FMOps/LLMOps: Operationalise Generative AI using MLOps principles

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MLOps Foundation Expected Outcomes

STANDARDIZE OPERATIONS AND INFRASTRUCTURE FOR YOUR DATA SCIENCE

	Business Goal	Technical Metric	Before MLOps	MLOps Expected Outcomes	Business Value				
1	Be more efficient in delivery	Time to value (from idea to production)	up to 12 months	< 3 months	Improve Speed-to-Value by 4x				
2	Simplify route-to-live	Time to productionize existing ML use cases	3-6 months	< 2 weeks	Reduce FTE overhead in average 8x				
3	Standardize infrastructure, data, & code	% Template driven development	n/a	> 85%	Focus on innovation increasing re-usability by 85%				
4	Standardize onboarding of new teams and ML use cases	Time to instantiate a new MLOps infrastructure & ML projects	40 days	< 1 hours	Accelerate ML adoption across all business areas				
5	Ensure high security standards	Execute the ML solutions without internet access in a private cloud	n/a	No internet	Your data is safe in your private cloud				
Reduce platform, people and operation costs									

Customer references building MLOps foundation and business benefits:

- NatWest: https://aws.amazon.com/solutions/case-studies/natwest-group-case-study
- BP: https://aws.amazon.com/solutions/case-studies/bp-machine-learning-case-study



MLOps Key Personas and Roles

Advance Analytics Team Data Lake



Data Engineer

Prepare & Ingest data building ETL pipelines



Data Owners

Manage data sharing and provide access

Data Science Team Experimentation & MLOps



Data Scientist

Create the best ML models to solve business problems



ML Engineer

Collaborate with DS to productionize ML

Platform Team Secure Cloud/Data/ML Platform



MLOps Engineer/Admin

Standardize CI/CD, user/service role, model consumption, testing and deployment methodology



