CMPT 983

Grounded Natural Language Understanding

March 23, 2022

Instruction Following - RoboNLP

Experience Grounds Language

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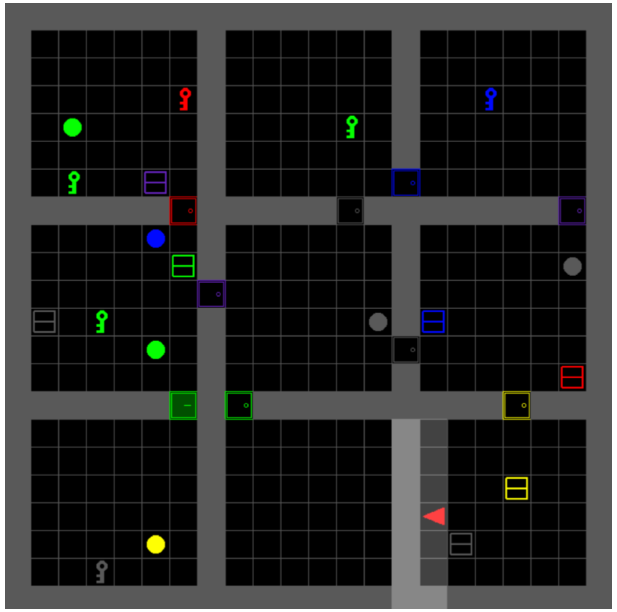
Vision-and-Language Navigation
Anderson et al 2018



BabyAI
Chevalier-Boisvert et al 2019

Observation: **West of House** You are standing in an open field west of a white house, with a boarded front door. There is a small mailbox here.

Action: **Open mailbox**

Observation: Opening the small mailbox reveals a leaflet.

Action: **Read leaflet**

Observation: (Taken) "WELCOME TO ZORK! ZORK is a game of adventure, danger, and low cunning. In it you will explore some of the most amazing territory ever seen by mortals. No computer should be without one!"

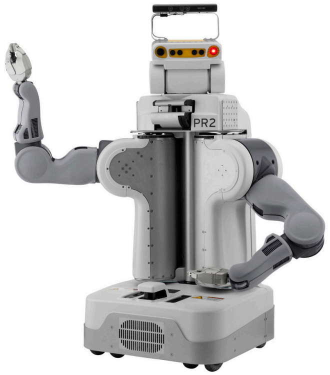
Action: **Go north**

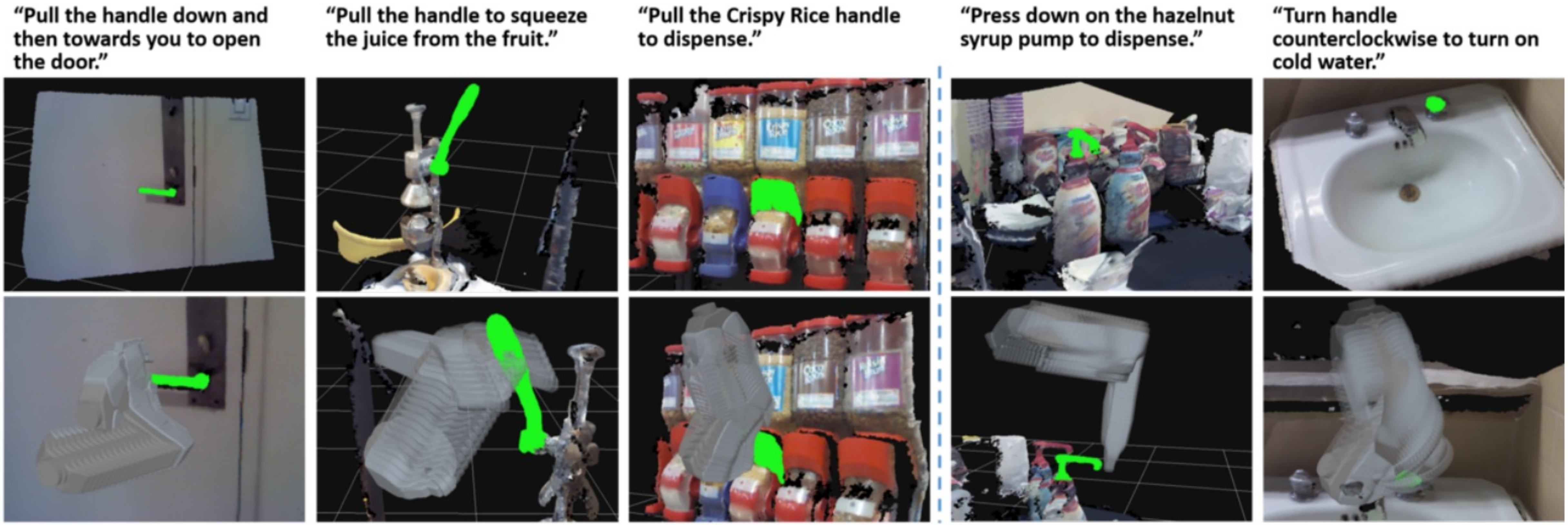
Observation: **North of House** You are facing the north side of a white house. There is no door here, and all the windows are boarded up. To the north a narrow path winds through the trees.

Zork
[Modeling Worlds in Text, Ammanabrolu and Riedl, 2021]

Robobarista

- PR2 robot make coffee?



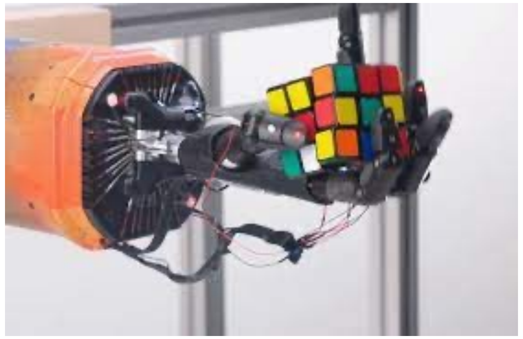


Deep Multimodal Embedding: Manipulating Novel Objects with Point-clouds, Language and Trajectories, Sung et al, ICRA 2017

RoboNLP

Robot following instructions

- Navigation
- Interaction
- Manipulation



Last week: Instruction-guided Visual Navigation

Leave the bedroom, and enter the kitchen. Walk forward, and take a left at the couch. Stop in front of the window.

Slide credit: Stefan Lee

Navigation

Pioneer AT

"Go to the break room and report the location of the blue box."
(Dzifcak et al, ICRA 2009)

CoBot

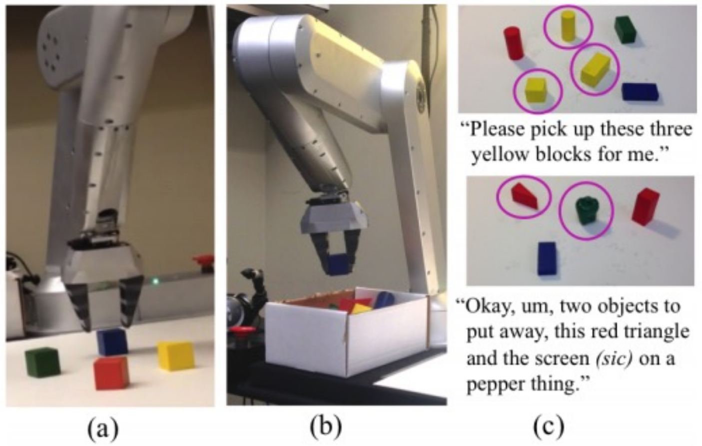
Commands
- Go to the bridge.
- Go to the lab.
- Bring me to the elevator.
- Go to Christina's office.
- Take me to the meeting room.

"Take me to the meeting room."
(Kollar et al, ICRA 2013)

Examples from "Robots that use language: A survey", Tellex et al, 2020
https://h2r1.cs.brown.edu/wp-content/uploads/tellex20.pdf

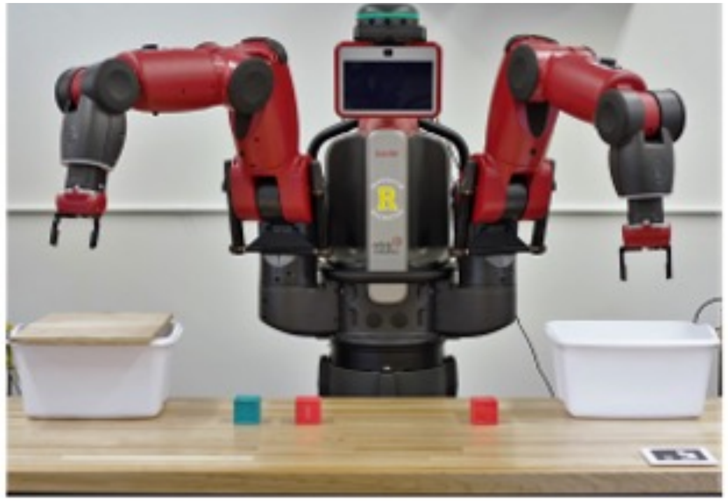
Manipulation

Gambit manipulator



Pick and place
(Matuszek et al, AAAI 2014)

Baxter



"Pick up the blue block and drop it in the box on your right. Pick up the red block and drop it in the box on your left"
(Boteanu et al, IROS 2016)

Baxter

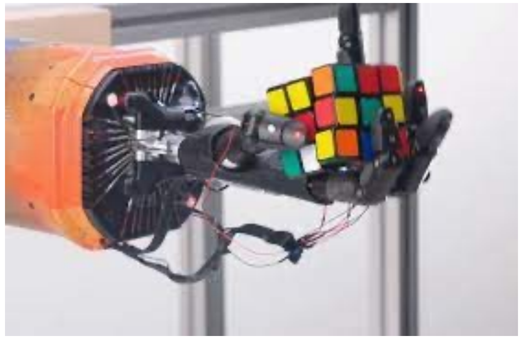
Learn from dialog and demonstrations
(Chai et al, IJCAI 2018)

Examples from "Robots that use language: A survey", Tellex et al, 2020
https://h2r1.cs.brown.edu/wp-content/uploads/tellex20.pdf

RoboNLP

Robot following instructions

- Navigation
- Interaction
- Manipulation



Communication in embodied environments

- Human providing information
- Robot providing information
  - Question answering
- Robot asking for help
- Dialogue

Tasks (involving language)

