MLOps Landscape in 2025: From Experiment Tracking to Model Deployment

Figure: The MLOps and LLMOps landscape in 2025 spans a wide range of tools and platforms across the machine learning lifecycle[1]. This includes open-source frameworks and enterprise services for experiment tracking, data pipelines, model serving, monitoring, and more.

The global MLOps ecosystem in 2025 is *highly comprehensive*, featuring numerous tools that streamline the machine learning lifecycle from development to production[2]. Industry teams leverage a mix of **open-source tools** (valued for flexibility and community support) and **managed platforms** (offering scalability, integration, and support)[3]. Below, we break down the MLOps landscape into key categories – **Experiment Tracking**, **Data Pipelines**, **Model Deployment & Serving**, **Model Monitoring**, and **End-to-End Platforms** – and highlight notable open-source projects, cloud services, and emerging startups in each area.

Experiment Tracking and Model Metadata Management

Tracking experiments and managing model metadata is a foundational aspect of MLOps. These tools let data scientists log training runs, parameters, metrics, and artifacts for reproducibility and model versioning[4]. Key solutions in industry include:

- **MLflow:** An open-source platform for the ML lifecycle that provides experiment tracking, model versioning, and a central model registry[5]. MLflow enables logging of parameters/metrics and packaging models for deployment, supporting multiple languages (Python, R, Java, REST) and integration into different environments[6]. It is widely adopted for its simplicity in experiment logging and its ability to later serve or deploy the recorded models[5].

- **Weights & Biases (W&B):** A popular cloud-based experiment tracking platform used in industry for tracking ML experiments, dataset versions, and hyperparameters[7]. W&B logs metrics and artifacts (datasets, models, etc.) with rich visualizations, and supports collaboration across teams[7]. It integrates with many ML frameworks (TensorFlow, PyTorch, Hugging Face, etc.) and is known for its ease of use.

- **Neptune.ai:** An experiment management tool (available as cloud or self-hosted) focused on experiment tracking and model metadata storage[8]. Neptune allows logging of metrics, comparing runs, and sharing results in a centralized workspace. Companies use Neptune to securely track thousands of experiments and make results accessible organization-wide[8].

- **Comet ML:** A SaaS platform for experiment tracking and optimization. Comet enables logging of code, hyperparameters, metrics, and model outputs, with a

web UI for comparing experiments[9]. It supports interactive charts and integrates with popular ML libraries, providing a comprehensive solution to manage experiments in one place[9].

- **ClearML:** An open-source MLOps suite offering experiment tracking, pipeline orchestration, and model deployment in a unified platform[10]. ClearML (formerly Trains) emphasizes collaboration and reproducibility – it can automatically log experiments (parameters, results) and version datasets, while also scheduling jobs and serving models in production[10][11]. This makes it a "one-stop shop" for teams seeking a single tool for tracking experiments, managing data, and even deploying models.

Other notable experiment tracking tools include **AimStack**, **TensorBoard** (for deep learning metrics), **DagsHub** (which integrates MLflow tracking with Git), and **Polyaxon** (which offers experiment tracking and model management as part of its platform)[12]. These solutions help ensure that model development in research can be faithfully reproduced and audited later in production.

Data Pipelines and Workflow Orchestration

Dataflow and pipeline orchestration tools handle the data and process automation side of MLOps – from data preparation and feature engineering to training workflow management. These tools ensure that data is collected, processed, and fed into model training/serving reliably and on schedule[13][14]. In industry, teams often use general-purpose workflow orchestrators as well as ML-specific pipeline frameworks:

- **Apache Airflow:** A widely adopted open-source orchestration tool for programmatically scheduling and monitoring workflows (including ML pipelines)[15]. Airflow was originally developed at Airbnb and has a large community and plugin ecosystem[16]. It's used to create DAGs (directed acyclic graphs) of tasks for ETL pipelines, model training jobs, etc. Airflow's maturity and versatility (support for Python, Bash, SQL, and more operators) make it a common choice for orchestrating data and ML tasks in production[16]. *(Airflow excels at batch workflows but is less suited to real-time event processing, which has spurred newer solutions.)*