Security

Assess data, user, and service access creating policies and guardrails



Architects/ SysOps Engineer

Standardize account infrastructure, connectivity, user roles implementation

Business Viz Dashboards, ML Adoption, & ROI



Business Stakeholder Product Owners

Define business problem, business KPIs, and make business decisions





Business Stakeholder Data & ML Consumers

Consumers of ML results from other BUs, driving business decision making

Risk & Compliance Approve & Review Models



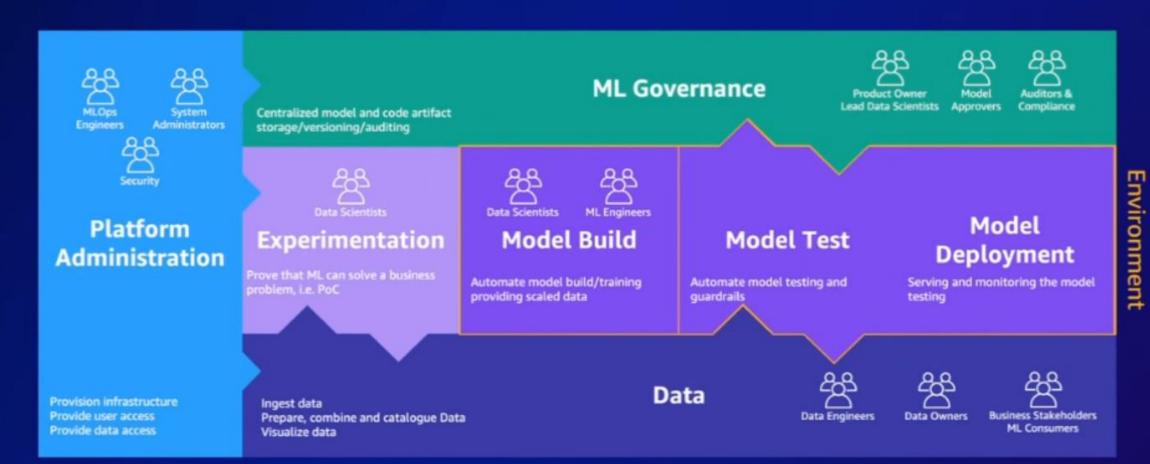
Auditors/Risk & Compliance

Review models, data sources, code artifacts



MLOps Foundation People & Processes

SEPARATION OF CONCERNS IS KEY FOR SUCCESS



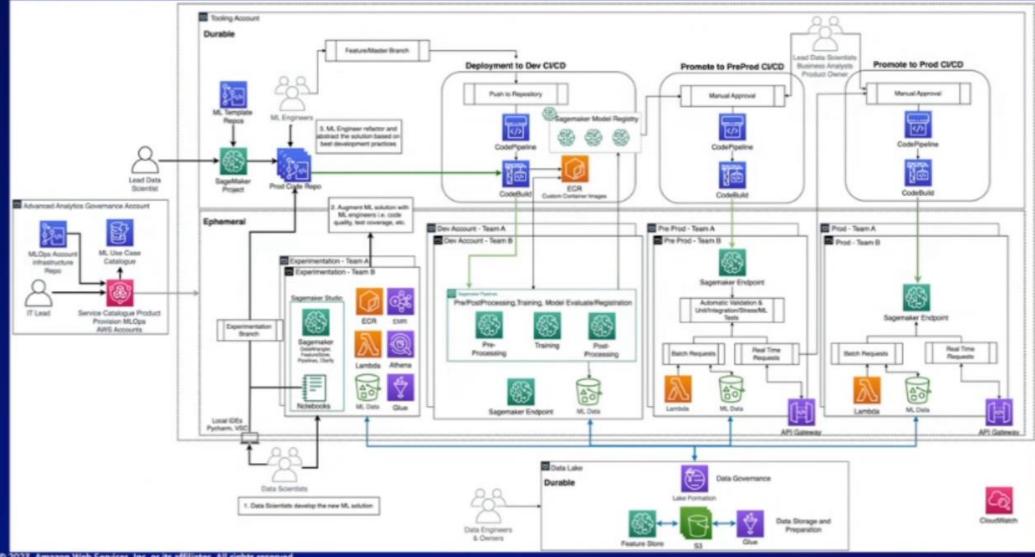
ML Production

MLOPs Scalable Phase

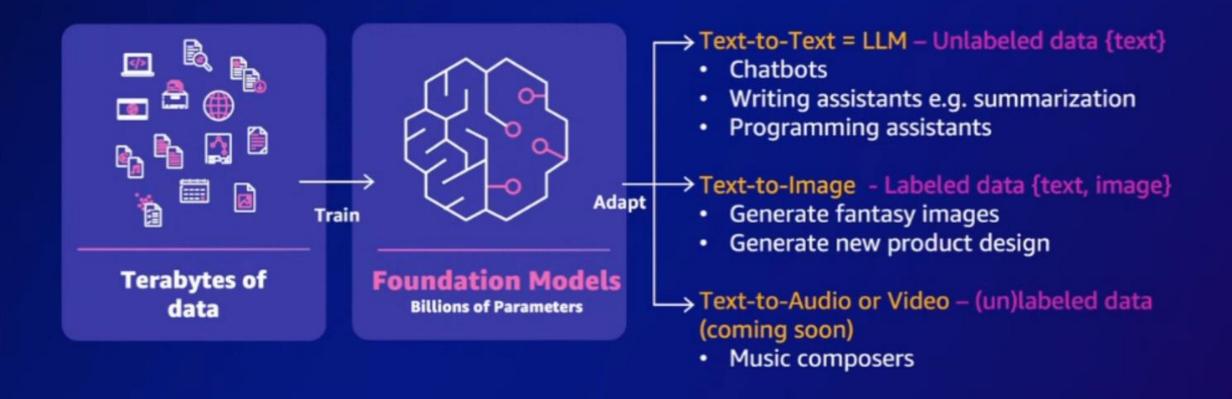
MLOps foundation roadmap for enterprises https://aws.amazon.com/bloqs/machine-learning/mlops-foundation-roadmap-for-enterprises-with-amazon-sagemaker



MULTIPLE TEAMS AND ML USE CASES ADOPT MLOPS



GenAl Use Case Domains

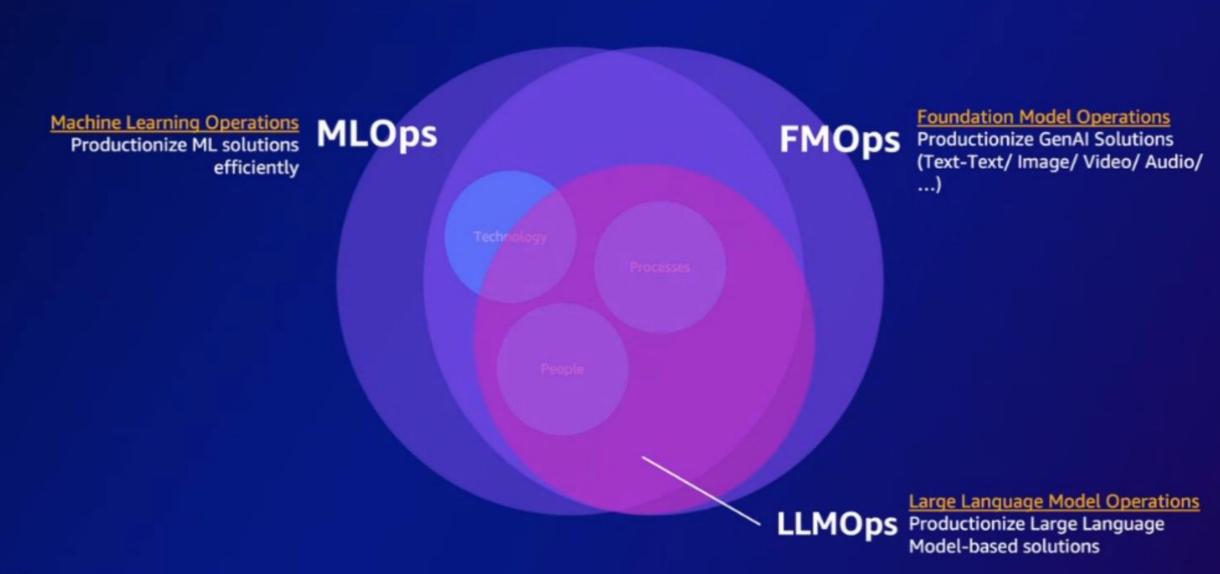


Key Definitions

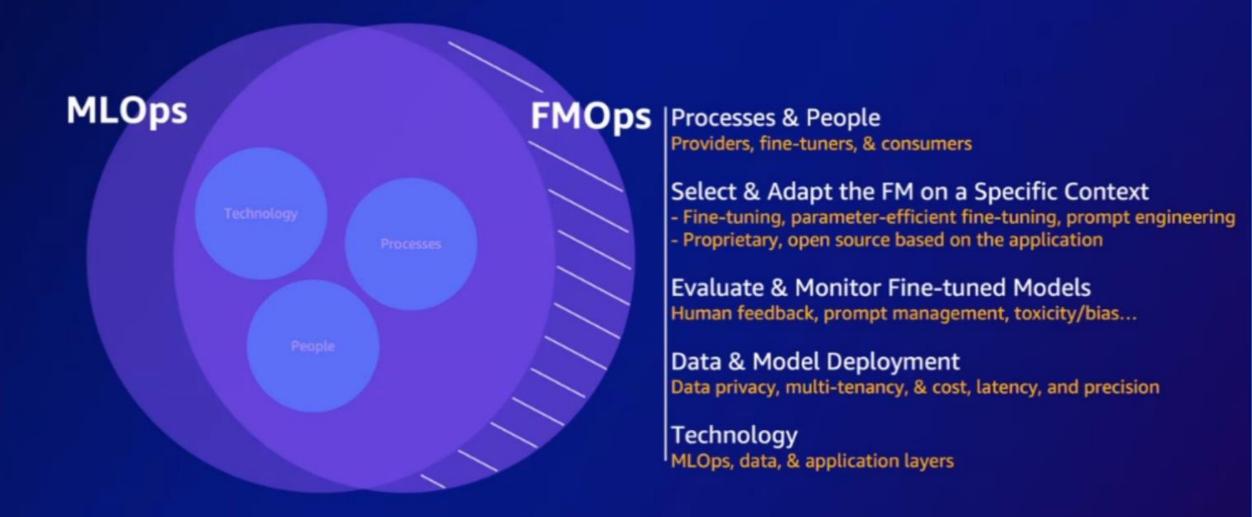
Machine Learning Operations
Productionize ML solutions **MLOps FMOps** efficiently

Foundation Model Operations
Productionize GenAl Solutions
(Text-Text/ Image/ Video/ Audio/

Key Definitions



MLOps & FMOps Differentiators





GenAl User Types & Skills



can be also



can become





Generative Al User Types

Providers

Entities who build foundation models from scratch themselves and provide them as a product to tuner and consumer.

Fine-Tuners

Fine-tune foundational models from providers to fit custom requirements. Orchestrate the deployment of the model as a service for use by consumers.

Consumers

Interact with Generative AI services from provider or tuner by text prompting or visual interface to complete desired actions.

