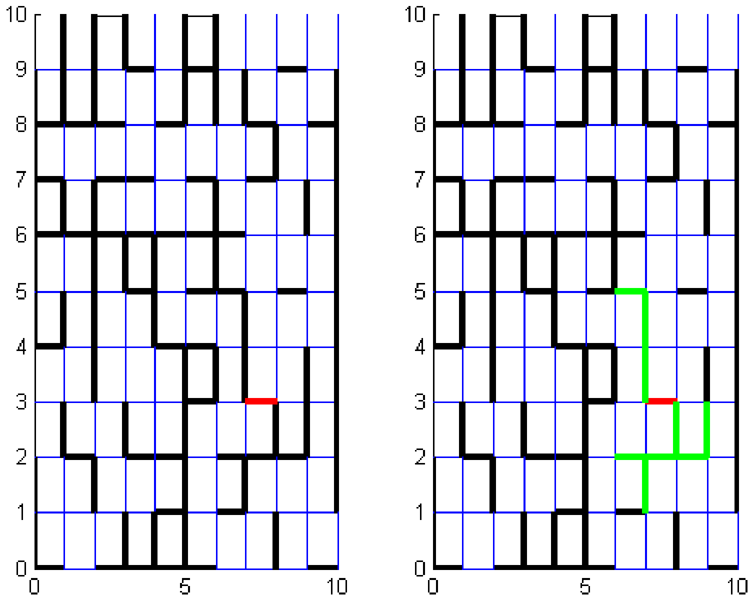

Modeling congestion propagation in urban transportation networks

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Abstract

In urban transportation networks, research work has been focusing on alleviating the traffic congestion to optimize the network performance, such as increasing the traffic flow and decreasing the user travel time. However, studying the physical properties of traffic propagation and congestion growing has always been a difficult task, especially in a large and complex transportation network. Previous research has seen the main challenges of high complexity of modeling the traffic flow mechanism and the unpredictability of vehicle or user behaviors. The concept of maximum connected component (MCC) is recently used in analyzing the robustness and fragility of a given network structure, such as the catastrophic failure propagation of electrical blackout in a large city network. This paper studies the traffic growing and propagation in a large network based on the concept of MCC, without modeling the traffic flow mechanics. Firstly, a congestion propagation model is developed and a metric evaluating the congestion was introduced. Secondly, simulations with different parameters are developed based on the model. The results are compared with real traffic data from San Francisco network and the model is validated. It mainly shows the strong dependency of congestion among links. Finally, we show that the propagation effect is linked to the scaling law, which is a key property of the urban transportation networks.

Keywords

traffic propagation, maximum connected component, network structure, scaling law

1 Introduction

Modeling propagation based on traffic flow mechanism and vehicle behaviors has always been a difficult task, due to the high complexity of physical models and unpredictability of user behaviors. Spatial correlation and spillovers have been studied in Geroliminis and Sun (2011); Geroliminis and Skabardonis (2011). We aim at designing a simple model with few parameters but can properly and realistically capture congestion propagation dynamics in urban transportation networks.

The remainder of this paper is organized as follows. Section 2 describes a simple model and a metric on congestion propagation based on the spatial dependency among links. Section 3 conducts simulation in networks based on the proposed model and compares the results with real traffic data from San Francisco network. Section 4 investigates the congestion propagation effect under different network structures and properties. Section 5 concludes our work.

2 Propagation Modeling

Assume a network with congested and uncongested links. The spillovers occur due to congested links and the congestion propagation happens. Based on this observation, we model the congestion growing effect as follows. Let $p(i)$ be the probability that link i will become congested in the next time period based on current network state. Let $pe(i)$ denote the number of congested links that can reach link i through congested links with shortest path of length less than l. We call $pe(i)$ propagation effect on link i. In Figure 1.1, the red link is an uncongested link and all the other non-black are uncongested links and the black are congested links, which shows the current state of the network. Figure 1.2 shows the propagation effect $pe(i)$ on link i. The green links are the congested links that have a propagation effect on link i. All the green links have a shortest path to link i less than $l = 3$ through congested links. Thus the propagation effect $pe(i)$ is 9 under current network state. l is determined by the network property. $p(i)$ is determined by $pe(i)$ as shown in Equation 1, where parameter α can increase (or decrease) the relative propagation effect. In each step of the simulation, we let one and only one link become congested based on the probability model of Equation 1. Thus at each step, the event that a random link becomes congested forms a probability space. The physical meaning of this modeling is that the probability of link i becoming congested is proportional to the number of congested links it is surrounded by. The more congested links around it, the more likely it becomes congested. When $pe(i) = 0$, link i can still become congested based on the model. Parameter l serves as an upper bound controller on the propagation effect.

