Modeling Urban Traffic Dynamics in Coexistence with Urban Data Streams

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ABSTRACT
Classic paradigm of scientific modeling is mainly based on a set of previously, accepted or assumed theories about the target phenomena and a validation procedure by limited observations. Therefore, normally data has a supporting role in the modeling process. On the other hand, recent advances in computing technology have brought us a data deluge that may change the classic paradigm of scientific modeling. Information flows and data streams have reached a level of maturity that they can play the main role in modeling of the real systems, without relying on lots of assumptions and rules in the first step. This turn may cause an inversion in the concept of modeling as a rational process.

The proposed theoretical idea in this work is that traditional theory-driven models have a theoretical limit in modeling complex systems, known as curse of dimensionality and further, to highlight the fact that massive urban data streams can open up a new data-driven modeling approach, which goes beyond simple data driven analytics or eye catching info-graphics toward operational models of complex phenomena.

In this work we describe a conceptual framework for modeling city wide traffic dynamics that proposes a way to encapsulate the complexity based on abstraction power of Markov chains in a coexistence with continuous data streams. Therefore, finally as an experimental set up, we applied the proposed model to a real data set, consisting of GPS traces of taxi cabs in Beijing and the results have been explained.

Categories and Subject Descriptors
I.6.5 [**SIMULATION AND MODELING**]: Model Development – *Modeling methodologies*

General Terms
Algorithms, Experimentation

Keywords
Modeling, Traffic Dynamics, Markov Chain, Urban Data Streams

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1. INTRODUCTION
During the last decade, the developments in computer and communication technology have expanded to such an extent that the concept of computing not only applies to isolated computers anymore, but to entire networks of computing devices, which are pervasive and ubiquitous. As a result, new technological frameworks such as urban computing, mobile computing and crowd sourcing are emerging quickly and we have new forms of harvesting computing and communication power in social media [1]. These new ways of using technology induce a change in how we can understand the role of modeling in urban environments, while the classic paradigms for observation and empirical inference are challenged to integrate vast sources of data. In a field like urbanism and city planning we increasingly have a situation that flows of information from recorded urban data are more and more forming into continuous and live streams of data. This can be regarded as a potentially important extension of the empirical basis of urban planning and design.

However, specifically in transportation and traffic modeling research areas, traditional approaches such as partial differential equation systems [2,3] or multi-agent systems [4,5] rely on theoretical models to describe the underlying logic of the real system and then the models are validated by a set of expensive and inaccurate observations typically collected through survey data or via static sensors such as traffic cameras and loop detectors, which this information is often out-of-date, difficult to collect and aggregate, difficult to analyze and quantify, or all of the above[6]. In fact, in these classic approaches, theories are playing the main role in the modeling process, and data is for support and validation.

This analytical and rational approach, in which is mainly through a decomposition of real phenomena to a set of elements (analysis) and then to compose them back (synthesis) in order to mimic the real time behavior, has been used for a long time during centuries in simple mechanical systems. However, they reach to a limit in coping with complex systems, which is known as curse of dimensionality [7] in scientific modeling. Therefore, traditional transportation models either macro-simulation [2,3] or micro-simulations [4,5] are theoretically limited in approximating the real traffic systems and then, by adding more features or giving more data, models become more complicated, but not complex.

Meanwhile, with advancements in computer and communication technologies and democratization of data sharing as a part of daily life activities, large scale collected data can make a difference. [8] Our idea in this work is that with availability of urban data streams, an inversion in the process of modeling is happening, in which the data streams no longer play a supporting role, but the main part of modeling process. Therefore, new infrastructures are needed to be able to observe and manage data streams in a real time fashion. This is the case in several active research projects such as in London[1], IBM smart city initiative [9], mobile millennium Stockholm [10], WIKICITY [11] or Urban Computing at Microsoft [12-15].

However, this connectedness and data deluge has recently motivated more researchers in areas such as urban scaling [16] or those are claimed to be universal human mobility patterns [17, 18], which can be seen as a more efficient rational modeling paradigm but with the same curse of dimensionality problem.

