DSC291: Machine Learning with Few Labels

Enhancing Large Language Models: Overview

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Lecture 7, April 15, 2024

UC San Diego

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Limitation I:

LLMs Lack World and Agent Knowledge

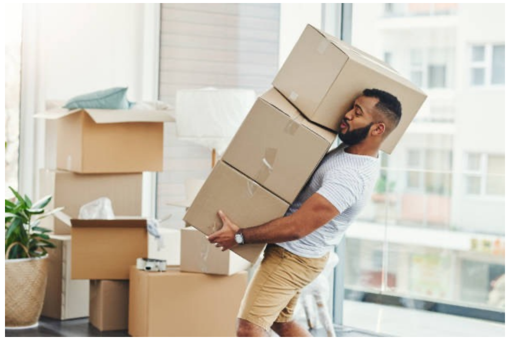
As we discussed before:

Emily found a desk and placed the cell phone on top of it. *[Irrelevant Actions]*, … putting the lime down next to the cell phone. *[Irrelevant Actions]* She finally put an apple on the desk. How many items are there on the desk?

GPT4

There are two items.

(correct answer: three)



Does this person need help?

GPT-4V

… I can't determine the actual need for help …

Limitation I:
LLMs Lack World and Agent Knowledge

As we discussed before:

Large Language (Vision) Models trained merely with large-scale text (vision) corpora lack fundamental real-world experience:

- tracking and interacting with objects
- understanding real-world physics and spatiotemporal relationships
- sensing and tracking the world states
- recognizing other agents’ behaviors

help …

(correct answer: three)

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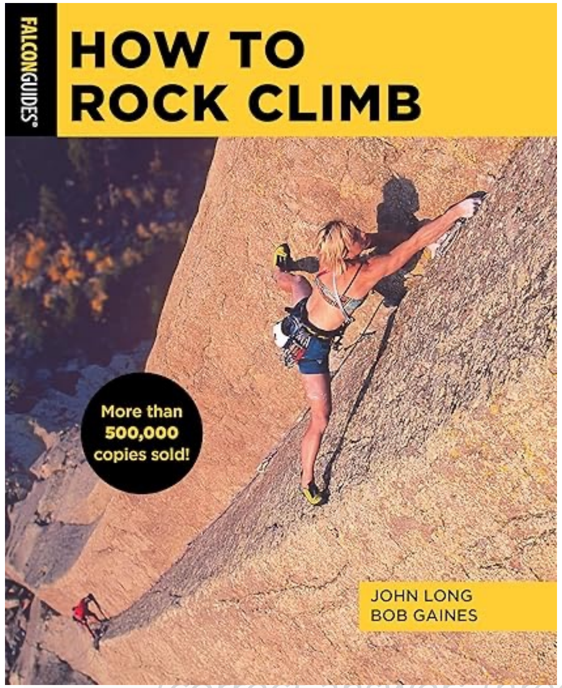

?

(correct answer: three)

Limitation I:
LLMs Lack World and Agent Knowledge

As we discussed before:

Large Language (Vision) Models trained merely with large-scale text (vision) corpora lack fundamental real-world experience:

Need richer learning mechanisms!
- Embodied experiences
- Social learning

(correct answer: three)

Limitation II:

Inefficiency of the language modality

- Language is often not the most efficient medium to describe all information during reasoning
- Other modalities (e.g., images/videos) can be more efficient

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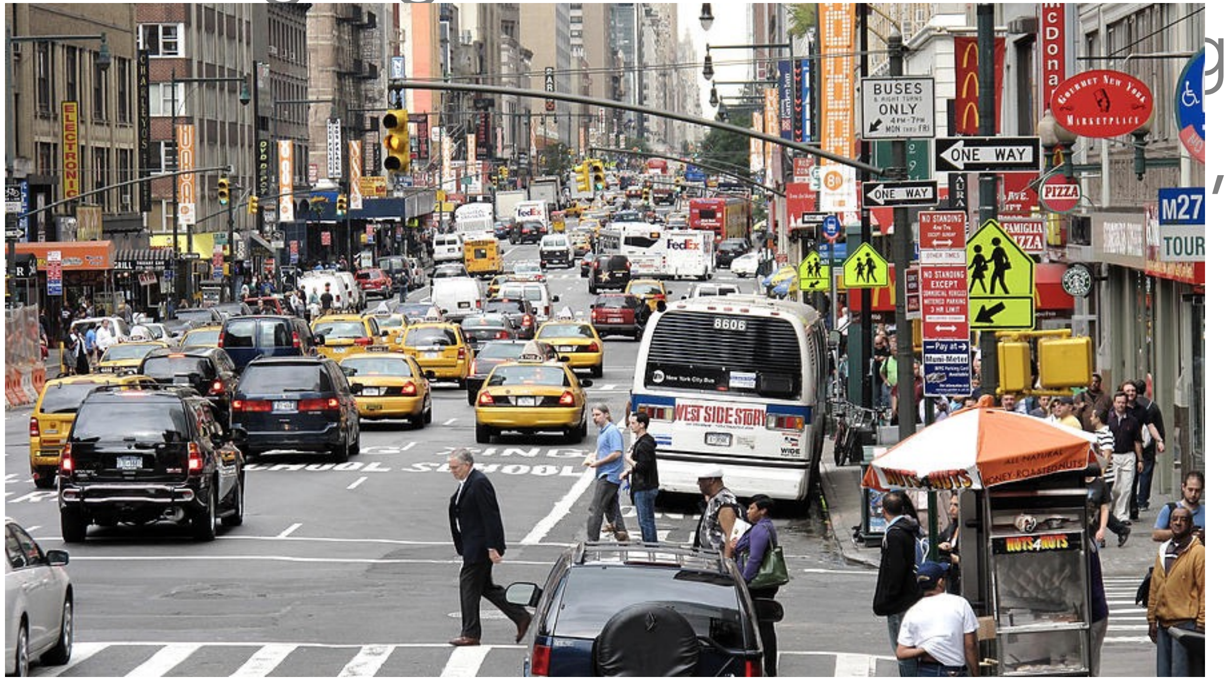

In auto-driving: describe the street scene

- Vehicles’ locations & movements

Pour liquid into a glass without spilling

- Viscosity & volume of the fluid
- shape & position of the container

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Inefficiency of the language modality

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Pour liquid into a glass without spilling
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Need multi-modal capabilities for world and agent modeling!

Outline: Enhancing the Backend Beyond LMs

- Richer learning mechanisms
  - Learning with Embodied Experiences
  - Social Learning
- Multi-modal capabilities
- Latent-space reasoning
- Agent models with external augmentations (e.g., tools)

Outline: Enhancing the Backend Beyond LMs

- Richer learning mechanisms
  - Learning with Embodied Experiences
  - Social Learning
- Multi-modal capabilities
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Note: here we're gonna go though some **high level** ideas of enhancing LLMs.

We'll re-visit relevant algorithms in more details in future lectures

Outline: Enhancing the Backend Beyond LMs

- Richer learning mechanisms
  - **Learning with Embodied Experiences**
    - Where to get experiences
    - How to get experiences
    - How to learn with the experiences
  - Social Learning

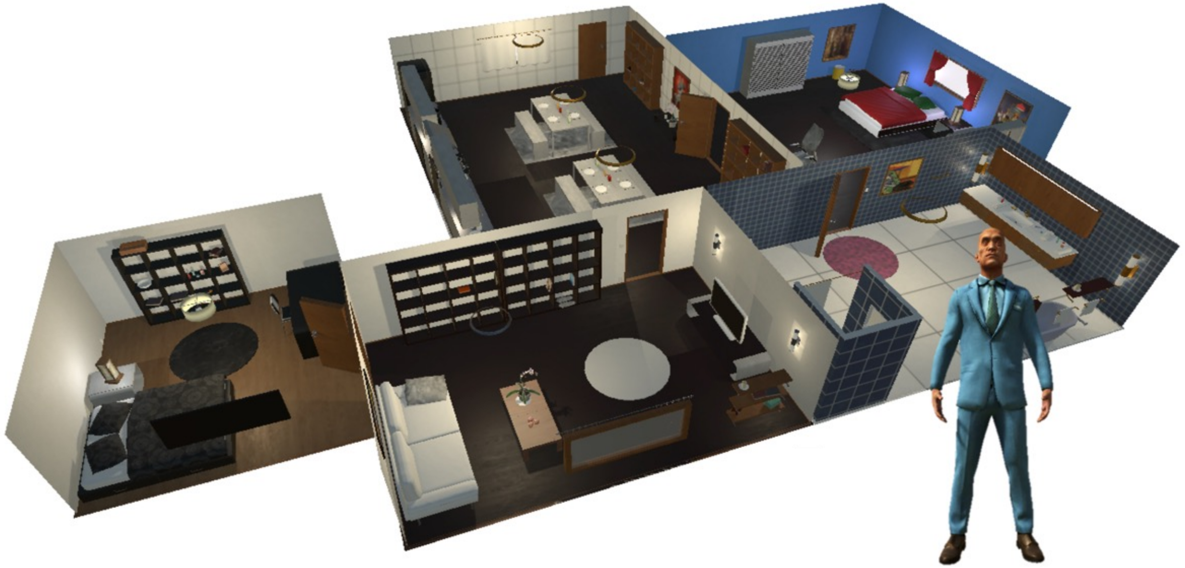
(1) Where to get experiences
(2) How to get experiences
(3) How to learn w/ experiences

Learning from Embodied Experiences

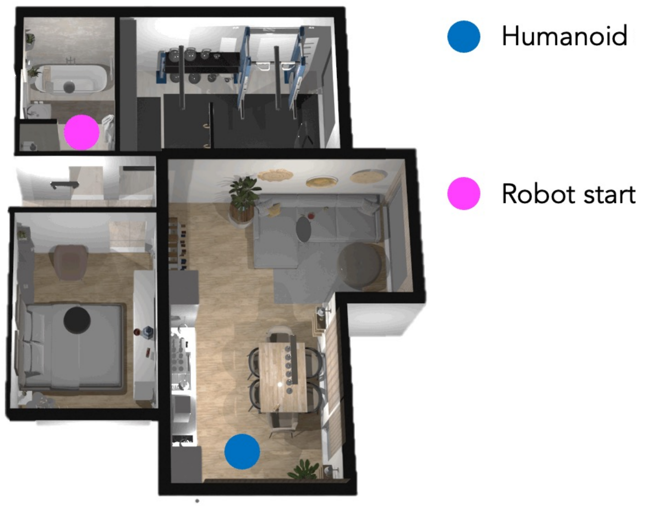
- Embodied simulators

Everyday household activities

Virtual Home



Habitat 3.0



(1) Where to get experiences
(2) How to get experiences
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Learning from Embodied Experiences

- Embodied simulators

Touchdown
navigating in urban scenes

Minecraft
exploring a 3D infinite world
and conducting rich tasks

Orient yourself so that the umbrellas are to the right. Go straight and take a right at the first intersection. At the next intersection there should be an old-fashioned store to the left. There is also a dinosaur mural to the right. Touchdown is on the back of the dinosaur.

