

Motivation

- Autonomy = many layers of **approximations**
- Decisions based on **incomplete/uncertain info**
- Certification standards** for autonomy: must account for non-determinism, complexity, adaptability, etc.
- Trust**: integral part of certification for autonomy



Trust and Self-Confidence

User Trust Model

- Trust**: willingness to depend on autonomy
 - Depends on situation and initial disposition/beliefs
 - Affects the user's actions
- Assurance**: autonomy's ability to affect trust
 - Positive or negative
 - Ultimately affects user's actions

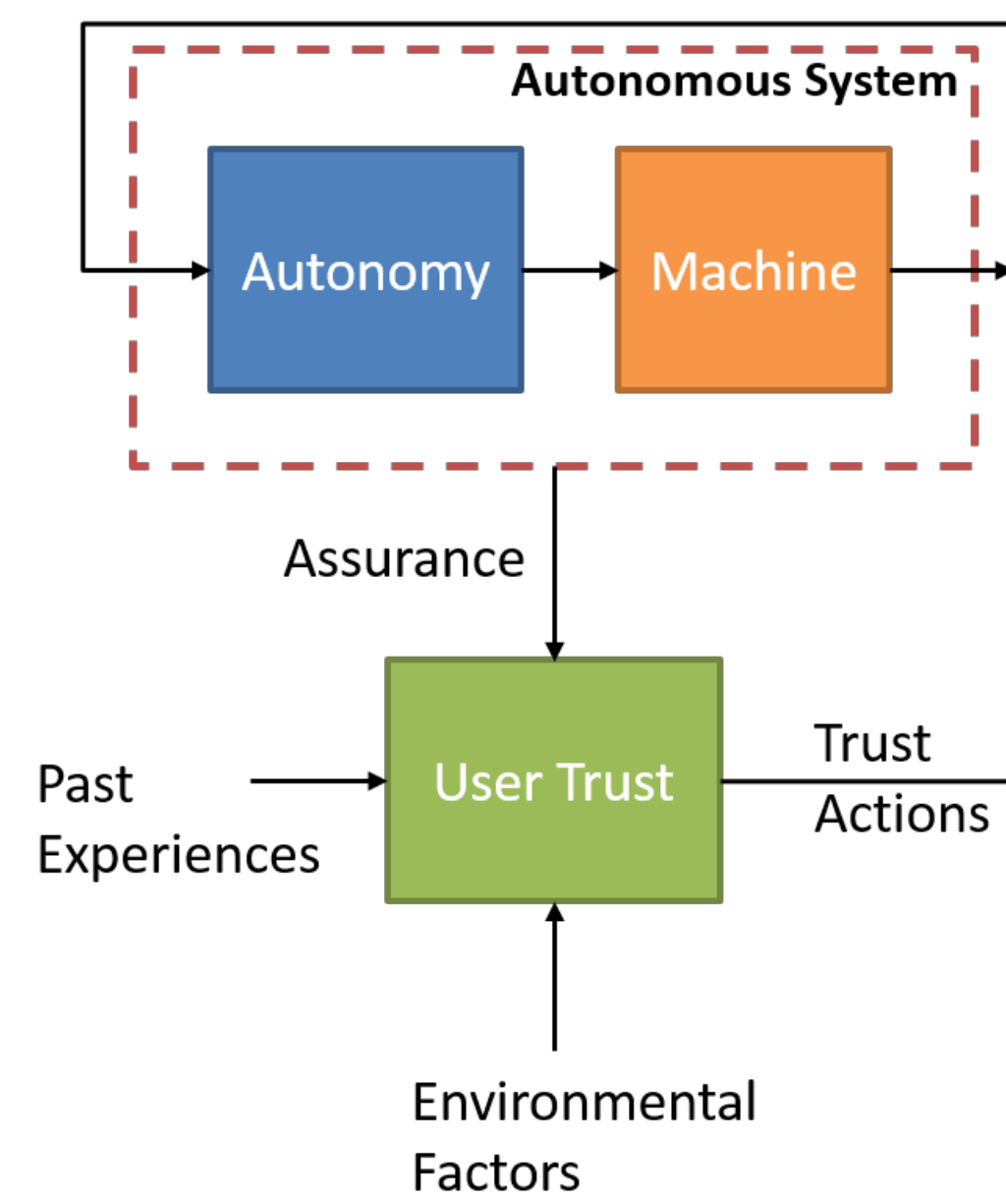


Fig. 1 – Trust Model

Self-Confidence as an Assurance

- Perceived ability to execute assigned tasks (within defined scope of autonomy) despite uncertainties in:
 - Its knowledge of world
 - Its knowledge of own self/state
 - Its reasoning and execution capabilities

