Running Your Own LLM

Emily Apsey, Senior Manager Technical Marketing Engineering | 17 November 2023

Agenda

- Self-Managed vs Hosted API-Based LLMs
- Choosing and Using Self-Managed LLMs
- Building Local Copilots
- Optimizing for Size and Speed
- Emerging LLM Applications

Considerations for Choosing Self-Managed vs. Hosted API-based LLMs

Advantages of Self-Managed LLMs

- Training flexibility
- Throughput/batch processing
- Cost at scale
- Compliance and data governance
- Portability
- Controlled latency

Advantages of Hosted API-based LLMs

- Time to market
- Ease-of-use / integration into apps
- IT/infrastructure management
- Access to proprietary models

Rapid ecosystem evolution changes tradeoffs

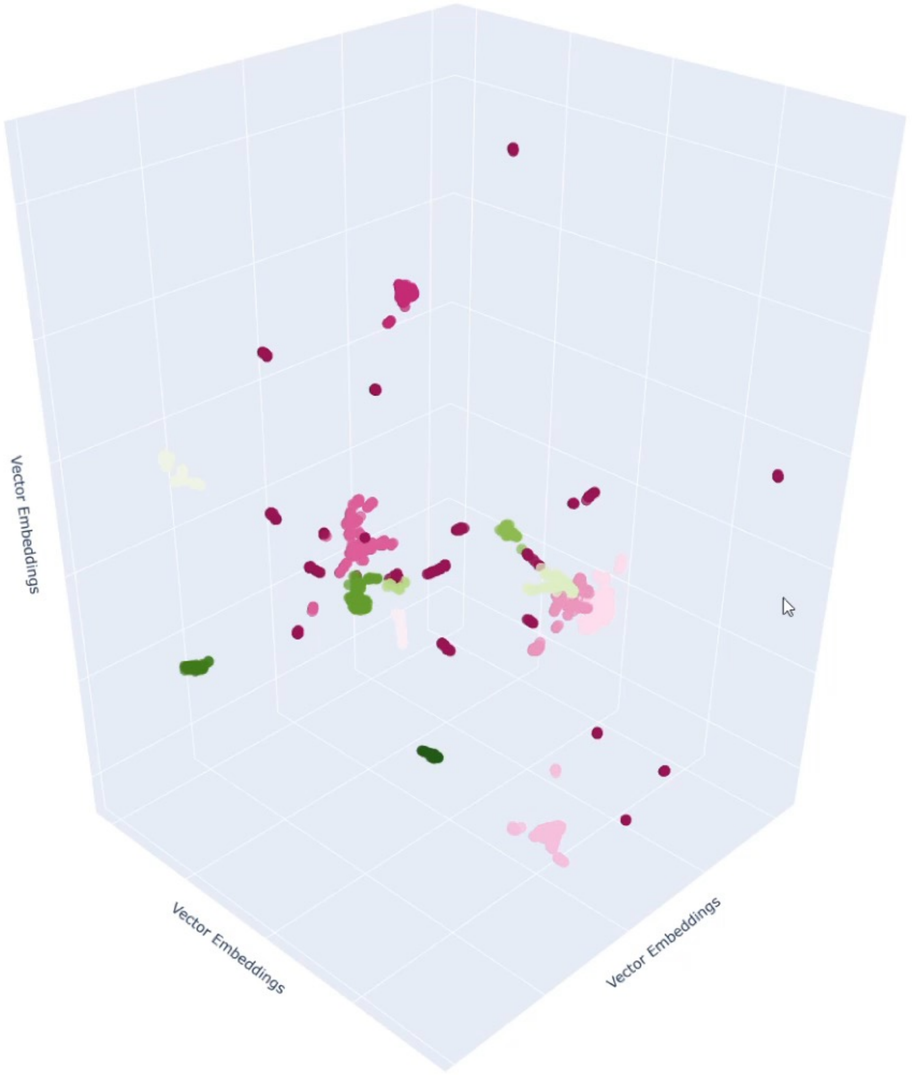
- Model hubs
- Inference engines, servers, and orchestrators
- Optimizers

Example App 1: Enterprise-scale Batch Data Processing

Enterprise-Scale Batch Data Processing

"I recently purchased the Celestial Cruiser from Star Bikes and have mixed feelings about my experience. The bike itself is beautifully designed and runs smoothly, however, the customer service I received was subpar. The delivery process was delayed, and the staff was not very helpful in addressing my concerns. Overall, I am satisfied with my bike, but I wish the customer service was better. I give it 3.5 out of 5 stars."


```
{
  "overall_sentiment": "mixed",
  "positive": [
    "beautifully designed",
    "runs smoothly"
  ],
  "negative": [
    "subpar customer service",
    "delayed delivery",
    "unhelpful staff"
  ],
  "model": "Celestial Cruiser",
  "rating": 3.5
}
```

Products with the most positive sentiments:

- Stellar Speedster: 88% positive sentiments, 1640 positive reviews, 223 negative reviews
- Orion Trailblazer: 82% positive sentiments, 1940 positive reviews, 425 negative reviews
- Cosmic Commuter: 81% positive sentiments, 1070 positive reviews, 250 negative reviews

Common positive themes:

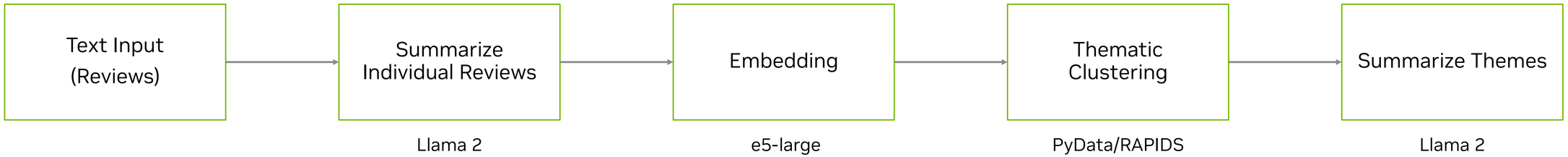
- Lightweight
- Easy to maneuver
- Sleek

Common negative themes

- Brakes not responsive
- Heavy
- Difficult to control

Product-specific highlights: the Stellar Speedster's lightweight and joy to ride features, the Orion Trailblazer's sleek and sturdy design, and the Cosmic Commuter's comfortable and efficient ride.

