Lecture 14:

Simulating Virtual Worlds to Train Agents

Visual Computing Systems
Stanford CS348K, Spring 2023

Today

- We've talked about how ML/AI techniques are used to improve visual computing applications: computational photography, rendering, video compression, etc…

- Today we'll talk about how rendering and simulation techniques are increasingly central to the progress of AI

Think back to earlier in course

What was the biggest practical bottleneck to training good models?

Snorkel: Rapid Training Data Creation with Weak Supervision

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ABSTRACT

Labeling training data is increasingly the largest bottleneck in deploying machine learning systems. We present Snorkel, a first-of-its-kind system that enables users to train state-of-the-art models without hand labeling any training data. Instead, users write labeling functions that express arbitrary heuristics, which can have unknown accuracies and correlations. Snorkel denoises their outputs without access to ground truth by incorporating the first end-to-end implementation of our recently proposed machine learning paradigm, data programming. We present a flexible interface layer for writing labeling functions based on our experience over the past year collaborating with companies, agencies, and research labs. In a user study, subject matter experts build models 2.8× faster and increase predictive performance an average 45.5% versus seven hours of hand labeling. We study the modeling tradeoffs in this new setting and propose an optimizer for automating tradeoff decisions that gives up to 1.8× speedup per pipeline execution. In two collaborations, with the U.S. Department of Veterans Affairs and the U.S. Food and Drug Administration, and on four open-source text and image data sets representative of other deployments, Snorkel provides 132% average

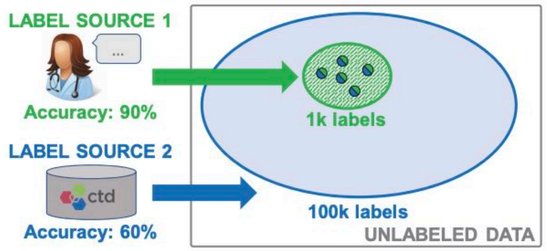


Figure 1: In Example 1.1, training data is labeled by sources of differing accuracy and coverage. Two key challenges arise in using this weak supervision effectively. First, we need a way to estimate the unknown source accuracies to resolve disagreements. Second, we need to pass on this critical lineage information to the end model being trained.

advent of *deep learning* techniques, which can learn task-specific representations of input data, obviating what used to be the most time-consuming development task: feature engineering. These learned representations are particularly effective for tasks like natural language processing and image

Using rendering/simulation to generate supervision to train better models

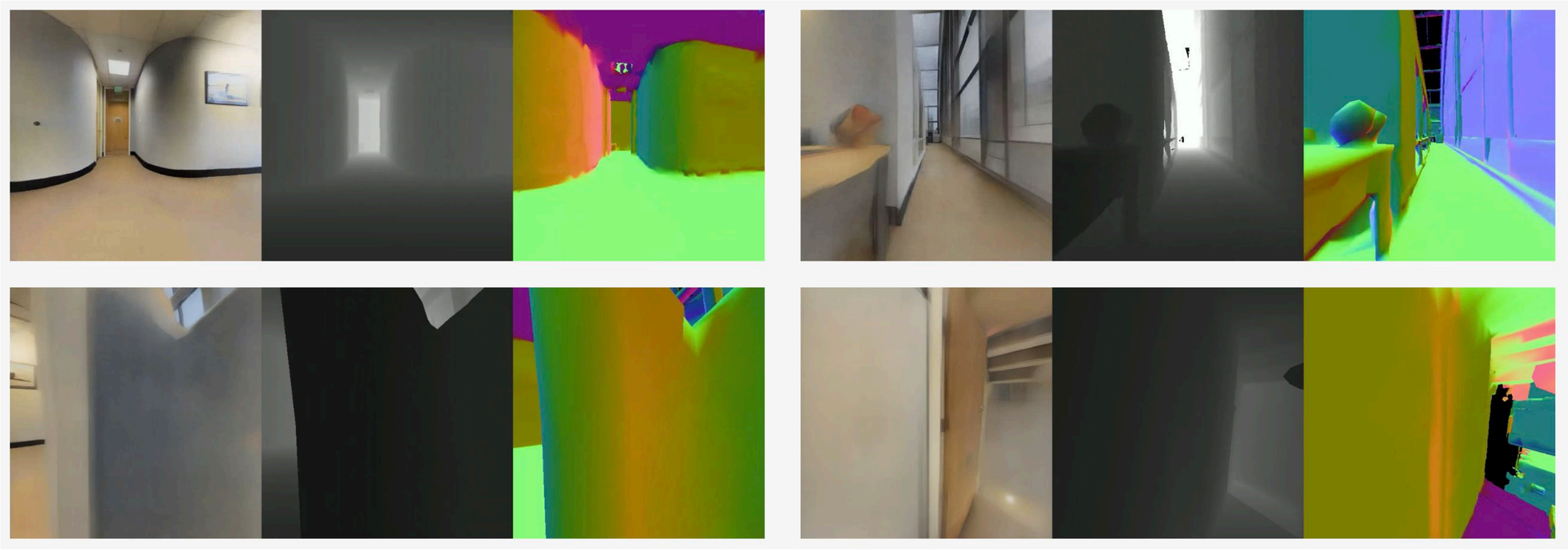
Part 1:
Use high-fidelity simulation to simulate what sensors would measure in hypothetical real-world situations
(Improving perception systems)

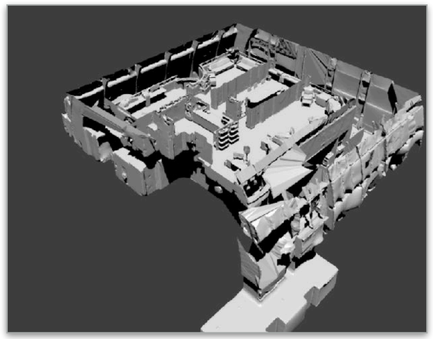
NVIDIA Drive Sim

NVIDIA Drive Sim

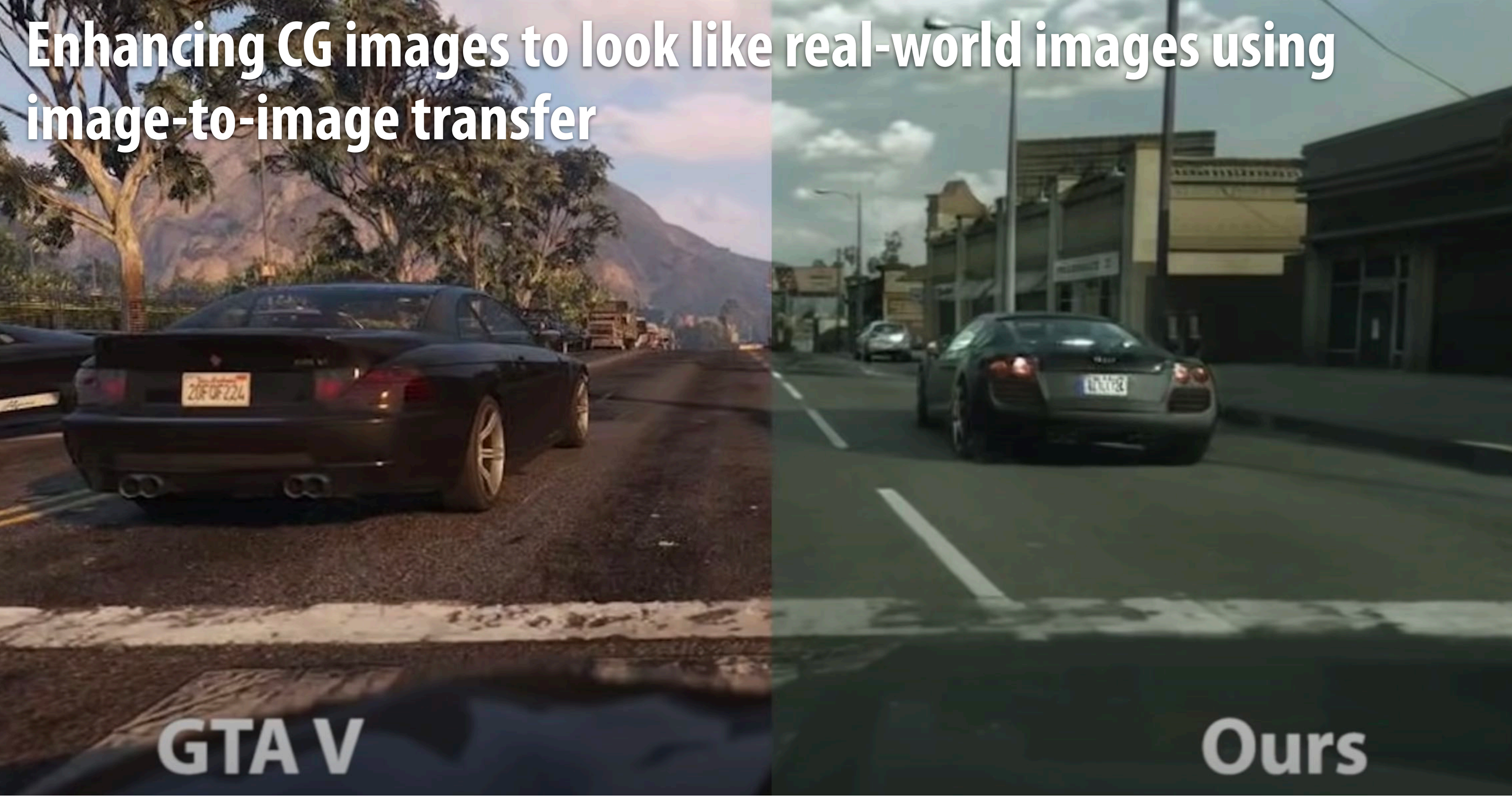
Stanford Gibson project: acquire/render real world data

- Dataset acquired via 3D scanning (3D mesh + texture)
- Geometry, normals, semantics, + (so-called) "photorealistic" 3D





Enhancing CG images to look like real-world images using image-to-image transfer



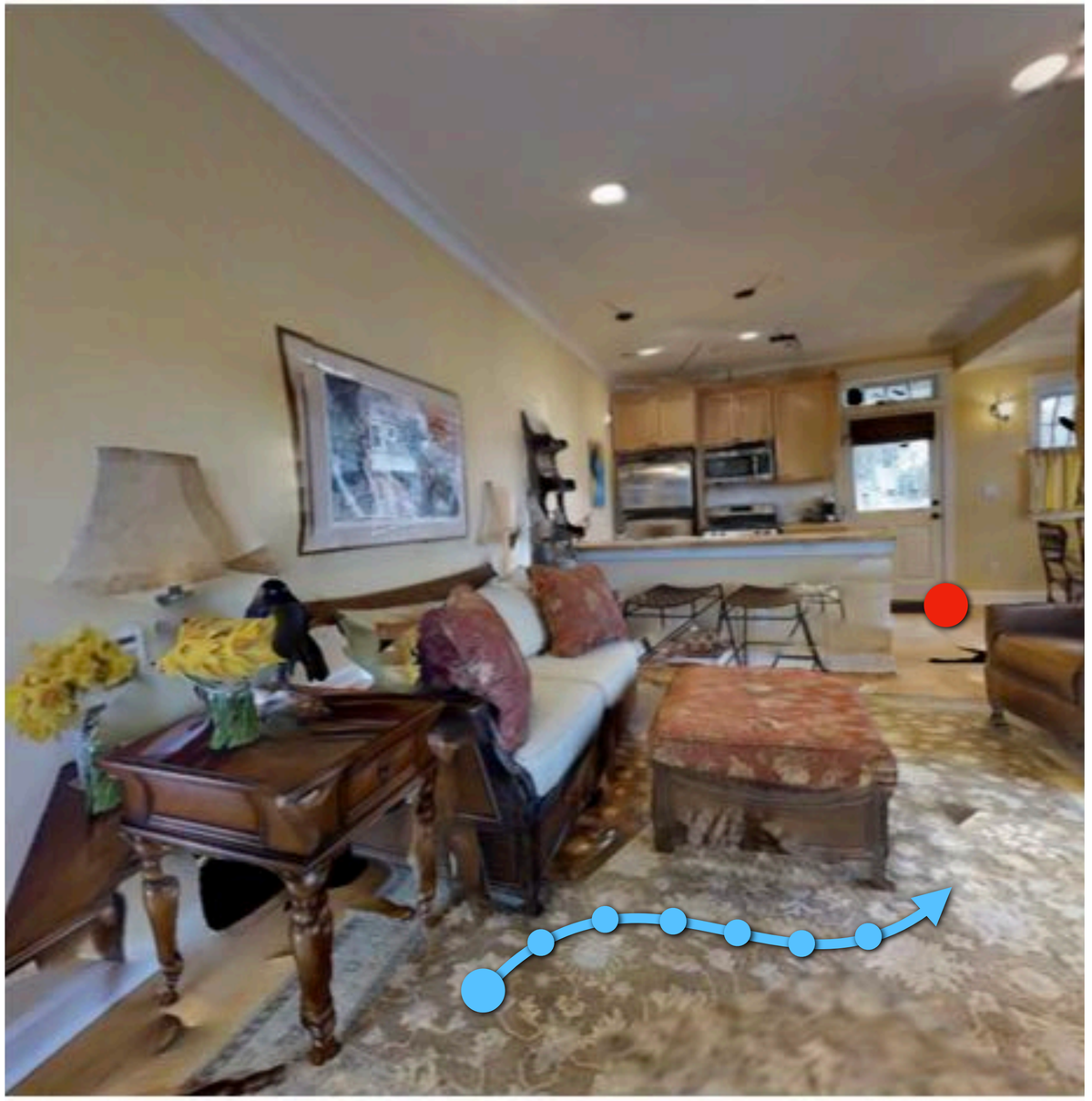
Modifying real-world images to create novel situations