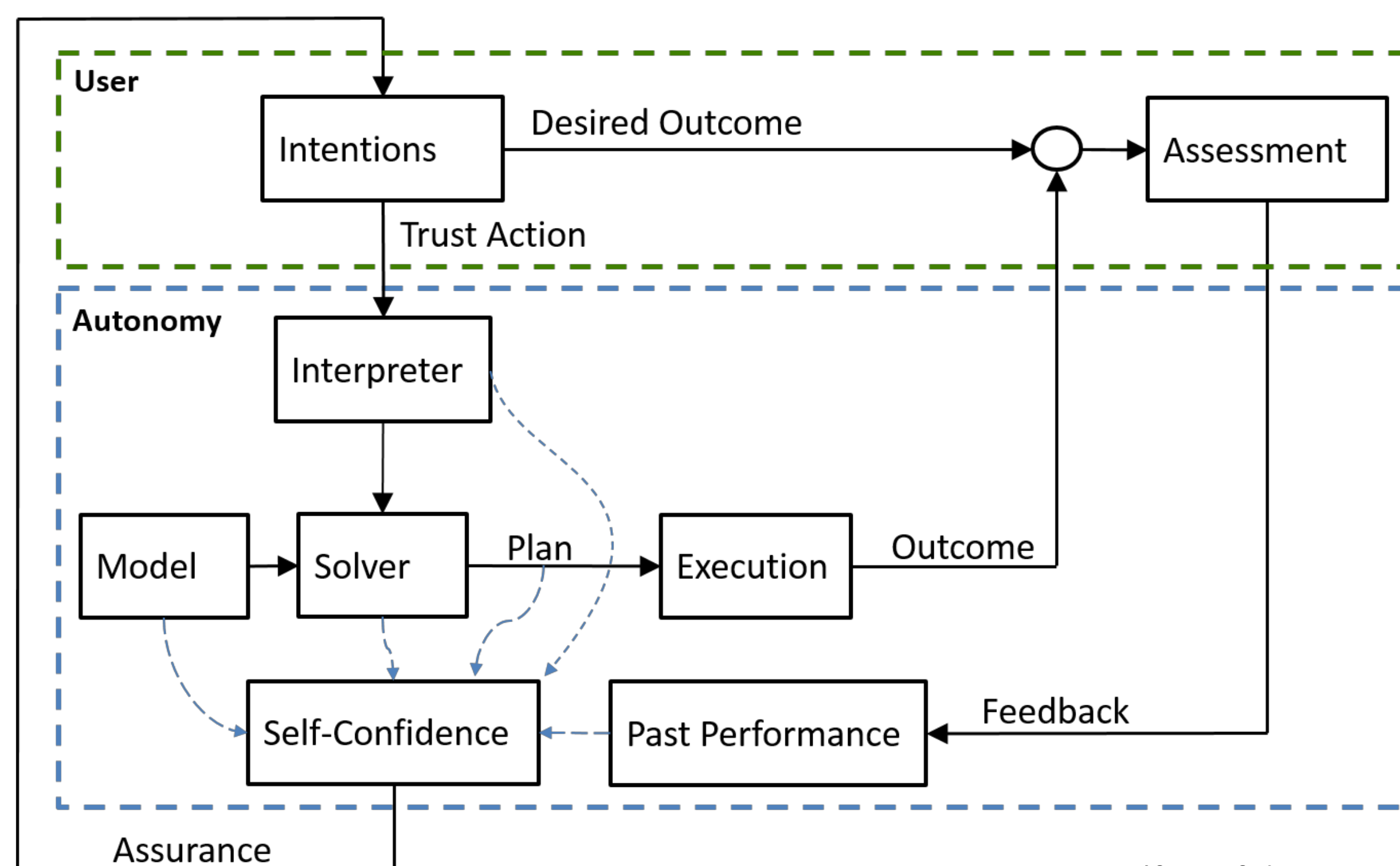


Fig. 2 – Self-Confidence Diagram

Scenario: Pursuit-Evasion on Road Network

Scenario Overview

- Unmanned ground vehicle (UGV) attempts to reach exit of a road network
- Pursuer attempts to capture the UGV
- UAV and unattended ground sensors (UGSs) gather data about pursuer's location
- Human supervisor interacts with UGV

