



Democratizing Gen Al Large Language Model (LLM) Deployment: Amazon SageMaker JumpStart Unleashed

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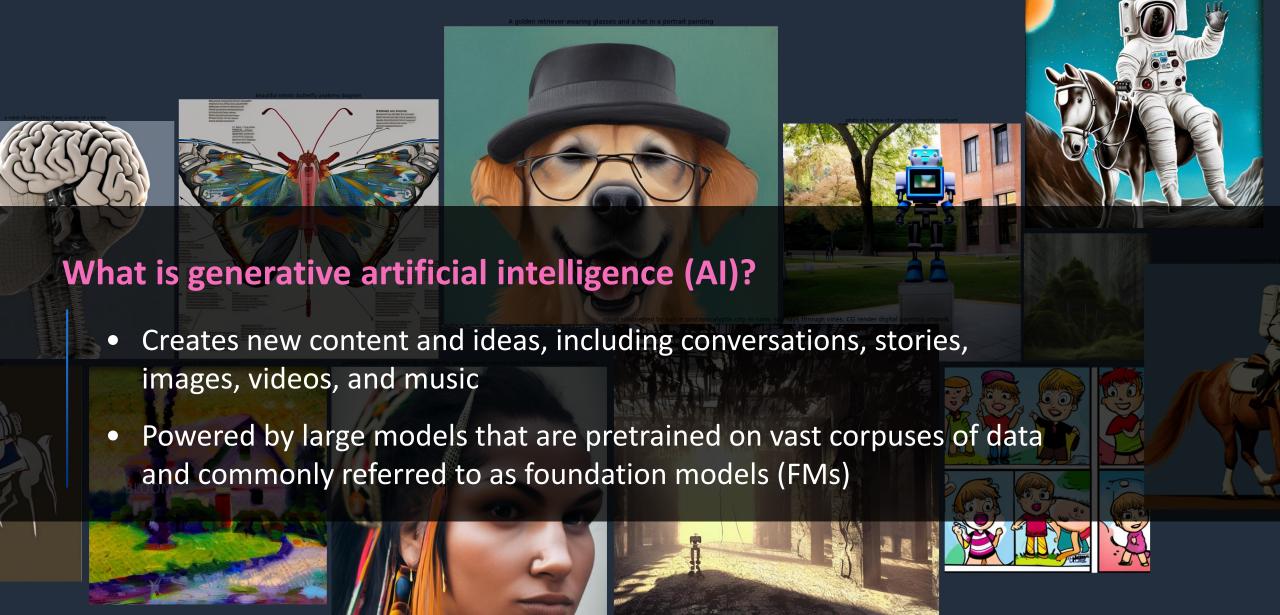
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Agenda

- Overview of Generative Al
- Generative Al offerings on AWS
- Overview of SageMaker JumpStart
- Customization of LLMs using SageMaker Jumpstart
- How to get started and CTA
- Exit Survey + Q&A







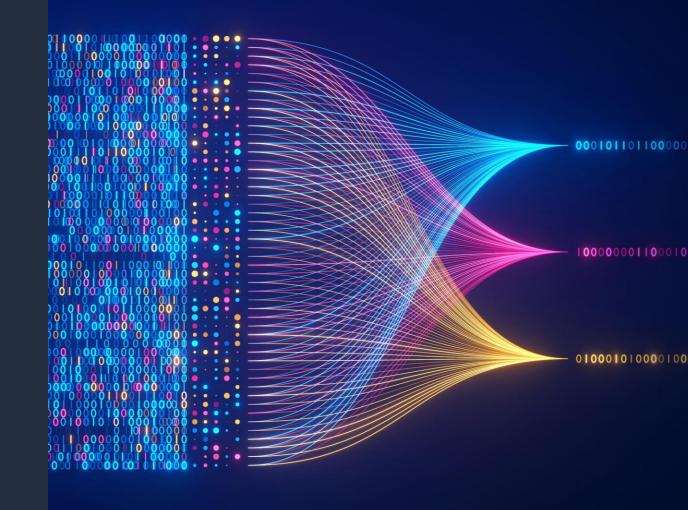
Generative AI is powered by foundation models

Pretrained on vast amounts of unstructured data

Contain large number of parameters that make them capable of learning complex concepts

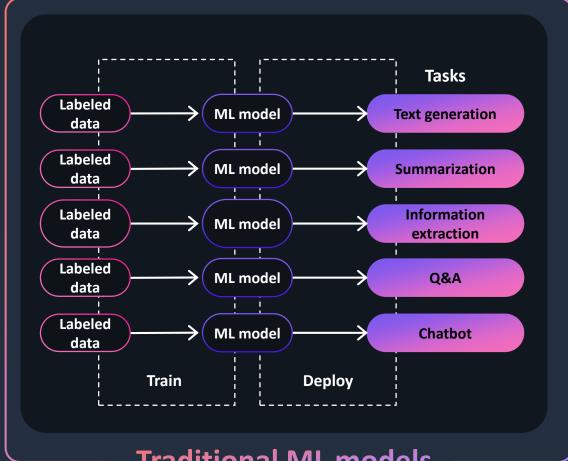
Can be applied in a wide range of contexts

