

Reasoning about Actions for Planning in Robotics

Shiqi Zhang
SUNY Binghamton

The SUNY System



- 64 campuses
- Four PhD-granting "University Centers"
 - Albany
 - **Binghamton – most selective SUNY**
 - Buffalo
 - Stony Brook



Community — Greater Binghamton

- Located in New York state
- Birthplace of IBM (Endicott, NY)
- Home to several hi-tech companies.
- One of the safest U.S. midsize cities
- Low cost of living (12% below U.S. average)
- Close to major cities



Rankings



Binghamton University--SUNY

Binghamton, NY



#38 in Top Public Schools

#87 in National Universities (tie)

\$24,403 (out-of-state), \$9,523 (in-state) Tuition and Fees

13,632 Undergraduate Enrollment

2018 Rank	School
#25 Tie	<u>Virginia Tech</u> Blacksburg, VA
#29 Tie	<u>University of Massachusetts—Amherst</u> Amherst, MA
#33 Tie	<u>Florida State University</u> Tallahassee, FL
#33 Tie	<u>Michigan State University</u> East Lansing, MI
#33 Tie	<u>Binghamton University—SUNY</u> Binghamton, NY
#38 Tie	
#39 Tie	<u>University of Colorado—Boulder</u> Boulder, CO
#41 Tie	<u>Stony Brook University—SUNY</u> Stony Brook, NY
#41	<u>University at Buffalo—SUNY</u> Buffalo, NY



Computer Science Faculty

- 33 full-time faculty
 - 8 full professors
 - 8 associate professors
 - 11 assistant professors
 - 6 lecturers
- 4 adjunct lecturers
- 3 new faculty members in Robotics/AI, Computer Vision/Machine Learning, and Computer Architecture will join in Fall 2018.

Department also has close to 40 teaching Assistants

Reasoning about Actions for Planning in Robotics

Shiqi Zhang
SUNY Binghamton

Why *planning* in robotics?

- Complex tasks in the real world require more than one action
- Robot actions (perception and actuation) are unreliable, and sometimes costly

***Robots need to plan actions*
to accomplish goals under uncertainty**

Why *reasoning* in robotics?

- Robot faces many objects (locations, people, tools, etc) and their properties
- World state estimation with incomplete (qualitative and quantitative) knowledge

***Robots need to reason*
to understand the current world state**

Reasoning (declarative) and planning (probabilistic)

**Declarative knowledge
representation & reasoning**

Correct and natural
Incomplete knowledge
Explanation (good for HRI)
Goal-independent
Transferability

Strengths

Non-deterministic action outcomes
Imperfect perception
Unspecified, long horizon
Learning from experience (RL)

Robo`tics
decision-making

**Probabilistic Planning &
Reinforcement learning (RL)**

***Logical-probabilistic reasoning for
probabilistic planning,
as illustrated in human-robot dialog***

Robot needs to identify <Coffee, Office 1, Bob>, through spoken dialog

Time: 9:00am
Rooms: Office 1, Office 2, ...
Persons: Alice, Bob, Carol, ...
Items: Coffee, Sandwich, ...

<Coffee, Office 1, Bob>

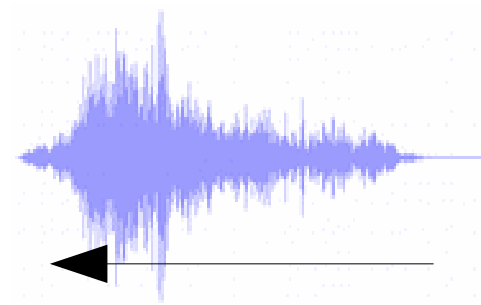


“I am a shopping robot, what item do you want?”

“Coffee, please”



“Toffee, please”



“Coffee, please”



“Do you want me to buy toffee?”