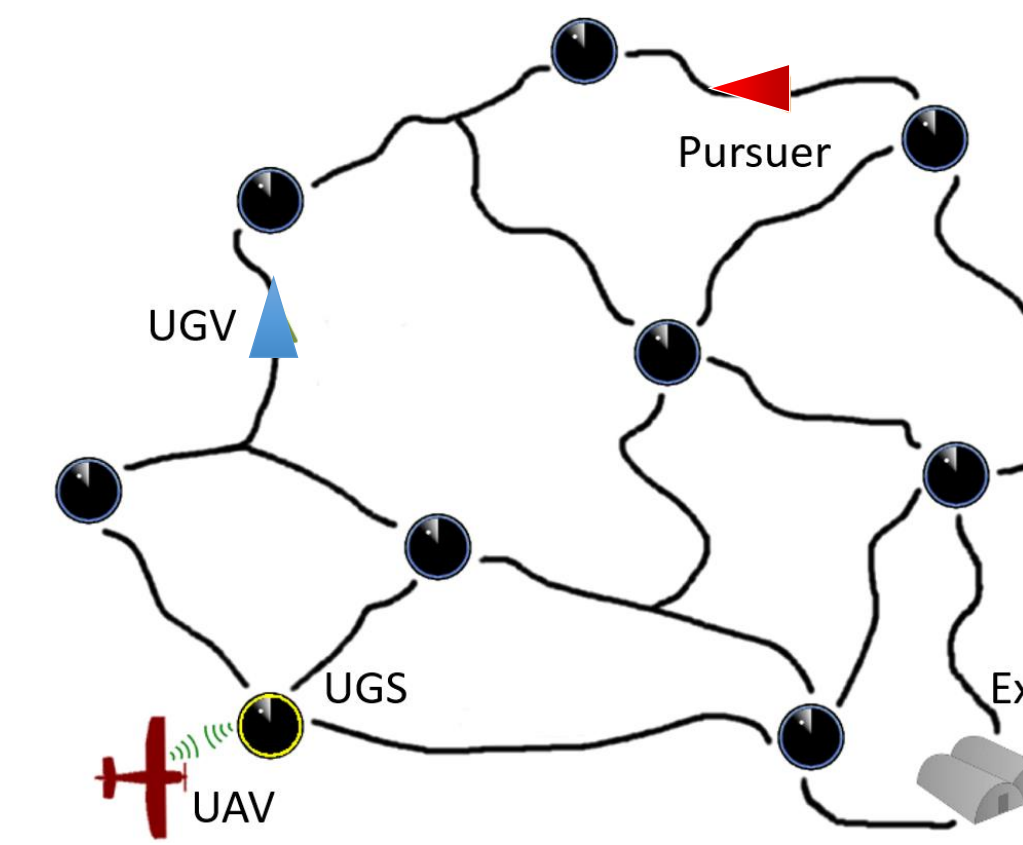


Fig. 3 – An example road network

Human-on-the-Loop

- No low level/expert system knowledge
- Comfortable with the problem
- Decisions influenced by trust
- Interrogate the autonomy
- Modify decision making via stance selection ('aggressive', 'defensive', etc.)
- Provide information, advice (identify intruder behavior, update map, etc.)