- **Kubeflow Pipelines:** An orchestration system developed by Google for building **scalable, reproducible ML workflows on Kubernetes**[17]. Kubeflow Pipelines allows data scientists to define complex ML pipelines (e.g. data prep -> train -> evaluate -> deploy) that run in containers. It supports versioned pipelines and facilitates tracking lineage of each step[18]. Kubeflow's integration with Kubernetes makes it powerful for enterprises needing to run ML workflows at scale on cloud or on-prem Kubernetes clusters.

- **Prefect:** A modern open-source workflow orchestration tool and an emerging alternative to Airflow. Prefect is Python-based and offers a **user-friendly UI and easier orchestration** of data pipelines with features like dynamic task scheduling,

dependency management, and error handling[19]. Compared to Airflow, Prefect is designed to be lightweight and flexible for both data engineering and ML tasks, enhancing productivity and reproducibility for teams[19]. (Other similar new orchestrators include **Dagster** and **Mage**, which focus on enabling Pythonic pipeline definitions and strong data engineering integration[20].)

- **Metaflow:** Originally developed at Netflix, Metaflow is a Python-centric framework for orchestrating ML workflows that simplifies experiment tracking and pipeline management. It helps engineers **design pipelines in code**, run them locally or on the cloud, and version artifacts automatically. Metaflow emphasizes developer productivity for data science projects, and it handles scaling by interfacing with AWS services (when using the cloud backend).

- **Flyte:** An open-source orchestration platform initially created by Lyft for **managing ML pipelines at scale**. Flyte supports defining workflows with typed inputs/outputs and manages execution, versioning, and concurrency on Kubernetes[21]. It integrates with feature stores like Feast and libraries like PyTorch or TensorFlow, covering tasks across the ML lifecycle[22]. Flyte has gained attention for enabling highly maintainable and reusable pipeline definitions in production ML systems[21].

In addition to the above, organizations use many other **data workflow tools** as part of MLOps. For example, **Apache Spark** (with libraries like MLlib) is used for large-scale data processing and training jobs; **Delta Live Tables** (Databricks) or **Kedro** (an open-source pipeline framework from QuantumBlack) help enforce data pipeline structure and reproducibility; and **Apache Beam/Google Dataflow** is leveraged for unified batch and streaming data pipelines feeding into ML models. The choice often depends on existing data infrastructure. What's common is the goal of making data flows and model training **automated, versioned, and reliable** so that ML models can be retrained and updated with fresh data seamlessly[23][24].

Data Versioning and Feature Stores

Managing data is a critical part of MLOps in industry – this includes **versioning datasets**, ensuring data quality, and providing a **feature store** for ML models. Tools in this category help maintain reproducibility and consistency between the data used in training and the data used in production:

- **Dataset Version Control (DVC):** An open-source tool that extends Git-like version control to datasets and machine learning models[25]. DVC allows teams to track changes in large data files and models, connecting them to code versions. By integrating with Git, it enables branching and merging for data, making collaboration on data as easy as code collaboration[25]. This ensures experiments and model training pipelines can use the exact versions of data they were developed on, improving reproducibility.

- **LakeFS:** An open-source *data lake versioning* system that brings Git-style version control to data in cloud object storage[26]. LakeFS sits as a layer on top of a data lake (e.g., S3 or HDFS) and lets you create commit points, branches, and rollbacks for your datasets. This is especially useful for managing large-scale, continuously updated datasets in production – teams can isolate changes and only promote data to "production" after validation, akin to code releases[26].

