Analysis and Visualization of the Decisions of Autonomous Agents Acting in Uncertain Environments

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Co-Supervisor: Dott. Giulio Mazzi
Co-Supervisor: Dott. Alberto Castellini

1 Motivation

Motivation

Autonomous Self-Driving car

Courtesy of Google

Autonomous Mobile Vacuum

Courtesy of Rumba

Motivation

Autonomous warehouse

Courtesy of Amazon

Robotics manipulator arms

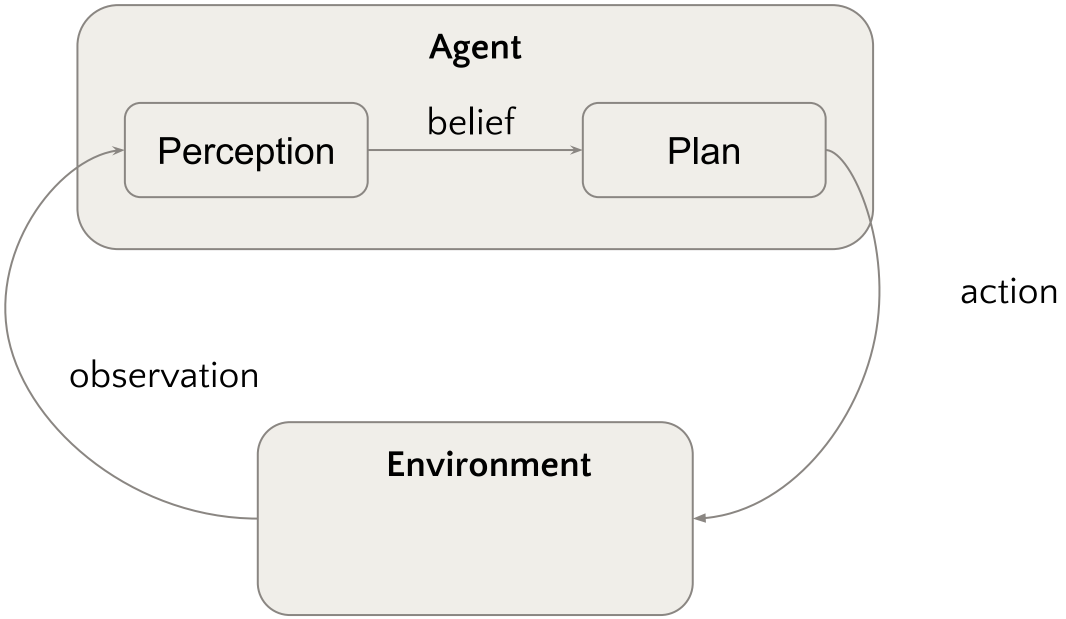
Courtesy of ICE-Lab

Motivation

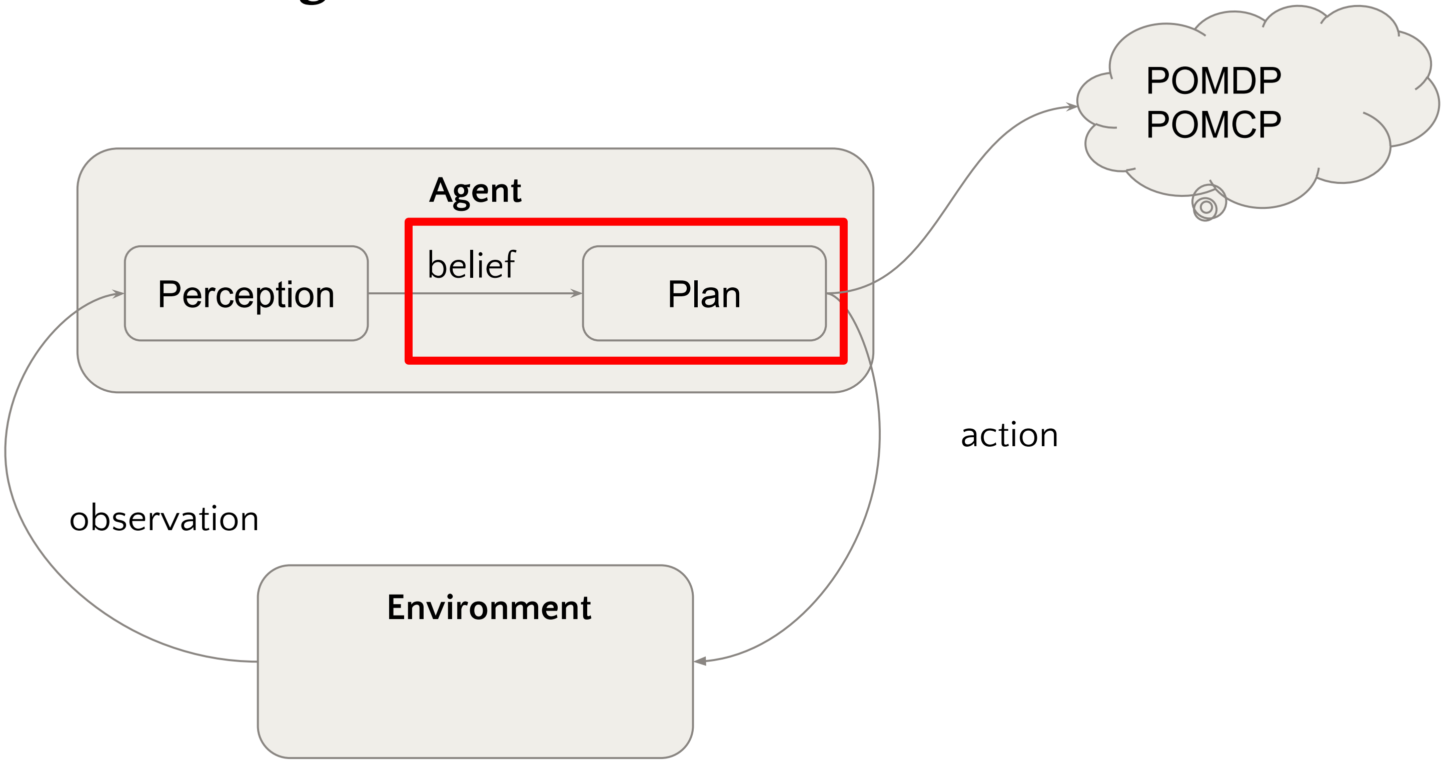
What about **safety**?

