Introduction to MLOps

# **Activity – Communication**

The purpose of this activity is to strengthen the machine learning operations (MLOps) communications in your environment. You will create a table to document your MLOps stakeholders.

Fill out the following table. For each of the idealized roles on the left (rows), look across the ML lifecycle stages (columns). Write the job title or the name of the person or people in your organization that are responsible for each kind of work.

If you are not sure who has these responsibilities in your environment, you might want to investigate and continue to completing the table after this course. You might discover other roles that are important in your environment, and you can use the “other” row for those.

**Example:**

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| --- | --- | --- | --- | --- | --- |
| **Roles** | **Data preparation** | **Model build** | **Model evaluation and selection** | **Deployment** | **Monitoring** |
| **Security engineer** | *Mateo Jackson*  *Data Security Analyst* |  |  | *Terry Whitlock*  *DevSecOps Manager* |  |

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| --- | --- | --- | --- | --- | --- |
| **Roles** | **Data preparation** | **Model build** | **Model evaluation and selection** | **Deployment** | **Monitoring** |
| **Business stakeholder** |  |  |  |  |  |
| **Data engineer** |  |  |  |  |  |
| **Data scientist** |  |  |  |  |  |
| **ML engineer** |  |  |  |  |  |
| **DevOps engineer** |  |  |  |  |  |
| **MLOps engineer** |  |  |  |  |  |
| **Governance officer** |  |  |  |  |  |
| **Model approver** |  |  |  |  |  |
| **Security engineer** |  |  |  |  |  |
| **Other** |  |  |  |  |  |

## Where do you see overlapping interests and responsibilities? What actions should you take to balance the interests and coordinate efforts?

## Do you see any gaps in the table? What problems could those gaps create? What actions should you take to mitigate these risks?

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## Action plan:

Consider the activities in this section of the workbook. List any action items you want to complete to advance MLOPs practices within your organization.

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| Action / outcome description | Stakeholders | Considerations |
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MLOps maturity level - initial

During module two, you learned about providing experimentation environments for data scientists. Data scientists use these environments for exploring data and creating new ML models. Providing standard experimentation environments promotes consistency in the data analysis and model creation steps of the ML lifecycle.

This section of the workbook helps you identify opportunities to implement what you’ve learned to set up experimentation environments in your organization.

## How are experimentation environments created in your organization? How could this practice be optimized?

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## To standardize experimentation environments, you might need to centralize approved model building resources. Which algorithms, frameworks, and libraries does your organization use? Note any custom-built components.

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| **Training algorithms** | **ML frameworks** | **Libraries** |
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## Consider the components listed in the previous question. Which methods of using Amazon SageMaker to implement training and inference support your existing tools?

Use container images managed by AWS with built-in algorithm

Use container images managed by AWS with your own algorithm in script mode

Bring your own container (BYOC) with a custom ML framework

Extend pre-built container with custom dependencies

Extend pre-built container with requirements.txt

Bring your own model (The model is built on premises and then brought to the cloud for hosting.)

Bring a third-party model (such as from AWS Marketplace.)

## Action plan:

Consider the activities in this section of the workbook. List any action items you want to complete to advance MLOPs practices within your organization.

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| Action / outcome description | Stakeholders | Considerations |
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MLOps maturity level – repeatable

After the data scientists are familiarized with SageMaker experimentation, the next step is to automate processes for model training and deployment. At the Repeatable level of MLOps maturity, you create ML pipelines for each step of the ML lifecycle.

## What DevOps practices that your organization already uses can be adopted for MLOps? What MLOps practices will be new or different?

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## Activity – From DevOps to MLOps

Fill out the following table. The purpose of this activity is to familiarize yourself with existing conditions in your environment, from an MLOps perspective. This table will help you verify the tools and processes that you are using, who is responsible, and potential opportunities to further improve MLOps in your environment.

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| --- | --- | --- | --- |
| Operations tools and processes | Do you have this?[Y/N] | Who is responsible for it? | If you do not have it, what are your next steps (action plan)? |
| Code building pipeline |  |  |  |
| Code version control |  |  |  |
| Model version control |  |  |  |
| Data version control |  |  |  |
| Model building pipeline |  |  |  |
| Data pipeline |  |  |  |
| Approval process |  |  |  |

## How does your team validate that a new or updated model meets quality standards and functions properly before making it available for deployment?

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## Of the different ways to implement inference that were discussed, which are most like those you use in production?

Real-time

Serverless

Asynchronous

Batch transform

## Action plan:

Consider the activities in this section of the workbook. List any action items you want to complete to advance MLOPs practices within your organization.

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| Action / outcome description | Stakeholders | Considerations |
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# MLOps maturity level – reliable

## After your repeatable processes and pipelines are in place, the next level of MLOps maturity focuses on reliability.

## Which deployment strategies are relevant for your organization?

A/B testing

Shadow testing

In-place deployment

Blue/green deployment: all-at-once, canary, linear

Rolling deployment

1. **Monitoring solutions**

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| Metric types | Owner | Monitoring tools | Types of alerts |
| Business KPIs |  |  |  |
| Infrastructure performance and health |  |  |  |
| Data and model performance |  |  |  |

Fill out the following table to illustrate your organization’s monitoring solutions. Consider how your infrastructure and model metrics impact your business KPIs. Also, consider how these metrics can alert you to the need for remediation.

## When the monitoring solutions in the previous table detect an issue, an automated remediation or notification should start. Use the space to follow to design one or more remediation paths.

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## Action plan:

Consider the activities in this section of the workbook. List any action items you want to complete to advance MLOPs practices within your organization.

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| --- | --- | --- |
| Action / outcome description | Stakeholders | Considerations |
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# MLOps maturity level – scalable

As your organization's use of ML matures, you will need a more scalable way to onboard additional ML use cases and teams to your ML environment. SageMaker supports options  such as customized SageMaker project templates, separate MLOps accounts per team and environment, and shared accounts for centralized, reusable resources.

You can learn more about these options at <https://aws.amazon.com/blogs/machine-learning/mlops-foundation-roadmap-for-enterprises-with-amazon-sagemaker/>