AWS Prescriptive Guidance

Planning for successful MLOps

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Planning for successful MLOps

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Deploying machine learning (ML) solutions in production introduces many challenges that don't arise in standard software development projects. ML solutions are more complex and trickier to get right in the first place. They also exist in usually volatile environments, where the data distribution deviates significantly over time for a variety of expected and unexpected reasons.

These issues are further aggravated by the fact that many ML practitioners don't come from a software engineering background, so they might not be familiar with the best practices of this industry, such as writing testable code, modularizing components, and using version control effectively. These challenges create technical debt, and solutions become more complex and difficult to maintain over time, powered by a compounding effect, for ML teams.

This guide enumerates ML operations (MLOps) best practices that help mitigate these challenges in ML projects and workloads.

Because MLOps is a cross-cutting concern, these issues affect not only deployment and monitoring processes, but the whole model lifecycle. In this guide, MLOps best practices are organized into four major areas:

- Data (p. 2)
- Training (p. 6)
- Deployment (p. 10)
- Monitoring (p. 13)

Targeted business outcomes

Deploying ML models in production is a task that requires continuous effort and a dedicated team to maintain these resources throughout their lifetime (in some cases, even years). ML models can unlock considerable value out of business data, but they have high costs. To minimize costs, enterprises should follow good practices in software development and data science. They should be aware of the nuances of ML systems, such as data drift, which makes models perform unexpectedly after a while. By being aware of these concerns, enterprises can meet their business goals safely and with agility in the short term and long term.

There are several kinds of ML models, and the industries they target have varying types of ML tasks and business problems, so you need to consider a different set of concerns for each model and industry. The practices laid out in this guide are not specific to a model or business, but apply to a broad set of models and industries to improve deployment times, generate higher productivity, and build stronger governance and security.

Putting models into production is a multi-disciplinary task that requires data scientists, machine learning engineers, data engineers, and software engineers. When you build your ML team, we recommend that you target these skills and backgrounds.

Data

DevOps is a software engineering practice that deals with the operationalization of software. Common elements of DevOps are version-controlled code, continuous integration and continuous delivery (CI/CD) pipelines, unit testing, and reproducible code builds and deployment, which all involve code. ML models are a product of code and data, so data has to meet the same standards as code. MLOps must address data-related questions such as how to maintain data quality, how to identify edge cases in data, how to secure data, and how to make data more maintainable.

Topics

- Labeling (p. 2)
- Splits and data leakage (p. 2)
- Feature store (p. 4)

Labeling

Provide clear labeling instructions

A dataset might include ambiguous samples that result in inconsistent labeling across the entire dataset. For example, consider the task of labeling images that contain a dog. Some samples might contain only a glimpse of the animal. Should those be marked with a positive or negative label? This type of problem might be solved by providing clear and objective instructions to labelers.

Use majority voting

Now consider the issue of labeling a speech-to-text dataset that contains noisy audio with words that are phonetically similar or identical to others, such as *know* and *go*, *shoe* and *two*, *cry* and *high*, or *right* and *write*. In this case, labelers might label these samples inconsistently.

To maintain a high degree of correctness in labeling, a common approach is to use majority voting, in which the same data sample is given to multiple workers and their results are aggregated. This method and its more sophisticated variations are described in the blog post Use the wisdom of crowds with Amazon SageMaker Ground Truth to annotate data more accurately on the AWS Machine Learning blog.

Splits and data leakage

Data leakage happens when your model gets data during inference—the moment the model is in production and receiving prediction requests—that it shouldn't have access to, such as data samples that were used for training, or information that will not be available when the model is deployed in production.

If your model is inadvertently tested on training data, data leakage might cause overfitting. Overfitting means that your model doesn't generalize well to unseen data. This section provides best practices to avoid data leakage and overfitting.

Split your data into at least three sets

One common source of data leakage is dividing (splitting) your data improperly during training. For example, the data scientist might have knowingly or unknowingly trained the model on the data that was used for testing. In such situations, you might observe very high success metrics that are caused by overfitting. To solve this issue, you should split the data into at least three sets: `training`, `validation`, and `testing`.

By splitting your data in this way, you can use the `validation` set to choose and tune the parameters you use to control the learning process (*hyperparameters*). When you have achieved a desired result or reached a plateau of improvement, perform evaluation on the `testing` set. The performance metrics for the `testing` set should be similar to the metrics for the other sets. This indicates there is no distribution mismatch between the sets, and your model is expected to generalize well in production.

Use a stratified split algorithm

When you split your data into `training`, `validation`, and `testing` for small datasets, or when you work with highly imbalanced data, make sure to use a stratified split algorithm. Stratification guarantees that each split contains approximately the same number or distribution of classes for each split. The scikit-learn ML library already implements stratification, and so does Apache Spark.

For sample size, make sure that the validation and testing sets have enough data for evaluation, so you can reach statistically significant conclusions. For example, a common split size for relatively small datasets (fewer than 1 million samples) is 70%, 15%, and 15%, for `training`, `validation`, and `testing`. For very large datasets (more than 1 million samples), you might use 90%, 5%, and 5%, to maximize the available training data.

In some use cases, it's useful to split the data into additional sets, because the production data might have experienced radical, sudden changes in distribution during the period in which it was being collected. For example, consider a data collection process for building a demand forecasting model for grocery store items. If the data science team collected the `training` data during 2019 and the `testing` data from January 2020 through March 2020, a model would probably score well on the `testing` set. However, when the model is deployed in production, the consumer pattern for certain items would have already changed significantly because of the COVID-19 pandemic, and the model would generate poor results. In this scenario, it would make sense to add another set (for example, `recent_testing`) as an additional safeguard for model approval. This addition could prevent you from approving a model for production that would instantly perform poorly because of distribution mismatch.

In some instances, you might want to create additional `validation` or `testing` sets that include specific types of samples, such as data associated with minority populations. These data samples are important to get right but might not be well represented in the overall dataset. These data subsets are called *slices*.

