GENERATIVE AI IMMERSION DAY

Implementing Generative AI in Organizations

Challenges and Opportunities

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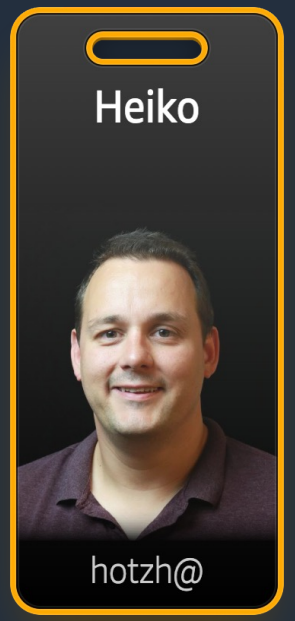
Thanks for having us...



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TIMINGS

Time	Duration	Session
10:00-10:15	15min	Kickoff
10:15-11:15	1h	Generative AI 101 Large Language Models 101 LLM Deployment & Inference
11:115-12:15	1h	Lab 1: LLM Deployment & Inference
12:15-13:15	1h	Lunch
13:15-13:45	30min	LLM Finetuning
13:45-15:00	1h 15min	Lab 2: LLM Finetuning
15:00-15:15	15min	Coffee Break
15:15-16:00	45min	Visual Foundation Models 101 Stable Diffusion
16:00-17:15	1h 15min	Lab 3: Stable Diffusion Deployment & Inference
17:15-17:30	15min	Wrapup
17:30		Get together

AGENDA

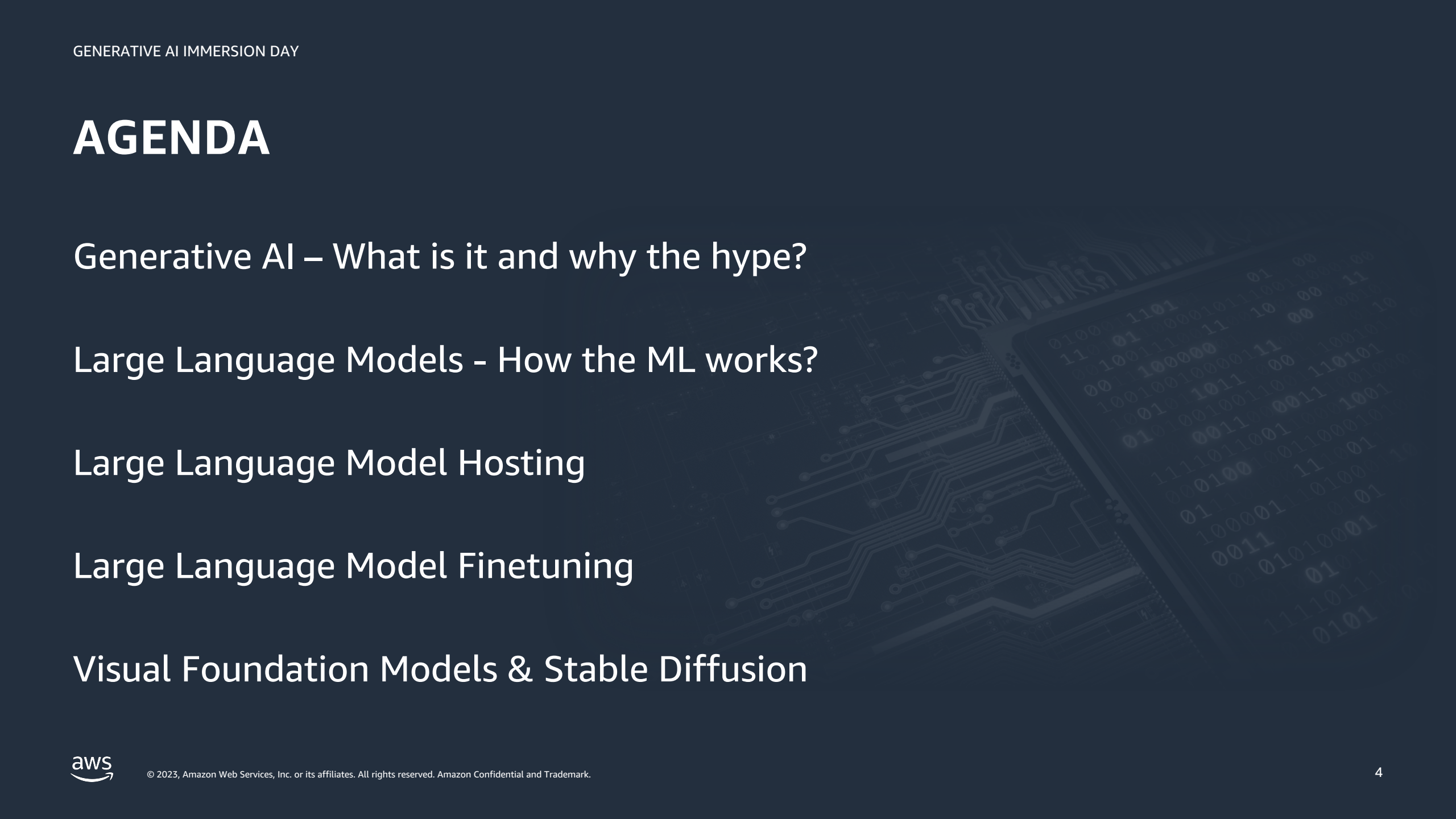
Generative AI – What is it and why the hype?

Large Language Models - How the ML works?

Large Language Model Hosting

Large Language Model Finetuning

Visual Foundation Models & Stable Diffusion



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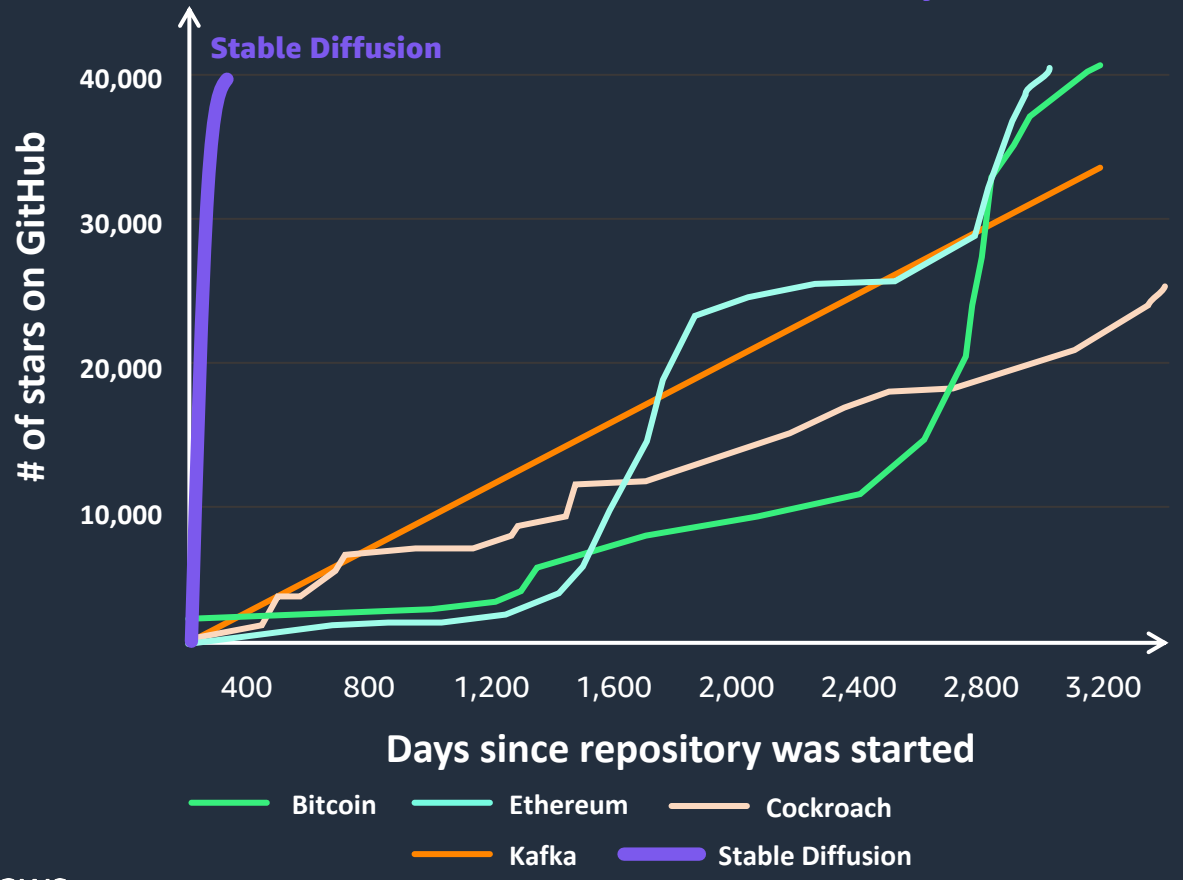
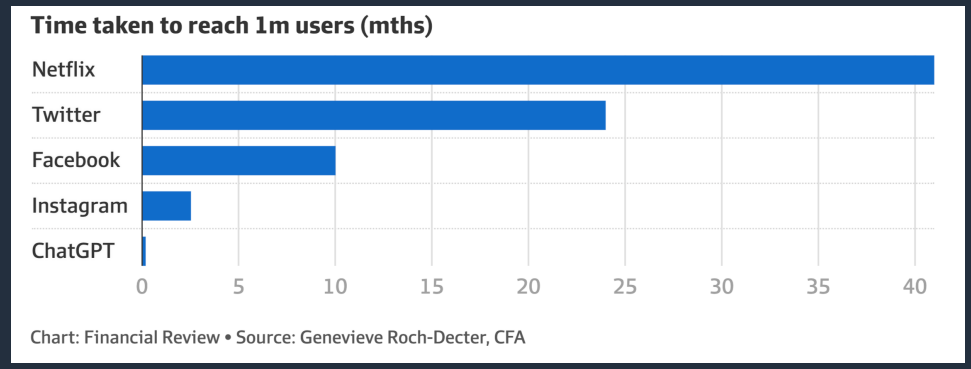
Generative AI is the fastest growing trend in AI

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



ChatGPT reached the 1 million users mark in just 5 days



What is generative AI?

AI that can produce original content close enough to human generated content for real-world tasks

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

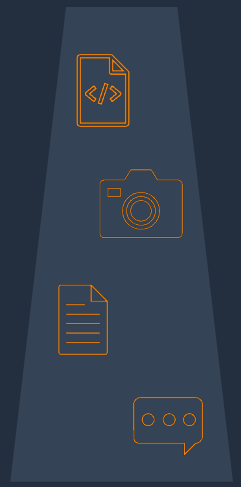
Tasks can be customized for specific domains with minimal fine-tuning

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

Reduces time and cost to develop ML models and innovate faster

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 is emerging across a range of domains ...

Productivity
Text generation

Chat
Virtual assistant

Summarization
Text extraction

Search

Code generation

Image generation

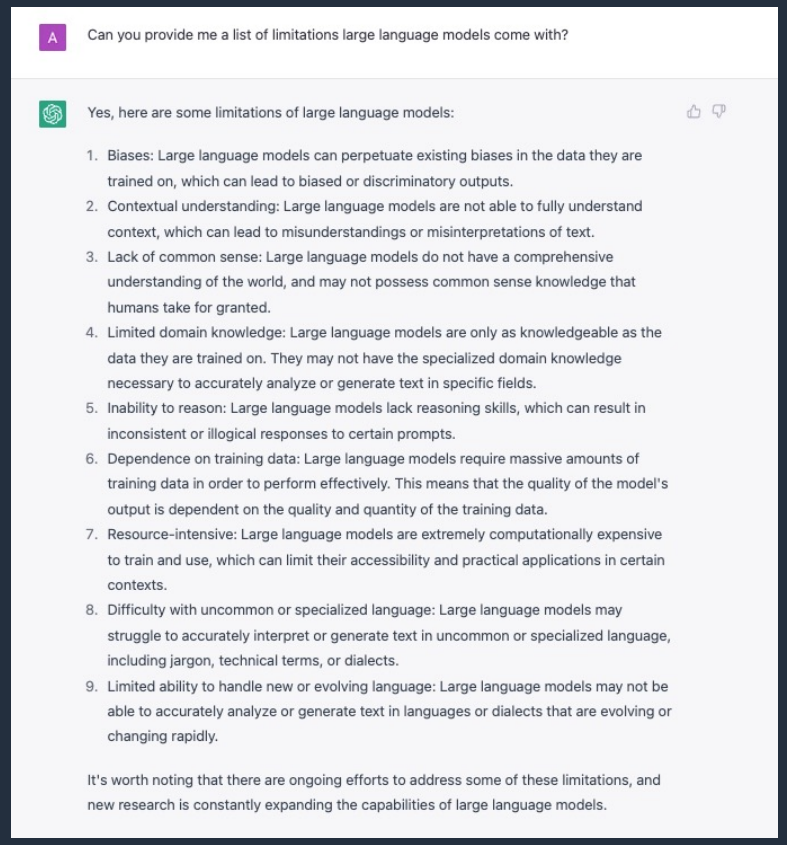
Image classification

Create music

Generate videos

… 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.

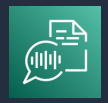
… and it came up with pretty good responses …

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

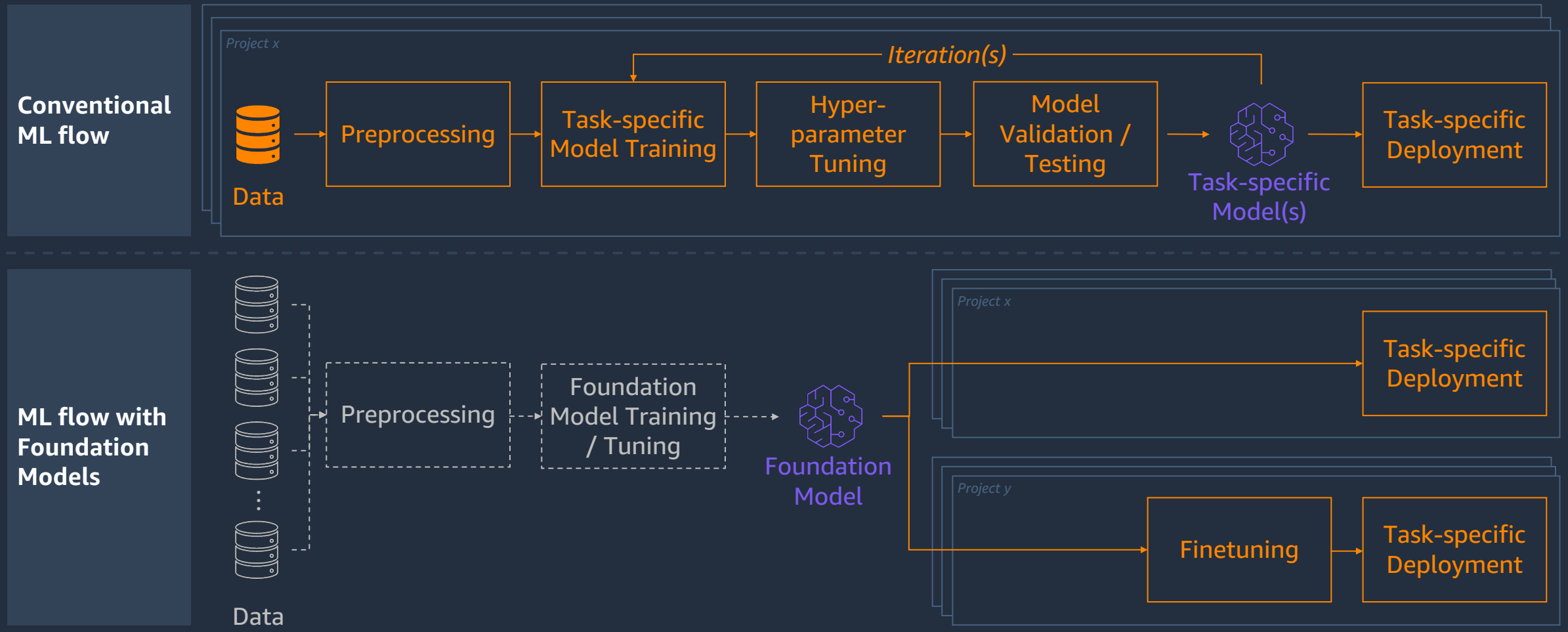
… but missed crucial aspects for enterprise applications

- 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

AGENDA

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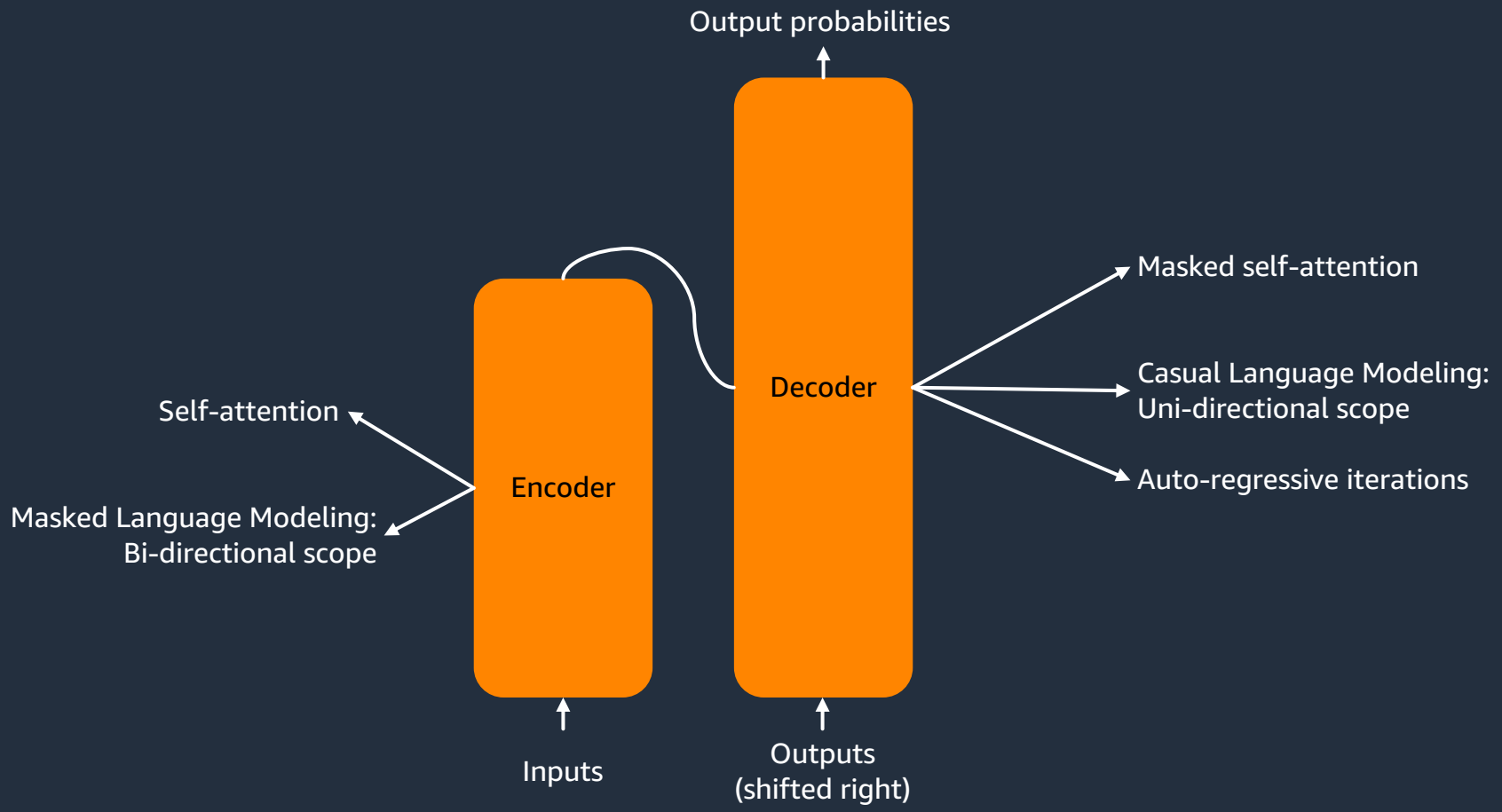
Transformer Models – Core characteristics of sequence-to-sequence transforms