Part 2:
Training agent behaviors using reinforcement learning

RL in 30 seconds

Model Inference

environment observation e.g. RGB image → π_θ → agent action



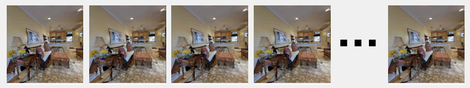
RL in 30 seconds

Model Inference

environment observation e.g. RGB image → π_θ → agent action

Model Training

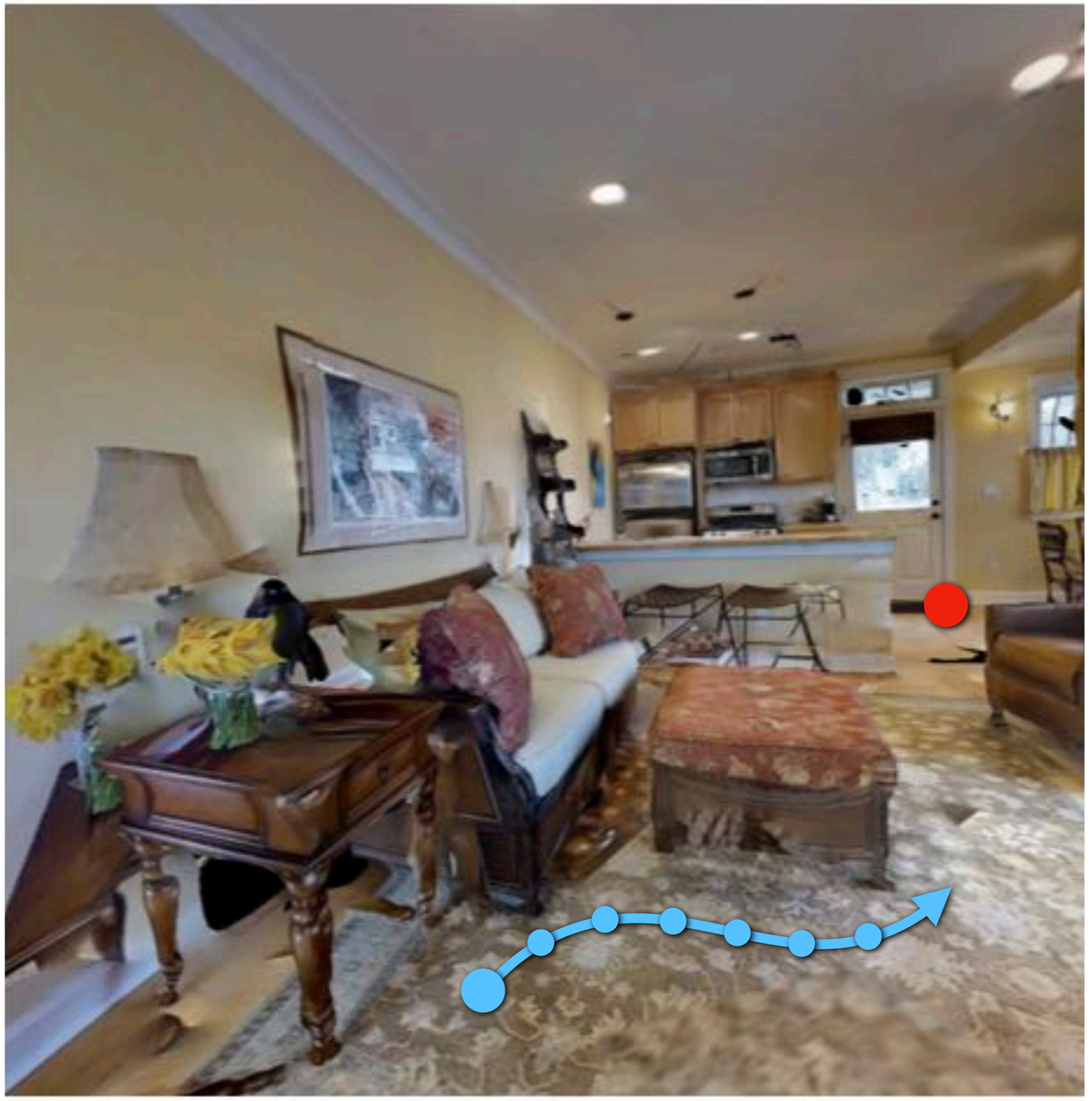
sequence of observations



sequence of agent actions

compute loss gradients π_θ → update model via SGD

Reward: change in distance from goal



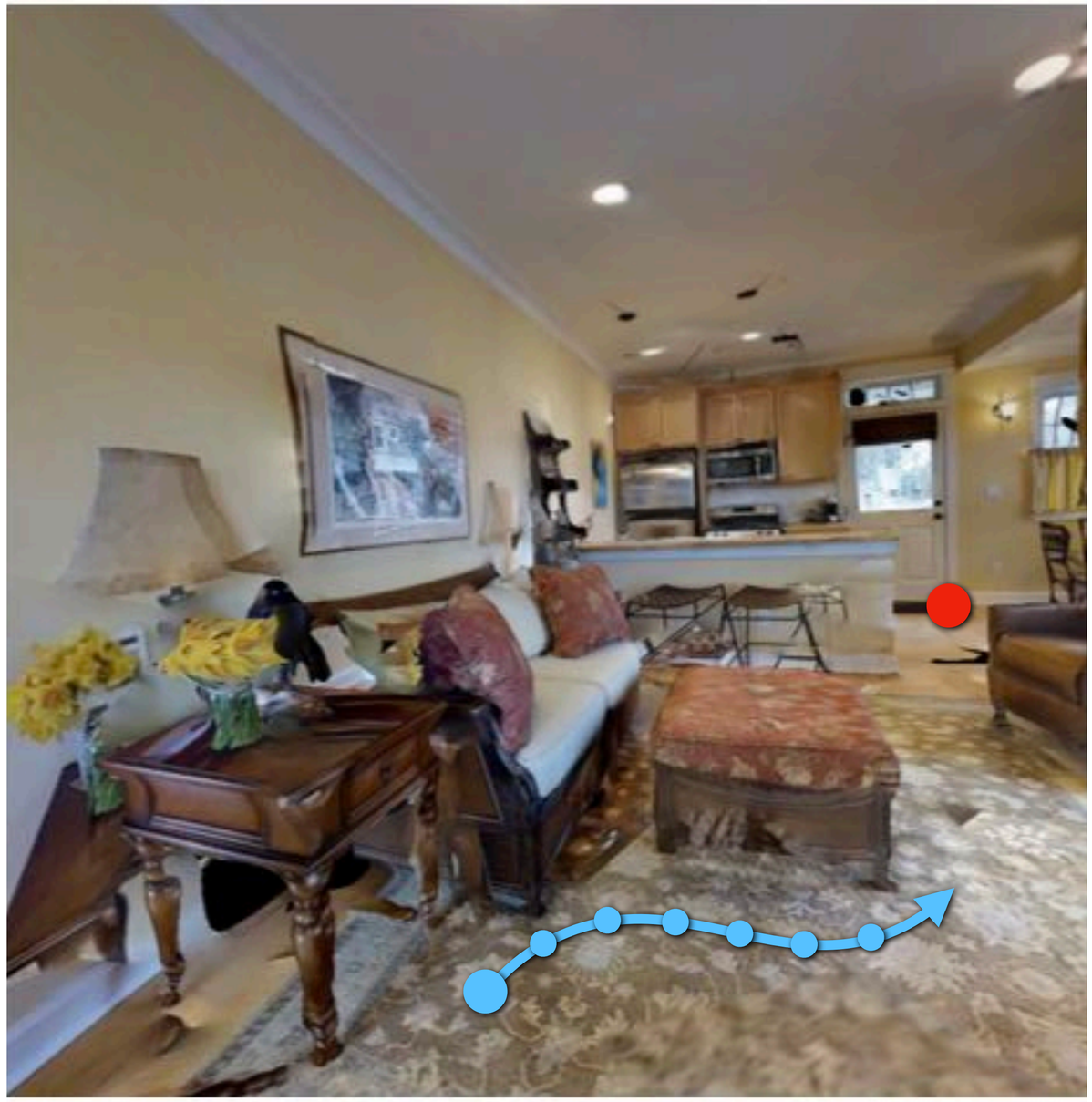
RL in 30 seconds

Model Inference

environment observation e.g. RGB image → π_θ → agent action

Model Training

Rollout → compute loss gradients π_θ → update model via SGD

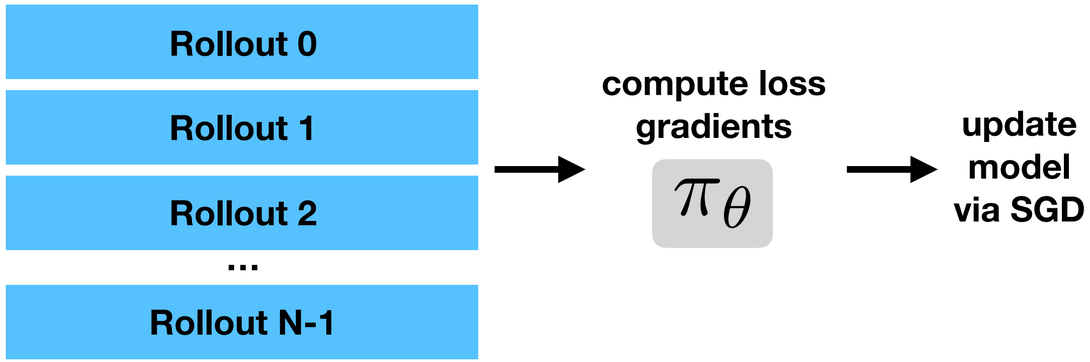


RL in 30 seconds

Many rollouts:

- **Agents independently navigating same environments**

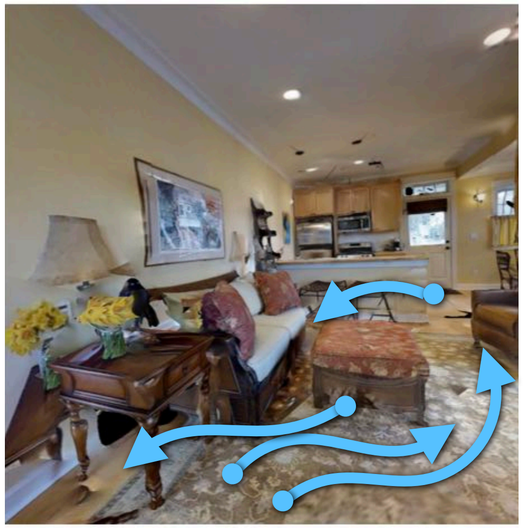
Batch Model Training

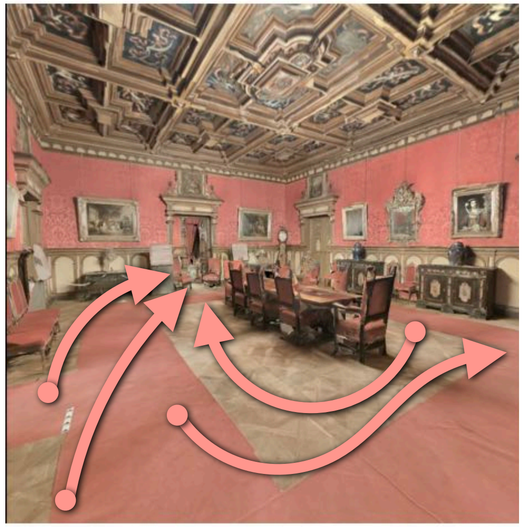


RL in 30 seconds

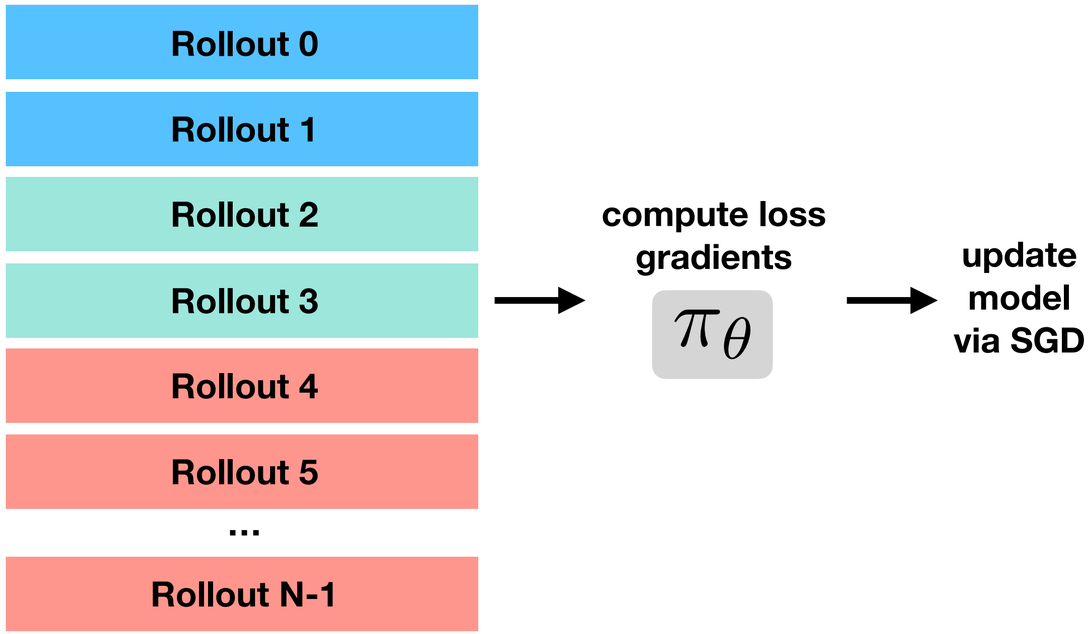
Many rollouts:

- **Agents independently navigating same environments**
- **Or different environments**