Consider the case of an ML model for credit analysis that was trained on data for an entire country, and was balanced to equally account for the entire domain of the target variable. Additionally, consider that this model might have a `City` feature. If the bank that uses this model expands its business into a specific city, it might be interested in how the model performs for that region. So, an approval pipeline should not only assess the model's quality based on the test data for the entire country, but should evaluate test data for a given city slice as well.

When data scientists work on a new model, they can easily assess the model's capabilities and account for edge cases by integrating under-represented slices in the validation stage of the model.

Consider duplicate samples when doing random splits

Another, less common, source of leakage is in datasets that might contain too many duplicate samples. In this case, even if you split the data into subsets, different subsets might have samples in common. Depending on the number of duplicates, overfitting might be mistaken for generalization.

Consider features that might not be available when receiving inferences in production

Data leakage also happens when models are trained with features that are not available in production, at the instant the inferences are invoked. Because models are often built based on historical data, this data might be enriched with additional columns or values that were not present at some point in time. Consider the case of a credit approval model that has a feature that tracks how many loans a customer has made with the bank in the past six months. There is a risk of data leakage if this model is deployed and used for credit approval for a new customer who doesn't have a six-month history with the bank.

Amazon SageMaker Feature Store helps solve this problem. You can test your models more accurately with the use of time travel queries, which you can use to view data at specific points in time.

Feature store

Using SageMaker Feature Store increases team productivity, because it decouples component boundaries (for example, storage versus usage). It also provides feature reusability across different data science teams within your organization.

Use time travel queries

Time travel capabilities in Feature Store help reproduce model builds and support stronger governance practices. This can be useful when an organization wants to assess data lineage, similar to how version control tools such as Git assess code. Time travel queries also help organizations provide accurate data for compliance checks. For more information, see Understanding the key capabilities of Amazon SageMaker Feature Store on the AWS Machine Learning blog.

Use IAM roles

Feature Store also helps improve security without affecting team productivity and innovation. You can use AWS Identity and Access Management (IAM) roles to give or restrict granular access to specific features for specific users or groups.

For example, the following policy restricts access to a sensitive feature in Feature Store.

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "VisualEditor0",
            "Effect": "Deny",
            "Action": "*",
            "Resource": "arn:aws:s3:::us-east-2-12345678910-features/12345678910/sagemaker/
us-east-2/offline-store/doctor-appointments"
        }
    ]
}
```

For more information about data security and encryption using Feature Store, see Security and access control in the SageMaker documentation.

Use unit testing

When data scientists create models based on some data, they often make assumptions about the distribution of the data, or they perform a thorough analysis to fully understand the data properties.

When these models are deployed, they eventually become stale. When the dataset becomes outdated, data scientists, ML engineers, and (in some cases) automated systems retrain the model with new data that is fetched from an online or offline store.

However, the distribution of this new data might have changed, which could affect the current algorithm's performance. An automated way to check for these types of issues is to borrow the concept of *unit testing* from software engineering. Common things to test for include the percentage of missing values, the cardinality of categorical variables, and whether real valued columns adhere to some expected distribution by using a framework such as hypothesis test statistics (*t*-test). You might also want to validate the data schema, to make sure it hasn't changed and won't generate invalid input features silently.

Unit testing requires understanding the data and its domain so you can plan the exact assertions to perform as part of the ML project. For more information, see Testing data quality at scale with PyDeequ on the AWS Big Data blog.

Training

MLOps is concerned with the operationalization of the ML lifecycle. Therefore, it must facilitate the work of data scientists and data engineers toward creating pragmatic models that achieve business needs and work well in the long term, without incurring technical debt.

Follow the best practices in this section to help address model training challenges.

Topics

- Create a baseline model (p. 6)
- Use a data-centric approach and error analysis (p. 7)
- Architect your model for fast iteration (p. 7)
- Track your ML experiments (p. 8)
- Troubleshoot training jobs (p. 9)

Create a baseline model

When practitioners face a business problem with an ML solution, typically their first inclination is to use the state-of-the-art algorithm. This practice is risky, because it's likely that the state-of-the-art algorithm hasn't been time-tested. Moreover, the state-of-the-art algorithm is often more complex and not well understood, so it might result in only marginal improvements over simpler, alternative models. A better practice is to create a baseline model that is relatively quick to validate and deploy, and can earn the trust of the project stakeholders.

When you create a baseline, we recommend that you evaluate its metric performance whenever possible. Compare the baseline model's performance with other automated or manual systems to guarantee its success and to make sure that the model implementation or project can be delivered in the medium and long term.

The baseline model should be further validated with ML engineers to confirm that the model can deliver the non-functional requirements that have been established for the project, such as inference time, how often the data is expected to shift distribution, if the model can be easily retrained in these cases, and how it will be deployed, which will affect the cost of the solution. Get multi-disciplinary viewpoints on these questions to increase the chance that you're developing a successful and long-running model.

Data scientists might be inclined to add as many features as possible to a baseline model. Although this increases the capability of a model to predict the desired outcome, some of these features might generate only incremental metric improvements. Many features, especially those that are highly correlated, might be redundant. Adding too many features increases costs, because it requires more compute resources and tuning. Too many features also affects day-to-day operations for the model, because data drift becomes more likely or happens faster.

Consider a model in which two input features are highly correlated, but only one feature has causality. For example, a model that predicts whether a loan will default might have input features such as customer age and income, which might be highly correlated, but only income should be used to give or deny a loan. A model that was trained on these two features might be relying on the feature that doesn't have causality, such as age, to generate the prediction output. If, after going to production, the model receives inference requests for customers older or younger than the average age included in the training set, it might start to perform poorly.

Furthermore, each individual feature could potentially experience distribution shift while in production and cause the model to behave unexpectedly. For these reasons, the more features a model has, the more fragile it is with respect to drift and staleness.

Data scientists should use correlation measures and Shapley values to gauge which features add sufficient value to the prediction and should be kept. Having such complex models increases the chance of a feedback loop, in which the model changes the environment that it was modeled for. An example is a recommendation system in which consumer behavior might change because of a model's recommendations. Feedback loops that act across models are less common. For example, consider a recommendation system that recommends movies, and another system that recommends books. If both models target the same set of consumers, they would affect each other.

For each model that you develop, consider which factors might contribute to these dynamics, so you know which metrics to monitor in production.

Use a data-centric approach and error analysis

If you use a simple model, your ML team can focus on improving the data itself, and taking a data-centric approach instead of a model-centric approach. If your project uses unstructured data, such as images, text, audio, and other formats that can be assessed by humans (compared with structured data, which might be more difficult to map to a label efficiently), a good practice to get better model performance is to perform error analysis.

Error analysis involves evaluating a model on a validation set and checking for the most common errors. This helps identify potential groups of similar data samples that the model might be having difficulties getting right. To perform error analysis, you can list inferences that had higher prediction errors, or rank errors in which a sample from one class was predicted as being from another class, for example.

Architect your model for fast iteration

When data scientists follow best practices, they can experiment with a new algorithm or mix and match different features easily and quickly during proof of concept or even retraining. This experimentation contributes to success in production. A good practice is to build upon the baseline model, employing slightly more complex algorithms and adding new features iteratively while monitoring performance on the training and validation set to compare actual behavior with expected behavior. This training framework can provide an optimal balance in prediction power and help keep models as simple as possible with a smaller technical debt footprint.

For fast iteration, data scientists must swap different model implementations in order to determine the best model to use for particular data. If you have a large team, a short deadline, and other project management-related logistics, fast iteration can be difficult without a method in place.

In software engineering, the Liskov substitution principle is a mechanism for architecting interactions among software components. This principle states that you should be able to replace one implementation of an interface with another implementation without breaking the client application or the implementation. When you write training code for your ML system, you can employ this principle to establish boundaries and encapsulate the code, so you can replace the algorithm easily, and try out new algorithms more effectively.

For example, in the following code, you can add new experiments by just adding a new class implementation.