2 Basic Knowledge

Basic Knowledge

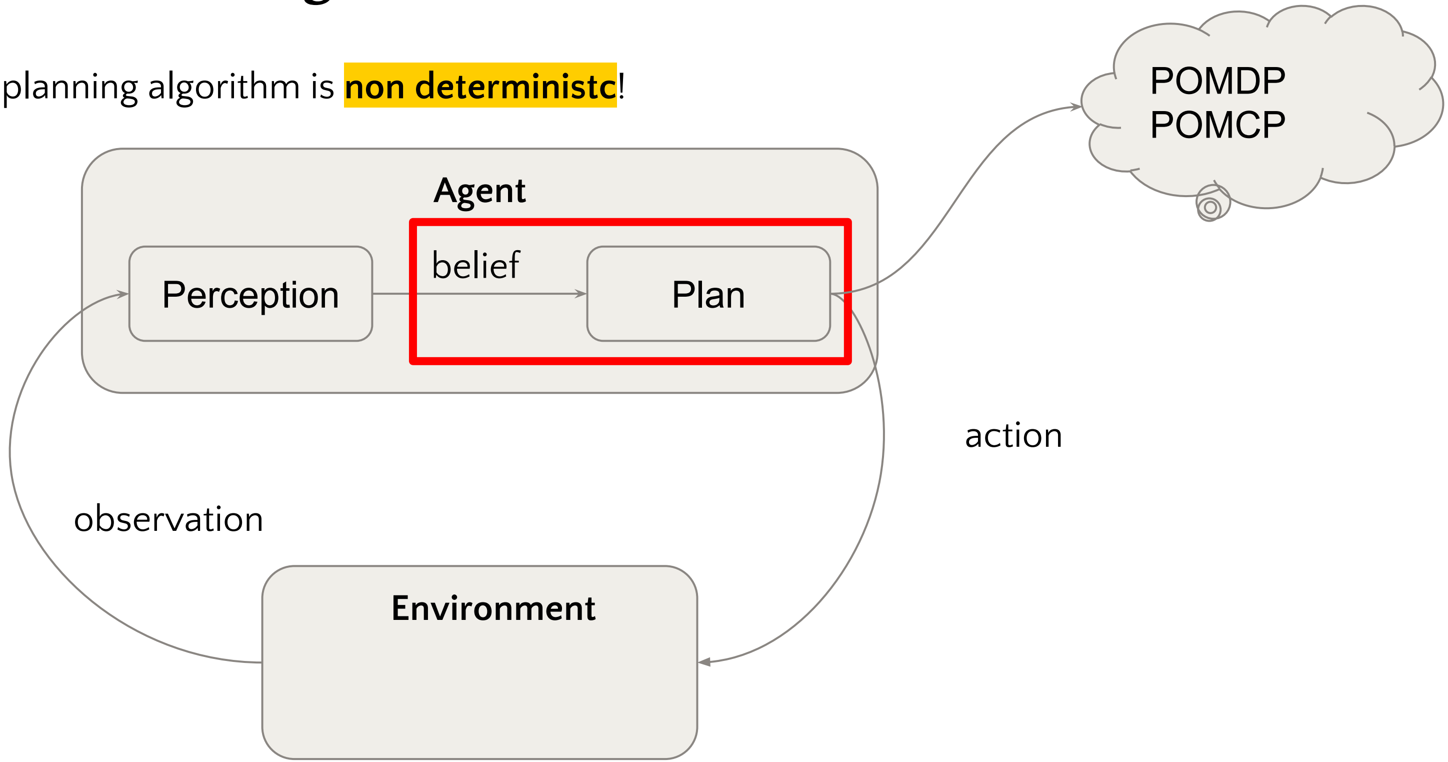


Basic Knowledge



Basic Knowledge

The planning algorithm is **non deterministc**!



Basic Knowledge

The full plan is not available

Trace

T1: observation, belief, action
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...

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Thesis Contribution

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- Analysis of the decisions of POMCP
  - Anomaly detection
  - Compact plan representation

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  - Velocity Regulation
  - Tiger

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- Analysis of the decisions of POMCP
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- Web Application
- Empirical Evaluation on two different problems domain
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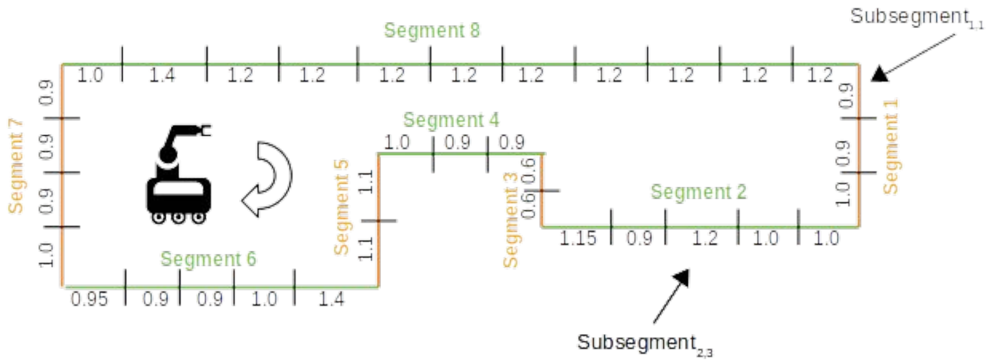
- Comparison with state of the art algorithms
  - Anomaly detection: Isolation Forest, XPOMCP
  - Compact plan representation: XPOMCP, Logistic Regression, DNN.

4 Problem domain

Problem Domains

- Velocity regulation:



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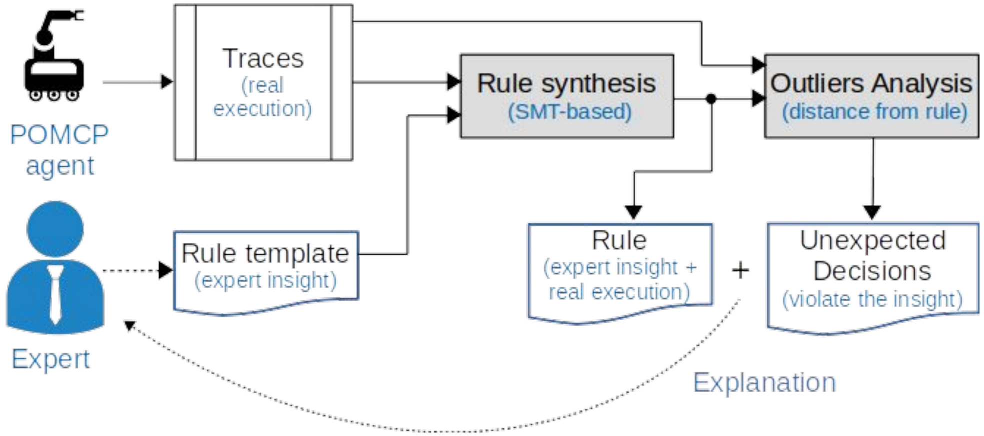
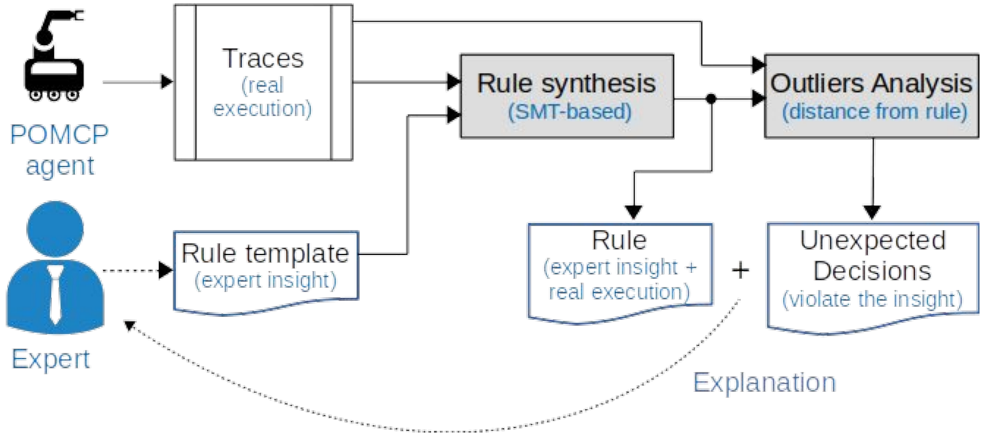
Explainable POMCP (XPOMCP)

XPOMCP



POMCP agent
Expert
Traces
(real execution)
Rule template
(expert insight)
Rule synthesis
(SMT-based)