“Coffee, please”





Demo video: integrated P-log and POMDP

[Zhang, Stone, AAAI 2015]

CORPP: commonsense reasoning and probabilistic planning, a complete example

defaults

$\neg \text{registered}(P) \leftarrow \text{not } \text{registered}(P), \text{ student}(P).$

Logical reasoner (LR)

possible
worlds

$W_0 = \{I = \text{coffee}, P = \text{alice}\}$

$W_1 = \{I = \text{toffee}, P = \text{alice}\}$

Probabilistic reasoner (PR)

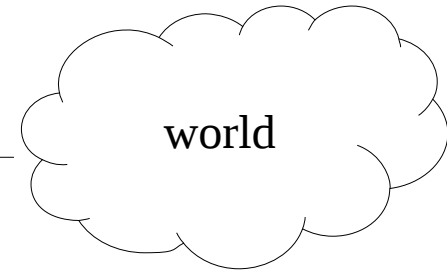
$\{W_0 : 0.8, W_1 : 0.2\}$

possible worlds
with probabilities

facts

$\text{student}(\text{alice}). \text{ student}(\text{bob}).$
 $\text{registered}(\text{alice}).$

$\text{item}(\text{coffee}).$
 $\text{item}(\text{toffee}).$
 $\text{curr_time} = \text{morning}.$



