Assumes you have individual object data.

Attempts to predict the total number of vehicles on an road at some time in the future. Uses graphs and suffix trees for calculation.

Does not change the destination probabilities based on historic data.

Statistical Density Prediction in Traffic Networks

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Abstract

Recently, modern tracking methods started to allow capturing the position of massive numbers of moving objects. Given this information, it is possible to analyze and predict the traffic density in a network which offers valuable information for traffic control, congestion prediction and prevention. In this paper, we propose a novel statistical approach to predict the density on any edge of such a network at some time in the future. Our method is based on short-time observations of the traffic history. Therefore, knowing the destination of each traveling individual is not required. Instead, we assume that the individuals will act rationally and choose the shortest path from their starting points to their destinations. Based on this assumption, we introduce a statistical approach to describe the likelihood of any given individual in the network to be located at a certain position at a certain time. Since determining this likelihood is quite expensive when done in a straightforward way, we propose an efficient method to speed up the prediction which is based on a suffix-tree. In our experiments, we show the capability of our approach to make useful predictions about the traffic density and illustrate the efficiency of our new algorithm when calculating these predictions.

1 Introduction

Traffic control systems for large traffic networks have attracted much attention, recently. One challenge of traffic controlling is the prediction of the traffic. What we need are efficient and effective methods that are able to estimate the traffic for any point of time in the future. Traffic predictions are very important as they enable to detect potential traffic jam spots. Based on the information provided from a traffic prediction system we could initiate certain traffic control methods to avoid the traffic jams.

One of the most important applications of traffic control systems is the control of road network traffic. In particular at rush-hour when the risk of the occurrence of traffic jams is very high traffic control systems would be very important. The combination of modern positioning and mobile communication systems enables us to capture real-time positions of mobile clients on a road network at a central server. These systems can be used to continuously track the current traffic at arbitrary locations in a traffic network. An example of a possible architecture of a traffic analysis system is illustrated in Figure 1. It consists of two modules, the Traffic Capture System (TCS) and the Traffic Analysis System (TAS).

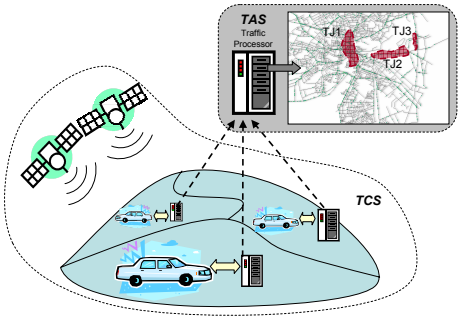


Figure 1: Architecture of the Traffic Capture System (TCS) and the Traffic Analysis System (TAS).

The TCS consists of mobile objects (which are objects of the traffic to be captured). Each mobile object is a client equipped with a GPS-System that can capture its actual position in space and a transmitter that can determine its actual position to the next receiving antenna. The receiving antennas forward the incoming information to a central server which is a component of the Traffic Analysis System. The infrastructure for the communication between the mobile clients and the central server would be currently realizable by the mobile cell-phones. Modern navigation systems are already able to communicate via cell-phones.

In this way, the central server of the TAS would be able to continually track the positions of individuals moving within a road network. The traffic processor can use this information to infer the future trend of

the current traffic in order to estimate the future traffic situation. Thereby further information like common driving behavior and the assumption that each mobile object moves on an intuitive path from its starting point to its destination can be incorporated in order to improve the traffic estimation. One possible output of a traffic analysis system is depicted in Figure 1. The output of the traffic processor in our example shows the traffic network with marked zones that indicate the places in which we would expect a high traffic in the next half hour. Such kind of information could now be reported back to the mobile clients that can subsequently use this knowledge to plan an alternative route in order to avoid the predicted traffic jams.

Let us assume we are given the current traffic information, for example provided from the TCS. Furthermore we assume that it would be possible to analyze and predict the future traffic density within the network. Then, we would be able to use this information to control the traffic and to make predictions and suggestions preventing traffic jams. In this paper, we propose a novel statistical approach to predict the density on any edge of such a network at some time in the future. Our method is based on short-time observations of the traffic history, i.e. the input for the traffic predictor are recent trajectories of the moving objects. The destinations and/or the next trajectories of the moving objects are unknown. Instead, we try to estimate the future motion of the objects in the network. Thereby, we assume that the moving objects will act rationally and choose the shortest path from their starting points to their destinations. Based on these assumptions and based on the assumption that the history of the motion of the individuals is available, we introduce a statistical approach for the computation of the likelihood that a certain individual is located at a certain network position at a certain time. If we perform this computation for each individual observed in the network, we can aggregate the results in order to estimate the traffic density at a certain position at a certain time. The allowed traffic capacity of an edge in the network, i.e. the maximal traffic density that does not lead to a traffic jam, and the estimated traffic density of the edge at a certain time would indicate the risk of a traffic jam. At the time the estimated traffic density exceeds the allowed traffic capacity of a network edge, we can assume that a traffic jam occurs.

Once we have predicted a high traffic density for a network segment, we can initiate strategies to avoid this problem. In case of a road network, navigation systems can try to bypass the critical zone. Furthermore, any traffic control systems can inform the drivers about the traffic jam risk in order to guide them around the critical zone. Similar effects can be achieved by dynamically adjusting the speed limits on highways which is already state-of-the-art.

