

# Privacy-Preserving Intersection Management for Autonomous Vehicles

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## Abstract

Traffic lights are a common instrument to regulate the traffic in junctions. However, when a vehicle has an urgency, it may violate the traffic lights. Since the other vehicles do not expect this, such violations lead to road accidents. Connected and autonomous vehicles can coordinate their actions and decide on the priority of passing without the need of traffic lights if they can share information about their current situation. That is, a vehicle with an urgency can communicate this with justifications to others and ask to go first. However, the shared information can potentially yield privacy violations while helping vehicles attain priority. We propose a privacy-preserving decision making framework for managing traffic at junctions. The vehicles are represented as autonomous agents that can communicate with each other and make priority-based decisions using auctions. The bids in the auctions are not monetary but contain information that each vehicle is willing to declare. Our experiments on real-world accident data show that our proposed bidding strategies help vehicles preserve their privacy while still enabling them to receive priority at junctions.

## 1 Introduction

Traffic accidents are the leading cause of casualties in many countries. Only in US, approximately 40,000 people died in traffic accidents in 2016 [National Safety Council, 2016] and millions of people have been injured. Most of these accidents happen because human drivers do not obey traffic rules, or are not aware of the physical conditions of the environment. Autonomous vehicles are expected to reverse this as they can be designed to follow the rules more strictly than human drivers [Crew, 2015]. However, human drivers also choose to violate the rules on purpose to address their own needs. For example, a driver can choose not to stop at a red light at a junction because of a special condition; i.e., she is in a hurry because of a sick passenger. In many occasions, if the other drivers were aware of the situation, they might accommodate it, for example by lending the road to that driver. This is widely seen in case of a fire truck or an ambulance, where the vehicles physically show their purpose

through sound and colors. However, with regular cars, there are no special symbols that can designate their purpose. Thus, in junctions, the decision making is done in a simple turn-taking manner that treats every vehicle equally. Ideally, it would be best if the vehicles could communicate with each other about their emergencies or constraints [Atherton, 2016] and automatically reach a decision as to which one should go first. Recent technologies, such as Vehicle-to-X (V2X) make it possible for vehicles to talk to each other as well as designated entities on a road [Lu *et al.*, 2014]. Using such a technology, vehicles could communicate information such as the purpose of their trip, physical conditions of the vehicle as well as the external properties of the environment.

While such a communication between autonomous vehicles could serve to reach a decision, it could also create important privacy challenges. For example, a vehicle could reveal that it is in an emergency because it is carrying the president and might actually end up passing through a junction before others, but disclosing this information could create other threats for the vehicle. Or, a stroke patient who has high blood pressure symptoms could be in hurry to go to hospital. However, he might prefer not sharing his health condition with other entities because the breach of this information can lead to loss of insurance or a job. Thus, preserving privacy of the vehicles while reaching a decision is of utmost importance.

This paper proposes an agent-based approach to realize privacy-preserving decision making for autonomous vehicles [Bazzan and Klugl, 2014]. Whenever two vehicles are at a junction, the vehicles bid with their information in an auction to decide which vehicle will go first. The vehicle whose bid yields a higher priority gets to pass before the other. Contrary to traditional auctions with monetary bids, here even when a bid does not win the auction, the bidder is at a loss because some information has been disclosed. To handle this, we propose bidding strategies where each vehicle bids incrementally so that private information is only revealed if it will help the vehicle in taking a priority. As a result, a vehicle that provides enough information to convince the intersection manager for its priority passes first. This enables the vehicles to preserve their privacy while reporting their situation.

The rest of this paper is organized as follows: Section 2 introduces a multiagent model where each autonomous vehicle is represented as an agent that uses auctions to make priority-based decisions. We explain various parameters and condi-

| Property               | Property Weight | Instance                | Instance Weight |
|------------------------|-----------------|-------------------------|-----------------|
| Vehicle Type (t)       | 0.25            | Ambulance               | 1.0             |
|                        |                 | Car                     | 0.9             |
|                        |                 | Taxi                    | 0.9             |
| Journey of Purpose (p) | 0.25            | Journey as part of work | 1.0             |
|                        |                 | Commuting to/from work  | 0.8             |
|                        |                 | Riding to/from school   | 0.8             |
| Age Band of Driver (b) | 0.25            | 0-5, 6-10, 66-75, 75+   | 0.8             |
|                        |                 | 11-65                   | 1.0             |
| Age of Vehicle (a)     | 0.25            | Numeric Value (0-105)   | 1.0             |

Table 1: An Example Set of Properties and Instances

tions that cause accidents. Section 3 develops our approach and bidding strategies. Section 4 evaluates the approach on real world accident data. Section 5 provides a discussion on relevant approaches for junction managements. Finally, Section 6 concludes with directions for future research.