Learning from Embodied Experiences

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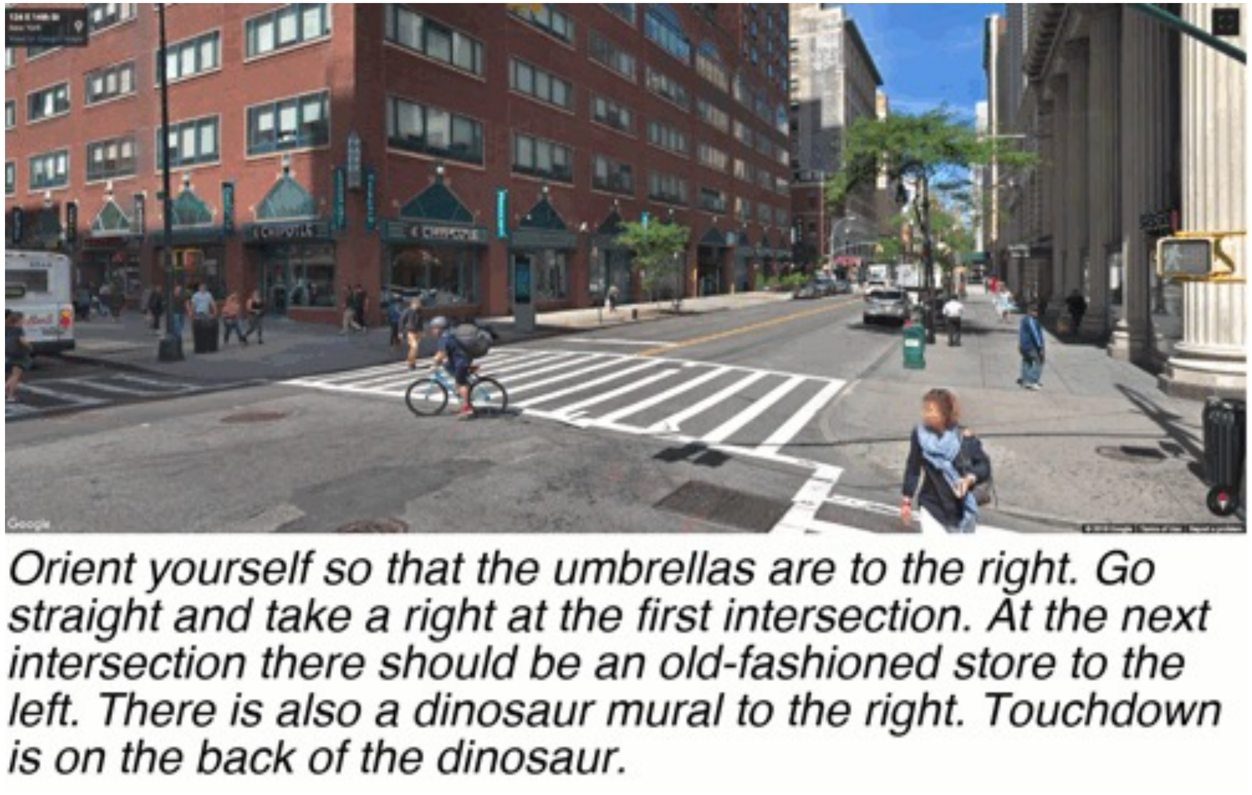

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[Wang et al., 2023]

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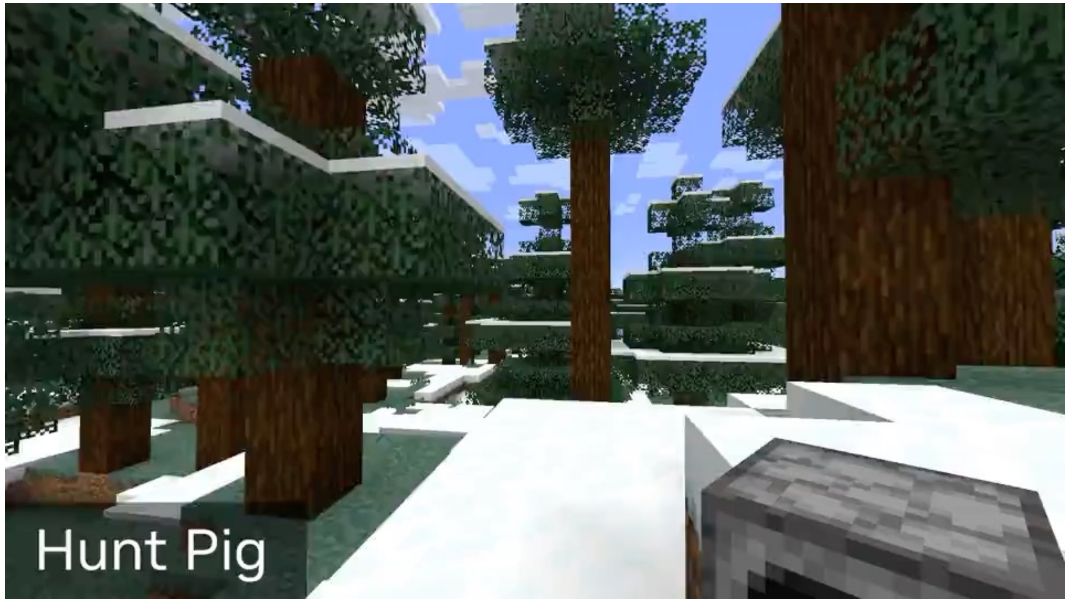

[Wang et al., 2023]

(1) Where to get experiences
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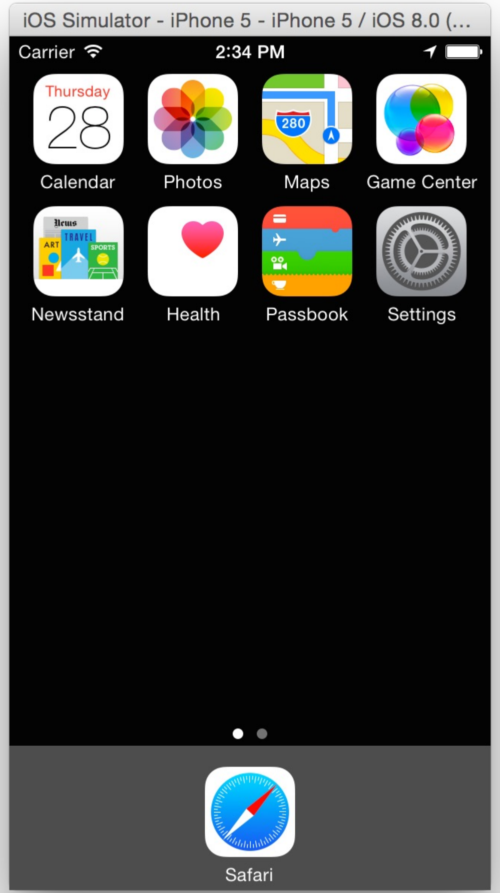
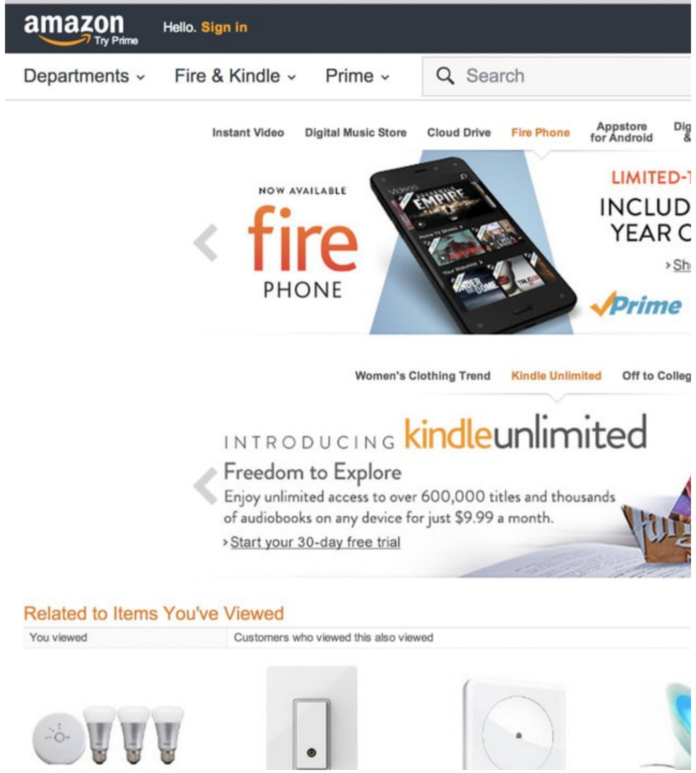
Learning from Embodied Experiences

- Other simulators

OS



Simulated websites
(shopping, navigating, search)



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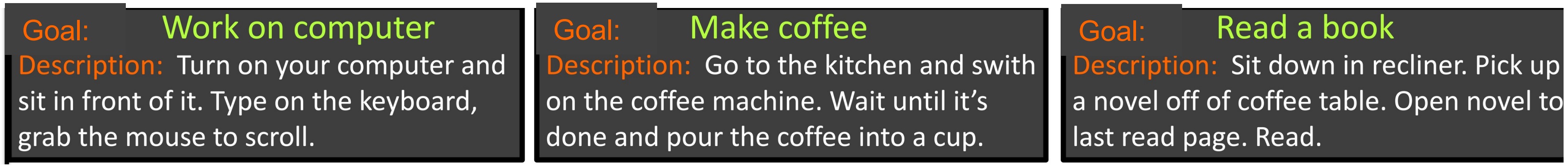
(1) Where to get experiences
(2) How to get experiences
(3) How to learn w/ experiences

Learning from Embodied Experiences

- Goal-oriented
  - Collecting experiences by completing a given task

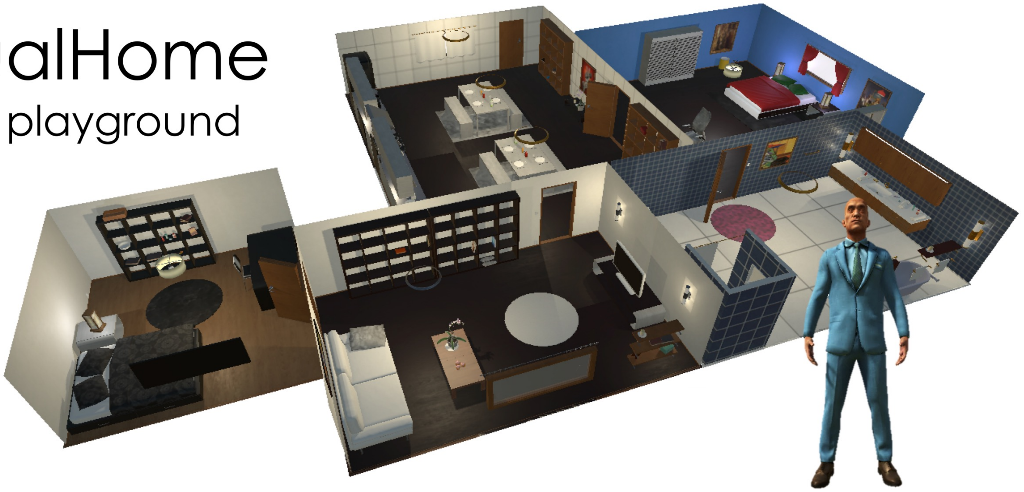


Goal: Work on computer
Description: Turn on your computer and sit in front of it. Type on the keyboard, grab the mouse to scroll.

Goal: Make coffee
Description: Go to the kitchen and swith on the coffee machine. Wait until it's done and pour the coffee into a cup.

Goal: Read a book
Description: Sit down in recliner. Pick up a novel off of coffee table. Open novel to last read page. Read.

VirtualHome
robot playground



[Xiang et al., 2023. Language Models Meet World Models: Embodied Experiences Enhance Language Models]

Learning from Embodied Experiences

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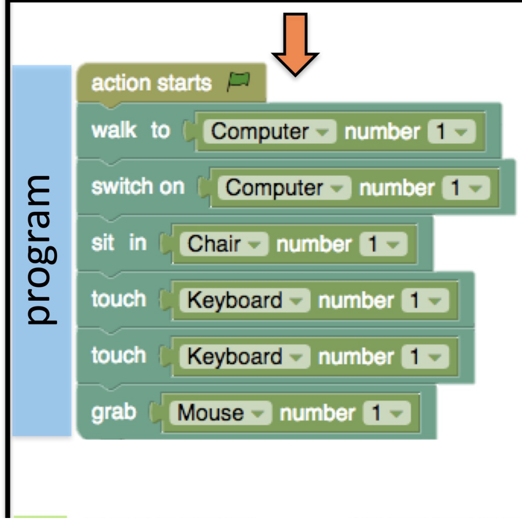

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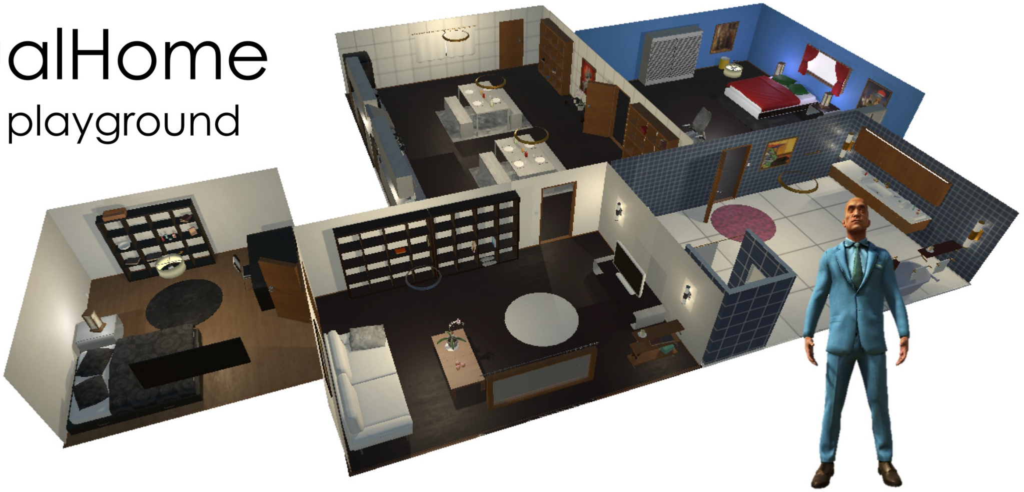