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

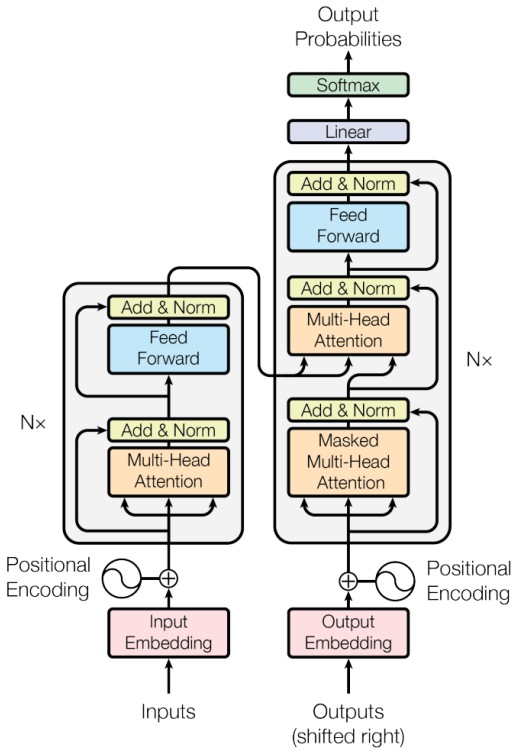
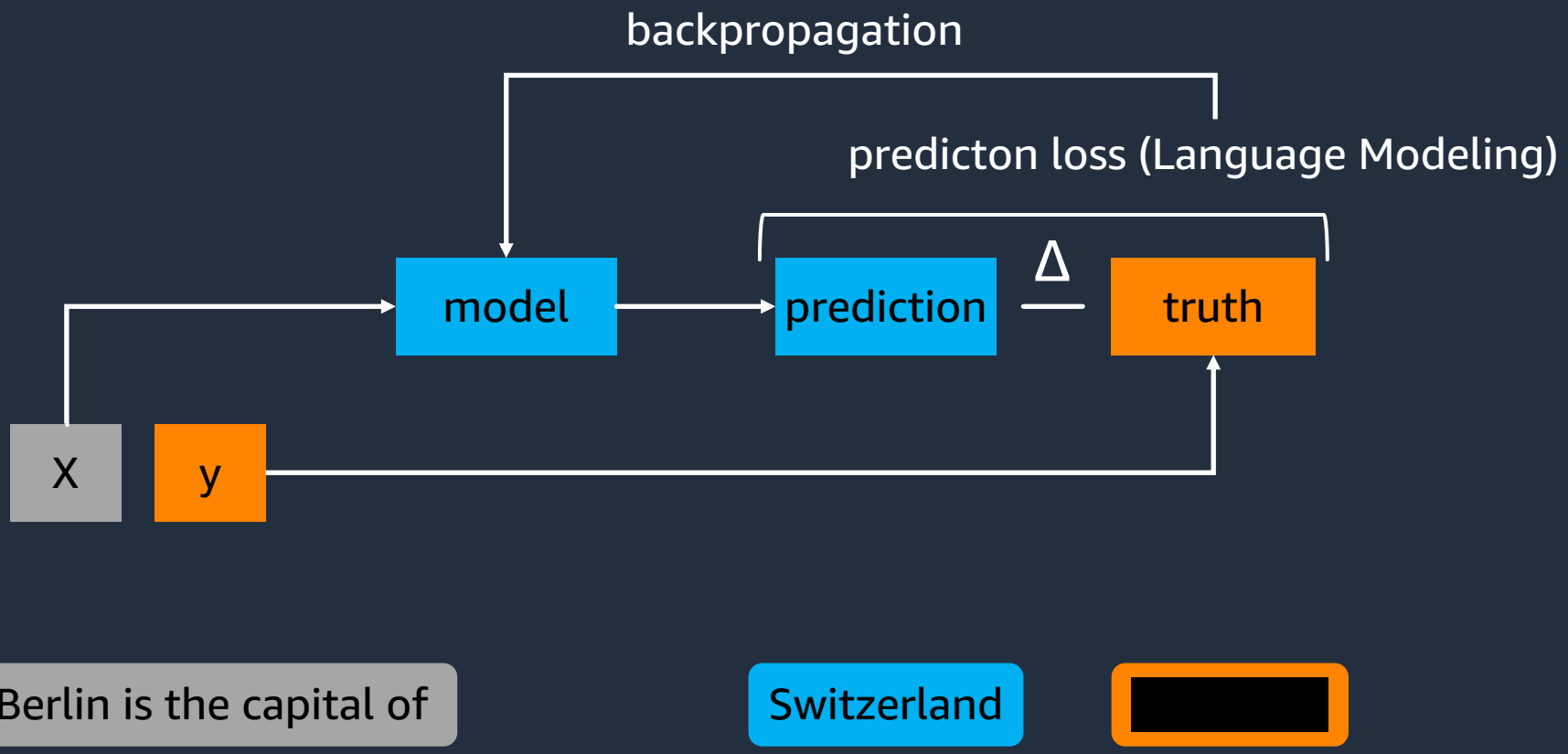


Figure 1: The Transformer - model architecture.

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?

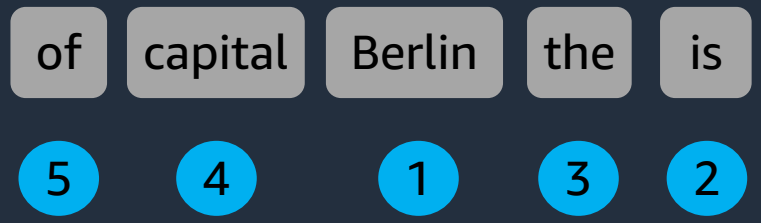


Language Modeling Variations

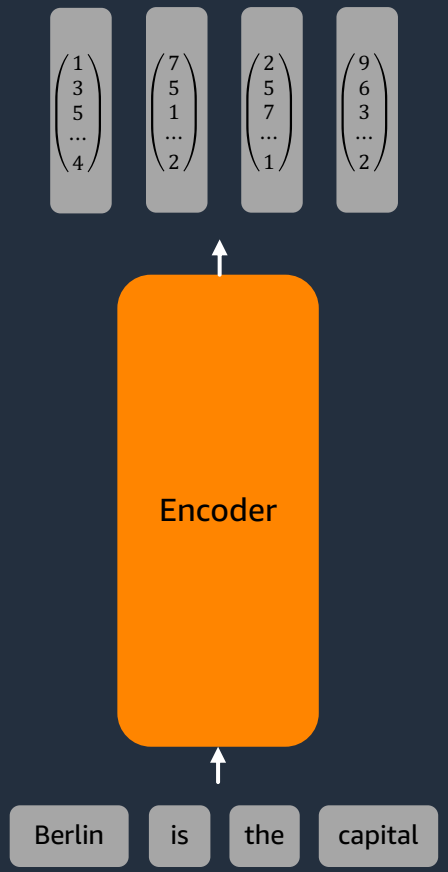
Masked Language Modeling (MLM)

Casual Language Modeling (CLM)

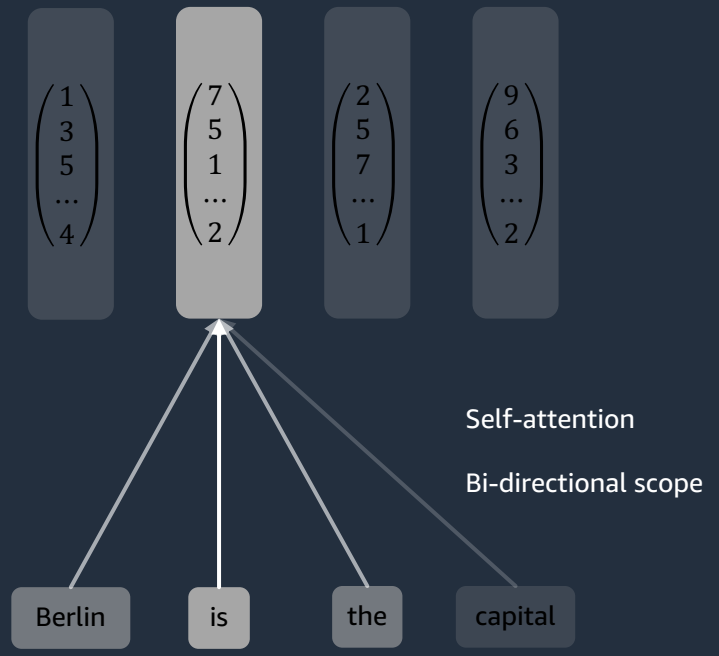
Permutation Language Modeling (PLM)



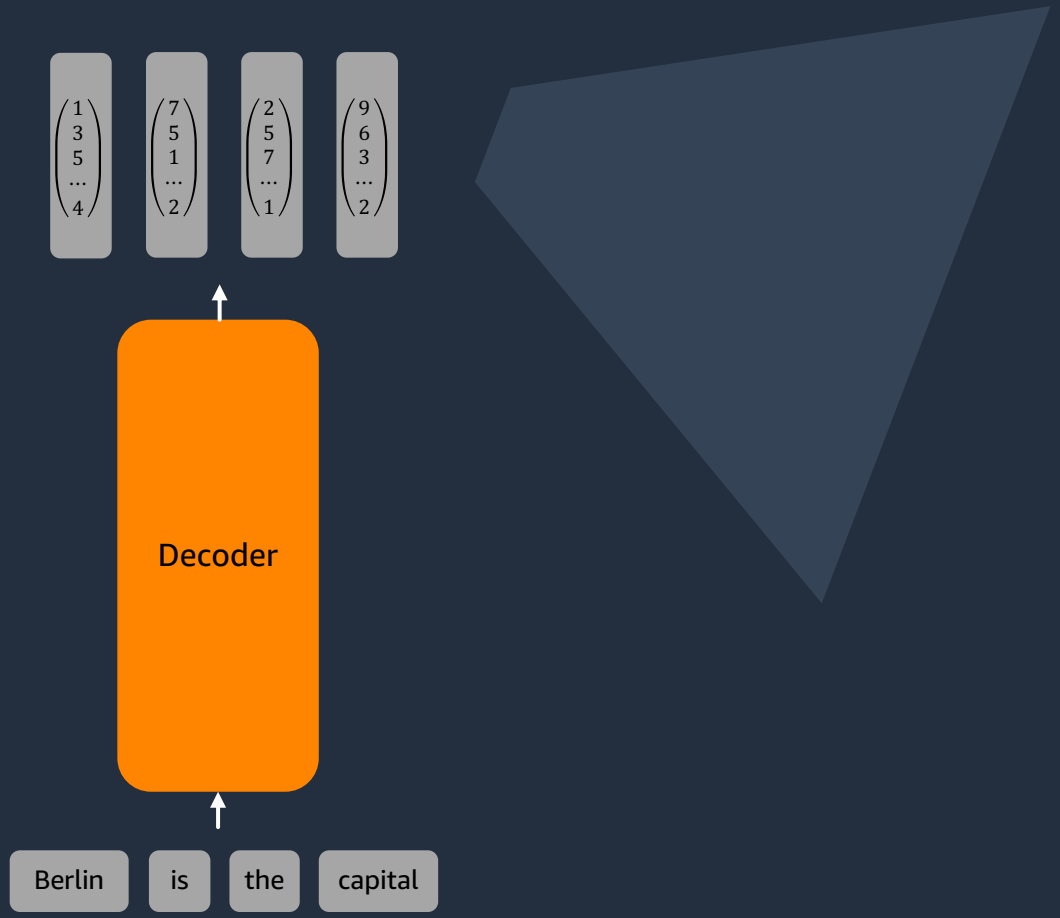
Transformer Models – How Encoders work



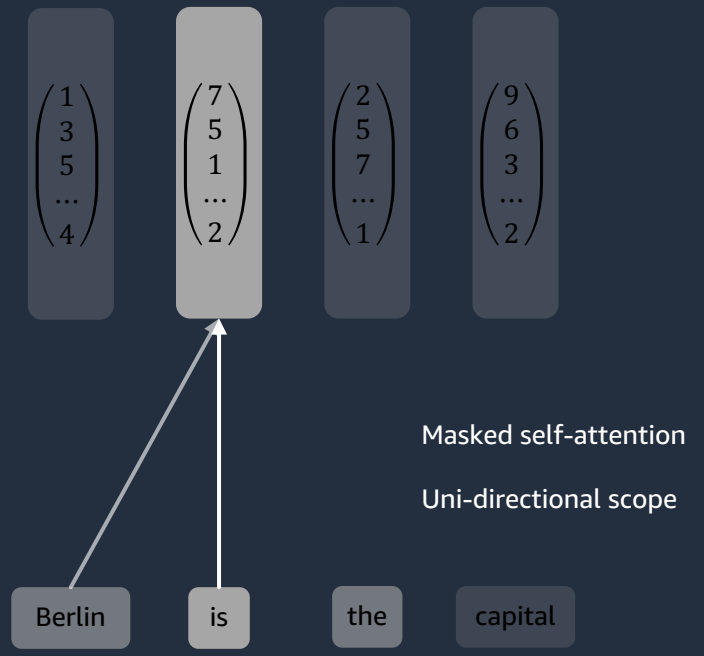
Masked Language Modeling (MLM)



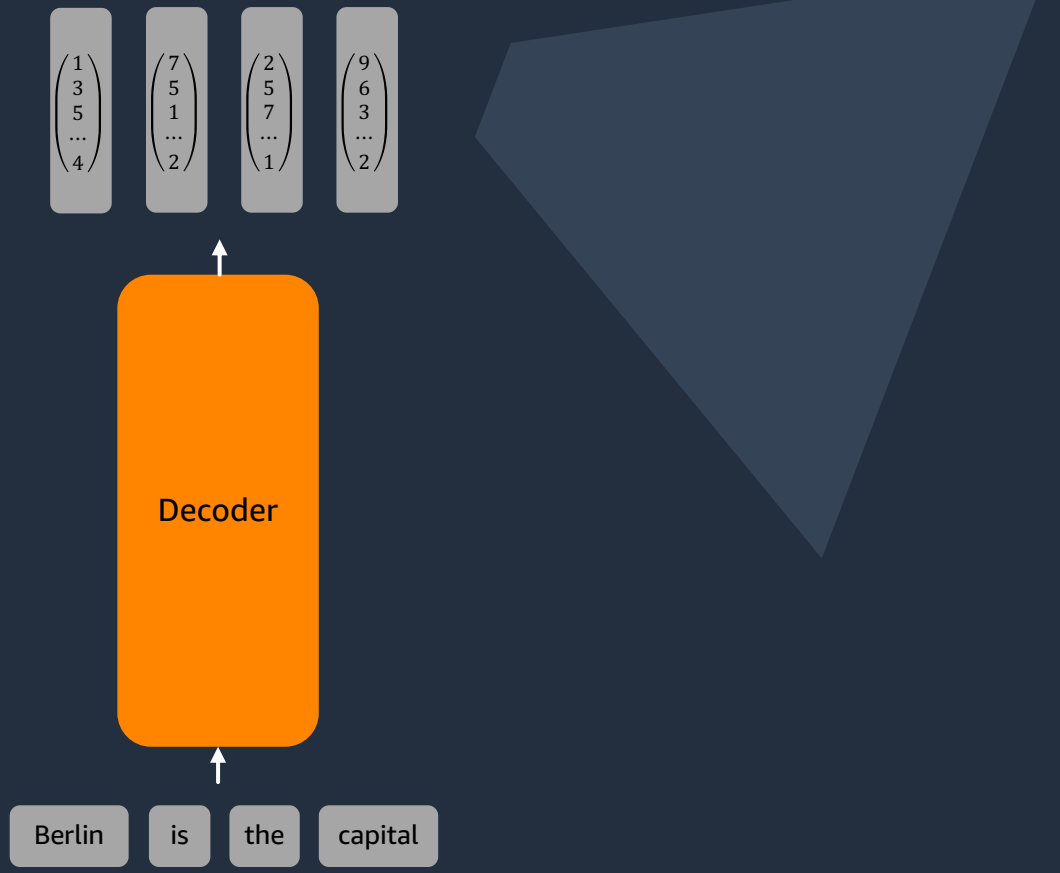
Transformer Models – How Decoders work



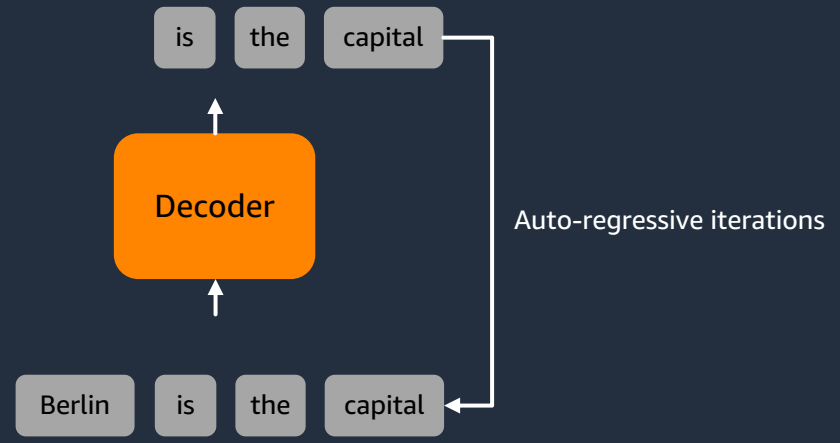
Casual Language Modeling (CLM)



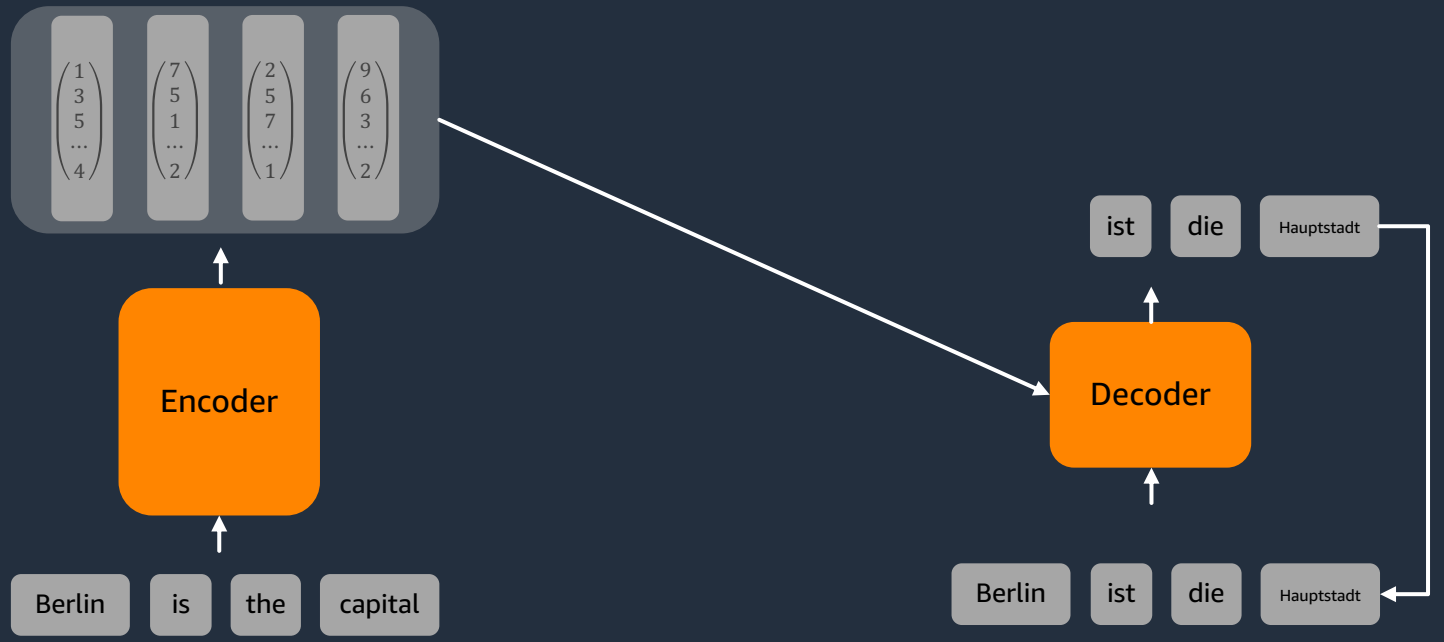
Transformer Models – How Decoders work



Casual Language Modeling (CLM)

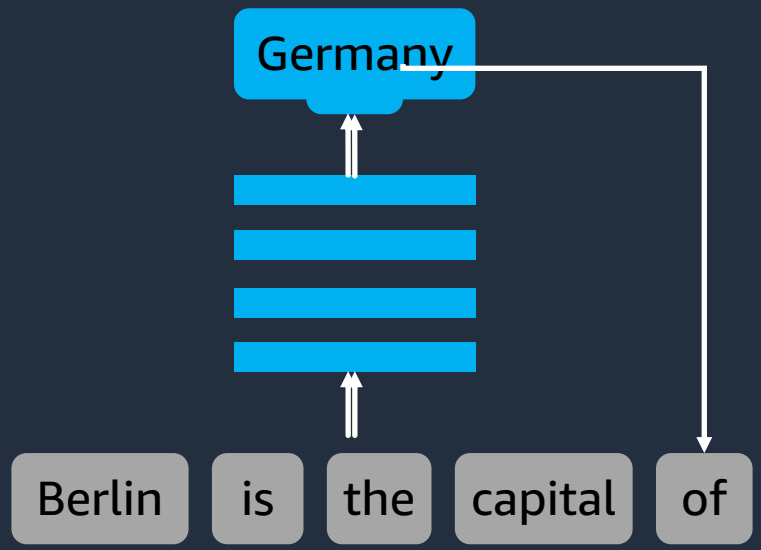


Transformer Models – How Encoders and Decoders work together



How do (decoder) LLMs make predictions?