Therefore, considering these new urban data streams as a new capability, the better research question could be whether one could directly encapsulate the richness of urban data streams into operational models without going through theorizing step, which is a limited theoretically in complex systems, and how to connect this richness to decision making processes.

In fact the conceptual approach that this work is proposing is how to construct data driven models with a continuous coexistence with real time data streams, in which the logic of the real behavior is not explicated in the model, but implicitly encapsulated in the streams of data and then if for example the underlying system is changing it is being reflected in the data streams and consequently in our data-driven models. This is the case, for example, for successful search engines like Google and its products such as Google map, which are heavily dependent to their connectivity to the real world [19] or the case of evolution of spoken languages among young generations, which can be tracked and recognized by a person with continuous engagement in real communications. Otherwise, it will be really hard to find the logic of change in these complex adaptive systems [8].

In this research which extends theoretical aspects of modeling in complex systems [20], we propose a technical framework for city wide traffic modeling based on the application of Markov chains [21] as the core mathematical technology. We implement an experimental set up with available GPS streams of taxicabs in Beijing, which is freely available [14]. In the next chapters, first we present our understanding of Markov chains and similar cases. Finally, we present the experimental set ups and finally the results and possible future research.

2. MARKOV CHAINS

2.1 Historical Account

A.A. Markov showed long ago (1913) [22, 23] how one can grasp the complexity of written language based on sequences of observations. In this work he considered the sequence of 20,000 letters in A.S. Pushkin's poem "Eugeny Onegin" as sequence of a set of symbols (letters, morphemes and words). He showed that in principle, Markov chain could produce an approximate result of the real text without considering any idealized model of the language, including, provided that we have enough observations. He says, "*Many mathematicians apparently believe that going beyond the field of abstract reasoning into the sphere of effective calculations would be humiliating.*" And in fact for a long time until advent of computing technology [24] there was no main citation of Markov chain. However, during last decade because of the availability of lots of sensory data in a form of data stream, Markov chain is getting more appealing. The main reason for this delay would be because Markov transition matrix as the main building block of Markov chain is data-driven and without enough observed data, Markov chain by itself cannot grasp the underlying logic of the real phenomena. And this is the opposite of traditional approaches (theory-driven models) that can be calibrated with few data sets. In fact, Markov chain is a light but powerful data-driven approach that does not ask directly for theoretical models of the target real systems, but can encapsulate the logic of observed behavior in a probabilistic way, after a certain threshold in size of data. Because of these conditions, may be one of the largest applications of Markov Chain and other similar probabilistic methods such as Bayesian networks can be found in Google search engine algorithm [19] and Google translate service [8], which are built on top of huge corpus of text. And these cases are great successful projects, when for example the classic search engines were not able to deal with ever growing amount of digital data.

The main idea in this paper is that urban systems are complex systems[2] and as it is mentioned, traditional rational models reach a limit in coping with complex phenomena. Therefore, now available urban data streams offer a similar approach as for the text and language modeling [24], which can be applied for city wide traffic modeling. Then, in this set up, each mover in the city (e.g. a taxi cab) can be assumed as an author, who is producing a text by his own intent (i.e. a personal driving behavior) and then, the observed GPS traces on city network are similar to the sequences of words in a text. Therefore, by observing a certain amount of sequences and building a Markov model on top of them, one can encapsulate the traffic dynamics in a flexible way.

Therefore, one of the applications of the proposed Markov chain could be the simulation of individual movement patterns [26]. Moreover, Markov chains have some other interesting features that can be used for specific tasks such as finding critical urban segments, empirical expected travel times, community detection, road engineering and traffic management [27].

2.2 Main Definitions

In this part, we briefly bring the main basic definitions related to Markov chain that will be used in the next parts.

State: $s(t),\ t=0,1,\ldots$ is a random variable that can take values from $1,\ldots,n$ which are possible states in a stochastic process. States can be finite or infinite.