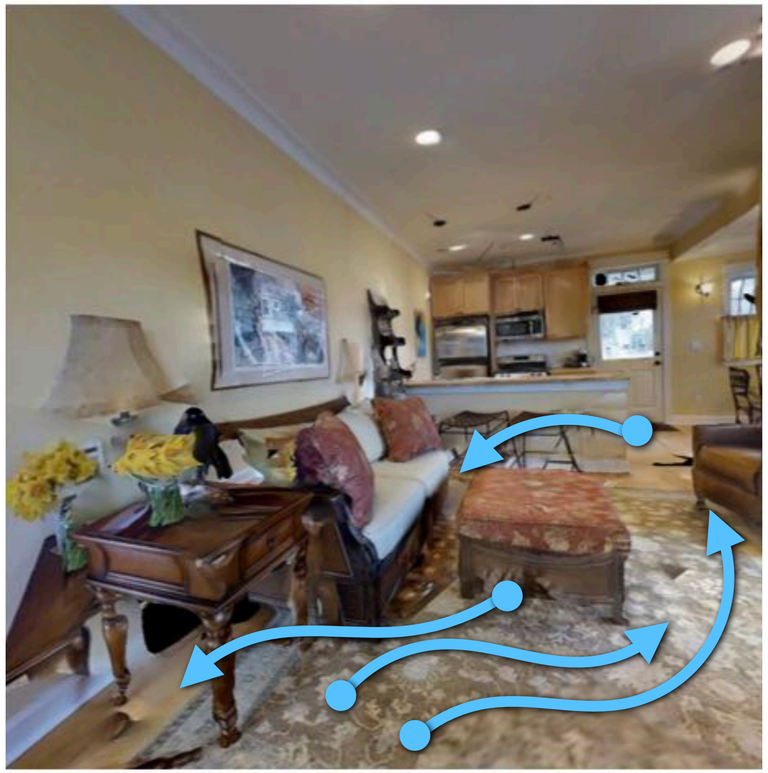


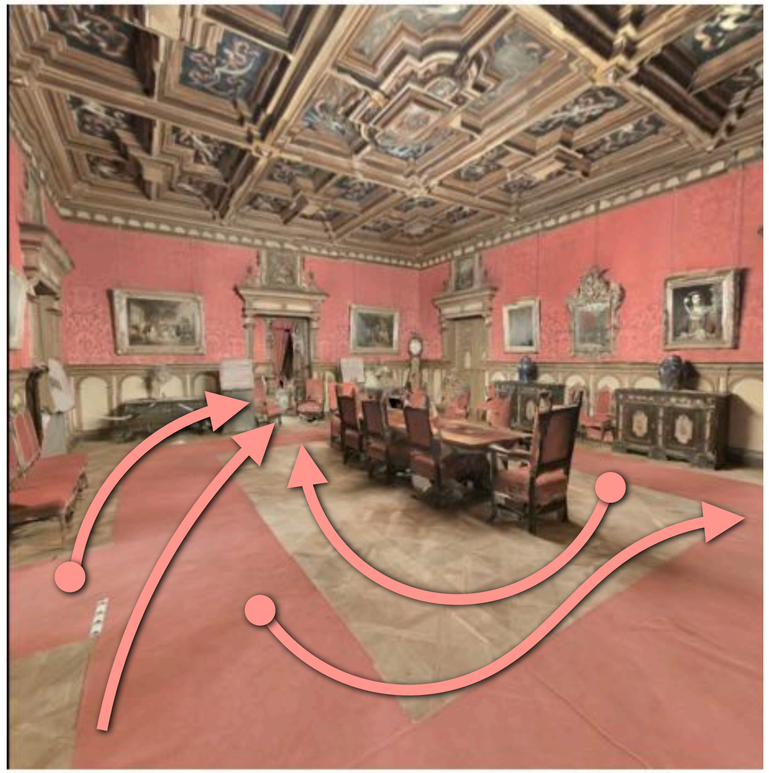
Batch Model Training



Learning robot skills requires many trials (billions) of learning experience

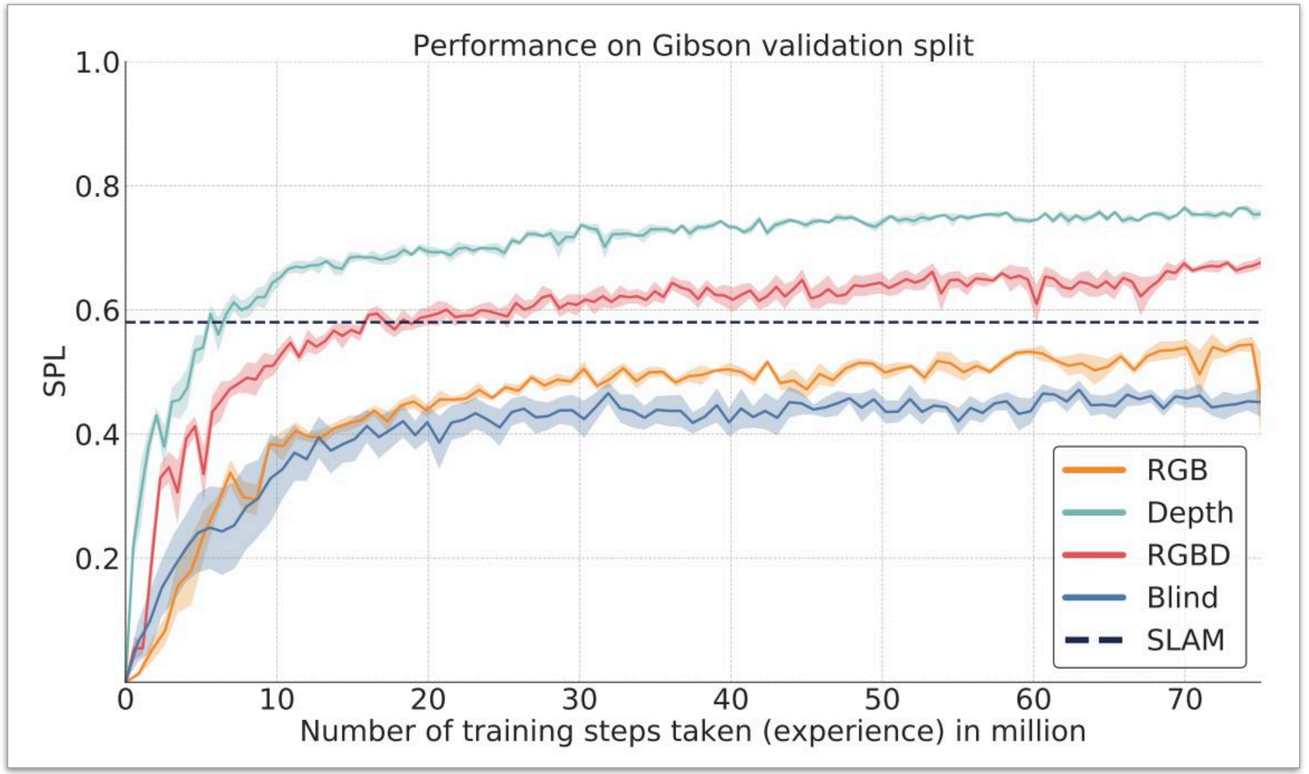
- Training in diverse set of virtual environments
- Many training trials in each environment



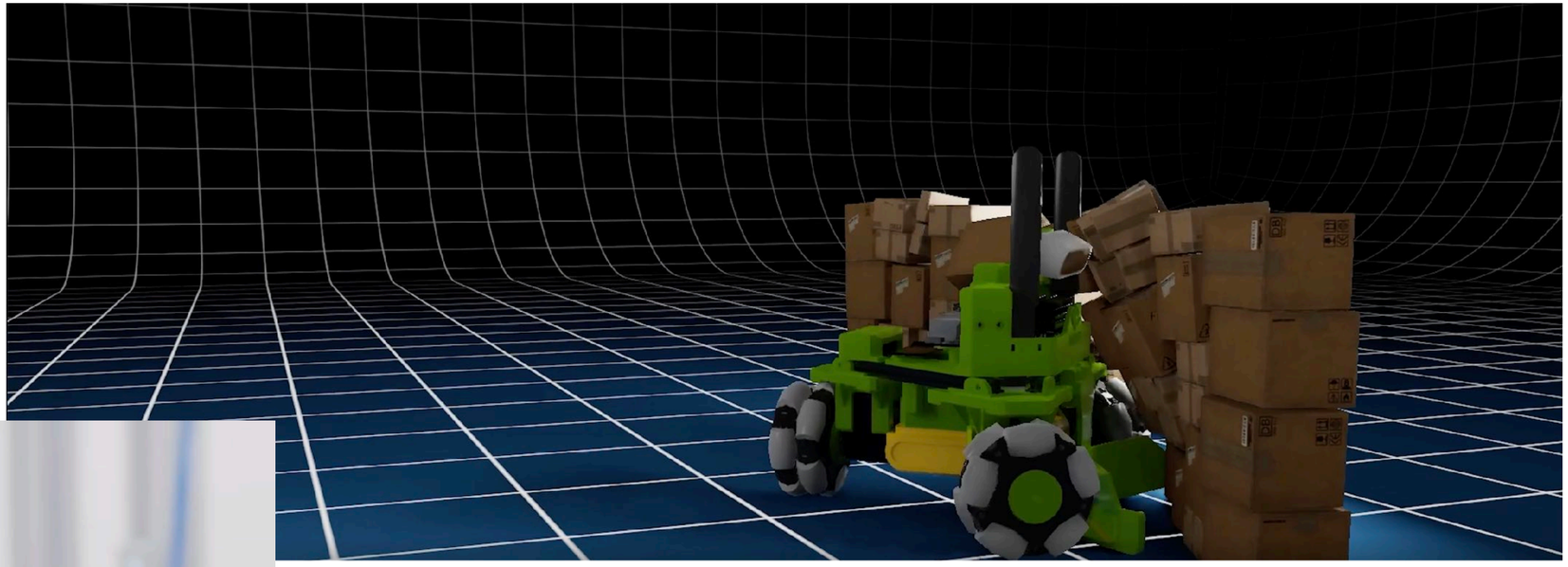


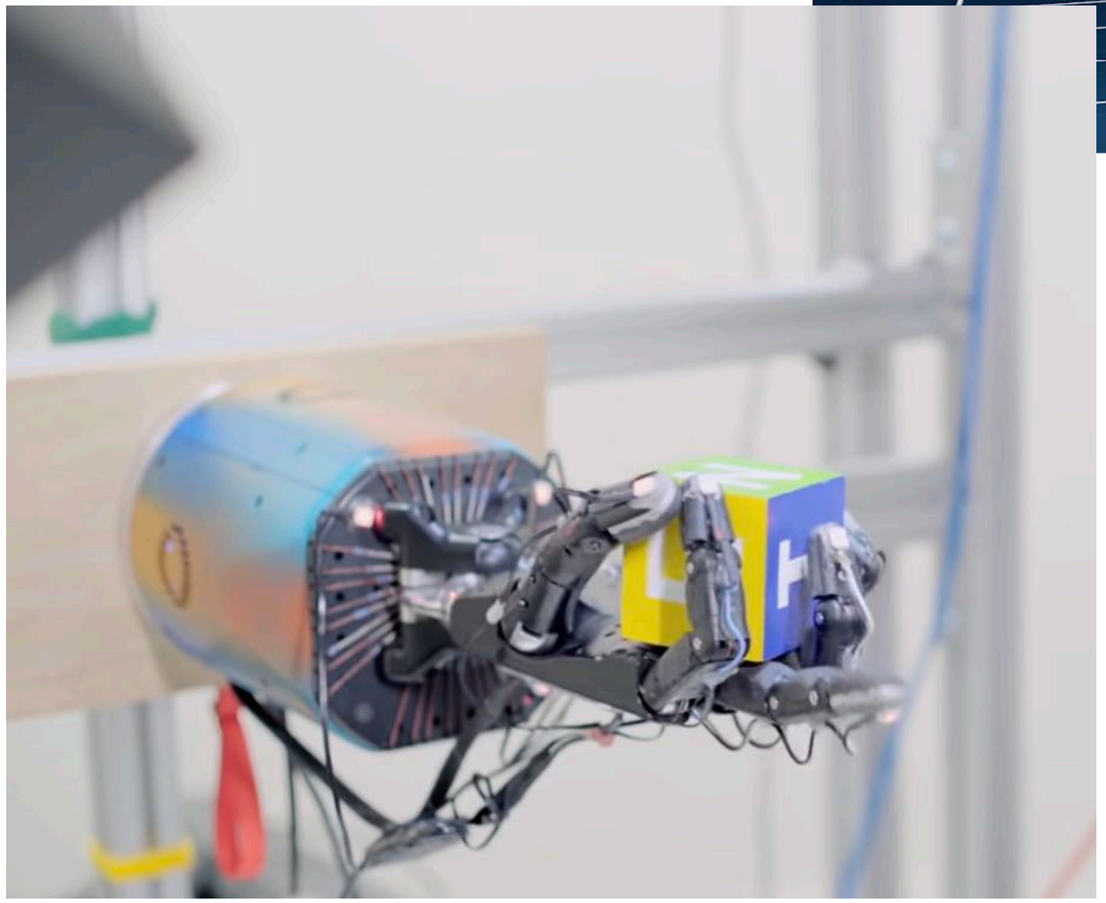
Need significant amounts of simulated experience to learn skills

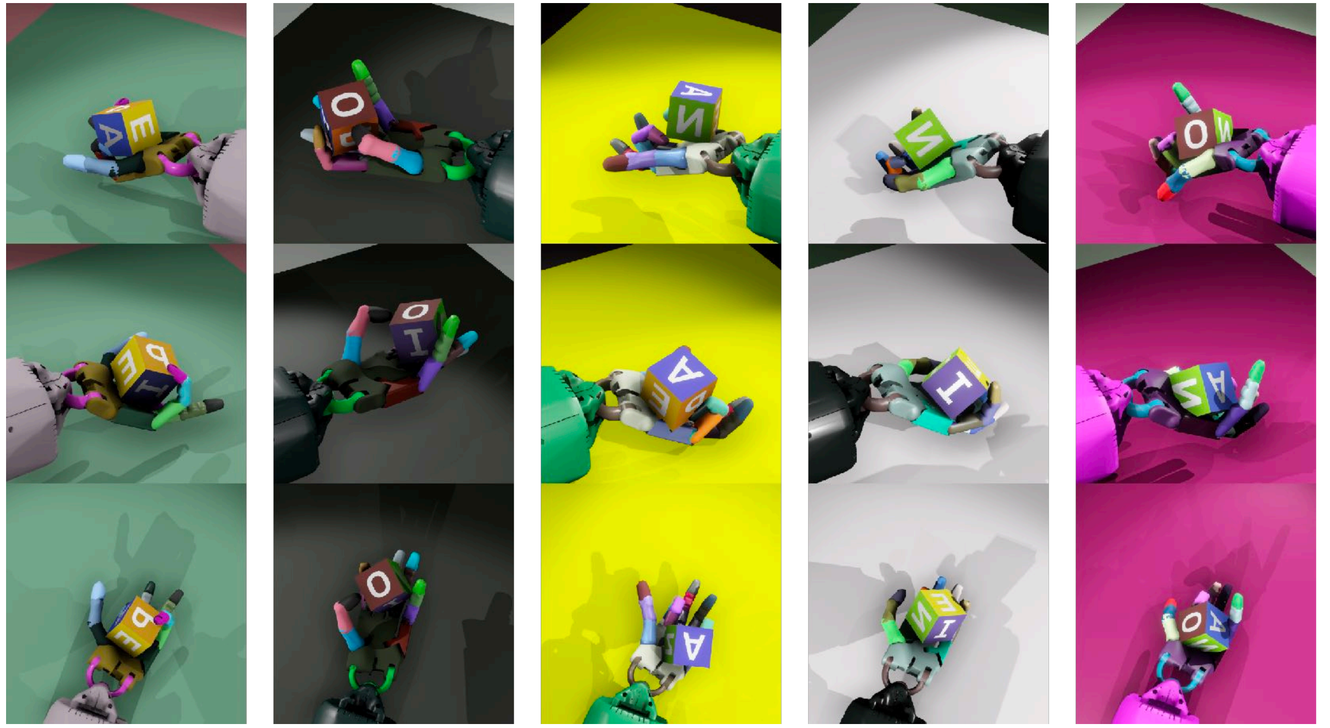
Example: even for simple PointGoal navigation task: need billions of steps of "experience" to exceed traditional non-learned approaches



