Agent-Based Approach to Traffic Congestion

Stanford CS221

Problem Statement and Task Definition Traffic Congestion Due to Individual Optimization: When each user selects the shortest path independently, popular routes become congested, leading to increased travel times and decreased overall efficiency. The real-world problem is the mismatch between individual route optimization and collective traffic dynamics, leading to suboptimal outcomes for the community. This project attempts to bridge the gap by incorporating cooperative behavior by encouraging users to consider the impact of their route choices on others thereby reducing overall congestion and improved travel times for everyone.

Input/Output Behavior The goal is to develop a system for fair routing where the system learns to distribute users across the network to minimize total travel time and prevent congestion, thus improving the collective experience. Input: Origin and destination pairs for multiple users. Current state of the pathways (e.g., congestion levels, capacities). Output: Route recommendations for each user that consider both personal travel time and the impact on overall congestion.

Evaluation Metric The proposed primary evaluation metric is “total well-being” or the sum of all travel times. However, we will examine more complex evaluation metrics, such as worst off groups (eg most delayed agents), as well as composite evaluation metrics including system congestion. System congestion can be thought of as a proxy for social good, describing how resilient the system is to the addition of new demand, or how busy the streets are.

Baseline and Oracle For baseline and oracle, we will use ShortestPath, simplified versions of the congestion problem. The oracle’s upper bound is ShortestPath, with no congestion being created or imputed. The baseline is selfish agents using ShortestPath on the base problem, with congestion not used dynamically in routing yet created and imputed to travel costs.

Methodology We will approach the problem as Multi-Agent Reinforcement Learning using Markov Decision Process (MDP). The problem can be modeled as a graph traversal with the cost of edges updated by the amount of current congestion. Each car is an agent that could be located at nodes, or in transit at one of the edges. We "pulse" the agents one time unit each through the graph. The cost at each edge will be a function of congestion (e.g. number of users exceeding the capacity). We will compare system outcomes (e.g. total welfare) but also group outcomes (e.g. most delayed agents) across 3 policies: 1) Full greedy agents looking for shortest path 2) Agents with cost function taking congestion generated into account with some hyperparameter of weight "C" 3) Centralized decision making, routing all agents.

Description of the challenges Model congestion levels: At each time step, the agents take an action that changes the congestion levels in the system. To account for this dynamism, we will revise the cost to incorporate current congestion levels at each time step. Set optimal route: In a multi-agent system, an agent might want to consider the behavior of other agents when deciding on its next action. We could introduce additional factors when computing our route recommendation to make the policy more “realistic”.

Related Works Choudhury et al. (2024) proposes a single black-box function to model over all roadways, instead of a separate set of parameters for each roadway. Data from all segments are pooled (a combination of static and dynamic, time-dependent features) and a feed-forward neural network is trained over this dataset, which, in test-time, is deployed to any segment in the area. Their approach is observed to have robust performance on both unobserved segments, in the same city as the training data comes from, and also in zero-shot transfer learning between other cities. Additionally, they also find that the approach also is able to approximate critical densities for individual road segments based on static features. Using a similar approach with machine learning models, Kelly and Gupta (2024) utilizes a dataset of trip logging metrics from commercial vehicles across 4,800 intersections, handling missing feature values through low rank models and label encoding. It uses 27 static features such as intersection coordinates, street names, time of day, and traffic metrics, and also incorporates other features such as rainfall/snowfall percentage, distance from downtown and outskirts, and road types, which were incorporated to enhance the model's predictive power. Augmenting the features utilized in training such models, Yasir et al. (2022) attempts to take into account dynamic features such as date, time, and several weather dependent variables, which is asserted to be absent from models proposed by papers addressing a similar task (prediction of traffic congestion for future decision making). The model is tested against the traffic data in New Delhi, and is concluded to be able to predict the congestion of a road one week ahead with average 1.12 RSME, showing promise for application in devising preventive measures for traffic congestion. Upon applying several algorithms, they conclude SVR achieves superior results, and thus use this method, mapping input data into a high dimensional feature space via the kernel function, and use the radial basis function kernel (rbf) for data transformation.

Closer to our approach, Nguyen et al. (2023) identifies a novel issue in the task of predicting traffic dynamics; it attempts to address the need of an effective database management system for information retrieval in utilizing the rapidly-growing volume of traffic data. Thus, it proposes the locating of similar traffic patterns in large databases as a promising faculty for further analyses in traffic management, and attempts to realize this through a content-based retrieval system for spatiotemporal patterns of highway traffic congestion. To interpret retrieval outcomes, the paper proposes a two component model, in which a prior component is a relation-graph for encoding traffic phenomena as does and their spatio-temporal relationships as edges, and the former customizes similarities between congestion patterns with various expectations according to user expectations. Additionally, also employing an agent-based approach, Zhang et al. (2023) proposes training a multi-agent driving policy that generalizes to different traffic flows, AV penetration, and road geometries, specifically encoded through a Cell Transition Model (CTM), that is asserted to be suitable for modeling congestion in traffic networks.

References

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