CS637: Course Project

TRUST-BASED ROUTE PLANNING FOR AUTOMATED VEHICLES

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Introduction

- The majority of automated vehicles available to the general public nowadays are Level 2 and Level 3 of automation, which allow the driver to turn away from the task of driving; but the driver must still be prepared to take over control of the vehicle.
- Human's decision on whether or not to rely on the automation is guided by trust.
- In this paper, we incorporate human trust into our planning dynamics.
- For example, if a driver has lower trust in a vehicle's capability for safely navigating busy urban streets as opposed to freeways. Then the driver would prefer a freeway even if the distance is longer.

Traditional Route Planning Methods

- Graph search algorithms such as Dijkstra's algorithm and A* algorithm can be applied to find the shortest distance path between any two locations.
- Kanoulas et al. extended A* algorithm by considering the speed change at different time of the day to compute the fastest route.
- Gonzalez et al. developed an adaptive fastest route planning method based on information learned from the historical traffic data.
- Andersen et al. proposed to find the most eco-friendly route by assigning eco-weights based on GPS and fuel consumption data.

Personalized Route Planning Methods

- Campigotto et al. developed a method for the personalized route planning by using Bayesian learning to update users' profile.
- Dai et al. recommended a personalized optimal route considering user preferences encoded as a ratio between different metrics such as distance, travel time, and fuel consumption.
- Zhu et al. proposed a personalized and time-sensitive route planning method, in which they inferred users' preferences with locations and visiting time through historical data.
- None of these route planning methods consider human trust as a state parameter.

Trust in Automation

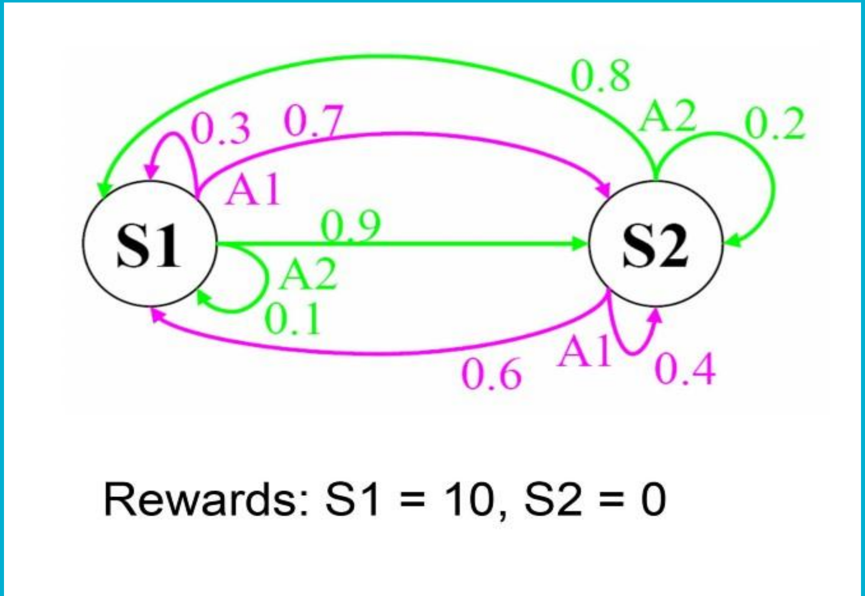
- CREDENTIALS BASED: Which is used mainly in security and determines if a user can be trusted based on a set of credentials.
- EXPERIENCE BASED: Which includes reputation-based trust, determines an agent's trust value based on its own experience in predicting the probability of the execution of a certain action by another agent.
- COGNITIVE TRUST: Which explicitly account for not only the human experience, but also subjective judgment about preferences and mental states.

How do we measure and model trust?

- Sensing technologies have been used for the continuous measurement of human trust in real-time, including gaze tracking, gestures , and biometrics (e.g., electroencephalogram and galvanic skin response).
- We measure human trust in a 7-point Likert scale via questionnaires in a online user study, and via continuous user control input in the driving simulator study.
- Several recent works have explored the idea of modeling trust with POMDPs.
- For e.g., A POMDP model for trust-workload dynamics in Level 2 driving automation and a POMDP-based method for human-robot collaboration in table cleaning tasks.

