Generative AI and Intel Offerings

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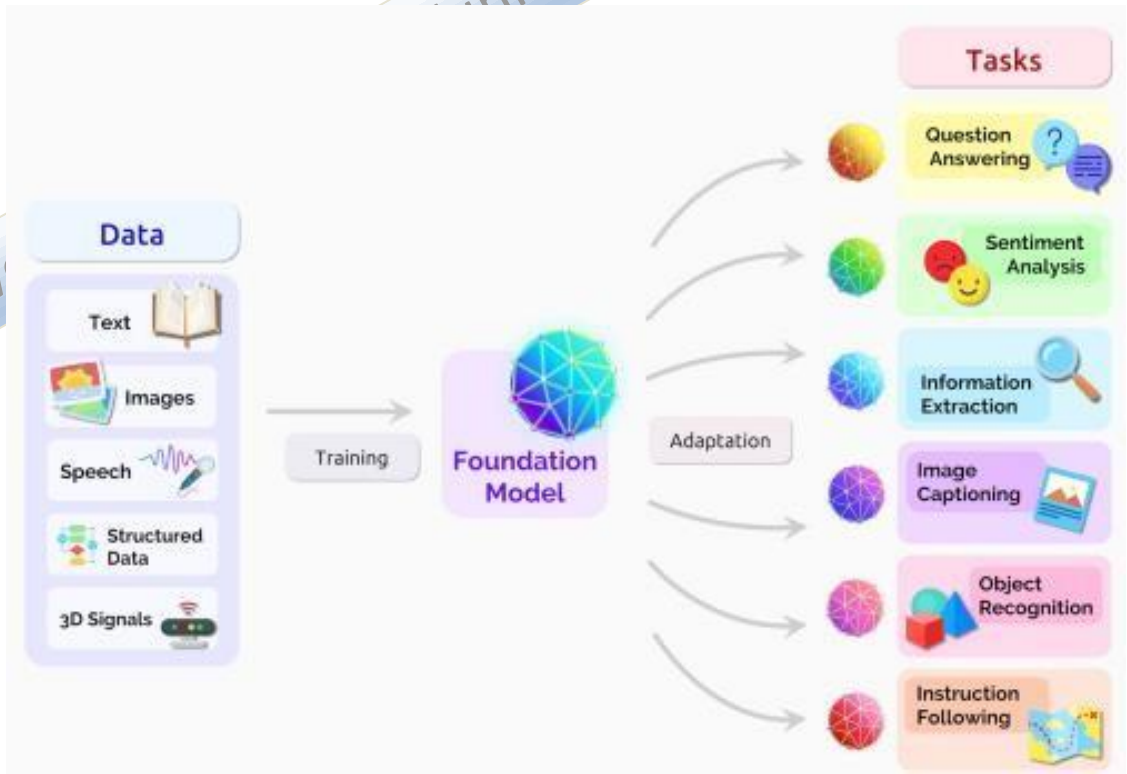
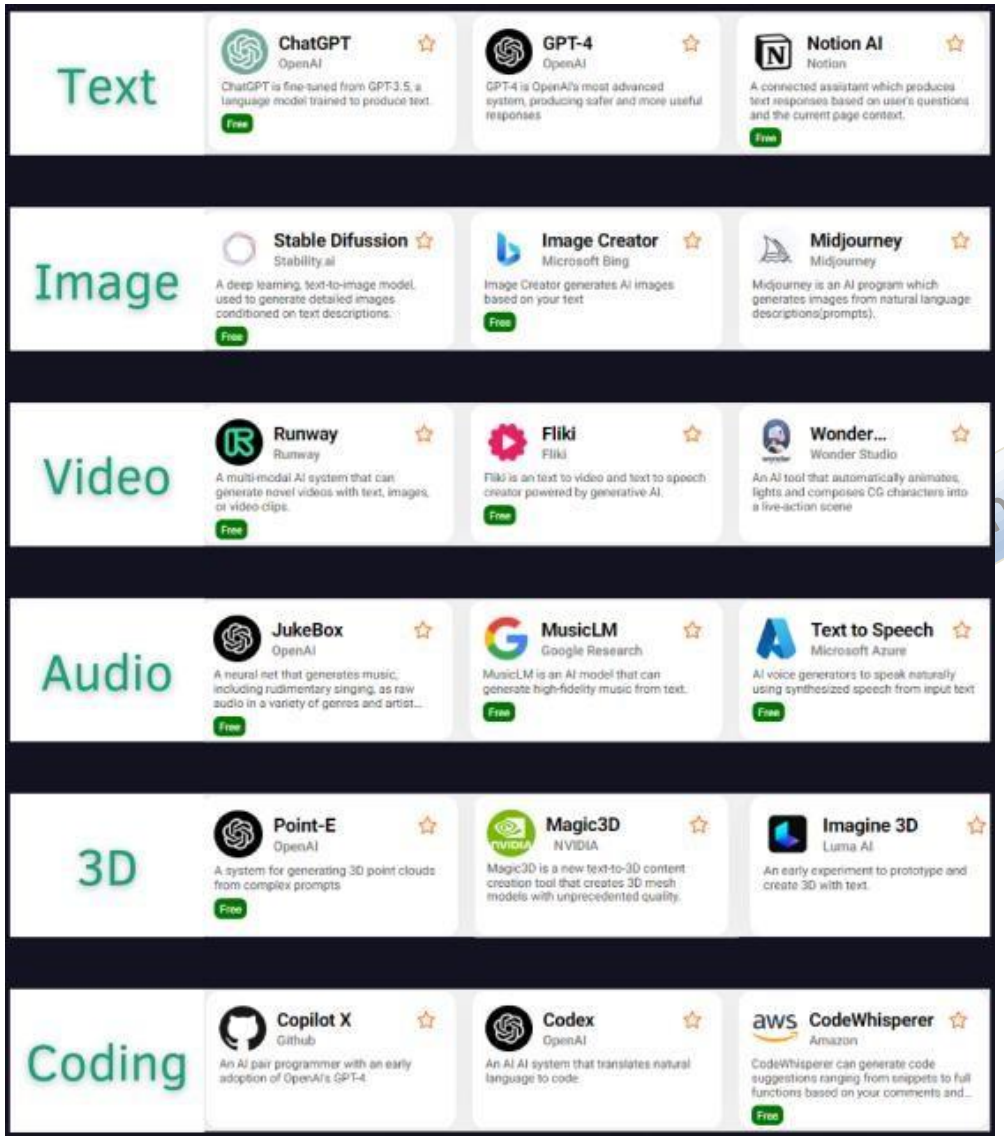
Generative AI – Market is exploding!

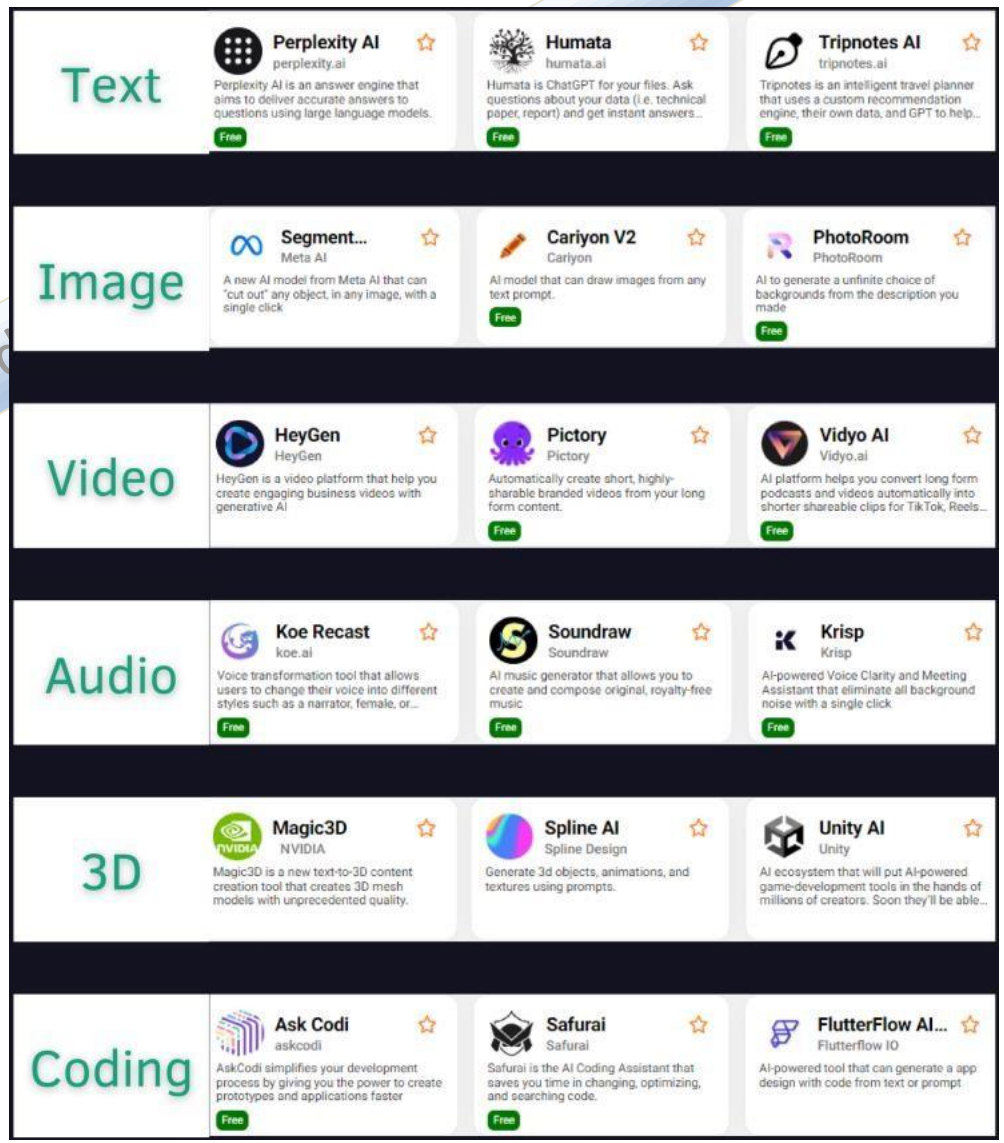


Generative AI - Definition

- Generative AI refers to AI solutions that generate content—whether it's a demand generation email, a fantastic landscape, or a dynamic chatbot reply—in response to a user prompt
- Solutions built using these technologies, such as ChatGPT, Stable Diffusion, and Dall-E, are making headlines every day, and organizations everywhere are seeking ways to operationalize them and capture their game-changing value
- Generative AI is trained on sets of unstructured data using transformer models that require data scientists and developers to fine-tune the output or experience that their business needs
- Organizations looking to apply generative AI to their business challenges have the option to train models from scratch or select a pretrained model that can be fine-tuned to the needs of their business
- Generative AI is built on and deployed in conjunction with language AI and natural language processing (NLP), which allow AI to process and understand human language. Together, generative AI and NLP can understand a user prompt to generate an appropriate response, whether it's text, video, imagery, or audio

Generative AI - https://genai.works/





Generative AI - Companies

- OpenAI
- Hugging Face
- Glean
- AI21 Labs
- Inworld AI
- Aqemia
- MOSTLY AI
- Copy.ai
- Cohere
- Synthesia
- IBM
- Tabnine
- Inflection AI
- Synthetaic
- Tavus
- Kinetix
- Anthropic
- Jasper AI
- DeepMind
- Meta
- Adobe
- Rephrase House
- Aleph Alpha
- Aimi

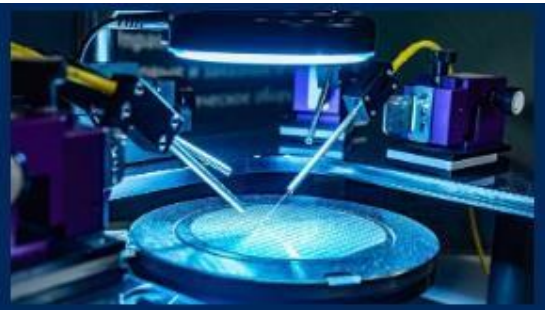
Generative AI – Applications

Healthcare and Life Sciences

Accelerate research and patient outcomes with faster, more accurate analysis across precision medicine, medical imaging, lab automation, and more.

Finance

Mitigate risk, identify fraud, automate processes, and reveal business optimization opportunities before your competition does.



Manufacturing

Transform data into insights that help you optimize plant performance, minimize downtime, improve safety, and drive profitability.

Media and Entertainment

Streamline workflows and bring amazing experiences to life more easily while you reduce costs, simplify archiving, and better understand viewer preferences.

Energy

Tap into connected operations data to balance supply and demand, enable predictive maintenance, identify issues, and discover usage trends.

Retail

Harness your ever-growing data to gain real-time understanding of customer behavior, inventory, internal loss, and other critical metrics.

Telecommunications

Improve efficiency while rapidly revealing opportunities for cost optimization, service enhancement, or new technologies such as AR and VR.

Government

Securely harness AI resources to unlock new possibilities, from scientific research to defense, mapping, and disaster response.

https://www.intel.com/content/www/us/en/artificial-intelligence/industries.html

Agenda - Part 1

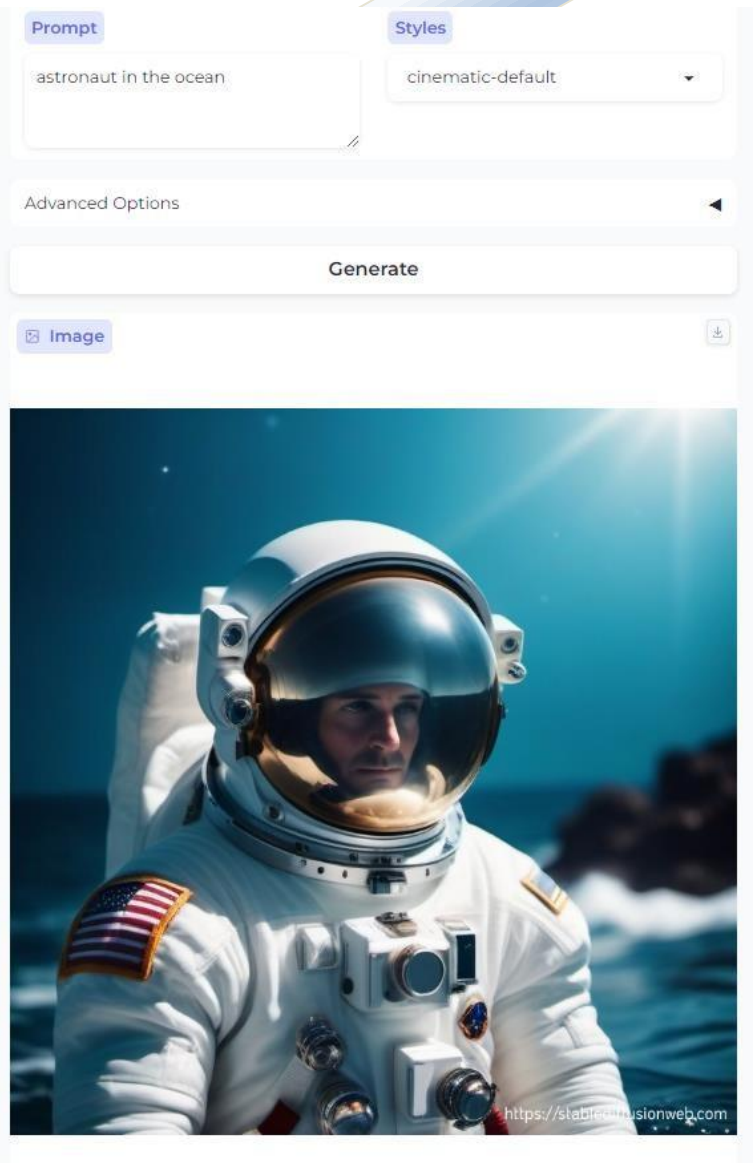
- What is Generative AI and Large Language Models (LLMs)
- Use Cases
- Prompt Engineering
- Transformer Architectures
- LLM fine tuning
- PEFT (Parameter Efficient Finetuning)
- RLHF (Reinforcement Learning with Human Feedback)
- Retrieval Augmented Generation (RAG)
- LLM deployment techniques
- Q and A

What is Generative AI

- Informally
  - **Generative** models can generate new data instances
  - **Discriminative** models discriminate between different kinds of data instances

- Formally, given a set of data instances X and a set of labels Y:
  - **Generative** models capture the joint probability p(X, Y), or just p(X) if there are no labels
  - **Discriminative** models capture the conditional probability p(Y | X)

- Generative artificial intelligence (AI) describes algorithms (such as ChatGPT and DALL-E) that can be used to create new content, including audio, code, images, text, simulations, and videos