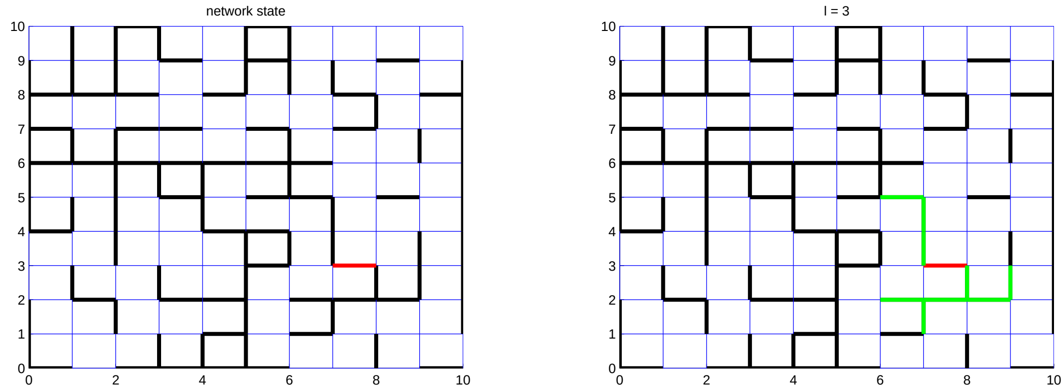

Figure 1: Examples of propagation effect on link i (the red link).

$$\frac{p(i)}{p(j)} = \left(\frac{pe(i)+1}{pe(j)+1}\right)^{\alpha} \tag{1}$$

We use maximum connected component (MCC) of the congested links as a metric to measure the congestion condition of a network. The maximum connected component is the biggest connected component (i.e., with maximum number of links) consisted of only congested links. The evolution of MCC is determined by the network structure and properties.

3 Simulation

Based on the proposed model, we simulate the congestion propagation process and observe the evolution of the MCC. Firstly, we do simulation in San Francisco network with less than 400 links. In the network setting, we let $\alpha = 1$ and $l = 5$. We start with an empty network with all the links uncongested. At each step, we add one congested link to the network based on the proposed propagation model, until the network is full of congested links. Figure 2.1 shows the MCC from real data and compare it with the simulation results based on the propagation model. We do the simulation for 1000 times and show the error bar of the MCC in the red curve. Figure 2.2 shows the evolution of the first three biggest connected component (the mean of all simulations). It is observed that the maximum connected component can represent most of the network condition throughout the time.

In order to further study the properties of the MCC, we mainly focus on the simulation in a grid network. We do simulation and study the MCC and second MCC for a grid network with 50×50 links and different levels of propagation effect l from 1 to 10, as shown in Figure 3. Figure 3.1 shows the evolution of the MCC with different l. It is again observed that after

