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Speed-Up Heuristics for Traffic Flow Estimation with Gaussian Process Regression

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Extended Abstract

Traffic volume estimation is a natural task in macroscopic street based traffic analysis systems and has important applications, e.g., quality-of-service evaluation, location evaluation or risk analysis. Nowadays, intelligent transportation systems rely on stationary sensors, which provide traffic volume measurements at predefined locations (Kinane et. al., 2014). However, imputation of the unobserved traffic flow values and short term-predictions are highly important research topics (Schnitzler et. al., 2014).

Application of Gaussian Processes is an appealing state-of-the-art method that outperforms recent methods (Liebig et. al., 2013). The method bases on a covariance matrix that denotes the correlations among the traffic flux values at various locations. Due to the computational complexity of Gaussian Process Regression, application to urban areas were restricted either to small sites or a sample of locations (Artikis et. al., 2014). This paper introduces and discusses the application of a speed-up heuristic to Gaussian process regression for the traffic flow estimation problem.

The computational complexity results from the kernel inversion which is part of the Gaussian Process Regression. We relax this global function to a focal one which incorporates not all data at once, but iteratively incorporates the data of the neighborhood. The neighborhood, however, has to be defined in advance. This neighborhood definition should be consistent to the correlation expressed by the kernel function. I.e., if a kernel models correlation based on the spatial closeness, the spatial closest neighbors are most likely the important locations for estimation of the unknown neighbor. Intuitively, this heuristic introduces a Markov assumption, whereas the traffic flow at one location is fully defined by the flow situation of its neighbors. Furthermore, as we want the Gaussian Process Regression to be applicable we may want to fix the kernel size and thereof the number of neighbors being incorporated for traffic flow prediction. This step seems to be

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similar to the k-Nearest Neighbor method. Indeed, with usage of a linear kernel the methods are identical. In general the Markov assumption does not hold (Liebig et. al. 2008, Liebig et. al. 2009) thus appropriate decision on the neighborhood is crucial in this heuristic.

With this heuristic, we expect the Gaussian Process Regression to perform well in smart city applications. We will apply the heuristic in the city of Dublin using traffic loop data of about 620 fixed stationary sensors, compare Figure 1. One smart-city application of this heuristic is the integration in the situation aware tripplanner, we presented in (Liebig et. al. 2014).

Figure 1. Visualization of the traffic loop sensors in Dublin City (red dots) and sketch of the heuristic to use closest neighbors for traffic flow imputation.

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References

Artikis, A., Weidlich, M., Schnitzler, F., Boutsis, I., Liebig, T., Piatkowski, N., Bockermann, C., Morik, K., Kalogeraki, V., Marecek, J., Gal, A., Mannor, S., Gunopulos, D., Kinane, D.: Heterogeneous Stream Processing and Crowdsourcing for Urban Traffic Management, in Proceedings of the 17th International Conference on Extending Database Technology (EDBT), Athens, Greece, (2014), 712-723

Kinane, D., Schnitzler, F., Mannor, S., Liebig, T., Morik, K., Marecek, J., Gorman, B., Zygouras, N., Katakis, Y., Kalogeraki, V., Gunopulos, D.: Intelligent Synthesis and Real-time Response using Massive Streaming of Heterogeneous Data (INSIGHT) and its anticipated effect on Intelligent Transport Systems (ITS) in Dublin City, Ireland, in Proceedings of the 10th ITS European Congress, Helsinki, (2014)

Liebig, T., Körner, C., May, M.: Scalable sparse bayesian network learning for spatial applications. Proceedings of the Workshops of the IEEE International Conference on Data Mining. ICDMW'08, Pisa, Italy, IEEE Press (2008) 420-425

Liebig, T., Körner, C., May, M.: Fast visual trajectory analysis using spatial bayesian networks. Proceedings of the Workshops of the IEEE International Conference on Data Mining. ICDMW'09, Miami, USA, IEEE Press (2009) 668-673

Liebig, L., Xu, Z., May, M.: Incorporating Mobility Patterns in Pedestrian Quantity Estimation and Sensor Placement, in Citizen in Sensor Networks, Springer Berlin Heidelberg, (2013), 67-80

Liebig, T., Piatkowski, N., Bockermann, C., Morik, K.: Predictive Trip Planning – Smart Routing in Smart Cities, in Proceedings of the Workshops of the EDBT/ICDT Joint Conference (EDBT/ICDT 2014), Athens, Greece, (2014), 331-338

Liebig, T., Piatkowski, N., Bockermann, C., Morik, K.: Route Planning with Real-Time Traffic Predictions, in Proceedings of the 16th LWA Workshops: KDML, IR and FGWM, Aachen, Germany, (2014), 83-94

Schnitzler, F., Artikis, A., Weidlich, M., Boutsis, I., Liebig, T., Piatkowski, N., Bockermann, C., Morik, K., Kalogeraki, V., Marecek, J., Gal, A., Mannor, S., Kinane, D., Gunopulos, D.: Heterogeneous Stream Processing and Crowdsourcing for Traffic Monitoring: Highlights, in Machine Learning and Knowledge Discovery in Databases, Springer Berlin Heidelberg, vol. 8726, (2014), 520-523.