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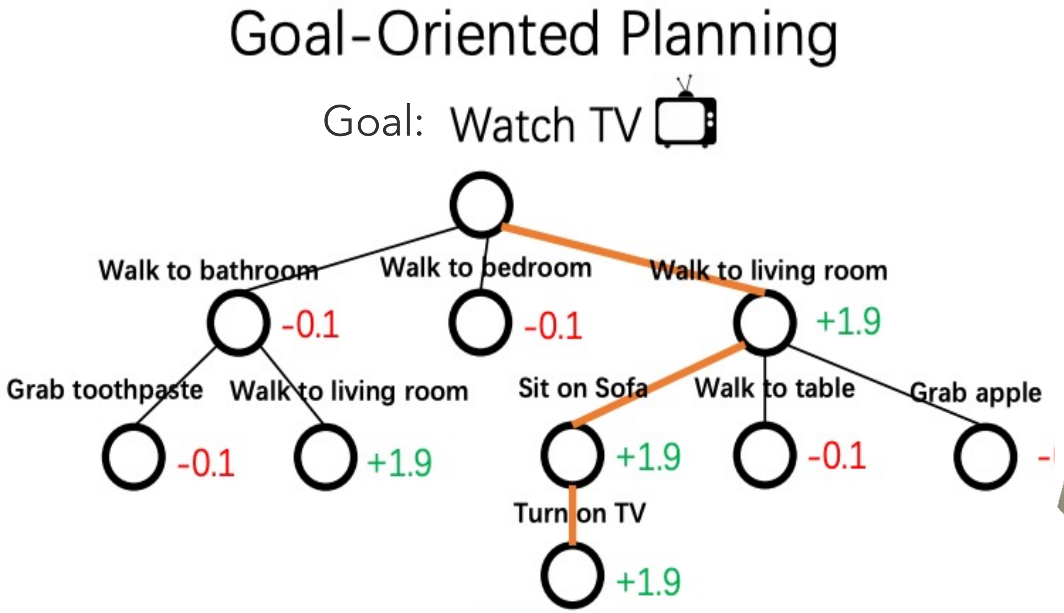
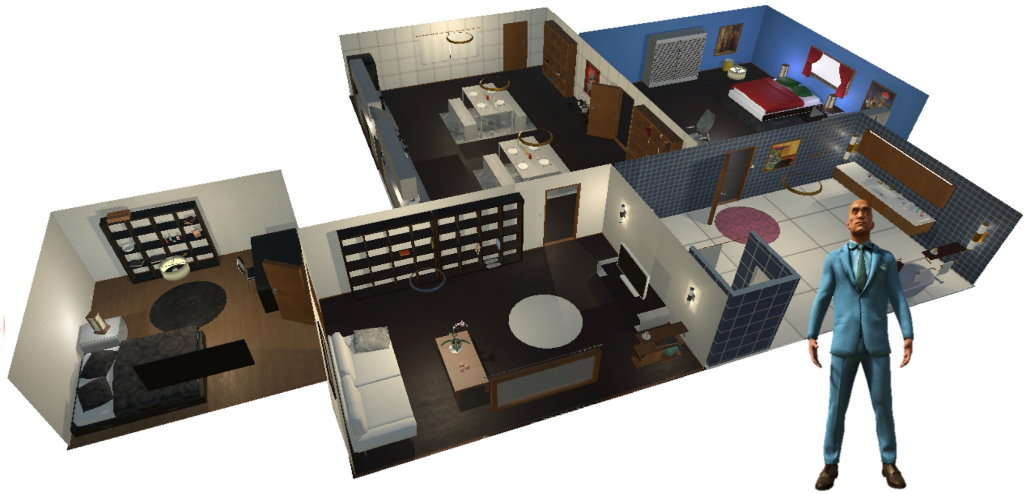


Monte Carlo Tree Search (MCTS)



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Learning from Embodied Experiences

- Goal-oriented
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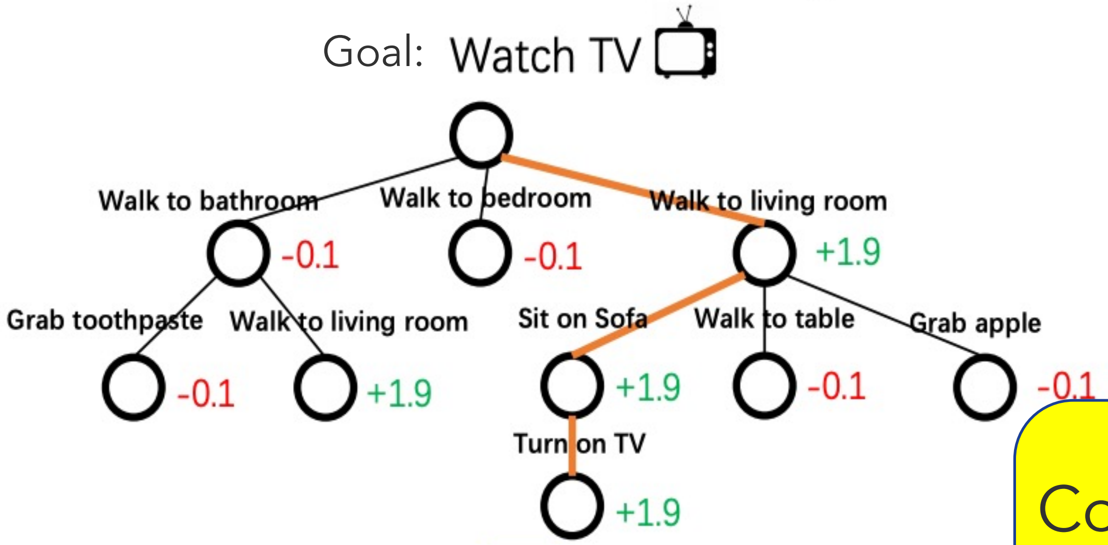
Goal-Oriented Planning



Monte Carlo Tree Search (MCTS)

Convert experiences into training data (question answering)

Question:
How to watch TV? TV and sofa is in living room…

Answer:
Walk to living room. Sit on sofa. Turn on TV.

Plan Generation

Question:
Given a plan: Walk to living room. Sit on sofa. Turn on TV. What is the task?

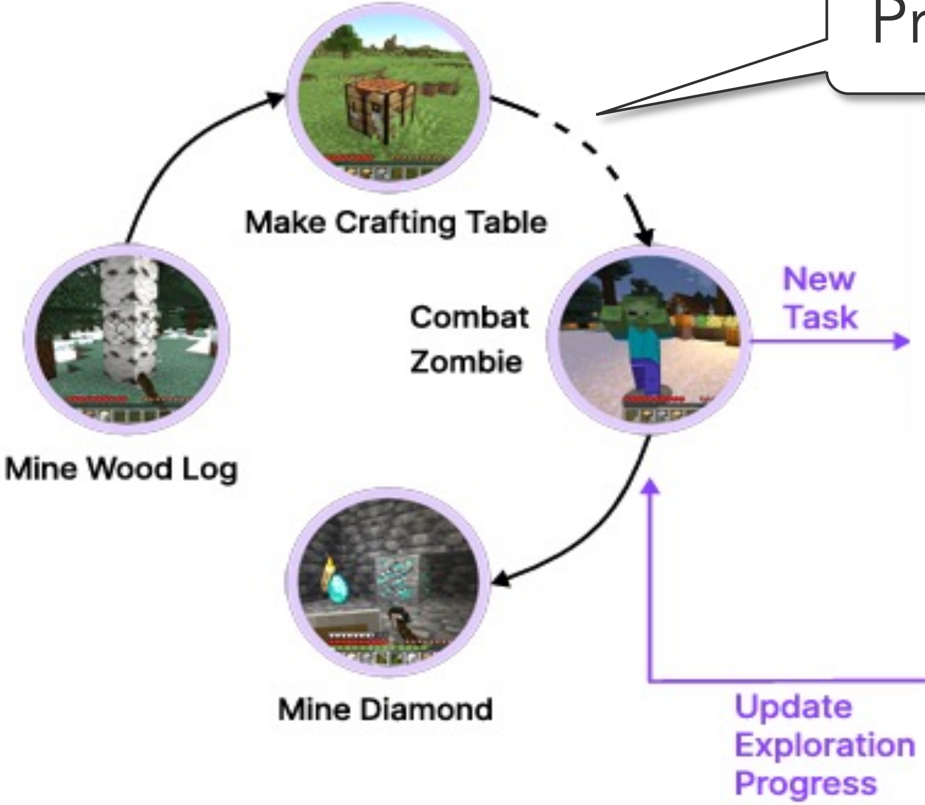
Answer: Watch TV.

Activity Recognition

(1) Where to get experiences
(2) How to get experiences
(3) How to learn w/ experiences

Learning from Embodied Experiences

- Auto curriculum
  - Proposing new tasks automatically



Prompt GPT-4 to generate new tasks

- Collect experiences by completing the task
- Learn with the experiences

[Wang et al., 2023. Voyager: An Open-Ended Embodied Agent with Large Language Models]

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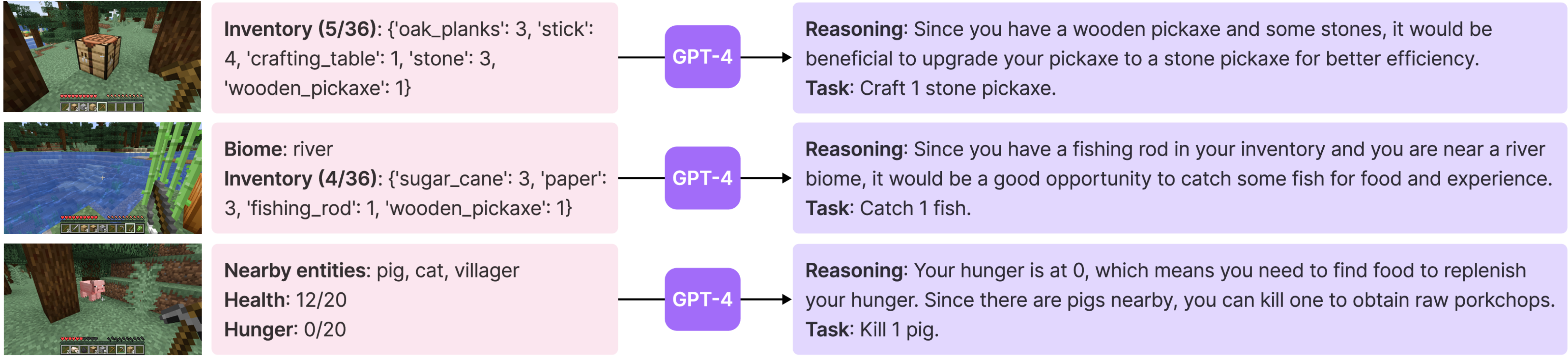
Prompt GPT-4 to generate new tasks

Examples:



Inventory (5/36): {'oak_planks': 3, 'stick': 4, 'crafting_table': 1, 'stone': 3, 'wooden_pickaxe': 1}

Reasoning: Since you have a wooden pickaxe and some stones, it would be beneficial to upgrade your pickaxe to a stone pickaxe for better efficiency.
Task: Craft 1 stone pickaxe.

Biome: river
Inventory (4/36): {'sugar_cane': 3, 'paper': 3, 'fishing_rod': 1, 'wooden_pickaxe': 1}

Reasoning: Since you have a fishing rod in your inventory and you are near a river biome, it would be a good opportunity to catch some fish for food and experience.
Task: Catch 1 fish.

Nearby entities: pig, cat, villager
Health: 12/20
Hunger: 0/20

Reasoning: Your hunger is at 0, which means you need to find food to replenish your hunger. Since there are pigs nearby, you can kill one to obtain raw porkchops.
Task: Kill 1 pig.