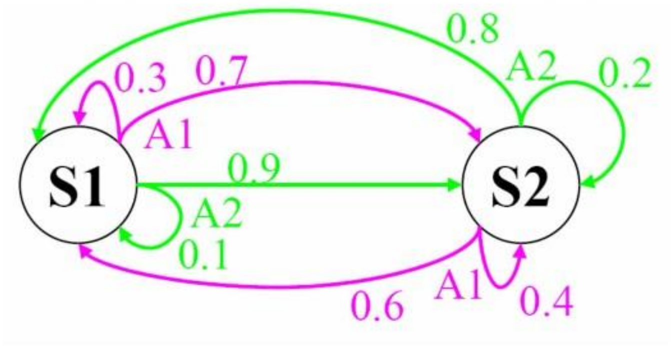
Markov Decision Processes

- Finite number of states.
- Probabilistic transitions between states and controllable actions in each state.
- Next state determined only by the current state and current action.



POMDPs

- Has same basic characteristics as MDPs.
- But here we do not deterministically know which state we are currently in.
- The states emit observations by which we update our belief of being in a particular state.
- Belief State is a probability distribution over the true states.



Rewards: S1 = 10, S2 = 0

Do not know state:
S1 emits O1 with prob 0.75
S2 emits O2 with prob 0.75

Formal Definition of a POMDP

- A 7-tuple $(S, A, T, R, O, \delta, \gamma)$
- $T(s_{t+1}|s_t, a_t)$ where $s_{t+1}, s_t \in S, a_t \in A$
- $R(s_t, a_t)$ where $s_t \in S, a_t \in A$
- $\delta(o_{t+1}|s_{t+1}, a_t)$ where $o_{t+1} \in O, s_{t+1} \in S, a_t \in A$
- The goal of POMDP planning is to compute the optimal policy that chooses actions to maximize the expectation of the cumulative reward given by:

$$E[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)]$$

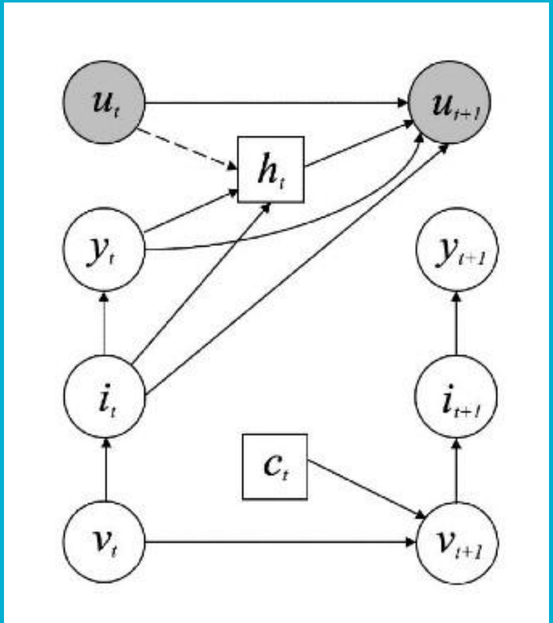
Motivating Problem

Proposed POMDP Framework

- The vehicle position v_t is one of the 11 locations $\{A, B, \ldots, K\}$ shown in the map.
- The incident i_t can take one of the four values: null, pedestrian, obstacle, and truck.
- The vehicle's capability y_t of handling incidents has binary outcomes: success(1), and failure(0). This is 1 for our implementation, but the agent or the participants in the study do not have any idea of this.
- Since human's trust is a partially observable variable u_t representing the hidden mental state, we use a observation variable $\hat{u}_t$ to represent the subjective trust in a 7-point Likert scale (1 and 7 indicate the lowest and highest levels of trust, respectively) measured via user questionnaires.
- The vehicle route choice is c_t and the human's takeover decision is given by h_t.

Proposed POMDP Framework

- $s_t = [v_t, i_t, y_t, u_t]$
- $a_t = [c_t, h_t]$
- The evolution of trust dynamics is modeled with a probabilistic transition function $T(u_{t+1} | u_t, y_t, i_t, h_t)$ based on a simplified assumption that trust evolves depending on the takeover decision and the vehicle's capability of handling an incident.



Reward Function

- For empty road: Reward is 5(highest)

	Pedestrian	Obstacle	Truck
Autopilot (Success)	3	2	1
Autopilot (Failure)	-9	-6	0
Manual driving	0	0	0

Online User Study for Data Collection

- Designed and conducted an online user study with 100 anonymous participants on the Amazon Mechanical Turk platform.
- Created a set of driving videos using the PreScan driving simulation software.
- Adapted the Muir's questionnaire and asked participants to answer the following questions in 7-point Likert scale:

1. To what extent can you predict the automated vehicle's behavior from moment to moment?
2. To what extent can you count on the automated vehicle to do its job?
3. What degree of faith do you have that the automated vehicle will be able to cope with similar incidents in the future?
4. Overall how much do you trust the automated vehicle?