How It Works



Benefits of self-managed, batch-processing deployment configuration:

- Cost efficiencies relative to always-on LLMs, direct benefit from continuous perf improvements (token/$)
- Ease of adoption, similar to existing developer workflows

Choosing and Using Self-Managed LLMs

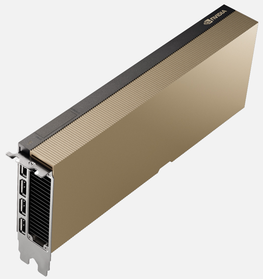
Interpreting Model Classes

Fastest Responses

Up to 20B

Deploy at the edge, low-latency, high-throughput
Domain-specific applications

Balance of Quality & Latency



20B-175B

Need single-node HW
General-purpose applications

Solving Complex Problems

Over 175B

Need specialized software/techniques
Most demanding applications

Software for Efficient Inference

LLM

Inference-optimized versions of SOTA LLMs

Accelerated workflow for at-scale inference

Open-source AI kernels of cutting-edge techniques

Inference Server

Parallelization (multi-device, multi-node)

Concurrency, scheduling and ensembling

Efficient inter-process communication

Token output streaming

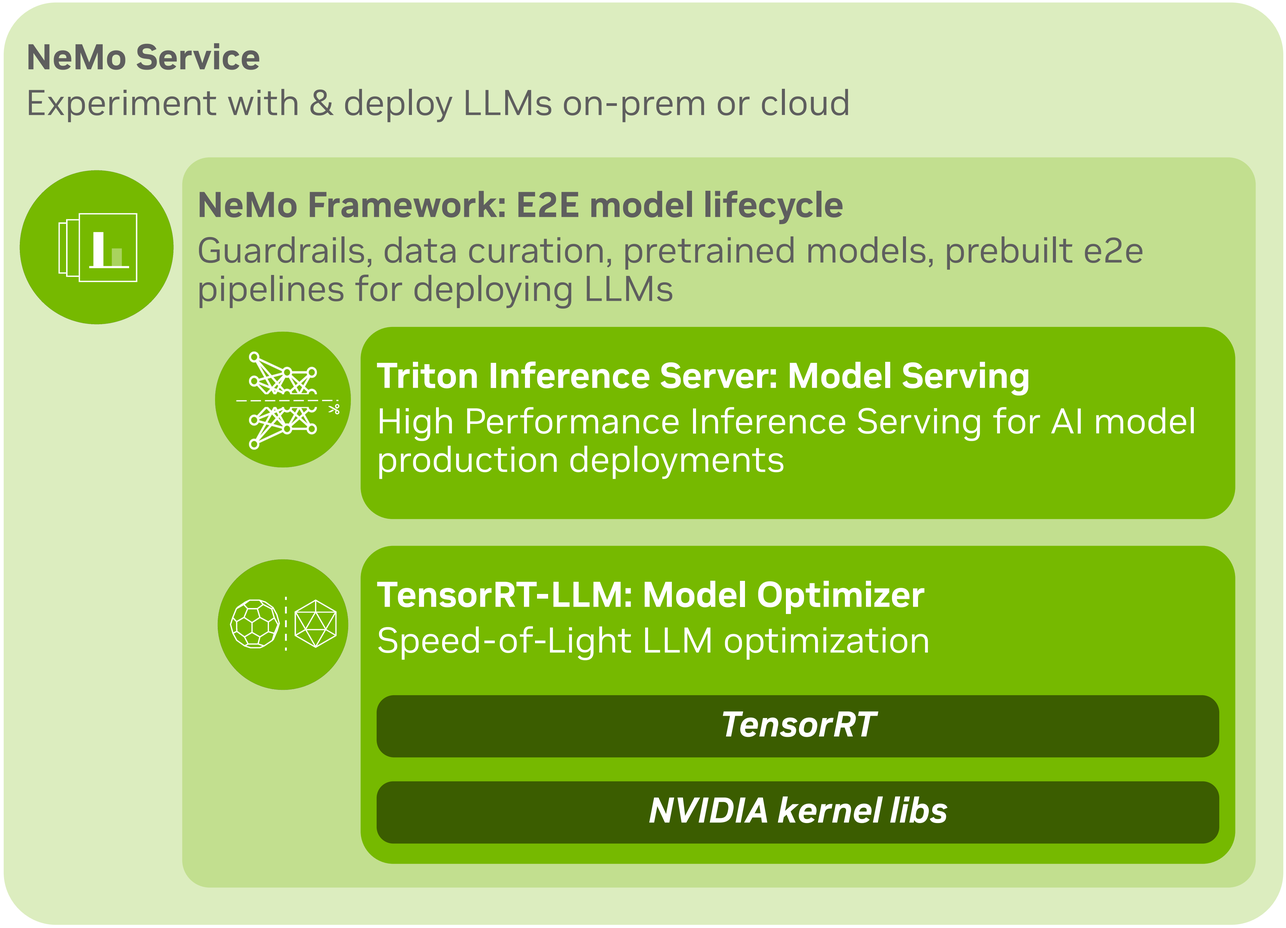
Optimizer

Dynamic batching

Quantization / mixed precision

Kernel fusion

NVIDIA LLM Inference Stack

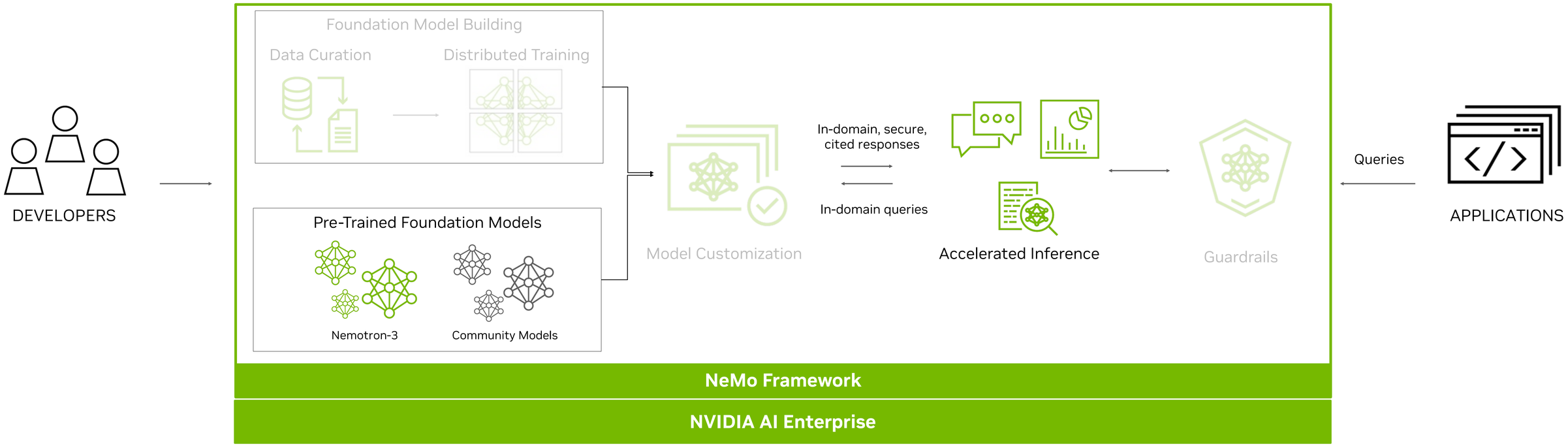


NVIDIA AI Enterprise

The Runtime for Production AI

NVIDIA NeMo Framework

From foundation model to application



Microsoft Azure aws ORACLE NVIDIA DGX Cloud DELL Technologies Hewlett Packard Enterprise Lenovo

NVIDIA

Example App 2: Portable Copilots

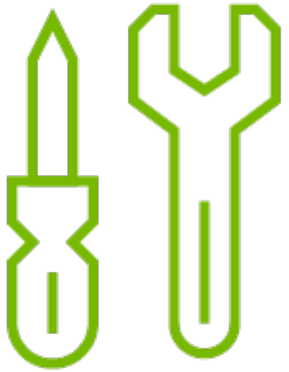
Why Deploy at the Edge?

