

DSC291: Machine Learning with Few Labels

Large Language Models
Self-Supervised Learning

Zhiting Hu

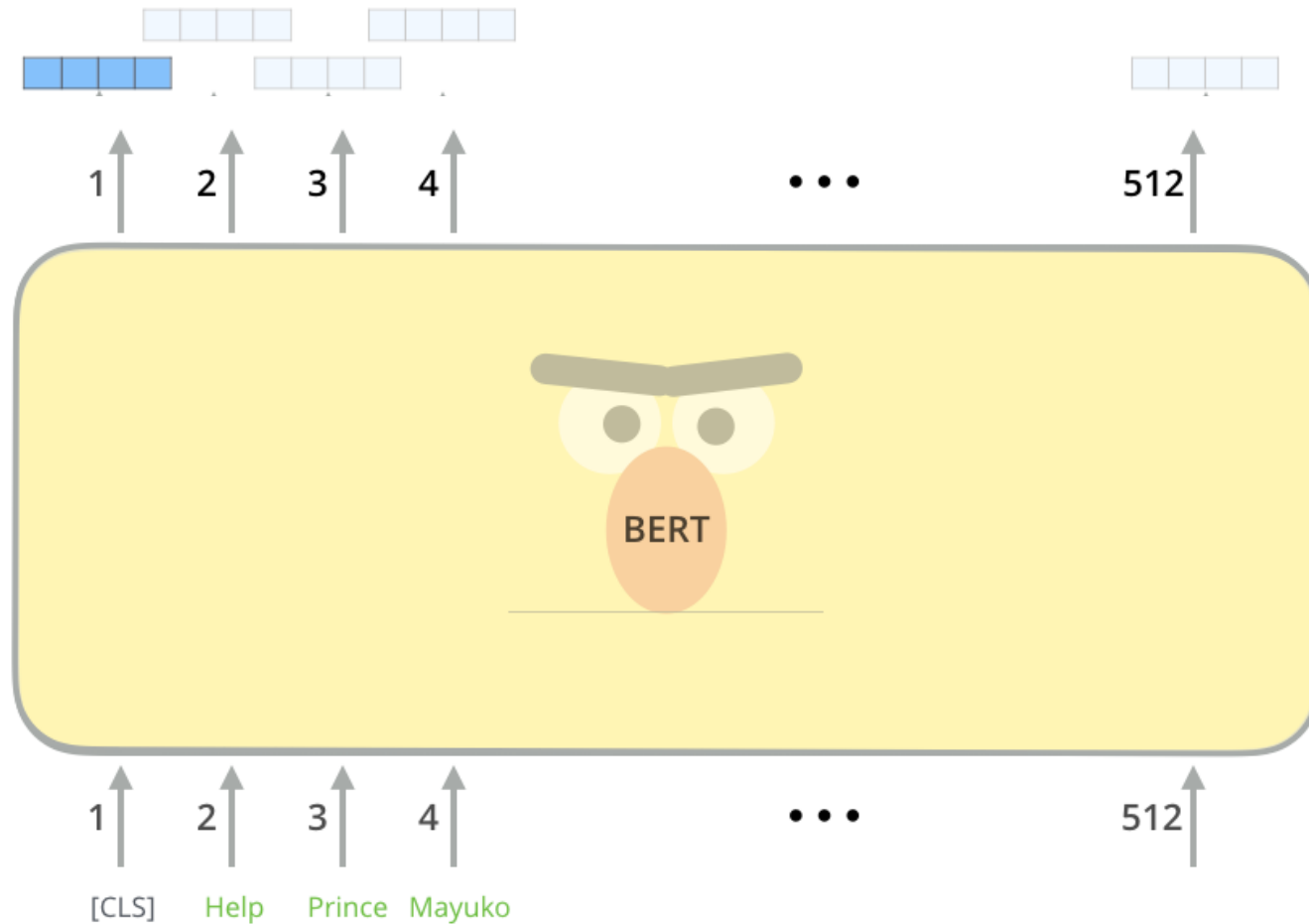
Lecture 6, April 12, 2024

UC San Diego

HALICIOĞLU DATA SCIENCE INSTITUTE

BERT

- BERT: A bidirectional model to extract contextual word embedding



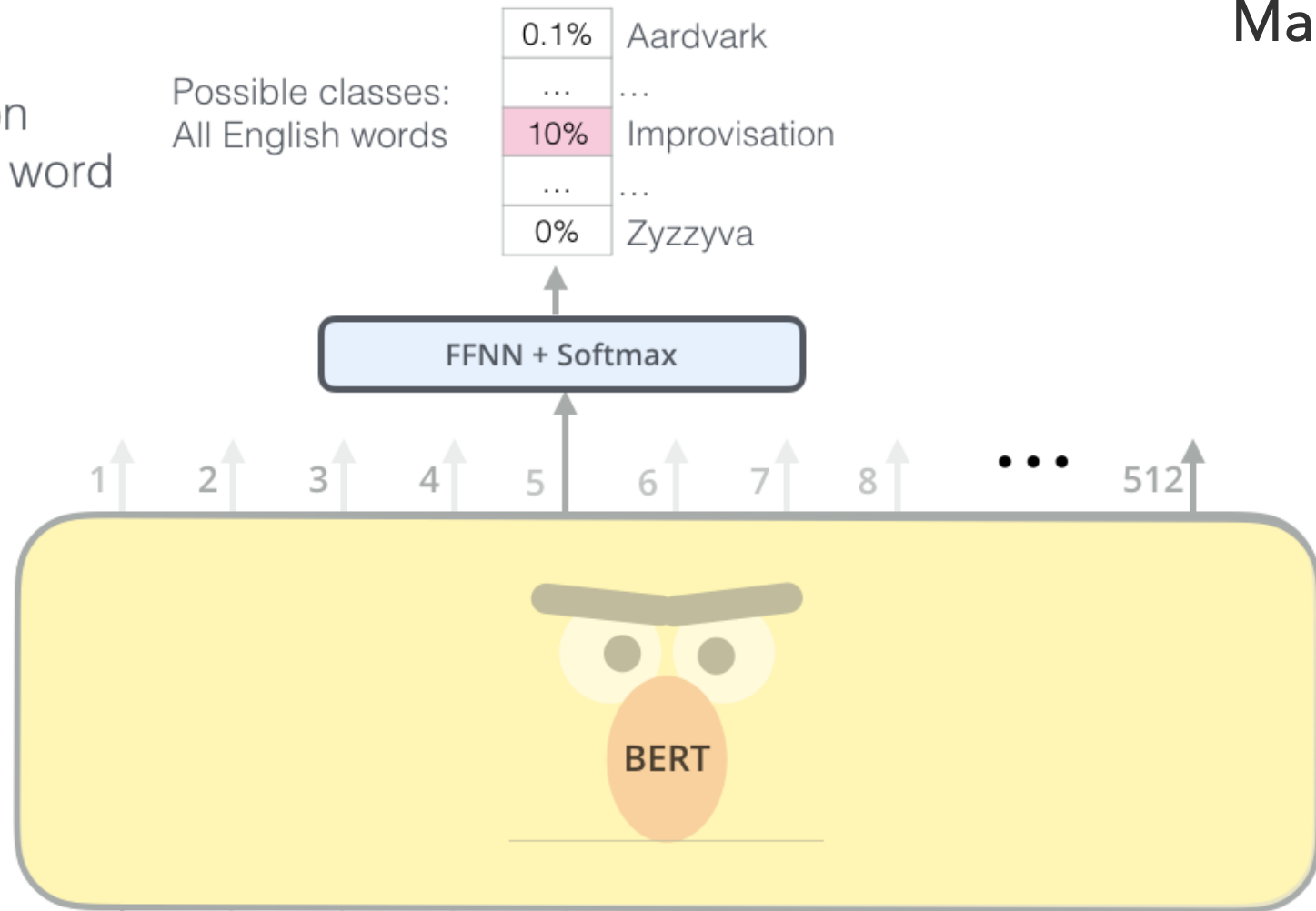
BERT: Pre-training Procedure

- Dataset:
 - Wikipedia (2.5B words) + a collection of free ebooks (800M words)

- Training:
 - Masked language model (MLM)
 - Masks some percent of words from the input and reconstructs those words from context

Masked LM

Use the output of the masked word's position to predict the masked word



Randomly mask 15% of tokens

1 [CLS] 2 Let's 3 stick 4 to 5 [MASK] 6 in 7 this 8 skit ... 512

Input

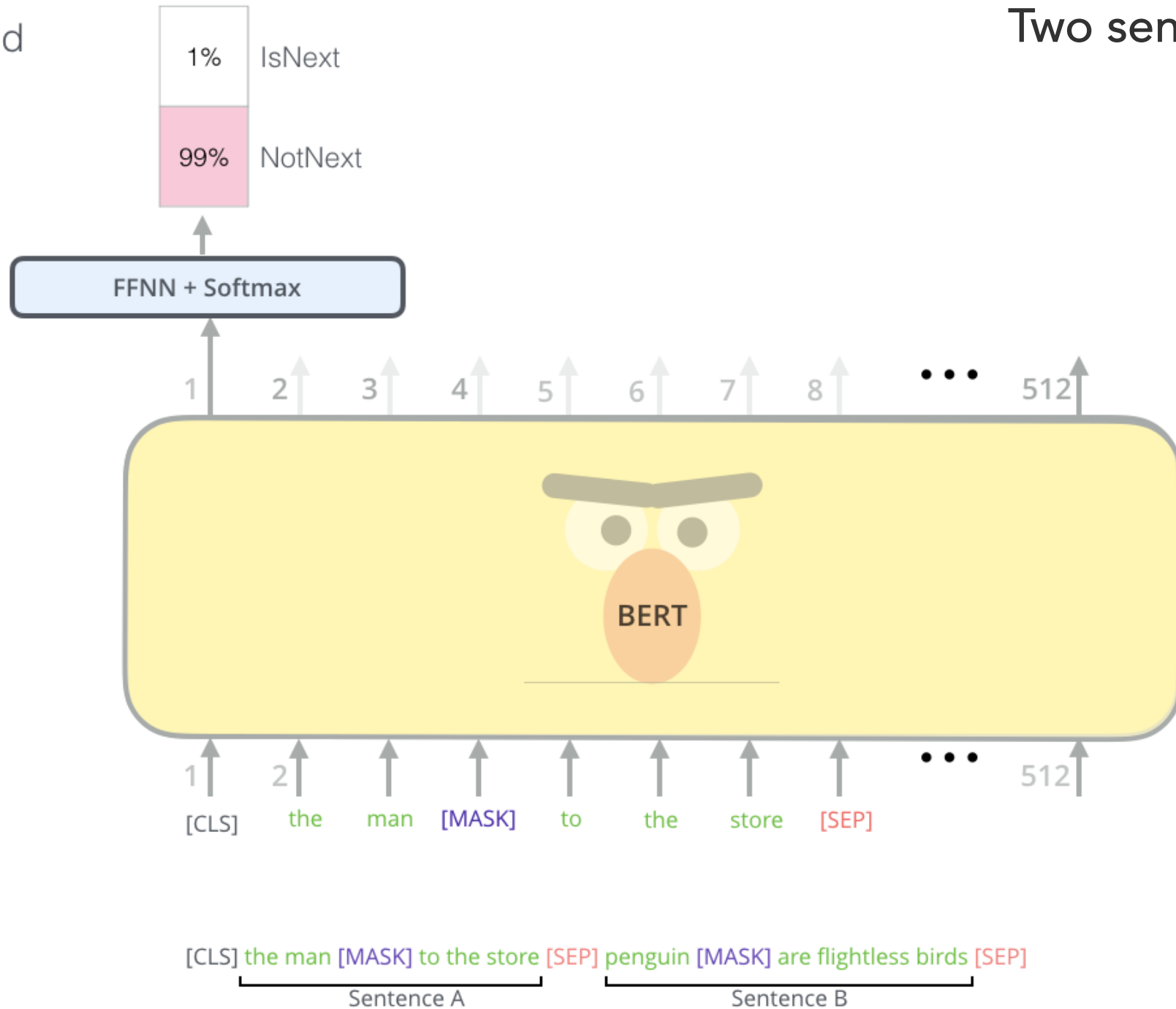
[CLS] Let's stick to improvisation in this skit

