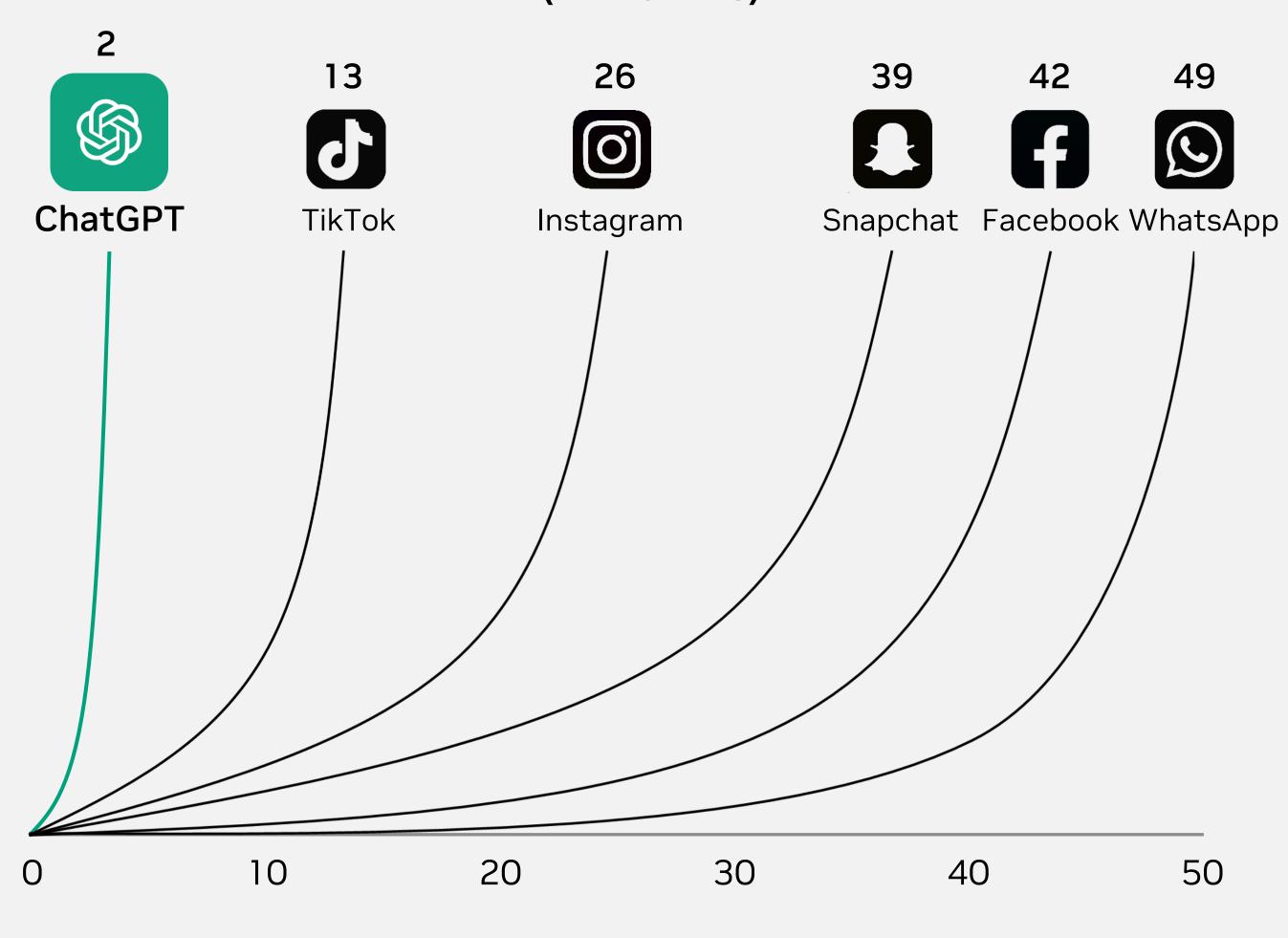


ChatGPT — 2022 "The Al Heard Around the World"

From AlexNet to ChatGPT in 10 years

Time to 100 Million Users (in months)