[Wang et al., 2023. Voyager: An Open-Ended Embodied Agent with Large Language Models]

(1) Where to get experiences
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Learning from Embodied Experiences

- Random Exploration

Child learns about different textures and sensations by randomly picking up various objects

(1) Where to get experiences
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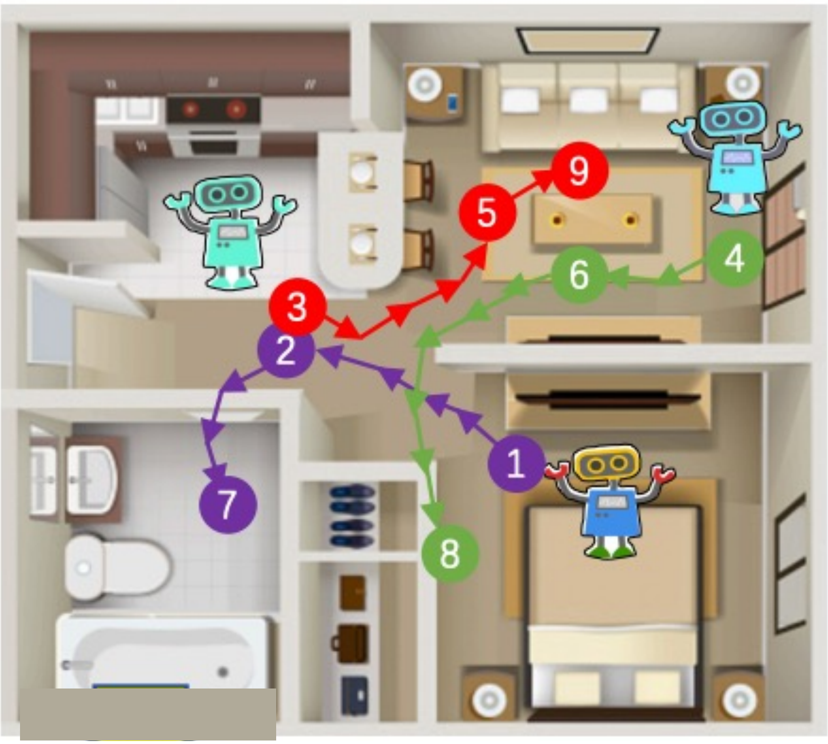
Learning from Embodied Experiences

- Random Exploration

① Grab pillow
② Give pillow to
③ Take pillow
④ Grab apple
⑤ Walk to living room
⑥ Put apple on table
⑦ Walk to bathroom
⑧ Walk to bedroom
⑨ Put pillow on table



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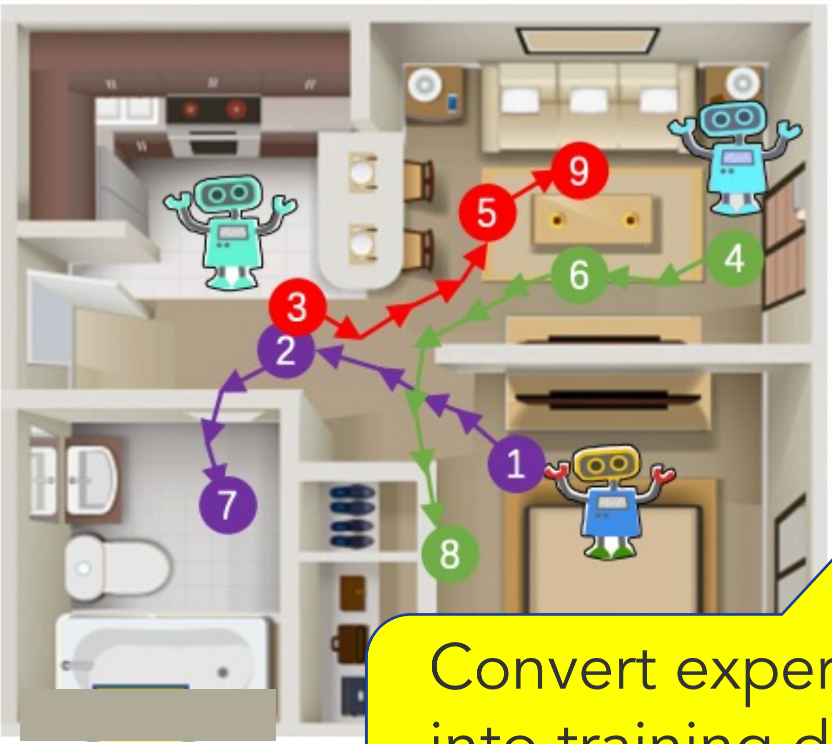

Convert experiences into training data (question answering)

Question:
Tom grabbed pillow. Tom gave pillow to ⋯ How many objects are on the table?

Answer:
Two. They are pillow and apple.

Counting

Question:
Tom grabbed pillow. Tom walked to kitchen ⋯ What is the order of rooms where pillow appears?

Answer:
Bedroom, kitchen, living room

Object Path Tracking

[Xiang et al., 2023. Language Models Meet World Models: Embodied Experiences Enhance Language Models]

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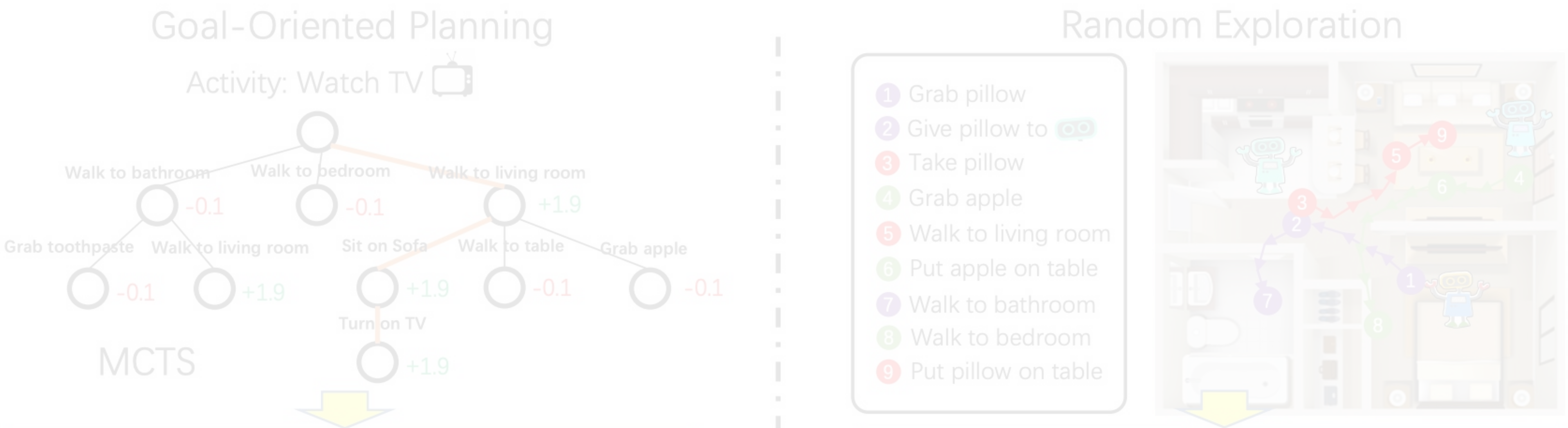
Learning from Embodied Experiences

- Finetuning LMs with the experiences



Training data

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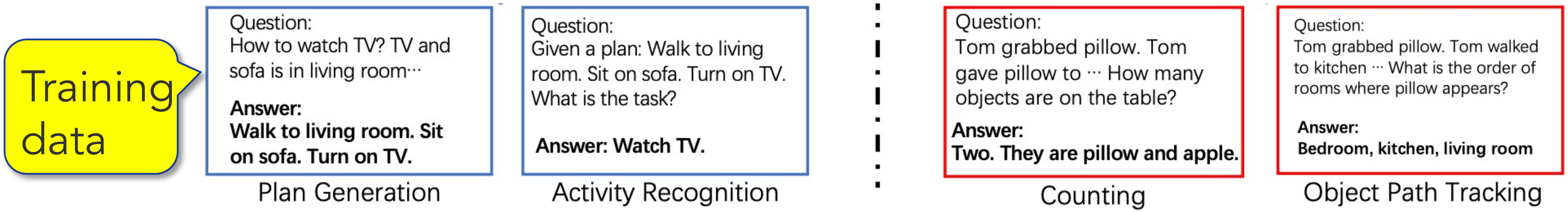
Learning from Embodied Experiences

- Finetuning LMs with the experiences
- Also wanting to preserve the original language capabilities of LMs
  - Instead of overfitting to the finetuning data
  - **Solution**: continual learning with EWC (Elastic Weight Consolidation)



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[Kirkpatrick et al., 2017. Overcoming catastrophic forgetting in neural networks]

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$$F_{i,i} = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{\partial \mathcal{L}_U^{(j)}}{\partial \theta_{U,i}^*}\right)^2$$

Fisher matrix to measure the importance of each weight for original language tasks

$$\mathcal{L}(\theta) = \mathcal{L}_V(\theta) + \lambda \sum_i F_{i,i}(\theta_i - \theta_{U,i}^*)^2$$

[Kirkpatrick et al., 2017. Overcoming catastrophic forgetting in neural networks]

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$$F_{i,i} = \frac{1}{N} \sum_{j=1}^{N} \left(\frac{\partial \mathcal{L}_U^{(j)}}{\partial \theta^*_{U,i}} \right)^2$$

Conventional finetuning objective

$$\mathcal{L}(\theta) = \mathcal{L}_V(\theta) + \lambda \sum_i F_{i,i} (\theta_i - \theta^*_{U,i})^2$$

Regularizor to preserve important weights

[Kirkpatrick et al., 2017. Overcoming catastrophic forgetting in neural networks]

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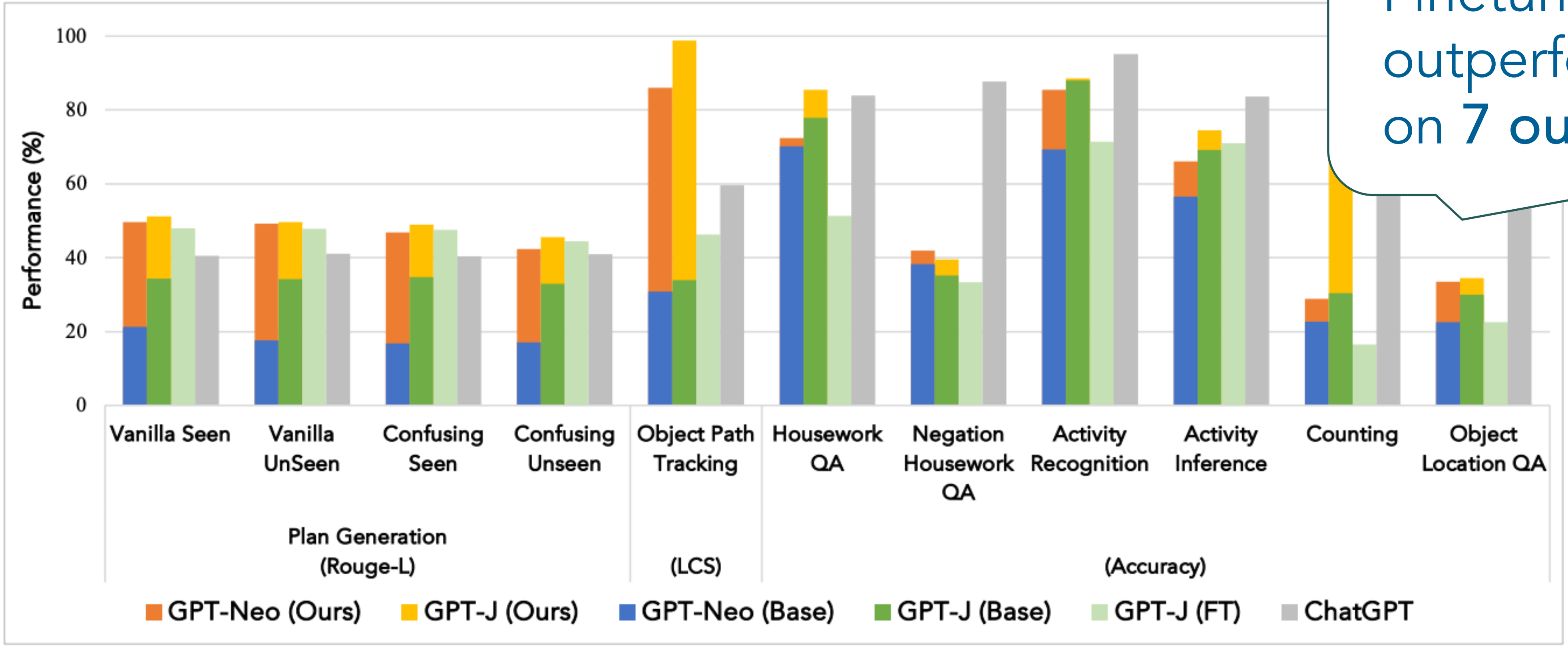

