



# Large Language Models Operations (LLMOps)



- LLMOPs introduction
- Deployment and scalability of LLMs
- Monitoring and maintenance of models in production
- Performance evaluation and continuous improvement
- Ethical considerations and privacy

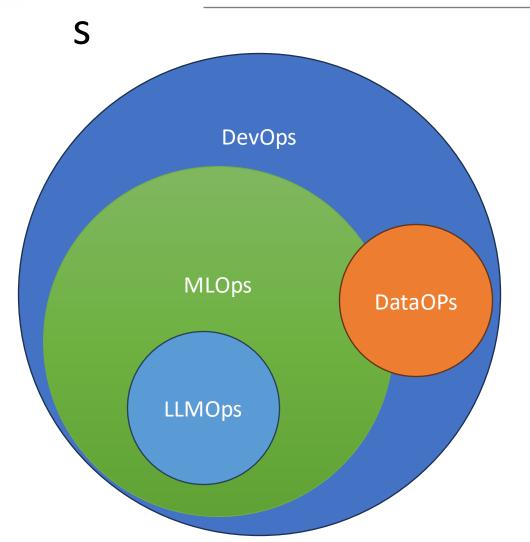








**XOP** 



Automation

Collaboration

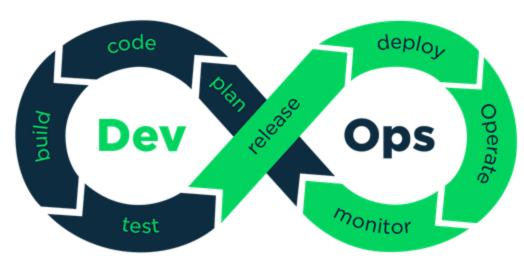
Reproducibility

CI/CD

Observability



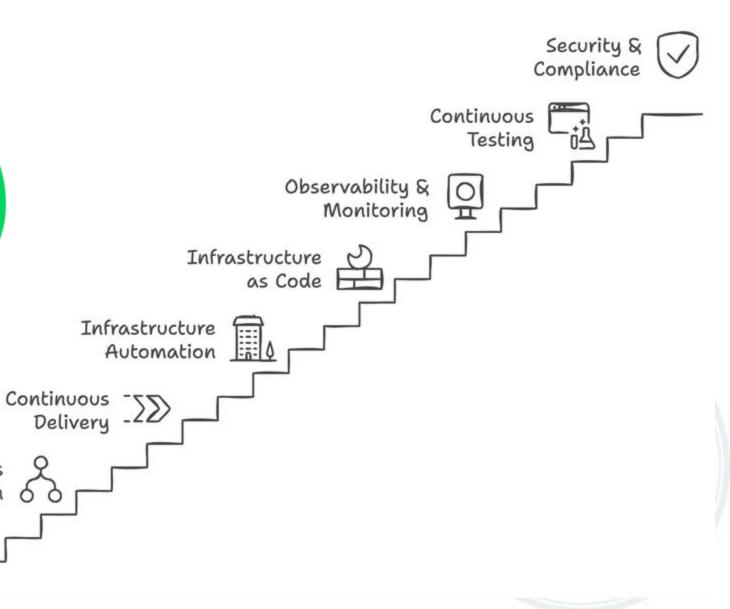
#### **DevOps**

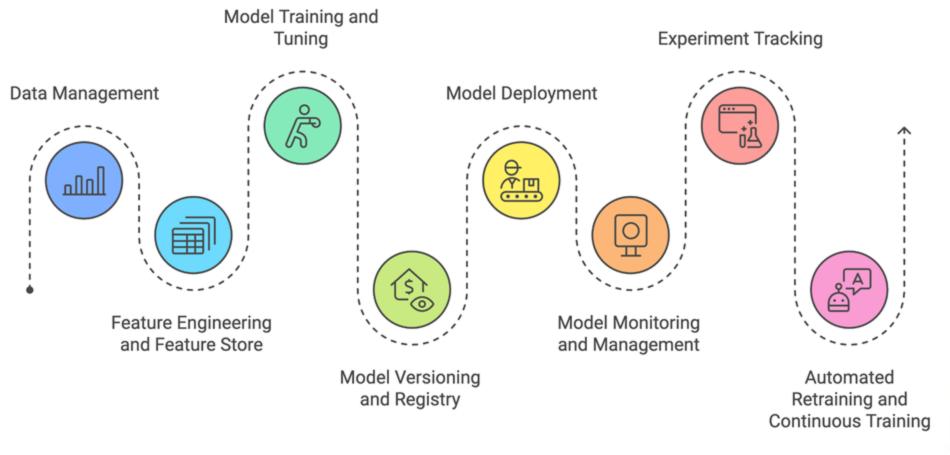


https://medium.com/@ritusherke86/what-is-devops-and-why-devops-86051071a42b

Continuous Integration

Collaboration & 2









## **LLMOps**









# Training and deployment of Large Language Models





#### Data Governance Officer



Data Engineer



#### Data Scientist



ML Engineer



**Business Stakeholder** 



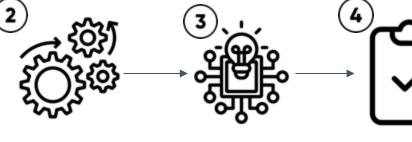
Data Preparation



Exploratory Data analysis



Feature Engineering



Model Training



Model Validation



Deployment



Monitoring

**<----**

#### What specific scaling challenges exist for LLMs?



**Initial training**: trillions of tokens, <u>hundreds to thousands of GBs</u> & very long run times.



**Fine-tuning**: updating model weights based on your own data, still requires relatively large data and long training times. Plus lots of evaluation!



**Storage**: the models contain billions of parameters, often <u>hundreds of GB</u>. This can be prohibitive for some devices.



Latency: Running inference on these models can be very costly in terms of time.



**Cost**: All of this costs \$\$\$!

#### What specific scaling challenges exist for LLMs?



Initial training: don't do it!