$I = \text{coffee}.$

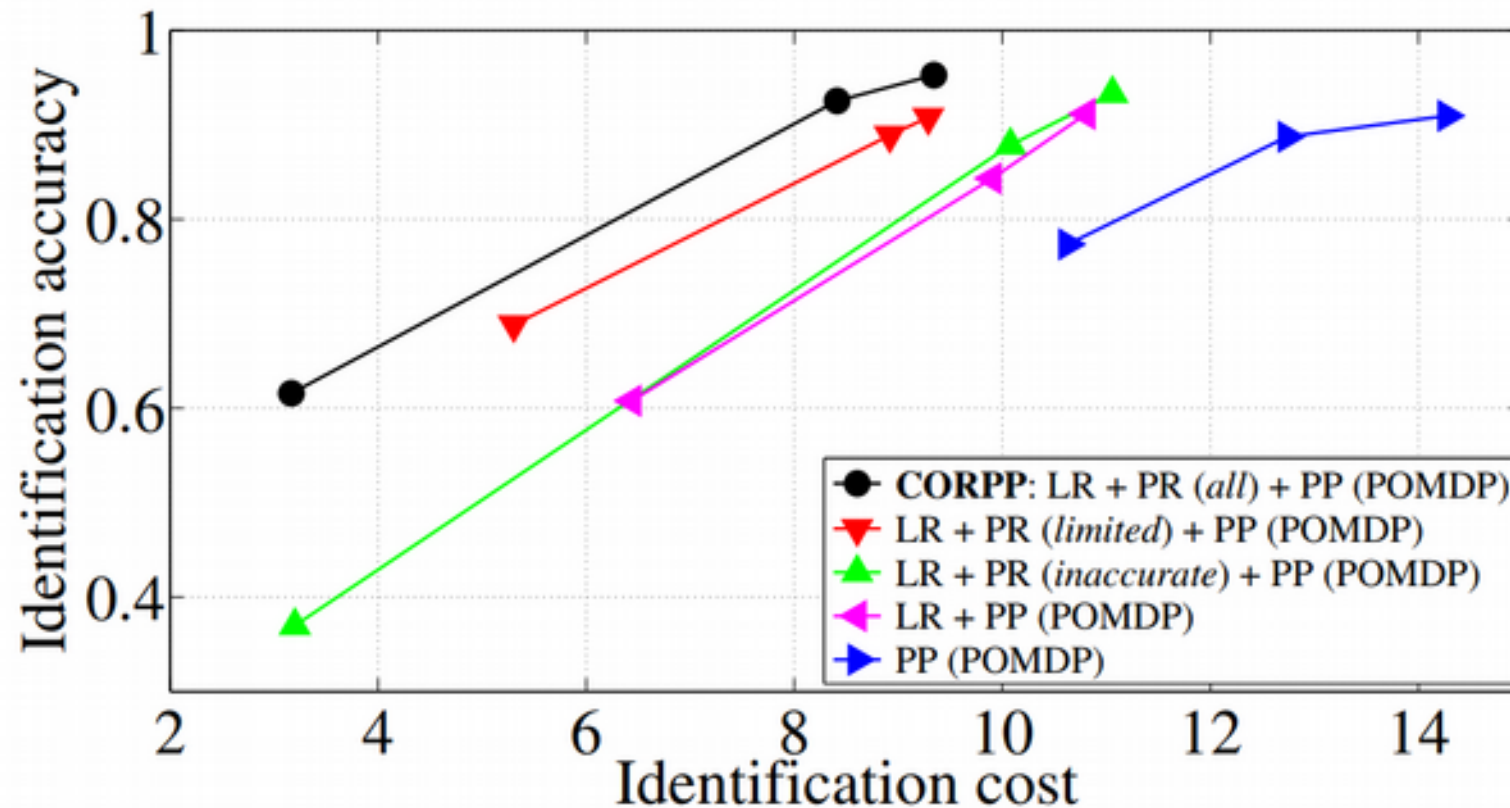
ask_item

$b_{t=0} = [0.8, 0.2]$

Probabilistic planner (PP)

