Stream Processing and Crowdsourcing for Urban Traffic Management

Thomas Liebig (TU Dortmund, DE)

Joint work of Artikis, Alexander; Bockermann, Christian; Boutsis, Ioannis; Gal, Avigdor; Gunopulos, Dimitrios; Kalogeraki, Vana; Kinane, Dermot; Liebig, Thomas; Mannor, Shie; Marecek, Jakub; Morik, Katharina; Piatkowski, Nico; Schnitzler, Francois; Weidlich, Matthias
URL http://www.insight-ict.eu/

The recent development of innovative technologies related to mobile computing combined with smart city infrastructures is generating massive, heterogeneous data and creating the opportunities for novel applications. In traffic monitoring, the data sources include traditional ones (sensors) as well as novel ones such as micro-blogging applications like Twitter; these provide a new stream of textual information that can be utilized to capture events, or allow citizens to constantly interact using mobile sensors.The long term goal of the related INSIGHT project is to enable traffic managers to detect with a highdegree of certainty unusual events throughout the network. We report on the design of a monitoring system that takes input from a set of traffic sensors, both static (intersection located, traffic flow and density monitoring sensors) and mobile (GPS equipped public transportation buses). We explore the advantages of having such an infrastructure available and address its limitations.We give an overview of the system developed to address the veracity, velocity and sparsity problems of urban traffic management. The system has been developed as part of the European FP7 project INSIGHT under grant 318225. The general architecture is given in [3]. We describe the input and output of the system, the individual components that perform the data analysis, and the stream processing connecting middleware.We base the stream processing based on the Streams framework [2]. Streams provides a XML-based language for the description of data flow graphs that work on sequences of data items which are represented by sets of key-value pairs, i.e. event attributes and their values. The actual processing logic, i.e. the nodes of the data flow graph, is realised by processes that comprise a sequence of processors. Processes take a stream or a queue as input and processors, in turn, apply a function to the data items in a stream. All these concepts are implemented in Java, so that adding customized processors is realised by implementing the respective interfaces of the Streams API. In addition, Streams allows for the specification of services, i.e. sets of functions that are accessible throughout the stream processing application.We extend and apply the system for individual trip planning that incorporates future traffic hazards in routing [3]. Future traffic conditions are computed by a Spatio-Temporal Random Field [6] based on a stream of sensor readings. In addition, our approach estimates traffic flow in areas with low sensor coverage using a Gaussian Process Regression [5, 4]. The conditioning of spatial regression on intermediate predictions of a discrete probabilistic graphical model allows to incorporate historical data, streamed online data and a rich dependency structure at the same time. We demonstrate the system and test model assumptions with a real-world use-case from Dublin city, Ireland.

References

1 A. Artikis, M. Weidlich, F. Schnitzler, I. Boutsis, T. Liebig, N. Piatkowski, C. Bockermann, K. Morik, V. Kalogeraki, J. Marecek, A. Gal, S. Mannor, D. Gunopulos, and D. Kinane. Heterogeneous stream processing and crowdsourcing for urban traffic management. In *Proceedings of the 17th International Conference on Extending Database Technology*, page (to appear), 2014.

2 C. Bockermann and H. Blom. The streams framework. Technical Report 5, TU Dortmund University, 12 2012.

3 T. Liebig, N. Piatkowski, C. Bockermann, and K. Morik. Predictive trip planning - smart routing in smart cities. In *Proceedings of the Workshop on Mining Urban Data at the International Conference on Extending Database Technology*, page (to appear), 2014.

4 T. Liebig, Z. Xu, and M. May. Incorporating mobility patterns in pedestrian quantity estimation and sensor placement. In J. Nin and D. Villatoro, editors, *Citizen in Sensor Networks*, volume 7685 of *Lecture Notes in Computer Science*, pages 67–80. Springer Berlin Heidelberg, 2013.

5 T. Liebig, Z. Xu, M. May, and S. Wrobel. Pedestrian quantity estimation with trajectory patterns. In P. A. Flach, T. Bie, and N. Cristianini, editors, *Machine Learning and Knowledge Discovery in Databases*, volume 7524 of *Lecture Notes in Computer Science*, pages 629–643. Springer Berlin Heidelberg, 2012.

6 N. Piatkowski, S. Lee, and K. Morik. Spatio-temporal random fields: compressible representation and distributed estimation. *Machine Learning*, 93(1):115–139, 2013.