- **Pachyderm:** A versioned data pipeline platform. Pachyderm tracks data lineage and versions through each step of complex data science workflows[27]. It uses containers to define pipeline steps and automatically maintains provenance (which data and code produced which output). This ensures that for any model result, you can trace back exactly which input data and transformation code were used[27]. Pachyderm is often used for large-scale batch processing and was recently updated to better support ML use cases.

- **Feature Stores:** These are specialized data repositories for machine learning features – they enable **consistent feature computation for training and serving**. A feature store ensures that the same logic used to generate features for model training is available to produce features for real-time predictions, avoiding training/serving skew. For example, **Feast** is an open-source feature store that provides a centralized platform to define, store, and serve features for ML models[28]. Feast supports batch processing and real-time streaming features, allowing teams to reuse features across models and serving scenarios[29]. There are also enterprise feature platforms like **Tecton**, which offers an end-to-end managed feature store (from transformation to online serving)[30], and **Hopsworks** Feature Store, an open-source platform often used with Hadoop/Spark that emphasizes data lineage and governance for features[31]. Cloud providers have introduced feature store services as well – e.g., **AWS SageMaker Feature Store**, **GCP Vertex AI Feature Store**, and **Databricks Feature Store** are integrated solutions that let you log features with their metadata and retrieve them in production with low latency[32][33].

- **Data Quality & Validation:** Hand-in-hand with versioning, tools like **Great Expectations** (open-source) are used to define "expectations" or tests on data (schema, ranges, distributions) and catch data anomalies before they break models[34]. **WhyLabs/WhyLogs** is another open tool to monitor data profiles for drift. These help maintain data integrity in the pipeline, ensuring that input data remains within the bounds the model was trained on.

By leveraging data versioning and feature store tools, organizations ensure that data is a first-class citizen in the ML lifecycle – every dataset and feature can be traced, updated safely, and used consistently between model training and inference. This greatly reduces the incidence of issues like models misbehaving in production due to unseen data or inconsistent preprocessing.

Model Deployment and Serving

Once a model is trained and validated, it needs to be **deployed** to production and served to end-users or applications. This stage of MLOps has seen a rich set of tools and frameworks that cater to different environments (on-premises, cloud, edge) and requirements (batch vs real-time serving, scale, latency). Key aspects include packaging the model (often as a Docker container or serialized file), deploying it on infrastructure (virtual machines, Kubernetes, serverless platforms), and **serving** it via an API or pipeline. The landscape for model deployment/serving includes:

- **Containers and Kubernetes:** Containerization is the de facto approach to deploying ML models in industry. Tools like Docker are used to package models with their environment (code, libraries) for consistency. **Kubernetes (K8s)** is widely adopted to manage these containers at scale. Specialized Kubernetes-based frameworks such as **KServe** (formerly KFServing) make it easier to deploy ML models on K8s by providing out-of-the-box prediction API servers, autoscaling, canary rollout, and support for various ML frameworks[35][36]. KServe standardizes serving and scaling for many model types, supporting TensorFlow, PyTorch, XGBoost, and more, and allows advanced deployment patterns (A/B tests, shadow deployments) to be implemented easily[35][36]. Similarly, **Seldon Core** is another open-source platform focused on **serving models on Kubernetes** with an emphasis on production needs like inference graphs, request logging, and metric monitoring via Prometheus[37][38]. Seldon provides inference servers and routing logic to deploy complex ensembles or transformation steps and integrates with K8s features for reliability and scaling[38].