- Instruction Following
  - Vision and language navigation
    - VLN paper: In static environments with navigation graph
    - Can also be interactive environments (objects move if you bump against them)
  - Rearrangement
    - Can involve manipulation (low level actions, grippers)
    - Can also be with just high-level actions (point and magic action commands)
- Language understanding
  - QA: Ask questions about the environment (may require agent to navigate around the environment to obtain answers)
  - Find and localize: Find and localize objects and referents
- Dialogue
  - Communication between human-agent or agent-agent
  - Convey information, intent, beliefs

Other tasks with manipulation

Jaco arm

Identify objects using attributes:
``silver, round, and empty''
(Thomason et al, IJCAI 2016)

Ask for help
(Tellex et al, RSS 2014)

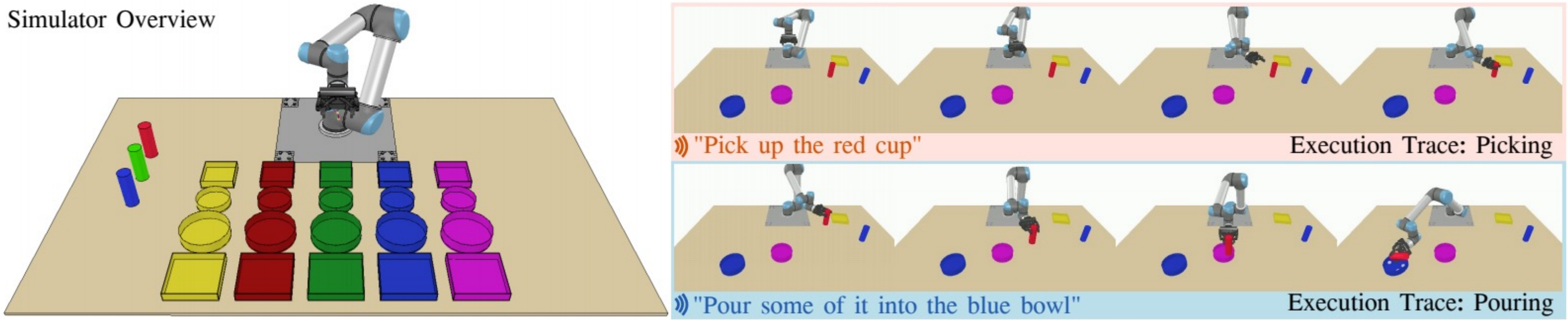
TUM-Rosie

Make pancakes using recipes from wikihow.com (Nyga and Beetz, IROS 2012)

Most of these are very limited and constrained:
very small vocabulary, very specific scenario (pre-deep learning)

Examples from "Robots that use language: A survey", Tellex et al, 2020
https://h2r1.cs.brown.edu/wp-content/uploads/tellex20.pdf

Manipulation



Language-Conditioned Imitation Learning for Robot Manipulation Tasks, https://arxiv.org/pdf/2010.12083.pdf, Stepputtis et al, 2020

Navigation + Interaction/Manipulation

Why challenging?

- Need data
- Large task space
- Real robots are challenging (slow and tricky to work with)
- Accurate simulations involving manipulations is also challenging (modeling physics is not easy)

(a) Robotic forklift

Commands from the corpus
- Go to the first crate on the left and pick it up.
- Pick up the pallet of boxes in the middle and place them on the trailer to the left.
- Go forward and drop the pallets to the right of the first set of tires.
- Pick up the tire pallet off the truck and set it down

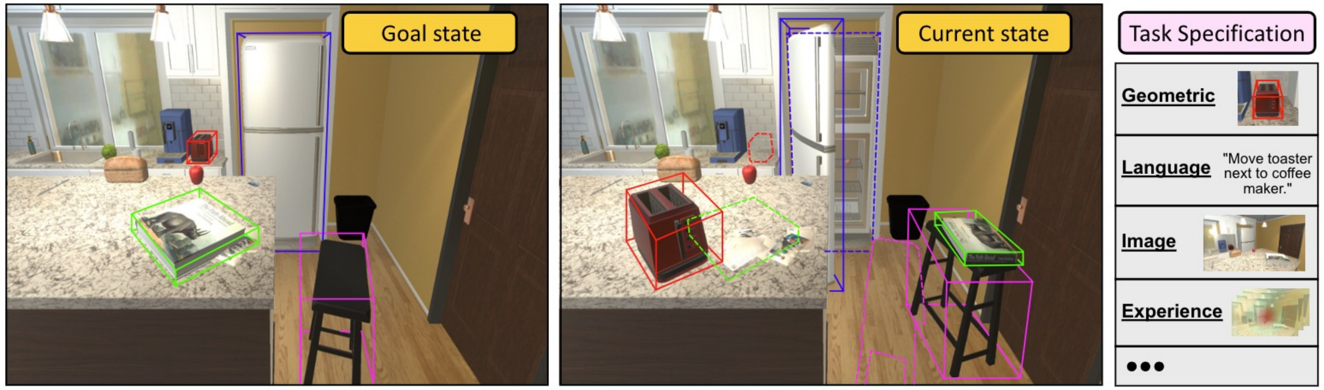
(b) Sample commands

Understanding Natural Language Commands for Robotic Navigation and Mobile Manipulation, Tellex et al, AAAI 2011

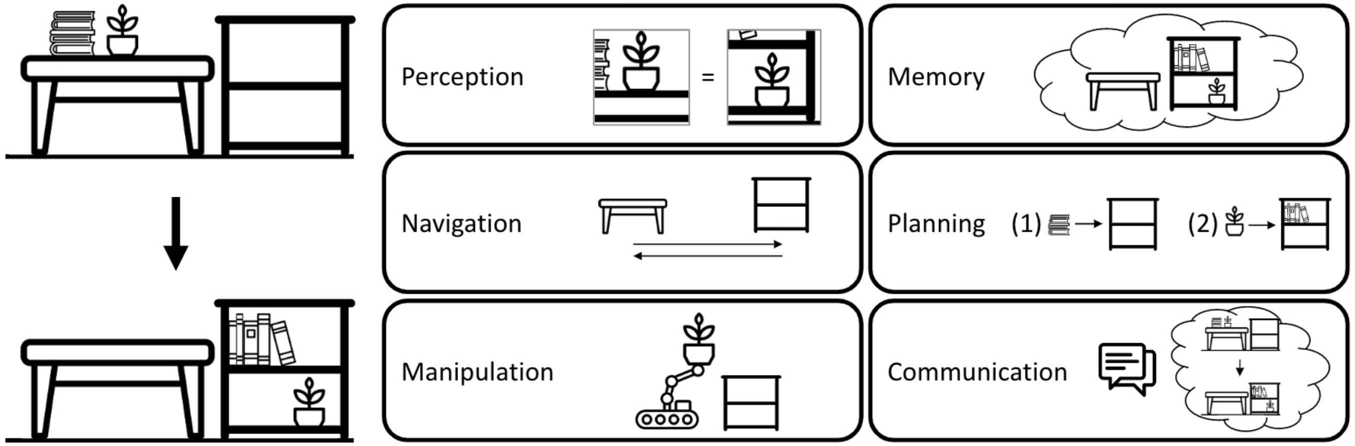
Re-arrangement https://arxiv.org/pdf/2011.01975.pdf

Meta-benchmark

Goal state can be specified using language



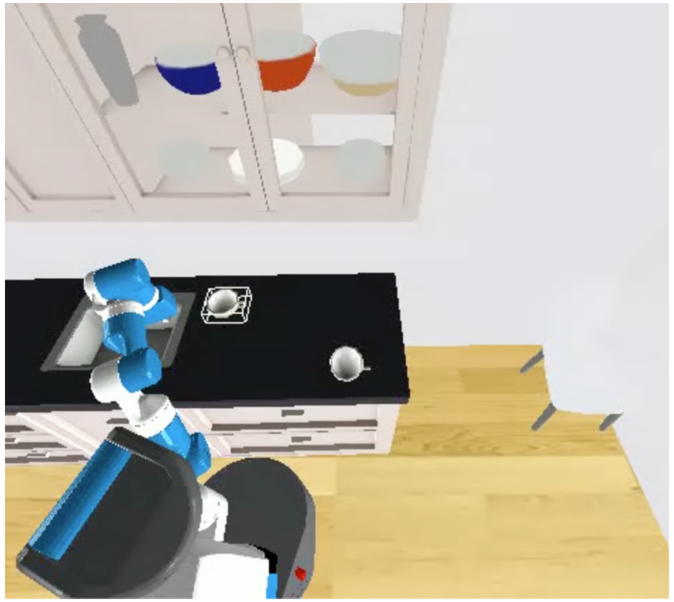
Encourage research across sub-areas



Whitepaper with

Intel, FAIR, AI2, Google, Berkeley, Princeton, GaTech, Imperial, UCSD

https://arxiv.org/pdf/2011.01975.pdf



Interactive Habitat

Embodied AI workshop (CVPR 2022)

Challenge	Task	Interactive Actions?	Simulation Platform	Scene Dataset	Observations	Stochastic Acuation?	Action Space
AI2-THOR FurnMove	Multi-agent Furniture Moving	✓	AI2-THOR	iTHOR	RGB, Localization		Discrete
AI2-THOR Rearrangement	Rearrangement	✓	AI2-THOR	iTHOR	RGB-D, Localization		Discrete
ALFRED	Vision-and-Language Interaction	✓	AI2-THOR	iTHOR	RGB		Discrete
Habitat	ObjectNav		Habitat	Matterport3D	RGB-D, Localization		Discrete
iGibson	Interactive Navigation	✓	iGibson	iGibson	RGB-D	✓	Continuous
iGibson	Social Navigation	✓	iGibson	iGibson	RGB-D	✓	Continuous
MultiON	Multi-Object Navigation		Habitat	Matterport3D	RGB-D, Localization		Discrete

https://embodied-ai.org/

Embodied AI workshop (CVPR 2022)

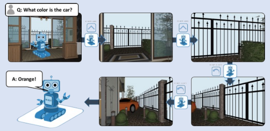
Challenge	Task	Interactive Actions?	Simulation Platform	Scene Dataset	Observations	Stochastic Acuation?	Action Space
Robotic Vision Scene Understanding	Rearrangement (SCD)		Isaac Sim	Active Scene Understanding	RGB-D, Pose Data, Flatscan Laser	✓	Discrete
Robotic Vision Scene Understanding	Semantic SLAM		Isaac Sim	Active Scene Understanding	RGB-D, Pose Data, Flatscan Laser	Partially	Discrete
RxR-Habitat	Vision-and-Language Navigation		Habitat	Matterport3D	RGB-D		Discrete
SoundSpaces	Audio Visual Navigation		Habitat	Matterport3D	RGB-D, Audio Waveform		Discrete
TDW-Transport	Rearrangement	✓	TDW	TDW	RGB-D, Metadata	✓	Discrete
TEACh	Vision-and-Dialogue Interaction	✓	AI2-THOR	iTHOR	RGB		Discrete, Text Generation

https://embodied-ai.org/

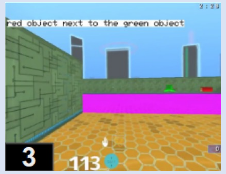
Simulators

Embodied AI Stack

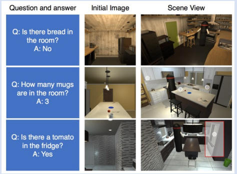
Tasks



EmbodiedQA
(Das et al., 2018)



