

In a Nutshell

This demonstration presents our uncertain-spatio-temporal (UST-) framework that we have developed in recent years. The main research focus of this UST-framework is the explicit consideration of uncertainty in spatio-temporal data. The UST-framework can be used to obtain a deeper intuition of the quality of spatio-temporal data models. Such models aim at estimating the position of a spatio-temporal object at a time where the object's position is not explicitly known, by using both historic (traffic-) pattern information, and by using explicit observations of objects.

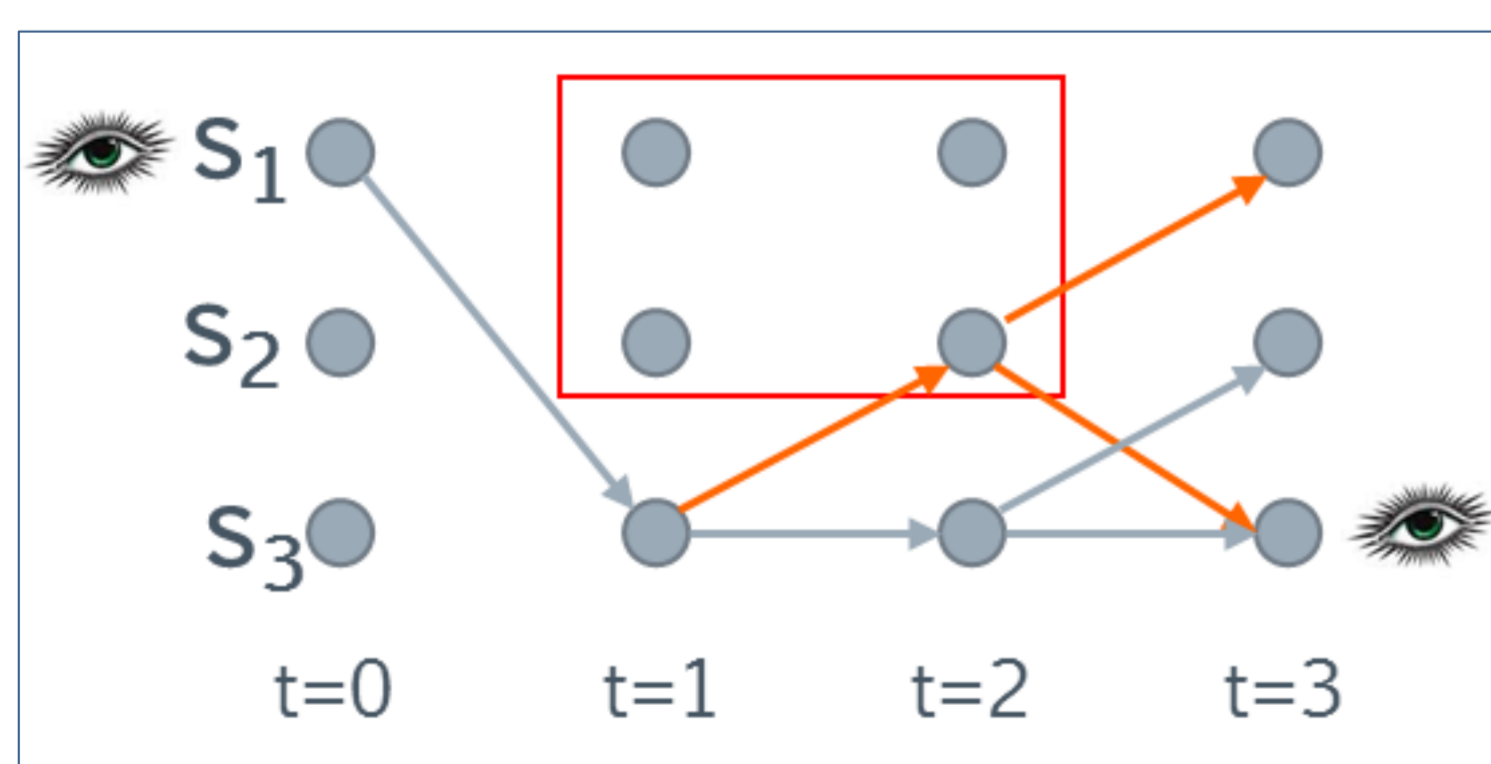
The UST-framework illustrates the resulting distributions by allowing a user to move forth and back in time. Additionally, the framework allows users to specify simple spatio-temporal queries, such as spatio-temporal window queries and spatio-temporal NN-queries. Based on recently published theoretic concepts, the UST-framework allows the user to visually explore the impact of different models and parameters on spatio-temporal data. The main result showcased by the UST-framework is a convincing minimization of uncertainty by employing stochastic processes, leading to small expected distances between ground truth trajectories and modelled positions.