Now we can state the problem to be solved in this paper: Given a set of objects that currently move on a shortest path between their starting point and destination point, where for each object only a short-time capture of the recent trajectory is available. The problem is to compute the expected traffic density (i.e. the expected number of objects located at a road segment at the same time) for all road segments at any time in the future. The road network is represented as directed weighted graph G(V,E). V denotes the set of vertices that correspond to street crossings or points connecting two intersecting road segments, and E denotes the set of directed edges that connect adjacent vertices and correspond to road segments. A weight is assigned to each edge that reflects the distance of the way between the two adjacent vertices. This information can now be used to compute the time an object requires to traverse this segment if the speed of the object is known. Alternatively, the weights can be used directly to specify the time any object requires to pass over the corresponding road segment. Due to the assumption that each object moves on a shortest path from a starting point A to a certain destination point B on the road network, it moves on a certain trajectory on the graph. If the future trajectory of an object is known and we assume a constant velocity for the object, one can accurately predict its location at any time in the future. Since we assume that the future trajectory of an object is unknown, we cannot make this prediction. However, as we assume that each object moves along a shortest path and if we are able to take parts of the already traversed trajectory into account, we can restrict potential destinations which reduces the destination space. The amount of achievable reduction of the destination space naturally depends on the length of the used trajectory observation. Usually, the longer the observed motion, the smaller the amount of possible destinations. This is the principle of our traffic density prediction based on a statistical model.

Traffic analysis methods can be principally classified into the following two categories:

- *Individual traffic analysis* takes the motion of single individuals into account.
- *Aggregate traffic analysis* takes the traffic aggregated over several individuals into account.

Our approach falls into the first category, since we make traffic estimations by taking probabilistic motion estimations of single individuals into account.

In summary, the main contributions of this paper include

- a statistical traffic model that can be used to predict the traffic density in a network at any edge.
- methods that take current traffic situations due to short-time traffic observations into account that can be incorporated into the statistical model to improve the traffic prediction.
- a suitable network organization approach that can be used to speed-up the prediction of the traffic density.

The remainder of this paper is organized as follows. In the next chapter we give a brief overview over existing approaches for traffic analysis and traffic jam prediction. In Chapter 3 we introduce our statistical approach to estimate the traffic in a network at a certain position at a certain time. Next in Chapter 4 we propose an efficient method to speed up the prediction which is based on a suffix-tree. In Chapter 5 we experimentally show the capability of our approach to make useful predictions about the traffic density. Furthermore we illustrate the efficiency of our new algorithm when calculating these predictions and finally conclude the paper with Chapter 6.

2 Related Work

In the recent year a lot of work has been published in the field of traffic data mining. One important problem in traffic mining is to detect areas with a significant high load of traffic. Some work has been published for detection of traffic jams. Approaches for traffic jam detection are proposed in [5] and [12]. Both proposals address the problem of clustering trajectories, namely sets of short sequences of data like movements of objects. The resulting clusters indicate routes with potentially high traffic load as the clusters represent sets of objects that simultaneously move nearly the same route. While in [5] a model-based clustering algorithm is proposed that clusters trajectories as a whole, the approach proposed in [12] works on partitions of trajectories. Each trajectory is first partitioned into a set of line segments. Afterwards, similar line segments of different trajectories are grouped together in order to discover common sub-trajectories from a trajectory database. The advantage of the latter approach against the first one for the detection of routes with high traffic is that it can also detect routes that do not necessarily span the complete object trajectories. Normally, the trajectory of objects moving in a traffic network are very long compared to the sections which form routes with high traffic, so only reasonably small parts of a trajectory contribute to such routes.

Another approach for traffic jam detection is addressed by X. Li et al. in [13]. Their approach tries to discover *hot routes* in a road network. *Hot routes* are road segments that frequently or even regularly have a high traffic density and mostly lead to a traffic jam problem. The detection of *hot routes* is an important problem, since each larger city has such *hot routes* that regularly block the traffic flow, often at rush hour, and involve that commuters spend long times waiting in traffic jams. While the approaches proposed in [5] and [12] are individual traffic analysis as the traffic is computed by observing the motion of single individuals, the approach in [13] is based on the FlowScan algorithm which is a kind of aggregate traffic analysis. It is able to extract *hot routes* by means of observing the traffic flow over some adjacent road segments. It does not completely fall into the category of aggregated traffic analysis, since it considers more than the pure density of traffic on single road segments. It is merely a mixture between the individual and aggregated traffic analysis.

Further approaches concerning traffic jam detection are based on the detection of dense areas of moving objects as proposed in [10]. This approach tries to find moving clusters in moving object databases. The difference of the addressed problem compared to clustering trajectories is that the identity of a moving cluster remains unchanged while its location and content may change over time. The same usually holds for traffic jams, in particular if the traffic jam is due to an obstacle that slows down the traffic. There are normally individuals that pass the obstacle at the beginning of the traffic jam, and, thus leave the traffic jam and those which arrive at the end of the traffic jam. Consequently, the contributors of the traffic jam change over time, while the identity of the traffic jam remains.

A quite similar problem is addressed in [7] where areas of moving objects that remain dense in a long period of time are detected. This approach is quite related to our approach as it addresses predictions of dense traffics where the prediction concerns any time slot in the future. Furthermore, like in our approach the predictions are made on the basis of observations of the current motion. However, there is a big difference from our approach concerning the assumption of available information of the object motions. The existing traffic prediction and traffic detection methods assume that the traffic motion and accordingly the object trajectories must be exactly known in advance. In reality however, the trajectory of an object is unknown in advance.

One thing is to detect any traffic patterns like high

traffic density. However the problem of prediction of any traffic pattern is more challenging. There exist approaches for traffic prediction by means of historical observations which are based on regression analysis as proposed in [15]. Regression can be used to predict the future motion of individuals. However regression is not applicable for the prediction of traffic densities, because it only considers the expected motion of an individual but disregards all possible future motions of them. Another method concerning traffic prediction based on current traffic observations is the approach presented in [18]. Here the current traffic data is derived from a sensor network measuring the traffic at certain locations in the traffic network. In the framework proposed in [18], the sensor network includes about nine hundred measurement stations. The data is collected in a data warehouse and used to infer interesting patterns. May be such kind of systems can possibly be used to learn patterns that allow us to predict traffic jams in the traffic network. This method falls into the category *aggregate analysis* and mainly differs from our approach as it aggregates the traffic at certain road segments instead of observing single individuals. Principally it is an inversion of our approach which might be able to predict specific traffic jams but disqualifies for the general traffic density prediction.

