CS 343H

Review and Conclusion

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TEXAS

The University of Texas at Austin

Announcements

- Please fill out the course survey
  - Feedback to both instructor and TAs
  - Positive and negative points are useful
  - Post on Ed your completion screenshot (in a private post) as a form of participation!

- Capture the Flag contest results!

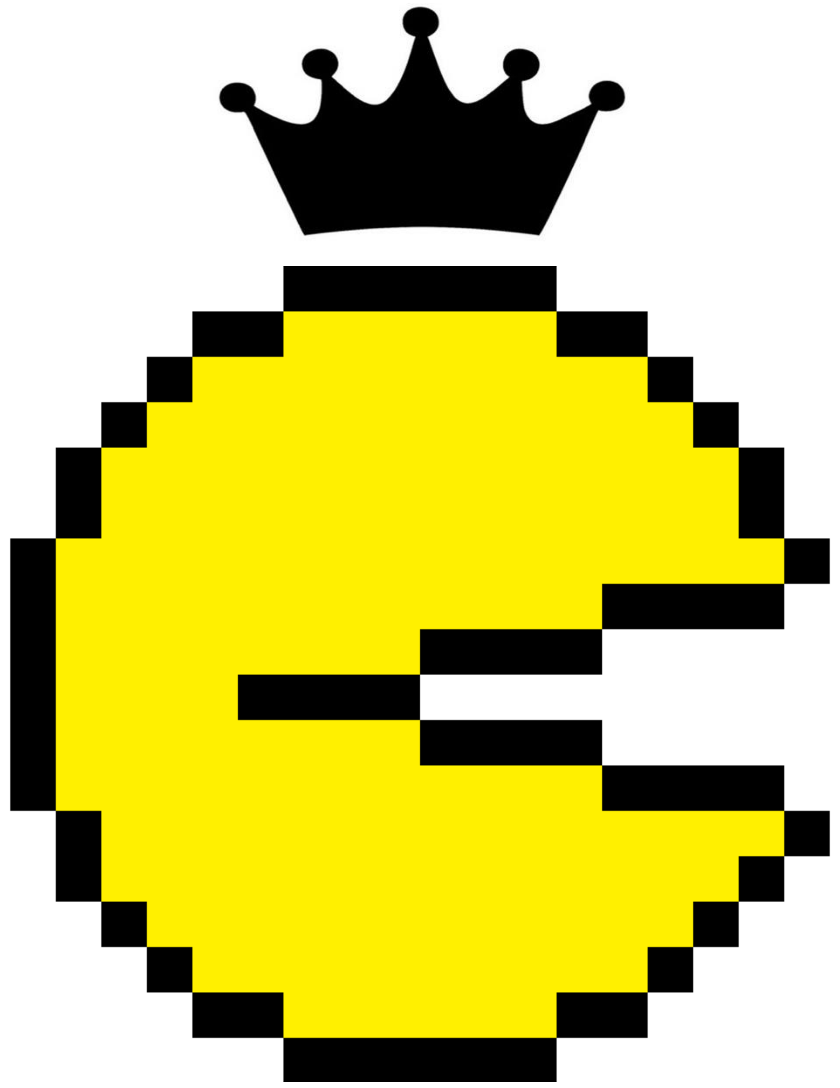
CTF Contest

23 teams participated, 15 qualified for tournament

Rankings

- 1st place: Beto An, Kevin Zhao (controllers)
- 2nd place: Angela Zhang, Tanuj Tekkale (lords of smiggles)
- 3rd place: Rishi Astra (temp_yeet2)

Congratulations!



Overview of AI Topics

Search / Planning

- Uninformed Search
- A* Search
- CSPs
- Local Search
- Minimax
- Expectimax
- MDPs

Machine Learning

- Reinforcement Learning
- Probability Theory
- Bayes Nets
- HMMs
- Particle Filters
- Decision Networks
- VPI
- Naive Bayes
- Perceptrons
- Neural Networks
- Deep Learning
- Clustering

Overview of Machine Learning

Supervised Learning

Discriminative Models

Perceptrons

Neural Networks

Generative Models

Bayes Nets

Naive Bayes

HMMs

Reinforcement Learning

MDPs

Value Iteration

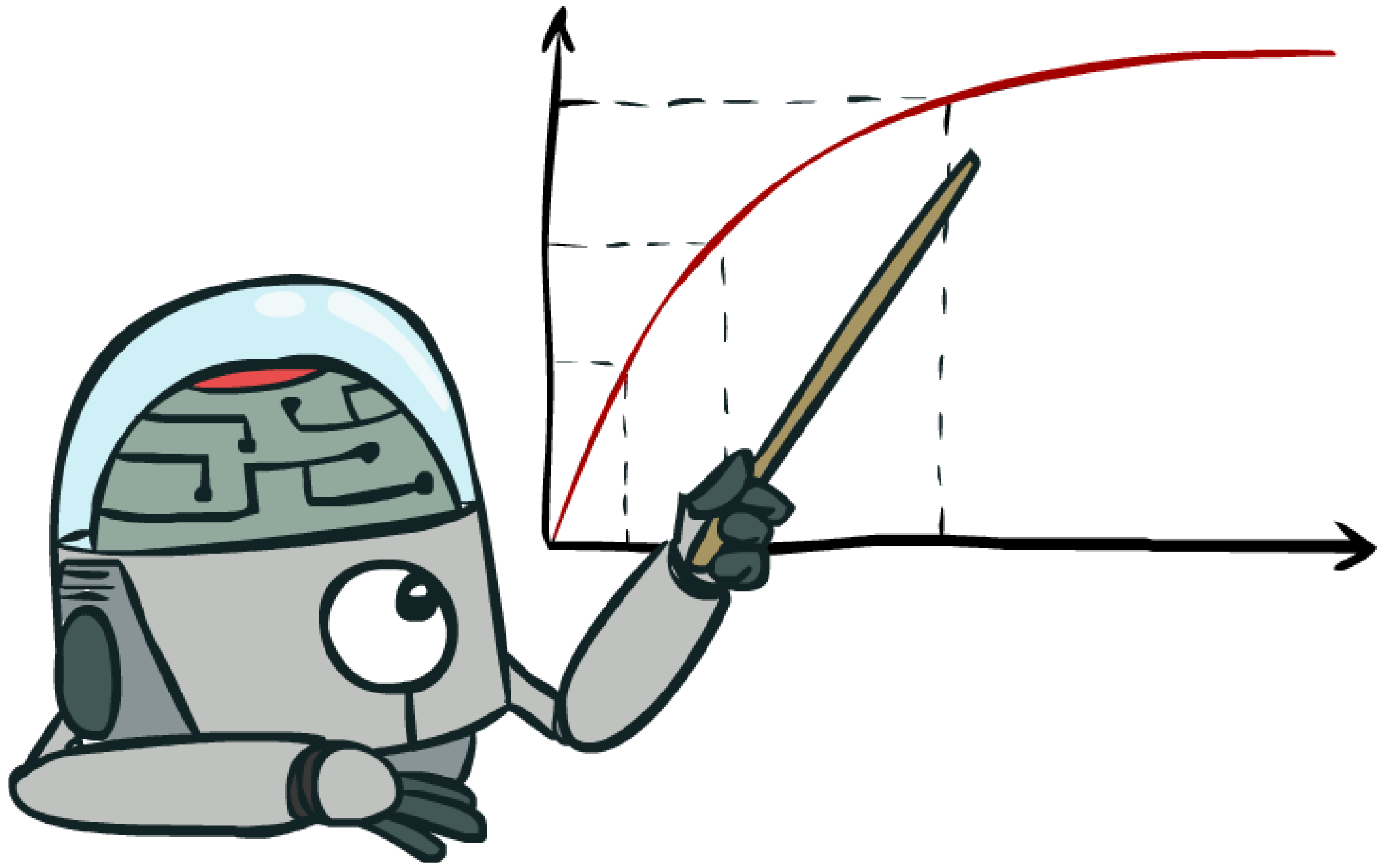
Policy Iteration

Q Learning

Unsupervised Learning

K-Means Clustering

Maximize Your Expected Utility



How Do AI Systems Maximize Utility?

Constraint satisfaction: searching intelligently for legal solutions

8			4		6			7
						4		
	1					6	5	
5		9		3		7	8	
				7				
	4	8		2		1		3
	5	2					9	
		1						
3			9		2			5

Example: Sudoku

Utility: Does the solution satisfy the rules / constraints?

Assumptions: We can write down the rules / constraints of the problem

How Do AI Systems Maximize Utility?

Planning: reasoning with models

Example: Robot navigation

Utility: Path length, collisions, surfaces, energy, social factors

Assumptions: We have a model of the world and the effects of the agent's actions

How Do AI Systems Maximize Utility?

Supervised Learning: learning from labeled examples

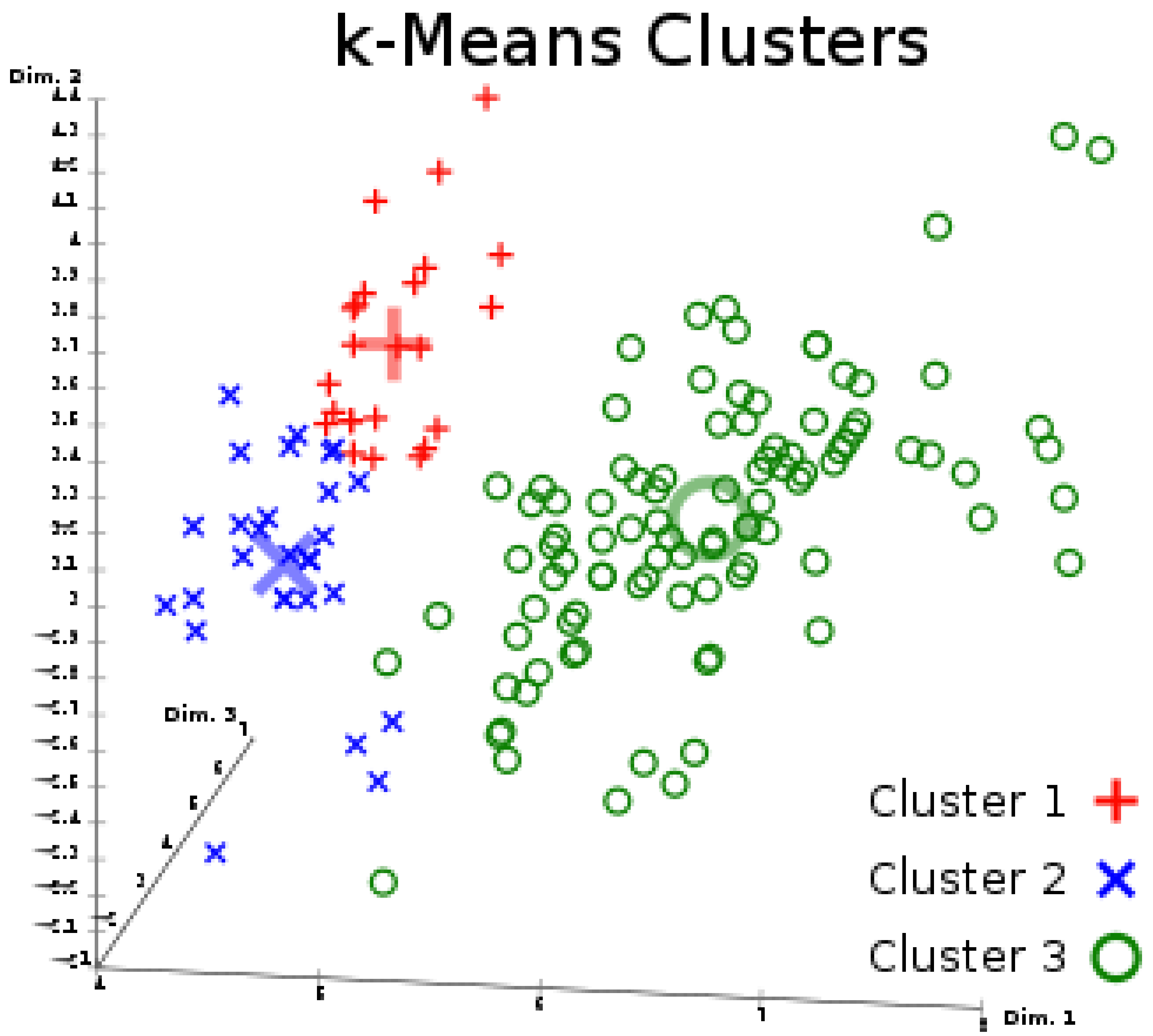
Example: Image classification

Utility: Classification accuracy on images not seen during training

Assumptions: We have access to a (usually large) labeled data set

How Do AI Systems Maximize Utility?

Unsupervised Learning: discovering patterns in unlabeled data



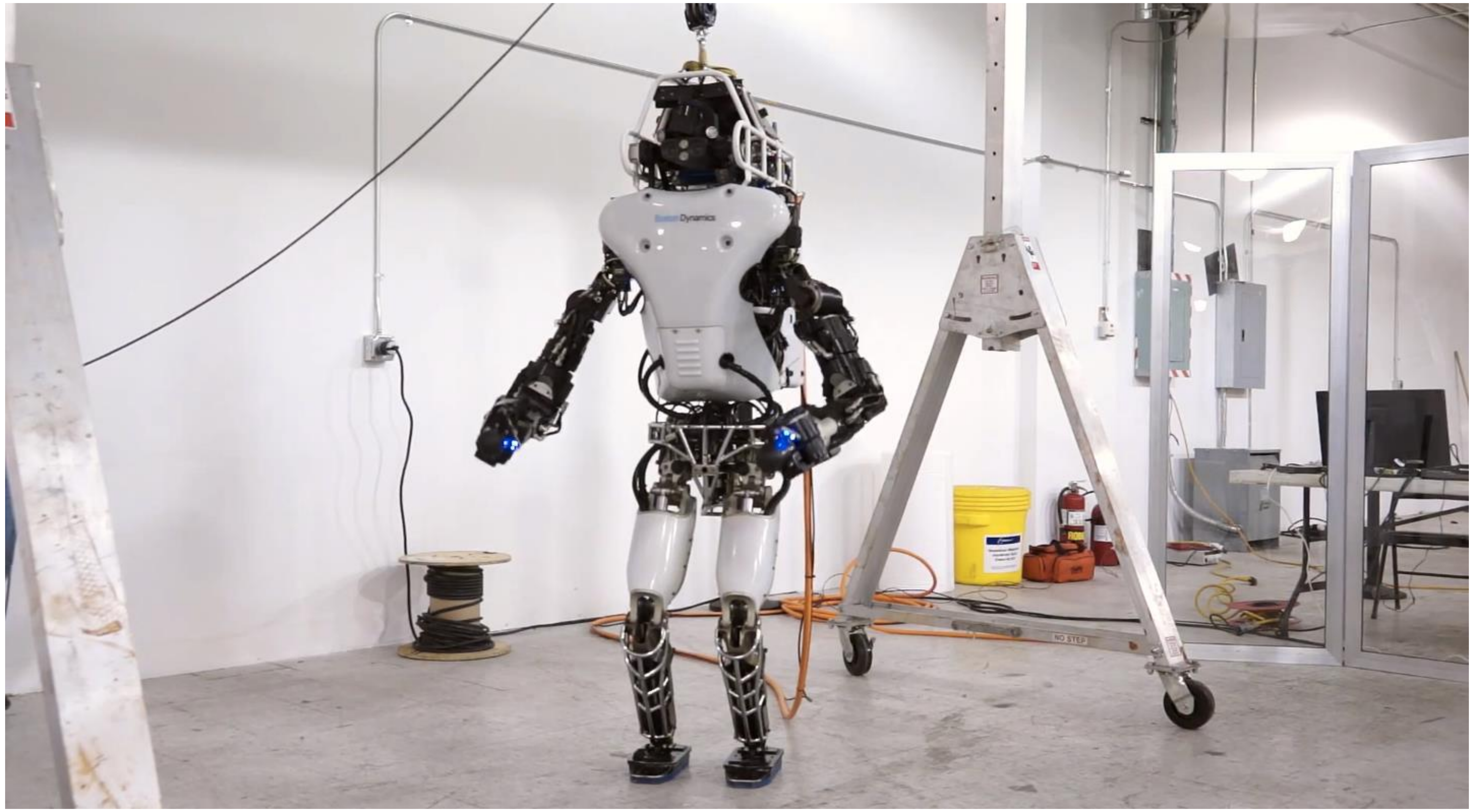
Example: Clustering species

Utility: “Best” explanation of data

Assumptions: Data points that should be clustered together are “close” together

How Do AI Systems Maximize Utility?