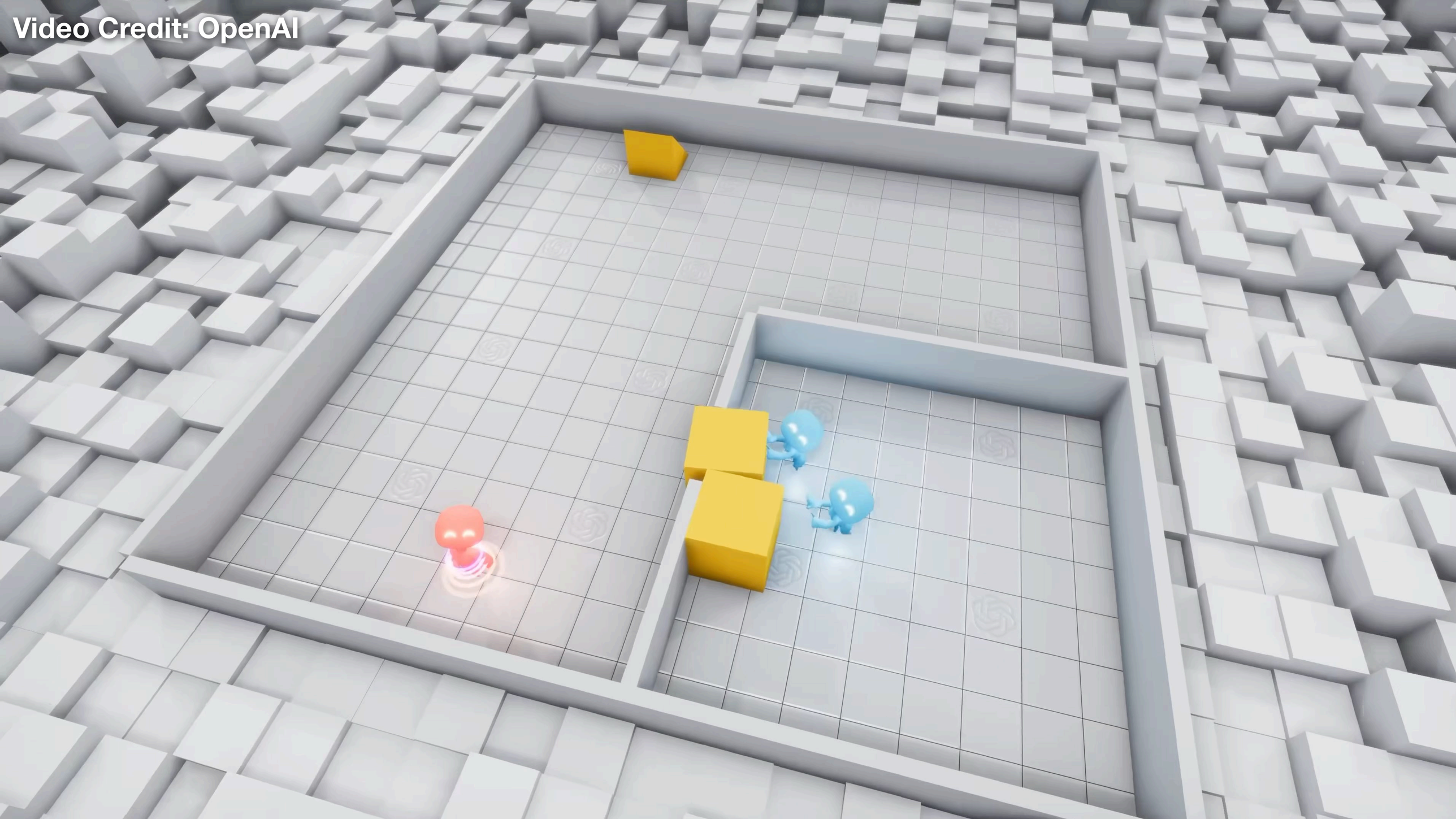
Physics simulation








Random incoming ball + Random target
Practice in simulation…


Video Credit: OpenAI

Many interactive virtual home environments

Navigate to a location

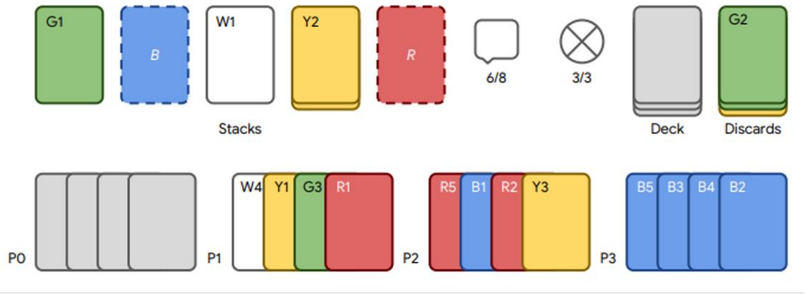
Find an object

Rearrange the room so objects are in desired locations

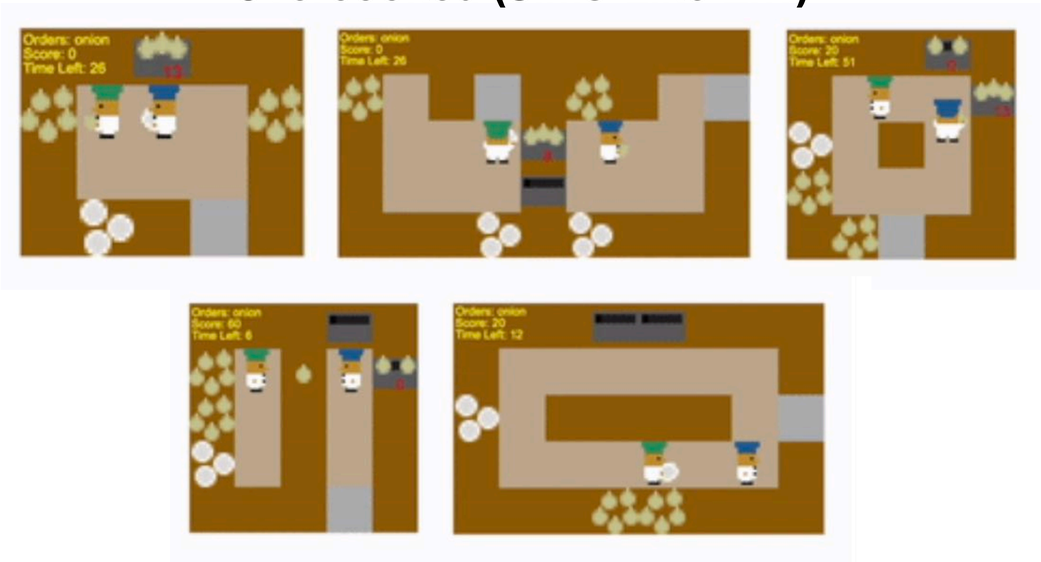
Pour oneself a glass of milk

Multi-agent games

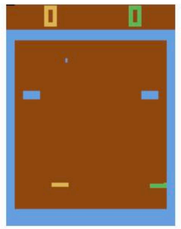
Hanabi (Card Game)

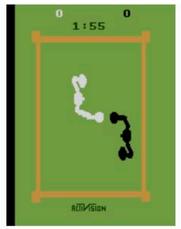


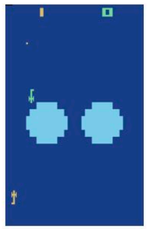
Overcooked (Sims-Like Env)

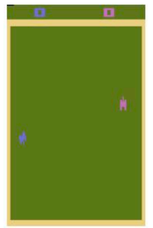


Atari Games

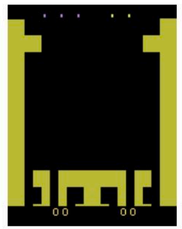

Basketball Pong

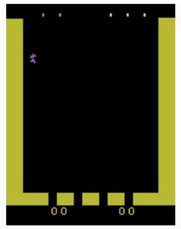

Boxing

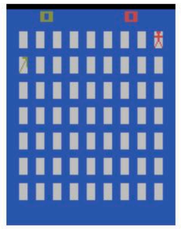

Combat Plane

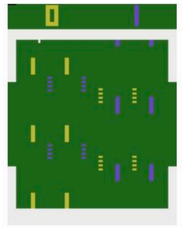

Combat Tank


Double Dunk


Entombed Competitive


Entombed Cooperative


Flag Capture


Foozpong


Ice Hockey


Joust

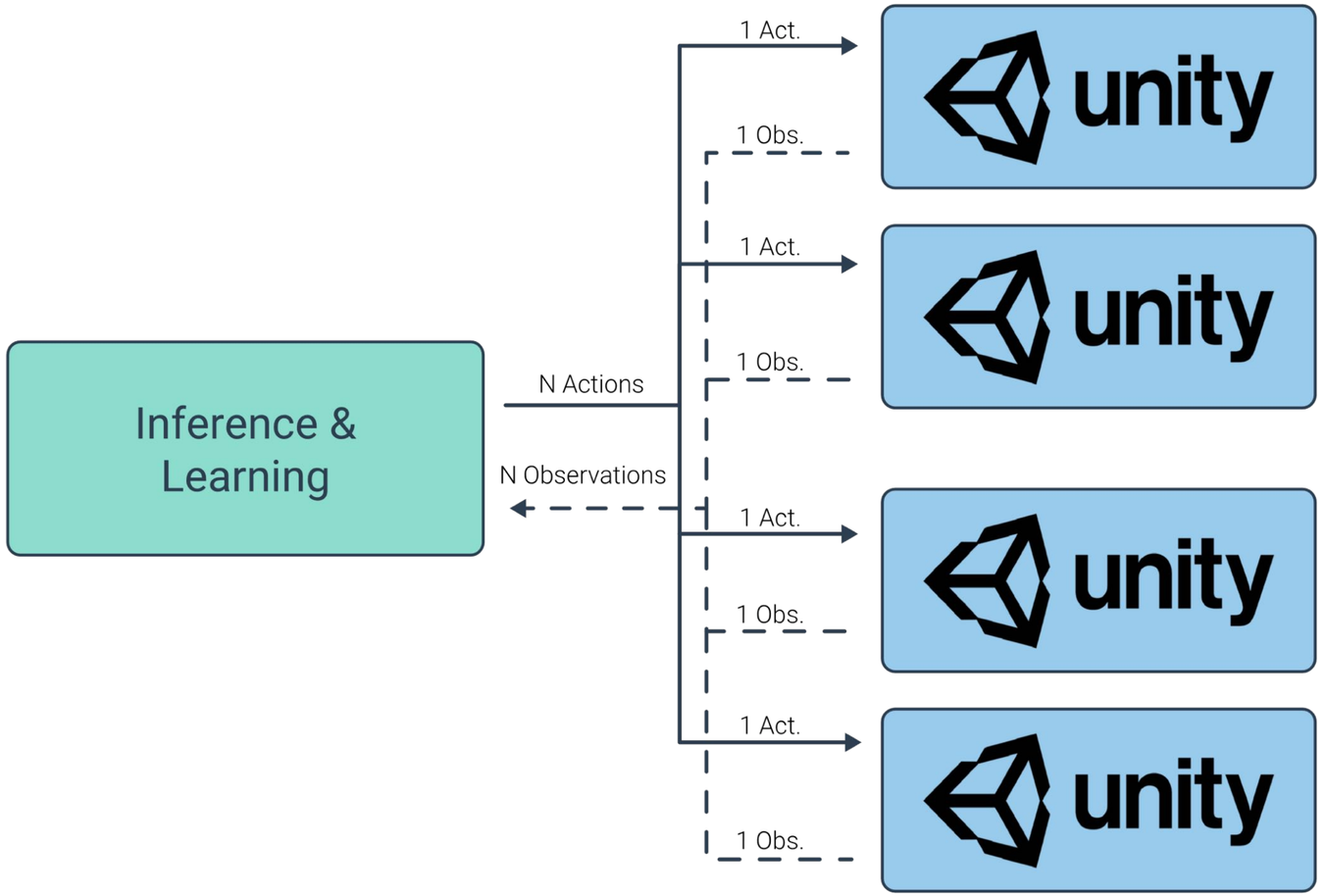

Mario Bros

RL workload summary

- Within a rollout
  - For each step of a rollout:
  - Render -> Execute policy inference -> simulate next world state

- Across *many* independent rollouts
  - Simulated agents may (or may not) share scene state
  - Diversity in scenes in a batch of rollouts is desirable to avoid overfitting, sample efficiency of learning

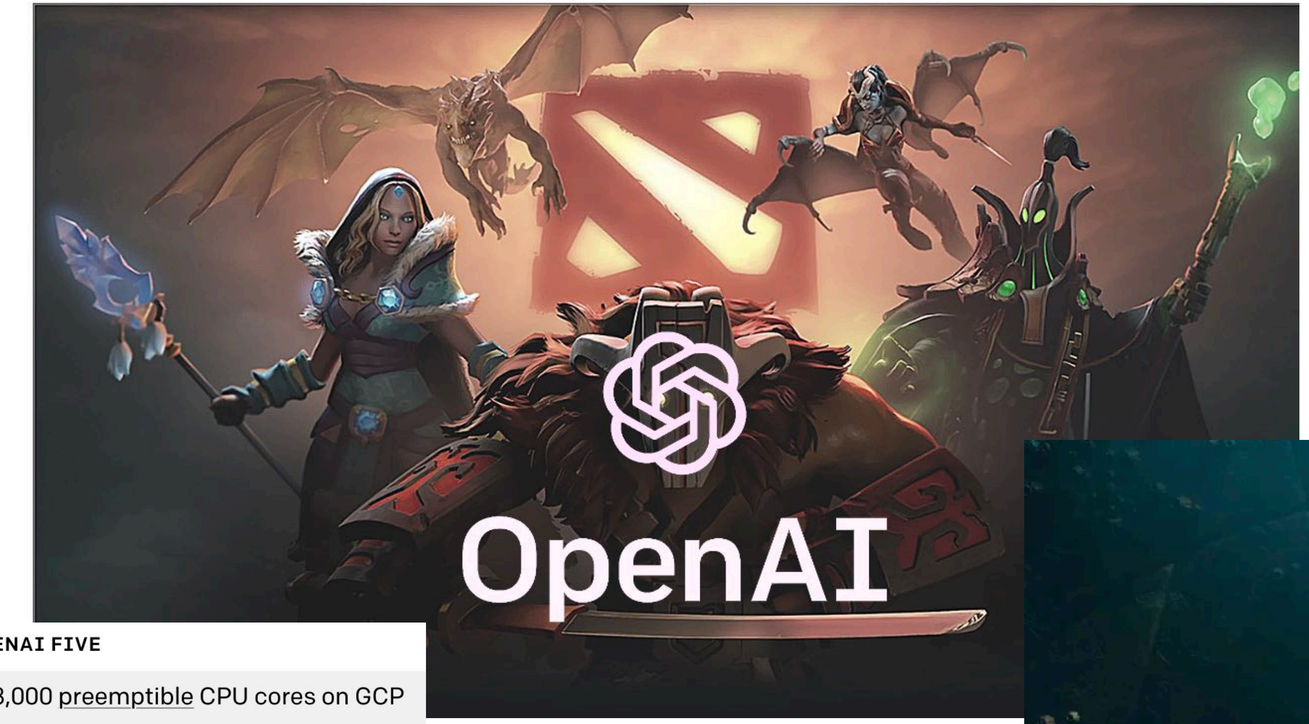
Common simulation approach: treat simulator as a black box, gain high throughput via scale-out parallelization



Treat existing simulation engines as a black box.

Run many copies of the black box in parallel.