## 2 Autonomous Vehicles as a Multiagent System

We propose an agent-based approach where each agent represents an autonomous vehicle [Chen and Cheng, 2010]. Each agent is aware of the properties that are associated with the vehicle and the journey, such as the purpose of the trip or the type of the vehicle. When they arrive at a junction, they need to reach a decision as to which vehicle will pass first. To do so, each vehicle can put forward its current status to convince other vehicles of its priority. In order to be able to compare the status of two different vehicles, it is best if the information can be transformed into a single priority value. However, if each vehicle computes this value for itself, there is no guarantee that they would report it correctly; i.e., each vehicle can report a high priority value to pass first. To overcome this, it is best if both vehicles can report information about their status and a mediator can compute the priority values and announce the decision. Such an entity can have further information about the environment and compute a priority value. Auctions serve as an ideal mechanism for decision making through a mediator, where the entities involved (e.g., autonomous vehicles) express their priorities independently. The general idea is that an auctioneer provides a service (e.g., selling an item) and wants to get the highest possible price. On the other hand, the potential bidders want to receive service at the lowest possible price [Weiss, 1999]. For example, in an *English auction*, the buyer with the highest bid wins an auction and gets the item.

Auctions have been studied before in the context of decision making for autonomous vehicles at junctions and have been shown to reduce delays significantly [Carlino *et al.*, 2013]. In that approach, autonomous vehicles bid money to measure the value of a trip in terms of the value of time. According to the result of the auction, the driver can cross the intersection or wait. In our work, the bids consist of properties, and the value of a bid is computed by a trusted Intersection

Manager (IM) who acts as the auctioneer. Each vehicle bids with information and based on the type of the auction, IM decides on the winner of the auction. The bidder that provides information with the highest priority value wins. Contrary to existing work, the autonomous vehicles bid information instead of money to preserve privacy. We assume that the IM represents an authoritative entity, such as traffic patrol and is equipped with the necessary security techniques to collect, save, and process the bids without compromise.

The auctions that have been used before have not taken into consideration the privacy of the autonomous vehicles. Since the vehicles are giving away information as their bids to reflect their situation, it could very well be that the information they provide contain sensitive information. Thus, it is necessary to account for privacy in handling decision making.

### 2.1 Understanding Accidents

To understand road accidents better, we have analyzed the Road Safety Data [The UK Government, 2016] published by the UK Government. This dataset contains more than 140,000 road accidents with numerous properties including details about the consequential casualties. We show a representative subset in Table 1.

Each property has a name and a sample set of instances. The first property is the *Vehicle Type* with instances of ambulance, car and taxi. We associate an instance weight that denotes the importance of each instance. A regular car usually gives priority to an ambulance, which gets a higher instance weight. The second property is the *Journey of Purpose*. For example, a car can be in a hurry because it is late for school. The third property is the *Age Band of the Driver*. For example, a vehicle may need to pass first because it has an older driver. The fourth property is the *Age of a Vehicle*, a value between 0 and 105. Older vehicles may have brakes that are not robust and thus may be preferred to lead the road to a high-speed car. As seen in Table 1, some properties are about the vehicle itself (e.g., vehicle type), whereas some properties give information about the passengers in the vehicle (e.g., journey of purpose).

In addition to the instances of properties, properties themselves can be associated a weight, to denote that one aspect of the vehicle is more important than a second one. The values in this table can be adjusted. Here, we assume that each

|                     | Vehicle Type (t) | Purpose of Journey (p) | Age Band of Driver (b) | Age of Vehicle (a) |
|---------------------|------------------|------------------------|------------------------|--------------------|
| Vehicle 1 ( $V_1$ ) | CAR<br>[0.76]    | SCHOOL<br>[0.885]      | 6<br>[0.15]            | 9<br>[0.452]       |
| Vehicle 2 ( $V_2$ ) | TAXI<br>[0.477]  | PARTOFWORK<br>[0.879]  | 9<br>[0.334]           | 5<br>[0.948]       |

Table 2: Properties for the Two Vehicles in Accident Number 2015331500103

property is equally important and thus assign a value of 0.25.