Number of Months to Reach 100M Users

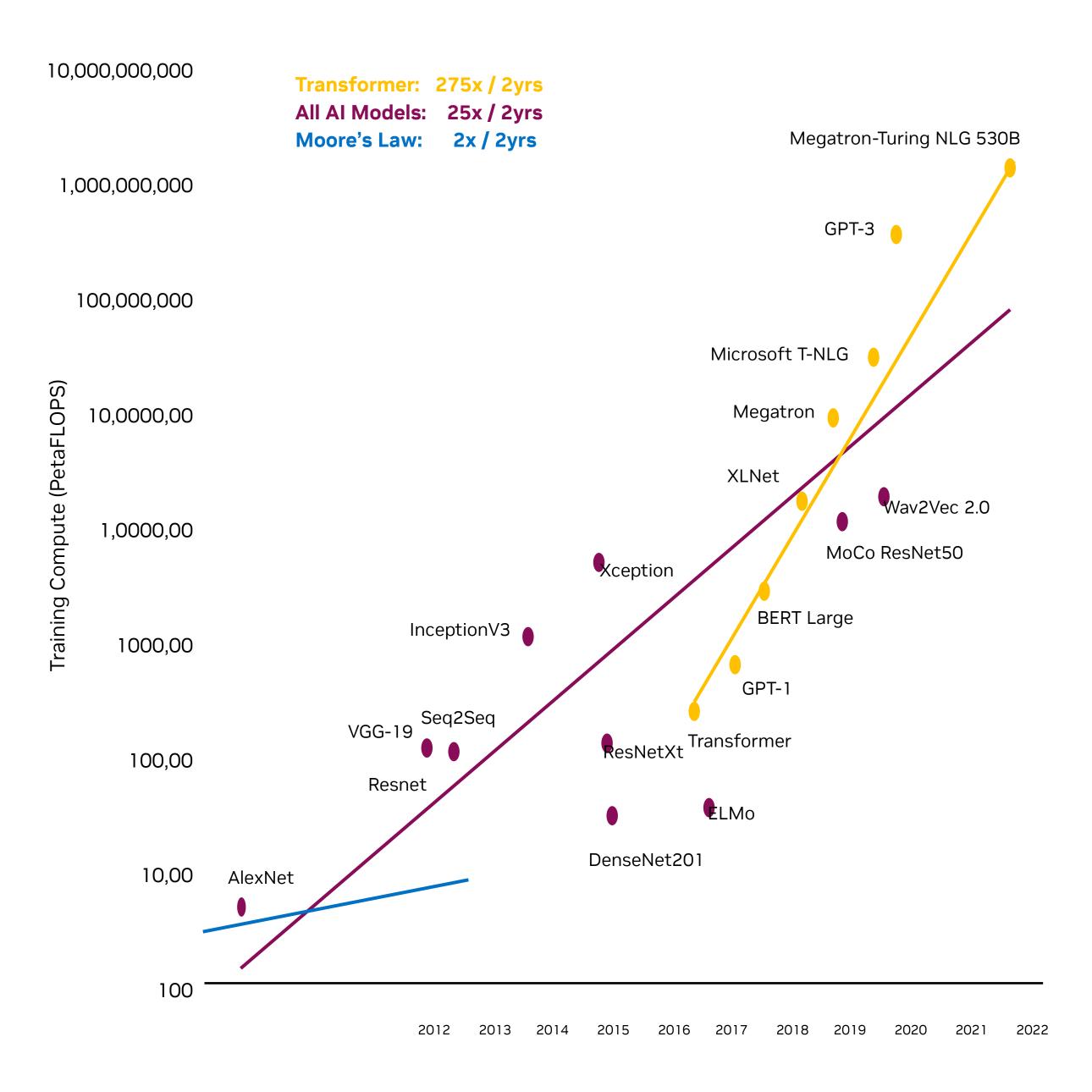
Massive Al Models Drive New Use Cases

LLMs and Gen Al Driving an Inflection Point

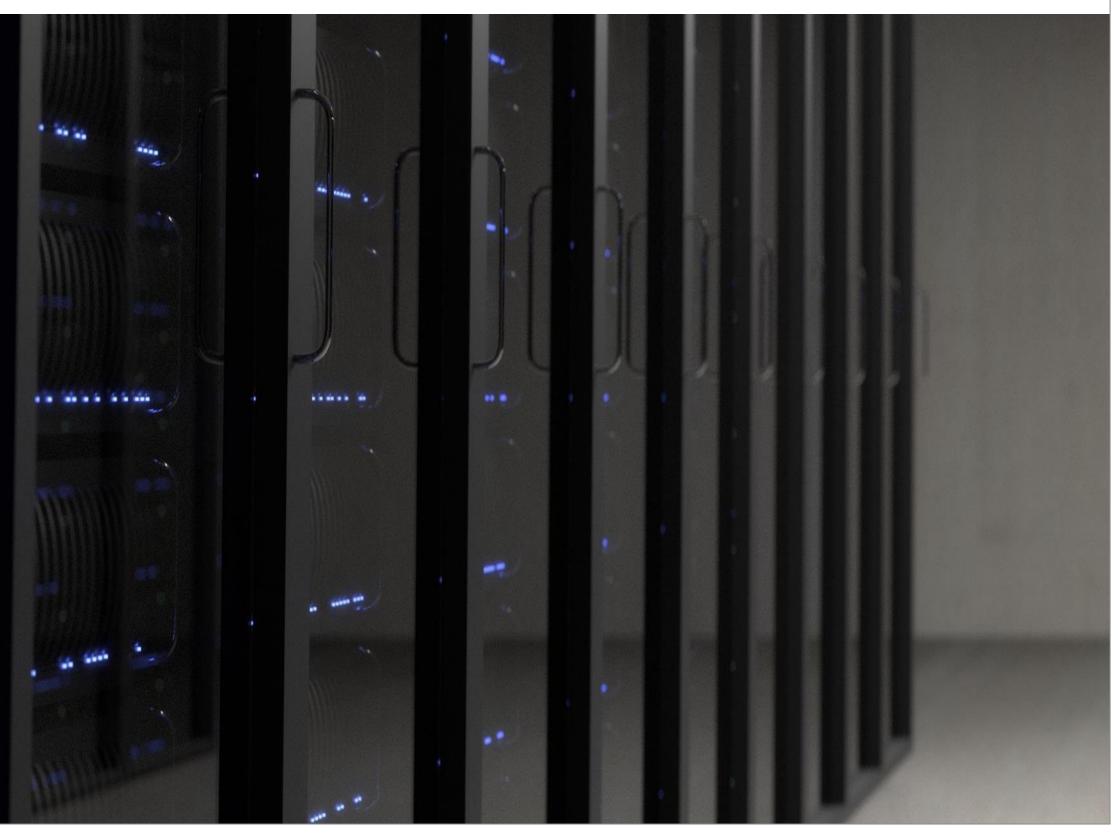


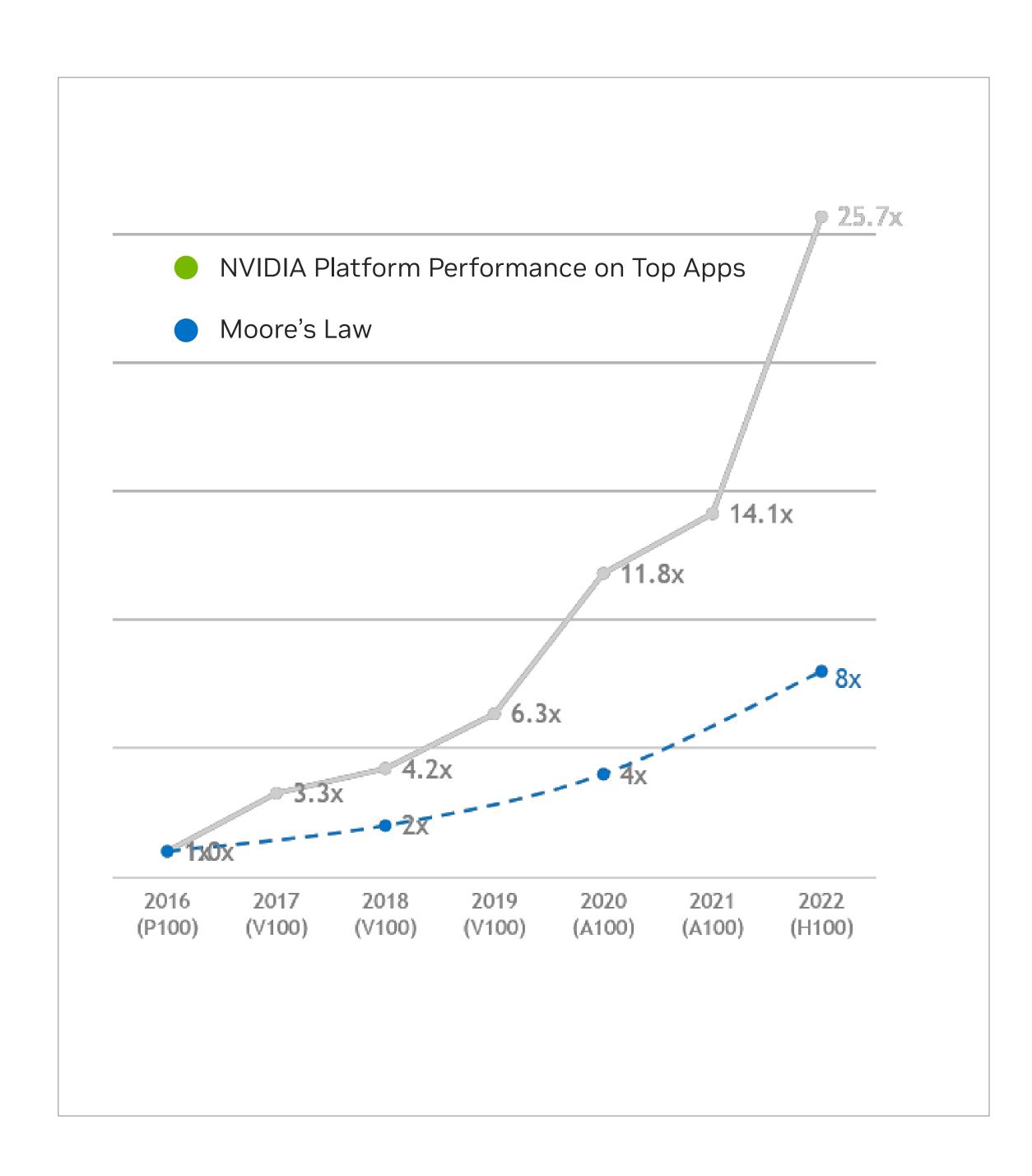
Moore's Law is Ending

Al has an enormous appetite for compute — we are only seeing the tip of the iceberg!



Forecasted Share of Energy Usage	2%
Share of Global Energy Usage	5% by 2030
Data Center through to Electricity Usage	>200 TWh/year





Models Growing Exponentially

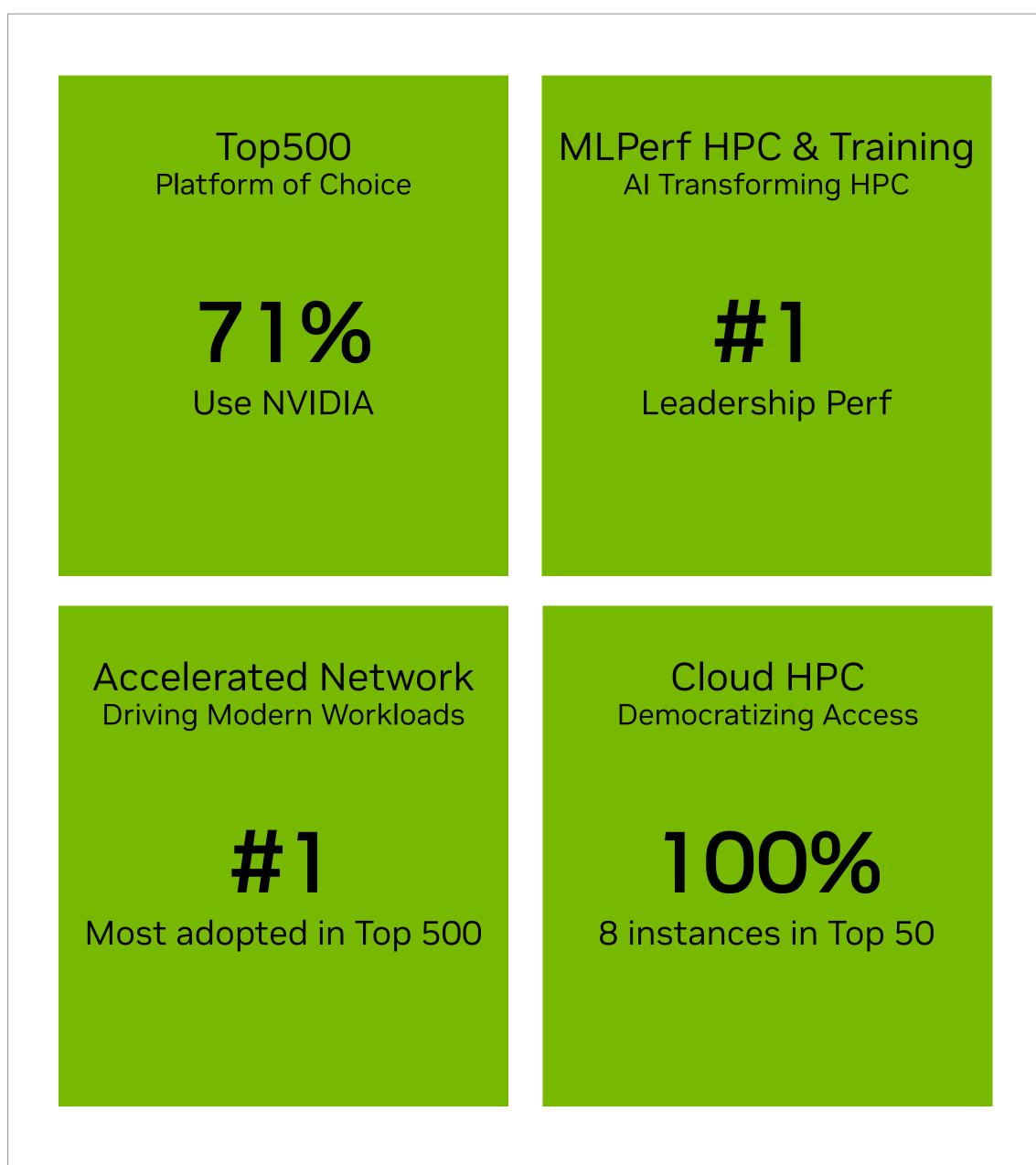
Data Centers are Power Limited Need to Become More Efficient

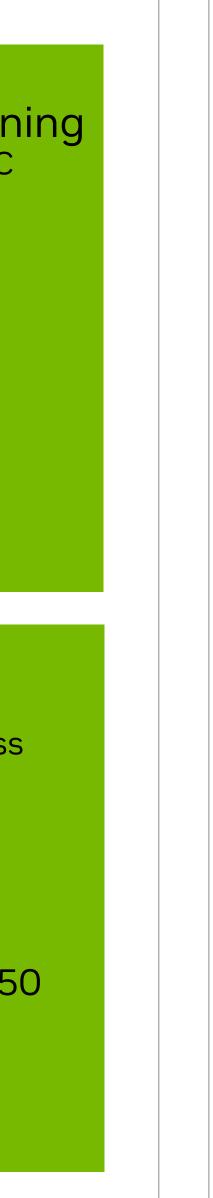
26x Performance In 6 Years

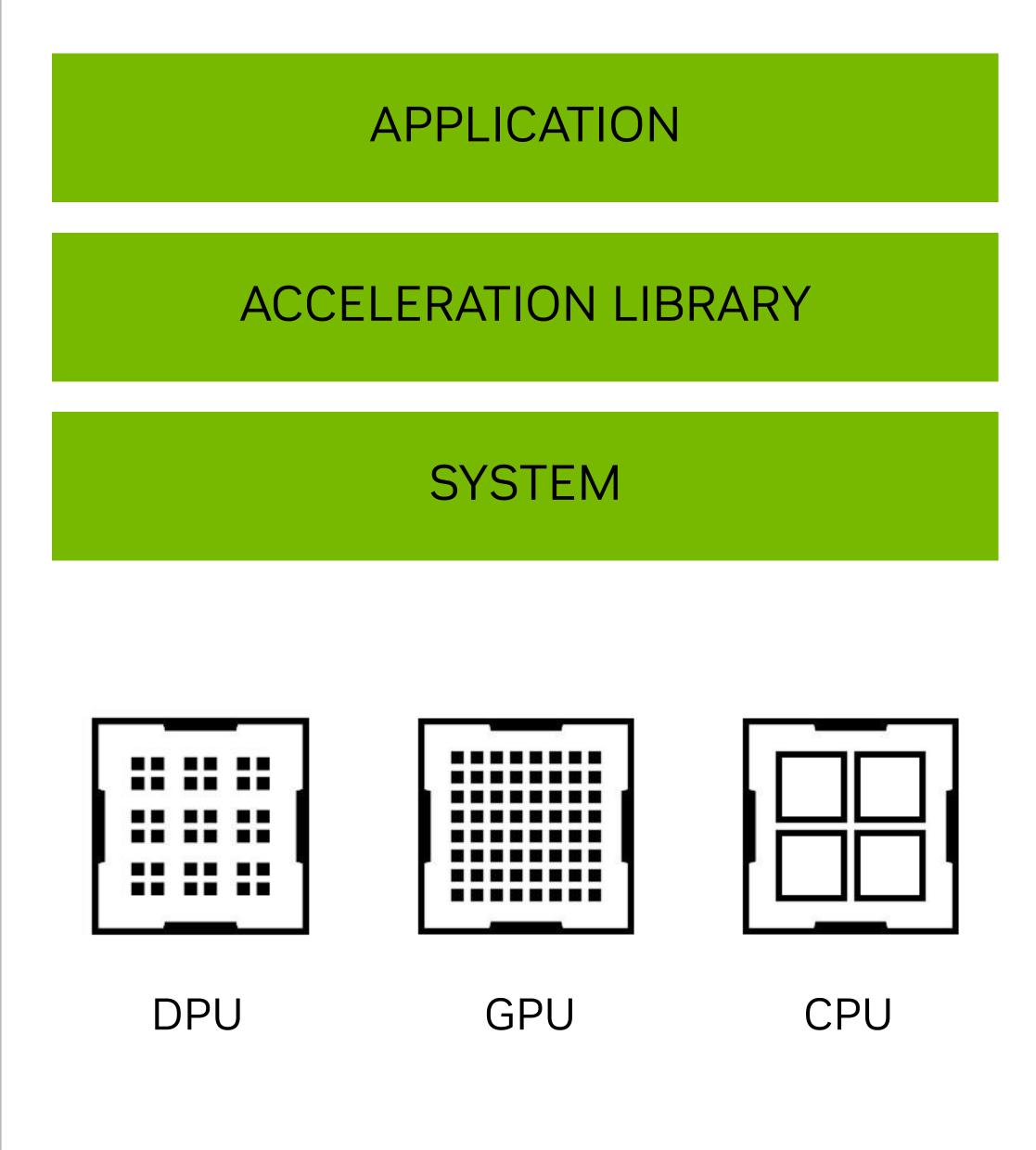


Accelerated Compute — Essential for Al

"The shift to accelerated compute away from conventional CPU is structural" — Vivek Arya, Bank of America, Analyst







1 month to 1 week Days hours 4K H100 70 175 530 1000 Time-to-Train by LLM Size (Billion parameters)

Lower is better

4K A 100

Powering World's Fastest Supercomputers

Acceleration Takes a Full Stack

H100 Supercharges Al





In 2012, Alex Kerchevsky, Ilya Suskever, and Geoff Hinton needed an insanely fast computer to train the AlexNet computer vision model.

The researchers trained AlexNet with 14 million images on nVidia GeForce GTX 580, processing 262 quadrillion floating-point operations, and the trained model won the ImageNet challenge by a wide margin and ignited the Big Bang of Al.

