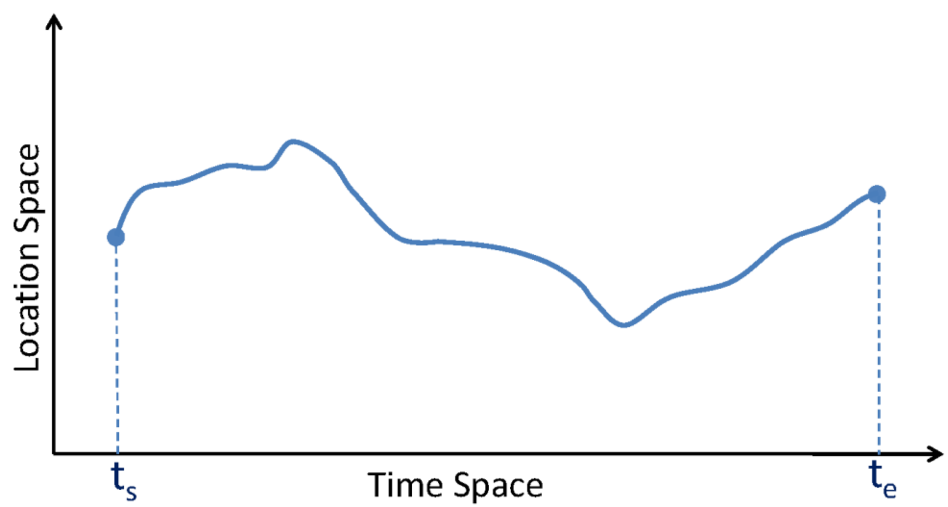
LMU
Ludwig-Maximilians-Universität München
Institut für Informatik
Lehr- und Forschungseinheit für Datenbanksysteme
香 港 大 學
THE UNIVERSITY OF HONG KONG

Querying Uncertain Spatio-Temporal Data

Tobias Emrich, Hans-Peter Kriegel, Matthias Renz, Andreas Züfle (LMU)
Nikos Mamoulis (HKU)

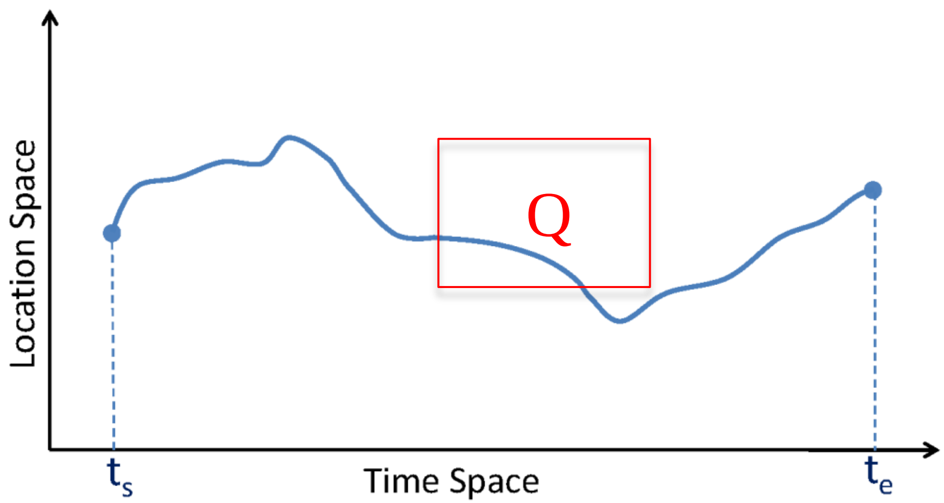
What is (certain) Spatio-Temporal Data?

- A spatio-temporal database stores triples (oid, time, loc)
- In the best case, this allows to look up the location of an object at any time