**Running Example.** *A taxi and a car meet at a junction, where the car is headed for school and the taxi for work. How to decide which vehicle will pass first?*

The vehicles ( $V_1$  and  $V_2$ ) have the properties specified in Table 2 with different privacy values, which will be detailed in Section 3. The age band of driver values of the vehicles are 6 and 9 respectively; the age of the vehicle  $V_1$  is 9 and the age of the vehicle  $V_2$  is 5. An immediate question is how the vehicles will generate the bids regarding the properties of the vehicles. We study three strategies that vary in how they preserve privacy.

## 2.2 Strategy 1: Bid-All.

The simplest strategy is when the vehicles decide to reveal all their properties in their bids. This type of strategy corresponds to the *Blind auction*, where each bidder places a bid without considering the bids of others. The auctioneer announces the highest bidder who pays the amount of his bid.

The Intersection Manager (IM) should make a decision to compute a priority value for the received bids, and let the vehicle with the highest priority value to move first at the junction. Note that the priority values can be computed in different ways; we propose one such priority function in Equation 1.  $u_v$  is the priority value of the vehicle  $v$ . All the shared properties of a vehicle are added to the computation of the priority value.  $w_p$  is the weight of the property  $p$  and  $w_{p,i}$  is the weight for the instance of the property  $p$ .

$$u_v = \sum (w_p * w_{p,i}) \quad (1)$$

Figure 1 shows the interactions of two vehicles with IM, when the vehicles employ different bidding strategies. The dotted circles and the dotted squares show the possible bids of the two vehicles  $V_1$  and  $V_2$ . The winner of the auction has an underlined label. The first two strategies are single-shot auctions; whereas the third strategy requires multiple interactions with the IM.

In Figure 1a, when the vehicles follow Bid-All strategy, the two vehicles share all their properties (t, p, b, a). According to Equation 1, IM computes the priority values as 0.875 and 0.925 for  $V_1$  and  $V_2$  respectively.  $V_2$  is the vehicle with the highest priority value; hence, it wins the auction and moves first. This strategy is blind to privacy since all relevant information is shared without a privacy consideration.

## 3 Privacy-aware Strategies

A vehicle that is willing to share most of its properties might be in an urgent situation. However, there is a privacy tradeoff

to consider, since a vehicle may choose to keep some properties private to preserve its privacy instead of moving first. On the other hand, there is no guarantee that a vehicle will get the priority if it shares all its shareable properties. Recall that a vehicle only reveals its properties to the IM, which leads the auction and makes the decision about the winner.

To preserve privacy, each vehicle needs to prioritise its properties according to their privacy needs. Each property in Table 1 can be shared by a vehicle, if it meets the privacy needs of that vehicle. First, a vehicle assigns a privacy value for each property between 0 and 1. This value shows how much a property is private for the vehicle. In Table 2, the privacy values for each property are specified in brackets. For example, the vehicle type property has a privacy value of 0.76 for  $V_1$ . Second, a vehicle sets a single privacy threshold value between 0 and 1. A vehicle can only share a property with other IM entities if the privacy value of that property is below or equal to its threshold. We call such properties *shareable properties*. According to Table 2 and Figure 1, if the privacy threshold is set to 0.8 for both of the vehicles, the shareable properties of  $V_1$  are {t, b, a}; and those of  $V_2$  are {t, b}. A shareable property is a candidate property that can be shared. In other words, a vehicle can decide which shareable property to reveal according to the privacy-aware strategy that it employs. In the following, we propose two such privacy-aware strategies.

### 3.1 Strategy 2: Bid-Privacy-Aware

A privacy-aware strategy would be when the vehicles decide to reveal only all or some of their shareable properties. Bid-Privacy-Aware (BPA) strategy again corresponds to the Blind auction, but this time the vehicles place a privacy-preserving bid and share some of their shareable properties.