Theory

- Model spatio-temporal objects as stochastic processes.
- Family of Random variables $(X)_t$ parameterized over time.
- Estimate the position of an object at a time t where the exact position of an object is not explicitly stored in the database.
- Maximum Likelihood Estimation using
 - Observations of objects
 - Empiric knowledge of traffic patterns

Bayesian Learning

Condition a Markov-Model to observations in the past and in the future



Compute a-priori state probabilities in a forward-step.

Use a-priori knowledge to obtain adapted a-posteriori probabilities given all observations.

$$P(\blacksquare|\text{eyes}) = \frac{P(\text{eyes}|\blacksquare) * P(\blacksquare)}{P(\text{eyes})} = \frac{P(\blacksquare \wedge \text{eyes})}{P(\text{eyes})}$$

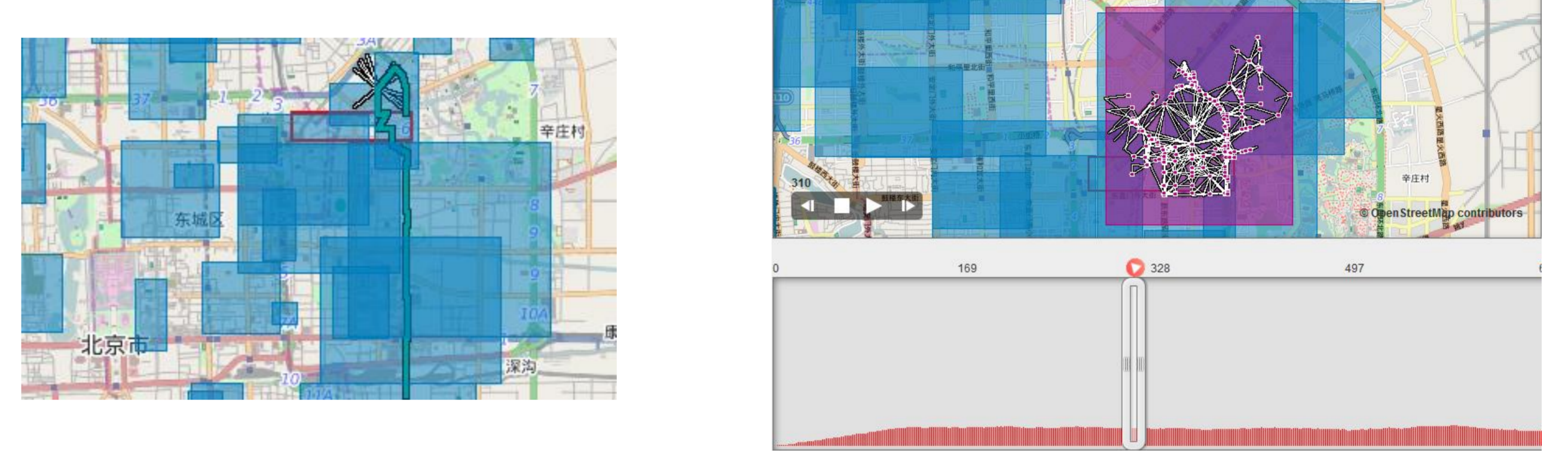
$$= \frac{P(\blacksquare \wedge \text{eyes})}{P(\text{eyes} \wedge \blacksquare) + P(\text{eyes} \wedge \neg \blacksquare)}$$

Fusion of Data Sources:

- Empiric traffic information stored in the a-priori Markov Chain
- Concrete observations of individual objects
- Yields a new model adapted to observations, describing unknown detours by empiric knowledge.