Skills

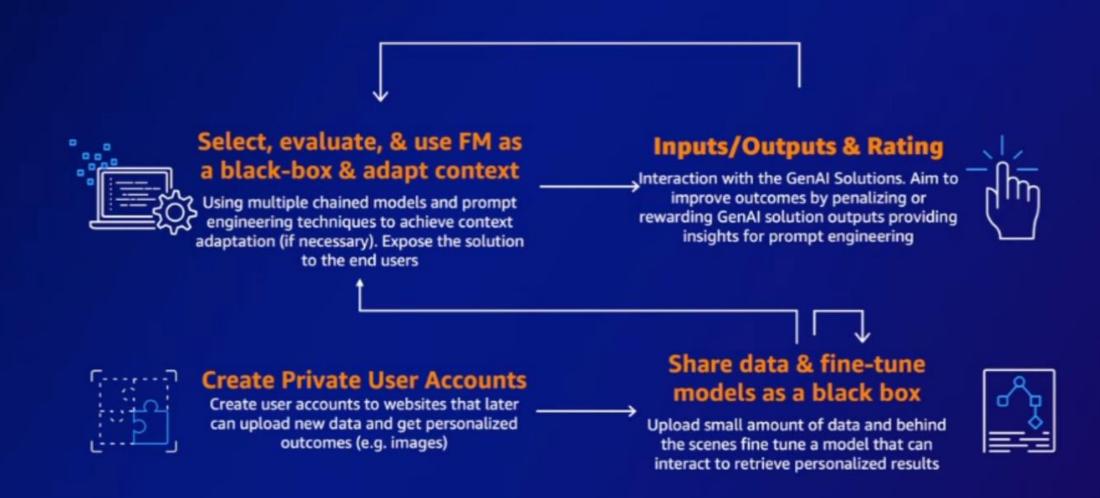
Deep end-to-end ML, NLP expertise and data science, labeler "squad" Strong end-to-end ML expertise and knowledge of model deployment and inference. Strong domain knowledge for tuning including prompt engineering. No ML expertise required. Mostly application developers or endusers with understanding of the service capabilities. Only prompt engineering is required for better results.

MLOps is required

Productionize applications where DevOps/AppDev is more relevant than MLOps



GenAl Processes - Consumers





Select FM - Consumers

Step 1. Understand Step 2. Test & evaluate the Step 3. Select the best top proprietary and top selected FMs (e.g. top 3) FM based on your open source FM priorities capabilities 13 K available 20 **FMs** Use case-based benchmarking: Priority-based decision: Quick short listing: Use a small set of test Evaluate the models based on Select based on business prompts based on the predefined prompts and outputs priorities cost, latency, precision task (prompt catalog)



Step 1. Understand top FM capabilities





Step 1. Proprietary FM Capabilities

Company Name	Model Name	Can be used Commercially	# Params	GPU instance req.	Available on AWS	Speed	Context Window	Trained on	Fine-tunable
	J2 Ultra Instruct	Yes	178 B	p4d.24xl	Bedrock, Jumpstart/SM		8 K	Internet Data, Code, Instructions	No
AI21	J2 Mid Instruct	Yes	17 B	g5.12xl	Bedrock, Jumpstart/SM		8 K	Internet Data, Code, Instructions	No
	Al21 Summarize	Yes		g4dn.12xl	Jumpstart/SM		~13 K	Internet Data, Instructions	No
Amazon	Titan Text Large	Yes	n/a	n/a	Bedrock		4 K	n/a	No
Anthropic	Claude	Yes	n/a	n/a	Bedrock		12 K	Internet Data, Code, Instructions, Human feedback	No
Cohere	Generate Model Command	Yes	n/a (50 B)	n/a	Jumpstart/SM		4 K	Internet Data, Instructions	No
Conere	Generate Model Command-Light	Yes	n/a (6 B)	n/a	Jumpstart/SM		4 K	Internet Data, Instructions	No
LightOn	Lyra-Fr 10B	Yes	10 B	g5.12xl	Jumpstart/SM		?	Internet Data (French)	No
Stability Al	SDXL	Yes	n/a	g5.xl	Bedrock, Jumpstart/SM		-	<text, image=""></text,>	No



Step 1. Open-source FM Capabilities

Company Name	Model Name	Can be used Commercially	# Params	GPU instance req.	Available on AWS	Speed	Context Window	Trained on	Fine-tunable
	FLAN-UL2	Yes	20 B	g5.12xl	Jumpstart/SM		2 K	Internet Data, Code, Instructions	Yes
Google	FLAN-T5-XXL	Yes	11 B	g5.xl	Jumpstart/SM		512	Internet Data, Code, Instructions	Yes
Eleuther	GPT-J	Yes	6 B	g5.xl	Jumpstart/SM		512	Internet Data, Code	Yes
711	Falcon-40B- Instruct	Yes	40 B	g5.12xl	Jumpstart/SM		2 K	Internet Data, Code, Instructions	Yes
TII	Falcon-7B- Instruct	Yes	7 B	g5.xl	Jumpstart/SM		2 K	Internet Data, Code, Instructions	Yes
Discode	Starcoder	Yes	15 B	g5.12xl	SM		8 K	Code	Yes
BigCode	Santa Coder	Yes	1.1 B	g5.xl	SM		2K	Code	Yes
LMSYS Org	Vicuna-13B	No	13 B	g5.xl	SM		2 K	Internet Data, Code, Instructions	Yes
Meta	Llama-65B	No	65 B	g5.48xl	SM		2 K	Internet Data, Code	Yes
Stability AI	SD 2.1	Yes	-	g5.xl	Jumpstart/SM			<text, image=""></text,>	Yes

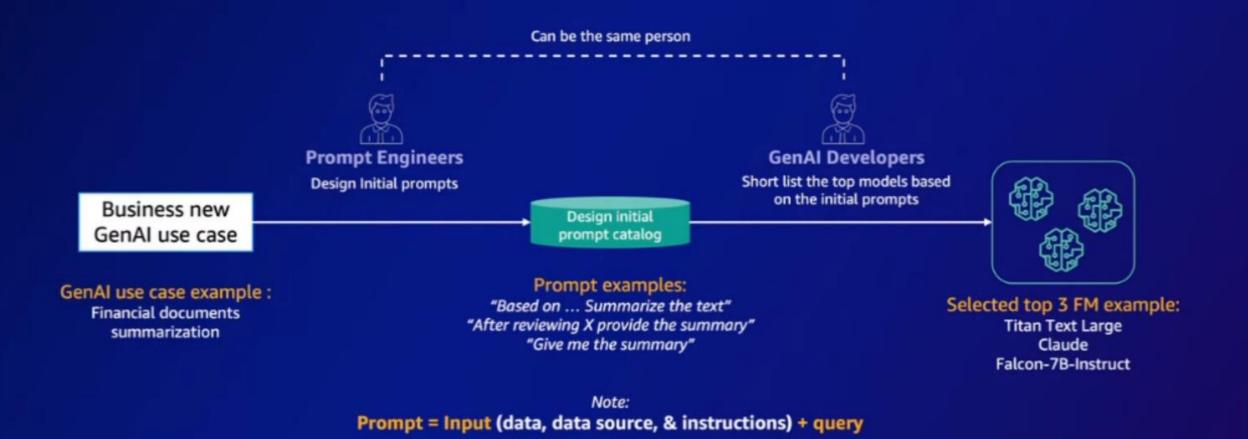
Step 1. EU AI Act Matters for FM Selection