Outliers Analysis
(distance from rule)
Rule
(expert insight + real execution)
+
Unexpected Decisions
(violate the insight)
Explanation

XPOMCP



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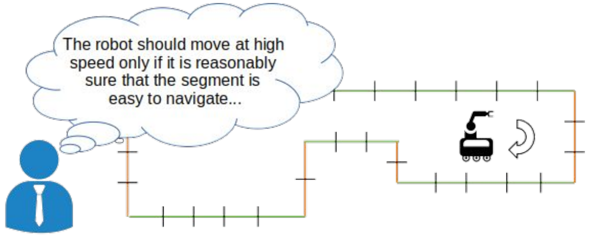
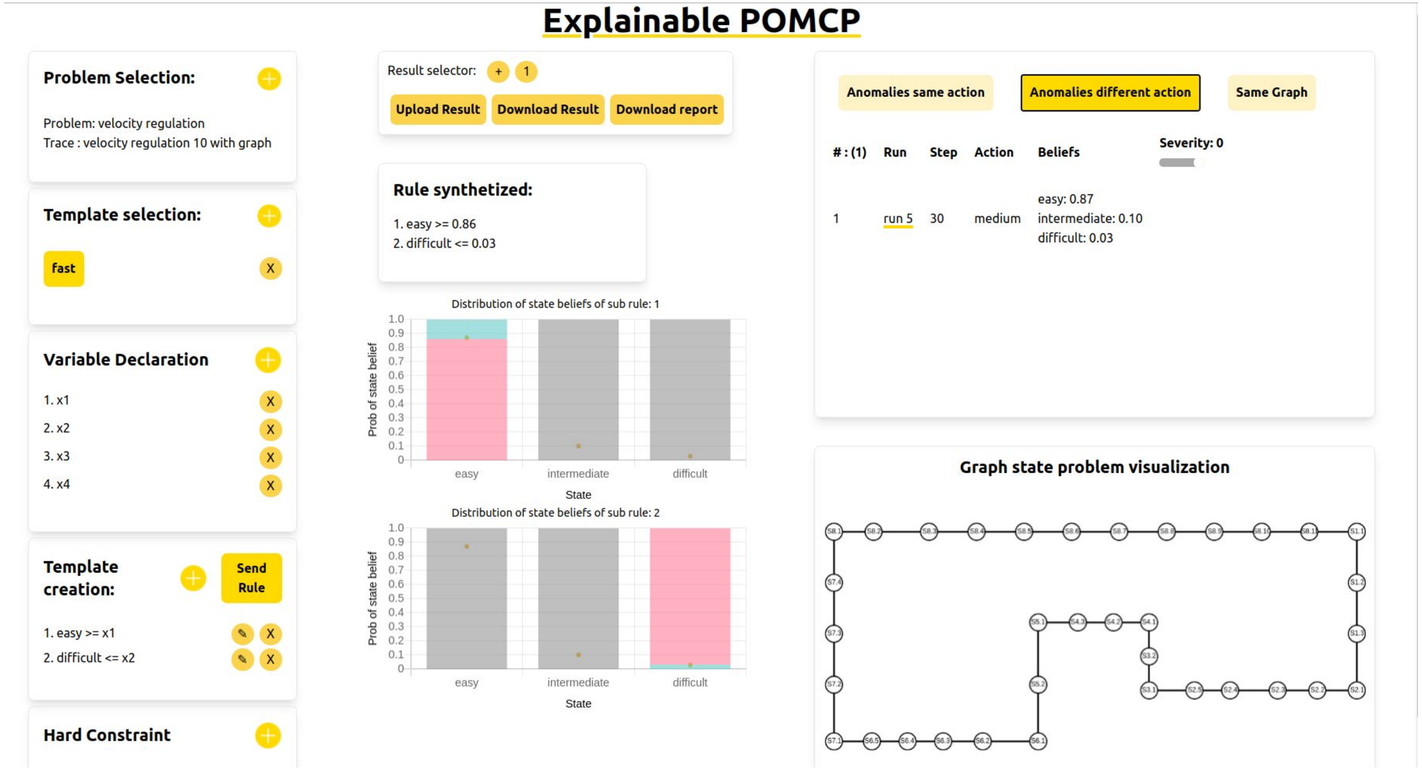