Online User Study for Data Collection

- Any vehicle crash video was not included in this study, because it was assumed that the automated vehicle is capable of handling all incidents safely. Participants are not aware of such information in advance.
- They make takeover decisions based on their trust beliefs about the automated vehicle's capability to safely handle certain incident, and the trust levels may change based on their experience of watching prior incident videos.
- Data collected from each participant had following format:

$$D = \{\hat{u}_0, i_0, h_0, \hat{u}_1, i_1, h_1, \ldots, i_8, h_8, \hat{u}_9\}$$

- $\hat{u}_t$ is the measured user trust, i_t is the incident type, h_t is the user decision of takeover or not, at each time step t.

Data-Driven Trust Dynamics Model

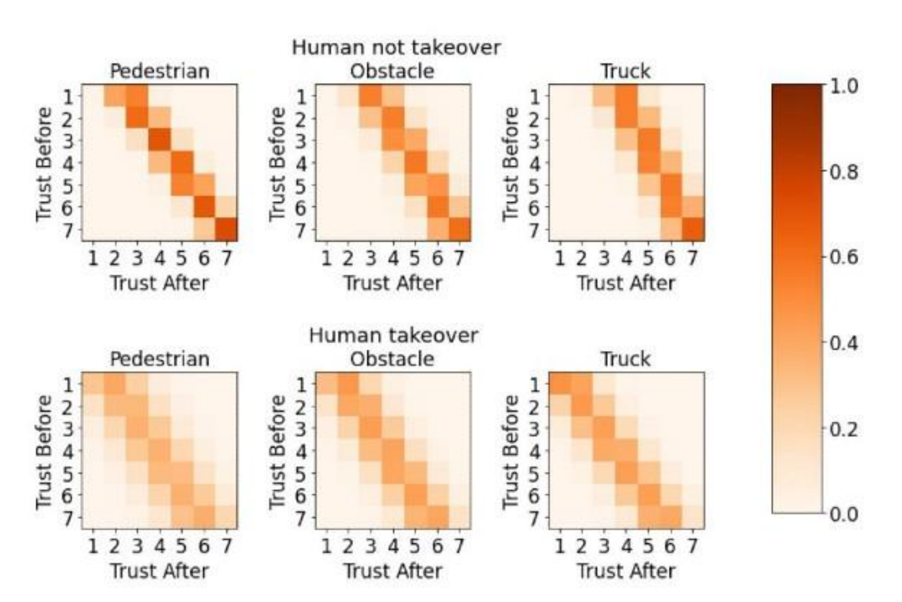
- Using the data collected from the online user study described, the trust dynamics and the POMDP observation function were modeled as a linear Gaussian system:

$$T(u_{t+1}|u_t, i_t, y_t, h_t) = \mathcal{N}(\alpha_t u_t + \beta_t, \sigma_t^2)$$

$$\hat{u}_t \sim \mathcal{N}(u_t, \sigma_u^2)$$

- Parameter values were estimated using full Bayesian inference with Hamiltonian Monte Carlo sampling algorithm.

Data-Driven Trust Dynamics Model



Data-Driven Takeover Decision Models

1. TRUST FREE DECISION TAKEOVER MODEL:

- b^i denote human's belief on the automated vehicle's capability of safely handling an incident i, which remains constant in the trust-free model.
- p_t denote the probability of human deciding to not take over at time step t. We define:

$$p_t = S(b^i r^{s,i} + (1 - b^i) r^{f,i}) \qquad S(x) = \frac{1}{1 + e^{-x}}$$

- $r^{s,i}$ and $r^{f,i}$ are rewards of the automated vehicle handling the incident i with success and failure.
- We model the takeover decision with a Bernoulli distribution, denoted by:

$$h_t \sim \mathcal{B}(p_t)$$

Data-Driven Takeover Decision Models

2. TRUST BASED DECISION TAKEOVER MODEL:

- b_t^i denotes human's belief on the automated vehicle's capability of safely handling an incident i at time step t, which evolves over time depending on the human trust u_t.
- κ^i and λ^i are linear coefficients associated with the incident i.
- b_t^i Is then given by: $b_t^i = S(\kappa^i u_t + \lambda^i)$.
- p_t assumes the form:

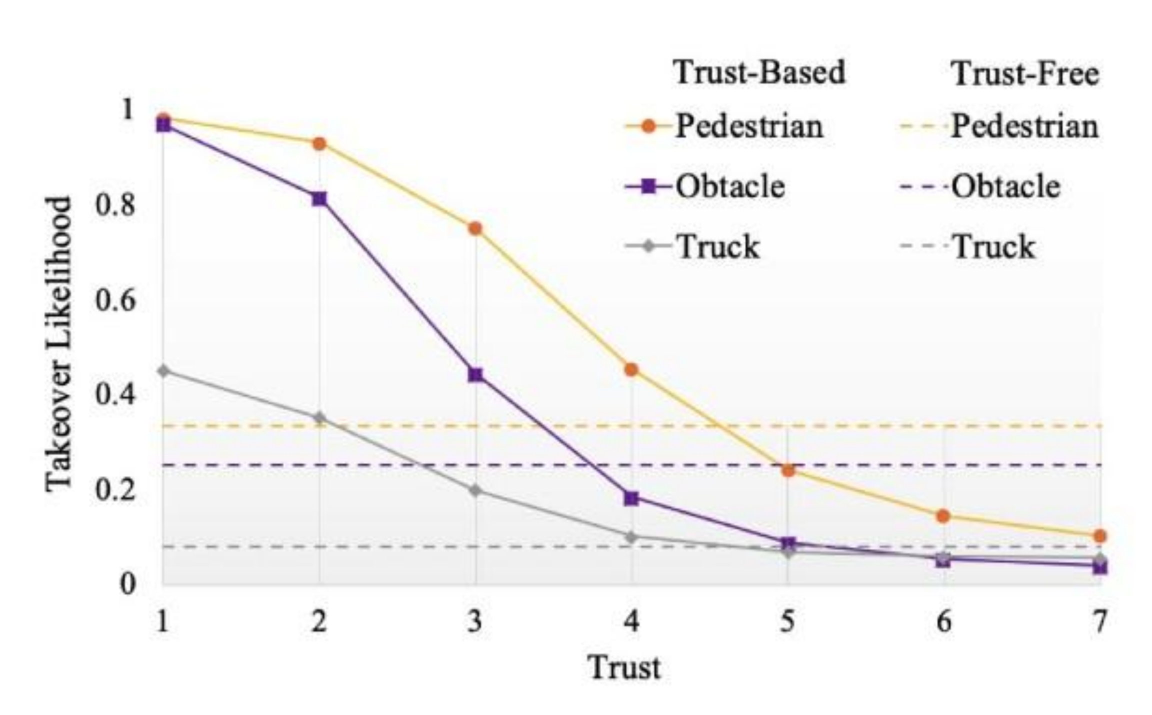
$$p_t = S(b_t^i r^{s,i} + (1 - b_t^i) r^{f,i})$$

- Takeover decision is given by: $h_t \sim \mathcal{B}(p_t)$

Data-driven modeling results

- Application of full Bayesian inference with Hamiltonian Monte Carlo sampling algorithm to estimate parameters in both the trust-free and trust-based models, using the data collected from the online user study.
- The difference in log-likelihood results shows that accounting for trust in the takeover decision model can achieve better prediction performance, which supports our assumption that human takeover decisions are influenced by trust.
- Furthermore, we observe from the results of both models that it is more likely for human to decide to take over with riskier incidents: pedestrian with the highest takeover probability, followed by obstacle and truck.

Predictions of takeover likelihood



Planning for the Motivating Example

- The Approximate POMDP Planning (APPL) Toolkit , which is an implementation of the point-based SARSOP algorithm for efficient POMDP planning , was applied to compute the optimal policies of the proposed POMDP framework.
- Depending on the use of trust-based and trust-free takeover decision models, two optimal routes were obtained:

1. Trust-based route: A-D-G-J-K
2. Trust-free route: A-C-E-H-K

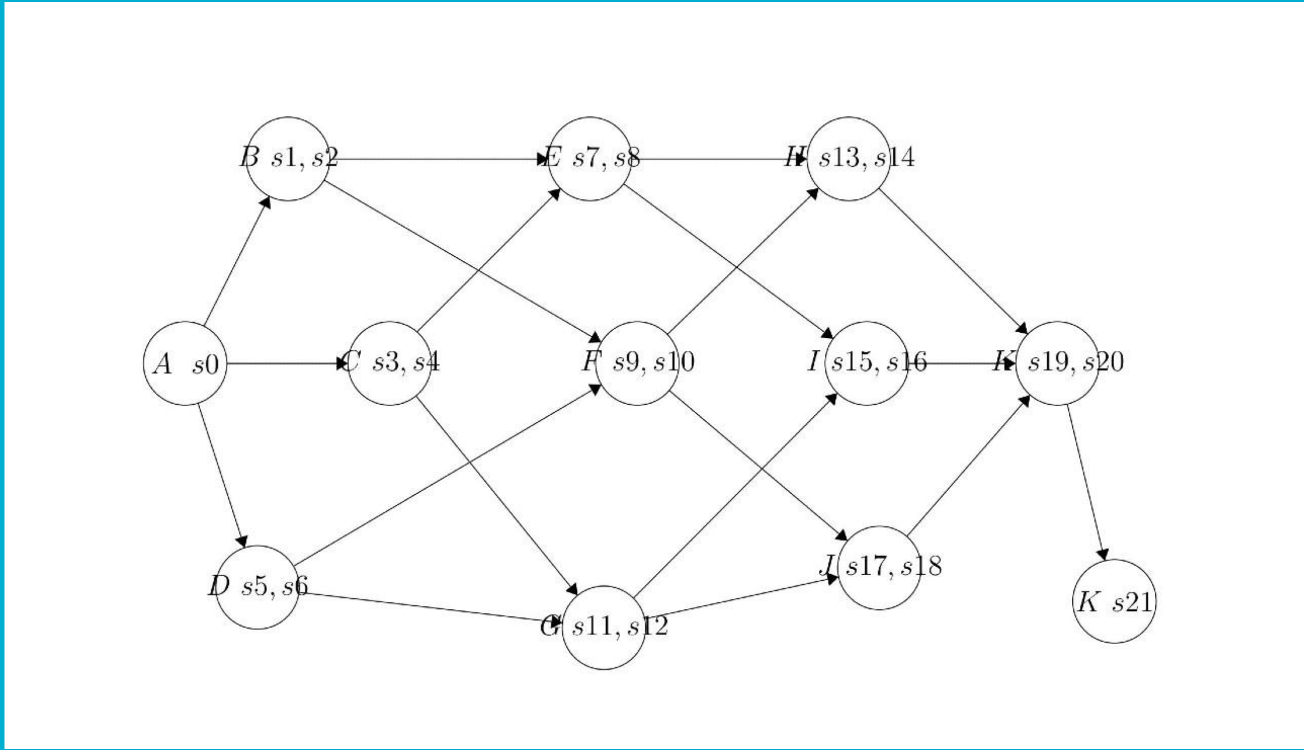
- The main difference between these two routes is the order of road incidents. In the trust-based route, the ordered incidents occurring in each road segment are oncoming truck (A-D), null (DG), obstacle (G-J), and pedestrian (J-K). In the trust-free route, the incidents follows the order of pedestrian (A-C), null (C-E), obstacle (E-H), and oncoming truck (H-K).

Modifications for Implementation

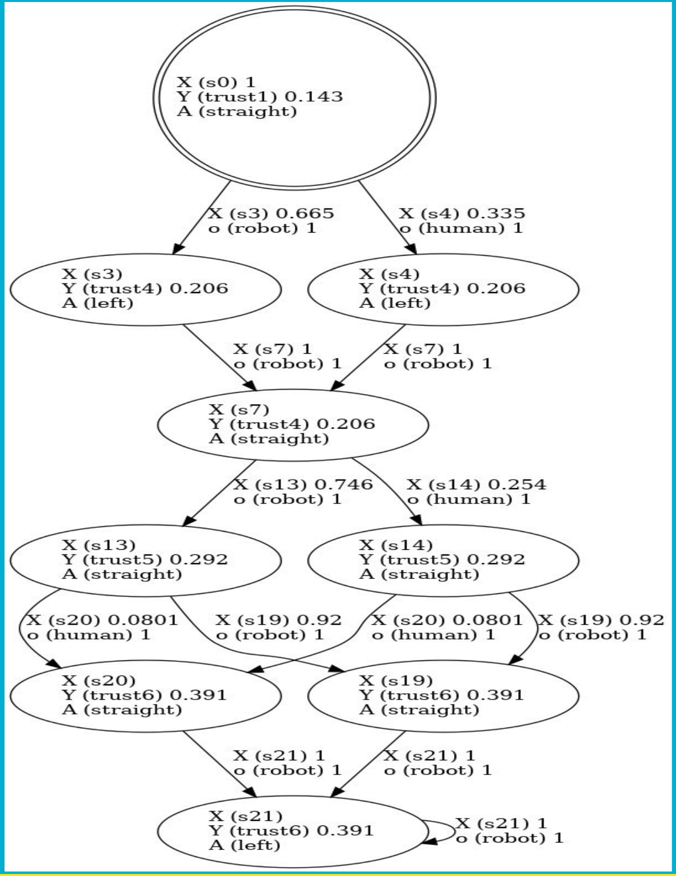
- State space:
1. One Fully observable State Variable: s0 to s21
2. One Partially observable State Variable: trust1, trust2, trust3 ..., trust7
- Observation Space:
1. One Observation Variable: robot or human
- Action Space:
1. Three Possible Actions: left, right and straight
- Rewards: Expected rewards and -999 for undesirable actions from a state