Reinforcement Learning: learning from experience



Example: Robot walking

Utility: Time until fall, speed, energy efficiency

Assumptions: We can "reward" and "punish" good and bad performance, but don't know what the correct action at each step should be

Properties of task environment

- Single-agent vs. multi-agent
- Deterministic vs. stochastic
- Fully observable vs. partially observable
- Episodic vs. sequential
- Static vs. dynamic
- Discrete vs. continuous
- Known vs. unknown

Single agent vs. multi-agent

- Not multi-agent if other agents can be considered part of the environment
- Only considered to be multi-agent if the agents are maximizing a performance metric that depends on other agents’ behavior
- Single agent example: Pacman with randomly moving ghosts
- Multi-agent example: Pacman with ghosts that use a planner to follow him

Single / Multi Agent

Single	Multi
Uninformed Search	Minimax
A* Search	Expectimax
Local Search	MDPs
CSPs	Reinforcement Learning

Deterministic vs. stochastic

- Deterministic: next state of environment is completely determined by the current state and the action executed by the agent
- Stochastic: actions have probabilistic outcomes
- Strongly related to partial observability — most apparent stochasticity results from partial observation of a deterministic system
- Example: Coin flip

Determinism

Deterministic	Stochastic
Uninformed Search	Expectimax
A* Search	MDPs
Local Search	Reinforcement Learning
CSPs	Decision Diagrams
Minimax	

Fully observable vs. partially observable

- Fully observable: agent's sensors give it access to complete state of the environment at all times
- Can be partially observable due to noisy and inaccurate sensors, or because parts of the state are simply missing from the sensor data
- Example: Perfect GPS vs noisy pose estimation
- Example: IKEA assembly while blindfolded

Almost everything in the real world is partially observable

Observability

Fully Observable

Uninformed Search

A* Search

Local Search

CSPs

Minimax

Expectimax

MDPs

Reinforcement Learning

Partially Observable

Bayes Nets

HMMs

Decision Networks

Known vs. unknown

- Agent’s state of knowledge about the “rules of the game” / “laws of physics”
- Known environment: the outcomes for all actions are given
- Unknown: agent has to learn how it works to make good decisions
- Possible to be partially observable but known (solitaire)
- Possible to be fully observable but unknown (video game)