Grading Foundation Model Providers' Compliance with the Draft EU AI Act

Source: Stanford Research on Foundation Models (CRFM), Institute for Human-Centered Artificial Intelligence (HAI)

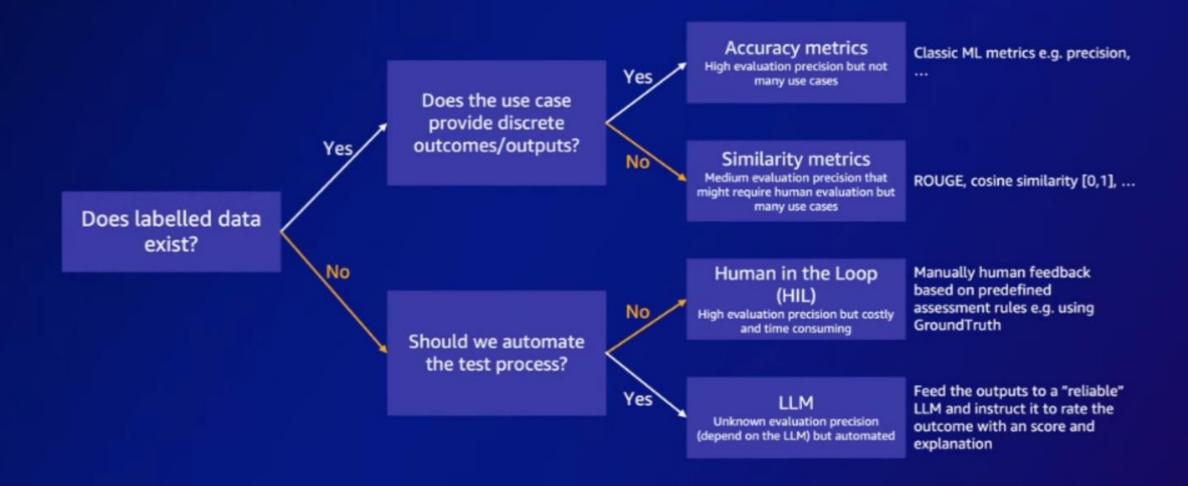
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	Member states	••00	0000	0000	••00		0000	0000	0000	•000	0000	9
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25/40 25/40 21/40 30/40 21/40 5/40 5/40	Totals	25 / 48	23/48	22 / 48	7/48	27 / 48	36 / 48	21/48	8/48	5/48	29 / 48	