In Figure 1b, the shareable properties of  $V_1$  are {t, b, a}; whereas  $V_2$  can share from {t, b}. When the vehicles follow the BPA strategy, IM collects the shareable properties of  $V_1$  and  $V_2$ . It computes the priority values as 0.675 and 0.425 (Equation 1).  $V_1$  wins the auction with the highest priority value. In the Bid-All strategy,  $V_2$  was the winner when it shared all its properties. In the BPA strategy,  $V_2$  lost the auction since it preferred not to share some of its properties. In other words,  $V_2$  chose to preserve its privacy by revealing some of its shareable properties. This is a prime example that depicts that vehicles might value their privacy more than the utility they will gain by revealing private information.

### 3.2 Strategy 3: Bid-Privacy-Incremental

The vehicles could decide when to make a bid regarding what properties they could share. If they knew that they would not

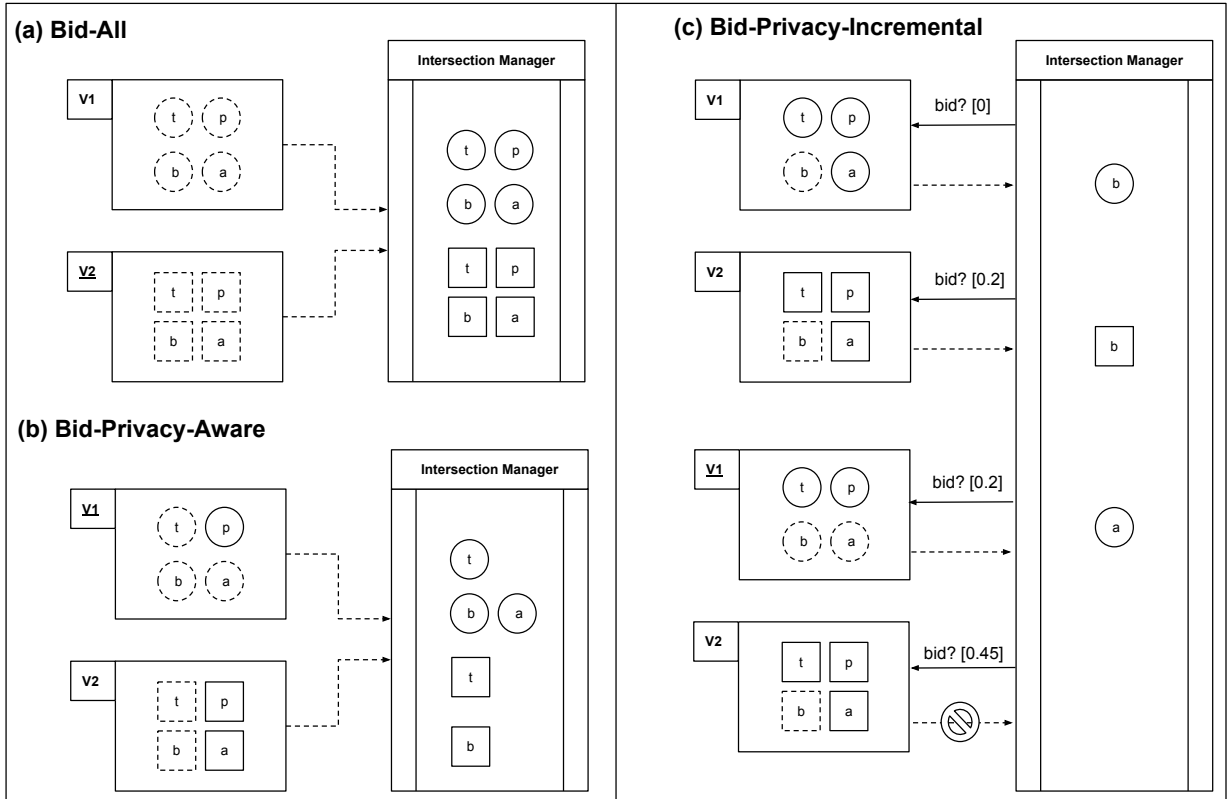


Figure 1: Bidding strategies applied on the running example (Accident Number 2015331500103). The privacy threshold is set to 0.8.

place a higher bid, they could choose not to place a new bid to preserve their privacy. In Bid-Privacy-Incremental (BPI) strategy, each time that IM is waiting for new bids from the vehicles, it broadcasts the priority value of the current highest bid. The auction continues with the vehicles that can raise the highest bid. In this strategy, the vehicles are free to leave an auction if they cannot beat the current highest bid. Different from the previous strategies, the auction may terminate in several iterations. As before, the vehicle placing the highest bid gets the priority in traffic. This strategy corresponds into an *English auction*.