BERT: Pre-training Procedure

- Dataset:
 - Wikipedia (2.5B words) + a collection of free ebooks (800M words)
- Training:
 - **Masked language model (MLM)**
 - Masks some percent of words from the input and reconstructs those words from context
 - **Two-sentence task**
 - To understand relationships between sentences
 - Concatenates two sentences A and B and predicts whether B actually comes after A in the original text

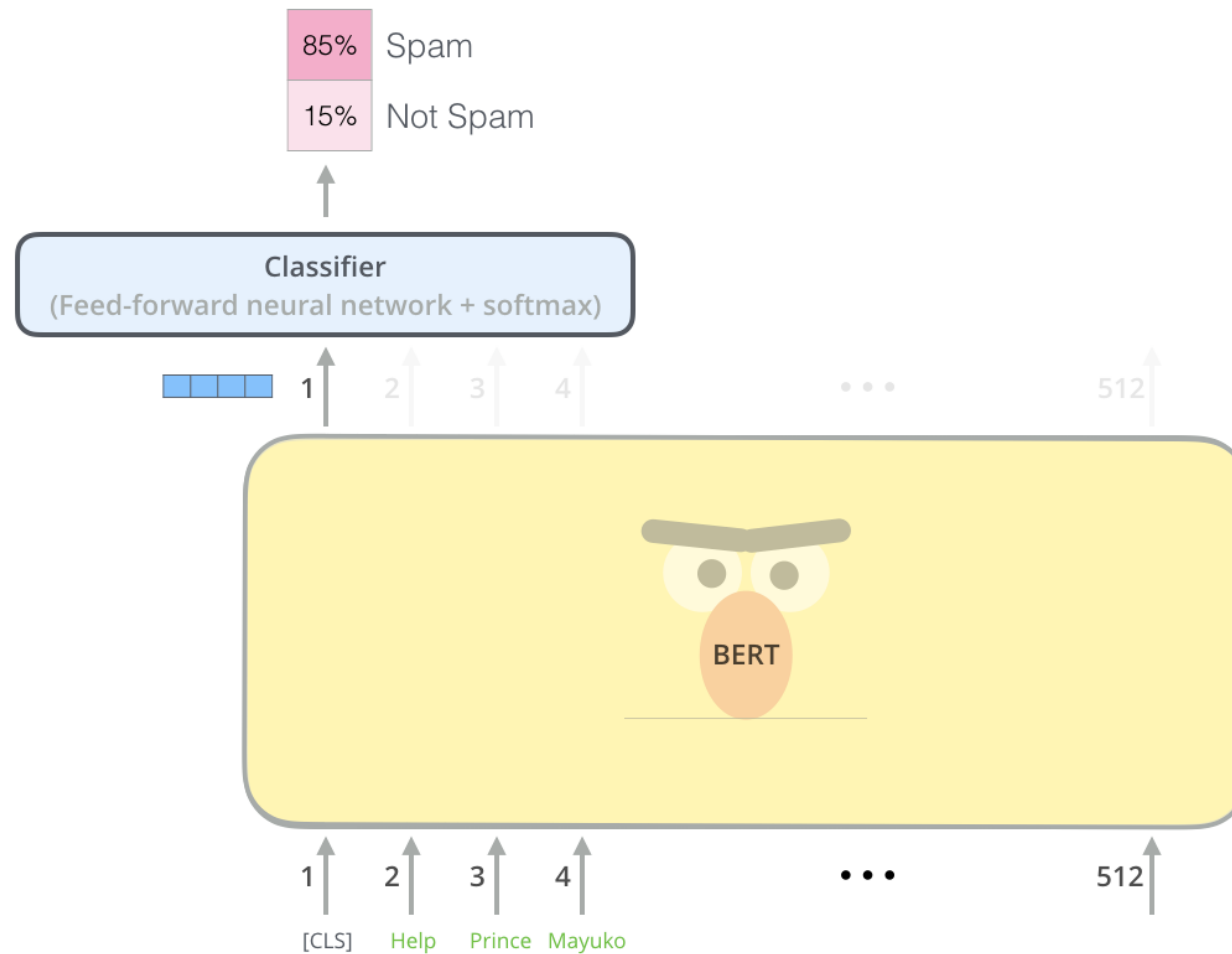
Two sentence task

Predict likelihood that sentence B belongs after sentence A



BERT: Downstream Fine-tuning

- Use BERT for sentence classification



Examples of self-supervised learning (SSL)

- Language models
- Learning contextual text representations
- Learning image / video representations

SSL from Images, EX (I): masked autoencoder (MAE)

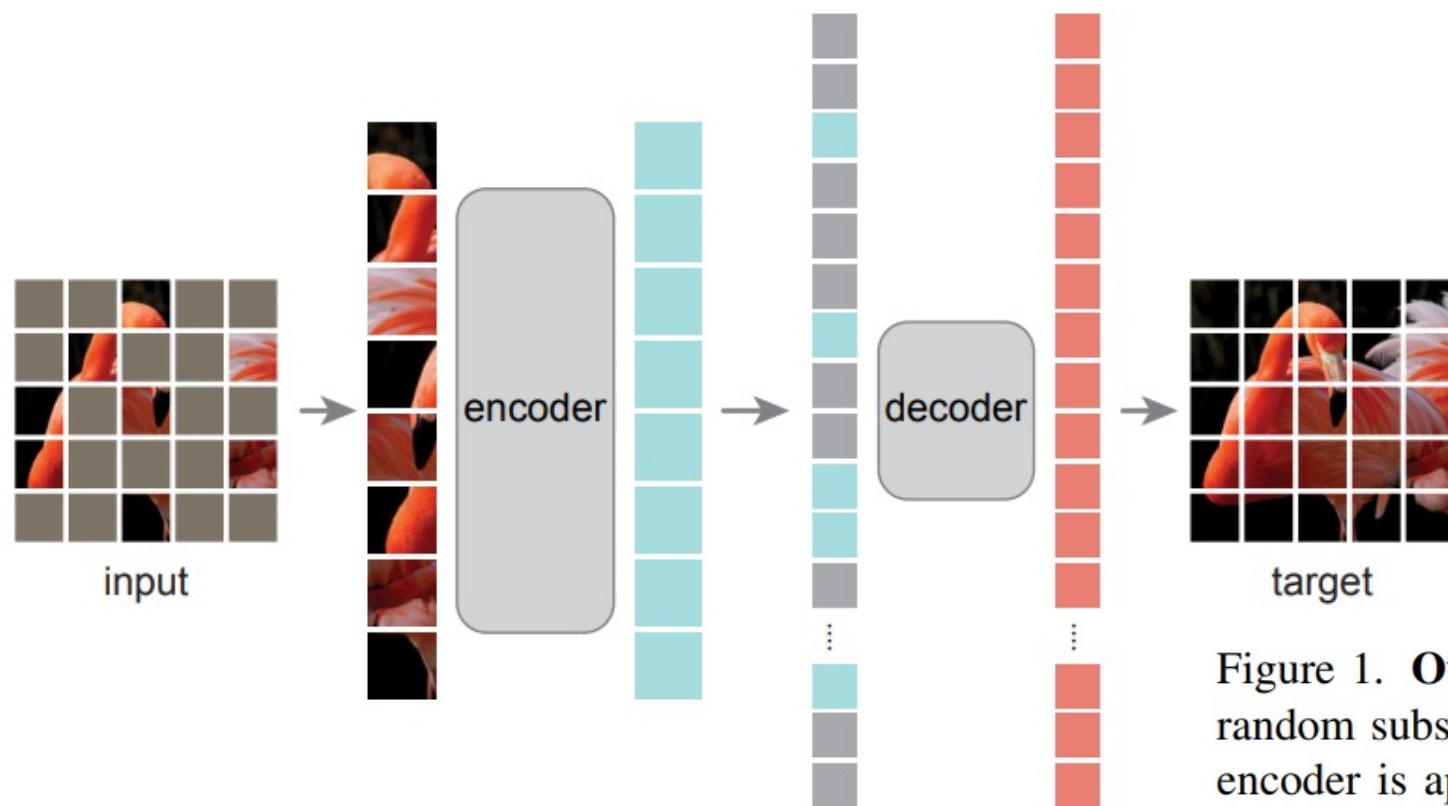
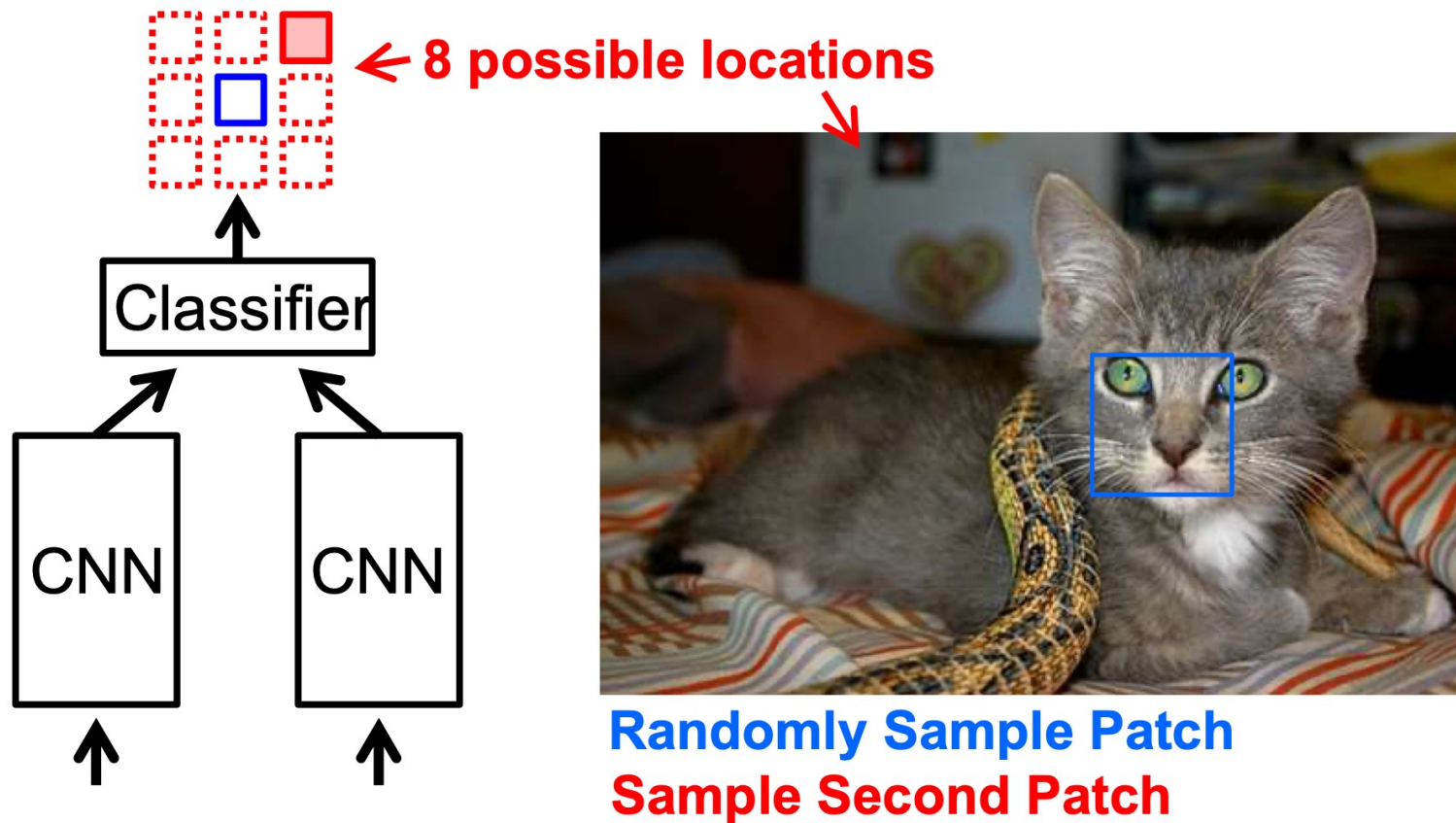


Figure 1. **Our MAE architecture.** During pre-training, a large random subset of image patches (*e.g.*, 75%) is masked out. The encoder is applied to the small subset of *visible patches*. Mask tokens are introduced *after* the encoder, and the full set of encoded patches and mask tokens is processed by a small decoder that reconstructs the original image in pixels. After pre-training, the decoder is discarded and the encoder is applied to uncorrupted images (full sets of patches) for recognition tasks.