A further related topic in traffic mining is the detection of suitable traveling paths for individuals that want to travel to a certain destination in a possibly most cost-efficient way. There is a lot of published work related to fastest path computations [2, 3, 4, 16, 8, 9, 11, 17]. However none of these proposals take the actual traffic into account. An efficient technique for fastest path computation taking traffic patterns into account has been addressed by H. Gonzales et al. [6]. They propose an adaptive navigation method based on historical traffic patterns mined from a large set of given traffic data.

Another field related to traffic mining is graph mining. In graph mining much more work has been done than for traffic mining. Graph mining seems to be very related to traffic mining as traffic flows normally occur in a network graph, e.g. a road network or the internet. Hoverer, most graph mining approaches concerns the topological structure within graphs or subgraphs. A lot of graph mining approaches aim at finding interesting patterns within graphs. A comprehensive survey of graph mining techniques is given in [1]. One topic that still works on static network graph topology but comes close to the problem of our approach is the discovery of *center-piece subgraphs* [19]. The *center-piece subgraph* problem is to find the node(s) and the resulting subgraph, that have strong connections to all or most of a given set of query nodes. Usual applications are connectivity mining in social networks, gene regularity networks and viral marketing. In a traffic network we usually have certain places of preferred travel destinations or starting points. Such kind of *hot spots* can be mall centers, theme parks, city centers, commercial centers, conjunction to highways and so on. These kind of hot spots can be used as query points in order to find *center-piece subgraphs* which indicate places of expected high traffic. Similar measures like "Closeness Centrality" and "Betweenness Centrality" [14] which are traditionally used for mining in biological interaction networks can be applied to identify road segments with high risk of traffic jams.

3 Statistical Traffic Model

In this chapter, we will formalize our view on traffic networks and the traffic that can be observed on them. Furthermore, we will discuss a statistical model that allows to predict future states of the network under the knowledge of the current state and a short time history.

3.1 Traffic Density in a Network A traffic network is modeled as a graph $G(V, E)$ where the vertices represent destinations and crossings. The edges represent ways or streets between the vertices. A walk is a sequence of edges $w = (e_1, .., e_n)$ where successive edges are connected, i.e. $e_i = (v_l, v_k) \Rightarrow e_{i+1} = (v_k, v_m)$ with $v_l, v_k, v_m \in V$. An object o may travel on this network from one vertex v_1 to another one v_2 by following some walk $w = (e_1, .., e_n), e_i \in E$ where e_1 is starting with v_1 and e_n is ending with $v2$.

The point of time t_i where the object reaches v_2 depends on the speed the object is traveling at on each edge. Therefore, we assume that there is a maximum speed for objects traveling on a certain edge e_i $speed_{e_i}$. Knowing the length of edge e_i $length(e_i)$, we can determine the time it takes object o to travel from v_l to v_k via e_i. Thus, given the walk $w = (e_1, ...e_n)$ we can calculate the time it takes object o to follow w by

$$time(o, w) = \sum_{i=1}^{n} \frac{length(e_i)}{speed(e_i)}$$

To find out the position of object o at time t traveling on a walk $w = (e_1, .., e_n)$, we have to calculate the $time(o, (e_1, .., e_i))$ for $i = 2$ to $i = n$. We can stop at the first edge for which $time(o, (e_1, .., e_i))$ is larger than t, because o will not reach e_i in a time shorter than t. As a result, we know that o will travel on edge e_{i-1} at time t.

After describing the movement of individual objects in the network, we will turn to describing the complete

state of the network. Thus, we define the density on edge e_i at time t as the number of objects traveling on e_i at time t. Formally, the density is defined as:

DEFINITION 3.1. (TRAFFIC DENSITY) *Let $G(V, E)$ be a traffic network and let $O = o_1, .., o_m$ be a set of objects traveling on the network. Furthermore, let $\rho : E \times O \rightarrow \{0, 1\}$ be the following indicator function*

$$\rho(o, e) = \begin{cases} 1 & \text{if } o \text{ is on } e \\ 0 & \text{else} \end{cases}$$

Then, the traffic density on edge e is defined as:

$$density(e) = \sum_{i=1}^{m} \rho(o_i, e)$$

Clearly, it is possible to determine the density of each edge at the current time t when observing the network.

Additionally, it is possible to compute the density for any future point of time $t + \Delta t$ if all objects $O = \{o_1, .., o_m\}$ and their corresponding paths w_{o_i} are already known at time t. As mentioned above the position of object o_i at the point of $t+\Delta t$ can be derived easily when knowing the walk o_i is traveling on.

The problem of traffic prediction is caused by the absence of knowledge about the walk w an object o is traveling on. In other words, we can observe each object on the network at time t but without knowing its route, we cannot exactly tell its position at time $t + \Delta t$.

Though we cannot tell the exact density of each edge at some future time $t+\Delta t$, it is possible to calculate an expected density employing the available knowledge about the objects and their behavior. Generally, our model for determining the expected density is based on the probability that a given object o is traveling on edge e at time $t + \Delta t$, $Pr[o, e, t + \Delta t]$.

This probability depends first of all on the existence of a walk that allows o to travel on edge e at the time of prediction $t+\Delta t$. If there is no walk allowing o to reach e in Δt time, then $Pr[o, e, t + \Delta t]$ can be considered to be zero.