Assume that  $V_1$  is the first vehicle that communicates with the IM. In Figure 1c,  $V_1$  places a bid that consists of  $b$  in the first iteration. Note that in previous strategies,  $V_1$  revealed all its shareable properties. Then, IM computes the priority value of the received bid that is 0.2. IM asks  $V_2$  to place a new bid and announces the current priority value.  $V_2$  places a bid that consists of  $b$ . IM computes the priority value of the received bid that is 0.2. IM asks  $V_1$  to place a new bid that values more than 0.2.  $V_1$  makes a bid that consists of  $a$ . IM computes the current priority value as 0.45.  $V_2$  is not able to make a better bid since the only property that it can share is  $t$ . In such case, its priority value would become 0.425, which is less than the  $V_1$ 's bid value.  $V_2$  leaves the auction without placing a new bid, and chooses to keep the property  $t$  private. Compared to Bid-Privacy-Aware strategy, the privacy loss for  $V_1$  and  $V_2$  is minimized.  $V_1$  wins the auction by only disclosing  $b$  and  $a$ ;  $V_2$  loses the auction by only sharing  $b$ .

This strategy cannot change the outcome of an auction where the vehicles follow Bid-Privacy-Aware strategy. However, it can help the vehicles to disclose their shareable properties minimally as shown in this particular example.

## 4 Evaluation

So far we have introduced three strategies: Bid-All, Bid-Privacy-Aware and Bid-Privacy-Incremental. The first strategy does not consider any privacy concerns of the agents involved in an auction. However, the other two strategies can be employed by the agents to preserve their privacy. In this section, we first introduce a privacy loss metric and we show how this metric would be applied to our running example. By using a real-world dataset, we report the privacy loss results when the agents employ various strategies for different privacy thresholds.

### 4.1 The Privacy Loss Metric

In auctions, the vehicles put their bids by revealing all or some of their properties. However, revealing a property results in privacy loss. In Equation 2, we introduce a metric to measure the privacy loss of a vehicle.  $PL_v$  is the privacy loss value for the vehicle  $v$ . The privacy loss is basically the ratio of the privacy value of shared properties per the privacy value of all properties. In this equation,  $K$  is the number of shared properties provided by  $v$ ,  $N$  is the number of total properties and  $P_k$  is the privacy value of the  $k$ th property chosen by

*v*. In this work,  $N$  is set to four as we refer to the auction properties described in Table 1.

$$PL_v = \frac{\sum_{k=1}^K P_k}{\sum_{k=1}^N P_k} * 100 \quad (2)$$

In Table 2, for each vehicle, the privacy values of the properties are shown. The total privacy value of  $V_1$  is 2.247 (i.e., the sum of all the privacy values); whereas  $V_2$ 's total privacy value is 2.638. To compare the different strategies, we refer to Figure 1. In Table 3, we report the privacy loss results of  $V_1$  and  $V_2$  when the vehicles employ different strategies. In Bid-All strategy, the privacy value of shared properties (the lost privacy value) is equal to the total privacy. Hence, the privacy loss is 100% for both of the vehicles. Recall that the privacy threshold value is set to 0.8 for the recurring example. In Bid-Privacy-Aware strategy, for  $V_1$ , the journey of purpose ( $p$ ) is not shared, then the lost privacy value becomes 1.362. According to Equation 2, the privacy loss is computed as  $136.2/2.247 = 60.62\%$ . In a similar way, the privacy value for  $V_2$  is computed as 30.74% (i.e., the properties  $t$  and  $b$  are shared). In Bid-Privacy-Incremental strategy, for  $V_1$  the properties  $b$  and  $a$  are shared, and the privacy loss becomes 26.79%. For  $V_2$ ,  $b$  is the only shared property and the privacy loss becomes 12.66%. If we look at the privacy-aware strategies, both vehicles preserve their privacy better when they win or lose the auctions that they are involved in. For example, when both vehicles employ Bid-Privacy-Incremental strategy,  $V_2$  loses the auction by only revealing one property, which results in a low privacy loss value.

| th=0.8                  | $PL_{v_1}$ | $PL_{v_2}$ |
|-------------------------|------------|------------|
| Bid-All                 | 100%       | 100%       |
| Bid-Privacy-Aware       | 60.62%     | 30.74%     |
| Bid-Privacy-Incremental | 26.79%     | 12.66%     |

Table 3: Privacy loss results for the two vehicles

## 4.2 Results

We use the Road Safety Data [The UK Government, 2016] with the auction properties discussed in Table 1 and create a real-world multiagent environment. We focus on the road accidents that occurred between two vehicles at junctions. There are 4563 road accidents where complete information about the vehicles and their properties have been revealed.