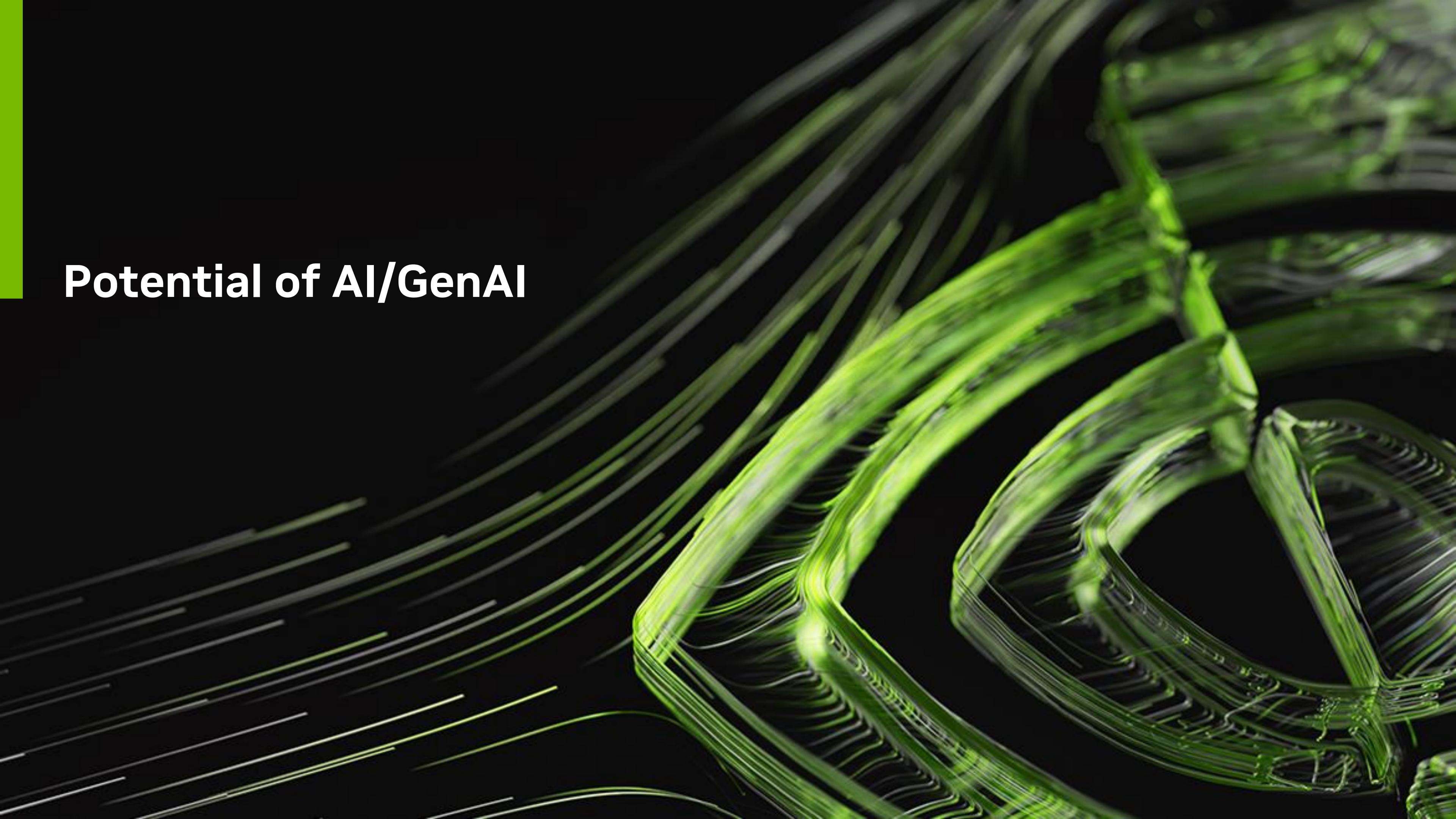
A decade later, the transformer model was invented.

And Ilya, now at OpenAI, trained the GPT-3 large language model to predict the next word.

323 sextillion floating-point operations were required to train GPT-3.

One million times more floating-point operations than to train AlexNet.

The result this time - ChatGPT, the AI heard around the world.



Generative Al Unlocks New Opportunities



How has NVIDIA contributed to acceleration of AI?

NVIDIA has been a pioneer in the field of Al since the very beginning. Our GPU platform has enabled the rapid development of AI – from the training of neural networks, to inference in the data center, on-device AI in the car and in the cloud, and the deployment of AI to tackle challenging problems like conversational Al and translation.

NVIDIA's GPU-accelerated computing platform is the engine of AI – it is the most important computing platform of our time.



530B

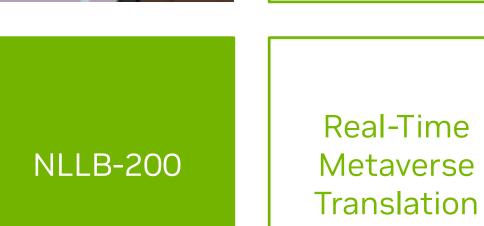
TEXT GENERATION











TRANSLATION





CODING





Function Generation

IMAGE GENERATION

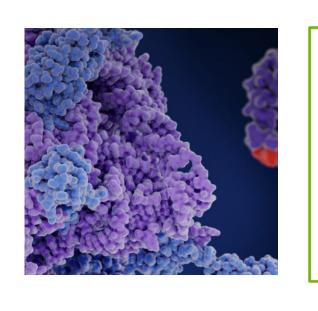




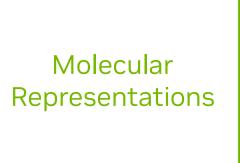
Gaming

Characters





LIFE SCIENCE



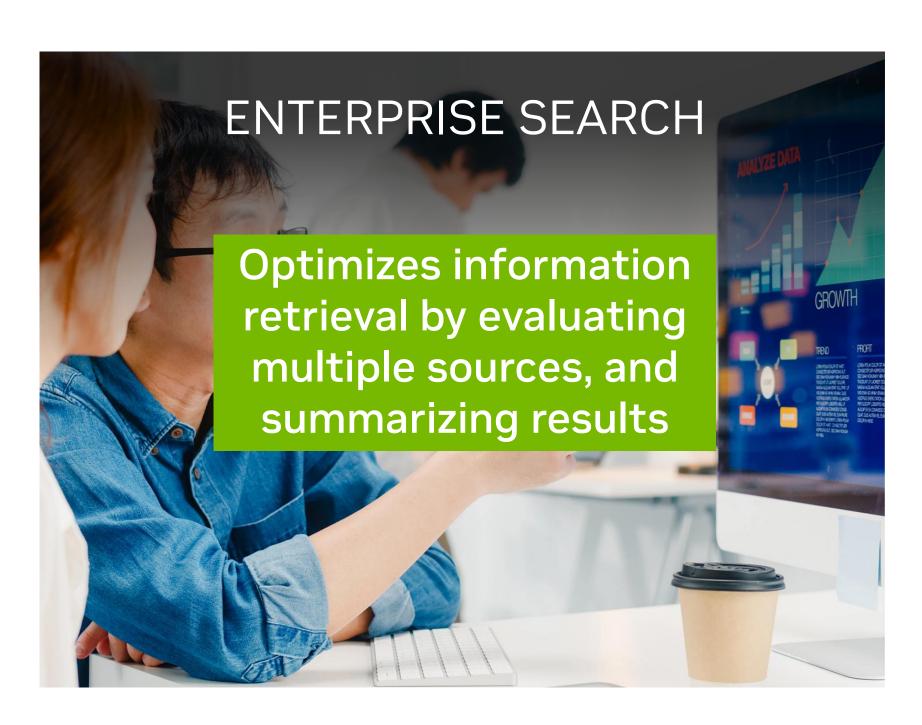


Drug Discovery



^{**}Generated using NVIDIA NeMo service

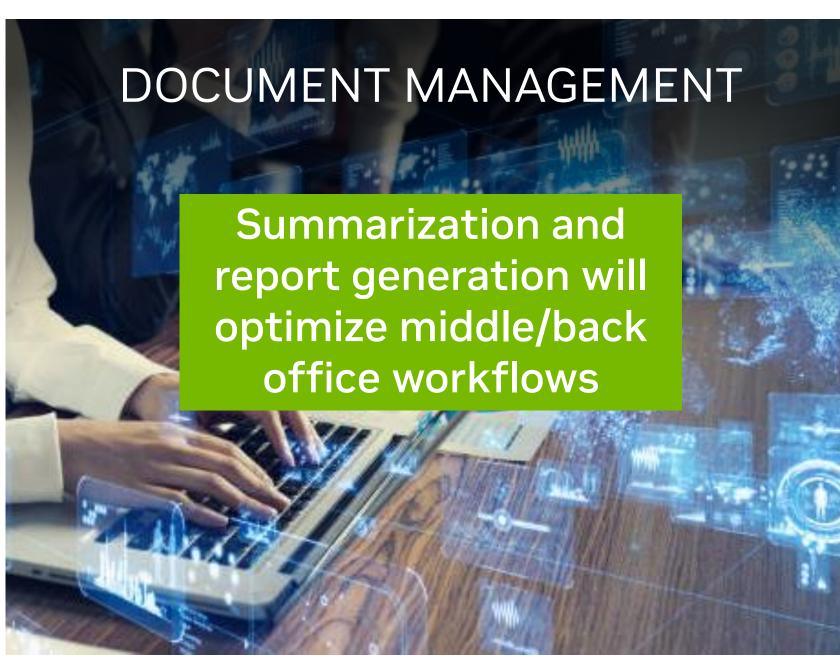
Generative Al Impacts Every Function in a Bank

