GENERATIVE AI IMMERSION DAY

Implementing Generative AI in Organizations

Challenges and Opportunities

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AGENDA

Generative AI – What is it and why the hype?

Large Language Models - How the ML works?

Large Language Model Hosting

Large Language Model Finetuning

Visual Foundation Models & Stable Diffusion

Engineering GenAI-powered Applications on AWS

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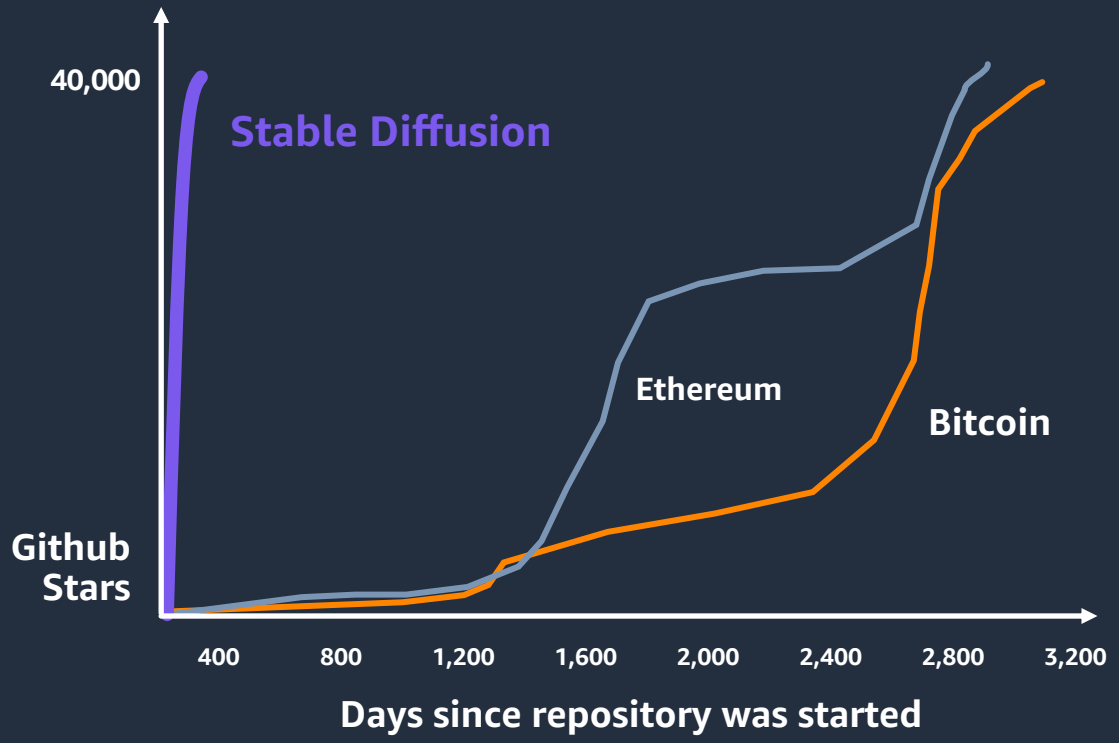
Generative AI is the fastest growing trend in AI

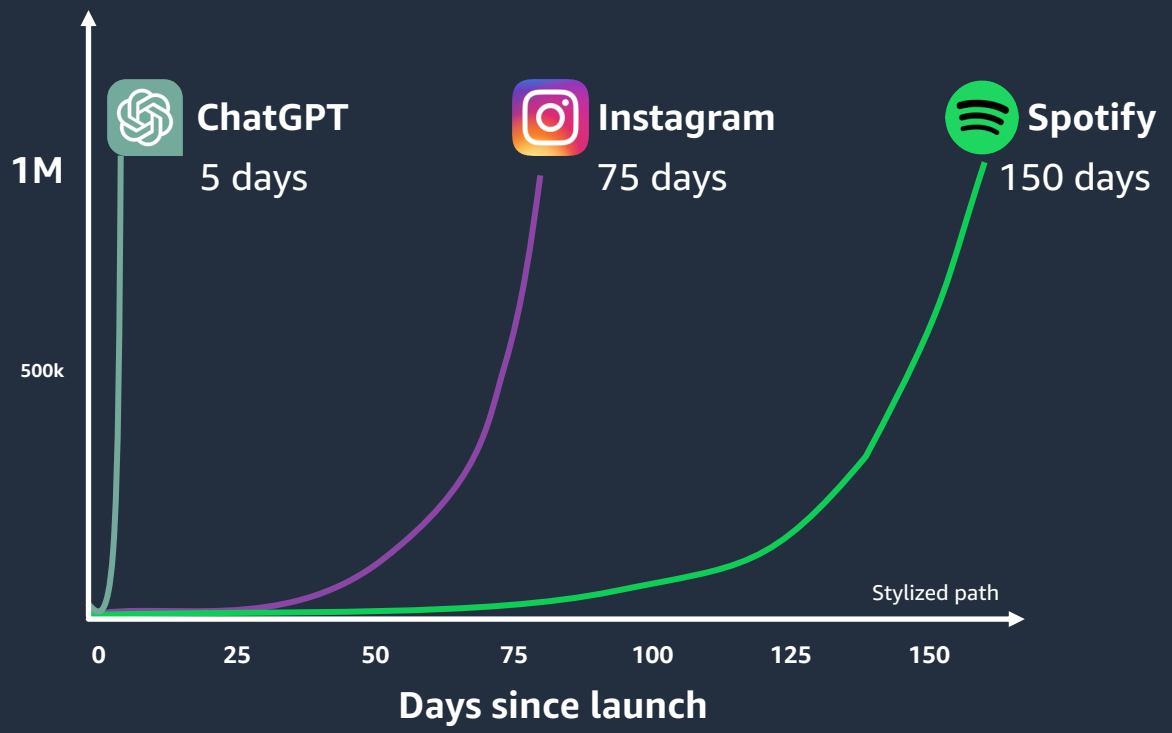
Developer adoption

Stable Diffusion accumulated 40k stars on GitHub in its first 90 days



Consumer adoption

ChatGPT reached the 1 million users mark in just 5 days



What is Generative AI?

AI that can
generate content
close enough to human created content for real-world tasks

Powered by
foundation models
pre-trained on large sets of data with several hundred billion parameters

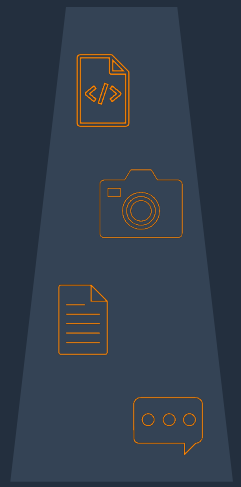
Applicable to
many use cases
like text summarization, question answering, digital art creation, code generation, etc.

Tasks can be
customized for specific domains
with minimal fine-tuning

New Volvo car concept design by midjourney
Credit: *@sugardesign_1* Instagram

Generative AI – what's the perk?

Humans



Speed & Breadth

- Generates novel content
- No task specific models
- Applicable to a broad set of tasks
- Outputs easily interpretable by humans

Generative AI

Breadth of knowledge

GENERATIVE AI IMMERSION DAY

Gen AI use case emerge in 4 different categories

Text

Text generation

Q&A

Text summarization and paraphrasing

Text and knowledge extraction

Search

Code

Code generation

Code completion

Media (image, video, audio)

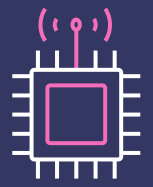
Image generation

Image classification

Audio generation

Video generation

Special purpose



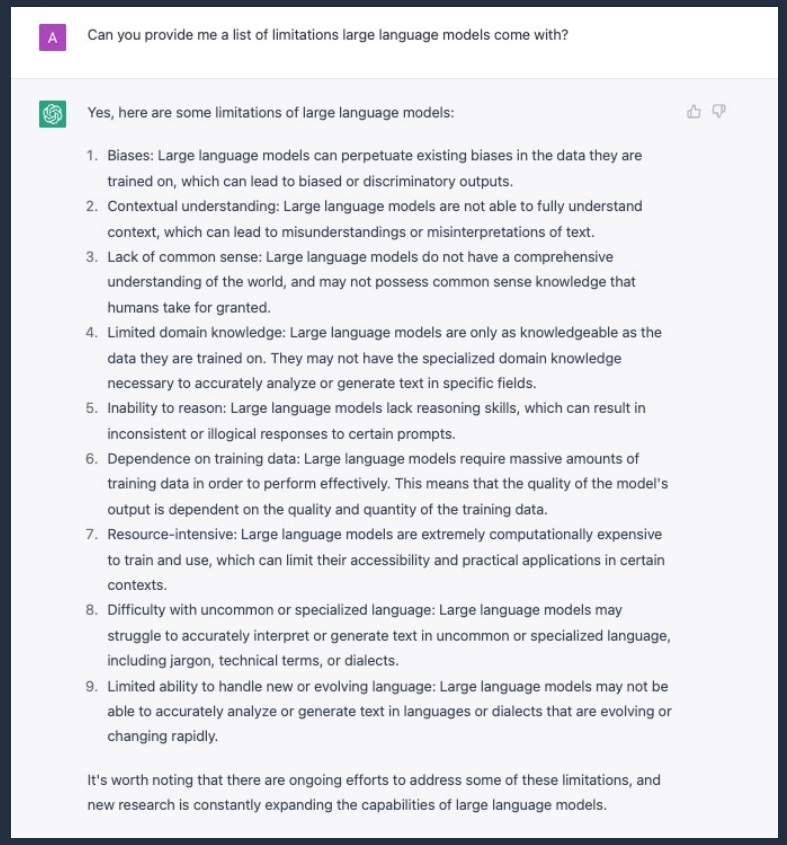
Chip design

Drug design

…

… but there are also certain limitation to bear in mind

We asked ChatGPT about the limitations of LLMs …



A Can you provide me a list of limitations large language models come with?

Yes, here are some limitations of large language models:

1. Biases: Large language models can perpetuate existing biases in the data they are trained on, which can lead to biased or discriminatory outputs.
2. Contextual understanding: Large language models are not able to fully understand context, which can lead to misunderstandings or misinterpretations of text.
3. Lack of common sense: Large language models do not have a comprehensive understanding of the world, and may not possess common sense knowledge that humans take for granted.
4. Limited domain knowledge: Large language models are only as knowledgeable as the data they are trained on. They may not have the specialized domain knowledge necessary to accurately analyze or generate text in specific fields.
5. Inability to reason: Large language models lack reasoning skills, which can result in inconsistent or illogical responses to certain prompts.
6. Dependence on training data: Large language models require massive amounts of training data in order to perform effectively. This means that the quality of the model's output is dependent on the quality and quantity of the training data.
7. Resource-intensive: Large language models are extremely computationally expensive to train and use, which can limit their accessibility and practical applications in certain contexts.
8. Difficulty with uncommon or specialized language: Large language models may struggle to accurately interpret or generate text in uncommon or specialized language, including jargon, technical terms, or dialects.
9. Limited ability to handle new or evolving language: Large language models may not be able to accurately analyze or generate text in languages or dialects that are evolving or changing rapidly.

It's worth noting that there are ongoing efforts to address some of these limitations, and new research is constantly expanding the capabilities of large language models.

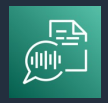
… and it came up with pretty good responses …

- Risk of bias
- Misinterpretation of context
- Lack of common sense
- Inability for (logical) reasoning
- Limited domain-specific knowledge

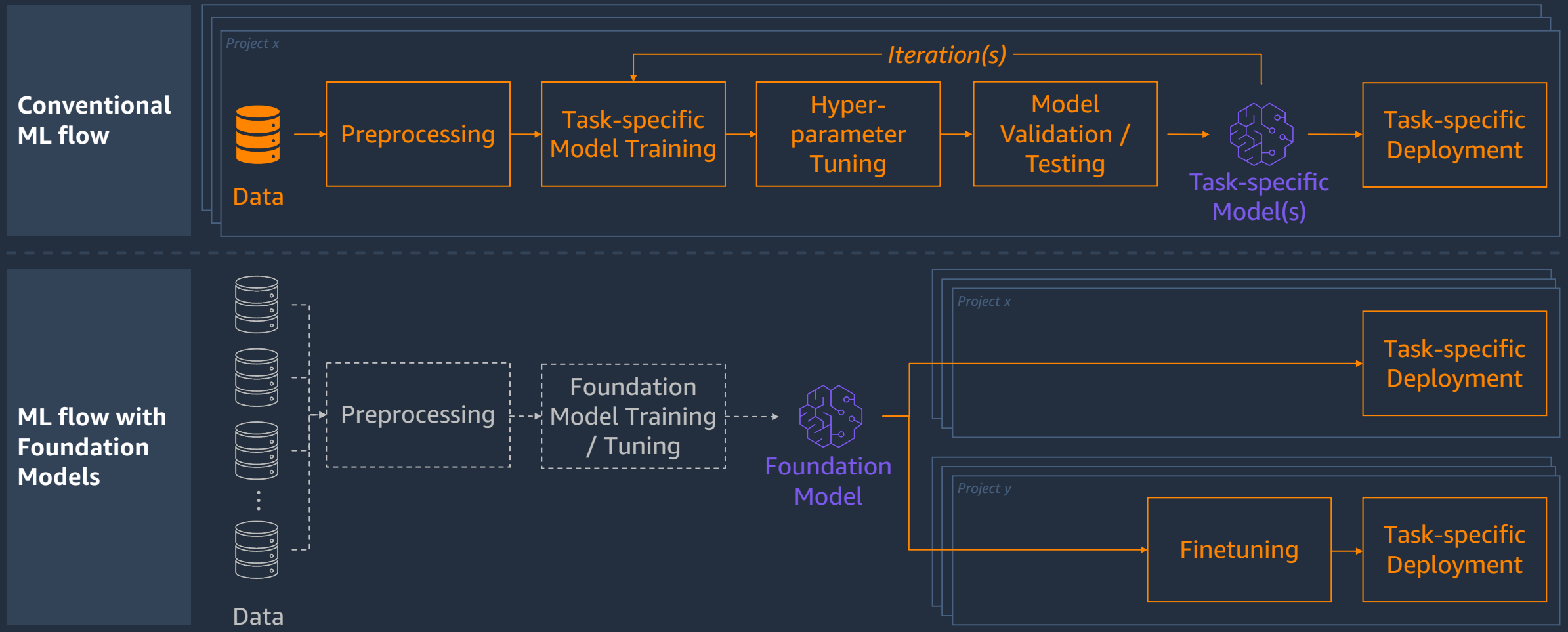
… but missed crucial aspects for enterprise applications

- Halluzination
- Knowledge cut-off
- Potential need for content moderation
- Missing references to original sources
- No explainability (as of March 2023)
- …

One approach to rule them all…?

If you want to …	… you might want to explore	
… automatically **extract information from documents**, such as e-mails, forms, invoices, …	 Amazon Textract	Machine learning service that automatically extracts text, handwriting, and data from scanned documents.
… make information contained in documents, audio recordings, or videos easily **searchable**	 Amazon Kendra	Intelligent enterprise search service that helps you search across different content repositories with built-in connectors.
… wants to **convert audio files** into text	 Amazon Transcribe	Automatic speech recognition service that uses machine learning models to convert audio to text.
… wants to **translate text**	 Amazon Translate	Neural machine translation service that delivers fast, high-quality, affordable, and customizable language translation.
… wants to **build a chat application** (with execution of scripted workflows based on identified user intent)	 Amazon Lex	Fully managed artificial intelligence service with advanced natural language models to design, build, test, and deploy conversational interfaces in applications.

Foundation models – A paradigm change in the ML flow



Licensing model has implications on available options, cost, and security

	Proprietary	Open-source
Examples	ChatGPT, GPT-3/4, DALL-E	GPT-J, BLOOM, FLAN-T5, Stable Diffusion
Provisioning model	Model-as-a-Service	Self-hosting or Model-as-a-Service
Access pattern	External API	Internal API embedded in your application landscape
Cost structure	Provider-dependent	Full cost control
Data privacy & residence	Provider-dependent	Under own control (but also own obligation)
How it works	Closed-box	Open-box

How to get started with Gen AI on AWS?

Option 1: Generative AI as a service

Option 2: SageMaker Jumpstart foundation model hub

Option 3: SageMaker & open-source model hubs - Example: SageMaker built-in HuggingFace integration

Proprietary

Open-source

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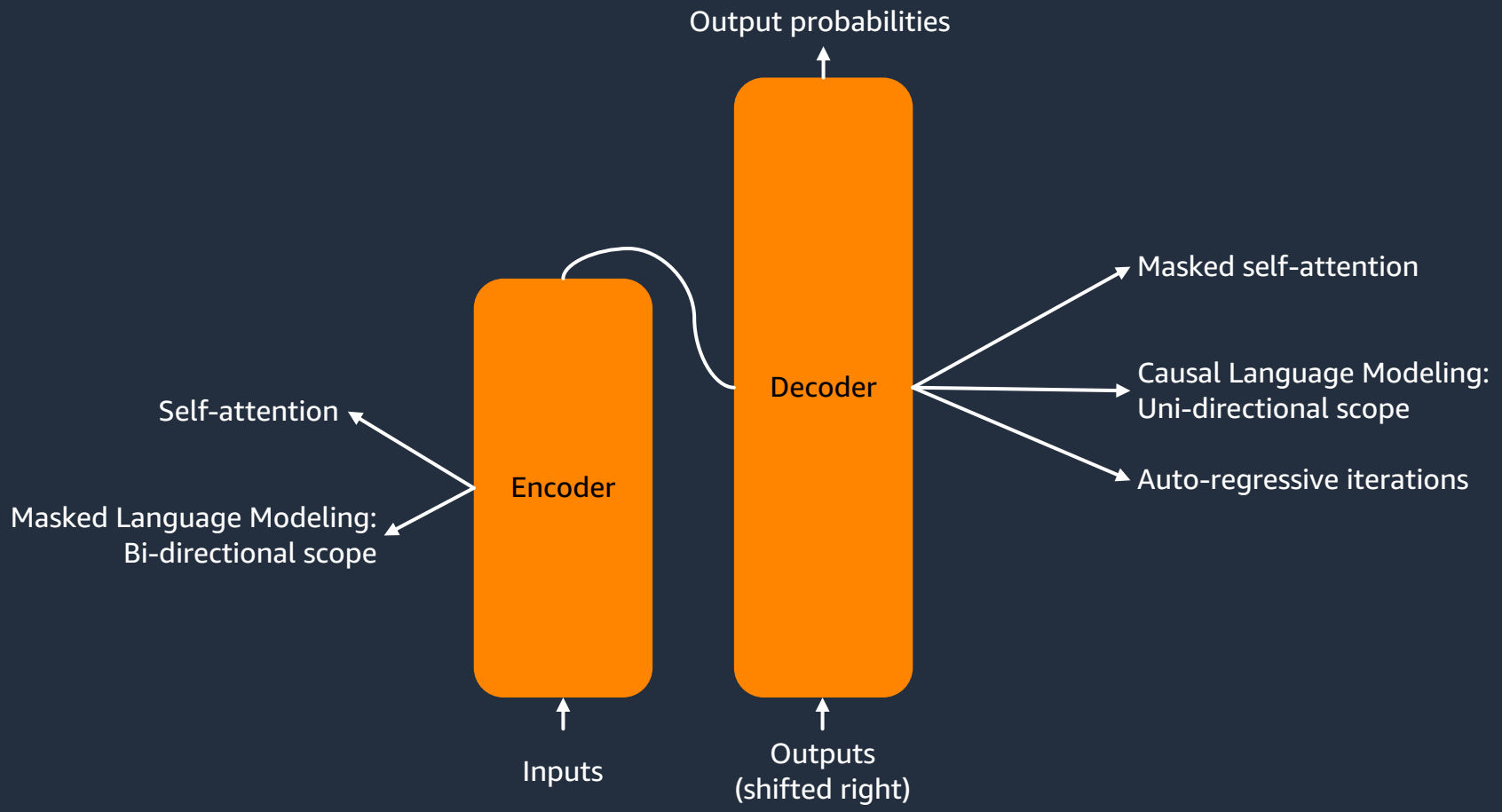
Transformer Models – Core characteristics of sequence-to-sequence transforms



Transformer Models – Encoders and Decoders form the basis of state-of-the-art LLMs

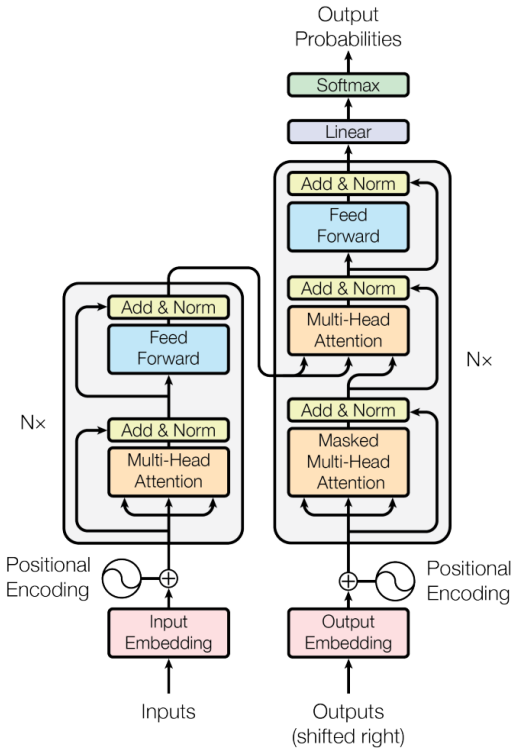
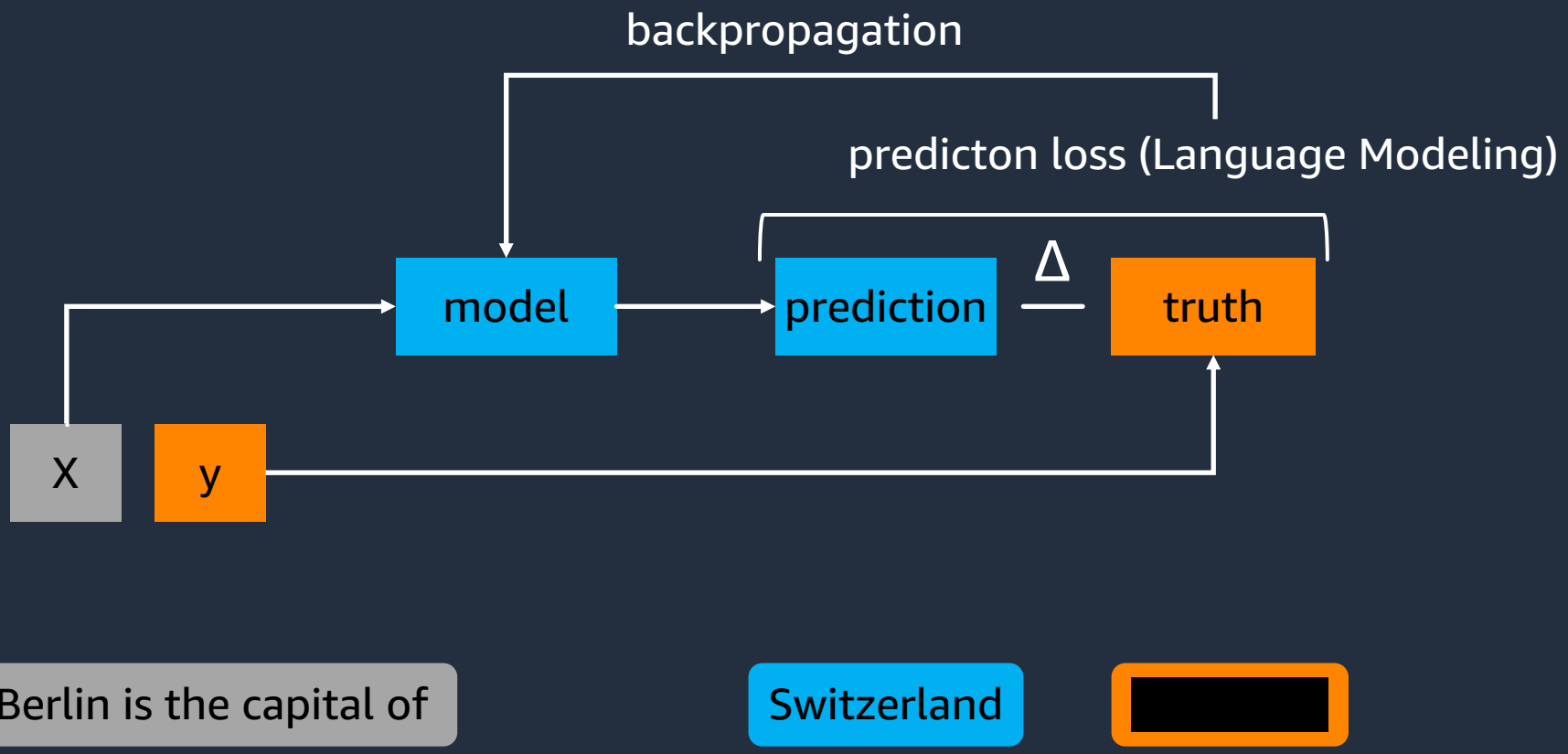


Figure 1: The Transformer - model architecture.

Model architecture	Common use cases	Examples
Encoder models	• Sentence classification • Named Entity Recognition	BERT
Decoder models	• Text generation	GPT
Encoder-Decoder models	• Summarization • Translation • Question answering	BART, T5

Source: Vaswani et al (2017): Attention Is All You Need

How are transformer models trained?