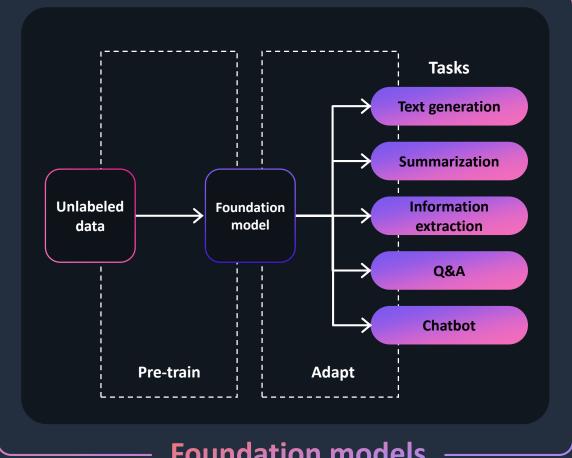
Customize FMs using your data for domain specific tasks





How foundation models differ from other ML models





Traditional ML models

Foundation models



Types of foundation models

Input



FM



Output

[Text]

"Summarize this article"

Text-to-text

Generate text from simple natural-language prompts for various applications

[Text]

"Ten thousand steps per day is optimum for maintaining a healthy heart"

[Text]

"hand soap"

Text-to-embeddings

Generate numerical representation of text that reflect the semantic meanings

[Vectors]

[0.21, 0.18, 0.92, 0.47, 0.85,...] Hand soap [0.19, 0.15, 0.93, 0.45, 0.82,...] Liquid soap [0.15, 0.19, 0.99, 0.49, 0.80,...] Shower gel

[Text]

"a photo of an astronaut riding a horse on mars"

Text-to-Image

Generate and edit images from natural-language prompts





[Image]



(optional) "a rose'

Image-to-Image

Generate a new image using another image as guidance and (optionally) a prompt

[Image]



[Text]

"A young couple walking in rain." "Children singing nature songs" "Write Python code to sort array ..."

Multimodal



generation model



[Audio]



Democratizing AI/ML through collaborations

AWS has collaborated with Meta PyTorch to help enterprise customers to move DL models from research into production seamlessly.

AWS has collaborated with Hugging Face to easily fine-tune and deploy next generation ML models on EC2 and SageMaker.

AWS has collaborated with Anthropic selects to become its primary cloud provider



Meta and AWS collaborate to build, train, and deploy ML models with PyTorch: PR Link



Hugging Face and AWS collaborate to make open source models and AI more accessible: PR Link

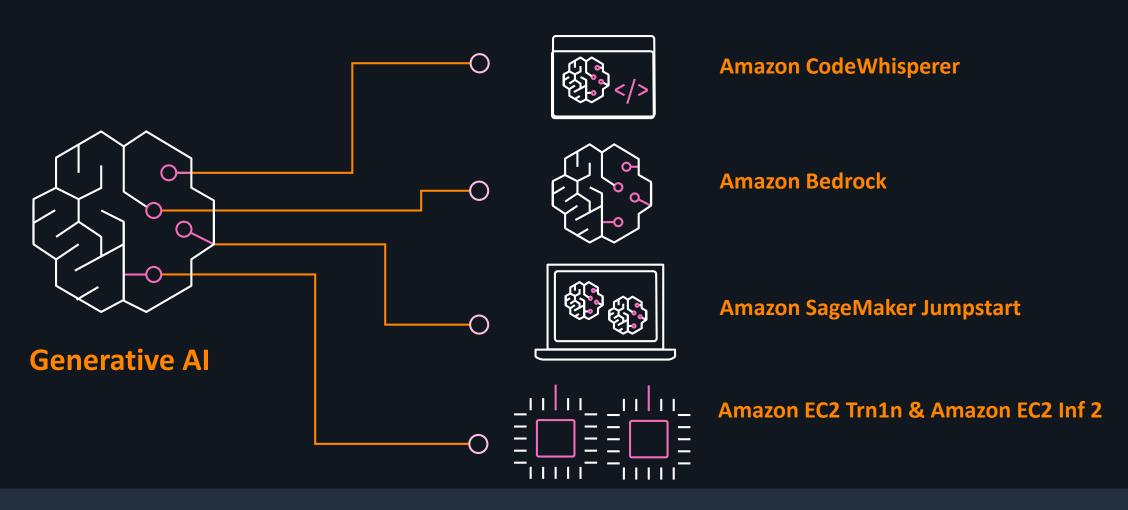
Platforms for sharing ML models & datasets



Anthropic and AWS announce strategic collaboration to advance generative AI: PR Link



AWS offers a broad choice of Generative AI capabilities







Amazon SageMaker JumpStart



SageMaker JumpStart Overview



Machine learning hub

Browse through 400+ built-in algorithms with pretrained models, pretrained foundation models, solutions, and example notebooks



Pre-built training and inference scripts

Compatible with SageMaker and configurable with custom dataset



UI as well as API-based

Use the user interface for single click model deployment or API for the Python SDK-based workflow



Notebooks with examples

Jump into notebooks to use selected model with examples to guide you through the entire ML workflow



Share and collaborate within your organization

Share models and notebooks with others within your organization, and allow them to train with their own data or deploy as-is for inferencing