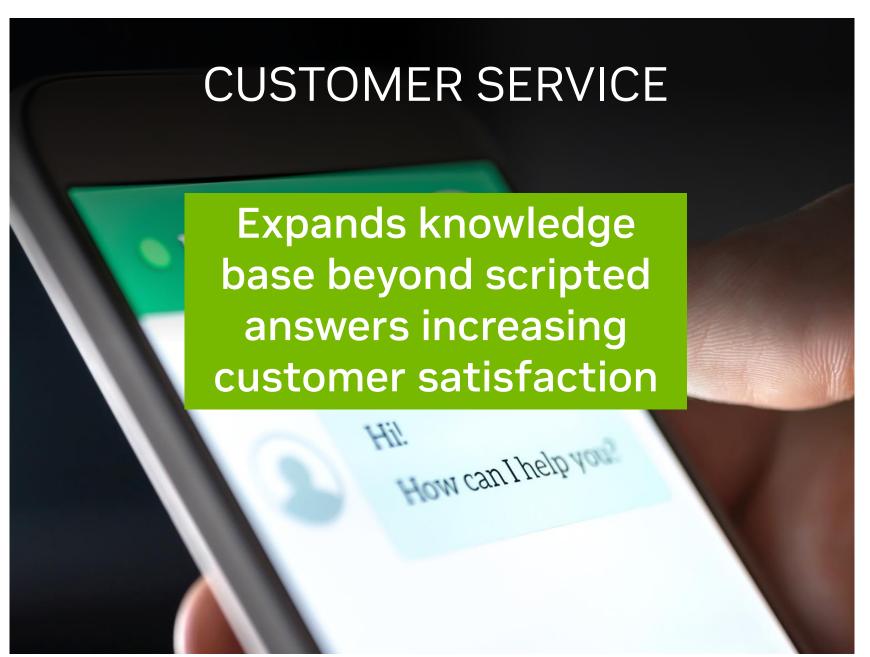


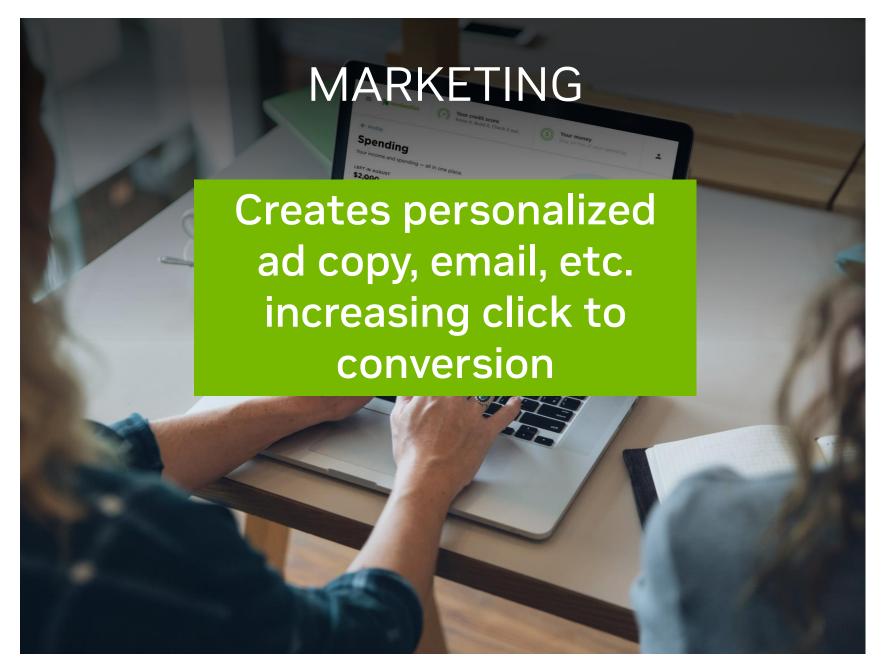






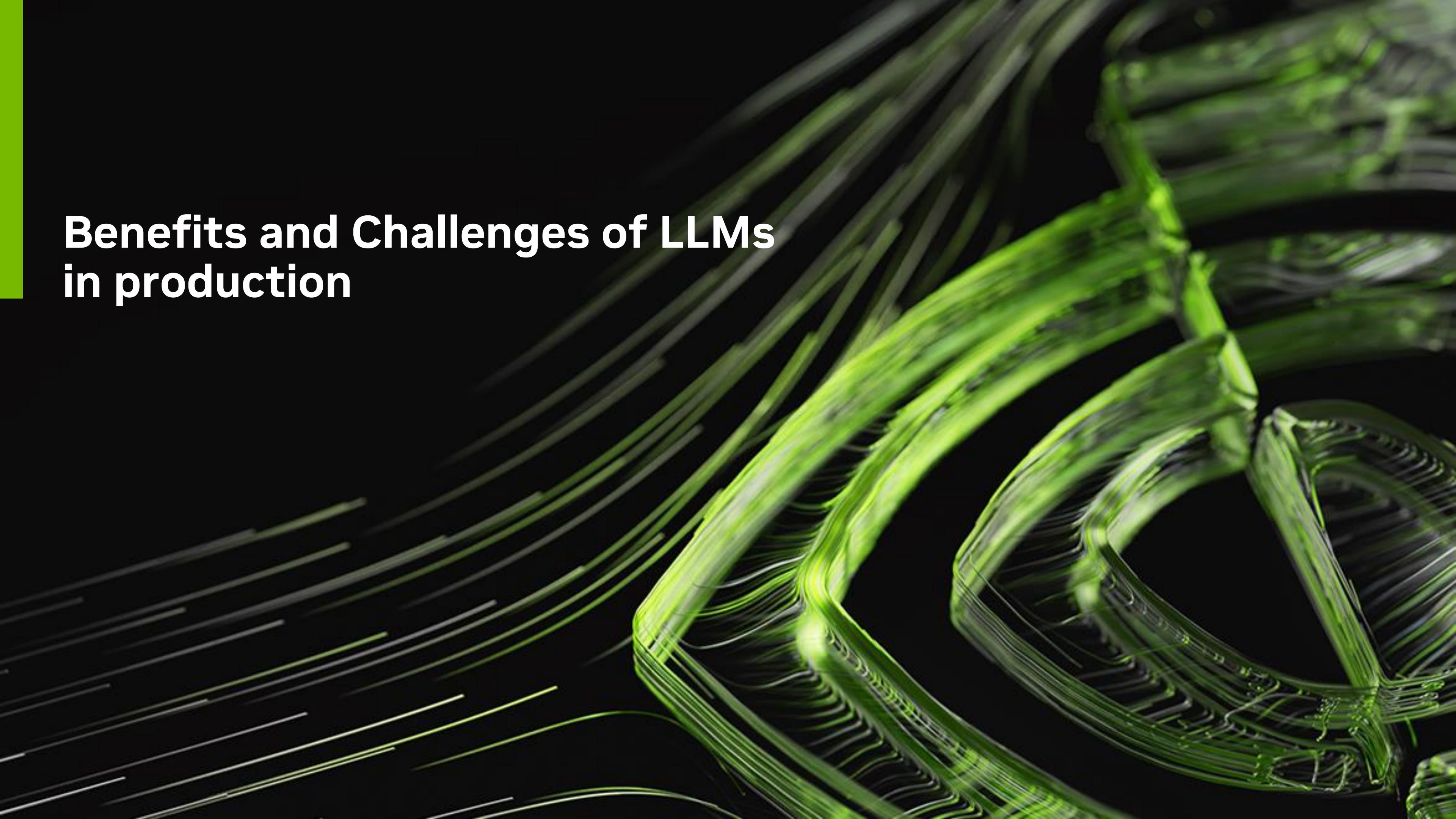




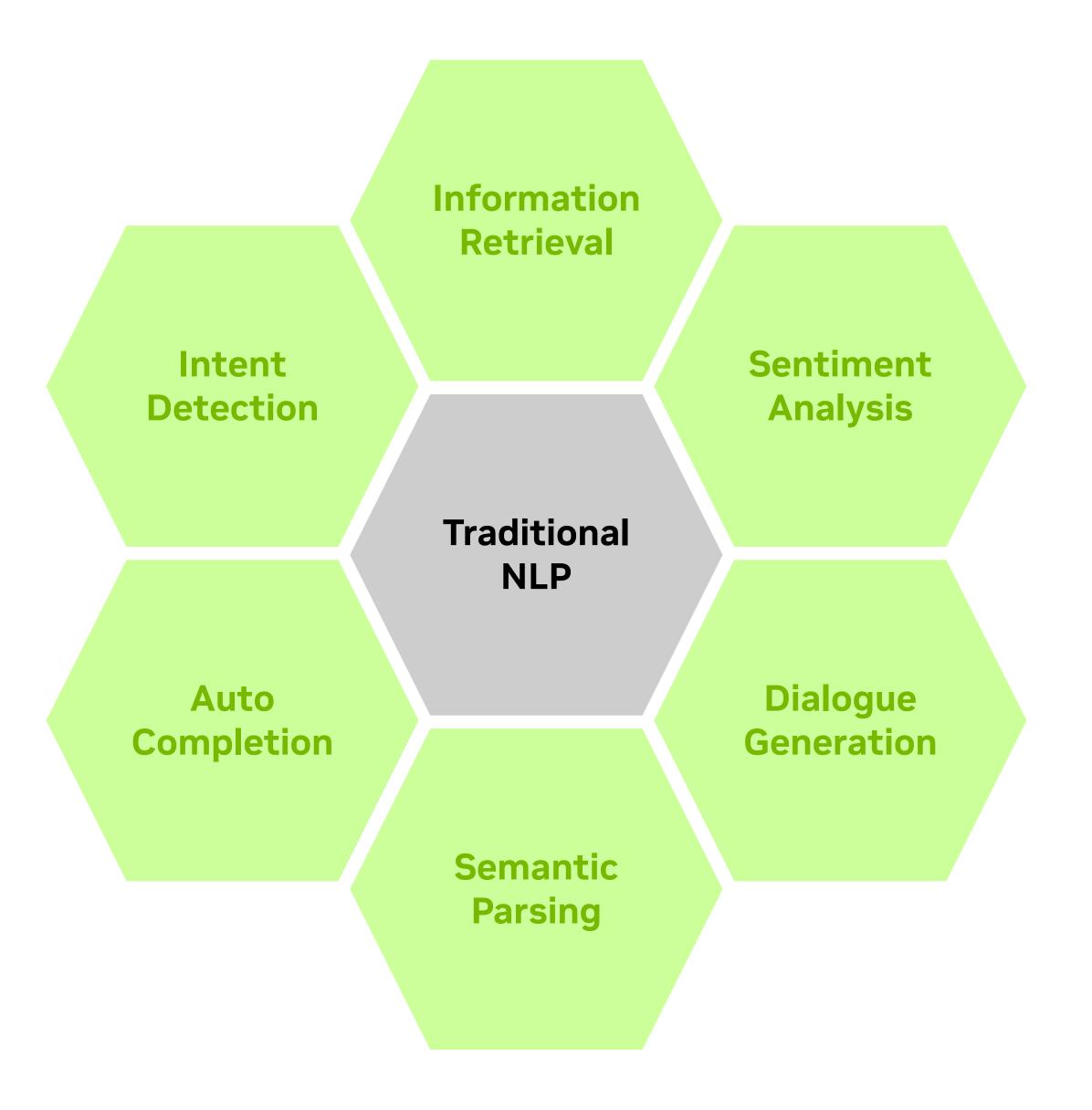








Traditional NLP Use-Cases



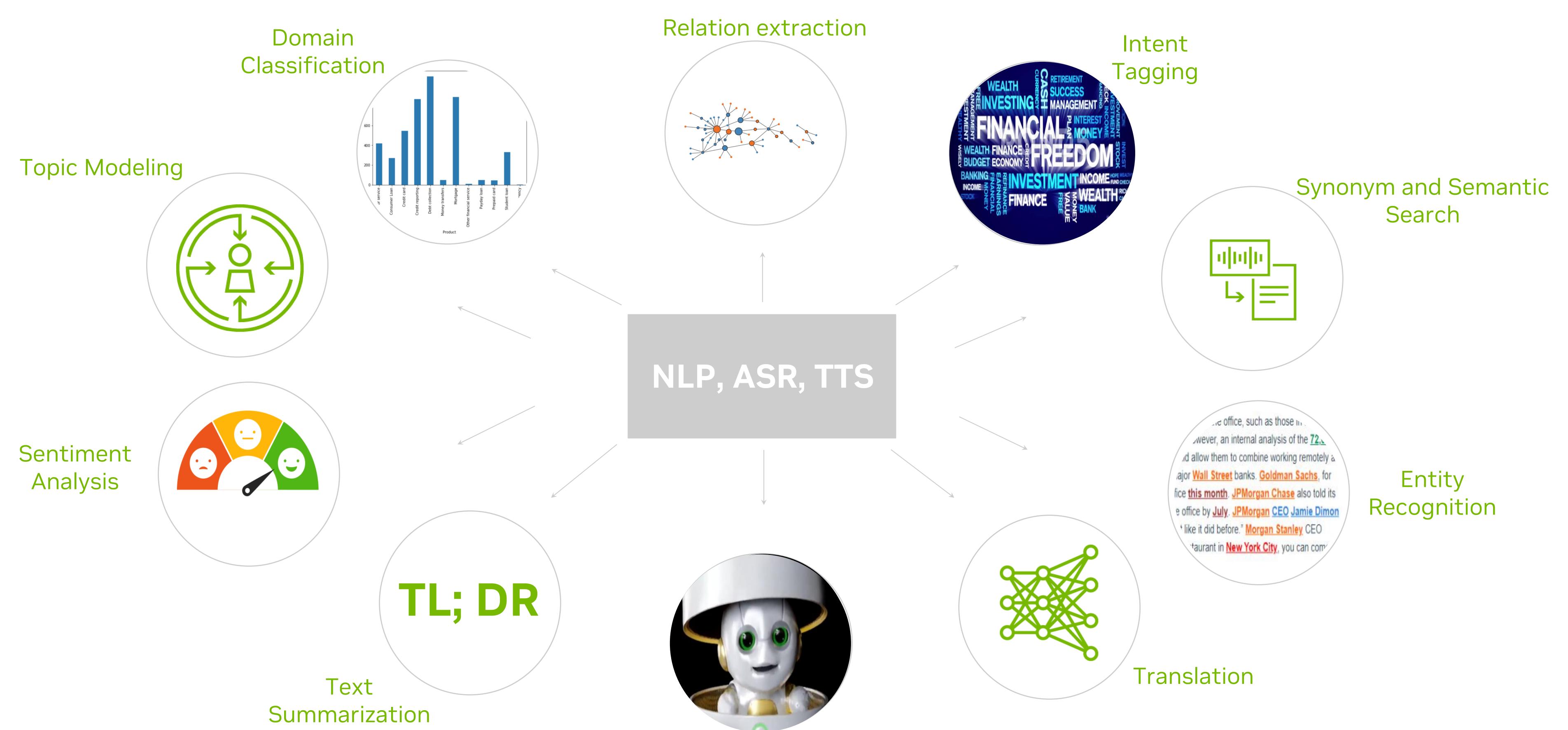
Current State of Traditional NLP

Challenges of Traditional NLP

- Need to build models for domain specific use-cases
- Requires extensive data inputs and data labeling
 - Intents and Entities
- Frequent (re)training for out of vocabulary use cases, and for new data. Model drifts over time
- Challenges in deciphering meaning of complex/dual inputs