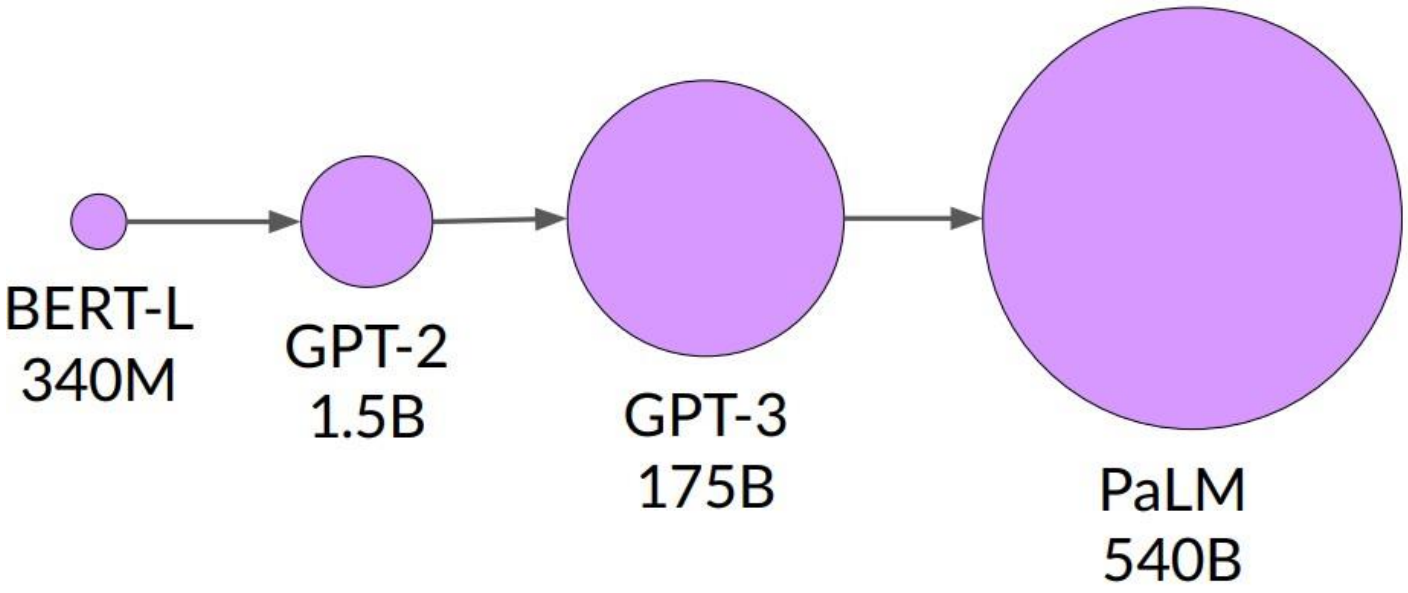


What is Generative AI and LLMs

- Estimating the probability of a token or sequence of tokens occurring within a longer sequence of tokens
  - When I hear rain on my roof, I _____ in my kitchen.
    - cook soup 9.4%
    - warm up a kettle 5.2%
    - relax 2.2%

- "Large" in Large Language Models (LLMs) can refer either to the number of parameters in the model, or the number of words in the dataset

Model Size vs Time



Growth powered by:

- Introduction of transformer
- Access to massive datasets
- More powerful compute resources

2018 2022 2023

Source - https://www.deeplearning.ai/courses/generative-ai-with-llms/

Generative AI – Use Cases

- **Content generation**: Automatically create articles, blog posts, product descriptions, and other written materials
- **Chatbots**: Power dynamic and intelligent conversational AI models that your customers can interact with through text or speech
- **Image, video, and audio generation**: Create new visuals and sounds by examining preexisting materials and working against a user prompt
- **Language translation**: Translate text from one language to another
- **Data augmentation**: Create synthetic data for other machine learning models to help improve their accuracy and performance
- **Text summarization**: Summarize large pieces of text into a concise format so readers can quickly understand the main points and ideas

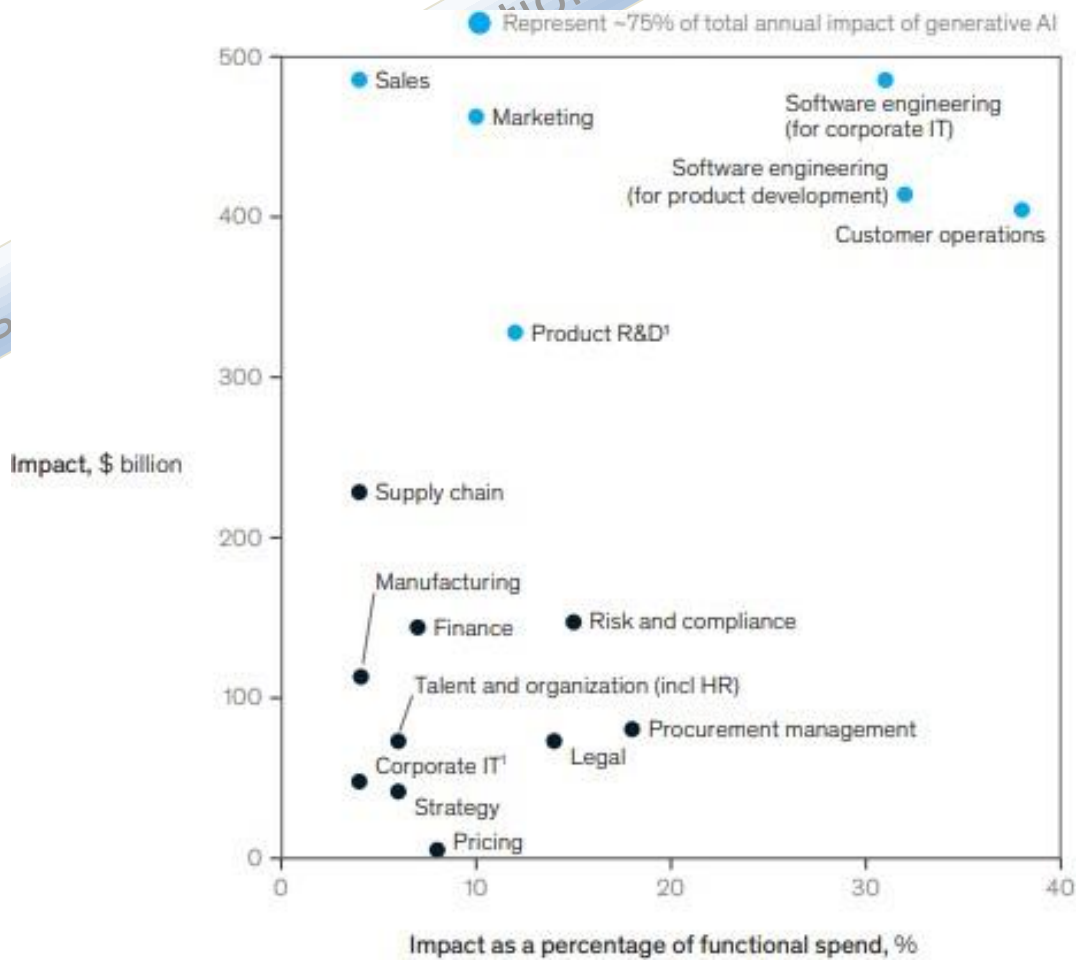
Generative AI Global Impact

- In a McKinsey study, they believe that Generative AI can add an equivalent of $2.6 to $4.4 trillion annually to the global economy. This is more than the entire GDP of the United Kingdom

- 75% of the use cases fall under the four areas of Marketing and sales, software engineering, R&D, and Customer Operations

- They identified 63 use cases total include retail and packaging, and banking

- Source: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#business-value



Generative AI LLM tasks

Translate

French:

J'aime l'apprentissage automatique.

German:

Ich liebe maschinelles Lernen.

Generate

Code AI

Prompt:

Write some python code that will return the mean of every column in a dataframe.

Generate

Code:

```
import pandas as pd

df = pd.DataFrame({
    'A': [1, 2, 3, 4, 5],
    'B': [2, 3, 4, 5, 6],
    'C': [3, 4, 5, 6, 7]
})

mean_values = df.mean()
```

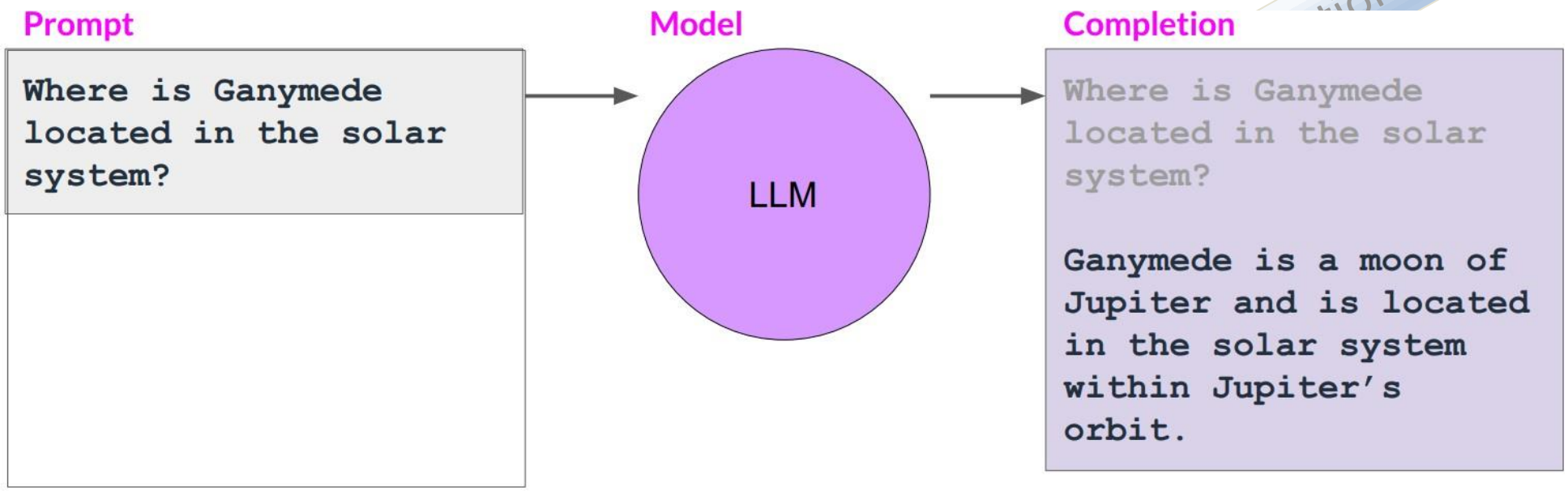
Summarize

Text file: support.txt

Generate

In the chat session, Support efficiently and effectively assists Alex, who was initially unable to access their account due to issues with a password reset email, leading to a positive customer service experience.

Prompts and Completions



Context window: typically a few thousand words

Wíiting well stíuctuíed píompts is an essential paít of ensuíing accuíate, high-quality íesponses fíom a language model

Source - https://www.deeplearning.ai/courses/generative-ai-with-llms/

Prompt Engineering (In-context learning during inference)

Prompt // Zero Shot

```
Classify this review:
I loved this movie!
Sentiment:
```

Prompt // One Shot

```
Classify this review:
I loved this movie!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment:
```

Prompt // Few Shot >5 or 6 examples

```
Classify this review:
I loved this movie!
Sentiment: Positive

Classify this review:
I don't like this
chair.
Sentiment: Negative

Classify this review:
Who would use this
product?
Sentiment:
```

Context Window
(few thousand words)

Source - https://www.deeplearning.ai/courses/generative-ai-with-llms/

Chain-of-Thought Prompting

Prompt

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11.The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model

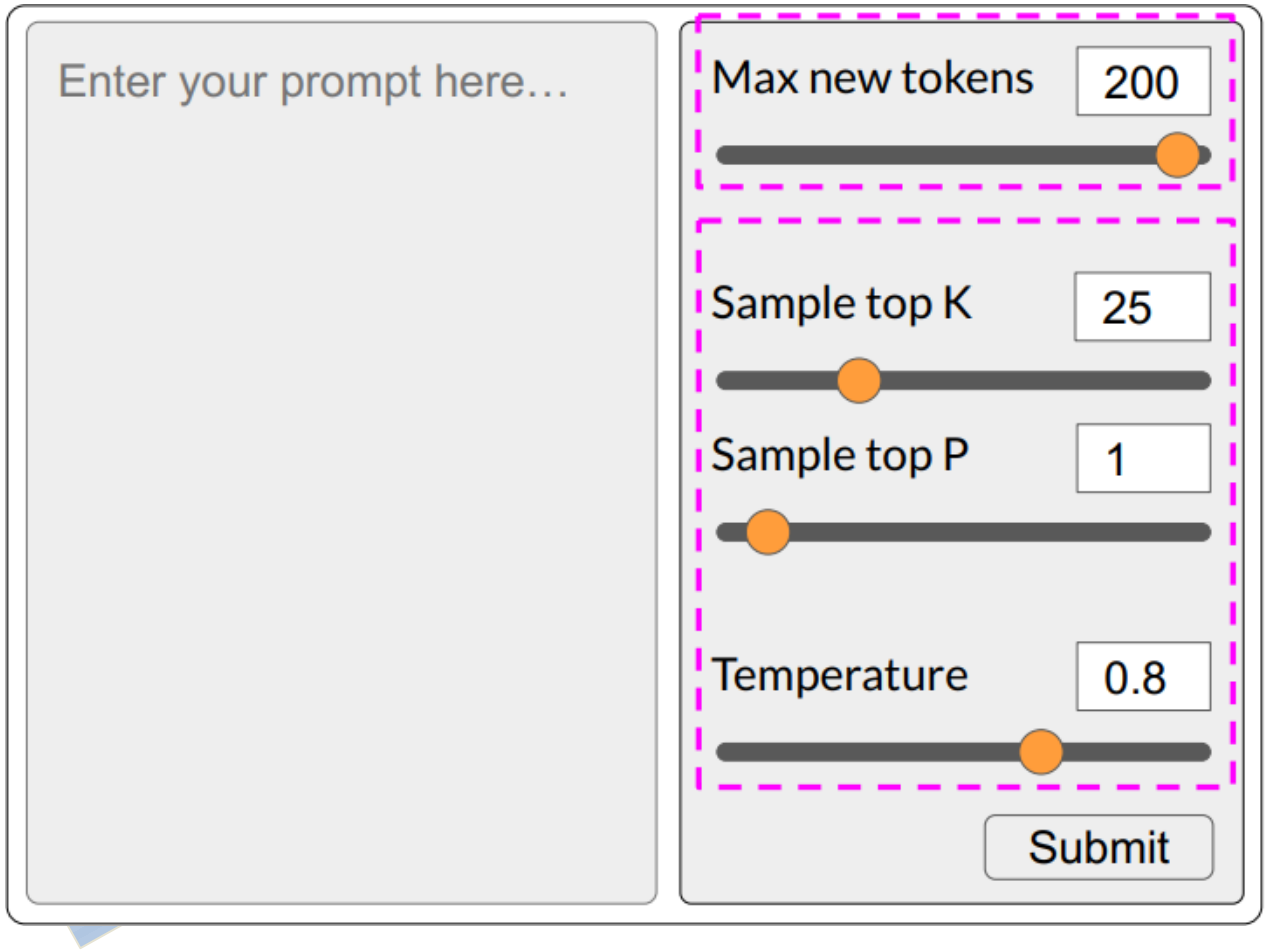
LLM

Completion

Q: Roger has 5 tennis balls.
...
...
...
how many apples do they have?