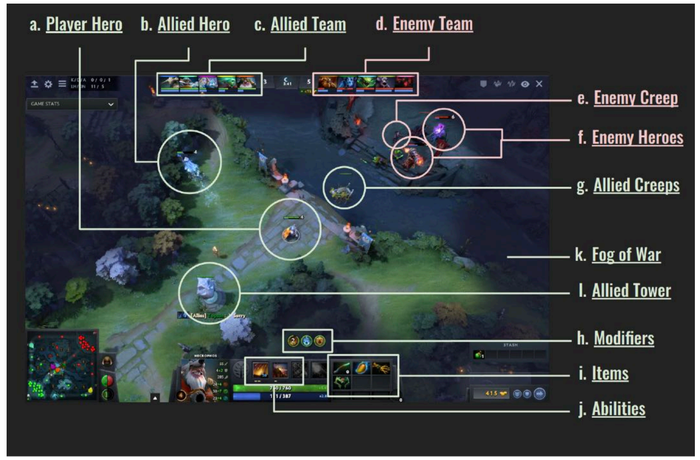
OpenAI's "OpenAI 5" Dota 2 bot



	OPENAI FIVE
CPUs	128,000 preemptible CPU cores on GCP
GPUs	256 P100 GPUs on GCP
Experience collected	~180 years per day (~900 years per day counting each hero separately)
Size of observation	~36.8 kB
Observations per second of gameplay	7.5
Batch size	1,048,576 observations
Batches per minute	~60

Generating simulated experience is computationally demanding

OpenAI Five

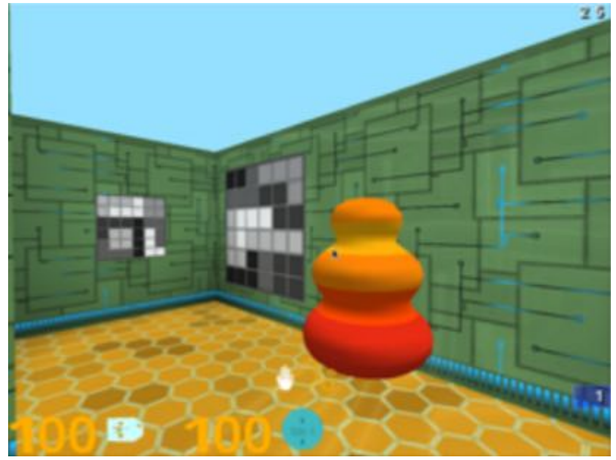


Rapid: 128,000 CPUs,
days of training

Navigation in 3D scanned environments

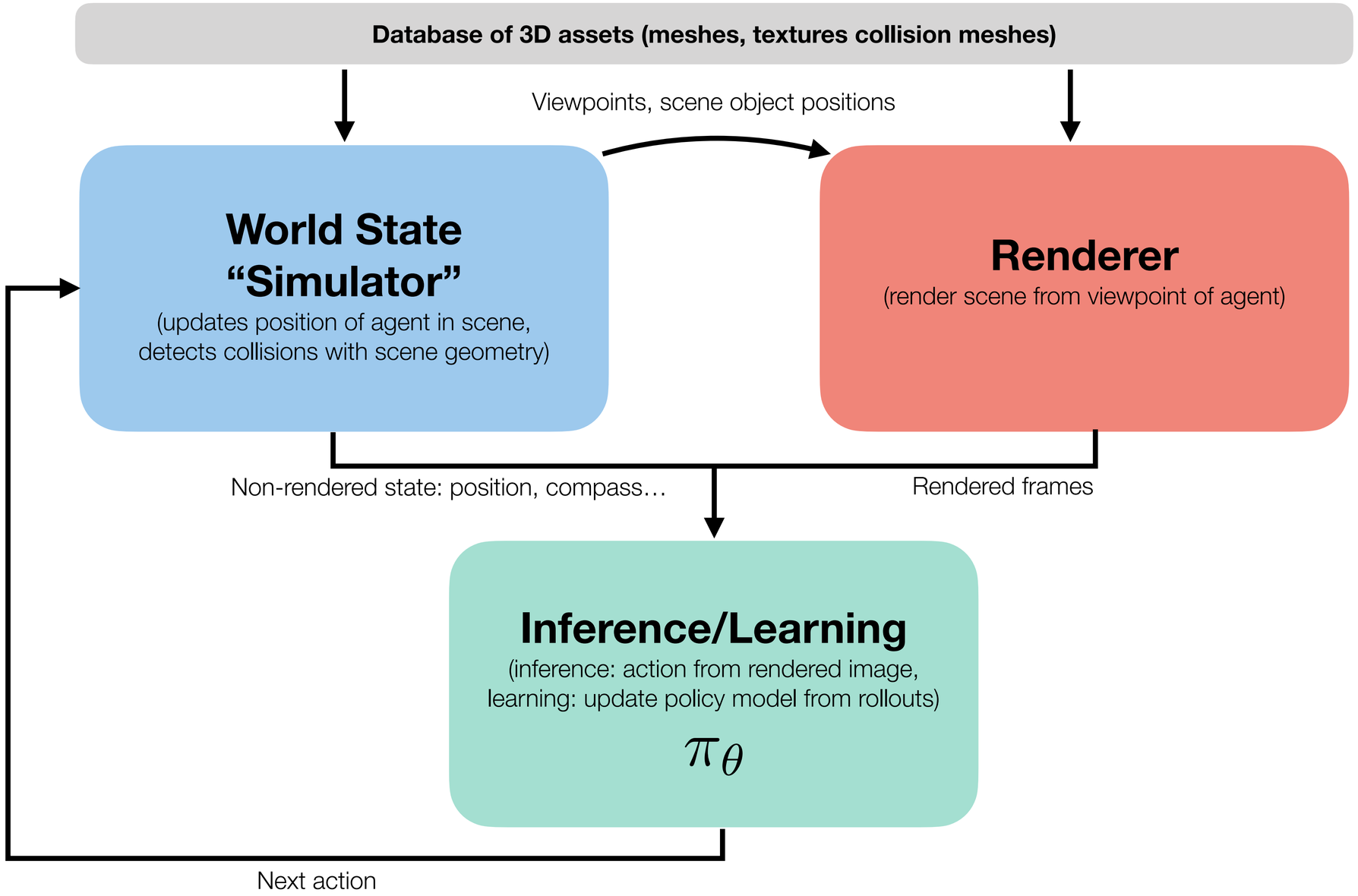
64 GPUs over 2.5 days
(2B experience samples)

Game playing

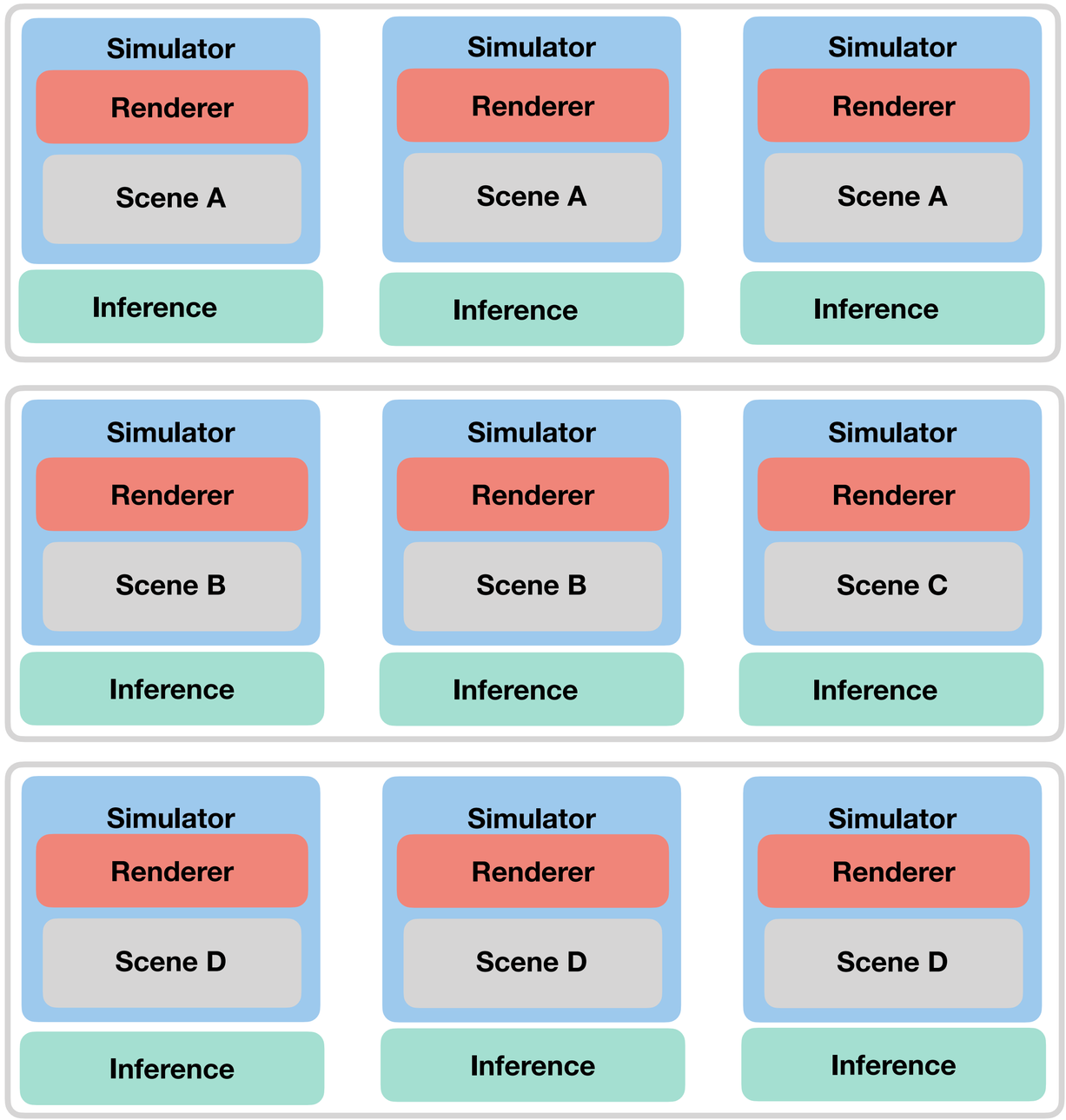


Deepmind Lab Training with
4000 CPUs and 64 TPUs

Example: PointGoal navigation task system components



Basic design: parallelize over workers



Ask yourself:

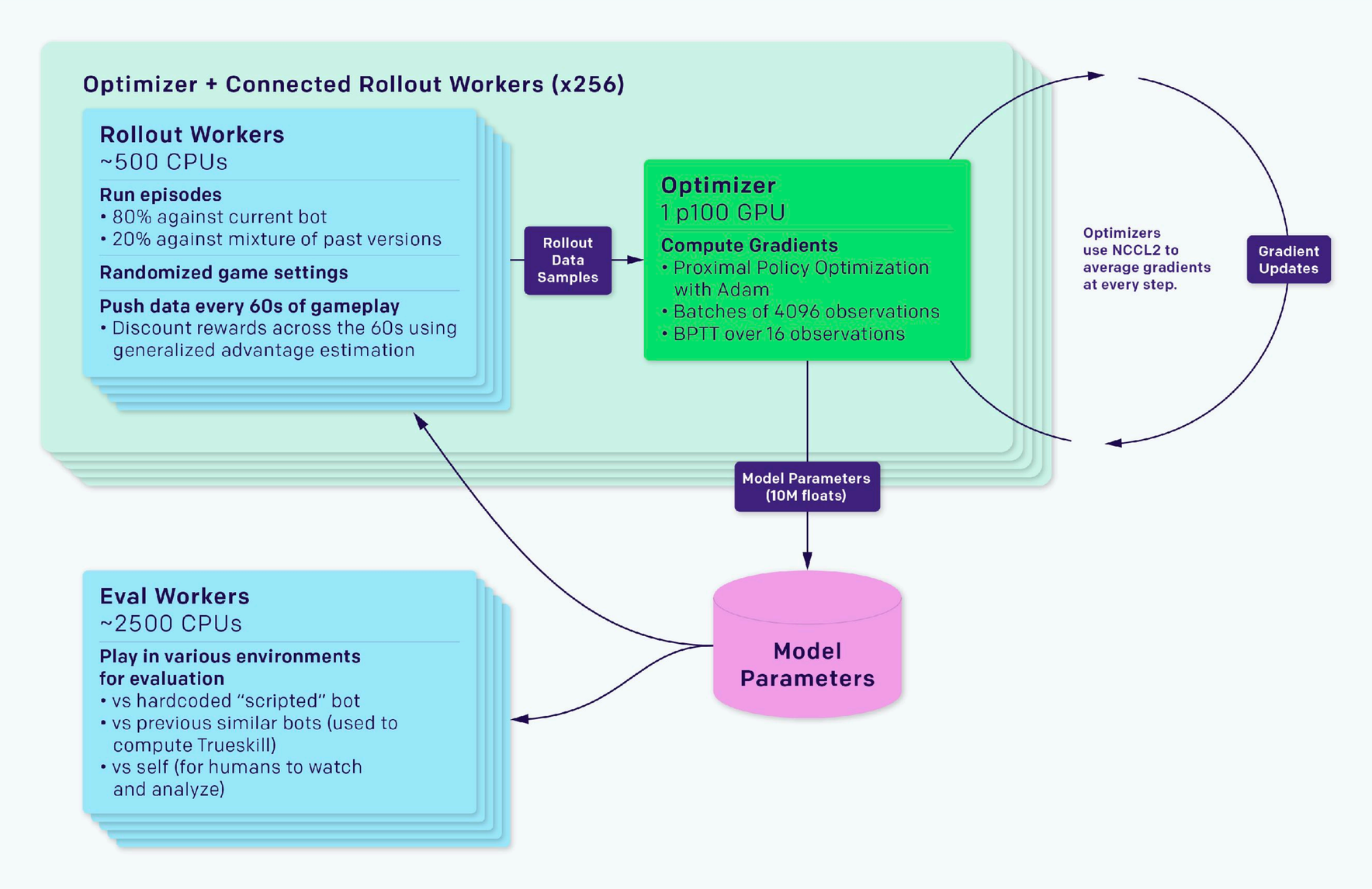
1. **What data gets communicated?**
2. **Can the system scale to sufficient parallelism?**
3. **Are there sync bottlenecks**

Learning

learning: update policy model from rollouts)

π_θ

Example: Rapid (OpenAI)