Foundation Models available on SageMaker JumpStart

Al21 lal	bs ∞Meta Al	s cohere	Hugging Face	stability.ai	Lightூn	databricks	alexa
Models Jurassic-2 Ultra, Mid	Models Llama 2 7B, 13B, 70B	Models Cohere Command X L	Models Falcon-7B, 40B Open LlaMA	Models Stable Diffusion XL 1.0	Models Lyra-Fr 10B, Mini	Models Dolly	Models AlexaTM 20B
Contextual answers Summarize Paraphrase Grammatical error correction Tasks Text generation Long-form generation Summarization	Tasks Question answering Chat Summarization Paraphrasing Sentiment analysis Text generation	Tasks Text generation Information extraction Question answering Summarization	RedPajama MPT-7B BloomZ 176B Flan T-5 models (8 variants) DistilGPT2 GPT NeoXT Bloom models (3 variants) Tasks Machine translation	2.1 base Upscaling Inpainting Tasks Generate photo- realistic images from text input Improve quality of generated images	Tasks Tasks Text generation Keyword extraction Information extraction Question answering Summarization Sentiment analysis Classification	Tasks Question answering Chat Summarization Paraphrasing Sentiment analysis Text generation	Tasks Machine translation Question answering Summarization Annotation Data generation
Paraphrasing Chat Information extraction aws			Question answering Summarization				



Recent updates/releases for public models

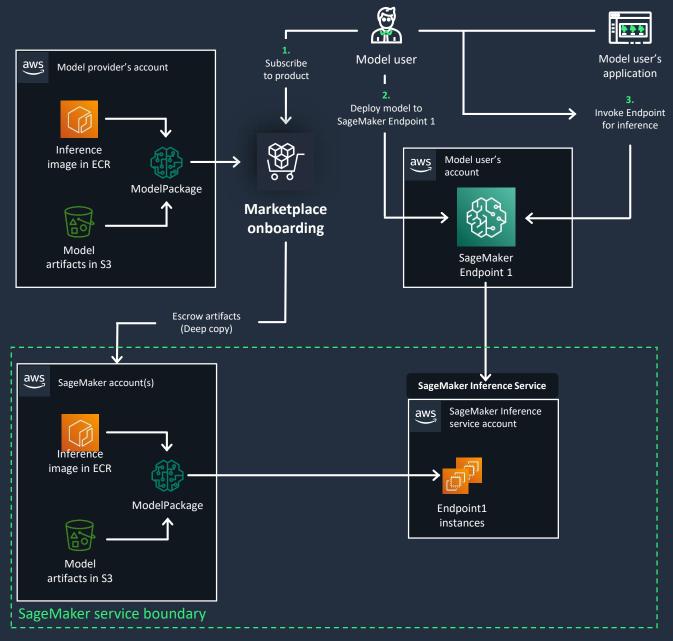
Latest inference only models

- Stable Diffusion XL 1.0 and 0.8
- Llama 2 and Llama 2 chat 70B, 13B and 7B
- Falcon and Falcon Instruct 40B
- Dolly V2
- RedPajama

Fine-tunable models

- Falcon 7B
- Red Pajama
- LightGPT
- FLAN T5 XL, XXL
- GPT-J 6B, GPT-NeoX
- Stable Diffusion 2.1



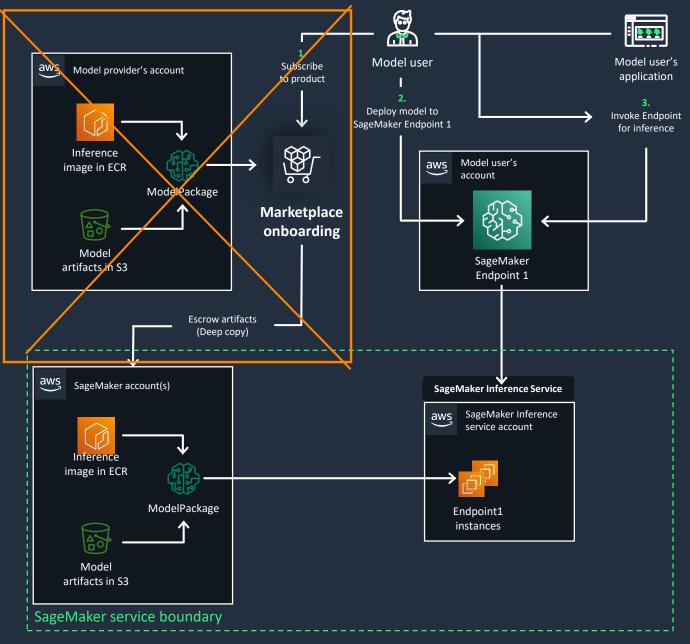




Deploying Proprietary Models through SageMaker JumpStart

- Proprietary model package and endpoint is hosted in SageMaker owned account
- Containers have no outbound network access; user data and model provider IP is protected the same time
- No data is used to update/train the base model that JumpStart provides to customers







Deploying Publicly Available Models through SageMaker JumpStart

- Public model package and endpoint is hosted in SageMaker owned account
- SageMaker distributes Open-source model artifacts in world readable S3 buckets
- Containers can be enabled to run without network access