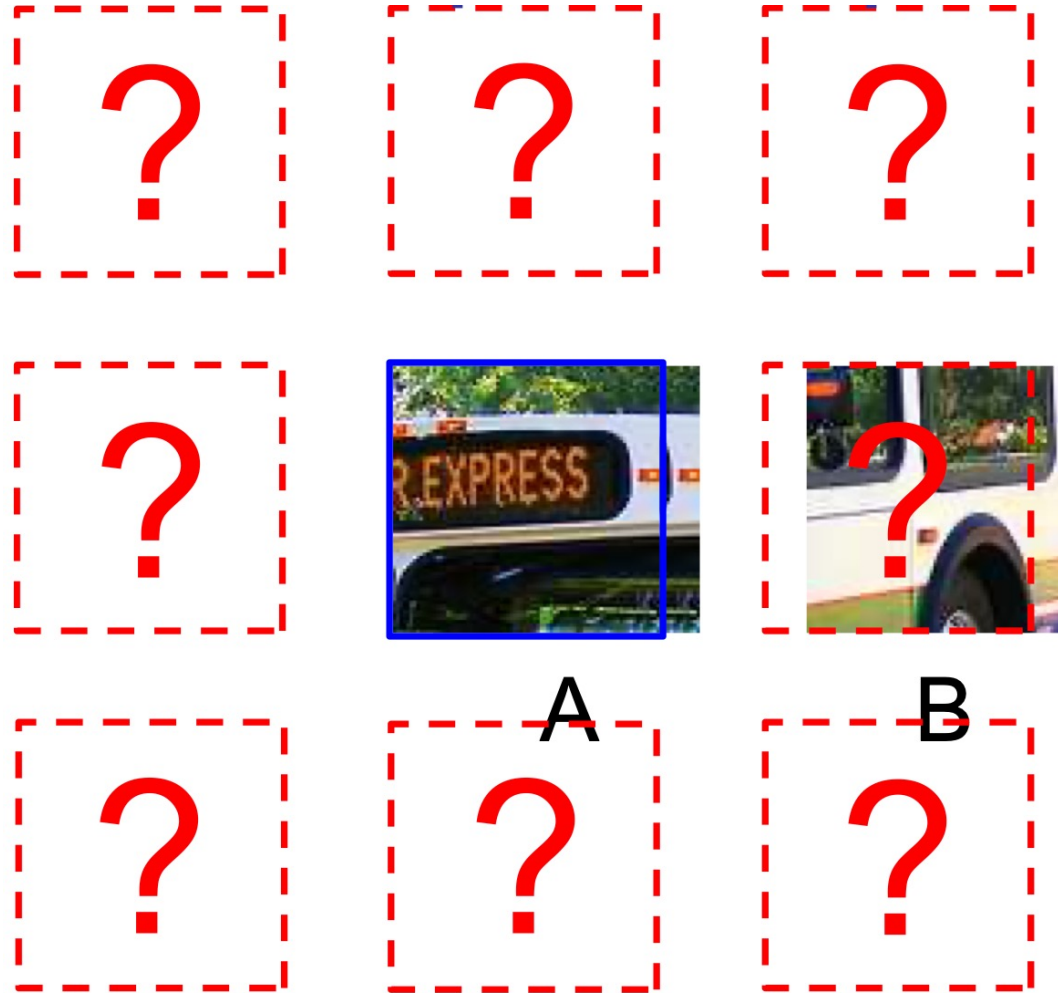
SSL from Images, EX (II): relative positioning

Train network to predict relative position of two regions in the same image



Unsupervised visual representation learning by context prediction,
Carl Doersch, Abhinav Gupta, Alexei A. Efros, ICCV 2015

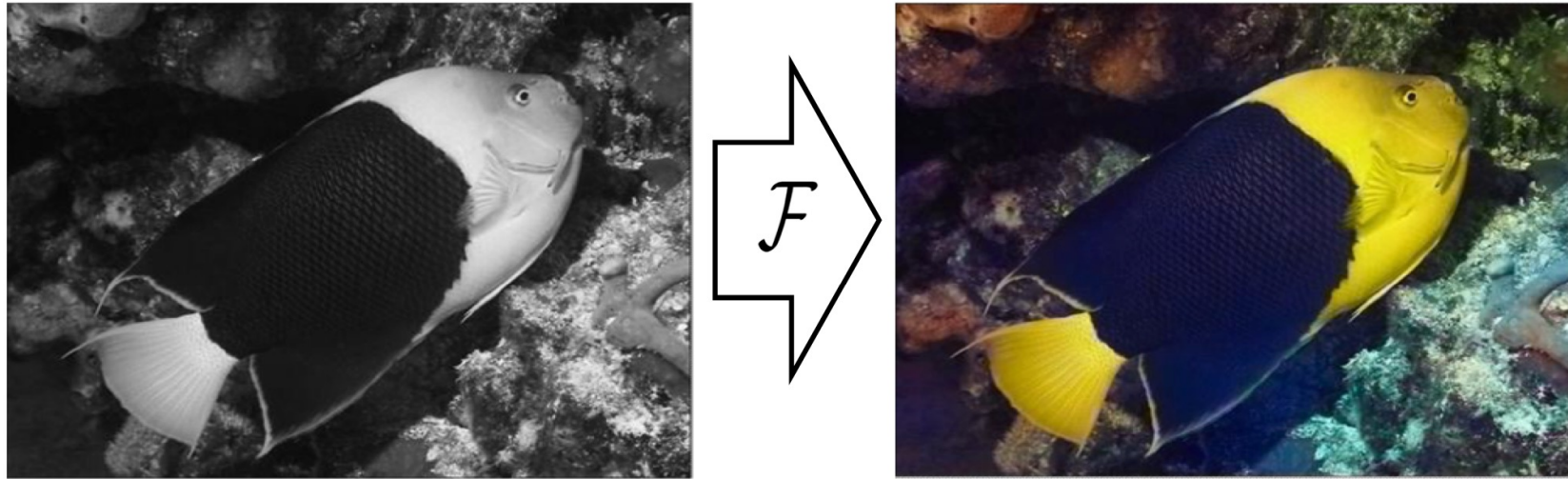
SSL from Images, EX (II): relative positioning



Unsupervised visual representation learning by context prediction,
Carl Doersch, Abhinav Gupta, Alexei A. Efros, ICCV 2015

SSL from Images, EX (III): colorization

Train network to predict pixel colour from a monochrome input

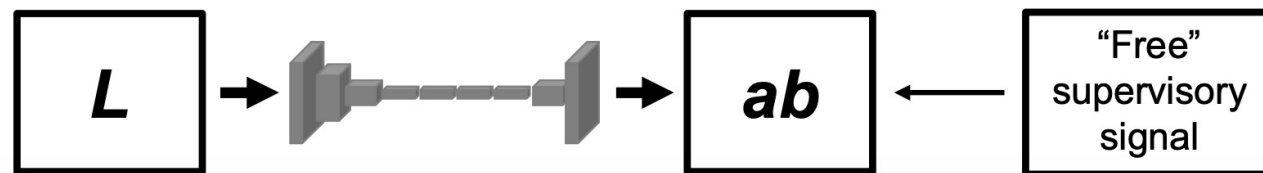


Grayscale image: L channel

$$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$$

Concatenate (L, ab)

$$(\mathbf{X}, \hat{\mathbf{Y}})$$



SSL from Images, EX (III): colorization

Train network to predict pixel colour from a monochrome input



SSL from Images, EX (IV): exemplar networks

- Exemplar Networks (Dosovitskiy et al., 2014)
- Perturb/distort image patches, e.g. by cropping and affine transformations
- Train to classify these exemplars as same class

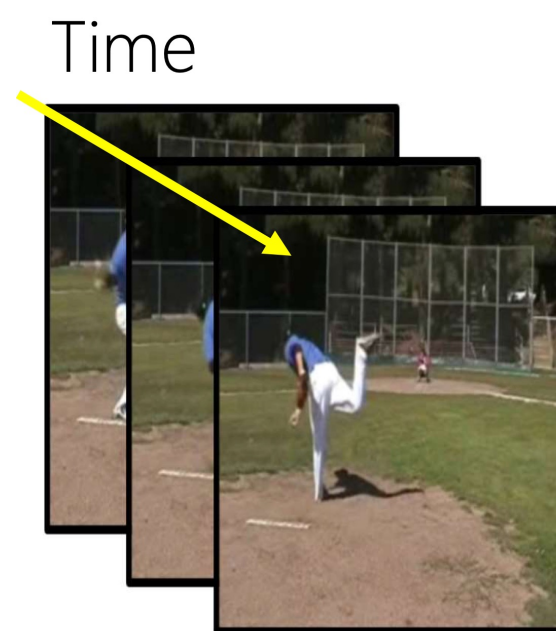


SSL from Videos

SSL from Videos

Example SSL prediction tasks:

- Video sequence order
 - Sequential Verification: Is this a valid sequence?



"Sequence" of data

SSL from Videos

Example SSL prediction tasks:

- Video sequence order
 - Sequential Verification: Is this a valid sequence?
- Video direction
 - Predict if video playing forwards or backwards

SSL from Videos

Example SSL prediction tasks:

- Video sequence order
 - Sequential Verification: Is this a valid sequence?
- Video direction
 - Predict if video playing forwards or backwards
- Video tracking
 - Given a color video, colorize all frames of a gray scale version using a reference frame



SSL from Videos

Example SSL prediction tasks:

- Video sequence order
 - Sequential Verification: Is this a valid sequence?
- Video direction
 - Predict if video playing forwards or backwards
- Video tracking
 - Given a color video, colorize all frames of a gray scale version using a reference frame
- Next frame prediction
 - Similar to next word prediction for text

Key Takeaways

- **Self supervision learning**
 - Predicting any part of the observations given any available information
 - The prediction task forces models to learn semantic representations
 - Massive/unlimited data supervisions
- **SSL for text:**
 - Language models: next word prediction
 - BERT text representations: masked language model (MLM)
- **SSL for images/videos:**
 - Various ways of defining the prediction task

Enhancing Large Language Models

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 ...