We developed a Java-based simulation environment that can represent the accidents that are of interest from the dataset. In our work, we have focused on accidents that have all the properties reported for the vehicles. The dataset is split into databases and collections, which are stored in MongoDB<sup>1</sup>. Our developed system can represent agents with various settings and test different auction strategies to see how

<sup>1</sup><https://www.mongodb.com/>

well they help preserve the privacy of autonomous vehicles. In each imported accident, there are two vehicles, which are the vehicle agents in the simulation. Our program reports the privacy loss results for each agent, and it makes use of MongoDB to store the experiment results for different privacy thresholds. Our implementation is available online at our GitHub page<sup>2</sup>.

For each accident, we generate two vehicle agents from the dataset and one IM agent. Each vehicle agent represents a vehicle involved in the accident from the dataset, and is equipped with the four auction properties (see Table 1). The dataset does not contain any privacy values for such properties. Therefore, the privacy value for each property is generated randomly, each privacy value is a uniformly distributed double value between 0 and 1. Note that these privacy values are only generated once and used throughout the experiments.

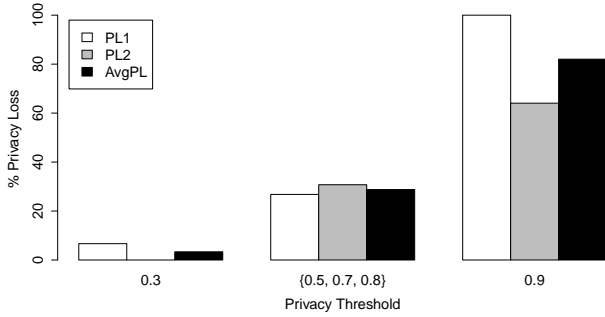
For each accident in the dataset, the IM agent starts an auction with the vehicle agents, where both vehicle agents use either Bid-All (BA), Bid-Privacy-Aware (BPA) or Bid-Privacy-Incremental (BPI) strategy. In Bid-All strategy, a vehicle shares all its properties, leading to a privacy loss of 100% at all times. In privacy-aware strategies, the privacy loss depends on the privacy threshold of the vehicle. If the vehicle is in an urgent situation, it can choose a high privacy threshold to move first at the junction by sharing most of its properties. To observe such variations, we run our experiments with different privacy thresholds: 0.3, 0.5, 0.7, 0.8 and 0.9. For each accident, a privacy loss value is computed per vehicle according to the metric in Equation 2. Hence, we can also compute the average privacy loss value of both vehicles involved in an accident. For the accident number 2015331500103, the generated privacy values are shown in Table 2. We report the privacy loss results for this accident in Figure 2 when the vehicles employ privacy-aware strategies. The privacy loss values are the same for both strategies when the privacy threshold is 0.3. When this threshold is one of 0.5, 0.7 and 0.8, we observe that the privacy loss of Vehicle 2 is less (12.66%) when it uses Bid-Privacy-Incremental strategy. Similarly, when the privacy threshold is 0.9, the privacy loss values are minimized for both vehicles when they prefer using Bid-Privacy-Incremental strategy instead of Bid-All and Bid-Privacy-Aware strategies. The main reason for this is that the vehicles do not disclose their shareable properties if they realize that they cannot place a better bid.

|     | 0.3    | 0.5    | 0.7    | 0.8    | 0.9    |
|-----|--------|--------|--------|--------|--------|
| BA  | 100%   | 100%   | 100%   | 100%   | 100%   |
| BPA | 11.84% | 30.1%  | 54.46% | 68.73% | 83.98% |
| BPI | 7.01%  | 20.57% | 42.87% | 58.19% | 76.2%  |