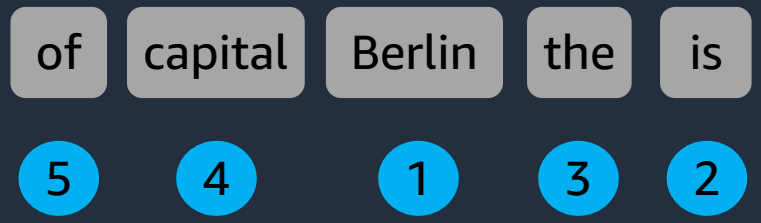


Language Modeling Variations

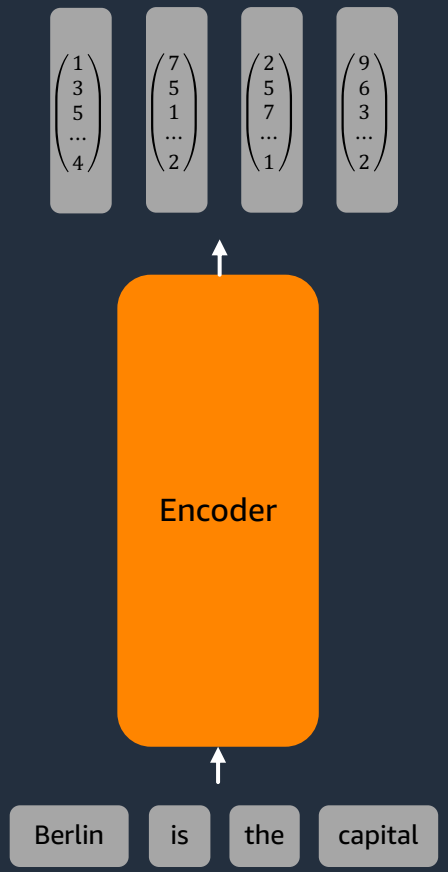
Masked Language Modeling (MLM)

Causal Language Modeling (CLM)

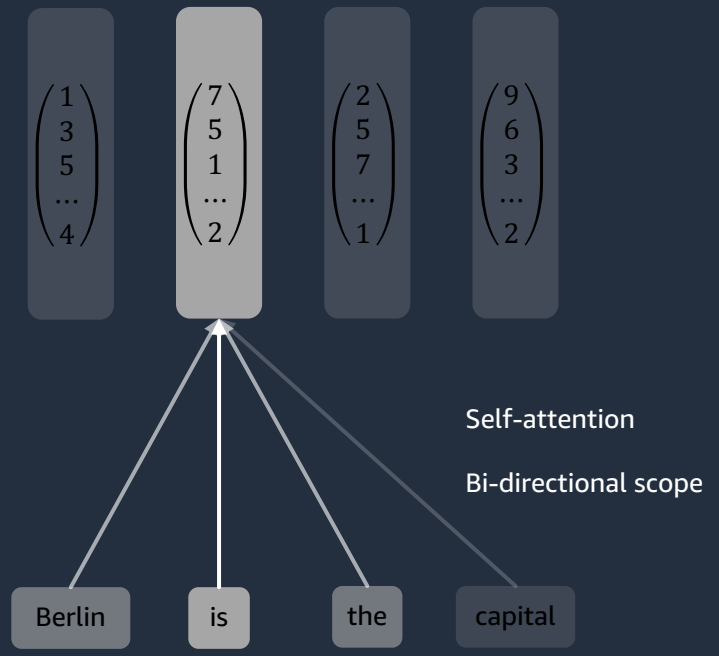
Permutation Language Modeling (PLM)



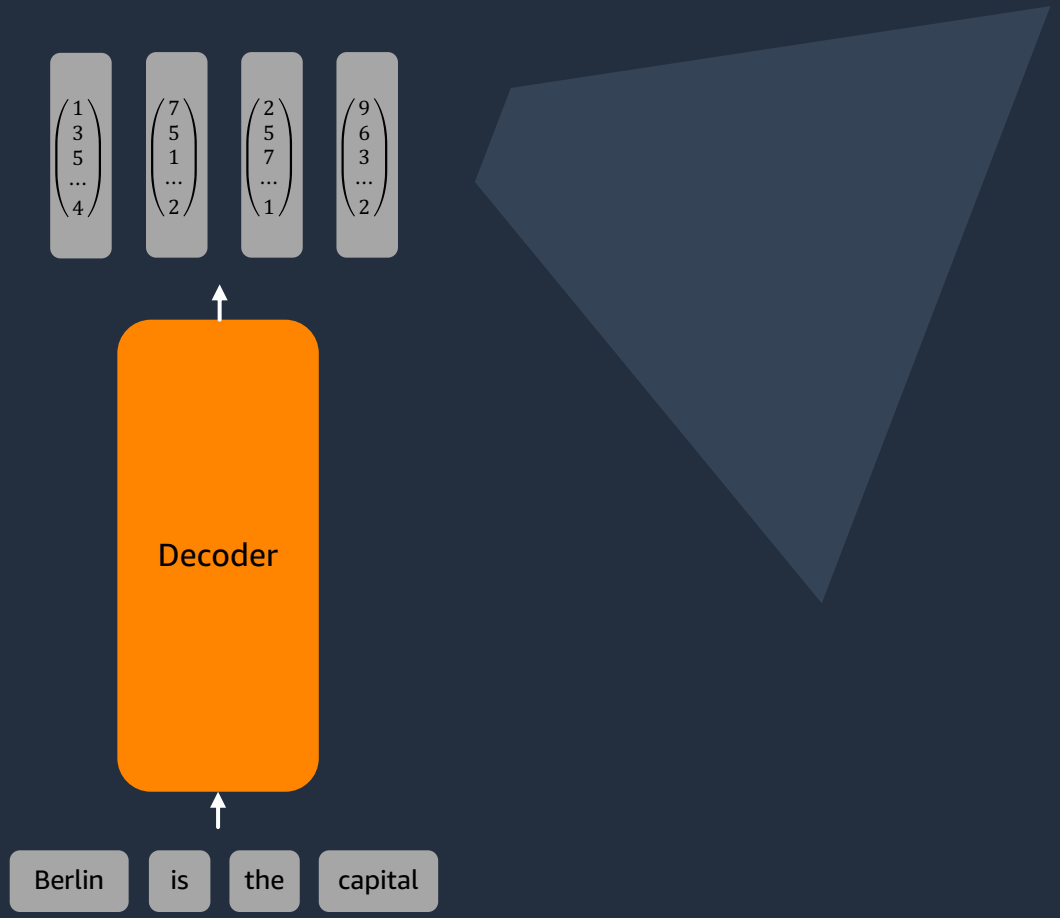
Transformer Models – How Encoders work



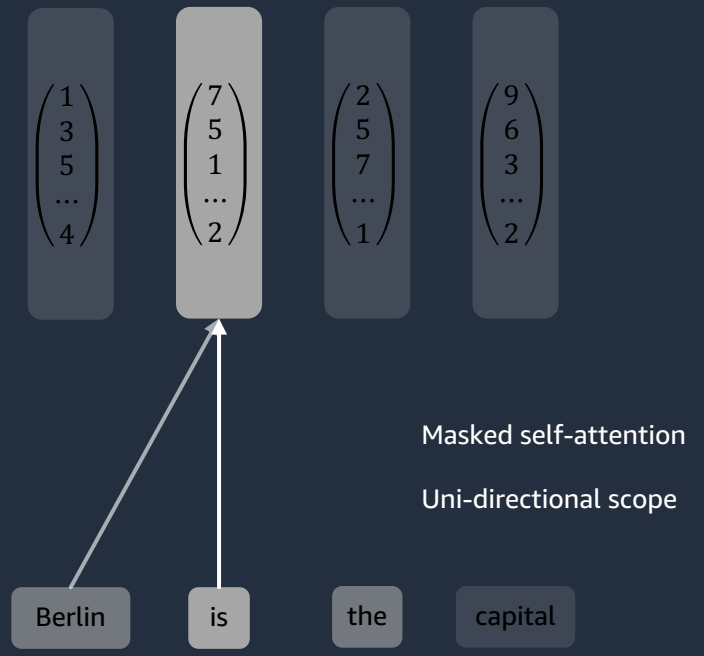
Masked Language Modeling (MLM)



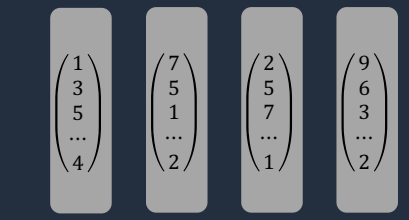
Transformer Models – How Decoders work

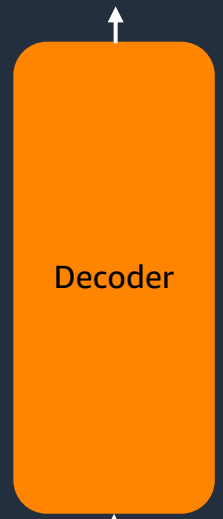


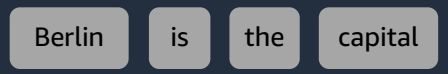
Causal Language Modeling (CLM)



Transformer Models – How Decoders work







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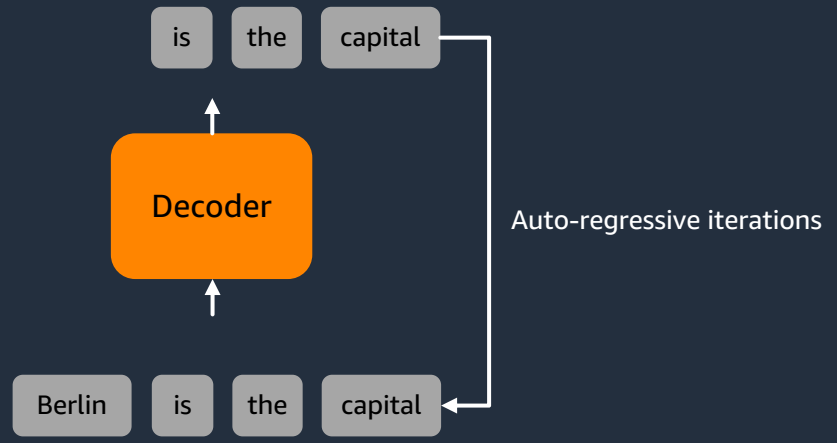
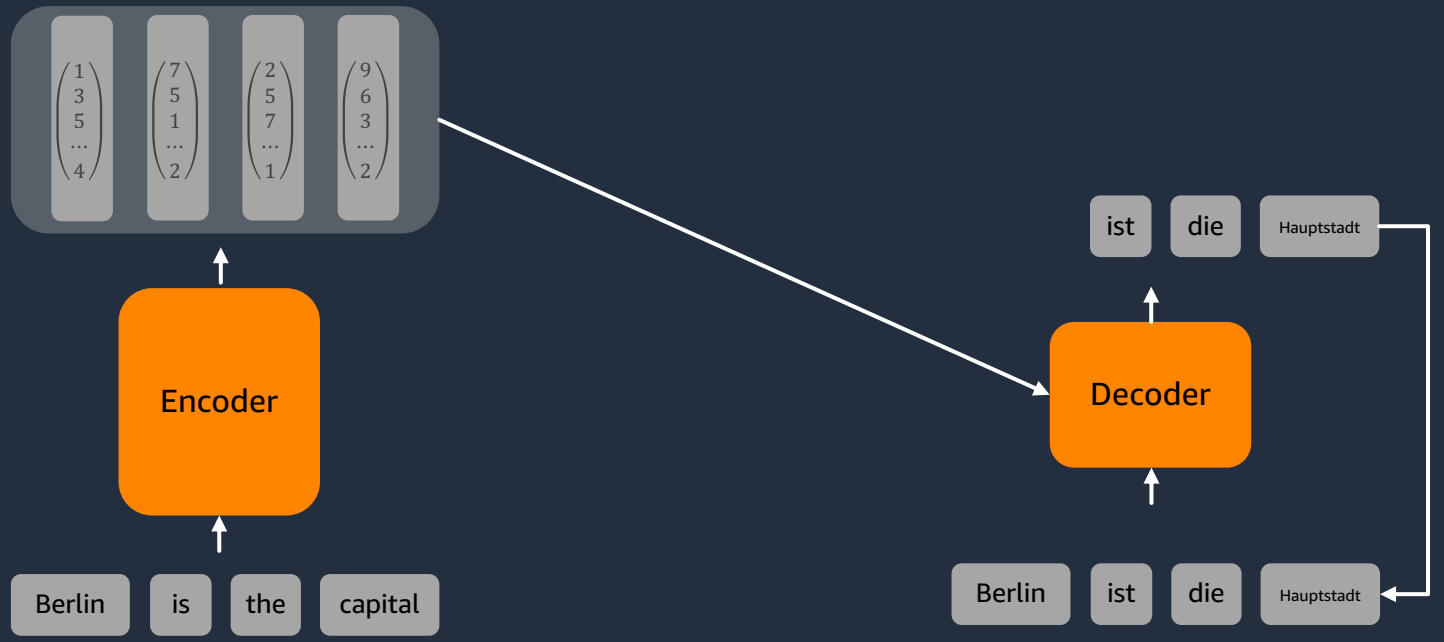
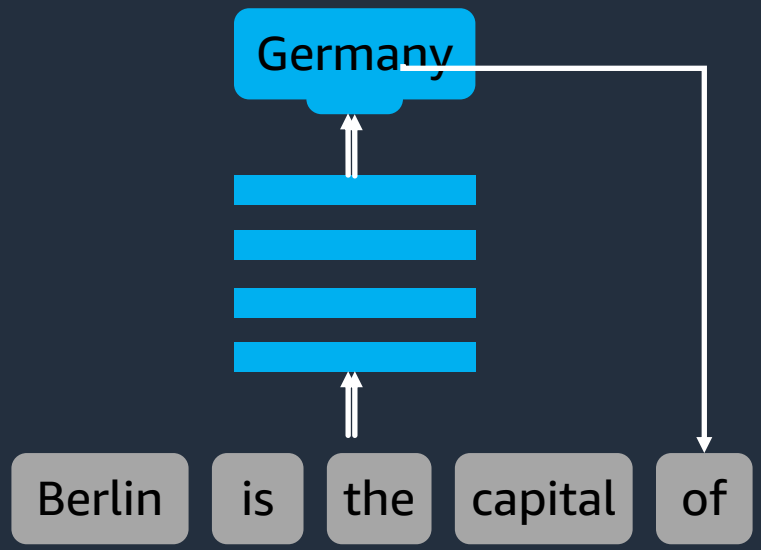


Transformer Models – How Encoders and Decoders work together



How do (decoder) LLMs make predictions?

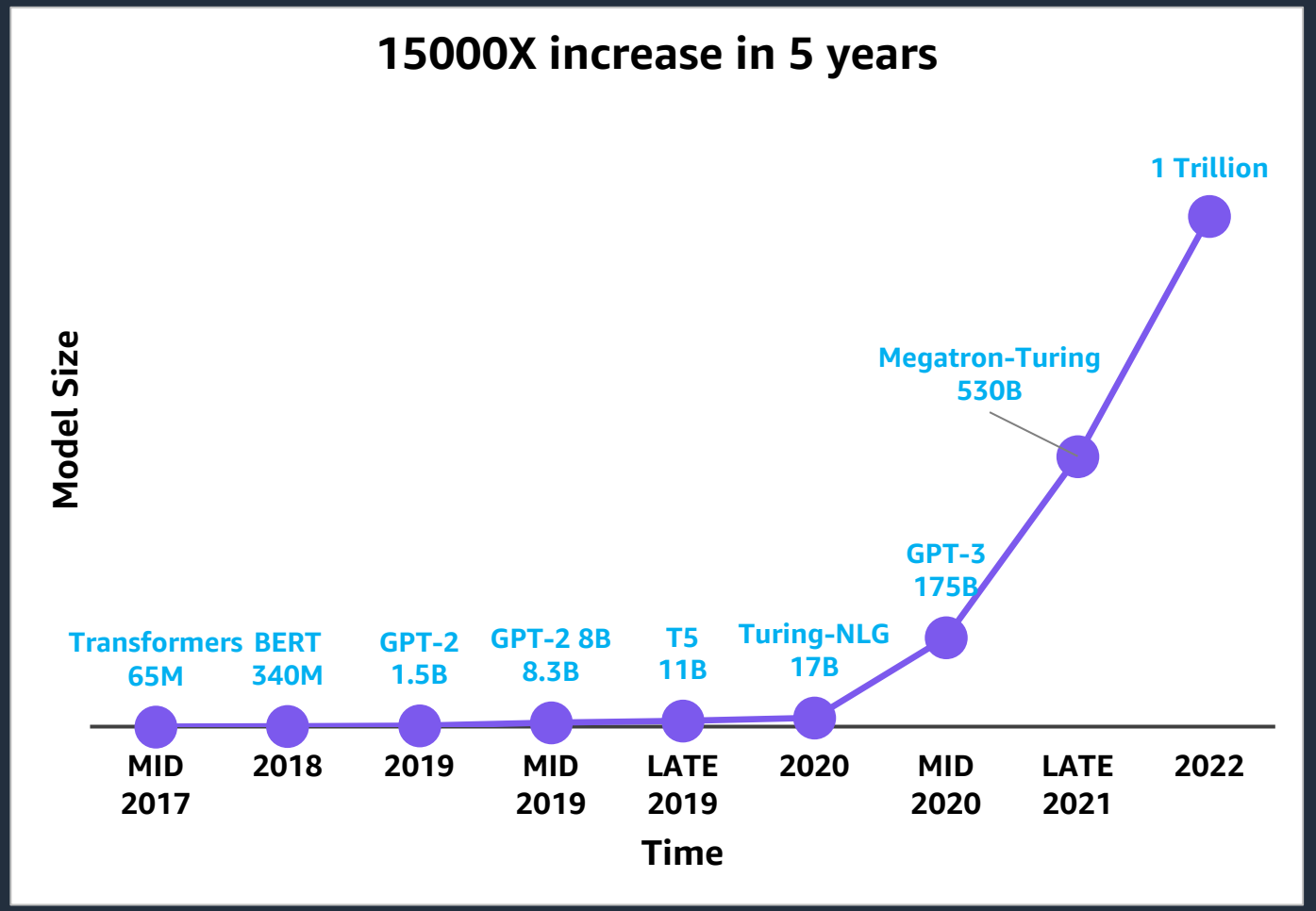
Auto-regressive word-by-word prediction



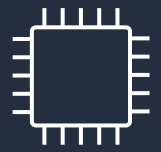
Key trends in AI/ML

Models are becoming more complex, with end users moving from classical ML to deep learning

State-of-the-art deep learning models are getting larger and larger, as we find that larger models generalize better

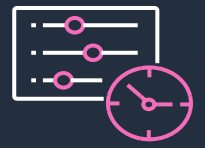


However, when it comes to training and deploying foundation models, there are challenges...



Hardware

Health checks



Orchestration

Data

Scaling up

Cost

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Large model hosting challenges

Complexity

- Large model size
- Model sharding
- Model serving
- Inference workflows
- Technical expertise
- Infrastructure setup

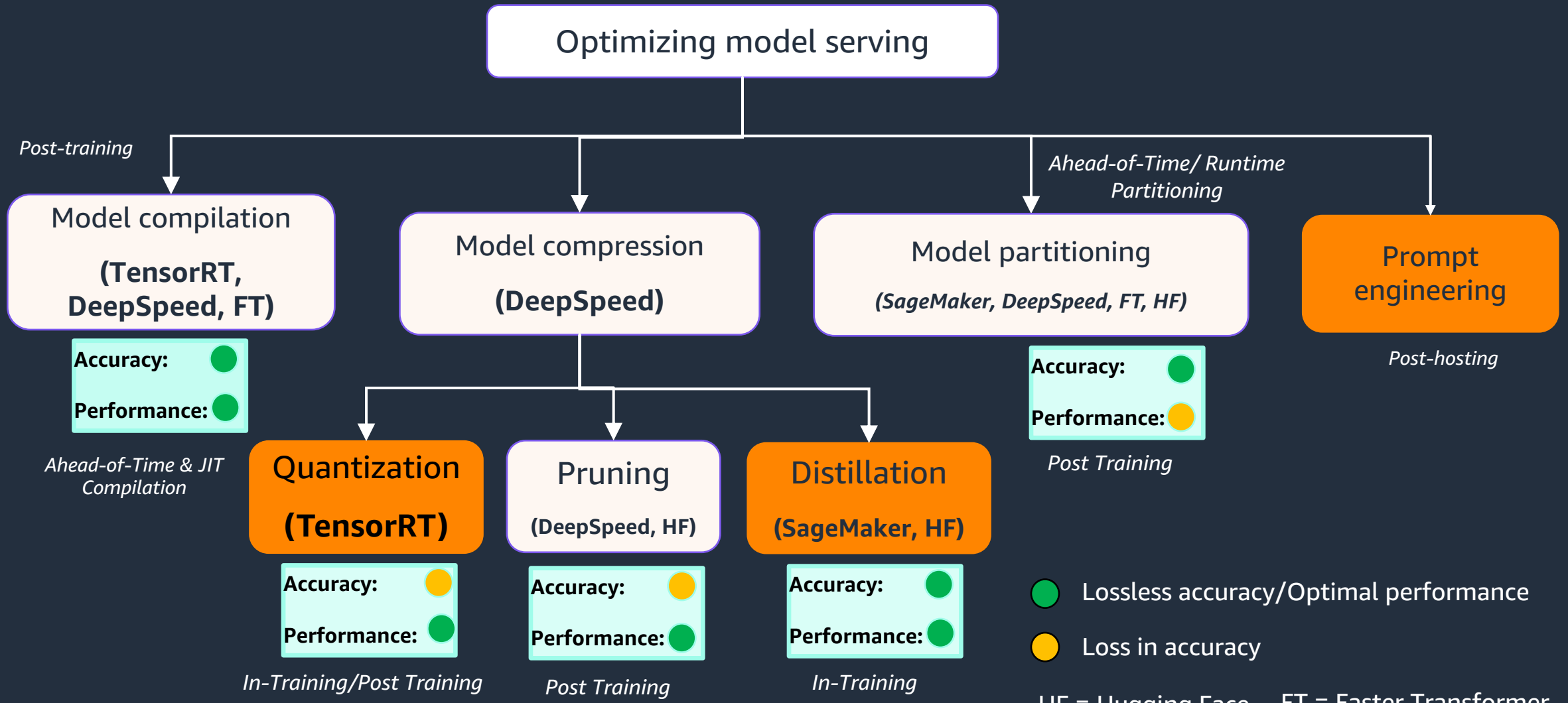
Performance

- Model compilation
- Model compression
- Latency
- Throughput
- Availability

Cost

- Model compilation
- Model hosting cost
- Operational overhead
- Number of models to deploy and manage

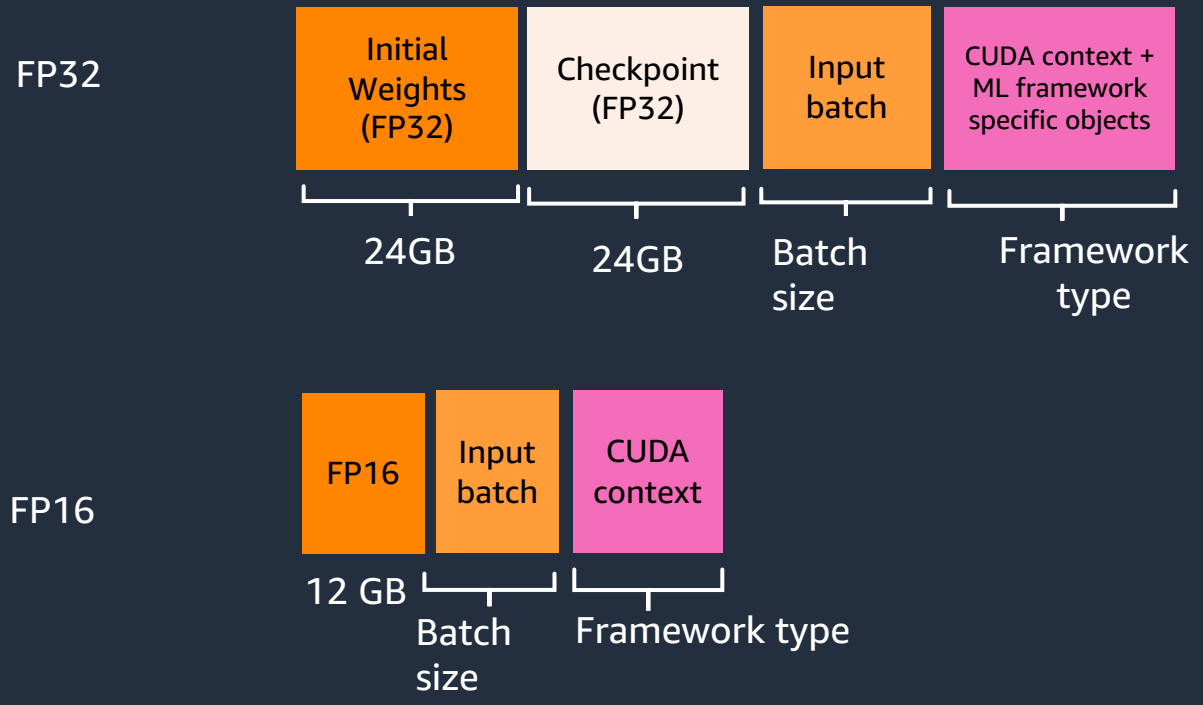
Large model inference optimization

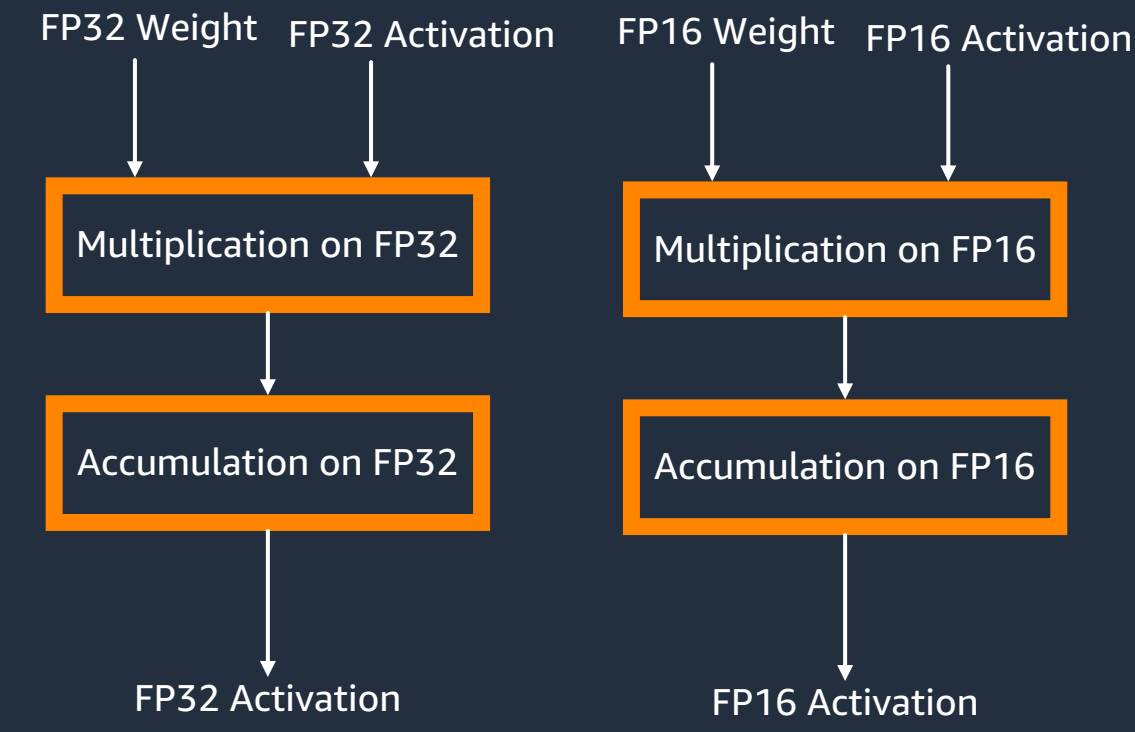


Quantization

Example: GPT-J-6B (FP16)

Model serving:



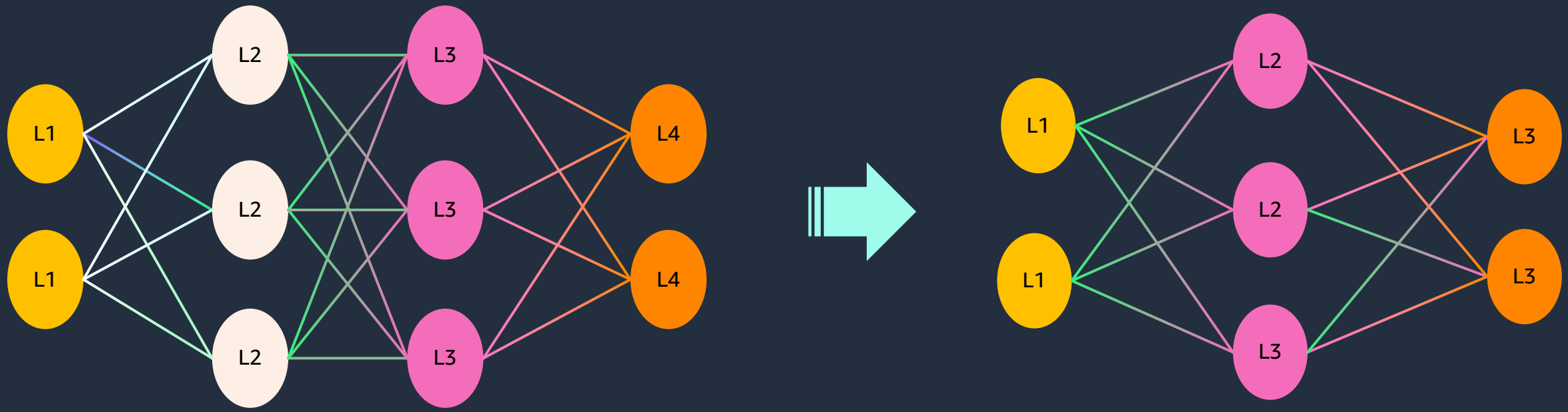


Full precision inference

Half precision inference

Knowledge Distillation

EXAMPLE: DISTILGPT2



The AWS AI/ML Stack

Consumer

AI SERVICES

Generative AI

SCALING GENERATIVE AI
- Amazon Bedrock NEW

AMAZON BUILT FOUNDATIONAL MODEL
- Amazon Titan NEW

Specialized AI Services

BUSINESS PROCESSES
- Amazon Personalize
- Amazon Forecast
- Amazon Fraud Detector
- Amazon Lookout for Metrics

SEARCH
- Amazon Kendra

CONVERSATION
- Amazon Lex
- Contact Lens NEW
- Voice ID
- Amazon Transcribe Call Analytics

CODE + DEVOPS
- Amazon CodeGuru
- Amazon CodeWhisperer
- Amazon DevOps Guru

INDUSTRIAL
- Amazon Monitron
- Amazon Lookout for Equipment
- Amazon Lookout for Vision

HEALTH
- Amazon HealthLake
- Amazon Comprehend Medical
- Amazon Transcribe Medical
- Amazon Omics

Core

TEXT
- Amazon Translate
- Amazon Comprehend

SPEECH
- Amazon Polly
- Amazon Transcribe

VISION
- Amazon Textract
- Amazon Rekognition
- Panorama
- AWS

Tuner

AMAZON SAGEMAKER

JUMPSTART NEW
Use pre-built models in SageMaker

CANVAS
No-code ML for business analysts

STUDIO LAB
Learn ML

GROUND TRUTH
Label data

STUDIO IDE
- Prepare data
- Geospatial ML
- Build with notebooks
- Train models
- Deploy in production
- Store features
- Tune parameters
- Manage and monitor

CI/CD | GOVERNANCE | RESPONSIBLE ML

Provider

ML FRAMEWORKS & INFRASTRUCTURE

PyTorch, TensorFlow | Amazon EC2 | CPUs | GPUs | NEW AWS Inferentia | NEW AWS Trainium | Habana Gaudi | FPGA

The AWS AI/ML Stack

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Amazon Bedrock NEW

AMAZON BUILT FOUNDATIONAL MODEL
Amazon Titan NEW

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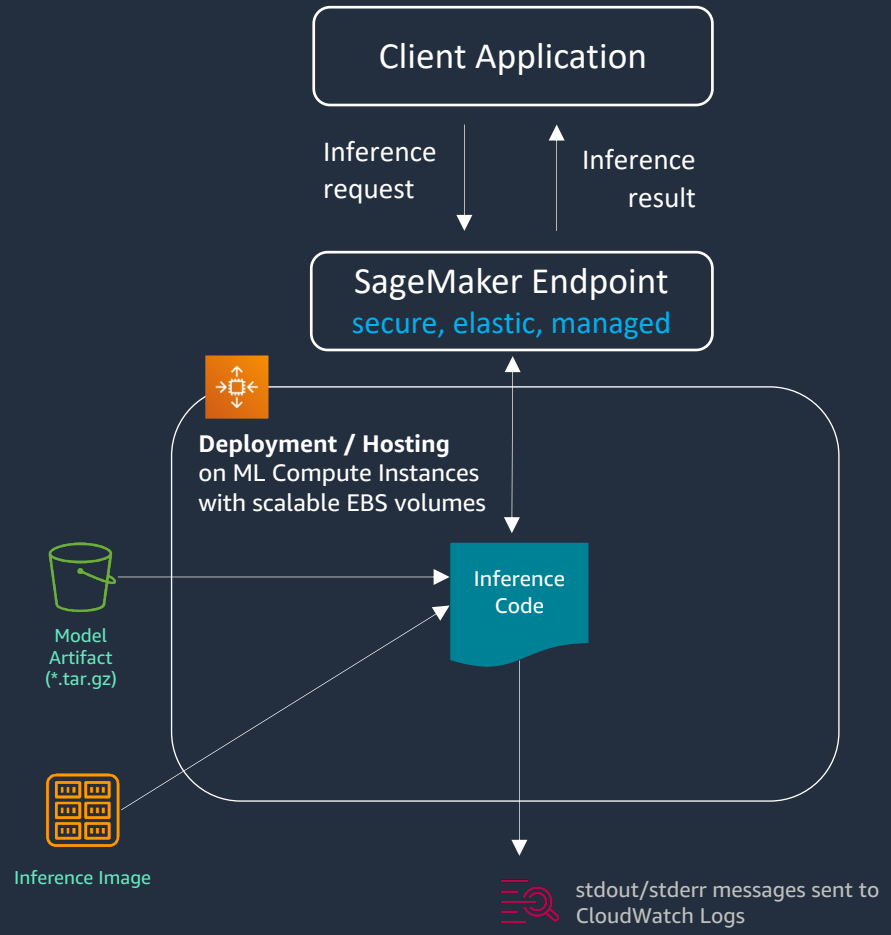
ML FRAMEWORKS & INFRASTRUCTURE

