of a predictive model or a set of predictions. Organizations that integrate machine learning into their data platforms face the same challenges in this area as organizations that pursue machine-learning operations in isolation, and the research literature provides guidance. Internal data-sharing agreements that govern who can use the data for what purposes are important. Such agreements must explicitly address unfair use of data for model training, such as using models for selecting, promoting, or evaluating employees and models that over-represent a specific group.

5.6.1. Data privacy and security

Machine learning methods can capture and analyze patterns in the data and make predictions or decisions that seem sensible. However, they cannot intrinsically tell whether their inferences are accurate. Therefore, the ML community increasingly harbors concerns about the ethical implications of deploying machine learning applications that could cause damage. A key aspect of ethical ML is data privacy. Many organizations that wish to do machine learning with data from hospitals, banks, or other domains are not allowed to share these raw data, and some jurisdictions even have regulations for the handling of such data. ML requires either the actual raw data or some sort of synthetic data, like the kind produced by Generative Adversarial Networks (GANs), that contain enough statistical similarities with the real data to be useful for training the model. The need for preserving the privacy of the raw data has led to several solutions. Federated Learning is an ML training approach in which the training data remain decentralized. Rather than sending the training data to a central cloud server, only the model updates (i.e., the model gradients) are sent.

In addition to data privacy, security is another important consideration. Many cybercrimes are facilitated by data, either to switch money from one account to another

or to take control of a computer system in order to mine bitcoins. The growing opportunities for cybercrime in terms of criminal proceeds and asymmetry of punishment (an inch of a crime usually leads to years of enjoyment of the criminal proceeds) have led hackers to target not only personal user data but also the information stored on global cloud services for performing machine learning tasks. The trend toward standardizing the deployment of ML workloads using containers such as Docker and Kubernetes has enabled hackers to infiltrate these systems and inject hidden malware, allowing them to steal clouds key resources such as GPU power for free.

Fig 5.3: Integrating machine learning with data security

5.6.2. Bias, fairness, and accountability

The integration of machine learning into data platforms opens new threats and risks for individuals and society, which must be managed. Such risks include the potential release of private data, the embedding of ethical biases in models that make decisions affecting people, and processes that are not transparent enough to allow for meaningful external scrutiny. Both general principles and specific risks related to bias and fairness are discussed.

Located at the foundations of ethical, equitable, and accountable AI practices, fairness is a major preoccupation in the development and deployment of (many) data-driven systems. Many observers feel that algorithms can and must sort individuals into categories in relation to “sensitive attributes,” most commonly categorized according to

demographics, race or gender but that can incorporate additional humanities and socially related aspects. Algorithms embedded into data-driven platforms frequently analyze these sensitive attributes, sometimes forming the basis for decisions or predictions about individuals. In such contexts, sensitive attributes are seen to be "protected characteristics." Their use in data-driven systems requires specific justification and consideration: not only of the responsibility on the part of the system owners or developers to explain their use, but also of their potential consequences. However, sensitive attributes—and the data that describe them—should be included selectively in a data-driven system, and their use within such systems should not be considered innocuous.

5.7. Conclusion

Enterprise, and cloud service provider data platforms are increasingly offering the ability to house and manage the entire breadth of the machine learning lifecycle—data ingestion and integration, feature engineering and feature serving, model training and testing—all within a single platform. The attraction lies not only in the promise of improved quality, efficiency, and speed but also greater accessibility to machine learning methods. With the preeminence of large-scaled machine learning in data platform usage, such a Machine Learning-as-a-Service offering appears destined to eventually deliver the entire machine learning workflow within a single platform. It is not uncommon for industries to not only use Machine Learning-as-a-Service for their large models but to also federate multiple platform providers—for example, Google, Amazon, and Microsoft when it comes to public cloud Azure—because their platforms do differ.

Machine Learning-as-a-Service seems to encapsulate the ideal holistic implementation, and there is also evidence to support such a conclusion. All workloads tend to be optimized behind the scene and packaged up within the pandas format.

5.7.1. Emerging Trends

Enabling Machine Learning (ML) services and applications in existing data platforms (DPs) is a complicated undertaking since ML typically has integration patterns and architecture choices that are fairly specialized. Engineers have to focus on tools and systems that ensure certain properties of their Machine Learning pipelines. As in conventional DPs, data have to be identified, ingested, integrated, and cleaned before being released for ML services or applications. In contrast to traditional DPs, DPs for ML incorporate data-specific components and patterns to support essential capabilities such as feature engineering and a feature engineering store, data and model governance,

data representation formats, model serving, explainability, and bias detection, to mention just a few.

A trend that naturally aligns with enabling ML on a DP is the definition of a federated architecture. The rationale is that modeling initiatives tend to be of a more localized nature, so embracing a federated approach might be sensible in many cases. In this context, the adoption of DPs is also a trend being pursued by federated ML service design. The main thrust is that much of the operationalization of ML services is embedded in the DP design itself..

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