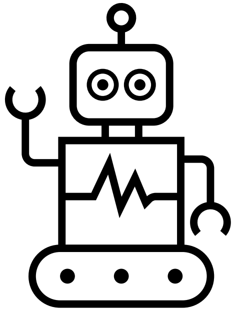
Egocentric Planning for Scalable Embodied Task Achievement

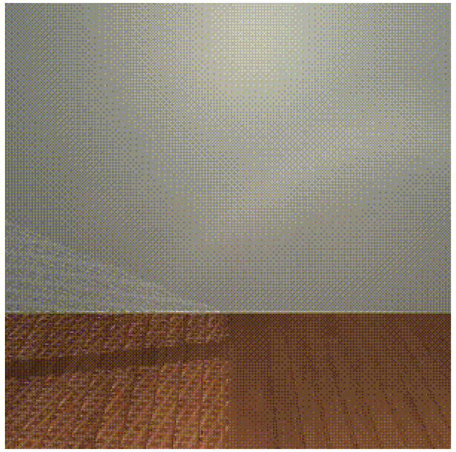
Xiaotian Liu[1,2], Hector Palacios[2], Christian Muise[3]

1.University of Toronto 2. ServiceNow Research 3. Queen's University

Embodied Instruction Following (EIF)

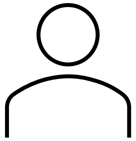
Visual Observation





Action Sequence

Put a chilled mug in a cabinet.



Language Instruction

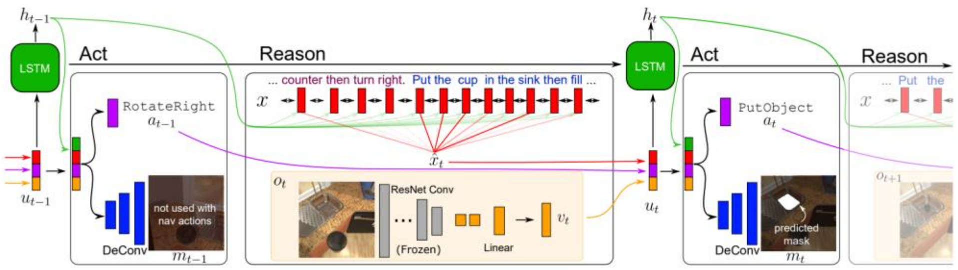
ALFRED Benchmark

Challenges for EIF

- Language/visual grounding
- Partially observable environment
- Long horizon/Sparse Reward

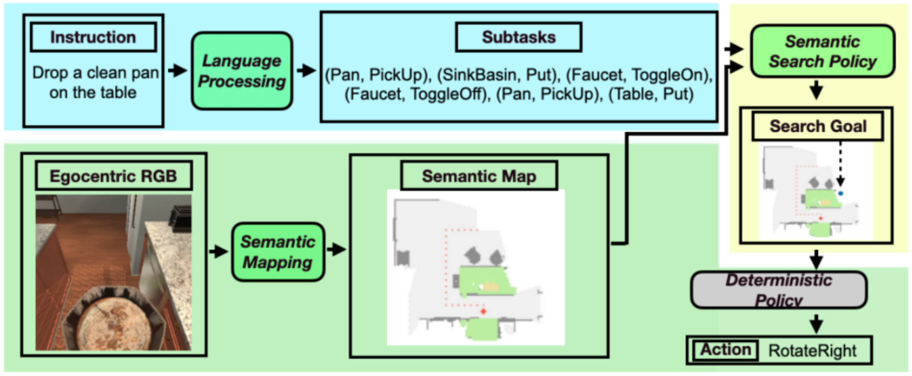
Approach

- End-to-end neural approach
  - Minimal human knowledge
  - Computation/Sample inefficient
  - Performance degradation for long horizon