After finding all walks $W = \{w_1, .., w_l\}$that allow o to be at e at time $t+\Delta t$, we can sum up the likelihoods $Pr[o, e, w_i]$ that o would take walk w_i:

$$Pr[o, e, t + \Delta t] = \sum_{i=1}^{l} Pr[o, e, w_i]$$

To determine $Pr[o, e, w_i]$, we assume that w_i is the result of a Markov chain on the network where the vertices correspond to the states and the edges to the allowed transitions. The chain is started at the current position of o. Each time o reaches a new vertex v, o has to decide for one of $deg(v) + 1$ options. $deg(v)$ denotes the degree of v, i.e. the number of adjacent edges. Thus, an object can either stop traveling at the vertex v or take any of the adjacent edges to continue its journey. To find out the likelihood that o follows the walk w, we need to assume a probability distribution describing the likelihood of each of these options. Formally, we can calculate the probability that object o follows walk $w = (e_1, .., e_n)$ where $start_i$ and end_i denote the starting and ending node of edge e_i as:

$$Pr[o, e_n] = \prod_{i=1}^{n} Pr_o[end_i | start_i]$$

$Pr_o[end_i|start_i]$ is the likelihood that o enters e_i under the condition of being previously on node $start_i$. Let us note that we do not distinguish whether o intends to stop at the end_i or continues its travel. In a classical Markov chain $Pr_o[end_i|start_i]$ usually depends on the previously visited edge e_{i-1}. However, in order to keep our framework as general as possible, we do not limit our method to a certain type of distribution and thus, allow arbitrary probability distributions. For example, we might assume that the underlying probability distributions are uniform. In this case, the likelihood that o is taking walk w follows the random walk assumption, i.e. at each node an object would take any of the given options with the same likelihood with no regard of any global destination. However, since objects in a traffic network usually behave more rationally, we will introduce more sophisticated probability distributions in the next subsection.

After describing the likelihood $Pr[o, e, t + \Delta t]$ that object o will be at edge e in Δt time, we can now calculate the expected density for edge e at $t + \Delta t$.

DEFINITION 3.2. (EXPECTED DENSITY) *Let $G(V, E)$ be a traffic network and let $O = \{o_1, .., o_m\}$ be a set of objects traveling on the network. Then, the traffic density on edge e at time $t + \Delta t$ is defined as:*

$$density(e, t + \Delta t) = \sum_{i=1}^{m} Pr[o_i, e, t + \Delta t]$$

3.2 The Shortest Path Assumption Though the expected density allows us to predict the expected state of a traffic network for any future point of time, its applications pose serious problems. First of all, the prediction is strongly dependent on the underlying probability distributions. Thus, if these distributions do not model the behavior of the objects well enough, the expected density will significantly differ from the real density after a short period of time. A second

problem is the computational cost of determining all walks between the current position of an object o and a future position e. The number of possibilities we have to check is exponentially increasing with Δt. Thus, finding all walks allowing o to travel on edge e an $t + \Delta t$ is very expensive for larger values of Δt.

Fortunately, the random walk assumption made above is not realistic for most traffic networks and we can employ more realistic assumptions to derive more suitable probability distributions and reduce the number of walks.

For example, a driver traveling from New York to Los Angeles would not randomly decide at each highway intersection in which direction he drives next. The reason for the more rationale behavior in traffic networks is that each object has usually a predefined destination, it wants to reach as fast as possible. Furthermore, the topology of the network is known to each object and thus, the object does not have to stray through the network until it accidentally reaches its destination. Since each object wants to reach its destination as fast as possible, we can assume that each object travels along a shortest path where each edge e is weighted by the time it takes to traverse it, i.e. $\frac{lenght(e)}{speed(e)}$. A path in contrast to a walk is not allowed to contain the same vertex twice. We will refer to this observation as the *Shortest Path Assumption*.

Though the general framework for computing the expected density can remain unchanged, the shortest path assumption has a major impact on the quality of prediction and the computational complexity.

A first implication is that in order to determine whether object o might be at edge e after the time period Δt, we only have to consider the shortest paths of the current position of o to the end vertex of e. If there is no path ending with edge e, then o travels on edge e with a probability of 0%. If e is the last edge of some shortest path, we can calculate the time period o would travel on e. Only if $t+\Delta t$ is within this time period, it is possible to observe o on edge e at the time of prediction $t + \Delta t$. Let us note that it is not necessary to consider any other shortest path because an object traveling on any other shortest path must arrive at the end of e at the same time. To conclude the shortest path assumption significantly reduces the number of walks that have to be considered.

A further implication of the shortest path assumption is that it is possible to find meaningful probability distributions that can be used to determine the likelihood that object o travels along path p.

We know that each object o heads towards one predefined destination v_o^{dest}. Furthermore, we know that o travels along a shortest path to reach v_o^{dest}. Thus, the set of all possible paths o could follow, is the union of all shortest paths to any possible destination. Now the likelihood that o travels along path $p = (v_1, .., v_n)$ depends on the probability that v_n is o's target, $Pr_{dest}[o, v_n]$. Without further knowledge we might assume that each destination is equally likely. Additionally, it is possible to increase the likelihood of more popular destination to integrate domain knowledge. Let us note that in the case that there is more than one shortest path leading to v_n, we assume that all paths are equally likely.