User needs

Lower latency
Reduced dependency on internet access

Security & Compliance

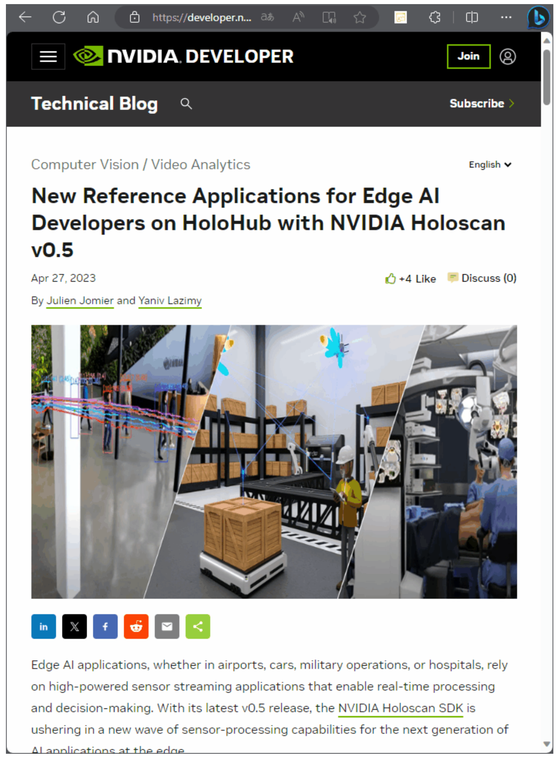
Data locality and governance



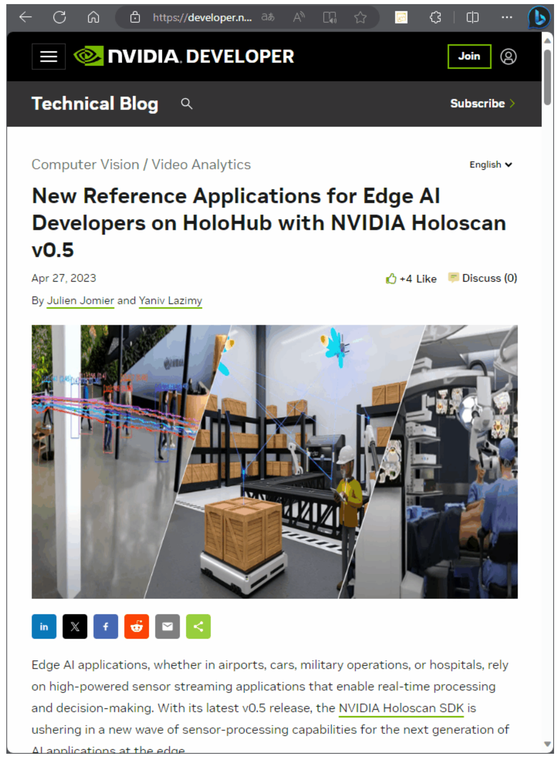
Tools and Efficiency

Take advantage of multipurpose hardware

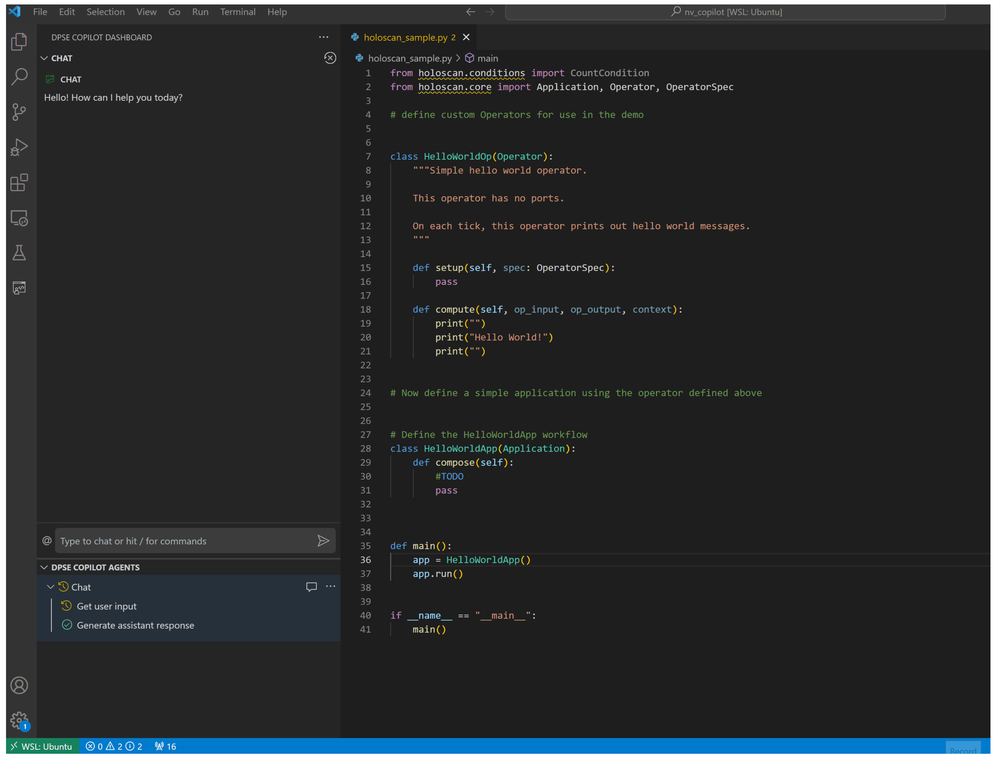
Example Copilots



Summarization

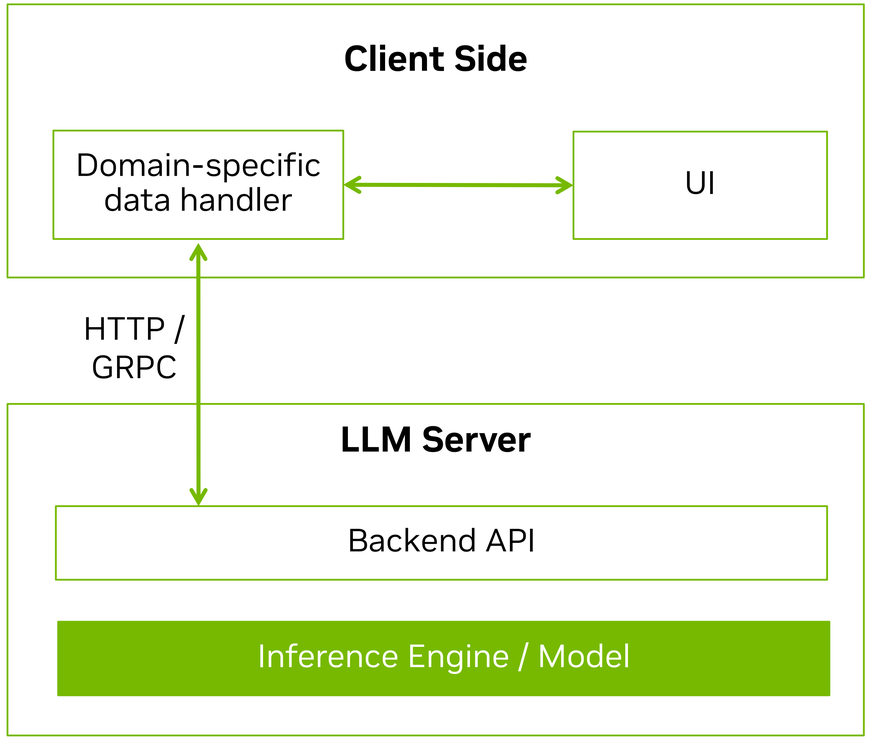


Question Answering



Chatbot and interactive code generation
with VS Code Extension

How It Works



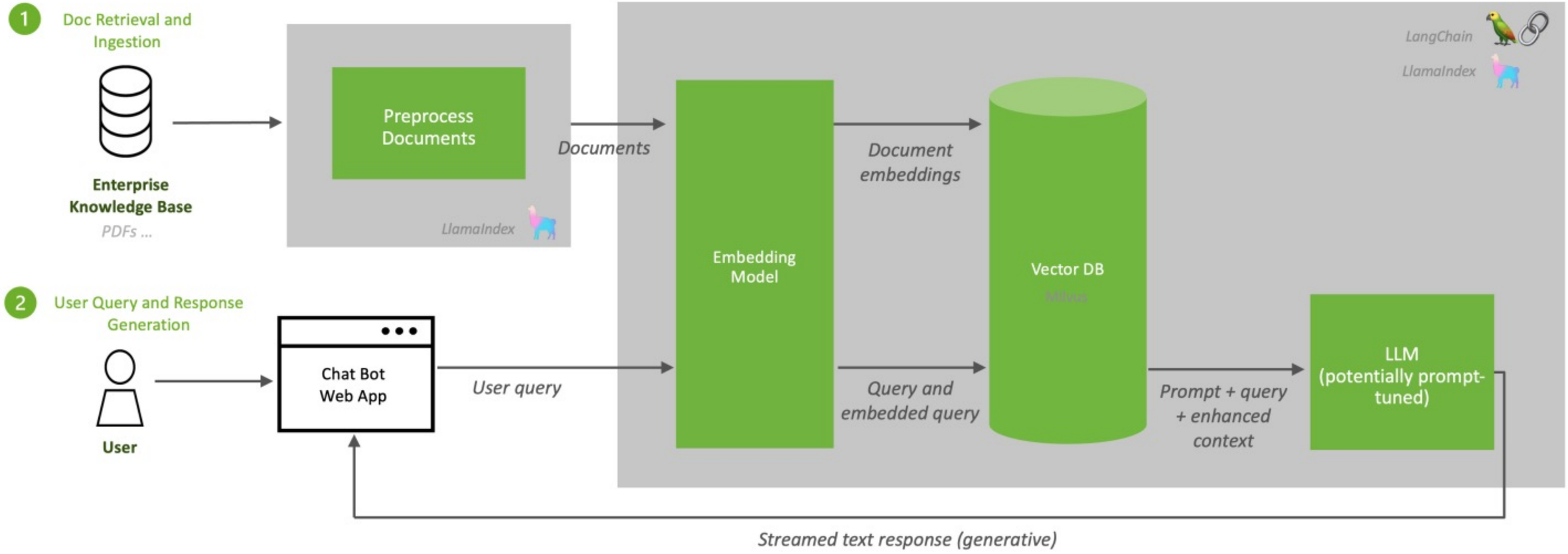
Portable Package

LLM server deployed on-device, on-prem, or in cloud

Building Local Copilots

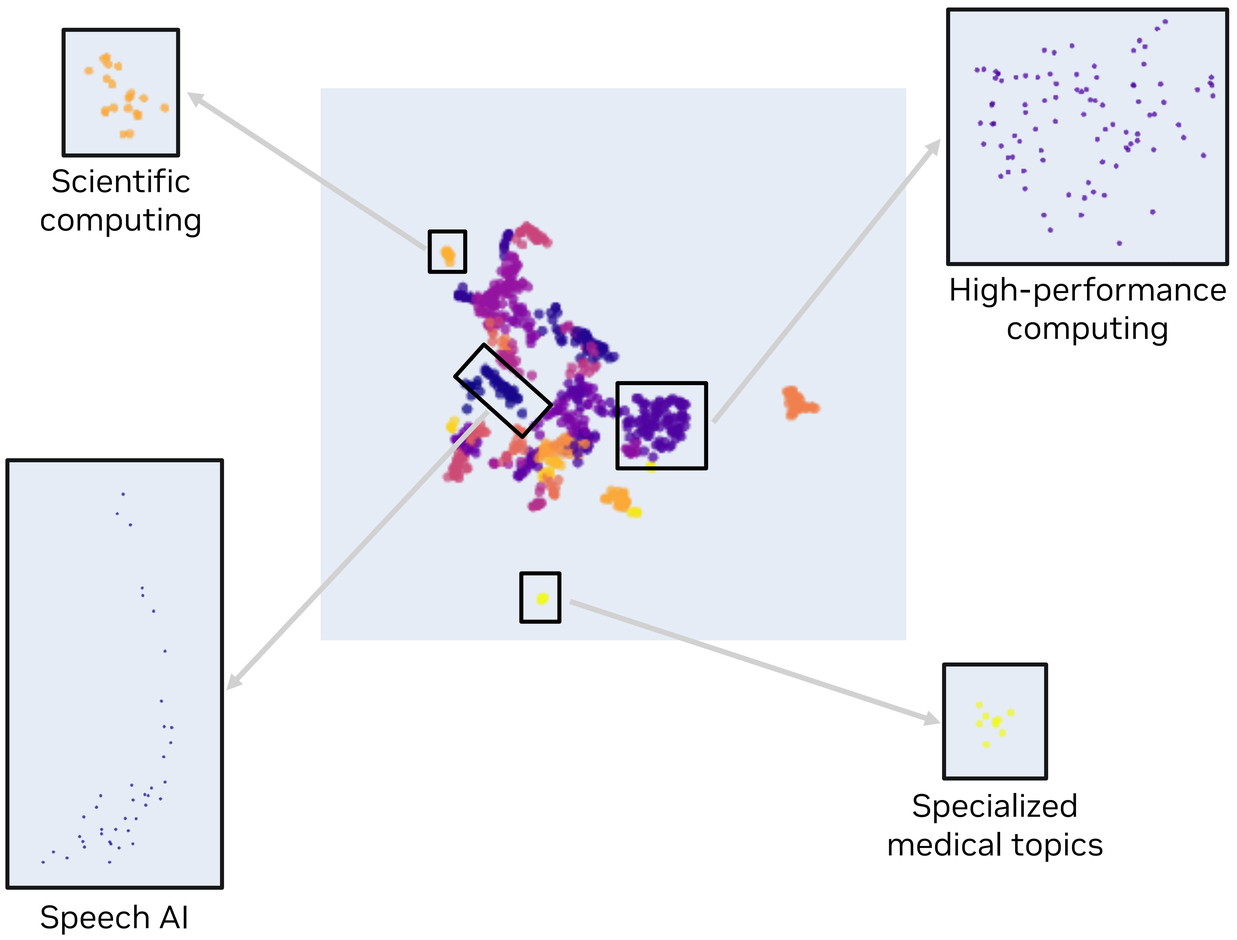
Canonical RAG Workflow

Self-managed examples



Embeddings and the Vector Database

Searching via semantic similarity



2D representation of a 768-dimension embedding space

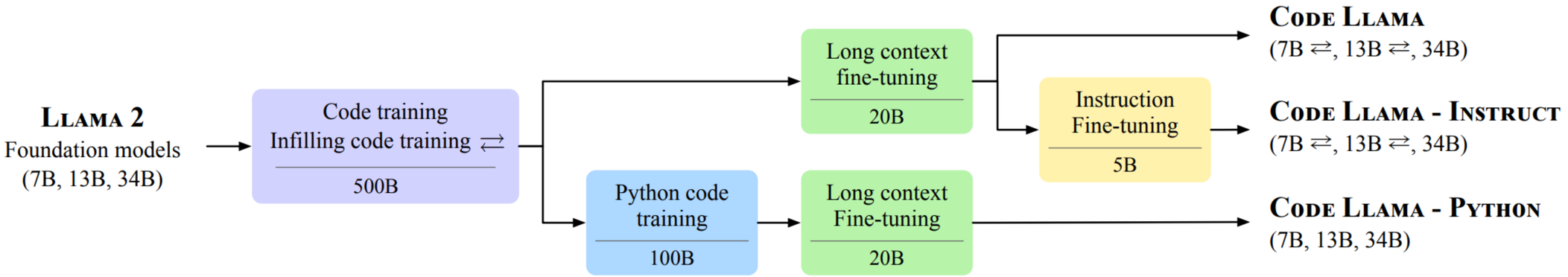