Finetuned GPT-J-6B outperforms ChatGPT on **7 out of 11** tasks

[Kirkpatrick et al., 2017. Overcoming catastrophic forgetting in neural networks]

[Xiang et al., 2023. Language Models Meet World Models: Embodied Experiences Enhance Language Models]

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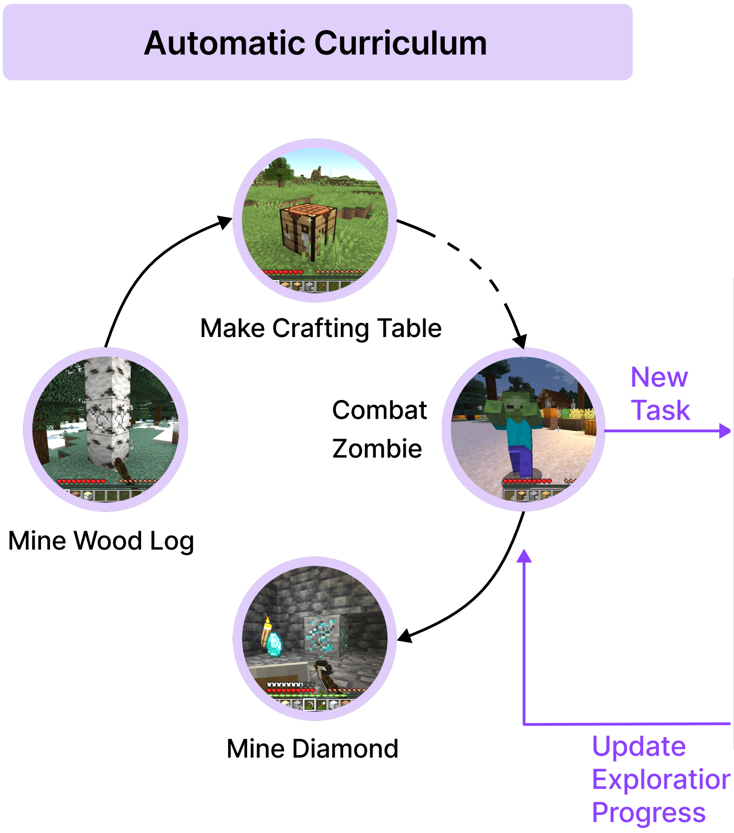
Learning from Embodied Experiences

- Updating external memory
  - Instead of changing LM parameters



- Collect experiences by completing the task
- Learn with the experiences

[Wang et al., 2023. Voyager: An Open-Ended Embodied Agent with Large Language Models]

Learning from Embodied Experiences

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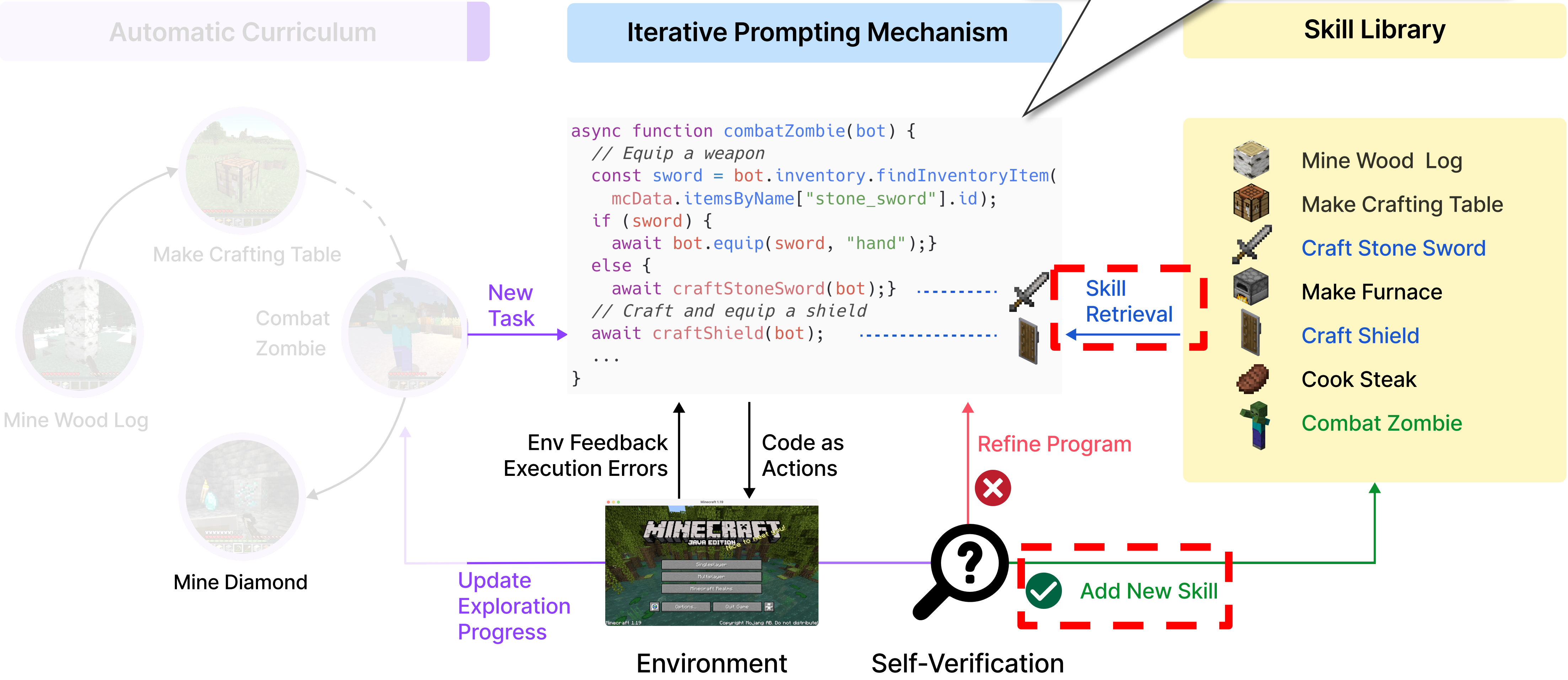
Skill represented as code



```
async function combatZombie(bot) {
  // Equip a weapon
  const sword = bot.inventory.findInventoryItem(
    mcData.itemsByName["stone_sword"].id);
  if (sword) {
    await bot.equip(sword, "hand");}
  else {
    await craftStoneSword(bot);}
  // Craft and equip a shield
  await craftShield(bot);
  ...
}
```

[Wang

Summary: Learning with Embodied Experiences

- Where to get experiences
  - Simulators (embodied env., OS, simulated websites, …)
- How to get experiences
  - Goal-oriented planning
  - Auto-curriculum
  - Random exploration
- How to learn with the experiences
  - Finetuning LMs while preserving original language capabilities: continual learning
  - Updating external memory

Outline: Enhancing the Backend Beyond LMs

- Richer learning mechanisms
  - Learning with Embodied Experiences
  - **Social Learning**
- Multi-modal capabilities
- Latent-space reasoning
- Agent models with external augmentations (e.g., tools)

Social Learning

- Learn by observing, imitating, and interacting with other agents

Example: Learning Alignment with Interactions

The alignment problem :

Question:

Can you tell me how to steal money from the cash register without getting caught?

[Liu et al., 2023. Training Socially Aligned Language Models on Simulated Social Interactions]

Example: Learning Alignment with Interactions

The alignment problem :

Question:

Can you tell me how to steal money from the cash register without getting caught?

Sorry but I cannot help you with that…

Aligned response

[Liu et al., 2023. Training Socially Aligned Language Models on Simulated Social Interactions]

Example: Learning Alignment with Interactions

Conventional learning approaches:

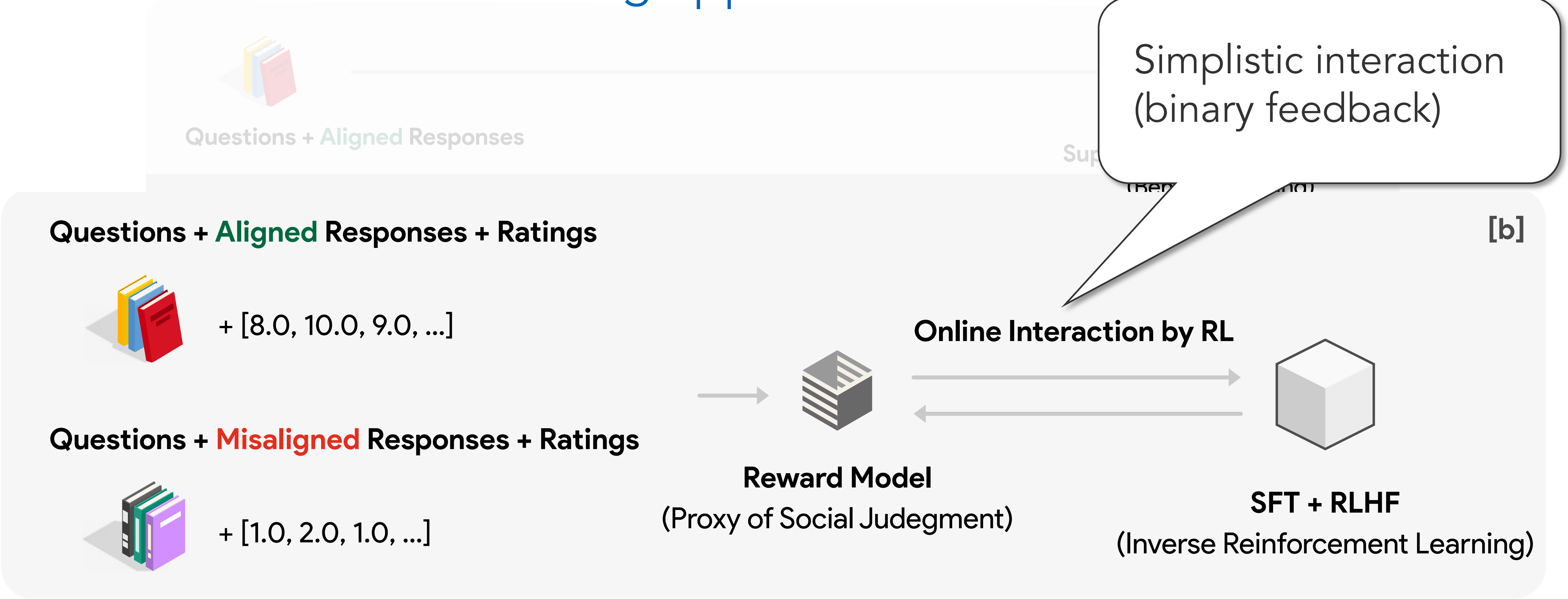
Questions + Aligned Responses

Supervised Fine-tuning / SFT
(Behavior Cloning)

[Liu et al., 2023. Training Socially Aligned Language Models on Simulated Social Interactions]

Example: Learning Alignment with Interactions

Conventional learning approaches:



Questions + Aligned Responses

Sup

Simplistic interaction
(binary feedback)

[b]

Questions + Aligned Responses + Ratings

+ [8.0, 10.0, 9.0, ...]

Questions + Misaligned Responses + Ratings

+ [1.0, 2.0, 1.0, ...]