Motivating Problem

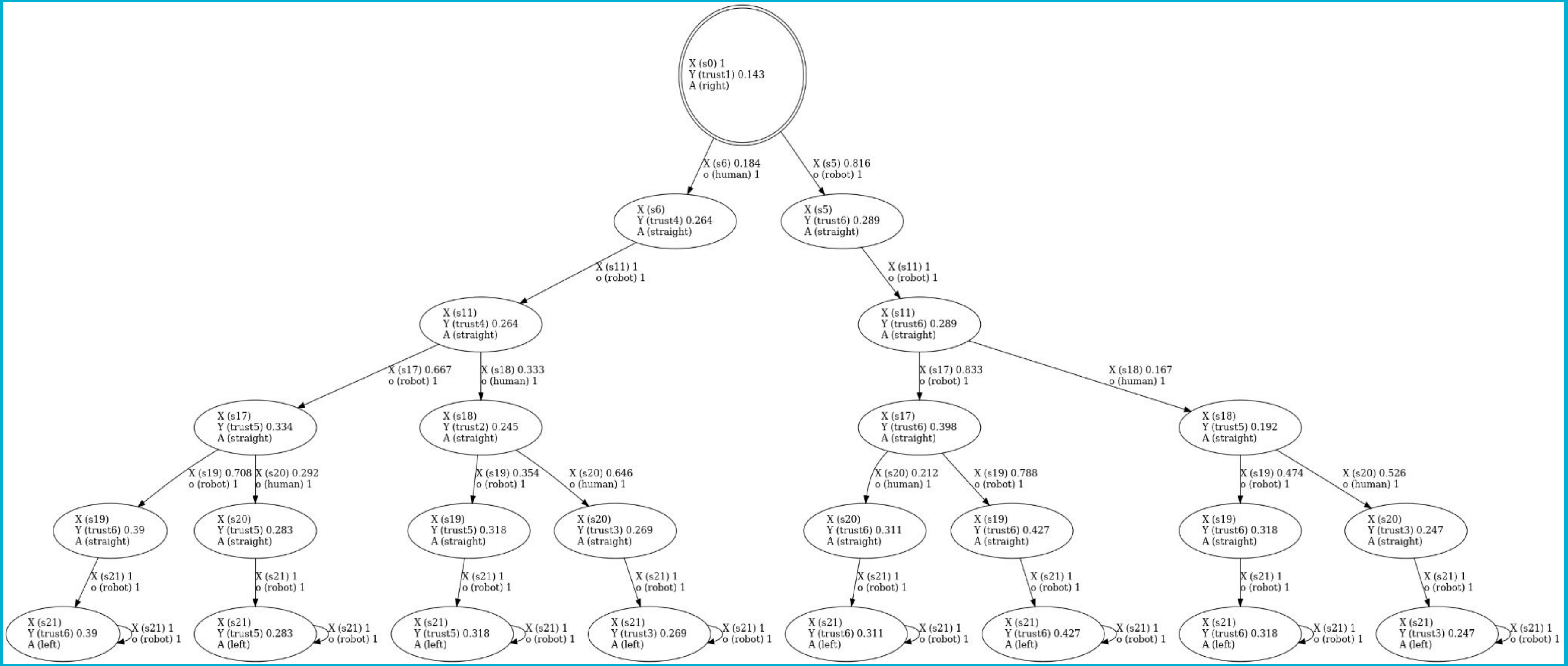
New State Space for the Motivating Example



Policy Graph for Trust Free Model



Policy Graph for Trust Based Model



DRIVING SIMULATOR EXPERIMENTS

- Apparatus:

1. The hardware platform is based on the Force Dynamics 401CR driving simulator, which is a four-axis motion platform that tilts and rotates to simulate the experience of being in a vehicle.
2. The simulator's control input was programmed such that the driver can switch between automated and manual driving by pressing the two buttons simultaneously. In addition, we used the same set of buttons to measure participants' trust in automated vehicles during the experiments.

DRIVING SIMULATOR EXPERIMENTS

- Driving Scenario:

1. A driving scenario based on the motivating example described was created
2. An autopilot controller for the simulated automated vehicle, which has the capability of leveraging the integrated sensors (radar, Lidar, and GPS) in PreScan for various driving tasks such as lane keeping, detecting and handling incidents.