- Embeddings are data (text, image, or other data) represented as numerical vectors
  - Input text to embedding model to output vector
- Part of **semantic search**
  - Model trained to embed similar inputs close together
- Other use cases: classification, clustering, topic discovery
- Many pretrained and trainable embedding model sources
  - Modern ones are often deep neural networks

Query: Who will lead the construction team?
Chunk 1: The construction team found lead in the paint.
Chunk 2: Ozzy has been picked to lead the group.

Chunk 1 shares more keywords with the query, but semantic search can differentiate the meanings of "lead" and understand that "team" and "group" are similar, so Chunk 2 may be more helpful for the query.

Code Generation Models

Building from foundation models



Key capabilities: Completion, Infilling, Zero-shot

Other popular code models:

- Trained on code only: AlphaCode (Li et al., 2022) , InCoder (Fried et al., 2023) StarCoder (Li et al., 2023)
- Fine-tuned from a general language model: Codex (Chen et al., 2021), Code Llama

Code Llama: Open Foundation Models for Code (https://ai.meta.com/research/publications/code-llama-open-foundation-models-for-code/)

Optimizing for Size and Speed

TensorRT-LLM in the LLM Ecosystem

Open-source library for custom deployments

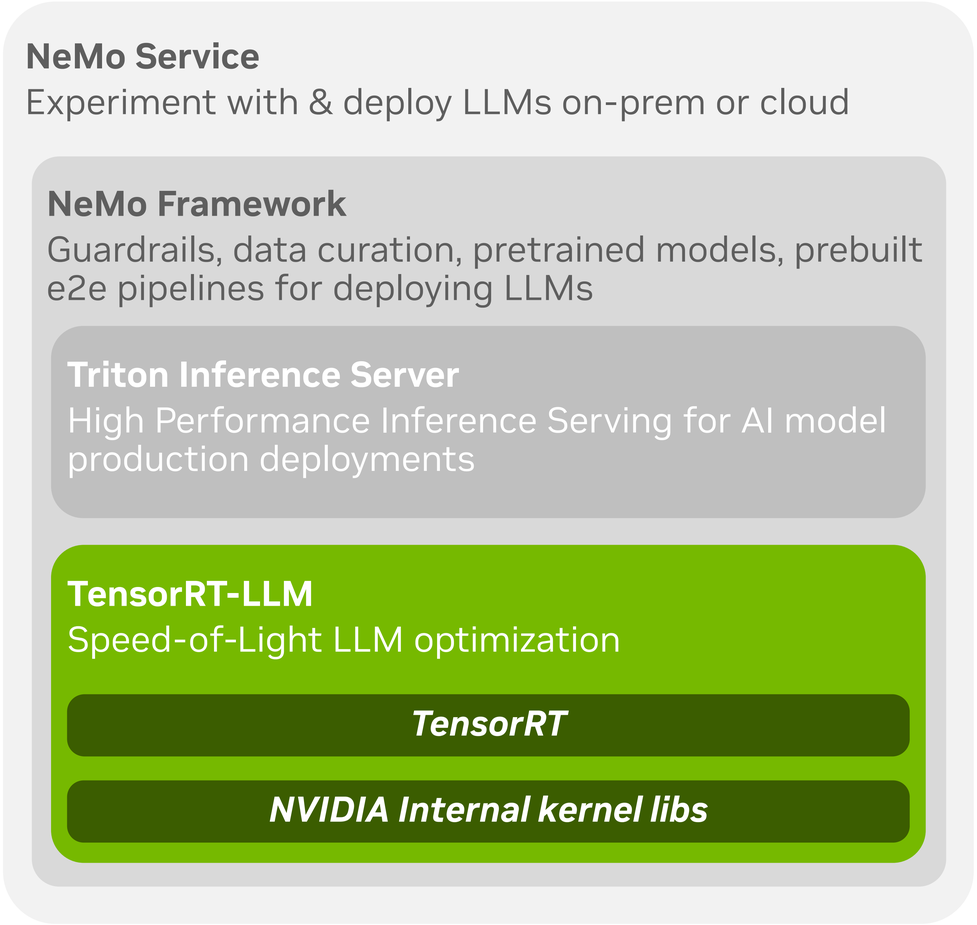
Challenges

- Multi-GPU/Multi-Node support for latest large models
- Variable workload (short/long query and responses)
- Maximize GPU efficiency for different serving scenarios latency/throughput/TCO

TensorRT-LLM

- For deployments with high amounts of customization or control required
  - New or customized model architectures
  - Fine-tuned control over optimizations, quantization, & performance
- In-flight batching, reduced precision/quantization, mixed precision