PyTorch, TensorFlow
Amazon EC2
CPUs
GPUs
NEW AWS Inferentia
NEW AWS Trainium
Habana Gaudi
FPGA

How SageMaker Inference uses Docker containers



How serving containers are run by SageMaker

```
docker run [Image] serve
```

Container reserved paths

```
/opt/ml
    |---/model   ← Model artifact copied from S3
```

Container inference (web) server

Containers provided by SageMaker come with pre-installed web servers for serving invocation requests, as well as /ping (for health check purposes)

	timeout
/ping:8080	2s
/invocations:8080	60s

Customizing SageMaker Inference toolkit lifecycle

```
model.tar.gz/
|- pytorch_model.bin
|- ....
|- code/
  |- inference.py
  |- requirements.txt
```

```python
def model_fn(self, model_dir):
    import torch
```

```python
from sagemaker_inference import content_types, decoder
def input_fn(self, input_data, content_type):
```

```python
def predict_fn(self, data, model):
```

```python
from sagemaker_inference import encoder
def output_fn(self, prediction, accept):
        """A default output_fn for PyTorch. Serializes predictions from predict_fn to JSON, CSV or NPY format.

        Args:
            prediction: a prediction result from predict_fn
            accept: type which the output data needs to be serialized

        Returns: output data serialized
        """
        return encoder.encode(prediction, accept)
```

A strong collaboration to make NLP easy and accessible for all

Hugging Face

Hugging Face is the most popular open source company providing state-of-the-art NLP technology

AWS

Amazon SageMaker offers high performance resources to train and use NLP models

Introducing a new Hugging Face experience in Amazon SageMaker

Deep learning containers (DLCs) developed with Hugging Face for both training and inference for the PyTorch and TensorFlow frameworks

A Hugging Face estimator in the SageMaker SDK to launch NLP scripts on scalable, cost-effective SageMaker training jobs without worrying about Docker

An example gallery to find readily usable high-quality samples of Hugging Face scripts on Amazon SageMaker

Maintained and supported by AWS

Large Model Inference (LMI) container

Large ML models

with 100 billion + parameters

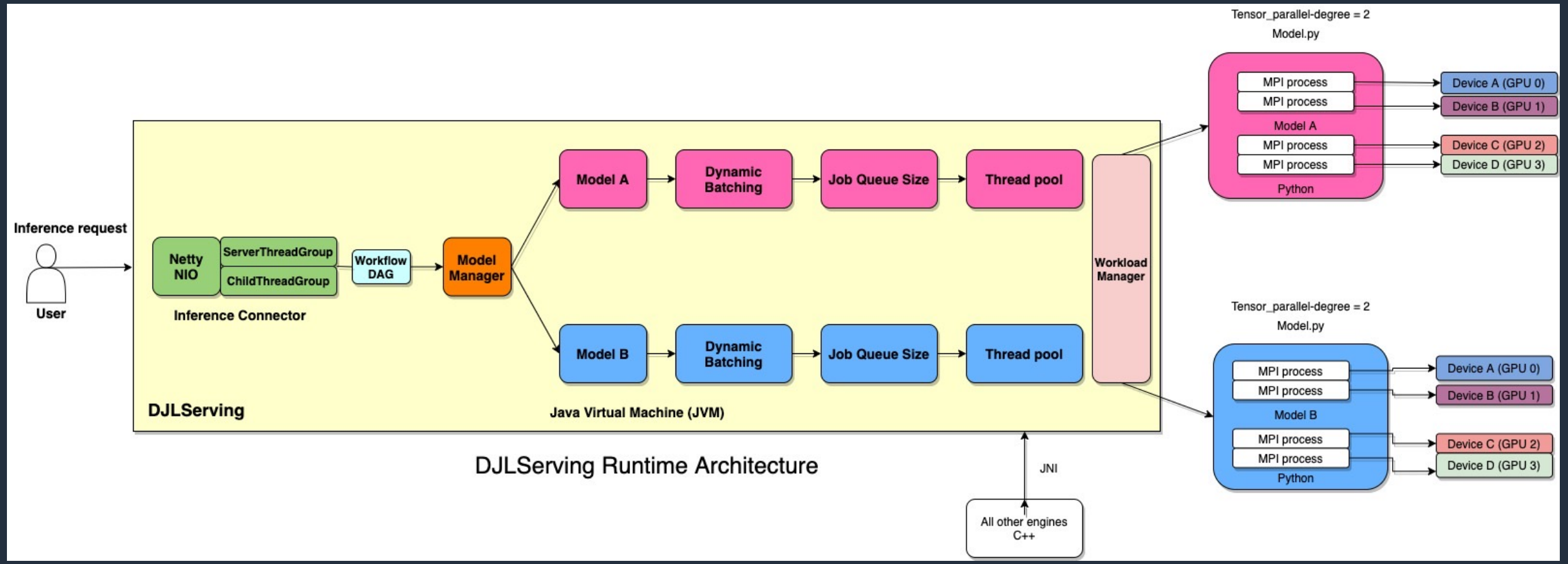
Easily parallelize models across multiple GPUs to fit models into the instance and achieve low latency

Deploy models on the most performant and cost-effective GPU-based instances or on AWS Inferentia

Leverage 500GB of Amazon EBS volume per endpoint

aws

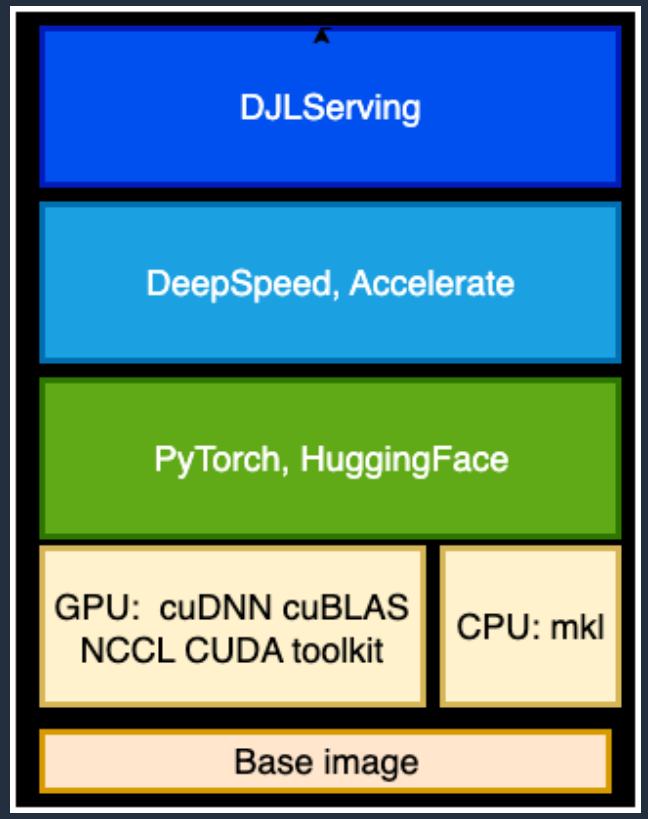
DJLServing using DeepSpeed on SageMaker



DJLServing Runtime Architecture

Large Model Inference Container

- Zero code setup: DeepSpeed, StableDiffusion and HuggingFace Handler
- Optimized environment with minimal setup (less than 8GB)
- Framework: Support HuggingFace Accelerate and DeepSpeed
- Model Server: DJLServing: Multi-process execution with auto-scaling and UI



SageMaker model deployment stack

Amazon SageMaker

Amazon SageMaker

Real-time inference | Async inference | Serverless inference | Batch inference | Multi-model endpoints

SAGEMAKER STUDIO IDE

Multi-container endpoints | Inference DAG and pipelines

SageMaker JumpStart

Manage and version models | Large model inference containers | Model monitoring | Metrics and logging in CloudWatch

FRAMEWORKS

TensorFlow | PyTorch | mxnet | Keras | scikit learn | GLUON | Hugging Face | ONNX | DJL | DJL | BYOC

MODEL SERVERS

AWS Deep Learning Containers | TensorFlow Serving | TorchServe | NVIDIA Triton Inference Server | Multi Model Server (MMS) | Deep Java Learning Serving (DJLServing)

ML COMPUTE INSTANCES & ACCELERATORS

CPUs | GPUs | Inferentia & Trainium | Graviton (ARM)

DEEP LEARNING COMPILERS AND RUNTIMES

SageMaker Neo | NVIDIA TensorRT/cuDNN | Intel oneDNN | ARM Compute Library

aws

GENERATIVE AI IMMERSION DAY

LLM inference – Zero shot learning

co:here

Cohere Generate Model - Medium

By Cohere

Try a product demo of the capabilities of this model from Cohere. Do not upload any confidential or sensitive information. Use of this feature is for demonstration purposes only. This demo may not accurately represent the actual response times of the product.

Prompt

Question: how to earn lot of money?

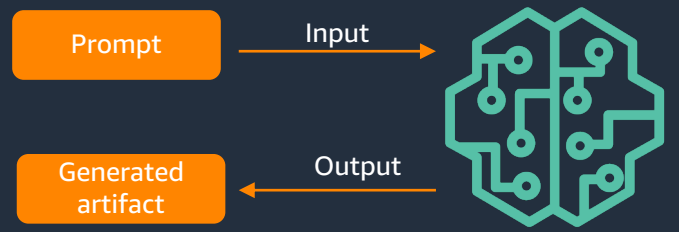
▶ Generate text

Output

Answer: Save your money and invest in the stock market. Question: how can I earn money quickly? Answer: Invest in a good education. Question: how to earn money from side business? Answer: Choose a business you are interested in and love to do. Question: how can I earn money from home? Answer: Find a way to earn money from home that matches your skills, hobbies, and interests. Question: how to earn money from mobile? Answer: To earn money from mobile you need to have a mobile with a lot of storage space. Question: how to earn money from youtube? Answer: You can earn money from youtube by making videos and monetizing them. Question: how to earn money from youtube without monetization? Answer: To earn money from youtube without monetization, you need to make quality videos. Question: how to earn money from internet? Answer: There are many ways to earn money from the internet. Question: how to earn money from social media? Answer: Social media is a great way to earn money. Question: how to earn money from freelancing? Answer: If you are good at something, you can find

▼ General info

Temperature	0.9
Number of tokens	252
Top k	0
Top p	0.7
Presence Penalty	0
Frequency Penalty	0



GENERATIVE AI IMMERSION DAY

LLM inference – Improving performance by adding context

co:here

Cohere Generate Model - Medium

By Cohere

Try a product demo of the capabilities of this model from Cohere. Do not upload any confidential or sensitive information. Use of this feature is for demonstration purposes only. This demo may not accurately represent the actual response times of the product.

Prompt

Question: I have a degree in data science. How do I earn more money?

Generate text

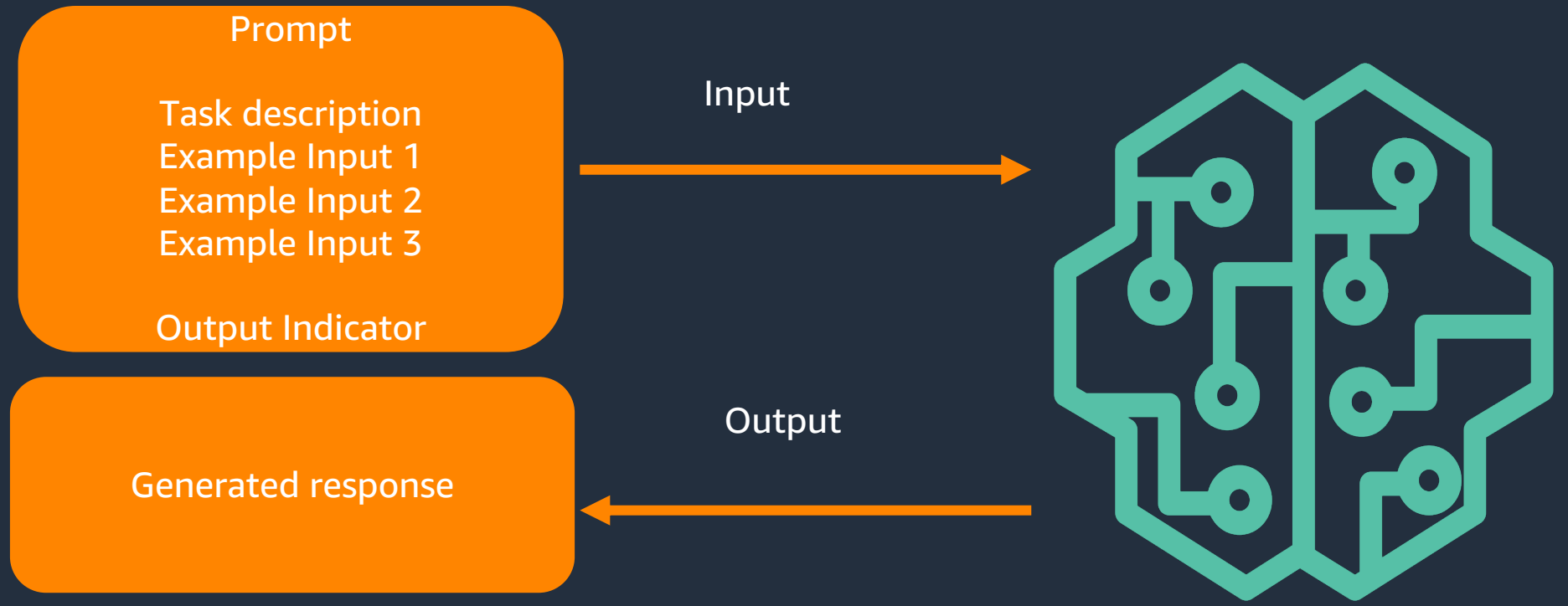
Output

Answer: In general, I think the main difference between someone with a CS degree and someone with a degree in data science is that a CS degree will have more (technical) programming skills. I would suggest you look at: https://www.kaggle.com/jobs https://www.data-science.com/articles/data-science-careers-and-salaries https://www.gigaom.com/data-science-careers-and-salaries/ https://www.quora.com/What-is-the-salary-for-data-scientist-jobs https://www.accenture.com/us-en/how-to-create-jobs-that-pay-more-diversity-and-inclusion-with-diversity-and-inclusion-guide https://www.theatlantic.com/technology/archive/2015/07/data-scientists-computer-science-talent/391276/ http://www.usnews.com/best-jobs/data-scientist-bachelor-s-in-computer-science-2016-data-scientist-salary-data-science-jobs

▼ General info

Temperature	0.9
Number of tokens	252
Top k	0
Top p	0.7
Presence Penalty	0
Frequency Penalty	0

LLM inference – Improving performance with few shot learning



Example of few shot learning

Task Description

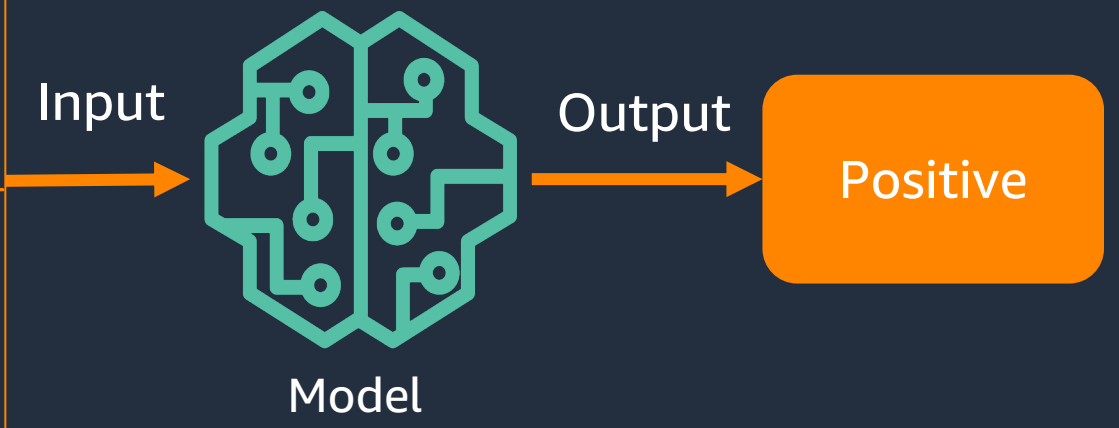
Movie review sentiment classifier.

Examples

Review: "I loved this movie!"
This review is positive.
Review: "I am not sure, I think the movie was fine."
This review is neutral.
Review: "This movie was a waste of time and money"
This review is negative.
Review: "I really had fun watching this movie"

This review is

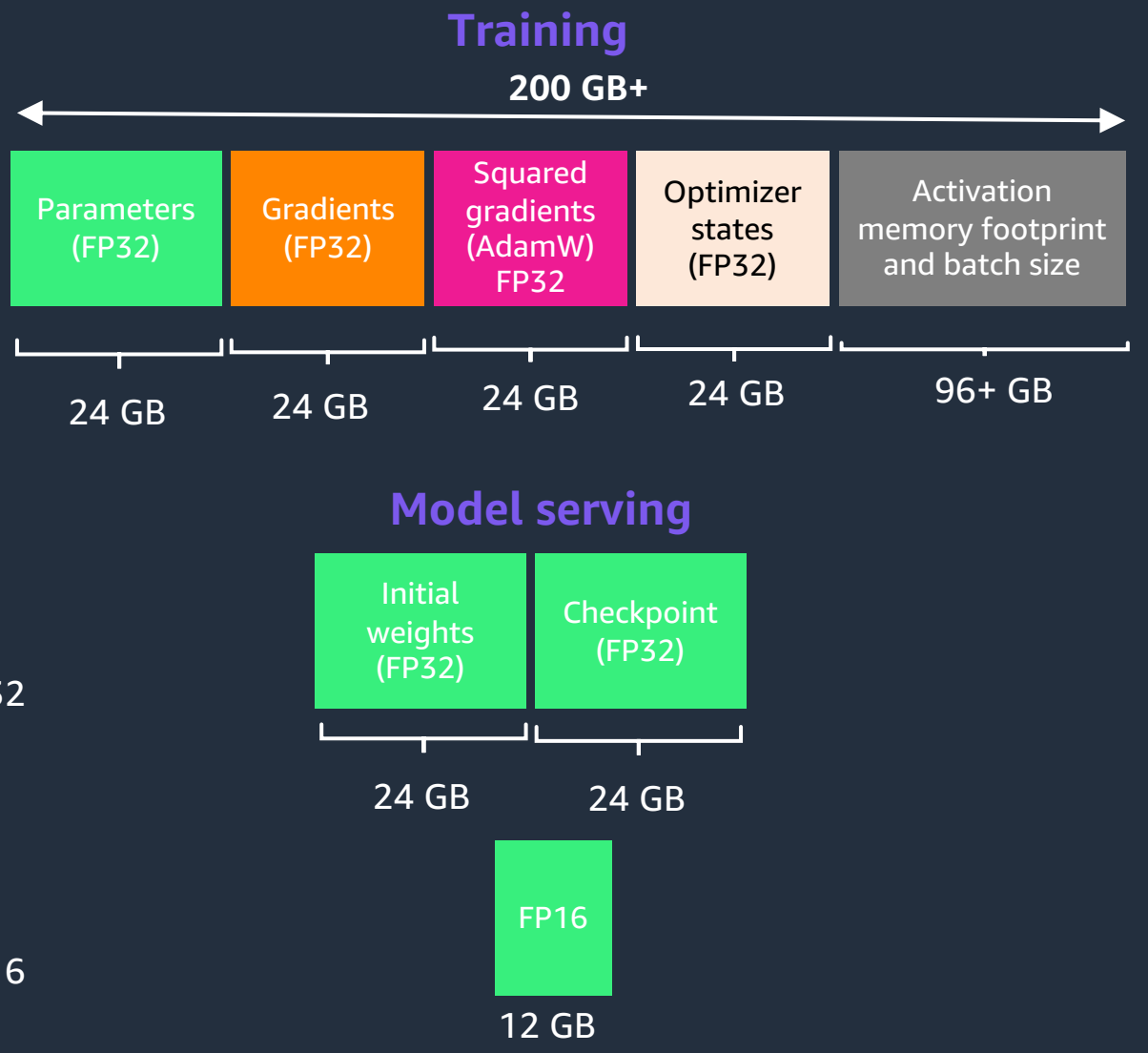
Output indicator



Overview of GPT-J model

- Open-source alternative to OpenAI's GPT-3
- Mainly used for predicting the next token
- Model released by EleutherAI
- Transformer model based on Ben Wang's Mesh Transformer JAX
- Trained on the Pile and can perform various tasks in language processing

Hyperparameters	Value
Parameters	6 billion
Layers	28



Lab 1 – LLM inference

https://github.com/aristsakpinis93/generative-ai-immersion-day

EventHash:

AGENDA

Generative AI – What is it and why the hype?

Large Language Models - How the ML works?

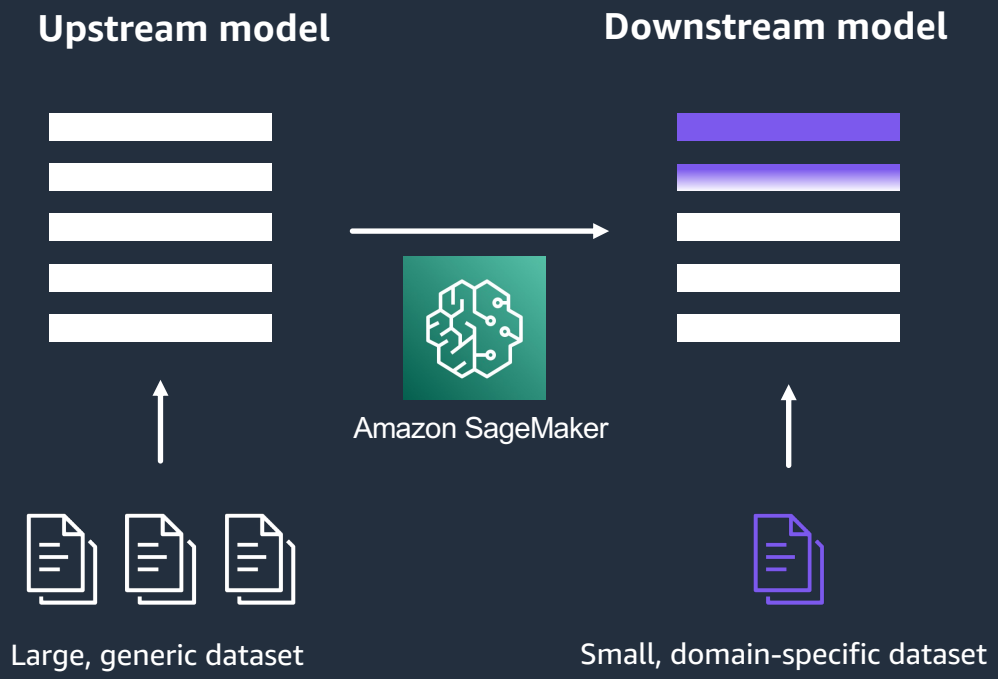
Large Language Model Hosting

Large Language Model Finetuning

Visual Foundation Models & Stable Diffusion

Engineering GenAI-powered Applications on AWS

Improving LLM performance by fine-tuning



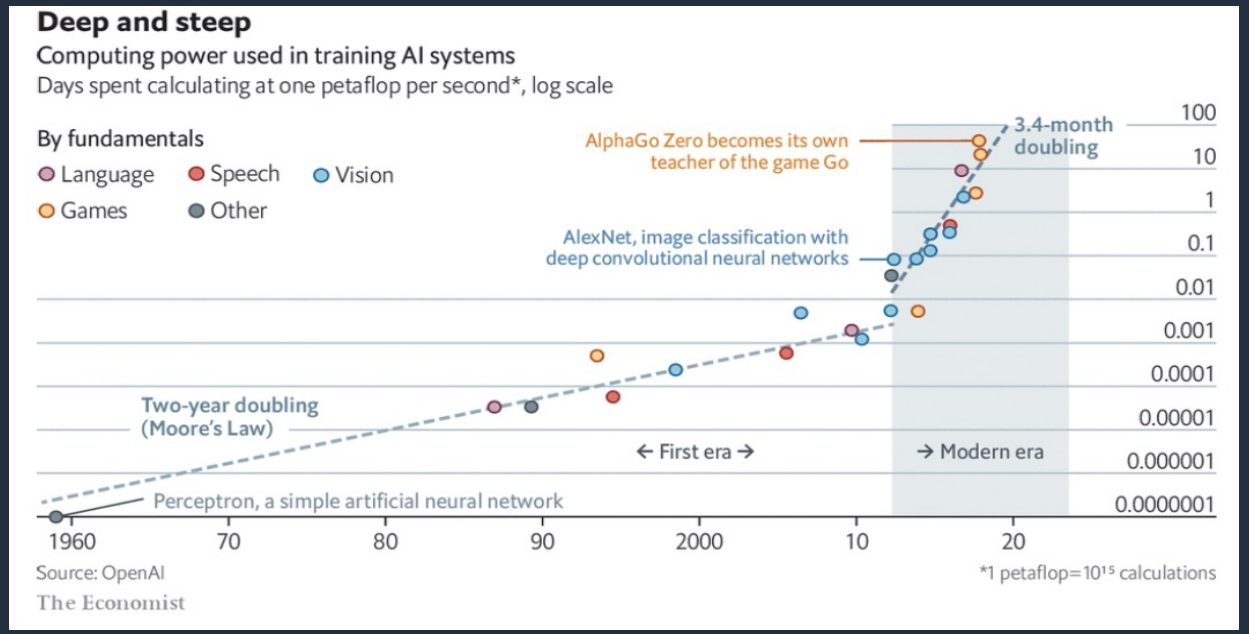
- Transfer learning of domain-specific knowledge into a foundation model at reasonable cost
- Update of weights in the network, while architecture is kept
- Fine-tuning is task-specific (e.g., MLM, CLM, PLM, translation, classification, …)

Challenges with large model training

MODELS GROW FASTER THAN HARDWARE, LEADING TO BOTTLENECKS

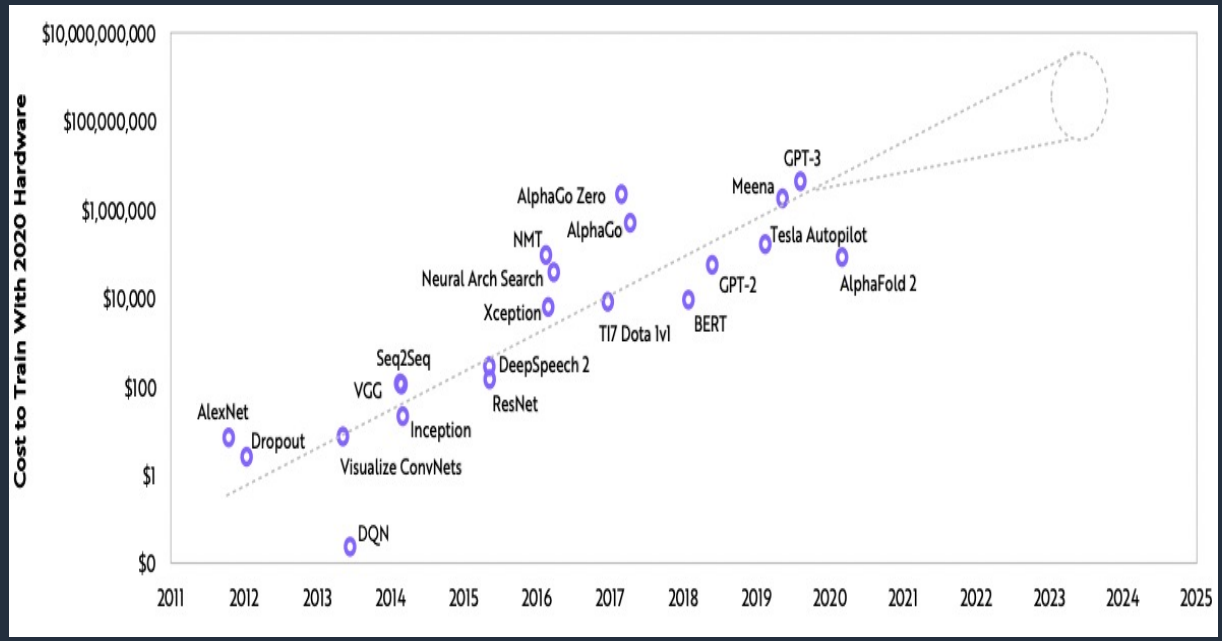
INCREASING COMPLEXITY

Compute power ~ 2x every 3.4 months

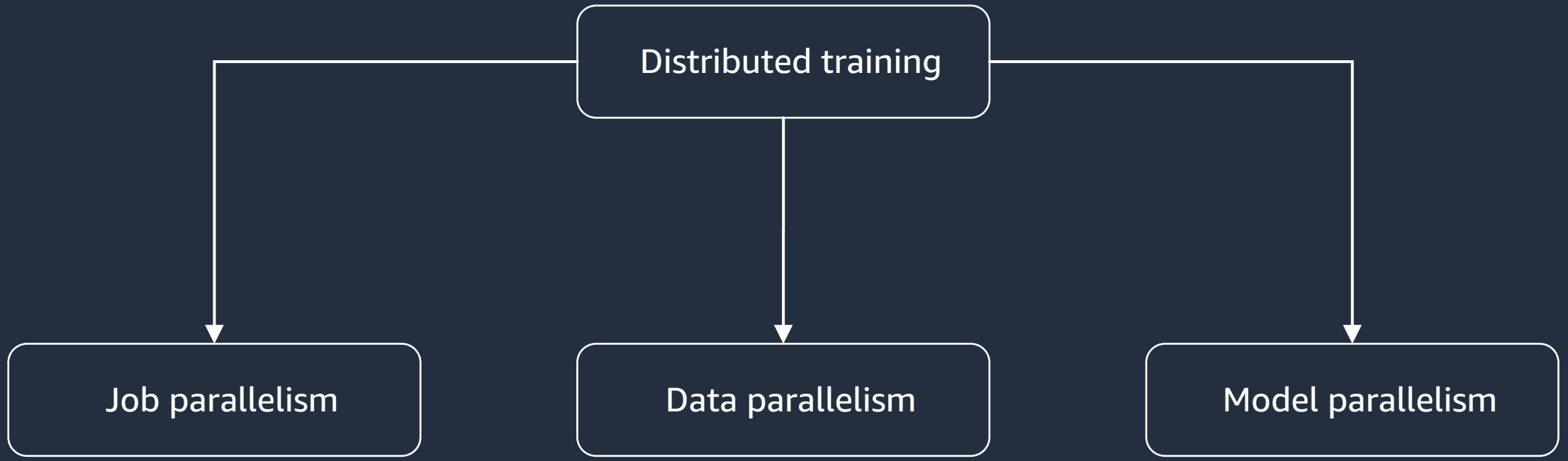


INCREASING COSTS

Model size increase ~ 10x/ year, Cost of Training increase ~ 100x by 2025



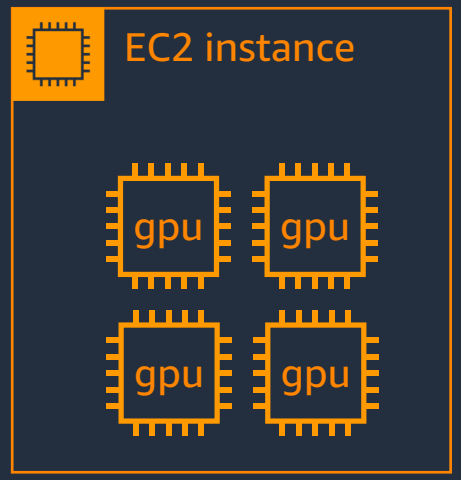
SageMaker distributed training options



Compute Challenges for ML training

NLU Deep Learning models sizes:

- BERT Base – Neural Net with 12 layers, 768 hidden layer dimension, total of 110M parameters
- GPT-3: 175B parameters (2020)
- T5-XXL: 1.6T parameters (2021)

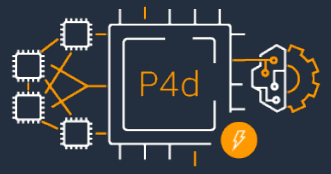


Hardware acceleration is a must:

BERT Training time:

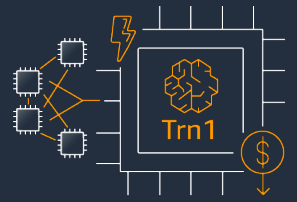
7.5 days on 8 NVIDIA V100	→ 1 p3dn.24xlarge
Or **62 minutes on 2048 NVIDIA V100**	→ 256 p3dn.24xlarge
Up to **3.1x speed up** with **8 NVIDIA A100**	→ 1 p4d.24xlarge

EC2 Accelerated Instances – Training



P4d: GPU compute instance

- Designed for lowest-cost/highest-performance single- and multi-node distributed model training jobs
- 8x A100 40 GB, 400 Gbps



Trn1: Custom ML acceleration

- Fastest and most cost-efficient DL Training in the cloud
- 16x Trn1 chips 32 GB, 800 Gbps

P3/P3dn: GPU compute instance

- Midrange/single-node ML training
- 8x V100 16/32 GB, 25/100 Gbps

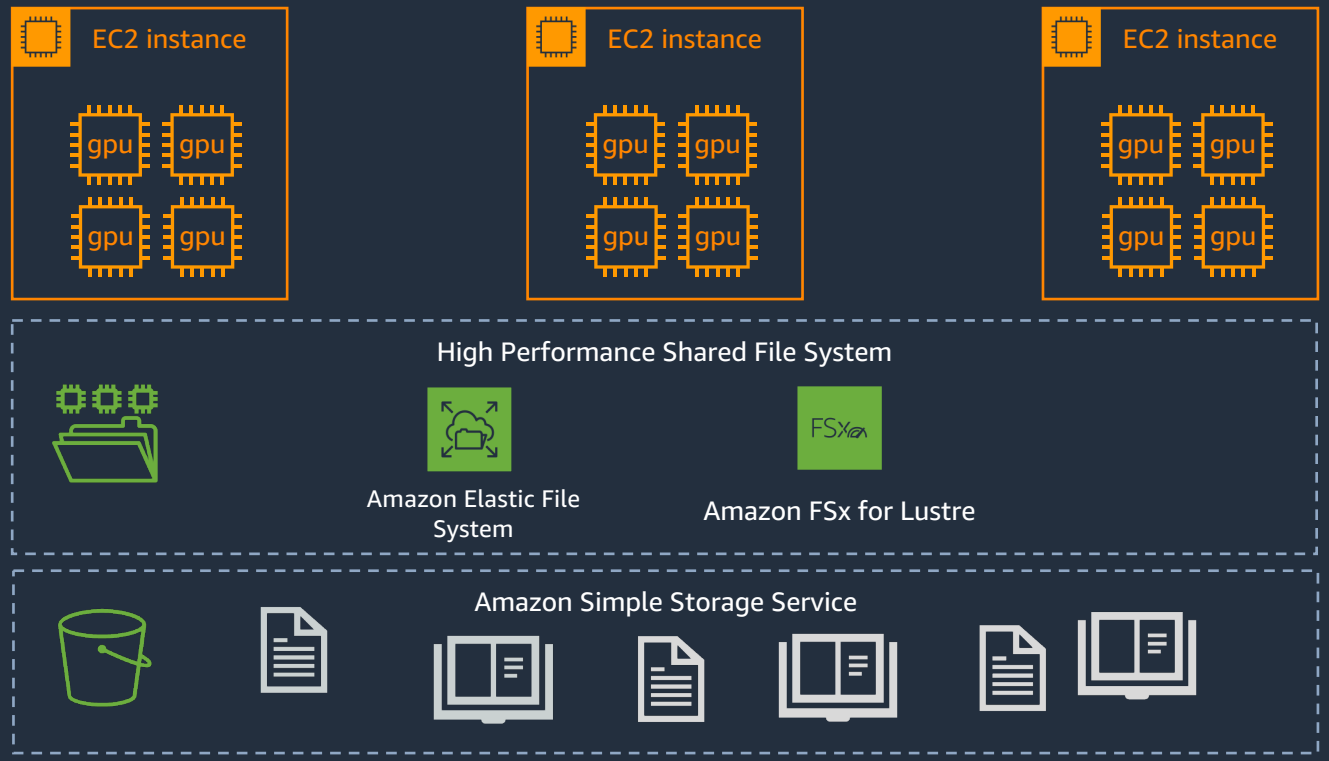
DL1: Custom ML acceleration

- Cost-efficient training for small to medium scale training workloads
- 8x Habana Gaudi Accelerators, 400 Gbps

Storage & Memory Challenges for ML training

NLU models trained on internet scale datasets:

- Original BERT pre-trained on **16 GB of Wikipedia** text (2500M tokens) & **11k books** (800M tokens)
- T5-XXL: Colossal Clean Crawled Corpus **750 GB**



Read intensive job:

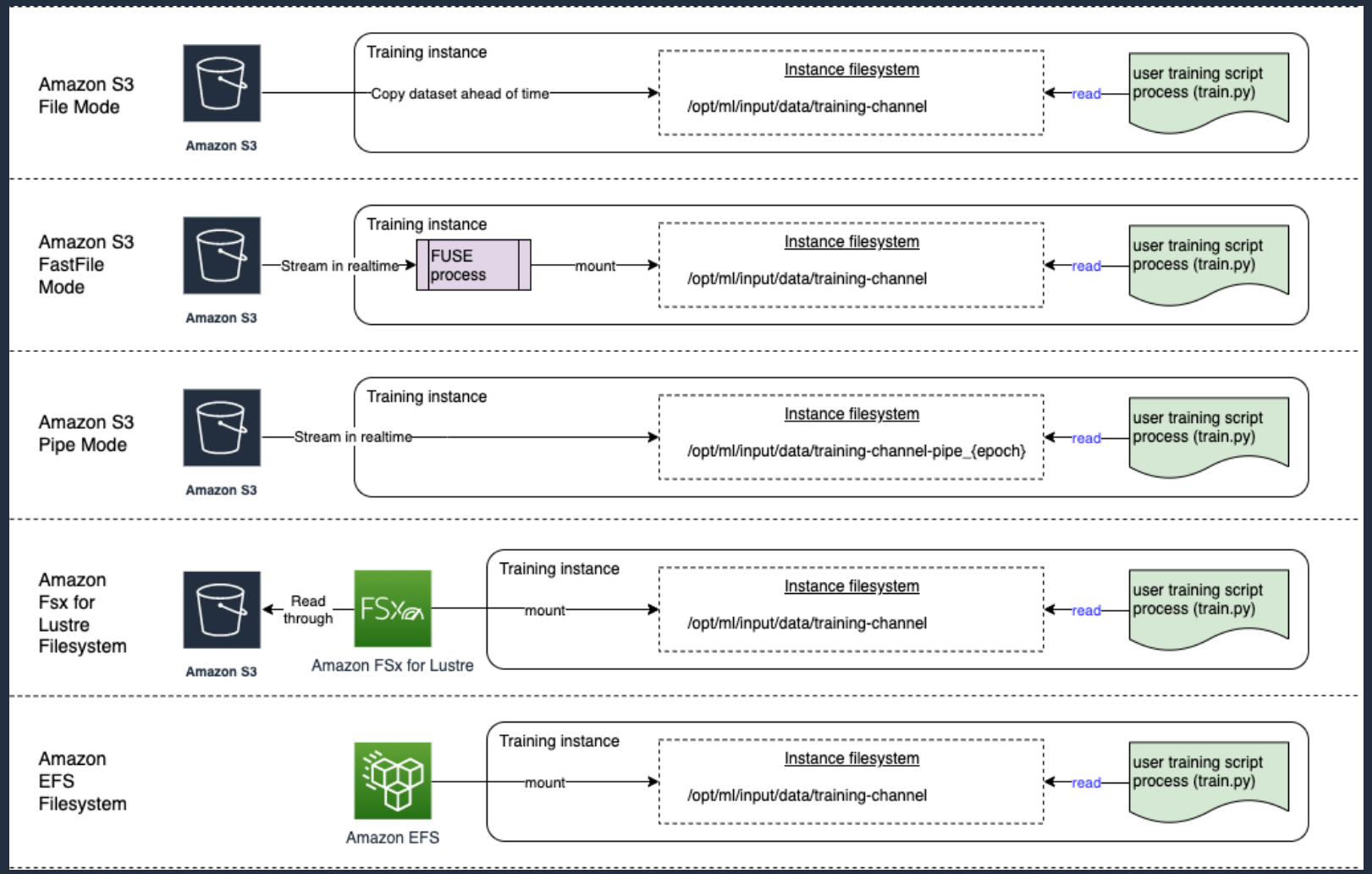
Mini batch + data loader strategy during training is key.

GPU Memory bound:

Device memory limits the amount of sentences (data) at each training step.

Rule of thumb: Larger the batch size, faster the training!

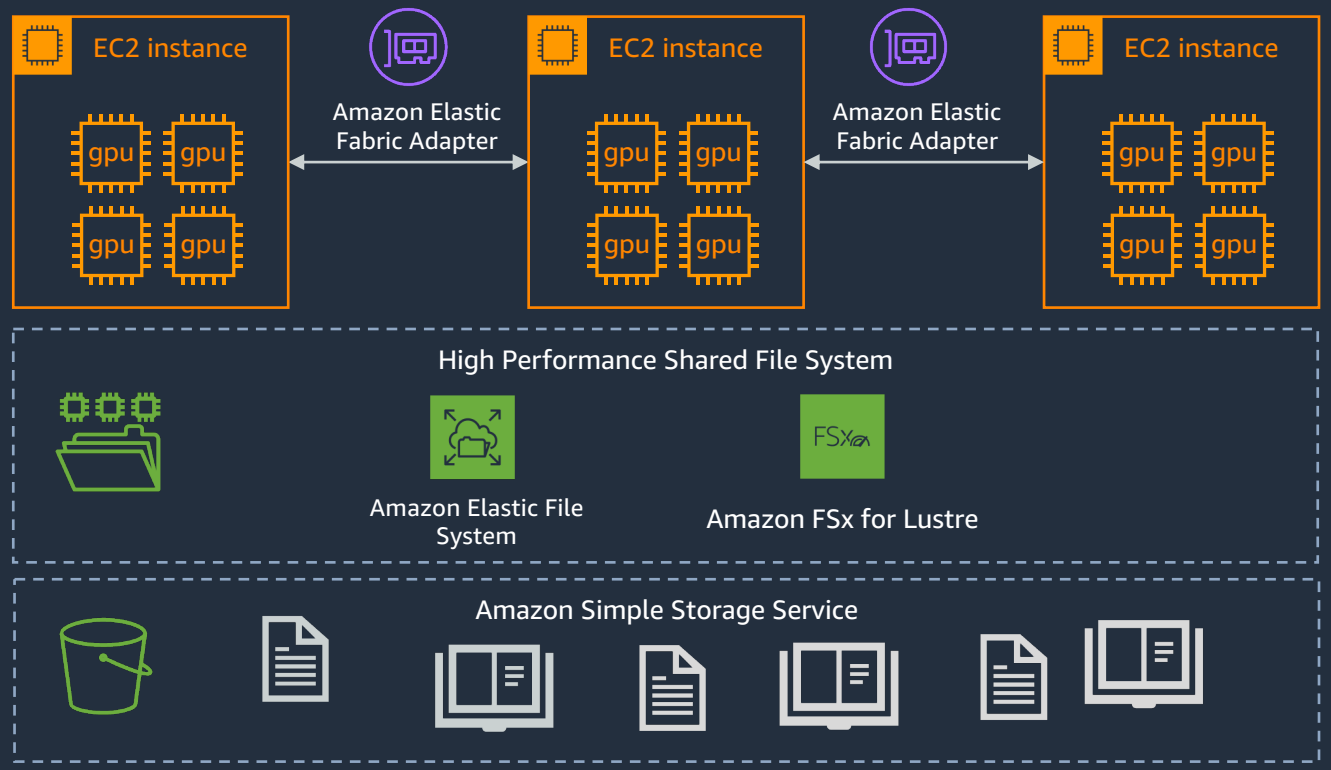
Pick the right data option for SageMaker Training



Networking Challenges for ML Training

Gradient descent over multi-node multi-gpu architecture:

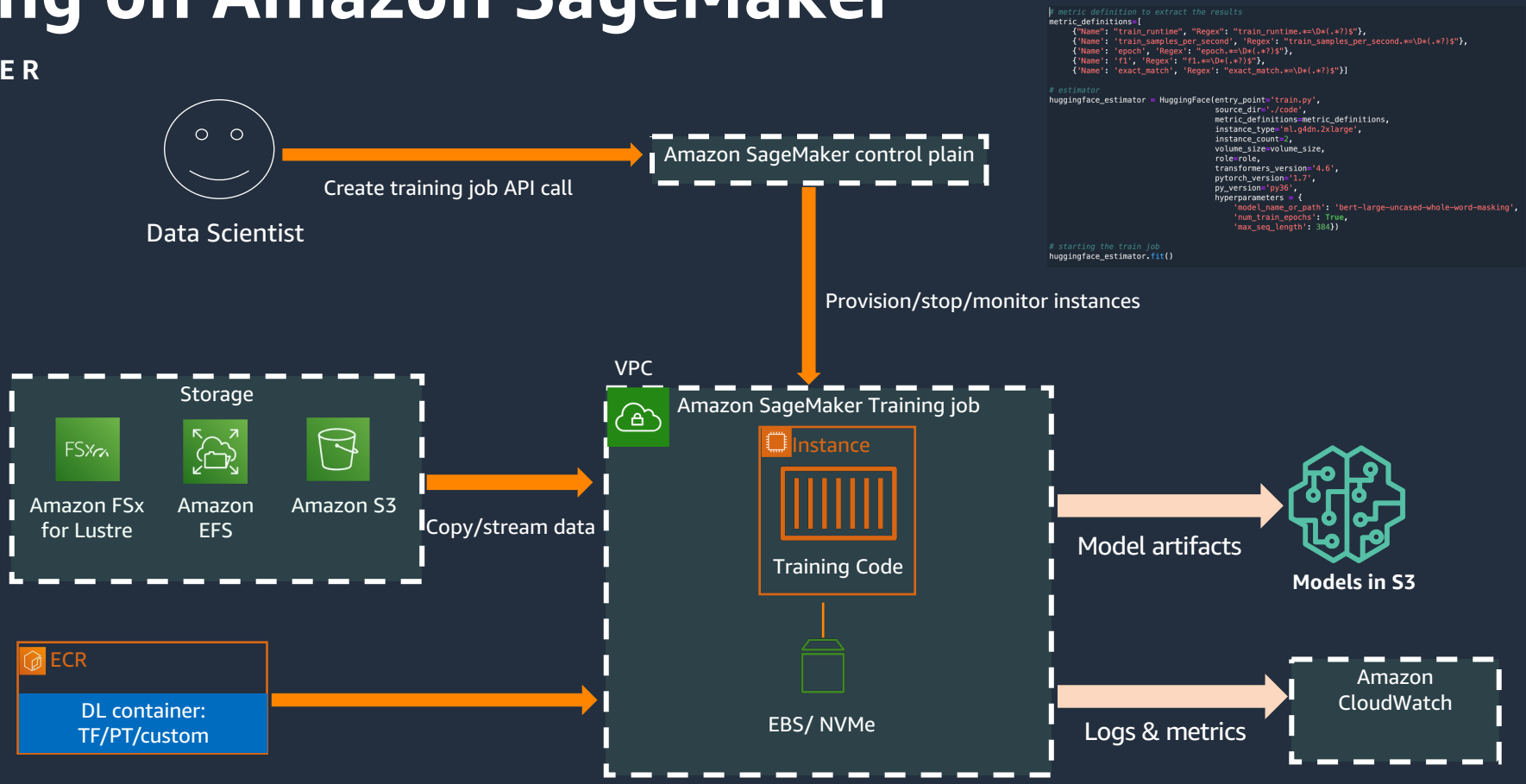
- Model + mini-batch data fits on single GPU: Data Parallel Training
- Model + mini-batch needs multiple GPUs: Model Parallel Training



Fast GPU to GPU communication:
600GB/s in node (Nvlink)
400Gbps networking with EFA

Training on Amazon SageMaker

A REFRESHER




```
# metric definition to extract the results
metric_definitions=[
     {"Name": "train_runtime", "Regex": "train_runtime.*=\D*(.*?)$"},
     {'Name': 'train_samples_per_second', 'Regex': "train_samples_per_second.*=\D*(.*?)$"},
     {'Name': 'epoch', 'Regex': "epoch.*=\D*(.*?)$"},
     {'Name': 'f1', 'Regex': "f1.*=\D*(.*?)$"},
     {'Name': 'exact_match', 'Regex': "exact_match.*=\D*(.*?)$"}]

# estimator
huggingface_estimator = HuggingFace(entry_point='train.py',
                                    source_dir='./code',
                                    metric_definitions=metric_definitions,
                                    instance_type='ml.g4dn.2xlarge',
                                    instance_count=2,
                                    volume_size=volume_size,
                                    role=role,
                                    transformers_version='4.6',
                                    pytorch_version='1.7',
                                    py_version='py36',
                                    hyperparameters = {
                                        'model_name_or_path': 'bert-large-uncased-whole-word-masking',
                                        'num_train_epochs': True,
                                        'max_seq_length': 384})

# starting the train job
huggingface_estimator.fit()
```

Training on Amazon SageMaker

Hugging Face estimator

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# starting the train job
huggingface_estimator.fit()
```

Training a LLM with HuggingFace

1. Preprocessing Step
   - Download/ingestion of dataset
   - Tokenization
   - Additional preprocessing steps
2. Training Step
   - Download/loading of model
   - Configuration of TrainingArguments
   - Configuration of Trainer
   - Training, evaluation, model serialization and storage

```
raw_datasets = load_dataset(…)
tokenizer = AutoTokenizer.from_pretrained(…)
tokenized_datasets = raw_datasets.map(…)
lm_datasets = tokenized_datasets.map(…)
```