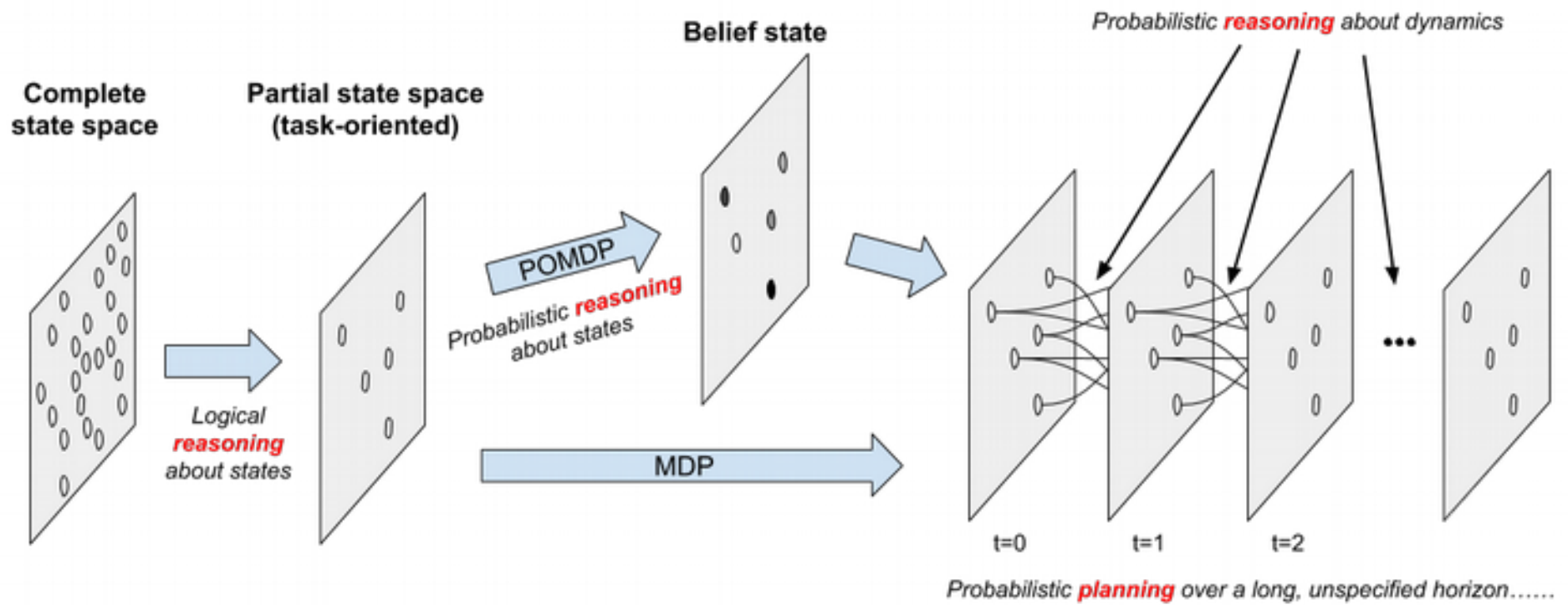
e.g., $\text{coffee} > \text{toffee}!$

delivery



CORPP reasons with logical and probabilistic knowledge, improving robot behaviors

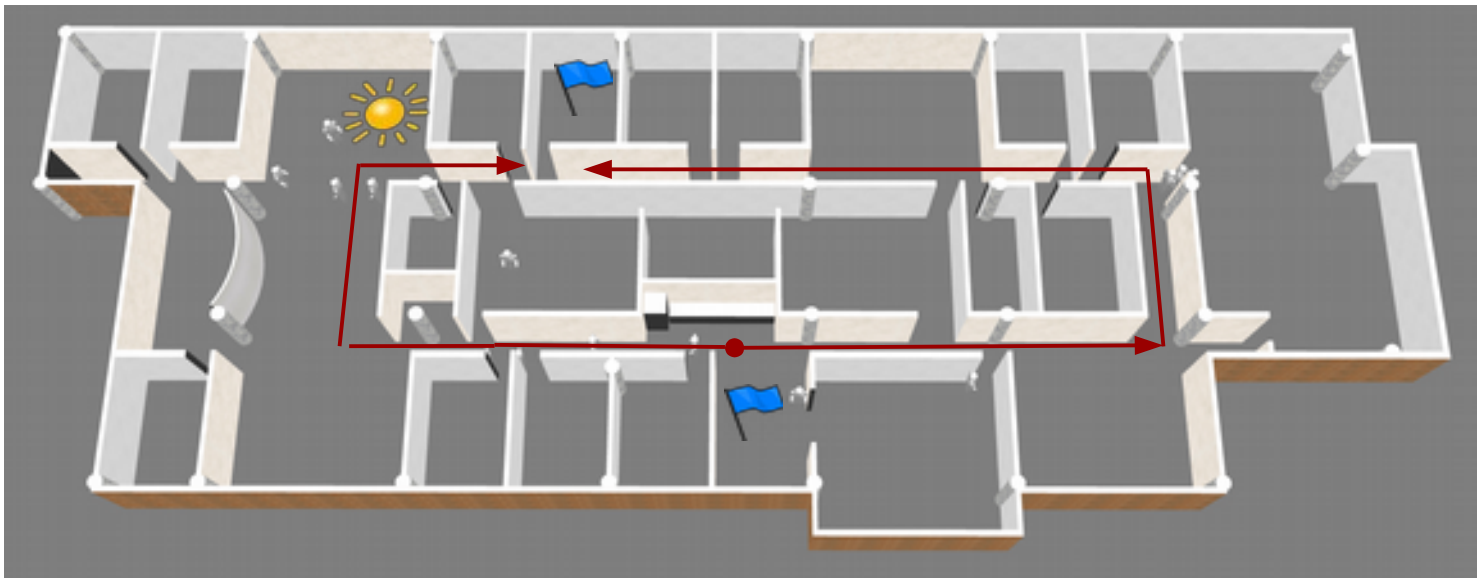
Interleaved CORPP (iCORPP)



[Zhang, Khandelwal, Stone, AAAI 2017]

Interleaved CORPP (iCORPP): Dynamically Constructed (PO)MDPs for Adaptive Robot Planning