Sequences of observed states: As the starting point for a Markov chain, observations are arranged such that data form a timely sequence of states as follows:

$$\ldots,s(t),s(t+1),s(t+2),\ldots$$

The time difference between $s(t)$ and $s(t+1)$ which is called transition time, is a unique time step such as location of a car in every 10 minutes. Note that time steps could be different as well or to be a continuous range. However, in this work we assume homogenous and discrete transition time.

Probabilistic transitions between states: if a Markov chain is in first order, then from the observed sequences, transition probabilities between two sequential states, p_{ij} can be calculated as a conditional probability as follows.

$$p_{ij}= Pr(s(t+1)=j \mid s(t)=i)$$

Markov transition matrix: as a result of mutual transition probabilities, we have a square matrix P, with n rows and n

[1] http://www.tfl.gov.uk/businessandpartners/syndication/default.aspx

[2] For a theoretical definition of complexity and city, please refer to [23].

columns, which shows the transition probability of flows from one state to another state.

In this work we used a discrete-time finite-state first order Markov chain, as a row stochastic matrix that means that the sum of probabilities in each row is equal to one.

Now by starting from any state, *s(t)*, the *kth* step transition of the system can be calculated by *kth* power of Markov transition matrix, P^k as follows:

$$s(t+k) = P^k * s(t), \quad t,k=0,1,\ldots$$

However, in addition to this macro-level simulation, one could do a Monte Carlo simulation of Markov Chain, in short (MCMC) to simulate the corresponding system on the micro-level similar to agent based approaches. In [24] it has been shown that the resulting Markov Chain based on GPS traces can approximate the traffic flow in a city scale road network. However, Markov chain has some other interesting properties, which are not so well-known outside of mathematics, but can be helpful for real analysis and assessment of traffic flow. In [25] it has been discussed in detail that if the constructed Markov matrix has certain conditions to be irreducible and aperiodic, it can be applied into the following tasks:

- ***Expected density of each state***: According to Perron-Frobenius theorem, the matrix P has an Eigenvalue 1 and the corresponding Eigenvector is showing the steady state probability of the Markov chain, which in case of traffic dynamics, it shows the normalized distribution of cars in the urban network.
- ***Mean first passage time,*** is the expected number of steps to arrive at destination *j* when the origin is *i*. Therefore, in the case of traffic flow, we have a new matrix, which shows the expected empirical travel times between each pair of points in the city.
- ***Kemeny constant*** is a holistic measure of the Markov network, which shows the expected transition time (steps) from any state to a randomly selected state as destination, which is astonishingly invariant for any state as the origin. Therefore, it can be used to compare different networks with different structures or to be used for the effect of each state (e.g. road segment) on the total performance of the network.

Further, considering Markov chain as a directed and weighted network, one could calculate all the possible classic network measures such as different centrality measures, but instead of a plain road network, now in a rich one.

3. SIMILAR WORKS

Availability of huge GPS-equipped taxi cabs in cities can be considered as a great potential for probing city dynamic through these pervasive mobile sensors, but the biasedness or sufficiency of this data for city wide traffic modeling could be an issue. However, a recent research [5] concludes that GPS tracks of taxis can be used to approximate traffic patterns in a city-scale road network accurately.

Using GPS traces, several interesting research have been conducted recently. From micro-level applications, in [12] a framework for large-scale taxi ridesharing service, which efficiently serves real-time requests sent by taxi users and generates ridesharing schedules that reduce the total travel distance significantly, is presented. In [13] the aim is to mine the time-dependent and practically quickest driving route for end users using GPS-equipped taxicabs traveling in a city.

From macro-level point of view of modeling, in [11], different spatial clusters of land-use functions have been discovered combining Point Of Interests (POI) and GPS traces data set. In [14], GPS traces of taxicabs have been used to detect flawed urban planning and regions with traffic problems.

Regarding the application of Markov chain, majority of the cases are from a micro-level point of view, mainly for predicting the most expected movement paths in urban networks. For example in [26] they have shown with Markov chain it is possible to predict the path between two points in the road network up to 100% accuracy. And therefore, it can be used for traffic simulation.