```
from abc import ABC, abstractmethod

from pandas import DataFrame


class ExperimentRunner(object):

    def __init__(self, *experiments):
        self.experiments = experiments
```

```
    def run(self, df: DataFrame) -> None:
        for experiment in self.experiments:
            result = experiment.run(df)
            print(f'Experiment "{experiment.name}" gave result {result}')


class Experiment(ABC):

    @abstractmethod
    def run(self, df: DataFrame) -> float:
        pass

    @property
    @abstractmethod
    def name(self) -> str:
        pass


class Experiment1(Experiment):

    def run(self, df: DataFrame) -> float:
        print('performing experiment 1')
        return 0

    def name(self) -> str:
        return 'experiment 1'


class Experiment2(Experiment):

    def run(self, df: DataFrame) -> float:
        print('performing experiment 2')
        return 0

    def name(self) -> str:
        return 'experiment 2'


class Experiment3(Experiment):

    def run(self, df: DataFrame) -> float:
        print('performing experiment 3')
        return 0

    def name(self) -> str:
        return 'experiment 3'


if __name__ == '__main__':
    runner = ExperimentRunner(*[
        Experiment1(),
        Experiment2(),
        Experiment3()
    ])
    df = ...
    runner.run(df)
```

Track your ML experiments

When you work with a large number of experiments, it's important to gauge whether the improvements you observe are a product of implemented changes or chance. You can use Amazon SageMaker

Experiments to easily create experiments and associate metadata with them for tracking, comparison, and evaluation.

Reducing the randomness of the model build process is useful for debugging, troubleshooting, and improving governance, because you can predict the output model inference with more certainty, given the same code and data.

It is often not possible to make a training code fully reproducible, because of random weight initialization, parallel compute synchronicity, inner GPU complexities, and similar non-deterministic factors. However, properly setting random seeds, to make sure that each training run starts from the same point and behaves similarly, significantly improves outcome predictability.

Troubleshoot training jobs

In some cases, it might be difficult for data scientists to fit even a very simple baseline model. In this case, they might decide that they need an algorithm that can better fit complex functions. A good test is to use the baseline of a very small part of the dataset (for example, around 10 samples) to make sure that the algorithm overfits on this sample. This helps rule out data or code issues.

Another helpful tool for debugging complex scenarios is Amazon SageMaker Debugger, which can capture issues related to algorithmic correctness and infrastructure, such as optimal compute usage.

Deployment

In software engineering, putting code in production requires due diligence, because code might behave unexpectedly, unforeseen user behavior might break software, and unexpected edge cases can be found. Software engineers and DevOps engineers usually employ unit tests and rollback strategies to mitigate these risks. With ML, putting models in production requires even more planning, because the real environment is expected to drift, and on many occasions, models are validated on metrics that are proxies for the real business metrics they are trying to improve.

Follow the best practices in this section to help address these challenges.

Topics

- Automate the deployment cycle (p. 10)
- Choose a deployment strategy (p. 11)
- Consider your inference requirements (p. 12)

Automate the deployment cycle

The training and deployment process should be entirely automated to prevent human error and to ensure that build checks are run consistently. Users should not have write access permissions to the production environment.

Amazon SageMaker Pipelines and AWS CodePipeline help create CI/CD pipelines for ML projects. One of the advantages of using a CI/CD pipeline is that all code that is used to ingest data, train a model, and perform monitoring can be version controlled. Git and AWS CodeCommit are version control tools that you can use. Sometimes you have to retrain a model by using the same algorithm and hyperparameters, but different data. The only way to verify that you're using the correct version of the algorithm is to use source control and tags. You can use the default project templates provided by SageMaker as a starting point for your MLOps practice.

When you create CI/CD pipelines to deploy your model, make sure to tag your build artifacts with a build identifier, code version or commit, and data version. This practice helps you troubleshoot any deployment issues. Tagging is also sometimes required for models that make predictions in highly regulated fields. The ability to work backward and identify the exact data, code, build, checks, and approvals associated with an ML model can help improve governance significantly.

Part of the job of the CI/CD pipeline is to perform tests on what it is building. Although data unit tests are expected to happen before the data is ingested by a feature store, the pipeline is still responsible for performing tests on the input and output of a given model and for checking key metrics. One example of such a check is to validate a new model on a fixed validation set and to confirm that its performance is similar to the previous model by using an established threshold. If performance is significantly lower than expected, the build should fail and the model should not go into production.

The extensive use of CI/CD pipelines also supports pull requests, which help prevent human error. When you use pull requests, every code change must be reviewed and approved by at least one other team member before it can go to production. Pull requests are also useful for identifying code that doesn't adhere to business rules and for spreading knowledge within the team.

For more information about performing code reviews with AWS CodeCommit, see the blog post Using CodeCommit Pull Requests to request code reviews and discuss code on the AWS DevOps blog.

Choose a deployment strategy

MLOps deployment strategies include blue/green, canary, shadow, and A/B testing.

Blue/green

Blue/green deployments are very common in software development. In this mode, two systems are kept running during development: blue is the old environment (in this case, the model that is being replaced) and green is the newly released model that is going to production. Changes can easily be rolled back with minimum downtime, because the old system is kept alive. For more in-depth information about blue/green deployments in the context of SageMaker, see the blog post Safely deploying and monitoring Amazon SageMaker endpoints with AWS CodePipeline and AWS CodeDeploy on the AWS Machine Learning blog.