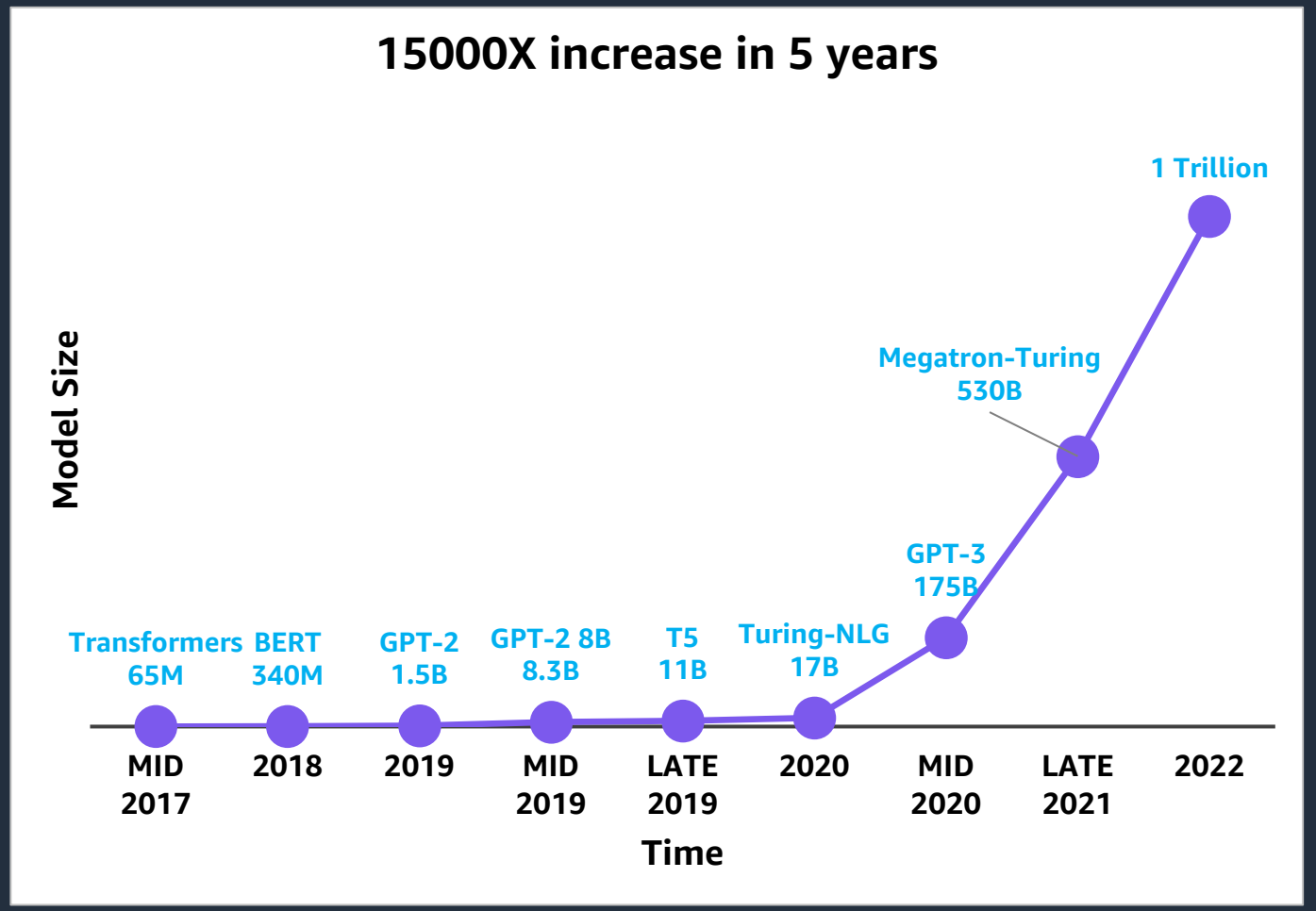
Auto-regressive word-by-word prediction



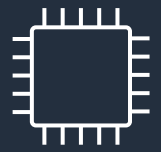
Key trends in AI/ML

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

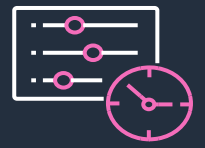


However, when it comes to training and deploying foundation models, there are challenges...



Hardware

Health checks



Orchestration

Data

Scaling up

Cost

AGENDA

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Large model hosting challenges

Complexity

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

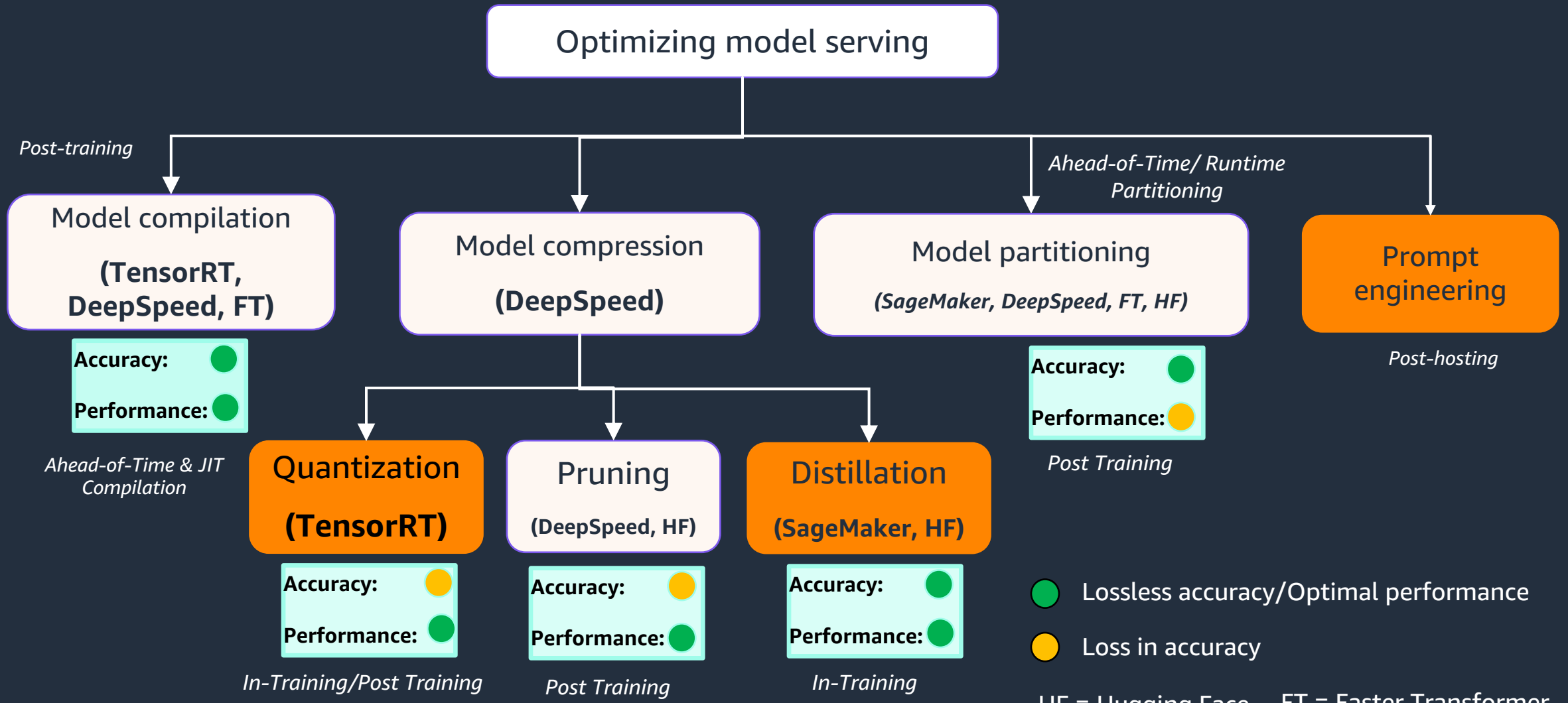
Performance

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

Cost

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

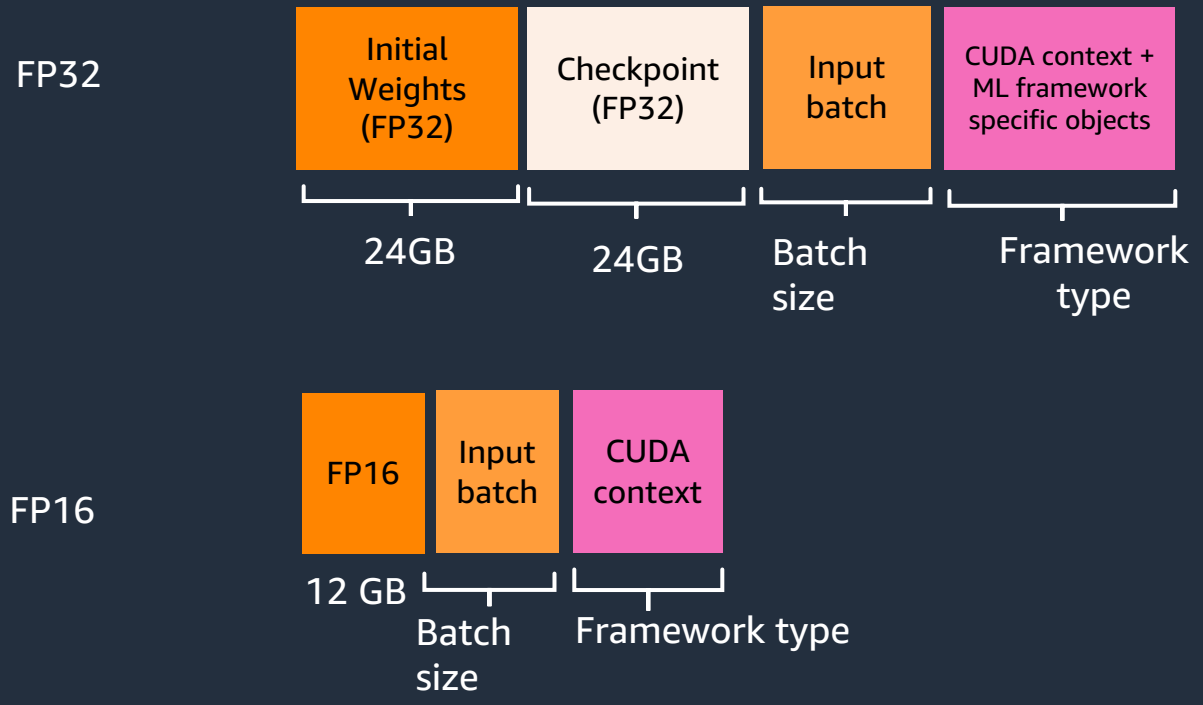
Large model inference optimization

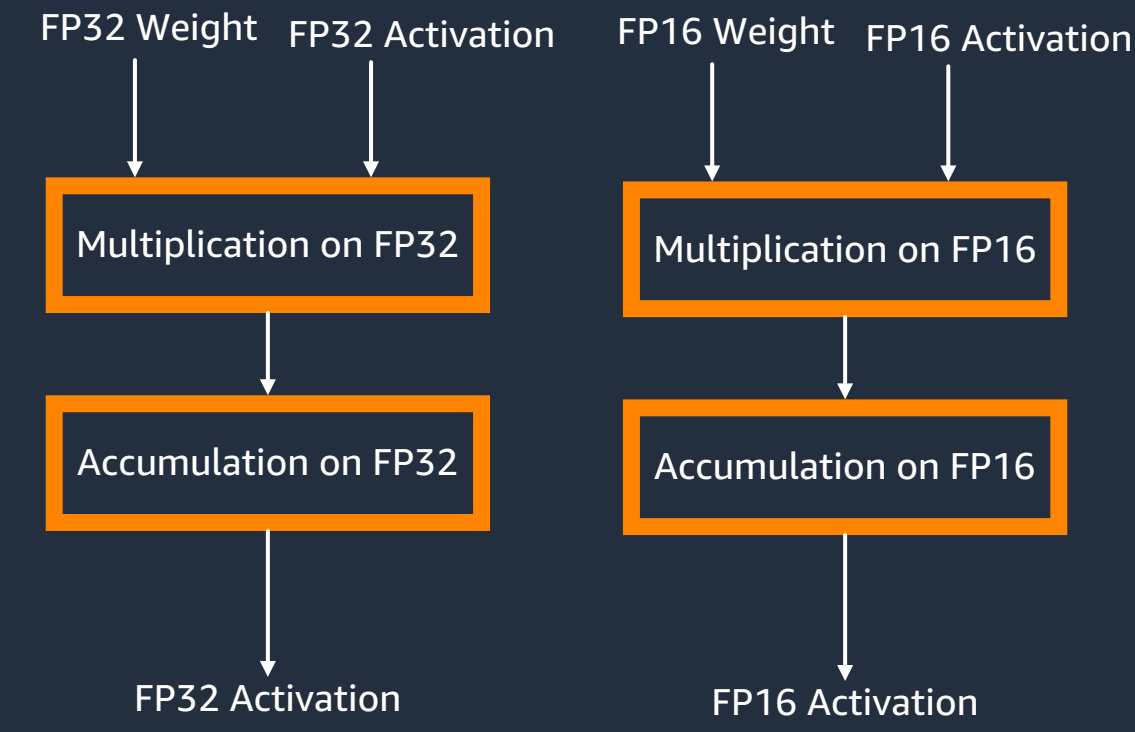


Quantization

Example: GPT-J-6B (FP16)

Model serving:



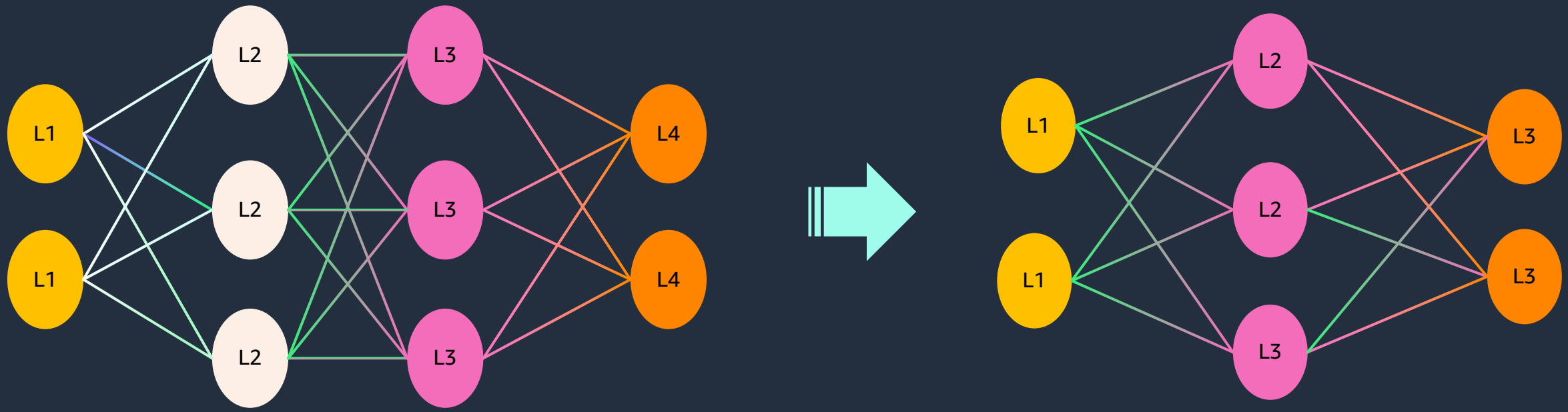


Full precision inference

Half precision inference

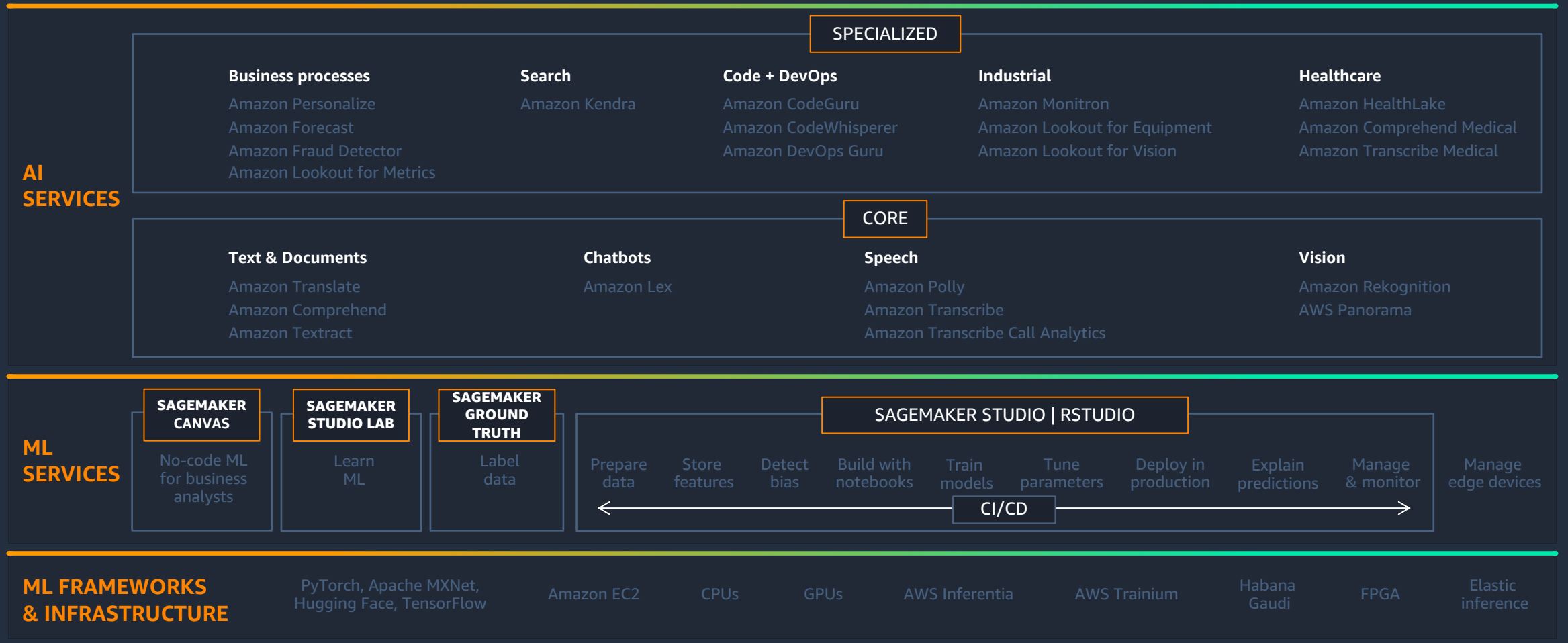
Knowledge Distillation

EXAMPLE: DISTILGPT2

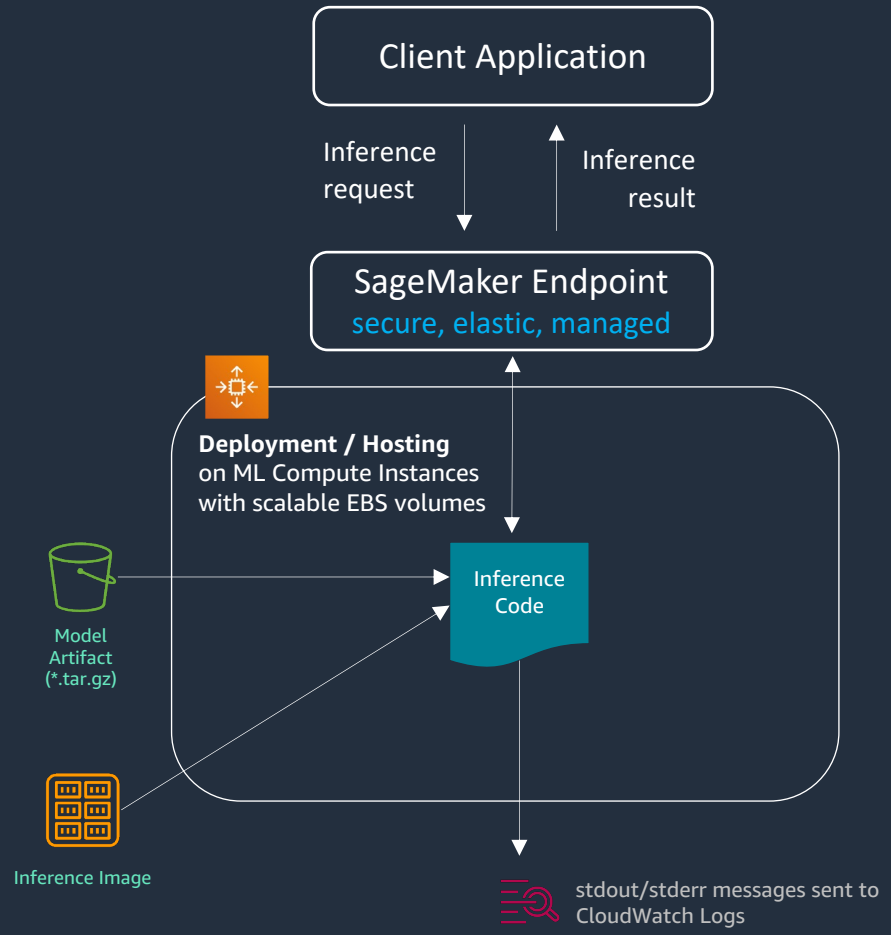


The AWS ML stack

BROADEST AND MOST COMPLETE SET OF MACHINE LEARNING CAPABILITIES



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

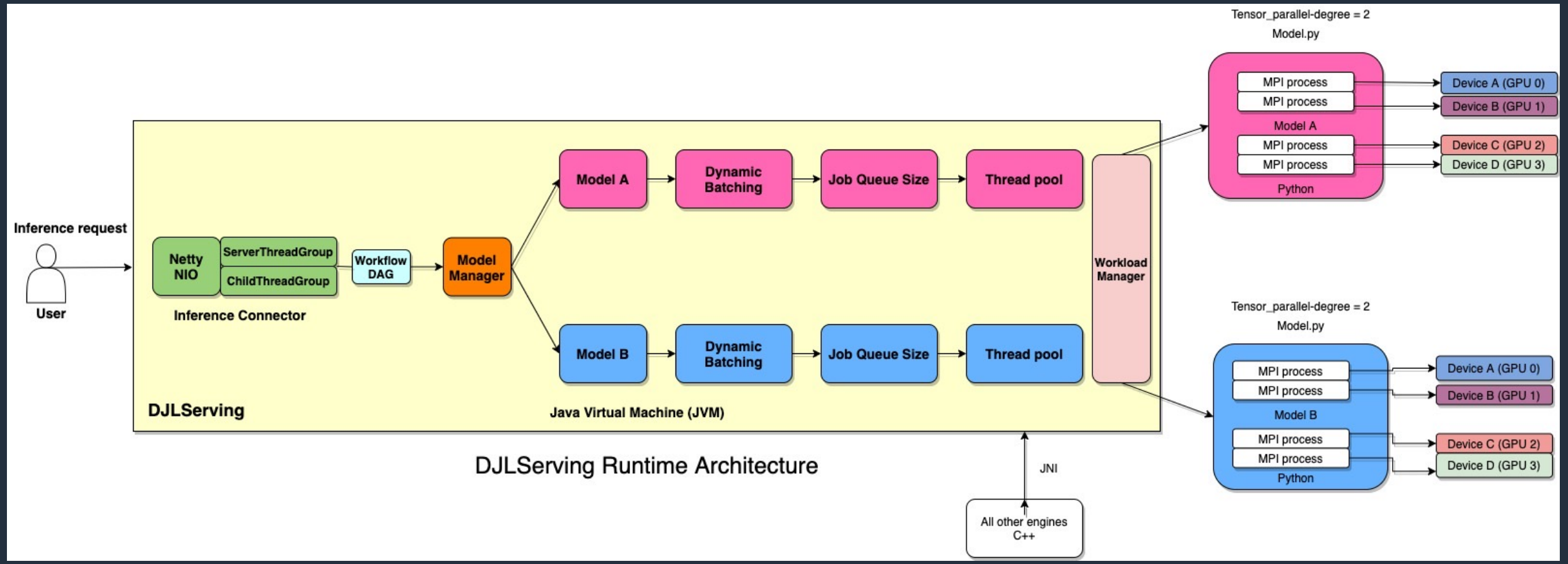
Easily parallelize models across multiple GPUs to fit models into the instance and achieve low latency

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

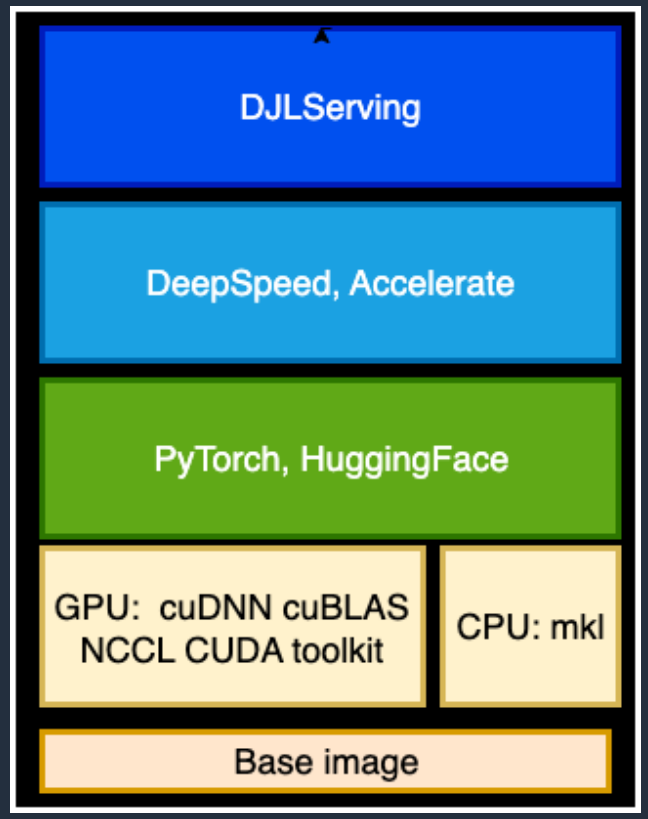
DJLServing using DeepSpeed on SageMaker



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



aws

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 | ONNX | 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?

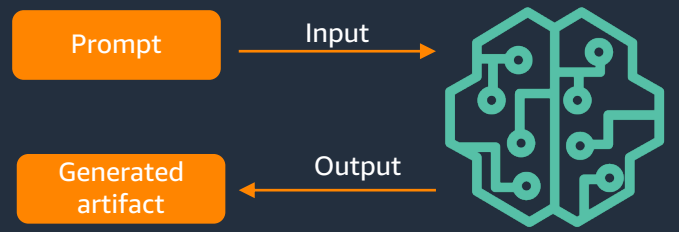
▶ Generate text

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

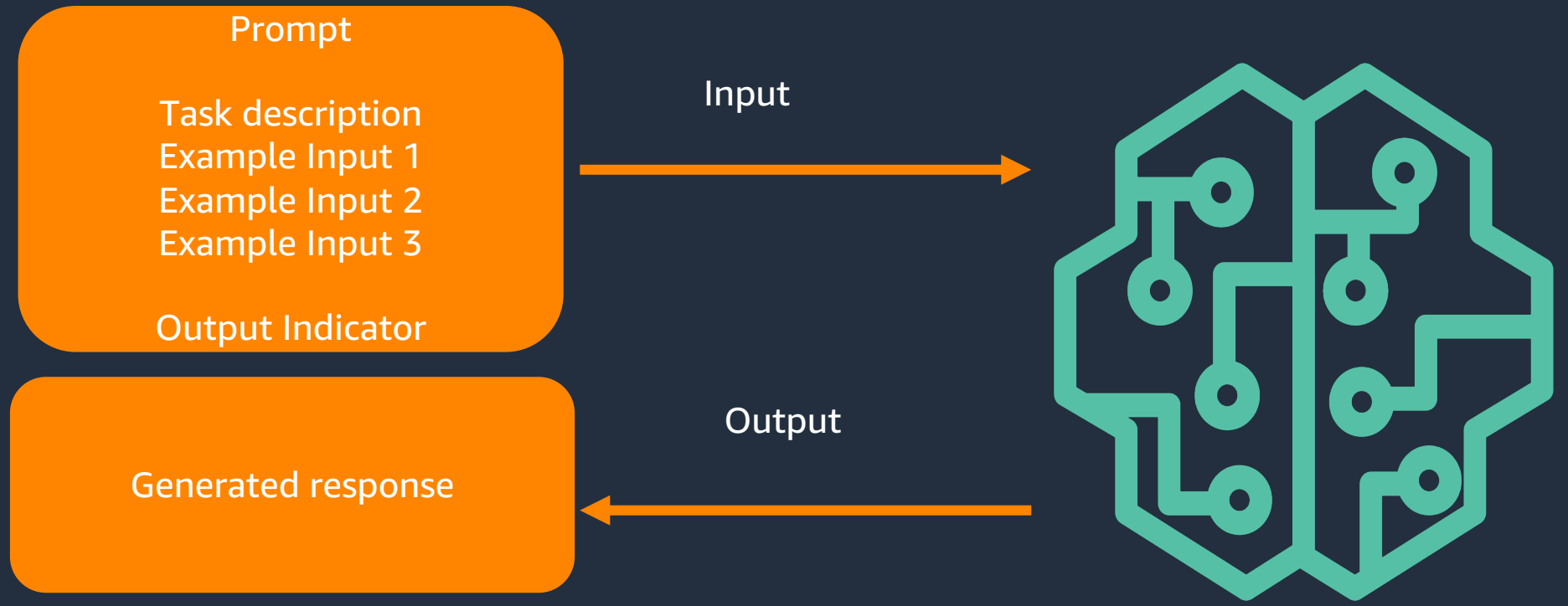
Output

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

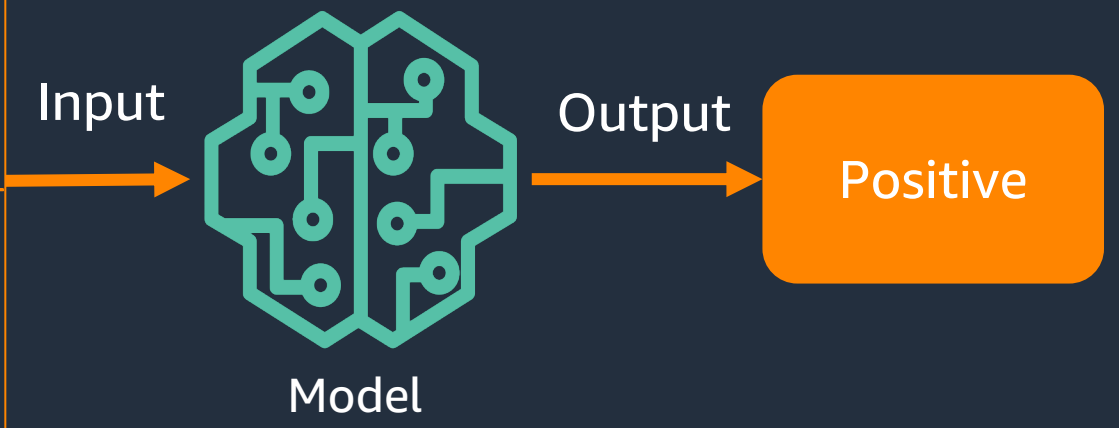
Movie review sentiment classifier.

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

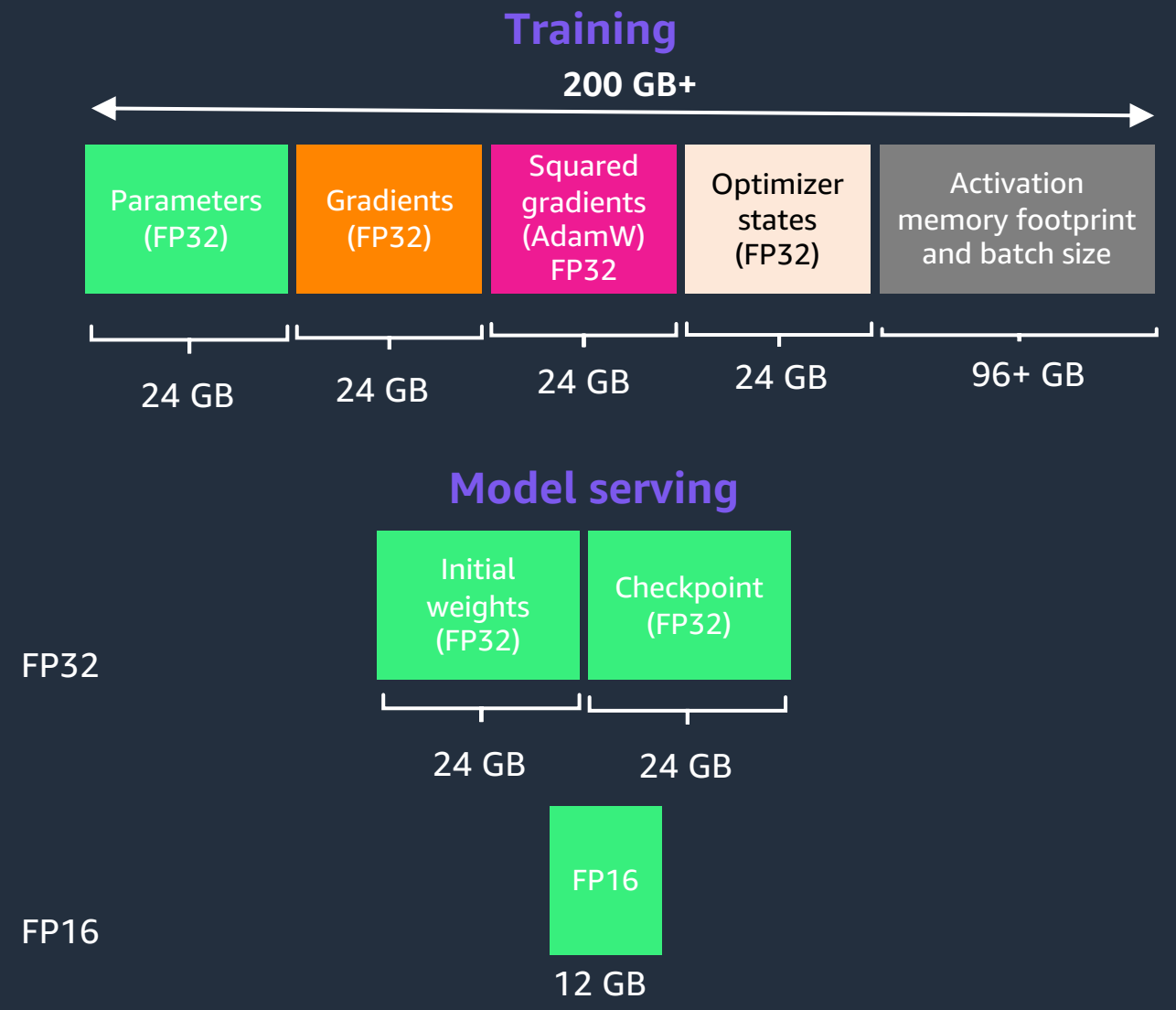
Output indicator



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?

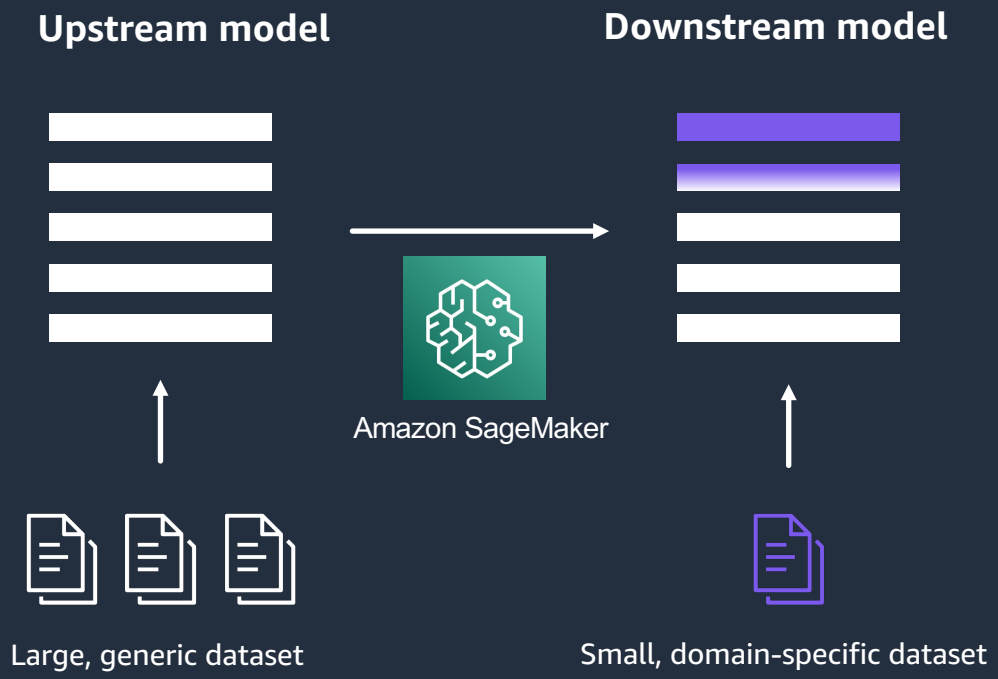
Large Language Models - How the ML works?