- Manipulated factor: The route that the autopilot controller follows.
- Dependent measures: We are interested in studying the route which brings more cumulative reward.

Recruitment of Participants

- 22 participants (average age: 23.7 years, SD=4.3 years, 31.8% female) from the university community were recruited.
- Recruitment Criteria: valid driver license, at least one year of driving experience, and normal or corrected-to-normal vision.
- To avoid participants' bias, a between-subject study design was adopted, i.e., randomly allocation of 11 participants to take the trust-based route and the other 11 participants to experience the trust-free route

Experiment Procedure

- The journey started in the autopilot mode.
- When the vehicle approached an incident (i.e., pedestrian, obstacle, or truck), it alerted the participant by issuing an auditory alarm and displaying textual information about the incident type in the GUI.
- Participants could switch between taking control or choosing the autopilot.
- The participant was required to periodically record their trust in the automated vehicle using the buttons on the steering wheel.
- After the driving session, the participant had to answer some specific survey questions in the 7-point Likert scale.

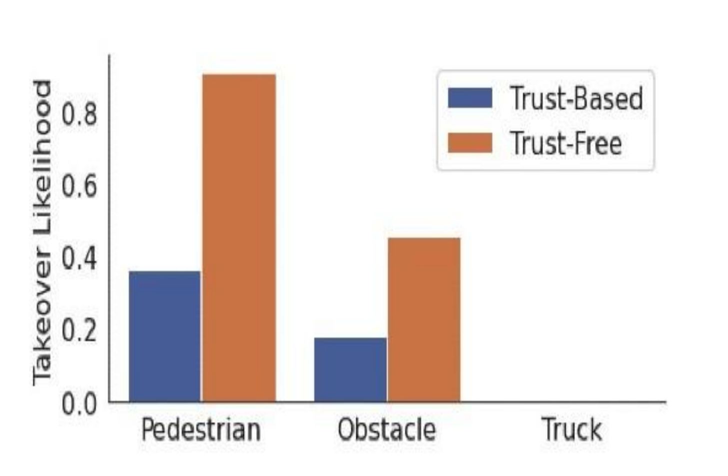
After Survey Questions

1. I believe that the automated vehicle can get me to the destination safely.
2. I find the route easy to drive.
3. I find it easy to take over control of the automated vehicle.
4. I have concern about using the automated vehicle to drive through this route.
5. I believe that the selected route is not dangerous.
6. I think the selected route fits well with the way I would like to drive.
7. I can depend on the reliability of the automated vehicle.