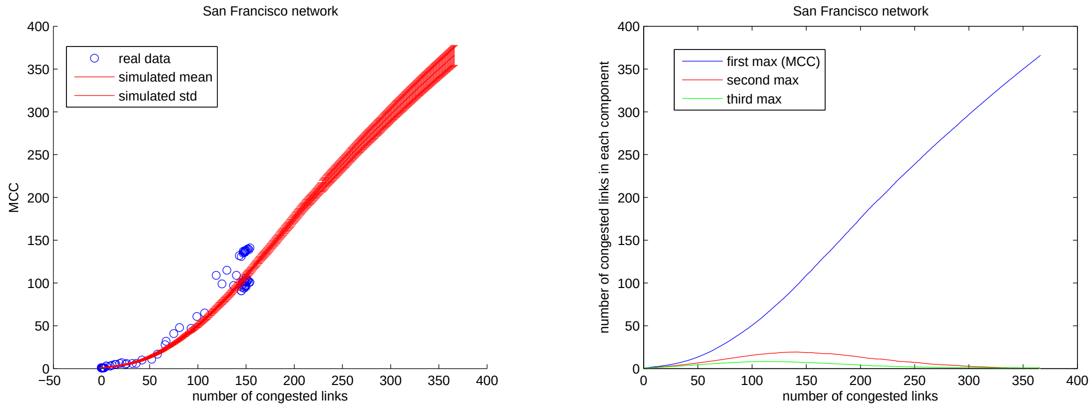

Figure 2: Real data and simulated data from San Francisco network

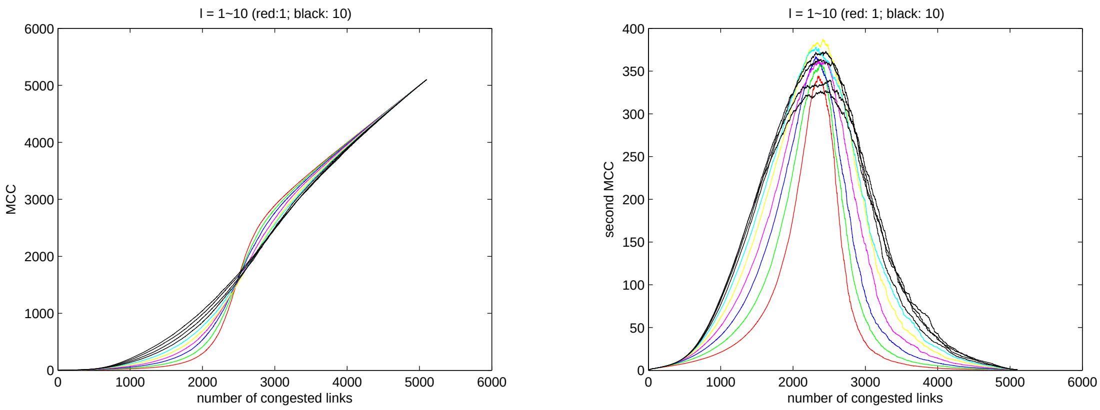

Figure 3: MCC and second MCC in a 50×50 network

some critical point when the number of congested links reaches some certain value (around half in this grid network), the network has only one very big connected component and all the other components are ignorable. In addition, with a larger l, all the components grow earlier but the MCC is smaller after the critical point, since larger l helps the formation of several big components.

4 Network Structure

In addition to the propagation effect of a network, we show that the evolution of MCC is strongly determined by the scaling law of the network structure. The scaling law says that the number of nodes n_v a node v can reach within a certain distance constraint d follows a scaling law as shown in Equation 2. We obtain the average n_v of all the nodes in the network for each specific d. Then we estimate β for different networks and do simulation on MCC in these networks based on the proposed propagation model. The main results are shown in Figure 4. Figure 4.1 shows that under different network structure (identified by β), as the β increases,

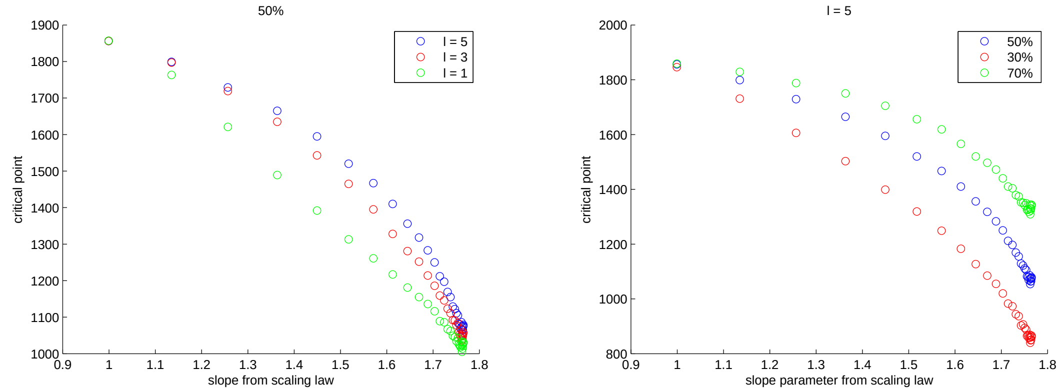

Figure 4: Network property and MCC

the critical point of reaching a certain number of congested links decreases. Figure 4.2 shows the relation between critical point and β under different network threshold (the size of MCC). It implies that with β, the congestion is growing more easily and thus a large MCC will form at an earlier stage.

$$n_v \sim l^\beta \tag{2}$$

5 Conclusions

Modeling traffic has been a difficult task. In this paper, we propose a simple probability model for congestion propagation based on link dependency and spillovers. Based on the model, we do simulation in different networks and compare the results with real data. In addition, we identify the relation between some network property and the evolution of congestion. In the future, we will focus more on network structure and their effect on congestion formation and growing.

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