Canary

Canary deployments are similar to blue/green deployments in that both keep two models running together. However, in canary deployments, the new model is rolled out to users incrementally, until all traffic eventually shifts over to the new model. As in blue/green deployments, risk is mitigated because the new (and potentially faulty) model is closely monitored during the initial rollout, and can be rolled back in case of issues. In SageMaker, you can specify initial traffic distribution by using the InitialVariantWeight API.

Shadow

You can use shadow deployments to safely bring a model to production. In this mode, the new model works alongside an older model or business process, and performs inferences without influencing any decisions. This mode can be useful as a final check or higher fidelity experiment before you promote the model to production.

Shadow mode is useful when you don't need any user inference feedback. You can assess the quality of predictions by performing error analysis and comparing the new model with the old model, and you can monitor the output distribution to verify that it is as expected. To see how to do shadow deployment with SageMaker, see the blog post Deploy shadow ML models in Amazon SageMaker on the AWS Machine Learning blog.

A/B testing

When ML practitioners develop models in their environments, the metrics that they optimize for are often proxies to the business metrics that really matter. This makes it difficult to tell for certain if a new model will actually improve business outcomes, such as revenue and clickthrough rate, and reduce the number of user complaints.

Consider the case of an e-commerce website in which the business goal is to sell as many products as possible. The review team knows that sales and customer satisfaction correlate directly with informative and accurate reviews. A team member might propose a new review ranking algorithm to improve sales. By using A/B testing, they could roll the old and new algorithms out to different but similar user groups, and monitor the results to see whether users who received predictions from the newer model are more likely to make purchases.

A/B testing also helps gauge the business impact of model staleness and drift. Teams can put new models in production with some recurrence, perform A/B testing with each model, and create an age versus performance chart. This would help the team understand the data drift volatility in their production data.

For more information about how to perform A/B testing with SageMaker, see the blog post A/B Testing ML models in production using Amazon SageMaker on the AWS Machine Learning blog.

Consider your inference requirements

With SageMaker, you can choose the underlying infrastructure to deploy your model in different ways. These inference invocation capabilities support different use cases and cost profiles. Your options include real-time inference, asynchronous inference, and batch transform, as discussed in the following sections.

Real-time inference

Real-time inference is ideal for inference workloads where you have real-time, interactive, low-latency requirements. You can deploy your model to SageMaker hosting services and get an endpoint that can be used for inference. These endpoints are fully managed, support automatic scaling (see Automatically scale Amazon SageMaker models), and can be deployed in multiple Availability Zones.

If you have a deep learning model built with Apache MXNet, PyTorch, or TensorFlow, you can also use Amazon SageMaker Elastic Inference (EI). With EI, you can attach fractional GPUs to any SageMaker instance to accelerate inference. You can select the client instance to run your application and attach an EI accelerator to use the correct amount of GPU acceleration for your inference needs.

Another option is to use multi-model endpoints, which provide a scalable and cost-effective solution to deploying large numbers of models. These endpoints use a shared serving container that is enabled to host multiple models. Multi-model endpoints reduce hosting costs by improving endpoint utilization compared with using single-model endpoints. They also reduce deployment overhead, because SageMaker manages loading models in memory and scaling them based on traffic patterns.

For additional best practices for deploying ML models in SageMaker, see Deployment best practices in the SageMaker documentation.

Asynchronous inference

Amazon SageMaker Asynchronous Inference is a capability in SageMaker that queues incoming requests and processes them asynchronously. This option is ideal for requests with large payload sizes up to 1 GB, long processing times, and near real-time latency requirements. Asynchronous inference enables you to save on costs by automatically scaling the instance count to zero when there are no requests to process, so you pay only when your endpoint is processing requests.

Batch transform

Use batch transform when you want to do the following:

- Preprocess datasets to remove noise or bias that interferes with training or inference from your dataset.
- Get inferences from large datasets.
- Run inference when you don't need a persistent endpoint.
- Associate input records with inferences to assist the interpretation of results.

Monitoring

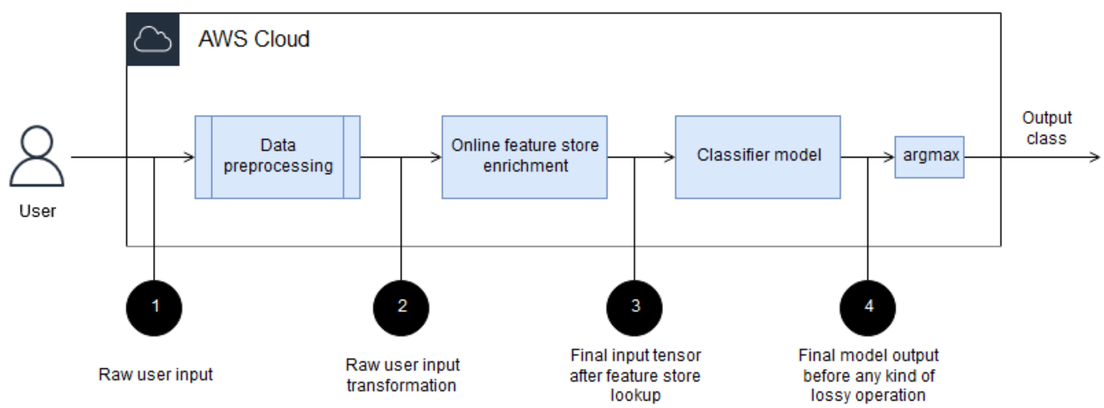
When models are already in production and delivering business value, run continuous checks to identify when models must be retrained or taken action upon.

Your monitoring team should behave proactively, not reactively, to better understand the data behavior of the environment, and to identify the frequency, rate, and abruptness of data drifts. The team should identify new edge cases in the data that might be underrepresented in the training set, validation set, and other edge case slices. They should store quality of service (QoS) metrics, use alarms to immediately take action when an issue arises, and define a strategy to ingest and amend current datasets. These practices start by logging requests and responses for the model, to provide a reference for troubleshooting or additional insights.

Ideally, data transformations should be logged in a few key stages during processing:

- Before any kind of preprocessing
- After any kind of feature store enrichment
- After all main stages of a model
- Before any kind of lossy function on the model output, such as `argmax`

The following diagram illustrates these stages.