After assuming a distribution over all destinations, it is possible to derive local probability distributions that can be employed to estimate the likelihood that object o travels on a certain edge e. Therefore, we need to sum up the probabilities for each shortest path containing edge e. Formally, we can define this probability as follows:

DEFINITION 3.3. (VISITING PROBABILITY) *Let $G(V, E)$ be a traffic network, let o be an object having the current position v_{start} and, let $sp(v_{start}, v)$ denote the set of shortest paths from v_{start} to any other vertex $v \in V$. Furthermore, let $\hat{P}_{v_{start}}(e_n) = \{p | p \in sp(v_{start}, v) \wedge v \in V \wedge e_n \in p\}$ be the set of all shortest paths beginning with v_{start} and containing the edge e_n. Now, the probability that o follows the path $p = (v_{start}, ..., v_k)$ $Pr_o[p]$ is defined as :*

$$Pr_o[p] = \frac{1}{|sp(v_{start}, v_k)|} \cdot Pr_{dest}[o, v_k]$$

where $Pr_{dest}[o, v_k]$ is the likelihood that v_k is the destination of object o. Then, the probability under the shortest path assumption that object o travels on edge e_n is defined as follows:

$$Pr_{sp}[o, e_n] = \sum_{p_i \in \hat{P}(v_{start}, e_n)} Pr_o[p_i]$$

The probability $Pr_{dest}[o, v]$ describing the likelihood of each possible destination has an important impact on the accuracy of the prediction. Furthermore, under the shortest path assumption this likelihood depends on the path $p^o_{history}$,i.e. the path o has already traversed until the current point of time. If $p^o_{history}$ is unknown, we generally have to assume that all vertices are possible destination of o. However, knowing $p^o_{history}$ allows us to prune some of these destinations. Since o is traveling on a shortest path, we can exclude all destinations for which there exists no shortest path starting with $p^o_{history}$. Thus, knowing the previous movement of each object o significantly reduces the number of possible destinations and thus, allows us to find a better estimation of $Pr_{dest}[o, v]$.

To conclude, the shortest path assumption can be derived from assuming that all objects have knowledge of the network topology and try to reach a certain destination as fast as possible. Based on the shortest path assumption, we can derive more reasonable probability distributions for the decisions each object makes at some vertex. Thus, it is possible to find a more suitable expected density for the edges in the traffic network.

4 Efficient Traffic Prediction

In the previous chapter, we defined the expected density for single edges in a traffic network at a certain time of prediction. In this chapter, we will turn to calculating the complete density in a network at some future point of time consisting of the expected densities of each edge in the network. After introducing a straight-forward method to calculate this expected network density, we will introduce a data structure allowing a much more efficient computation of density predictions.

4.1 Traffic Density Prediction The goal of our approach to is to predict the state of a traffic network for a future point in time or even a time period in the future. Therefore, we first of all formalize the expected density in a traffic network.

Definition 4.1. (Expected Network Density) *Let $G(V, E)$ be a traffic network and let $O = \{o_1, .., o_m\}$ be a set of objects traveling on G under the shortest path assumption. For each object $o_i \in O$, we know a short time history $p^o_{history}$ containing the path o_i has traversed before the current time t. Furthermore, the destination of each object o_i is unknown. Then, the **Expected Network Density** at time $t + \Delta t$ is defined as the set of expected densities for each edge e: $density(e, t + \Delta t)$.*

The Expected Network Density consists of the complete traffic density that can be expected to be observed at some future point of time.

In the following, we will discuss a straight-forward method for calculating the expected network density, i.e. the expected density of each edge in the network at the time of prediction $t + \Delta t$.

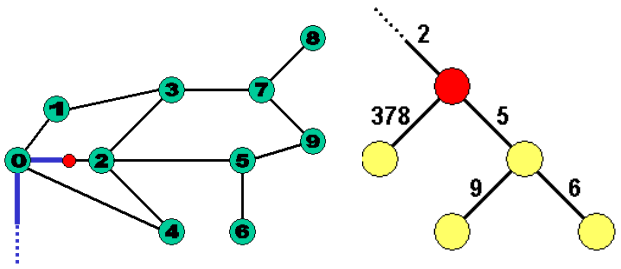
The basic idea of the following method is to determine all possible positions for each object o at prediction time $t + \Delta t$. Thus, we increase the density of each edge e by the probability $Pr_{sp}[o, e]$ if o might visit e at the time of prediction. To find out all possible positions and their corresponding likelihoods, we first of all have to determine all possible destinations. As mentioned before, the number of possible destinations depends on the path $p^o_{history}$ that o has already traversed. Therefore, we start with the first known position of o,i.e. the first node in $p^o_{history}$, and employ Dijkstra's algorithm to determine all shortest paths to any other node in the network. Now, to determine all possible positions of o at time $t + \Delta t$, we only have to consider the shortest paths being extensions of $p^o_{history}$. Each of these extending paths leads to a still possible destination. Thus, we follow each of the paths p for the time period Δt and thus, determine a possible position of object o. Now, the expected density of the edge corresponding to this position is increased by $Pr_{sp}[o, p]$, i.e. the likelihood that o travels along path p. After processing each possible position for each object in the system, the expected network density is derived.

A variation of this method can be applied if we are not only interested in the traffic density at a special point of time $t + \Delta t$, but in the expected density at all points of time between t and $t + \Delta t$. In this case, the prediction of the expected density is represented by a time series displaying the expected change of traffic on a given edge. However, computing the time series is quite similar to computing a single prediction. For each path p, extending $p^o_{history}$, we traverse p and update the edges of p for the period of time o might travel on them. Whenever o could enter a new edge the expected density is increased by $Pr_{sp}[o, p]$. Correspondingly, the expected density has to be reduced each time o leaves some edge e.

Though this method can be employed to determine predictions according to the traffic model introduced in section 3, it has serious short-comings from a computational point of view. The problem is that in order to determine the possible paths of object o, it is always necessary to consider each node of the network and determine all possible shortest paths starting with its first known position. This poses an enormous computational overhead because some of the paths are computed for multiple objects. However, since the usefulness of a prediction is rather perishable, a fast computation of the prediction is mandatory. Thus, in order to derive predictions in efficient time, a solution has to be found avoiding this computational overhead at prediction time and allowing efficient density predictions for the complete network.

4.2 A Shortest Path Suffix Tree In the following, we will present a data structure that is significantly speeding up the computation of the expected network traffic density. The core idea is to store all possible shortest paths in a compact data structure. Thus, the computation of shortest paths at prediction time can be avoided.

