**Impact of the technology: autonomous cars**

Autonomous vehicles will reduce the number of road fatalities, give us greater independence during retirement and the ability to go anywhere anytime, independently of our state of mind. As society grows, more and more cars circulate and consequently more traffic, which leads to increased time in traffic and human error. Autonomous vehicles would also allow the time spent in cars to me productive.

As Volvo is aiming to bring an end to traffic fatalities by the year 2020, autonomous cars are becoming more a tangible reality and less a fictional dream only seen in movies. Yet challenges remain regarding performance and safety under all circumstances.

Socially compliant driving, including cooperation and interactivity, is important to guarantee safety in dynamic and uncertain environments. Since an agent’s actions are interdependent on all other agents’ actions, an uncertainty explosion in future states arises and results in a complete stop of the vehicle, because all possible actions become unsafe. Consider the situation when collision is inevitable, for example, when a pedestrian unexpectedly stumbles into the road, what should the decision be? Should the vehicle endanger the driver or the pedestrian? What if the vehicle has passengers? We might want the vehicle to protect the pedestrian since the driver and passengers assume some level of risk by getting into the vehicle, but you would want to buy a vehicle that does not maximize the drivers safety?

A way to describe this system can be threw a partially observable markov decision process (POMDP) which models the relationship between an agent and its environment. In this case, the agent is the vehicle. At each time, the environment is in some state s and the agent takes an action a causing the environment to be at a new state s’ according to some transition probability. At this new state, the agent receives an observation o’, which depends on the state, according to some observation probability. Finally, the agent receives a reward r according to the utility of the state.

Therefore, behaviour can be modelled as expected utility maximization, in other words, an agent is expected to execute the most beneficial controls. Therefore, a reward or utility function needs to be known or learned. So, this planning can be done as a two-player-game, where the autonomous vehicle computes an action and then models the other vehicles in a way that maximizes both expected reward, assuming the vehicles can communicate. This shows that this behaviour can be highly interactive instead of reactive, because on vehicles reward depends on another’s actions.

The problem with this approach is that increases complexity with the number of agents, since now all agents communicate and affect each other. A way to simplify the problem is to restrict the action space and exhaustively search all possible options. The search space can be characterized by a tree that each node represents a possible action at a given time. Another way to change the exponential growth to liner growth with the number of agents, is to have a hierarch of agents. Where the leader takes its decision independently, the second one considers the previous one and so one and so forth. With this approach allows a real time response for more than 30 agents.

Leaning-based approaches might also be used in the decision process. This kind of approach uses a neural network that has the capability to extract relevant features from high-dimensional data, by passing the high-dimensional data through a function-approximator that utilizes a multi-layer computational graph. This model is inspired by natural structures in the human brain. For example, a possible neural network might use the data from the vehicle’s state and surrounding, past actions and road geometry to produce a set of prediction hypotheses that capture plausible actions. To better achieve the best function-approximator to the problem we want to model, examples are given to the network consisting one group of data and the corresponding result.

One of the drawbacks of deep learning is that these networks need large amounts of data to correctly model a behaviour. Besides, in the case of autonomous vehicles the data acquired only describes almost ideal situations, being necessary to synthetically simulate this data so that non-ideal scenarios can be safely simulated.

So, as we can see these problems, that sometimes occur while driving, can be resolved using many approaches. The ethical problem presented in the beginning of the essay, can be modelled used any of the two approaches described, either by maximizing the expected utility or by reinforcement learning, where in both the problem can be described as a POMDP. On one hand, using the first approach, a utility must be defined for each possible outcome. On the other hand, for the second approach, the system must be exhaustively trained for it to be prepared to correctly act in every possible environment.

As engineers it is our job to evaluate each one of them, and exhaustively go throw all advantages and disadvantages, since the consequences of a malfunction of a system used among all people are probably disastrous.