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

Generative AI - Inference

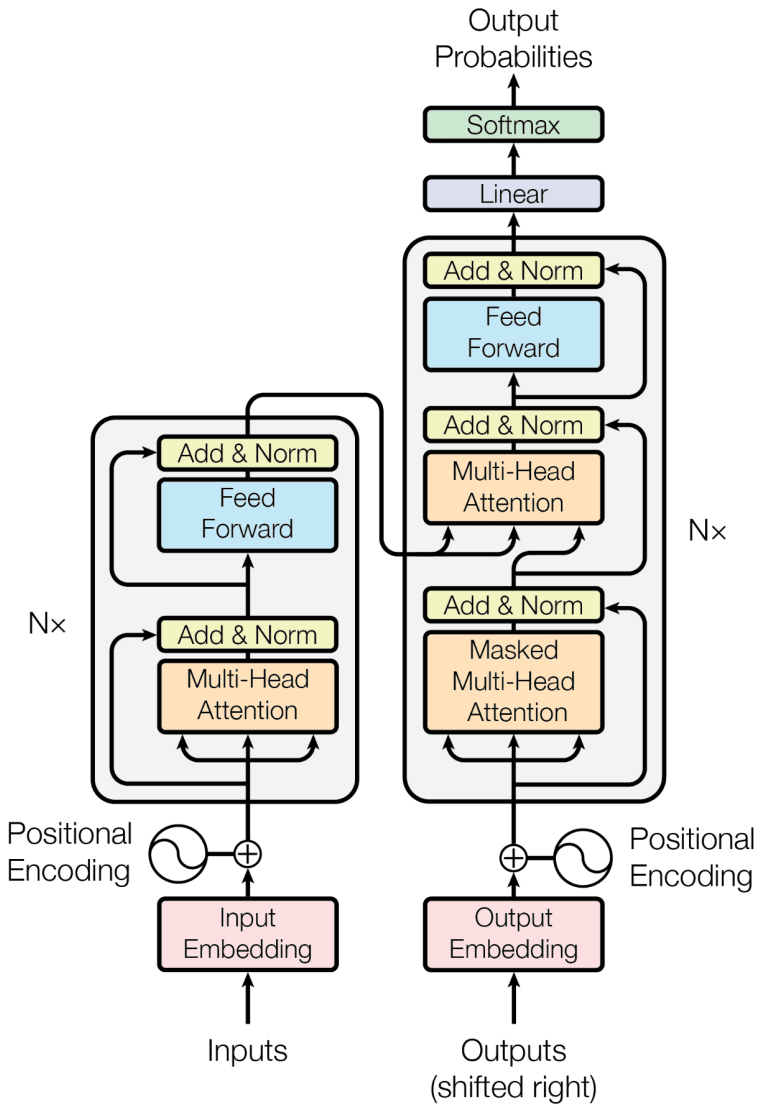


Inference configuration parameters

$$\sigma(z_i) = \frac{e^{\frac{z_i}{\theta}}}{\sum_{j=0}^{N} e^{\frac{z_j}{\theta}}}$$

Source - https://lukesalamone.github.io/posts/what-is-temperature/

Transformer – Attention Is All you Need

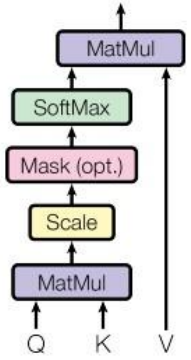


$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

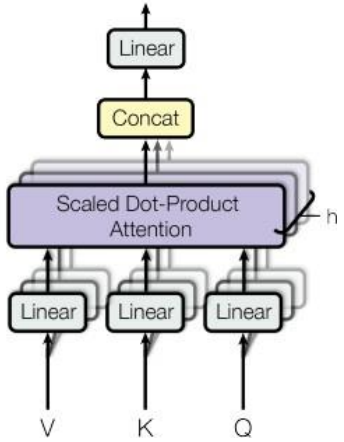
$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$

$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Scaled Dot-Product Attention

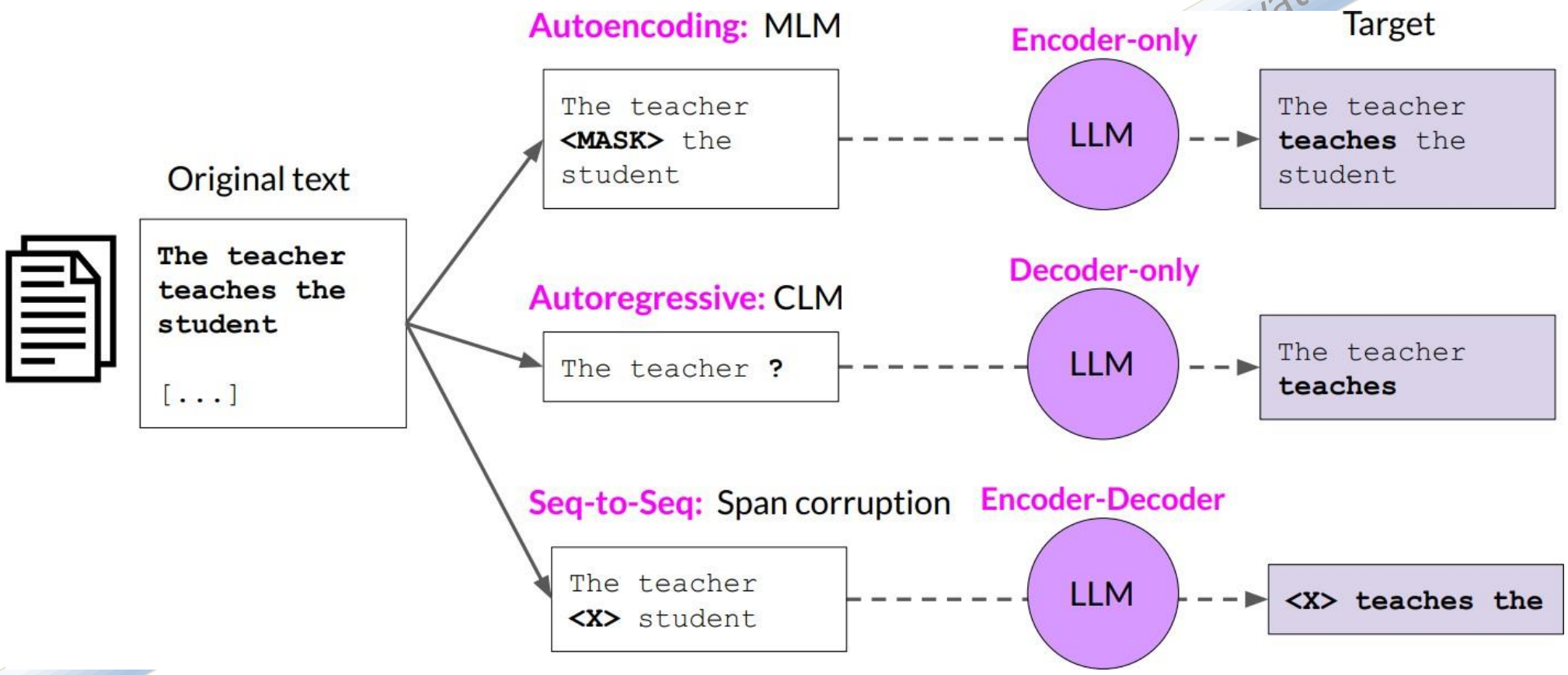


Multi-Head Attention



Source - https://arxiv.org/abs/1706.03762

Model Architectures and Training Objectives



Source - https://www.deeplearning.ai/courses/generative-ai-with-llms/

Computational Challenges for training LLMs

1billion parameters model

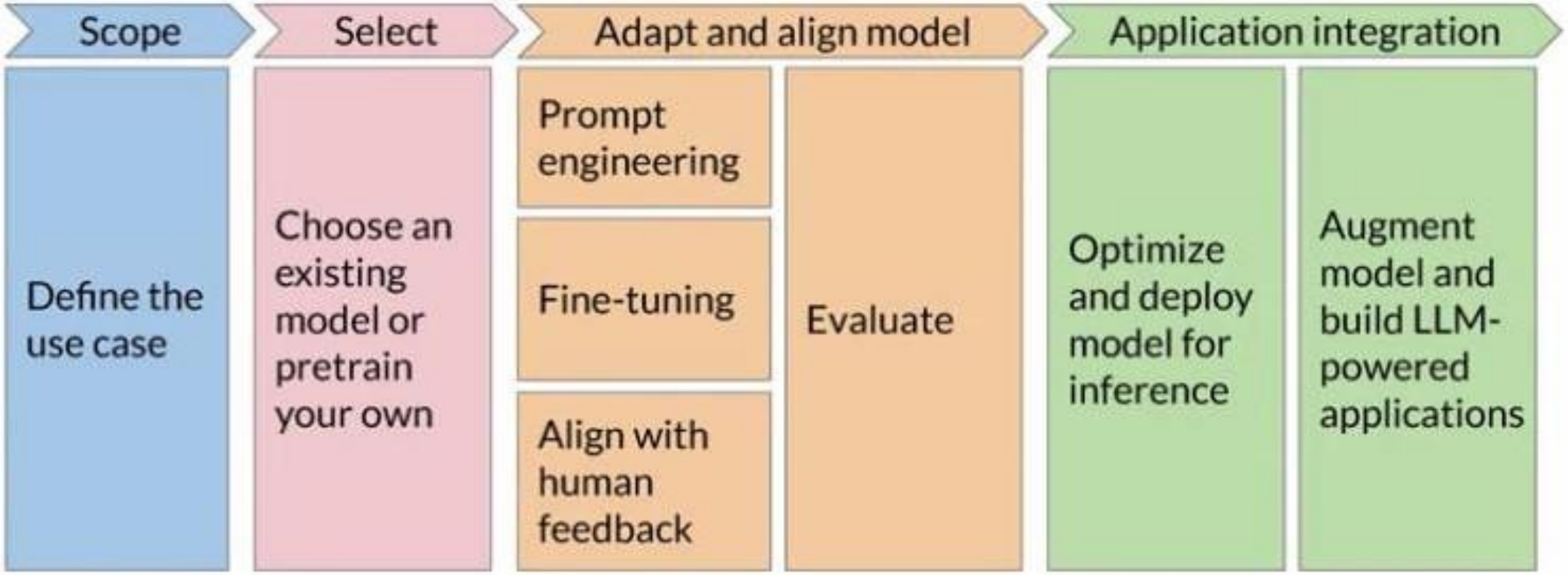
	Bytes per parameter
Model Parameters (Weights)	4 bytes per parameter
Adam optimizer (2 states)	+8 bytes per parameter
Gradients	+4 bytes per parameter
Activations and temp memory (variable size)	+8 bytes per parameter (high-end estimate)
TOTAL	=4 bytes per parameter +20 extra bytes per parameter

~20 extra bytes per parameter

Memory needed to train model

80GB @ 32-bit full precision

Generative AI – Project Lifecycle



Source - https://www.deeplearning.ai/courses/generative-ai-with-llms/

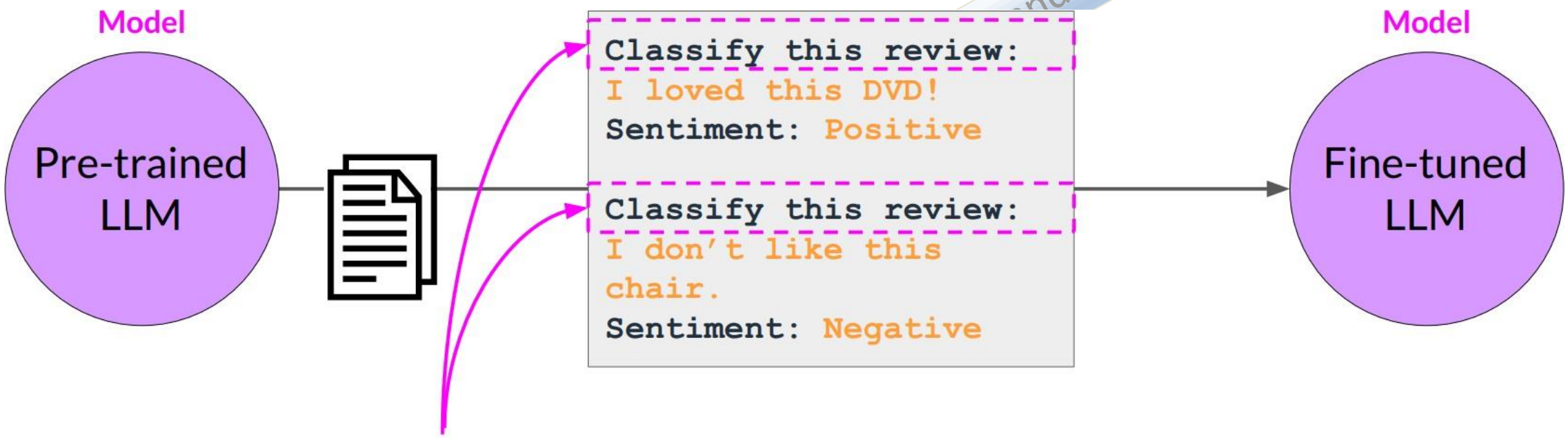
Why finetune a model?

Base Model

Finetuned Model

- Steers the model to more consistent outputs
- Reduces hallucinations
- Customizes the model to a specific use case
- Process is similar to the model's earlier training

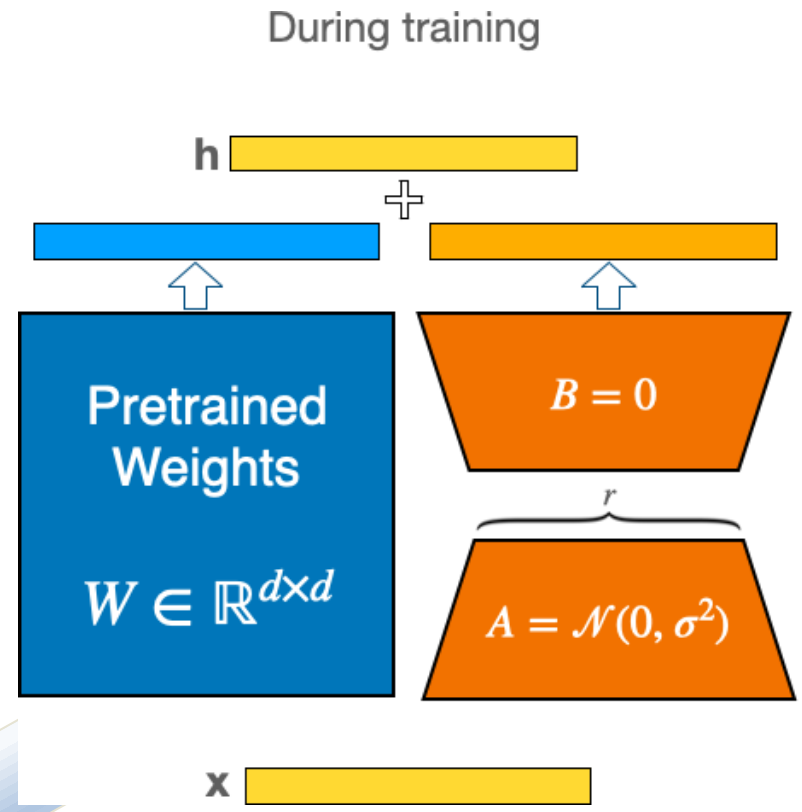
LLM Instruction fine tuning



Each prompt/completion pair includes a specific "instruction" to the LLM

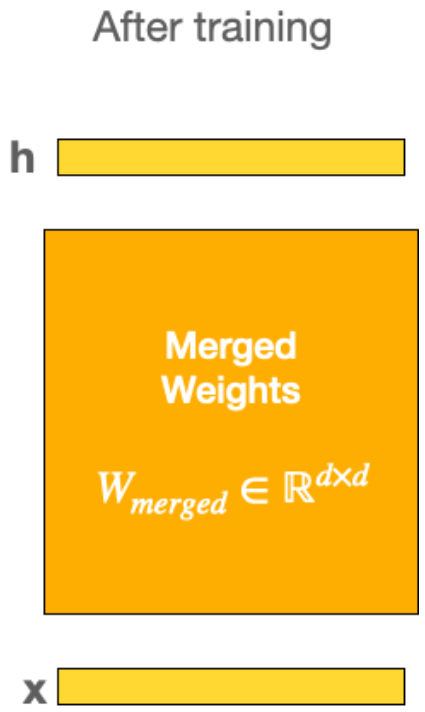
PEFT LoRA

Re parameterize model weights using a low-rank representation

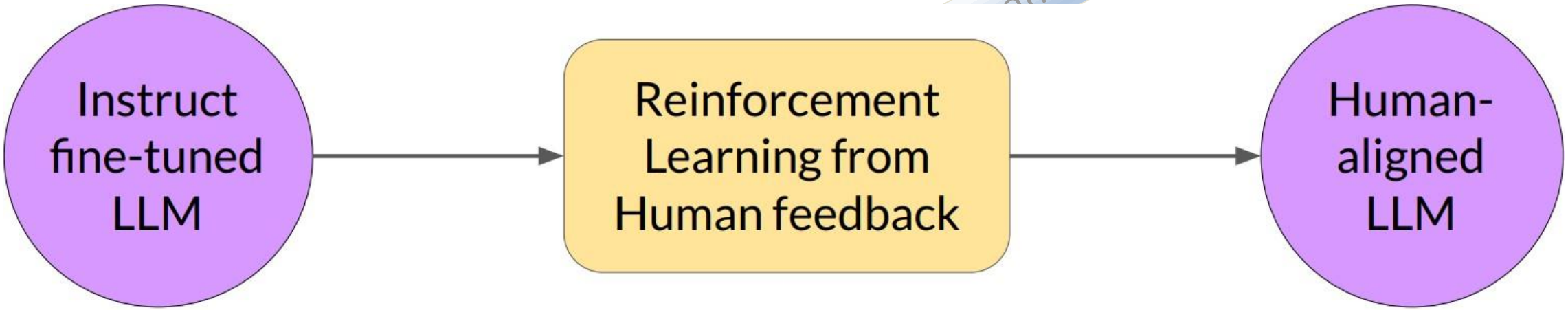


$$h = Wx + BAx$$

$$h = \underbrace{(W + BA)}_{W_{merged}}x$$

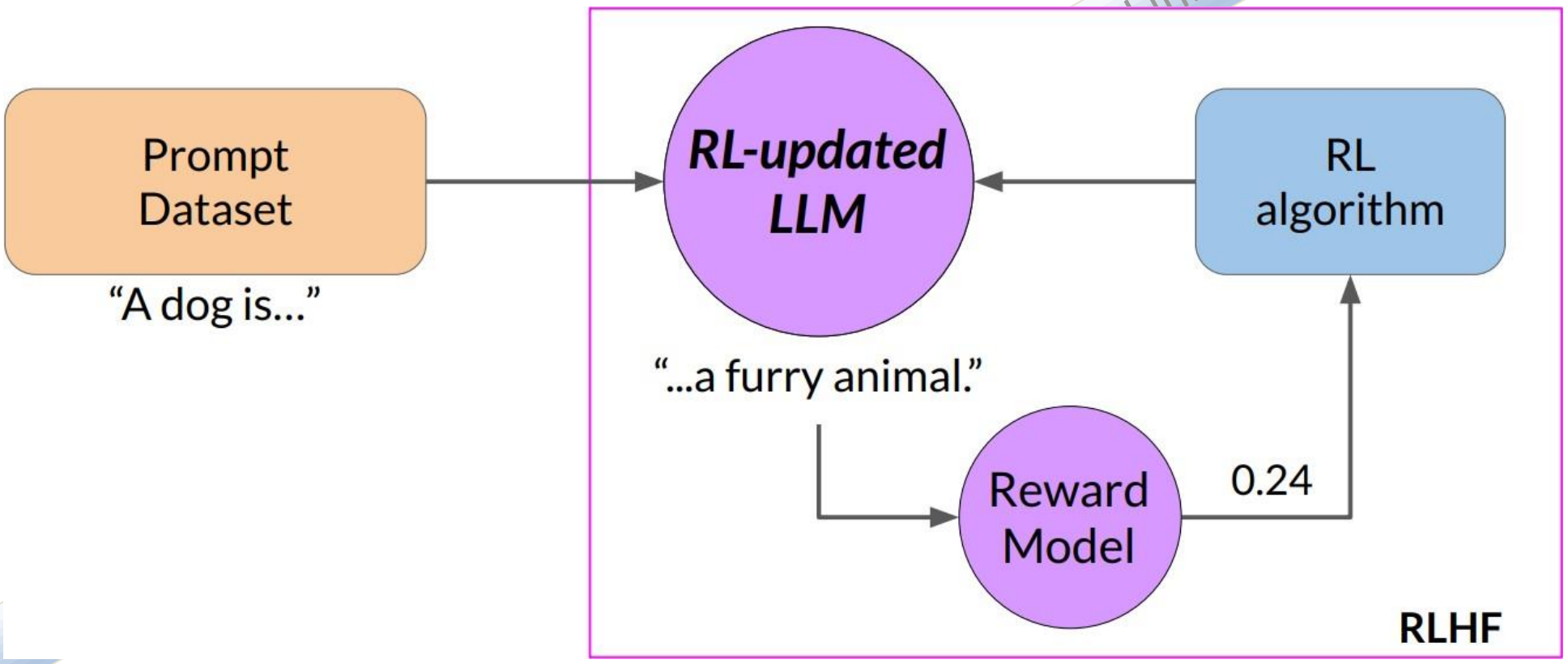


Reinforcement Learning from Human feedback (RLHF)



- Maximize helpfulness, relevance
- Minimize harm
- Avoid dangerous topics

Use reward model to fine-tune LLM



LLM Evaluation Metrics

ROUGE

- Used for text summarization
- Compares a summary to one or more reference summaries

BLEU SCORE

- Used for text translation
- Compares to human-generated translations

LLM Evaluation Metrics – ROUGE-1

Reference (human):

It is cold outside.

