

PRESENTER: MASSIMO STEFAN

# **WATCH-AND-HELP A CHALLENGE FOR SOCIAL PERCEPTION AND HUMAN-AI COLLABORATION**



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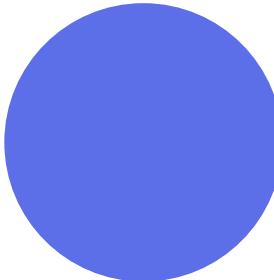
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# INTRO

They **main contributions** are:

- The Watch-and-Help (WAH) challenge
- The VirtualHome-Social environment
- The evaluation protocol and benchmark for the challenge



**? Problem:** AI systems lack at recognizing others' goals and assisting them

**💡 Idea:** develop AI agents with social perception and collaborative planning abilities

**🎯 Goal:** test the social intelligence of AI agents

**📄 Social perception:** the ability to use the behavior, appearance, and communication of others to form opinions or make inferences about them, especially regarding their motives, attitudes, or values

**📄 Human-AI collaboration:** the study and practice how humans and AI agents work together to accomplish a shared goal

The background features a black and white perspective grid that curves and recedes towards the center. A large, solid blue circle is positioned in the lower-left foreground, partially overlapping the grid.

# **THE WATCH-AND- HELP CHALLENGE**

# WATCH-AND-HELP CHALLENGE

## ⌚ WATCH STAGE

The AI agent (**Bob**) **observes** a human-like agent (**Alice**) performing a task once and **infers** Alice's goal from her actions.

⌚ **Goal:** evaluate AI agents' social perception and their ability to collaborate with others

**WATCH stage:** Bob watches Alice's behaviors and infers her goal



## sos HELP STAGE

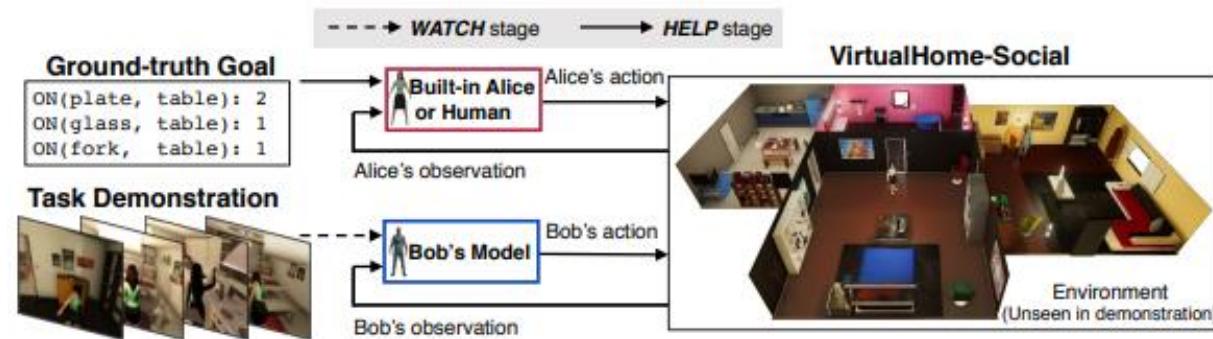
Bob **assists** Alice in achieving the same goal in a different environment as quickly as possible.

**HELP stage:** Bob works with Alice to achieve her goal



# SPECIFICATIONS

- Alice is **built-in into the system** → plans her actions based on her goal and partial observation of the environment
- Bob is an **external agent** → does not know Alice's ground-truth (GT) goal and only has access to a single observation
- ONLY during training the GT goal of Alice is shown to Bob as supervision (at test time has to infer it)