	Traditional NLP Approach	Large Language Models
Requires labelled data	Yes	No
Parameters	100s of millions	Billions to trillions
Desired model capability	Specific (one model per task)	General (model can do many tasks, also new ones)
Training frequency	Retrain frequently with task- specific training data	Never retrain, or retrain minimally

One to rule them all



Question Answering



LLMs are more efficient

They can leverage prompts as in-context information | Prompt Engineering and Prompt Tuning approaches

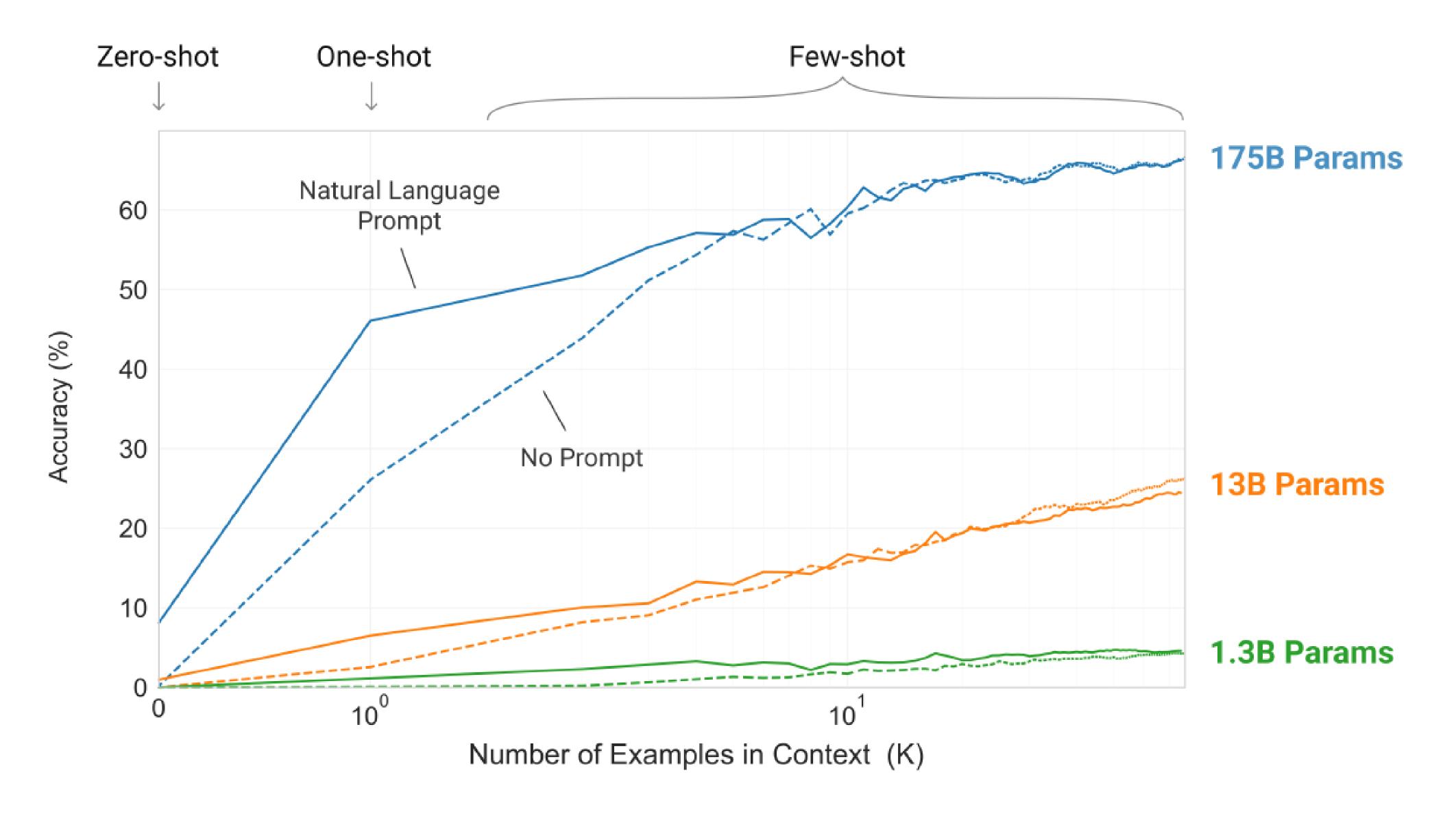
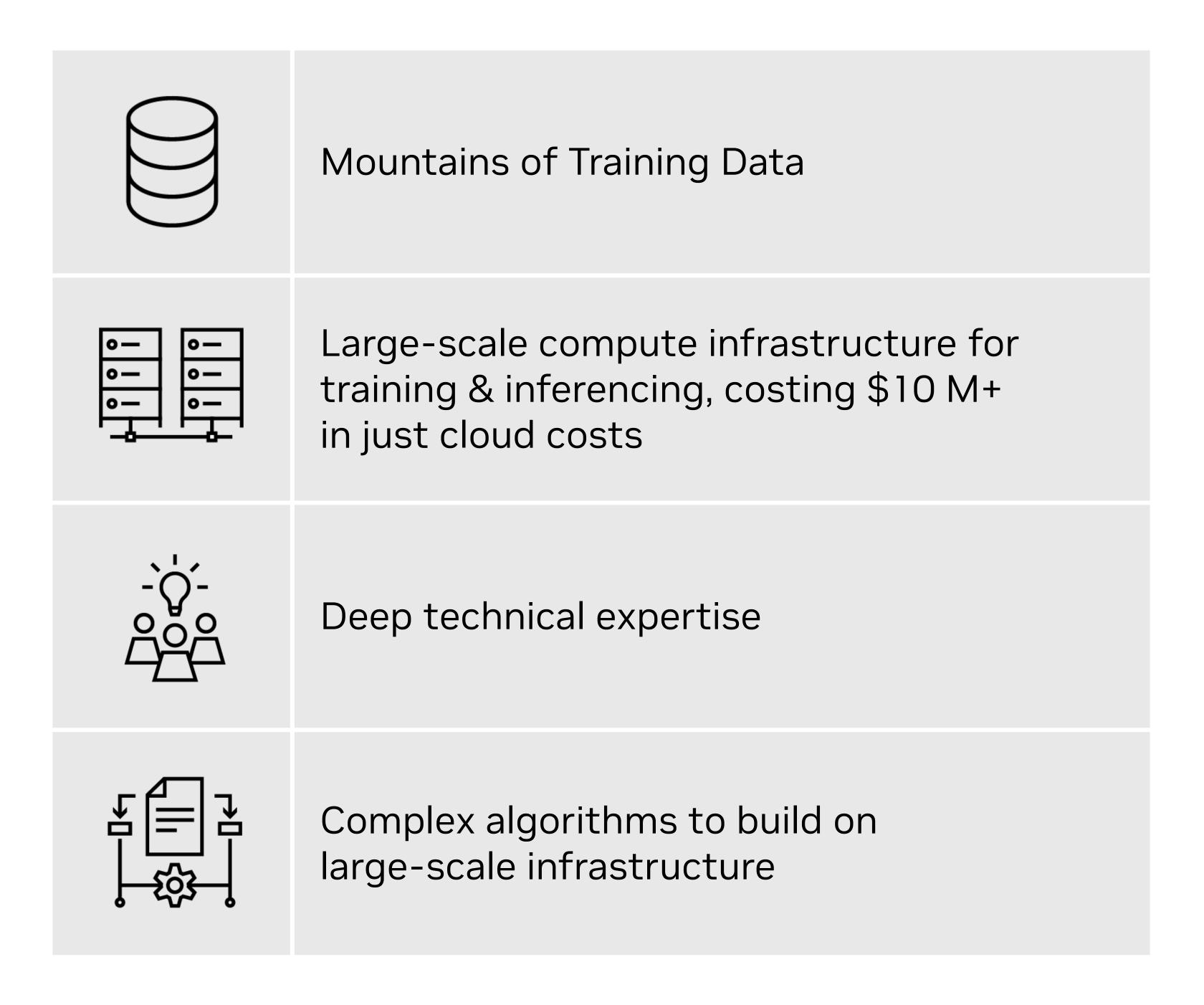


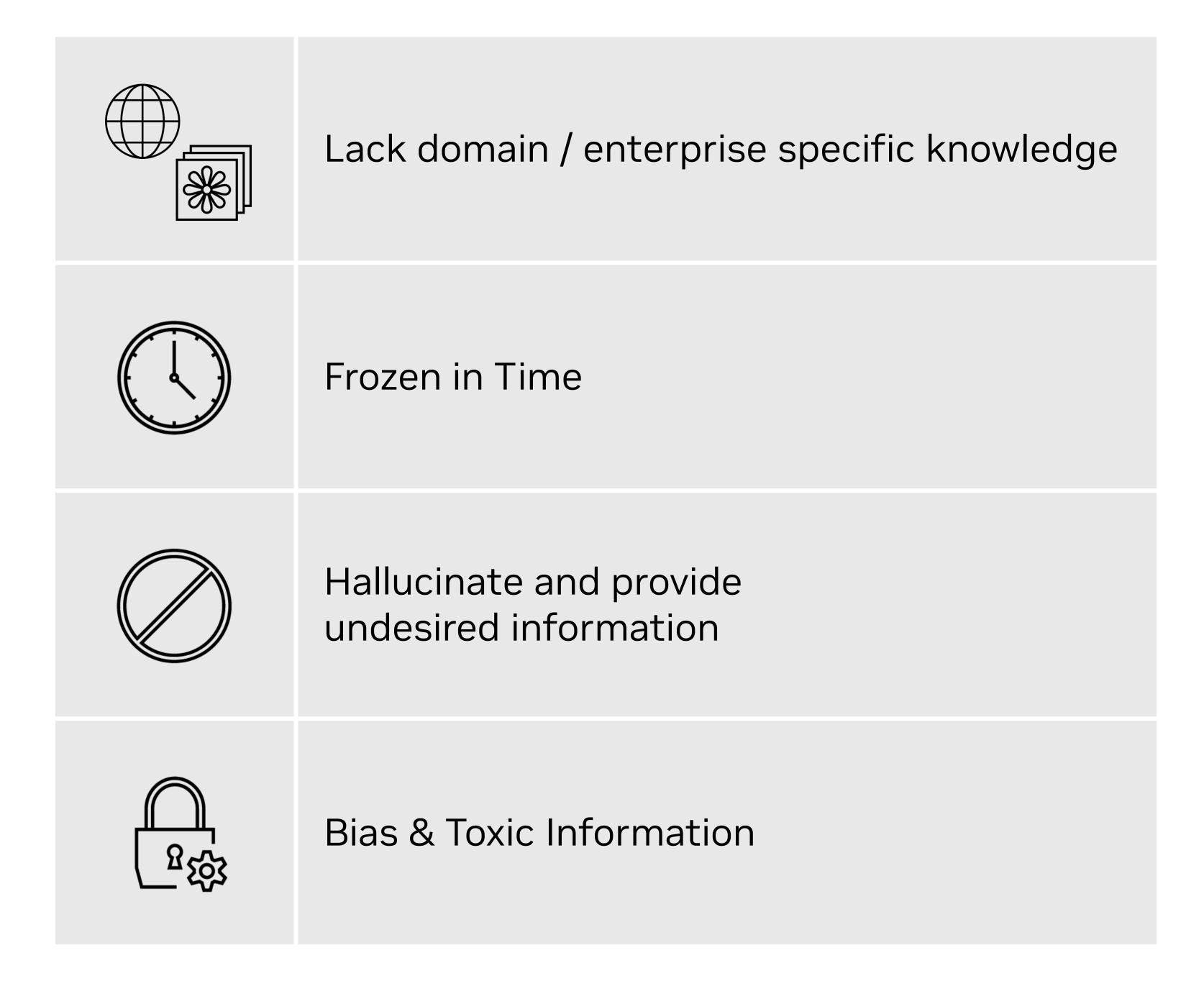
Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning curves" for large models demonstrate improved ability to learn a task from contextual information. We see qualitatively similar behavior across a wide range of tasks.