Generated output:

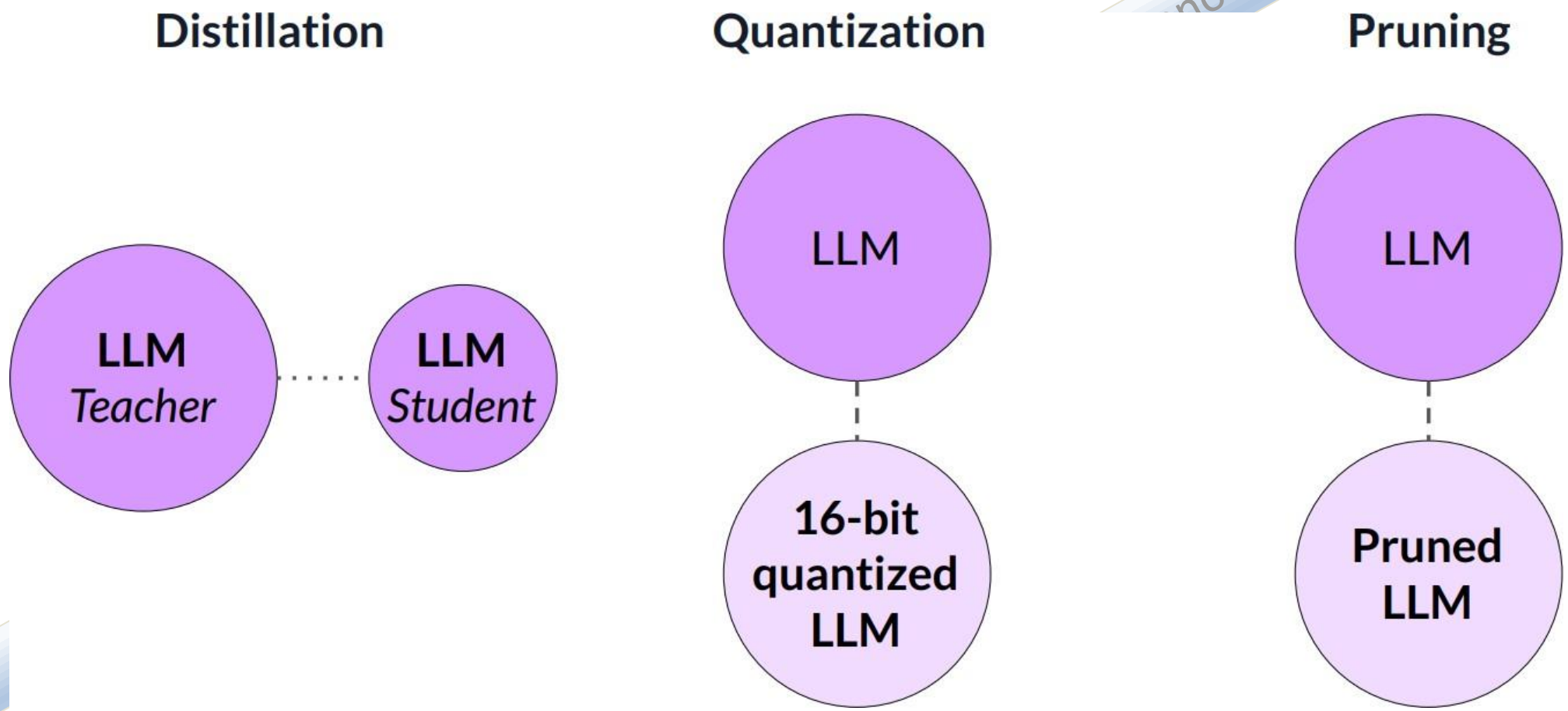
It is very cold outside.

$$\text{ROUGE-1 Recall} = \frac{\text{unigram matches}}{\text{unigrams in reference}} = \frac{4}{4} = 1.0$$

$$\text{ROUGE-1 Precision:} = \frac{\text{unigram matches}}{\text{unigrams in output}} = \frac{4}{5} = 0.8$$

$$\text{ROUGE-1 F1:} = 2\,\frac{\text{precision x recall}}{\text{precision + recall}} = 2\,\frac{0.8}{1.8} = 0.89$$

LLM Optimization Techniques for deployment/inference



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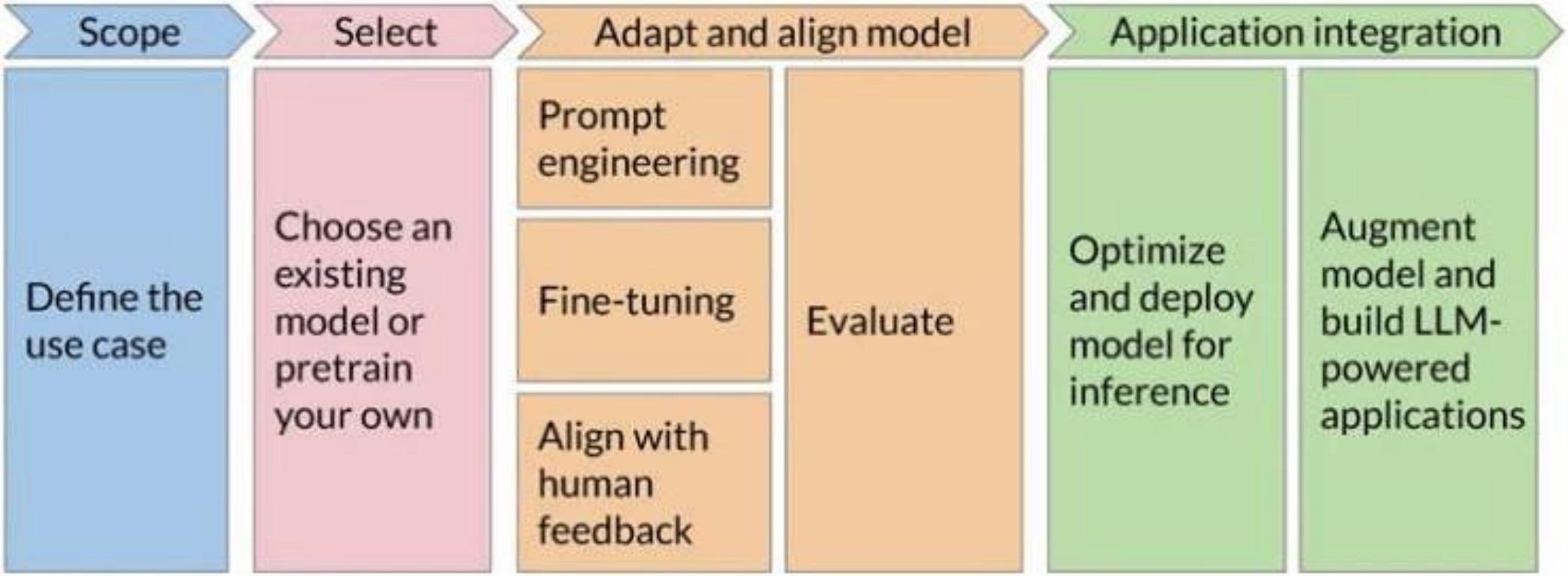
Generative AI – Project Lifecycle



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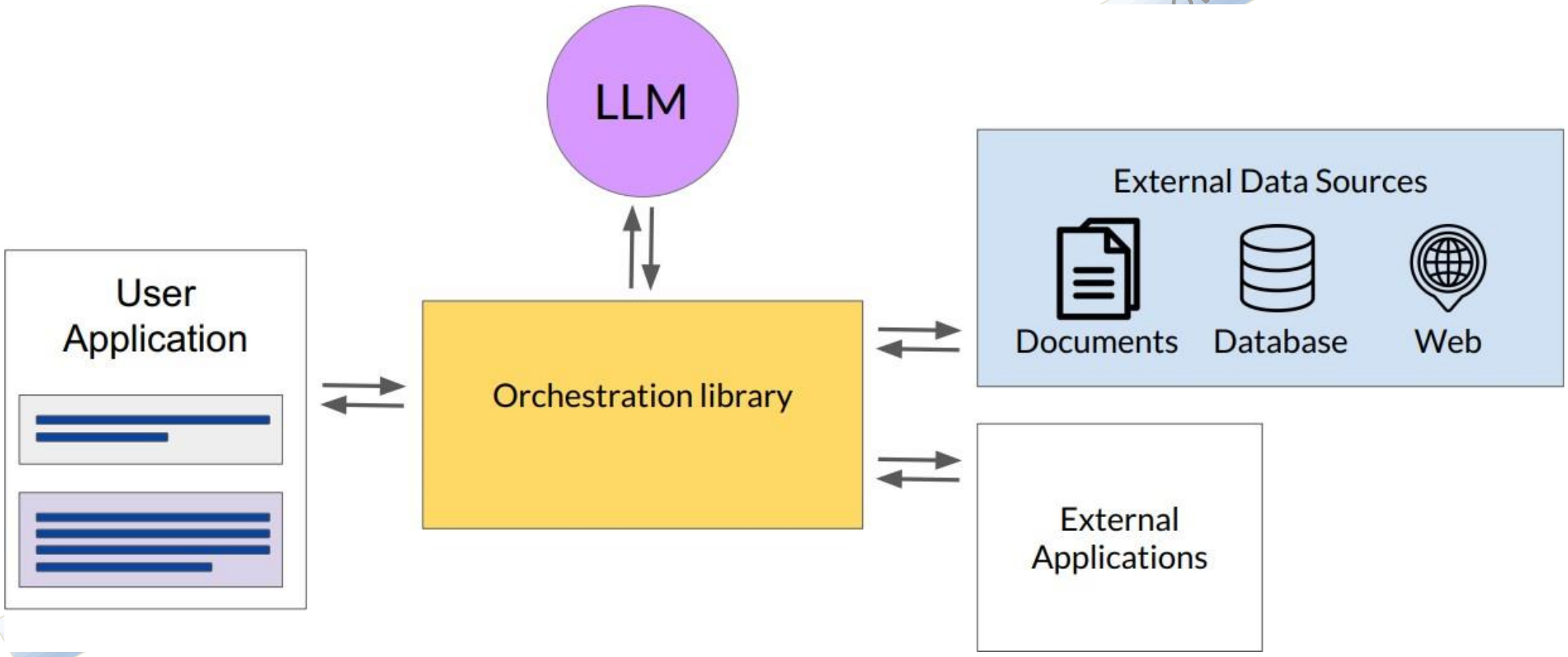
Retrieval Augmented Generation (RAG)



LLM Lifecycle summary

	Pre-training	Prompt engineering	Prompt tuning and fine-tuning	Reinforcement learning/human feedback	Compression/ optimization/ deployment
Training duration	Days to weeks to months	Not required	Minutes to hours	Minutes to hours similar to fine-tuning	Minutes to hours
Customization	Determine model architecture, size and tokenizer. Choose vocabulary size and # of tokens for input/context Large amount of domain training data	No model weights Only prompt customization	Tune for specific tasks Add domain-specific data Update LLM model or adapter weights	Need separate reward model to align with human goals (helpful, honest, harmless) Update LLM model or adapter weights	Reduce model size through model pruning, weight quantization, distillation Smaller size, faster inference
Objective	Next-token prediction	Increase task performance	Increase task performance	Increase alignment with human preferences	Increase inference performance
Expertise	High	Low	Medium	Medium-High	Medium

Source - https://www.deeplearning.ai/courses/generative-ai-with-llms/

References

- https://developers.google.com/machine-learning/resources/intro-llms
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- What is generative AI? https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-generative-ai
- Prompt Engineering for Generative AI https://developers.google.com/machine-learning/resources/prompt-eng
- Parameter-efficient fine-tuning of large-scale pre-trained language models https://www.nature.com/articles/s42256-023-00626-4
- Parameter-Efficient Fine-Tuning of Large Language Models with LoRA and QLoRA https://www.analyticsvidhya.com/blog/2023/08/lora-and-qlora/
- Attention is All You Need: https://research.google/pubs/pub46201/
- Solving a machine-learning mystery: https://news.mit.edu/2023/large-language-models-in-context-learning-0207
- https://medium.com/beaucoupdata/generative-ai-101-whats-up-with-chatgpt-1bfbb3f04ed
- https://www.deeplearning.ai/short-courses/
- https://learnprompting.org/docs/intro
- What Language Model Architecture and Pretraining Objective Work Best for Zero-Shot Generalization https://arxiv.org/pdf/2204.05832.pdf
- Language Models are Few-Shot Learners https://arxiv.org/pdf/2005.14165.pdf
- Guide to Parameter-Efficient Fine-Tuning https://arxiv.org/pdf/2303.15647.pdf
- ROUGE - https://aclanthology.org/W04-1013.pdf
- FLAN T5 model - https://blog.research.google/2021/10/introducing-flan-more-generalizable.html
- Llama model - https://ai.meta.com/blog/large-language-model-llama-meta-ai/
- LLM prompting - https://www.kaggle.com/competitions/llm-prompting-with-makersuite

Agenda – Part 2

- Generative AI Models Training and Deployment @ Intel
- Intel AI Software Tools – OneAPI, OpenVINO
- Intel Hardware Offerings
- Habana Gaudi2 – Hardware/Software Overview
- Large Language Models on Gaudi2
- Hugging Face – Optimum Habana
- Gaudi2 Performance - MLPerf Results
- Demo – LLaVA Model https://llava-vl.github.io/
- How to Access Habana Gaudi2
- Q and A