Model of the World

Known

Uninformed Search

A* Search

Local Search

CSPs

Classic Planning

Minimax

Expectimax

MDPs

Value Iteration

Decision Diagrams

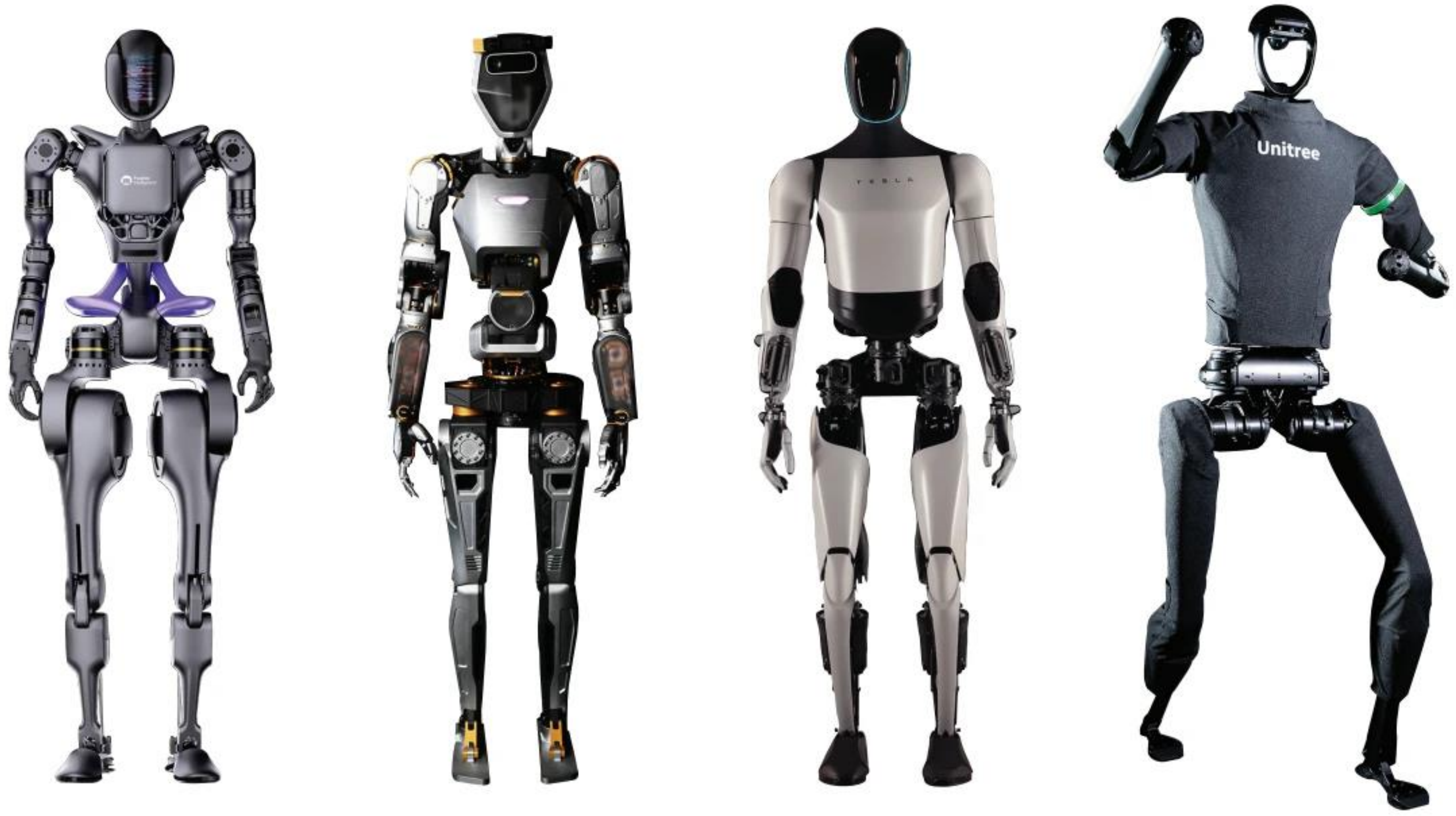
Unknown

Q Learning

Learning parameters of Bayes Net

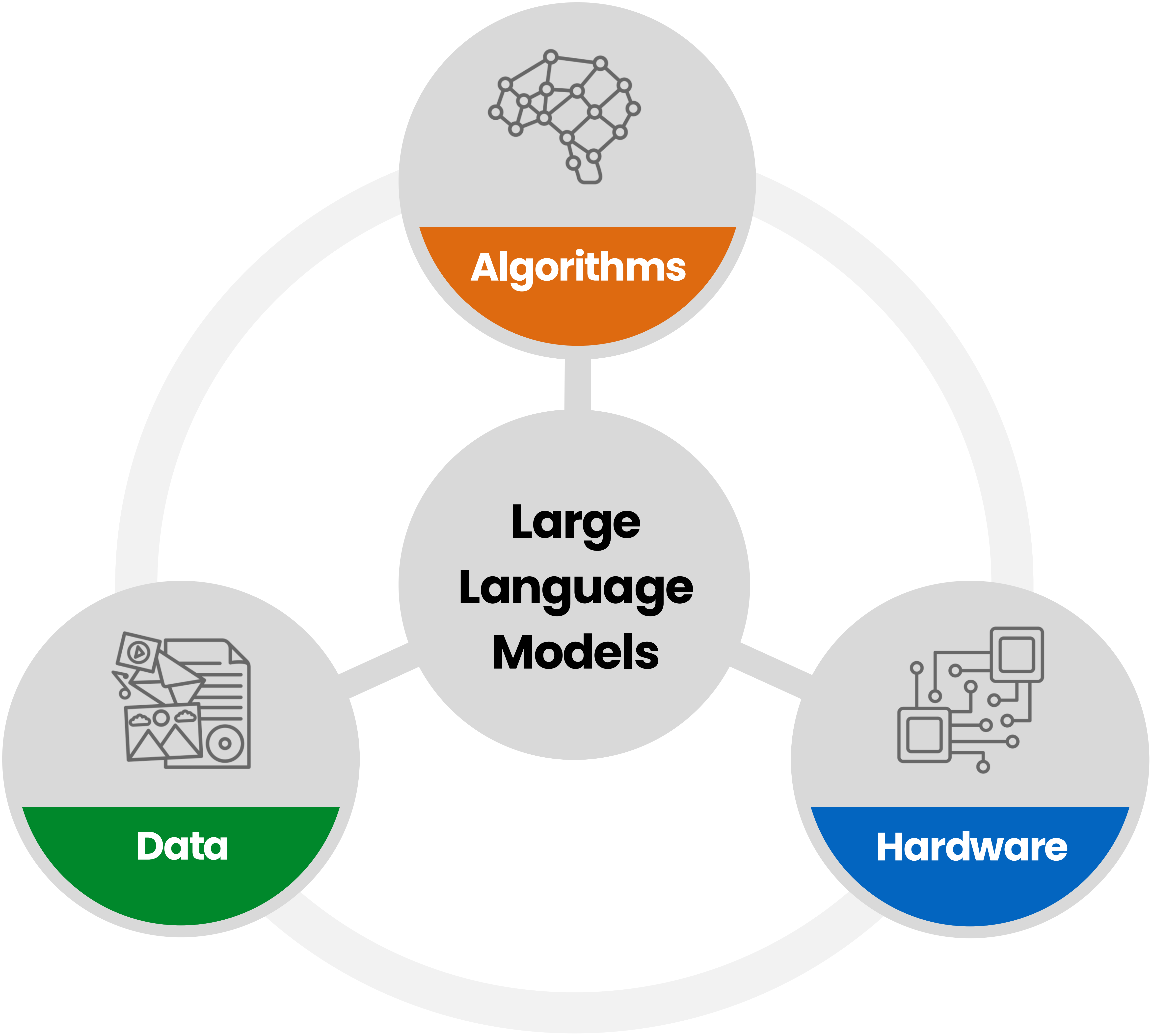

research.nvidia.com/labs/gear

Building Robotic Foundation Models



One “AI Brain” for All (Humanoid) Robots

Recipe for Building Large Language Models



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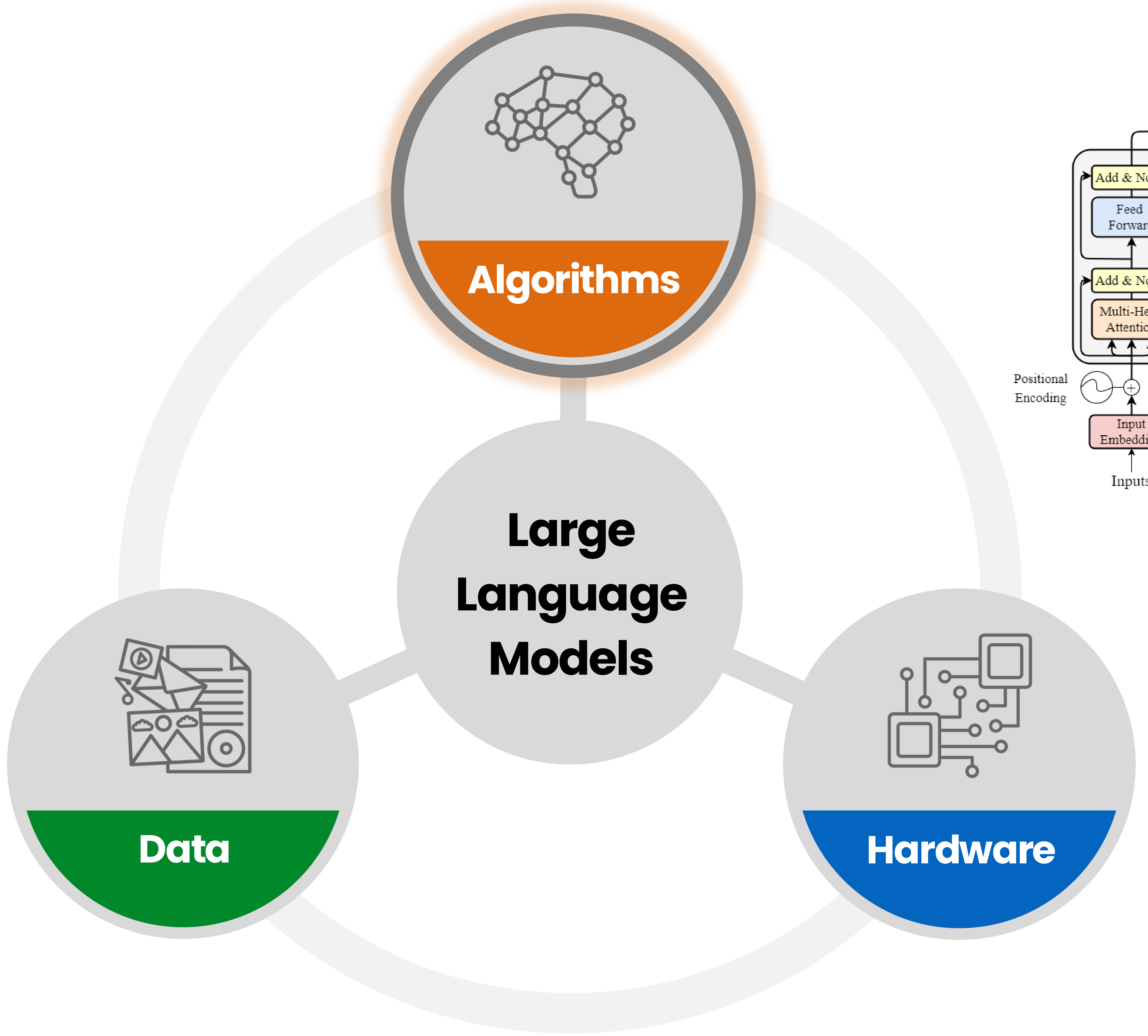
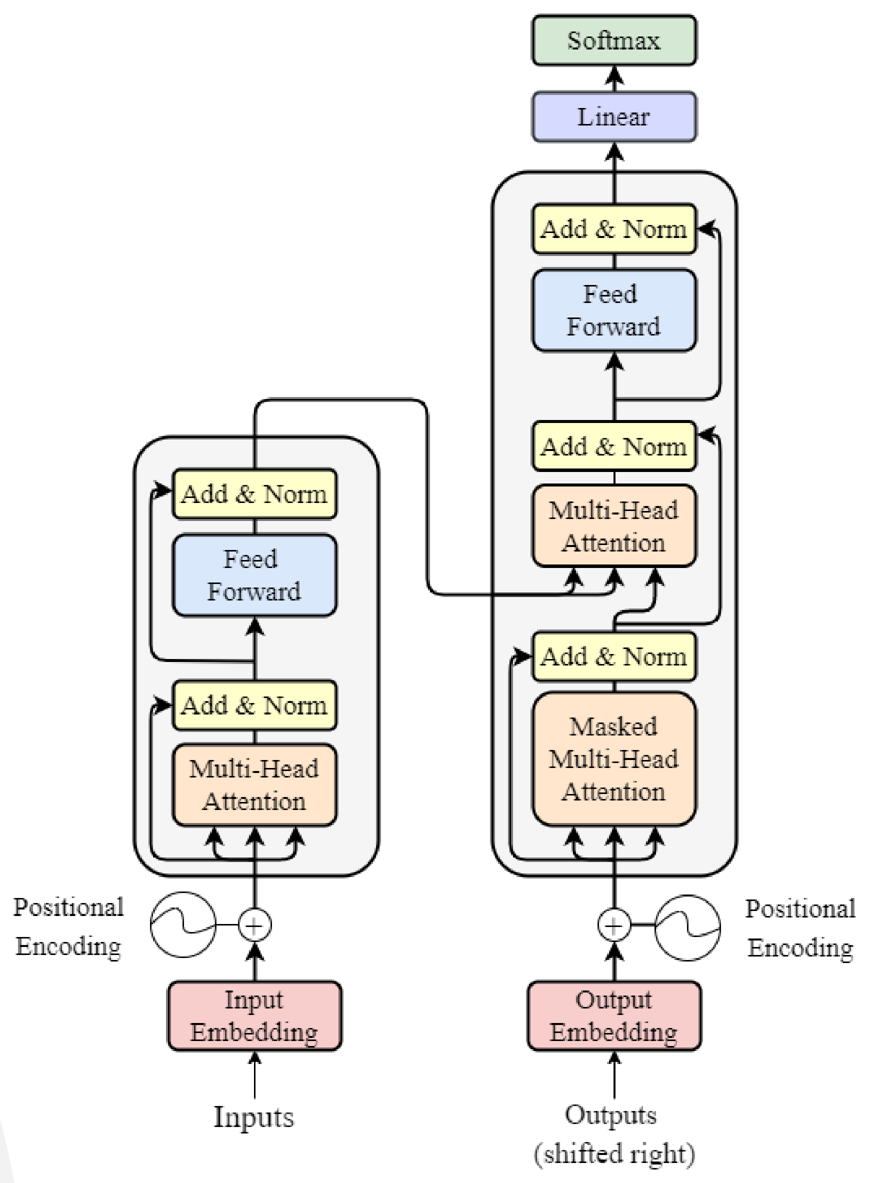
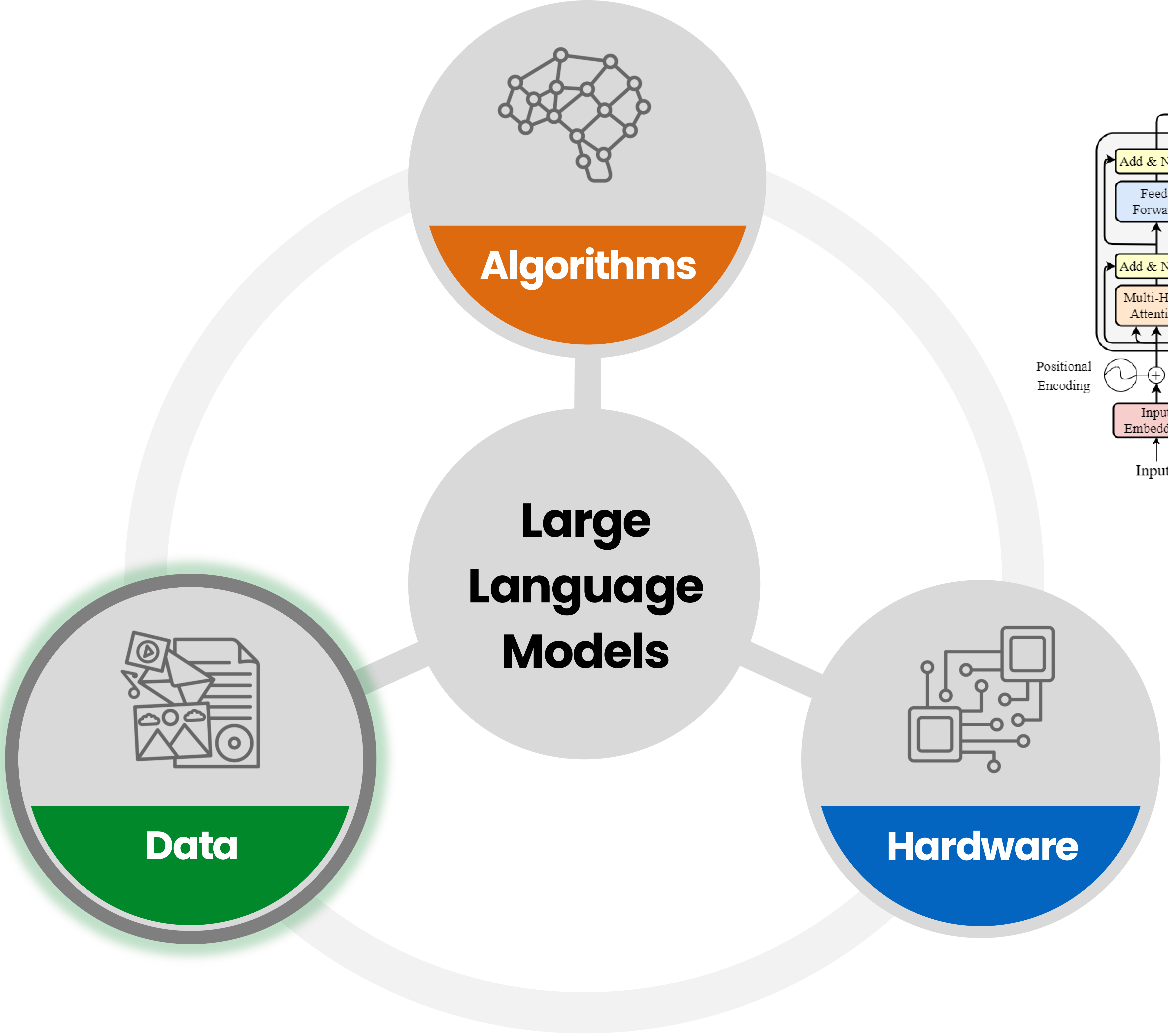


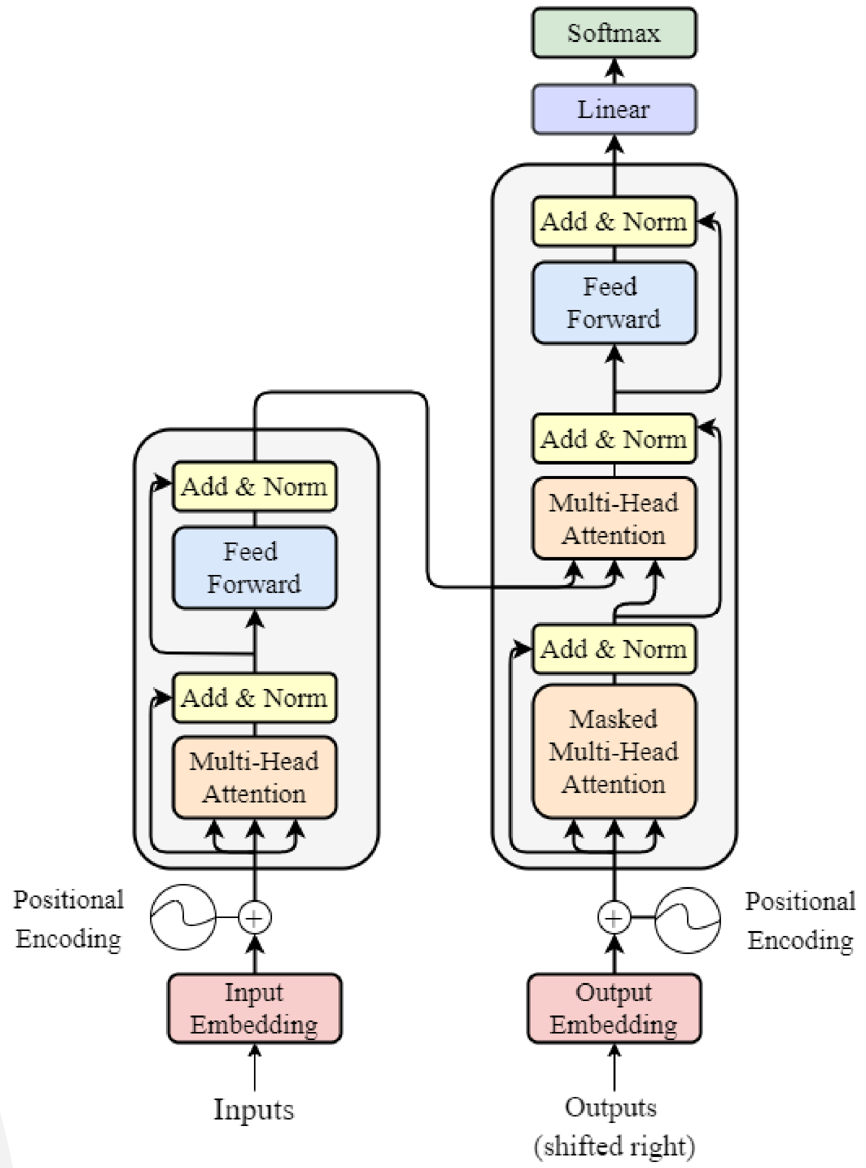


Recipe for Building Large Language Models

WIKIPEDIA
The Free Encyclopedia

GitHub





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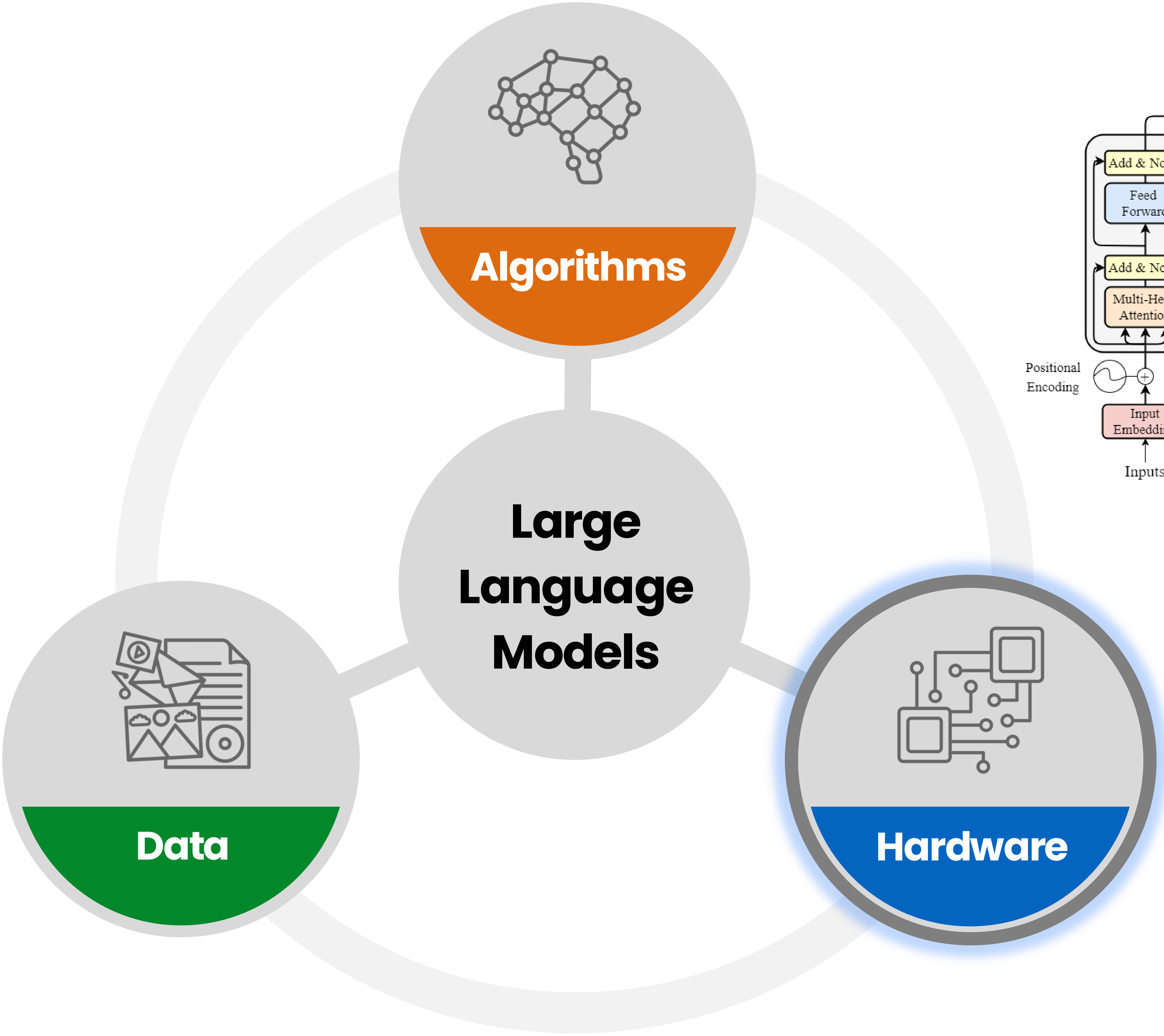