Most developers should start with NeMo Framework



NVIDIA LLM Inference Stack

Llama E2E Example

2x faster with just 10 lines of code

1. Instantiate Llama & load the weights

```
builder_config = builder.create_builder_config([…])
trtllm_llama = trtllm.models.LLama([…])
load_from_hf_llama(tensorrt_llm_llama, hf_llama, […])

network = builder.create_network()
network.set_named_parameters(trtllm_llama.named_parameters())
engine = builder.build_engine(network, builder_config)
serialize_engine(engine, path)

with open(path, ‘rb’) as f:
    engine_buffer = f.read()
llama = trtllm.runtime.GenerationSession(engine_buffer, […])

output = llama.decode(input, input_lengths, sampling_config)
```

Instantiating, building, and executing inference in TRT-LLM

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Instantiating, building, and executing inference in TRT-LLM

Llama E2E Example

2x faster with just 10 lines of code

1. Instantiate Llama & load the weights
2. Build & serialize the engines
3. Load the engines
4. Run optimized inference using TRT-LLM runtime offering

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```

Instantiating, building, and executing inference in TRT-LLM

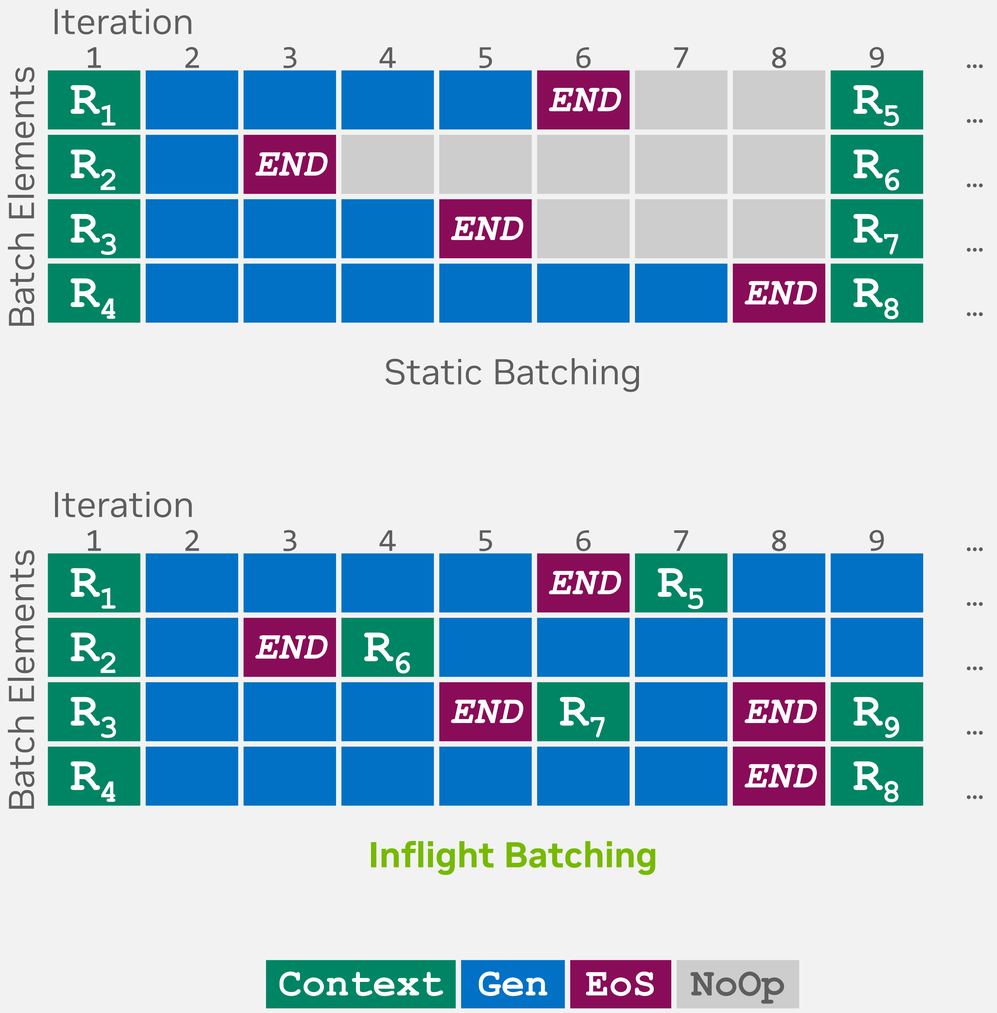
Optimization in TensorRT-LLM

Standard Dynamic Batching vs Inflight Batching

Inflight Batching

Maximizing GPU Utilization during LLM Serving

- Replaces completed requests in the batch
- Improves throughput, time to first token, & GPU utilization
- Integrated directly into the TensorRT-LLM Triton backend
- Accessible though the TensorRT-LLM Batch Manager



Optimization in TRT-LLM

Quantization for Better Throughput, Latency, Portability, and Scale

Llama-2 Quantization Comparison: FP16 v.s. INT4 Weights

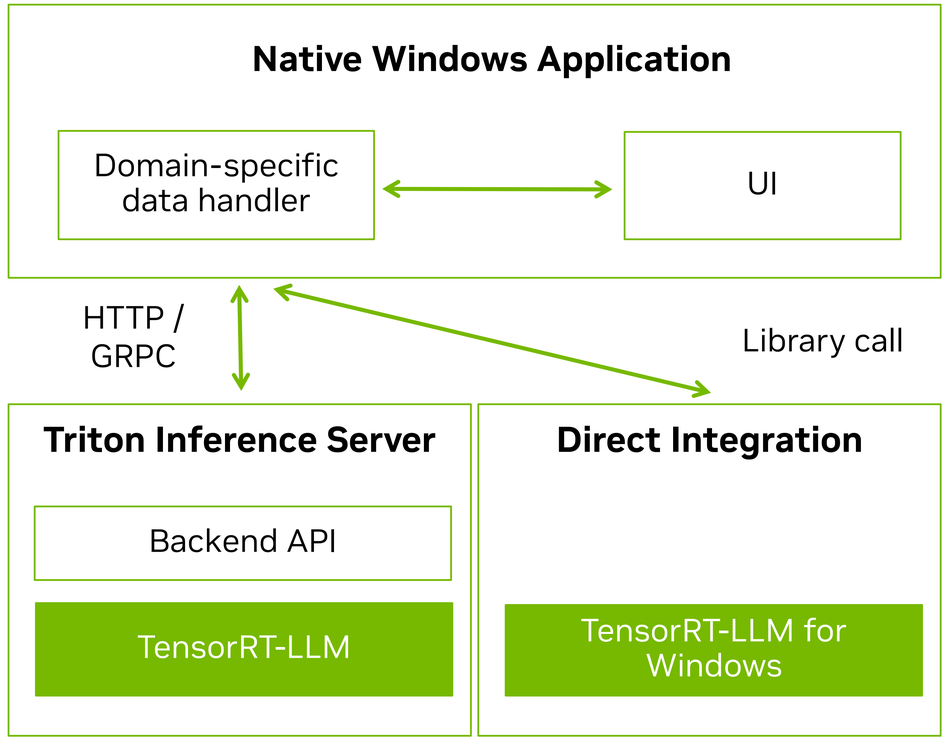
LLMs on Windows with TensorRT-LLM and RTX