Large Language Model Hosting

Large Language Model Finetuning

Visual Foundation Models & Stable Diffusion

Improving LLM performance by fine-tuning



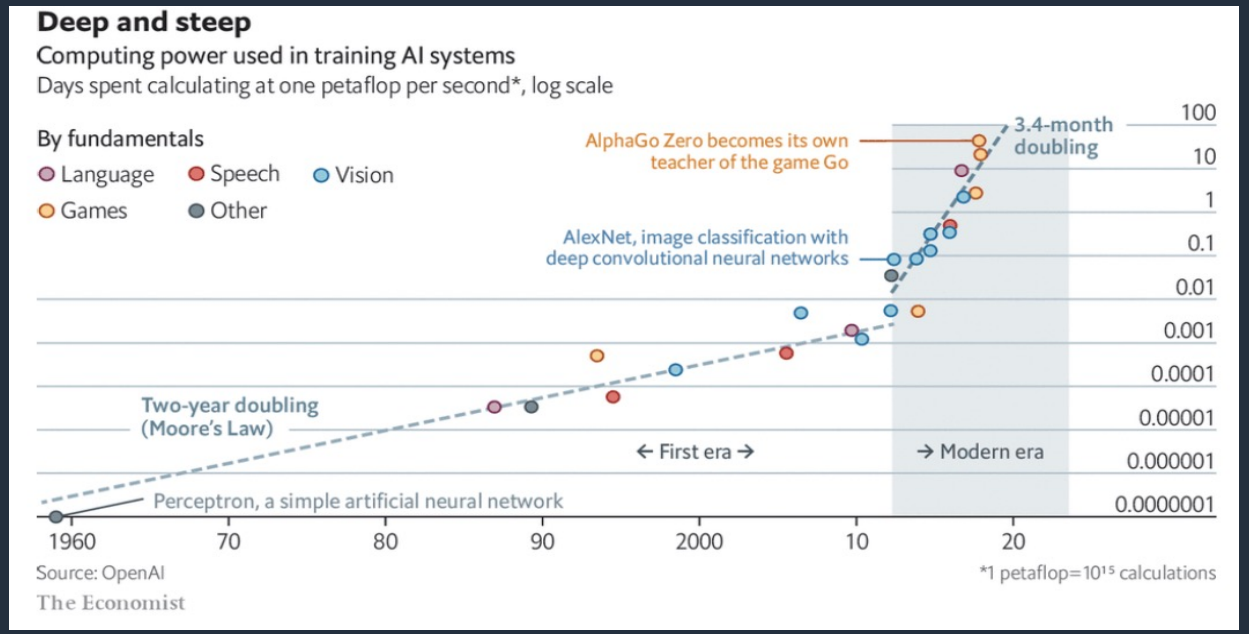
- Transfer learning of domain-specific knowledge into a foundation model at reasonable cost
- Update of weights in the network, while architecture is kept
- Fine-tuning is task-specific (e.g., MLM, CLM, PLM, translation, classification, …)

Challenges with large model training

MODELS GROW FASTER THAN HARDWARE, LEADING TO BOTTLENECKS

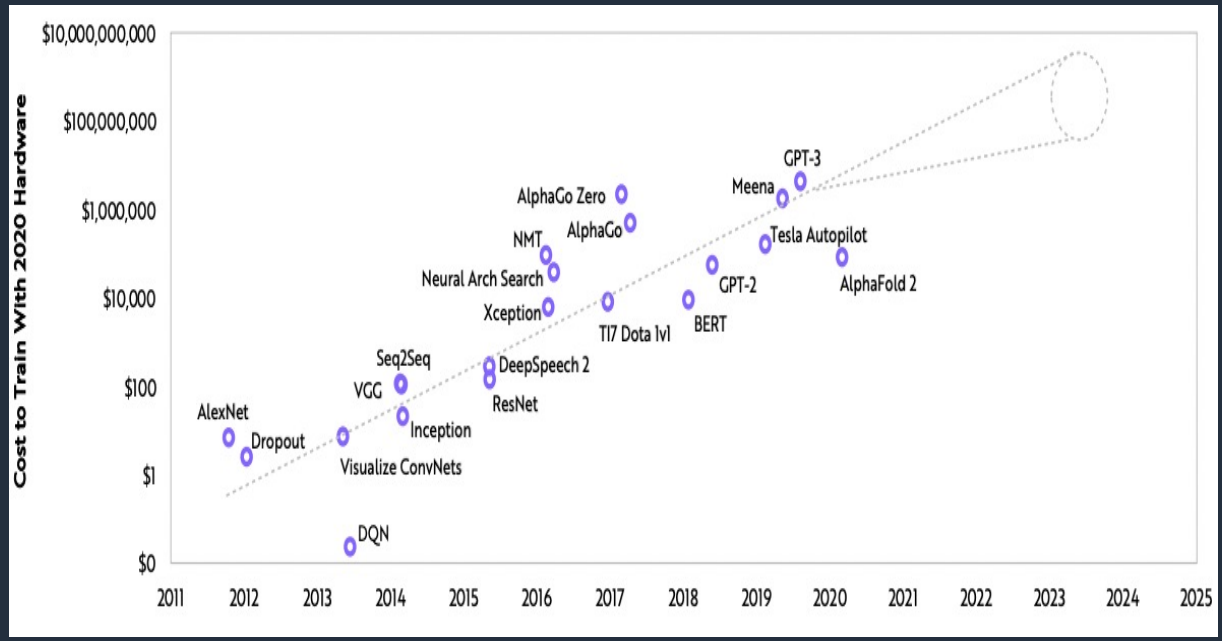
INCREASING COMPLEXITY

Compute power ~ 2x every 3.4 months

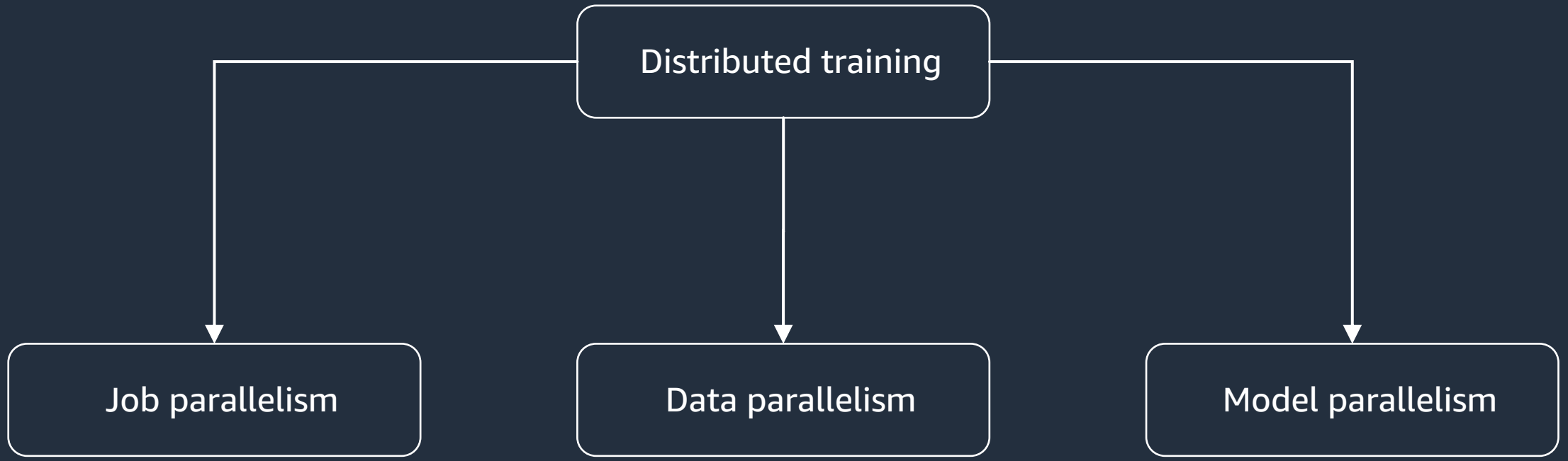


INCREASING COSTS

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



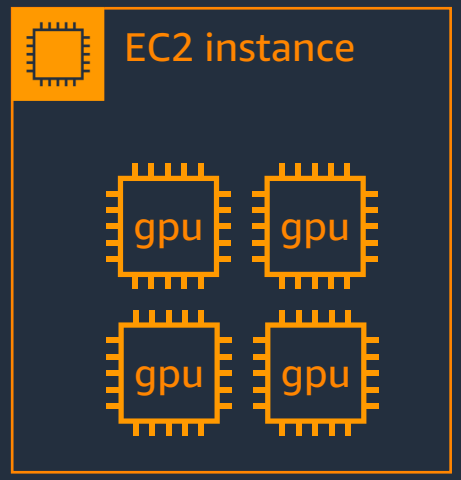
SageMaker distributed training options



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)

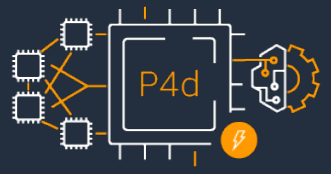


Hardware acceleration is a must:

BERT Training time:

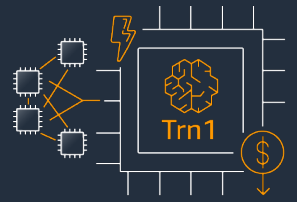
7.5 days on 8 NVIDIA V100	→ 1 p3dn.24xlarge
Or **62 minutes on 2048 NVIDIA V100**	→ 256 p3dn.24xlarge
Up to **3.1x speed up** with **8 NVIDIA A100**	→ 1 p4d.24xlarge

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

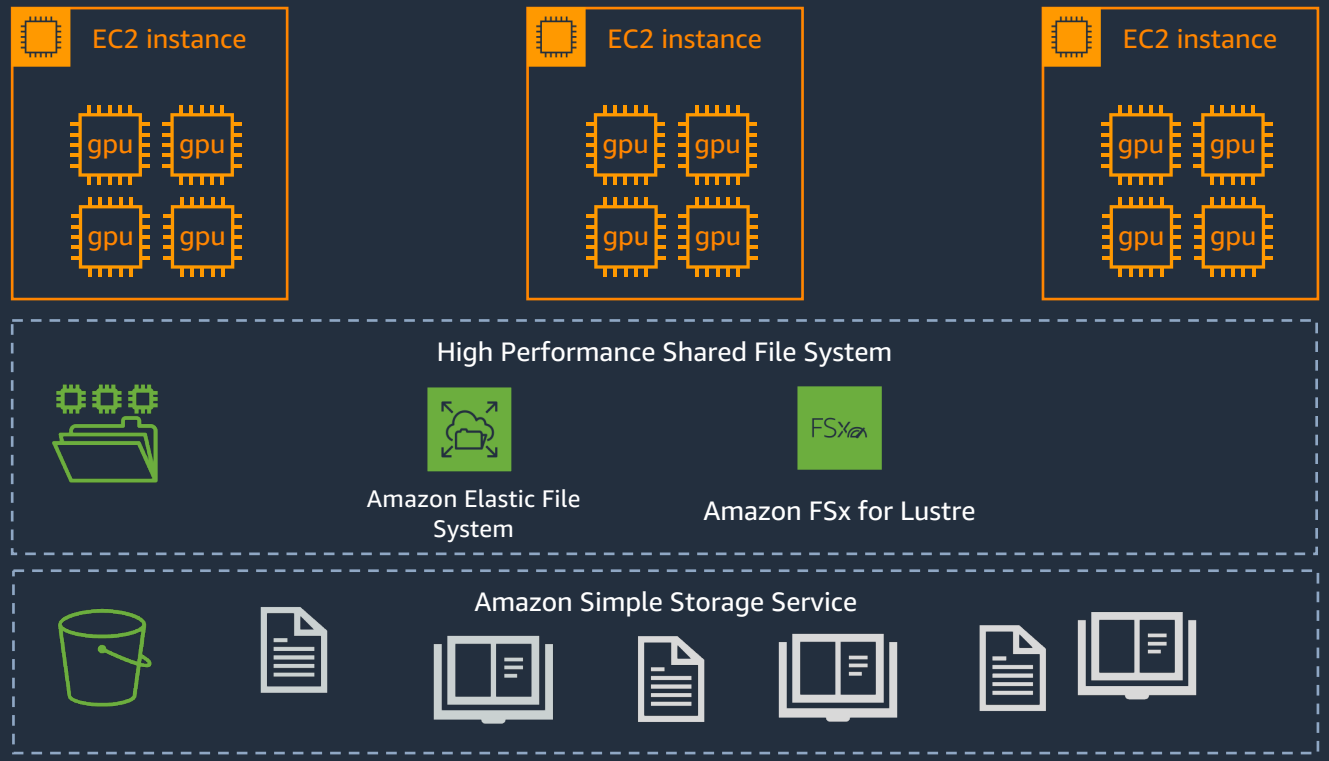
DL1: Custom ML acceleration

- 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:

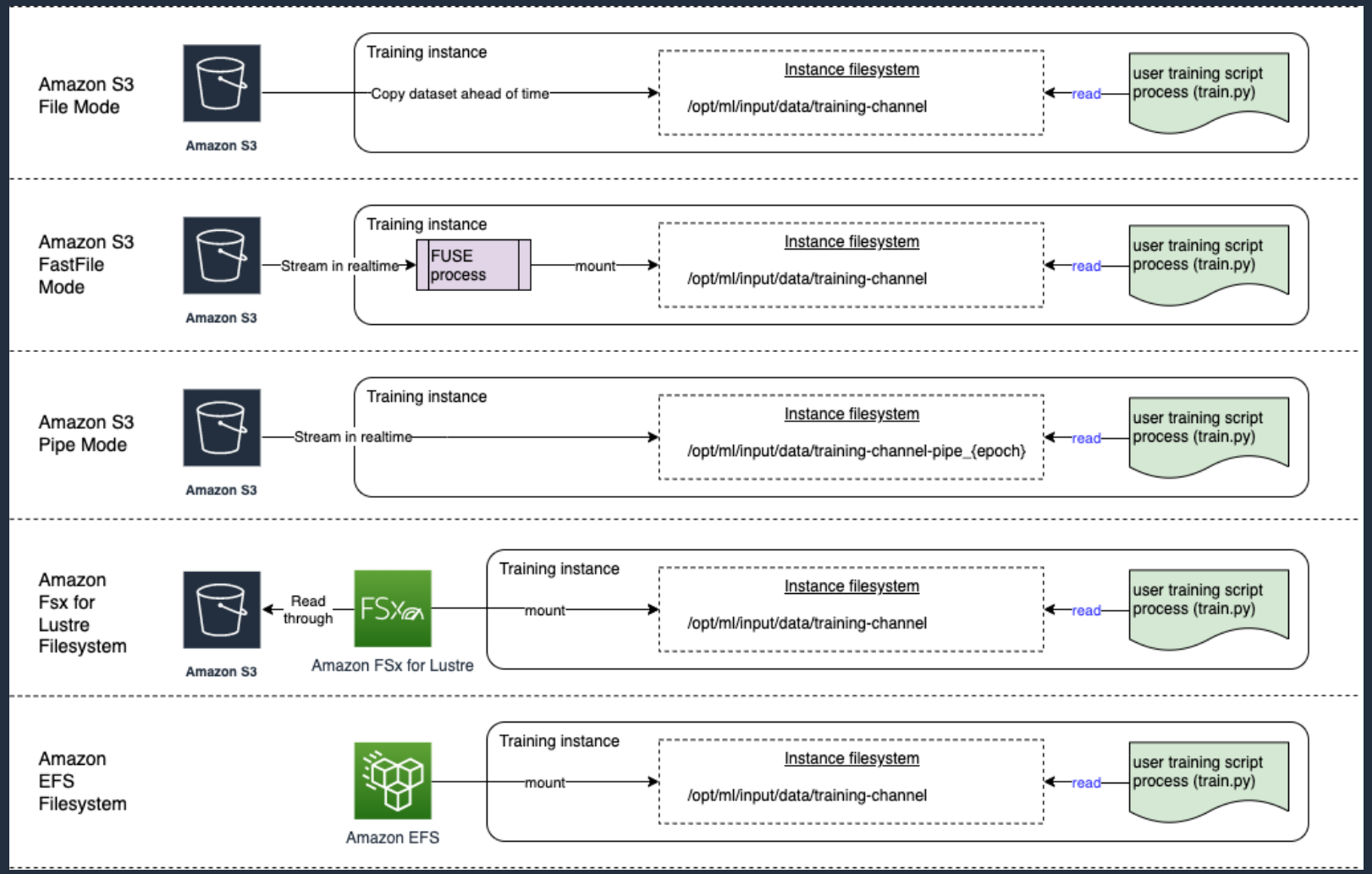
Mini batch + data loader strategy during training is key.

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!

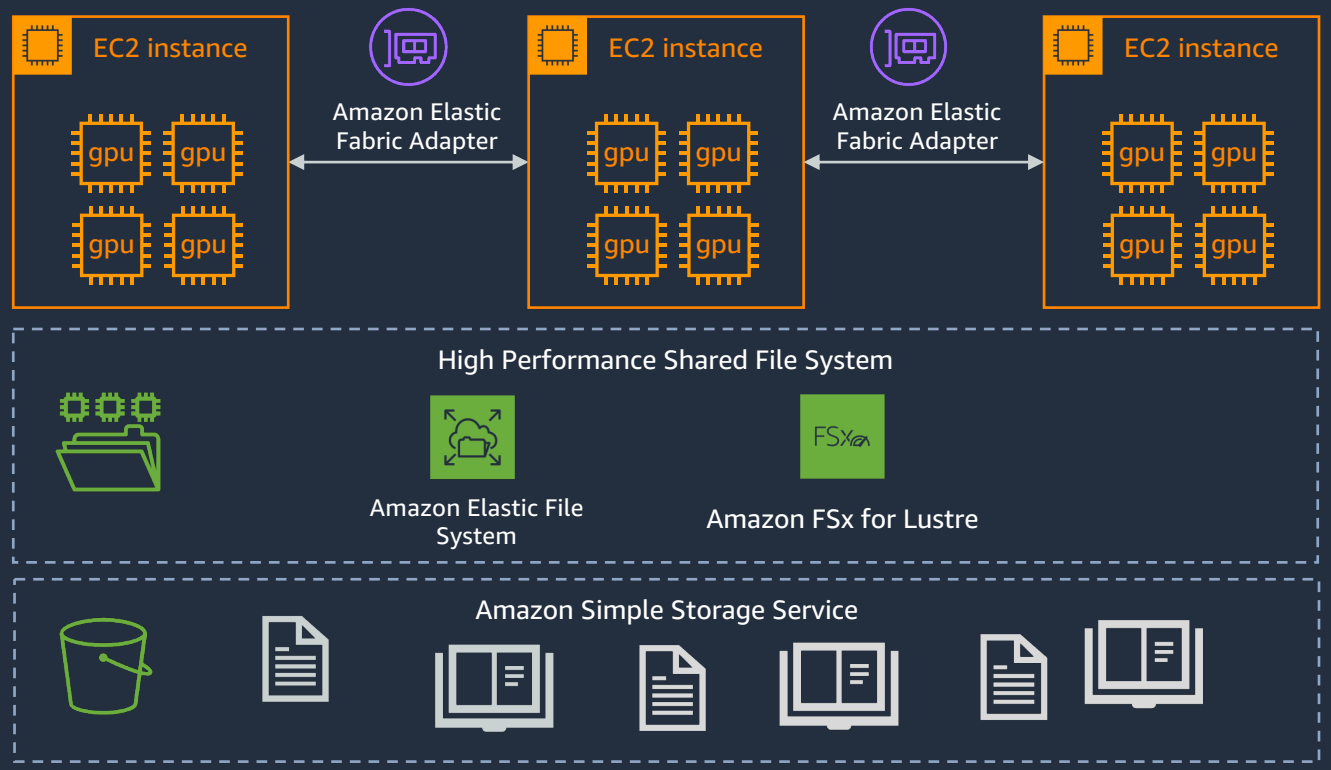
Pick the right data option for SageMaker Training



Networking Challenges for ML Training

Gradient descent over multi-node multi-gpu architecture:

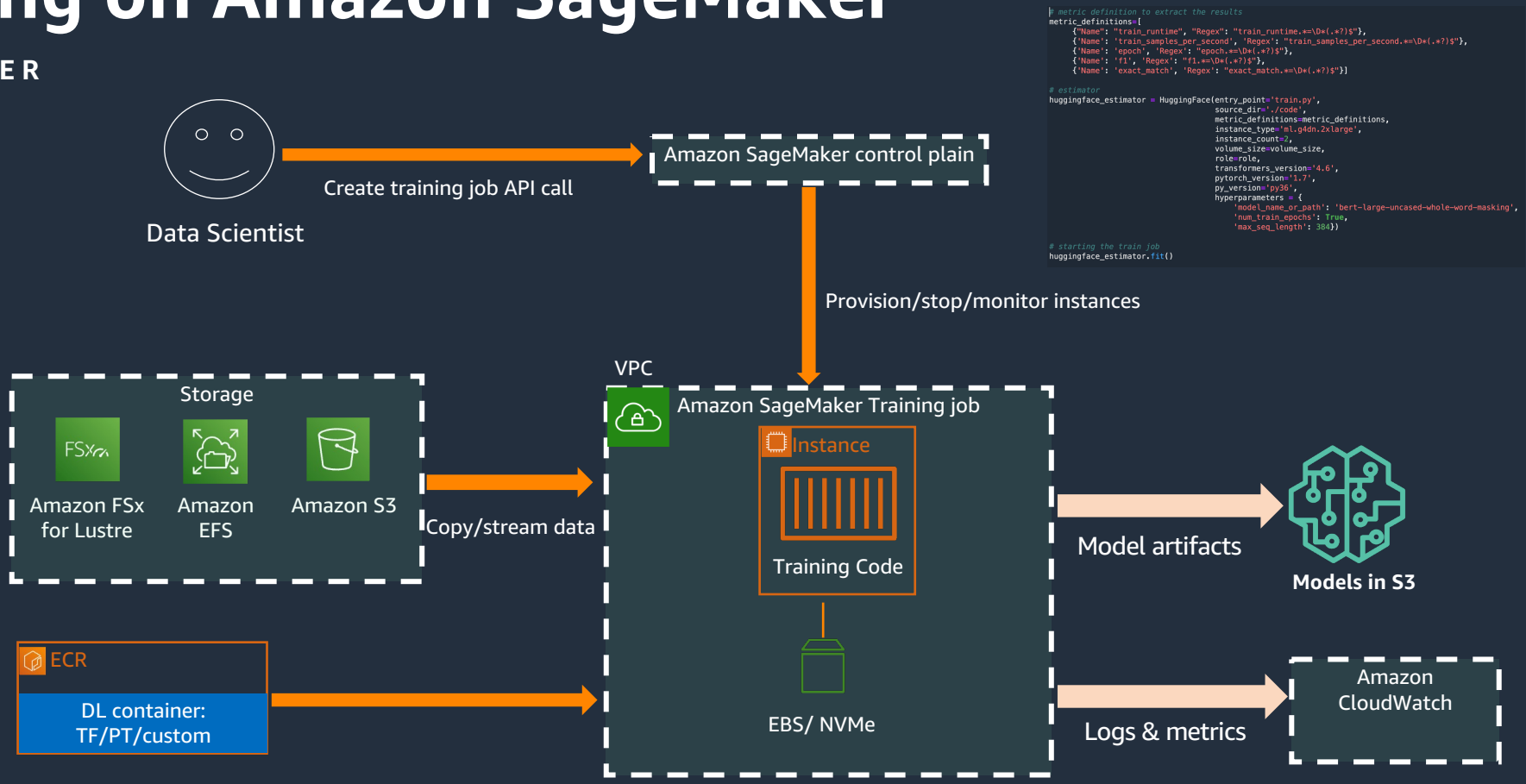
- Model + mini-batch data fits on single GPU: Data Parallel Training
- Model + mini-batch needs multiple GPUs: Model Parallel Training