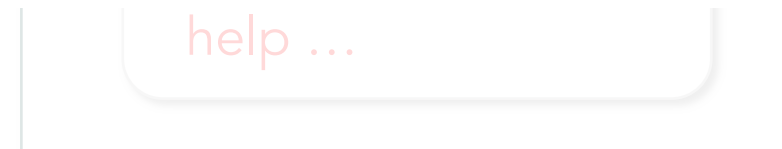
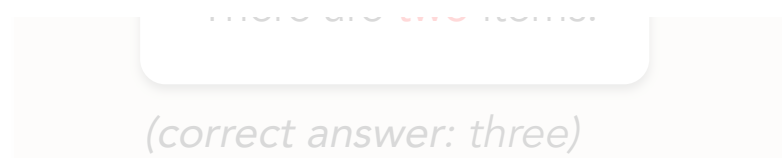
Limitation I:

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:

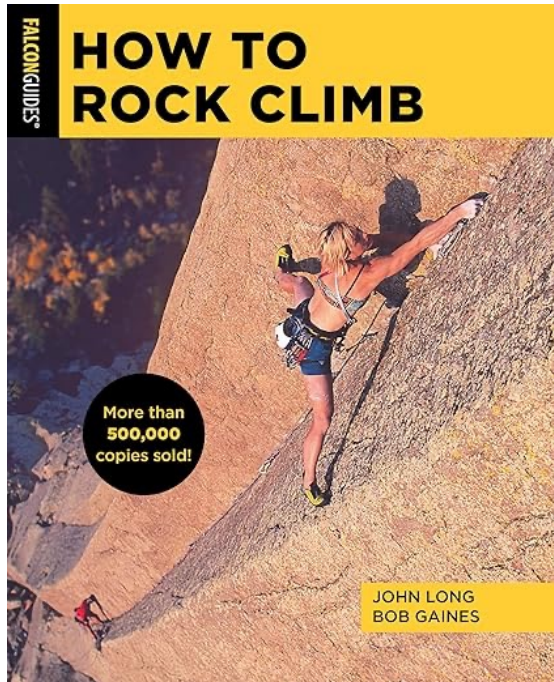
- tracking and interacting with objects
- understanding real-world physics and spatiotemporal relationships
- sensing and tracking the world states
- recognizing other agents' behaviors



Limitation I: LLMs Lack World and Agent Knowledge

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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

Limitation II: Inefficiency of the language modality

- Language is often not the most efficient medium to



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

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



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
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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**
 - **Where** to get experiences
 - **How to get** experiences
 - **How to learn** with the experiences
 - Social Learning

Learning from Embodied Experiences

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

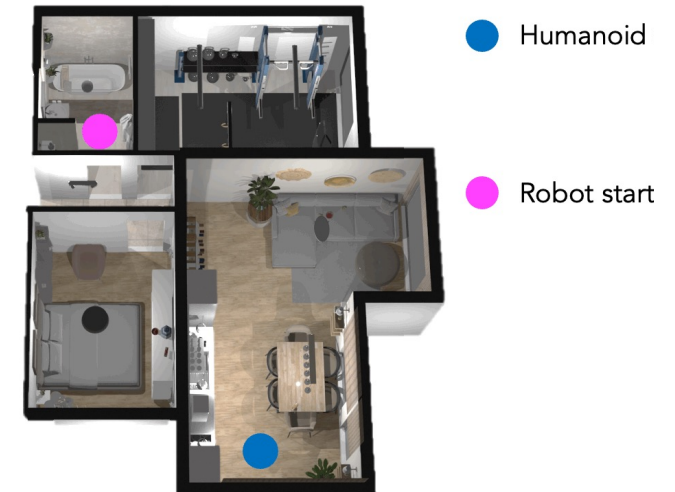
- Embodied simulators

Everyday household activities

Virtual Home



Habitat 3.0



Learning from Embodied Experiences

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

- Embodied simulators

Touchdown

navigating in urban scenes



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.

Minecraft

exploring a 3D infinite world
and conducting rich tasks



Learning from Embodied Experiences

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Mine Amethyst

[Wang et al., 2023]

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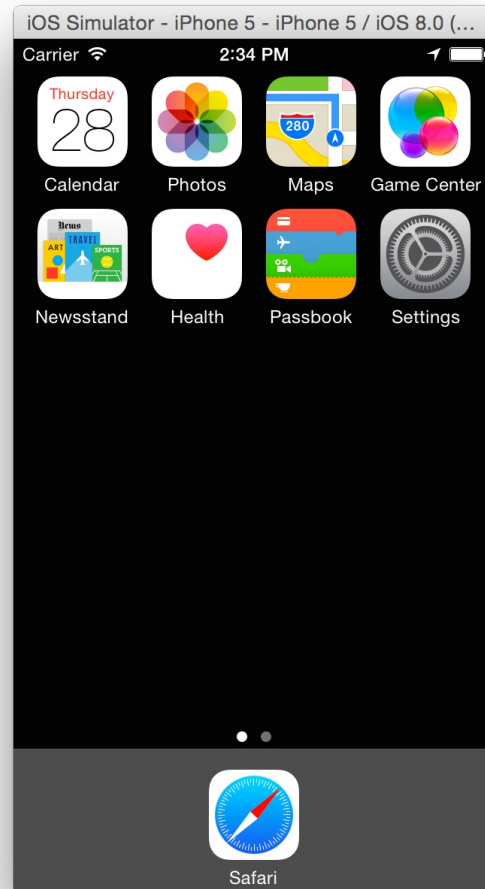
[Wang et al., 2023]

Learning from Embodied Experiences

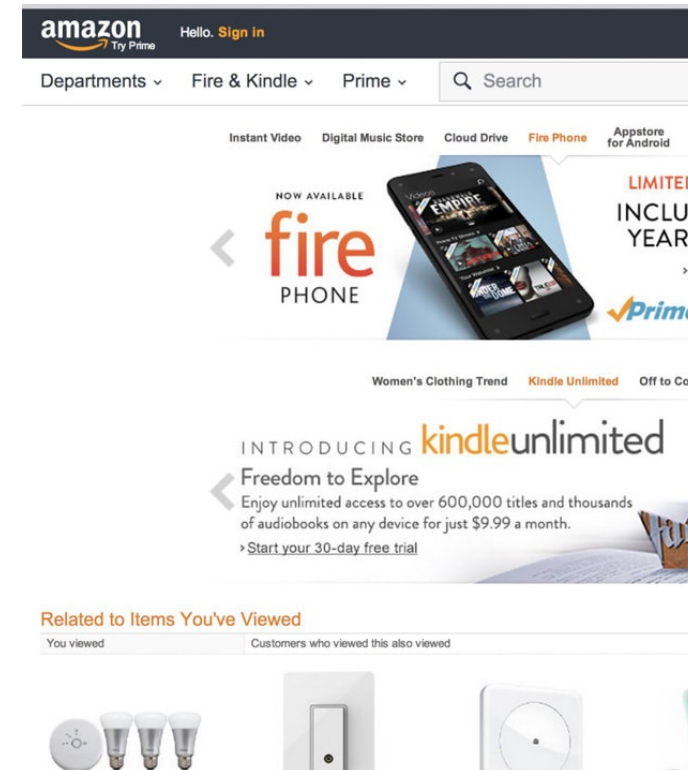
- (1) Where to get experiences
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- Other simulators

OS



Simulated websites
(shopping, navigating, search)



Learning from Embodied Experiences

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

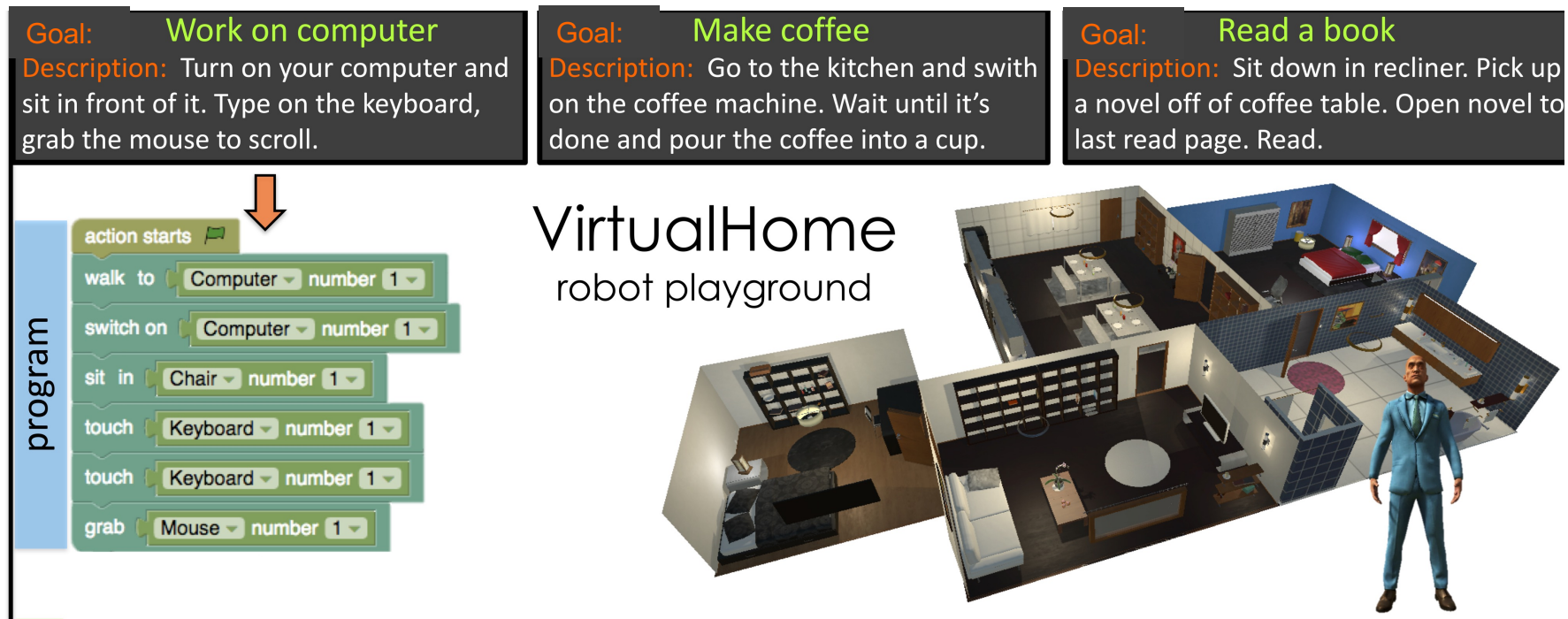
VirtualHome
robot playground



Learning from Embodied Experiences

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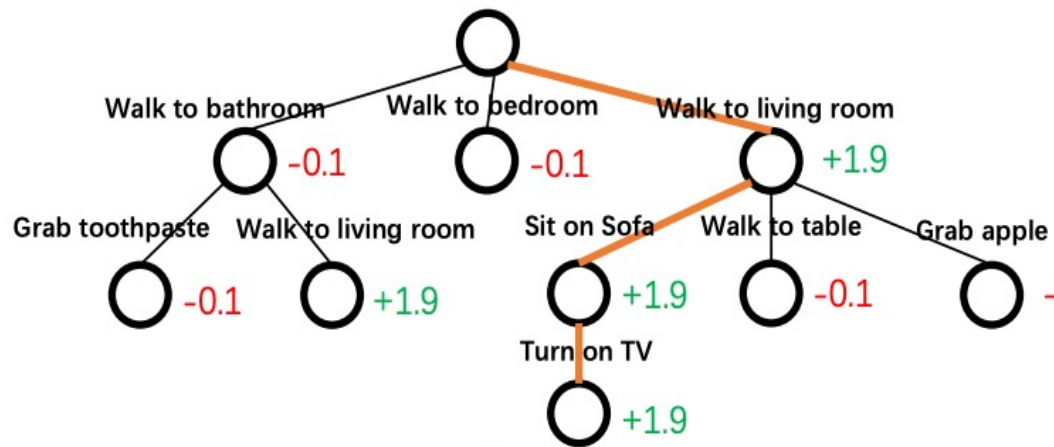
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Learning from Embodied Experiences