In similar cases such as [28, 29] vehicle trajectories in urban road network have been predicted. However, according to [27], Markov Chain as an abstract mathematical tool has some other features that can be used for macro-level modeling of citywide traffic dynamics. In this work, we proposed a method for constructing time-dependent and scalable Markov chains from GPS traces with applications of some macroscopic features of Markov chain. We implemented the framework based on a released data set of taxicabs in Beijing from Microsoft research Asia [14].

4. EXPERIMENTAL SET UP

Figure 1, shows the proposed conceptual framework. As it is shown, a Markov chain is being constructed periodically in coexistence with a continuous data stream, being emitted from moving taxi cabs as a part of the daily life in the city. Also since, Markov chain is an abstract tool, it can be used for different segments of road network, different time periods (e.g. week days, weekends or time slots of the day and based on different observation periods), and with different time resolutions depending on the frequency rate of GPS traces. Then, for each constructed Markov chain, several properties, such as community detection, time-dependent expected travel times, real time path planning and road network engineering can be calculated, which is not easy to calculate directly from data or via traditional theory driven approaches. These results finally can lead to planning interventions in the urban network.

However, it is important to have a continuous loop of model building and assessment and in fact Markov models can be meaningful in a full interaction with real systems and can have value added if connected with real time monitoring infrastructures.

In this work, as an experimental set up, we used a sample data set consisting of GPS trajectories of 10,000 taxicabs during first week of February 2008 in Beijing [14]. Therefore, the presented result in this paper is just like a snapshot of one iteration of this conceptual framework.

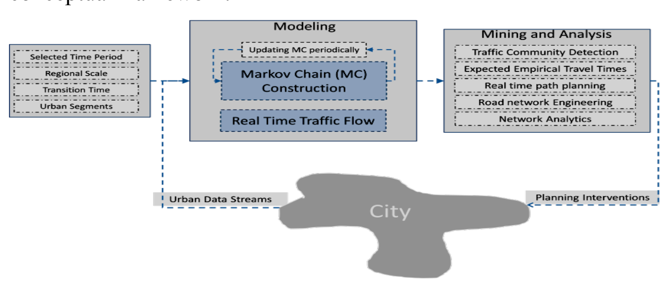

Figure 1. A conceptual framework for Markovian modeling of traffic flow in coexistence with urban data streams

For segmentation of urban network, three different approaches have been presented in [30], but in this framework because of the simplicity and further, in order not to just focus on road networks (as just one aspects of the real cities) we divided the area of Beijing to simple rectangular cells. The selection of cell size is important since, for very small size cells, there are not enough samples, while for large sizes the sequences will be aggregated into one cell.

In addition to cell size, the time unit for transition steps is important, but depends on the frequency of GPS traces. It should be noted that, including the time difference between to GPS tracks in Markov chain has an important advantage. Because for example, if a car is moving in traffic jam slowly, the probability of transition from that state (road segment) to another state (next road segment) in a fixed time unit is less than the times with no traffic jams, and this will be reflected in a Markov transition with higher value for diagonal element, p_{ii}. On the other hand, if the driving speed is high it is more probable to leave one state in one transition time. Therefore, the resulting Markov model encapsulates implicitly, several important factors such as speed, traffic flow and traffic lights, which are neglected in traditional network analysis that are based on plain road networks and some rule sets for modeling the individual movements.

Another issue is about the selected border on the city map, which causes that the trajectories outside of the grid not to be considered. Therefore, if one uses Markov chain with fixed number of grid cells, there could be some transitions to outside of the grid (we call it state null) and then back to one of the states in Markov chain in a few time units later, while in theory, we include all the possible movements in the Markovian states. Therefore, in order to solve this problem, final Markov matrix can be updated as follows, which makes the matrix irreducible as well.

$$\hat{P_{ij}} = \alpha P_{ij} + (1-\alpha).1/n, \qquad \alpha<1$$

The added element on the right side, assumes that with $(1-\alpha).\ 1/n$ probability, one car goes from state i to the outside of grid and will return to state j.

5. RESULTS

Figure 2 shows a sample sequence of a taxicab in a selected part of the grid on Beijing.