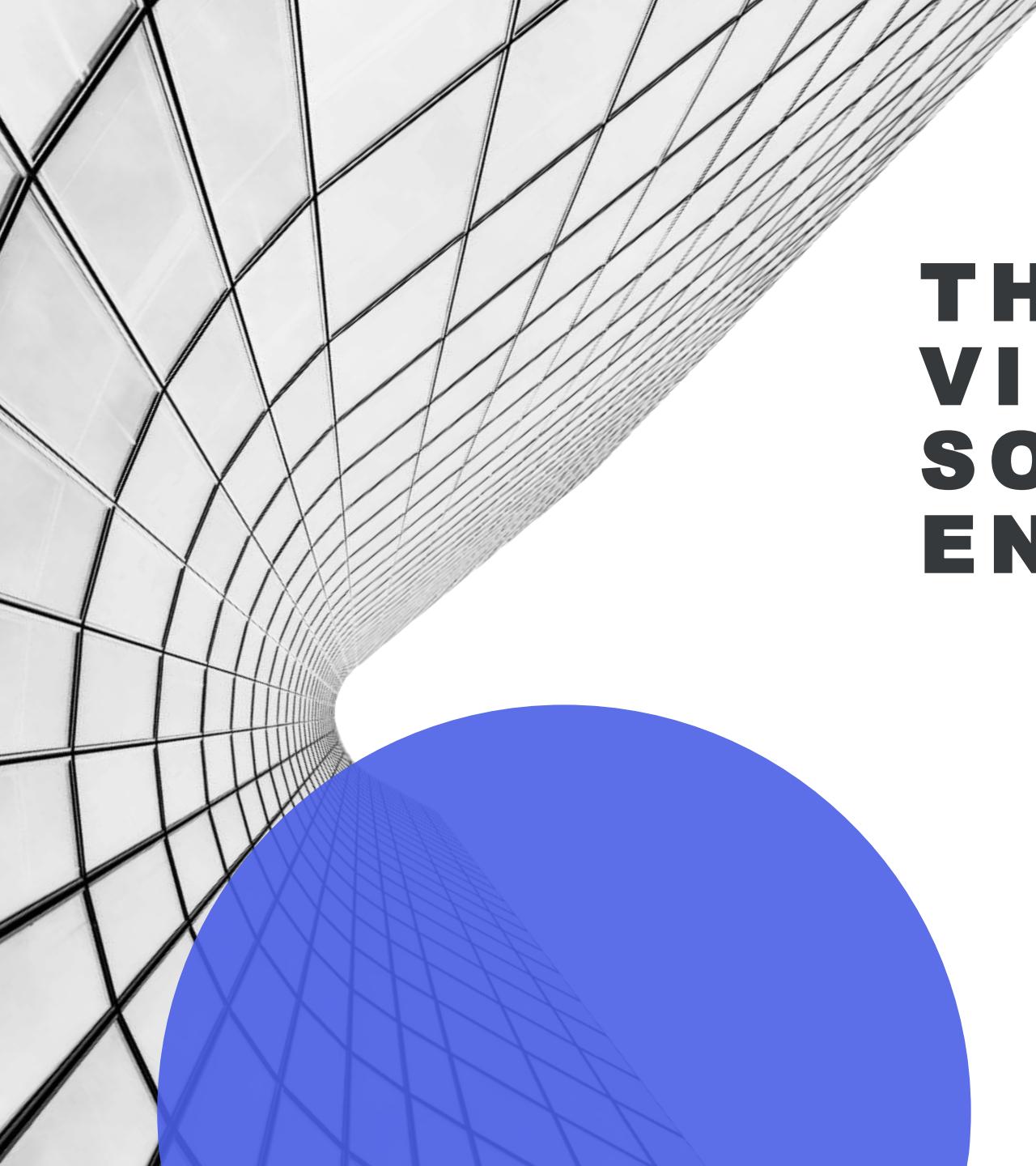


# PROBLEM SETUP



Each task in the challenge is defined by:

- Alice's **goal**  $g$ : a set of predicates and their count
  - ☒ Example: {ON(plate, dinnertable):2; ON(wineglass, dinnertable):1} → "putting 2 plates and 1 wine glass onto the dinner table"
- Alice's **actions** to achieve that goal  $D = \{s_{Alice}^t, a_{Alice}^t\}_{t=1}^T$  (state, action)
- An **environment** where Bob collaborates with Alice
  - ☒ **Note 1:** the objects in a predicate refer to object classes, NOT instances
  - ☒ **Note 2:** they designed 5 predicate sets ("setting up dinner table", "wash", ...)



# **THE VIRTUALHOME- SOCIAL ENVIRONMENT**

# VIRTUAL HOME-SOCIAL

## ⌚ OBJECTS AND AGENTS INTERACTIONS

Simulate realistic home environments where agents can **interact** with objects and other agents.