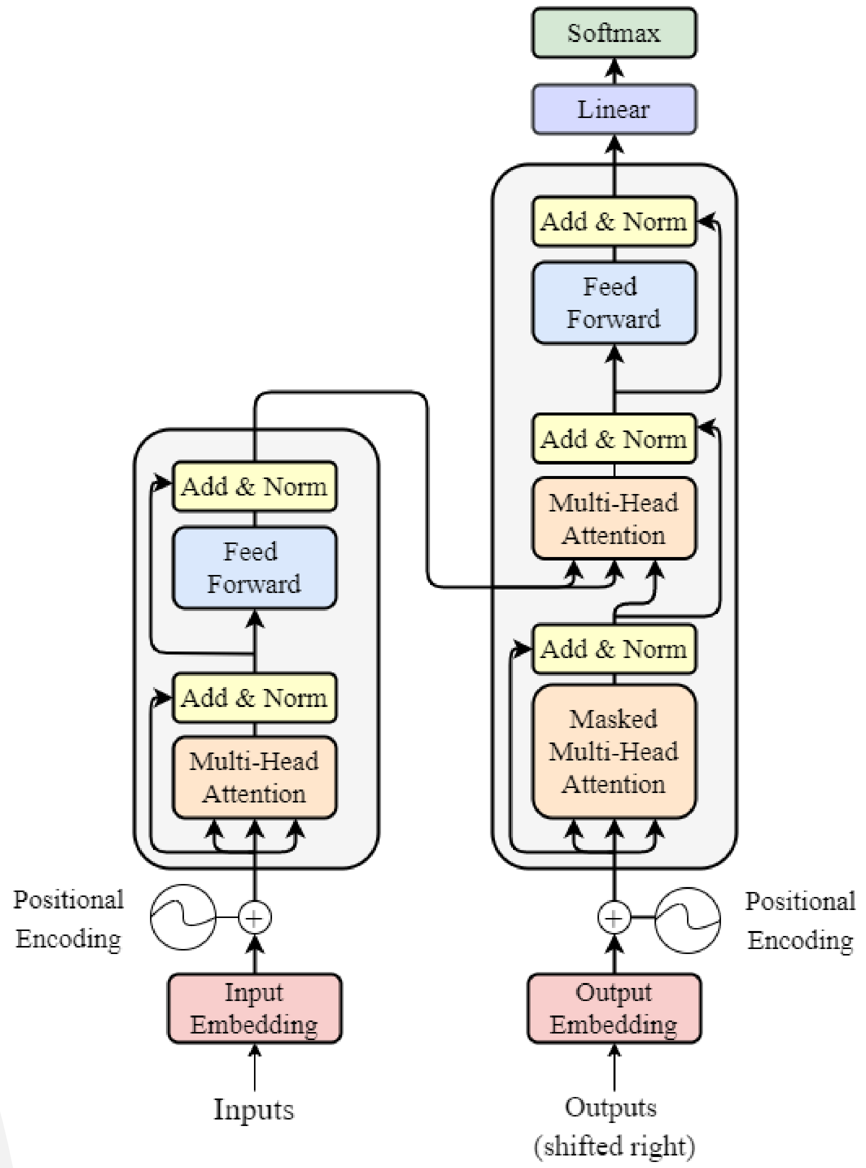

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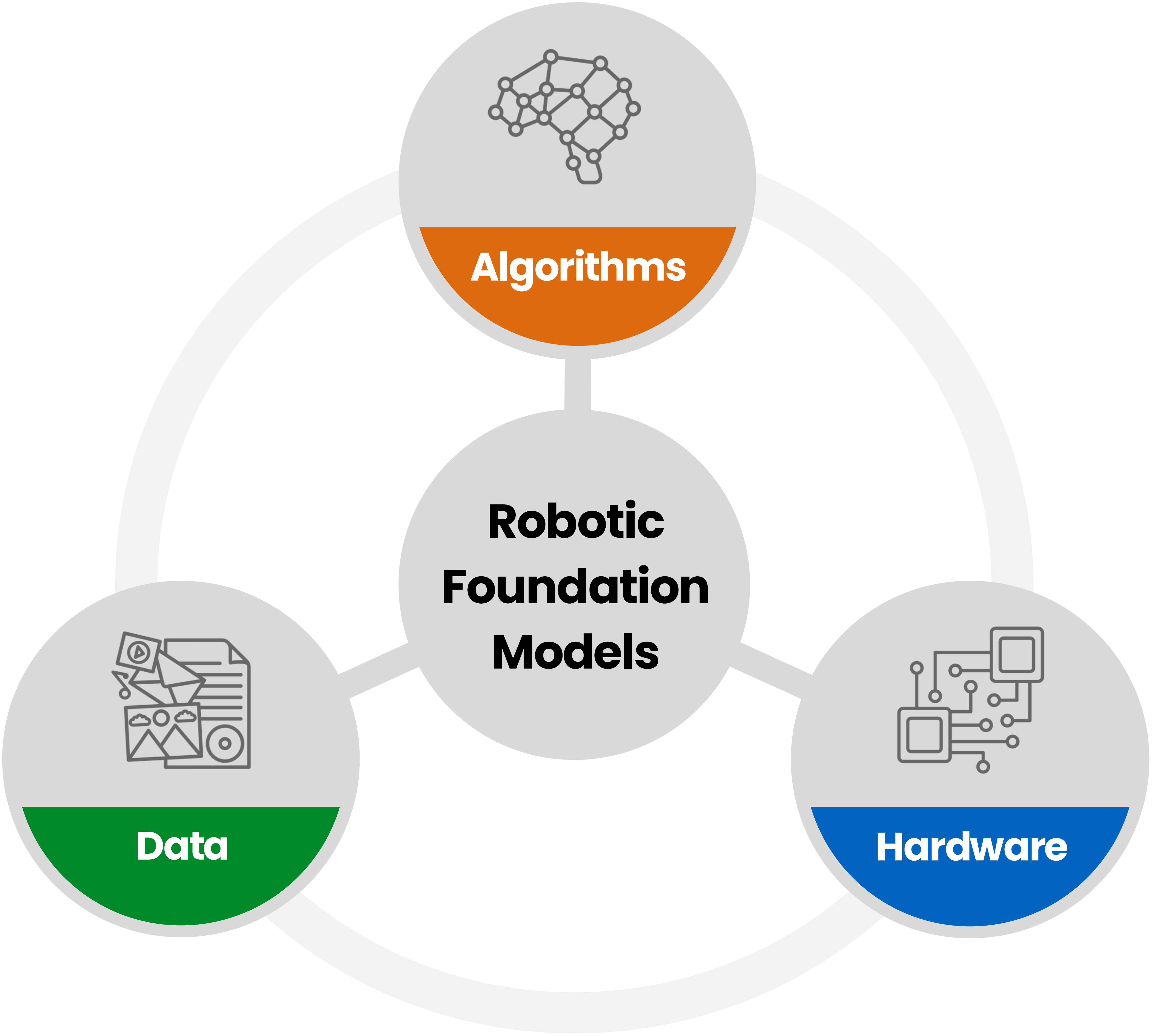
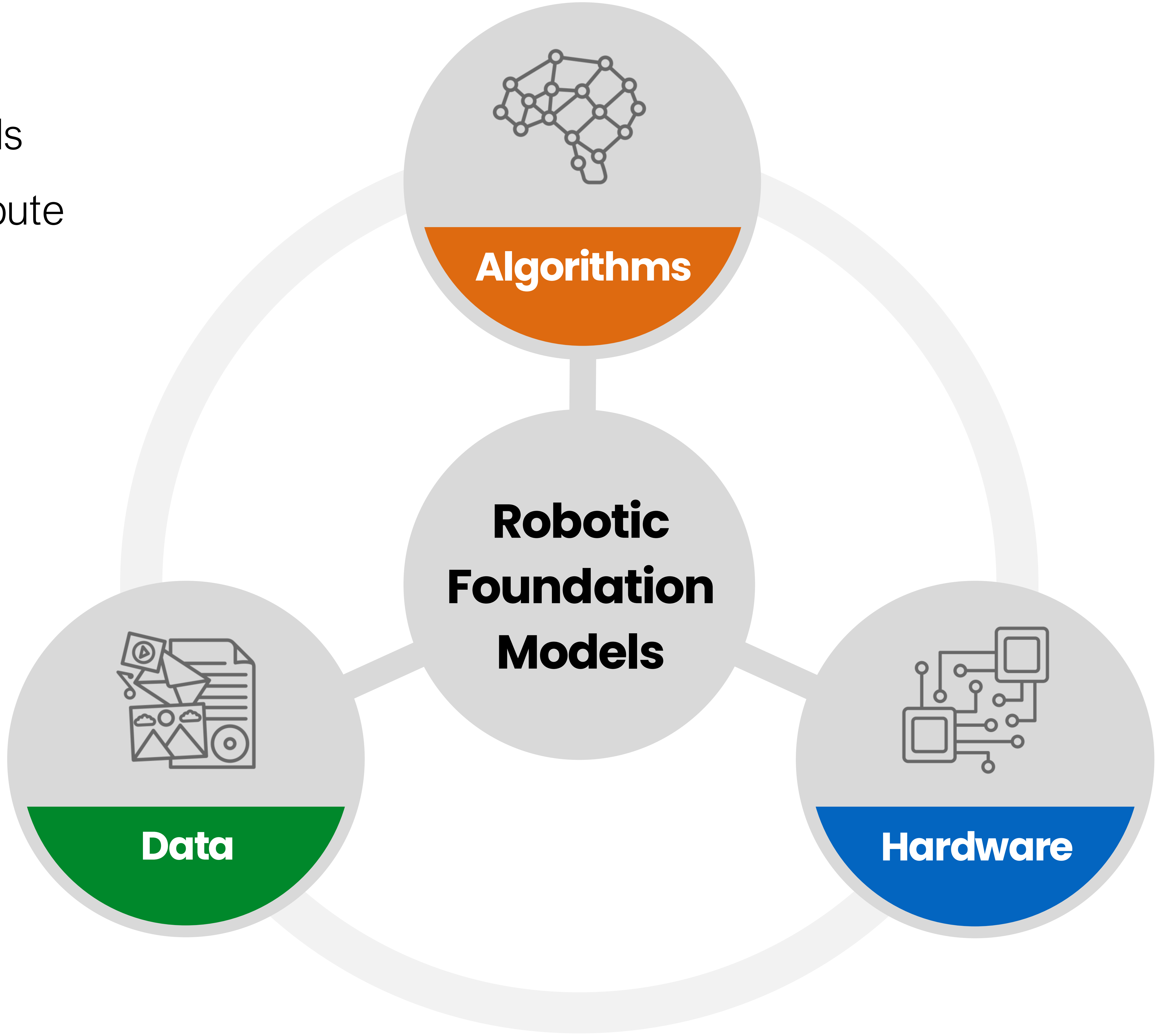


Recipe for Building Robotic Foundation Models

Scalable Algorithms

Powerful robot learning models that scale with data and compute



Data Engine

New mechanisms to produce massive training data

Human-like Embodiment

Humanoid robot platform for broad applications

Recipe for Building Robotic Foundation Models

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Powerful robot learning models
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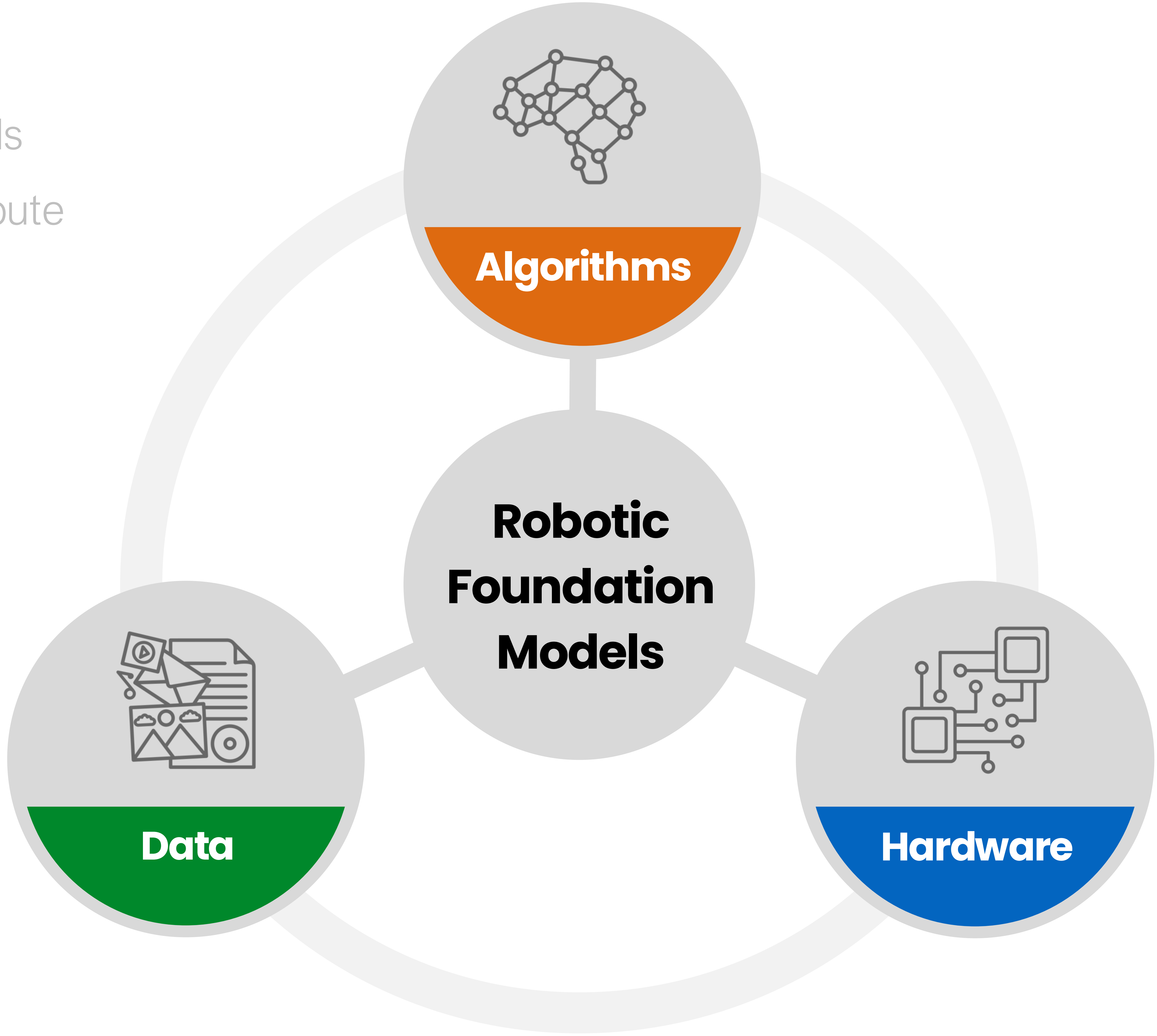

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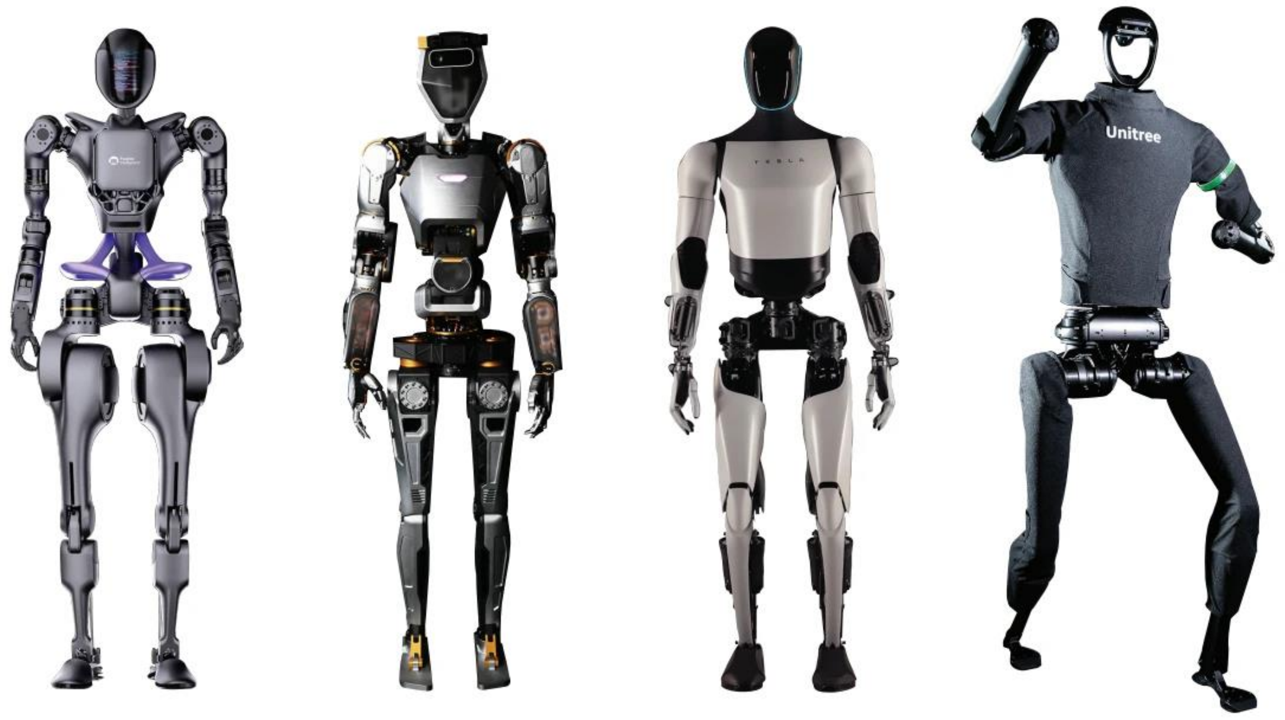