- **Model Serving Frameworks:** A number of frameworks exist to serve models with high performance:

- **TensorFlow Serving:** A *high-performance serving system* for machine learning models, optimized for TensorFlow models but also supporting others via the SavedModel format[39]. It is designed for production environments, offering a gRPC/REST API to load one or multiple model versions and handle large volumes of inference requests with low latency.
- **TorchServe:** An open-source model server for PyTorch models, maintained by Meta and AWS. TorchServe simplifies deploying PyTorch models at scale by handling model loading, request processing, and exposing a REST API[40]. It supports multi-model management, versioning, and basic monitoring of inference metrics[41]. This is typically used when an organization has standardized on PyTorch and wants a straightforward way to serve those models without writing custom web servers.
- **NVIDIA Triton Inference Server:** A universal open-source serving solution that supports models from various frameworks (TensorFlow, PyTorch, ONNX, XGBoost, etc.) under one server[42]. Triton is optimized for GPUs and can

manage deployments of multiple models, doing dynamic batching of requests and adapting to different hardware accelerators. It's popular in industry for maximizing throughput on GPU servers, and it provides robust monitoring and scaling options[43][44].

- **BentoML:** An open-source platform that simplifies **model packaging and deployment** for any ML framework[45]. With BentoML, developers can wrap trained models (from scikit-learn, TensorFlow, PyTorch, etc.) along with preprocessing code into a **"Bento" bundle**, which can then be deployed as a REST API server or saved as a container image[46]. It provides tools for scaling, batch processing, and managing dependencies, making it easier to deploy AI services without needing to start from scratch on the serving logic[47][48]. BentoML also offers a hosted option (BentoCloud) and supports deployment to various cloud infrastructures.

- **Serverless and Cloud-Specific Deployment:** All major cloud providers offer fully managed services for model deployment:

- **AWS SageMaker** provides one-click deployment of models to HTTPS endpoints (backed by auto-scaling clusters) and supports batch transform jobs for offline predictions. SageMaker handles provisioning the servers (including GPU instances if needed) and also offers SageMaker **Serverless Inference** for scaling down to zero when idle.
- **Google Cloud Vertex AI** enables deploying models to **Vertex Endpoints**, including an option for serverless scaling. It also integrates with Google's infrastructure (like Cloud Run or GKE under the hood) to manage the serving.
- **Azure Machine Learning** allows model deployment to **Azure ML Endpoints** or to Azure Kubernetes Service. It provides both real-time inference endpoints and batch inference pipeline jobs.

These services abstract away a lot of the operational overhead – users can deploy by pointing to a model artifact, and the service handles load balancing, scaling, and even updated deployments (with features like blue/green or canary). They also often integrate monitoring and logging by default (e.g., logging request/response sizes, latency, errors to cloud monitor dashboards).

- **Emerging Tools and Platforms:** There are many startups and projects focusing on streamlining model deployment. For example, **OctoML** is a platform that optimizes models for deployment on any hardware (using techniques like compilation and quantization) to achieve maximum performance on target devices[49]. It helps engineers deploy models to cloud or edge by automating the performance tweaking (built on Apache TVM compiler)[49]. Another example is **TrueFoundry** or **Qwak**, which are young companies offering an end-to-end MLOps platform with a strong focus on painless model deployment (often providing a Heroku-like experience for ML models). These emerging solutions indicate the ongoing innovation to simplify the last-mile delivery of models.

In practice, many companies combine these approaches. Some may use **CI/CD pipelines** (Jenkins, GitHub Actions, GitLab CI, or specialized ML CI tools like **CML** from DVC) to automatically build and deploy model containers to a Kubernetes cluster using KServe or Seldon. Others fully embrace a cloud service to manage deployment. The common theme is to ensure that deploying a new model (or updating an existing one) is **fast, repeatable, and low-risk**, so that ML models can be pushed to production frequently as data or business needs evolve.

Model Monitoring and Observability

Deploying a model is not the end of the story – **monitoring models in production** is crucial to ensure they continue to perform well and behave as expected. Model monitoring (also called ML observability) involves tracking metrics like prediction accuracy (if ground truth is later available), response latency, as well as **data drift** and **concept drift** (changes in input data distribution or the relationship between features and target). The 2025 MLOps landscape has given rise to specialized tools and startups focusing on model monitoring:

- **Arize AI:** A prominent **ML observability** platform that helps monitor model performance, detect data drift, and troubleshoot issues in production[50][51]. Arize can ingest model predictions and actual outcomes, then provide analytics to pinpoint where models are degrading (e.g., specific segments of data where error rate is increasing)[52]. It is used to ensure models maintain quality and to alert teams when anomalies occur in model outputs or input data.