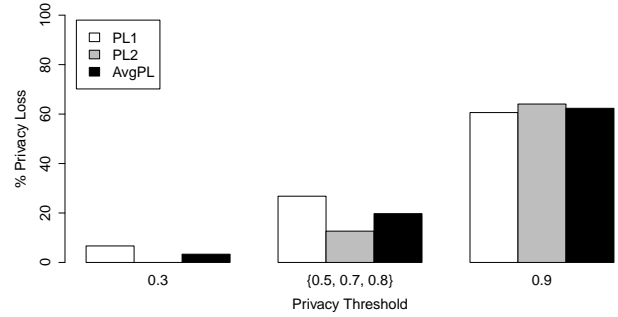
Table 4: Average privacy loss results when the privacy threshold is set to different values

In Table 4, we report the average privacy loss results of 4563 road accidents from the dataset. We observe that Bid-

<sup>2</sup><https://github.com/PrivacyInInternetOfThings/AuctionBasedTraffic>



(a) Bid-Privacy-Aware (BPA)



(b) Bid-Privacy-Incremental (BPI)

Figure 2: The Privacy Loss of the Vehicles in Accident Number 2015331500103 with different strategies and privacy thresholds. The privacy loss of Vehicle 1, Vehicle 2 and their average are denoted as PL1, PL2 and AvgPL, respectively.

Privacy-Incremental strategy helps the vehicles to preserve their privacy more in every case. When the vehicles prefer a low privacy threshold value (i.e., the vehicles are conservative about privacy), their privacy is preserved more. For example, when the privacy threshold is 0.3, the average privacy loss is only about 7%. The privacy loss increases when the vehicles decide to share most of their properties to pass first at the junction. For example, when the privacy threshold is 0.8, the average privacy loss is 68.73% in Bid-Privacy-Aware strategy. The vehicles can preserve their privacy better by using Bid-Privacy-Incremental strategy. In that case, the privacy loss becomes 58.19%. As a result, vehicles that employ Bid-Privacy-Incremental strategy achieve the same level of success at passing at intersections, while they enjoy a higher level of privacy.

## 5 Related Work

Agent-based approaches have been used to study traffic flow. Through multiagent simulations, the effect of traffic jams or speed limits have been studied. Doniec *et al.* [Doniec *et al.*, 2008] develop a multiagent model to study the traffic flow at intersections. They represent the behavior of drivers with rules, with an emphasis on capturing an opportunistic behavior, where drivers may prefer to violate norms. Their evaluation shows that their proposed behavior models capture real life traffic flow better. In our approach, we facilitate the coordination of agents based on their particular context and information, which might be private. Our coordination mechanism preserves the privacy of the vehicles as much as possible.

An alternative approach to coordinating traffic is to design intelligent traffic signaling. Choy *et al.* [Choy *et al.*, 2003] represent the signaling as a multiagent system, where each agent is responsible for controlling an intersection. Each agent employs a fuzzy-neural decision making module to influence the traffic policy. The agents learn over time how they should produce the policies. They evaluate their approach on a large traffic network. On a similar line, Abdoos *et al.* [Abdoos *et al.*, 2014] develop an approach where traffic signals are controlled hierarchically by agents that employ Q-learning. Using tile coding, the approach is made to scale

even to large networks. Both approaches show that by agent-based signaling, the total amount of time that vehicles stop is reduced significantly. While the main idea of those approaches is to reduce overall traffic, our focus here is to enable urgent vehicles to express their situation and take priority. In doing so, we emphasize the fact that agents' privacy need to be preserved.

Intersection management has been studied extensively from different angles [Lu *et al.*, 2014]. Zohdy, Kamalanathsharma, and Rakha develop a tool called iCACC to regulate and optimize autonomous vehicles through intersection [Zohdy *et al.*, 2012]. They show that compared to signal control iCACC can minimize delays and fuel usage. Miculescu and Karaman propose a polling-systems-based algorithm for autonomous vehicles to adjust their speeds when they arrive in a traffic intersection [Miculescu and Karaman, 2016]. They show that no accidents happen when the road length is above certain threshold. In our model, an intersection manager collects information provided by the vehicles to compute their priority values; accordingly, it coordinates the traffic. Dresner and Stone propose a mechanism for coordinating autonomous vehicles at intersections based on information such as time of arrival and vehicle characteristics [Dresner and Stone, 2008]. Similarly, they use an intersection manager that grants or rejects the requests of the vehicles and give priority to emergency vehicles such as ambulances. However, in our model, we assume that each vehicle can communicate with the intersection manager private information. Another well-known work on intersection management is that of Virtual Traffic Lights [Ferreira *et al.*, 2010], where the vehicles that approach an intersection first choose a leader, who then creates a virtual signal using predefined rules based on the observable data that the vehicles communicate such as their speed and location. However, in our approach, we also consider the sensitive information of the passengers in the vehicle as well. Hence, we want to consider the particular situation in the vehicle (e.g., a patient in the vehicle). While all discussed approaches are important, they do not explicitly consider the privacy of the autonomous vehicles.