Human-like Embodiment

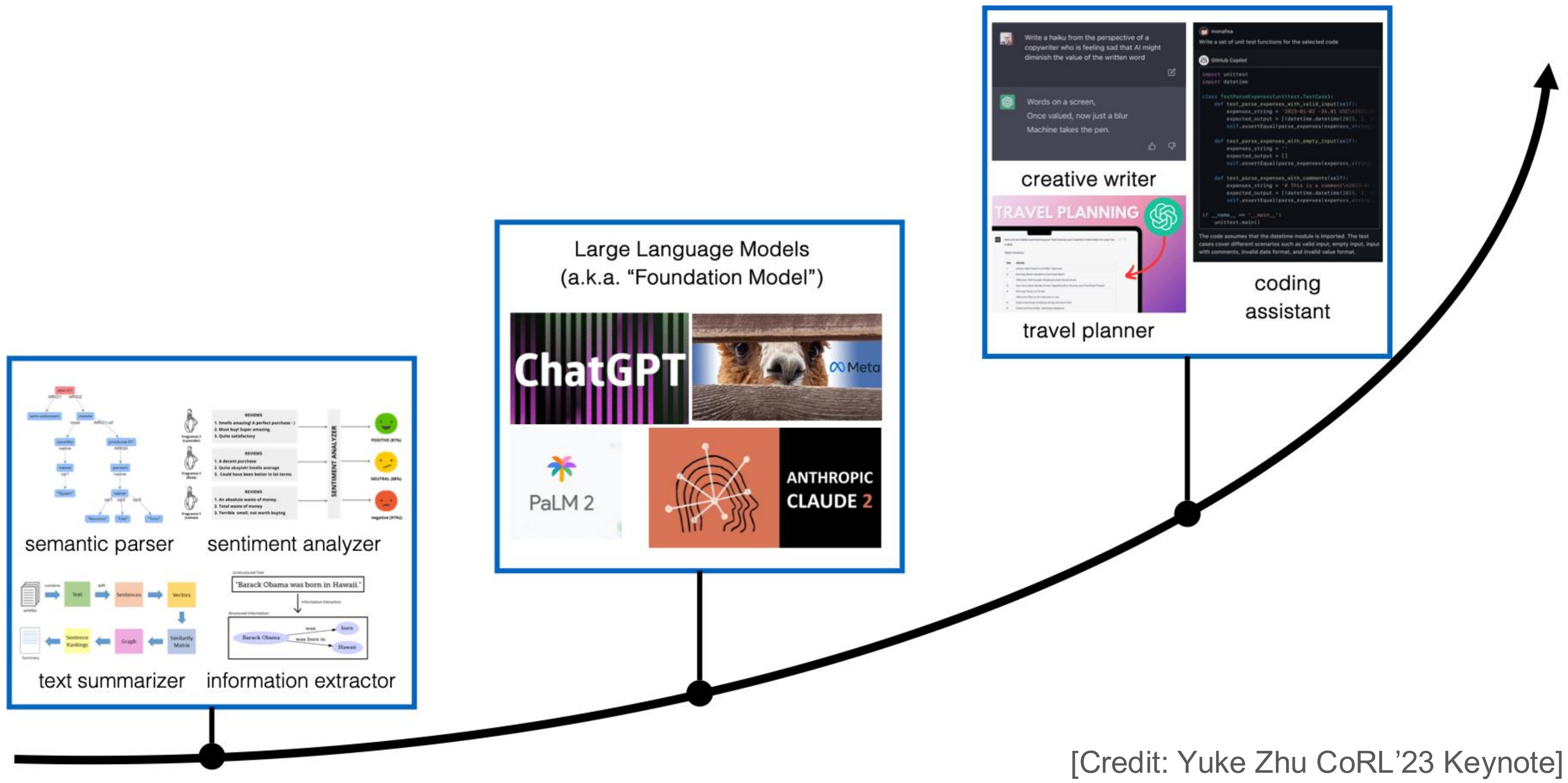
Humanoid robot platform for
broad applications

Why Humanoids?

- **Versatility:** General-purpose robot autonomy needs a versatile body.
- **Costs:** Hardware becomes cheaper and more robust to democratize transformative research.
- **Safety:** Humanoid robots can be more predictable and safer for human-robot interaction.
- **Data:** Their similar physique unlocks Internet-scale, human-centered data sources.
- …

Research Principle #1:

First Generalist, then Better Specialist



[Credit: Yuke Zhu CoRL'23 Keynote]

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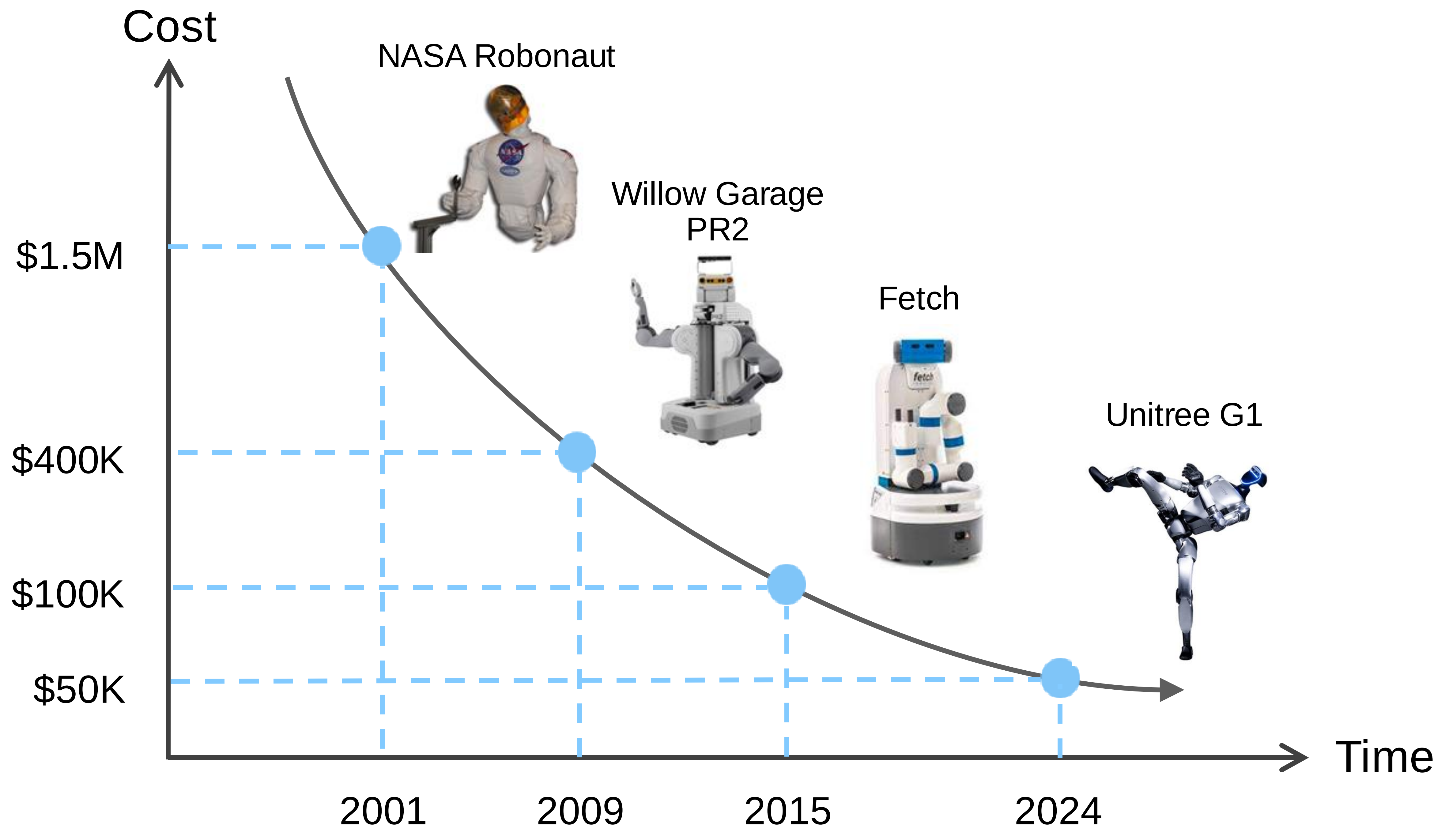

[Credit: Chad Jenkins]

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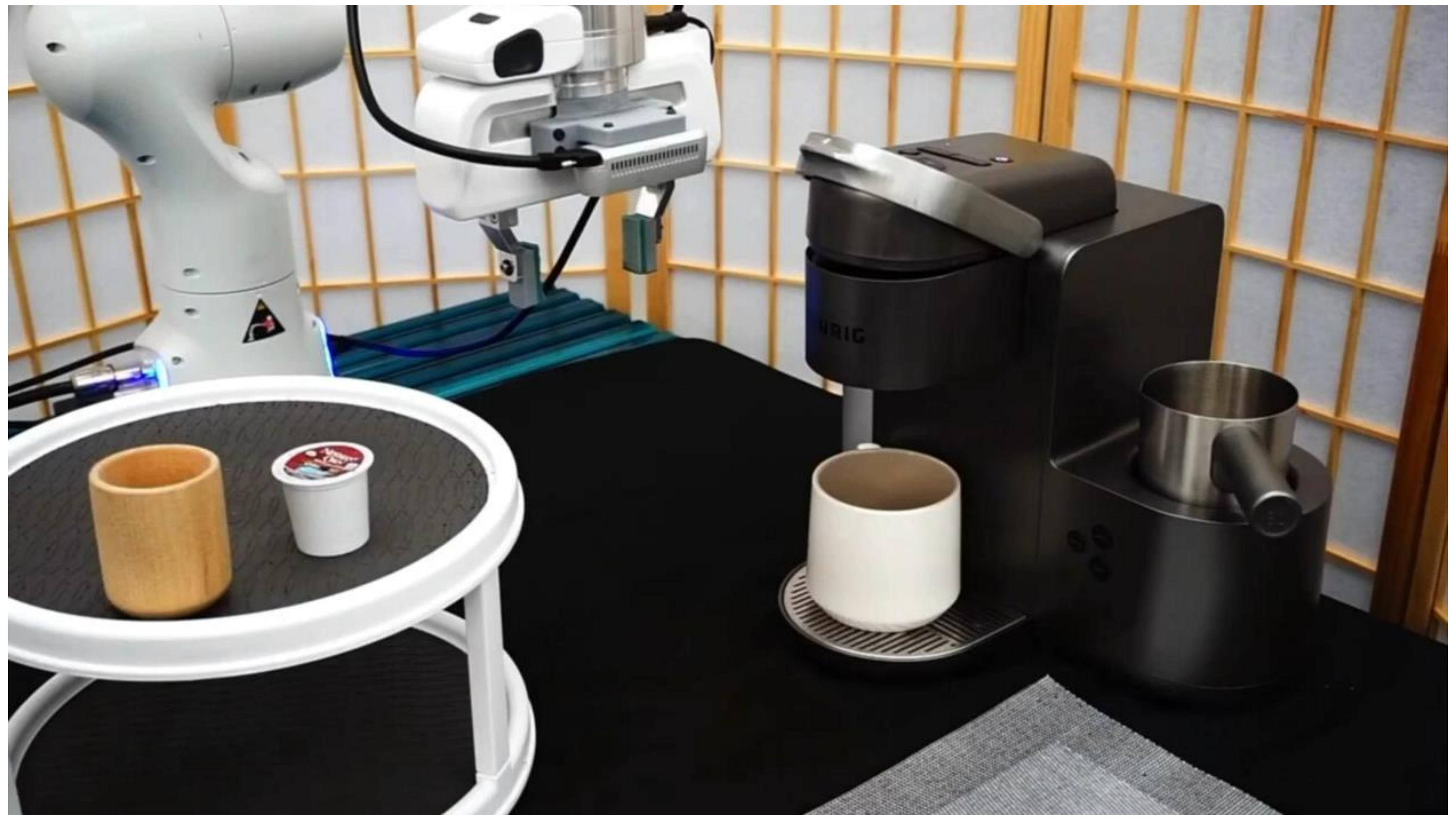
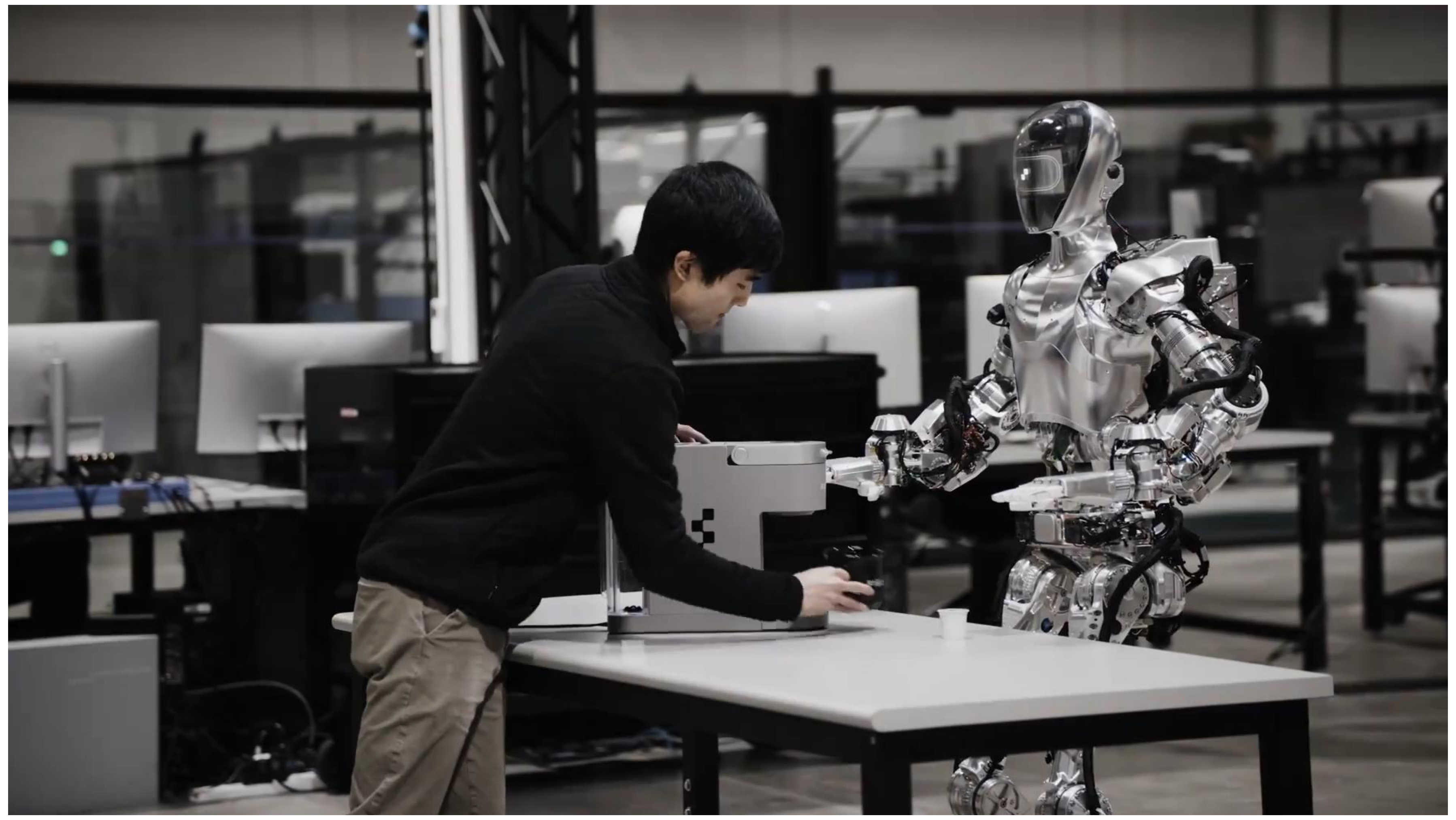