Data Privacy and security is our #1 priority



Customer is always in control of their data

Customer data is not used for service improvement - training or re-training of 3rd Party models

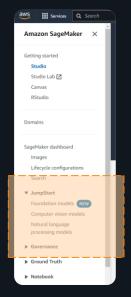
Customer data (prompts or responses) not shared with Amazon or 3rd Party model providers

Customer data (prompts, responses, fine-tuned models) are kept in the region where they were created

3 ways to use FMs with SageMaker JumpStart

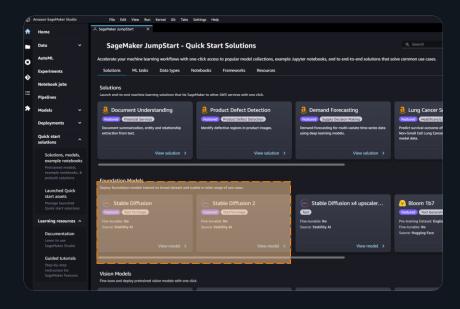
AWS console

Preview



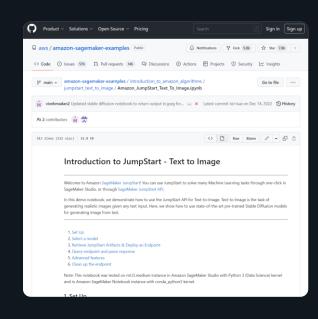
SageMaker Studio

One-click deploy



SageMakerNotebooks

SDK





Pre-trained Foundation Models

Pre-Training

Large corpus + custom task or corpus



Unsupervised /Self-Supervised Learning



Pre-Trained Model

Models

1- DIY or 2: Proprietary and public models

Transformers based architecture:

- Based on a <u>neural network architecture</u> in processing sequential natural language data.
 - Encoder-only/Autoencoder Models eg: BERT, ROBERTA
 - Decoder-only/Autoregressive Models eg: GPT, BLOOM
 - Sequence-to-Sequence Models eg: T5, BART
- Far better than traditional like RNN based models

Advantages:

- Gives the LLM a strong foundation
- Teaches the LLM general language understanding





Demo 1-

Overview of SageMaker JumpStart and run inference on a pre-trained text to image stable diffusion model



What are challenges with foundation models?

- Larger budget
- Infrastructure requirements
- Front-end development
- Lack of comprehension
- Unreliable answers
- Bias





LLM Customizations methods



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Emerging LLM customisation patterns

Prompt engineering (In-context learning)

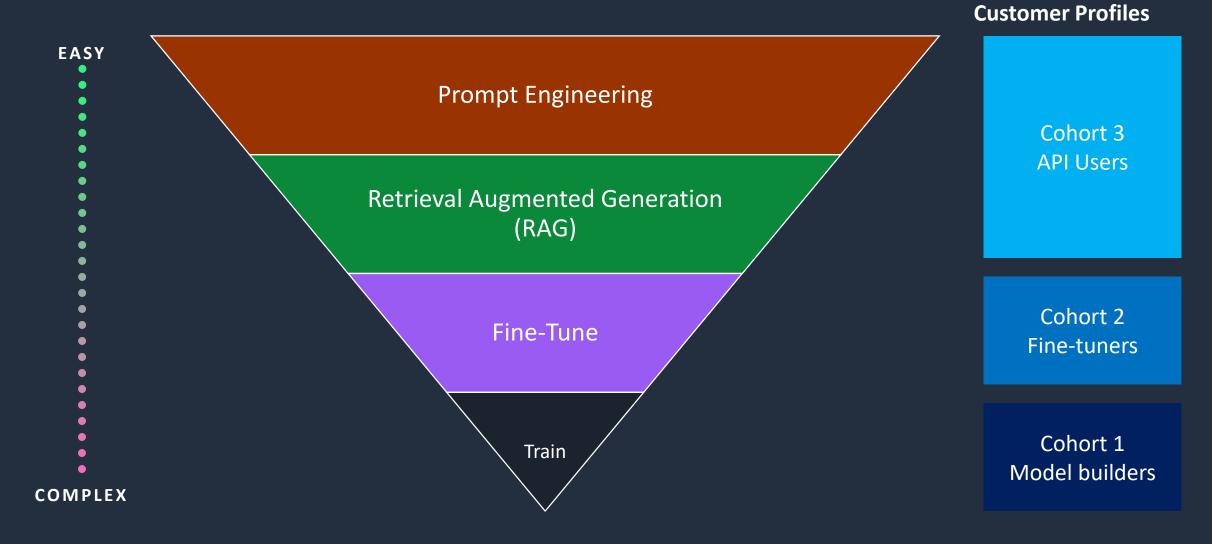
Retrieval Augmented Generation (RAG)