Step 1. Understand FM Capabilities



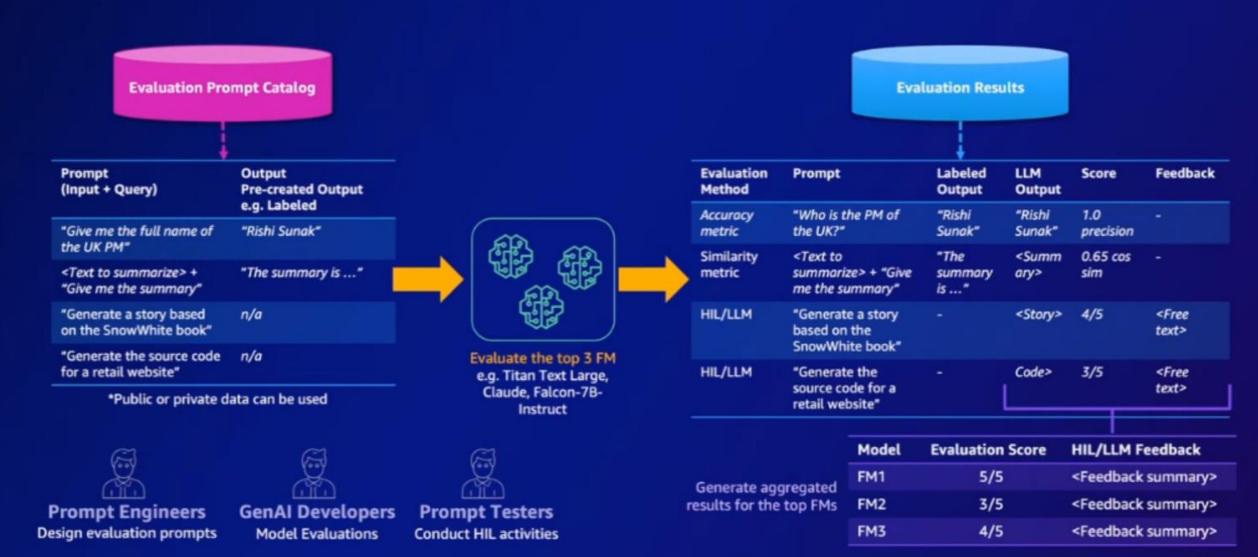


Step 2. Evaluate the top FMs

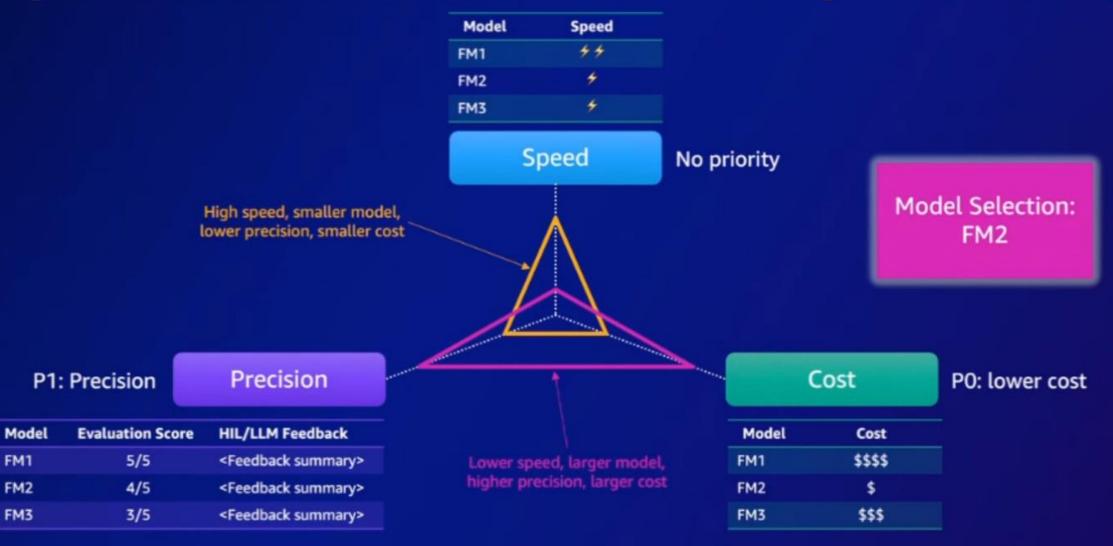




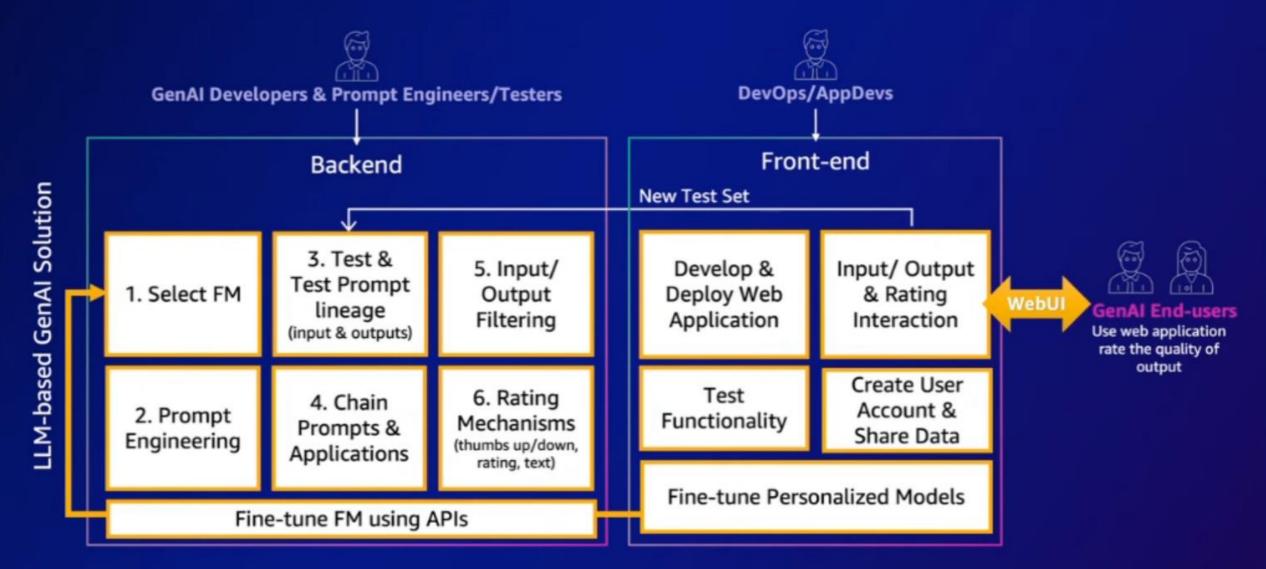
Step 2. Evaluate the top FMs - Examples



Step 3. Select the best FM based on priorities

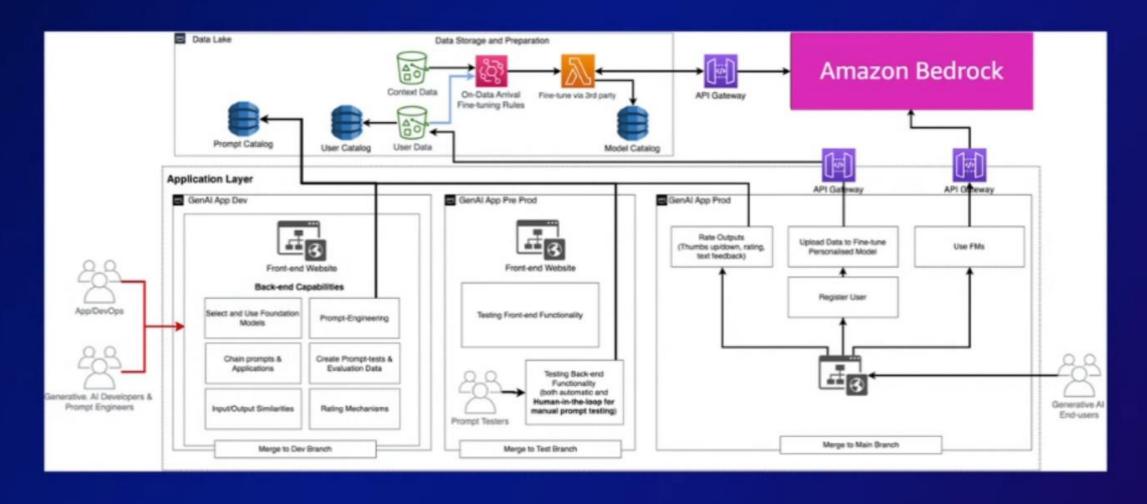