- **Superwise:** Another model observability startup offering end-to-end monitoring for production AI systems[53]. Superwise tracks model metrics and data quality, and provides drift detection and root cause analysis. The goal is to **identify issues weeks in advance** of noticeable failures by continuously tracking performance indicators[54].

- **Fiddler AI:** A platform that combines model monitoring with **explainable AI**. Fiddler monitors predictions for drift and performance drop, and also provides explainability tools (feature importance, counterfactuals) to understand *why* a model is making certain predictions[55][56]. This helps with both detecting problems and satisfying requirements for responsible AI (bias detection, transparency).

- **Open-Source Monitoring Tools: Evidently AI** is an open-source library that can analyze model performance and data for drift, generating interactive reports on data distribution changes over time[57]. Teams can incorporate Evidently into their pipeline to regularly check if input features or output predictions have shifted from the training baseline. Another open-source tool, **WhyLogs** (from WhyLabs), enables logging statistical profiles of data in production to catch drift or anomalies; it can be paired with dashboards or alerting systems. Additionally, many engineering teams leverage general monitoring stacks – using **Prometheus**

to scrape custom model metrics and **Grafana** to visualize them – similarly to how they'd monitor any web service. In fact, frameworks like Seldon come with integration to export model metrics (like request rates, error counts) to Prometheus and Grafana out-of-the-box[58].

- **Cloud Provider Monitoring:** The major cloud MLOps platforms integrate model monitoring capabilities. AWS SageMaker, for instance, has **Model Monitor** which can automatically detect data drift or anomalies in model input/output by comparing to a baseline, and AWS **Clarify** for bias detection in production. GCP's Vertex AI provides **Model Monitoring** for drift detection on features and target, alerting when statistically significant changes occur. These services save teams from implementing their own monitoring infrastructure by providing ready-made solutions within the platform.

The importance of model monitoring in industry cannot be overstated – models can decay in accuracy due to changing data or external changes, so having these observability tools ensures **issues are caught early**[54]. Many organizations adopt a combination: using a SaaS like Arize or Fiddler for advanced analytics and drift detection, while also plugging basic metrics into existing APM (application performance monitoring) tools like Datadog, Dynatrace, or Splunk[59] for system-level monitoring. This multi-layered approach helps maintain both the **performance** and the **reliability** of ML services in production.

End-to-End MLOps Platforms and Services

Given the complexity of juggling multiple tools, there is a strong trend toward **end-to-end MLOps platforms** that cover many stages of the ML lifecycle under one umbrella. These platforms can significantly streamline workflows by providing integrated capabilities – from data handling to model training, deployment, and monitoring – without requiring the team to stitch together many disparate tools. The landscape includes both open-source platforms and commercial (often cloud-based) services:

- **Amazon SageMaker:** A fully managed MLOps platform from AWS that supports every step: data labeling, hosted notebook development, experiment tracking (SageMaker Experiments), training (including distributed training on AWS instances), model registry, deployment to scalable endpoints, and monitoring[60][61]. SageMaker is popular for its tight integration with the AWS ecosystem – it can easily consume data from S3, and deployed models can utilize AWS Lambda or GPU instances. SageMaker Feature Store and SageMaker Pipelines add to its completeness. Companies already on AWS often choose SageMaker to reduce the Ops burden through a *pay-as-you-go* managed solution[62].