**Fine-tuning**: Optimize and use a scalable framework, such as Ray.



**Storage**: Quantization, memorization, caching ...



**Latency**: Quantization, memorization, caching, hardware and memory bandwidth optimization...



**Cost**: Above plus use 'open source' models

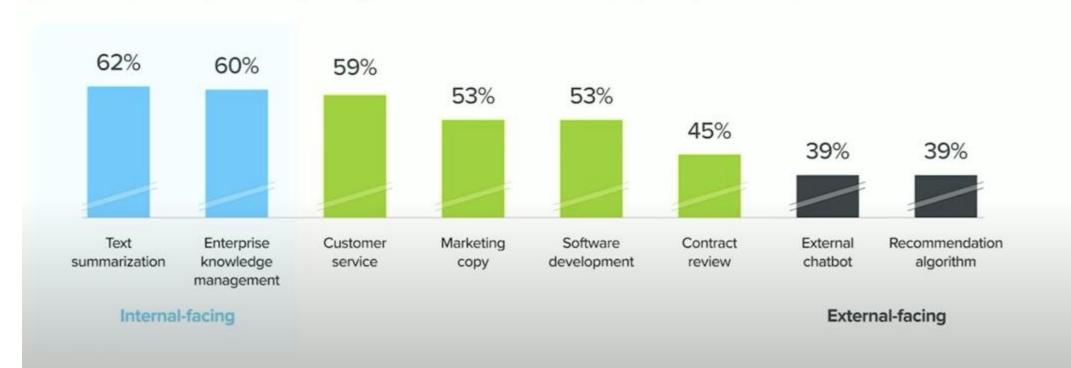


### Types of use-cases for Enterprises

#### How willing are enterprises to use LLMs for different use cases?



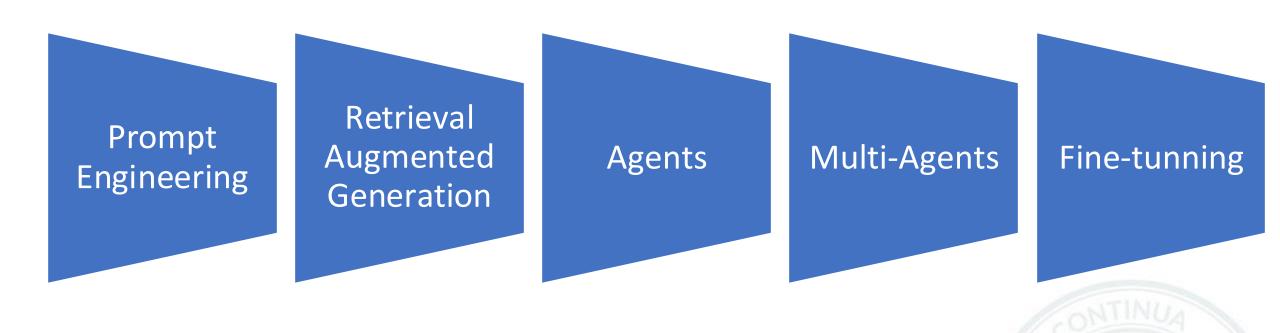
(% of enterprises experimenting with given use case who have deployed to production)