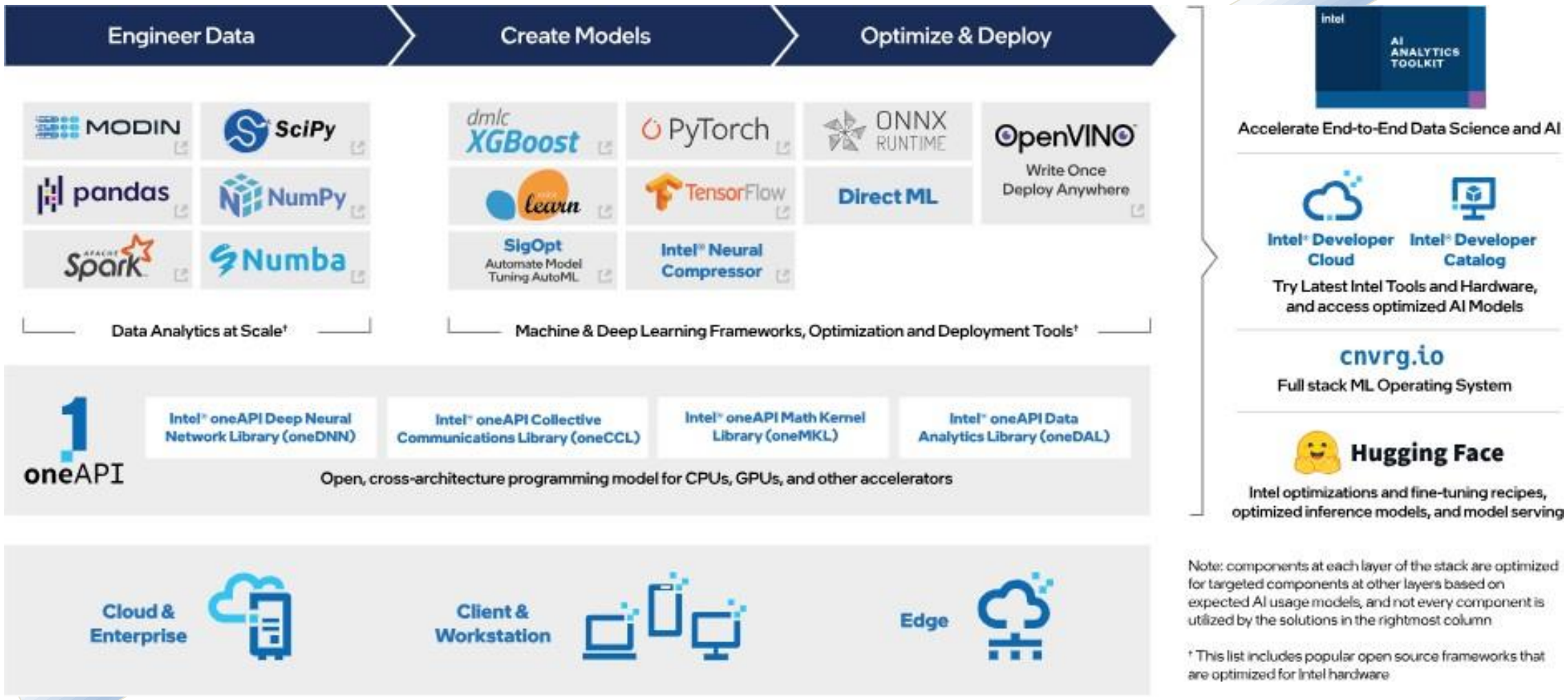
Generative AI Models Training @Intel

- Intel offers a purpose-built portfolio of both hardware and software technologies that combine to help streamline the business initiative and accelerate ROI
- Our mission is to enable AI innovators to deploy AI anywhere it is needed—from the edge to the cloud and data center—with optimal performance, scalability, and cost
- Software Resources to Simplify Generative AI Training and Deployment
  - Intel offers developers and data scientists a wide range of software tools and optimizations that can help maximize performance and dramatically boost productivity both during training and deployment

Generative AI Training – Software Tools

- oneAPI unified programming language, Intel® oneAPI Deep Neural Network Library with highly optimized implementations of deep learning building blocks
  - The oneAPI® unified programming model can also be used to support heterogeneous hardware platforms with less effort from development teams
- Intel® Extension for Transformers is another critical tool that helps to accelerate transformer-based models on Intel® platforms
  - This toolkit features a seamless user experience for model compression, advanced software optimizations, a unique compression-aware runtime, and optimized model packages, including Stable Diffusion, GPT-J-6BM, and BLOOM-176B
- Accenture partnership offers a range of reference kits that can help kick-start the generative or language AI project

Intel AI Software Tools

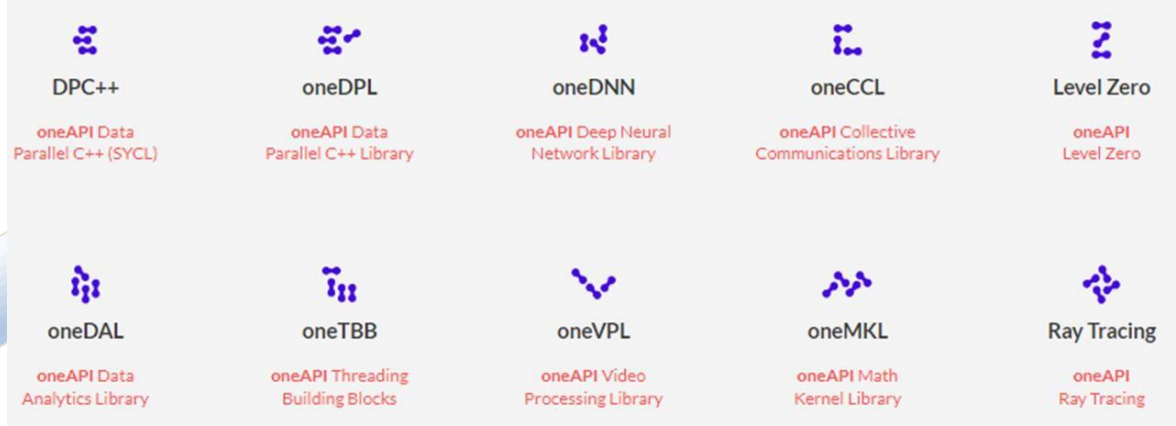


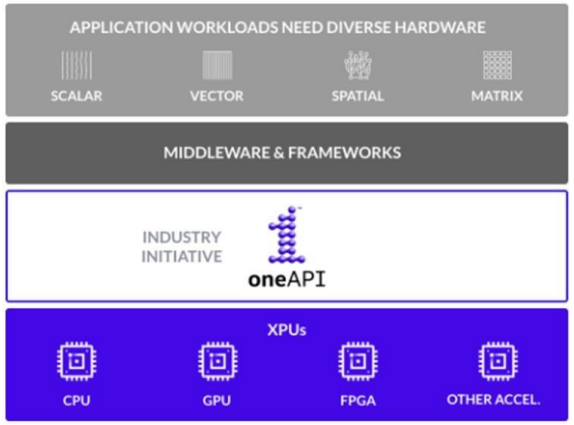
https://cnvrg.io

https://www.intel.com/content/www/us/en/developer/topic-technology/artificial-intelligence/overview.html

oneAPI Specification - https://spec.oneapi.io/versions/latest/index.html

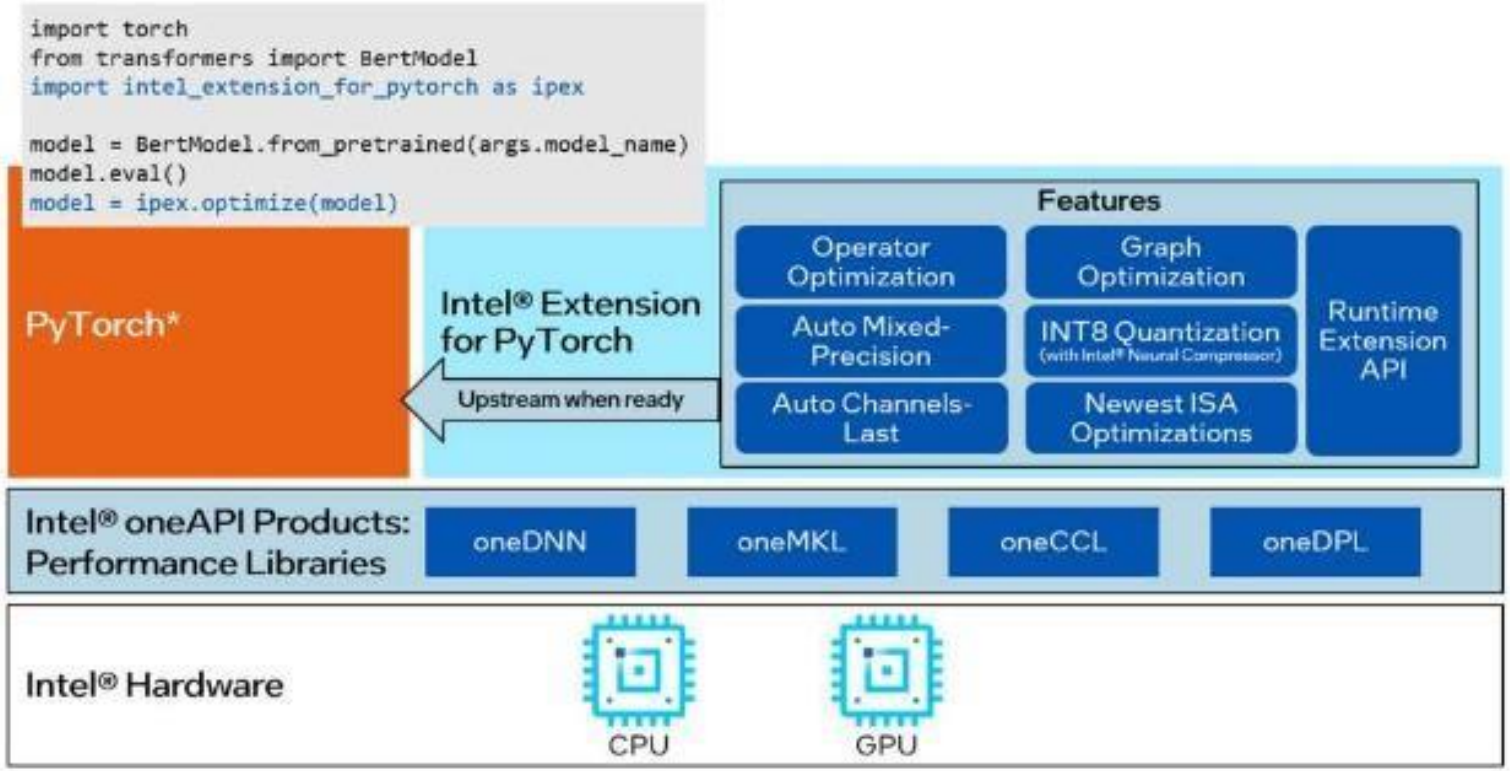
- oneAPI consists of a language and libraries for creating parallel applications
  - SYCL: oneAPI's core language for programming accelerators and multiprocessors. SYCL allows developers to reuse code across hardware targets (CPUs and accelerators such as GPUs and FPGAs) and tune for a specific architecture
  - oneDPL: A companion to the DPC++ Compiler for programming oneAPI devices with APIs from C++ standard library, Parallel STL, and extensions
  - oneDNN: High performance implementations of primitives for deep learning frameworks
  - oneCCL: Communication primitives for scaling deep learning frameworks across multiple devices
  - Level Zero: System interface for oneAPI languages and libraries
  - oneDAL: Algorithms for accelerated data science/Analytics
  - oneTBB: Library for adding thread-based parallelism to complex applications on multiprocessors
  - oneVPL: Algorithms for accelerated video processing
  - oneMKL: High performance math routines for science, engineering, and financial applications
  - Ray Tracing: A set of advanced ray tracing and high-fidelity rendering and computation routines for use in a wide variety of 3D graphics uses including, film and television photorealistic visual effects and animation rendering, scientific visualization, high-performance computing computations, gaming, and more





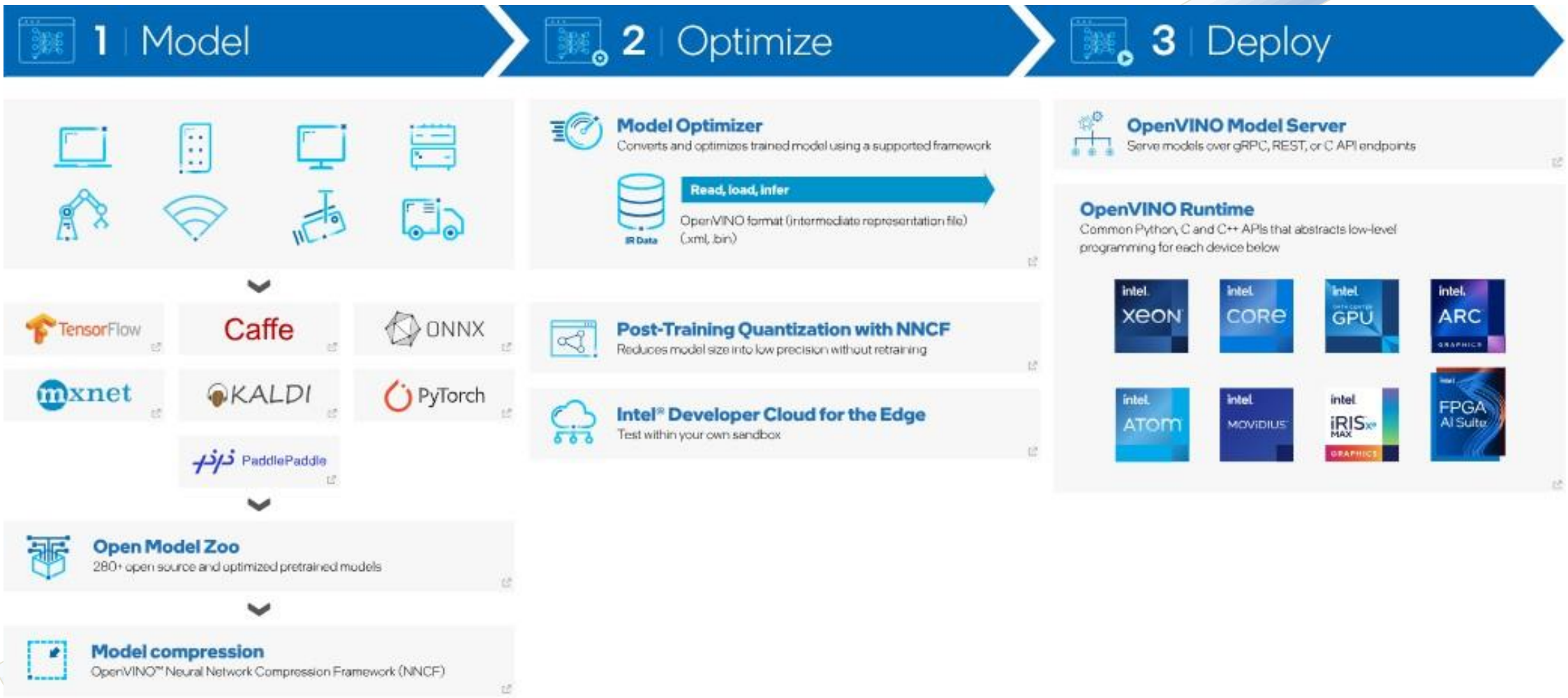
PyTorch Optimizations from Intel

- Intel releases its newest optimizations and features in Intel Extension for PyTorch before upstreaming them into open source PyTorch



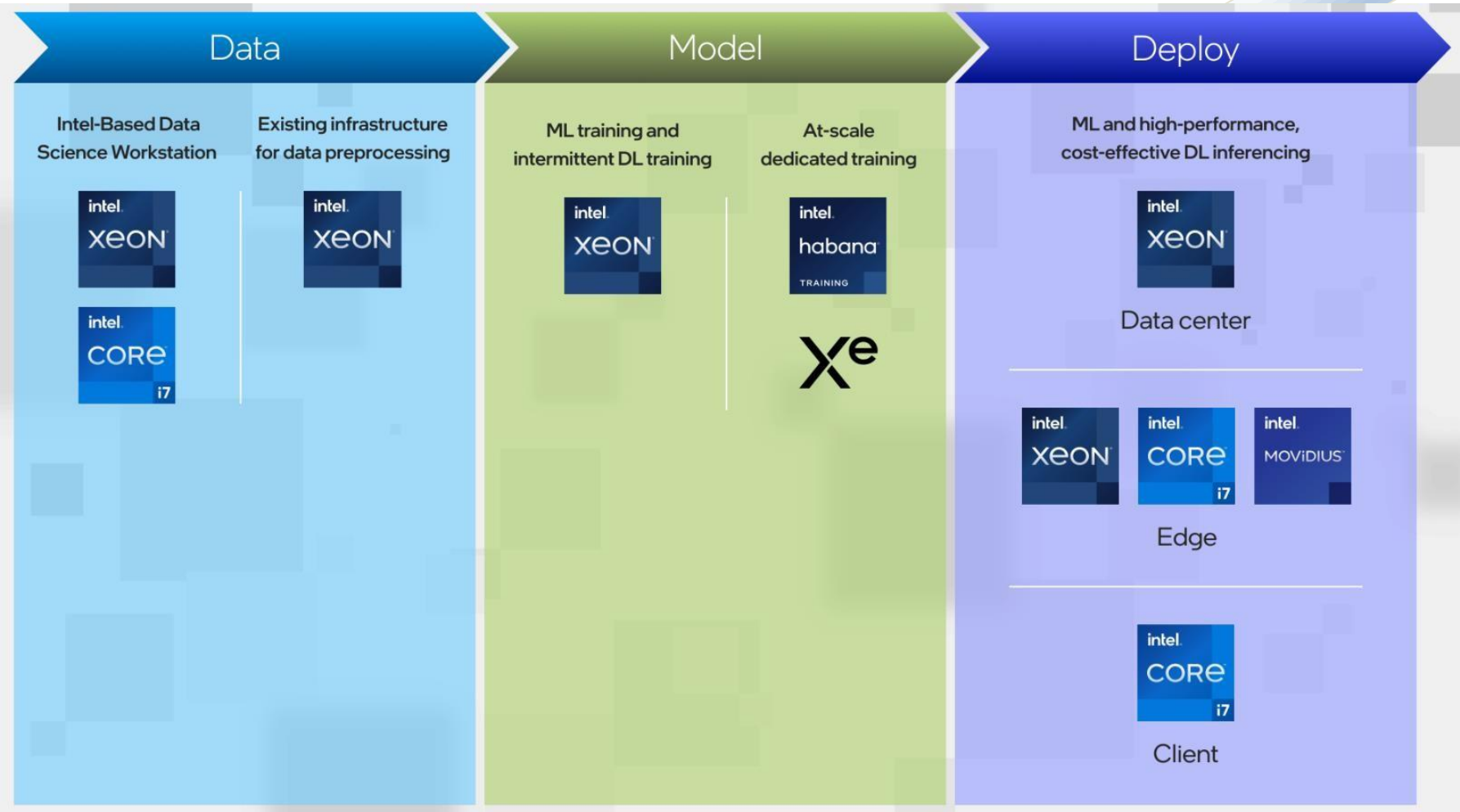
https://www.intel.com/content/www/us/en/developer/tools/oneapi/optimization-for-pytorch.html