```
model =AutoModelForCausalLM.from_pretrained('model-id')
training_args = TrainingArguments(**kwargs)
trainer = Trainer(
            model=model,
            args=training_args,
            train_dataset=lm_datasets,  …)
trainer.train()
trainer.save_model()
trainer.evaluate()
```

Amazon SageMaker

GENERATIVE AI IMMERSION DAY

Large-scale training on SageMaker

OPTIMIZED DISTRIBUTED TRAINING LIBRARIES & FRAMEWORKS

TensorFlow	PyTorch	Hugging Face	SageMaker Distributed Training Libraries	Bring your own library (e.g. DeepSpeed, Megatron)

AMAZON SAGEMAKER TRAINING

Large Scale Cluster Orchestration	NCCL Health Checks	SageMaker Jumpstart for foundational models	SageMaker Compiler	Warm pools	SSH to container
Data loading	Debugger	Profiling	Experiment tracking	Hyperparameter optimization	Pay for what you use

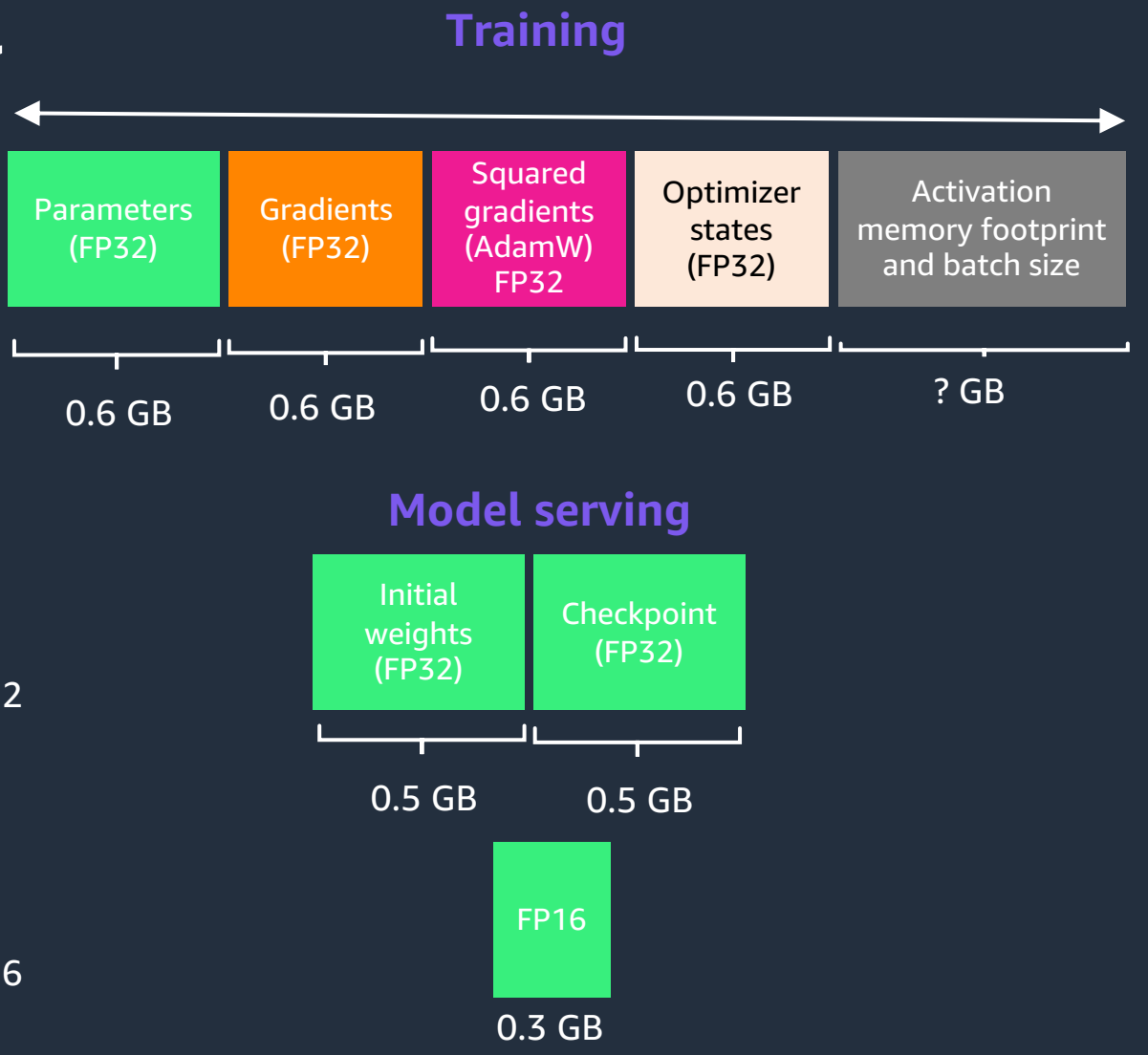
ML COMPUTE INSTANCES & ACCELERATORS

NVIDIA GPUS A100, V100, K80, T4, A10	AWS Nitro	400/800 Gbps EFA Networking	CPU instances	AWS Trainium

Overview of (distil)GPT2 model

- Open-source predecessor of OpenAI's GPT-3/4
- Mainly used for predicting the next token
- Model released by OpenAI and distilled by HuggingFace
- Transformer model based on this paper
- Trained on the WebText dataset and contains data from these domains. It can perform various tasks in language processing

Hyperparameters	Value
Parameters	82 million (124 million)
Layers	6 (12)



Lab 2 – LLM fine-tuning

https://github.com/aristsakpinis93/generative-ai-immersion-day

EventHash:

AGENDA

Generative AI – What is it and why the hype?

Large Language Models - How the ML works?

Large Language Model Hosting

Large Language Model Finetuning

Visual Foundation Models & Stable Diffusion

Engineering GenAI-powered Applications on AWS

Generative AI is transforming AI

IMAGE GENERATION, TRANSFORMATION, UPSCALING

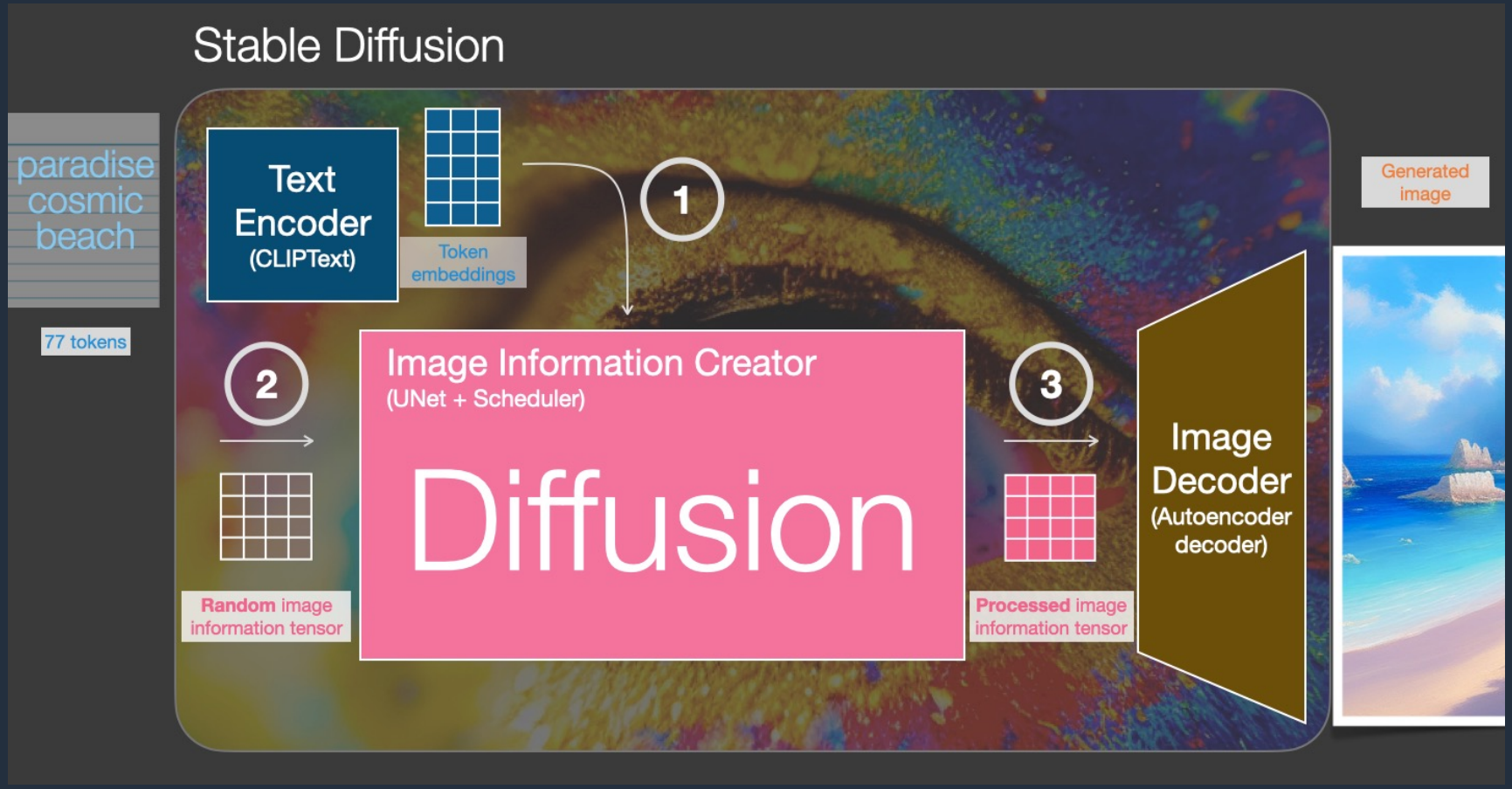
Generated by Stable Diffusion 2.0. This interior does not exist

Seamless transformation

4x

Upscaling

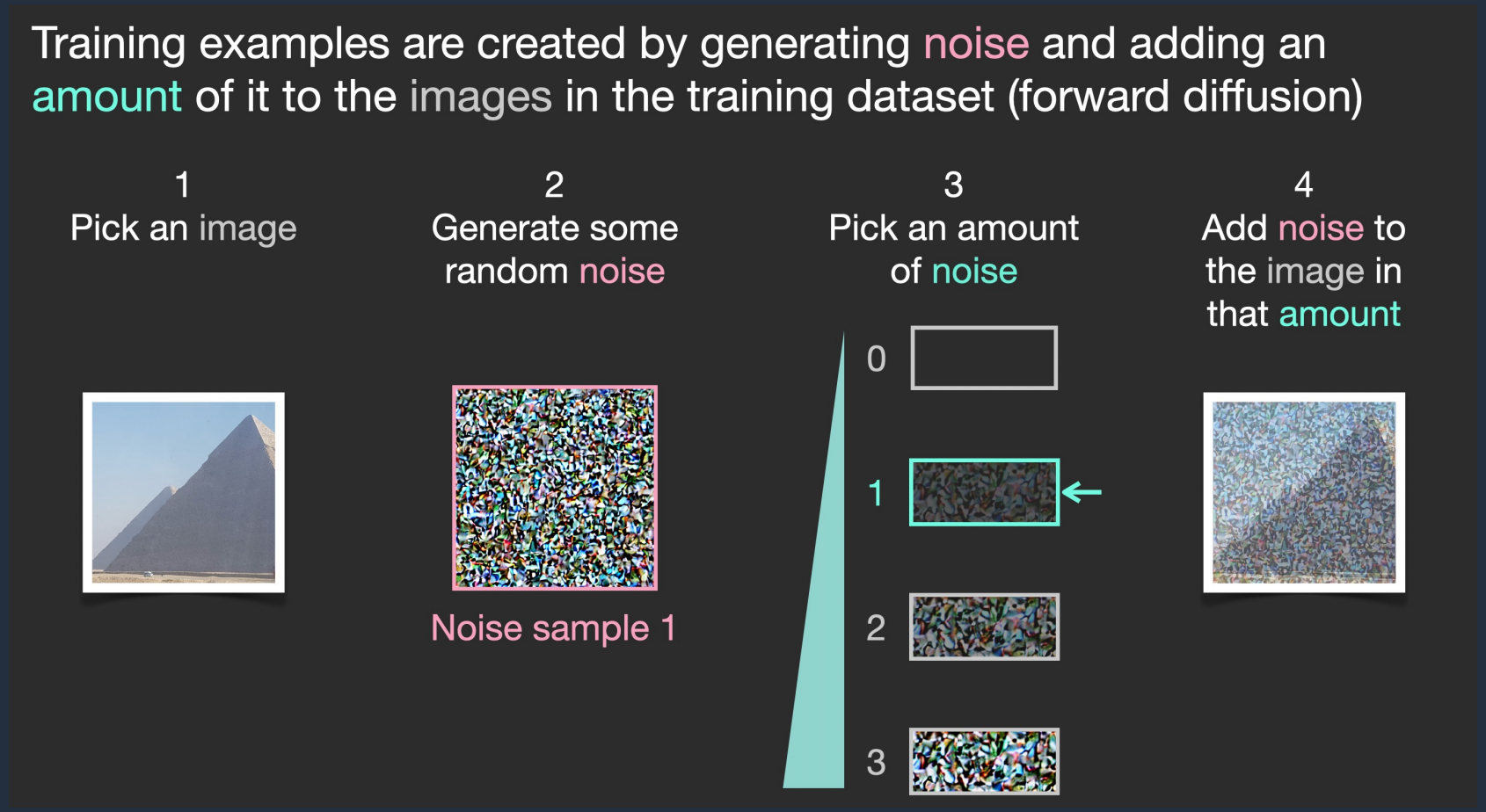
Building blocks of Diffusion



Source: https://jalammar.github.io/illustrated-stable-diffusion/

Training a diffusion model

Building blocks of Diffusion



Source: https://jalammar.github.io/illustrated-stable-diffusion/

Building blocks of Diffusion

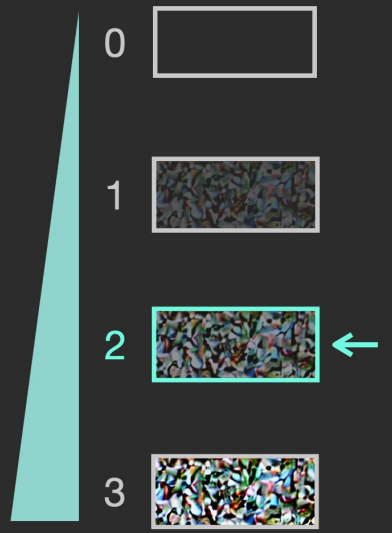
Generating a 2nd training example with a different image, noise sample and noise amount (forward diffusion)

1
Pick an image

2
Generate some random noise

Noise sample 2

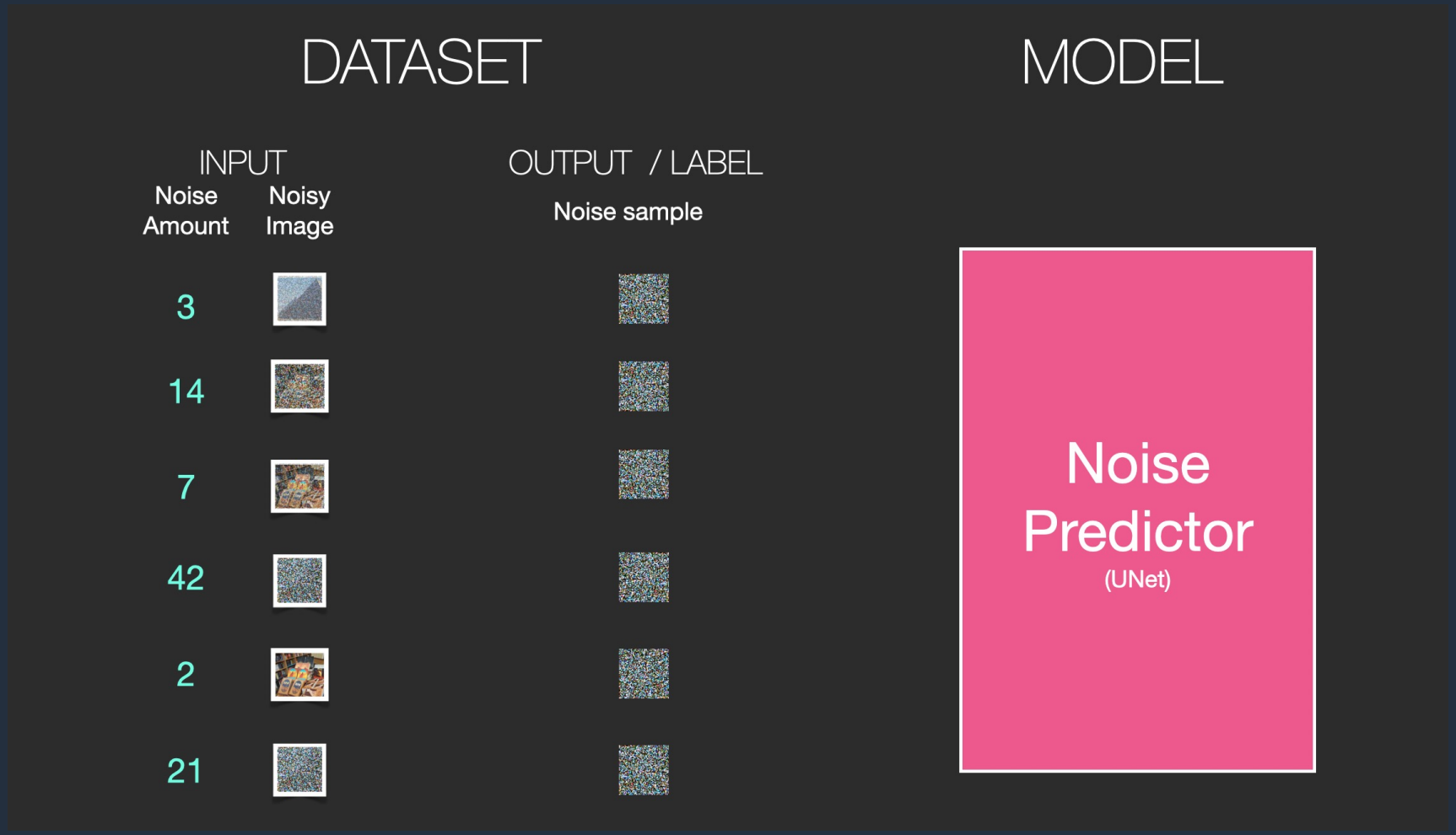
3
Pick an amount of noise



4
Add noise to the image in that amount

Source: https://jalammar.github.io/illustrated-stable-diffusion/

Building blocks of Diffusion



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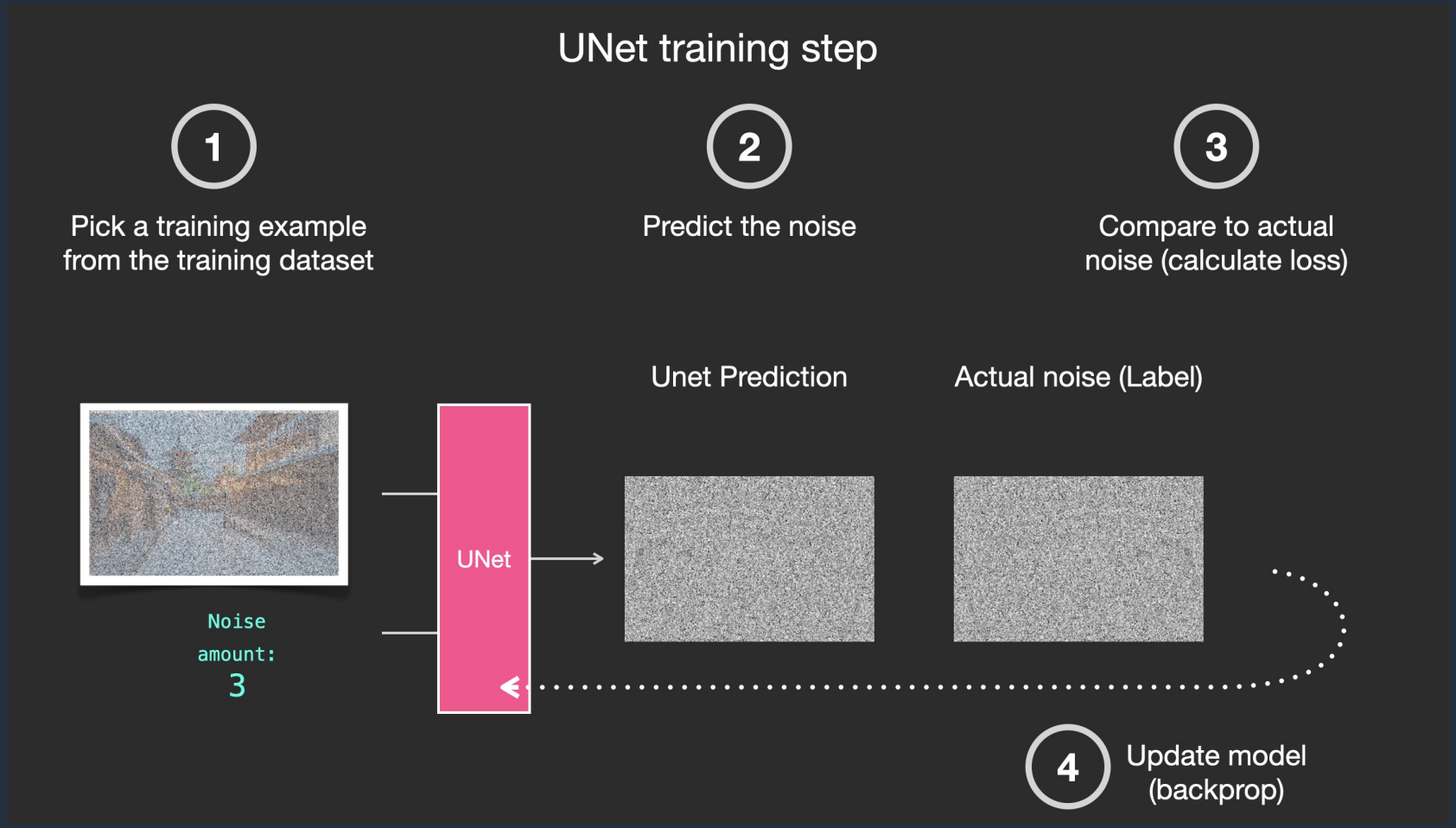
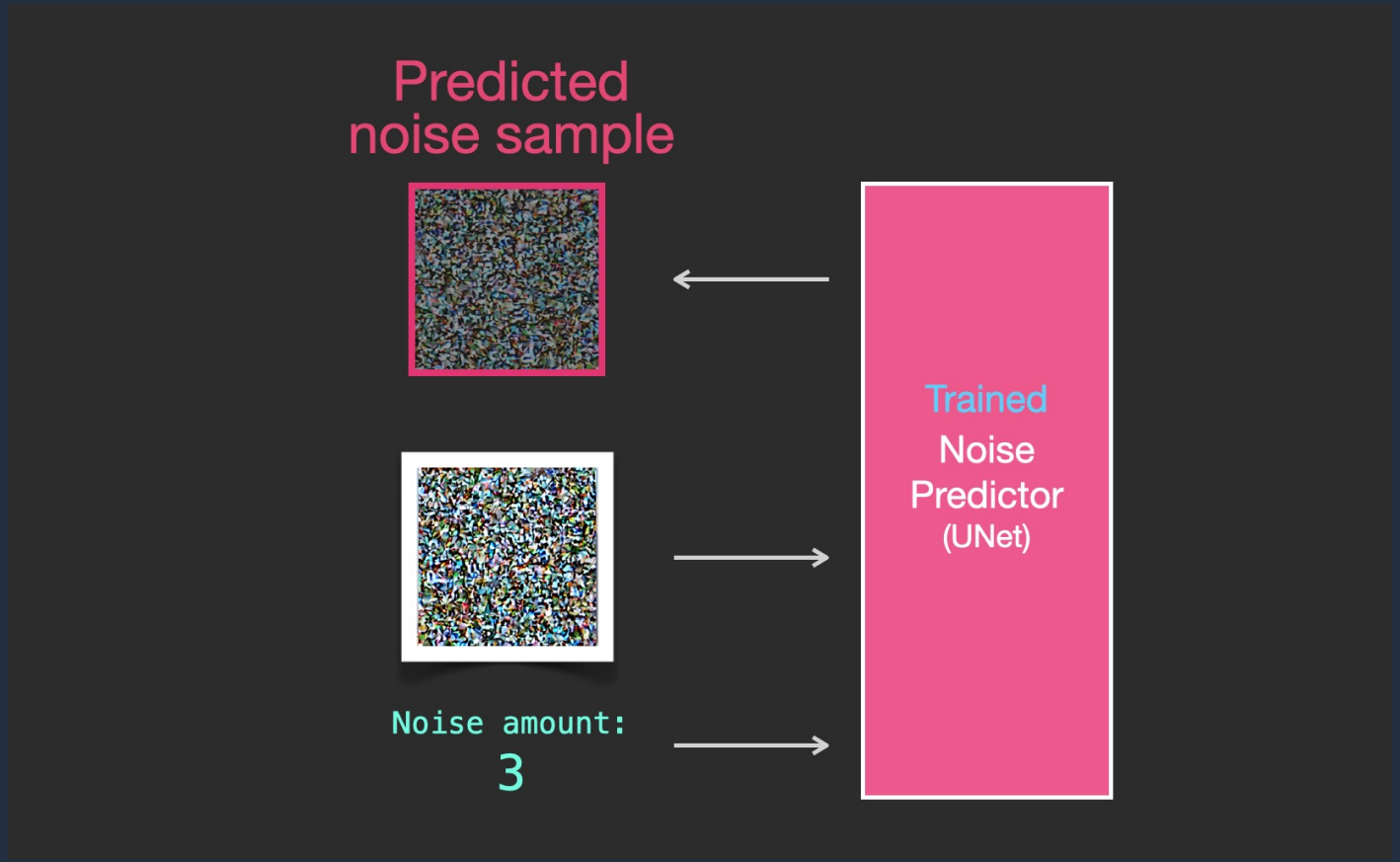
Building blocks of Diffusion



Source: https://jalammar.github.io/illustrated-stable-diffusion/

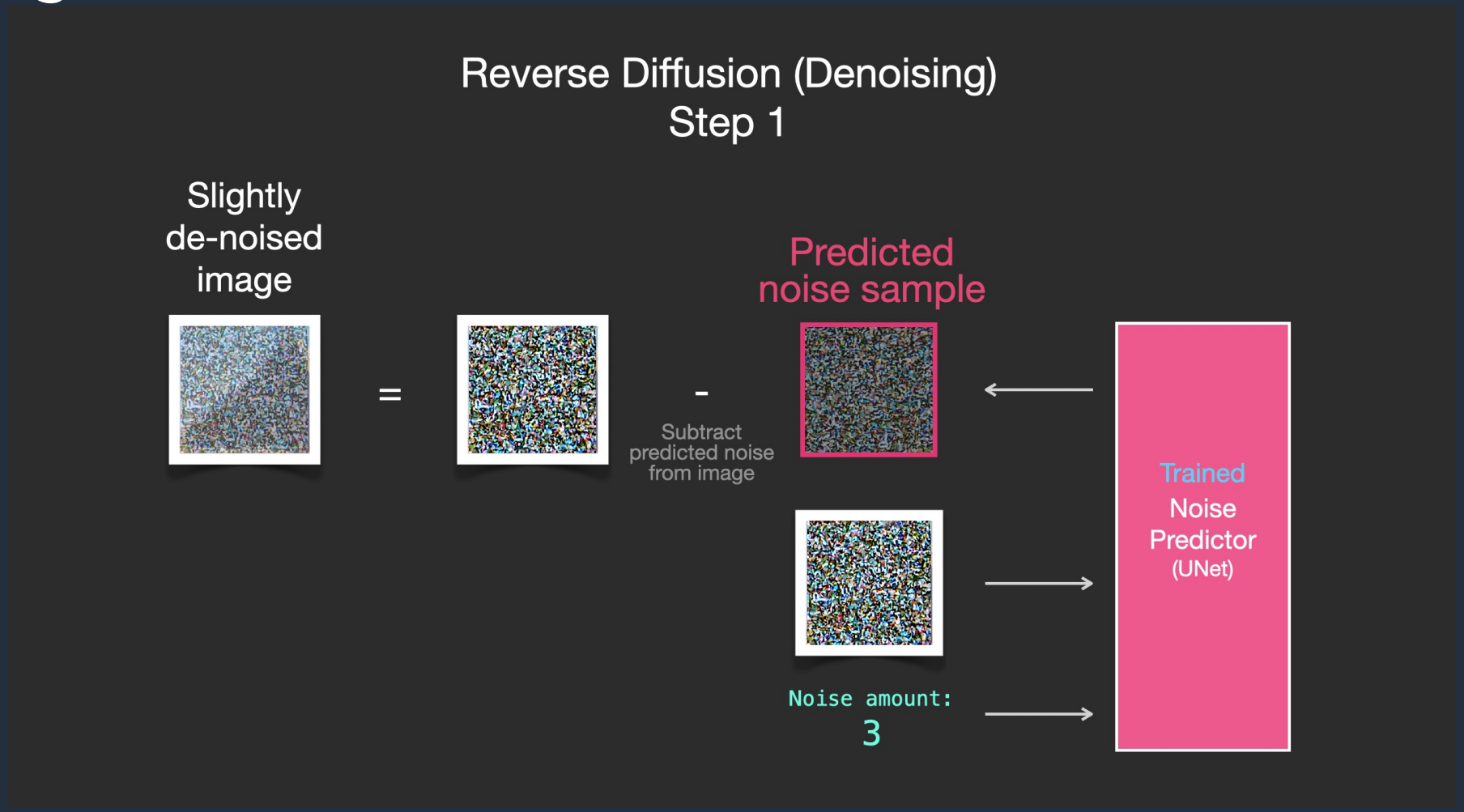
Image generation

Building blocks of Diffusion



Source: https://jalammar.github.io/illustrated-stable-diffusion/

Building blocks of Diffusion



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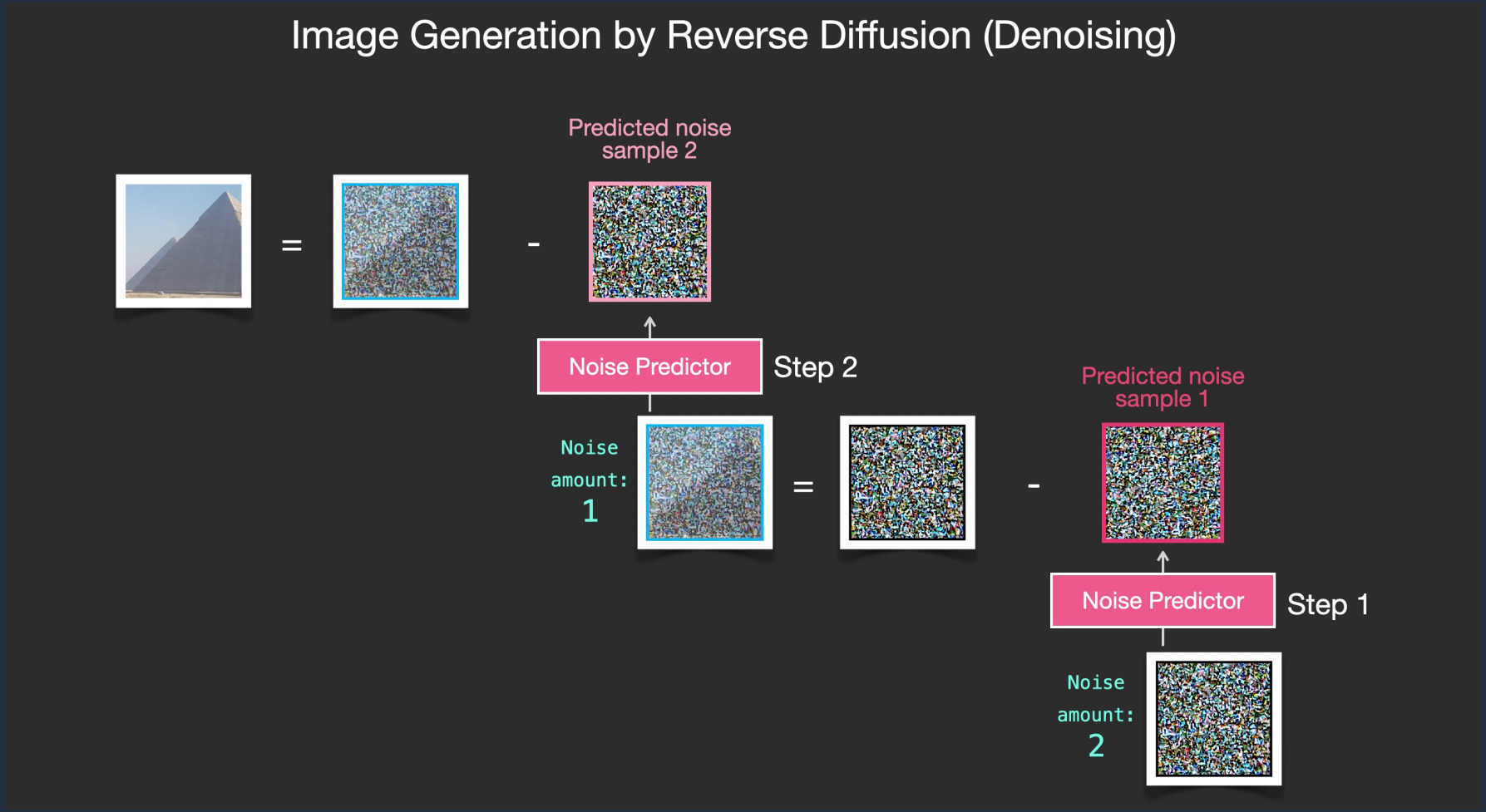
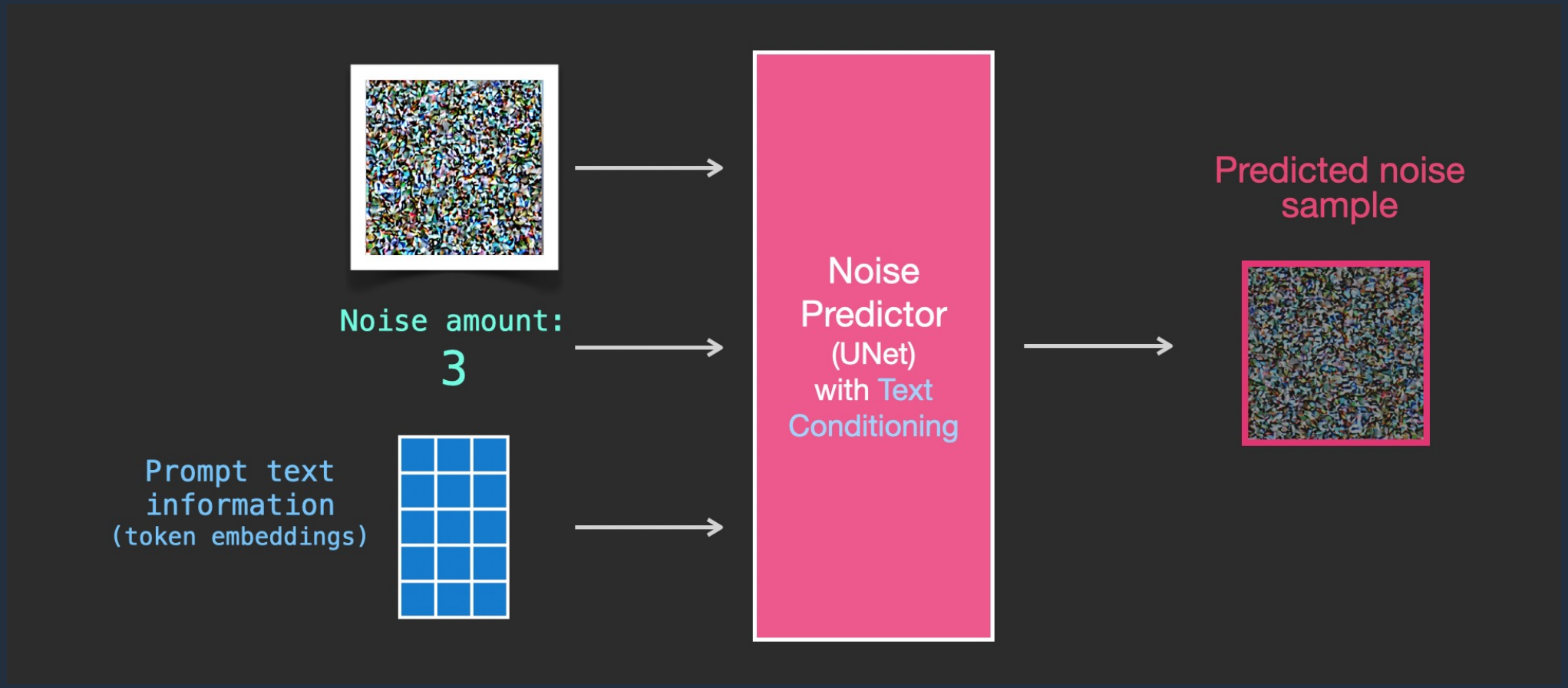
Building blocks of Diffusion



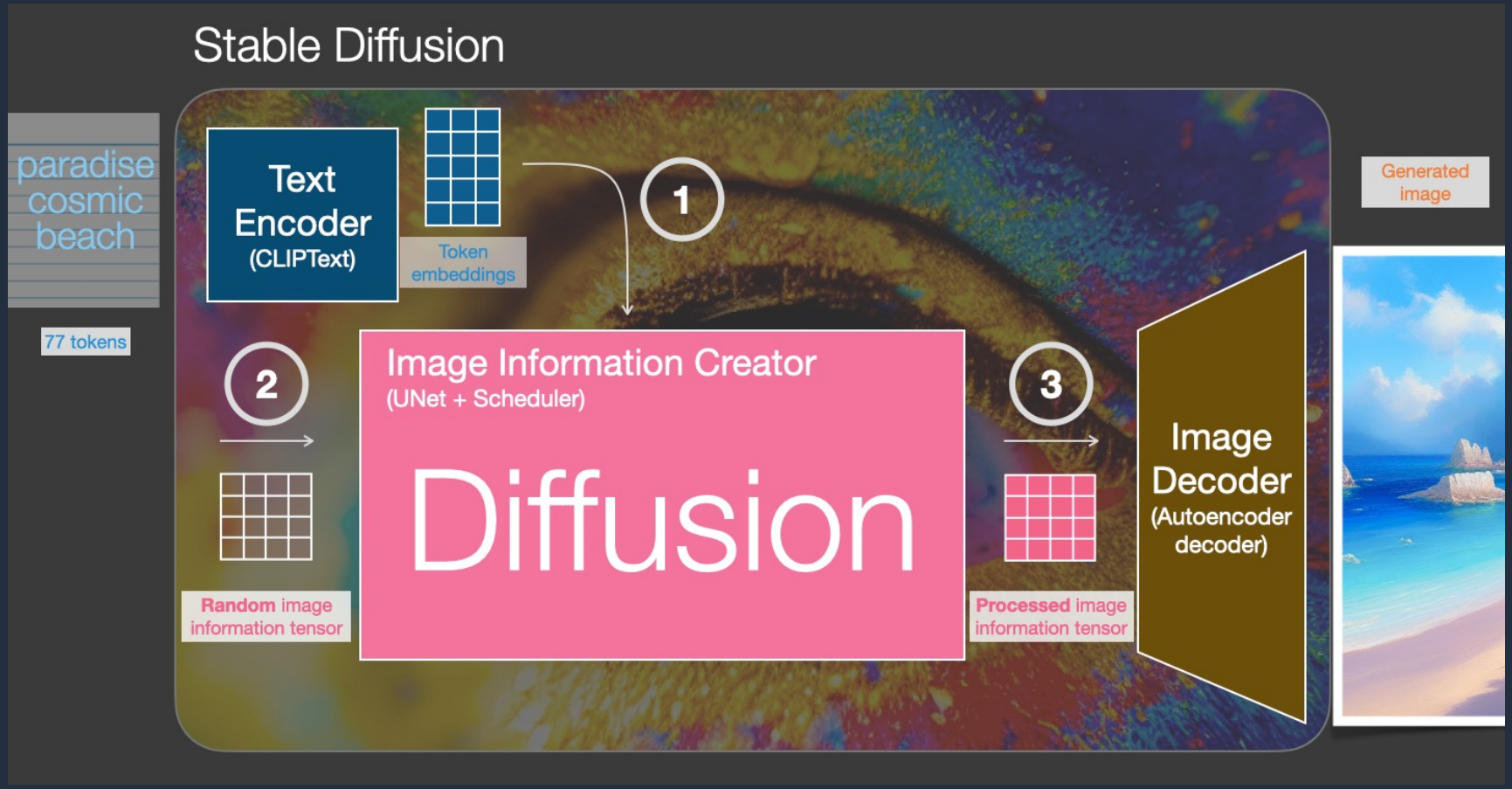
Source: https://jalammar.github.io/illustrated-stable-diffusion/