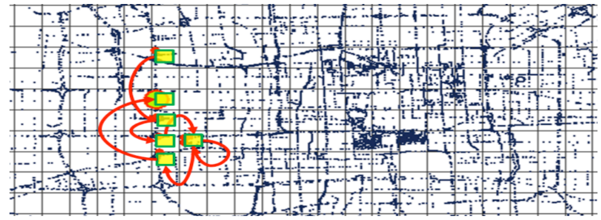

Figure 2. Selected area of Beijing with rectangular grid and a sample sequence from a Taxi cab as a random walk

In this work, we selected a 30 by 30 grid (900 states) and 600 seconds as transition time. Then, for each taxi, we have the records as follows:

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CarID , Date, Lon, Lat, State (cell number)
100,2008-02-02 21:22:11,116.36263,39.93097,374
100,2008-02-02 21:24:56,116.36708,39.92274,405
100,2008-02-02 21:29:57,116.34696,39.92226,403
100,2008-02-02 21:32:14,116.34557,39.91717,403
100,2008-02-02 21:34:59,116.33843,39.92169,402
100,2008-02-02 21:37:16,116.32875,39.92175,401
100,2008-02-02 21:40:01,116.31468,39.9225,400
100,2008-02-02 21:42:18,116.29511,39.92328,398
100,2008-02-02 21:45:02,116.29542,39.9306,368