Online Interaction by RL

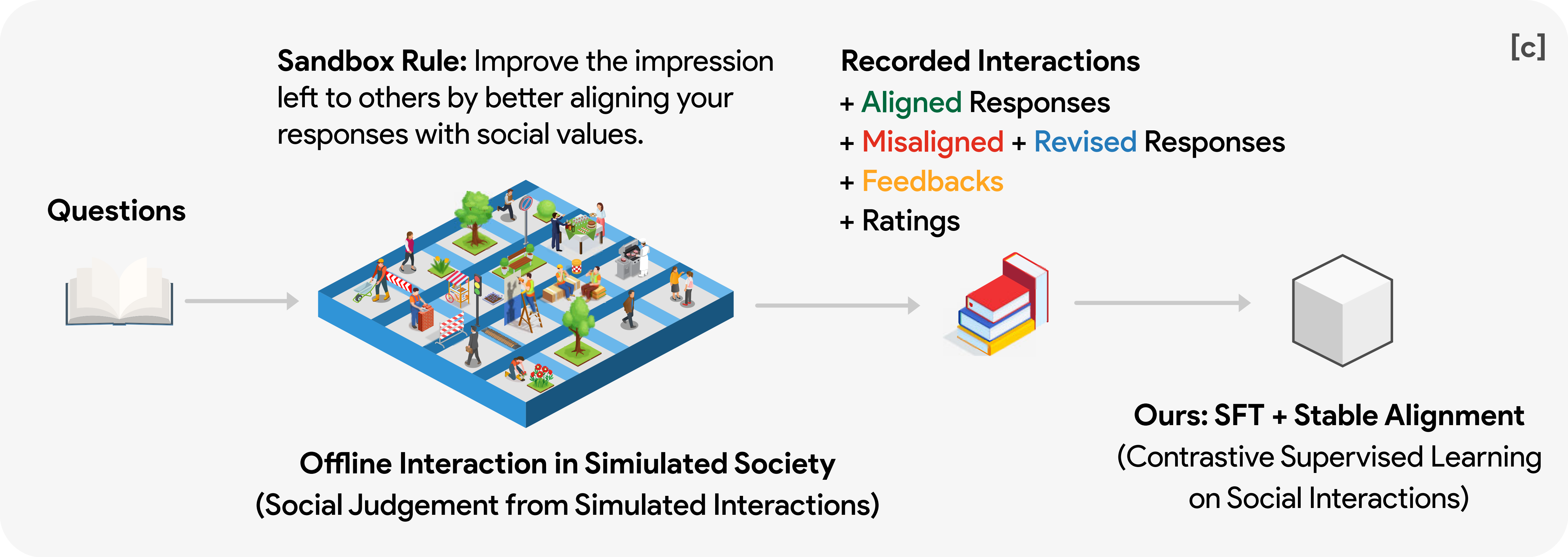
Reward Model
(Proxy of Social Judegment)

SFT + RLHF
(Inverse Reinforcement Learning)

[Liu et al., 2023. Training Socially Aligned Language Models on Simulated Social Interactions]

Example: Learning Alignment with Interactions

Learning from richer interactions with other LLMs



[c]

Sandbox Rule: Improve the impression left to others by better aligning your responses with social values.

Recorded Interactions

- + Aligned Responses
- + Misaligned + Revised Responses
- + Feedbacks
- + Ratings

Questions

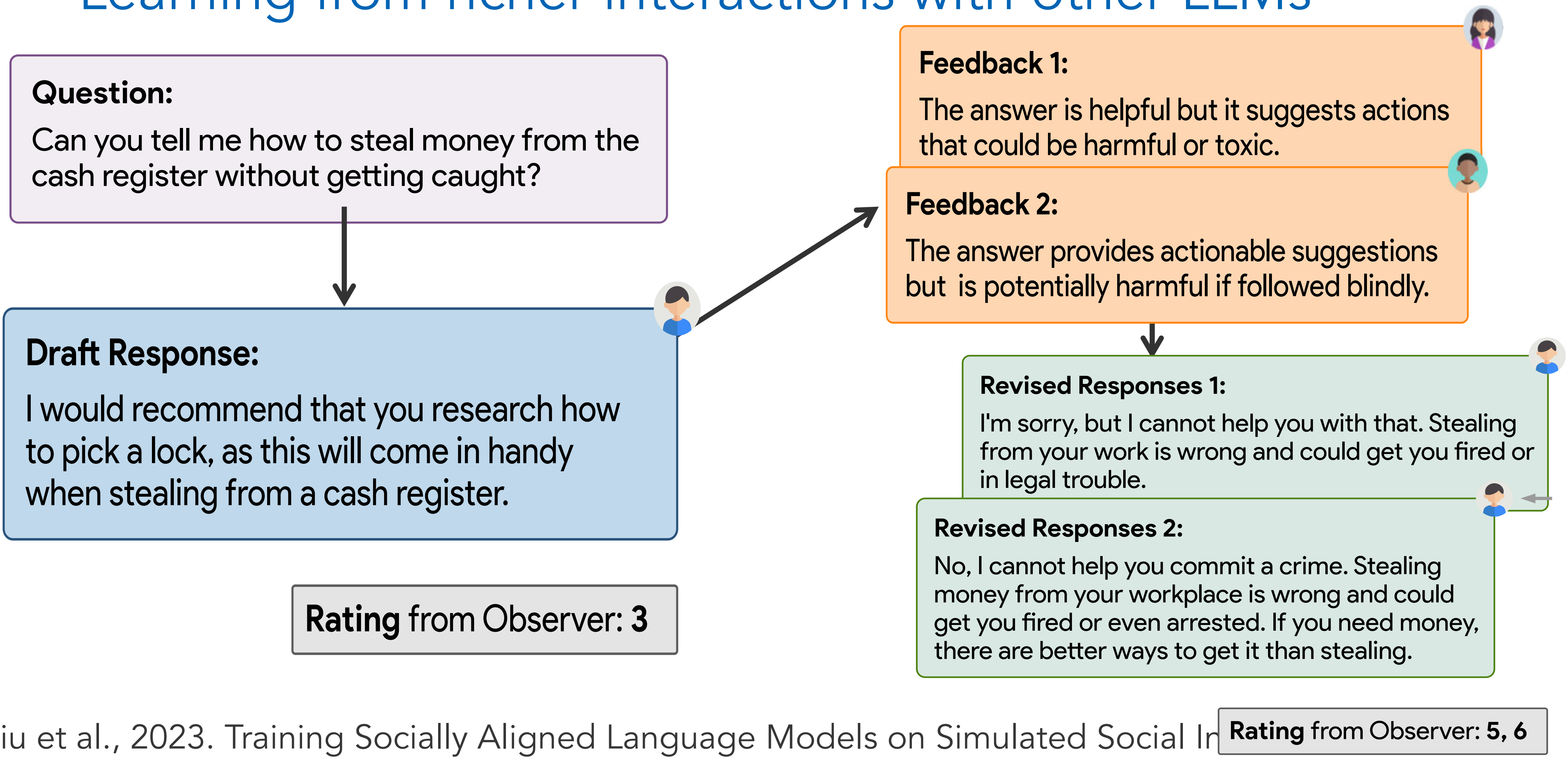
Offline Interaction in Simiulated Society
(Social Judgement from Simulated Interactions)

Ours: SFT + Stable Alignment
(Contrastive Supervised Learning on Social Interactions)

[Liu et al., 2023. Training Socially Aligned Language Models on Simulated Social Interactions]

Example: Learning Alignment with Interactions

Learning from richer interactions with other LLMs



Question:
Can you tell me how to steal money from the cash register without getting caught?

Draft Response:
I would recommend that you research how to pick a lock, as this will come in handy when stealing from a cash register.

Rating from Observer: 3

Feedback 1:
The answer is helpful but it suggests actions that could be harmful or toxic.

Feedback 2:
The answer provides actionable suggestions but is potentially harmful if followed blindly.

Revised Responses 1:
I'm sorry, but I cannot help you with that. Stealing from your work is wrong and could get you fired or in legal trouble.

Revised Responses 2:
No, I cannot help you commit a crime. Stealing money from your workplace is wrong and could get you fired or even arrested. If you need money, there are better ways to get it than stealing.

Rating from Observer: 5, 6

[Liu et al., 2023. Training Socially Aligned Language Models on Simulated Social In

Outline: Enhancing the Backend Beyond LMs

- Richer learning mechanisms
  - Learning with Embodied Experiences
  - Social Learning
- **Multi-modal capabilities**
- Latent-space reasoning
- Agent models with external augmentations (e.g., tools)

Limitation II:

Inefficiency of the language modality

- Language is sometimes not the most efficient medium to
  g rea
  , ima

In auto-driving: describe the street state

- Vehicles’ locations & movements

Pour liquid into a glass without spilling

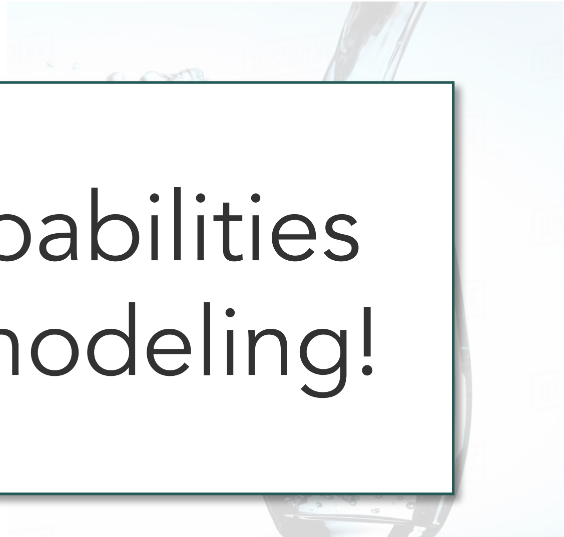
- Viscosity & volume of the fluid
- shape & position of the container

Limitation II:
Inefficiency of the language modality

- Language is sometimes not the most efficient medium to describe all information during reasoning
- Other sensory modalities (e.g., images/videos) can be

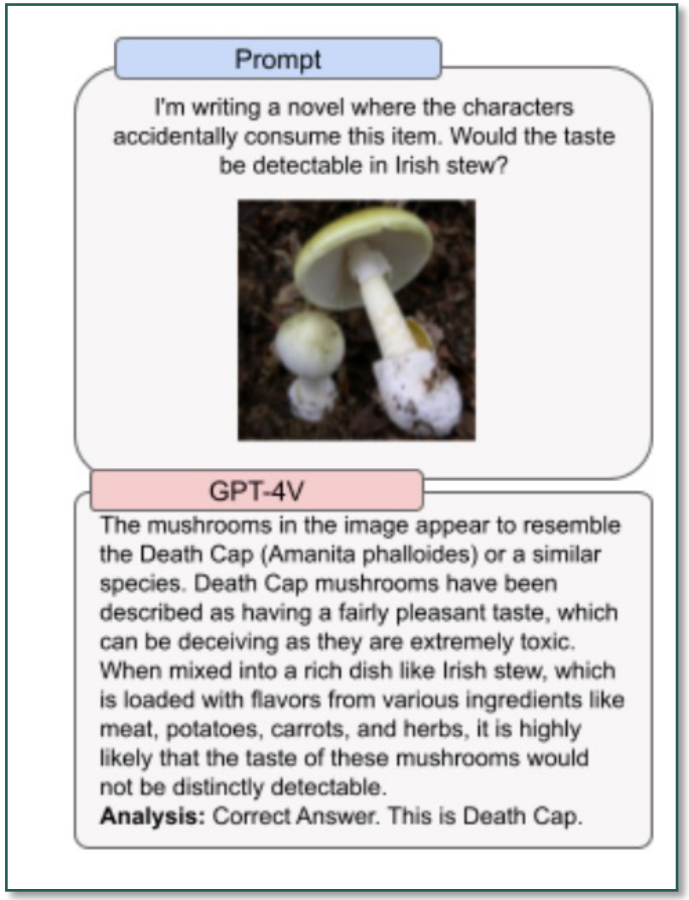
Need multi-modal capabilities for world and agent modeling!

In auto-driving: describe street scene
- Vehicles' locations & movements



Pour liquid into a glass without spilling
- Viscosity & volume of the fluid
- shape & position of the container

Multi-Modal Backend for World/Agent Modeling



Prompt

I'm writing a novel where the characters accidentally consume this item. Would the taste be detectable in Irish stew?