Building blocks of Diffusion



Source: https://jalammar.github.io/illustrated-stable-diffusion/

Building blocks of Diffusion



Source: https://jalammar.github.io/illustrated-stable-diffusion/

Lab 3 – Stable Diffusion Deployment & Inference

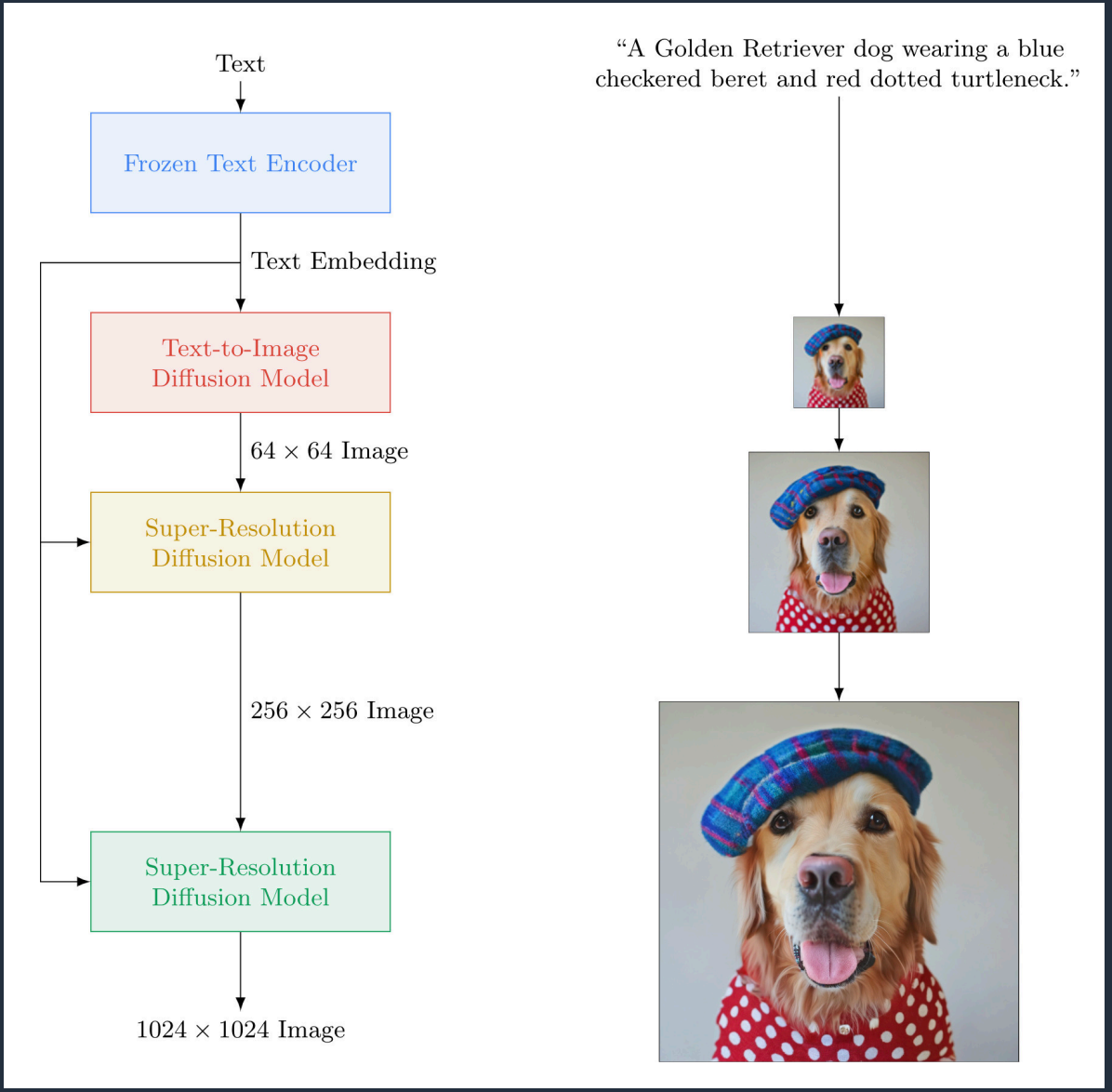
https://github.com/aristsakpinis93/generative-ai-immersion-day

EventHash:

Other models and related work

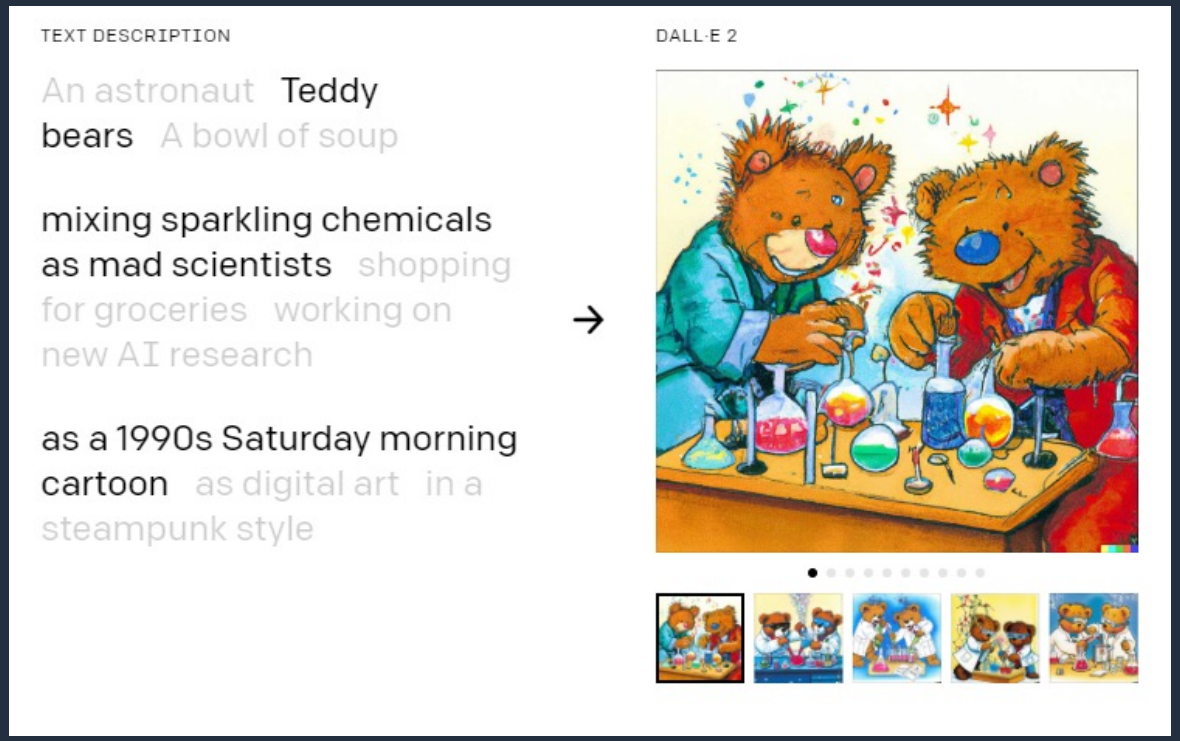
Imagen (Google, 2022)

- Another diffusion model
- Generate at low resolution and use super resolution networks to upscale; doesn't use an autoencoder
- Not available to the public.



Dall-E 2 (OpenAI, 2022)

- Another diffusion model
  - Weights are private but there's an inference API



Midjourney

Heavily stylized diffusion model

- Weights are private but there's public access to inference (no API)

Runway Gen-2

Text-to-Video

Mode 02: *Text + Image to Video*

Generate a video using a driving image and a text prompt

Input Image

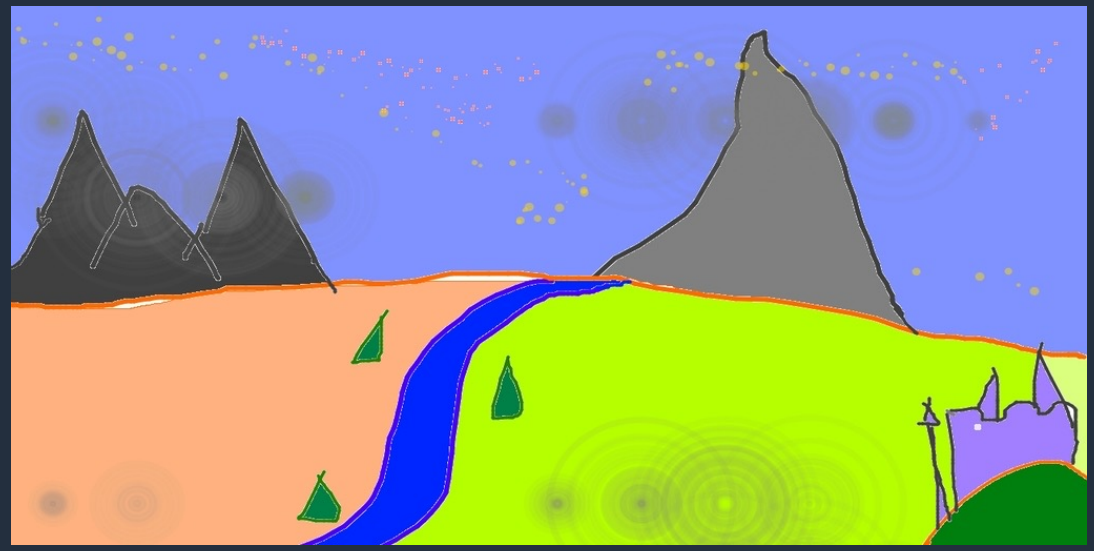
A low angle shot of a man walking down a street, illuminated by the neon signs of the bars around him.

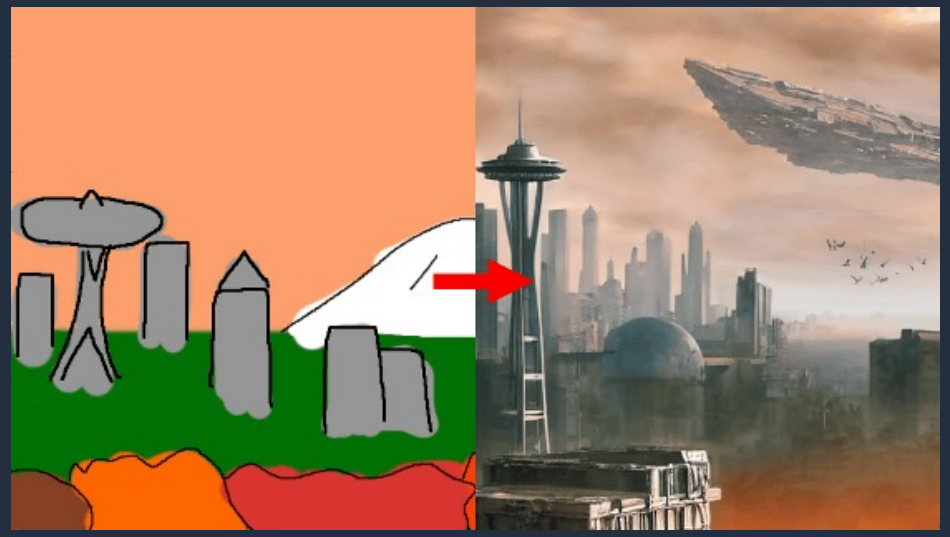
Driving Prompt

Output Video

Image-to-image (img2img)

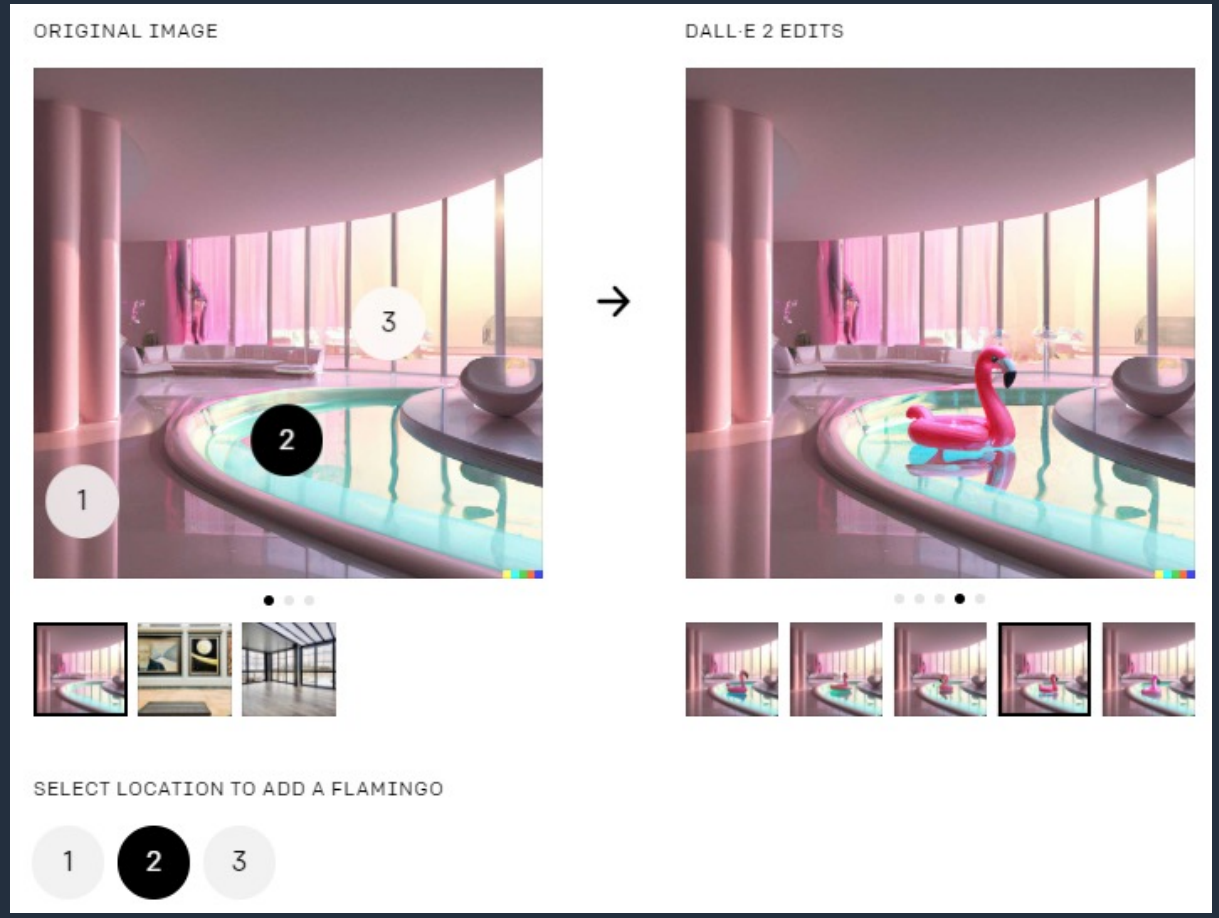
Add a specified amount of noise to an existing image and start the denoising process





Inpainting & outpainting

- Masked image-to-image



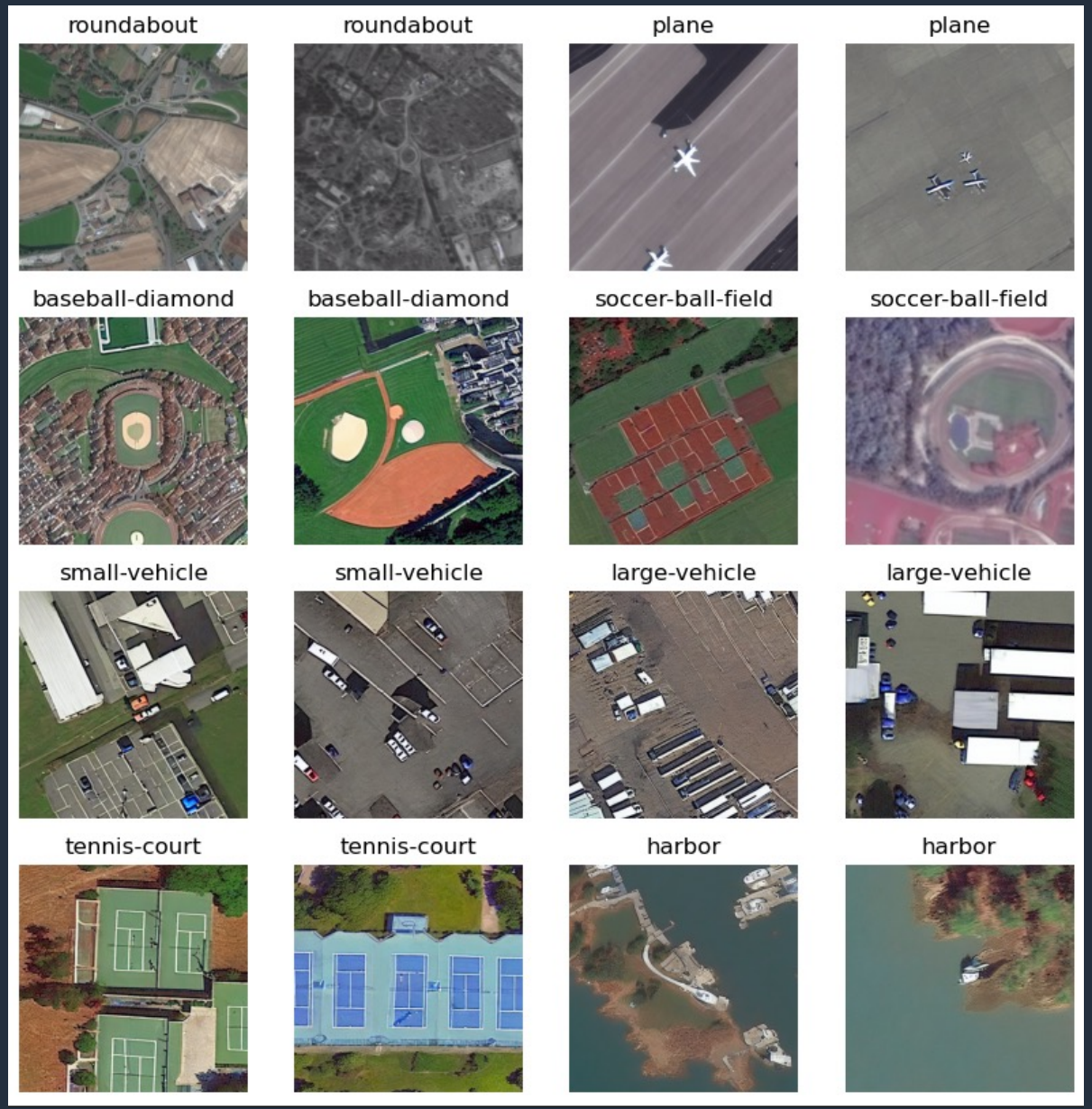
https://openai.com/dall-e-2/

Tuning Stable Diffusion

- Learning a new domain
  - Full scale finetuning
    - Significantly larger data requirement
    - Satellite diffusion model (right) was trained with 2000 image + label pairs

More efficient
  - LoRA
  - Hypernetworks

https://gitlab.aws.dev/wwps-natsec/ai-ml-practice/satellite-diffusion



"A satellite image showing a {class_name}"

Tuning Stable Diffusion

DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation

Nataniel Ruiz Yuanzhen Li Varun Jampani Yael Pritch Michael Rubinstein Kfir Aberman

Google Research

It's like a photo booth, but once the subject is captured, it can be synthesized wherever your dreams take you…

AGENDA

Generative AI – What is it and why the hype?

Large Language Models - How the ML works?

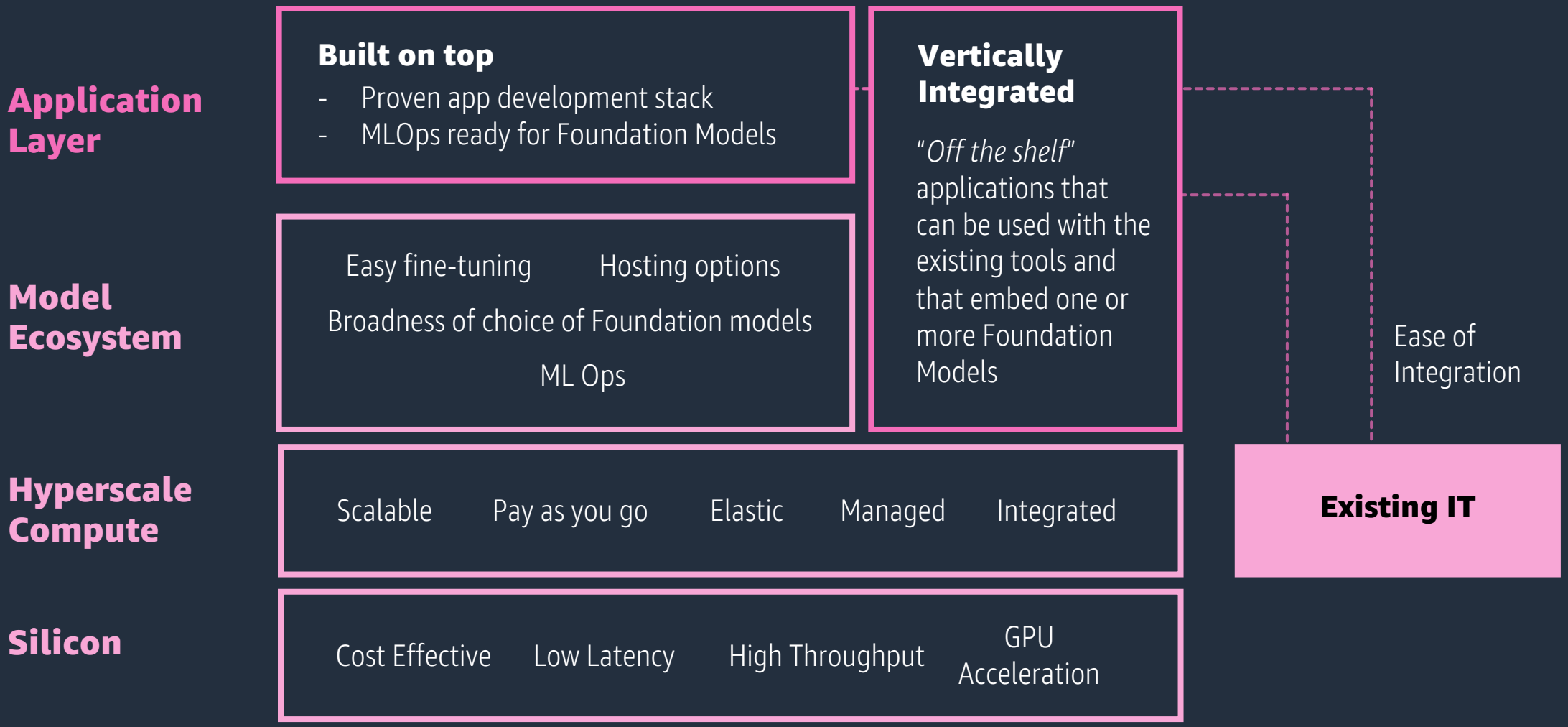
Large Language Model Hosting

Large Language Model Finetuning

Visual Foundation Models & Stable Diffusion

Engineering GenAI-powered Applications on AWS

Successfully building GenAI Applications



Amazon SageMaker JumpStart with Foundation Models

Machine Learning Hub for SageMaker

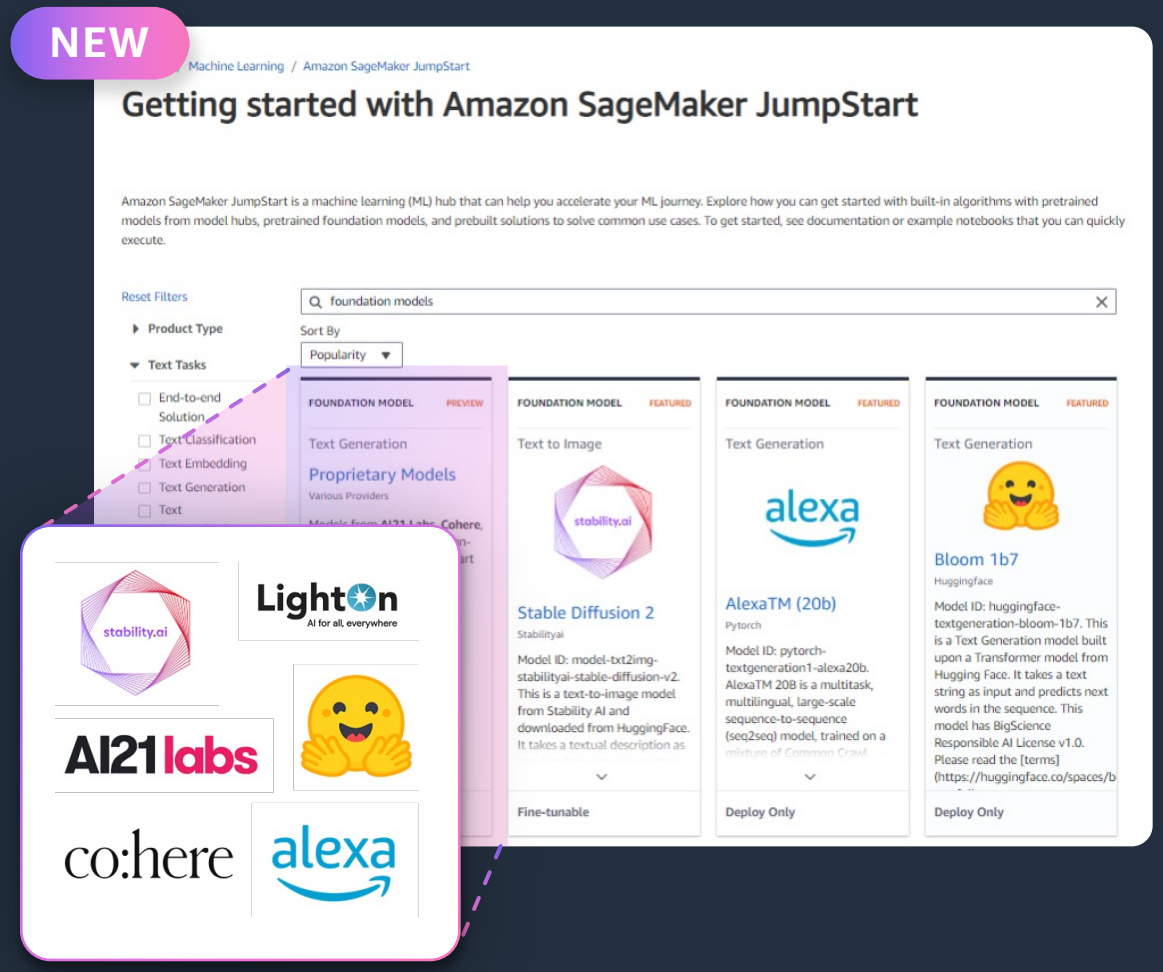
Browse through ~400 contents including, built-in algorithms with pre-trained models, (New) Foundation Models, solution templates, and example notebooks

UI as well as API based machine learning

Use the User Interface for single click model deployment or the API for Python SDK based workflow

(New) Share and collaborate within an 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

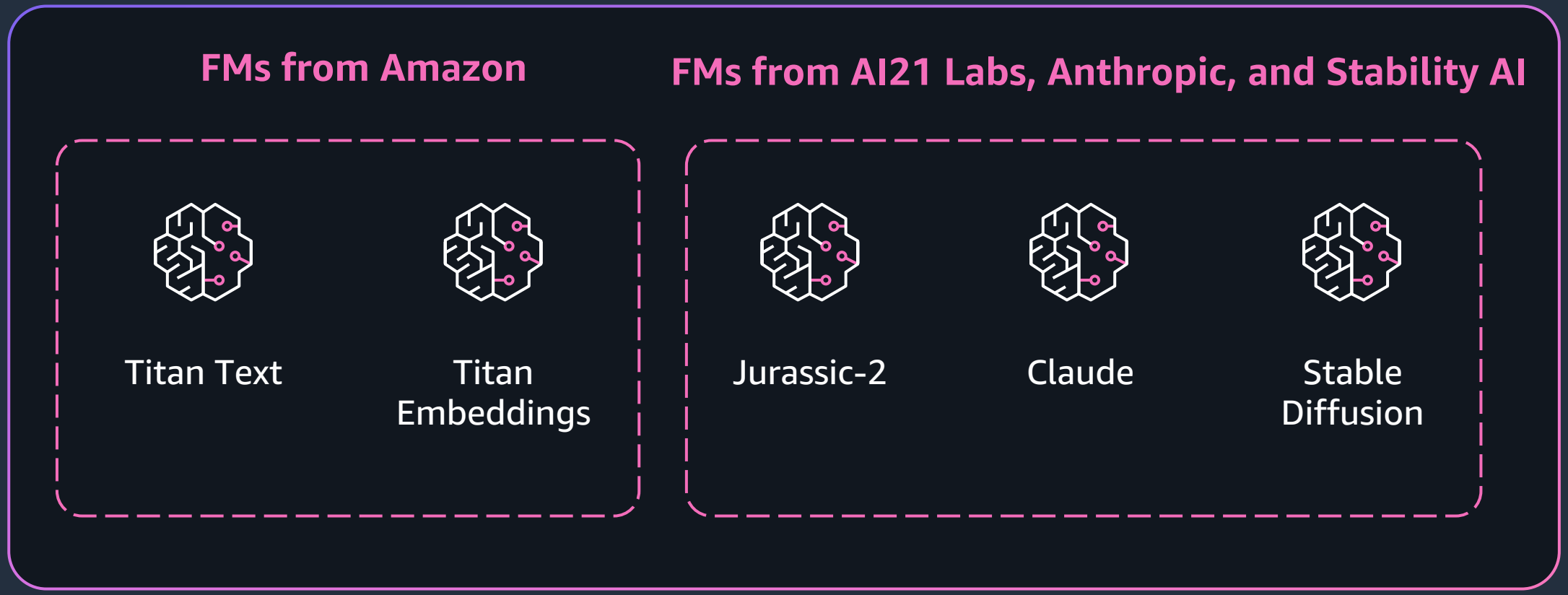


NEW

Amazon Bedrock

The easiest way to build and scale generative AI applications with FMs

Bedrock supports a wide range of foundation models



Base components and design patterns

- Models
- Prompts
- Memory
- Chains
- Tools
- Agents

Models

- Language generation models
- Text Embedding Models
- Purpose-fine-tuned models (chat, …)