Assuming that there exists an unique identifier denoting each node in the network, we can use these



(a) Network graph (b) Suffix tree

Figure 2: Example of a network graph and the corresponding suffix tree used to efficiently compute an objects probability distribution.

node identifiers as alphabet and represent each path as a string over this alphabet. Our algorithm needs an efficient way to determine all shortest paths being extensions of the already observed history of a given object o. Considering each shortest path as string, we need to find a way to efficiently determine all suffixes extending the prefix represented by $p^o_{history}$. Therefore, we propose to store all shortest paths that can be found in the given network in a suffix tree.

The suffix tree is well known in text processing and bio informatics for its space-efficient storage of massive amounts of string data. Formally, a suffix tree ST for string $S = S[0..n-1]$ of length n over the alphabet A is a tree with the following properties:

- ST has exactly $n+1$ leaf nodes, numbered consecutively from 0 to n
- all internal nodes (except the root) have at least two children.
- edges spell non-empty strings
- all edges from the same node start with a different element of A
- for each leaf node i, the concatenation of all edges from the root node to i matches $S[i..n-1]$

In order to employ the suffix tree for our problem, we store all shortest paths in the given network in the suffix tree. Therefore we use the all-pair-shortest-path-algorithm by Floyd and Warshall to efficiently derive all possible shortest paths. Afterwards, all shortest paths are converted to strings over the alphabet of node identifiers and stored in the suffix tree. In this suffix tree, each direct son of the root represents a vertex v in the network and the corresponding sub tree represents all shortest paths starting with v. Let us note that each path in this sub tree corresponds to a shortest path and the paths to the leaf node represent shortest paths that are maximal, i.e. it is not possible to extend these paths to any longer shortest path. Each inner node v_n of the suffix tree represents a crossing in the network where some object o could arrive after traversing the path corresponding to its history $p^o_{history}$. The sons of v_n represent all possible shortest paths extending $p^o_{history}$. Figure 2(a) illustrates an example of an object traversing a network graph. The corresponding suffix tree representing all possible destinations is depicted in Figure 2(b).

To efficiently calculate the expected network density, it is not sufficient to directly access the information about the existence of a shortest path. Additionally, the likelihood that an object o follows some path p is of great importance. Therefore, we additionally store the probability distributions describing $Pr_o[end_i|start_i]$ in the tree, i.e. the likelihood o would turn into the direction of the node end_i after reaching $start_i$. In our model, this probability depends on the cumulated likelihood that o takes any of paths being extensions of the edge $(start_i, end_i)$. In the tree, these paths are represented by the sub tree under the node end_i. To speed up the computation of the likelihood of each path during prediction, we add up the likelihoods of possible directions right after generating the tree. Therefore, we first of all mark each ending point of each path, with the likelihood that o would take this path. Let us note that inner nodes are valid ending points as well. Afterwards, we assign the cumulated likelihood over all paths extending edge $\hat{e}$ to $\hat{e}$ in the tree. Let us note that for any node e in the network there usually exist multiple edges $\hat{e}$ in tree, one for each possible prefix. Due to this modification, it is now possible to calculate the likelihood that some object o might visit edge e while traversing the tree.

To calculate the expected network traffic density using the proposed shortest path suffix tree, we can proceed as follows. For each object o, we enter the tree traversing along the string corresponding to the already observed path of o $p^o_{history}$. After reaching the node in the tree corresponding to the current position of o, we can derive all possible positions of o at $t+\Delta t$. Therefore, we traverse every path in the sub tree under the current position of o and calculate the likelihood that o would travel this path during traversal. Traversing each path is stopped if extending the path would demand more time than Δt. Finally, we add the current likelihood to the expected density at the edge corresponding to the current position of o and continue by extending the next path in the sub tree.

To conclude, employing a shortest path suffix tree allows us to avoid shortest path computations during traffic density prediction. Furthermore, the number of edges that have to be traversed for prediction is also reduced to necessary sub paths.

5 Experimental Evaluation

In this section we show the capability of our approach to make useful predictions about the traffic density and illustrate the efficiency of our new algorithm when calculating these predictions. For all experiments, we simulated the traffic in a realistic traffic network as depicted in Figure 3 containing about 679 road segments and 533 intersection nodes. Our traffic simulator contains about 1250 cars (illustrated by small dots in Figure 3) moving from individual starting points to their destinations on a shortest path. The starting points as well as the destinations are equally distributed over the entire network graph. Here, each car moves with a certain velocity which is assumed to be constant during the whole journey. The velocities of the moving cars are randomly selected for each car and it took about 60 minutes until all cars have reached their destinations. If not stated otherwise, as soon as a car has reached its destination it was removed from the network and, thus, did not contribute to the traffic anymore.

All experiments are based on java implementations. The runtime experiments were conducted on a dual core Opteron Dual Core processor with a clock time of 2.6 GHz and 32GB of RAM.

5.1 Experiments on Quality of the Traffic Density Prediction The first experiments concerns the quality of our traffic density predictions. The traffic density of a road segment is simply given by the number of cars that pass through this road segment at a certain point of time. In order to show the quality of the traffic density prediction, we continuously measured the traffic density *prediction error* during a certain range of time. The *prediction error* is computed by the difference between the predicted traffic density and the observed traffic density for a road segment. In our experiments, we use the parameter *prediction time* Δt which denotes the forecasting horizon. In other words, the prediction time denotes the difference between the time the actual traffic is measured, (i.e., the time the traffic prediction is related to) and the time at which the traffic prediction was done.