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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                                        'max_seq_length': 384})

# 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

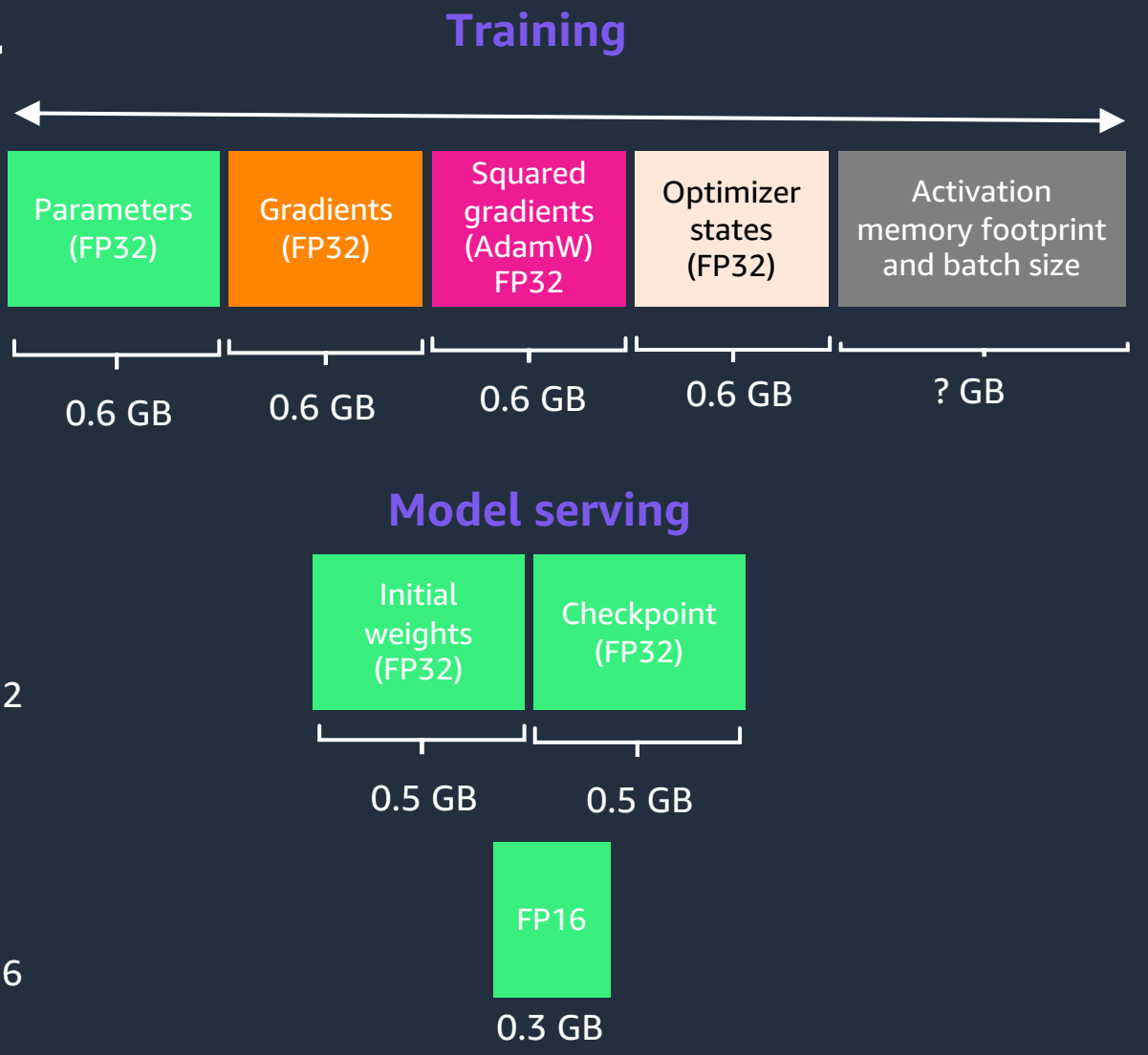
ML COMPUTE INSTANCES & ACCELERATORS

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

Generative AI is transforming AI

IMAGE GENERATION, TRANSFORMATION, UPSCALING

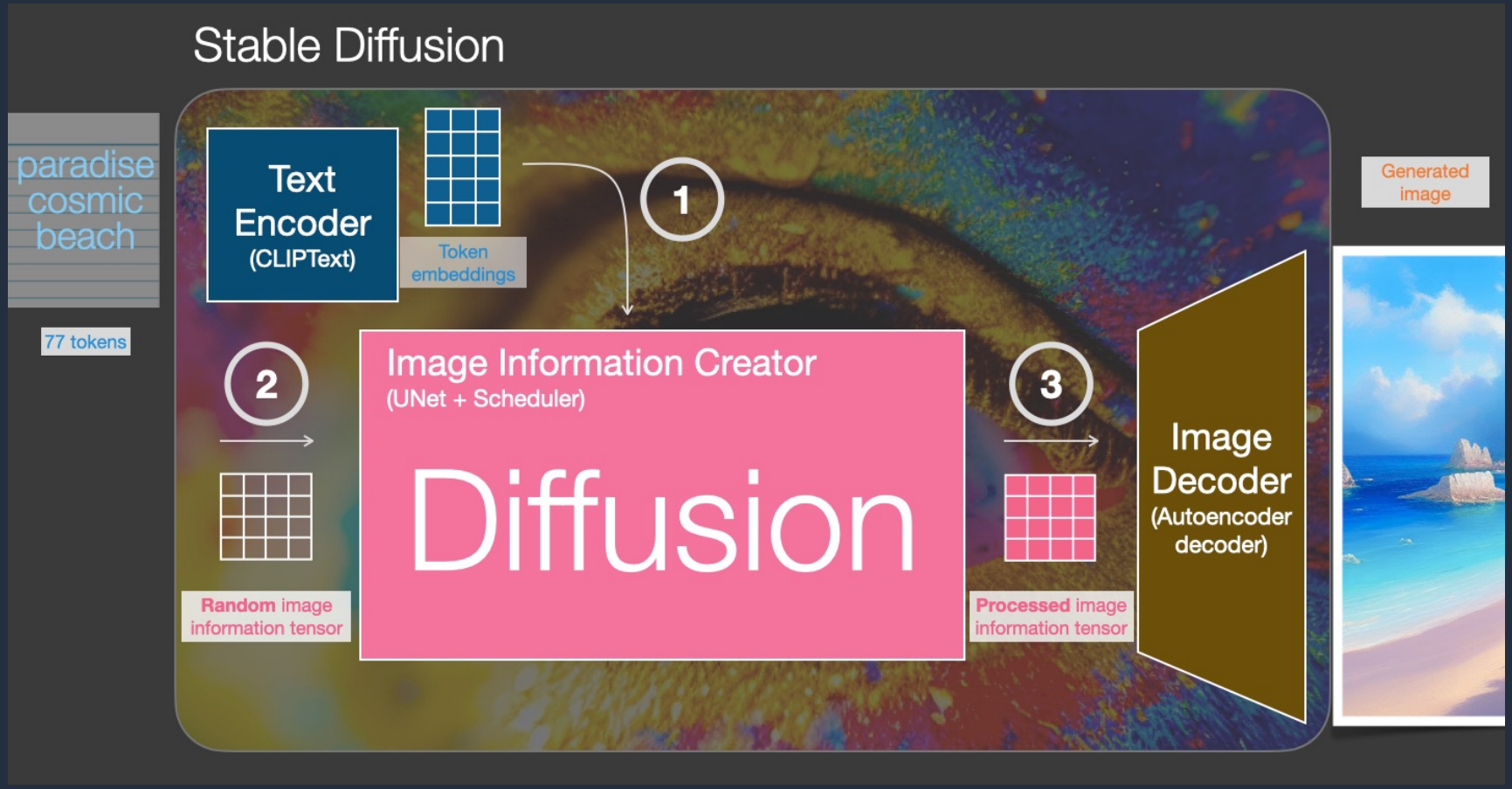
Generated by Stable Diffusion 2.0. This interior does not exist

Seamless transformation

4x

Upscaling

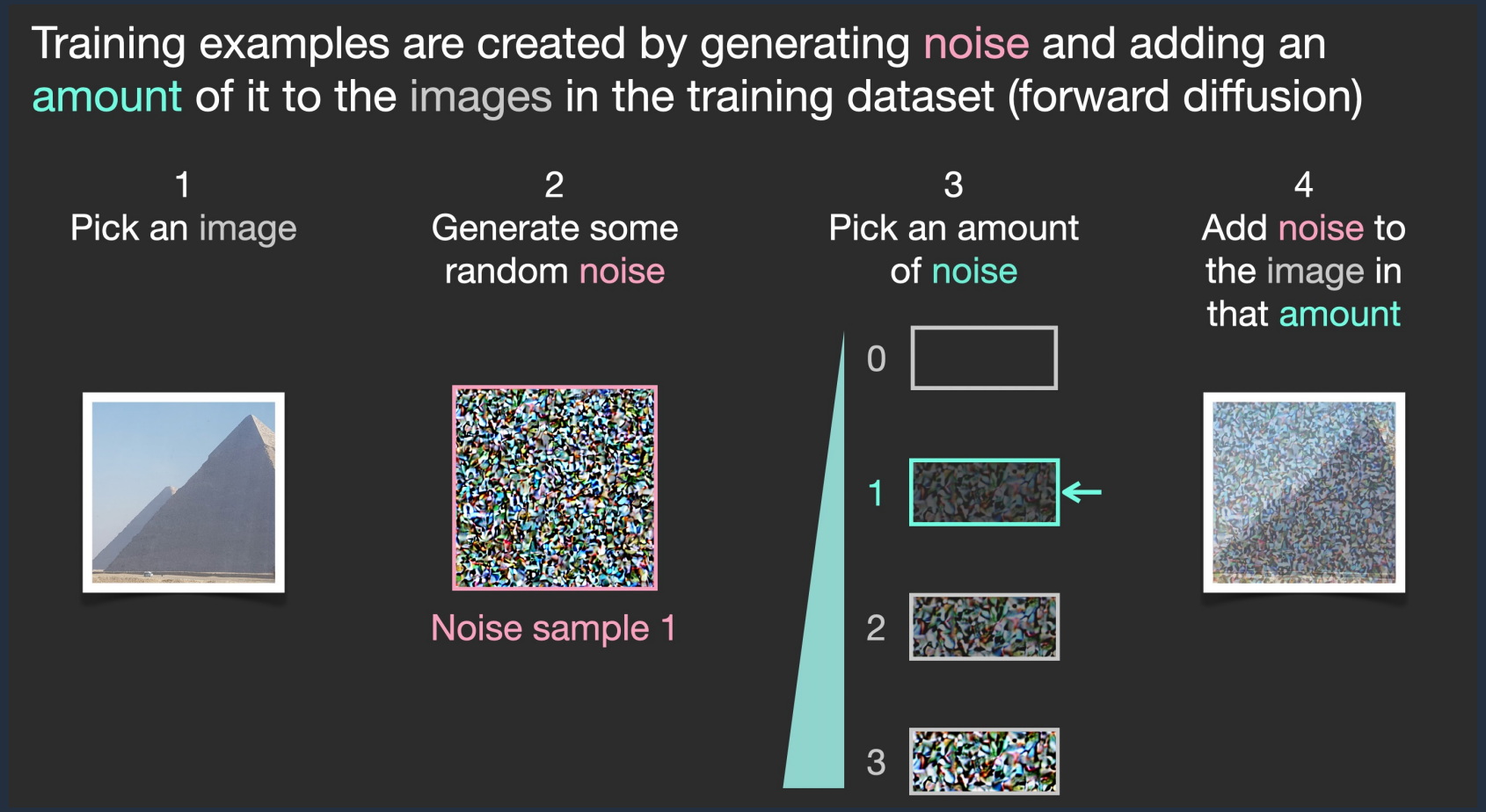
Building blocks of Diffusion



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

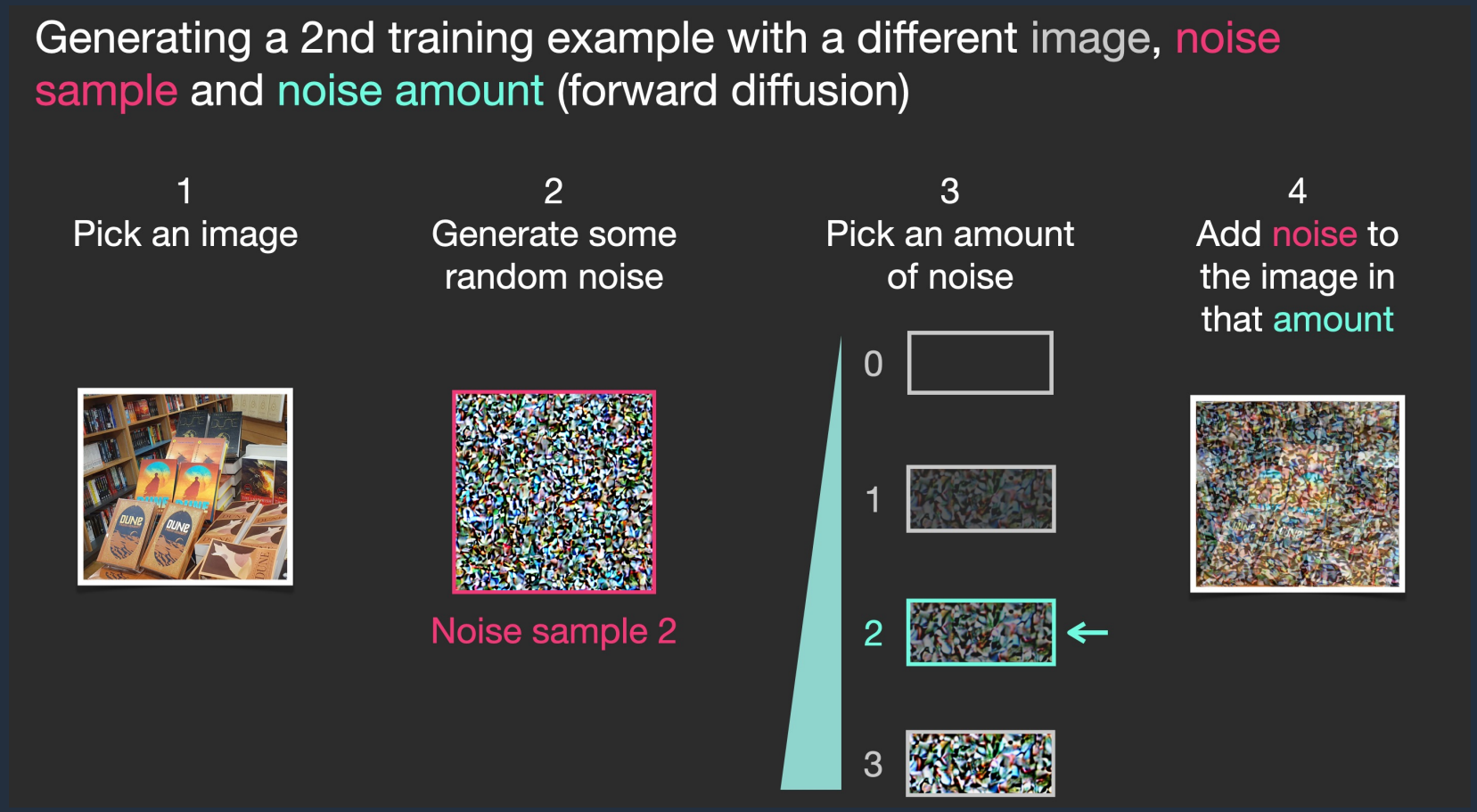
Training a diffusion model

Building blocks of Diffusion



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

Building blocks of Diffusion



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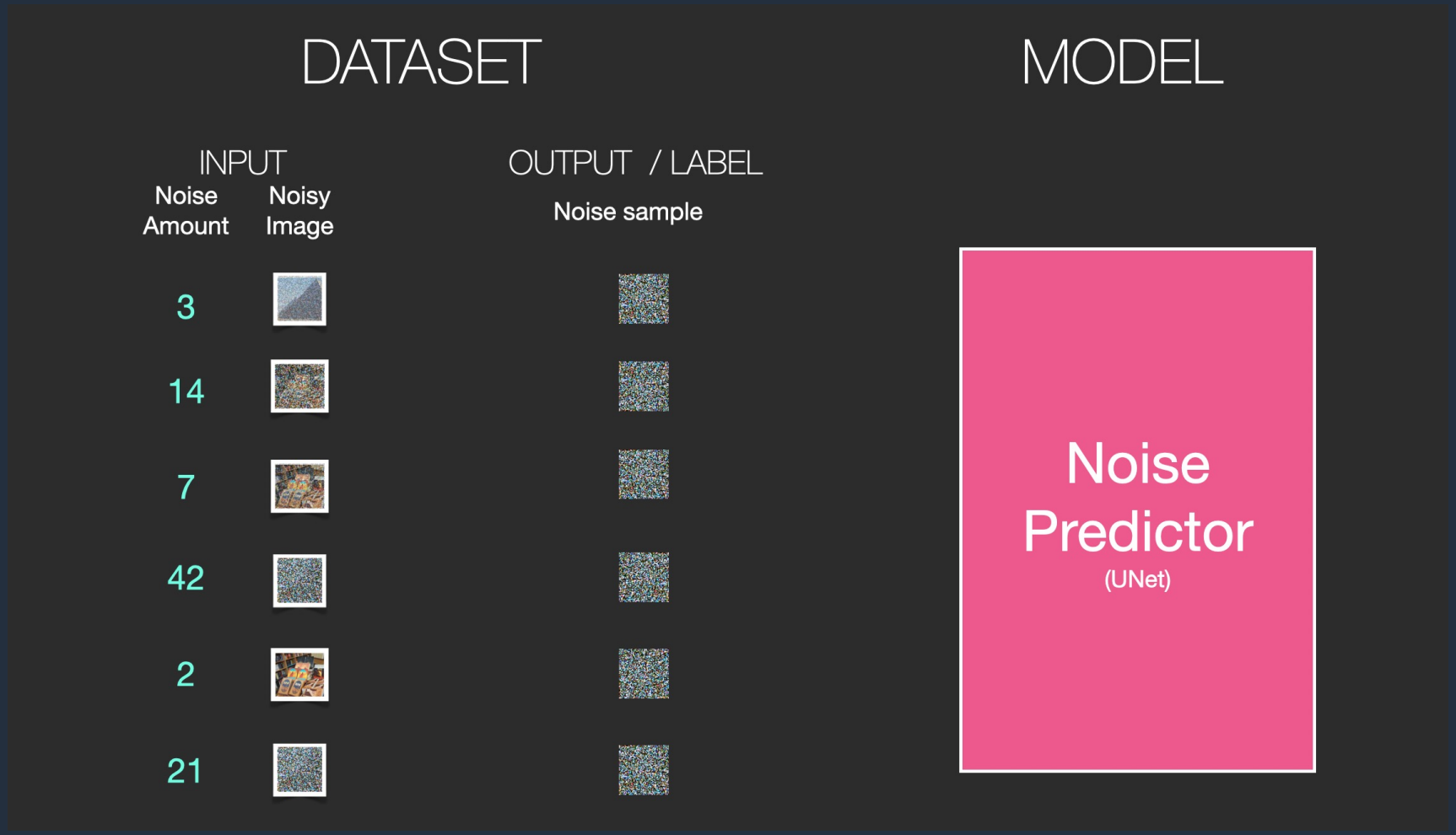
Building blocks of Diffusion