…,374,405,403,403,402,401,400,398,368,
```

Then, after translating all the locational data to sequences, a Markov matrix (900 by 900) was constructed considering the transition time between two sequential traces. The following results have been calculated based on this set up.

5.1 Expected Car Density in the Network

As it is mentioned in previous section, the first eigenvector of the Markov chain shows the expected long term vehicular density in the network. If, we take taxis as samples of overall traffic flow [6], this result can be considered as the expected hot spots in urban road network, with high traffic jams. However, in case of availability of other information such as taxi status (i.e. hired or vacant) the same method could be used to estimate the distribution of taxis and potential passengers. Figure 3 shows the expected traffic jams in different areas of the Beijing.

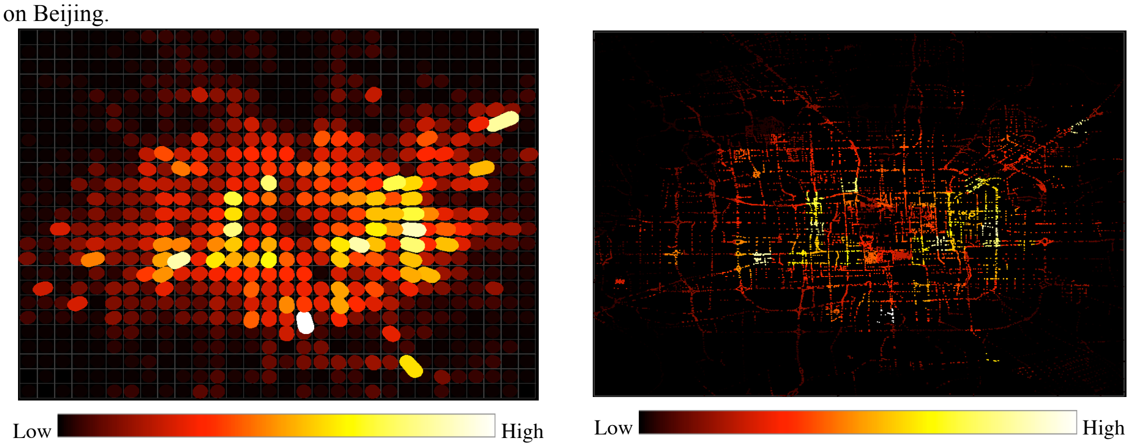

Figure 3. Expected car density in the network (the first eigenvector of Markov matrix)

5.2 Identification of Critical Road Segments

As it has been mentioned before, Kemeny constant provides a global measure for travel times within the network. Therefore, it can be used for sensitivity analysis of a network to its nodes (i.e. road segments). Then, by removing a segment of the network and calculating the Kemeny constant of the new matrix, it is possible to see the contribution of that road in the whole traffic flow. In principle new constant value can be higher (slower traffic in the case of closure or removal of this segment) or lower (better and faster travel flow). In figure 3 (left), the color of each region shows the difference of Kemeny constant of the network with absence of that region to the Kemeny constant of the full network. As it can be seen, the majority of road segments do not have specific effect in the whole network (values around zero), but a few of them are playing important communicative roles either in positive or negative way.

Comparing the values of two measures in figure 3 shows an interesting phenomenon. It can be seen that removal or closure of several segments with high expected traffic density (red colors in figure 3, right), will improve the total quality of the flow (blue colors in figure 3, left), while removing some roads with low expected density will have very bad results for the network. This result is in agreement by the famous network paradox, known as Braess's paradox, which can be interpreted that when a network is not congested adding a new street will indeed make things better. But in the case of congested networks, sometimes instead of adding more capacity, it is better to reduce the capacity [31].

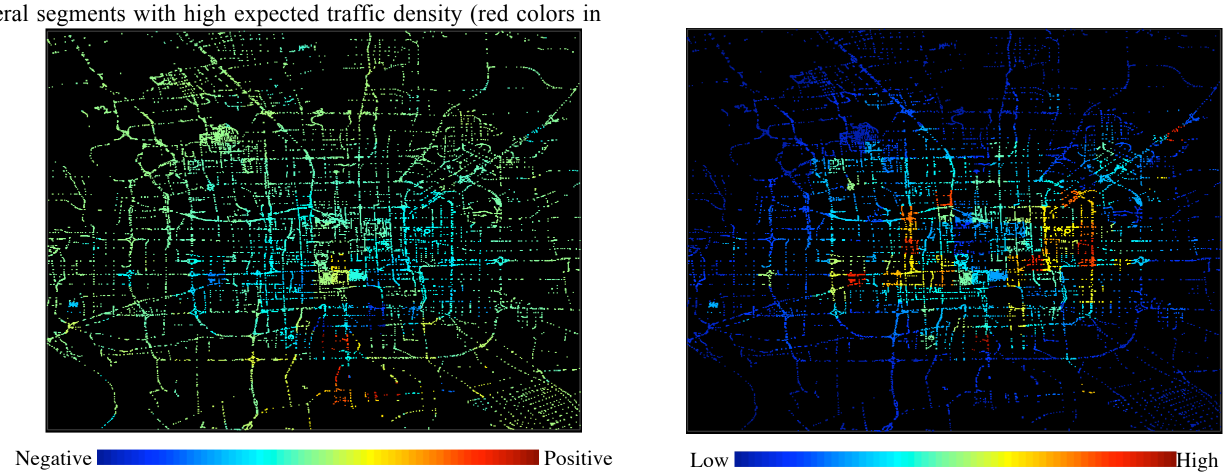

Figure 4. The effect of removing each cell in the total performance (Kemeny constant) of the network (left), compared to the expected car density in the network

5.3 Detecting Spatiotemporal Communities

Considering a Markov chain as a spatiotemporal encapsulation of real movements in the city, in comparison to a plain road network, one can cluster the Markov chain to detect the sub-communities of movements within the city. Each row (state) of the Markov chain is an *n* dimensional vector, which shows the probabilistic relation of that state to the other states. Further, one can construct an augmented matrix, in which each state is represented by a *2n* dimensional vector, *n* dimensions from each row (probabilistic outgoing flows) and *n* dimensions by each column (probabilistic in-coming flows) of the Markov matrix. For the clustering a Markov network, there are several algorithms available from graph analysis research domain. In this case, we used a Self Organizing Map (SOM) as a nonlinear data clustering algorithm [32]. Briefly, a SOM is the collection of multidimensional sorted