Fine-tuning

Training your own LLM

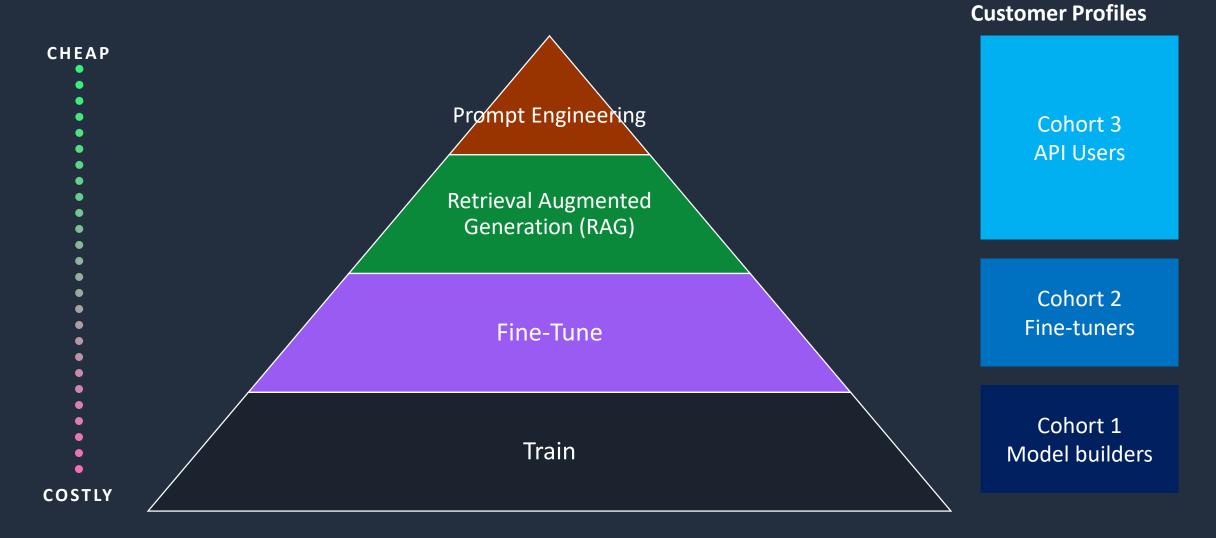


LLM customisation skills required





LLM customisation cost







LLM In-Context Learning (Prompt Engineering)



In-Context Learning (ICL)

- Learn from examples (demonstrations) given during inference. Called few-shot learning.
- ICL is similar to the decision process of human beings by learning from analogy.
- No parameter updates.
- Performance relies on the demonstration format and the order of examples.

1 In-Context Learning

Prompt engineering types

Zero shot prompts

One shot or few shot prompts

Role or Chain of Thought prompts

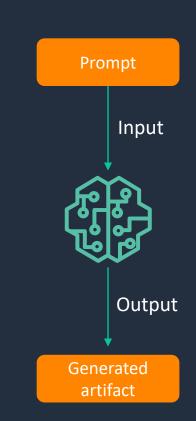
Direct request with sufficient context

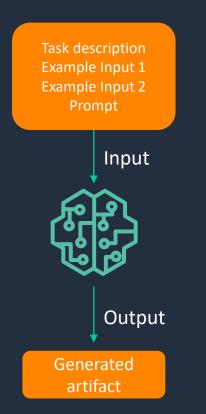
Provide one or more examples with a • request

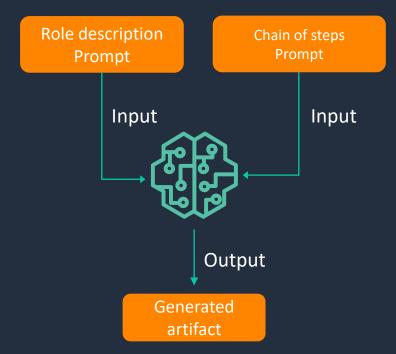
Provide the model with a role or persona for the task

Provide a chain of steps for the model to follow

1 In-Context Learning







Zero shot prompt: prompting by instruction

 Zero-shot prompting allows language models to perform tasks for which they have not been explicitly trained on

Using LLM out of the box

In-Context
Learning

Prompt

Avila, wide hearts, alree them in the resolve. The passionate romances her? Her fl soared after never justing rapturous reform of a source of a religious order in Italy.

Avila, wide hearts, alree them in the resolve. The passionate romances her? Her fl soared after never justing rapturous reform of a source.

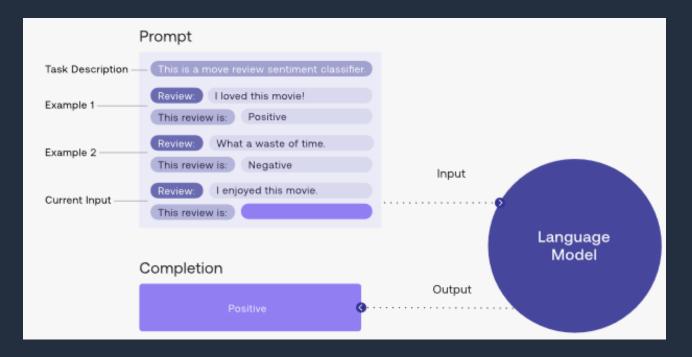
Theresa was a young girl of Spanish origin who became a member of a religious order in Italy.