Fig. 4 – A UAS Operator

Mixed Observability Markov Decision Process

- States $s = (x, y)$: UGV and pursuer position
- Actions a : valid UGV step directions
- Observations o : $O = (o_1, o_2)$, $o_i \in \{\text{detect, no detect}\}$, $p(o_i|y)$ given
- Reward: $r(s, a) = \begin{cases} +1000 & \text{if } x = \text{exit} \wedge x \neq y, \\ -1000, & \text{if } x = y, \\ -1, & \text{o'wise} \end{cases}$
- Transition Probabilities: $p(y'|y)$, $p(x'|x, a)$
- Belief b : $b = [x, \vec{p}(y|O)]$
- Bayes' filter updates: $b' = \tau(b, a, O) \propto \sum_s p(s'|s, a)p(O|s')$

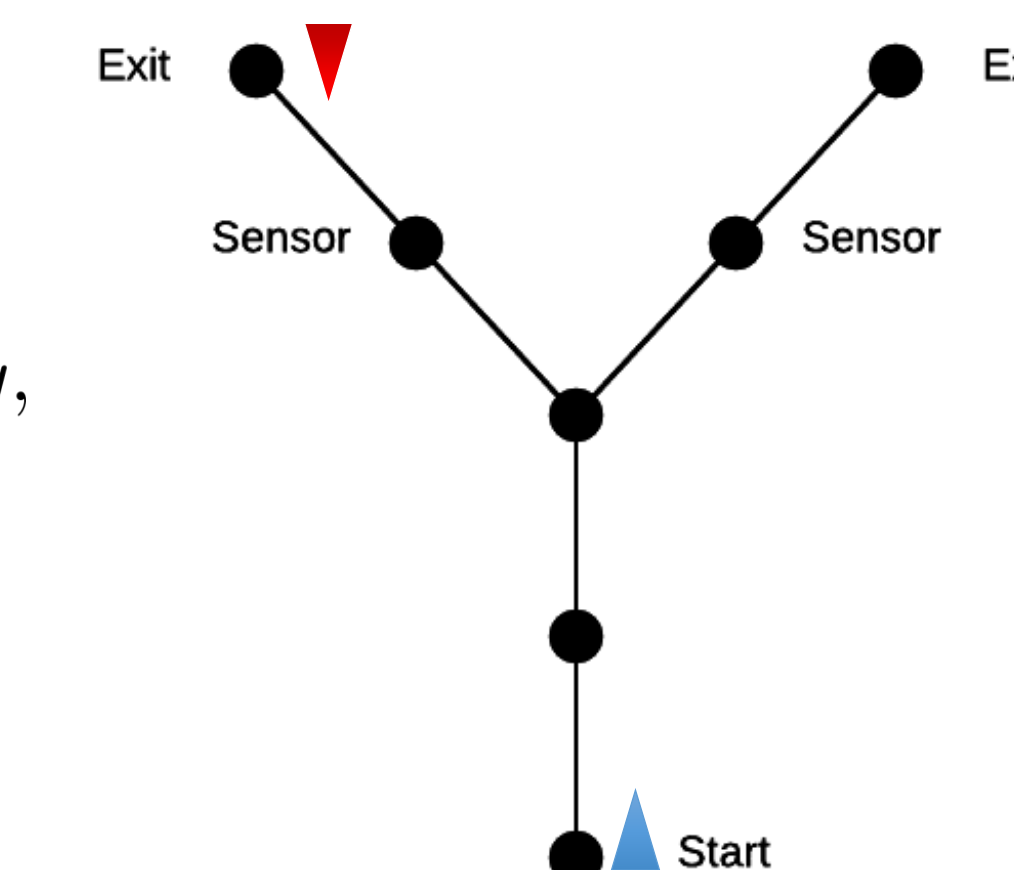


Fig. 5 – Simple Road Network Scenario

Policy Generation

- Goal: Maximize expected reward V : $V^\pi(b_0) = \sum_{t=0}^{\infty} \gamma^t r(b_t, a_t) = \sum_{t=0}^{\infty} \gamma^t E[R(s_t, a_t)]$
- Find optimal policy: $\pi^* = \operatorname{argmax}_{\pi} V^\pi(b_0)$ – solution intractable
- Approximate using SARSOP and APPL software