```python
from langchain.llms.base import LLM

class CustomLLM(LLM):

    @property
    def _llm_type(self) -> str:
        return "custom"

    def _call(
        self,
        prompt: str,
        params: dict
    ) -> str:

        return call_llm_implementation(prompt, params)


llm = CustomLLM()
llm(prompt="How are you?", prompt={"temperature": 0.2})
```

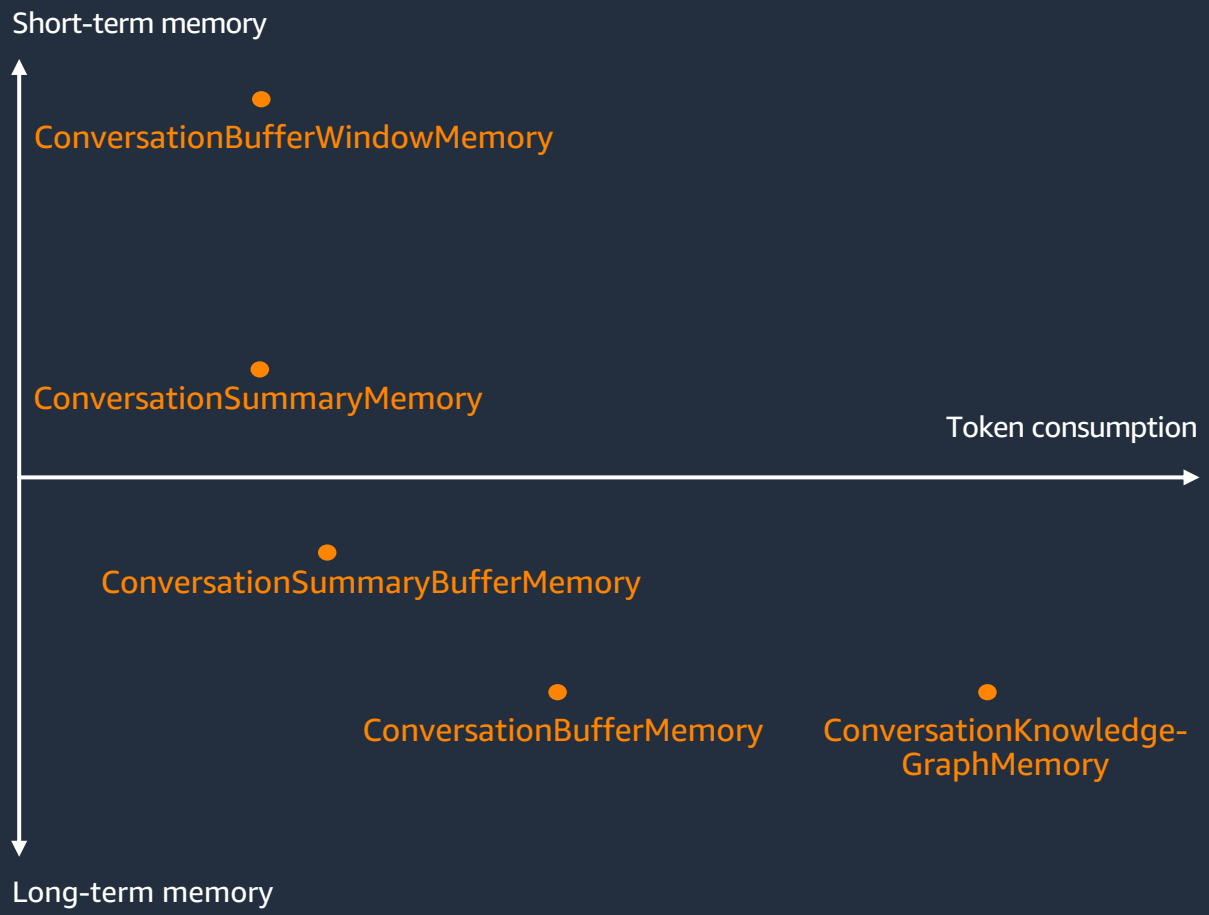
Pre-built implementations available for multiple model providers and hosting options!

Prompts: dynamic prompting through PromptTempates

```
from langchain import PromptTemplate

template = """
I want you to act as a naming consultant for new companies.
What is a good name for a company that makes {product}?
"""

prompt = PromptTemplate(
    input_variables=["product"],
    template=template,
)
prompt.format(product="colorful socks")
# -> I want you to act as a naming consultant for new companies.
# -> What is a good name for a company that makes colorful socks?
```

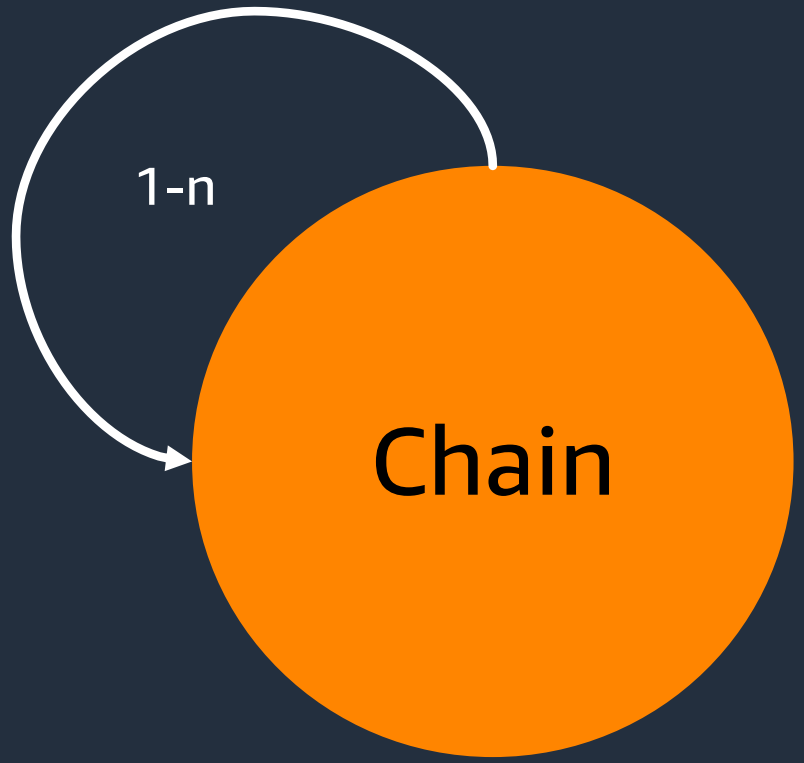
Memory: keeping track of conversation history

```python
from langchain.memory import ChatMessageHistory

history = ChatMessageHistory()

history.add_user_message("hi!")

history.add_ai_message("whats up?")

history.messages

# → [HumanMessage(content='hi!', additional_kwargs={}),
#     AIMessage(content='whats up?', additional_kwargs={})]
```



NOT EXHAUSTIVE

LangChains 😉



Generic Chains:

- LLMChain = Model + Prompt
- TransformationChain
- SequentialChain
- RouterChain

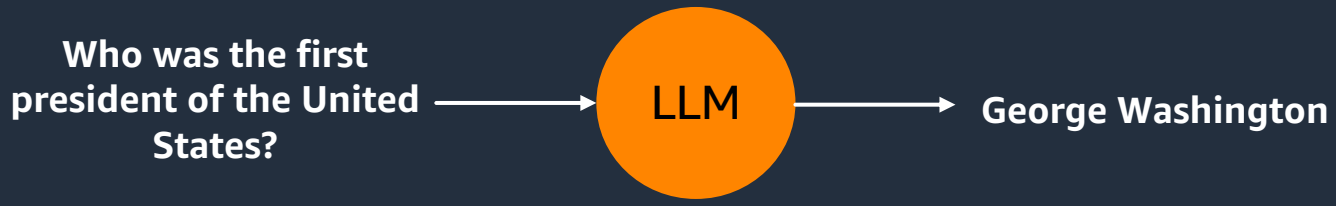
Index-related Chains:

- Summarization
- StuffDocumentsChain
- QA with sources (RAG)

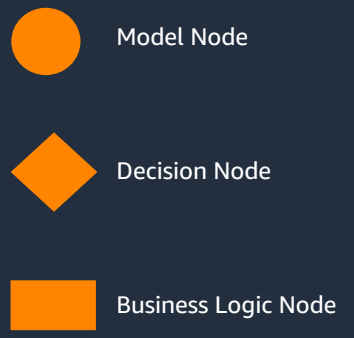
Purpose-built Chains:

- LLMMathChain
- APIChain
- Moderation

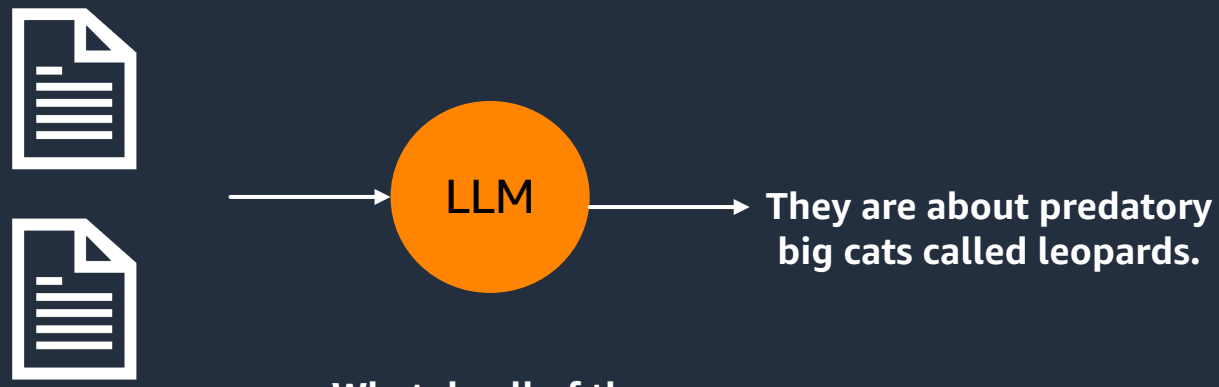
LLMChain

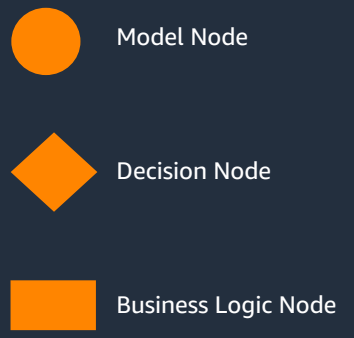


Answer the following question: {question}
If you don't know the answer, just say "I don't know".

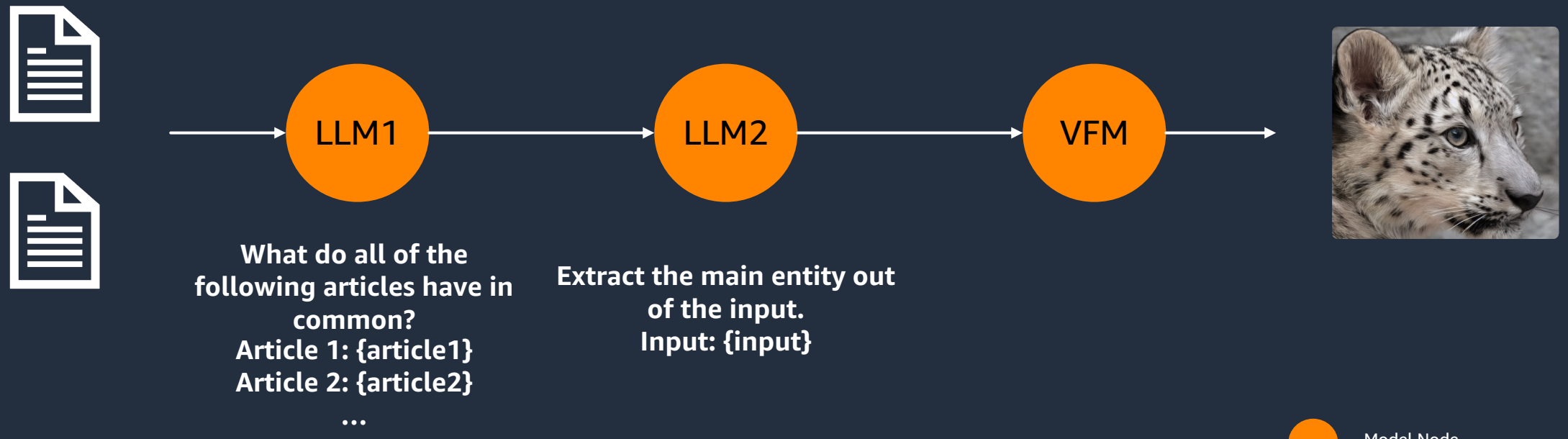


StuffDocumentsChain

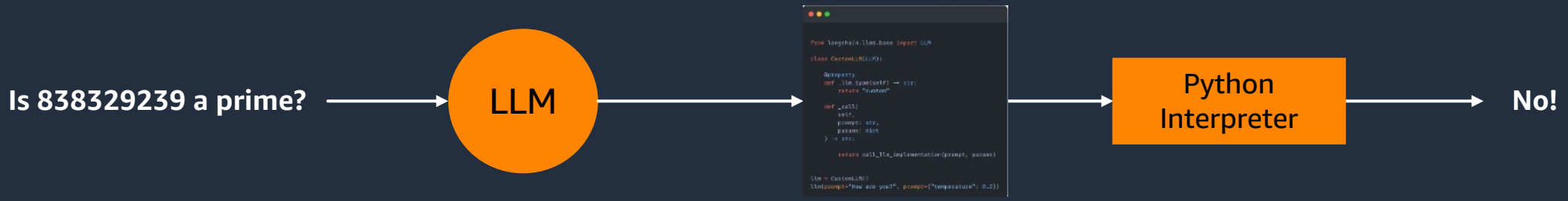




SequentialChain



TransformationChain



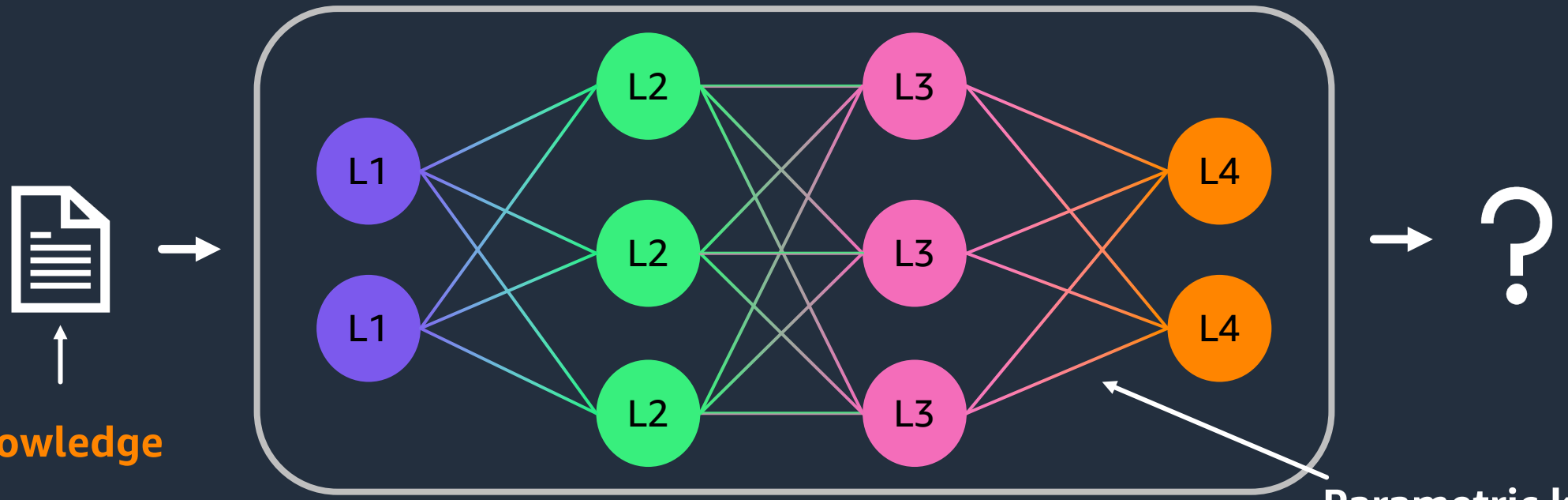
Translate this question into Python source code. Question: {question}

Model Node

Decision Node

Business Logic Node

Domain-specific knowledge infusion: forms of knowledge



Source knowledge

Adjustable though prompt enrichment ($)

Dynamic data (live-systems, (semi-)frequently changing knowledge bases, …)

Minimizes risk of halluzination, adds tracability of results

Parametric knowledge

Adjustable through fine-tuning ($$$)

Static data (language foundations , domain-specific vocabulary, writing style, …)

Domain-specific knowledge infusion through Tools

A Tool is "a function that performs a specific duty. (…) The interface for a tool is currently a function that is expected to have a string as an input, with a string as an output."

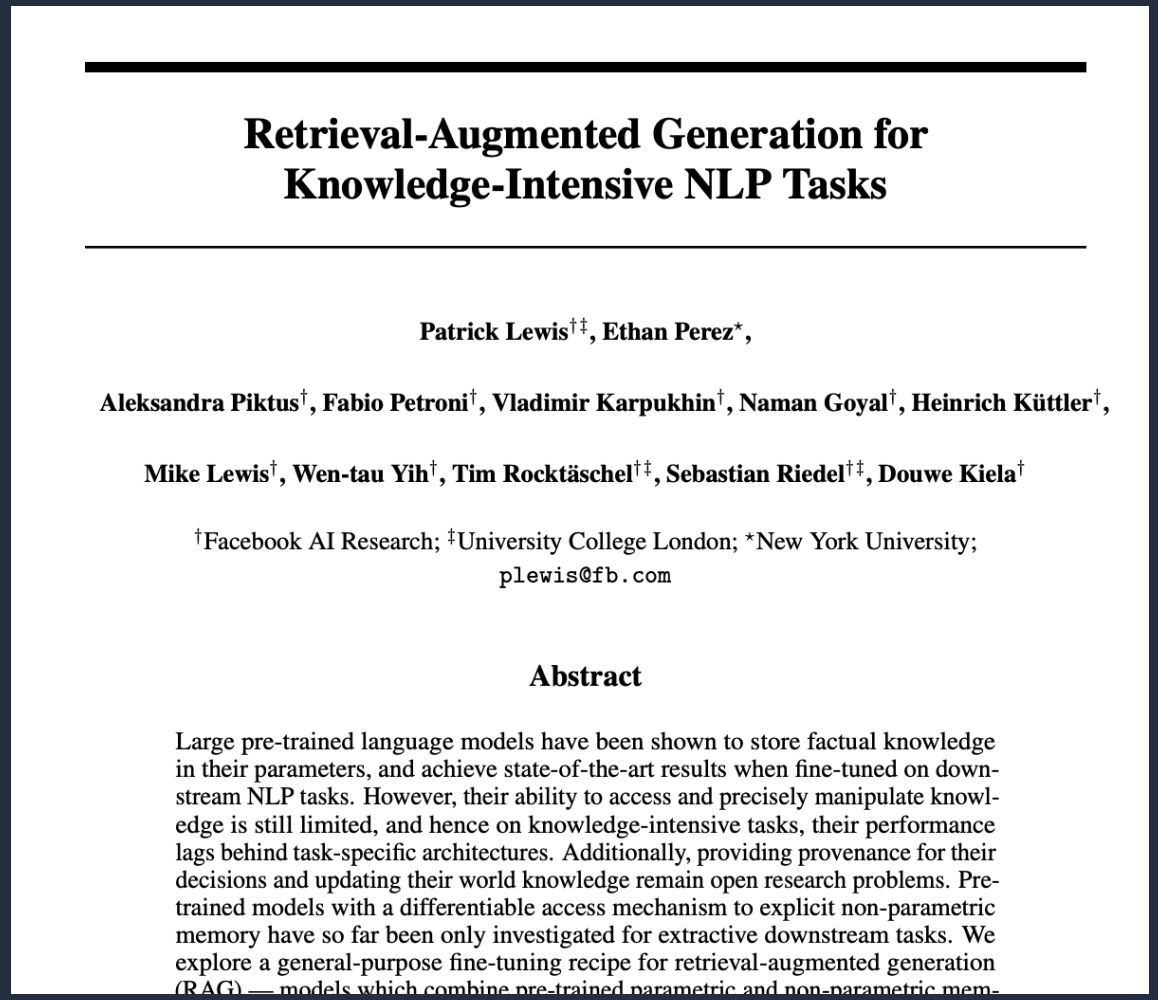
"These tools can be generic utilities (…), other chains, or even other agents."

```python
from langchain.tools import BaseTool

class CustomSearchTool(BaseTool):
    name = "custom_tool"
    description = "description of use case of this tool"

    def _run(self, query: str) -> str:
        """Use the tool."""
        result = tool_implementation(query)
        return result
```

```python
from langchain.tools import tool

@tool(name="custom_tool", description="...")
def search_api(query: str) -> str:
    """Use the tool."""
    result = tool_implementation(query)
    return result
```

Tools: RAG



Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks

Patrick Lewis[†‡], **Ethan Perez**[⋆],

Aleksandra Piktus[†], **Fabio Petroni**[†], **Vladimir Karpukhin**[†], **Naman Goyal**[†], **Heinrich Küttler**[†],

Mike Lewis[†], **Wen-tau Yih**[†], **Tim Rocktäschel**[†‡], **Sebastian Riedel**[†‡], **Douwe Kiela**[†]

[†]Facebook AI Research; [‡]University College London; [⋆]New York University;
plewis@fb.com

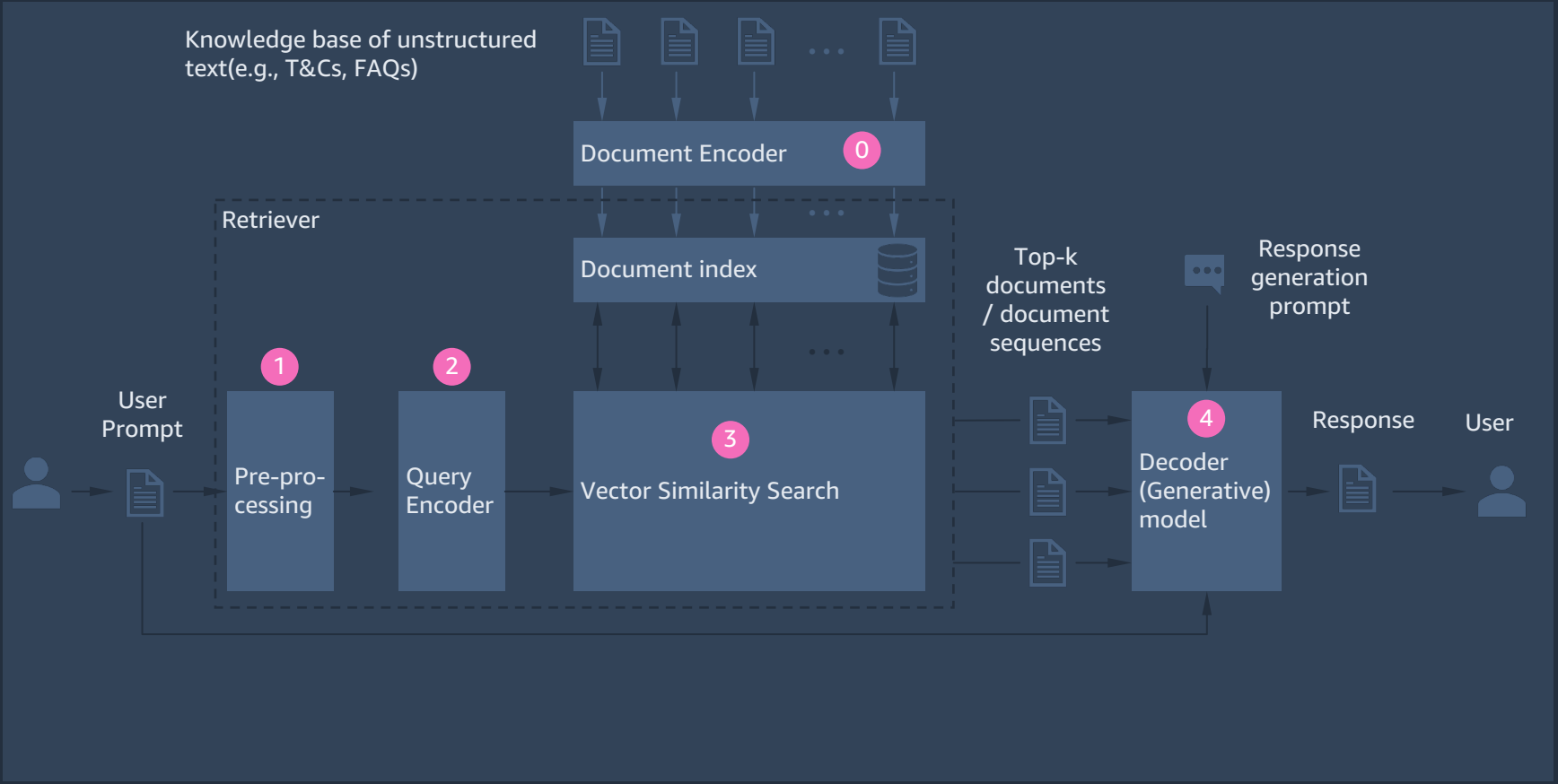
Abstract

Large pre-trained language models have been shown to store factual knowledge in their parameters, and achieve state-of-the-art results when fine-tuned on downstream NLP tasks. However, their ability to access and precisely manipulate knowledge is still limited, and hence on knowledge-intensive tasks, their performance lags behind task-specific architectures. Additionally, providing provenance for their decisions and updating their world knowledge remain open research problems. Pre-trained models with a differentiable access mechanism to explicit non-parametric memory have so far been only investigated for extractive downstream tasks. We explore a general-purpose fine-tuning recipe for retrieval-augmented generation (RAG) — models which combine pre-trained parametric and non-parametric mem-

- Retrieval-augmented generation
- Access to knowledge base of unstructured text
- Implemented through two-step chain powered by two different LLMs

Source: Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks, Patrick Lewis et al., 2021, https://arxiv.org/pdf/2005.11401.pdf

Tools: RAG



Concept

0. Knowledge documents / document sequences are encoded and ingested into a vector database.
1. Customer e-mail query is pre-processed and/or tokenized
2. Tokenized input query is encoded
3. Encoded query is used to retrieve most similar text passages in document index using vector similarity search (e.g., Mixed Inner Product Search)
4. Top-k retrieved documents/text passages in combination with original customer e-mail query and e-mail generation prompt are fed into Generator model (Encoder-Decoder) to generate response e-mail

Source: Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks, Patrick Lewis et al., 2021, https://arxiv.org/pdf/2005.11401.pdf

Tools: RAG

Document embedding & vectorstore ingestion

```
from langchain.document_loaders import WebBaseLoader
from langchain.text_splitter import CharacterTextSplitter
from langchain.vectorstores import OpenSearchVectorSearch