Generally, in our experiments we only consider those cars that are existent in the road network at prediction time, i.e. all objects that enter the network graph after the time the prediction is made are not considered. However, in realistic scenarios new cars continuously enter the network. In order to evaluate traffic predictions under these circumstances, an additional statistical model would be required. For example, the entry of new objects in the network could be modeled using a spatial temporal Poisson-process. The prediction based on such a model is depicted in Figure 4. Obviously, the absolute prediction error increases with the number of new objects entering after the time the prediction is made. The rational of this is that we have no information of the new cars while the number of cars which are considered for the prediction diminishes. The expected number of cars which are considered for the traffic prediction is the difference between the predicted number of cars and the expected number of new cars. This number approaches zero when all objects considered for the traffic prediction have reached their destination. In the following experiments we only focus on objects which are present in the network at the time the prediction is made and do not allow objects to enter after that.

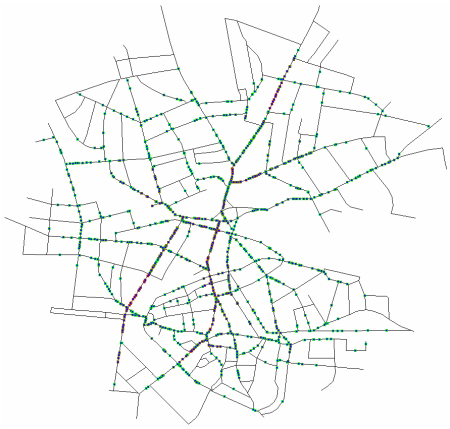


Figure 3: Traffic network graph with simulated cars used as experimental test bed.

Since the prediction error is an absolute value measured in number of cars, the quality of the prediction depends on both the prediction error and the number of cars on the corresponding road segment. If not stated otherwise, we averaged the prediction error over a set of road segments. In order to achieve more representative results, we measured the prediction quality only for a subset of road segments. Here we left out those road segments that contain only very low traffic over the measured time. Thereby, we try to avoid that the quality results are inherently biased by road segments with low traffic which are expected to yield high prediction quality. Since there are a lot of such kind of road segments with little traffic in our traffic network we did not consider them in order to obtain fair quality measurements. In the remainder, we will call the

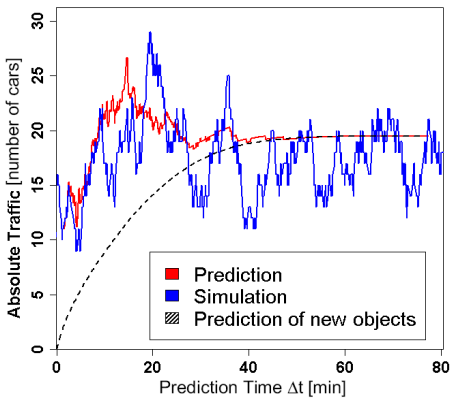


Figure 4: Prediction using a spatial temporal poisson model for the entry of new cars.

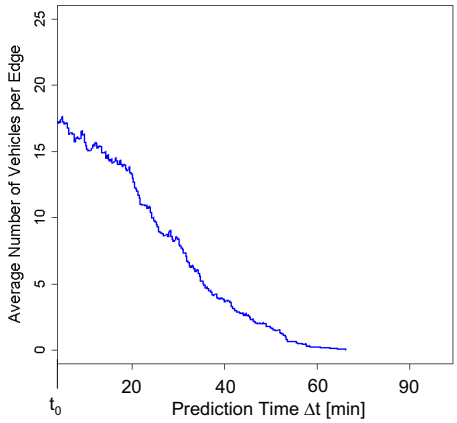


Figure 5: Average number of cars on a road segment.

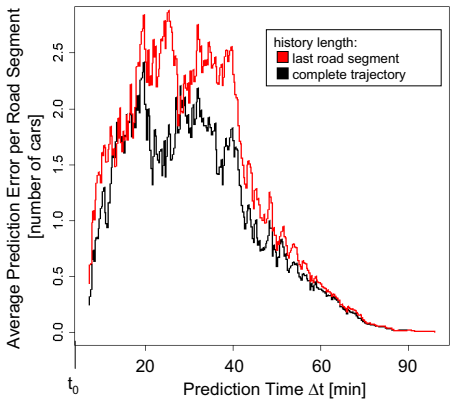


Figure 6: Average prediction error in number of cars on a relevant road segment.

set of road segments taken into account for the quality measurements *relevant road segments*. This set contains twenty road segments.

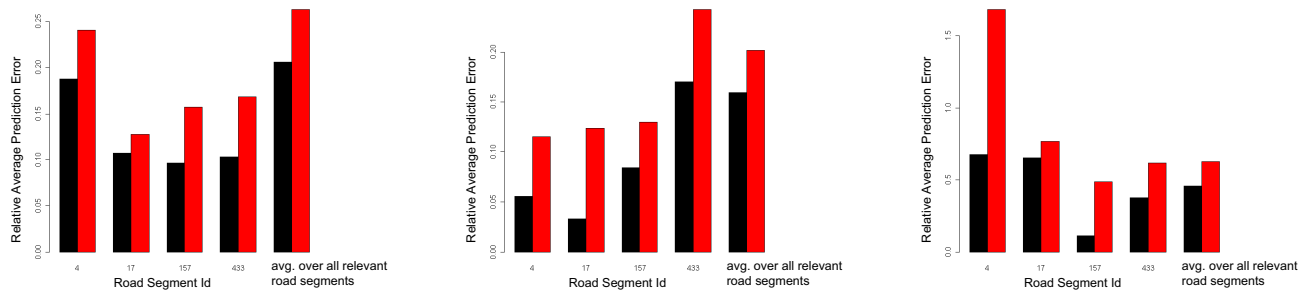
The average number of cars on a relevant road segment is given in Figure 5. It shows that the number of cars decreases with the running time of the simulation as the cars which reach their destination are removed from the traffic simulation. Although the overall number of objects in the simulation in fact decreases monotonically, here we did not observe a monotone decrease in the number of cars because we only counted the objects on the relevant road segments which can fluctuate a little bit.