Source: a16z survey of 70 enterprise AI decision makers

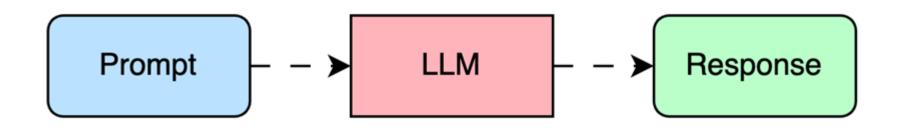


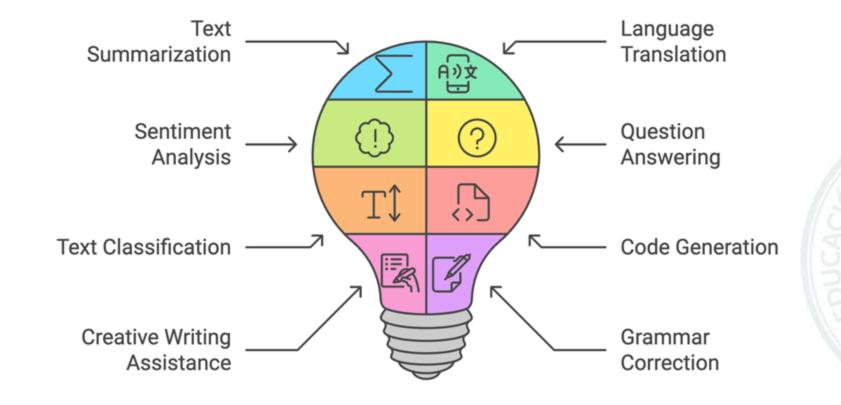
## LLM application archetypes





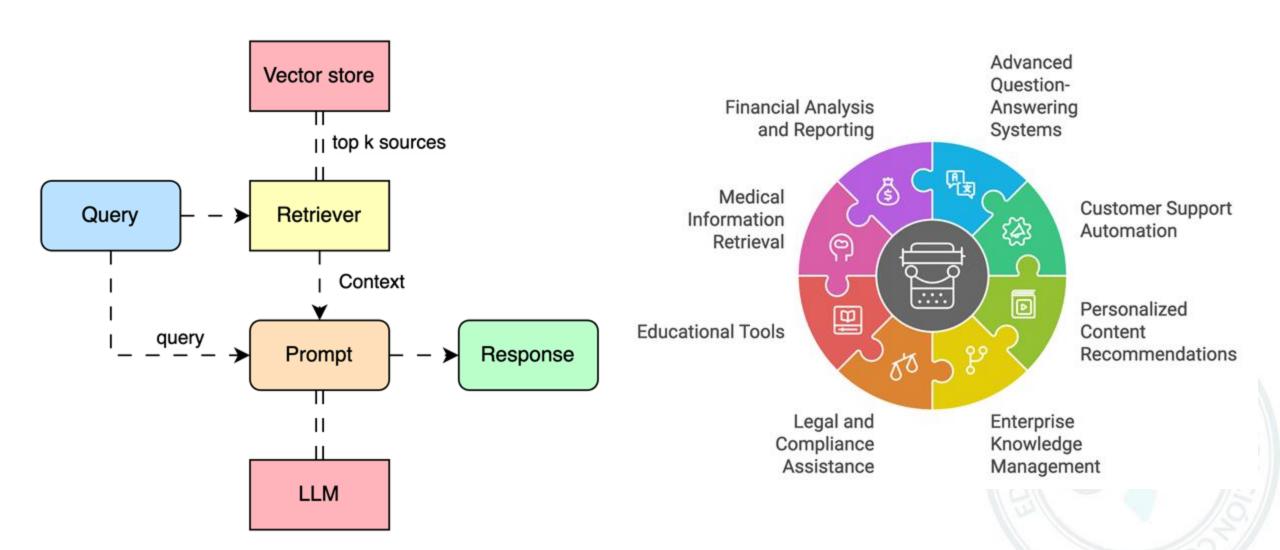
### **Prompt Engineering Applications**



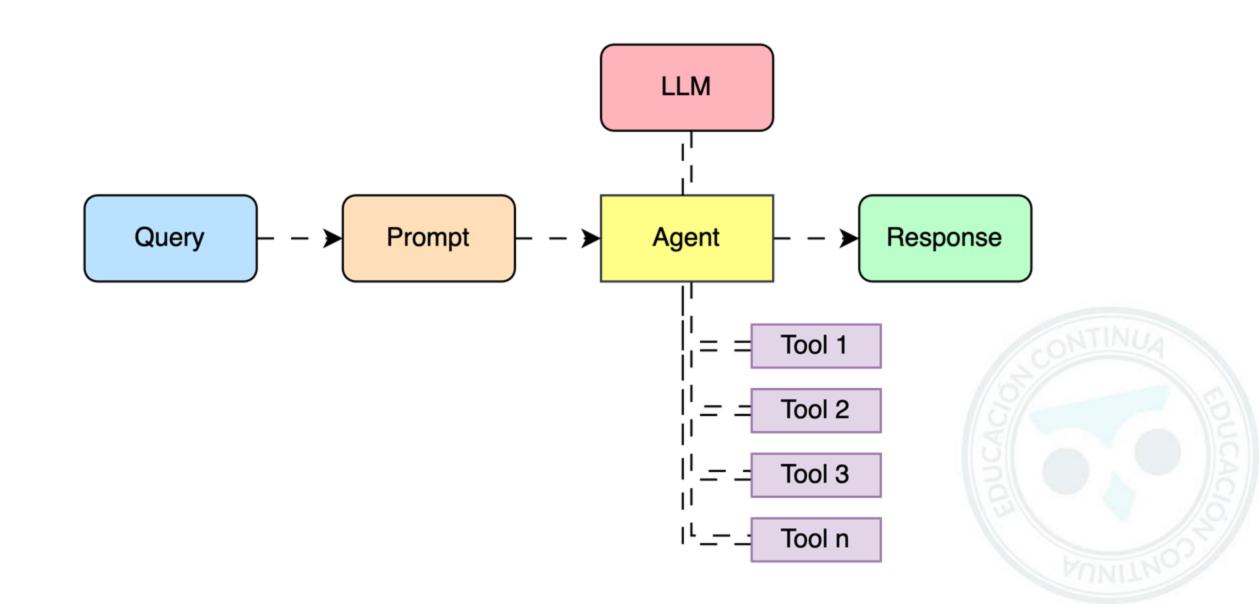




### Retrieval Augmented Generation Applications

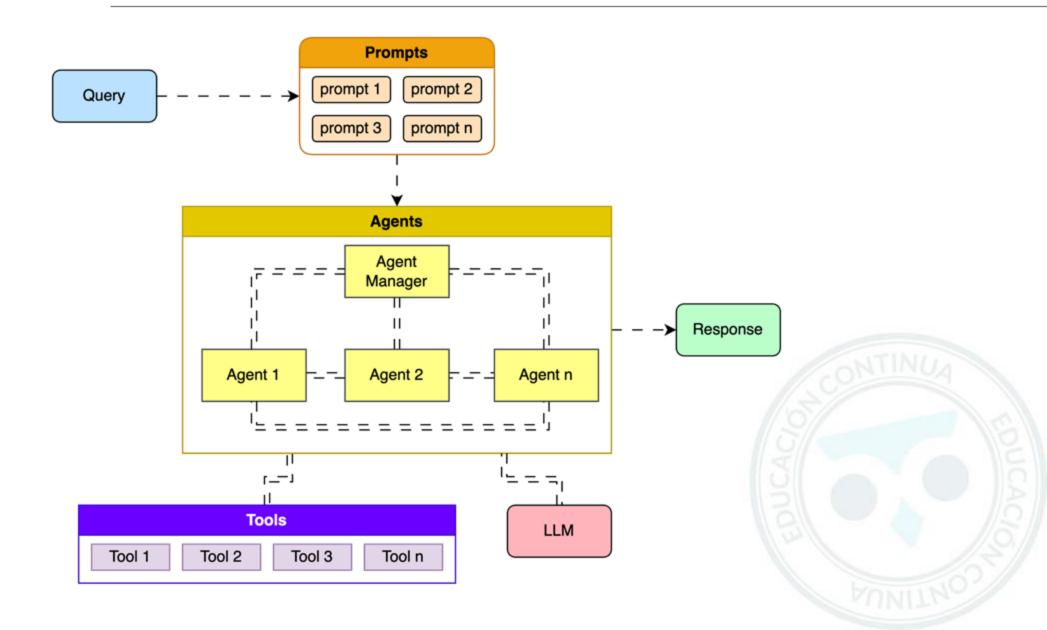


## **Agentic Applications**





## Multi-Agent Applications

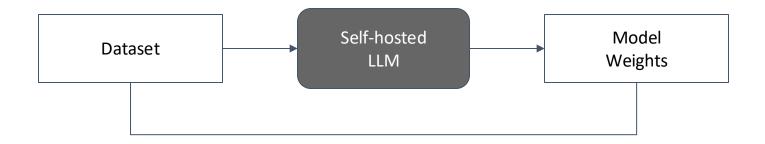




### Fine-tunning LLM Applications

#### Operationalizing Fine-tuning Pipelines

- Automation, version control, reproducibility
- Distributed training infrastructure
  - DeepSpeed, PEFT, GPUs
- Similar to classical model training serving
- Optimization techniques
  - vLLM, MLC, CudaGraph, MQA, Quantization, TensorRT
- Deeper understanding of GPUs, TTFT, TPOT