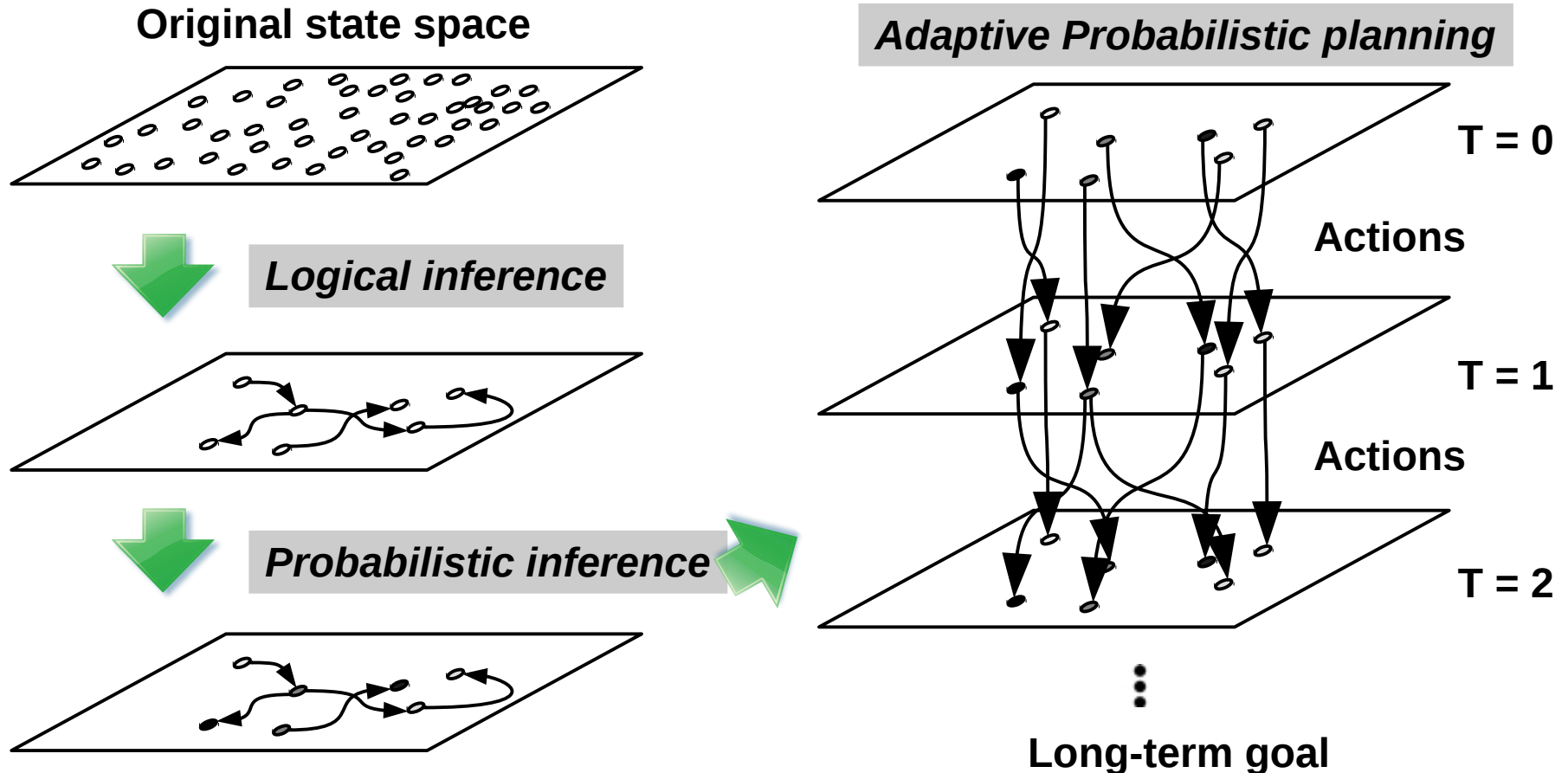
Example domain: *robot navigation*



Robot locations	Areas under sunlight	Areas blocked	Weather	Time
10	2^{10}	2^{10}	5	3

More than 2^{27} states!