Some approaches focus on using auctions to solve transportation problems in a multiagent setting. Seshadri *et al.* al-

leviate the traffic congestion and propose a multiagent system for reducing the node pressure [Seshadri *et al.*, 2017]. They introduce a multi-unit combinatorial auctioning system to allocate the resources and re-route the vehicle agents. Each vehicle submits a bid, which is a binary vector, to change its current path if it wins the auction. In our work, a bid is not a numeric value but it consists of piece(s) of information. According to the internal reasoning of the agent, the agent decides to reveal some of its properties. The IM agent is the one that gives a value to the bids (i.e., pieces of information received from other agents), and makes a decision about which vehicle gets the priority, according to its decision-making mechanism. Ito *et al.* propose a multiagent setting for common value auctions [Ito *et al.*, 2000]. Each agent is trying to predict an approximate market value of an item to avoid the winner's curse. Gerding *et al.* consider a market where the seller employs a single second-price auction [Gerding *et al.*, 2008]. Two types of bidders are involved in an auction. A global bidder can bid in multiple auctions; whereas, a local bidder is only allowed to bid only in a single auction. In this work, the goal is to find the optimal bid (which is the value of an item) under various settings.

## 6 Future Directions

Intersections can be managed effectively and safely when vehicles can inform others about their situation. However, ensuring the privacy of the entities are of utmost importance. We show that privacy-preserving bidding strategies can both help vehicles preserve their privacy while enabling intersections to be managed dynamically.

This work opens up interesting directions for research. Here, we ran our experiments for specific settings. There are more settings that we would like to work on as part of our future work. For example, what would happen if each agent employs a different strategy when they meet at a junction? Or, would it be possible for them to collaborate independently to abuse the system? Or, how our proposed strategies would work if more than two vehicles meet at a junction? Or, how an agent can choose a privacy threshold automatically according to its previous auction results, the variables of its environment? In other words, a vehicle can learn how to bid better to win the auctions by preserving its privacy at the same time.

In some cases, vehicles would need to move in groups (i.e., vehicle platoons) for various reasons; e.g., people in the vehicles would be traveling together. This would require groups to go into auctions, rather than the individual vehicles as we have shown above. However, different vehicles in the group could have different privacy concerns that might not have been revealed even to the other vehicles in the group, requiring extended mechanisms to be in place. As a motivating example, consider this case: A vehicle  $v$  does not want to reveal any of its properties because it wants to preserve its privacy. Such a vehicle would lose all of the auctions since the other vehicles would be winners by just sharing at least one property. Now assume that the vehicle  $v$  is part of a group of vehicles and it is ahead of an ambulance, which has a high chance of getting priority at a junction. In such a case,  $v$  could pass first without revealing any of its properties thanks

to the ambulance being the group leader. It would be interesting to extend our approach to handle such cases and study it on the Road Safety Data dataset to measure its applicability and effect on possible delays.

Another important extension would be adding a semantic layer to the auctions. Currently, each agent views various dimensions of the information as private with a certain weight and acts accordingly. However, it is important to be able to capture what the privacy constraints of the vehicles are semantically so that at different situations, the agents can assign the privacy values based on environment, context, and other available information [Kökciyan and Yolum, 2016; Kökciyan and Yolum, 2017]. This would require the agent to make inferences and decide based on that.

For our proposed approach to be applied in real life, many underlying technologies need to be in place. For example, we assume that each vehicle reports its bids to the IM and thus IM is the only entity with this information. However, if at the time of sharing, used communication technology results in the information to reach third parties, there would be a violation of privacy. It would be interesting to use a test-bed environment to realize the approach on actual vehicles using existing communication technologies.

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