You can use SageMaker Model Monitor to automatically capture input and output data and store it in Amazon Simple Storage Service (Amazon S3). You can implement other types of intermediate logging by adding logs to a custom serving container.

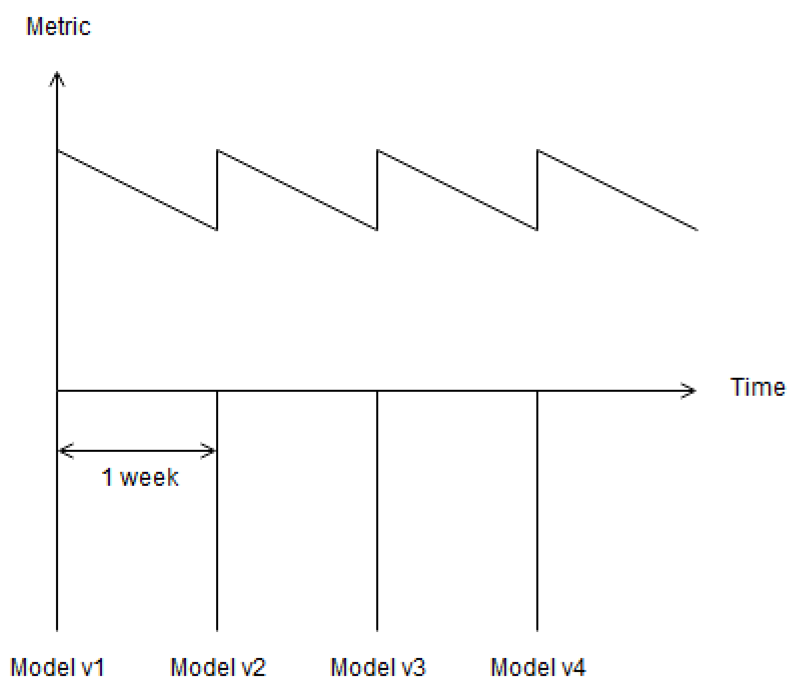
After you log the data from models, you can monitor distribution drift. In some instances, you can get ground truth (data that's correctly labeled) soon after inference. A common example of this is a model that predicts the most relevant ads to display to a user. As soon as the user has left the page you can determine whether they clicked the ad. If the user has clicked the ad, you might log that information. In this simple example, you can easily quantify how successful your model is by using a metric, such as accuracy or F1, that can be measured both in training and in deployment. For more information about these scenarios in which you have labeled data, see Monitor model quality in the SageMaker documentation. However, these simple scenarios are infrequent, because models are often designed to optimize mathematically convenient metrics that are only proxy to actual business outcomes. In such cases, the best practice is to monitor the business outcome when a model is deployed in production.

Consider the case of a review ranking model. If the defined business outcome of the ML model is to display the most relevant and useful reviews at the top of the webpage, you can measure the success of the model by adding a button such as "Was this helpful?" for each review. Measuring the clickthrough rate of this button could be a business outcome measure that helps you measure how well your model is doing in production.

To monitor the drift of the input or output labels in SageMaker, you can use the data quality capabilities of SageMaker Model Monitor, which monitor both the input and output. You can also implement your own logic for SageMaker Model Monitor by building a custom container.

Monitoring the data that a model receives both in development time and in runtime is critical. Engineers should monitor the data not only for schema changes but also for distribution mismatches. Detecting schema changes is easier and can be implemented by a set of rules, but distribution mismatch is often trickier, especially because it requires you to define a threshold to quantify when to raise an alarm. In cases where the monitored distribution is known, often the easiest way is to monitor the distribution's parameters. In the case of a normal distribution, that would be the mean and standard deviation. Other key metrics, such as the percentage of missing values, maximum values, and minimum values, are also useful.

You can also create ongoing monitoring jobs that sample training data and inference data and compare their distributions. You can create these jobs for both model input and model output, and plot the data against time to visualize any sudden or gradual drift. This is illustrated in the following chart.



To better understand the drift profile of the data, such as how often the data distribution significantly changes, at what rate, or how sudden, we recommend that you continuously deploy new model versions and monitor their performance. For example, if your team deploys a new model every week and observes that the model performance significantly improves every time, they can determine that they should deliver new models in less than a week at the minimum.

Next steps and resources

This guide walks you through on a few considerations when planning the lifecycle of the machine learning models you want to bring to production. It discusses challenges and best practices in four areas—data, training, deployment, and monitoring—and includes additional relevant resources.

AWS provides the Well-Architected Framework, which helps cloud architects build secure, high-performing, resilient, and efficient infrastructures for a variety of applications, workloads, and technology domains. For additional reading, see the Machine Learning Lens offered by AWS Well-Architected.

Resources

Amazon SageMaker documentation

- Amazon SageMaker Feature Store
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AWS Prescriptive Guidance glossary

AI and ML terms (p. 16) | Migration terms (p. 17) | Modernization terms (p. 21)

AI and ML terms

The following are commonly used terms in artificial intelligence (AI) and machine learning (ML)-related strategies, guides, and patterns provided by AWS Prescriptive Guidance. To suggest entries, please use the **Provide feedback** link at the end of the glossary.

binary classification	A process that predicts a binary outcome (one of two possible classes). For example, your ML model might need to predict problems such as “Is this email spam or not spam?" or "Is this product a book or a car?"
classification	A categorization process that helps generate predictions. ML models for classification problems predict a discrete value. Discrete values are always distinct from one another. For example, a model might need to evaluate whether or not there is a car in an image.
data preprocessing	To transform raw data into a format that is easily parsed by your ML model. Preprocessing data can mean removing certain columns or rows and addressing missing, inconsistent, or duplicate values.
deep ensemble	To combine multiple deep learning models for prediction. You can use deep ensembles to obtain a more accurate prediction or for estimating uncertainty in predictions.
deep learning	An ML subfield that uses multiple layers of artificial neural networks to identify mapping between input data and target variables of interest.
exploratory data analysis (EDA)	The process of analyzing a dataset to understand its main characteristics. You collect or aggregate data and then perform initial investigations to find patterns, detect anomalies, and check assumptions. EDA is performed by calculating summary statistics and creating data visualizations.
features	The input data that you use to make a prediction. For example, in a manufacturing context, features could be images that are periodically captured from the manufacturing line.
feature transformation	To optimize data for the ML process, including enriching data with additional sources, scaling values, or extracting multiple sets of information from a single data field. This enables the ML model to benefit from the data. For example, if you break down the “2021-05-27 00:15:37” date into “2021”, “May”, “Thu”, and “15”, you can help the learning algorithm learn nuanced patterns associated with different data components.