ALFRED: https://arxiv.org/pdf/1912.01734.pdf

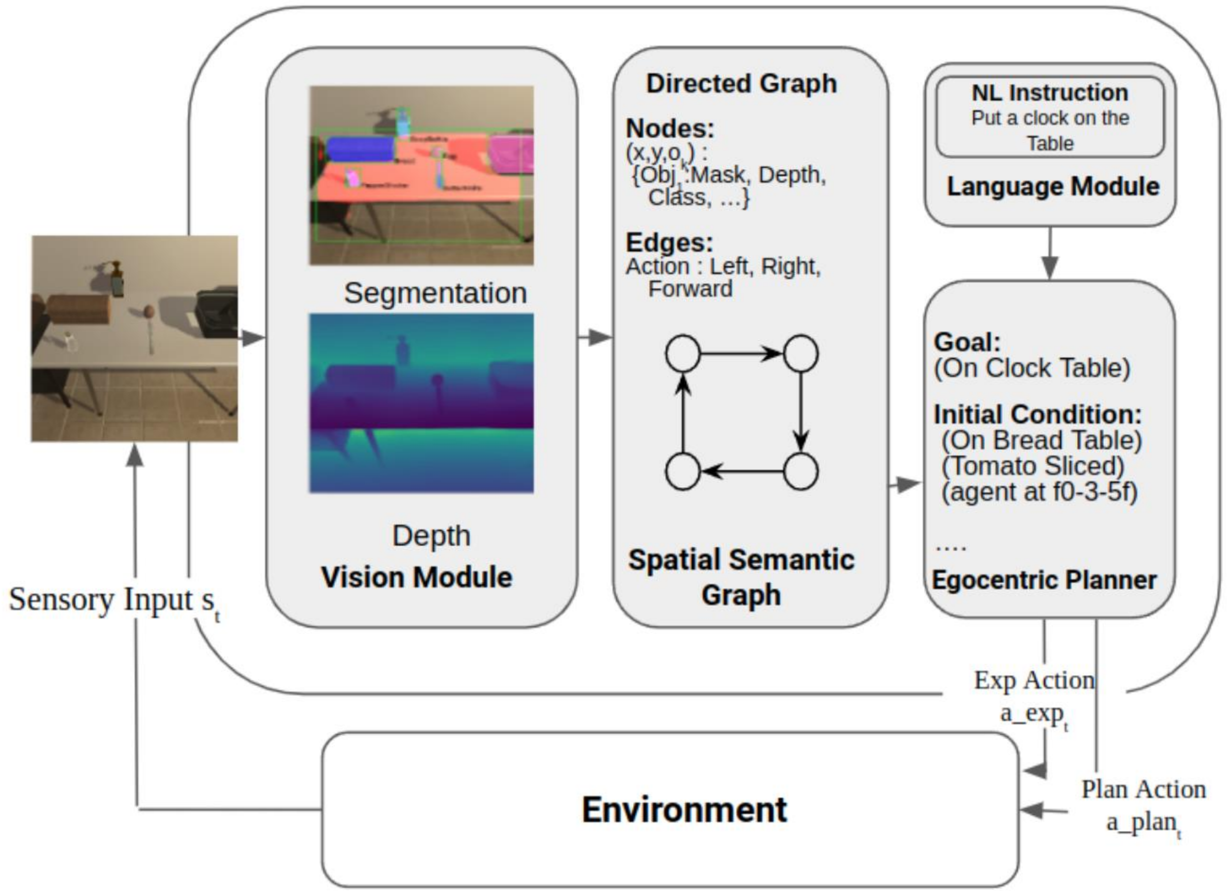
- Hybrid neural-symbolic approach
  - Better performance
  - Modularity
  - Human modeling
  - Fixed policy