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

Goal-Oriented Planning

Goal: Watch TV 



Monte Carlo Tree Search (MCTS)

Learning from Embodied Experiences

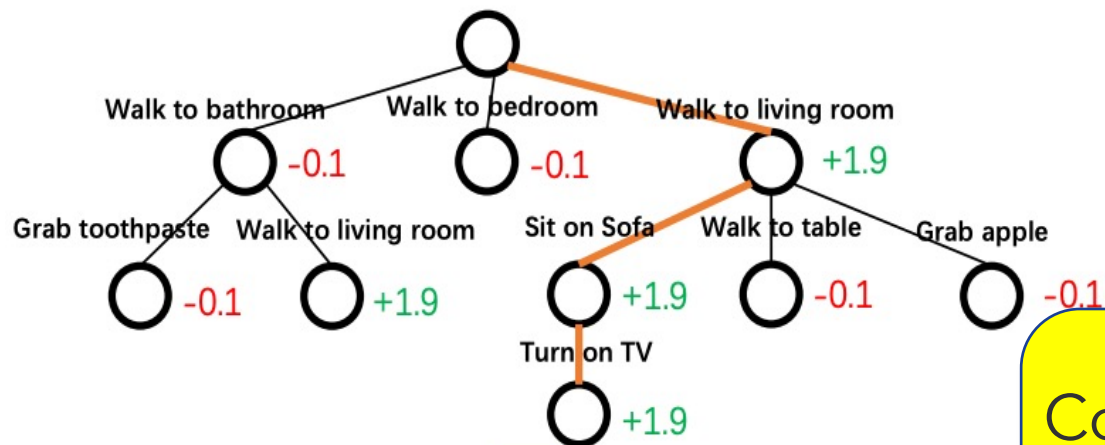
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- Goal-oriented

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Goal-Oriented Planning

Goal: Watch TV 



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?

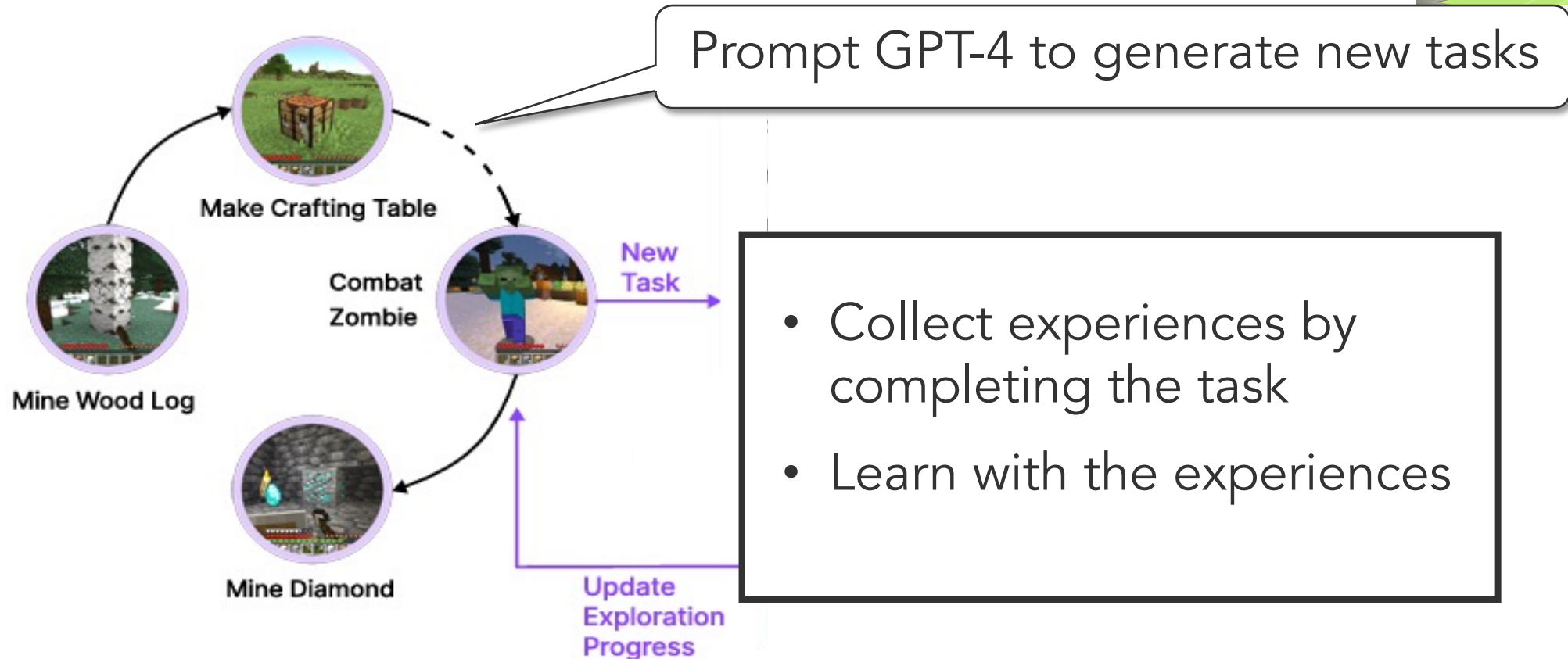
Answer: **Watch TV.**

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



Learning from Embodied Experiences

- (1) Where to get experiences
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Prompt GPT-4 to generate new tasks

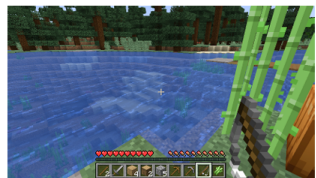
Examples:



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

GPT-4

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}

GPT-4

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

GPT-4

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.

(1) Where to get experiences

(2) How to get experiences

(3) How to learn w/ experiences

Learning from Embodied Experiences

- Random Exploration

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

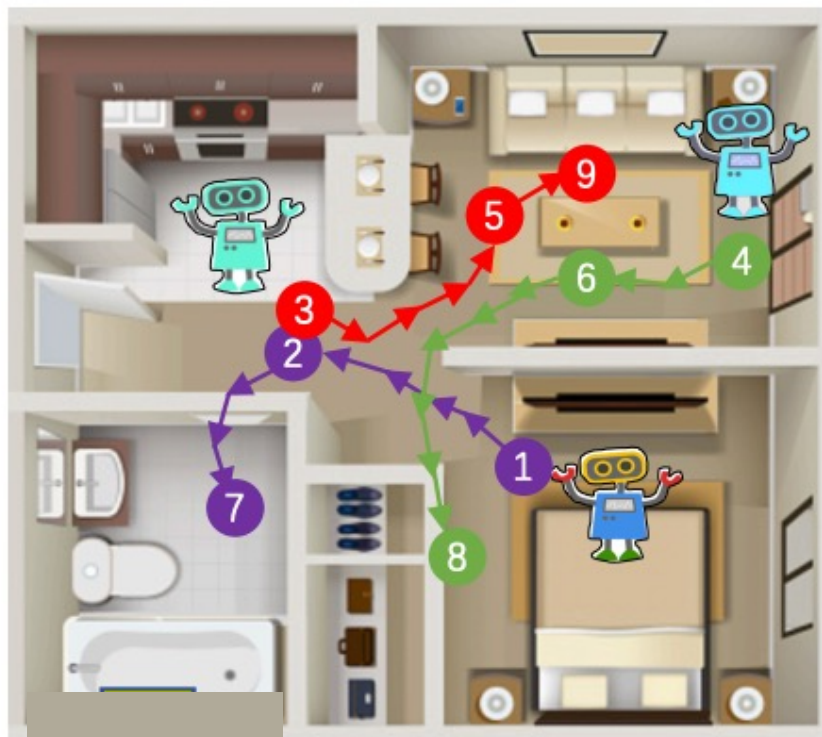


Learning from Embodied Experiences

- (1) Where to get experiences
- (2) How to get experiences
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- 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

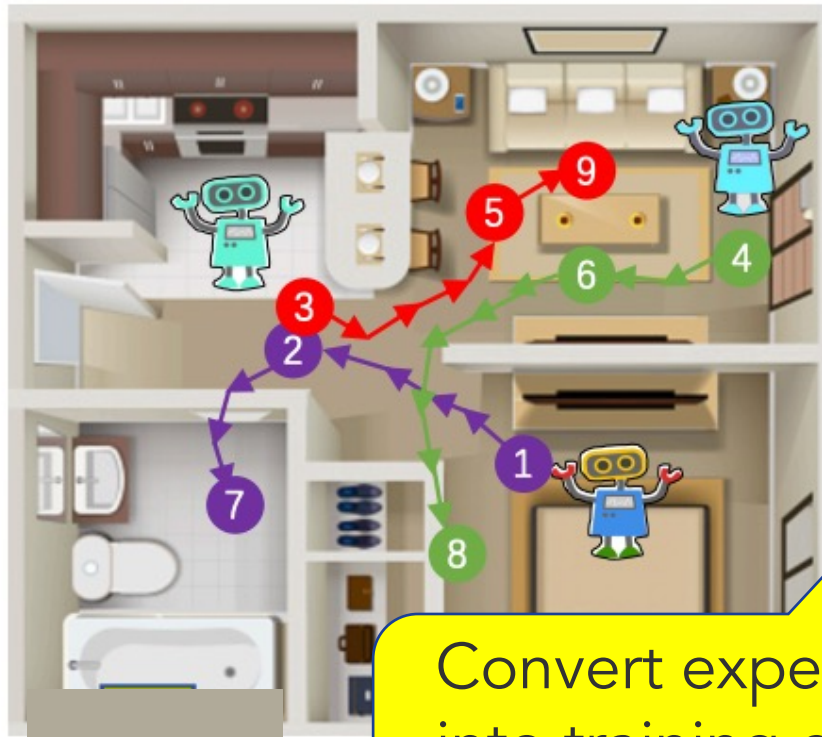


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Convert experiences into training data (question answering)

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:

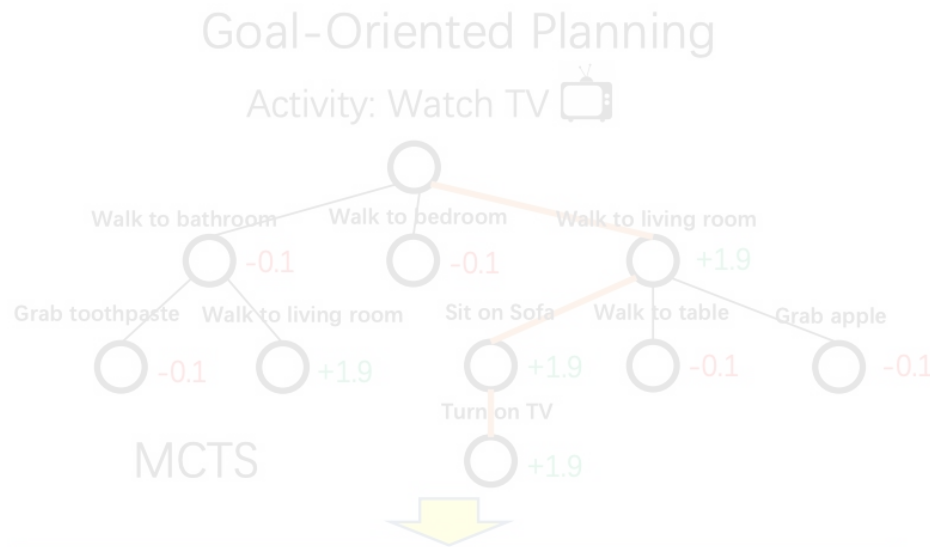
Bedroom, kitchen, living room

Object Path Tracking

Learning from Embodied Experiences

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

- Finetuning LMs with the experiences



Question:
How to watch TV? TV and
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Answer:
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Plan Generation