Enterprise Challenges Of Developing Generative Al

Challenges of Building Foundation Models



Challenges of Using Foundation Models

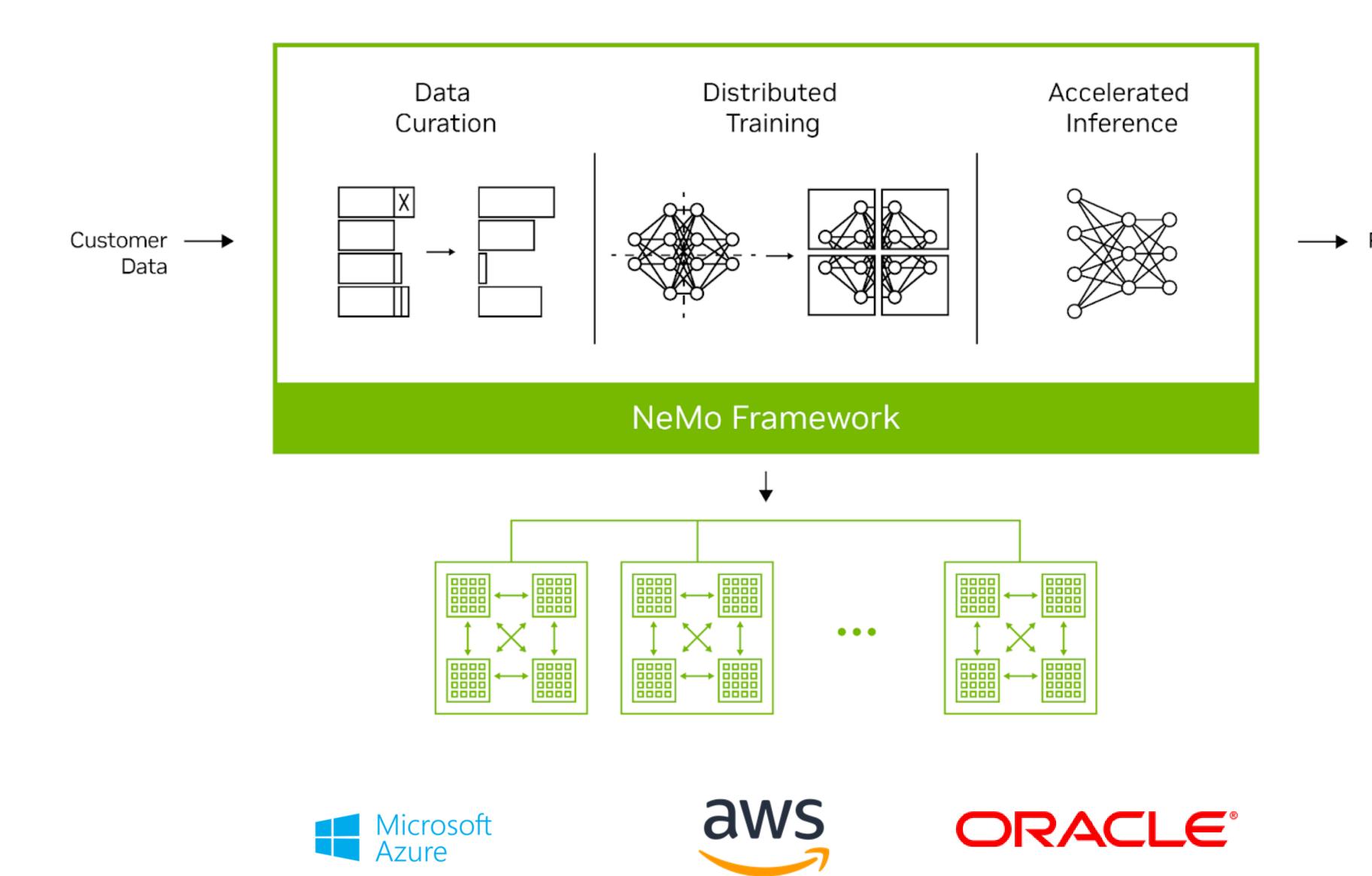






NeMo Framework

An end-to-end, cloud-native enterprise framework to build, customize and deploy generative AI models



- open-source framework LLMs with billions and trillions of parameters
- hyper-personalization and at-scale deployment (e.g. Inference)
- simplifying and accelerating the path to build and deploy LLMs
- guardrails: reduce bias and toxicity, to align to human intentions
- finding optimal hyperparameters, convergence of models
- retrieval augmented models based on-prem data

Deploy anywhere



DGX SuperPODs
DGX Cloud
DGX Systems

Multi-modality support

Build language, image, generative Al models

Accelerated Workflow

Speed up workflows with 3D parallelism & distributed training and inference techniques

Data Curation

Mine and curate highquality training data @ scale

Customize Foundation Models

State of the art customization techniques for LLMs including Adapters, RLHF, AliBi, SFT

Support

NVIDIA AI Enterprise keep projects on track

Deploy Anywhere

On any NVIDIA accelerated system: NVIDIA DGX Cloud, major CSPs (Azure, AWS, OCI), or on-prem



Overcoming Challenges Of Using Foundation Models

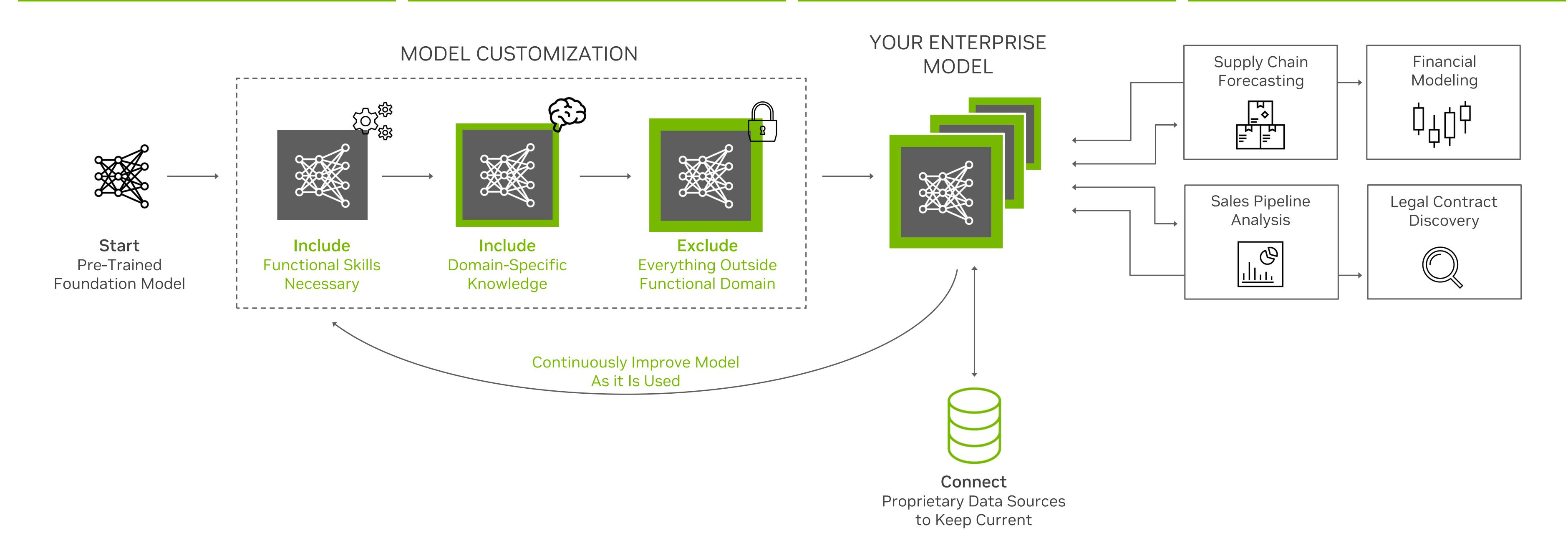
Generalized Al Will Not Work; Enterprises Need Their Own Al

Answer proprietary information

Update knowledge base with latest information

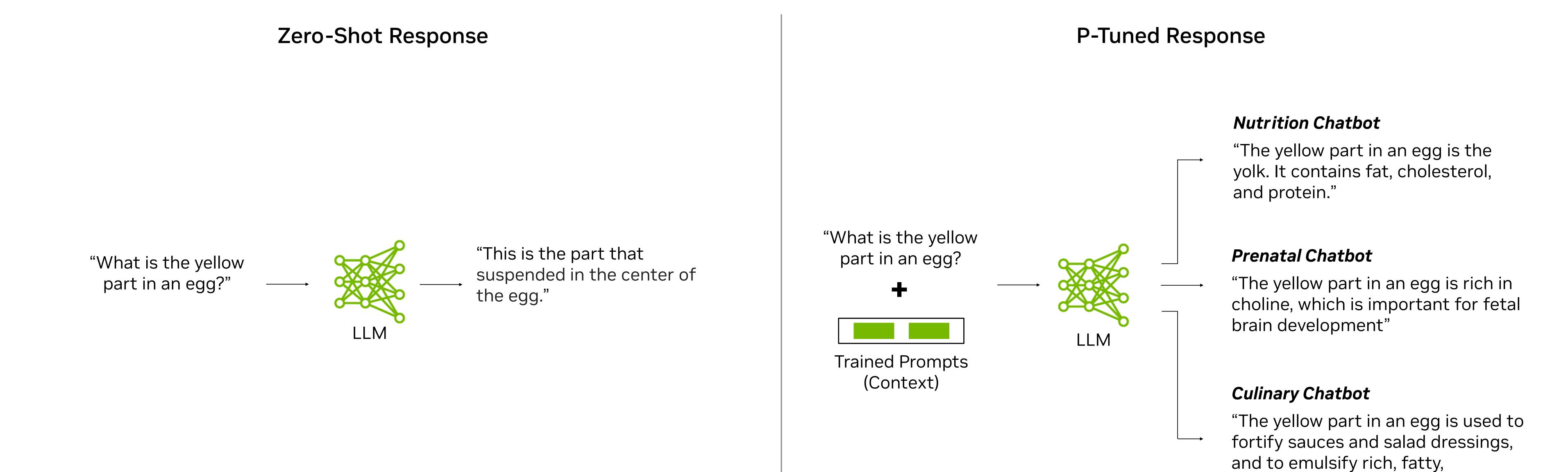
Factual correctness with specific context, domain & voice

Bias & toxicity management





Customization is Required to Address Business-specific Tasks





ingredients like oil and butter"