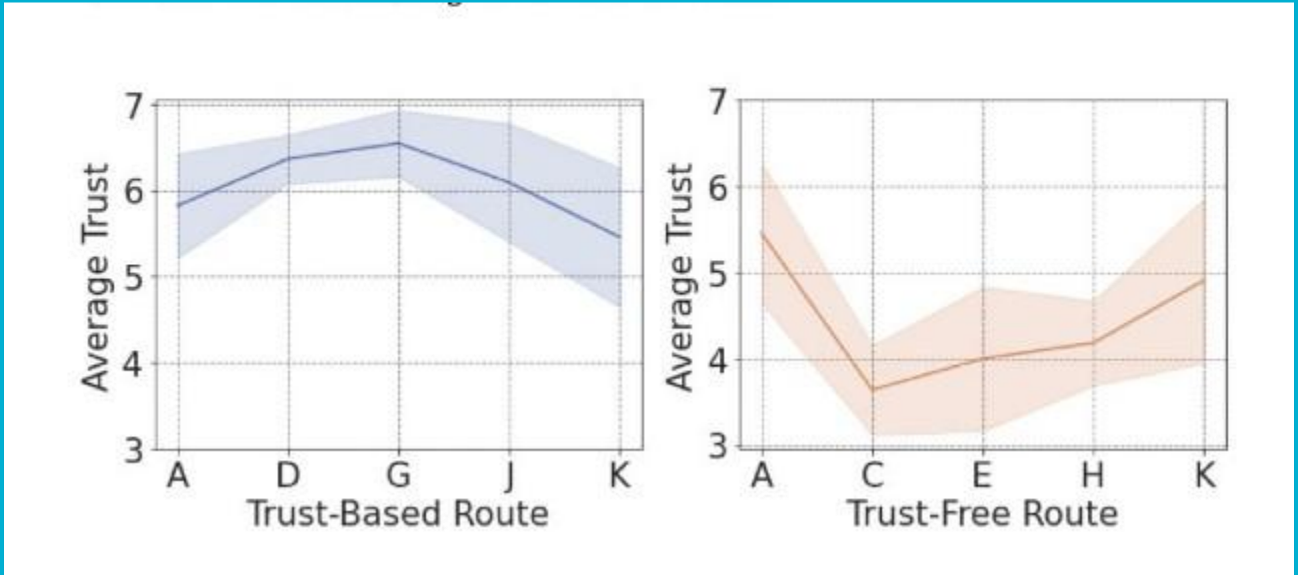
Results

- Participants taking the trust-based route tended to achieve higher cumulative rewards than participants taking the trust-free route, which is consistent with our study hypothesis.
- One-way analysis of variance (ANOVA) was also performed to evaluate this hypothesis, i.e, comparing the observed F -test statistics with F (d1, d2) (F -distribution with between-group degree of freedom d1 and within-group degree of freedom d2). The observed statistics F (1, 20) = 9.14 is greater than the critical value at significance level 0.01. Thus, the hypothesis is supported by ANOVA results statistically.

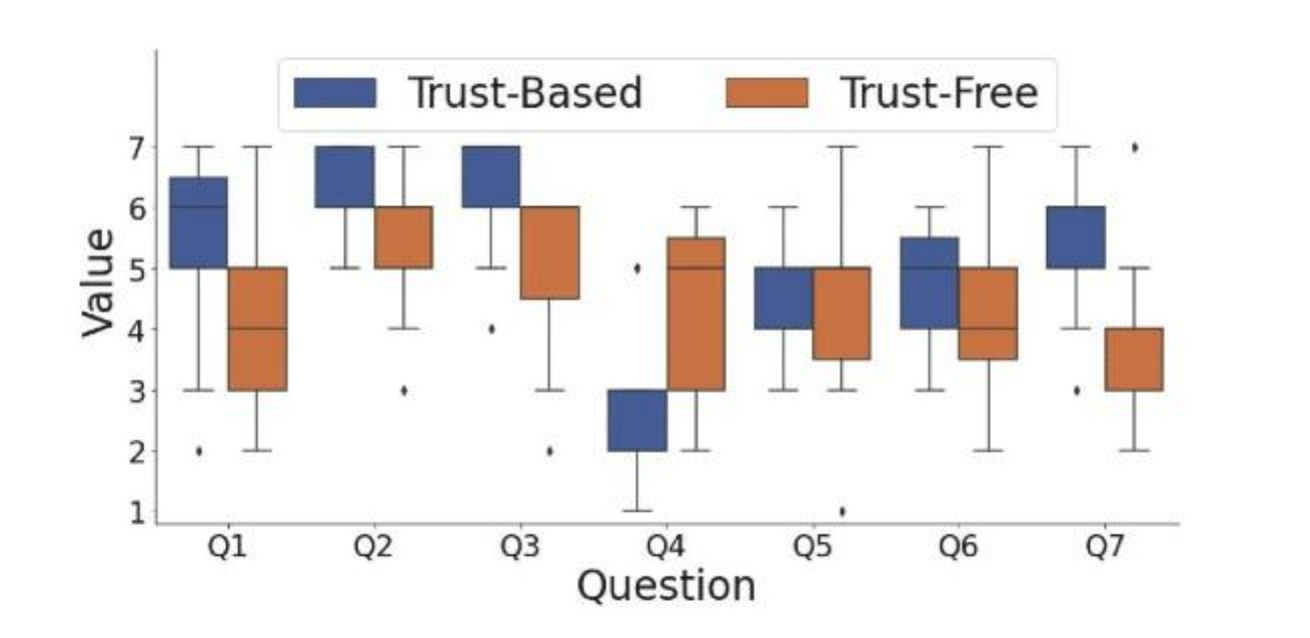
Takeover Likelihood and Cumulative rewards



Evolution of participants' average trust



After-driving survey results



Summary of Results

- Participants taking the trust-based route generally resulted in higher cumulative POMDP rewards than those taking the trust-free route.
- Participants were more likely to take over in the trust-free route than in the trust-based route; and riskier incidents led to higher takeover likelihood.
- Participants' trust in the automated vehicle evolved over time during the driving experience and was influenced by different types of incidents.
- Participants experienced the trust-based route had more positive responses in the after-driving survey than those driving through the trust-free route.

Future Work

- The proposed POMDP-based approach can be applied to larger route planning problems such as larger maps, more locations, and more route choices.
- Consider a richer set of incident types to reflect the complex road conditions that automated vehicles may encounter in the real-world.
- Explore the POMDP modeling of other factors that may influence human’s trust in automated vehicles, such as the system transparency and predictability.

THANK YOU