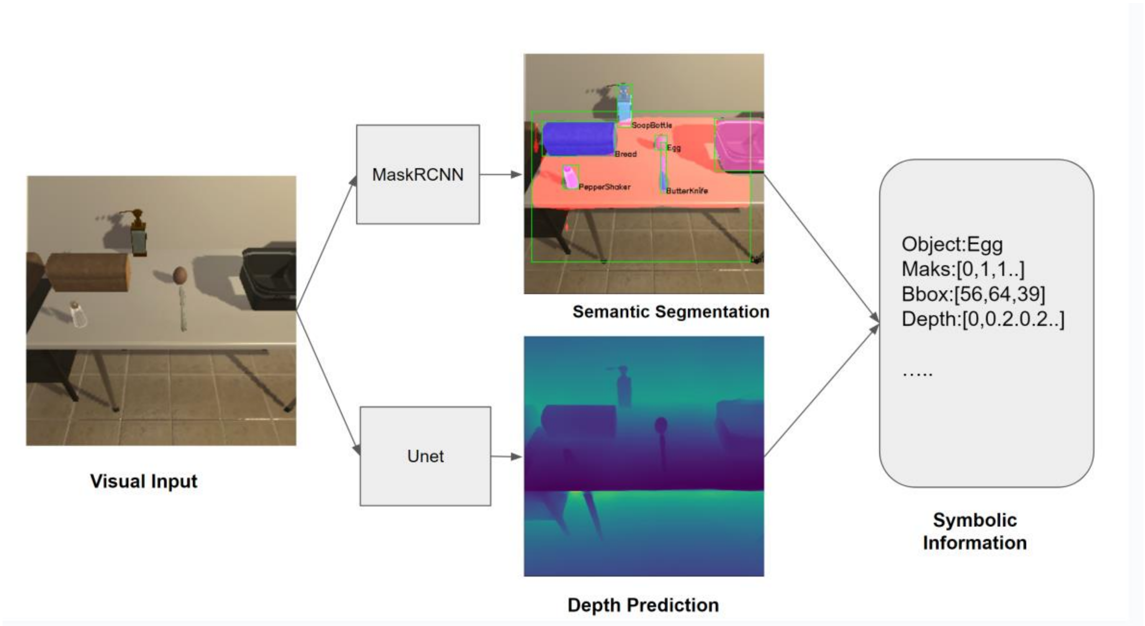
FILM: https://arxiv.org/pdf/2110.07342.pdf

Approach

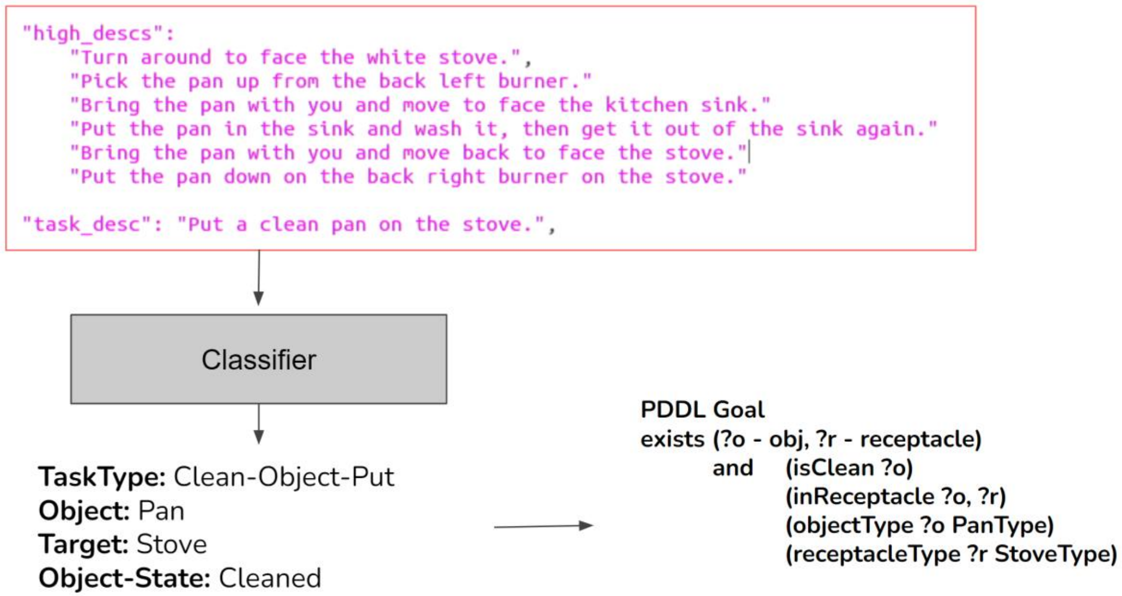
- Reasoning via AI planning problem
- Egocentric Planning
  - Handles unknown environmental observations
  - Works with off-shell planner
  - Robust to observation errors and action failures
- Zero-shot generalization to new task types