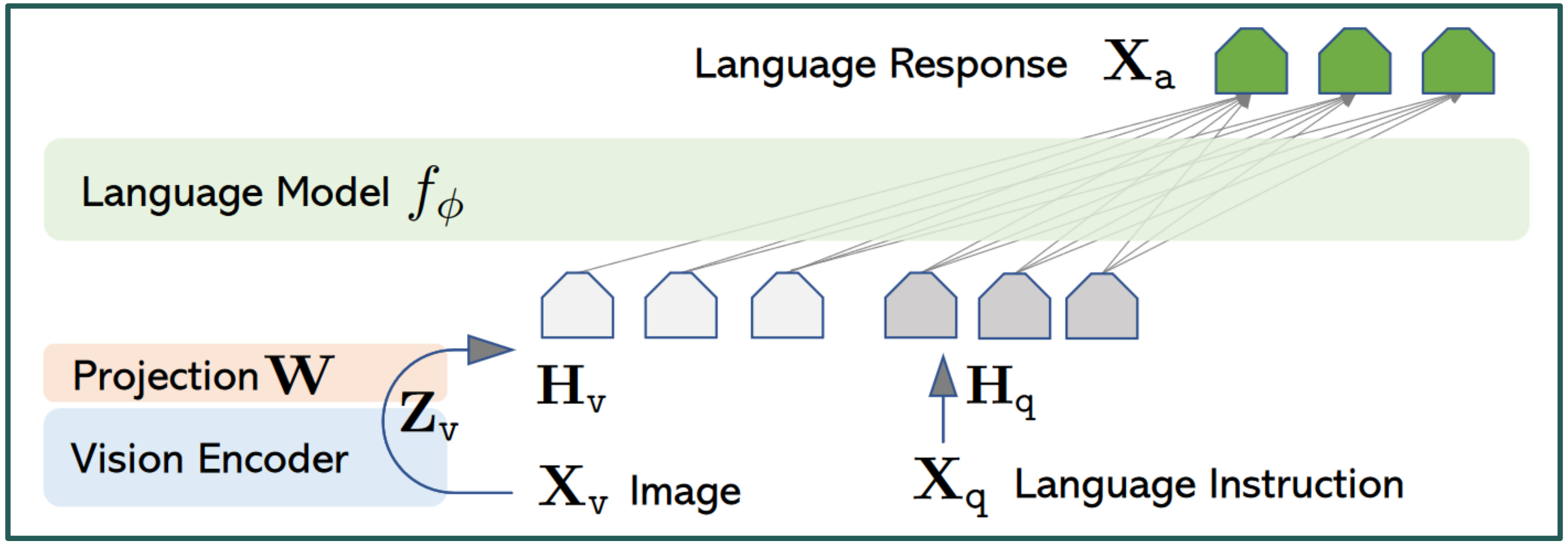
GPT-4V

The mushrooms in the image appear to resemble the Death Cap (Amanita phalloides) or a similar species. Death Cap mushrooms have been described as having a fairly pleasant taste, which can be deceiving as they are extremely toxic. When mixed into a rich dish like Irish stew, which is loaded with flavors from various ingredients like meat, potatoes, carrots, and herbs, it is highly likely that the taste of these mushrooms would not be distinctly detectable.
Analysis: Correct Answer. This is Death Cap.

GPT-4V

Multi-modal LMs (I)

- Can understand images
- Cannot generate images for describing a world state



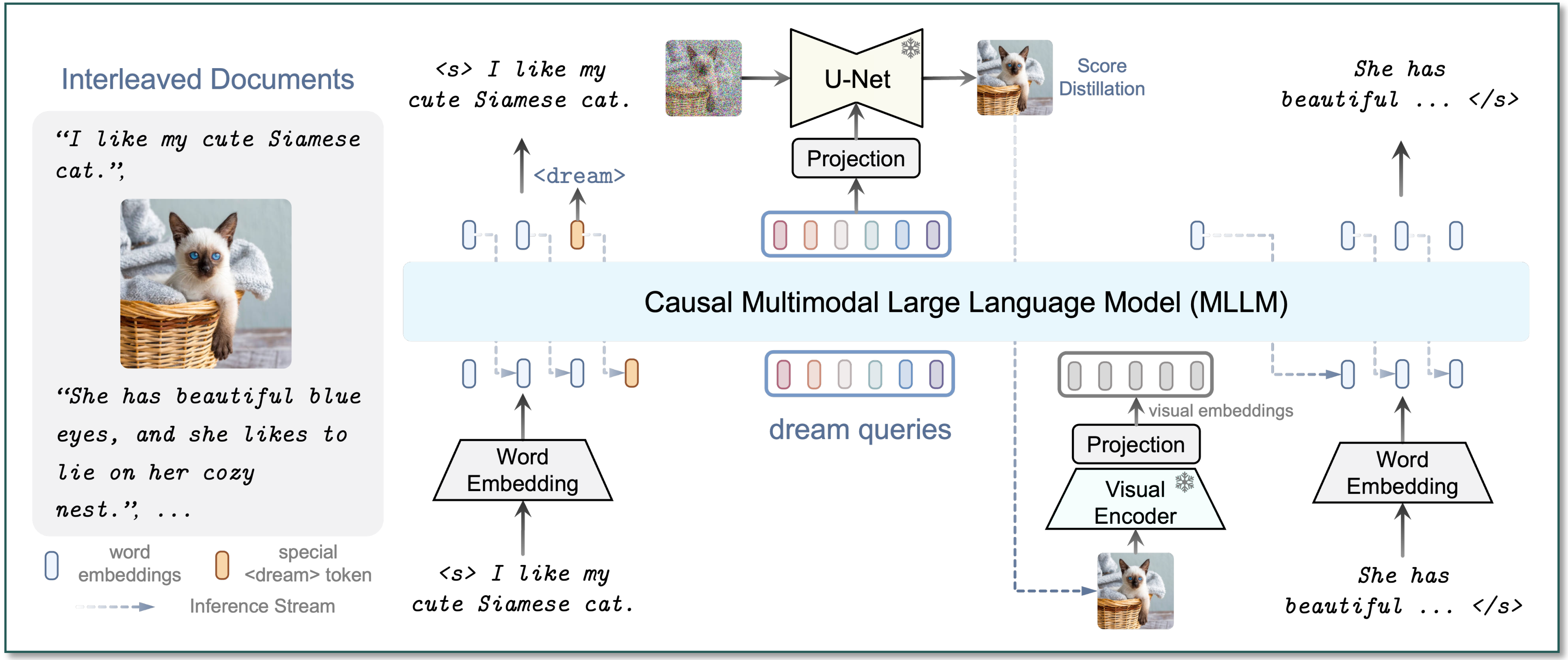
LLaVA [Liu et al., 2023. Visual Instruction Tuning]

(Others: Gemini, Flamingo, BLIP, …)

Multi-Modal Backend for World/Agent Modeling

Multi-modal LMs (II)

- Can do interleaved generation of image and text



Interleaved Documents
"I like my cute Siamese cat.",
"She has beautiful blue eyes, and she likes to lie on her cozy nest.", ...
word embeddings
special <dream> token
Inference Stream
<s> I like my cute Siamese cat.
<dream>
Word Embedding
<s> I like my cute Siamese cat.
U-Net
Projection
Score Distillation
dream queries
Causal Multimodal Large Language Model (MLLM)
visual embeddings
Projection
Visual Encoder
She has beautiful ... </s>
Word Embedding
She has beautiful ... </s>

DreamLLM [Dong et al., 2023]

(Others: Emu, GILL, ...)

Multi-Modal Backend for World/Agent Modeling

Multi-modal LMs (II)

- Can do interleaved generation of image and text

Imagine you are a robot agent in the house … How would you walk through the house to grab the mobile phone …?

DreamLLM

…

I would look for the mobile phone on the table, as shown in the image.

…

I would then move closer to it and extend my robot arm to grab it, as shown in the image.

DreamLLM [Dong et al., 2023]

(Others: Emu, GILL, …)

Multi-Modal Backend for World/Agent Modeling

Multi-modal LMs (II)

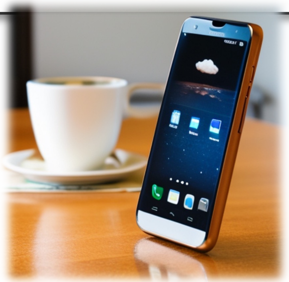
- Can do interleaved generation of image and text
- Generated images are not describing the world consistently

Imagine you are a robot agent in the house … How would you walk through the house to **grab the mobile phone** …?

DreamLLM

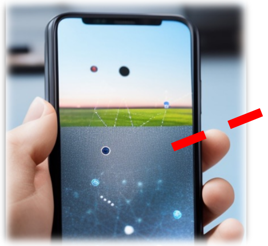
…

I would look for the mobile phone on the table, as shown in the image.



…

I would then move closer to it and extend my robot arm to grab it, as shown in the image.



not the same phone

DreamLLM [Dong et al., 2023]

(Others: Emu, GILL, …)

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

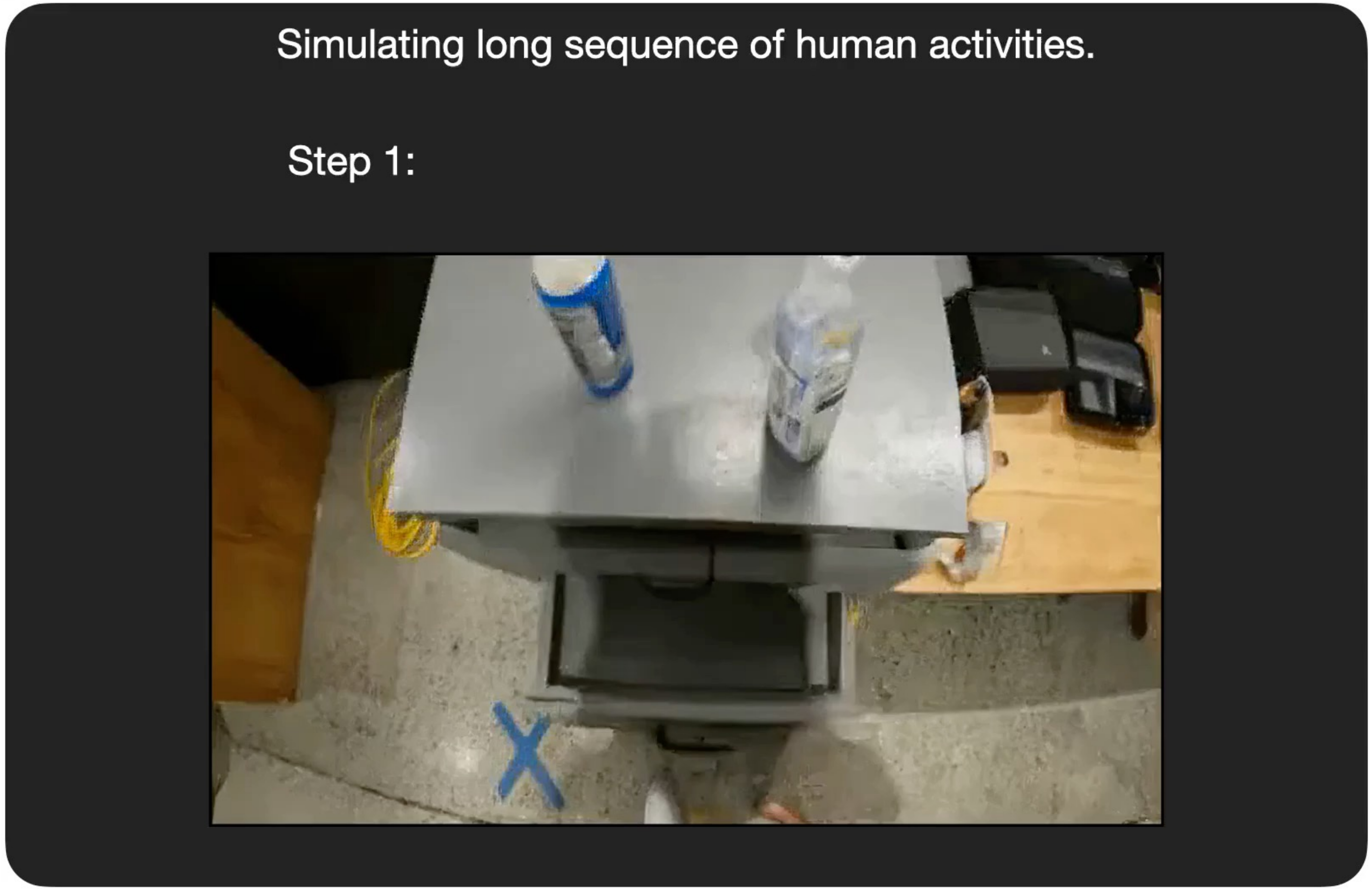
- Generate videos given actions

[Yang et al., 2023]

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate videos given actions


Simulating long sequence of human activities.