OpenVINO Toolkit



https://www.intel.com/content/www/us/en/developer/tools/openvino-toolkit/overview.html

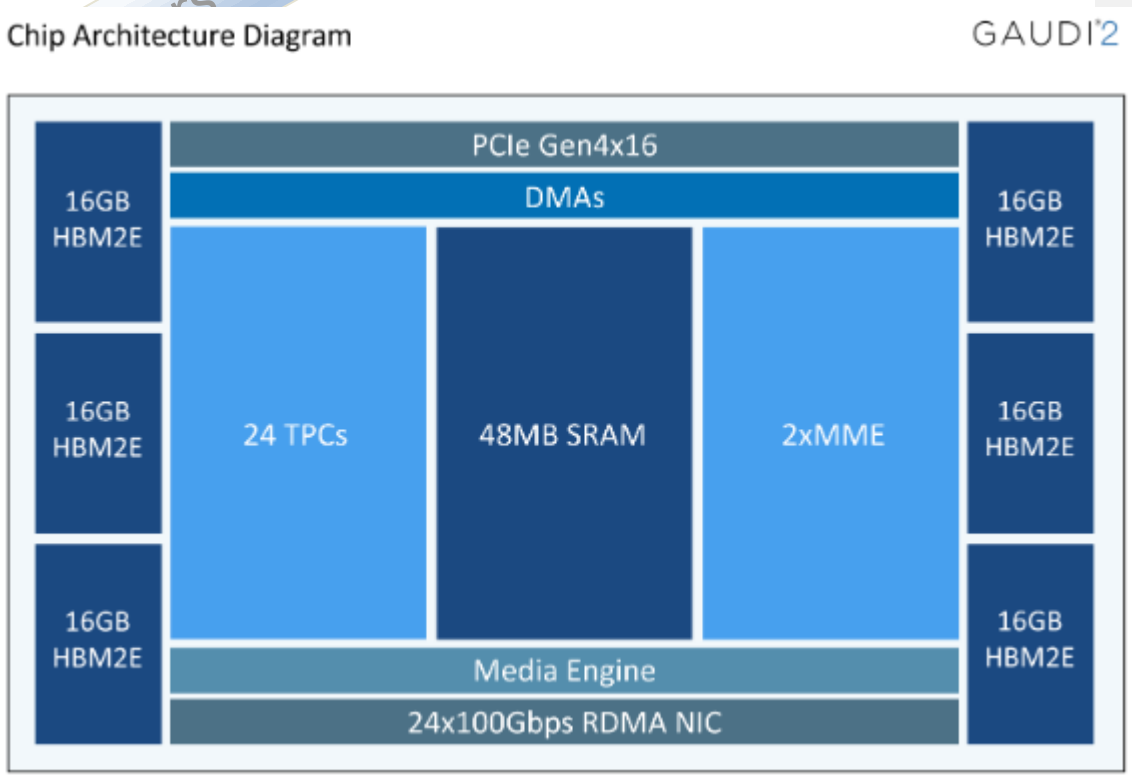
AI Hardware @ Intel



https://www.intel.com/content/www/us/en/artificial-intelligence/hardware.html

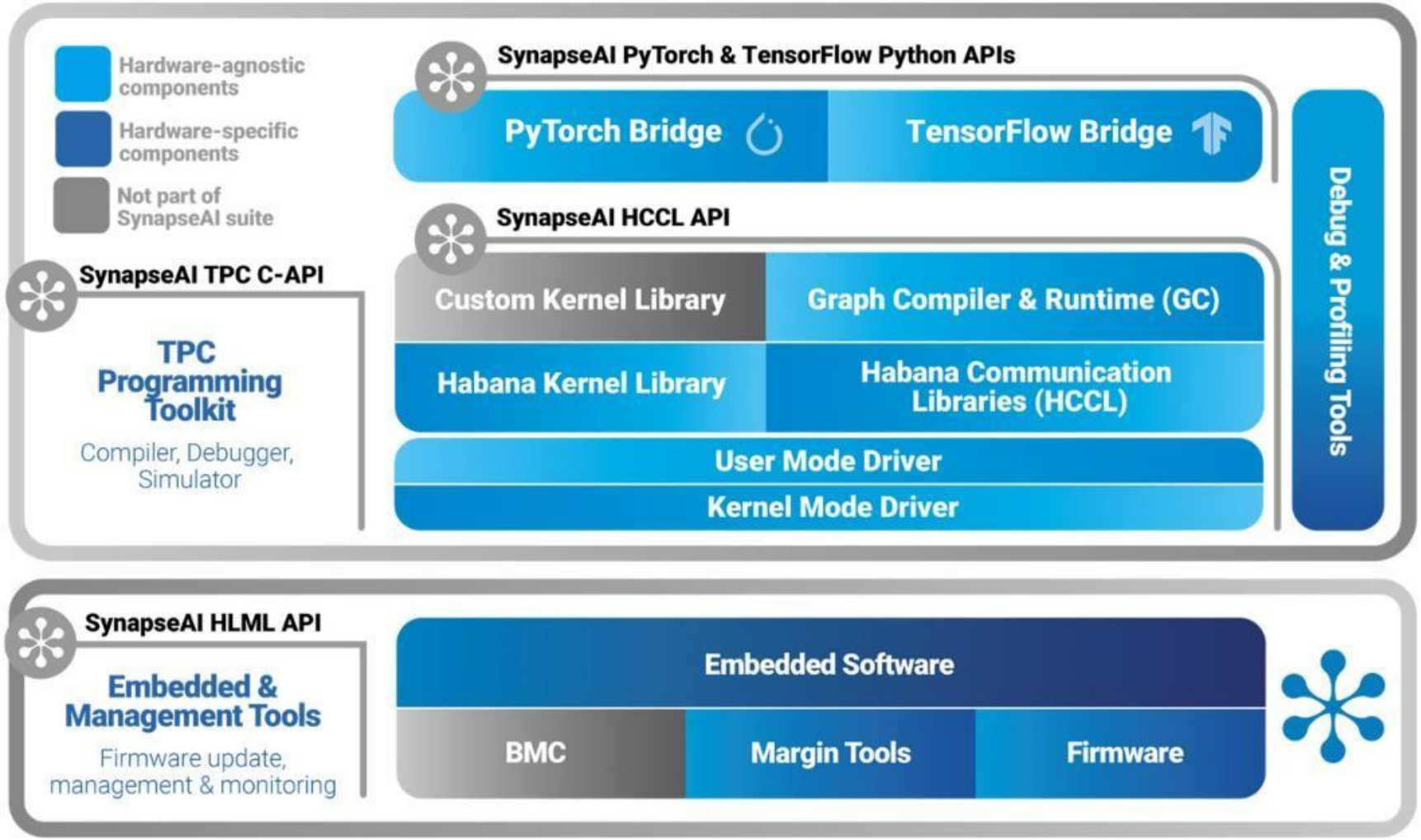
Habana Gaudi2 – Hardware Architecture

- 7nm process technology
- Heterogeneous compute
- 24 Tensor Processor Cores
- Dual matrix multiplication engines
- 24 100 Gigabit Ethernet integrated on chip
- 96 GB HBM2E memory on board
- 48 MB SRAM
- Integrated Media Control



https://habana.ai/products/gaudi2/

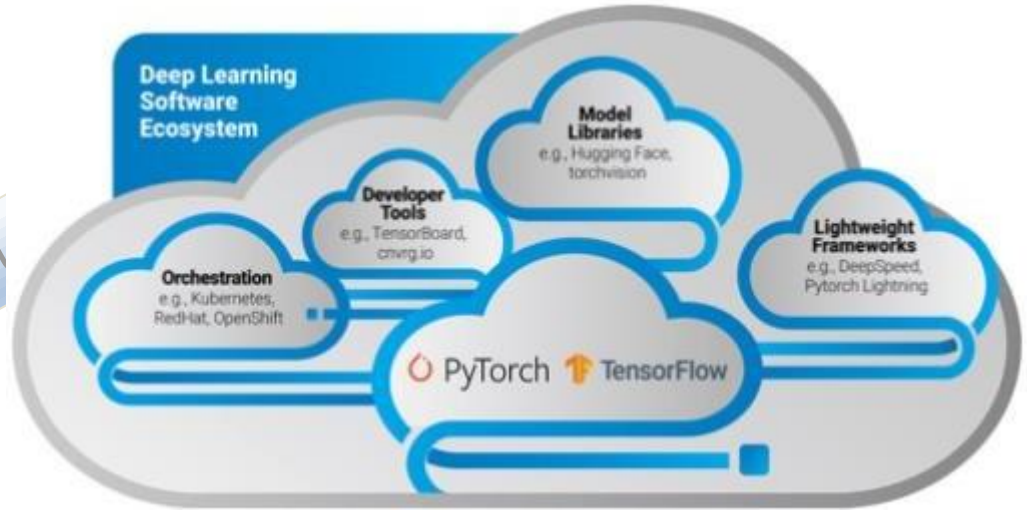
Habana Gaudi2 – Software Architecture



https://habana.ai/training-software/

Habana Gaudi2 – Software Ecosystem

Habana Deep Learning Software Ecosystem brings together leading software providers, tools and code to accelerate development of state-of-the-art deep learning models based on PyTorch, TensorFlow, PyTorch Lightning and DeepSpeed frameworks



Hugging Face: over 50,000 AI models and 90,000+ GitHub stars. Habana Optimum library on Hugging Face provides customers using Gaudi and Gaudi2 hardware access to the entire Hugging Face model universe. Checkout a list of Hugging Face Habana optimized models here.

PyTorch Lightning

Lightning: acceleration of PyTorch deep learning workloads

deepspeed

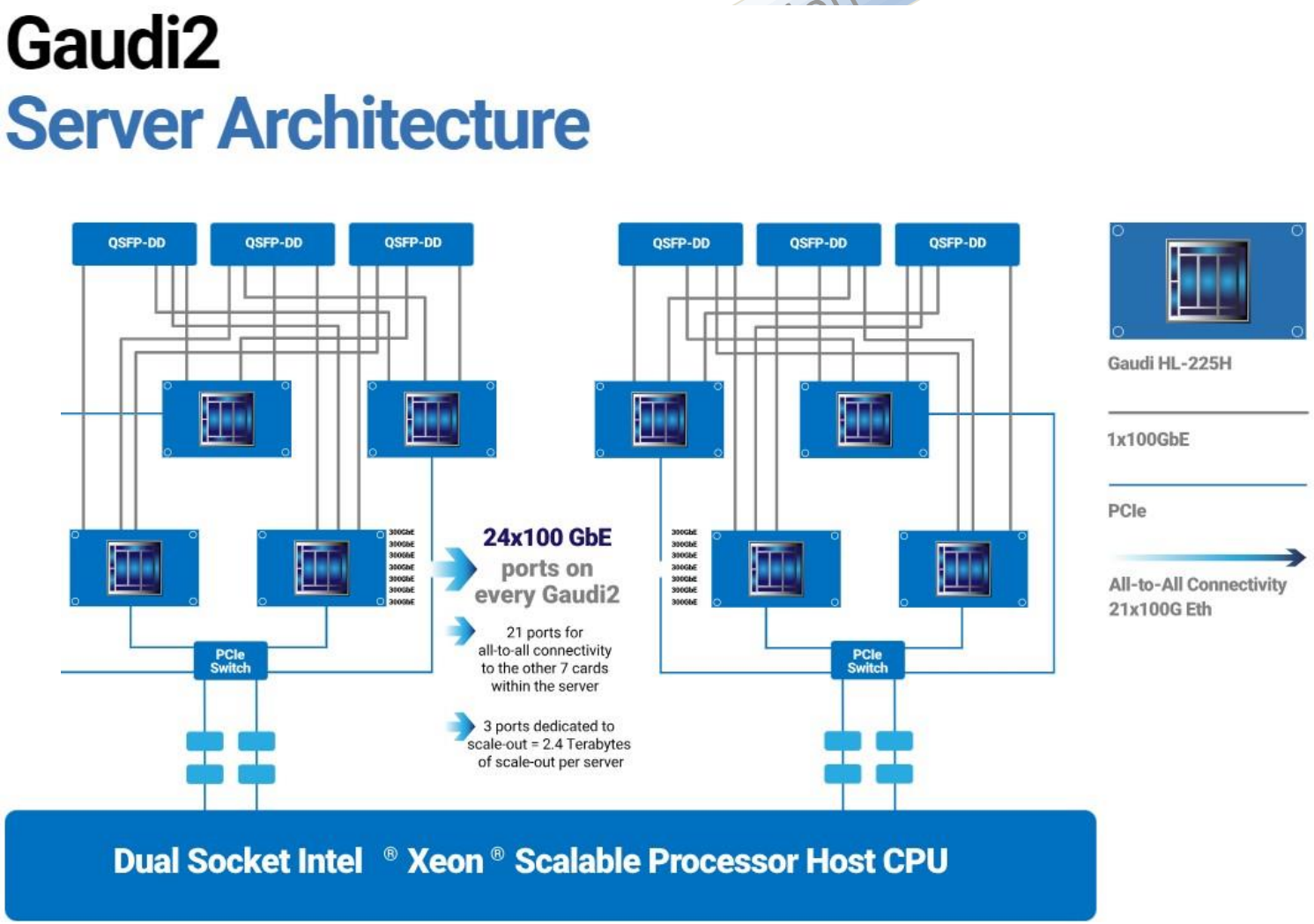
Deep Speed: easy-to-use deep learning optimization software that enables scale and speed with particular focus on large scale models

cnvrg.io

Cnvrg.io: MLOps support for customers implementing Habana processor solutions

https://habana.ai/training-software/

Habana Gaudi2 - Server Architecture



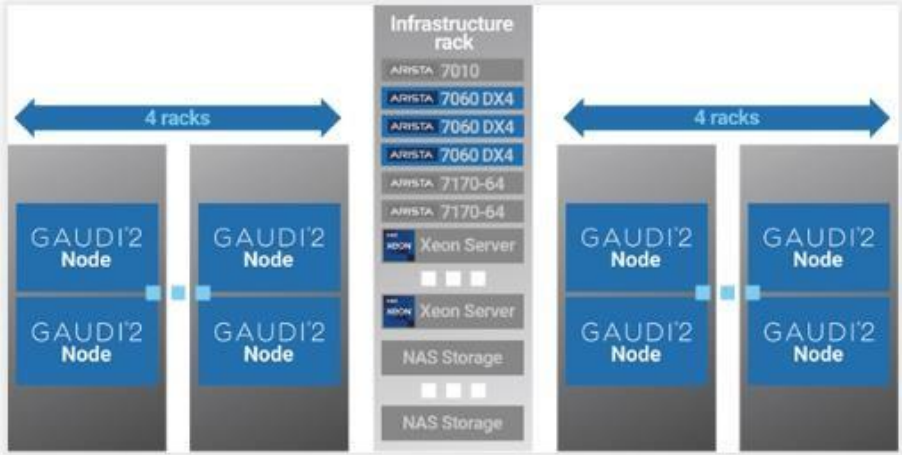
Habana Gaudi2 - Scale Out Scenarios

Small Pod Architecture

16-40 Gaudi2s (2-5 servers, with 8x Gaudi2 each)

Large Pod Architecture

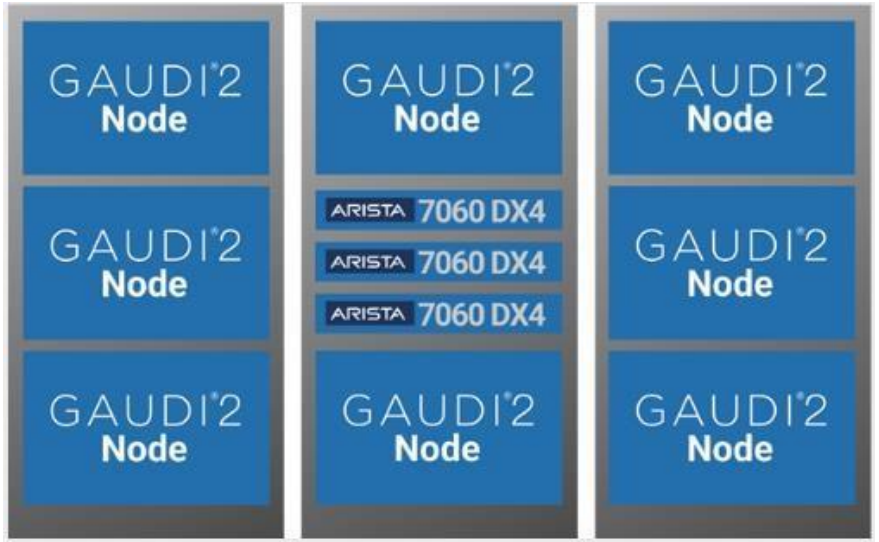
- Supports variable ratio of nodes-to-switches
- 3x 400G switches + up to 128 Gaudi2s (16 servers with 8x Gaudi2 each)



Gaudi2 MegaPod Architecture

Large clusters can be easily built using multiple MegaPods

- 8 Gaudi2 servers & 3 switches
- 8x Gaudi2 per node (server)
- Leaf switches are placed close to Gaudi2 nodes to minimize communication latency
- Copper cables can be used within pod