multiclass classification	A process that helps generate predictions for multiple classes (predicting one of more than two outcomes). For example, an ML model might ask "Is this product a book, car, or phone?" or "Which product category is most interesting to this customer?"
regression	An ML technique that predicts a numeric value. For example, to solve the problem of "What price will this house sell for?" an ML model could use a linear regression model to predict a house's sale price based on known facts about the house (for example, the square footage).
training	To provide data for your ML model to learn from. The training data must contain the correct answer. The learning algorithm finds patterns in the training data that map the input data attributes to the target (the answer that you want to predict). It outputs an ML model that captures these patterns. You can then use the ML model to make predictions on new data for which you don't know the target.
target variable	The value that you are trying to predict in supervised ML. This is also referred to as an *outcome variable*. For example, in a manufacturing setting the target variable could be a product defect.
tuning	To change aspects of your training process to improve the ML model's accuracy. For example, you can train the ML model by generating a labeling set, adding labels, and then repeating these steps several times under different settings to optimize the model.
uncertainty	A concept that refers to imprecise, incomplete, or unknown information that can undermine the reliability of predictive ML models. There are two types of uncertainty: *Epistemic uncertainty* is caused by limited, incomplete data, whereas *aleatoric uncertainty* is caused by the noise and randomness inherent in the data. For more information, see the Quantifying uncertainty in deep learning systems guide.

Migration terms

The following are commonly used terms in migration-related strategies, guides, and patterns provided by AWS Prescriptive Guidance. To suggest entries, please use the **Provide feedback** link at the end of the glossary.

7 Rs	Seven common migration strategies for moving applications to the cloud. These strategies build upon the 5 Rs that Gartner identified in 2011 and consist of the following: • Refactor/re-architect – Move an application and modify its architecture by taking full advantage of cloud-native features to improve agility, performance, and scalability. This typically involves porting the operating system and database. Example: Migrate your on-premises Oracle database to the Amazon Aurora PostgreSQL-Compatible Edition. • Replatform (lift and reshape) – Move an application to the cloud, and introduce some level of optimization to take advantage of cloud capabilities. Example: Migrate your on-premises Oracle database to Amazon Relational Database Service (Amazon RDS) for Oracle in the AWS Cloud. • Repurchase (drop and shop) – Switch to a different product, typically by moving from a traditional license to a SaaS model. Example: Migrate your customer relationship management (CRM) system to Salesforce.com. • Rehost (lift and shift) – Move an application to the cloud without making any changes to take advantage of cloud capabilities. Example: Migrate your on-premises Oracle database to Oracle on an EC2 instance in the AWS Cloud.

- Relocate (hypervisor-level lift and shift) – Move infrastructure to the cloud without purchasing new hardware, rewriting applications, or modifying your existing operations. This migration scenario is specific to VMware Cloud on AWS, which supports virtual machine (VM) compatibility and workload portability between your on-premises environment and AWS. You can use the VMware Cloud Foundation technologies from your on-premises data centers when you migrate your infrastructure to VMware Cloud on AWS. Example: Relocate the hypervisor hosting your Oracle database to VMware Cloud on AWS.
- Retain (revisit) – Keep applications in your source environment. These might include applications that require major refactoring, and you want to postpone that work until a later time, and legacy applications that you want to retain, because there's no business justification for migrating them.
- Retire – Decommission or remove applications that are no longer needed in your source environment.

application portfolio

A collection of detailed information about each application used by an organization, including the cost to build and maintain the application, and its business value. This information is key to the portfolio discovery and analysis process and helps identify and prioritize the applications to be migrated, modernized, and optimized.

artificial intelligence operations (AIOps)

The process of using machine learning techniques to solve operational problems, reduce operational incidents and human intervention, and increase service quality. For more information about how AIOps is used in the AWS migration strategy, see the operations integration guide.

AWS Cloud Adoption Framework (AWS CAF)

A framework of guidelines and best practices from AWS to help organizations develop an efficient and effective plan to move successfully to the cloud. AWS CAF organizes guidance into six focus areas called perspectives: business, people, governance, platform, security, and operations. The business, people, and governance perspectives focus on business skills and processes; the platform, security, and operations perspectives focus on technical skills and processes. For example, the people perspective targets stakeholders who handle human resources (HR), staffing functions, and people management. For this perspective, AWS CAF provides guidance for people development, training, and communications to help ready the organization for successful cloud adoption. For more information, see the AWS CAF website and the AWS CAF whitepaper.

AWS landing zone

A landing zone is a well-architected, multi-account AWS environment that is scalable and secure. This is a starting point from which your organizations can quickly launch and deploy workloads and applications with confidence in their security and infrastructure environment. For more information about landing zones, see Setting up a secure and scalable multi-account AWS environment.

AWS Workload Qualification Framework (AWS WQF)

A tool that evaluates database migration workloads, recommends migration strategies, and provides work estimates. AWS WQF is included with AWS Schema Conversion Tool (AWS SCT). It analyzes database schemas and code objects, application code, dependencies, and performance characteristics, and provides assessment reports.

business continuity planning (BCP)

A plan that addresses the potential impact of a disruptive event, such as a large-scale migration, on operations and enables a business to resume operations quickly.