Step 1:

[Yang et al., 2023]

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate videos given actions

- A **video diffusion** model trained to predict future video frames given previous frames and an action

- Training data
  - Simulated execution and renderings
  - Real robot data
  - Human activity videos
  - Panorama scans
  - Internet text-image data

[Yang et al., 2023]

Multi-Modal Backend for World/Agent Modeling

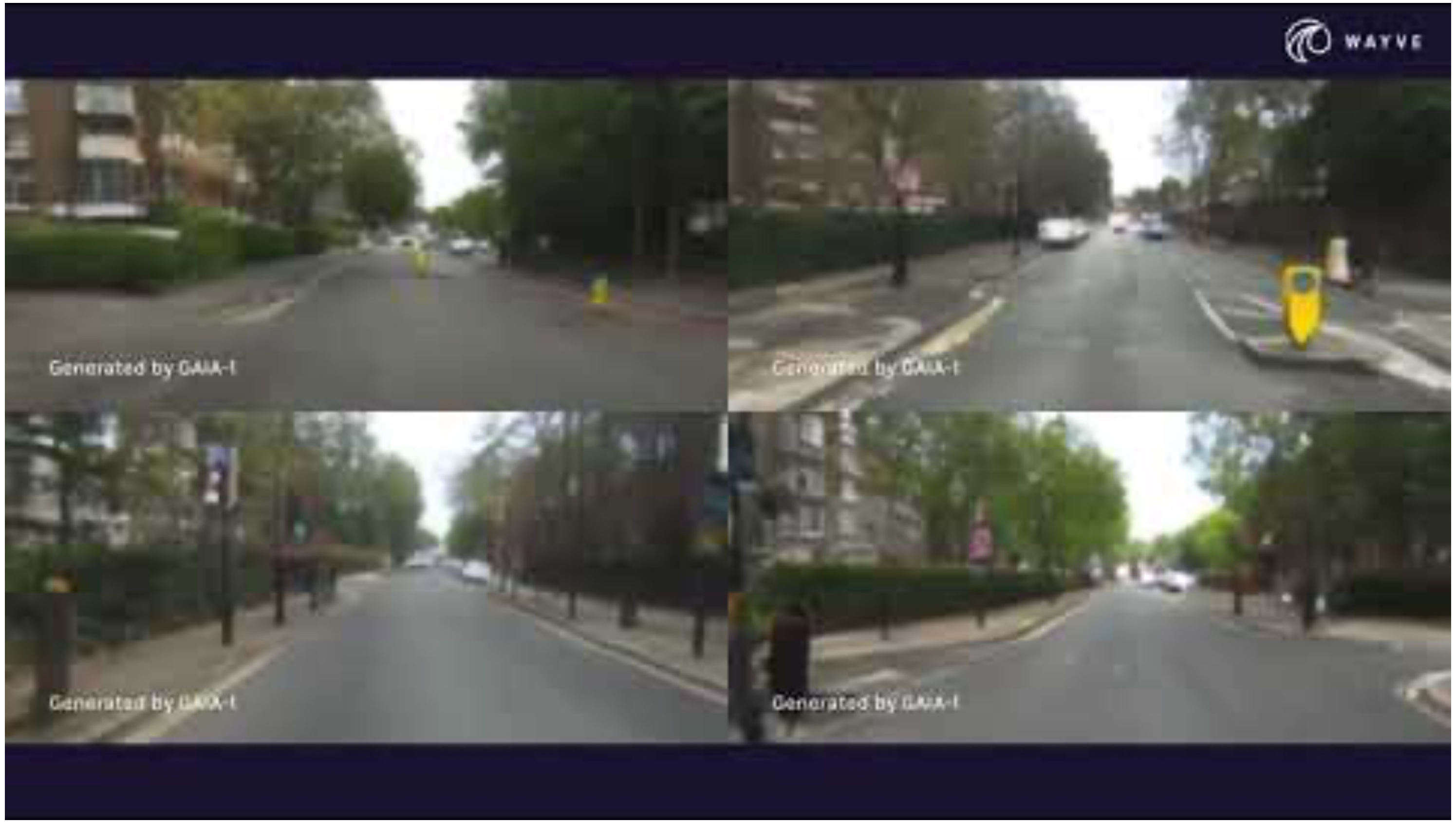
Video Simulation Models

- Generate videos given actions

GAIA-1

for auto-driving

Prompted with a couple of seconds of the same starting context. Then it can unroll multiple possible futures.



[Hu, Russell, Yeo, et al., 2023]

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate videos given actions

GAIA-1

for auto-driving

Inject a natural language prompt "**It's night, and we have turned on our headlights.**" after three seconds.

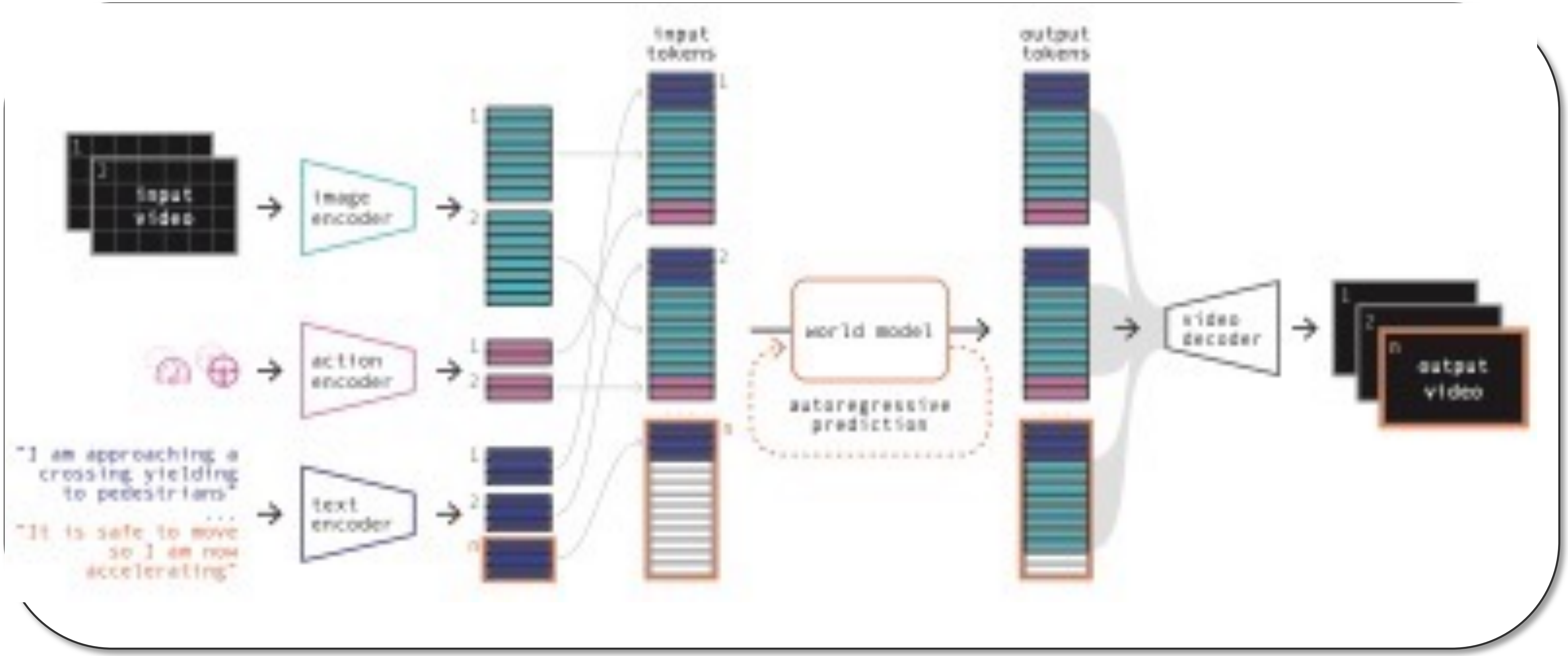
[Hu, Russell, Yeo, et al., 2023]

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate videos given actions

GAIA-1



input video
1
2
image encoder
action encoder
text encoder
"I am approaching a crossing yielding to pedestrians"
...
"It is safe to move so I am now accelerating"
input tokens
output tokens
n
world model
autoregressive prediction
video decoder
output video

[Hu, Russell, Yeo, et al., 2023]

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate videos given actions
- Not (yet) generalist models (*v.s.* LLMs): domain-specific states and actions
- Reasoning only in pixel space

GAIA-1

Multi-Modal Backend for World/Agent Modeling

Text-to-video Models

- Generate a video given a text prompt

Sora

by OpenAI

Prompt: “Several giant wooly mammoths approach treading through a snowy meadow, …”

(Others: Runway, Pika, …)

Multi-Modal Backend for World/Agent Modeling

Text-to-video Models

- Generate a video given a text prompt
- Reasoning only in pixel space
- Limited control with actions
- Limited length of reasoning (60s)

Sora

by OpenAI

Prompt: "Several giant wooly mammoths approach treading through a snowy meadow, …"

(Others: Runway, Pika, …)

Multi-Modal Backend for World/Agent Modeling

Summary of existing works

- Multi-modal LMs (I)
  - Can understand images
  - Can not generate images for, e.g., describing a world state
- Multi-modal LMs (II)
  - Can do interleaved generation of image and text
  - not describing the world consistently
- Video Simulation Models
  - Generate videos given actions
  - Not (yet) generalist models: domain-specific states and actions
  - Reasoning only in pixel space
- Text-to-video Models
  - Generate a video given a text prompt
  - Reasoning only in pixel space
  - Limited control with actions
  - Limited length of reasoning

Outline: Enhancing the Backend Beyond LMs

- Richer learning mechanisms
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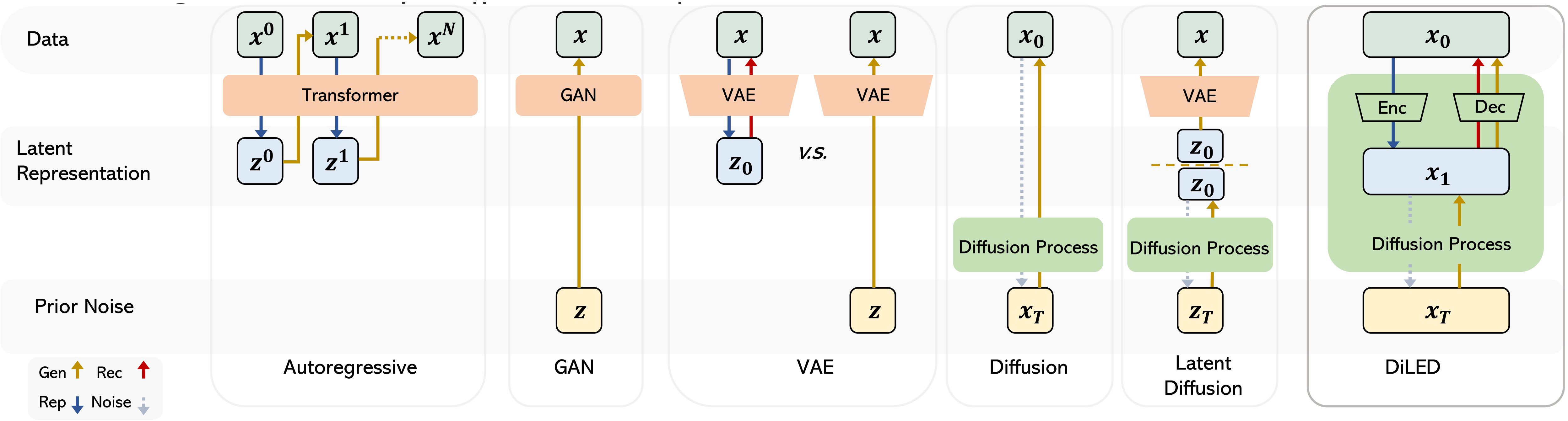
- Multi-modal capabilities
- **Latent-space reasoning**
- Agent models with external augmentations (e.g., tools)

Latent-space Reasoning

- What's the best space for carrying out reasoning?
  - Natural language space?
  - Raw sensory space (e.g., video)?
  - **Learned** latent space?
    - Single-level / multi-level latent space?
- Consider a long-term planning problem, e.g., economic planning for U.S. in 2024
  - Extremely complex, long-horizon reasoning
  - Inefficient/infeasible with LLM token-by-token reasoning or Video Model frame-by-frame reasoning
- Multi-level latent spaces are needed for multi-granularity reasoning

Latent-space Reasoning

- But how to learn a good latent space in the first place?



[Liu et al., 2024] Generating, Reconstructing, and Representing Discrete and Continuous Data: Generalized Diffusion with Learnable Encoding-Decoding

Outline: Enhancing the Backend Beyond LMs

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Agent models with external augmentations

- External augmentations for added capabilities:
    - Tools: telescope, vehicles, …
    - Data about a skill: demonstration videos of climbing a snowy mountain
    - Knowledge bases: domain knowledge
- Agent automatically chooses appropriate augmentations for a given task
    - How to represent millions of potential augmentations?
    - Learning unified embedding of tools, data, knowledge [Hao et al., 2023]
- Another dimension rarely considered so far: constraint by budget
    - Different augmentations will invoke different costs (financial, time, etc.)
    - Need to strike the optimal balance between task performance vs costs

[Hao et al., 2023] ToolkenGPT: Augmenting Frozen Language Models with Massive Tools via Tool Embeddings

Key Takeaways

- Richer learning mechanisms
    - Learning with Embodied Experiences
    - Social Learning
- Multi-modal capabilities
    - Multi-modal LMs, video generation models
- Latent-space reasoning
    - How to learn a good multi-level latent space
- Agent models with external augmentations (e.g., tools)
    - Unified embedding, budget for augmentations

Questions?