The robot should move at high speed only if it is reasonably sure that the segment is easy to navigate...

6 Web Application

Empirical Evaluation



7 Conclusions

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  - Authors: Giulio Mazzi, Giovanni Bagolin, Alberto Castellini, Alessandro Farinelli
  - Workshop: Autonomous Robots and Multi Robot Systems (2021)

Conclusions

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- Anomaly detection: XPOMCP, IF
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- Future Work: Autonomous Rule Generation

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Thanks!

9 Empirical Evaluation

Empirical Evaluation

Approximation results on Velocity Regulation using **XPOMCP**:

- r_1: select action **fast** when:

$$easy \geq \mathbf{x_1} \vee$$
$$difficult \leq \mathbf{x_2} \vee$$
$$easy \geq \mathbf{x_3} \wedge intermediate \geq \mathbf{x_4}$$

Free variable, detailed specified in the synthesis process

- r_2: select action **medium** when:

$$easy \geq \mathbf{y_1} \vee$$
$$difficult \geq \mathbf{y_2} \vee$$
$$easy \geq \mathbf{y_3} \wedge intermediate \geq \mathbf{y_4}$$

- r_3: select action **slow** when:

$$easy \leq \mathbf{z_1} \vee$$
$$difficult \geq \mathbf{z_2} \vee$$
$$easy \leq \mathbf{z_3} \wedge intermediate \leq \mathbf{z_4}$$

Empirical Evaluation

Comparison of Approximation results on Velocity Regulation among **XPOMCP, Logistic Regression, Deep Neural Network**:

XPOMCP	LR	DNN
Accuracy action "slow": 99%	Accuracy model for segment 0: 72%	Accuracy model for segment 0: 75%
Accuracy action "medium": 95%	Accuracy model for segment 1: 62%	Accuracy model for segment 1: 80%
Accuracy action "fast": 92%	Accuracy model for segment 2: 79%	Accuracy model for segment 2: 92%
	Accuracy model for segment 3: 89%	Accuracy model for segment 3: 98%

Accuracy: ration between the number of equal prediction, and total number of steps

Empirical Evaluation

Anomaly Detection on Tiger using **XPOMCP**:

RewardRange	**Threshold**	**F1-score**	**Accuracy**	**time (s)**
85	0.061	0.979 (± 0.081)	0.999 (± 0.0001)	14.30 (± 0.50)
65	0.064	0.999 (± 0.002)	0.999 (± 0.0001)	14.75 (± 0.80)
40	0.045	0.980 (± 0.072)	0.987 (± 0.049)	12.78 (± 0.83)

Empirical Evaluation

Anomaly Detection on Tiger using **Isolation Forest**:

W	Threshold	F1-score	Accuracy	time (s)
85	0.01	0.020 (± 0.033)	0.990 (± 0.001)	0.72 (± 0.013)
65	0.03	0.771 (± 0.044)	0.988 (± 0.001)	0.71 (± 0.010)
40	0.5	0.437 (± 0.035)	0.585 (± 0.026)	0.64 (± 0.037)