Who that cares much to know the history of man, and how the mysterious mixture behaves under the varying experiments of Time, has not dwelt, at least briefly, on the life of Saint Theresa, has not smiled with some gentleness at the thought of the little girl walking forth one morning hand-in-hand with her still smaller brother, to go and seek martyrdom in the country of the Moors? Out they toddled from rugged Avila, wide-eyed and helpless-looking as two fawns, but with human hearts, already beating to a national idea; until domestic reality met them in the shape of uncles, and turned them back from their great resolve. That child-pilgrimage was a fit beginning. Theresa's passionate, ideal nature demanded an epic life: what were many-volumed romances of chivalry and the social conquests of a brilliant girl to her? Her flame guickly burned up that light fuel; and, fed from within, soared after some illimitable satisfaction, some object which would never justify weariness, which would reconcile self-despair with the rapturous consciousness of life beyond self. She found her epos in the reform of a religious order.

Prompt Engineering: N shots example

- Same as standard prompt but A few-shot prompt normally includes n examples
 of (problem, solution) pairs known as "shots".
- Help to guide model performance.

In-Context Learning





Prompt Engineering: Chain of Thought Prompting Examp

- Improves reasoning abilities in foundation models
- Addresses multi-step problem-solving challenges in arithmetic and commonsense reasoning task
- Generates intermediate reasoning steps, mimicking human train of thought, before providing the final answer.

1 In-Context Learning

Standard Prompting

Model Input

- Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
- A: The answer is 11.
- Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27.

Chain-of-Thought Prompting

Model Input

- Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?
- A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.
- Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.



Important parameters

Parameter settings to customize results:

- Temperature:
 - controls randomness.
 - Lower values pick probable tokens
 - higher values add randomness and diversity.
 - => Use lower for factual responses, higher for creative
- Top-p: also adjusts determinism with "nucleus sampling".
 - Lower values give exact answers
 - higher values give diverse responses

Note:

- Only adjust one parameter at a time.
- Outcomes vary between language model types

1 In-Context Learning



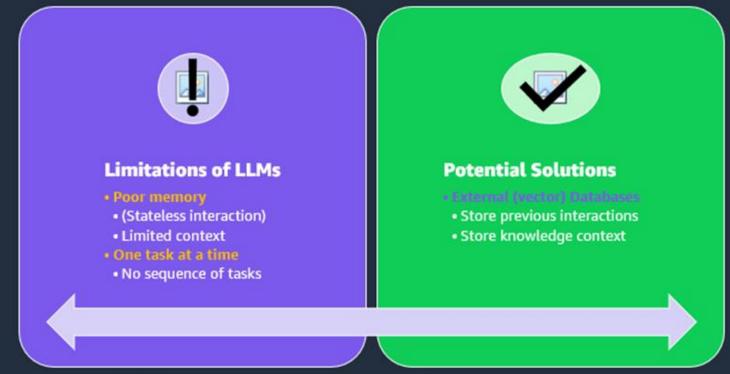
Demo 2 – Prompt engineering



LLM and prompting limiation

- What about complex and knowledge-intensive tasks,
- accessing external knowledge sources to complete tasks.
- => Retrieval Augmented Generation method

1 In-Context Learning





LLM In-Context Learning (RAG)



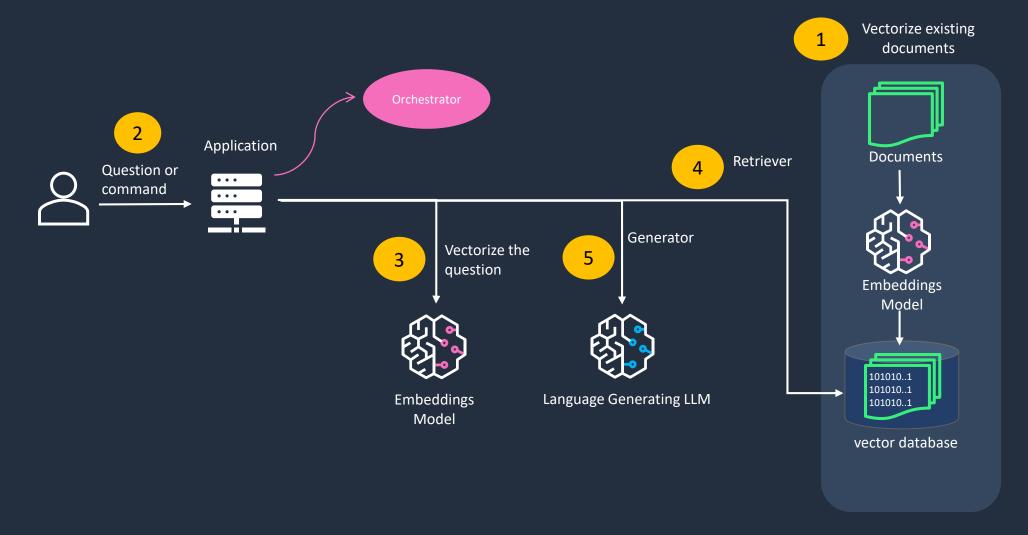
Retrieval Augmented Generation (RAG)

A sweet spot for many organisations

- Concise and relevant context
- Evolve knowledge base on the fly
- No need of complex LLM training and retraining
- No need to host a dedicated LLM



Architecture components in a RAG solution





Which Vector Database to use in AWS?