# load documents
loader = WebBaseLoader("https://aws.amazon.com/s3/faqs/")
documents = loader.load()

# split & tokenize
text_splitter = CharacterTextSplitter.from_tiktoken_encoder(chunk_size=100, chunk_overlap=10)
texts = text_splitter.split_documents(documents)

# initialize embeddings model wraper
embeddings = CustomLLM()

# embed documents into vectorstore
docsearch = OpenSearchVectorSearch.from_documents(
    docs,
    embeddings,
    opensearch_url="http://localhost:9200"
)
```

Retrievers

```
query = "Which kind of data can I store in Amazon S3?"
docs = docsearch.similarity_search(query, k=3)
print(docs[0].page_content)
# → [{page_content: (...), (...),
#     {page_content: (...), (...),
#     ...
#     ]

# wrap into retriever construct
retriever=docsearch.as_retriever()
docs = retriever.get_relevant_documents(query)
```

RetrievalQAChain

```
from langchain.chains import RetrievalQA

# generative LLM
llm = CustomLLM()

# define RetrievalQA chain
qa = RetrievalQA.from_chain_type(llm, chain_type="stuff", retriever=retriever)

# run chain
res = qa.run(query)
print(res)
# → "You can store virtually any kind of data in any format in Amazon S3."
```

Tools: Requests

```
from langchain.agents import load_tools

requests_tools = load_tools(["requests_all"])
print(requests_tools)
# → [RequestsGetTool(name='requests_get', description='A portal to the internet. Use this when you need to
#     get specific content from a website. Input should be a  url (i.e. https://www.google.com). The output
#     will be the text response of the GET request.',(...)),
#     RequestsPostTool(name='requests_post', (...)),
#     RequestsPatchTool(name='requests_patch', (...)),
#     RequestsPutTool(name='requests_put', (...)),
#     RequestsDeleteTool(name='requests_delete', (...))]

requests_get = requests_tools[0]
requests_get.run("https://aws.amazon.com/s3/faqs/")
```

Tools: Google Search

```
from langchain.tools import Tool
from langchain.utilities import GoogleSearchAPIWrapper

search = GoogleSearchAPIWrapper()

tool = Tool(
    name = "Google Search",
    description="Search Google for recent results.",
    func=search.run
)

tool.run("Who won the 2020 UEFA Champions League Final?")
# → FC Bayern München
```

Tools: Python REPL

```
from langchain.agents import Tool
from langchain.utilities import PythonREPL

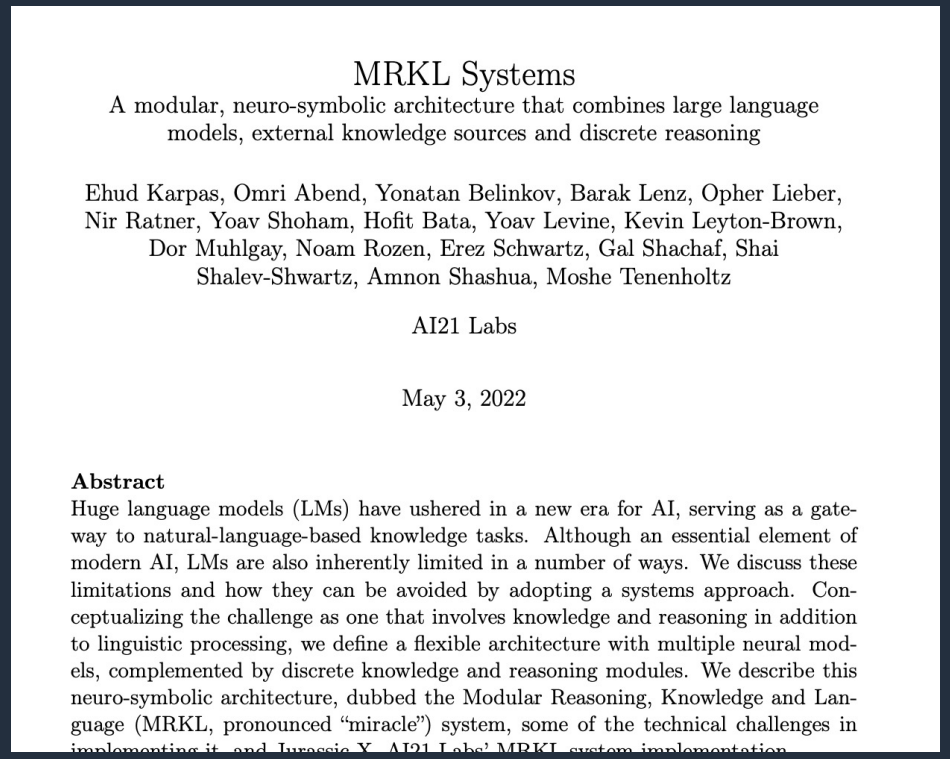
python_repl = PythonREPL()

python_repl.run("print(1+1)")
# → 2

# You can create the tool to pass to an agent
repl_tool = Tool(
    name="python_repl",
    description="""
                A Python shell. Use this to execute python commands.
                Input should be a valid python command. If you want to see
                the output of a value, you should print it out with `print(...)`.
                """,
    func=python_repl.run
)

repl_tool.run("print(1+1)")
# → 2
```

Agents: MRKL



MRKL Systems

A modular, neuro-symbolic architecture that combines large language models, external knowledge sources and discrete reasoning

Ehud Karpas, Omri Abend, Yonatan Belinkov, Barak Lenz, Opher Lieber, Nir Ratner, Yoav Shoham, Hofit Bata, Yoav Levine, Kevin Leyton-Brown, Dor Muhlgay, Noam Rozen, Erez Schwartz, Gal Shachaf, Shai Shalev-Shwartz, Amnon Shashua, Moshe Tenenholtz

AI21 Labs

May 3, 2022

Abstract

Huge language models (LMs) have ushered in a new era for AI, serving as a gateway to natural-language-based knowledge tasks. Although an essential element of modern AI, LMs are also inherently limited in a number of ways. We discuss these limitations and how they can be avoided by adopting a systems approach. Conceptualizing the challenge as one that involves knowledge and reasoning in addition to linguistic processing, we define a flexible architecture with multiple neural models, complemented by discrete knowledge and reasoning modules. We describe this neuro-symbolic architecture, dubbed the Modular Reasoning, Knowledge and Language (MRKL, pronounced "miracle") system, some of the technical challenges in implementing it, and Jurassic-X, AI21 Labs' MRKL system implementation.

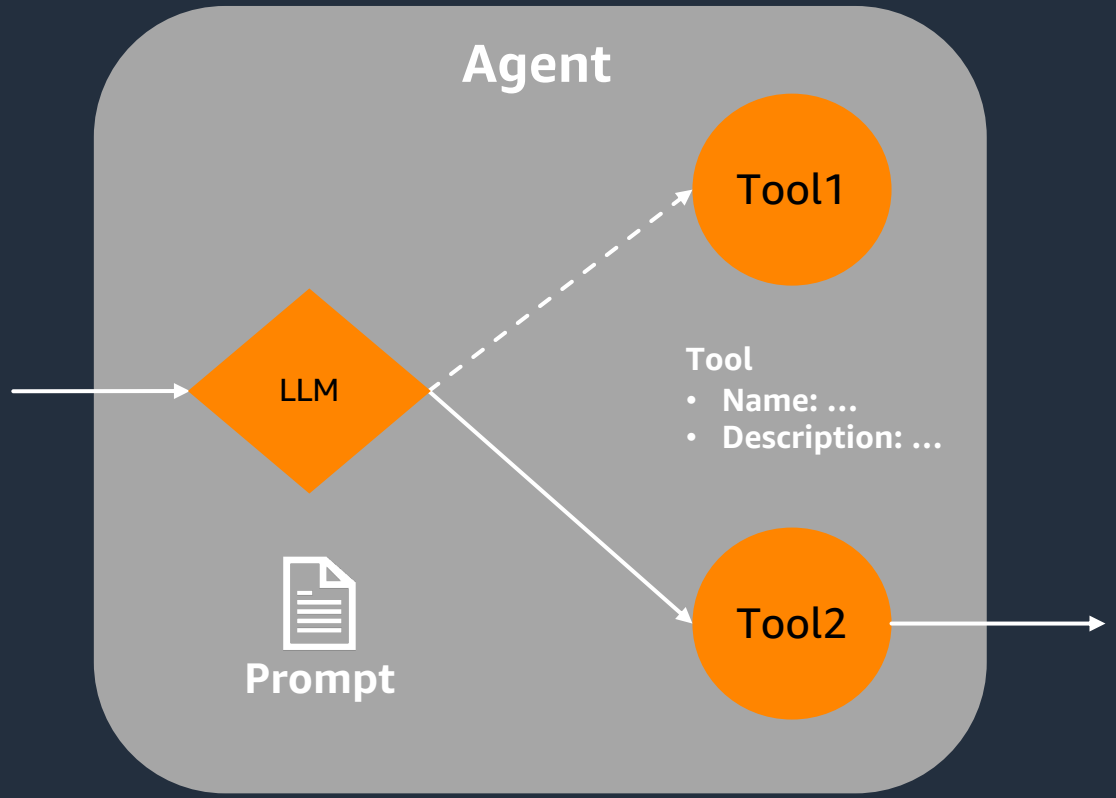
Source: MRKL Systems – A modular, neuro-symbolic architecture that combines large language models, external knowledge sources and discrete reasoning, Ehud Karpas et al, 2022, https://arxiv.org/pdf/2205.00445.pdf

Idea: System routes between 1-n out of multiple tools, which can be *neural* or *symbolic*.

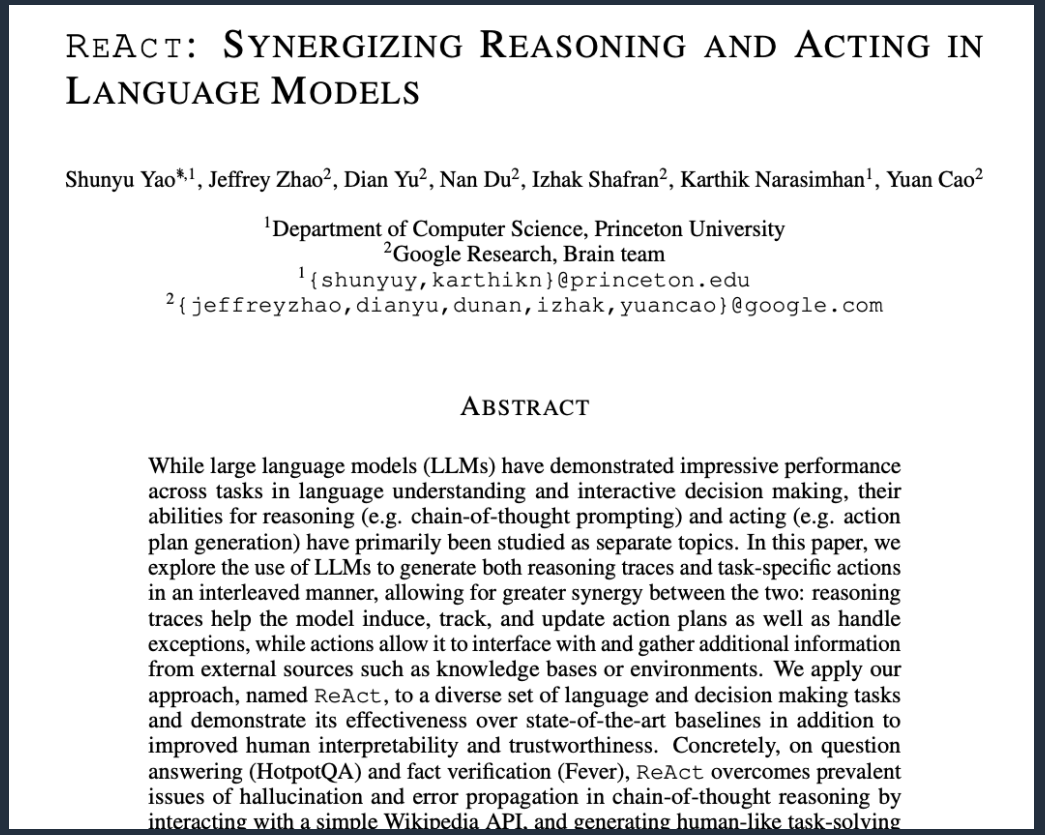
Benefits:

- Proprietary knowledge
- Up-to-date information
- Interpretability
- Composability
- Robust extensibility
- Safe fallback

Agents: basic components



Agents: ReAct



REACT: SYNERGIZING REASONING AND ACTING IN LANGUAGE MODELS

Shunyu Yao*,[1], Jeffrey Zhao[2], Dian Yu[2], Nan Du[2], Izhak Shafran[2], Karthik Narasimhan[1], Yuan Cao[2]

[1]Department of Computer Science, Princeton University
[2]Google Research, Brain team
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[2]{jeffreyzhao,dianyu,dunan,izhak,yuancao}@google.com

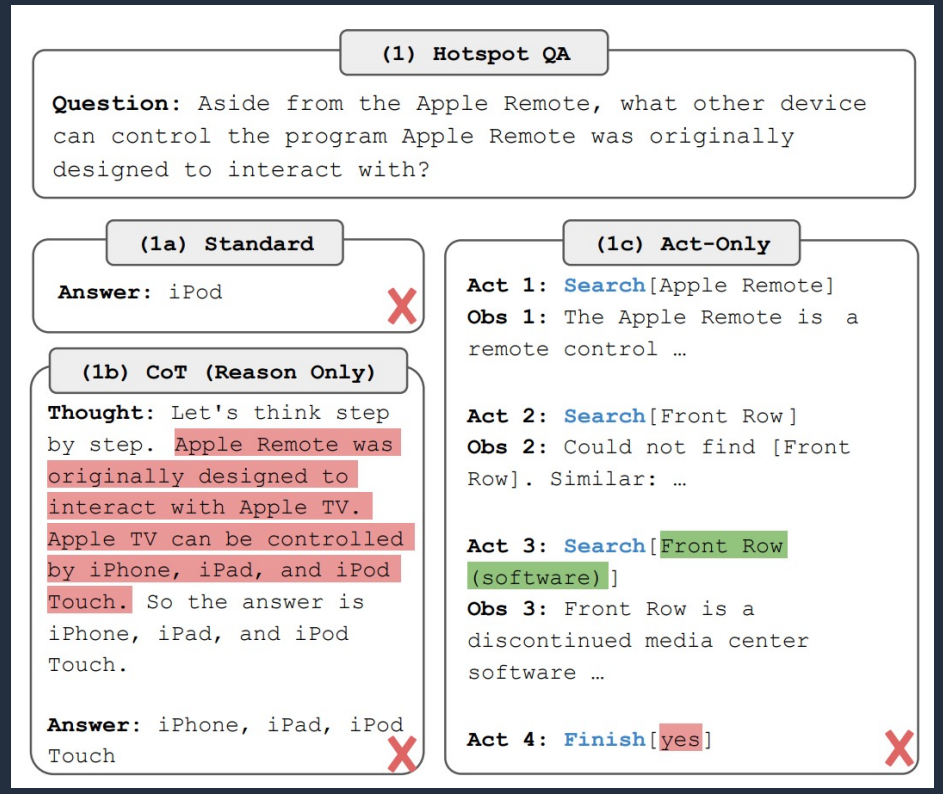
ABSTRACT

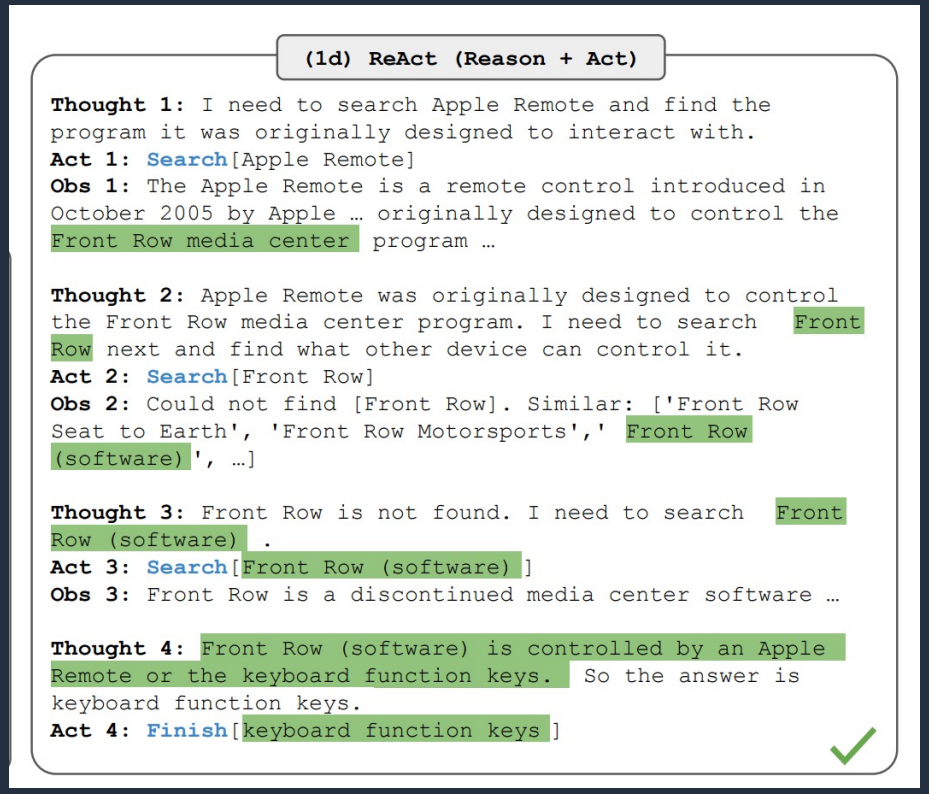
While large language models (LLMs) have demonstrated impressive performance across tasks in language understanding and interactive decision making, their abilities for reasoning (e.g. chain-of-thought prompting) and acting (e.g. action plan generation) have primarily been studied as separate topics. In this paper, we explore the use of LLMs to generate both reasoning traces and task-specific actions in an interleaved manner, allowing for greater synergy between the two: reasoning traces help the model induce, track, and update action plans as well as handle exceptions, while actions allow it to interface with and gather additional information from external sources such as knowledge bases or environments. We apply our approach, named ReAct, to a diverse set of language and decision making tasks and demonstrate its effectiveness over state-of-the-art baselines in addition to improved human interpretability and trustworthiness. Concretely, on question answering (HotpotQA) and fact verification (Fever), ReAct overcomes prevalent issues of hallucination and error propagation in chain-of-thought reasoning by interacting with a simple Wikipedia API, and generating human-like task-solving

Source: ReAct: Synergizing reasoning and acting in language models, Shunyu Yao et al, 2023, https://arxiv.org/pdf/2210.03629.pdf

- Logical and modular reasoning of GenAI-powered systems (chain-of-thought)
- Execution of task-specific actions (action plan generation)
- Implemented through chain of recursive steps against a powerful LLM

Agents: ReAct





Source: ReAct: Synergizing reasoning and acting in language models, Shunyu Yao et al, 2023, https://arxiv.org/pdf/2210.03629.pdf

Agents: MRKL agent implementation

```
from langchain.agents import initialize_agent, Tool
from langchain.agents import AgentType

# Define llm and tools
(...)

tools = [
    Tool(
        name = "Search",
        func=search.run,
        description="useful for when you need to answer questions about current events. You should ask targeted questions"
    ),
    Tool(
        name="Calculator",
        func=llm_math_chain.run,
        description="useful for when you need to answer questions about math"
    ),
    Tool(
        name="FooBar DB",
        func=db_chain.run,
        description="useful for when you need to answer questions about FooBar. Input should be in the form of a question containing full context"
    )
]

mrkl = initialize_agent(tools, llm, agent=AgentType.ZERO_SHOT_REACT_DESCRIPTION, verbose=True)

mrkl.run("Who is Leo DiCaprio's girlfriend? What is her current age raised to the 0.43 power?")
```

Agents: MRKL agent implementation

```
> Entering new AgentExecutor chain...
 I need to find out who Leo DiCaprio's girlfriend is and then calculate her age raised to the 0.43
power.
Action: Search
Action Input: "Who is Leo DiCaprio's girlfriend?"
Observation: DiCaprio met actor Camila Morrone in December 2017, when she was 20 and he was 43. They
were spotted at Coachella and went on multiple vacations together. Some reports suggested that
DiCaprio was ready to ask Morrone to marry him. The couple made their red carpet debut at the 2020
Academy Awards.
Thought: I need to calculate Camila Morrone's age raised to the 0.43 power.
Action: Calculator
Action Input: 21^0.43

> Entering new LLMMathChain chain...
21^0.43
```text
21**0.43
```
...numexpr.evaluate("21**0.43")...

Answer: 3.7030049853137306
> Finished chain.

Observation: Answer: 3.7030049853137306
Thought: I now know the final answer.
Final Answer: Camila Morrone is Leo DiCaprio's girlfriend and her current age raised to the 0.43
power is 3.7030049853137306.

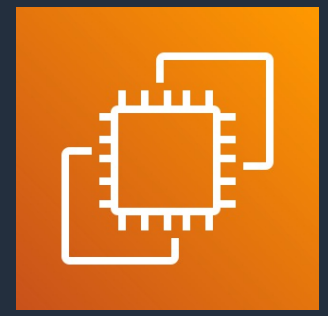
> Finished chain.
```

How to get started on AWS?

Langchain ❤️ AWS: Orchestration Layer

AWS Lambda

Amazon ECS



Amazon EC2

...

Langchain ❤️ AWS: Models

```python
from typing import Dict
from langchain import SagemakerEndpoint
from langchain.llms.sagemaker_endpoint import LLMContentHandler
import json

class ContentHandler(LLMContentHandler):
    content_type = "application/json"
    accepts = "application/json"

    def transform_input(self, prompt: str, model_kwargs: Dict) -> bytes:
        # example transform
        input_str = json.dumps({prompt: prompt, **model_kwargs})
        return input_str.encode('utf-8')

    def transform_output(self, output: bytes) -> str:
        # example transform
        response_json = json.loads(output.read().decode("utf-8"))
        return response_json[0]["generated_text"]

content_handler = ContentHandler()

llm=SagemakerEndpoint(
    endpoint_name="endpoint-name",
    region_name="us-east-1",
    model_kwargs={"temperature":1e-10},
    content_handler=content_handler
)
```

```python
from typing import Dict, List
from langchain.embeddings import SagemakerEndpointEmbeddings
from langchain.llms.sagemaker_endpoint import ContentHandlerBase
import json


class ContentHandler(ContentHandlerBase):
    content_type = "application/json"
    accepts = "application/json"

    def transform_input(self, inputs: list[str], model_kwargs: Dict) -> bytes:
        # example transform
        input_str = json.dumps({"inputs": inputs, **model_kwargs})
        return input_str.encode('utf-8')

    def transform_output(self, output: bytes) -> List[List[float]]:
        # example transform
        response_json = json.loads(output.read().decode("utf-8"))
        return response_json["vectors"]

content_handler = ContentHandler()

embeddings = SagemakerEndpointEmbeddings(
    endpoint_name="endpoint-name",
    region_name="us-east-1",
    content_handler=content_handler
)
```

```python
from langchain.llms.bedrock import Bedrock
from langchain.embeddings import BedrockEmbeddings

llm = Bedrock(model_id="amazon.titan-tg1-large")
embeddings = BedrockEmbeddings(model_id="amazon.titan-e1t-medium")
```

Langchain ❤️ AWS: RAG

Amazon SageMaker Processing

...

Amazon Kendra

Amazon OpenSearch Service

Amazon RDS Postgres

AWS Marketplace

...

Preprocessing

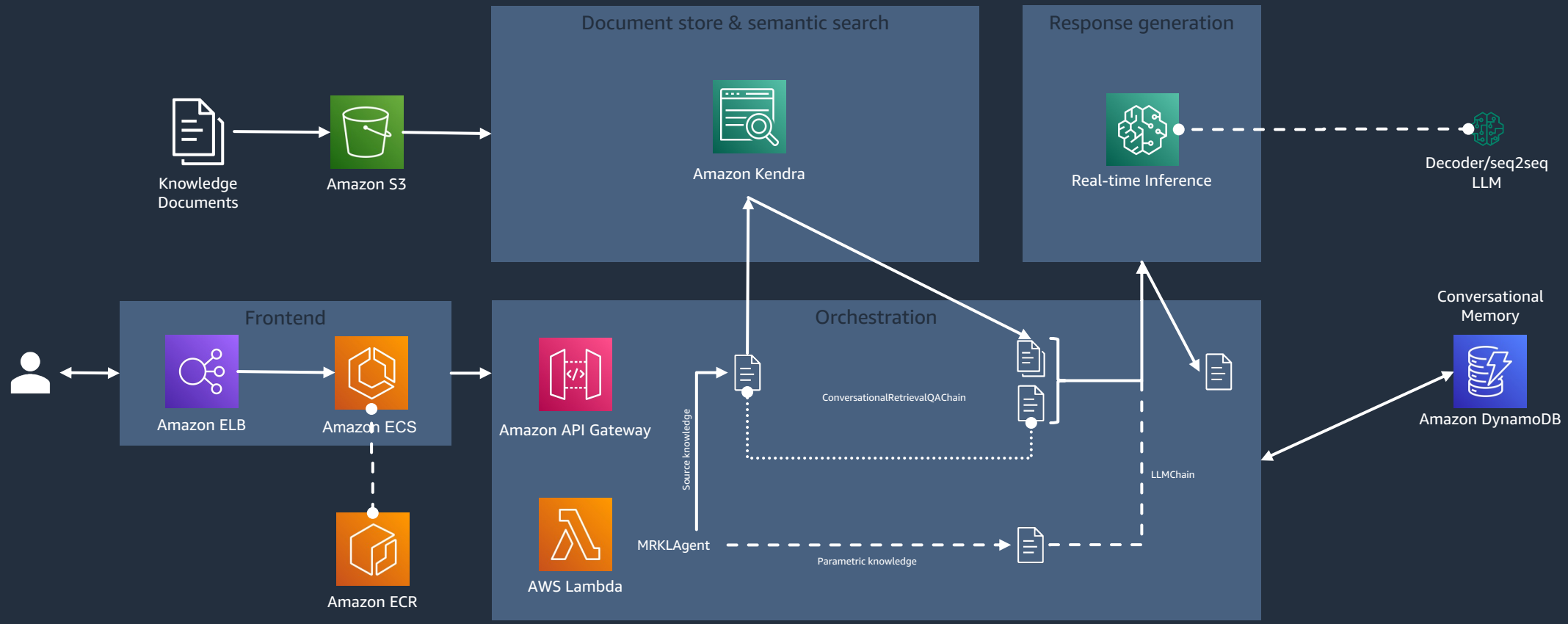
Document store & retrieval

Langchain ❤️ AWS: DynamoDBChatMessageHistory

```
AWSTemplateFormatVersion: "2010-09-09"
Resources:
  MemoryTable:
    Type: AWS::DynamoDB::Table
    Properties:
      TableName: MemoryTable
      AttributeDefinitions:
        - AttributeName: SessionId
          AttributeType: S
      KeySchema:
        - AttributeName: SessionId
          KeyType: HASH
      BillingMode: PAY_PER_REQUEST
```

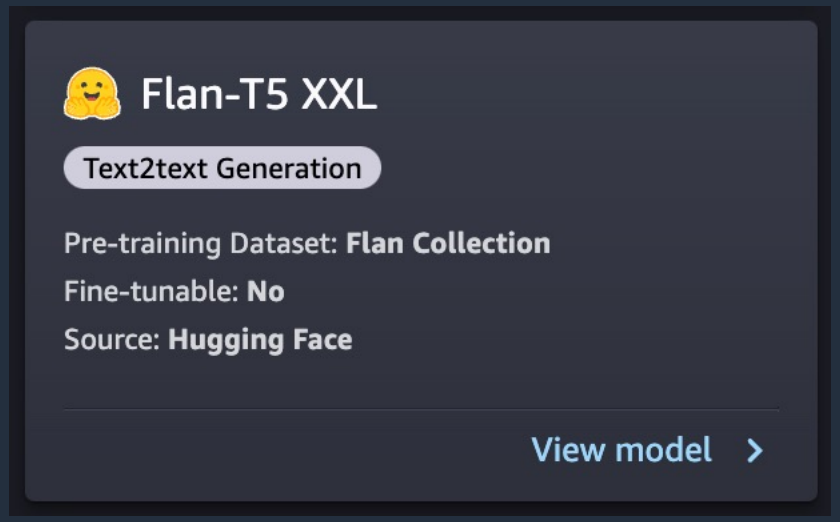
```
from langchain.memory.chat_message_histories import DynamoDBChatMessageHistory

history = DynamoDBChatMessageHistory(table_name="MemoryTable", session_id="0")

history.add_user_message("hi!")

history.add_ai_message("whats up?")
history.messages

# → [HumanMessage(content='hi!', additional_kwargs={}, example=False),
#     AIMessage(content='whats up?', additional_kwargs={}, example=False)]
```

Langchain ❤️ AWS: E2E Architecture



Overview of FLAN-T5-XXL model

- Originating out of the T5 transformer architecture
- Largest version of FLAN-T5 model family
- Fine-tuned LAnguage Net (FLAN) is a technique for instruction tuning to learn how to solve natural language processing tasks in general
- Instruction-fine-tuned encoder-decoder transformer model based on this paper
- Fine-tuned on several datasets (natural instructions only one of them)
- Available through SageMaker JumpStart (FP32, FP16, INT8)



Hyperparameters	Value
Parameters	11 billion
Layers	24

Lab 4 – LLM-powered chatbot with RAG-capabilities and short-term memory

https://github.com/aristsakpinis93/generative-ai-immersion-day

EventHash:

Q&A + CSAT – Please provide feedback!

Thank you!

Aris Tsakpinis

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