Abstract

The rapid expansion of the tourism industry has led to a growing body of research focused on tourist route planning. However, most existing studies concentrate on individual tourist routing, leaving a significant gap in addressing scenarios that involve multiple tourists. Traditional approaches for multi-tourist route planning, often adapted from single-tourist models, tend to emphasize tourist preferences and advantages. This has resulted in challenges such as popularity-biased route planning, which intensifies issues like overtourism in highly popular areas and hinders sustainable tourism practices. To overcome these challenges, we propose a multi-agent reinforcement learning (MARL) framework for planning routes for multiple tourists, integrating tourist distribution into the process. Our method comprises two essential components: first, a novel reinforcement learning environment tailored for tourism, allowing interactions with multiple tourists; second, a dual-congestion model that accounts for both localized congestion at attractions and the broader city-wide distribution of tourists. This dual-congestion concept formulates the reward structure within our MARL framework. We validate our approach through extensive experiments using real-world human mobility data from Kyoto, a renowned global tourist destination. The results demonstrate that our model outperforms current approaches in optimizing route rewards while managing tourist distribution effectively. Furthermore, we conducted a user study to assess the impact of our congestion-aware mechanism on tourist experiences. The findings suggest that while our dual-congestion model may slightly impact tourists who favor popular destinations, it underscores the generally conflicting relationship between sustainable tourism and individual tourist preferences. Importantly, our model shows potential in transforming this conflict into a more cooperative interaction.

Additionally, we explore multi-agent communication protocols. To alleviate the non-stationary problem in MARL, we employ techniques to denoise irrelevant information and perform information fusion effectively. Our implementation of two types of selectors and three attention-based QA methods shows the framework’s capability to handle large-scale agents' interaction. Moreover, experiments indicate that traditional methods provide limited improvements for the non-stationary challenges in our scenario, pointing to future research directions focusing on sequential actions of agents and the adaptation of joint optimization in collaborative-adversarial scenarios. Next, we reveal the similarity between multi-agent communication and Multi-hop Question Answering (QA), and apply our proposed communication framework on Multi-hop QA. We develop the advancements in Multi-hop QA by developing the "Answer Multi-hop questions by Single-hop QA" (AMS) system. This innovative approach employs a denoise component and a single-hop QA model adopting the co-attention and self-attention architecture. Our AMS system outperforms existing GNN-based models on the HotpotQA dataset, showcasing improvements in Joint EM and Joint F1 scores while using fewer resources. It illustrates our framework's effectiveness in other complicated task.

In summary, this research advocates a comprehensive approach for multiple tourists route planning with MARL. This work establishes a robust and collaborative framework for addressing

the complex issue of popularity-biased tourists route planning, significantly advancing the capabilities for achieving sustainable tourism and efficient information sharing in complex environments.

Keywords: Multiple Tourists Route Planning, Multi-agent Reinforcement Learning, Multi-agent System Communication, Unbiased Route Planning, Sustainable Tourism Sightseeing.