Diffusion and Large Language Models on Gaudi2

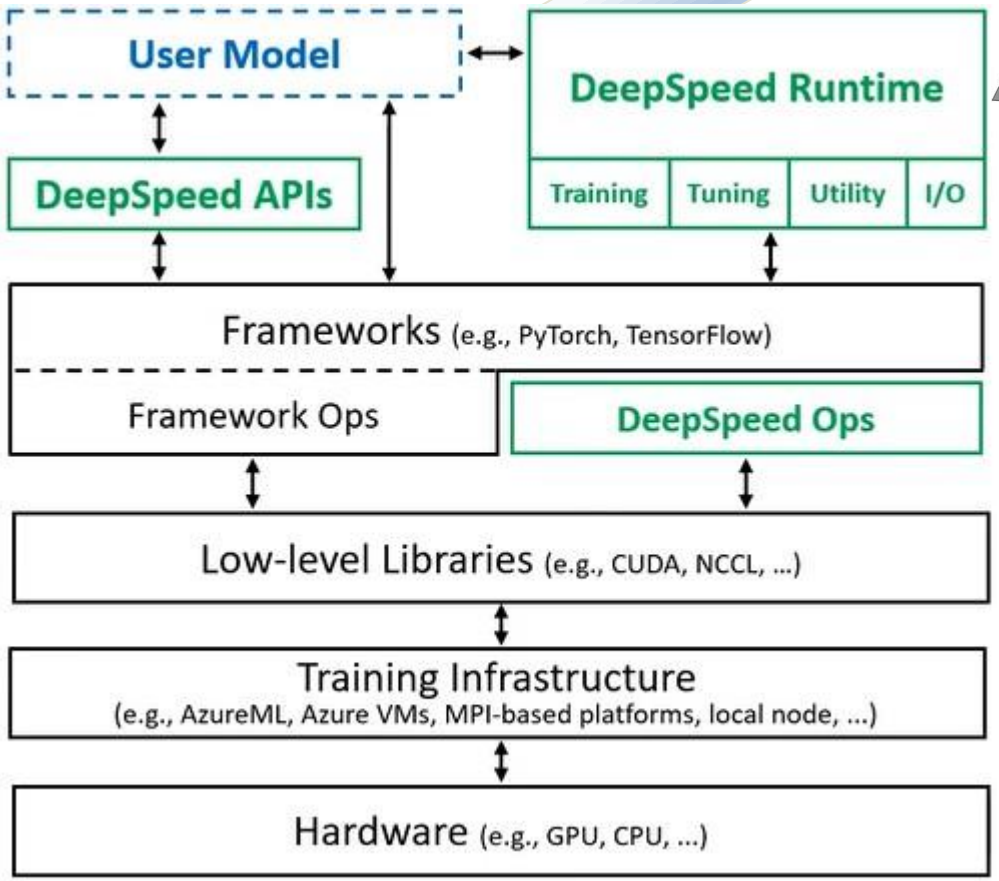
- Diffusion Models
  - Stable Diffusion Training
  - Stable Diffusion Inference
  - Hugging Face Stable Diffusion

- Large Language Models (LLMs)
  - Inference
    - BLOOM Models (7B & 176B)
  - Training
    - Megatron-DeepSpeed LLaMA 13B
    - MLPerf GPT3
    - Megatron-DeepSpeed BLOOM 13B
    - DeepSpeed BERT Models
  - Hugging Face Models

https://developer.habana.ai/resources/generative-ai-and-large-language-models/

DeepSpeed Architecture

- Efficiency features
  - Memory: Zero Redundancy Optimizer (ZeRO)
  - Compute: fastest transformer kernels
  - Communication: sparse gradient
  - IO: overlapping IO with compute
  - Parallelism: ZeRO-powered data parallelism, combination of data + model parallelism
- Effectiveness features
  - Adaptive hyperparameter tuning
  - Optimizers for large-batch training
- Usability features
  - Distributed training with mixed precision, gradient accumulation, etc.
  - IO: simplified data loader with auto batch creation
  - Training agnostic checkpoint / recompute
  - Performance profiling



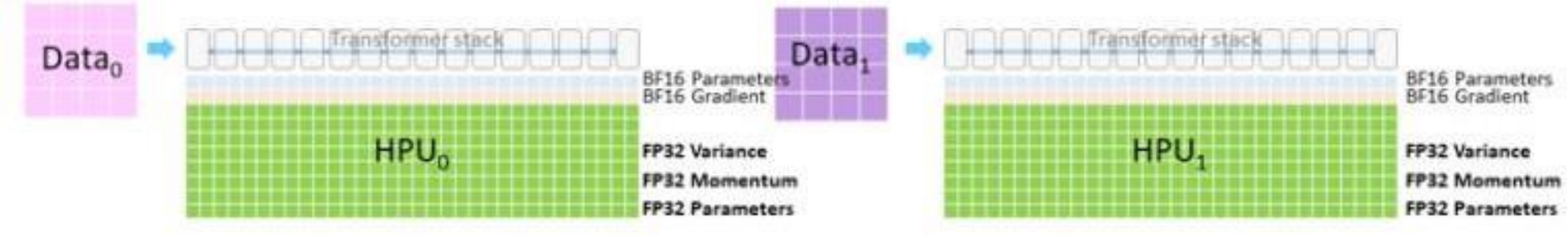
- Deploy training job across distributed devices
- Data partitioning
- Model partitioning
- System optimizations
- Tuning for effectiveness
- Utility, e.g., failure detection and checkpointing.

https://youtu.be/lQCG4zUCYao

https://github.com/microsoft/DeepSpeed

LLMs - Memory Efficient Training using DeepSpeed

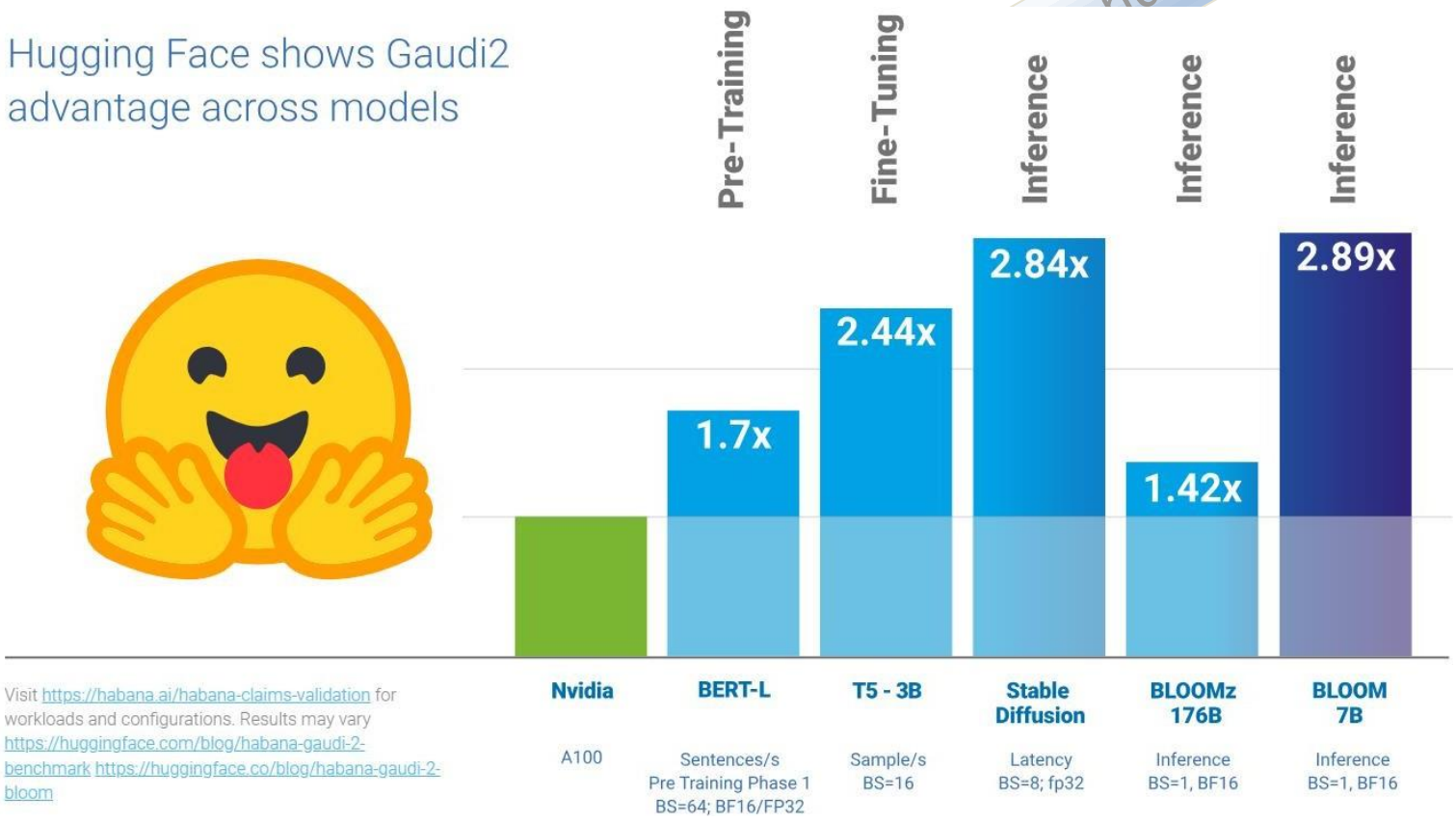
- Memory is used for the following
  - BF16 parameters
  - BF16 gradients
  - FP32 optimizer states which includes FP32 momentum of the gradients, FP32 variance of the gradients and FP32 Parameters
- DeepSpeed includes ZeRO (Zero Redundancy Optimizer), a memory-efficient approach for distributed training
  - ZeRO-1 stage - partitions the optimizer states alone across the data parallel processes
  - ZeRO-2 stage - partitions both the optimizer states and gradients across the data parallel processes



https://youtu.be/lQCG4zUCYao
https://docs.habana.ai/en/latest/PyTorch/DeepSpeed/index.html
https://developer.habana.ai/blog/memory-efficient-training-on-habana-gaudi-with-deepspeed/

Habana Gaudi2 – LLMs using Optimum Habana

- Optimum Habana is the interface between the 🤗 Transformers and 🤗 Diffusers libraries and [Habana's Gaudi processor (HPU)]



Gaudi2 - Hugging Face – Optimum Habana Models

- Transformers

Architecture	Training	Inference	Tasks
BERT	✓	✓	• text classification • question answering • language modeling
RoBERTa	✓	✓	• question answering • language modeling
ALBERT	✓	✓	• question answering • language modeling
DistilBERT	✓	✓	• question answering • language modeling
GPT2	✓	✓	• language modeling • text generation
BLOOM(Z)	✗	• DeepSpeed	• text generation
StarCoder	✗	• Single card	• text generation
GPT-J	• DeepSpeed	• Single card • DeepSpeed	• language modeling • text generation
GPT-NeoX	• DeepSpeed	• DeepSpeed	• language modeling • text generation
OPT	✗	• DeepSpeed	• text generation
Llama 2 / CodeLlama	• DeepSpeed • LoRA	• DeepSpeed • LoRA	• language modeling • text generation
StableLM	✗	• Single card	• text generation
Falcon	✗	• Single card	• text generation
CodeGen	✗	• Single card	• text generation
MPT	✗	• Single card	• text generation
T5	✓	✓	• summarization • translation • question answering
ViT	✓	✓	• image classification
Swin	✓	✓	• image classification
Wav2Vec2	✓	✓	• audio classification • speech recognition
CLIP	✓	✓	• contrastive image-text training
BridgeTower	✓	✓	• contrastive image-text training
ESMFold	✗	• Single card	• protein folding

- Diffusers

Architecture	Training	Inference	Tasks
Stable Diffusion	✗	• Single card	• text-to-image generation
LDM3D	✗	• Single card	• text-to-image generation

https://huggingface.co/docs/optimum/habana/index

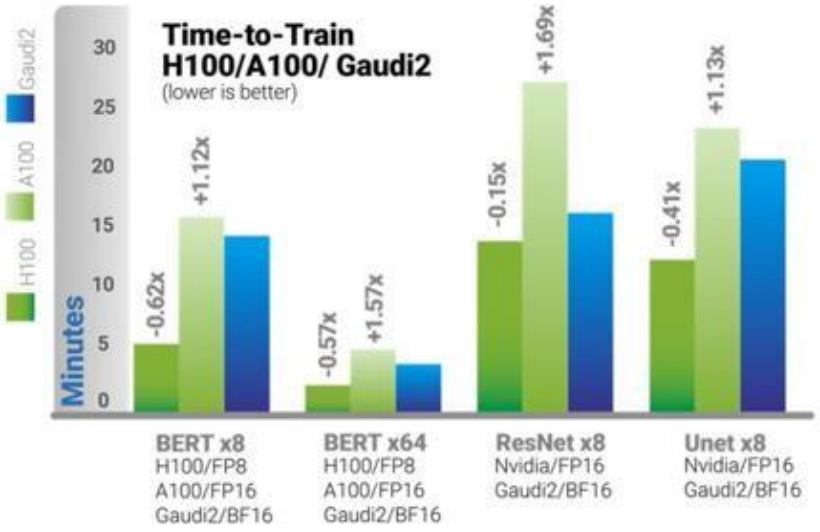
Gaudi2 - MLPerf 3.0 Training Benchmark Results – Jun'23

Gaudi2 performance >A100 today;
Gaudi2 price/performance with FP8 expected >H100*

- Gaudi2 software coverage expands: GPT-3 and Unet
- Gaudi2 performance > A100 on 4 models

	H100	A100	Gaudi2
GPT-3	64.3/512 GPUs	Not reported	311.9/384 G2s
		Not reported	442.6/256 G2s
Bert x8	5.4	15.8	14.1
Bert x64	0.9	3.3*	2.1
ResNet x8	13.5	27.0	16.0
Unet x8	12.0	23.2	20.5

* Nvidia reported A100 BERT x64 with 40 GB; other Nvidia metrics cited here are 80 GB.



Performance metrics based on MLPerf Training 3.0 benchmark. For configuration details, see the results provided under embargo by MLPCommons. Results may vary.
Performance expectations for FP8 based on Intel internal evaluation.

https://mlcommons.org/en/training-normal-30/

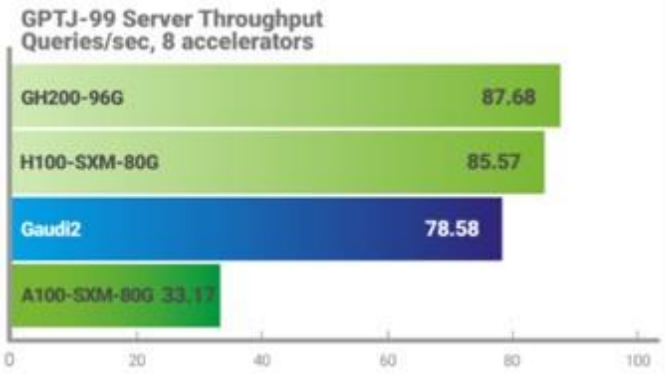
https://habana.ai/blog/new-mlcommons-results-highlight-impressive-competitive-ai-gains-for-intel/

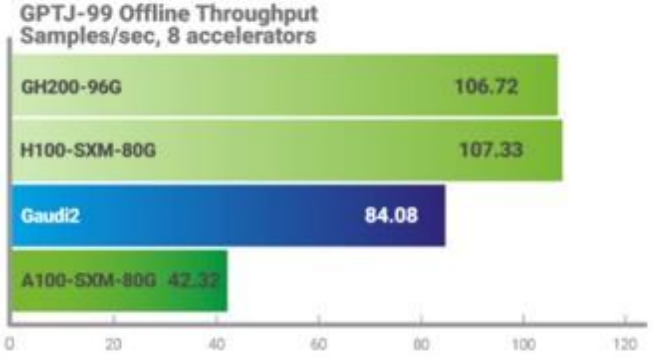
https://www.forbes.com/sites/karlfreund/2023/09/11/intel-gaudi2-looked-to-be-a-credible-alternative-to-nvidia-until/?sh=36c922db2882

Gaudi2 - MLPerf 3.1 LLM Inference Performance – Jun'23

GPT-J Benchmark:
Outstanding Gaudi2 LLM Inference Performance

- H100 slightly outperforms Gaudi2 on GPT-J with 1.09x (Server) and 1.28x (Offline)
- Gaudi2 outperforms A100 by 2.4x (Server) and 2x (offline)
- Gaudi2 employed FP8 and reached 99.9% accuracy
- Gaudi2 offers significantly competitive price-performance as compared to A100, H100 and GH-200





			GPTJ-99				GPTJ-99.9			
			Server	Vs. Gaudi2	Offline	Vs. Gaudi2	Server	Vs. Gaudi2	Offline	Vs. Gaudi2
Submitter	a#	Accelerator	Queries/Sec		Samples/Sec		Queries/Sec		Samples/Sec	
Intel-Habana Labs	8	Habana Gaudi2	78.58	1	84.08	1	78.58	1	84.08	1
Supermicro	8	NVIDIA H100-SXM-80GB	85.57	x1.09	107.33	x1.28	85.43	x1.09	107.06	x1.27
Dell	8	NVIDIA A100-SXM-80GB CTS	33.17	x0.42	42.32	x0.5	Not Submitted			
Nvidia	1	NVIDIA GH200-96G	10.96	x1.12	13.34	x1.27	10.96	x1.12	13.34	x1.27