Perception Modules

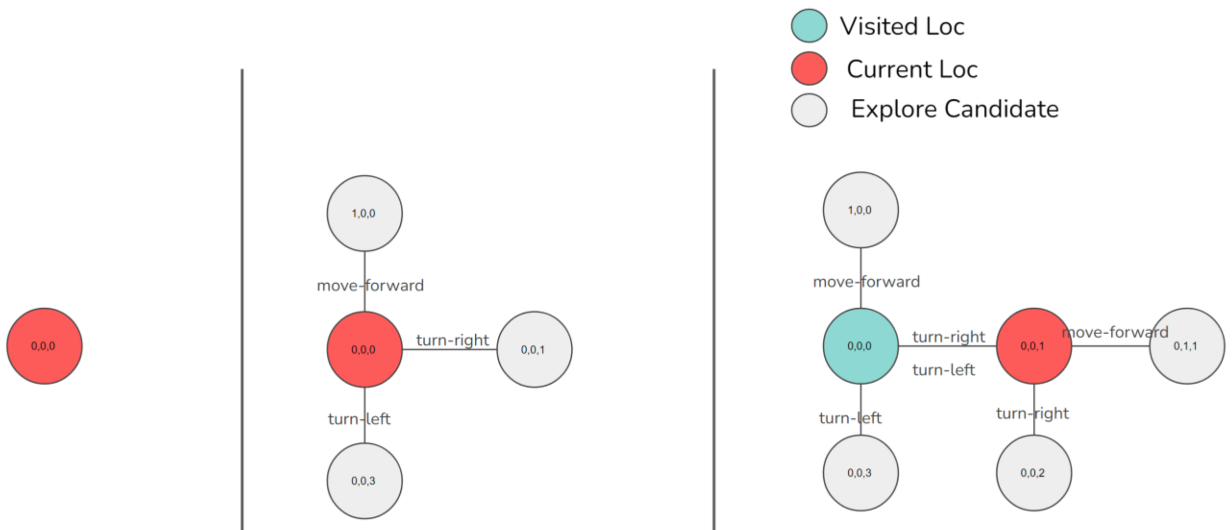


Visual Perception



Goal Extraction

Semantic Location Graph



Agent Start at location (0,0,0)

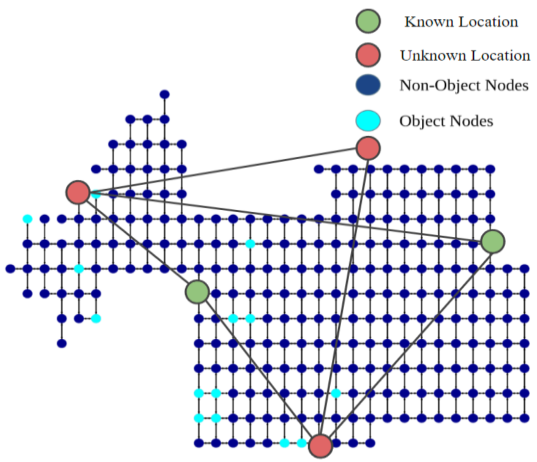
Exploration generated for each movement

move-right action is taken and new exploration candidate is added

Node Information:

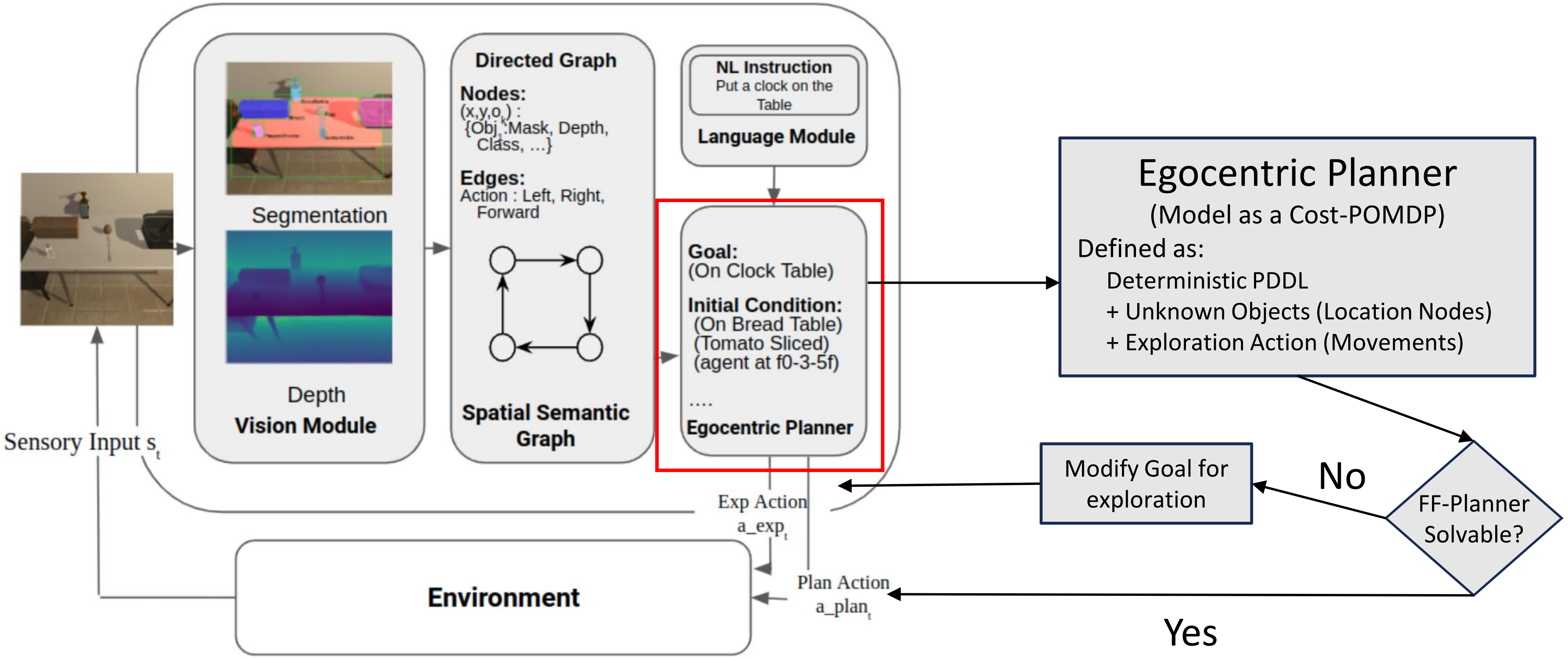
1. Depth Mask
2. Segmentation Masks
3. Object Information

{‘Object_1’:
{“Type: ‘TableType’
Average Pixel Dist: 0.75
Mask: [[0,0,1...]....],
Status: {‘TogOn:False, ..}



*Initial 500 random Exploration to generate exploration candidate

Egocentric Planning



Algorithm 1
Iterative Exploration Replanning (IER)