Benefits of LLMs on Windows Clients

- Latency – low latency tolerances for some use cases (e.g. gaming, digital assistants)
- Availability – still need to write docs on an airplane
- Data privacy/locality – Keep private/proprietary data on-device

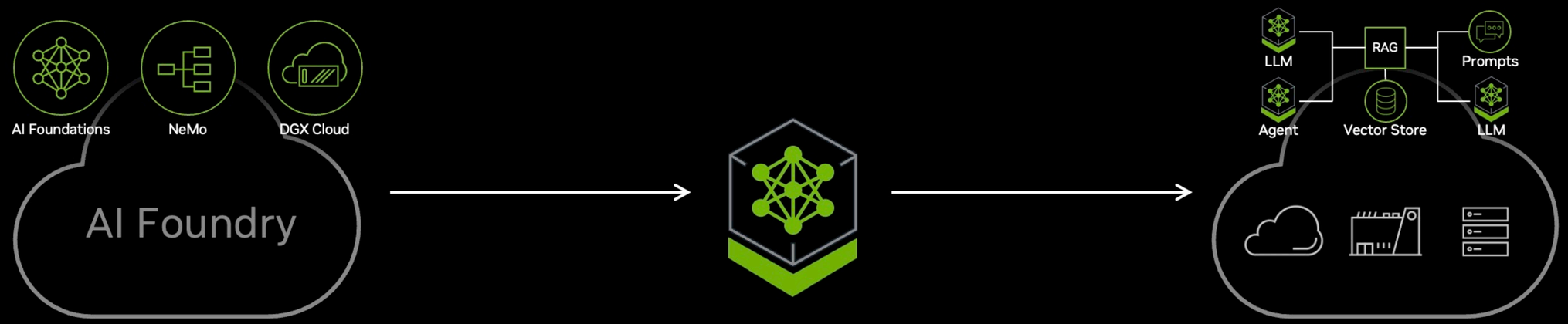
Development and Deployment

- Develop/train models with NeMo Framework, deploy on client
- TensorRT-LLM for Windows - simple direct integration
- Triton Inference Server on WSL - portability
- Compatibility with ChatGPT API



Get started with tutorials, resources, and reference projects: developer.nvidia.com/accelerate-ai-applications