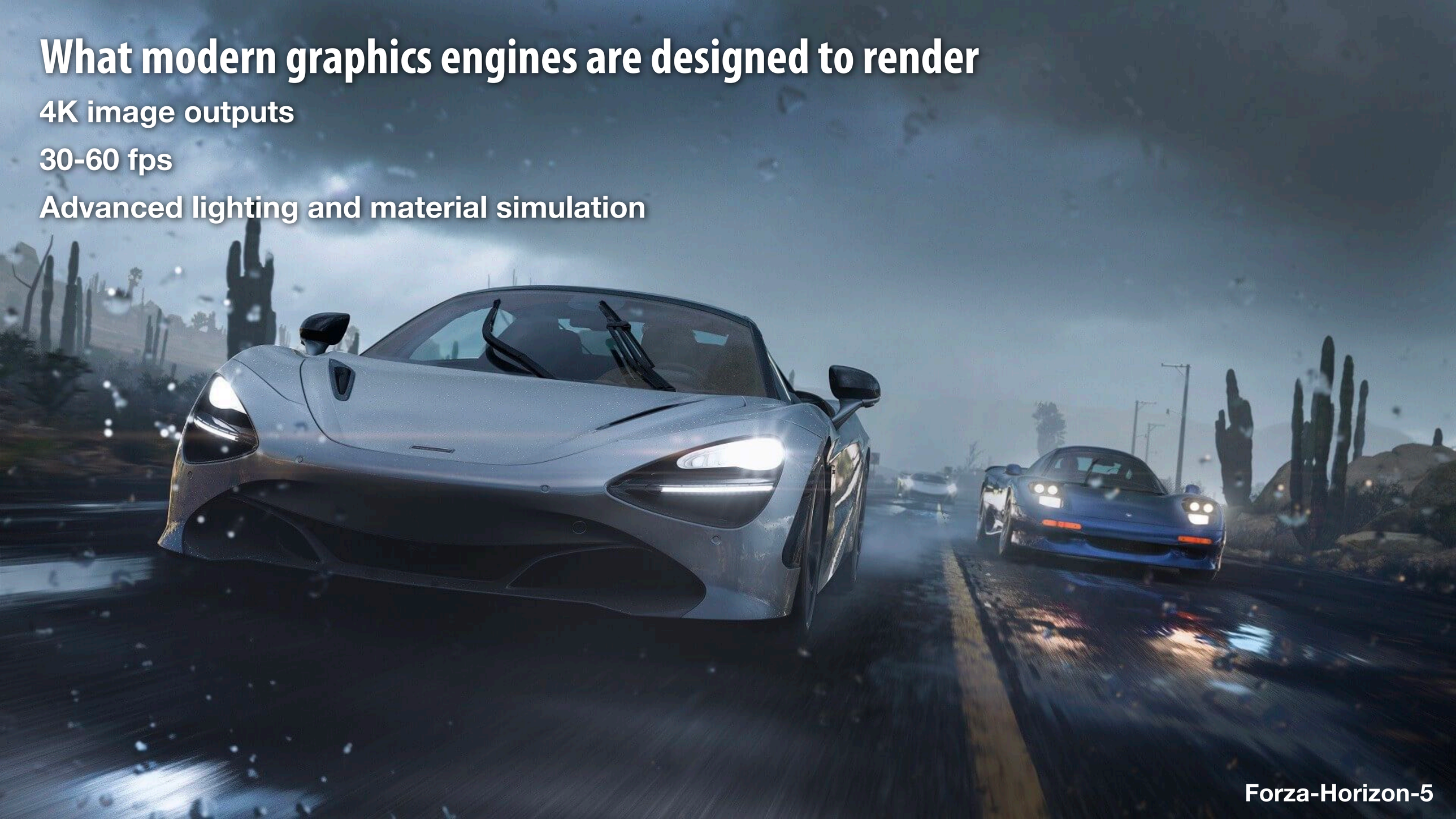


What modern graphics engines are designed to render

4K image outputs

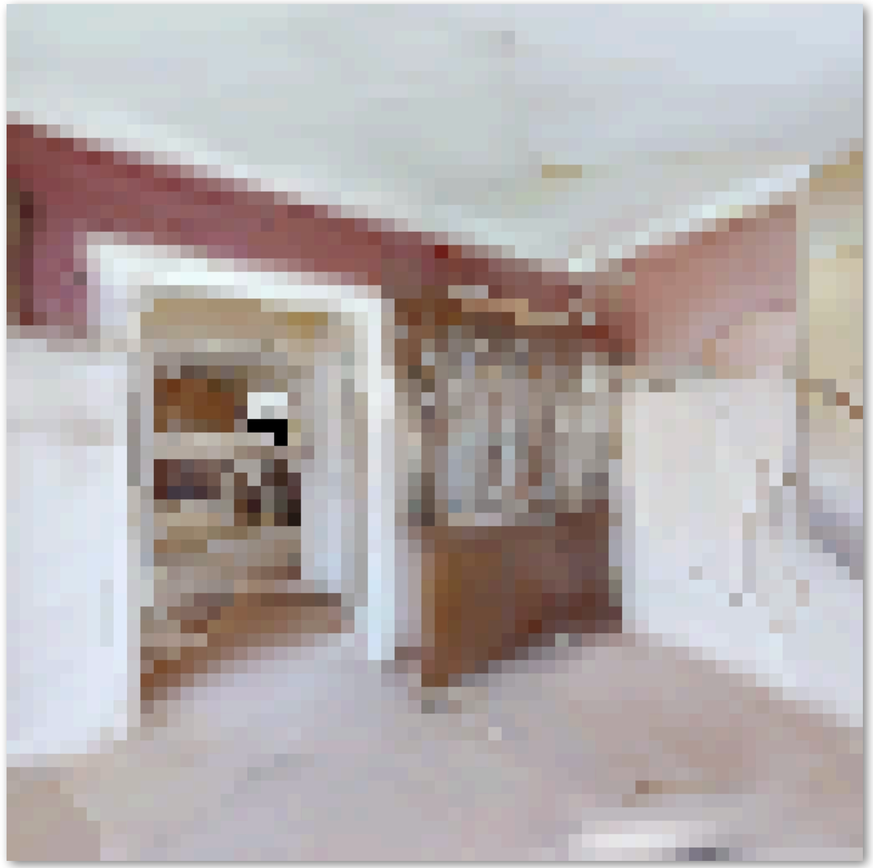
30-60 fps

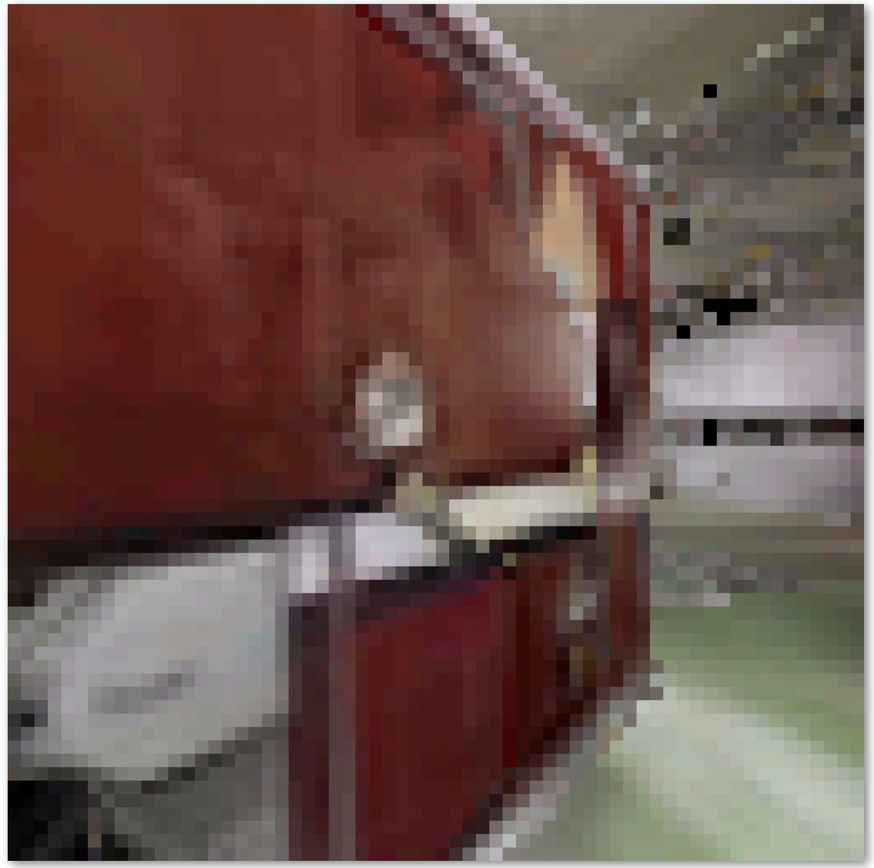
Advanced lighting and material simulation



Forza-Horizon-5

Low-resolution images with pre-captured lighting (from Gibson): clearly not state-of-the-art rendering! ;-)





Design issues

- Inefficient simulation/rendering: rendering a small image does not make good use of a modern GPU (rendering throughput is low)

- Duplication of computation and memory footprint (for scene data) across renderer/simulator instances

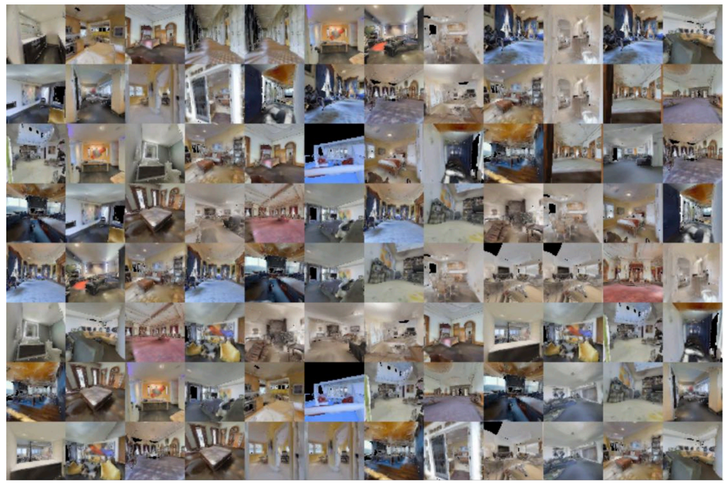
Often the best way to reduce communication / increase efficiency is to make the most efficient use out of one node

Can we make simulation faster?

Trend: cracking open the black box: 100x end-to-end training speedups using optimized “batch simulators”

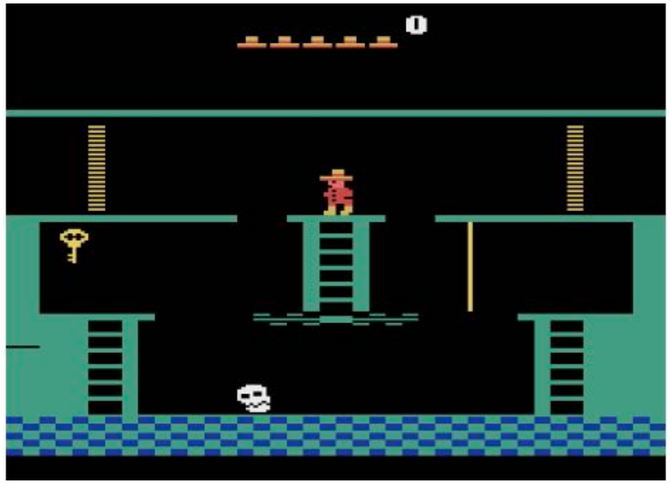
New simulators specifically designed to efficiently execute 1000’s of worlds at once on a single GPU or multi-core CPU

BPS3D: Pointgoal Navigation



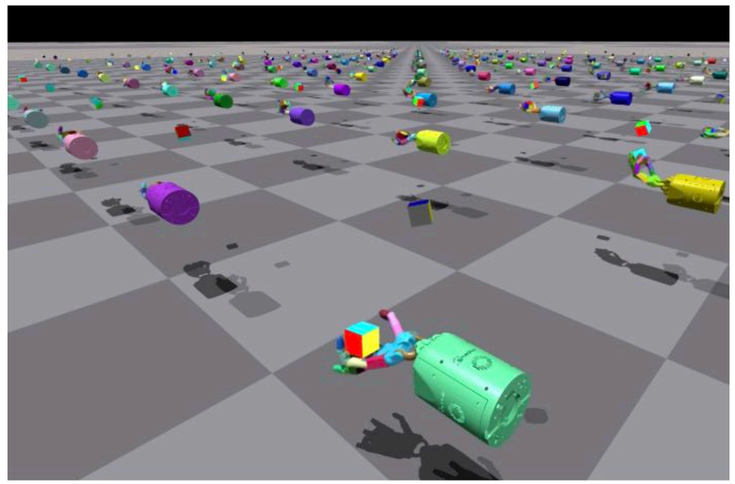
~1000 Worlds per GPU

CuLE: Atari on the GPU



~5000 Worlds per GPU

Isaac Gym: GPU Physics

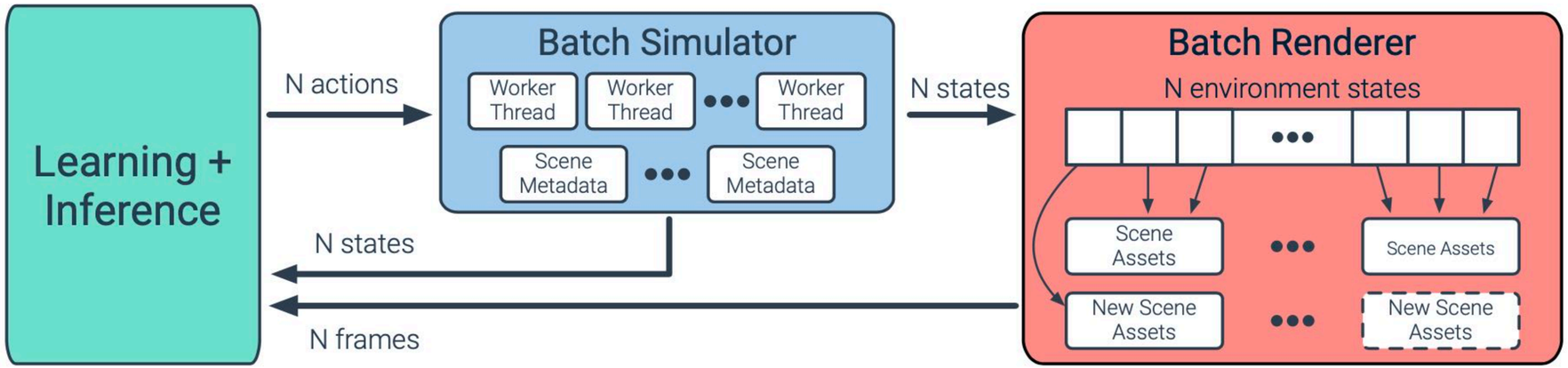


~10000 Worlds per GPU

Main idea: design a renderer that executes rendering for 100s-1000's of unique rollouts in a single request

Inference/training, simulation, and rendering all operate on batches of N requests (rollouts)

Efficient bulk communication between three components



Renderer output

Opportunities provided by a batch rendering interface

- Wide parallelism: rendering each scene in a batch is independent
  - "Fill up" large parallel GPU with rendering work
  - Enables graphics optimizations like pipelining frustum culling (removing off-screen geometry before drawing it) for one environment with rendering of another

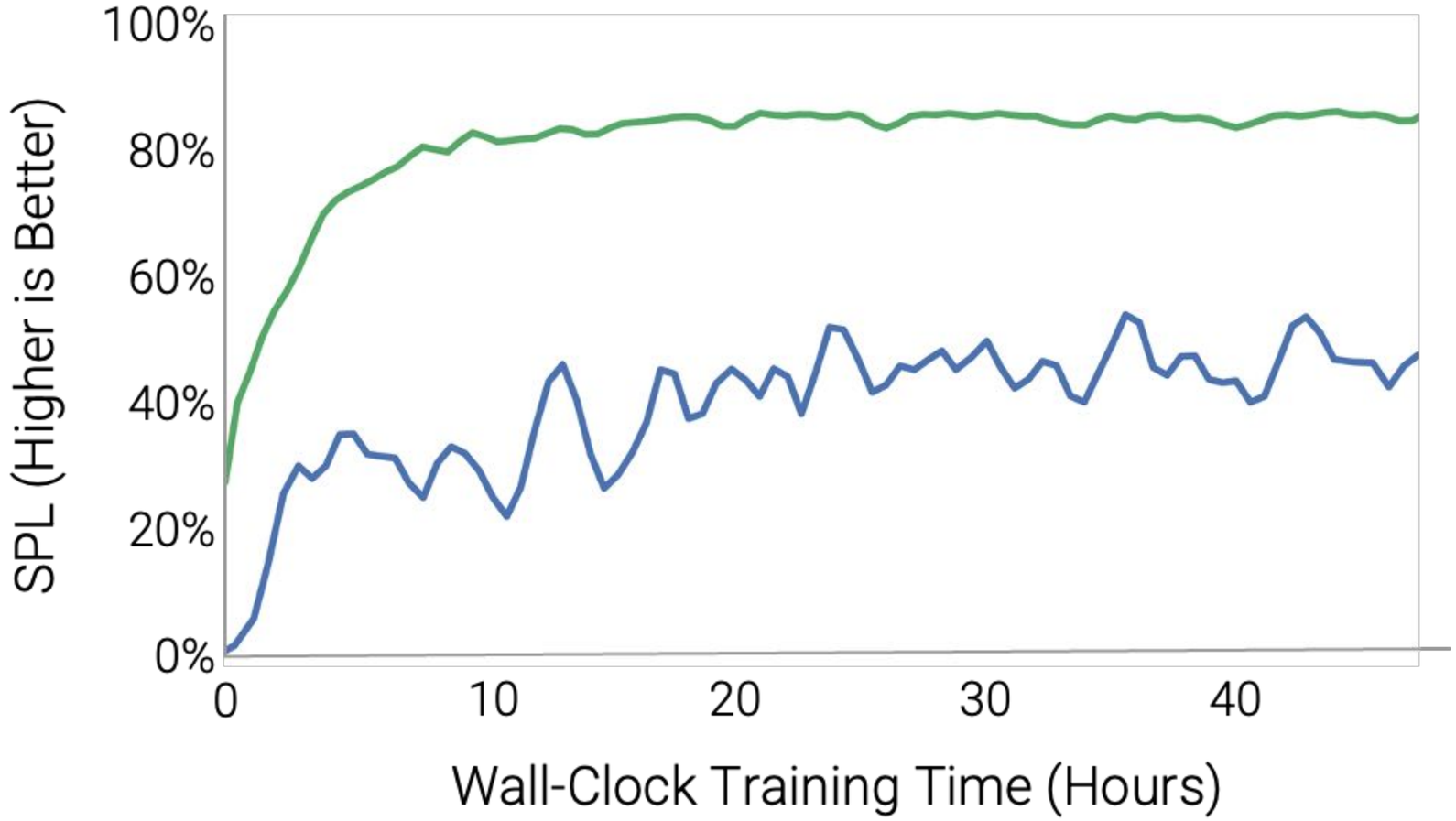
- Footprint optimizations: rendering requests in a batch can share same geometry assets
  - Significantly reduces memory footprint, enables large batch size
  - $N \sim 256\text{-}1024$ (per GPU) in our experiments: fills up large GPU
  - Limit number of unique scenes in a batch to $K \ll N$ scenes.
    - GPU RAM and scene size determines K