[VIOLA, Zhu et al. CoRL 2022]



[Credit: Figure AI 2024]

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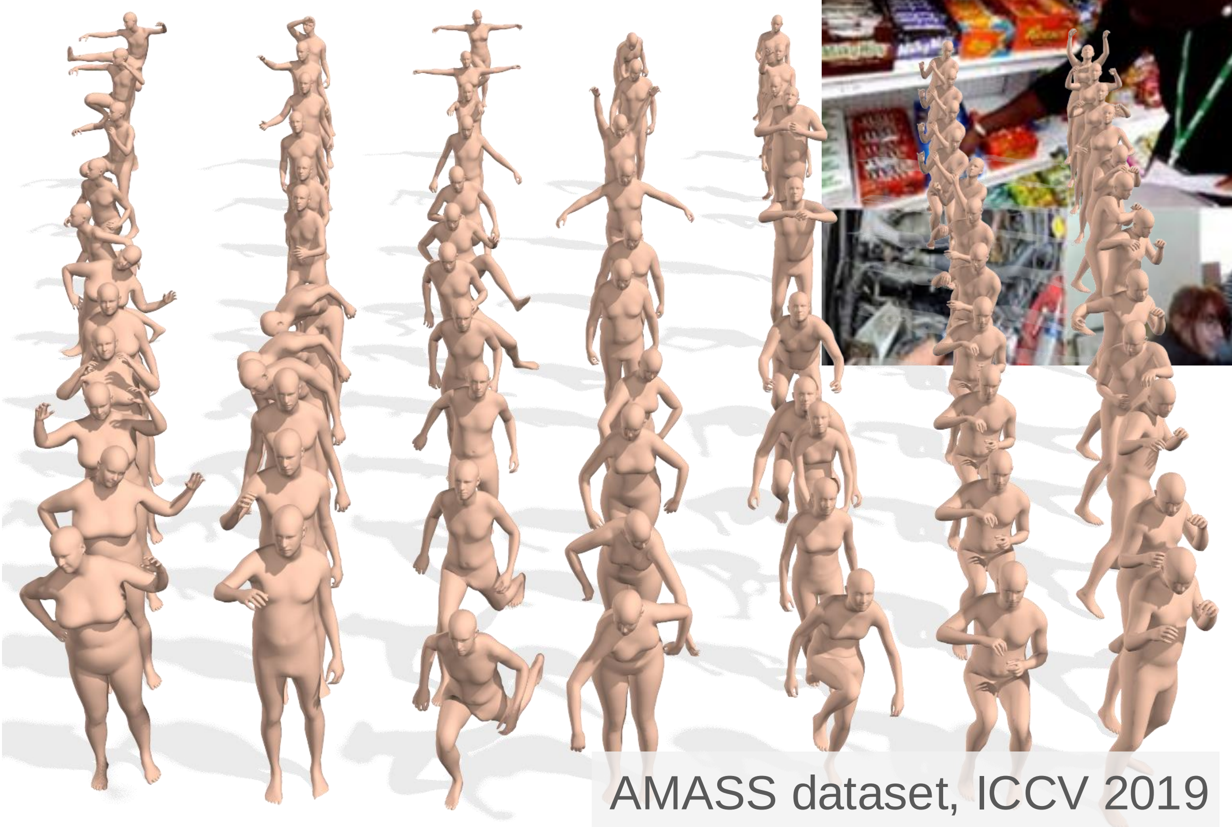
Ego4D dataset, CVPR 2022



AMASS dataset, ICCV 2019

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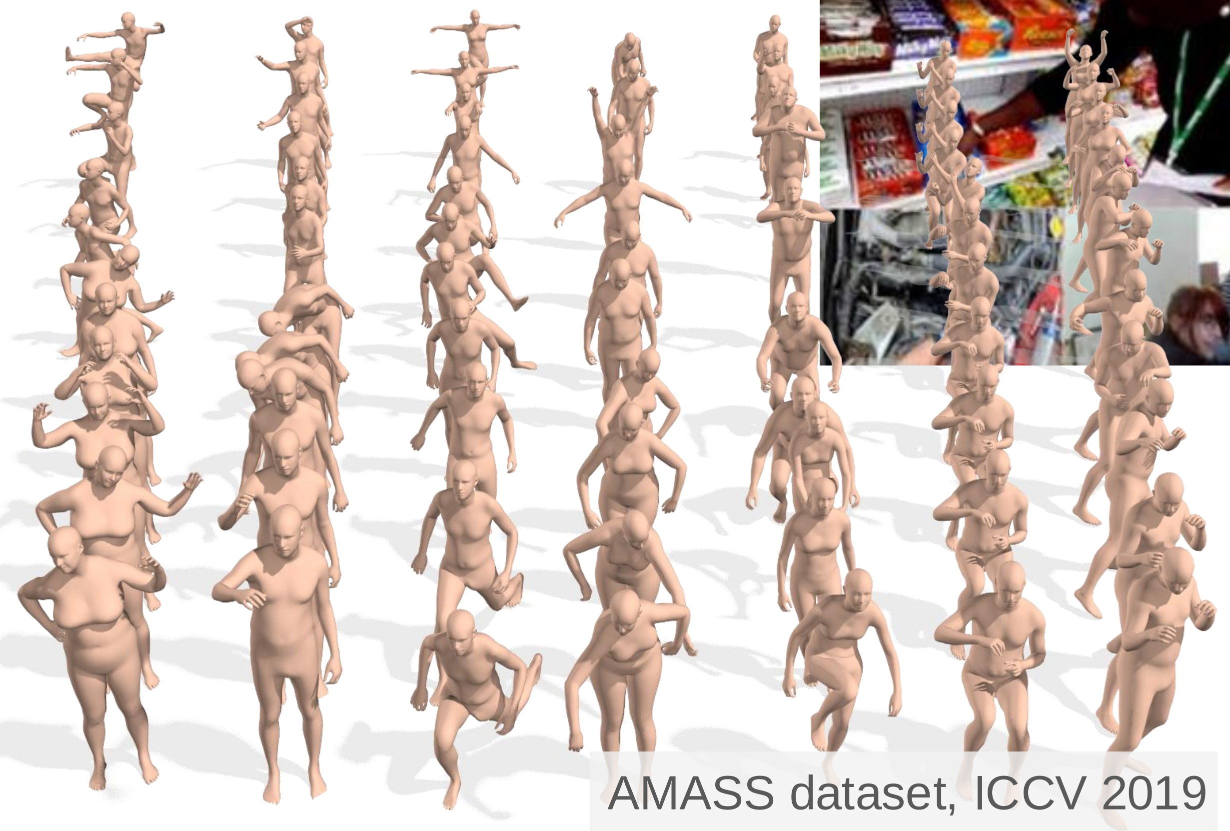


AMASS dataset, ICCV 2019

Note: humanoid robotics is still incredibly hard (!) — huge challenges in mechanical designs, dynamics & control, sensor technologies, compute and power, AI algorithm designs…

Learning from Human Videos

single video
demonstration

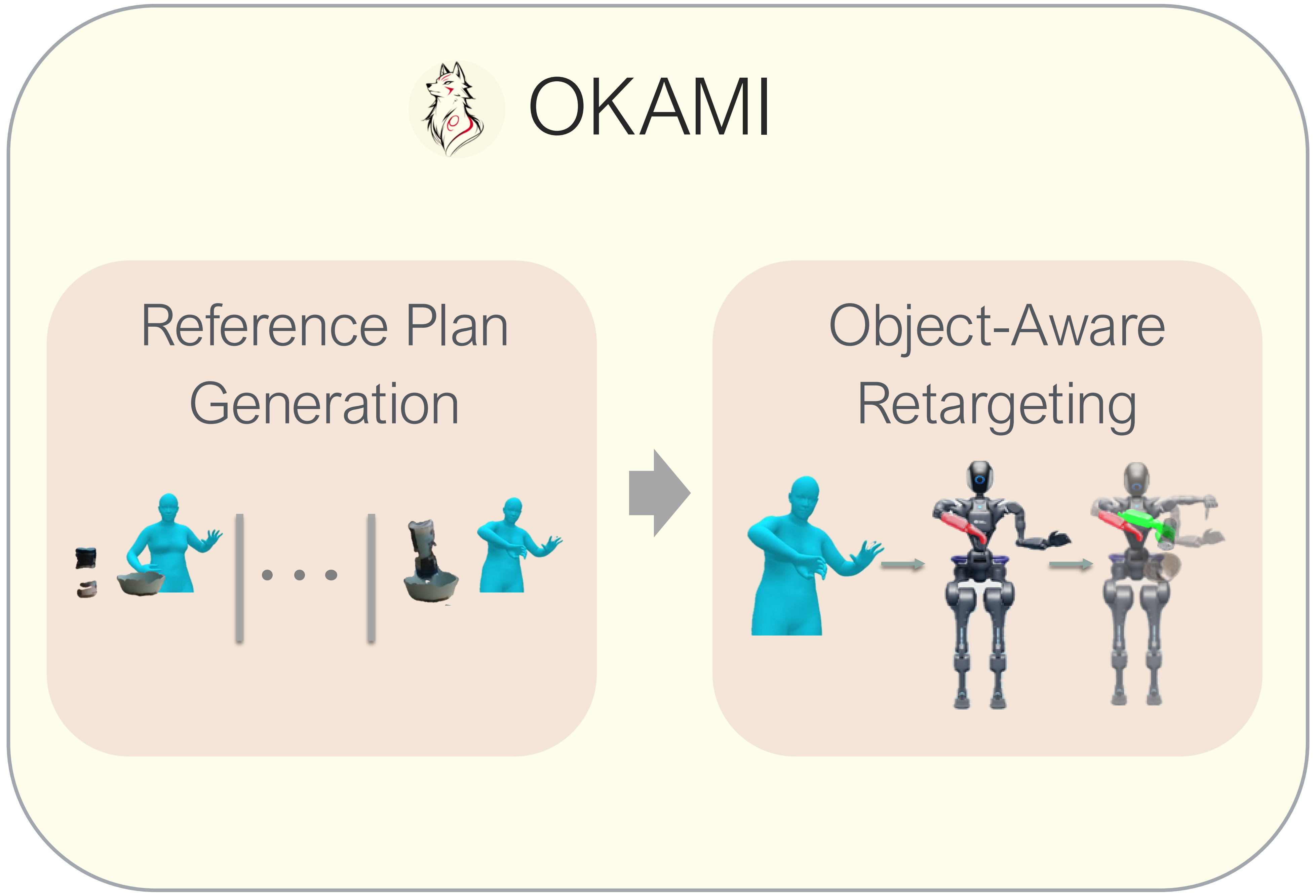
OKAMI

trajectory rollouts
in diverse scenes

"OKAMI: Teaching Humanoid Robots Manipulation Skills through Single Video Imitation." Li et al. CoRL 2024

Learning from Human Videos

single video
demonstration



trajectory rollouts
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Learning from Human Videos

single video demonstration

trajectory rollouts in diverse scenes

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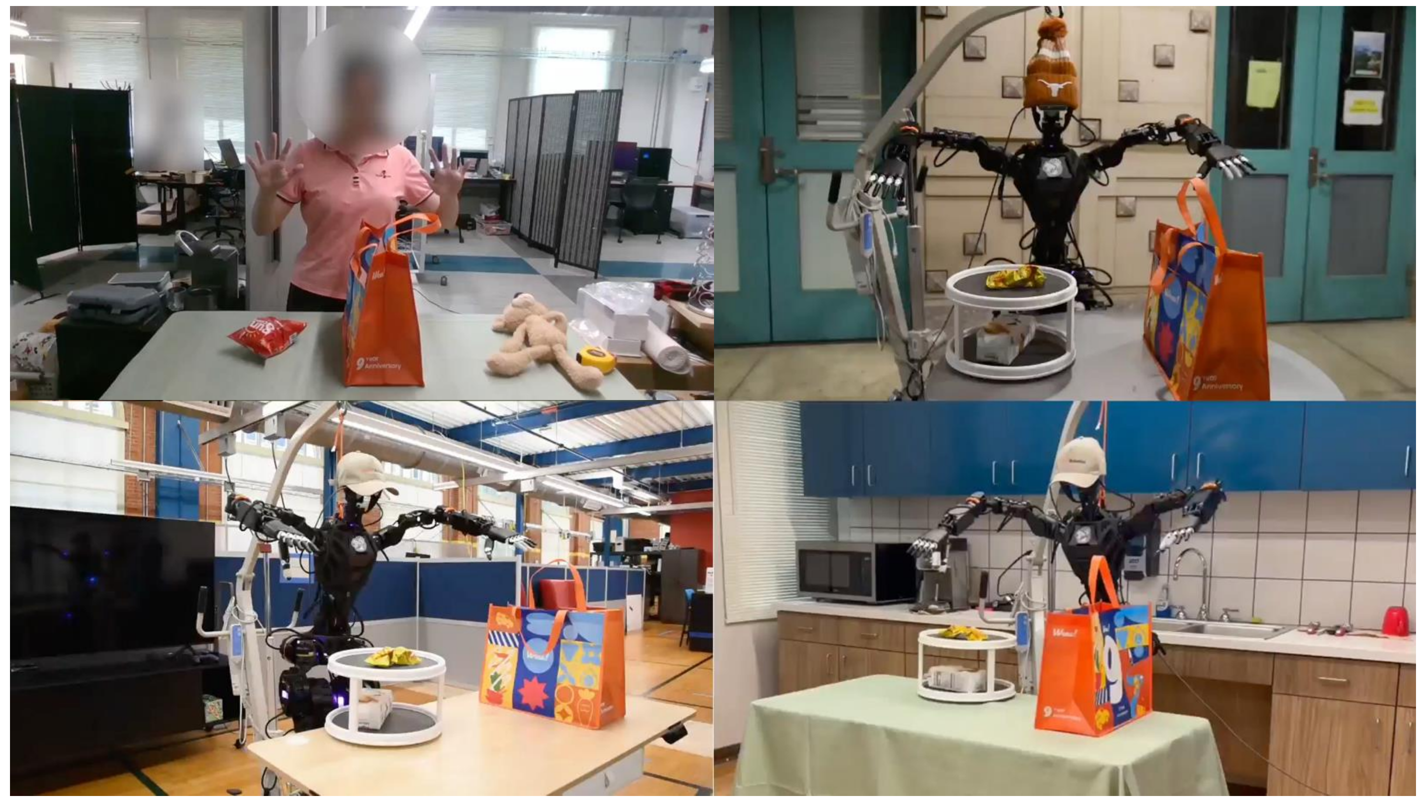
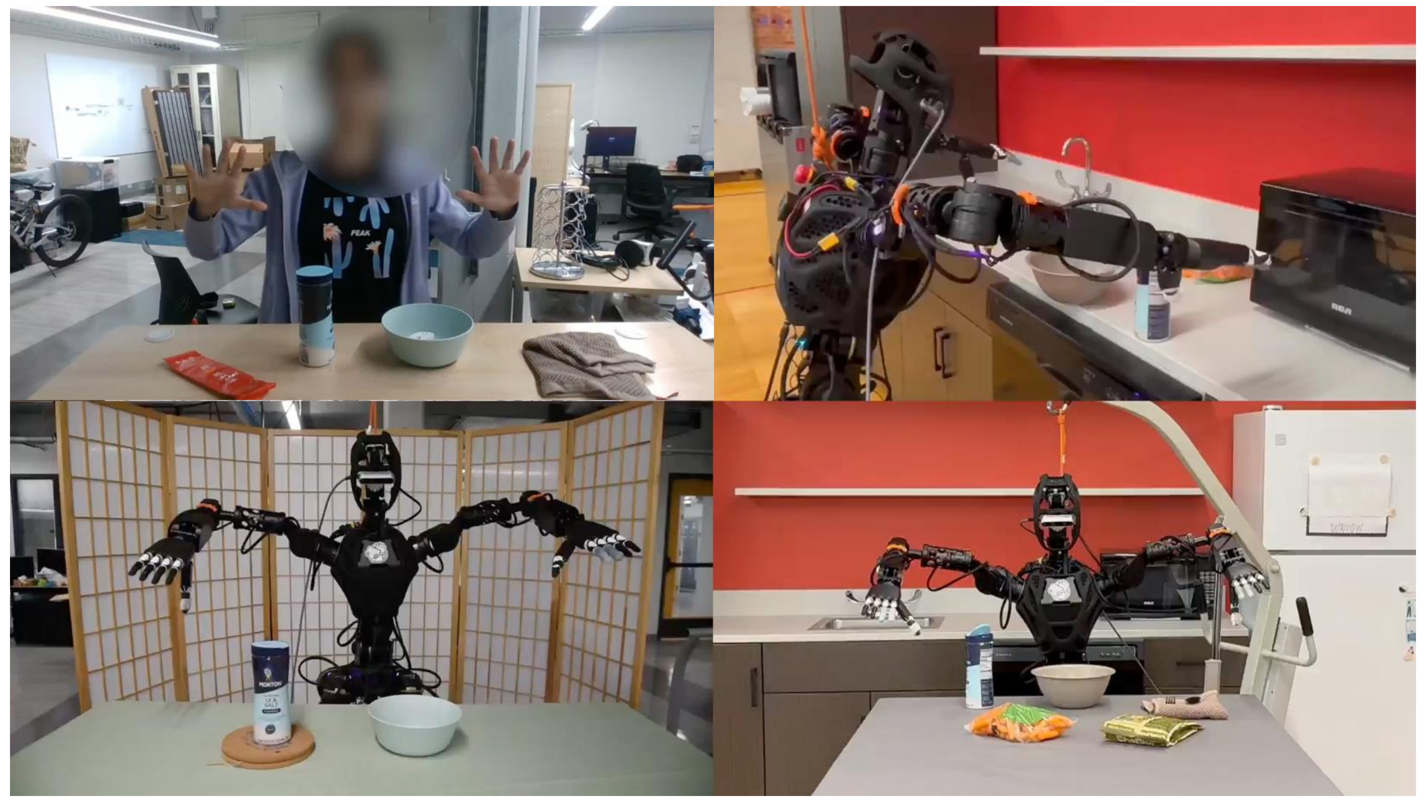
Learning from Human Videos