Language grounding
(Hill et al., 2017)



Interactive QA
(Gordon et al., 2018)

Vision-Language Navigation
(Anderson et al., 2018)

Visual Navigation
(Zhu et al., 2017, Gupta et al., 2017)

Capabilities

Rendering

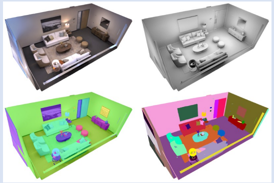
Physics

Agents/ Robots

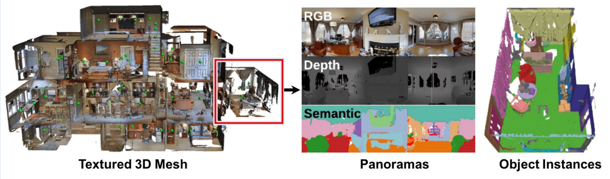
Multi-agent support

Human Input (VR)

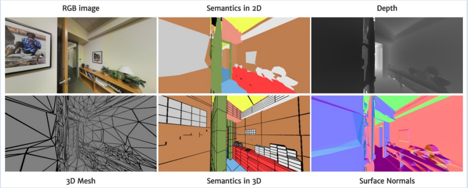
Assets



Replica (Straub et al., 2019)



Matterport3D (Chang et al., 2017)



2D-3D-S (Armeni et al., 2017)

3D assets for 3D environments
simpler 2D assets for simpler worlds

Simulation Engines

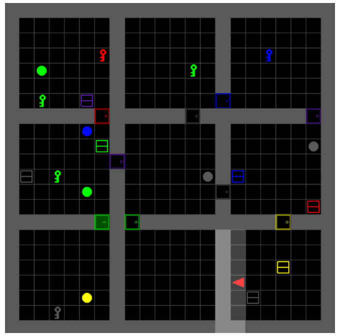
- Environment: Indoor/Outdoor/Maze
  - Can be procedurally generated, manually designed, or captured
- Simulator

  Components
  - Renderer
  - Physics Engine

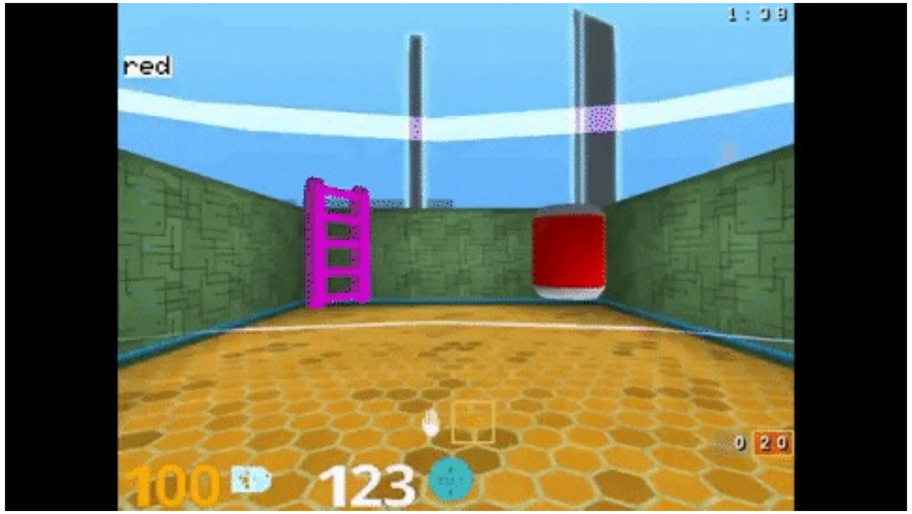
  Implementation
  - Game Engine
    - Unreal Engine (CARLA) / Unity (AI2Thor, ThreeDWorld)
  - Custom
    - Gibson, Sapien, Habitat

Procedurally Generated Environments

- Mazes
  - BabyAI (Chevalier-Boisvert et al 2019)
  - 3D environments



Deepmind Lab



https://github.com/mwydmuch/ViZDoom

https://github.com/deepmind/lab

Physical reasoning

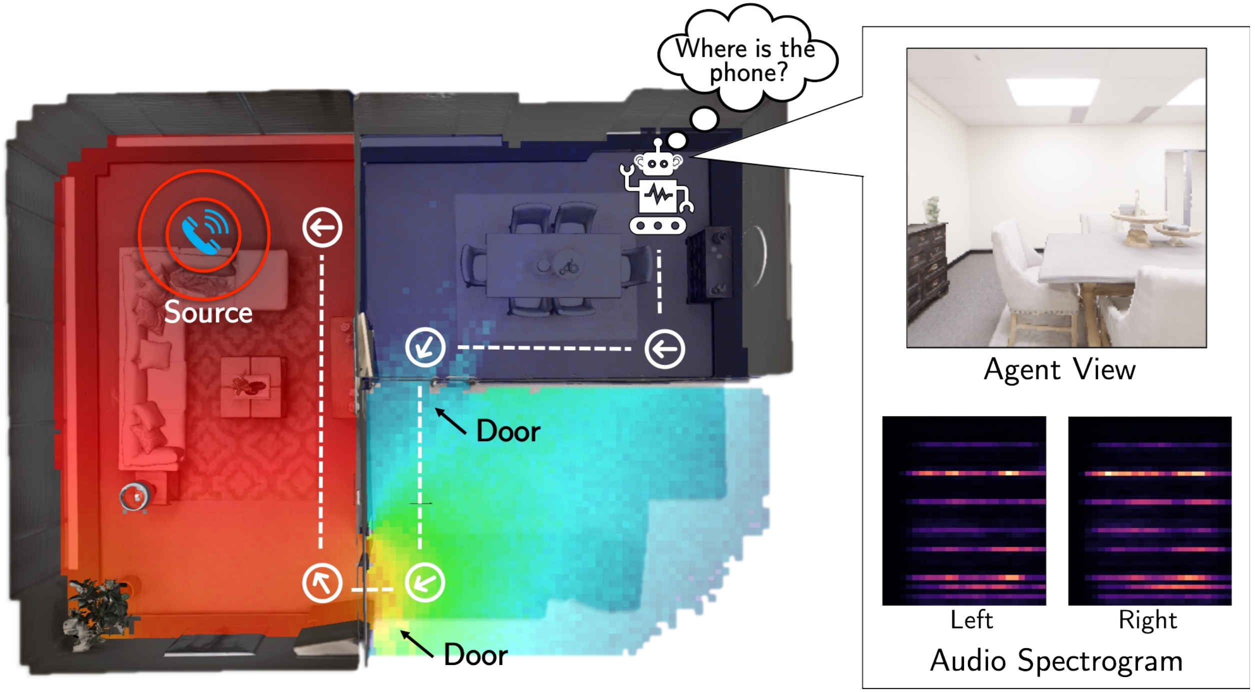
https://www.threedworld.org/

MINOS: interaction through language

Savva et al. 2017

Habitat

Habitat 1.0
Savva et al, ICCV 2019



SoundSpaces: Audio-Visual Navigation in 3D Environments
Chen et al, ECCV 2020
https://soundspaces.org/

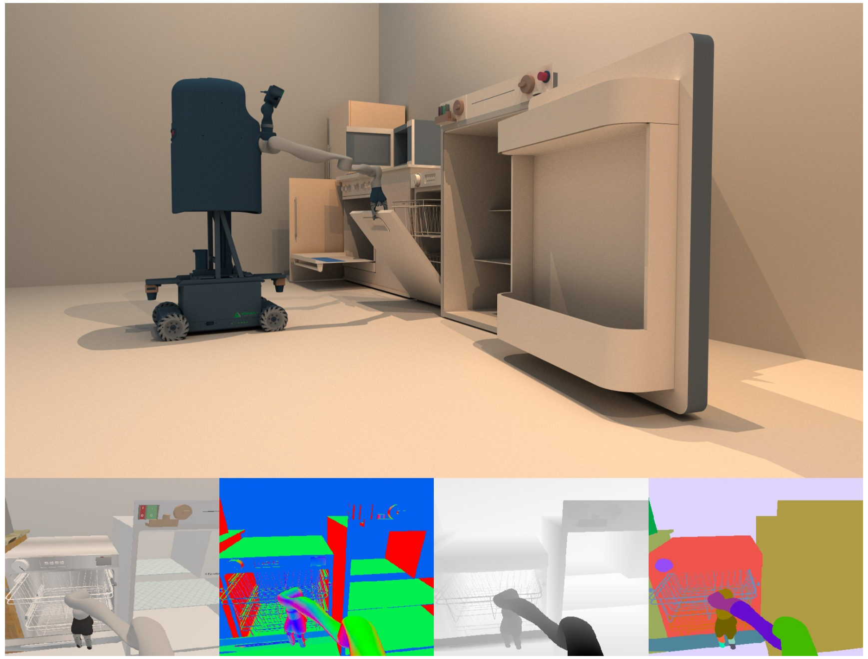
facebook AI Research

FACEBOOK REALITY LABS

THE UNIVERSITY OF TEXAS AT AUSTIN

ILLINOIS

Interactive Simulation Environments



SAPIEN

https://sapien.ucsd.edu/

[Xiang et al. 2020]

