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Trust in Smart City Mobility Applications: A Multi-Agent System Perspective

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Abstract

This chapter presents a recommendation system framework for smart mobility applications, emphasizing traffic monitoring and parking management in smart cities. Using Reinforcement Learning (RL) and Social Network (SN) concepts, the methodology classifies agents as trustworthy or untrustworthy, tackling multi-agent system challenges in uncertain environments. The research aims to create algorithms and models for safe, efficient, sustainable mobility solutions, addressing data exchange and decision-making issues. Agents gather and process information, make decisions with incomplete data, and interact to achieve goals. Real-world data will validate the approach, enhancing decision-making and improving urban mobility.

1. Introduction

One of the important parts of a smart and intelligent city is the transportation system. As the automobile industry continues to grow worldwide, the number of cars on the road is increasing, leading to higher rates of accidents and traffic volume. To address these challenges and create smart cities of the future, it is crucial to develop efficient and sustainable transportation systems. As transportation systems become more advanced and interconnected, securely transporting data and building trust in these systems becomes increasingly important. With the increasing use of sensors and other Internet of Things (IoT) devices in transportation, a vast amount of data is being generated and transmitted. However, this data is often sensitive and personal, including information such as location data and travel patterns, which must be handled with care to maintain user privacy. Additionally, ensuring the security of transportation systems is essential to prevent malicious actors from accessing or tampering with critical data or infrastructure. To address these challenges, it is important to implement robust data privacy and security measures in transportation systems.

The research methodology integrates Reinforcement Learning (RL) and Social Network (SN) concepts to classify agents in a multi-agent system as trustworthy or untrustworthy. This approach addresses the inherent challenges of operating in open environments with uncertain and potentially malicious agents. The methodology involves several key steps:

1. **Data Collection**: Real-world data from specific smart mobility applications, such as traffic monitoring and parking management, will be gathered.
2. **RL and SN Integration**: RL algorithms will be employed to enable agents to learn optimal behaviors from their environment, while SN concepts will model and propagate trust among agents.
3. **Trust Classification**: Agents will be classified based on their behavior and interactions, identifying trustworthy and untrustworthy agents.

4. **Evaluation**: The proposed system will be evaluated on its ability to enhance safety, efficiency, and sustainability in mobility solutions, using the collected data for validation. This chapter considers different aspects of trust in the transportation system. This work serves as a valuable and reliable reference for other authors exploring this subject.

This methodology aims to create a robust framework that improves decision-making and quality of life in smart city contexts.

By enhancing trust in the transportation system, we can improve road safety, reduce accidents, and prevent malicious attacks from unauthorized nodes. This involves implementing robust data privacy and security measures in transportation systems to protect sensitive and personal data, such as location and travel patterns. By utilizing techniques to increase trust in data transmission and implementing access controls to restrict sensitive information access, we can ensure that transportation systems are safe, secure, and trusted by their users.

The field of Multi-Agent Systems (MAS) research has developed a range of collective decision-making mechanisms, such as voting (Pitt et al. 2006), that aims to achieve consensus on the combined preferences of the agents involved. Developing trust plays a crucial role in the field of MAS (Multi-Agent Systems) applications.

The trust model in the recent papers is divided into two groups: logical trust and trust computational models (Drawel et al. 2022). Some approaches to individual trust focus on the relationship between two agents, where one agent trusts another. In such cases, trust does not propagate within a group. However, there are other approaches where trust can spread among multiple agents within a group. The goal is to increase trust in MASs applications such as transportation systems that have an important role in the smart city these days for people's life. Some methods are for this goal such as Machine Learning, Reinforcement Learning, and using some techniques in Social Networks in the relationship between agents.

The chapter is organized as follows. This chapter is divided into 5 subsections: Sect. 1 describes an introduction related to MASs and trust in the transportation system; Sect. 2 describes related work done into MASs and trust in the transportation system; Sect. 3 describes Logical Trust and Trust Computational Models; Sect. 4 describes Multi-Agents Reinforcement Learning (MARL) and We end by concluding the chapter in Sect.5.

2. Related Works

Multi-agent systems (MAS) have advantages over single-agent systems (Rădulescu et al. 2020). They can operate in dangerous situations, allow parallel processing, offer scalability, and distribute decision-making (Geng et al. 2020), resulting in increased fault tolerance (Amirkhani and Barshooi 2022). With growing heterogeneity/decentralization of the future internet and the involvement of many network entities, trust strategies, and trust-based decision-making have become a major concern within MAS. In uncertain network environments where communication topologies may change, each entity may need to make local decisions to improve network performance (Li et al. 2022). Recently, (Ramos, Silvestre, and Aguiar 2022) developed a reputation-based consensus method using a switching system to exclude communication data from suspicious/malicious nodes. The ideas of how to compute a distributed reputation score are presented in (Ramos, Silvestre, and Aguiar 2022) and on design for MAS based on privacy-preserving (both works co-authored by the supervisor). will be exploited in the proposed research plan. Note that trusted cooperative nodes reduce network connectivity requirements (Zhai et al. 2021), making them advantageous for trust-based communication, and using local/neighbor information for decision-making helps overcome scalability issues in decentralized environments (Zhang et al. 2018).