GenAl Processes for LLM - Consumers





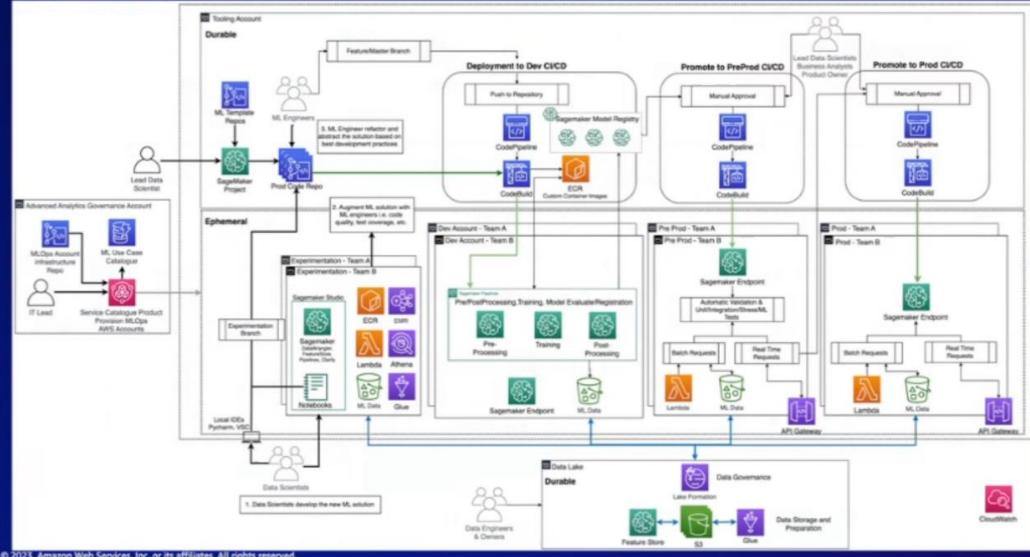
GenAl Technology for LLM - Consumers





GenAl Providers Productionize FM using MLOps

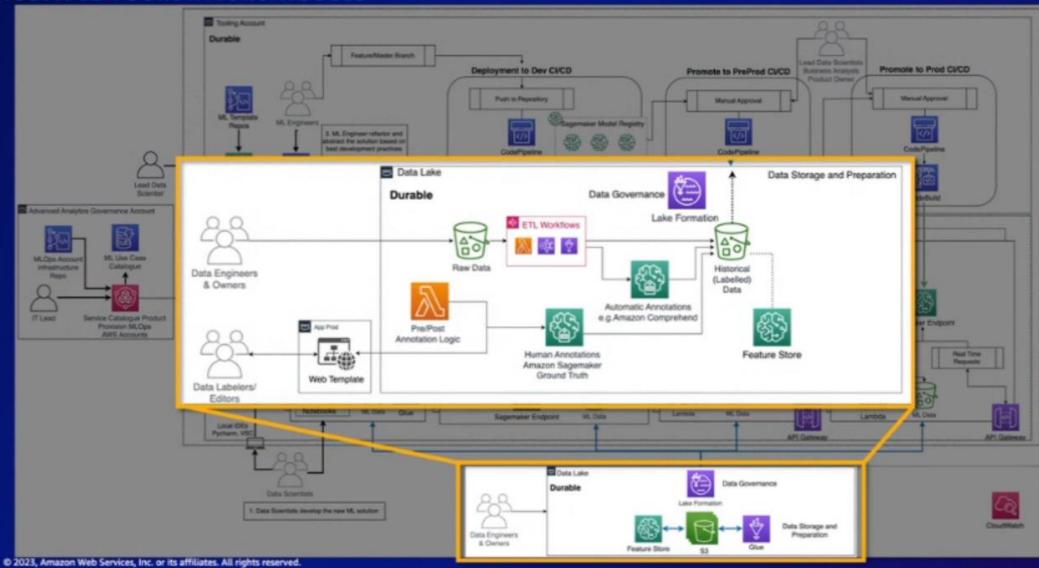
TRAIN MULTIPLE FOUNDATIONS MODELS





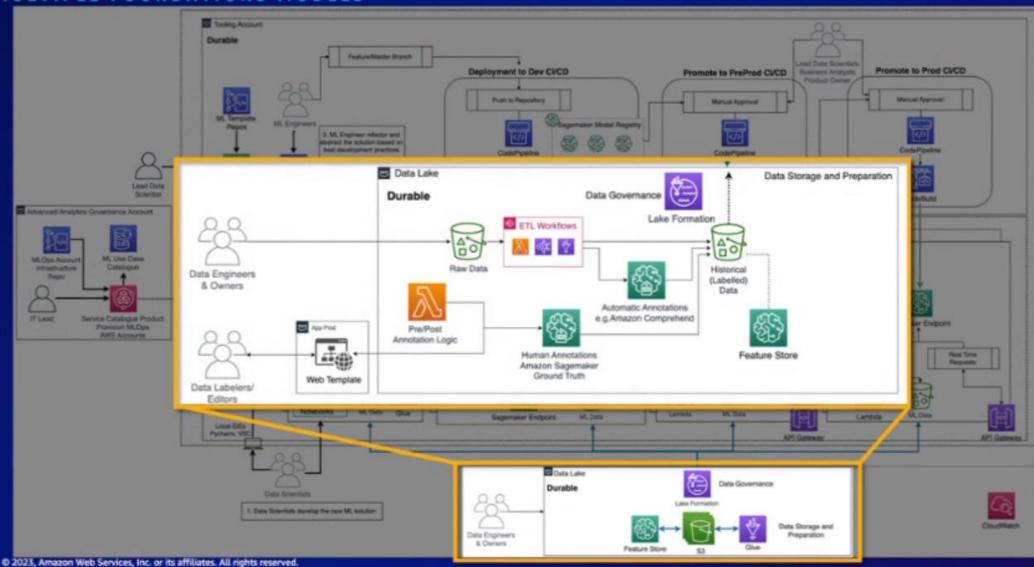
GenAl Providers Productionize FM using MLOps