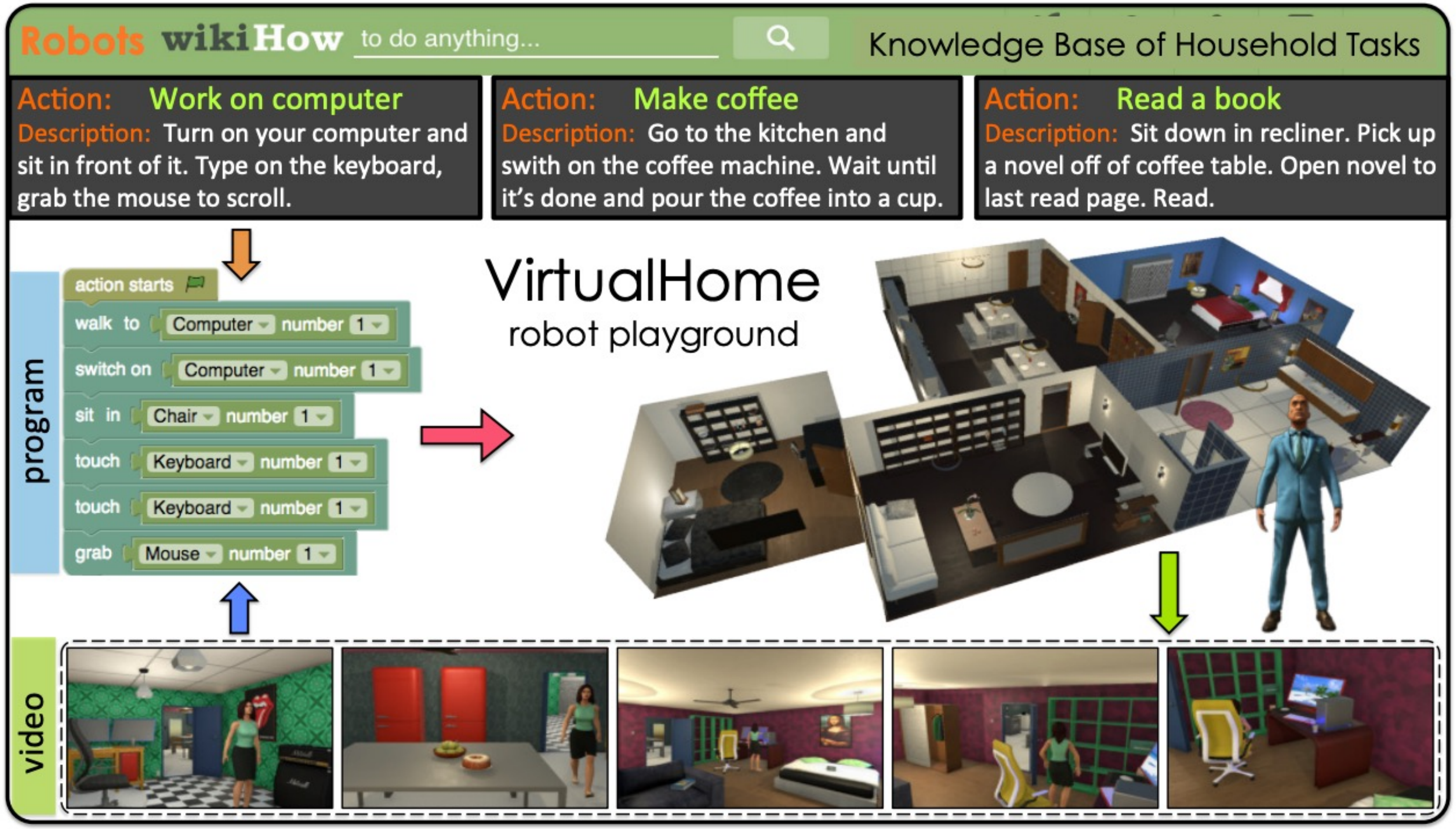
Habitat 2.0

https://aihabitat.org/

UC San Diego Stanford University SFU SIMON FRASER UNIVERSITY facebook AI Research Berkeley UNIVERSITY OF CALIFORNIA Georgia Tech intel

Existing language + interaction work

VirtualHome http://virtual-home.org/

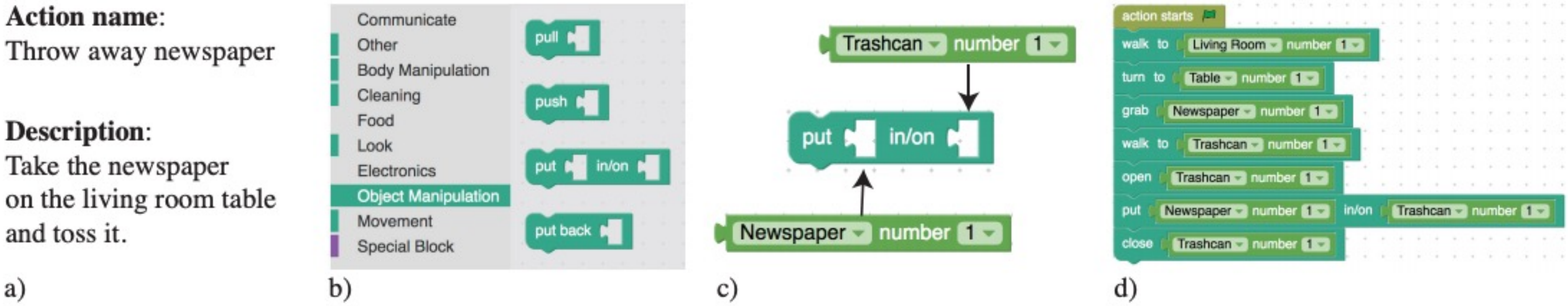


- Collect common activities for 8 scene types
- Collect descriptions, and programs
- Use programs to generate videos

VirtualHome: Simulating Household Activities via Programs
https://arxiv.org/pdf/1806.07011.pdf
Puig et al, CVPR 2018

VirtualHome: Data collection

"Visual interface" to allow crowdworkers to piece together program

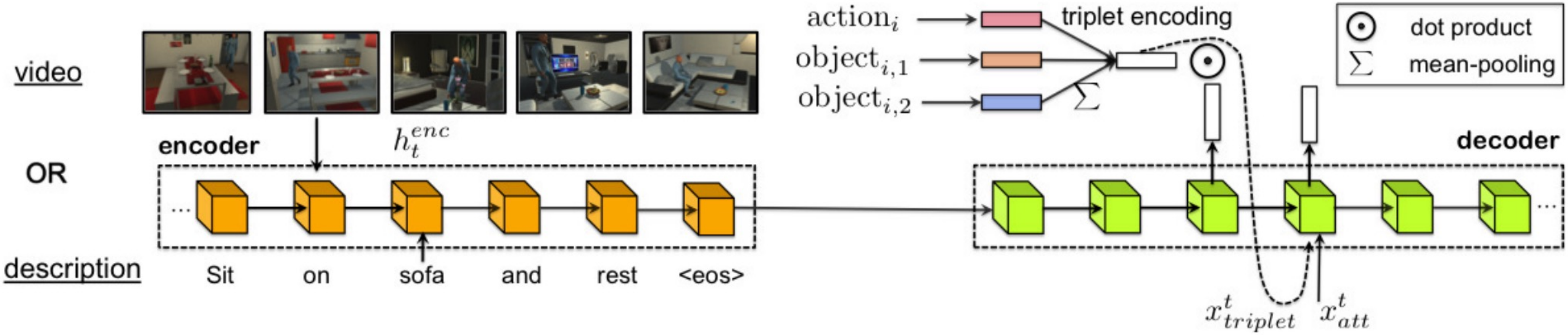


Two datasets:

- ActivityPrograms: 1814 descriptions, 2821 programs for 75 actions, 308 objects
- VirtualHome Activity: synthesized 5193 programs (with human provided description),12 most common actions

VirtualHome: Simulating Household Activities via Programs
https://arxiv.org/pdf/1806.07011.pdf
Puig et al, CVPR 2018

VirtualHome: Generate program from language or video



VirtualHome: Simulating Household Activities via Programs
https://arxiv.org/pdf/1806.07011.pdf
Puig et al, CVPR 2018

VirtualHome: Generated programs

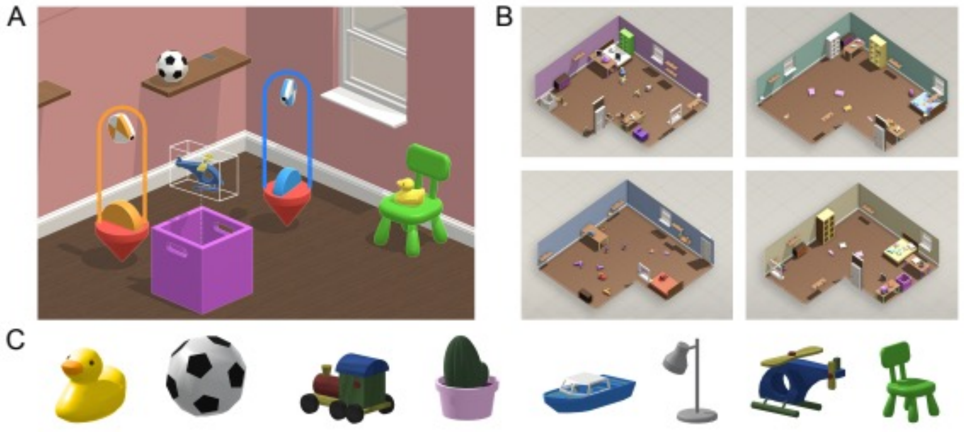
Description: Get an empty glass. Take milk from refrigerator and open it. Pour milk into glass.

Description: Go watch TV on the couch. Turn the TV off and grab the coffee pot. Put the coffee pot on the table and go turn the light on.