NVIDIA AI Foundry

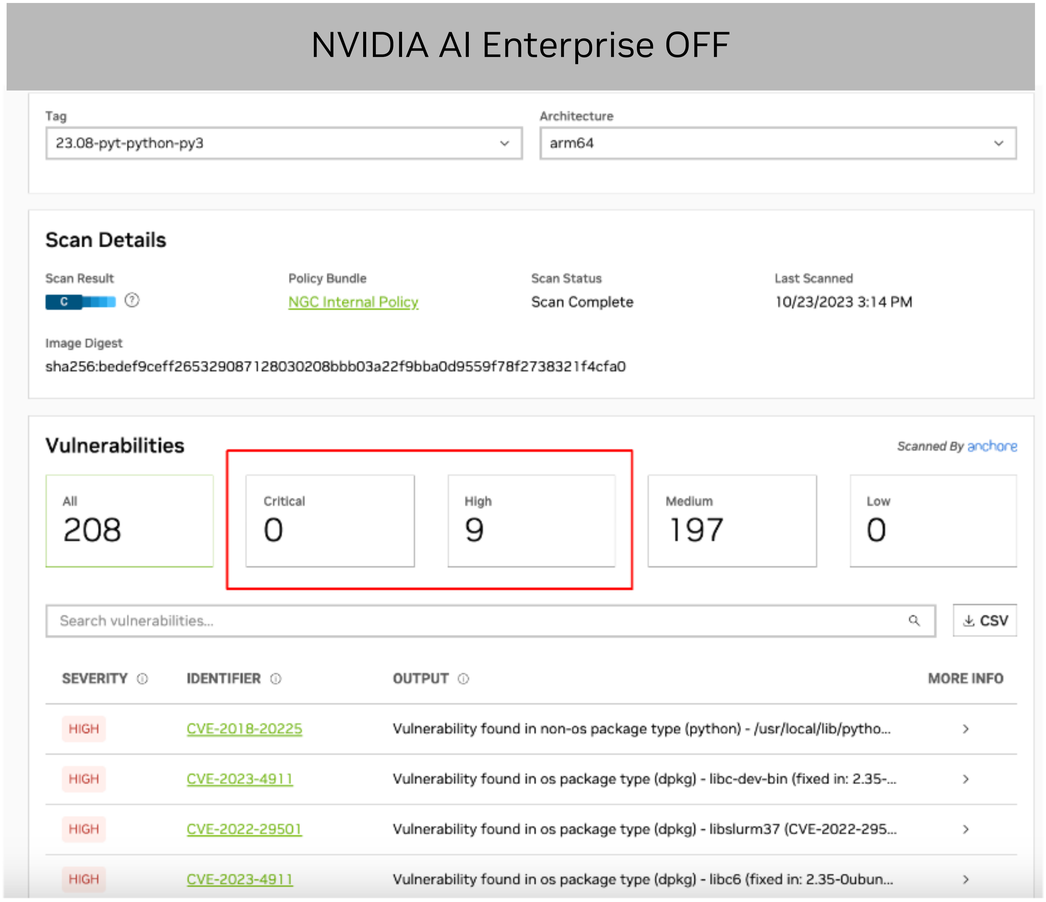


Create from Foundation Model

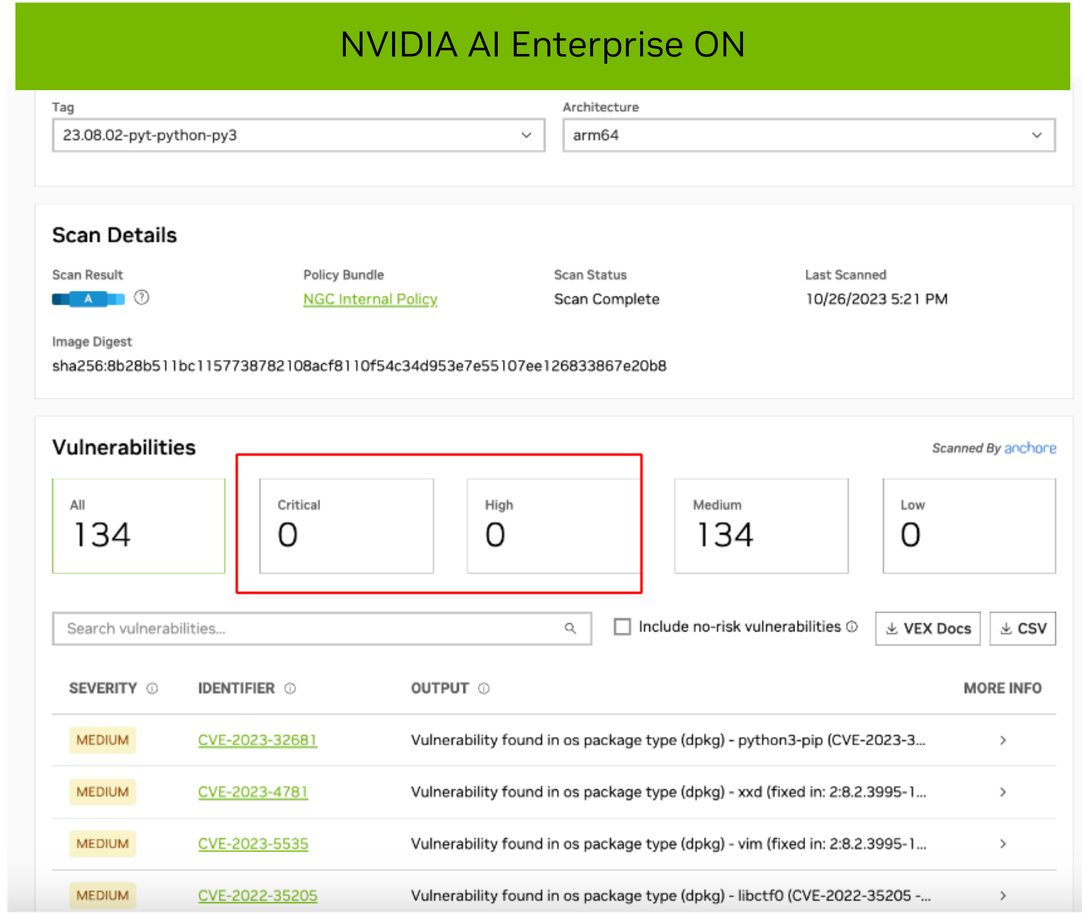
Your Enterprise Model

Run Anywhere

NVIDIA AI Enterprise OFF



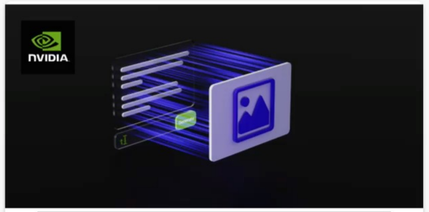
NVIDIA AI Enterprise ON



Emerging LLM Applications

NeVA: NeMo Vision and Language Assistant

Fine Tune Model | Get API Access



Description
NeVA is a multi-modal vision-language model that understands text and images and generates informative responses.

Publisher
NVIDIA

Modified
October 13, 2023

Language Generation
Large Language Model | Vision Assistant
Visual Question Answering
Object Detection | NeMo
Computer Vision

Playground | Overview | Model Card++

AI models generate responses and outputs based on complex algorithms and machine learning techniques, and those responses or outputs may be inaccurate or indecent. By using this Playground, you assume the risk of any harm caused by any response or output of the model.

Playground Mode: User Interface | Run on Windows with RTX

By using this demo, you acknowledge that you have read and agreed to the terms & conditions.

Model Description

NeVA is a multi-modal vision-language model that understands text and images and generates informative responses. This demo shows NeVA's ability to generate responses based on the image or text as an input.

Model Input Instructions

Upload an image and/or enter a prompt to receive an AI-generated response.

NeVA-43b

Image

Drop Image Here
- or -
Click to Upload

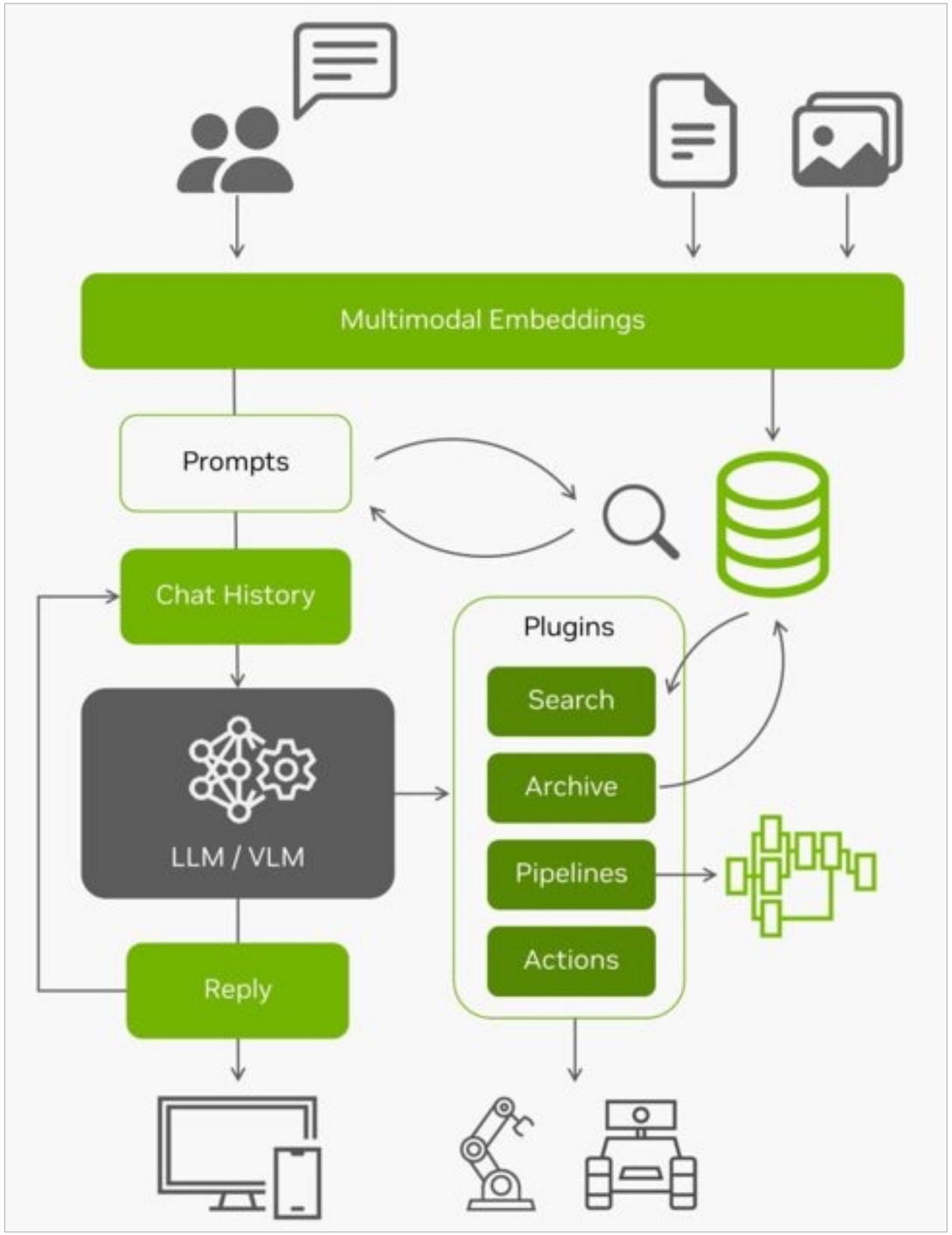
Preprocess for non-square image
Crop | Resize | Pad

Examples

NeVA Chatbot

LLM Agents

Beyond deterministic prompt chaining



Q&A

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