Interleaved CORPP (iCORPP): Dynamically Constructed (PO)MDPs for Adaptive Robot Planning



This work enables robot behaviors to **adapt** to exogenous domain changes **without including** these exogenous attributes in probabilistic planning models

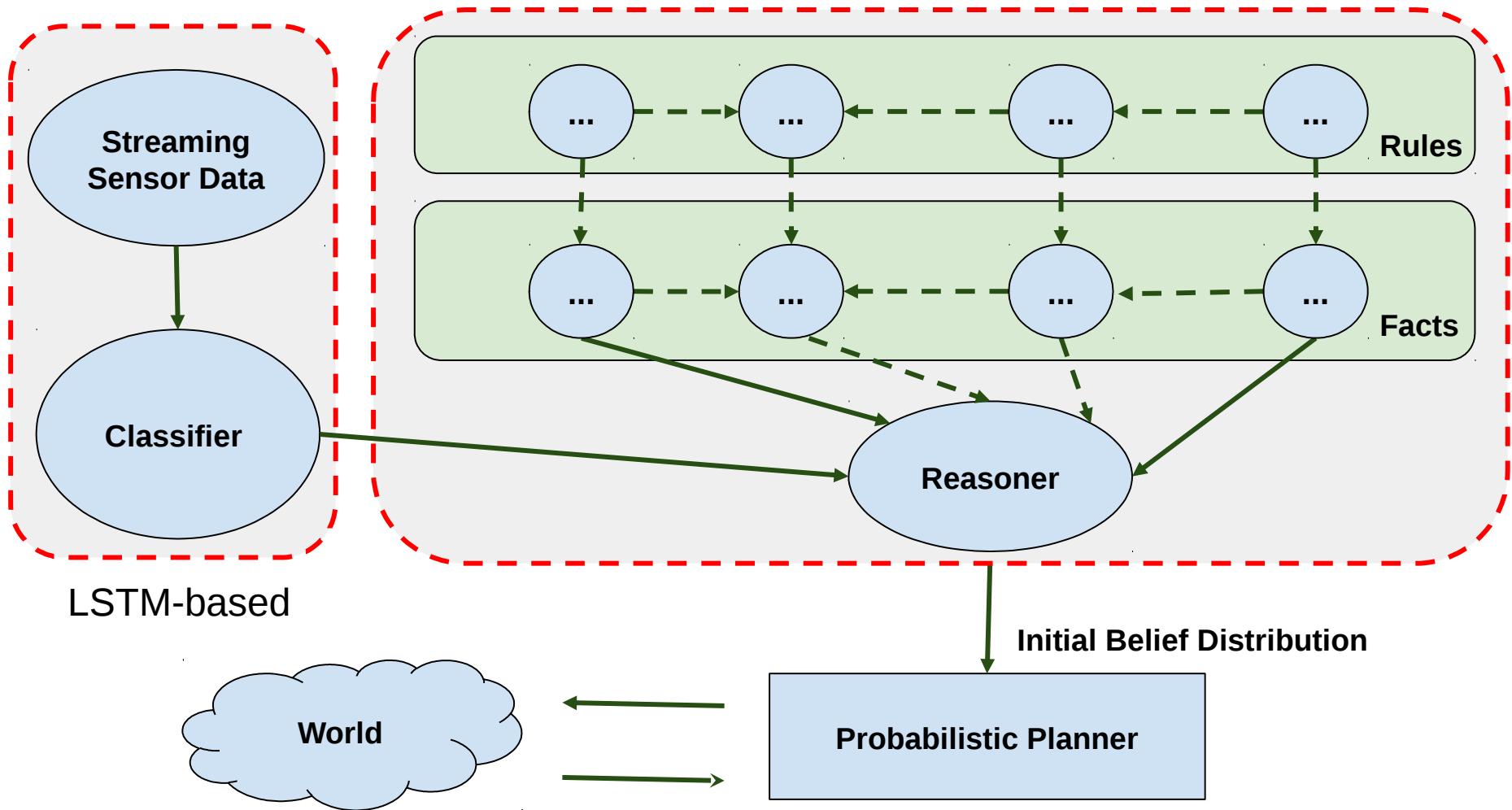
Integrated *learning*, *reasoning*, and *planning*
for robot sequential decision-making