VirtualHome: Simulating Household Activities via Programs
https://arxiv.org/pdf/1806.07011.pdf
Puig et al, CVPR 2018

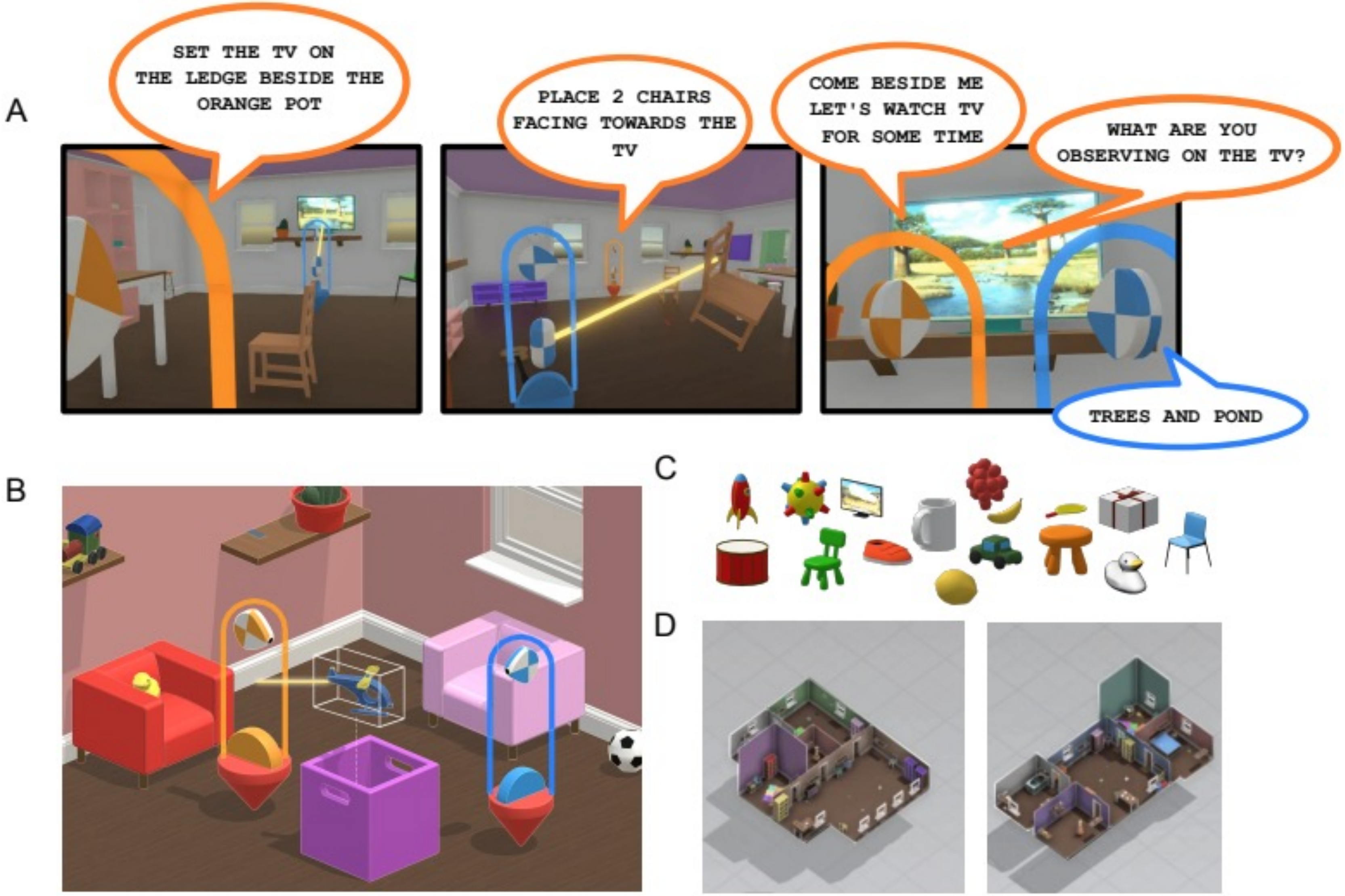
DeepMind Playhouse

- Interactive Agents Team
- Random set of rooms with containers, furniture, and randomly placed objects
- Humans and agents interact
- Collect data and train some agents!



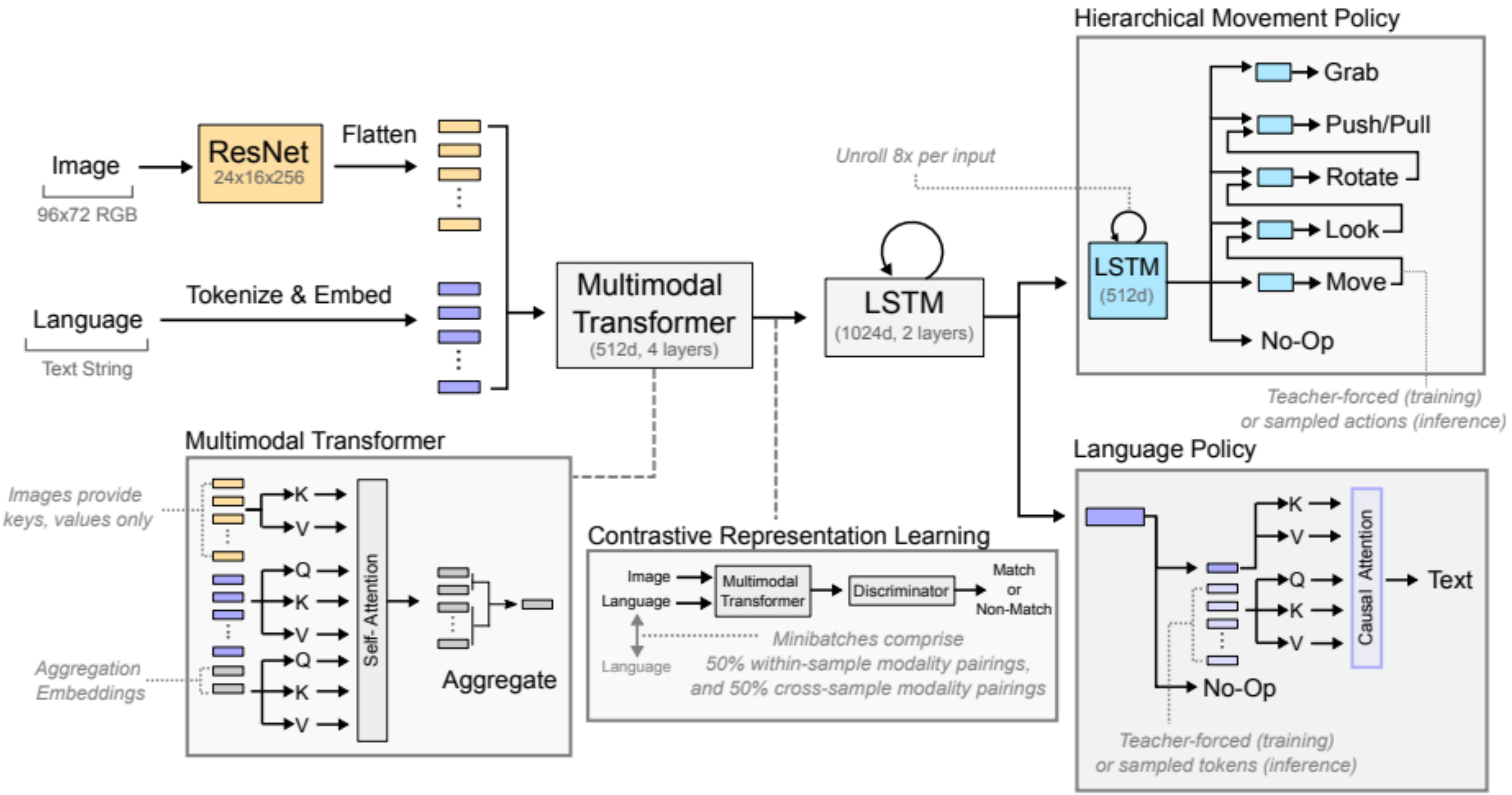
https://arxiv.org/pdf/2012.05672.pdf

DeepMind Playhouse



https://arxiv.org/pdf/2112.03763.pdf

Model Architecture



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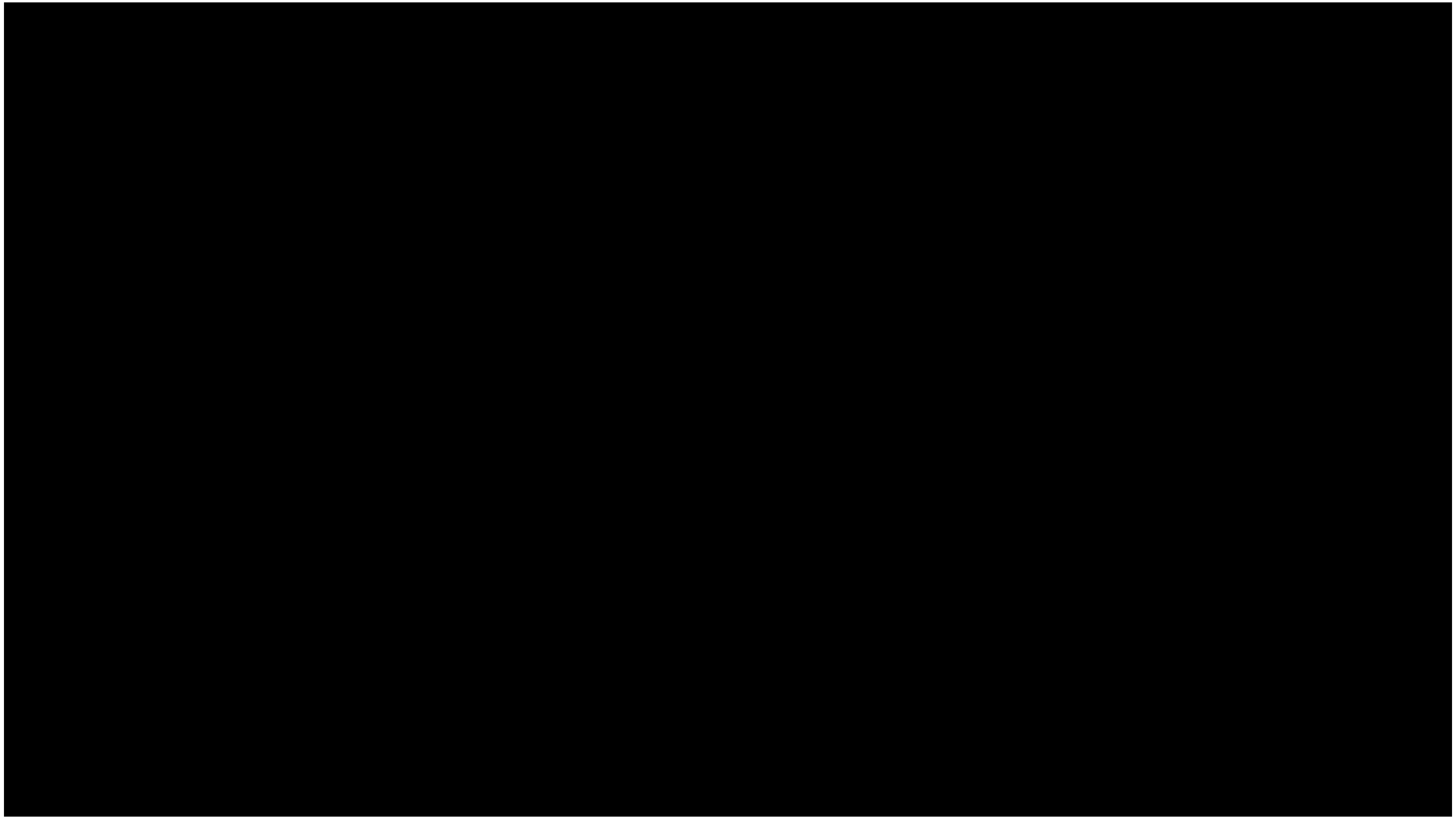
DeepMind Playhouse