nodes, in which nodes that are close together representing similar data vectors. In this case, each point of the SOM is representing one or more road segments (states of Markov chain as *n* or *2n* dimensional vectors). Then, one can find cluster of similar nodes and consequently similar road segments on the SOM. In this case, we used K-means clustering algorithm to perform the clustering on SOM. The following figure shows the detected clusters on a SOM network and their spatial distribution on the road map. Therefore, considering Markov chain as encapsulation of car movements in the city network, the detected clusters shows the sub-communities of road segments.

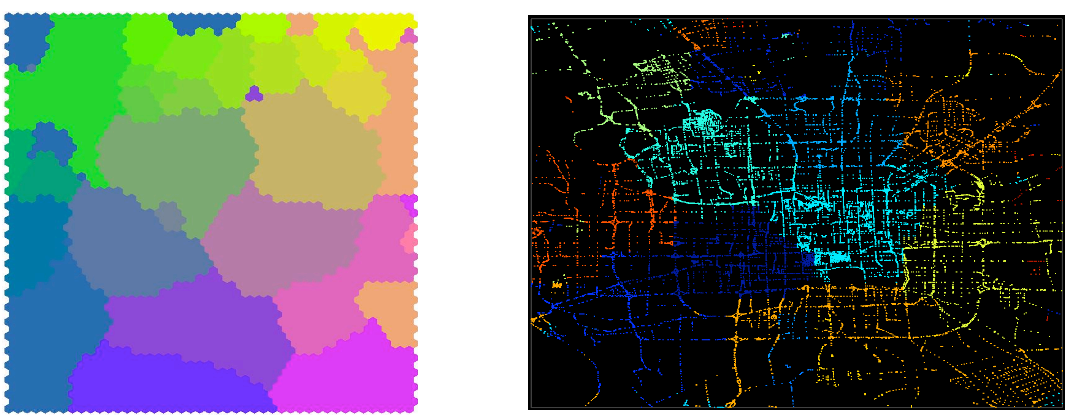

Figure 5. The color coded cluster indices in a SOM as a clustering algorithm (left) and on the spatial map (right)

5.4 Other Important Measures

The presented results can be considered as a part of possible by-products of a Markov chain model of traffic dynamics, which can be used for different practical applications. In addition, there are other interesting properties of Markov chain that can be used for analysis of traffic networks. For example, being able to calculate the expected travel time from each point of the city to another point is very important for routing and scheduling problems. In traditional approaches, this is done based on a plain road network, physical distances and some assumptions such as shortest path selection, which can be different than reality. On the other side, the proposed Markov chain implicitly has considered lots of factors and then, for example, mean first passage time [27], which can be calculated from Markov chain, can be used as a spatio-temporal travel times between any two points, and this acquired information can be used for real time scheduling [13] or can be embedded in real time path finding.

Further, according to [27] a Markov chain (based on primal network, in which junctions of roads are representing states) can be used for timing of traffic lights, traffic congestion estimation in the junction of roads.

6. Conclusions and Future Works

Ever growing access to data streams coming from different probes in the city, gave us the opportunity of implementing data-driven mathematical models that can overcome the limits of theory-driven models in dealing with complex urban system. In this work, we proposed a conceptual data driven traffic modeling framework, which is mainly based on the application of Markov chains in a continuous coexistence with data streams. The proposed framework is inspired by the idea of learning how two persons can communicate via a continuous dialogue in comparison to communication via referring to an idealized model of spoken language (as a reference model).

In principle, this set up has an important methodological advantage over traditional traffic modeling and simulation approaches because the logic of real complex phenomena is not explicated by a set of rules or theories, but encapsulated in Markov chains, which is being updated by urban data streams frequently. Further, as a result of using Markov chain we can analyze different aspects of traffic dynamics or simulate the flows, which are difficult tasks in traditional simulations.

In this case, as an experimental set up, we applied the proposed framework to a set of taxi cabs' GPS traces in Beijing. However, in future, our aim would be to apply the proposed approach in a real set up, with real time access to GPS traces[3]. We claim that in a real time set up the proposed framework can grasp the complexity of city dynamics, which is theoretically beyond the limit of rational and theory driven models.

7. ACKNOWLEDGMENTS

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http://youtu.be/0aQxJgHknGs

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