Enterprises Require Responses Based on Current Information



70%

Of Enterprise Data is Untapped

Unlock new opportunities for greater intelligence



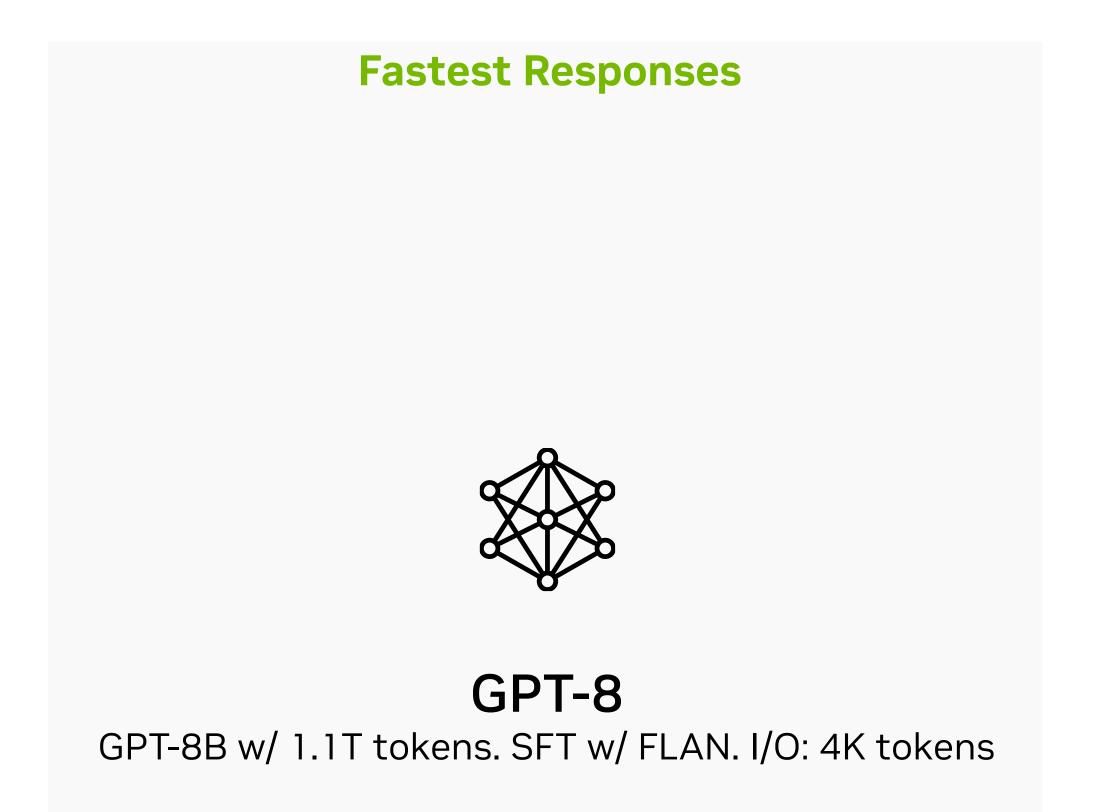
Less Frequent Re-Training

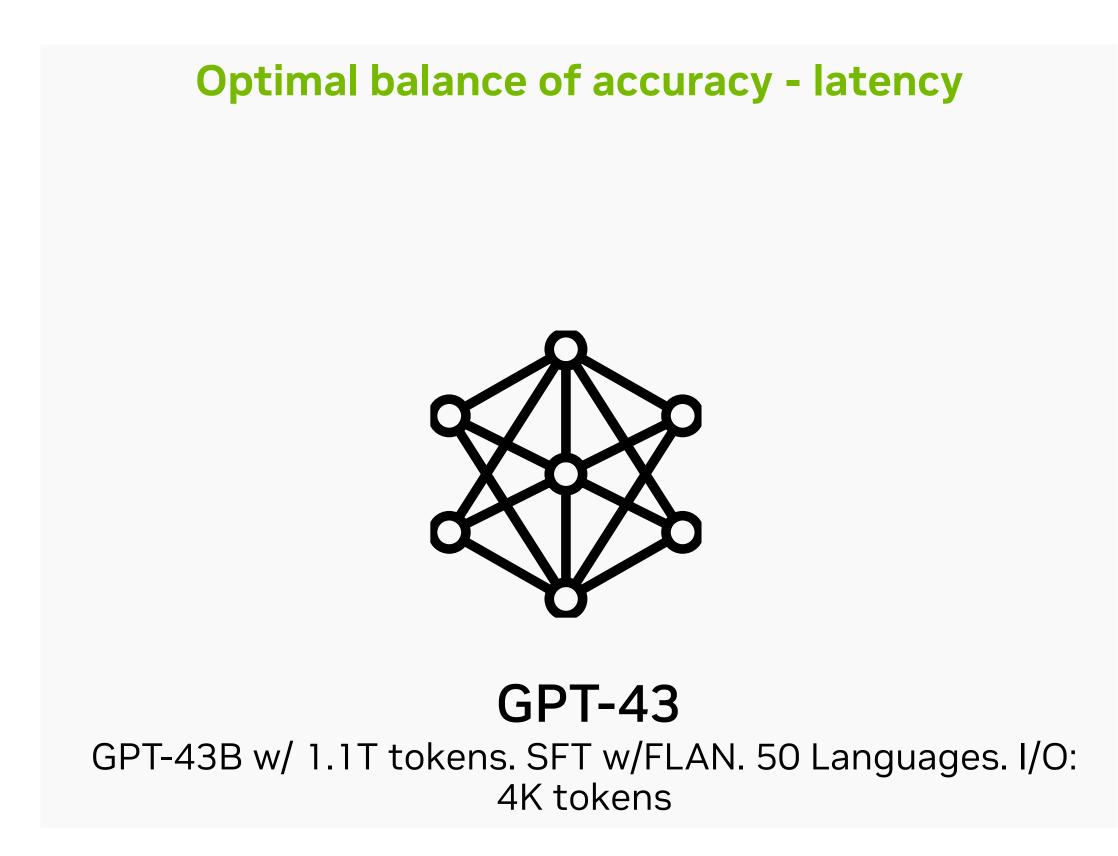
Significant cost and time savings to maintain LLMs

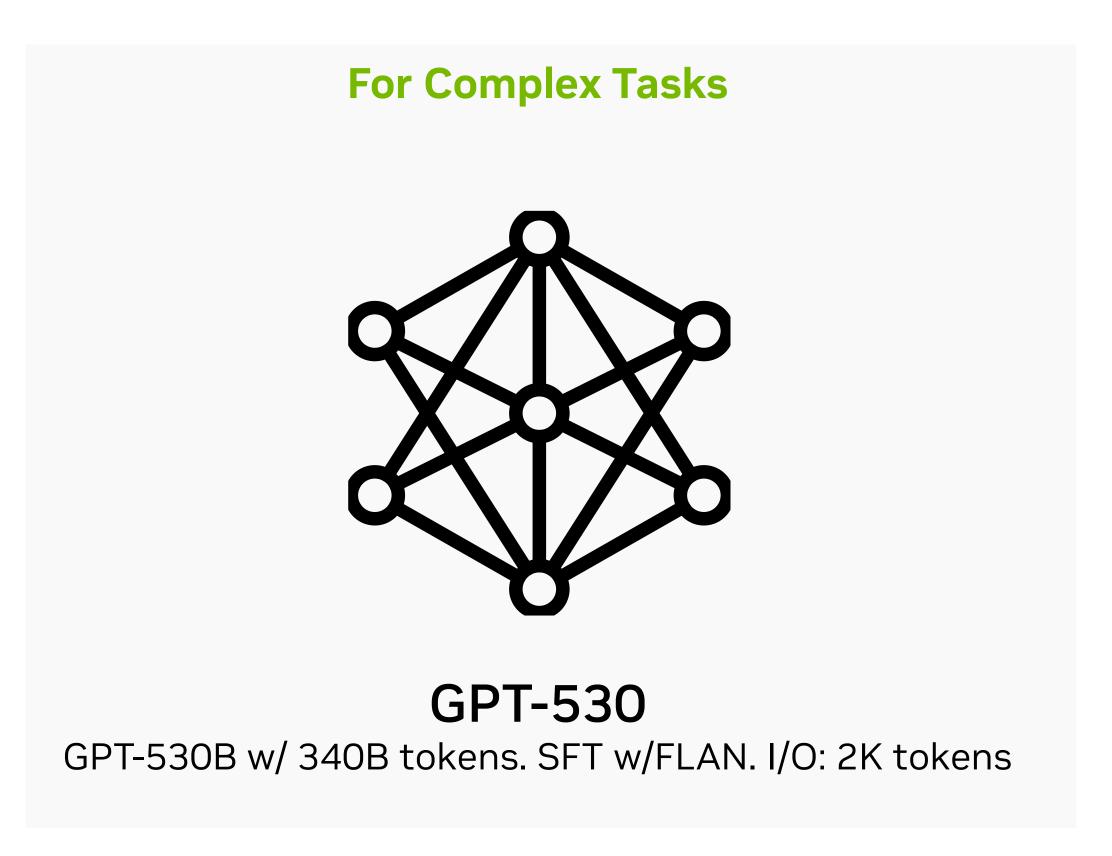


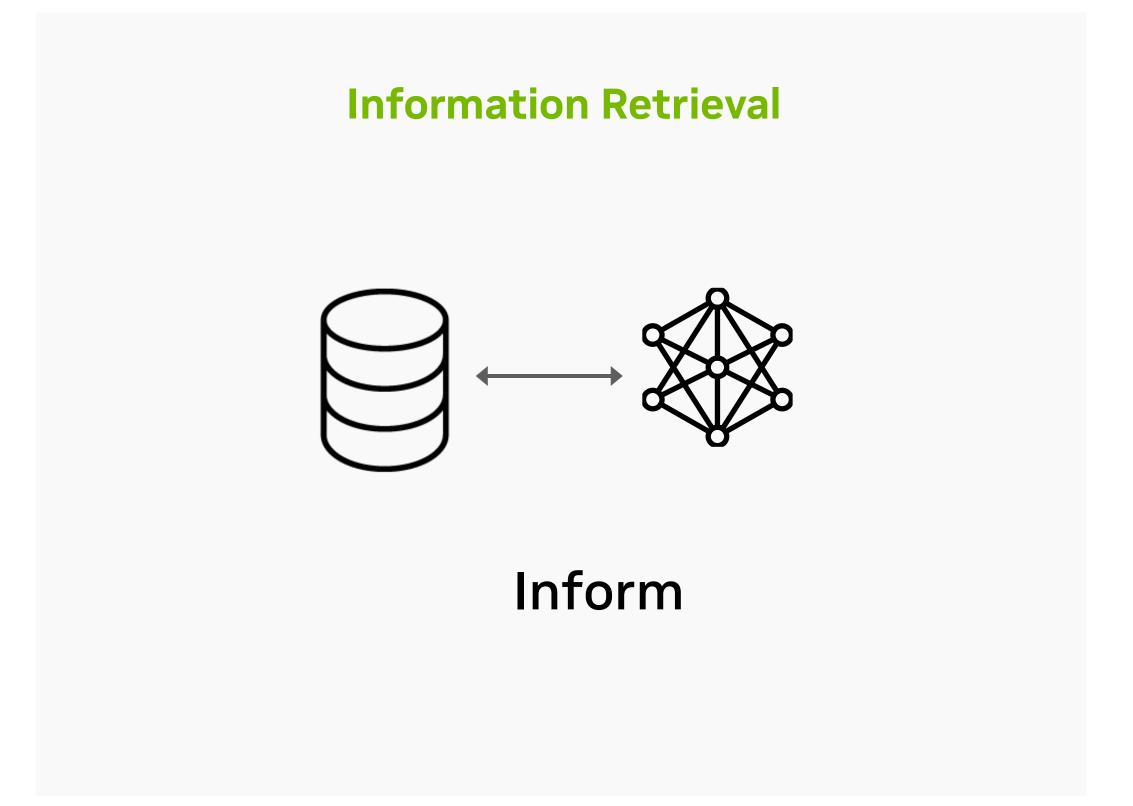
NeMo Generative Foundation Models

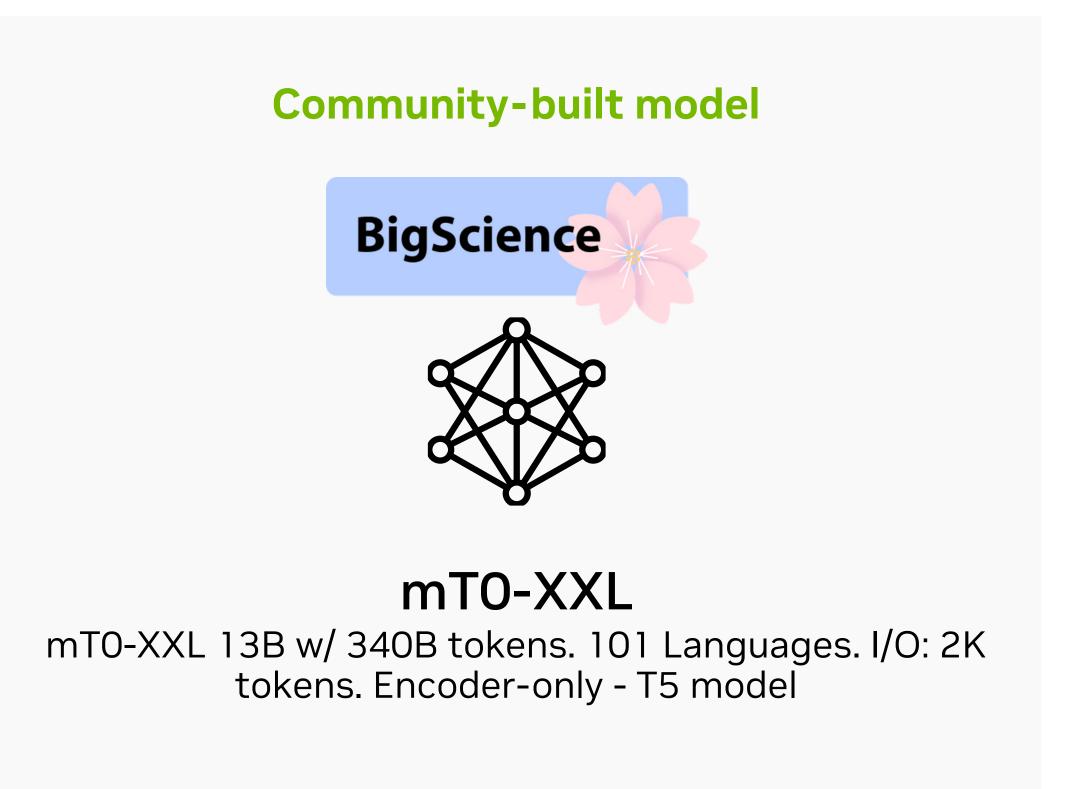
Suite Of Generative Foundation Language Models Built For Enterprise Hyper-personalization