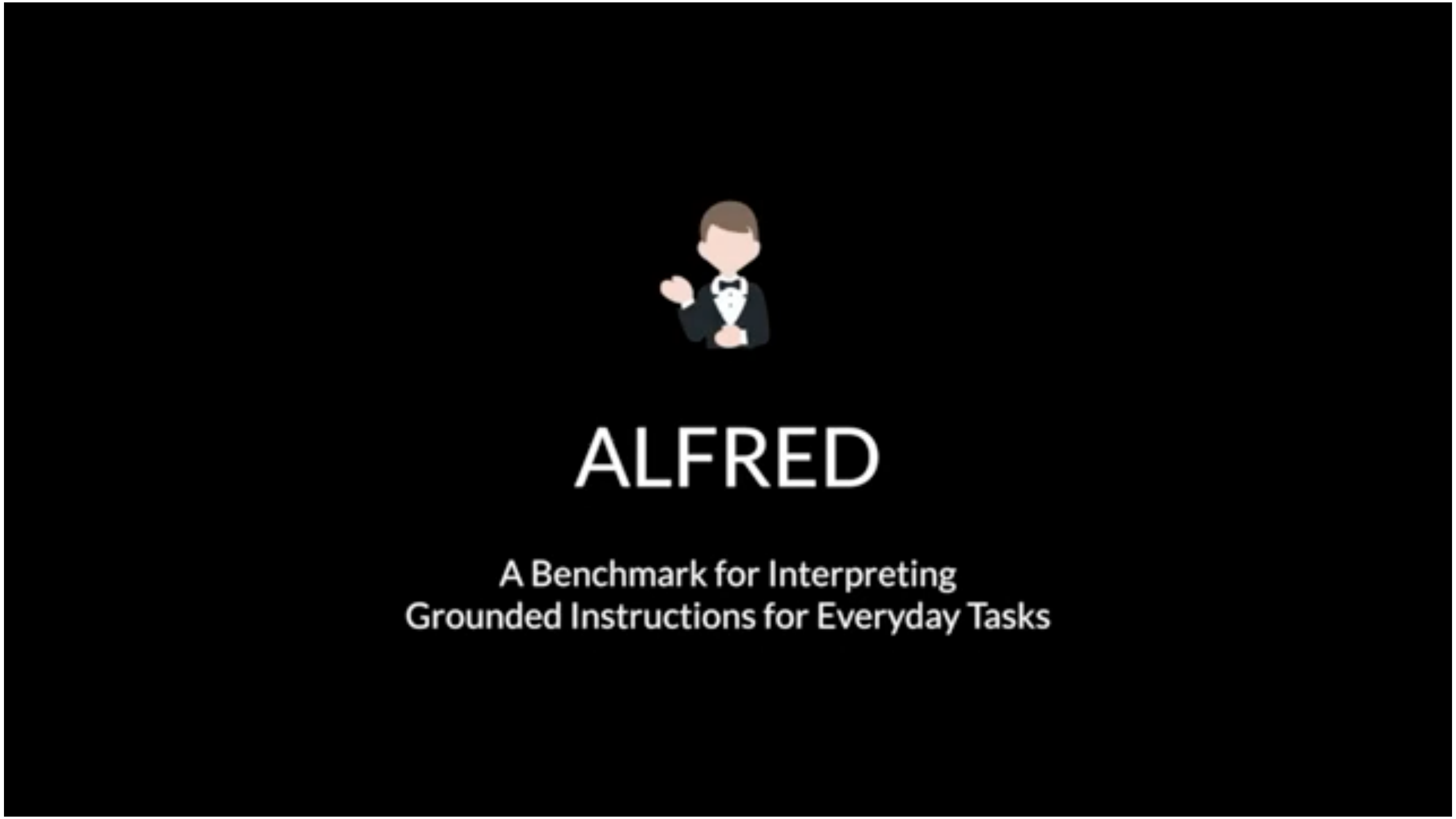
https://youtu.be/ZFgRhviF7mY

Alfred

https://askforalfred.com/

25K English instructions
8K expert demonstrations (average 50 steps)
430K image-action pairs

A Benchmark for Interpreting Grounded Instructions for Everyday Tasks
https://arxiv.org/pdf/1912.01734.pdf
Shridhar et al, CVPR 2020

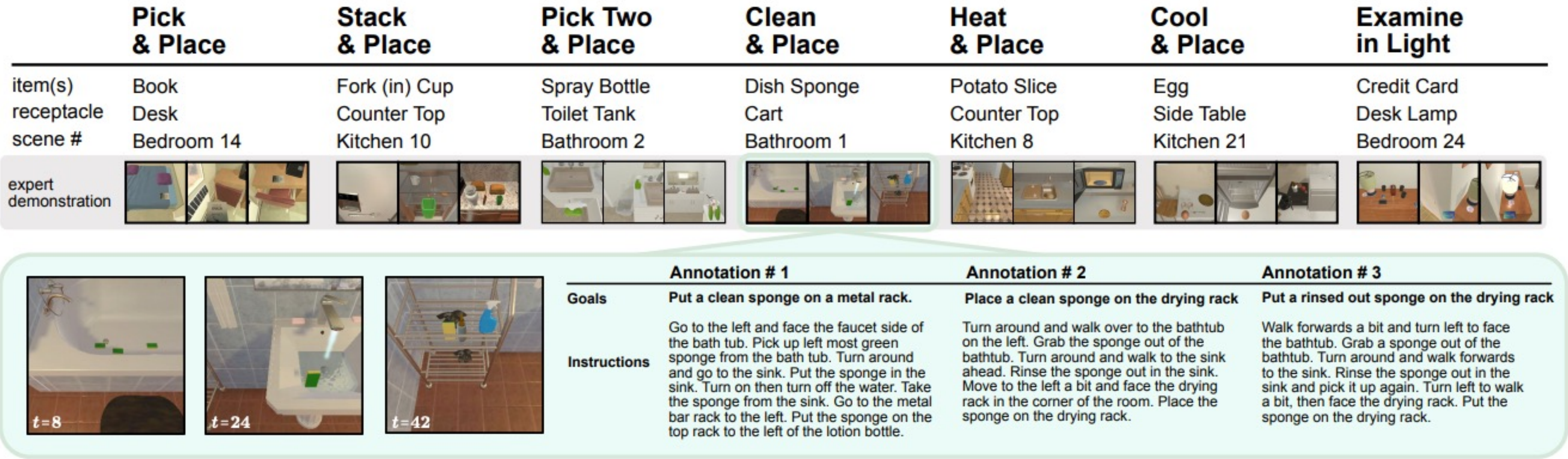

ALFRED
A Benchmark for Interpreting
Grounded Instructions for Everyday Tasks

Alfred dataset

- 7 task types
- 84 object classes in 120 scenes

Episodes with Navigation + Interaction

- Generate expert demonstrations using planner and specifying task-specific planning rules with start and end position
- Interaction using object mask
- Collect instructions from AMT



Other datasets

	— Language —		— Virtual Environment —			— Inference —		
	# Human Annotations	Granularity	Visual Quality	Movable Objects	State Changes	Vis. Obs.	Navigation	Interaction
TACoS [43]	17k+	High&Low	Photos	✗	✗	–	–	–
R2R [3]; Touchdown [14]	21k+; 9.3k+	Low	Photos	✗	✗	Ego	Graph	✗
EQA [15]	✗	High	Low	✗	✗	Ego	Discrete	✗
Matterport EQA [55]	✗	High	Photos	✗	✗	Ego	Discrete	✗
IQA [20]	✗	High	High	✗	✓	Ego	Discrete	Discrete
VirtualHome [42]	2.7k+	High&Low	High	✓	✓	3rd Person	✗	Discrete
VSP [58]	✗	High	High	✓	✓	Ego	✗	Discrete
ALFRED	25k+	High&Low	High	✓	✓	Ego	Discrete	Discrete + Mask

A Benchmark for Interpreting Grounded Instructions for Everyday Tasks
https://arxiv.org/pdf/1912.01734.pdf
Shridhar et al, CVPR 2020

AI2Thor https://ai2thor.allenai.org/

- Unity game engine with designed actions and object states

AI2-THOR: "Actionable Properties"

https://ai2thor.allenai.org/ithor/documentation/objects/actionable-properties/

Properties on 126 objects indicating actions that can be performed

- Openable (OpenObject/CloseObject)
- Pickupable (PickupObject/PutObject/DropHandObject/Throw/Pull/Push)
- Moveable (Push/Pull - too large to be Pickupable)
- Toggleable (ToggleObjectOn/ToggleObjectOff)
- Receptable (other objects can be placed on/in these objects)
- Fillable (FillObjectWithLiquid)
- Sliceable (SliceObject, one-way state change)
- Cookable (CookObject, one-way state change)
- Breakable (BreakObject, one-way state change)
- Dirty (DirtyObject toggles the state)
- UsedUp (UseUp, one-way state change)

AI2-THOR

- Material Properties https://ai2thor.allenai.org/ithor/documentation/objects/material-properties/
  - Temperature (Hot/Cold/RoomTemp)
    - All objects have Temperature
    - Some objects can change the temperature of other objects (e.g. Refrigerator, Stove Burner)
  - Mass
  - Salient Materials (Metal, Wood, Plastic, Glass, Ceramic, Stone, Fabric, Rubber, Food, Paper, Wax, Soap, Sponge, Organic)
    - Individual objects will have different salient materials (material types)
- Contextual interactions https://ai2thor.allenai.org/ithor/documentation/objects/contextual-interactions/
  - Rules that specify state change to objects under certain conditions
  - Example: BreadSliced, becomes Cooked if:
    - PutObject is used to place BreadSliced into Toaster objects that is on
    - Moved over Stove Burner that is on