Input: Environment $\langle A_\mathcal{E}, \mathcal{T}_\mathcal{E}, \mathcal{V}_\mathcal{E}, \text{reset}, \text{step}\rangle$
Input: Planning domain $\mathcal{PD} = \langle \mathcal{T}, \mathcal{V}, \mathcal{P}, \mathcal{A}, \Phi\rangle$
Input: Anchor Types & Exploration Acts $\langle \mathcal{T}_a, \mathcal{X}\rangle$
Input: Mental state Init & Update $\langle M_I^{\mathcal{PD}}, M_U^{\mathcal{PD}}\rangle$
Input: Task $\langle I_\mathcal{E}, G_\mathcal{E}\rangle$
Output: Successful trace τ or Failure

$p \leftarrow \text{reset}(I_\mathcal{E}, G_\mathcal{E})$ ▷ Initial perception
$\mathcal{O}, I, G \leftarrow M_I^{\mathcal{PD}}(p, I_\mathcal{E}, G_\mathcal{E})$
$\mathcal{C} \leftarrow \{o' \mid \text{type}(o') \in \mathcal{T}_a$ and o' occurs in $I\}$ ▷ $\mathcal{C}$: Observed Anchor Objects
τ, solved $\leftarrow [], False$
while not solved **do**
  $\pi_{solve} \leftarrow \text{Solve}(\langle \mathcal{PD}, \mathcal{O}, I, G\rangle)$
  if π_{solve} is *None* **then**
    $\mathcal{A}_e \leftarrow \mathcal{A}$
    for $o \in \mathcal{O}$ and $\text{type}(o) \in \mathcal{T}_a$ **do**
      if $o \notin \mathcal{C}$ **then**
        $I \leftarrow I \cup \{(\text{unknown } o)\}$
      if $(\text{unknown } o) \in I$ **then**
        $\mathcal{A}_e \leftarrow \mathcal{A}_e \cup \{ExploreAct(a, o)$ for $a \in \mathcal{X}\}$
    $G_e \leftarrow \{(\text{explored})\}$
    $\pi_{explore} \leftarrow \text{Solve}(\langle \mathcal{PD}$ with $\mathcal{A}_e, \mathcal{O}, I, G_e\rangle)$
    return Failure **if** $\pi_{explore}$ is *None*
    for $a \in \pi_{explore}$ **do**
      $p, c \leftarrow \text{step}(a)$
      Break **if** failed $\in p$
      $\tau.\text{append}(a)$
      $\mathcal{O}, I \leftarrow M_U^{\mathcal{PD}}(\mathcal{O}, I, a, p, c)$
      if $a \in \mathcal{X}$ **then**
        $\mathcal{C} \leftarrow \mathcal{C} \cup \{o' \mid \text{type}(o') \in \mathcal{T}_a$ and o' argument of $a\}$
  else
    for $a \in \pi_{solve}$ **do**
      $p, c \leftarrow \text{step}(a)$
      Break **if** failed $\in p$
      $\tau.\text{append}(a)$
      $\mathcal{O}, I \leftarrow M_U^{\mathcal{PD}}(\mathcal{O}, I, a, p, c)$
    solved $\leftarrow$ True **if** I satisfies G
return τ

Results

	Test Seen				Test Unseen			
	SR	GC	PLWSR	PLWGC	**SR**	GC	PLWSR	PLWGC
Seq2Seq	3.98	9.42	2.02	6.27	0.39	7.03	0.08	4.26
ET	38.42	45.44	27.78	34.93	8.57	18.56	4.1	11.46
HLSM	25.11	35.15	10.39	14.17	24.46	34.75	9.67	13.13
FILM	28.83	39.55	11.27	15.59	27.8	38.52	11.32	15.13
LGS-RPA	40.05	48.66	21.28	28.97	35.41	45.24	15.68	22.76
EPA	39.96	44.14	2.56	3.47	**36.07**	39.54	2.92	3.91

Future Work

- More open-world Setting:
  - Unknown relationships
  - Unknown object types
- Integration with SLAM maps and 3D voxels
- Learned exploration policy based on objects/location
- LLM integration:
  - Generate knowledge base
  - Commonsense guided action

Thank You!