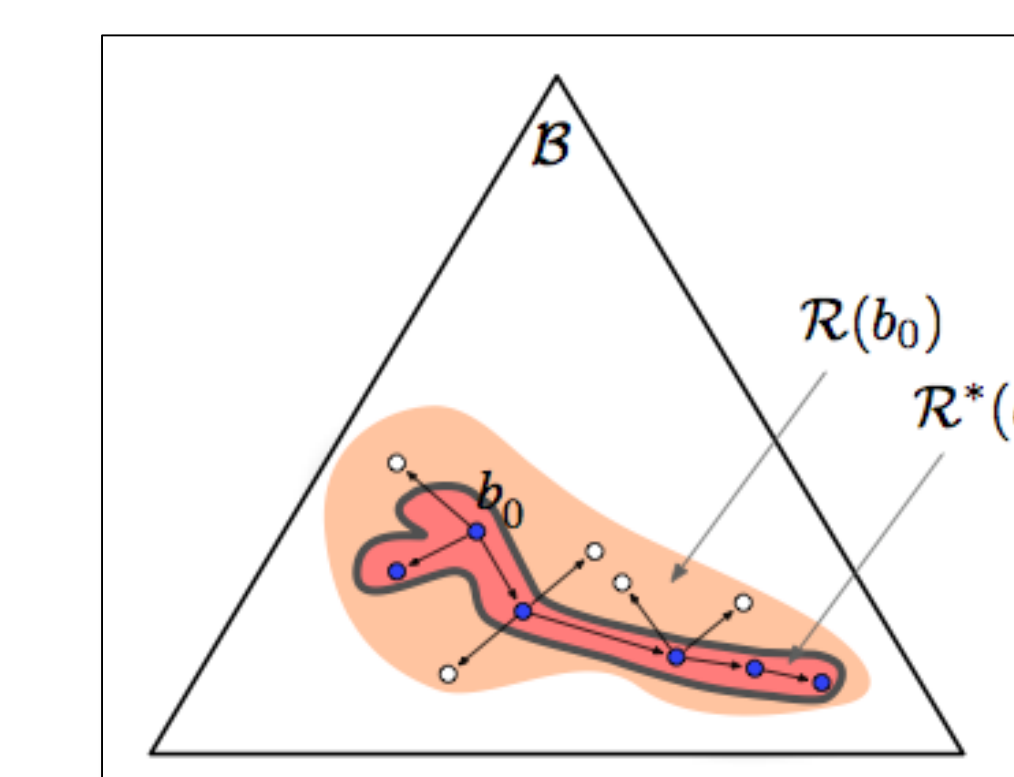


Fig. 6 – SARSOP algorithm [Kurniawati, et al 2008]

Self-Confidence Formulation

$$SC = f_{sc}(X_{sc}), \quad X_{sc} = [x_1, x_2, x_3, x_4, x_5, \dots]$$

- x_1 Command Interpretation
 - Are the autonomy and user 'on the same page'?
- x_2 Model Validity
 - How well does the autonomy's model reflect the real world?
- x_3 Solver Quality
 - How well can the solver use the model to generate policies?
- x_4 Outcome Assessment
 - How 'good' is the outcome distribution?
- x_5 Past Performance
 - How well has the autonomy done in similar circumstances?