Figure 6 shows the average prediction error w.r.t. the prediction time Δt (i.e. the forecasting horizon). The figure presents two curves, one curve depicts the prediction error when considering the complete history of each car for the prediction. The other curve represents the prediction error when taking only the last two passed road segments into account. Both curves have similar characteristics, because within the prediction of the close future the error increases drastically with increasing prediction time. This is due to the fact that the number of possible locations for each car is initially very small and increases drastically when the car passes through the first crossings. But with ongoing prediction time, the absolute prediction error decreases again. The rationale of this effect is the decreasing number of cars in the simulation. Less cars in the simulation obviously lead to a smaller absolute prediction error. But it can clearly be observed that the prediction based on the complete history has a significantly better quality than the prediction based on only the last two road segments. Generally speaking, both predictions have a good prediction quality, at least in the first few minutes. At a prediction time of about 20 minutes the prediction error adds up to two of fourteen cars in average, which is a relative prediction error of about 14%. With increasing prediction time the relative prediction error increases rapidly, e.g. at a prediction time of about 40 minutes the relative prediction error reaches 37%.

We also measured the relative prediction error at the four most relevant road segments averaged over different prediction time intervals. The relative prediction errors better reflects the quality of the traffic prediction than absolute prediction errors. The results are shown in Figure 7. The relative prediction error denotes the quotient

$$\frac{\text{absolute prediction error}}{\text{traffic in terms of the number of cars}}.$$

These results show that the relative prediction error is between 5% and 15% for short-term predictions and between 10% and 60% for long-term predictions when taking the motion history into account.



(a) prediction time = $0 - \infty$ (b) prediction time = 18-22 min (c) prediction time = 38-42 min

Figure 7: Relative traffic density prediction error averaged over certain intervals of prediction time.

Additionally, we measured the traffic at specific time intervals in terms of number of cars. The results are given in Table 1. If we compare the resulting traffic of the single road segments to the average of all relevant road segments, we can see that the road segments selected for this experiment show a heterogeneous traffic. This experiment shows that the consideration of the history of each car has significant influence on the prediction quality for short-term predictions (about 20 minutes prediction) as well as for long-term predictions (about 40 minutes prediction).

Road Segment Id	$0 - \infty$	18-22 min	38-42 min
4	11.97	16.93	3.00
17	24.94	30.50	6.00
157	11.68	16.88	4.46
433	14.72	16.33	5.14
sum.	142.84	257.19	74.12

Table 1: Traffic table for the experiments shown in Figure 7.

In the next experiment we evaluated how the length of the history which was taken into account for each car influences the prediction quality. For this experiment we have run the simulation with a set of 500 cars. We measured the average prediction error for several prediction times by varying lengths of observed histories. The results are depicted in Figure 8. An interesting observation is that the length of the history in terms of passed nodes has similar effect for short-term predictions and long-term predictions. A history longer than ten nodes does not make any difference in the prediction error.

5.2 Experiments Concerning the Efficiency In the next experiments we show the performance comparison between the proposed prediction strategies. In particular, we compare the first solution where the future path probabilities for each car are computed at run-time with the approach using the pre-computed suffix-tree. The performance is measured in terms of the number of network nodes which have to be accessed to predict the traffic density at each road segment for one certain point of time in the future. Additionally we measured the absolute runtime required to make the prediction. Without the suffix tree we measured about 500 000 accessed network nodes while we accessed only 100 000 network nodes utilizing the suffix tree.

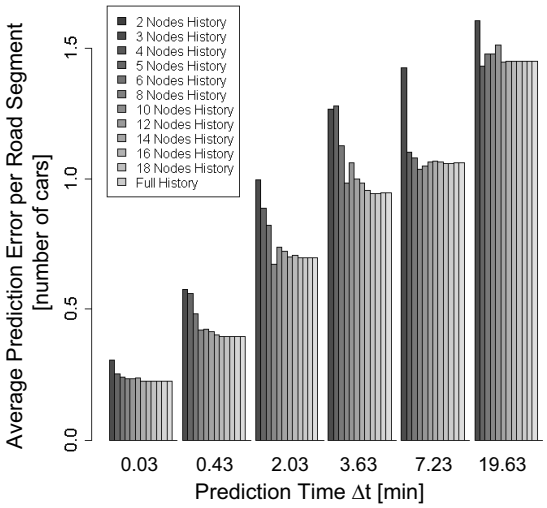


Figure 8: Average prediction error in number of cars for varying motion history taken into account.

Furthermore, we evaluated the scalability of our traffic prediction approach when using the suffix-tree in order to accelerate the prediction. Figure 9 demonstrates the time required to make a 4-minute traffic-prediction for the entire road network. We measured the runtime for varying number of cars in the traffic

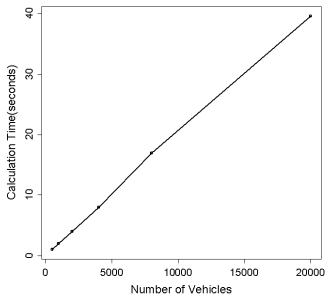


Figure 9: Performance of the traffic density prediction in terms runtime for varying number of cars.

network. Obviously, the prediction runtime increases linearly with increasing number of moving objects.

6 Conclusions

In this paper we proposed an approach for density prediction in traffic networks. We introduced a statistical model that is used to predict the traffic density on any edge of the network at some future point of time. Furthermore, we showed how short-term observations can be used to improve the prediction quality and how the traffic densities can be computed in an efficient way. We experimentally demonstrated that our approach achieves high prediction qualities in particular when taking the history of the moving individuals into account. However, we observed that only a quite small history suffices to reach adequate prediction qualities for both short-term and long-term predictions. In addition, our runtime experiments showed that the computation of the traffic predictions can be made in reasonable time. In the future, we plan to extend our statistical prediction model by taking further observable or even learnable motion parameters into account.

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