bagging (58.3%)

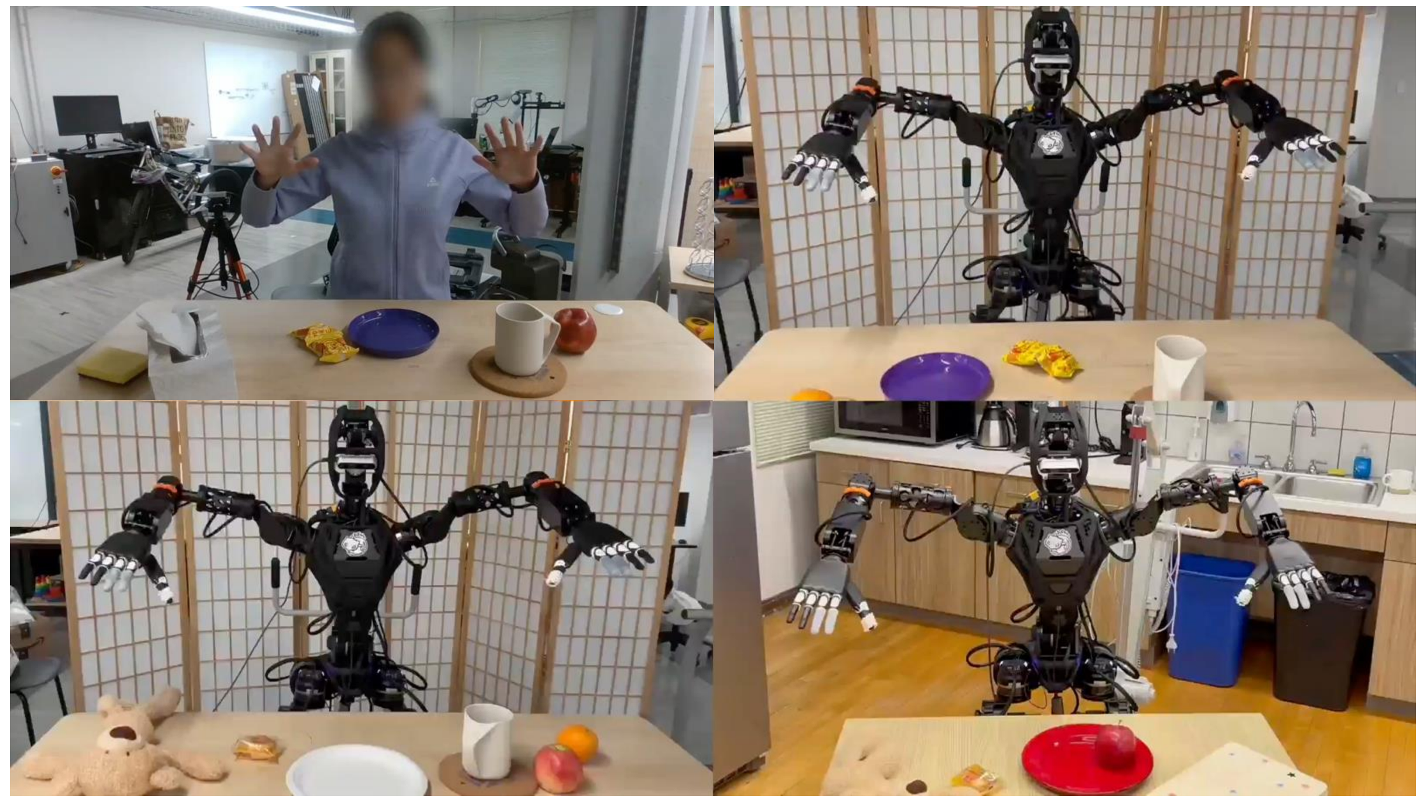


sprinkling salt (58.3%)



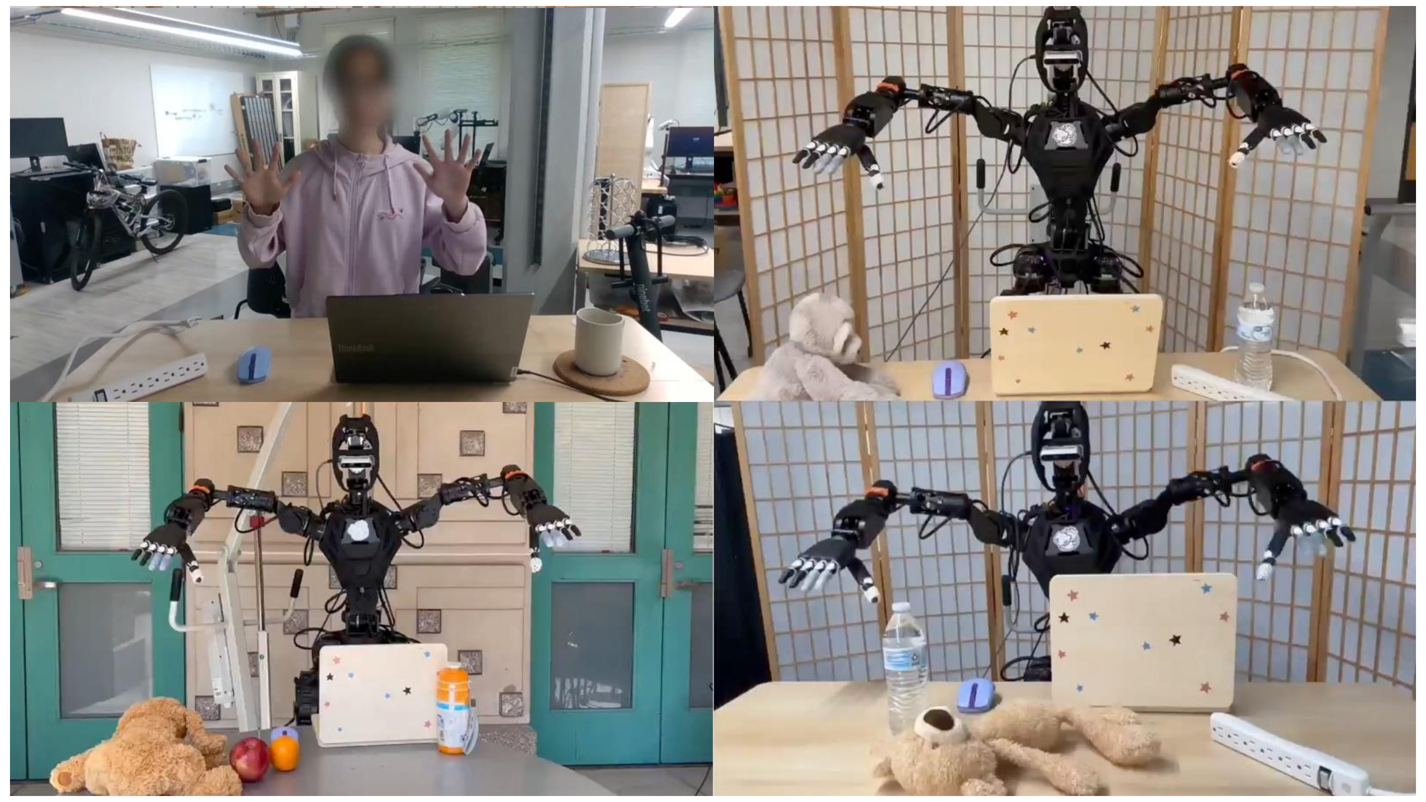
putting toy in basket (66.7%)

placing snacks on plate (75.0%)



closing the drawer (75.0%)

closing the laptop (83.3%)



"OKAMI: Teaching Humanoid Robots Manipulation Skills through Single Video Imitation." Li et al. CoRL 2024

HOVER: One Versatile Policy to Control All Modes

“HOVER: Versatile Neural Whole-Body Controller for Humanoid Robots.” He et al. 2024

Raise left hand and form a longhorn gesture.

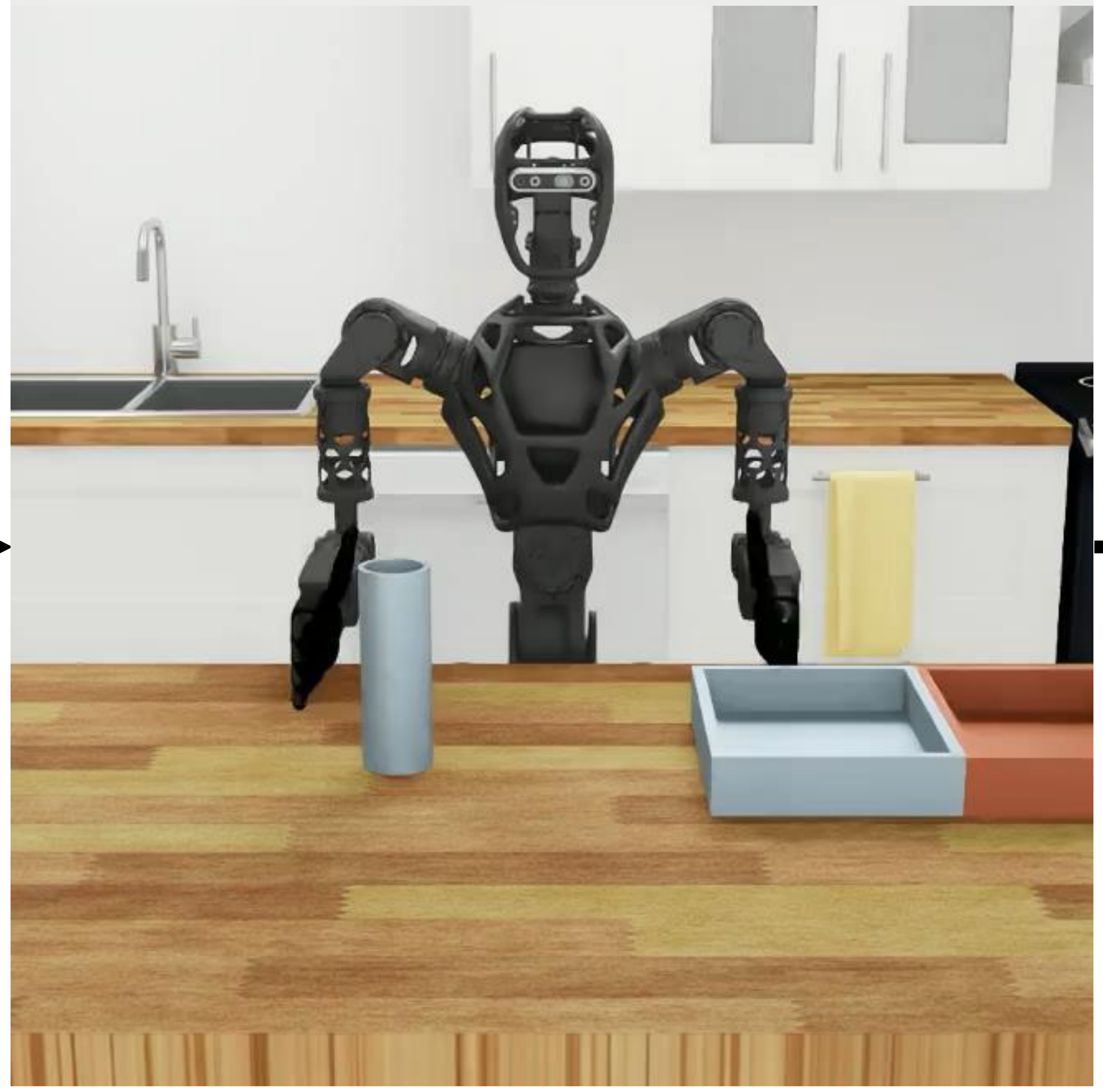
Do a dabbing pose.

Signal a goodbye by touching the head with the right hand, then extending it forward.