- Amortize communication: rendering requests in a batch can be packaged and drawn together
  - Render frames in batch to tiles in a single large frame buffer to avoid state update

2.5B frames of experience in 48 hrs on a single RTX 3090

“PointGoal Navigation” in Gibson environments (Habitat Labs)

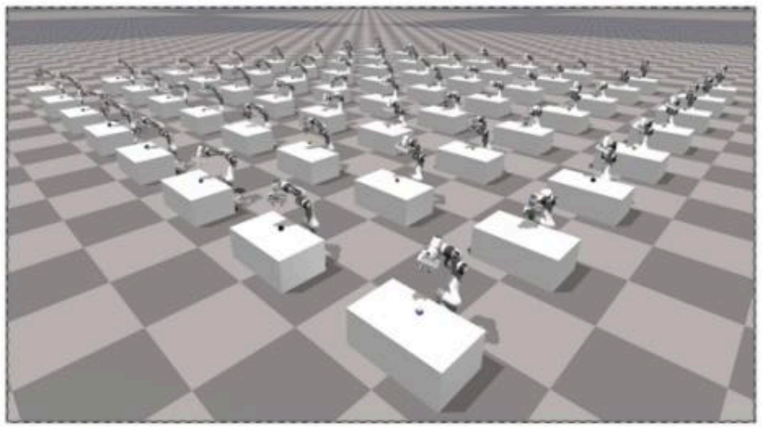
Run render->infer->train loop
runs at 13,000 fps per GPU



"Large Batch Simulation for Deep Reinforcement Learning", B. Shacklett, E. Wijmans, A.Petrenko, M. Savva, D. Batra, V. Koltun, K. Fatahalian, ICLR 2021

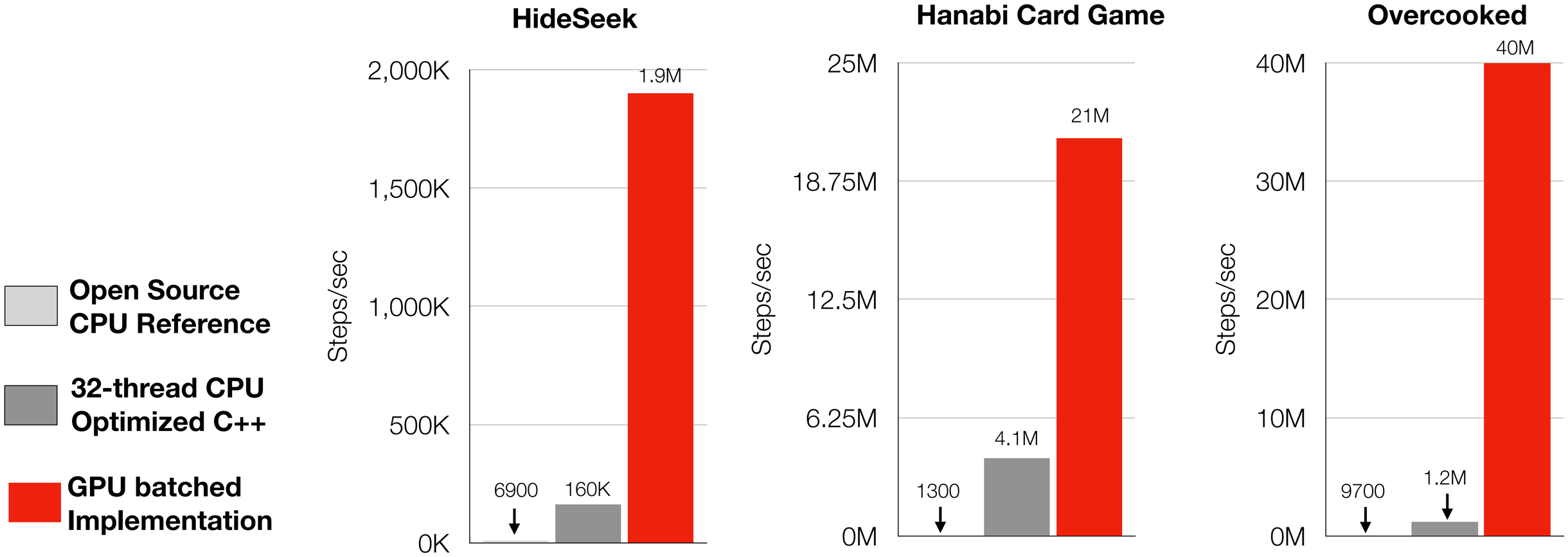
NVIDIA Issac Gym

- Same idea of batched many-environment execution, applied to physics
- Simulate 100's to 1000's of world environments simultaneously on the GPU
- Current state for all environments packaged in a single PyTorch tensor
- User can write GPU-accelerated loss/reward functions in PyTorch on this tensor
- Result: tight loop of simulate/infer/train



Tonight's reading

- How would you design game engine APIs to support creation of custom games that execute efficiently in "batch simulation" mode
- All game logic, not just rendering and physics



Part 3:
Growing interest in general purpose agent skills

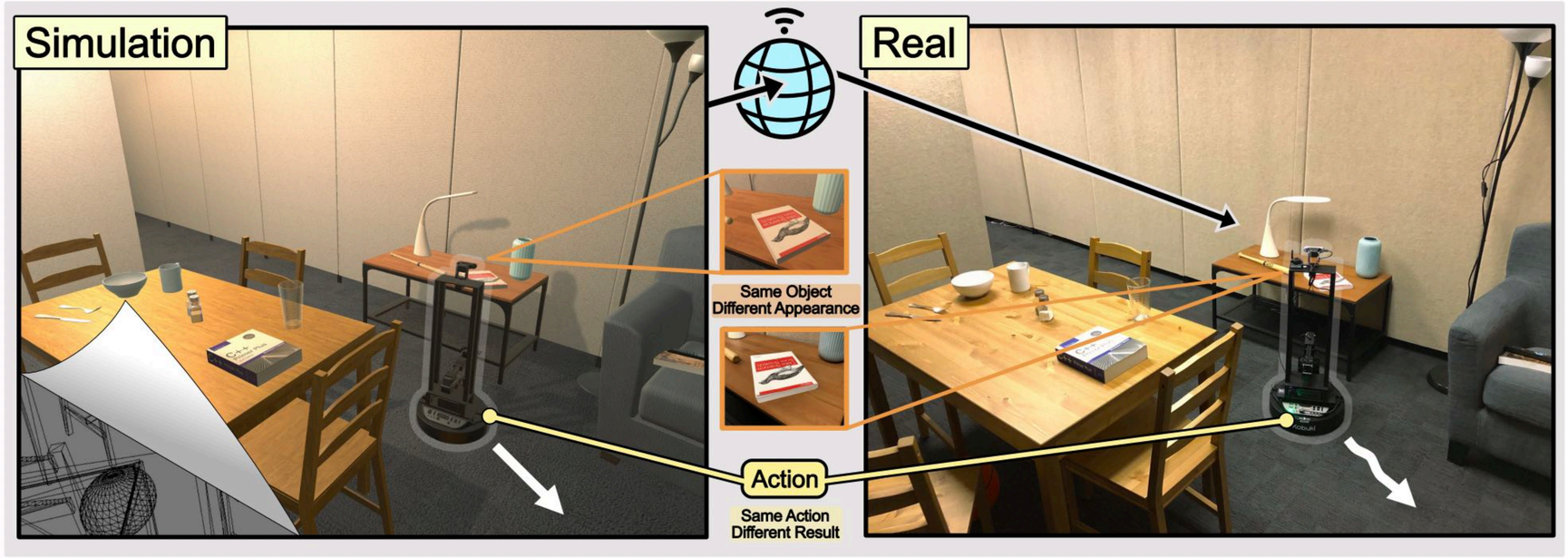
Interesting end-to-end systems research questions

- How much fidelity is needed to train models that successfully transfer into the real-world?
  - Do we even need photorealistic quality (or advanced physics) to train policies that work in the real world?

- Is it better to spend compute on higher fidelity simulation, or use the budget to train on a wider range of simulations, or even many tasks

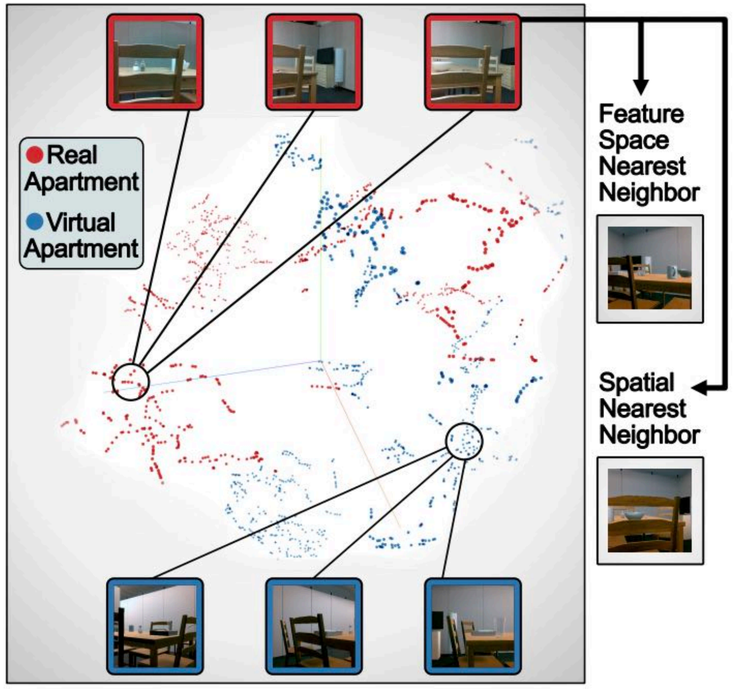
Example Sim2Real experiments: RoboTHOR

[Dietke 20]



Virtual environment

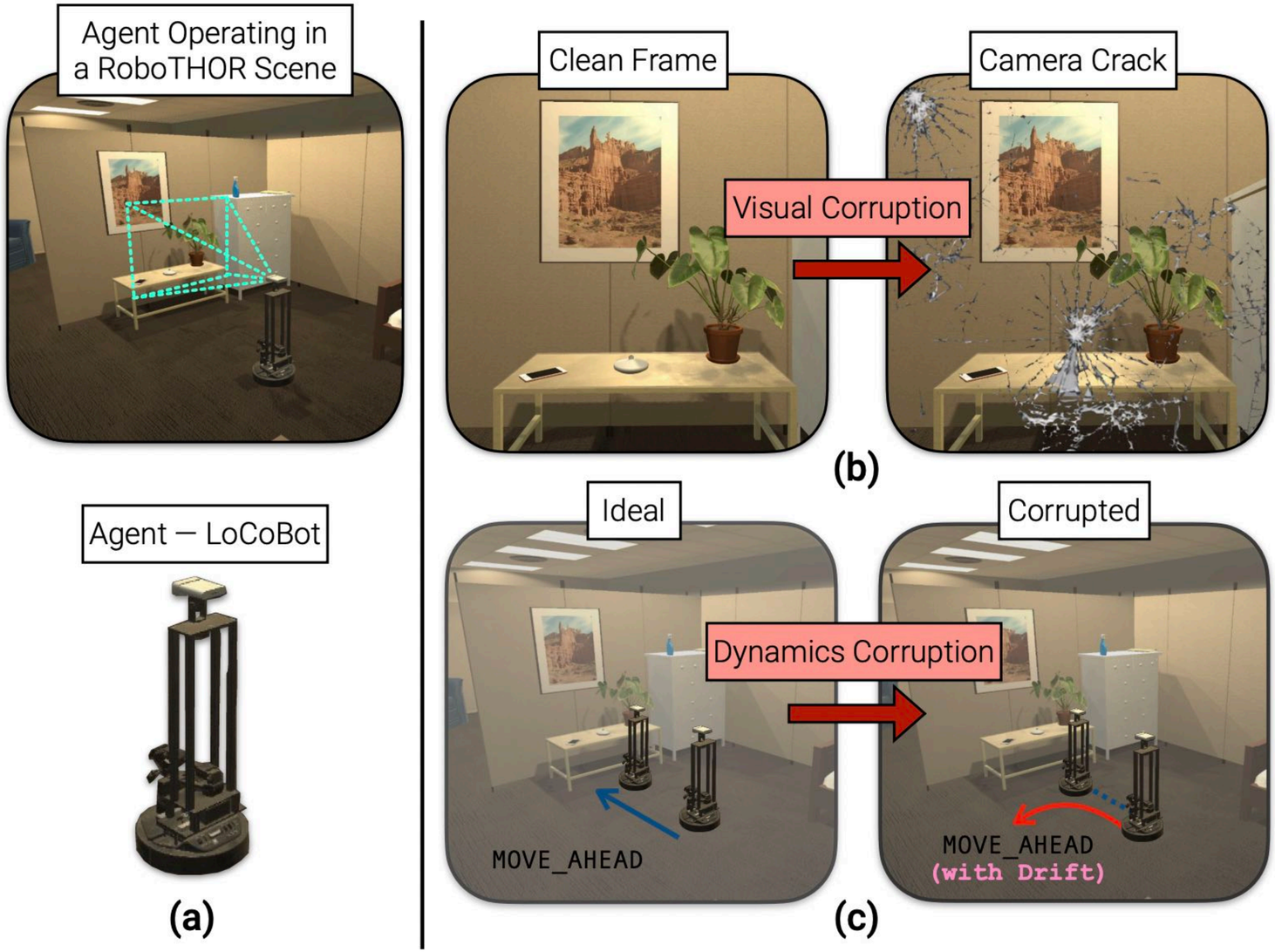
Real world photo of corresponding environment (in lab)



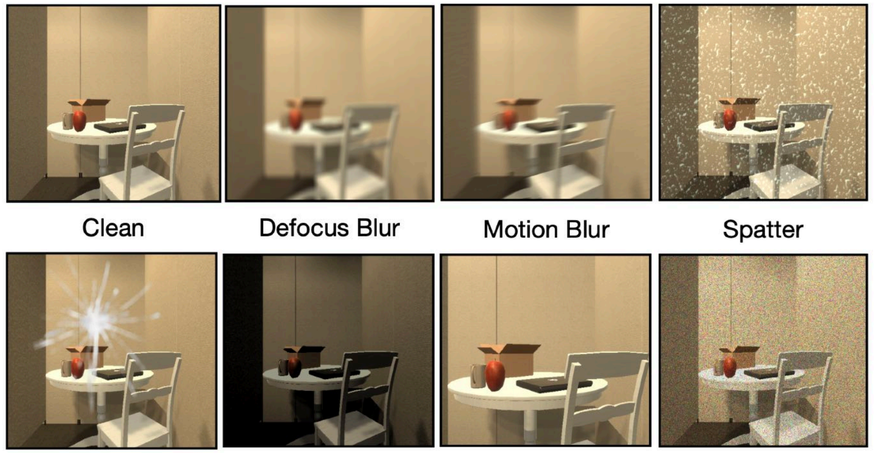
Understanding the effects of sim2real gap

[Chattopadhyay 21]

What parts of real-world sensing do we really need to model in simulation?