Hyper-personalizing Foundation Models for Enterprises

Methods To Build And Hyper-personalize Foundation Models For Specific Use-cases

Personalization / Customization

Methods & Techniques

Learn New Knowledge (New domain)	Foundation Model Training / Fine-Tuning – <i>Via NeMo framework</i>
Learn a skill (ex. Article summarization)	Incremental Knowledge - Prompt Learning Techniques (p-tuning, adapters)
Filter Bias & Inappropriate Content	Toxicity Classifiers to indicate toxicity score for both Inputs & Outputs
Include Proprietary and Topical Knowledge Base	Runtime Knowledge - Inform (Information Retrieval Models)
Learn to Implement Guardrails	Tune Model Parameters to Stay within Specified Domain - Supervised Fine Tuning
Continuously Improve Models Over-Time	Continuous Knowledge – Reinforcement Learning with Human Feedback

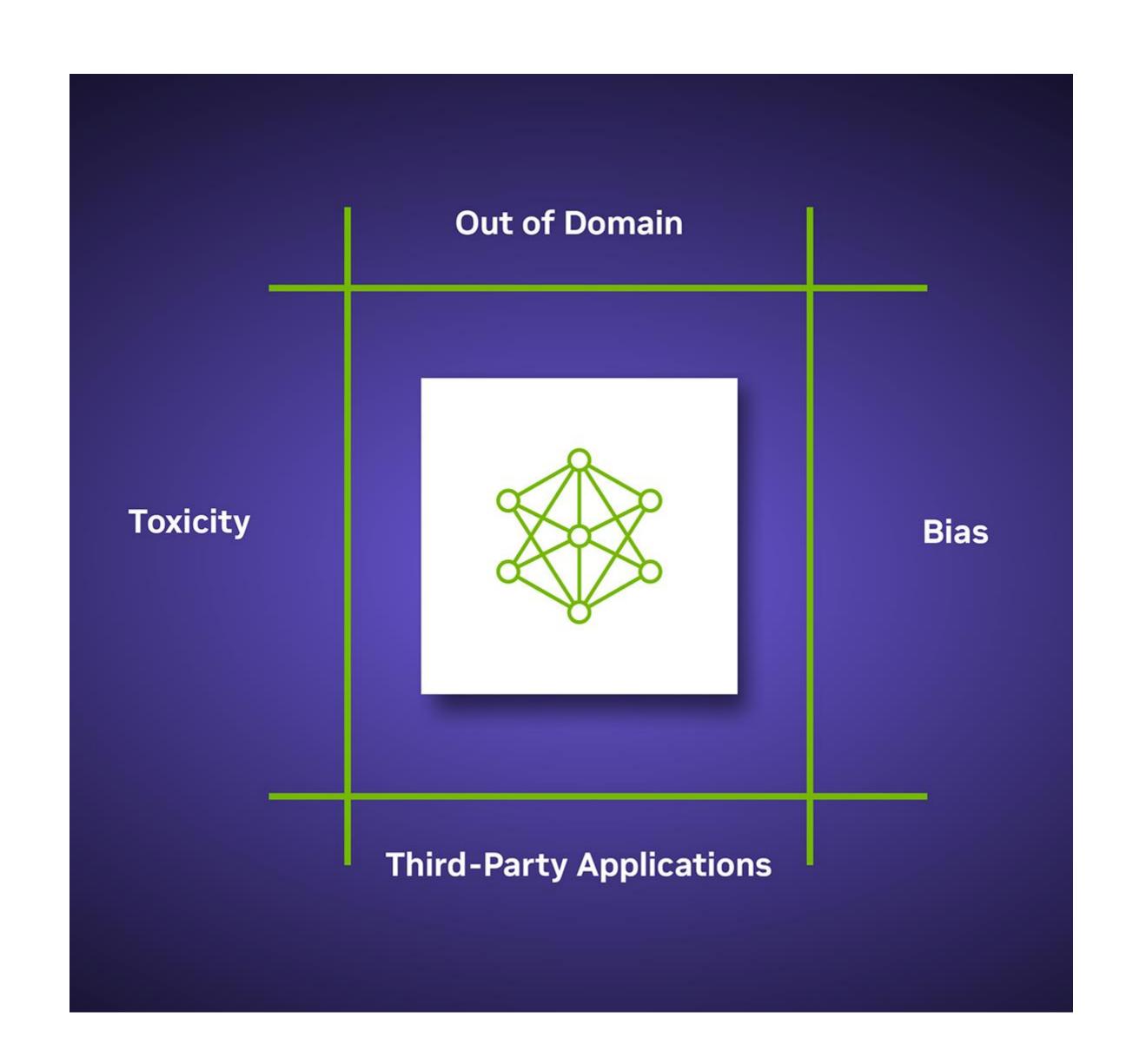
Legend: Available Today

On the Roadmap



Enterprise Use-Cases Require Guardrails

Exclude everything outside functional domain, eliminate bias and toxicity, to align to Enterprise goals



- **Topical guardrails** prevent apps from veering off into undesired areas. For example, they keep customer service assistants from answering questions about the weather.
- Safety guardrails ensure apps respond with accurate, appropriate information. They can filter out unwanted language and enforce that references are made only to credible sources.
- Security guardrails restrict apps to making connections only to external third-party applications known to be safe.

- Programmable rails for LLMs: Steering the LLM towards producing outputs that accurately and effectively meet user intent
- Align the LLMs with the business goals of the Enterprise
- Prevent the model from generating undesirable, biased, or harmful content
- Toxicity classifier (BERT based classifier) assigns a toxicity score for every input and output
- Developer can use the toxicity score to filter inappropriate responses for their use-case



Designed for Enterprise Adoption

Trustworthy and Responsible AI Development

Privacy



Safety & Security



Transparency & Explainability



Nondiscrimination



Training data not shared

Control logging of prompts & outputs

Toxicity Classification

Deploy Anywhere using NeMo Framework

Soc-2 compliance

Implement guardrails

Foundation models trained on licensed data

Connect to proprietary knowledge base

Cite sources for model answers

Bias classification

Legend:

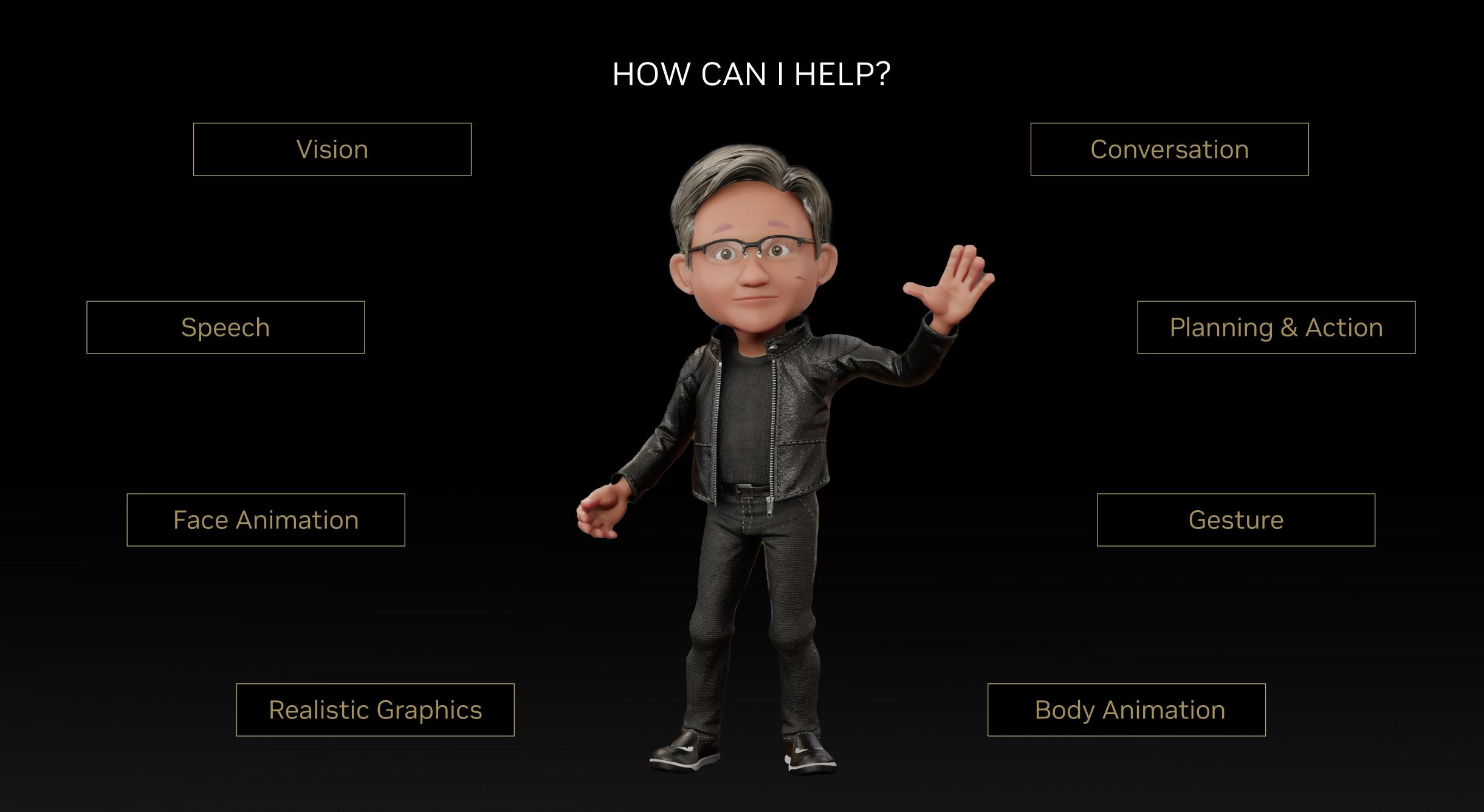
Available Today





AVATARS & DIGITAL HUMANS USE MANY AI/ML MODELS

BOT MAKER - EARLY ACCESS PROGRAM | NVIDIA DEVELOPER OMNIVERSE AVATAR CLOUD ENGINE (ACE) | NVIDIA DEVELOPER SOFTSERVE EXAMPLE





Accelerated Computing for AI Quality/Certification projects

Trustworthy and Responsible Al Development

The NVIDIA accelerated computing platform can be leveraged to develop, deploy and validate AI Quality

Scaling and (semi-)automation is the next level - establishing a stack with tools/technologies for effective execution and cost reduction is critical

Examples:

- Post-hoc Explainable Al
- Robustness tests and simulation (synthetic data)
- MLOps workflows at scale
- Selection of fittest model from large model pool
- •