Human Intention Estimation problem



Robot needs to identify human intention (e.g., interested to interact or not) as accurate and early as possible

LSTM-CORPP



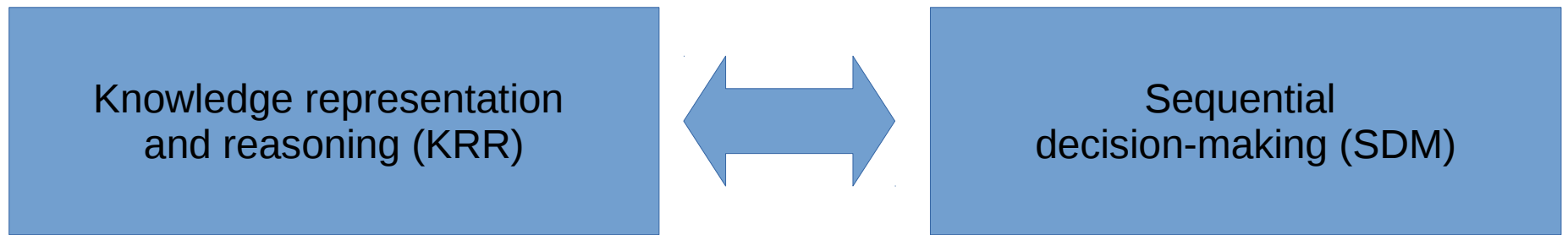
LSTM-CORPP: preliminary results

	Accuracy	Precision	Recall	F1 Score	Cost
Learning	0.61	0.56	0.30	0.39	N/A
Reasoning	0.60	0.54	0.62	0.58	N/A
Learning + Reasoning	0.58	0.51	0.72	0.60	N/A
Reasoning + Planning (CORPP)	0.79	0.67	0.94	0.78	21.6
LSTM-CORPP (Ours)	0.83	0.74	0.86	0.80	13.1

AAAI'19 Tutorial

Knowledge-based Sequential Decision-Making under Uncertainty

(1/4 day tutorial)



Papers

- Shiqi Zhang and Peter Stone, **CORPP: Commonsense Reasoning and Probabilistic Planning, as Applied to Dialog with a Mobile Robot**, AAAI 2015
- Shiqi Zhang, Mohan Sridharan and Jeremy Wyatt, **Mixed Logical Inference and Probabilistic Planning for Robots in Unreliable Worlds**, IEEE Transactions on Robotics (TRO), 31 (3): 699-713, 2015
- Shiqi Zhang, Piyush Khandelwal and Peter Stone, **Dynamically Constructed (PO)MDPs for Adaptive Robot Planning**, AAAI 2017
- Saeid Amiri, Mohammad Shirazi, and Shiqi Zhang, **Leveraging Supervised Learning and Automated Reasoning for Robot Sequential Decision-Making**, KR'18 R2K Workshop, 2018
- Keting Lu, Shiqi Zhang, Peter Stone, and Xiaoping Chen, **Robot Representation and Reasoning with Knowledge from Reinforcement Learning**, arXiv preprint: 1809.11074, 2018

How to integrate?

**Declarative knowledge
representation & reasoning**

Correct and natural
Incomplete knowledge
Explanation (good for HRI)
Goal-independent
Transferability

Non-deterministic action outcomes
Imperfect perception
Unspecified, long horizon
Learning from experience (RL)

Robotics
decision-making

**Probabilistic Planning &
Reinforcement learning (RL)**

Credits:

Mohan Sridharan, Peter Stone, Michael Gelfond, Jeremy Wyatt
Saeid Amiri, Piyush Khandelwal

Thank you!