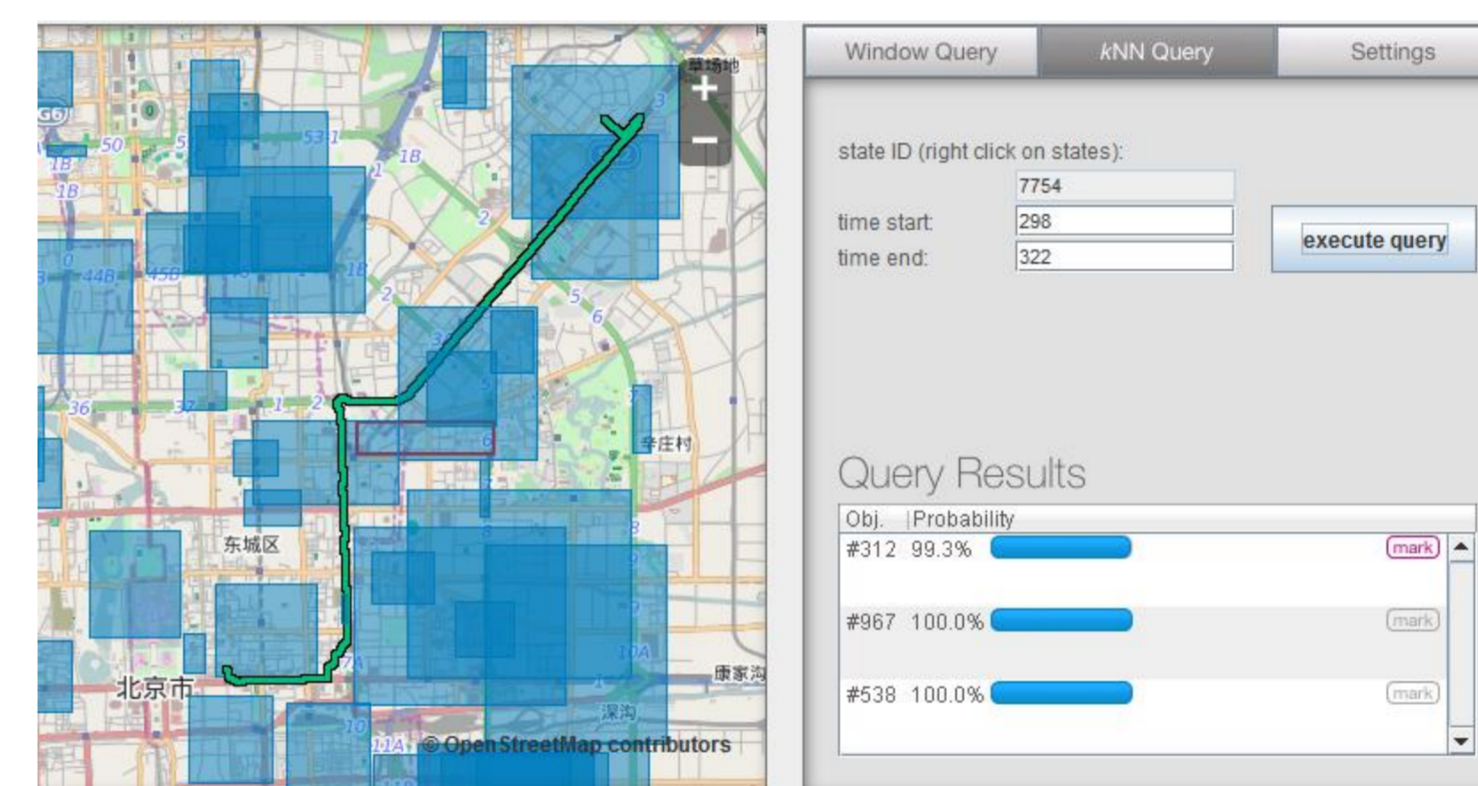