## ⚙️ BUILT-IN FUNCTIONS

- built-in agents that **emulate** human behaviors
- an **interface** for human players
- supports **concurrent actions** from multiple agents
- provides **observations** for the agents

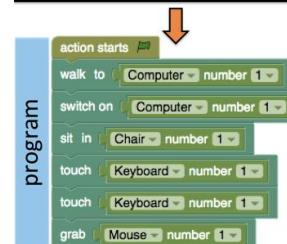
⌚ **Goal:** allow AI agents to perform complex household tasks by interacting with objects and with built-in agents or real humans



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

Action: 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.

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



video



VirtualHome  
robot playground



# SPECIFICATIONS

- The environment supports **symbolic** (a scene graph where nodes represent objects and edges spatial relationships between them) and **visual** observations
-  **Warning:** they do NOT specify how **Bob** process the visual input
- The environment provides a **large and diverse action space** for agents
-  **Note:** it changes at every step, based on the agent's state

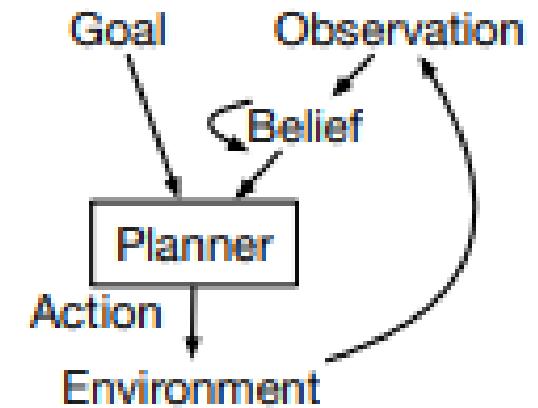
# HUMAN-LIKE AGENTS

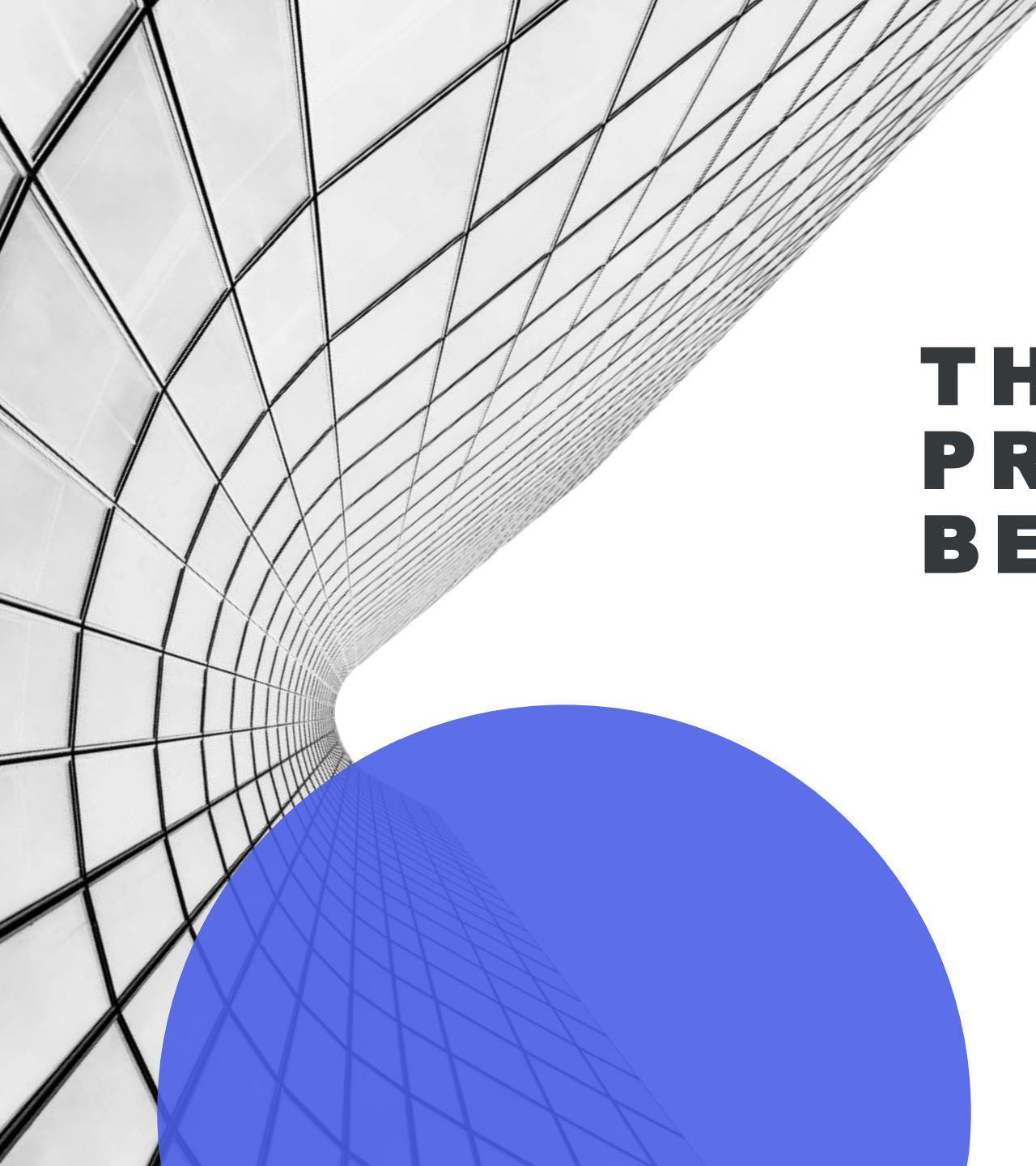
Agents operates on the symbolic representation, relying on:

1. A **belief of object locations** in the environment
2. A **hierarchical planner**, which uses Monte Carlo Tree Search (MCTS) and Regression Planning (RP)

to find a plan for a given goal based on its belief

 **Note:** permit to plan concurrently with other agents





# **THE EVALUATION PROTOCOL AND BENCHMARK**

# EVAL. PROTOCOL AND BENCHMARK

## EVALUATION PROTOCOL

Defines:

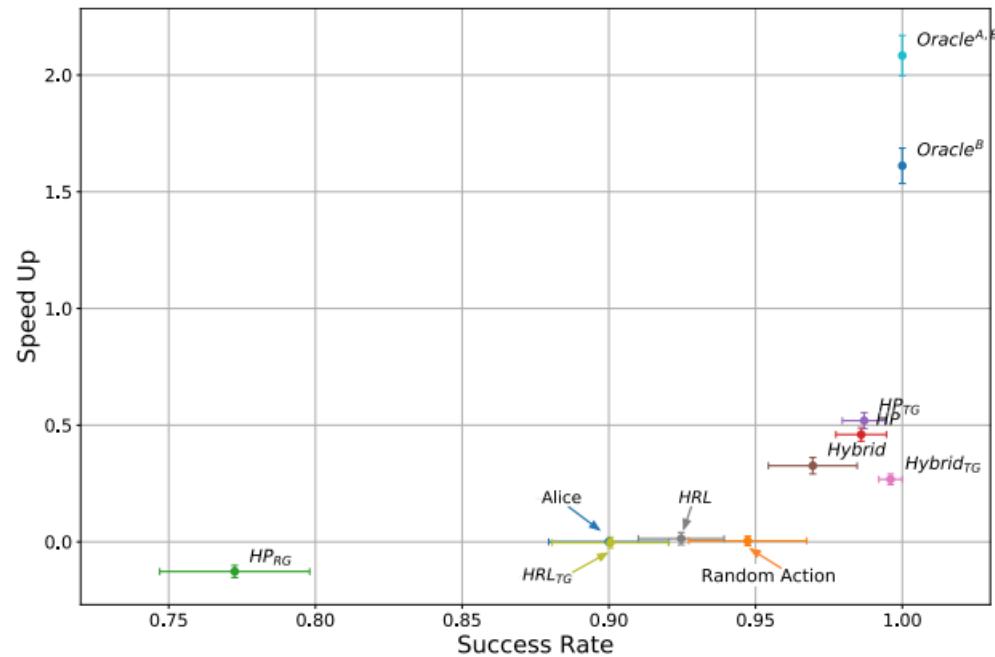
- the training and testing setup
- the goal definitions
- the metrics

of the AI agents.