Question:
Given a plan: Walk to living
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Answer: **Watch TV.**

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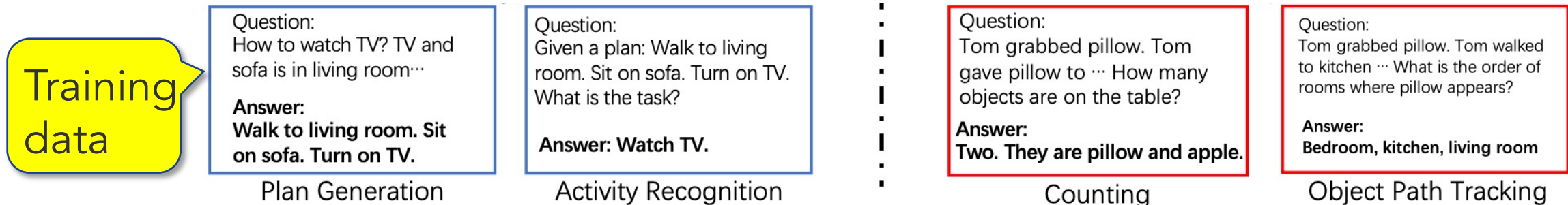
Object Path Tracking

Training
data

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

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)



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

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

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

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Conventional finetuning objective

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

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

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

Regularizer to preserve important weights

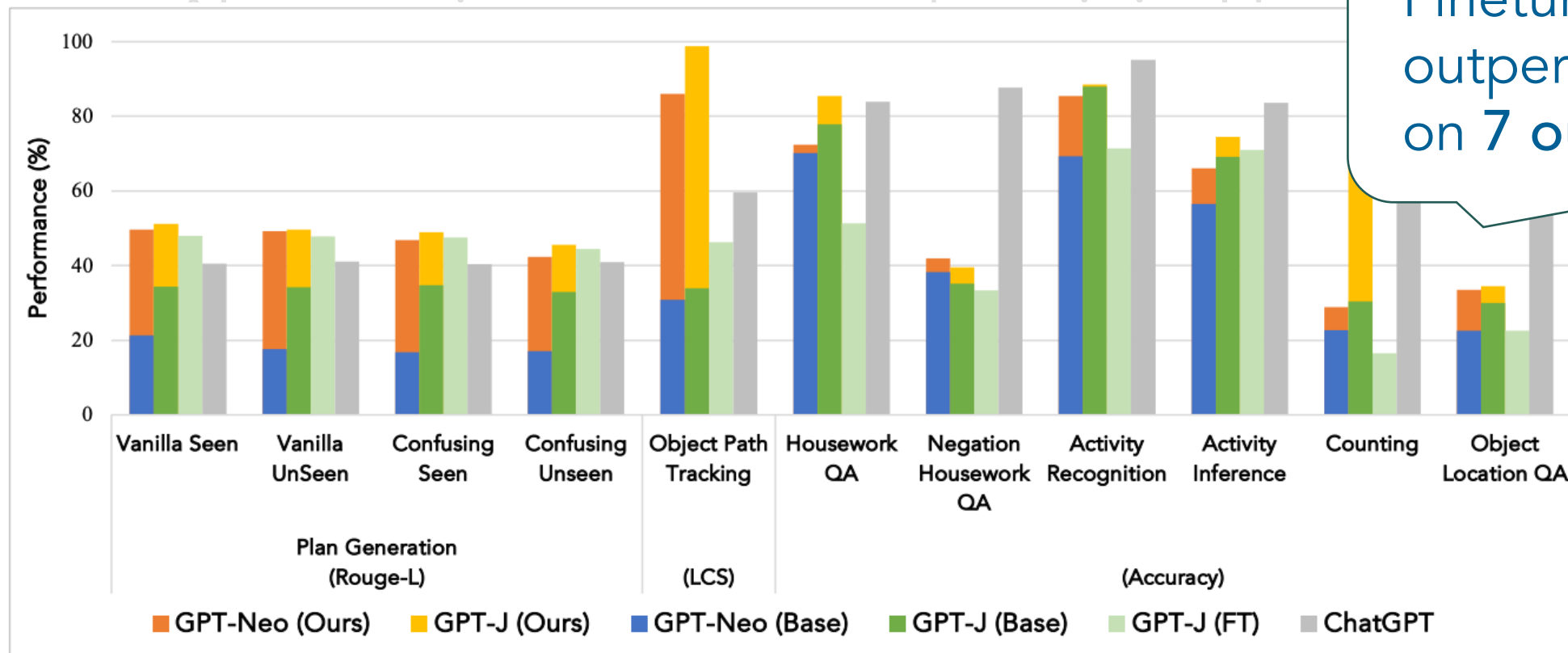
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Learning from Embodied Experiences

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

- Finetuning LMs with the experiences



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

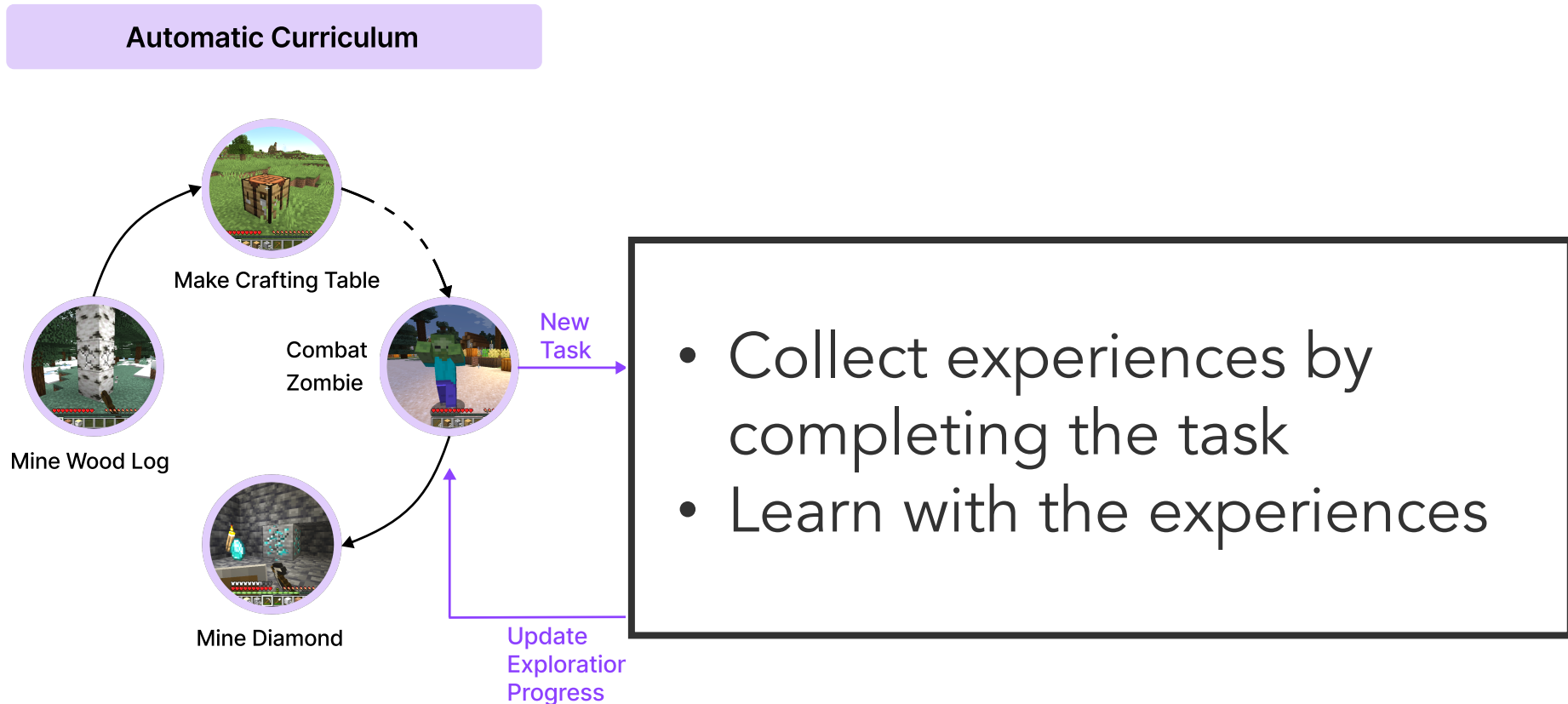
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Learning from Embodied Experiences

- Updating external memory
 - Instead of changing LM parameters

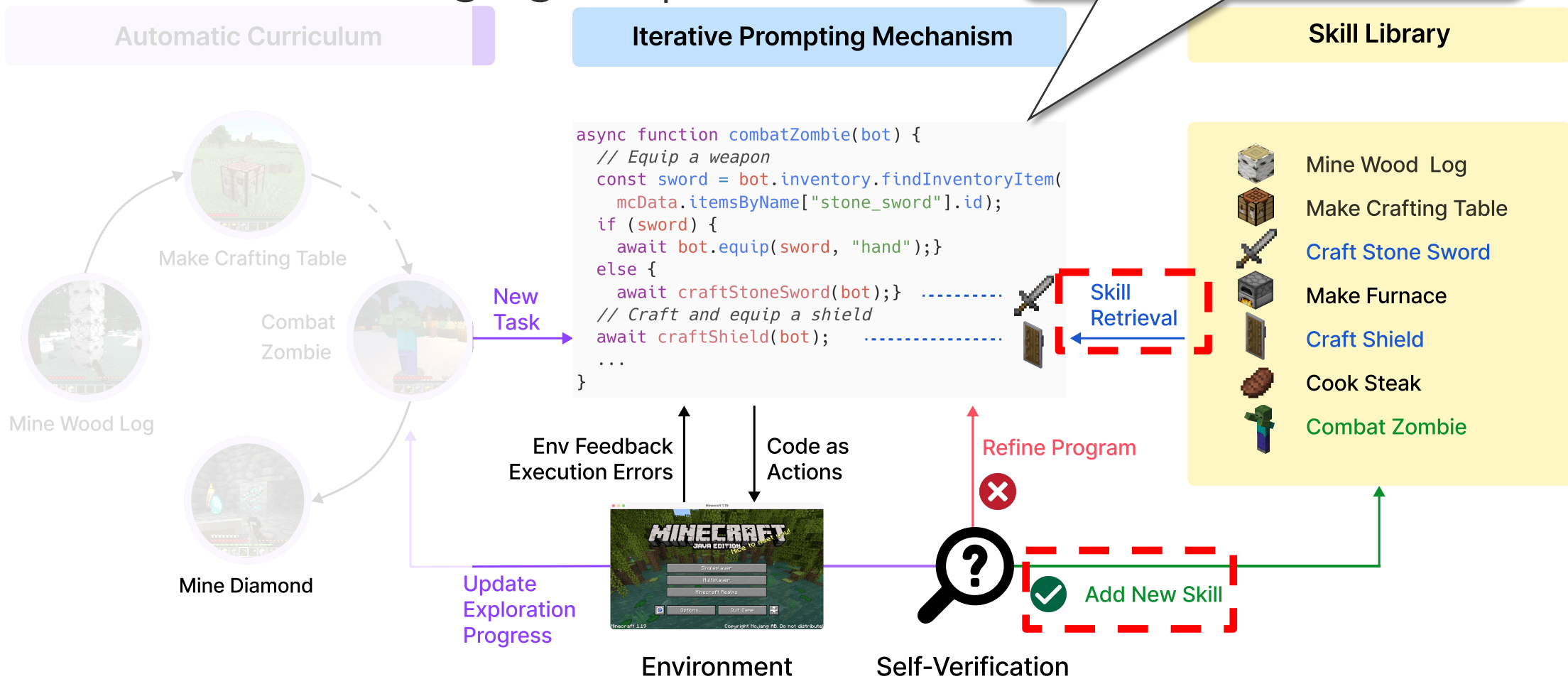


Learning from Embodied Experiences

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

- Updating external memory
 - Instead of changing LM parameters

Skill represented as code



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

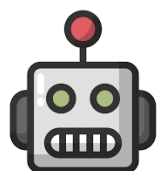


Example: Learning Alignment with Interactions

The alignment problem :

Question:

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



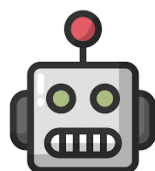
?