Performance metrics based on MLPerf Inference 3.1 benchmark. For configuration details, see the results published by MLCommons. Results may vary.

https://www.forbes.com/sites/karlfreund/2023/09/11/intel-gaudi2-looked-to-be-a-credible-alternative-to-nvidia-until/?sh=36c922db2882

Gaudi2 - Hugging Face - Visual-Language AI Models

- A new fine-tuning performance benchmark for BridgeTower, a Vision-Language (VL) AI model, has shown that there's life to the AI acceleration camp other than Nvidia's green
- While Nvidia does dominate the AI acceleration market (through exceptional foresight, a well-thought-out and documented software stack, and pure processing performance), other players are eager to take a piece of the AI market for themselves
- BridgeTower, Intel's own Gaudi 2 silicon has been shown by Hugging Face to outperform Nvidia's A100 80 GB by a staggering 2.5x - and it even beats Nvidia's prodigy-child H100 by 1.4x

Device	dataloader_num_workers=0	dataloader_num_workers=1	dataloader_num_workers=2	dataloader_num_workers=2 + mediapipe_dataloader
Gaudi 2 HPU				
H100 GPU				
A100 80 GB GPU				

https://www.tomshardware.com/news/intel-habana-gaudi-beats-nvidias-h100-in-visual-language-ai-models-hugging-face

Gaudi2 – MLPerf Training 3.1 Results – Nov' 23

Intel® Gaudi®2 Accelerator Performance Doubled with FP8

- Intel Gaudi team projected to customers +90% performance gain with FP8
- Delivered more than promised: 103% on GPT-3 industry benchmark

Intel Gaudi 2 MLPerf V3.1 GPT 3 FP8 Performance Boost

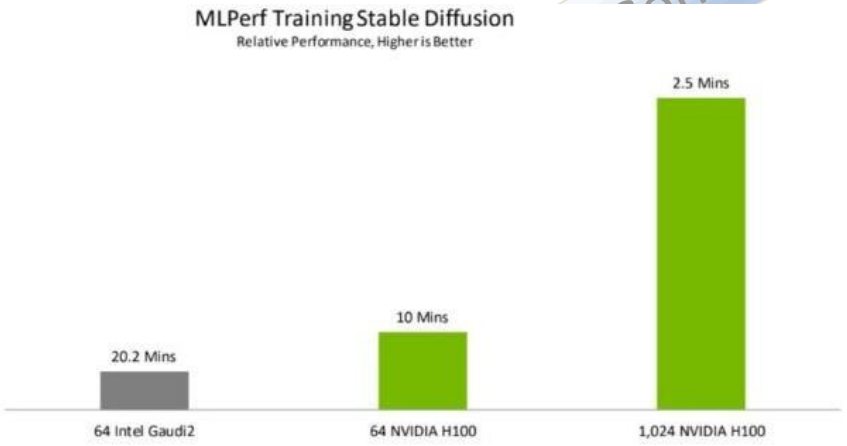
Outstanding Intel® Gaudi®2 AI Accelerator performance on MLPerf v3.1 Inference Benchmark (June)

Intel Gaudi2 Accelerator with FP8: near-parity performance on GPT-J (Server) with H100

- Gaudi 2 inference performance on GPT-J: -9% (Server) and -28% (Offline) vs H100
- Gaudi 2 outperformed A100 by 2.4x (Server) and 2x (Offline)
- Gaudi 2 employed FP8 and reached 99.9% accuracy

For complete results information and configurations, see MLCommons publication: https://mlcommons.org/en/

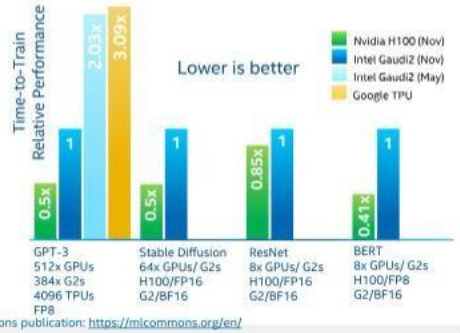
Intel Gaudi 2 MLPerf Inference V3.1 GPT 3 FP8 Performance Boost



MLPerf Training V3.1 NVIDIA Showing The Price Performance Advantage Of Intel Gaudi 2

Intel® Gaudi®2 performance advances strengthen competitive price-performance vs. H100

- Gaudi2 performance on ResNet near that of H100.
- H100 with FP8 outperformed Gaudi2 with BF16 on BERT.
- Vs. TPU, Gaudi2 delivered 3x performance on GPT-3.
- Given its significantly lower server cost vs. H100 server cost, Intel Gaudi2 delivers price-performance advantage vs. H100 across models.



For complete results information and configurations, see MLCommons publication: https://mlcommons.org/en/

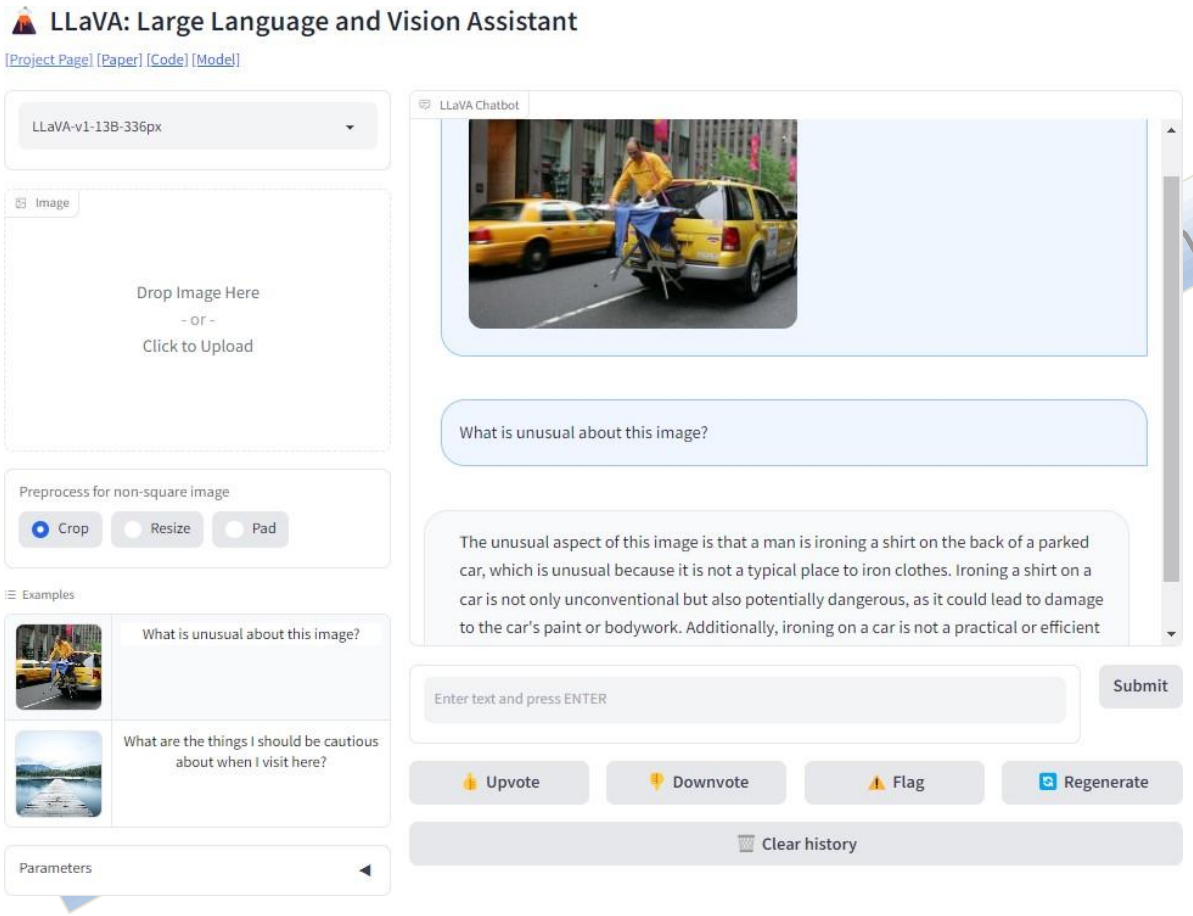
Intel Data Center and AI Group

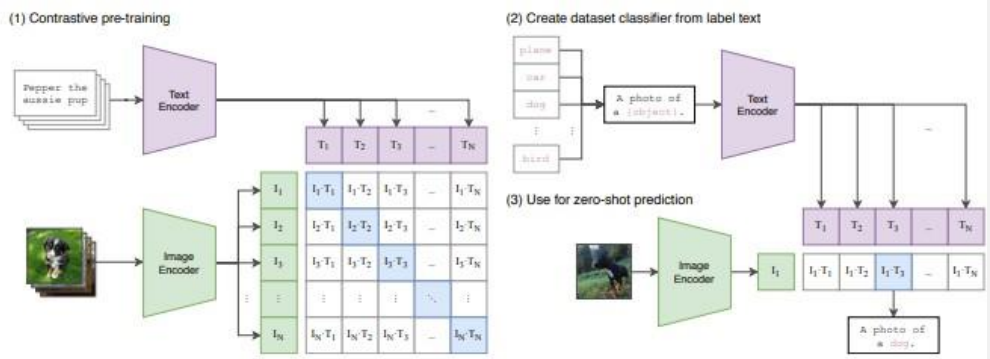
See backup for workloads and configurations. Results may vary.

intel.

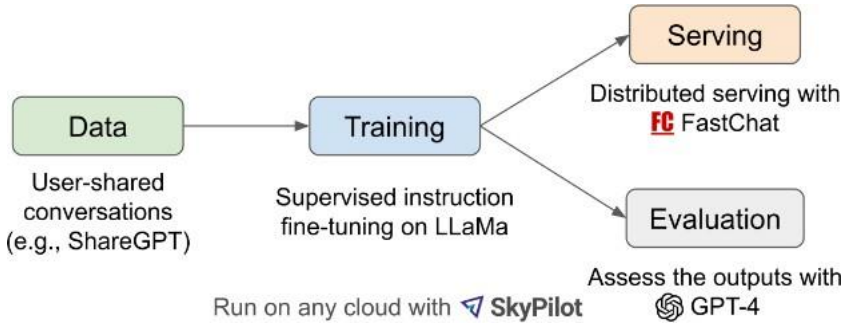
Gaudi2 - Demo – LLaVA - https://llava-vl.github.io/

LLaVa connects pre-trained CLIP ViT-L/14 visual encoder and large language model Vicuna, using a simple projection matrix





CLIP



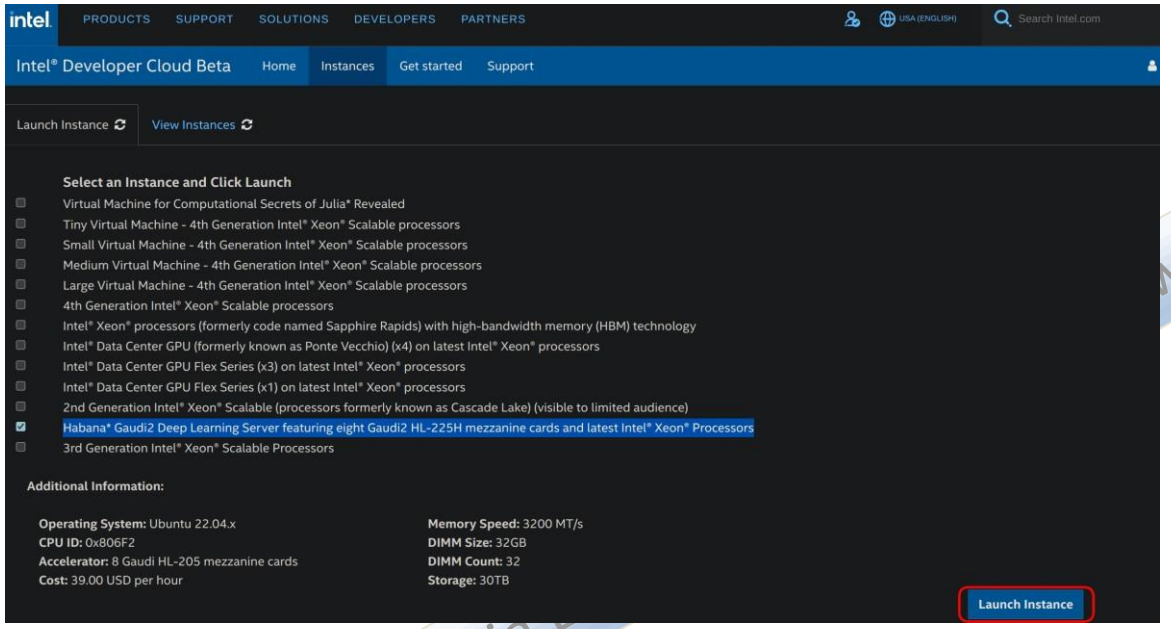
Vicuna

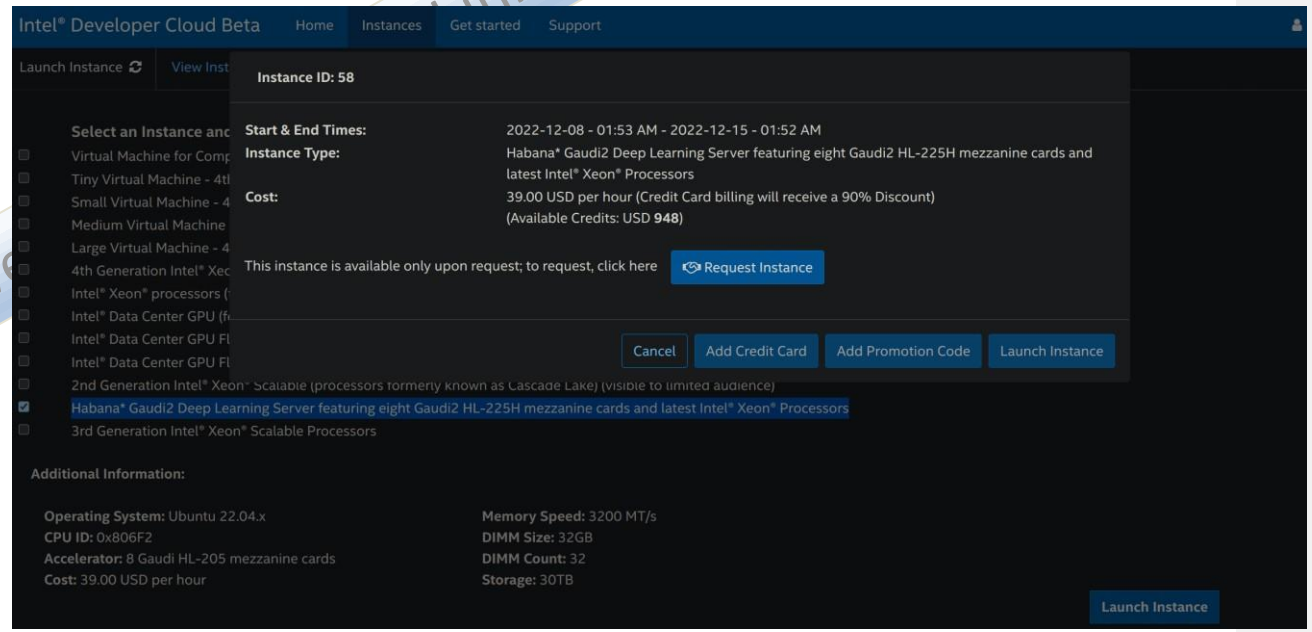
https://openai.com/research/clip

https://lmsys.org/blog/2023-03-30-vicuna/

Habana Gaudi2 Access

1. Go to the Intel Developer Cloud landing page and sign into your account or register if you do not have one
2. Go to the Intel Developer Cloud management console
3. Select Habana Gaudi2 Deep Learning Server featuring eight Gaudi2 HL-225H mezzanine cards and latest Intel® Xeon® Processors and click on Launch Instance in the lower right corner as shown below, and request an instance





- Once your request is validated, re-do step 3 and click on Add OpenSSH Publickey to add a payment method (credit card or promotion code) and a SSH public key that you can generate with ssh-keygen -t rsa -b 4096 -f ~/.ssh/id_rsa. You may be redirected to step 3 each time you add a payment method or a SSH public key.
- Re-do step 3 and then click on Launch Instance. You will have to accept the proposed general conditions to launch the instance
- Go to the Intel Developer Cloud management console and click on the tab called View Instances

https://scheduler.cloud.intel.com/public/Intel_Developer_Cloud_Getting_Started.html https://huggingface.co/blog/habana-gaudi-2-benchmark

References

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- https://docs.habana.ai/en/v1.6.0/Release_Notes/GAUDI_Release_Notes.html
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- https://www.microsoft.com/en-us/research/blog/zero-deepspeed-new-system-optimizations-enable-training-models-with-over-100-billion-parameters/
- https://www.microsoft.com/en-us/research/blog/zero-2-deepspeed-shattering-barriers-of-deep-learning-speed-scale/
- ZeRO: Memory Optimizations Toward Training Trillion Parameter Models. Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase and Yuxiong He.
- DeepSpeed Usage Guide
- Using DeepSpeed and Megatron to Train Megatron-Turing NLG 530B, the World's Largest and Most Powerful Generative Language Model

Thank You