TRAIN MULTIPLE FOUNDATIONS MODELS

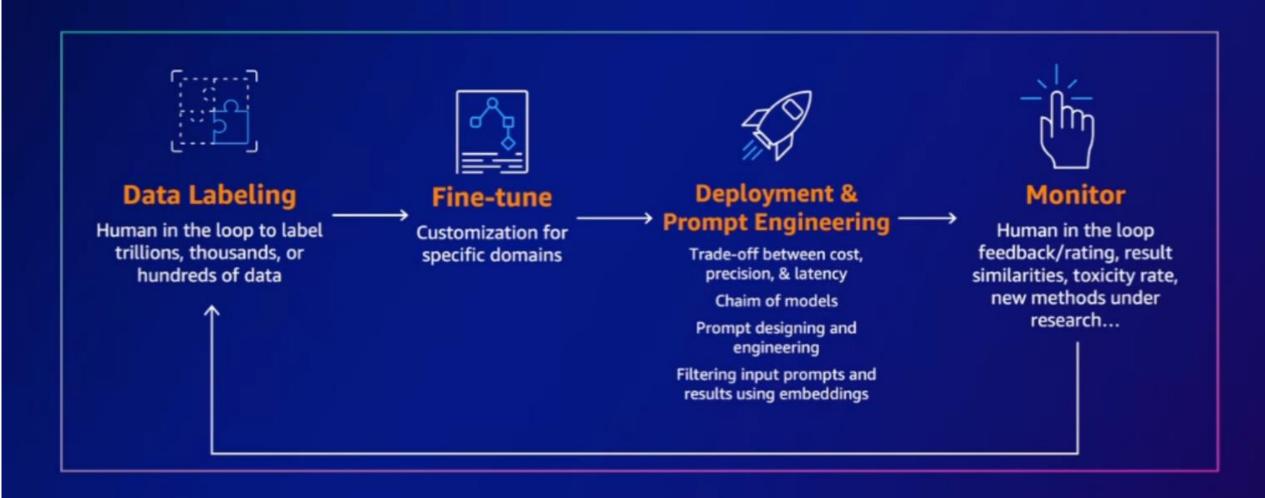


GenAl Providers Productionize FM using MLOps

TRAIN MULTIPLE FOUNDATIONS MODELS



GenAl Processes - Fine-Tuners





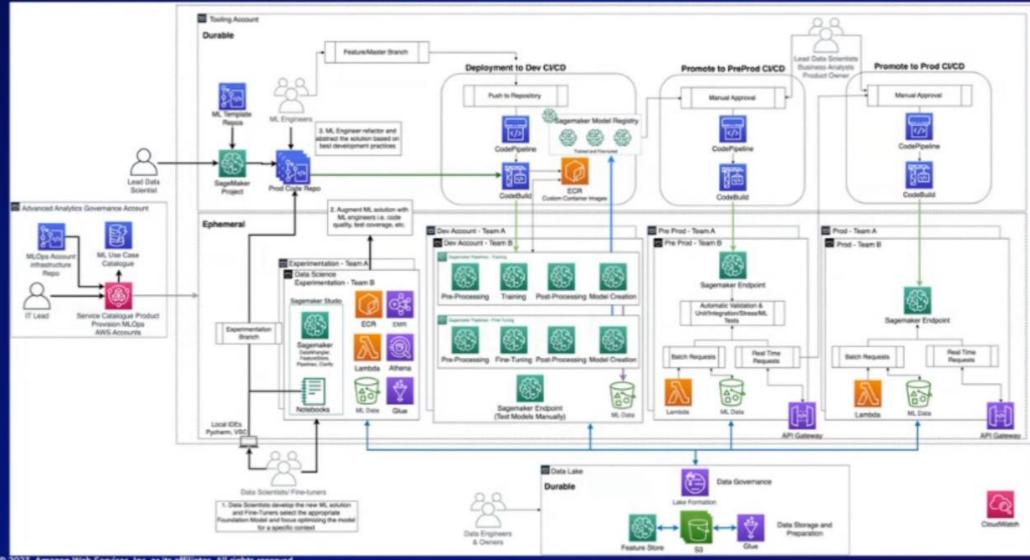
Fine-Tuning, PEFT & Training

Prompt (Inputs) Fine-Tuning (Training Job) Requires high computation power (high cost but lower **Pre-trained FM** than training) to calculate all the weights of Large FM (deep learning model) **Higher accuracy** Thousands of example Fine-Tuned FM input/outputs Parameter-Efficient Fine-Tuning (PEFT - Training Job) Completion Tens of example Requires low computation power (reduced cost e.g. 1/10 of fine-tuning) as it adds small new layers in the Large FM (deep input/outputs (Outputs) learning model) Lower accuracy

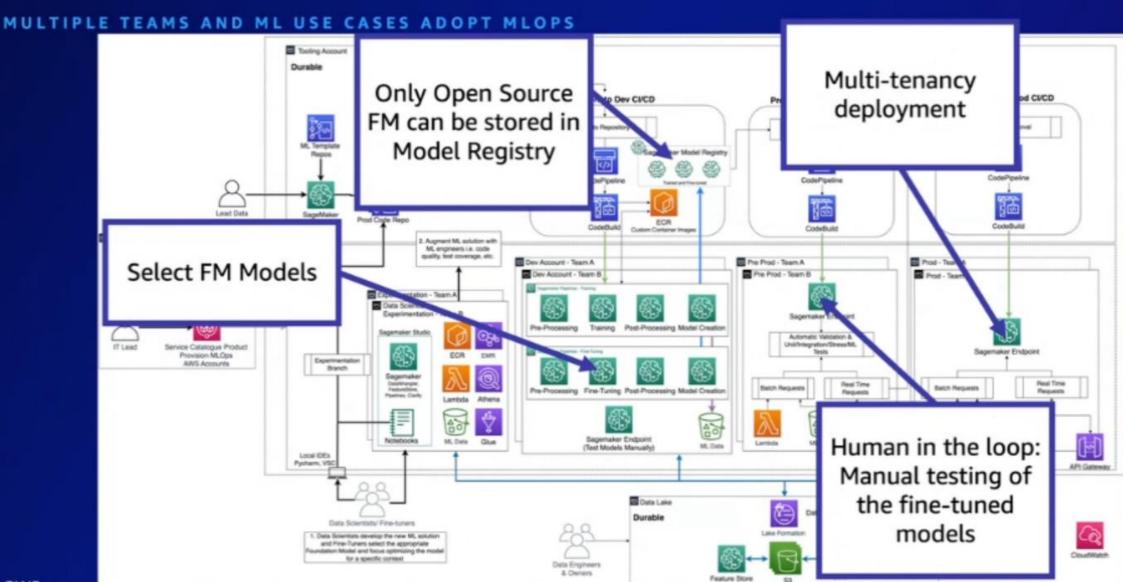


MLOPs & GenAl Technology - Fine-tuner

MULTIPLE TEAMS AND ML USE CASES ADOPT MLOPS



MLOPs & GenAl Technology - Fine-tuner



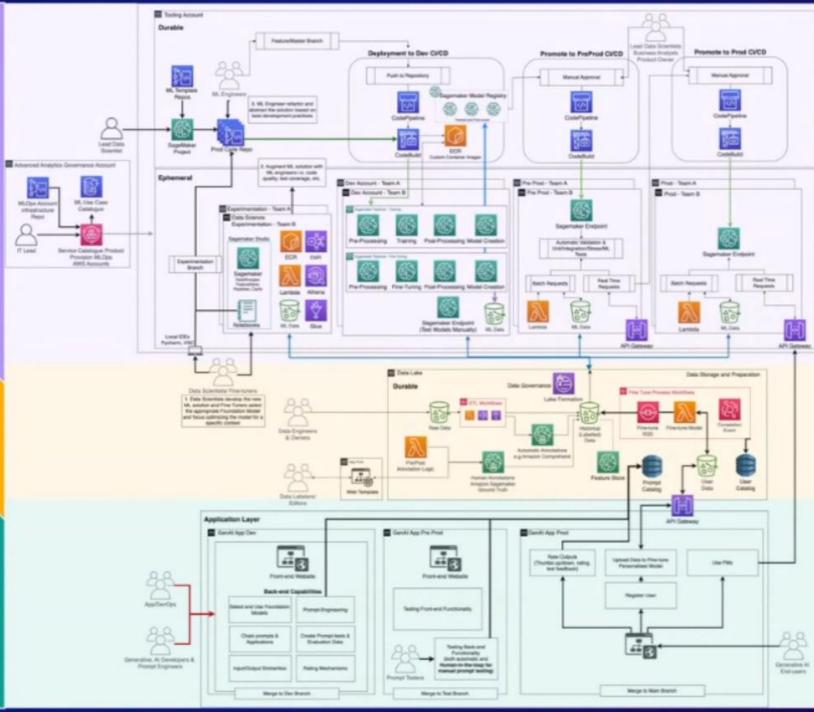
MLOPs & Generative Al Technology – Fine-tuner