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...

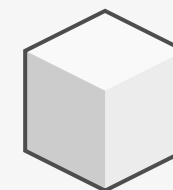
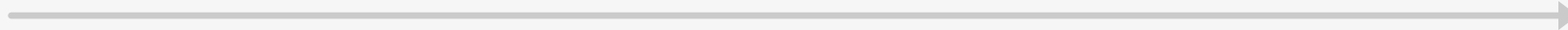
Aligned response

Example: Learning Alignment with Interactions

Conventional learning approaches:



Questions + **Aligned** Responses



Supervised Fine-tuning / SFT
(Behavior Cloning)

[a]

Example: Learning Alignment with Interactions

Conventional learning approaches:



Questions + Aligned Responses

Questions + **Aligned** Responses + Ratings

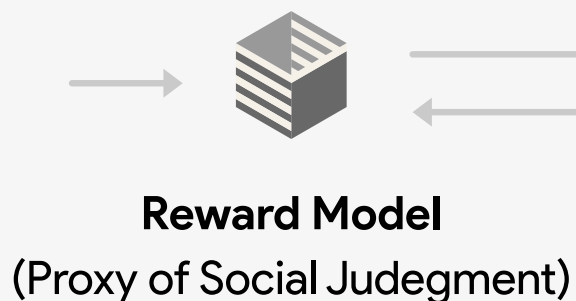


+ [8.0, 10.0, 9.0, ...]

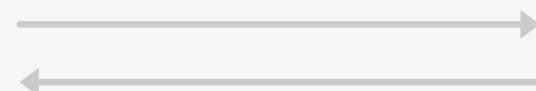
Questions + **Misaligned** Responses + Ratings



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



Online Interaction by RL



SFT + RLHF

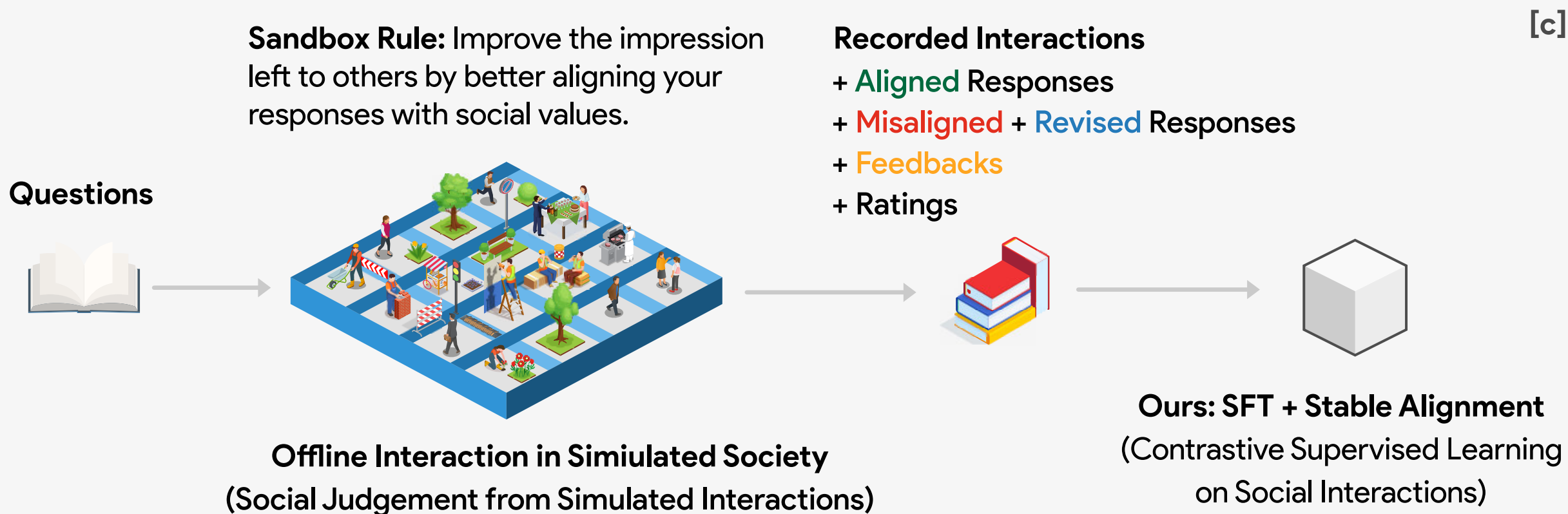
(Inverse Reinforcement Learning)

Simplistic interaction
(binary feedback)

[b]

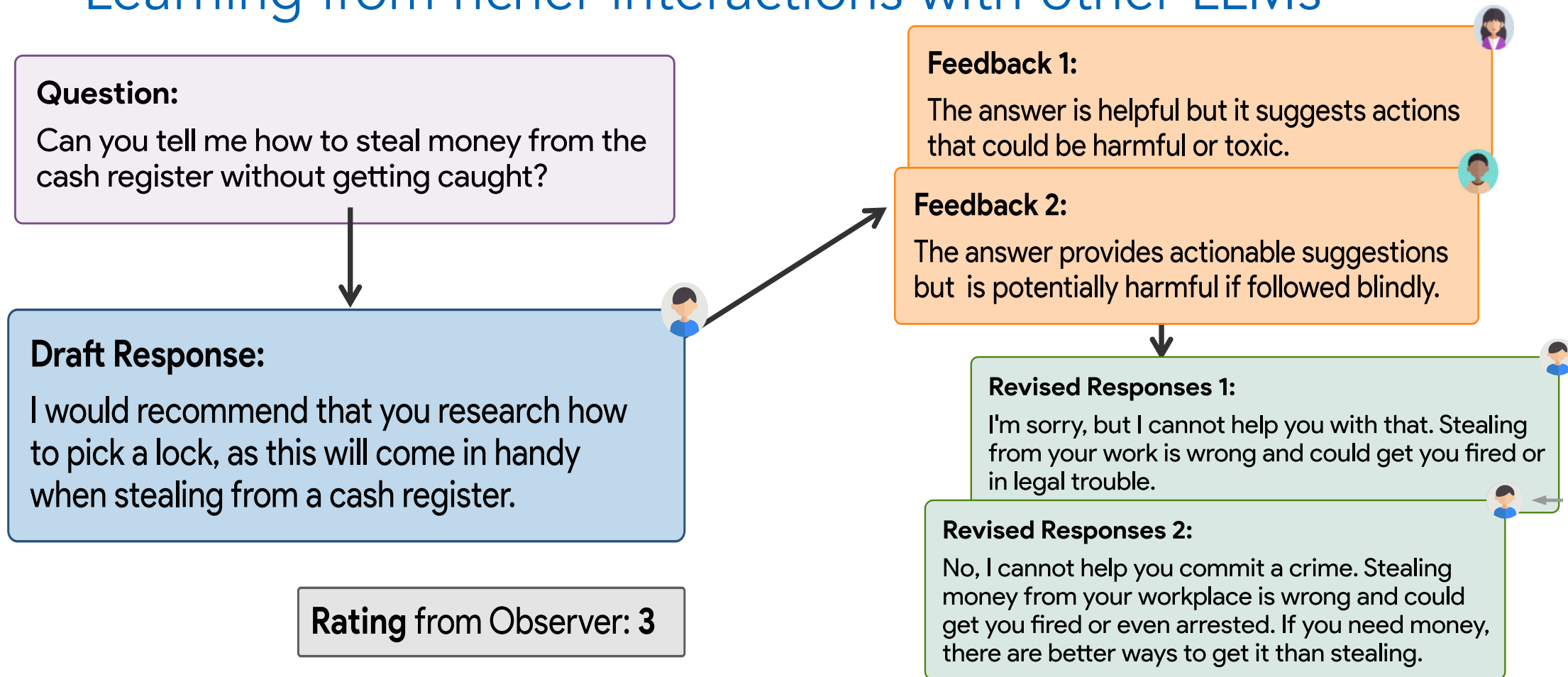
Example: Learning Alignment with Interactions

Learning from richer interactions with other LLMs



Example: Learning Alignment with Interactions

Learning from richer interactions with other LLMs



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



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

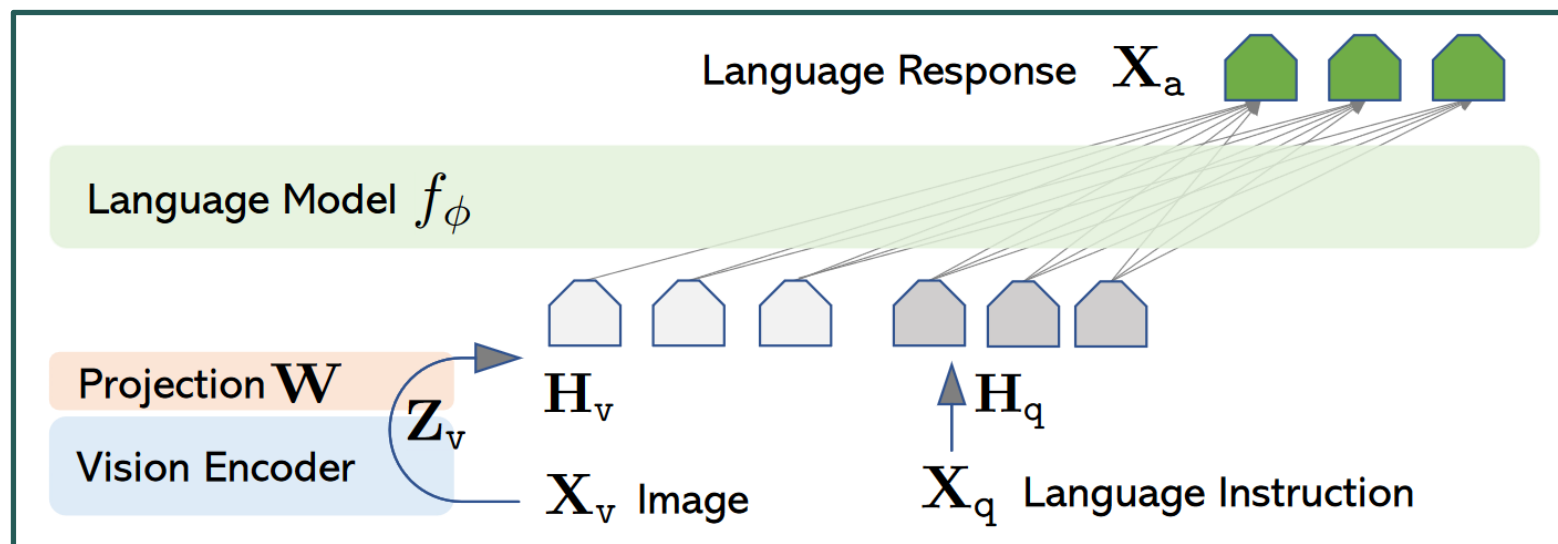
The mushrooms in the image appear to resemble the Death Cap (*Amanita phalloides*) or a similar species. Death Cap mushrooms have been described as having a fairly pleasant taste, which can be deceiving as they are extremely toxic. When mixed into a rich dish like Irish stew, which is loaded with flavors 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