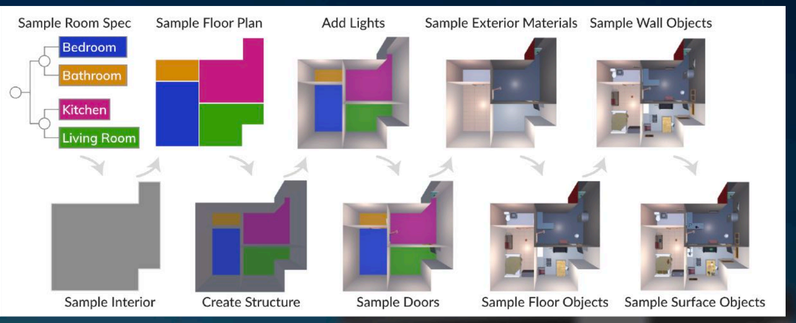
Example visual corruptions



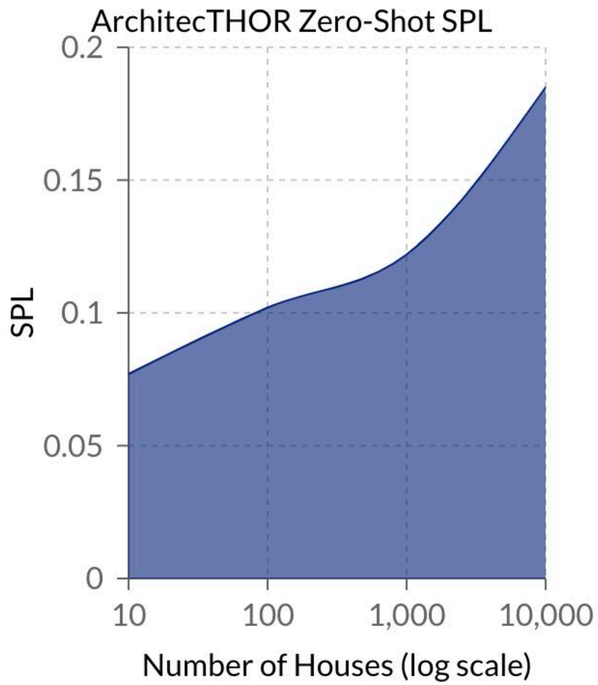
Value of diversity of scenes

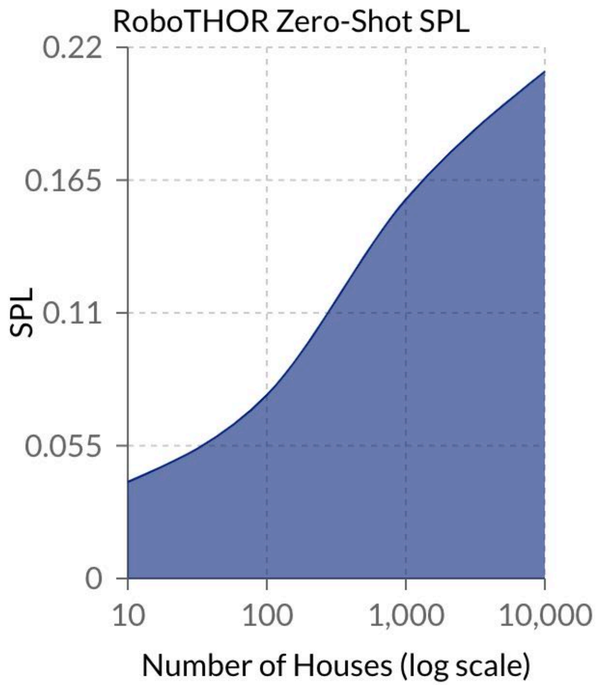
Example: ProcTHOR

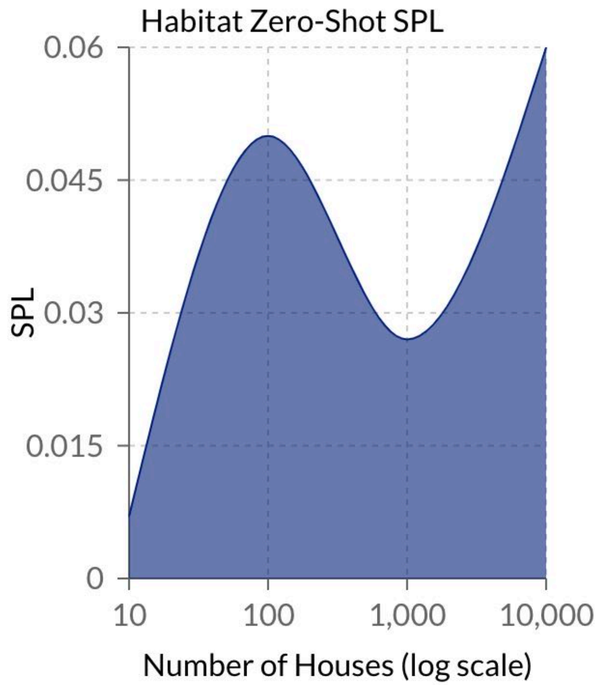
Procedurally generated floorpans, furniture arrangements, random material assigmments, etc.

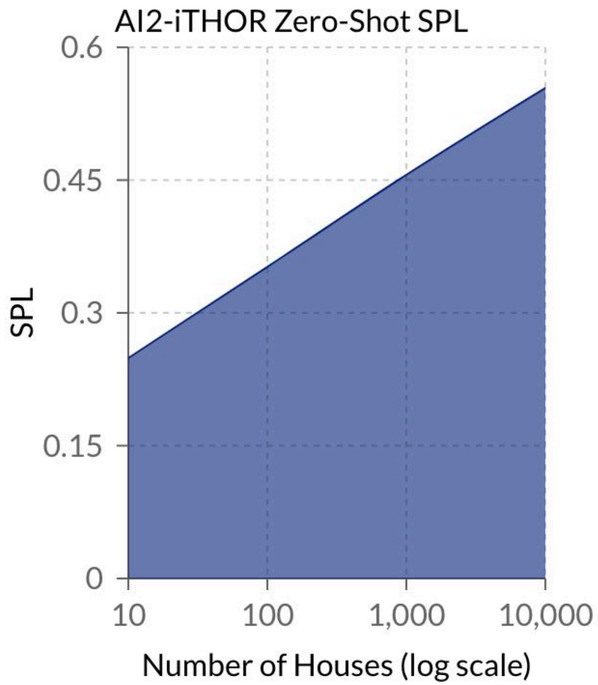


Greater diversity of scenes wins







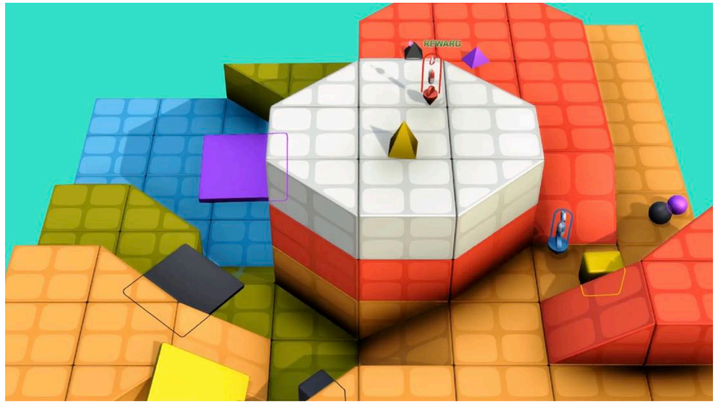


Better off training on a large number of highly diverse scenes than a small number of photorealistic ones

Value of diversity of tasks

DeepMind's XLand: procedurally generate terrains and the rules of the game.

Wide range of "games" requiring different strategies and skills can be defined by specifying goals for agents



Example 1: agent 1 must find a yellow sphere and hold it, while agent 2 must stand by a yellow pyramid

g_1 := `hold(me, yellow sphere)`

g_2 := `near(me, yellow pyramid)`

Example 2: goals for hide and seek: Agent 1 should move to see its opponent. Agent 2's goal is to not be seen by agent 1.

g_1 := `see(me, opponent)`

g_2 := `not(see(opponent, me))`

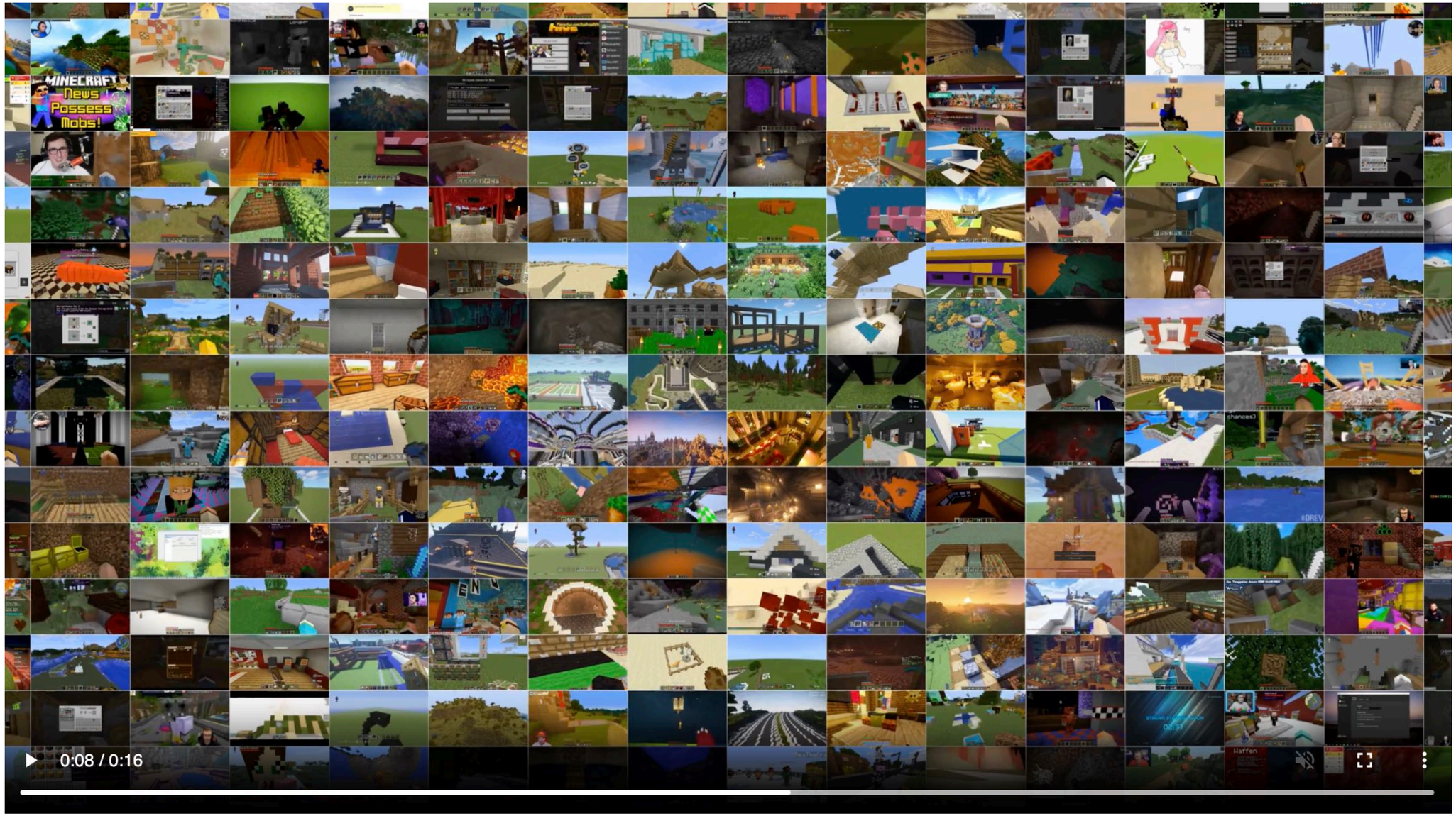
Example 3: encourage teamwork. Give both agents the same goal of moving one object by another

g_1 := `near(yellow pyramid, yellow sphere)`

g_2 := `near(yellow pyramid, yellow sphere)`

The result of this training process is an agent that is generally capable across the held-out evaluation space. Qualitatively, we observe the agent exhibiting behaviours that are generally applicable, rather than optimal for any specific task. Examples of such behaviours include: experimentation through directed exploration until the agent recognises a rewarding state has been achieved; seeking another player out to gather information of its state irrespective of its goal; and tagging another player if it is holding an object that is related to the agent's goal irrespective of that player's intention. We also probe quantitatively the behaviour of agents in test-time multi-agent situations and see evidence of cooperation emerging with training. In addition to the agent exhibiting zero-shot capabilities across a wide evaluation space, we show that finetuning on a new task for just 100 million steps (around 30 minutes of compute in our setup) can lead to drastic increases in performance relative to zero-shot, and relative to training from scratch which often fails completely.

Value of “open worlds”: many possible tasks



Example: learning to perform many MineCraft tasks (MineDojo)

Takeaways

- Higher performance simulation = higher fidelity simulation
  - Interest in high-fidelity simulation to learn skills from inputs that similar to real world inputs (minimize "sim2real" gap)
  - The hope is that skills transfer to real world

- Higher performance simulation = many more [lower fidelity] simulations
  - To learn "foundational" skills and knowledge, evidence suggests more diversity in environments and tasks is better
  - Train pretty-good-across-the-board "generalist" agents that are a good starting point to be quickly "fine tuned" or adapted to specific tasks in the future