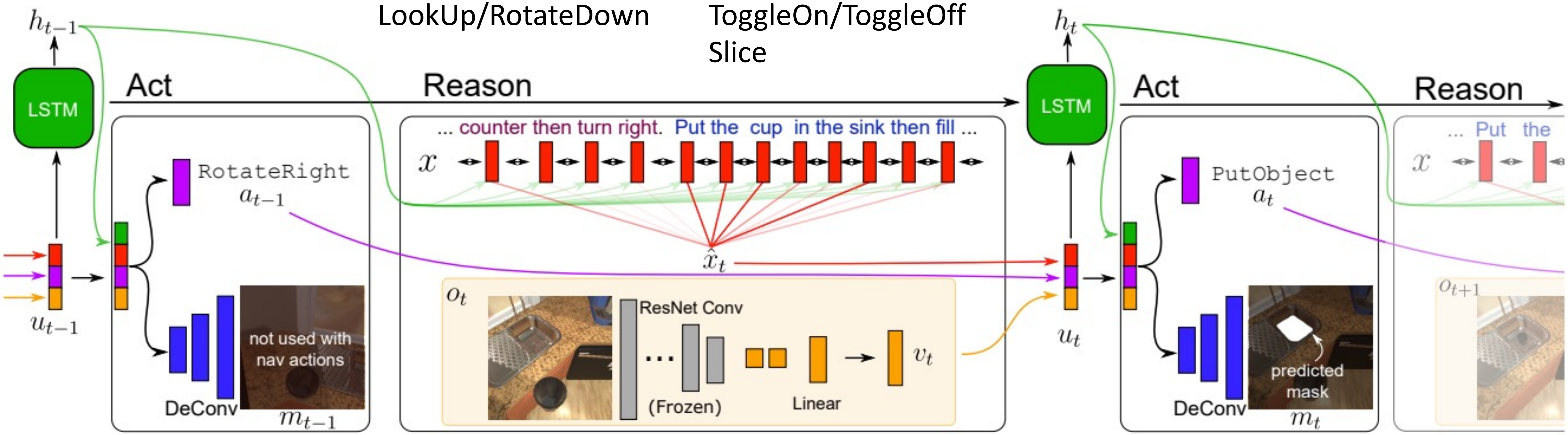
Alfred agent model

- Seq2seq model (CNN vision, LSTM language)
- Predicts action + binary mask of object from concatenated input
  - 13 actions (5 navigation + 7 interaction + stop)

Concatenated input
Vision
Language
Last action

Navigation
MoveAhead
RotateLeft/RotateRight
LookUp/RotateDown

Interaction
Pickup/Put
Open/Close
ToggleOn/ToggleOff
Slice



Alfred Training

- Train with imitation learning / teacher forcing
  - Dagger / student-forcing challenging
- Variations:
  - Progress Monitors
    - Estimate of progress toward goal
    - Helps to learn utility of each state
  - Two progress monitors (both trained with L2 loss)
    - Predict overall progress based on time t/T
    - Predict (normalized) number of subgoals accomplished
  - Uses as input LSTM hidden state + concatenated input (of vision + language + last action)

$$p_t = \sigma\left(W_p\left[h_t; u_t\right]\right)$$

$$c_t = \sigma\left(W_c\left[h_t; u_t\right]\right).$$

t = current time step
T = total length of expert demonstration

Alfred evaluation

- Task Success:
  - Does the final object position and state match goal? (1 or 0)
- Goal-Condition Success
  - Ratio of goals completed (1 → task success)
- Path weighted Task and Goal-Condition Success

$$p_s = s \times \frac{L^*}{max(L^*, \hat{L})}$$

Like SPL for navigation, but for action path

Alfred results

- Compare against simple no language and no vision baselines
- Random is at 0%, PM adds ~1% for seen environments
- Very poor performance!

	Validation				**Test**			
	Seen		*Unseen*		*Seen*		*Unseen*	
Model	Task	Goal-Cond	Task	Goal-Cond	Task	Goal-Cond	Task	Goal-Cond
No Language	0.0 (0.0)	5.9 (3.4)	0.0 (0.0)	6.5 (4.7)	0.2 (0.0)	5.0 (3.2)	0.2 (0.0)	6.6 (4.0)
No Vision	0.0 (0.0)	5.7 (4.7)	0.0 (0.0)	6.8 (6.0)	0.0 (0.0)	3.9 (3.2)	0.2 (0.1)	6.6 (**4.6**)
Goal-only	0.1 (0.0)	6.5 (4.3)	0.0 (0.0)	6.8 (5.0)	0.1 (0.1)	5.0 (3.7)	0.2 (0.0)	6.9 (4.4)
Instructions-only	2.3 (1.1)	9.4 (6.1)	0.0 (0.0)	**7.0** (4.9)	2.7 (1.4)	8.2 (5.5)	**0.5** (**0.2**)	7.2 (**4.6**)
Seq2Seq	2.4 (1.1)	9.4 (5.7)	**0.1** (0.0)	6.8 (4.7)	2.1 (1.0)	7.4 (4.7)	**0.5** (**0.2**)	7.1 (4.5)
+ PM Progress-only	2.1 (1.1)	8.7 (5.6)	0.0 (0.0)	6.9 (5.0)	3.0 (1.7)	8.0 (5.5)	0.3 (0.1)	**7.3** (4.5)
+ PM SubGoal-only	2.1 (1.2)	9.6 (5.5)	0.0 (0.0)	6.6 (4.6)	3.8 (1.7)	8.9 (5.6)	**0.5** (**0.2**)	7.1 (4.5)
+ PM Both	**3.7** (**2.1**)	**10.0** (**7.0**)	0.0 (0.0)	6.9 (**5.1**)	**4.0** (**2.0**)	**9.4** (**6.3**)	0.4 (0.1)	7.0 (4.3)
Human	-	-	-	-	-	-	91.0 (85.8)	94.5 (87.6)

Success metrics (with path weighted metrics in parenthesis)

Alfred results: Ablations

- Sub-Goal Evaluation
  - How well can the agent accomplish each sub-goal (assuming perfect performance up to that point)?

Sub-Goal Ablations - **Validation**

	Model	*Goto*	*Pickup*	*Put*	*Cool*	*Heat*	*Clean*	*Slice*	*Toggle*	Avg.
Seen	No Lang	28	22	71	**89**	**87**	64	19	90	59
	S2S	49	32	80	87	85	**82**	23	97	67
	S2S + PM	**51**	**32**	**81**	88	85	81	**25**	**100**	**68**
Unseen	No Lang	17	9	31	75	86	13	8	4	30
	S2S	21	20	**51**	**94**	88	21	**14**	**54**	45
	S2S + PM	**22**	**21**	46	92	**89**	**57**	12	32	**46**

Alfred progress (leaderboard)

Rank	Submission	Created	Unseen Success Rate	Seen Success Rate	Seen PLWSR	Unseen PLWSR	Seen GC	Unseen GC	Seen PLW GC Success Rate	Unseen PLW GC Success Rate
1	LWIT *Anonymous*	01/04/2021	**0.0942**	0.3092	0.2590	**0.0560**	0.4053	**0.2091**	**0.3676**	**0.1634**
2	E.T. *Anonymous*	02/22/2021	0.0857	**0.3842**	**0.2778**	0.0410	**0.4544**	0.1856	0.3493	0.1146
3	A test *A test*	03/09/2021	0.0530	0.2146	0.1472	0.0272	0.2771	0.1425	0.2171	0.0999
3	A new method *Anonymous*	10/26/2020	0.0530	0.2205	0.1510	0.0272	0.2829	0.1428	0.2205	0.0999
5	LWIT *Anonymous*	08/01/2020	0.0445	0.1239	0.0820	0.0224	0.2068	0.1234	0.1879	0.0944
6	Baseline Seq2Seq + Progress M... *Singh, Bhambri, Kim, Choi (GI...*	07/22/2020	0.0150	0.0541	0.0251	0.0070	0.1232	0.0808	0.0827	0.0520
10	Baseline Seq2Seq+PM (both) *Shridhar et. al (UW)*	03/28/2020	0.0039	0.0398	0.0202	0.0008	0.0942	0.0703	0.0627	0.0426

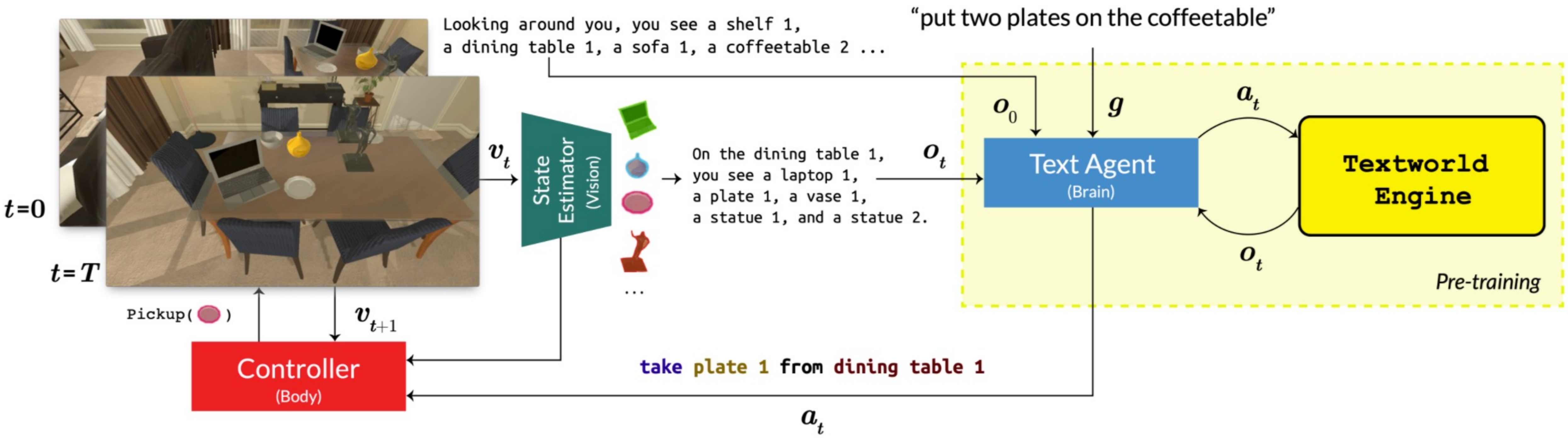
ALFWorld https://alfworld.github.io/

- Aligned tasks and scenarios in TextWorld and AI2Thor (Alfred)
- Is it possible to train an agent in a text-only world and transfer to embodied setting?