- **Google Cloud Vertex AI:** GCP's unified AI platform that brings together Google's AI offerings. Vertex AI provides managed Jupyter notebooks, an experiment tracking dashboard, autoML options, custom model training (including on Vertex

Training or user-managed compute), a model registry, deployment to Vertex Endpoints, and Vertex Model Monitoring[63][64]. It also includes a Feature Store and supports pipelines via integration with **Kubeflow Pipelines** or **TensorFlow Extended (TFX)**. Vertex's appeal is in offering Google's advanced tooling (e.g., TPUs for training, built-in explainable AI, etc.) in one place, which is convenient for teams on Google Cloud[63].

- **Azure Machine Learning:** Microsoft's enterprise-grade MLOps platform with similar end-to-end capabilities – an Azure ML workspace provides experiment tracking, dataset versioning, automated ML, pipeline orchestration, hosted training on Azure compute clusters, a model registry, and endpoints for deployment[65]. Azure ML emphasizes **enterprise integration** (with Azure DevOps, Active Directory, etc.) and has robust governance features, making it a choice for organizations needing compliance and IT integration[66]. Azure ML also introduced an integrated feature store and responsible AI dashboarding tools, reflecting the broader industry needs.

- **Databricks**: A commercial data/AI platform that started from Apache Spark for big data and now offers comprehensive MLOps support. Databricks provides a collaborative notebook environment on top of scalable Spark clusters, and it integrates **MLflow for experiment tracking and model management** natively[67]. It also has a Feature Store built-in and recently added real-time **Model Serving** endpoints, so you can serve models directly from the platform[32]. Databricks is especially suited for organizations working with big data (in Delta Lake or Spark) who want a unified platform for both data engineering and machine learning[67][68]. It's widely used in industry for its ability to handle large-scale data processing and ML in one place, often replacing the need for separate data lake and ML tools.

- **Open-Source Full-Stack Platforms: Kubeflow** (mentioned earlier for pipelines) can be seen as an open-source equivalent of an end-to-end platform when fully deployed – it includes not only Kubeflow Pipelines but also components like Notebook servers, hyperparameter tuning, and connections to KFServing (KServe) for deployment. Another example is **Polyaxon**, an open-source platform designed for managing the ML lifecycle with flexibility; it offers experiment tracking, pipeline orchestration, and deployment capabilities in a highly customizable way[12]. **H2O.ai** provides an open-source distributed ML platform and a commercial AutoML product (H2O Driverless AI) that many enterprises use for automated model development and deployment[69]. **Dataiku** is a commercial platform that provides an end-to-end environment with a mix of code and no-code interfaces for data preparation, model training (including using notebooks or AutoML), and deploying models, with a strong focus on collaboration across technical and non-technical users[70][71].

- **Specialized Hosted Platforms:** There are many other notable platforms: **IBM Watson Studio** (enterprise AI platform by IBM)[72], **DataRobot** (an

AutoML-focused platform that also provides deployment and monitoring), **Domino Data Lab** (platform for data science teams to develop and deploy, often used in regulated industries), **Paperspace Gradient** (mentioned as DigitalOcean Paperspace after acquisition, providing cloud VMs with built-in MLOps tools like hosted notebooks, workflow automation, and model deployment)[73]. These cater to various niches – some focus on ease of use, others on compliance, or on specific verticals.

Notably, **infrastructure providers** also offer "MLOps-ready" environments for those who prefer more control. For example, DigitalOcean's acquisition of Paperspace has made it easy to spin up GPU-equipped VMs and use their MLOps toolkit on top of that infrastructure (Notebooks, automated workflow runners, etc.)[74][75]. Similarly, one could use **NVIDIA AI Enterprise** offerings for optimized GPU clusters. These VM-centric approaches are sometimes favored by teams that want to avoid full platform lock-in – they provide base infrastructure and let you deploy open tools like MLflow, Kubeflow, or your choice of serving framework on VMs or containers.