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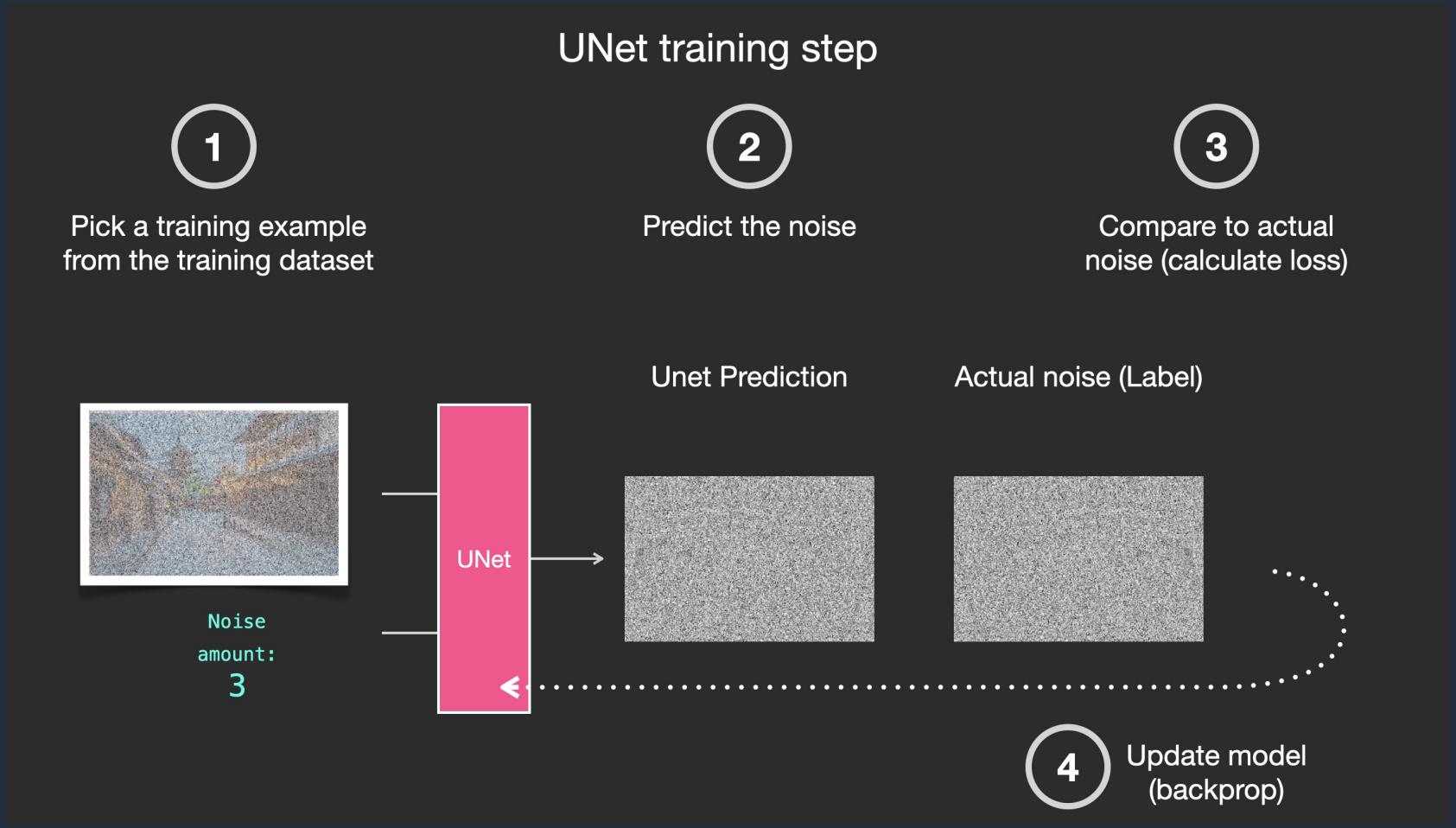
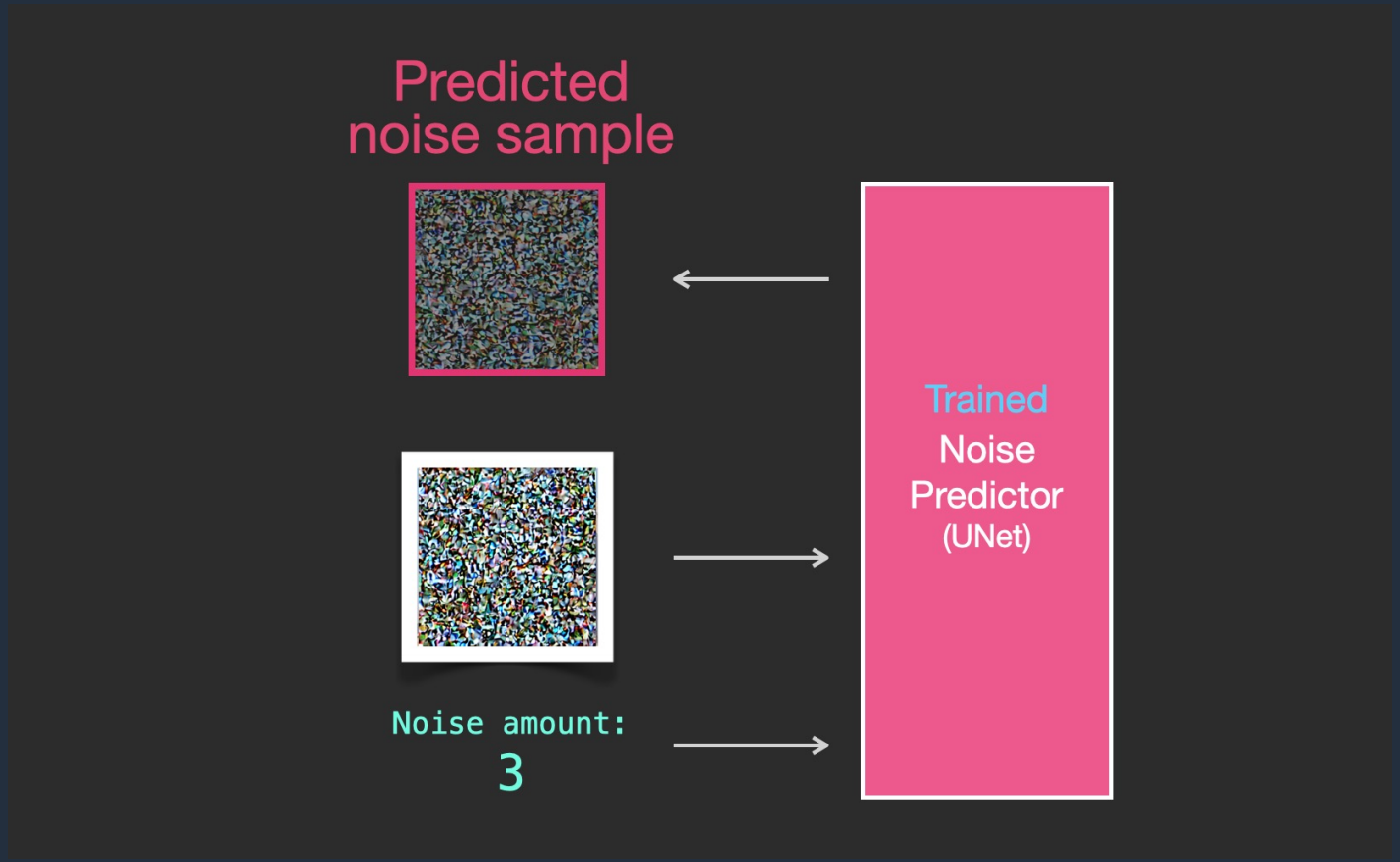


Source: https://jalammar.github.io/illustrated-stable-diffusion/

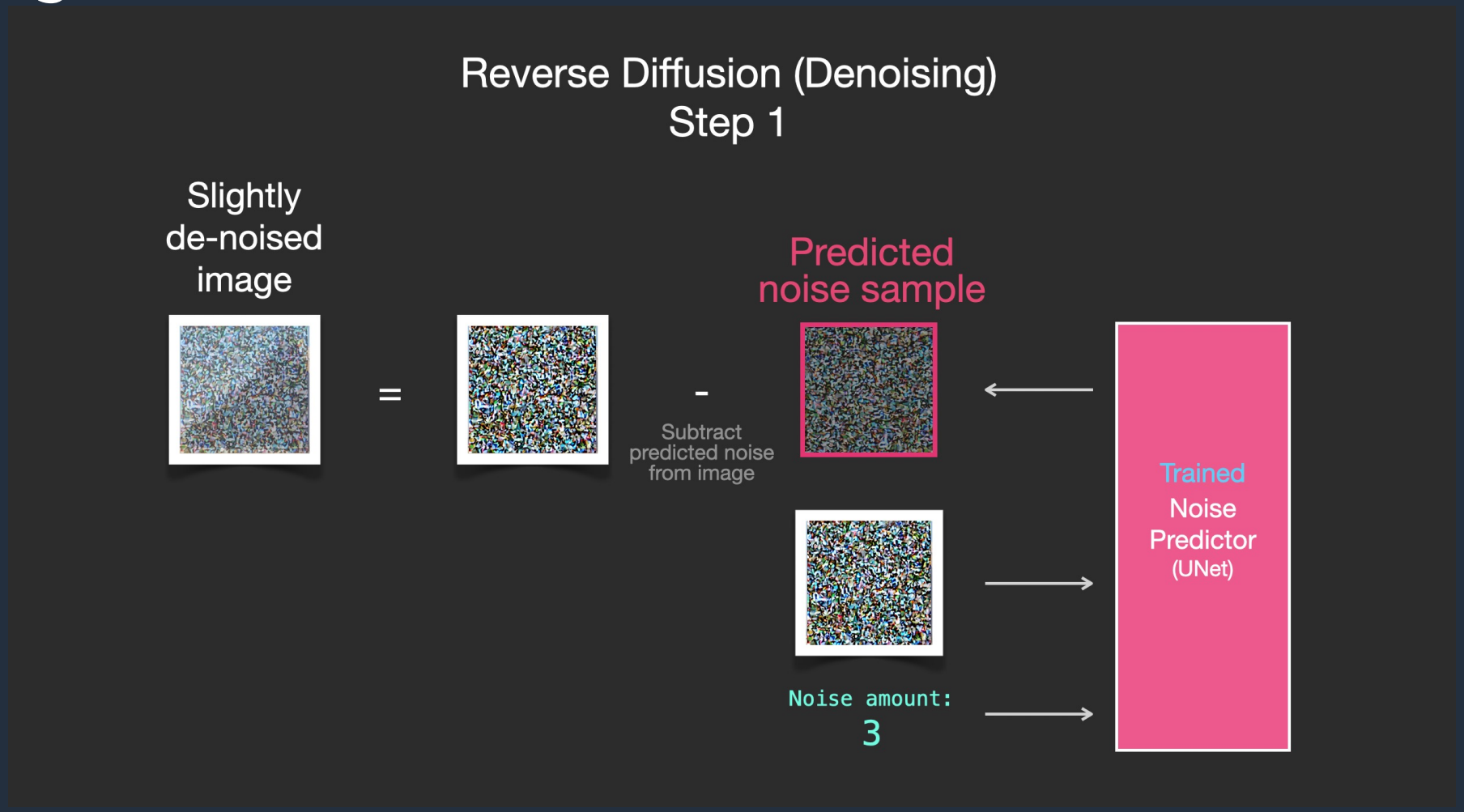
Image generation

Building blocks of Diffusion



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

Building blocks of Diffusion



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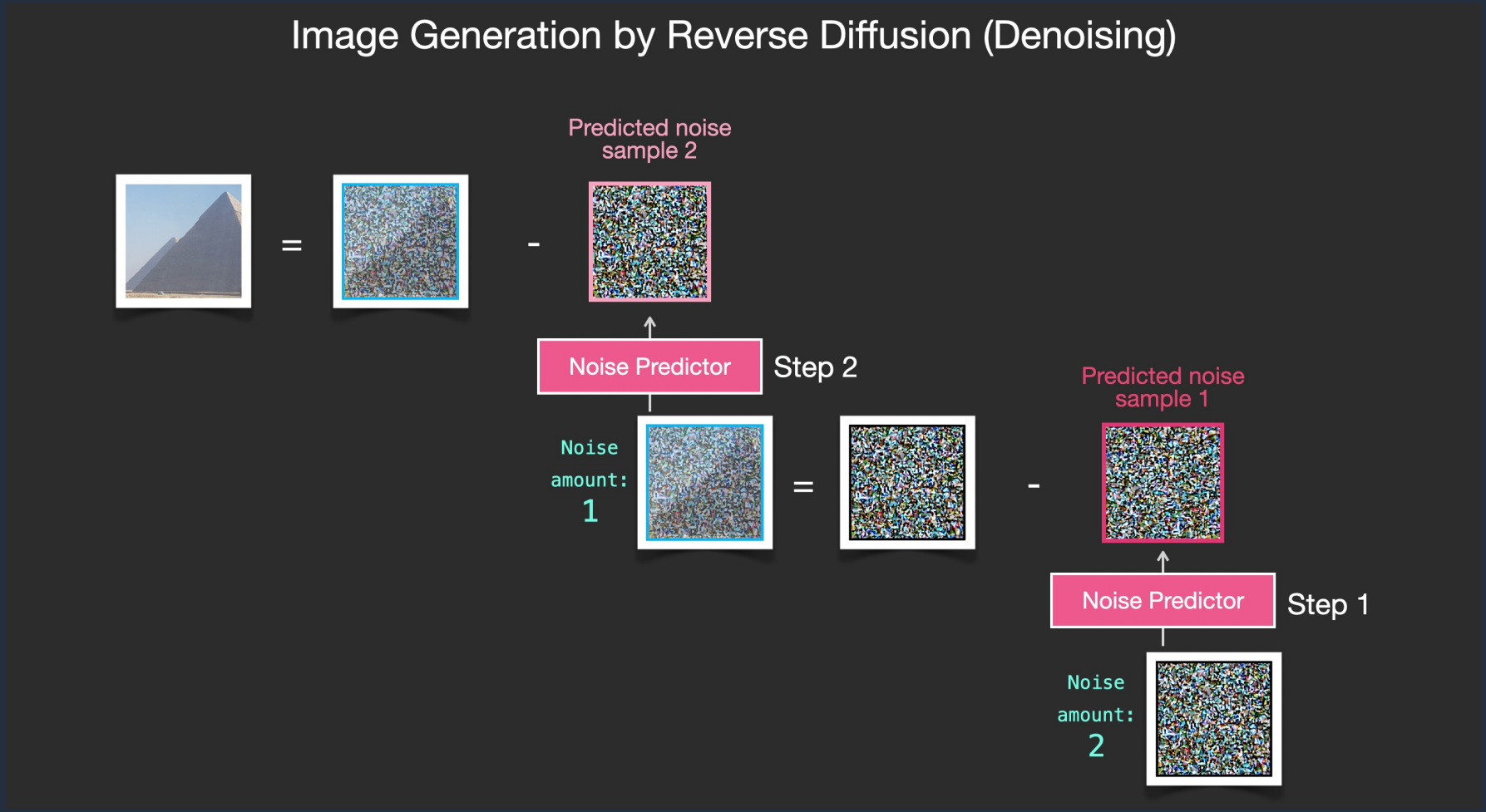
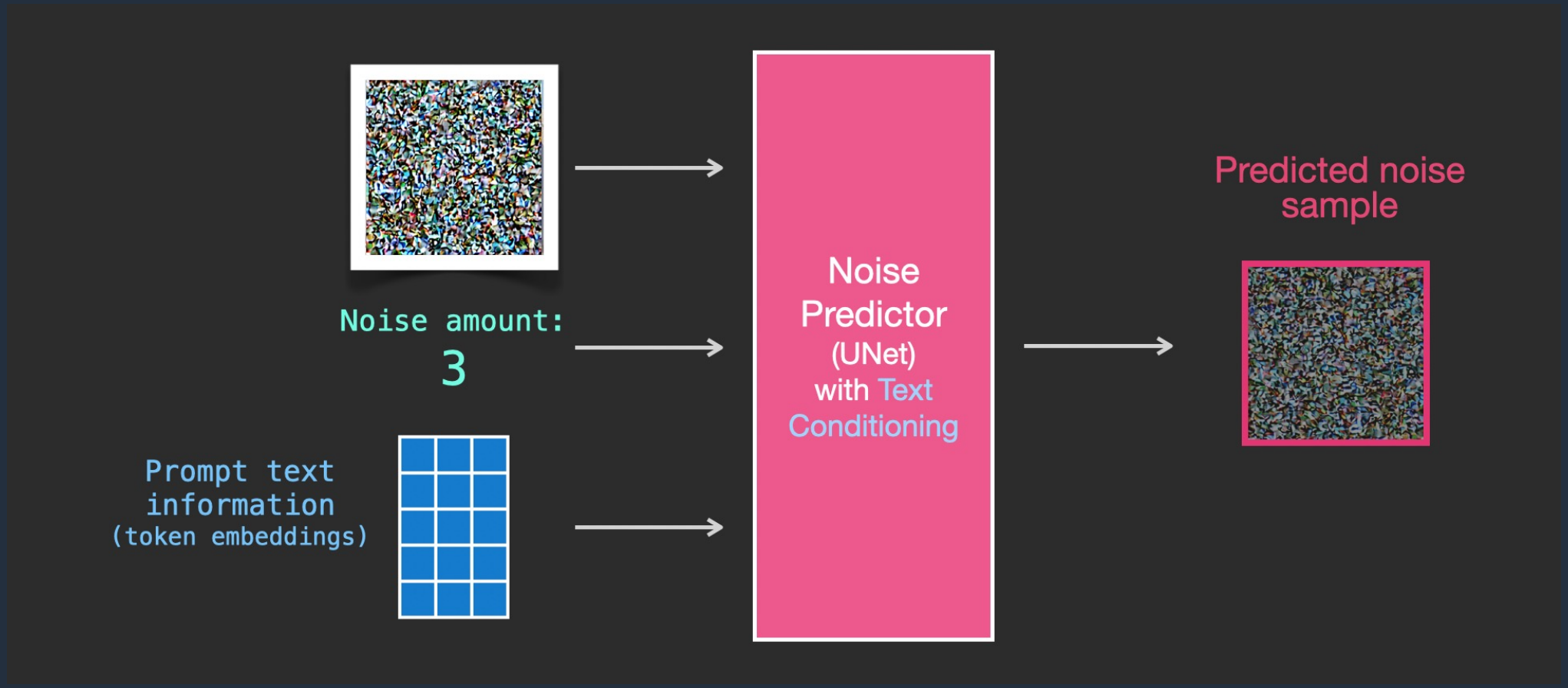
Building blocks of Diffusion