DexMimicGen: Automated Data Generation System

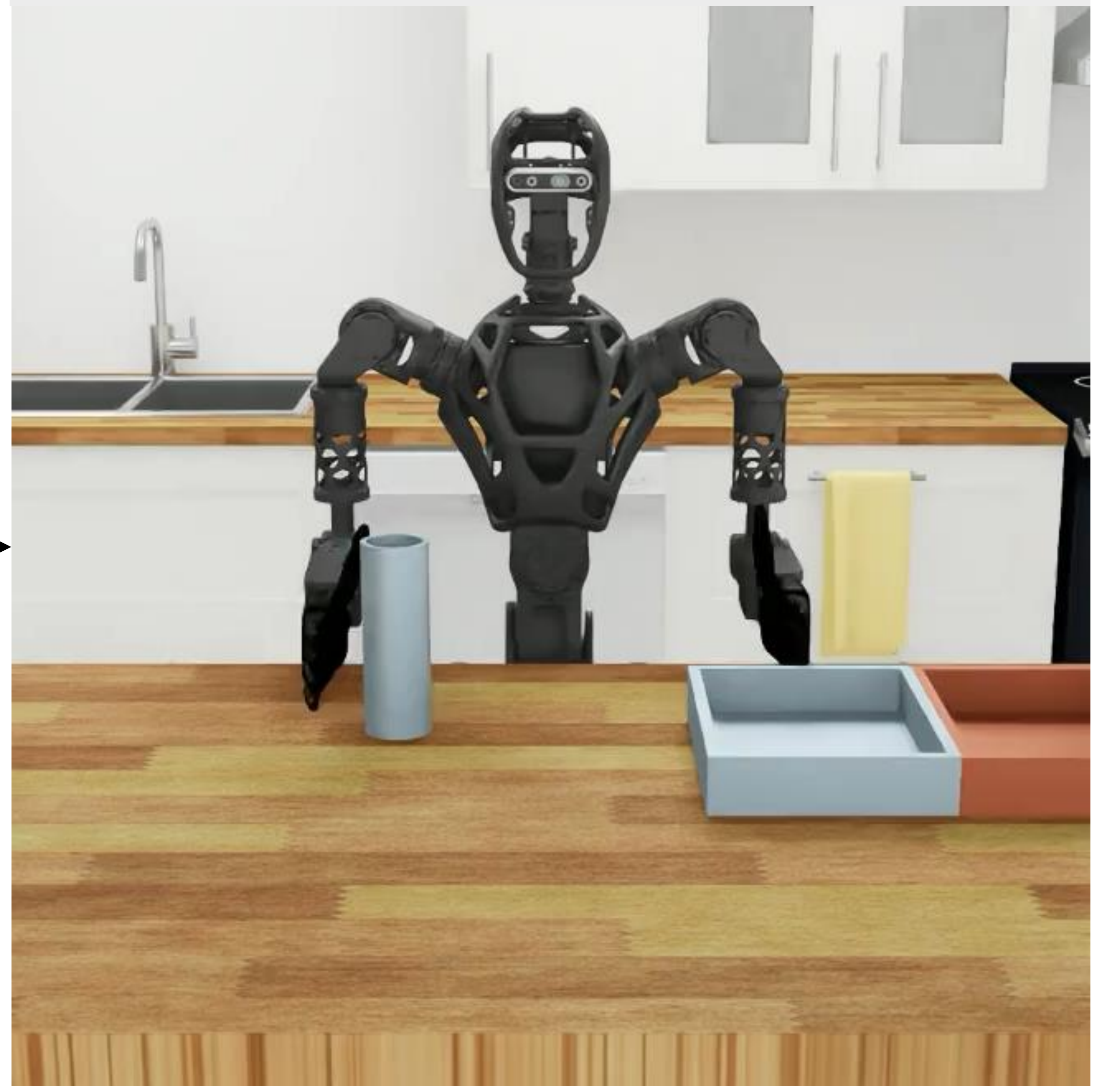
Human teleoperation

5 source demos



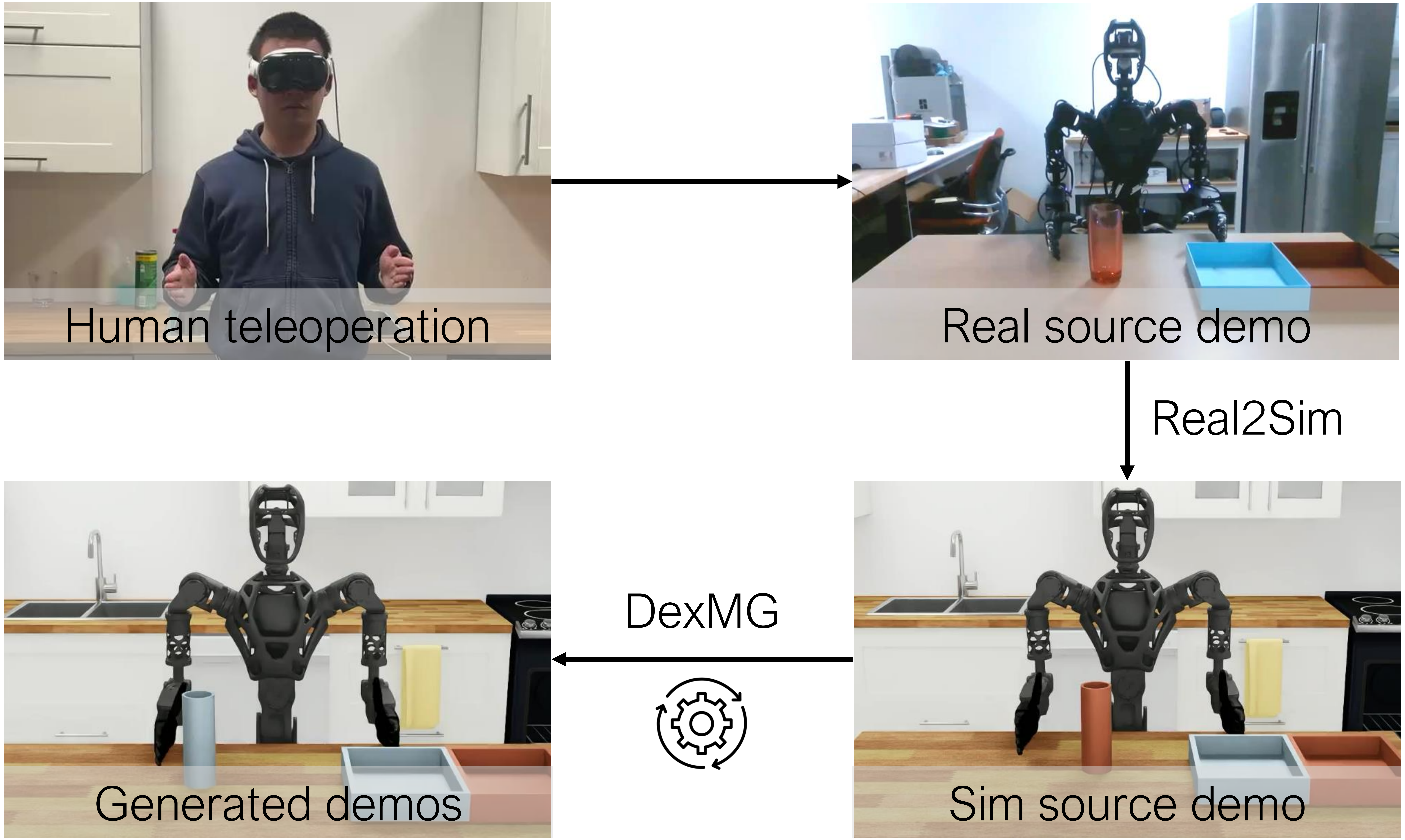
DexMimicGen

1000 generated demos



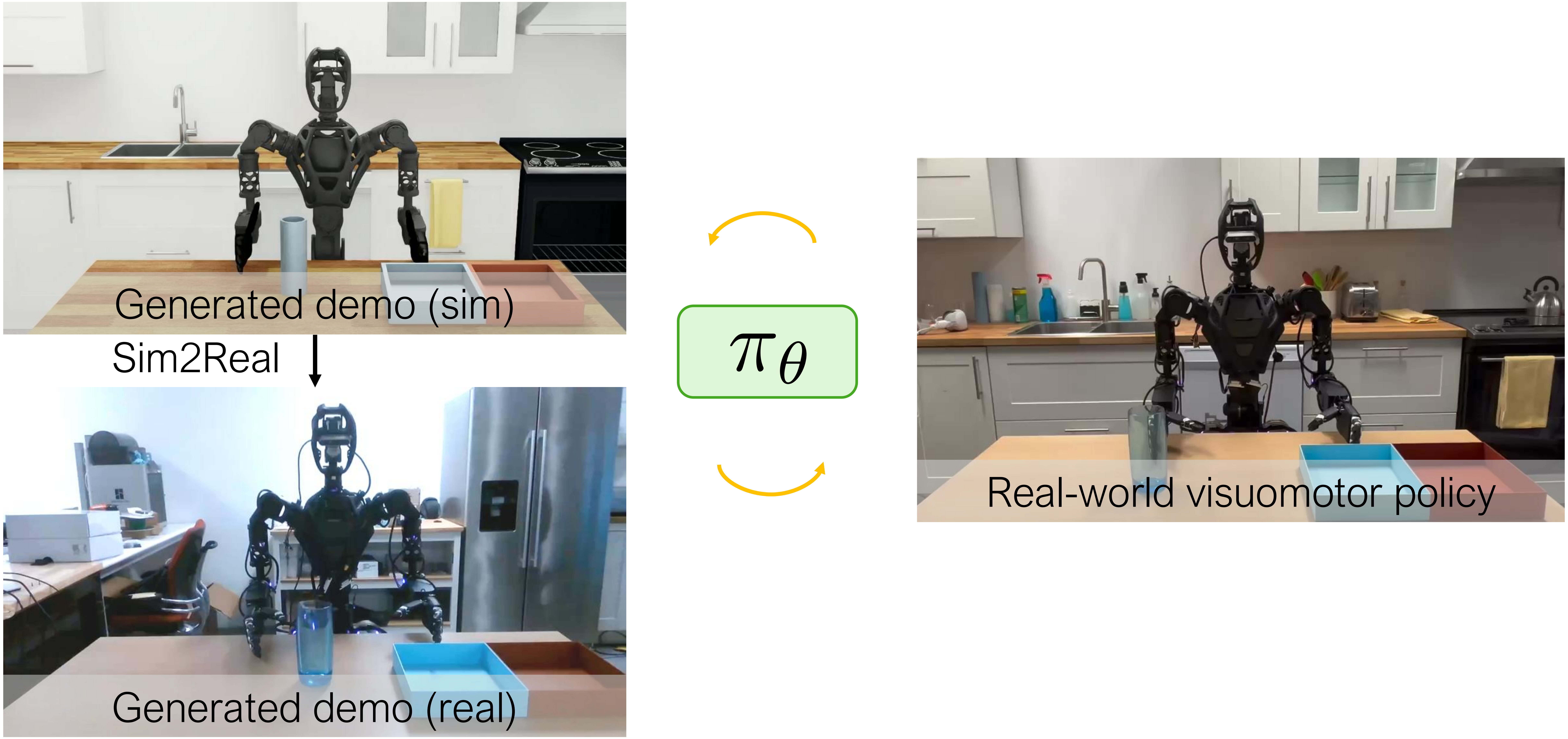
“DexMimicGen: Automated Data Generation for Bimanual Dexterous Manipulation via Imitation Learning.” Jiang*, Xie*, Lin*, et al. 2024

DexMimicGen can be used to train real-world visuomotor policy.



Transfer real demo to sim using digital twin to ensure the sim demos are valid in real

DexMimicGen can be used to train real-world visuomotor policy.



Transfer only **successful** generated demos from sim to real to train a visuomotor policy

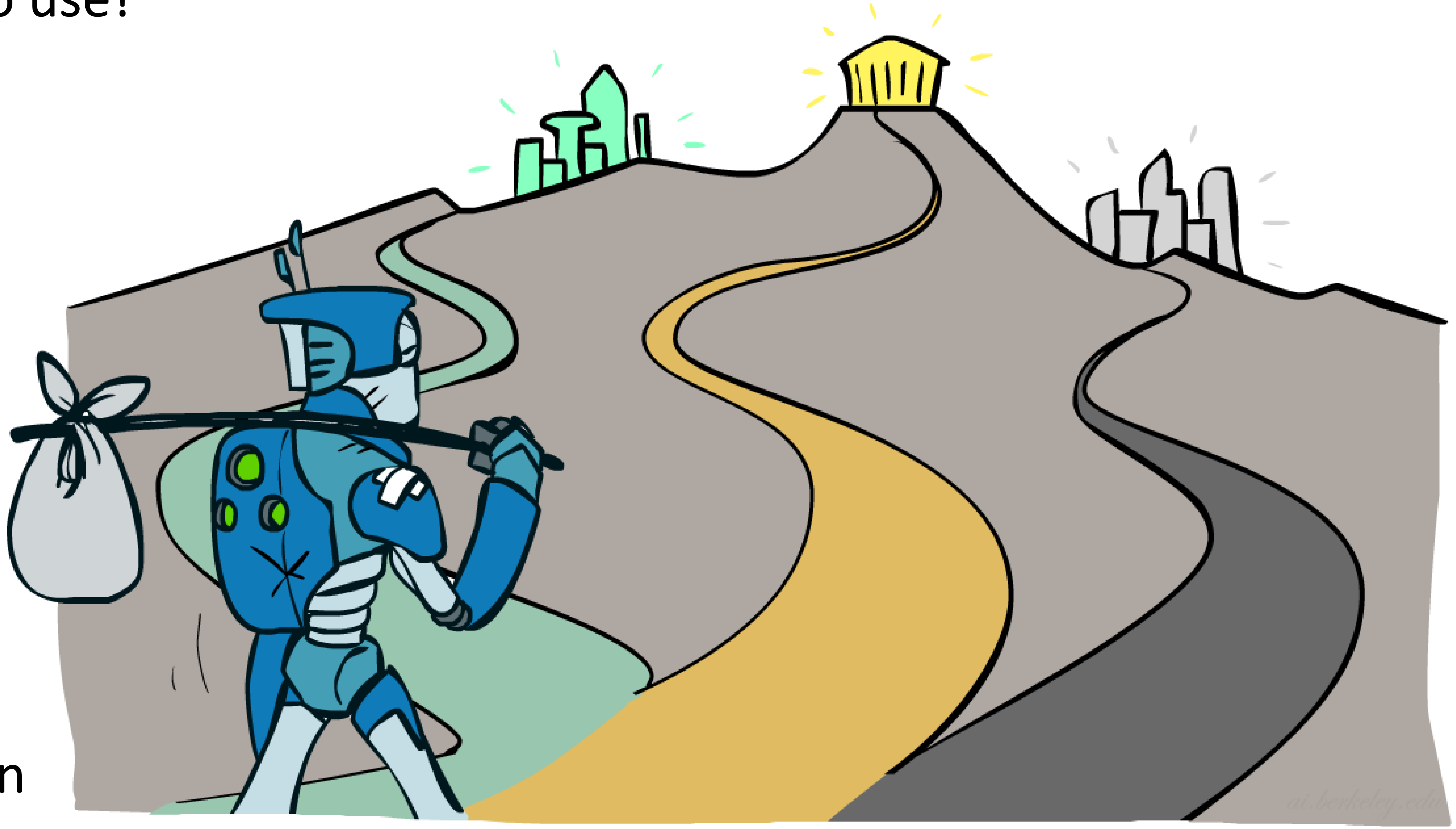
DexMimicGen can be used to train real-world visuomotor policy.

Real-world visuomotor policy rollouts (10X)

Where to Go Next?

Where to Go Next?

- Congratulations, you've seen the basics of modern AI
  - … and done some amazing work putting it to use!
- How to continue:
  - CS 395T Visual Recognition
  - CS 391R Robot Learning
  - ECE 382V Human Robot Interaction
  - CS 388 Natural Language Processing
  - CS 391L Machine Learning
  - CS 393R Autonomous Robots
  - CS 342 Neural Networks
  - EE 381V Advanced Topics in Computer Vision
  - CS 394R Reinforcement Learning: Theory and Practice
  - … and more; ask if you're interested



Final Remarks

- We have come a long way! Thank you!
- We are very proud that you have made it to the end of this demanding course!
- We are impressed by your ingenuity and critical thinking in the in-class discussions, Ed posts, projects, and assignments!
- Thanks to Huihan and Shuijing for handling the course logistics.
- If this course helps you kickstart your future endeavors in AI, please email us and let us know!

Thank you

Saturday 12/14   1 – 3pm   ECJ 1.202

1 page (front and back) of notes

Closed book

That’s it!

I had a great time teaching this course and
I hope you all enjoyed it as well

Have a great winter break!