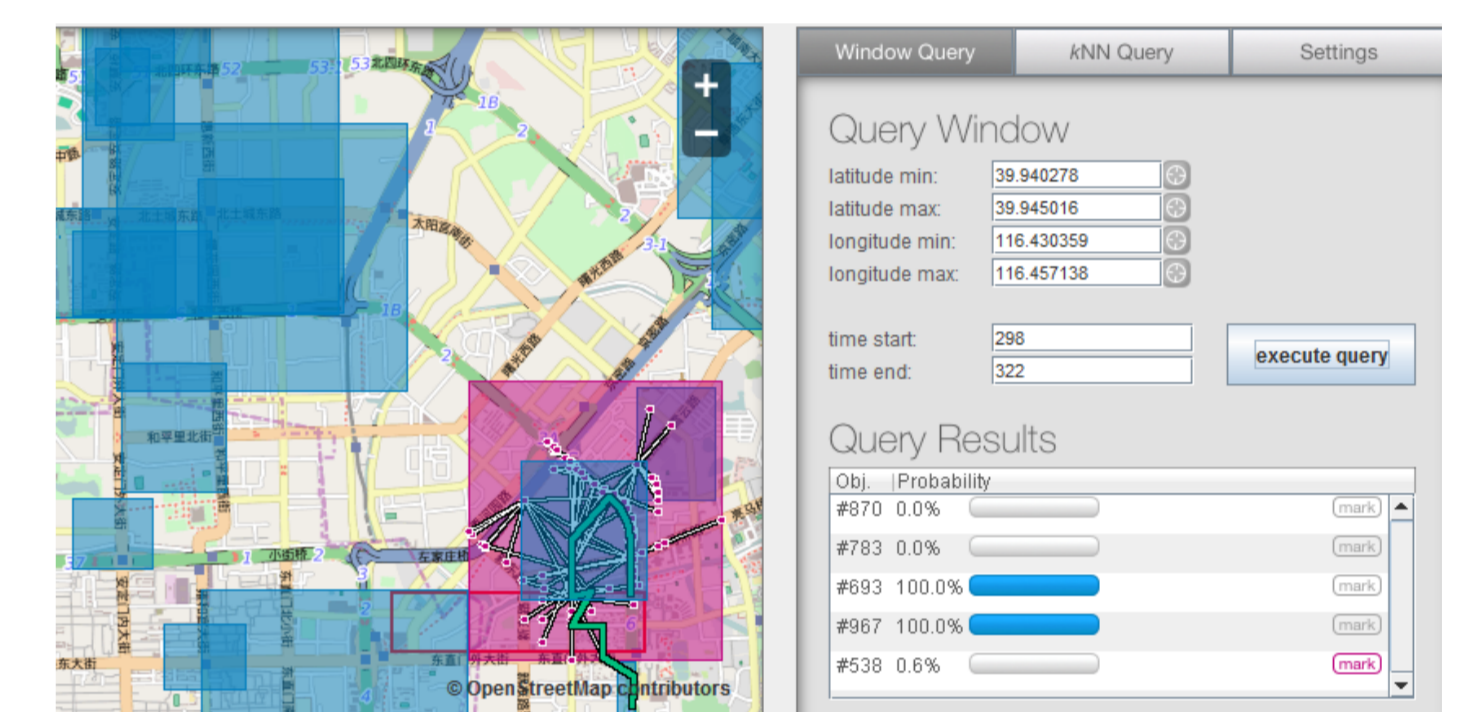
The Framework