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

Building blocks of Diffusion



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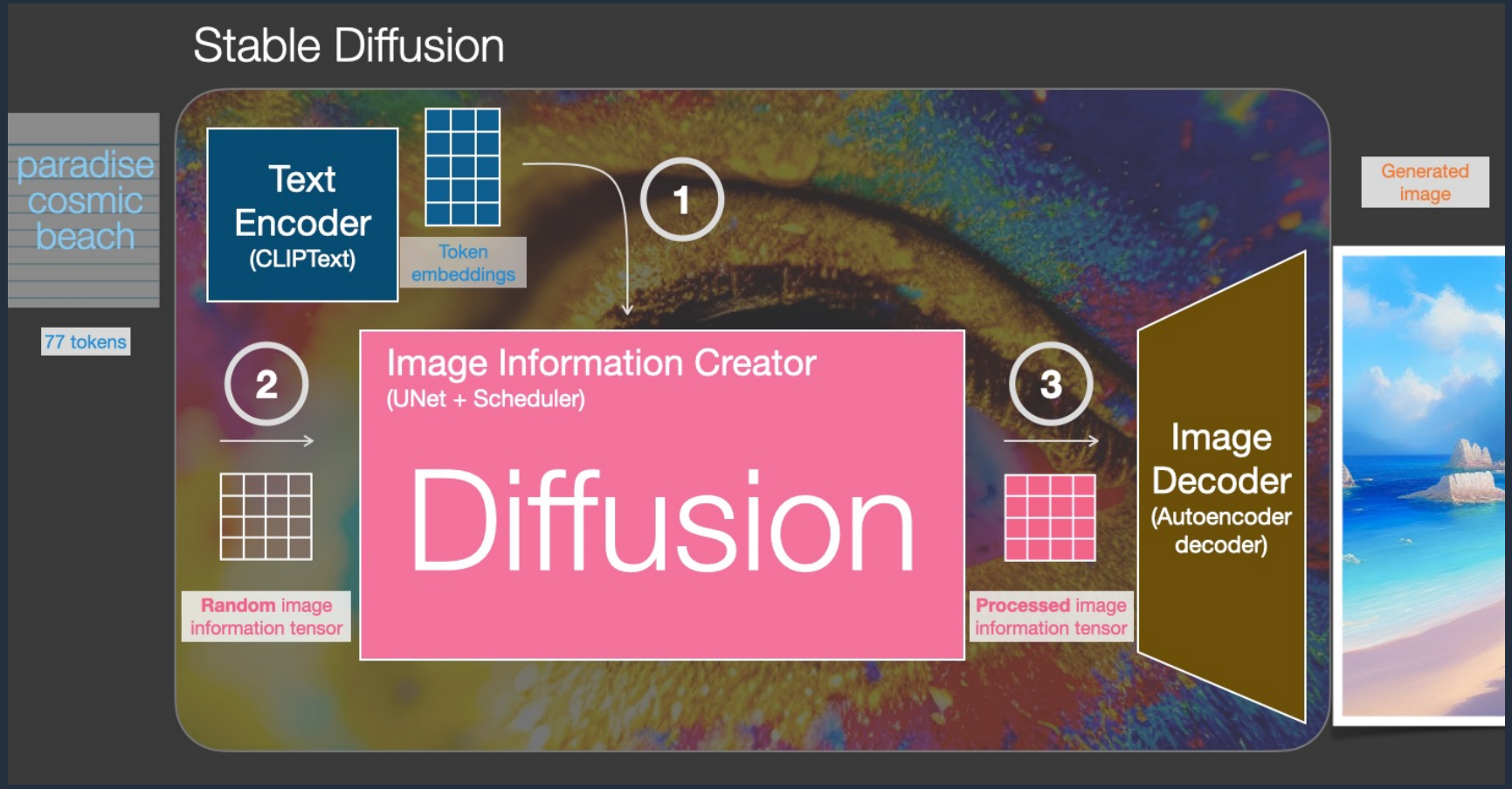
Building blocks of Diffusion



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

Lab 3 – Stable Diffusion Deployment & Inference

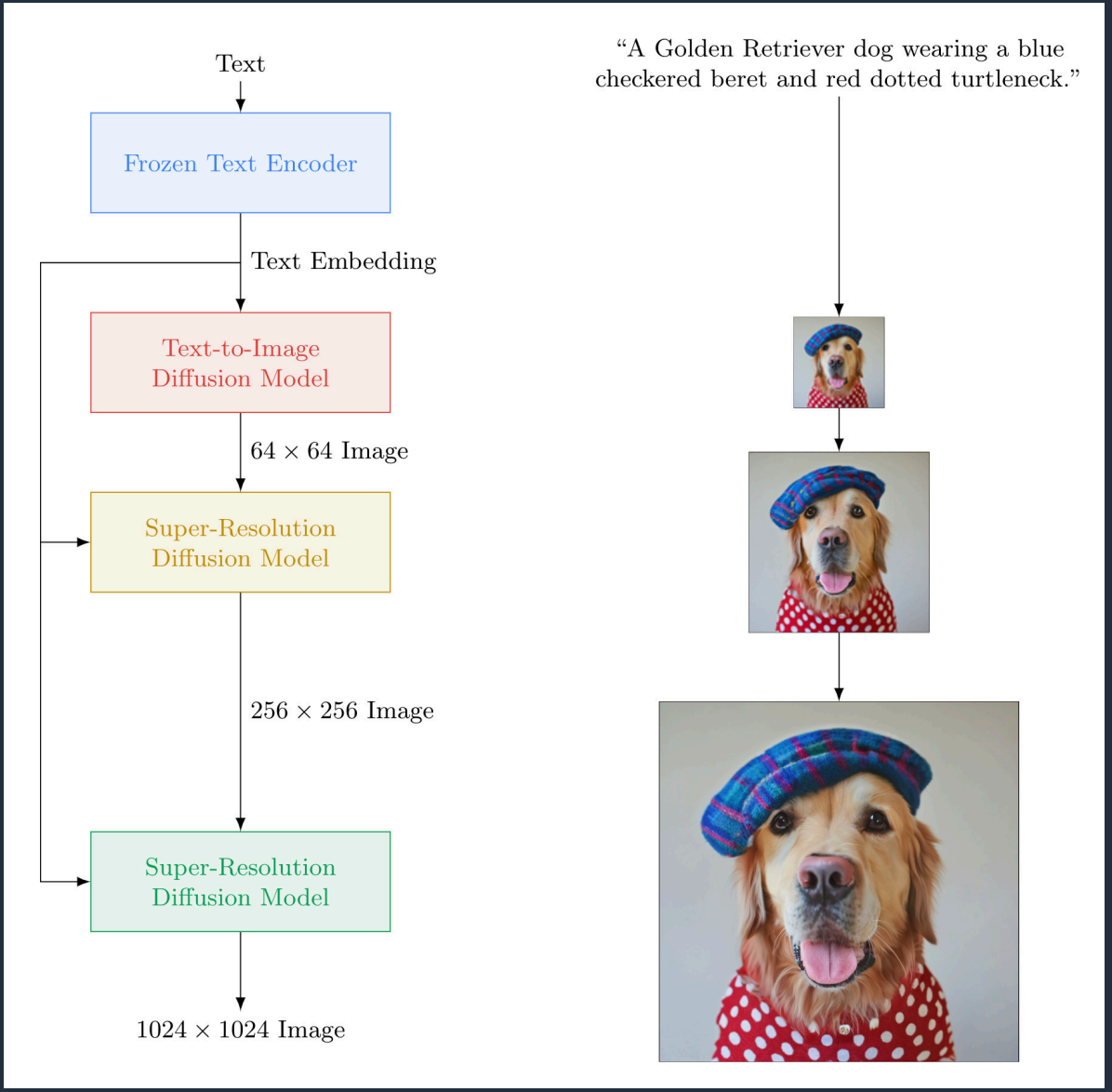
https://github.com/aristsakpinis93/generative-ai-immersion-day

EventHash:

Other models and related work

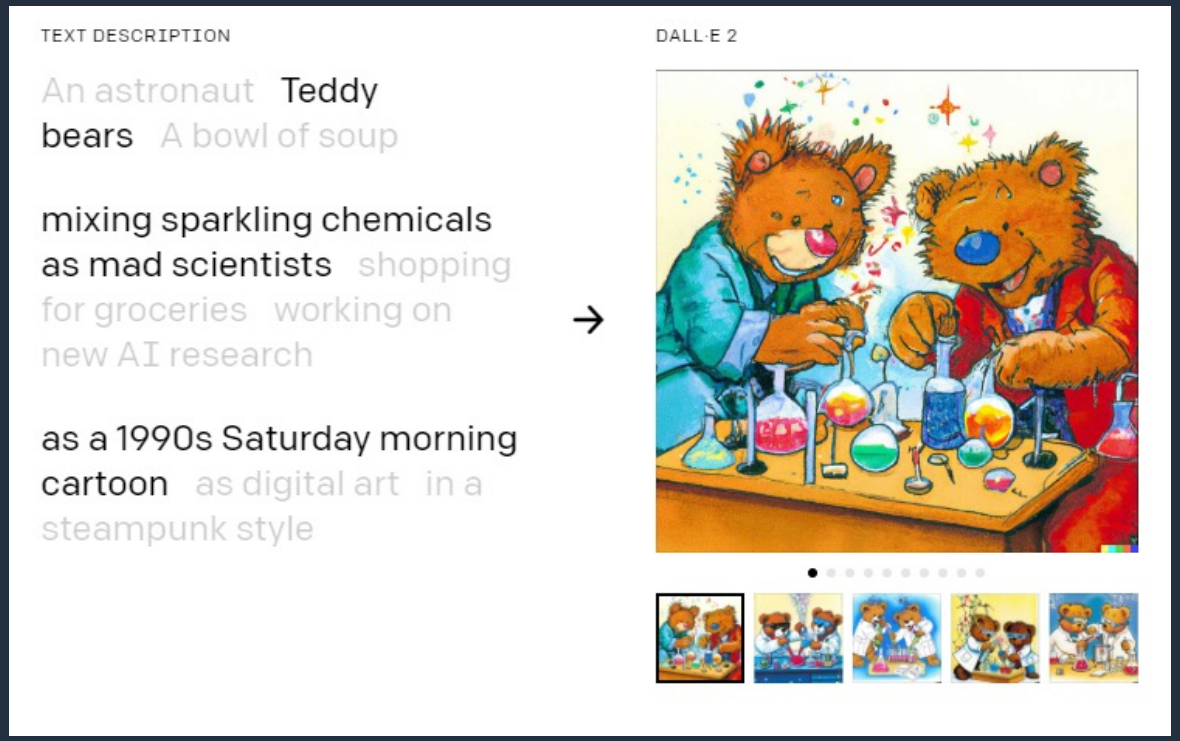
Imagen (Google, 2022)

- 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

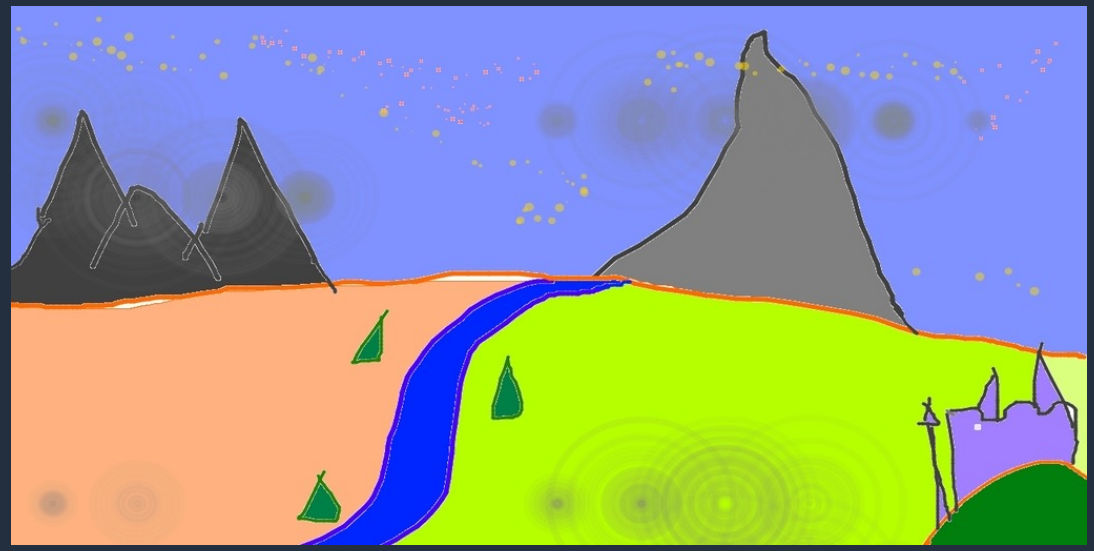
A low angle shot of a man walking down a street, illuminated by the neon signs of the bars around him.

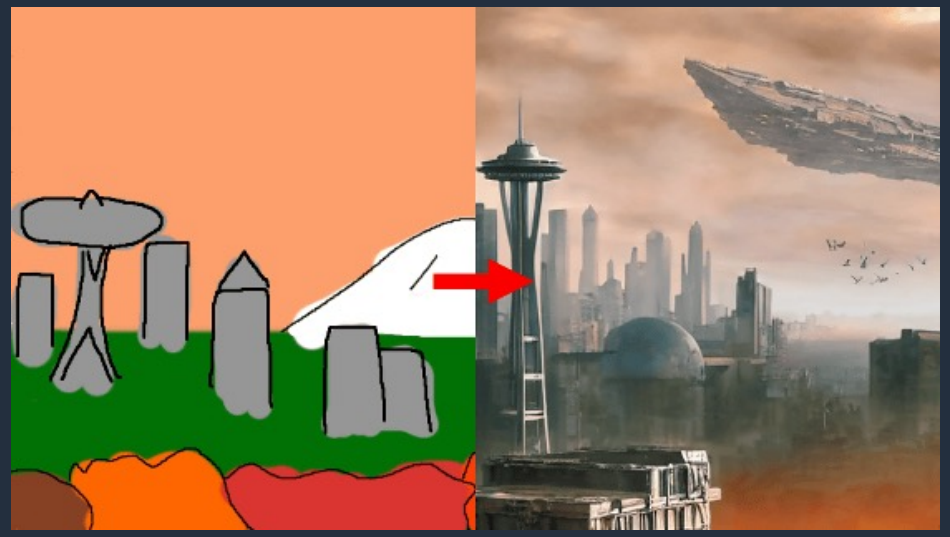
Driving Prompt

Output Video

Image-to-image (img2img)

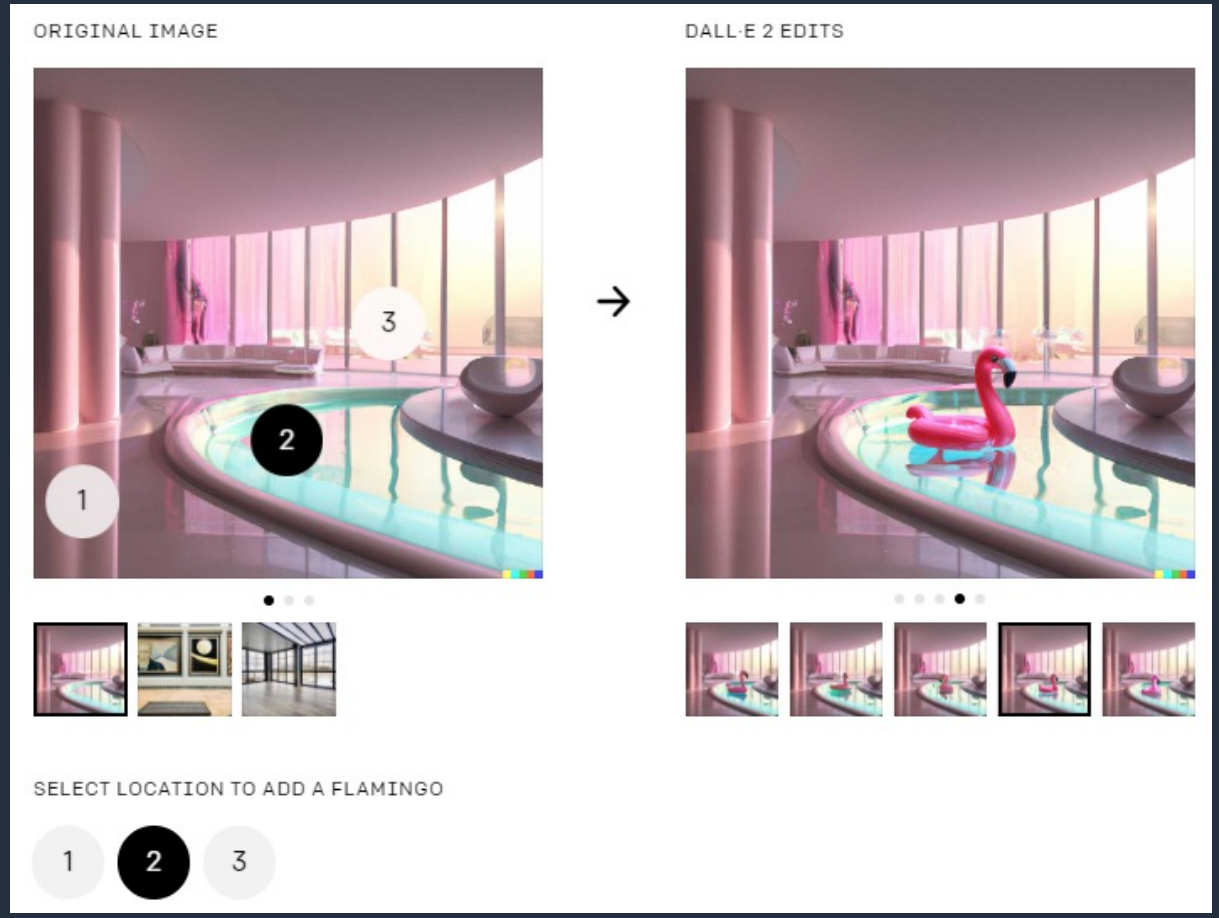
Add a specified amount of noise to an existing image and start the denoising process





Inpainting & outpainting

- Masked image-to-image



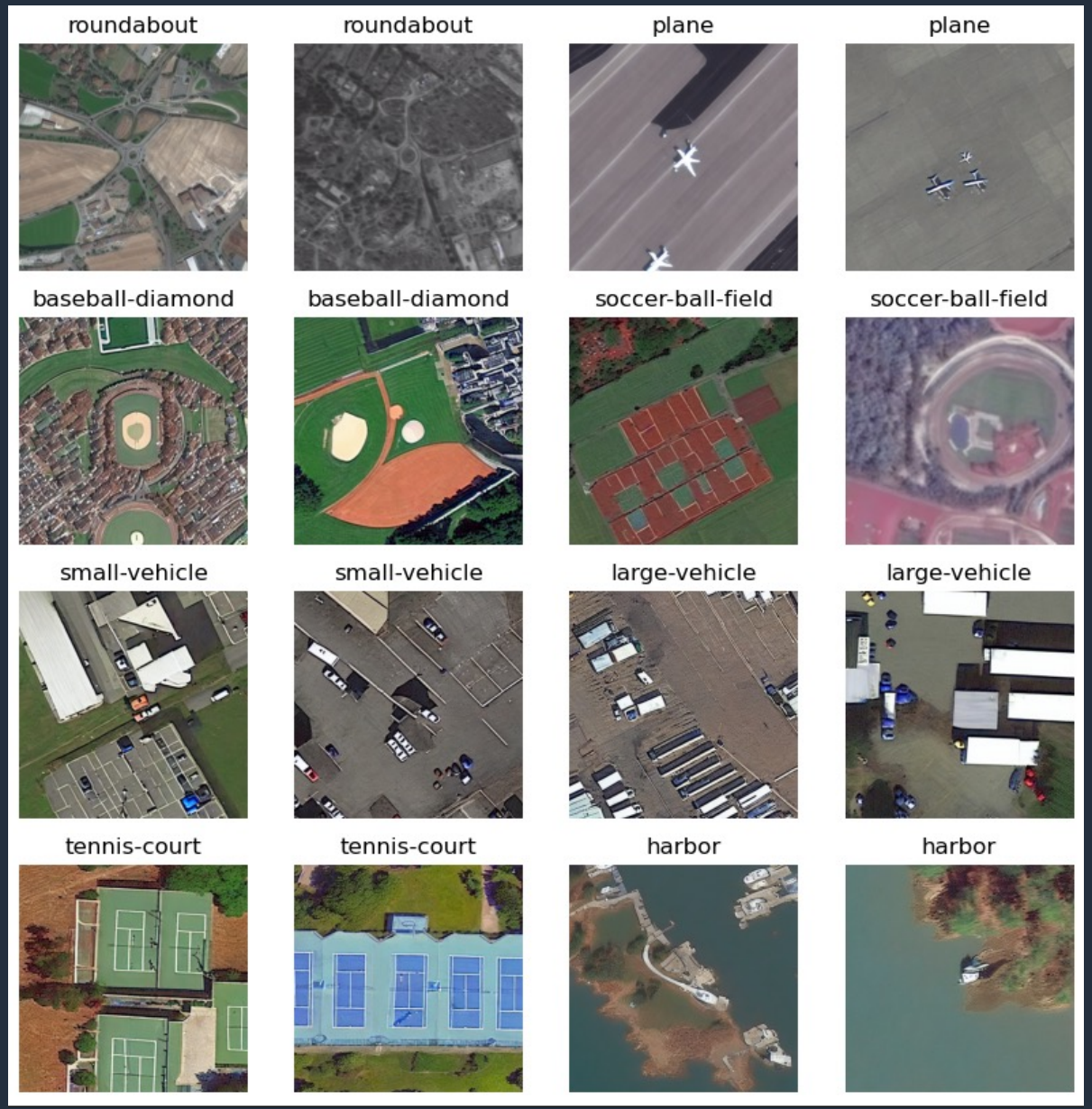
https://openai.com/dall-e-2/

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…

Q&A + CSAT – Please provide feedback!

Thank you!

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