Looking for low-code no-code solution and rapid deployment

Use out-of-the-box 40+ connectors to ingest

data from many data sources

 $\overline{}$

Do not want to deal with management of data chunking, embeddings, and indexing algorithm choices

Already using Amazon OpenSearch Service and comfortable with NoSQL

Need low latency with HNSW algorithm, and lower memory with product quantization

Need higher search accuracy using larger vector dimensions; flexibility to pick any vector embedding model Already using Amazon RDS/Aurora PostgreSQL and prefer using SQL

Keep application and AIML data and vectors in the same DB for better governance, faster clones

Need transactional and immediate consistency

Role Based Access Controls, Encryption, Authentication, Authorization, Auditing, and Fully Managed Services with Serverless Option



Amazon Kendra



Amazon OpenSearch Service or Amazon OpenSearch Serverless



Amazon RDS for PostgreSQL or Amazon Aurora PostgreSQL



Retrieval Augmented Generation (RAG)

Key Limitations:

- Increased Complexity => adding retriever component to generation model
- Limited Creativity => constrained by the retrieved information

Fine-tuning might help overcome the above limitations





LLM - Fine Tuning



Instruction(Instruct) Fine-Tuning

3 Fine-Tuning



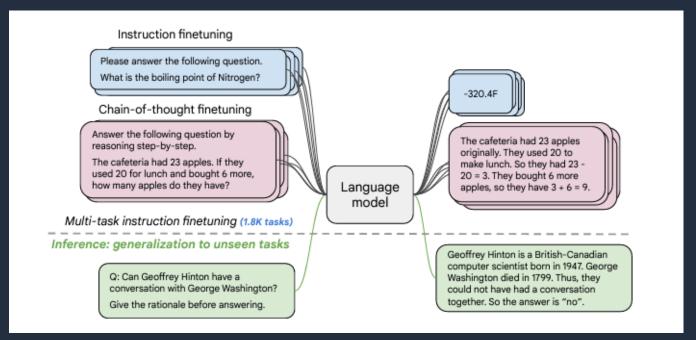
- Turn pre-trained model into a specialized model
- Better performance with fewer labeled examples
- Smaller (fine-tuned) model can often outperform larger (more expensive) models
- Catastrophic forgetting- Single task fine tuning

FLAN (Fine-tuned Language Net)

- Multi Task FT- Overcome Catastrophic forgetting
- Multiple-tasks such as summarization, review rating, code translation, and entity recognition
- Fine tuned on 473 datasets, 146 categories, 1.8K tasks:



- Requires lots of data
- Varients such as FLAN- T5, FLAN- PALM, FLAN- UL2
 - Flan-PaLM 540B on 1.8K tasks outperforms PALM 540B by 9.4%.
 - Flan-PaLM 540B achieves 75.2% on five-shot MMLU
- Further fine-tune for specific use-case

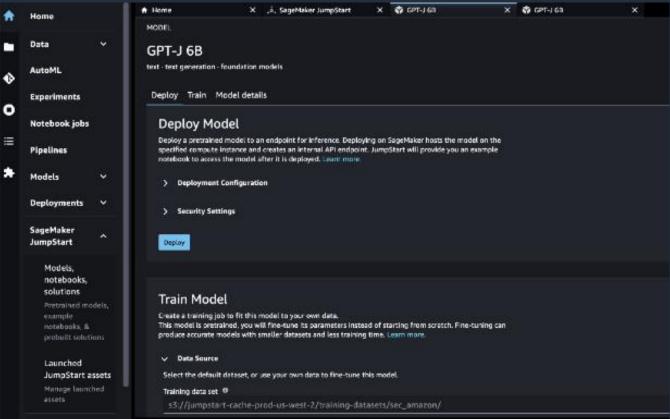


	MMLU	BBH-nlp	BBH-alg	TyDiQA	MGSM
Prior best	69.3 ^a	73.5^{b}	73.9 ^b	81.9°	55.0^{d}
PaLM 540B					
 direct prompting 	69.3	62.7	38.3	52.9	18.3
- CoT prompting	64.5	71.2	57.6	-	45.9
- CoT + self-consistency	69.5	78.2	62.2	-	57.9
Flan-PaLM 540B					
 direct prompting 	72.2	70.0	48.2	67.8	21.2
- CoT prompting	70.2	72.4	61.3	-	57.0
- CoT + self-consistency	<u>75.2</u>	<u>78.4</u>	66.5	-	<u>72.0</u>

Domain Adaptation Fine-Tuning on Amazon SageMaker

- Fine tuning <u>GPT-J 6B</u>
- On SEC filing dataset
- Use either JumpStart SDK or <u>Amazon</u>
 <u>SageMaker Studio</u> UI

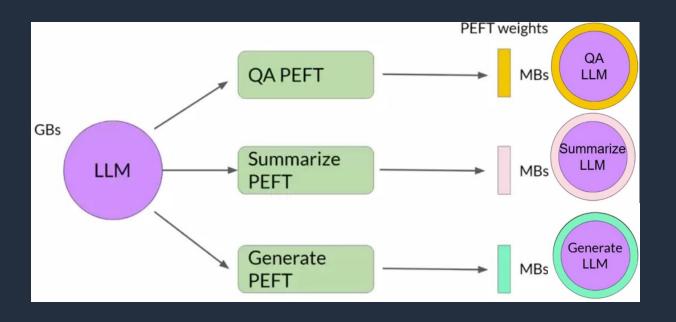




Domain-adaptation Fine-tuning of Foundation Models in Amazon SageMaker JumpStart on Financial data