- Visualize Spatio-Temporal Data



- Explore different interpolation models
 - Linear and Shortest-Path Interpolation
 - Geometric Models, e.g. [4]
 - Markov Models [1]
 - Bayesian Markov-Chain Adaption Model [3]
- Index support for query processing [2]
- Visualization of Query Results

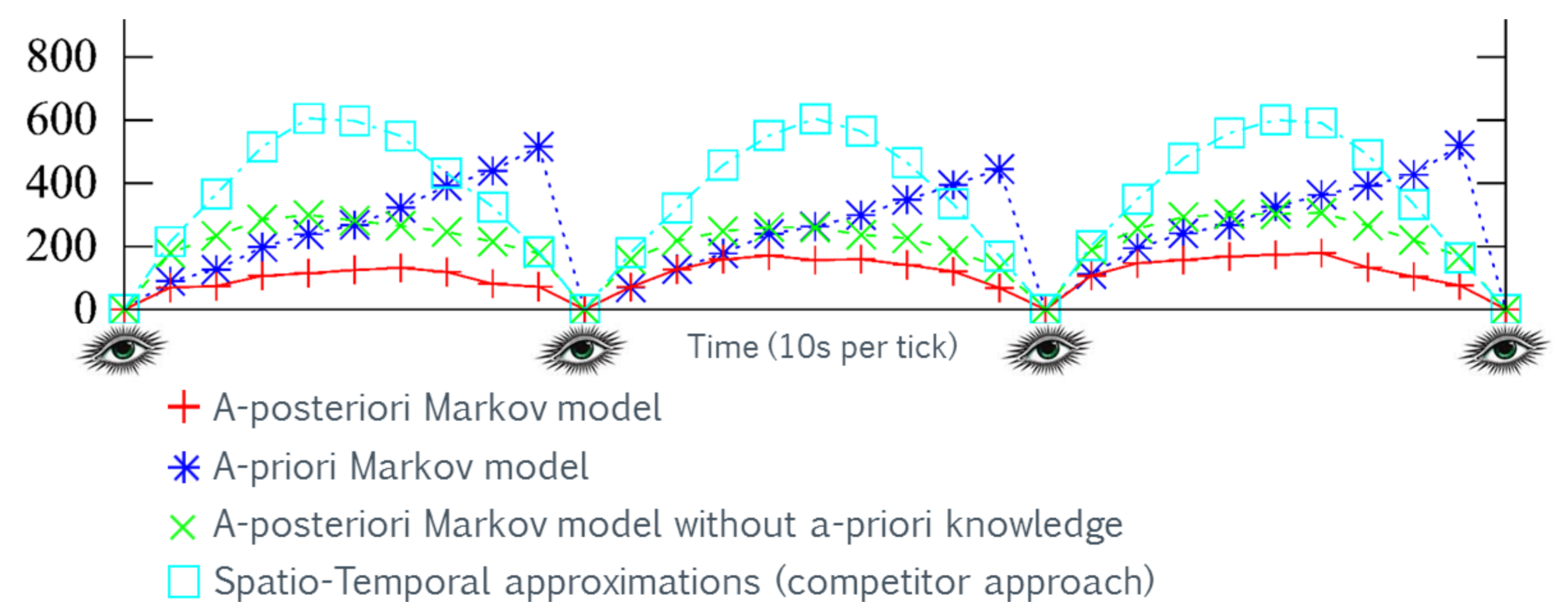
- Window Queries



- Nearest-Neighbor Queries

Model Evaluation

Evaluation of expected distances to the ground truth trajectory



[1] T. Emrich, H.-P. Kriegel, N. Mamoulis, M. Renz, and A. Züfle. Querying uncertain spatio-temporal data. In ICDE'12, pp. 354-365.

[2] T. Emrich, H.-P. Kriegel, N. Mamoulis, M. Renz, and A. Züfle. Indexing uncertain spatio-temporal data. In CIKM'12, pp.395-404.

[3] J. Niedermayer, A. Züfle, T. Emrich, M. Renz, N. Mamoulis, L. Chen, and H.-P. Kriegel. Probabilistic nearest neighbor queries on uncertain moving object trajectories. In VLDB, 2014.

[4] G. Trajcevski, O. Wolfson, K. Hinrichs, and S. Chamberlain. Managing uncertainty in moving objects databases. ACM Trans. Database Syst., 29(3):463-507, 2004.