## BENCHMARK

Provides a set of baseline models that consist of a goal inference model and a helping policy or planner, as well as 2 oracles that show the upper bound performance.

 **Goal:** evaluate the WAH challenge in realistic settings at scale



# SPECIFICATIONS

- The training set is composed by 1011 tasks
- The test set is composed by 2 sets (test-1 and test-2) each with 100 tasks
  - With different environments (different apartments with random initial stage)
  - With different goals (predicate combinations) unseen during training
- In test-1 → all predicates in each goal are from the same predicate set  
 **Example:** “preparing a simple meal”
- In test-2 → predicates are sampled from 2 different predicate sets  
 **Example:** “putting groceries to the fridge and washing dishes”



# EVALUATION METRICS



They used 3 types of metrics:

1. **Success rate** → the proportion of tasks where **Bob** successfully helps **Alice** achieve the goal within the given time limit
  2. **Speedup** → compare the episode length when **Alice** and **Bob** are working together ( $L_{Help}$ ) VS **Alice** working alone ( $L_{Alice}$ )
  3. **Cumulative reward** of an episode with  $T$  steps →  $R = \sum_{t=1}^T (s^t = s_g) - 0.004$  where  $s^t$  is the state at step  $t$  and  $s_g$  is the goal state
- Note:  $R$  ranges from  $-1$  (failure) to  $1$  (achieving the goal in zero steps)

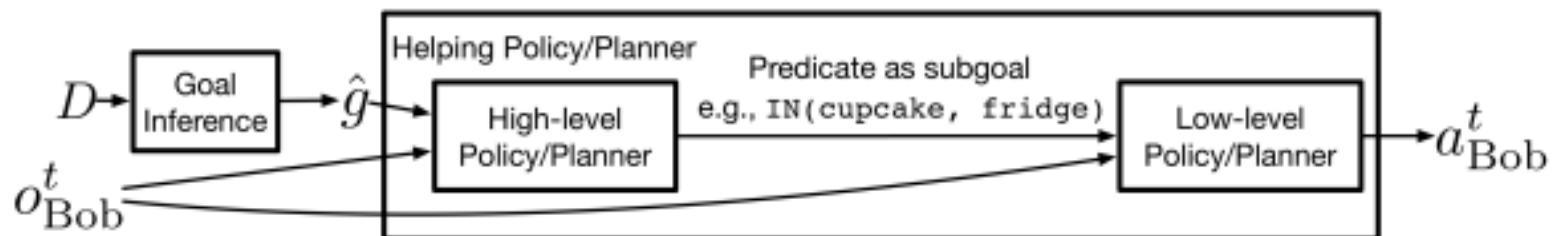


# BASELINES



The set of baselines consist of 2 components:

1. **Goal inference model:** trained based on the symbolic representation of states in the demonstration. At each step:
  1. Encode the state using a Transformer (over visible objects)
  2. Feed the encoded state into a LSTM
  3. Use average pooling to aggregate the latent states from the LSTM over time
  4. Build a classifier for each predicate to infer its count (**30 classifiers**)





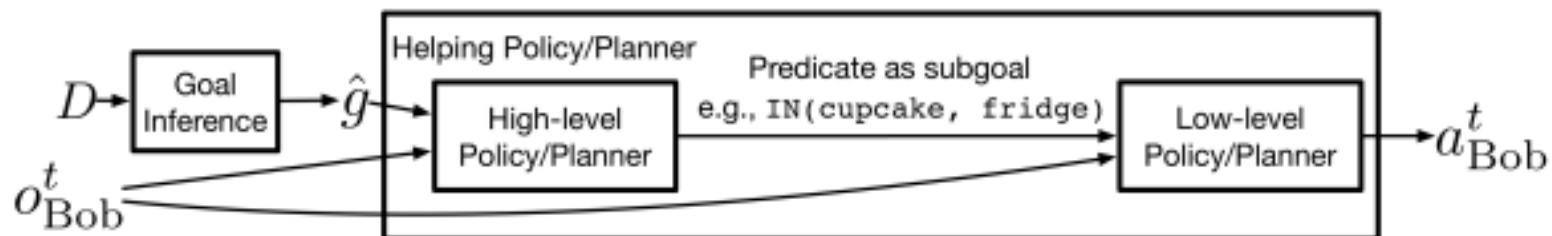
# BASELINES



The set of baselines consist of 2 components:

**2. Goal-conditioned helping planner/policy:** a hierarchical architecture with 2 modules for both planning and RL-based approaches. At every step:

1. Given the **Bob's** observation  $o_{Bob}^t$  and the goal inferred from the demonstration  $\hat{g}$
2. Output a predicate  $s$  the best subgoal to pursue the current step
3. Which will be fed to the Low-level planner/policy
4. Resulting in the **Bob's** action  $a_{Bob}^t$





# BASELINES



The baseline models follows different policies:

- **HP**: a selects actions based on predefined rules and heuristics
- **Hybrid**: combines handcrafted policy with a NN policy trained with SL
- **HRL**: HL policy selects subgoals, LL policy selects actions to achieve them
- **Random**: selects actions uniformly at random
- **Oracle<sup>B</sup>**: selects the best action according to the GT reward function
- **Oracle<sup>A,B</sup>**: selects the best action according to the GT reward function and the GT truth user state



# RESULTS

# 🏆 TEST-1 RESULTS 🏆

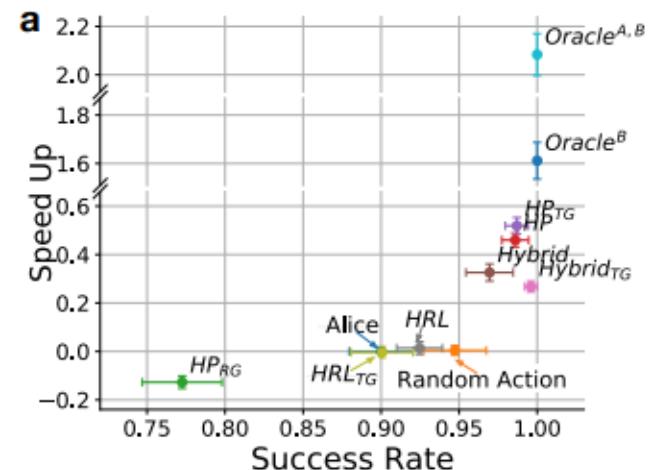
- ⌚ **Goal 1:** evaluate the stage (predict the goal predicates)
- 🔍 **How:** measuring the recognition performance of the predicates
- 📈 **Results:** precision of **0.85** and recall of **0.96** ()
- 📝 **Note 1:** performs better when it sees the full demonstration rather than just the last observation of the actions taken by [Alice](#)
- ⌚ **Remark:** the model can learn from the temporal and causal structure of the demonstration, not just from the final outcome
- 📝 **Note 2:** the chance precision and recall is 0.08 and 0.09

# 🏆 TEST-1 RESULTS 🏆

⌚ Goal 2: evaluate the  stage (predict the goal predicates)

## 📈 Results:

- Planning-based approaches (**Oracle**, **HP**, **Hybrid**) are the most effective
- DRL does not work well for **Bob** (fails to achieve the subgoals)
- No significant difference between **Random actions** and **Alice** working alone
- Using the inferred goals (**HP** and **Hybrid**) works well
- But, with a random goal inference (**HP<sub>RG</sub>**) becomes counter productive



# TEST-2 RESULTS

- ⌚ **Goal 1:** evaluate the  stage (predict the goal predicates)
- 🔍 **How:** measuring the recognition performance of the predicates
- 📈 **Results:** precision of **0.68** and recall of **0.64** ()
- 📝 **Note:** the model fails to generalize to multi-activity scenarios, overfitting to predicate combinations seen during training

# TEST-2 RESULTS

 **Goal 2:** evaluate the  stage (predict the goal predicates)

 **How:** evaluate the performance of **Alice** alone and **HP** (the best performing baseline)

 **Results:**

- **Alice** alone achieves a success rate of  **$95.40 \pm 0.01$**
- **HP** achieves
  - a success rate of  **$88.60 \pm 0.02$**
  - a speedup of  **$0.21 \pm 0.04$**

# THANK YOU

Massimo Stefan

Paper [pdf](#) and [GitHub](#) links

[Questions](#) link