Example Calculation: Outcome Assessment

Logistic UPM/LPM Metric

- Measure of 'goodness' of a reward distribution $p(\text{reward}|\pi)$
- $$x_4 = \frac{1}{1 - e^{-k(\log(\frac{UPM}{LPM})})}}, \quad UPM/LPM = \frac{\int_{r^*}^{\infty} (r - r^*) p(r) dr}{\int_{-\infty}^{r^*} (r^* - r) p(r) dr}$$
- r^* is the minimal acceptable reward, x_4 is a logistic function with steepness k applied to the log of the UPM/LPM ratio

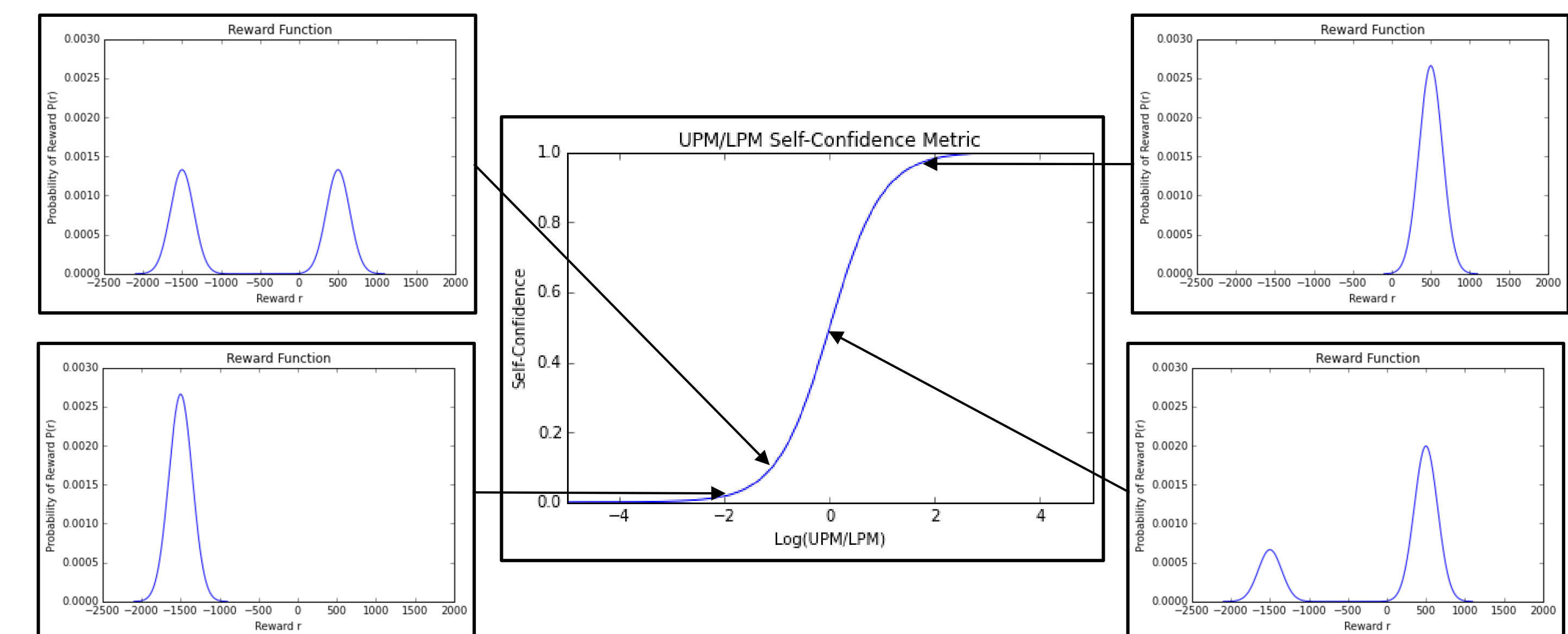


Fig. 7 – Outcome Assessment Self-Confidence ($r^* = 0, k = 1$)

Next Steps

- ROS/Gazebo scenario simulation
- Implement self-confidence reporting
- Design GUI and user study
 - First test: detect measurable difference in trust between users with and without self-confidence
- Run experimental user study



Fig. 8 – Husky from Clearpath Robotics