THREE MAIN LAYERS ARE INTERCONNECTED

MLOps

Jata

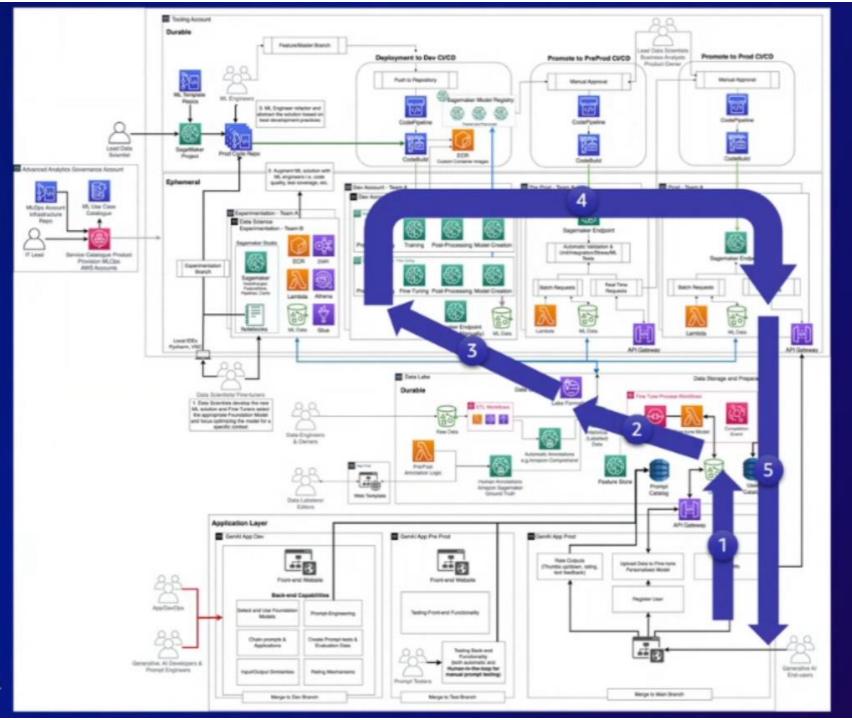
Generative Al Application





MLOPs & Generative Al Technology – Fine-tuner

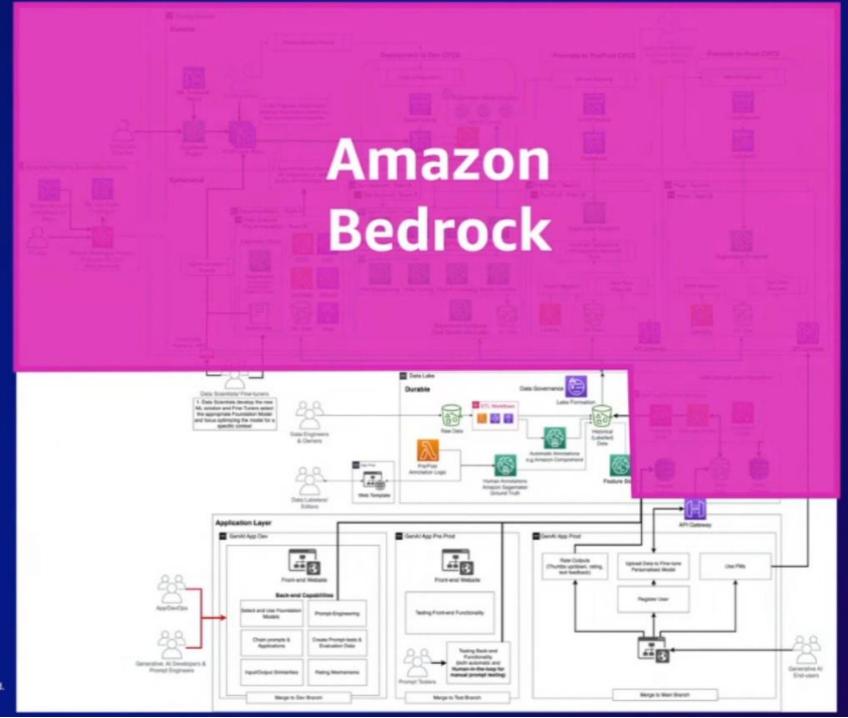
THREE MAIN LAYERS ARE INTERCONNECTED





MLOPs & Generative Al Technology – Fine-tuner

THREE MAIN LAYERS ARE INTERCONNECTED





MLOps & FMOps Key Personas and Roles

Advance Analytics Team Data Lake



Data Engineer

Prepare & Ingest data building ETL pipelines



Data Owners

Manage data sharing and provide access

Labeler Team
Data Preparation at Scale





Data Labelers/Editors

Label or edit billions of Data for FM models and hundreds of data for fine tuning interacting with data lake using a dedicated website

Data Science Team Experimentation & MLOps



Data Scientist

Create the best ML models to solve business problems



ML Engineer

Collaborate with DS to productionize ML

Data Science Team Extension
Context Adaptation



Fine Tuners

Select the corresponding FM, evaluate the model & design the deployment method/infrastructure Platform Team
Secure Cloud/Data/ML Platform



MLOps Engineer/Admin

Standardize CI/CD, user/service role, model consumption, testing and deployment methodology





Security & Architects

Assess data, user, and service access creating policies and infrastructure

Application Developer Team Integrate GenAI models in applications



Generative AI Developers, AppDev, & Prompt Engineers/Testers

Design prompt inputs, create examples of prompt input/outputs, and test the engineered prompts, develop the GenAl application and front-end Business
Viz Dashboards, ML Adoption, & ROI



Business Stakeholder Product Owners

Define business problem, business KPIs, and make business decisions





Business Stakeholder Data & ML Consumers

Consumers of ML results from other BUs, driving business decision making

End-Users
Consume Generative AI applications





Generative AI End-users

Consume Generative AI solutions as black box, share data and rate the quality of output



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Generative AI Personas

Labeler Team **Data Preparation at Scale**





Data Labelers/Editors

Label trillions of Data for FM models and hundreds of data for fine tuning interacting with data lake using a dedicated website

Data Science Team Extension Context Adaptation



Fine Tuners

Select the corresponding FM, evaluate the model & design the deployment method/infrastructure

Application Developer Team Integrate GenAI models in applications



Generative AI Developers

Select, test, evaluate the FM, filter inputs/outputs, and develop the GenAl application back-end (e.g. LangChain Experts)



AppDev

Develop the front-end of the GenAl application



Prompt Engineers

Design the input/output prompts to adapt the solution to the context and test the initial version



Prompt Testers

Test at scale the Generative Al solution (back-end/ front-end) and feed their results to the prompt test repository



End-Users

Consume Generative AI applications

Generative Al End-users

Consume Generative AI solutions as black

box, share data and rate the quality of

output

MLOps & GenAl Foundation People & Processes

SEPARATION OF CONCERNS IS KEY FOR SUCCESS