ALFWorld Aligning Text and Embodied Environments for Interactive Learning, https://arxiv.org/pdf/2010.03768.pdf
Shridhar et al, ICLR 2021

Transferring from text only domain

- State estimator translates from vision to text description



ALFWorld Aligning Text and Embodied Environments for Interactive Learning
https://arxiv.org/pdf/2010.03768.pdf, Shridhar et al, ICLR 2021

ALFWorld Results

Synthetic (generated) instructions

task-type	TextWorld seen	TextWorld unseen	Seq2Seq seen	Seq2Seq unseen	BUTLER seen	BUTLER unseen	BUTLER-ORACLE seen	BUTLER-ORACLE unseen	Human Goals seen	Human Goals unseen
Pick & Place	69	50	28 (28)	17 (17)	**30 (30)**	**24 (24)**	53 (53)	31 (31)	20 (20)	10 (10)
Examine in Light	69	39	5 (13)	0 (6)	**10 (26)**	0 **(15)**	22 (41)	12 (37)	2 (9)	0 (8)
Clean & Place	67	74	**32** (41)	12 (31)	**32 (46)**	**22 (39)**	44 (57)	41 (56)	18 (31)	22 (39)
Heat & Place	88	83	10 (29)	12 (33)	**17 (38)**	**16 (39)**	60 (66)	60 (72)	8 (29)	5 (30)
Cool & Place	76	91	2 (19)	**21 (34)**	**5 (21)**	19 (33)	41 (49)	27 (44)	7 (26)	17 (34)
Pick Two & Place	54	65	12 (23)	0 (26)	**15 (33)**	**8 (30)**	32 (42)	29 (44)	6 (16)	0 (6)
All Tasks	40	35	6 (15)	5 (14)	**19 (31)**	**10 (20)**	37 (46)	26 (37)	8 (17)	3 (12)

Task success percentage (averaged across 3 evaluation runs) with goal conditioned successes in parenthesis

Training Strategy	train (succ %)	seen (succ %)	unseen (succ %)	train speed (eps/s)
EMBODIED-ONLY	21.6	**33.6**	23.1	0.9
TW-ONLY	23.1	27.1	**34.3**	**6.1**
HYBRID	11.9	21.4	23.1	0.7

TW-Only (train in TW, zero-shot transfer to embodied), Hybrid (75% TW, 25% embodied)

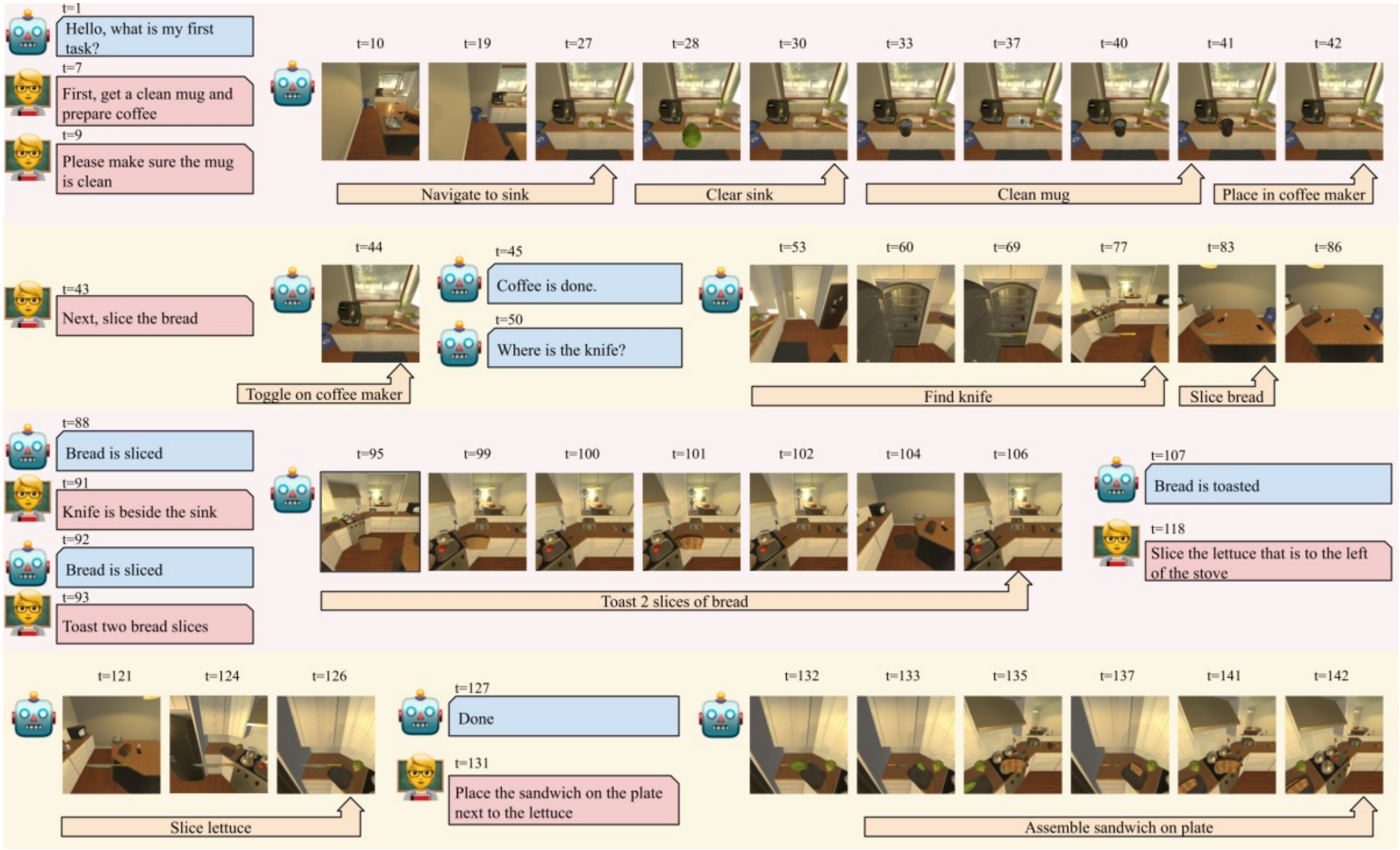
BUTLER

Building Understanding in Textworld via Language
for Embodied Reasoning

TEACh: Task-driven Embodied Agents that Chat

Public Benchmark of Alexa Simbot challenge

https://www.amazon.science/alexa-prize/simbot-challenge



https://www.amazon.science/blog/new-dataset-for-training-household-robots-to-follow-human-commands

TEACh: Task-driven Embodied Agents that Chat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"task_name": "Plate Of Toast",
"task_nparams": 0,
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"desc": "Make a plate of toast.",
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    "conditions": {
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      "isCooked":
        "The bread needs to be toasted."
    }
  }
  "plate": {
    "determiner": "a",
    "task_name": "Clean X",
    "task_params": ["Plate"]
  }
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    "tail_determiner_list": ["the"],
    "head_entity_list": ["toast"],
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    "failure_desc":
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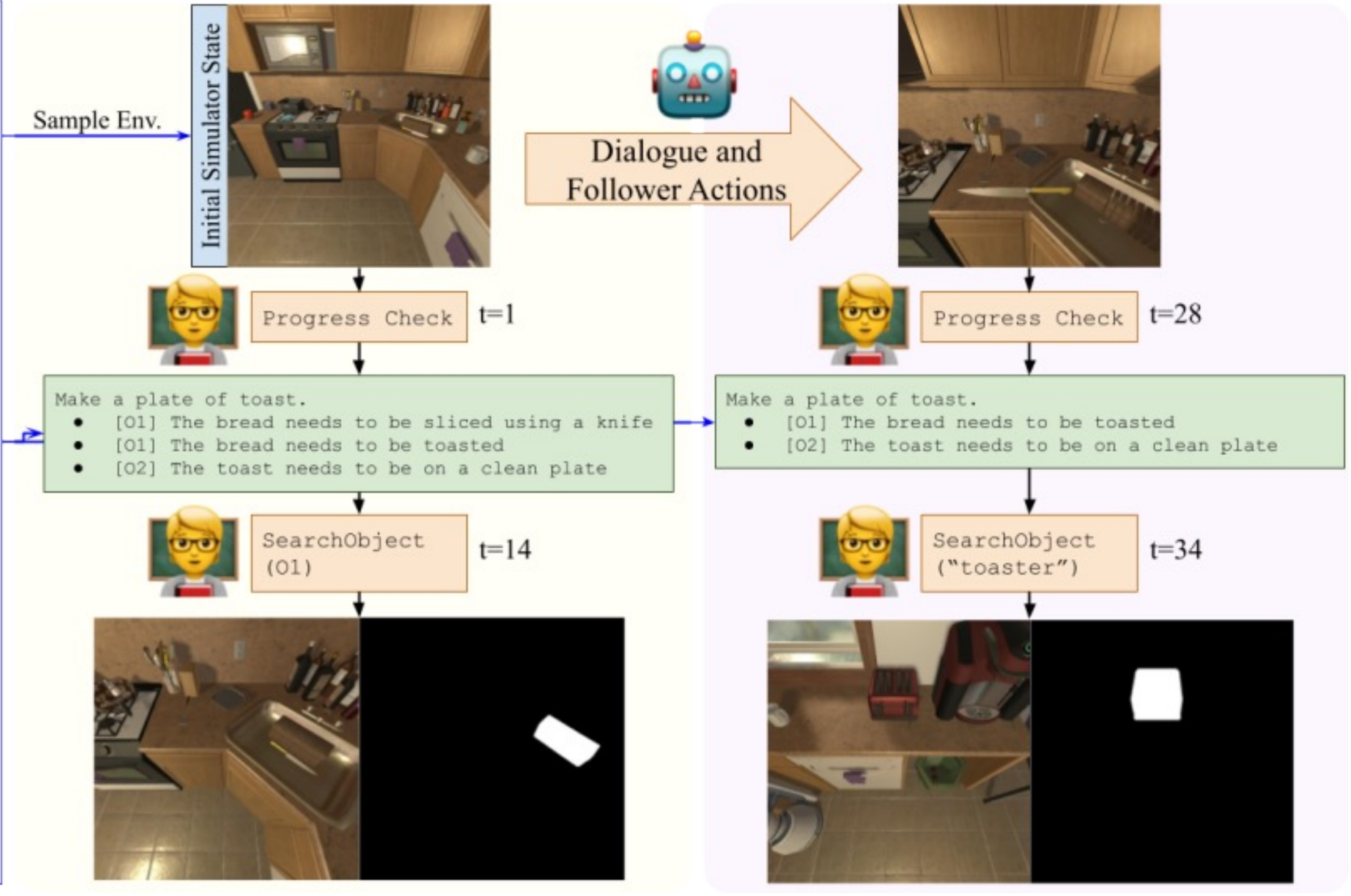
  }
]
```

https://www.amazon.science/blog/new-dataset-for-training-household-robots-to-follow-human-commands

Next time

- Paper presentations (3/28)
    - PIGLeT: Language Grounding Through Neuro-Symbolic Interaction in a 3D World (Alireza)
    - A Persistent Spatial Semantic Representation for High-level Natural Language Instruction Execution (Xiaohao)

- Wednesday (3/30): Speaker-listener models and dialogue