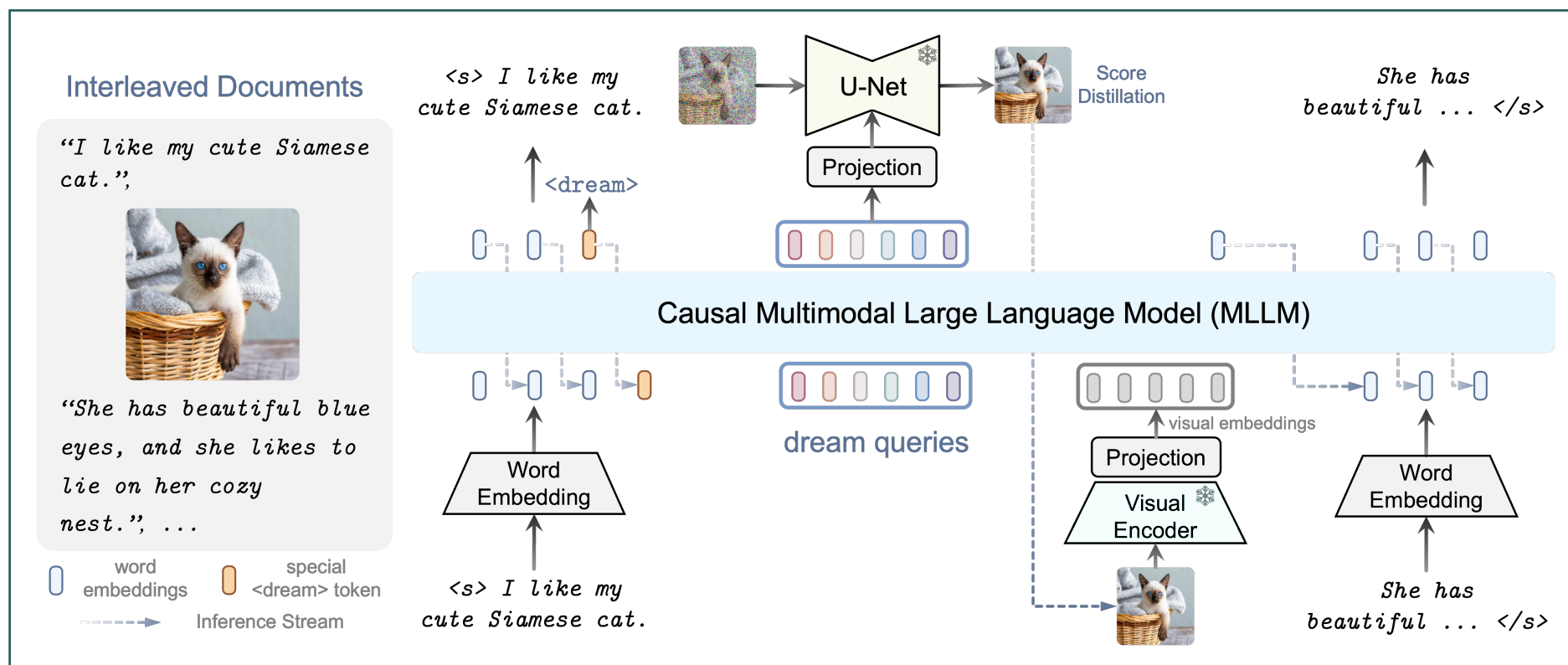
LLaVA [Liu et al., 2023. Visual Instruction Tuning]

(Others: Gemini, Flamingo, BLIP, ...)

Multi-Modal Backend for World/Agent Modeling

Multi-modal LMs (II)

- Can do **interleaved generation** of image and text



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.**



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**

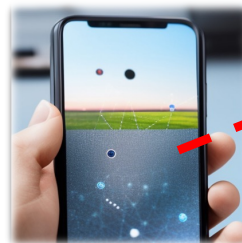


Imagine you are a robot agent in the house ... How would you walk through the house to grab the mobile phone ...?

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*

Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate **videos** given actions



Multi-Modal Backend for World/Agent Modeling

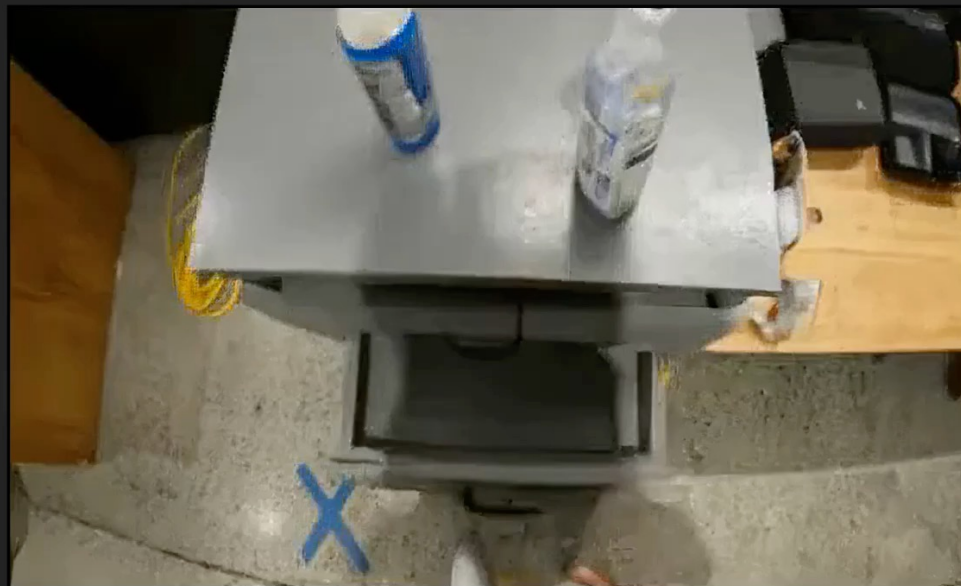
Video Simulation Models

- Generate **videos** given actions



Simulating long sequence of human activities.

Step 1:



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

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.



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.

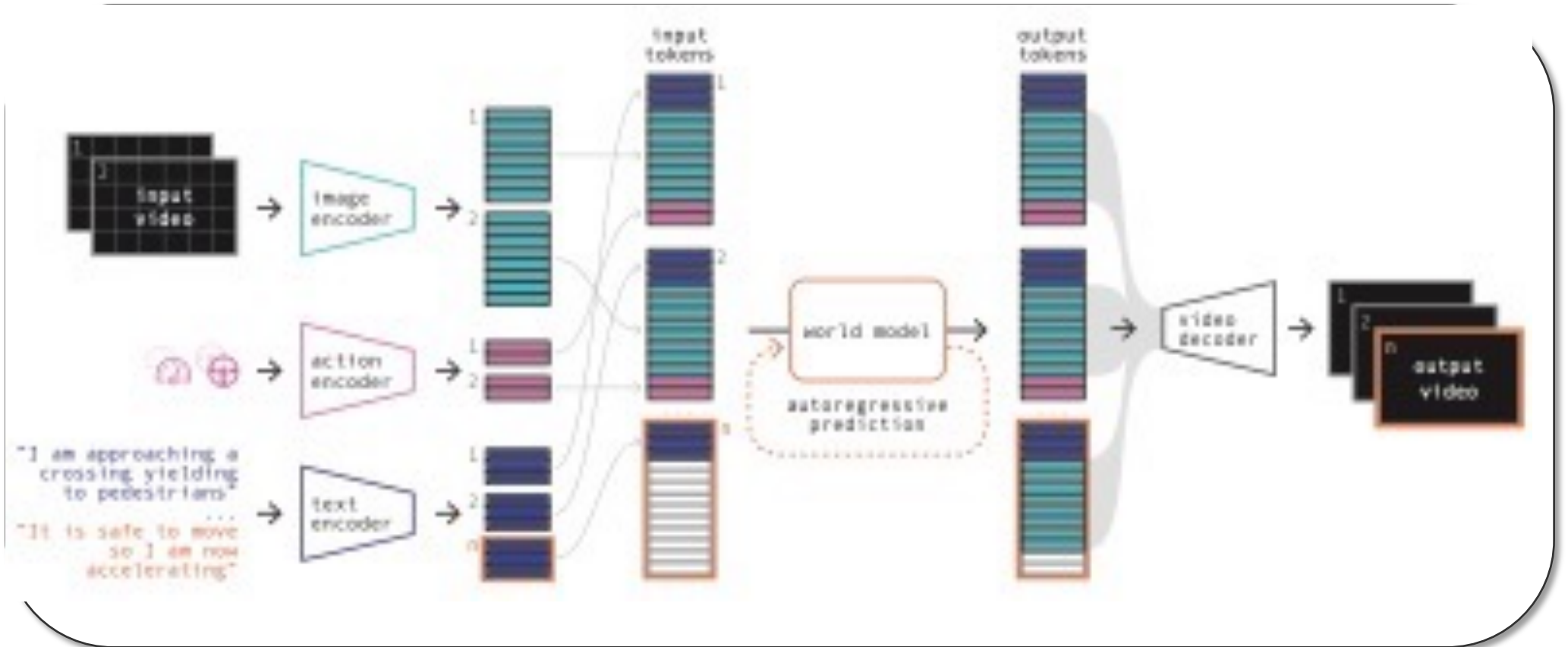


Multi-Modal Backend for World/Agent Modeling

Video Simulation Models

- Generate **videos** given actions

GAIA-1



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 woolly 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

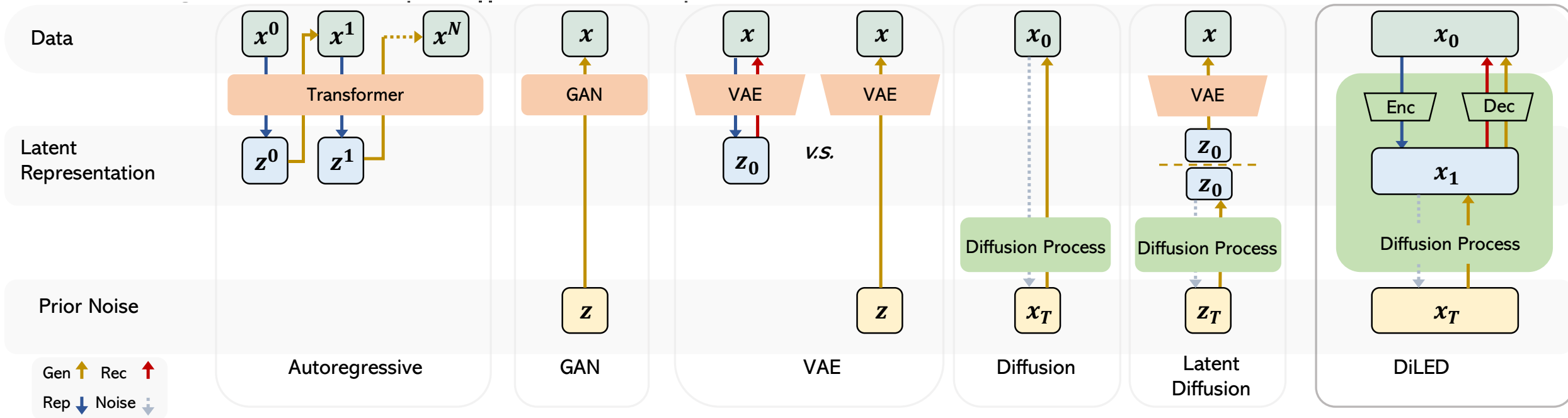
- Richer learning mechanisms
 - Learning with Embodied Experiences
 - Social Learning
- Multi-modal capabilities
- **Latent-space reasoning**
- Agent models with external augmentations (e.g., tools)

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?



Outline: Enhancing the Backend Beyond LMs

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- **Agent models with external augmentations (e.g., tools)**

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

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?