Cloud Center of Excellence (CCoE)

A multi-disciplinary team that drives cloud adoption efforts across an organization, including developing cloud best practices, mobilizing resources, establishing migration timelines, and leading the organization through large-

	scale transformations. For more information, see the CCoE posts on the AWS Cloud Enterprise Strategy Blog.
cloud stages of adoption	The four phases that organizations typically go through when they migrate to the AWS Cloud: • Project – Running a few cloud-related projects for proof of concept and learning purposes • Foundation – Making foundational investments to scale your cloud adoption (e.g., creating a landing zone, defining a CCoE, establishing an operations model) • Migration – Migrating individual applications • Re-invention – Optimizing products and services, and innovating in the cloud These stages were defined by Stephen Orban in the blog post The Journey Toward Cloud-First & the Stages of Adoption on the AWS Cloud Enterprise Strategy blog. For information about how they relate to the AWS migration strategy, see the migration readiness guide.
configuration management database (CMDB)	A database that contains information about a company's hardware and software products, configurations, and inter-dependencies. You typically use data from a CMDB in the portfolio discovery and analysis stage of migration.
epic	In agile methodologies, functional categories that help organize and prioritize your work. Epics provide a high-level description of requirements and implementation tasks. For example, AWS CAF security epics include identity and access management, detective controls, infrastructure security, data protection, and incident response. For more information about epics in the AWS migration strategy, see the program implementation guide.
heterogeneous database migration	Migrating your source database to a target database that uses a different database engine (for example, Oracle to Amazon Aurora). Heterogeneous migration is typically part of a re-architecting effort, and converting the schema can be a complex task. AWS provides AWS SCT that helps with schema conversions.
homogeneous database migration	Migrating your source database to a target database that shares the same database engine (for example, Microsoft SQL Server to Amazon RDS for SQL Server). Homogeneous migration is typically part of a rehosting or replatforming effort. You can use native database utilities to migrate the schema.
idle application	An application that has an average CPU and memory usage between 5 and 20 percent over a period of 90 days. In a migration project, it is common to retire these applications or retain them on premises.
IT information library (ITIL)	A set of best practices for delivering IT services and aligning these services with business requirements. ITIL provides the foundation for ITSM.
IT service management (ITSM)	Activities associated with designing, implementing, managing, and supporting IT services for an organization. For information about integrating cloud operations with ITSM tools, see the operations integration guide.
large migration	A migration of 300 or more servers.
Migration Acceleration Program (MAP)	An AWS program that provides consulting support, training, and services to help organizations build a strong operational foundation for moving to the cloud, and to help offset the initial cost of migrations. MAP includes a migration

	methodology for executing legacy migrations in a methodical way and a set of tools to automate and accelerate common migration scenarios.
Migration Portfolio Assessment (MPA)	An online tool that provides information for validating the business case for migrating to the AWS Cloud. MPA provides detailed portfolio assessment (server right-sizing, pricing, TCO comparisons, migration cost analysis) as well as migration planning (application data analysis and data collection, application grouping, migration prioritization, and wave planning). The MPA tool (requires login) is available free of charge to all AWS consultants and APN Partner consultants.
Migration Readiness Assessment (MRA)	The process of gaining insights about an organization's cloud readiness status, identifying strengths and weaknesses, and building an action plan to close identified gaps, using the AWS CAF. For more information, see the migration readiness guide. MRA is the first phase of the AWS migration strategy.
migration at scale	The process of moving the majority of the application portfolio to the cloud in waves, with more applications moved at a faster rate in each wave. This phase uses the best practices and lessons learned from the earlier phases to implement a *migration factory* of teams, tools, and processes to streamline the migration of workloads through automation and agile delivery. This is the third phase of the AWS migration strategy.
migration factory	Cross-functional teams that streamline the migration of workloads through automated, agile approaches. Migration factory teams typically include operations, business analysts and owners, migration engineers, developers, and DevOps professionals working in sprints. Between 20 and 50 percent of an enterprise application portfolio consists of repeated patterns that can be optimized by a factory approach. For more information, see the discussion of migration factories and the CloudEndure Migration Factory guide in this content set.
migration metadata	The information about the application and server that is needed to complete the migration. Each migration pattern requires a different set of migration metadata. Examples of migration metadata include the target subnet, security group, and AWS account.
migration pattern	A repeatable migration task that details the migration strategy, the migration destination, and the migration application or service used. Example: Rehost migration to Amazon EC2 with AWS Application Migration Service.
migration strategy	The approach used to migrate a workload to the AWS Cloud. For more information, see the 7 Rs (p. 17) entry in this glossary and see Mobilize your organization to accelerate large-scale migrations.
operational-level agreement (OLA)	An agreement that clarifies what functional IT groups promise to deliver to each other, to support a service-level agreement (SLA).
operations integration (OI)	The process of modernizing operations in the cloud, which involves readiness planning, automation, and integration. For more information, see the operations integration guide.