Trust research can be categorized into trust computational model and logical trust. The former calculates the trust level based on value for future interactions but oversimplifies the complex concept of trust (Sardana et al. 2018; Wahab et al. 2018). The logical approach (Drawel et al. 2022; Drawel et al. 2020) focuses on distributed trust among group members which is more sophisticated than individual trust between two agents (Guo, Chen, and Tsai 2017; You et al. 2017). Distributed trust is more functional but has a more complex structure resulting in fewer studies. Some works suggest simple trust models that compute global trust based on direct/indirect trust without feedback, but these models do not consider the dynamic nature of entities, rendering them less effective in scenarios where behavior evolves over time (You et al. 2017; Wang and Wang 2018).

Social-Network (SN) group decision-making techniques can use factors like feedback (Gai et al. 2022), weighting systems (Liu et al. 2023), and relationship factors (Nitti, Girau, and Atzori 2013) to increase trust values. The conventional Multi-Agents decision making process assumes decision-makers operate independently (Dong et al. 2022b; Dong et al. 2021b). However, with the emergence of information/network technology, decision-makers are increasingly part of SNs. This has given rise to a new form of decision-making called SN group decision-making (Chen et al. 2021; Chen et al. 2022) which presents its own challenges. Social recommender systems were developed in different domains (Vatani, Rahmani, and Haj Seyyed Javadi 2023; Walter, Battiston, and Schweitzer 2008) using a personality-based/trust-aware product recommendation system based on the similarity of personality-based user behaviors. Standard learning algorithms have limitations in modeling cooperative/competitive interactions among network entities. More advanced algorithms like Multi-agent Reinforcement Learning (MARL) are needed to address this problem. MARL extends RL to multi-agent environments, allowing each entity to learn its optimal policy by observing others' policies. It can address trust/security problems in various scenarios such as V2X in smart cities (Lee et al. 2023; Ribeiro, Nicolau, and Santos 2023), MANETs, and WSNs (Javaherian and Haghighat 2014). By enabling agents to learn collaboration and optimize behavior through communication with other agents, MARL can significantly reduce signaling overhead if agents select others based on trust for communication. Strategies like fuzzy logic can determine trustworthiness in these systems (Chahal and Singh 2016). Although much research has been done in MAS, few have addressed a trust-based framework with learning techniques for unknown/unstructured environments and trusted decisions for recommendation systems in smart cities using mathematical computations/logic. This proposal focuses on this with the novelty of using SNs to perform tasks in smart mobility applications.

3. **Logical Trust and Trust Computational Models**

Logical trust refers to how an agent's ability to trust another agent's behavior and actions. We want to consider logical trust in the distributed trust categories, distributed trust is when the trust is distributed among the members of the group. To incorporate this concept, we will utilize the logical trust class within one aspect of our system. On the other hand, we want to use computational trust in our framework, and We are also interested in trust that can propagate through the MAS from one agent to another. Computational trust measures the value of trust to compute the strength level at which an agent trusts other agents in order to establish future interactions. In this phase, we want to use trust propagation and social trust.

The goal of a trust propagation system is to estimate unknown trust values between pairs of agents using the known and available trust values. Then we want to consider reputation in this field, reputation is what is generally said or believed about a person's or thing's character or standing. This definition is aligned with the one given by social network researchers that states that reputation is a quantity measure derived from the underlying social network which is globally visible to all members of the network. social trust derives from the social relationship between agents, and it is measured by intimacy, honesty, privacy, centrality, and connectivity.

4. **Multi-Agents Reinforcement Learning (MARL)**

Study and develop a MARL where each agent in the network can learn their optimal policies by observing the environment and the policies of other entities. We exploit the fact that MARL has been increasingly used to solve with success diverse problems in emerging networks since it has the potential to enhance the learning efficiency of network entities and can also deal with trust and security issues. The goal is to make the network components tackle the problem of non-stationarity by considering the states and actions of other components. This allows for more stable policy learning compared to single-agent RL and DeepRL methods that do not consider information from other network components. By communicating with other entities, MARL allows network entities like mobile users to learn how to collaborate and cooperate with others and to learn the best policy for achieving their goals. The study of MARL combines the pursuit of ideal algorithms that maximize rewards with a more sociological set of concepts. In the MARL, social learning can involve agents learning from the actions/behaviors of other agents in the system exploiting the methodologies applied to Markov Games (MGs) or Stochastic Games (SGs) and decentralized partially observable Markov decision processes (Dec-POMDP).

5. **Conclusion and Future Works**

In conclusion, this research develops a robust recommendation system framework for smart mobility applications in smart cities, focusing on traffic monitoring and parking management. By integrating RL and SN concepts, the methodology classifies agents as trustworthy or untrustworthy, addressing the challenges of multi-agent systems in uncertain environments. This work contributes to developing safe, efficient, and sustainable mobility solutions. Future research should explore the scalability of the proposed system and its application to other smart city domains. Additionally, practical implementation challenges, such as real-time data processing and integration with existing urban infrastructure, should be addressed. Understanding the current model's limitations and incorporating stakeholder perspectives will further enhance the system's relevance and impact.

Trust is one of the most important subjects in MASs field study in recent decades. Making good decisions based on trust and proposing trust models. According to our current information and regarding the challenge of non-unique learning goals in Multi-Agent Reinforcement Learning (MARL), we believe it is important to incorporate considerations of Trust constraints in MARL approaches and it is still a relatively unknown area, especially in an open and distributed environment. In fact, trust and safe RL have been recognized as one of the most significant challenges in the single-agent setting (García and Fernandez 2015). Ensuring Trust and safety becomes a more complex task when multi-agents with potentially conflicting objectives are involved, as the safety requirement now encompasses the interdependencies among all agents (Zhang, Yang, and Başar 2021).

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