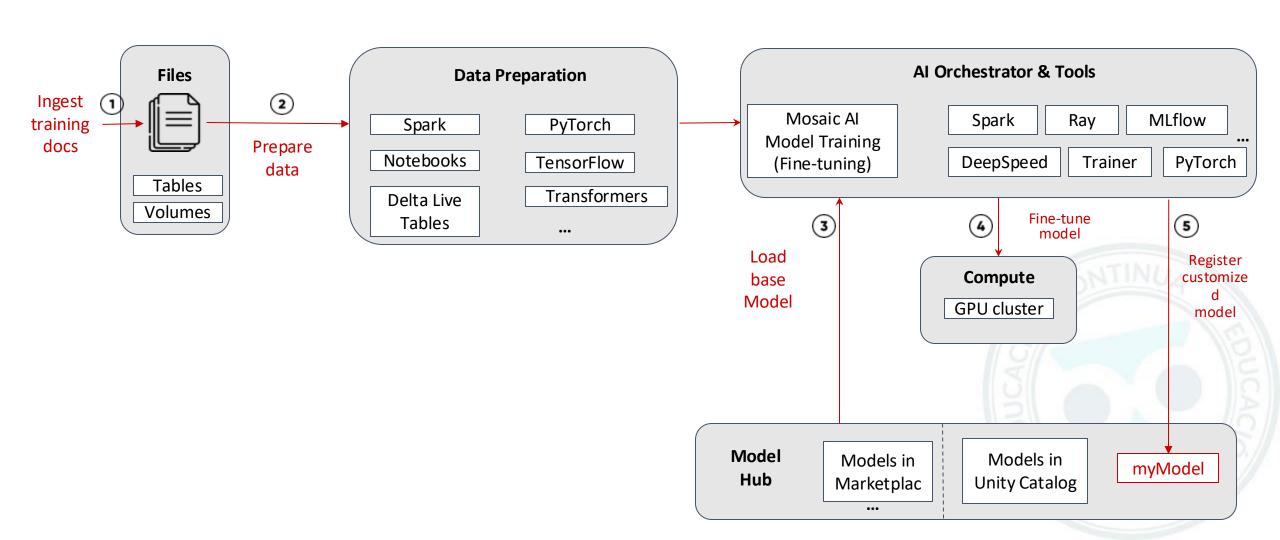






### Types of LLM Applications

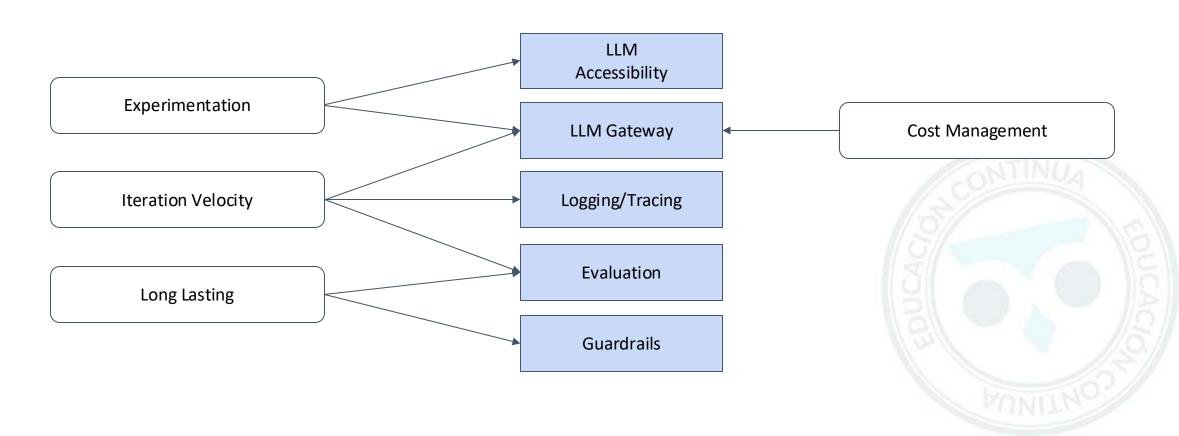
Architecture: fine-tuning



## Types of LLM Applications

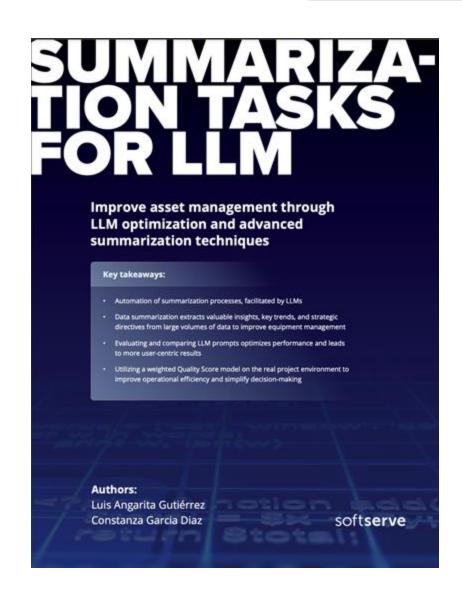
#### Practitioner's Perspective

#### **LLMOps Starting Points**





#### **Use-Case**



## Improve Asset Management with LLM Evaluation Pipelines

Creating efficient AI-powered summaries, LLMs save up to 93% of the time taken by traditional manual processes. Our white paper explains how this allows you to optimize asset management operations.

https://info.softserveinc.com/summarization-tasks-for-llm-white-paper