organizational change management (OCM)	A framework for managing major, disruptive business transformations from a people, culture, and leadership perspective. OCM helps organizations prepare for, and transition to, new systems and strategies by accelerating change adoption, addressing transitional issues, and driving cultural and organizational changes. In the AWS migration strategy, this framework is called *people acceleration*, because of the speed of change required in cloud adoption projects. For more information, see the OCM guide.

playbook	A set of predefined steps that capture the work associated with migrations, such as delivering core operations functions in the cloud. A playbook can take the form of scripts, automated runbooks, or a summary of processes or steps required to operate your modernized environment.
portfolio assessment	A process of discovering, analyzing, and prioritizing the application portfolio in order to plan the migration. For more information, see Evaluating migration readiness.
responsible, accountable, consulted, informed (RACI) matrix	A matrix that defines and assigns roles and responsibilities in a project. For example, you can create a RACI to define security control ownership or to identify roles and responsibilities for specific tasks in a migration project.
runbook	A set of manual or automated procedures required to perform a specific task. These are typically built to streamline repetitive operations or procedures with high error rates.
service-level agreement (SLA)	An agreement that clarifies what an IT team promises to deliver to their customers, such as service uptime and performance.
task list	A tool that is used to track progress through a runbook. A task list contains an overview of the runbook and a list of general tasks to be completed. For each general task, it includes the estimated amount of time required, the owner, and the progress.
workstream	Functional groups in a migration project that are responsible for a specific set of tasks. Each workstream is independent but supports the other workstreams in the project. For example, the portfolio workstream is responsible for prioritizing applications, wave planning, and collecting migration metadata. The portfolio workstream delivers these assets to the migration workstream, which then migrates the servers and applications.
zombie application	An application that has an average CPU and memory usage below 5 percent. In a migration project, it is common to retire these applications.

Modernization terms

The following are commonly used terms in modernization-related strategies, guides, and patterns provided by AWS Prescriptive Guidance. To suggest entries, please use the **Provide feedback** link at the end of the glossary.

business capability	What a business does to generate value (for example, sales, customer service, or marketing). Microservices architectures and development decisions can be driven by business capabilities. For more information, see the Organized around business capabilities section of the Running containerized microservices on AWS whitepaper.
microservice	A small, independent service that communicates over well-defined APIs and is typically owned by small, self-contained teams. For example, an insurance system might include microservices that map to business capabilities, such as sales or marketing, or subdomains, such as purchasing, claims, or analytics. The benefits of microservices include agility, flexible scaling, easy deployment, reusable code, and resilience. For more information, see Integrating microservices by using AWS serverless services.
microservices architecture	An approach to building an application with independent components that run each application process as a microservice. These microservices communicate through a well-defined interface by using lightweight APIs. Each microservice in this architecture can be updated, deployed, and scaled to meet demand for

	specific functions of an application. For more information, see Implementing microservices on AWS.
modernization	Transforming an outdated (legacy or monolithic) application and its infrastructure into an agile, elastic, and highly available system in the cloud to reduce costs, gain efficiencies, and take advantage of innovations. For more information, see Strategy for modernizing applications in the AWS Cloud.
modernization readiness assessment	An evaluation that helps determine the modernization readiness of an organization's applications; identifies benefits, risks, and dependencies; and determines how well the organization can support the future state of those applications. The outcome of the assessment is a blueprint of the target architecture, a roadmap that details development phases and milestones for the modernization process, and an action plan for addressing identified gaps. For more information, see Evaluating modernization readiness for applications in the AWS Cloud.
monolithic applications (monoliths)	Applications that run as a single service with tightly coupled processes. Monolithic applications have several drawbacks. If one application feature experiences a spike in demand, the entire architecture must be scaled. Adding or improving a monolithic application's features also becomes more complex when the code base grows. To address these issues, you can use a microservices architecture. For more information, see Decomposing monoliths into microservices.
polyglot persistence	Independently choosing a microservice's data storage technology based on data access patterns and other requirements. If your microservices have the same data storage technology, they can encounter implementation challenges or experience poor performance. Microservices are more easily implemented and achieve better performance and scalability if they use the data store best adapted to their requirements. For more information, see Enabling data persistence in microservices.
split-and-seed model	A pattern for scaling and accelerating modernization projects. As new features and product releases are defined, the core team splits up to create new product teams. This helps scale your organization's capabilities and services, improves developer productivity, and supports rapid innovation. For more information, see Phased approach to modernizing applications in the AWS Cloud.
two-pizza team	A small DevOps team that you can feed with two pizzas. A two-pizza team size ensures the best possible opportunity for collaboration in software development. For more information, see the Two-pizza team section of the Introduction to DevOps on AWS whitepaper.

Document history

The following table describes significant changes to this guide. If you want to be notified about future updates, you can subscribe to an RSS feed.

update-history-change	update-history-description	update-history-date
Initial publication (p. 23)	—	December 20, 2021