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Short-term speed predictions exploiting big data on large urban road networks

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A B S T R A C T

Big data from floating cars supply a frequent, ubiquitous sampling of traffic conditions on the road network and provide great opportunities for enhanced short-term traffic predictions based on real-time information on the whole network. Two network-based machine learning models, a Bayesian network and a neural network, are formulated with a double star framework that reflects time and space correlation among traffic variables and because of its modular structure is suitable for an automatic implementation on large road networks. Among different mono-dimensional time-series models, a seasonal autoregressive moving average model (SARMA) is selected for comparison. The time-series model is also used in a hybrid modeling framework to provide the Bayesian network with an a priori estimation of the predicted speed, which is then corrected exploiting the information collected on other links. A large floating car data set on a sub-area of the road network of Rome is used for validation. To account for the variable accuracy of the speed estimated from floating car data, a new error indicator is introduced that relates accuracy of prediction to accuracy of measure. Validation results highlighted that the spatial architecture of the Bayesian network is advantageous in standard conditions, where a priori knowledge is more significant, while mono-dimensional time series revealed to be more valuable in the few cases of non-recurrent congestion conditions observed in the data set. The results obtained suggested introducing a supervisor framework that selects the most suitable prediction depending on the detected traffic regimes.

1. Introduction

1.1. Motivation

Fast and accurate predictions of future traffic conditions are a crucial requirement for reliable applications of Intelligent Transportation Systems (ITS) devoted to traffic management and traveler information, whose intelligence is related to their capability to foresee future states of the system and individuate the most appropriate actions to undertake. Advances in Information and Communication Technologies (ICT) are currently making available an unprecedented amount of measures of traffic variables from the road network that are a premise for introducing new models and methods for traffic predictions (Shi and Abdel-Aty, 2015). Traditional traffic monitoring systems are based on fixed measure stations where flows, occupancy and possibly speed are detected. Collected data are then transmitted to the traffic control center, where they are

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processed to derive short-term predictions. The relatively high cost of investment and maintenance of fixed monitoring system was one of the most relevant limiting factors for a full ITS deployment although efficient algorithms for optimizing sensor locations were developed (Cipriani et al., 2006).

Availability of Floating Car Data (FCD) obtained by tracking GPS-enabled vehicles and mobile devices opens new perspectives to develop novel predicting models. In fact, they provide a pervasive tool to explore the road network and get information related to theoretically any point of the network (Fusco et al., 2015) and, in a near future, perform self-organizing monitoring techniques (Baiocchi et al., 2015). The existence of very detailed road graphs developed for on-board navigators would require equally detailed estimations of present and future traffic conditions. However, a suitable trade-off between reliability and accuracy of traffic estimates and predictions should be investigated. The main drawback of FCD is that the information is collected from only a sample of vehicles that send their current positions and speeds. Thus, they provide ubiquitous but partial information. This requires a supplementary effort to process these data and combine measures collected at different points and different instants. Moreover, while the sampling rule is usually specified, the actual sampling rate on each road link is unknown, so that the reliability of the measures is variable and difficult to estimate, except for the few links equipped with fixed traffic counting stations. Furthermore, in links not traveled by equipped vehicles data are missed at all. In the last years, several private companies have started collecting and selling real-time speed data from different sources, including floating car data. Aggregate measures supplied by private providers are usually paired with some qualitative confidence value and so preclude performing a rigorous estimation of the statistical significance of the data. Although the accuracy appeared to be improved since the earliest independent evaluation (Kim and Coifman, 2014), the reliability of traffic measures is still a crucial issue for studies dealing with short-term prediction methods that use floating car data. The huge amount of data collected in real-time on the road network requires also efficient analysis methods to catch the most useful information embedded in such time–space big data.

A large interest for machine learning methods arose in the last years in the literature on big data analysis and many network-based approaches, such as neural networks and Bayesian networks, were proposed with the aim of exploiting existing correlations among measures collected at different time intervals and on different links of the network. Specifically, Bayesian networks, which combine graph structure and Bayes approach to posterior probability from a priori estimate seem to offer a sound methodology for formulating short-term predictions from the pervasive sampling of traffic performances provided by floating car data.

In this paper, we aim at investigating the potentials of these methods to produce accurate short-term traffic predictions by exploiting floating car data collected ubiquitously on the network from a number of probe vehicles that is indeed large in absolute but is a relatively small fraction of the traffic flow on each link of the road network.

1.2. Approaches to short-term traffic predictions

Two main approaches can be individuated to perform short-term traffic predictions: either explicit or implicit traffic modeling. Explicit approach is based on mathematical models that represent the interactions between the physical variables that describe traffic phenomena. Traffic on freeways is usually modeled by macroscopic continuous models that discretize in time and space the partial differential equations that describe traffic dynamics. Traffic on urban road networks needs dynamic traffic assignment models that simulate the complex dynamic interactions between drivers' trip choices, vehicular congestion and road performances on the traffic networks.

Application of traffic models for real-time short-term predictions requires recursive methods implementable online. The rolling horizon method exploits current traffic measures to update trip demand estimation at every given short time interval and runs a new traffic simulation, which covers a longer time interval and holds until a new update is available. Relevant examples are the Dynasmart-X (Mahmassani et al., 2005) and Dynamit (Ben-Akiva et al., 2012). State-space models formulate the dynamic evolution of all traffic variables on the road network based on available real-time traffic measurements under a probabilistic environment (Muñoz et al., 2003). Typical applications for short-term real-time predictions imply the linear approximation of non-linear macroscopic traffic models that leads to the extended Kalman filter formulation (Stathopoulos and Karlaftis, 2003; Wang and Papageorgiou, 2005), although other approximation methods such as particle filter (Mihaylova et al., 2007) and Newtonian relaxation (Herrera and Bayen, 2010) were developed. The switching-mode model, which can be thought of as a combination of the hidden Markov model and the linear state-space model (Sun et al., 2003), was introduced to reproduce the possible transitions from a discrete traffic state to another, namely free-flow and congestion states that characterize the cell transmission model (Daganzo, 1994). A more complex architecture implements artificial neural networks to derive density values and determine transitions between traffic states on the linearized triangular fundamental diagram (Celikoglu, 2014).

Implicit approach derives dynamic relationships directly from time series of observed data and therefore is usually called data-driven approach. Although we acknowledge that explicit models have superior interpretation capabilities with respect to implicit models and can be applied to generate control and information strategies that prevent system over-reaction (Ben-Akiva, 1985), we recognize also that they require a huge effort to achieve an adequately accurate calibration of a large urban network. On the other hand, the enormous amount of available data on urban mobility makes implicit models a valuable alternative, easier to implement and open to possible integrations with explicit models within a hybrid rolling horizon framework that applies an explicit model to forecast traffic states over a time horizon of a few hours and an implicit model that adjusts prior model forecasts on the basis of real-time measures and supplies posterior short-term predictions. Thus, in