Finally, the MLOps landscape is evolving to include **LLMOps** (Large Language Model Ops) given the rise of foundation models. New tools for prompt management, vector database integration (for retrieval-augmented generation), and LLM monitoring (like **LangChain** for building LLM workflows or **LlamaIndex** for data indexing) are emerging. While these are specialized, they integrate with the broader MLOps stack – for instance, vector stores (Pinecone, Weaviate) might be used alongside model serving, and LLM monitoring tools overlap with model observability. This underlines that the core categories of experiment tracking, data pipelines, deployment, and monitoring are expanding to accommodate new types of models, but remain the pillars of MLOps.

Comparison of MLOps Tool Capabilities

The table below summarizes a selection of notable MLOps tools and platforms and the capabilities they offer across key categories (experiment tracking, pipeline orchestration, model deployment/serving, monitoring, and feature store). This comparison highlights how some solutions cover multiple stages (end-to-end platforms) while others specialize in one part of the workflow:

Tool / Platform	Experiment Tracking	Pipeline Orchestration	Deployment & Serving	Monitoring	Feature Store
MLflow (Open Source)	✔ Yes (tracking & model registry)[5]	◓ Limited (basic ML projects)[76]	◓ Limited (model packaging, REST serving)[5]	✘ No (not for prod monitoring)	✘ No

Tool / Platform	Experiment Tracking	Pipeline Orchestration	Deployment & Serving	Monitoring	Feature Store
Kubeflow (Open Source)	✘ No (metadata only)[17]	✔ Yes (Kubeflow Pipelines)[17]	✔ Yes (via KServe on Kubernetes)[35]	✘ No (relies on external tools)	✘ No
AWS SageMaker	✔ Yes (Experiments)[60]	✔ Yes (SageMaker Pipelines)[60]	✔ Yes (Managed endpoints)[60]	✔ Yes (Model Monitor)	✔ Yes (Feature Store)
Google Vertex AI	✔ Yes (Experiments)[63]	✔ Yes (Vertex Pipelines)[77]	✔ Yes (Endpoints)[63]	✔ Yes (Drift detection)	✔ Yes (Feature Store)[33]
Azure ML	✔ Yes (Run records)[65]	✔ Yes (Pipelines)[66]	✔ Yes (AKS/Endpoint deployment)[65]	✔ Yes (Alerts, drift in Azure)	◓ Partial (Preview feature store)
Databricks ML Platform	✔ Yes (MLflow Integration)[67]	◓ Partial (Jobs & workflows on Spark)[78]	✔ Yes (Databricks Model Serving)	✘ No (limited built-in, use external)	✔ Yes (Databricks Feature Store)[32]
Weights & Biases	✔ Yes (Experiment tracking)[7]	✘ No (integrates with others)	✘ No (no deployment service)	✘ No (focus on training phase)	✘ No
ClearML (Open Source)	✔ Yes (Tracking)[10]	✔ Yes (Orchestration & scheduling)[10]	✔ Yes (Model serving module)[11]	◓ Partial (basic perf. monitoring)[11]	✘ No

Legend: ✔ Yes = natively supported; ✘ No = not provided; ◓ Limited/Partial = some support or integration available.

As seen above, the big cloud platforms (SageMaker, Vertex, Azure ML) aim to provide **all** the capabilities under one roof, which is convenient for industry teams that prefer managed solutions. Open-source stacks often require combining tools: e.g. using MLflow for tracking, Airflow or Kubeflow for pipelines, KServe or BentoML for serving, and so on. Some platforms like Databricks and ClearML bridge multiple categories, giving a more unified experience (Databricks via tight integration of MLflow, Spark, and Delta Lake; ClearML via its all-in-one open suite).

Ultimately, the choice in the MLOps landscape depends on the team's needs and existing ecosystem: some opt for best-of-breed components pieced together, while others choose end-to-end platforms to accelerate deployment. The **landscape in 2025** is rich with options – from robust open-source libraries to cutting-edge startups and mature cloud services – all pushing the state of the art in helping ML models go **from development to production** in a reliable, reproducible, and efficient manner[2][3].

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