Parameter-Efficient Fine-Tuning (PEFT)



- A novel approach for fine-tuning
- Open-source library from HuggingFace
- Fine-tune a small number of (extra) model parameters
- State-of-the-Art PEFT achieve full fine-tuning performance
- Supported methods
 - LoRA & QLoRA are most widely used and effective.
 - Prefix Tunning
 - AdaLora

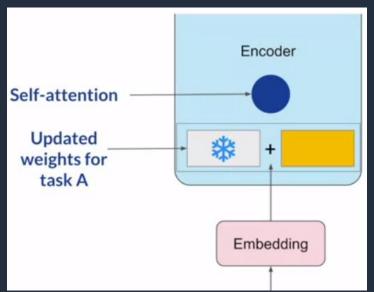
Etc..

<u>Github - HuggingFace - PEFT</u>



Low-Rank Adaptation (LoRA)

Training method that accelerates the training of large models while consuming less memory





- Freeze most of the original LLM weights eg: d x k = 512x64
- Inject 2 decomposition matrices (rank= 8) eg: r
 x k = 8 x 64, d x r = 512 x 8
- Train only the smaller matrices
- Add to the original weights
- GPT-3 175B- Reduces # of trainable parameters by 10000x and the GPU memory by 3x.
- Llama-2 7B- Fine-tune less than 1% of the parameters.

LORA: LOW-RANK ADAPTATION OF LARGE LANGUAGE MODELS



Quantized Low-Ranking Adaptation (QLoRA)

QLoRA extends LoRA to enhance efficiency by quantizing weight values

- Key optimizations:
 - 4-bit NormalFloat (FP32 → NF4)
 - Double Quantization (Constant unit variance)
 - Paged Optimizers (Prevent memory spikes during gradient checkpointing)
- Enables finetuning a 65B parameter model on a single 48GB GPU
- Matches the performance of fine-tuning and achieves state-of-the-art results on language tasks

QLORA: Efficient Finetuning of Quantized LLMs

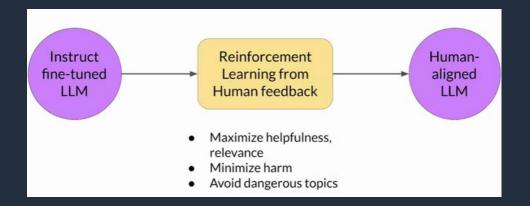
Fine Tuning LLM: Parameter Efficient Fine Tuning (PEFT) — LoRA & QLoRA

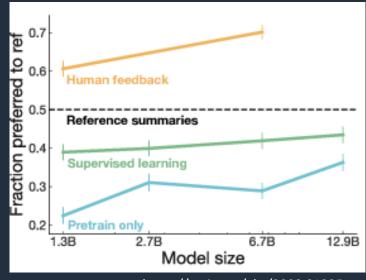


Responsible Al using RLFH

Reinforcement Learning with Human Feedback

- Align models with human values- helpfulness, honesty, and harmlessness (HHH)
- RLHF is popular technique for finetuning LLMs with human feedback
- RLHF shows better responses than a pretrained LLM, instruct fine-tuned LLM, and reference human baseline.
- RLHF is a complex and often unstable procedure.



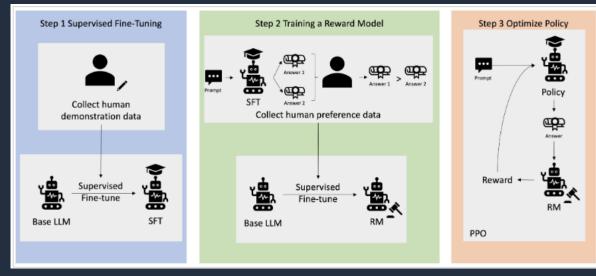






RLHF on Amazon SageMaker

- Human data annotators are tasked with authoring responses to various prompts.
- The collected responses (referred to as demonstration data) are used for supervised fine-tuning (SFT).
- Annotators rank model outputs based on HHH
- Human preference data is used to train a reward model (RM)
- RM is used by Proximal Policy Optimization (PPO) to train the supervised fine-tuned model



Improving your LLMs with RLHF on Amazon SageMaker

The Human Evaluation approach is defined, launched, and managed by the <u>Amazon SageMaker Ground Truth Plus</u> labeling service.





Demo 4 – Fine-tuning





How to get started / Call To Action

- AWS Digital Course <u>AWS Partner: Generative AI Essentials (Business) Gen AI skill badge launch</u>
- Partner Learning Plans on Generative Al
 - **Generative AI for Business Professionals**
 - Generative AI for Technical Professionals
 - Generative AI for Developers
 - Mastering Amazon SageMaker
- Workshop Studio
 - Discover and participate in AWS workshops and GameDays
- Labs
 - Amazon CodeWhisperer workshop
 - Amazon BedRock workshop
 - Amazon SageMaker Jumpstart

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Q&A





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