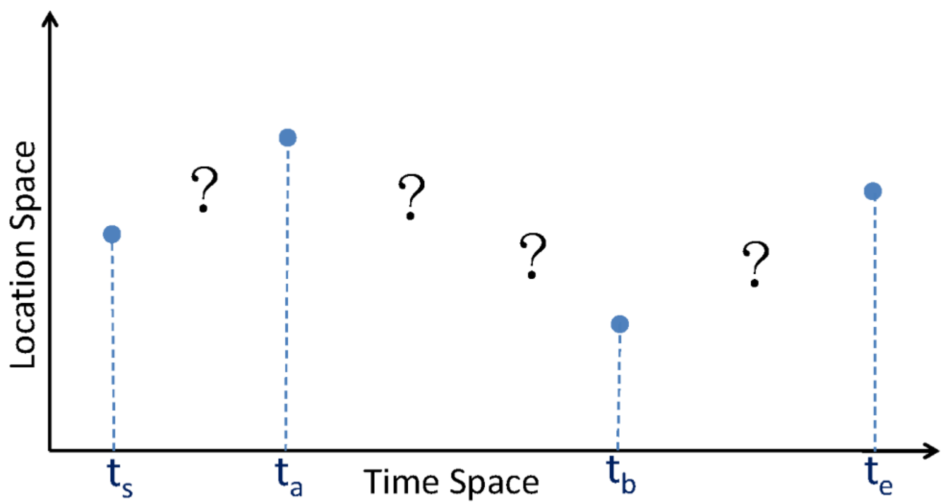
What is (certain) Spatio-Temporal Data?

- A spatio-temporal database stores triples (oid, time, loc)
- In the best case, this allows to look up the location of an object at any time
- Allows to answer queries such as *Return objects that intersects some spatial window within some time interval.*



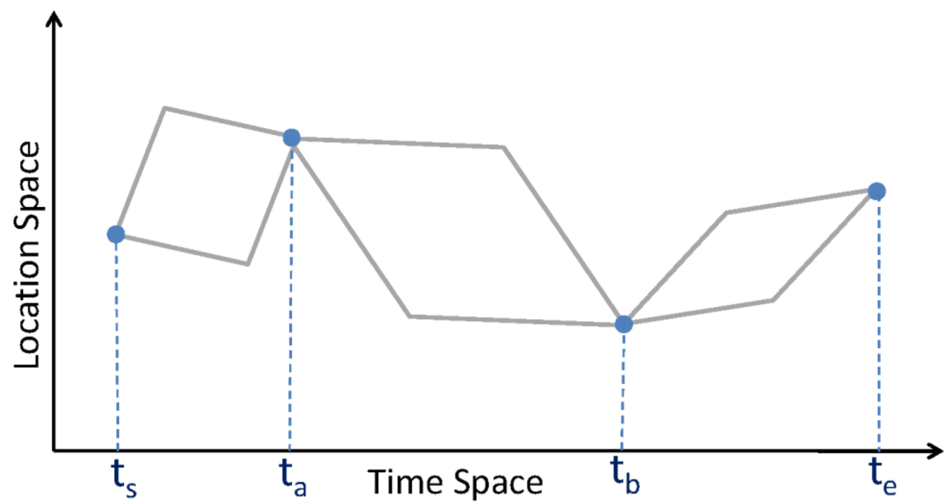
What is uncertain Spatio-Temporal Data?

- In most applications, this data is not complete
  - Delays between GPS signals
  - RFID sensors located only in certain locations
  - Wireless sensors nodes sending infrequently to preserve power
  - Geo-application check-ins



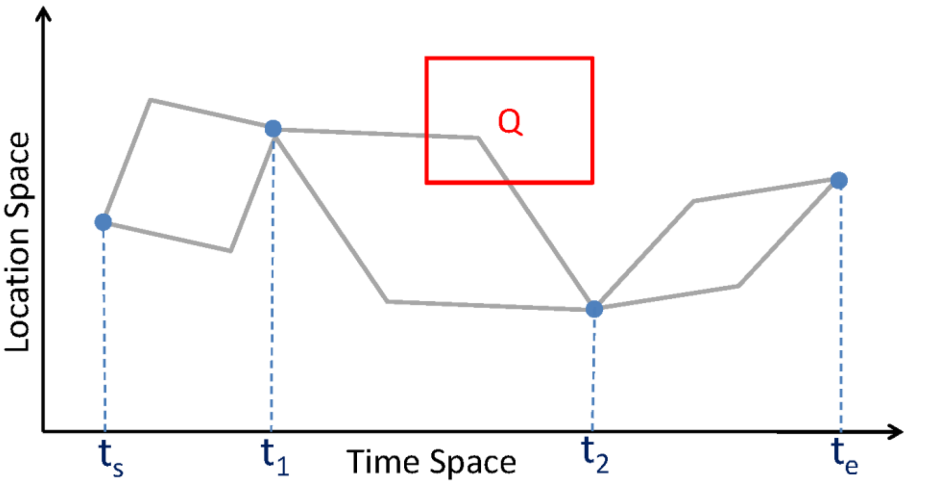
What is uncertain Spatio-Temporal Data?

- Existing works
  - Bound the set of possible (location,time) pairs of an object between observations
  - e.g. by modeling knowledge about maximum speed



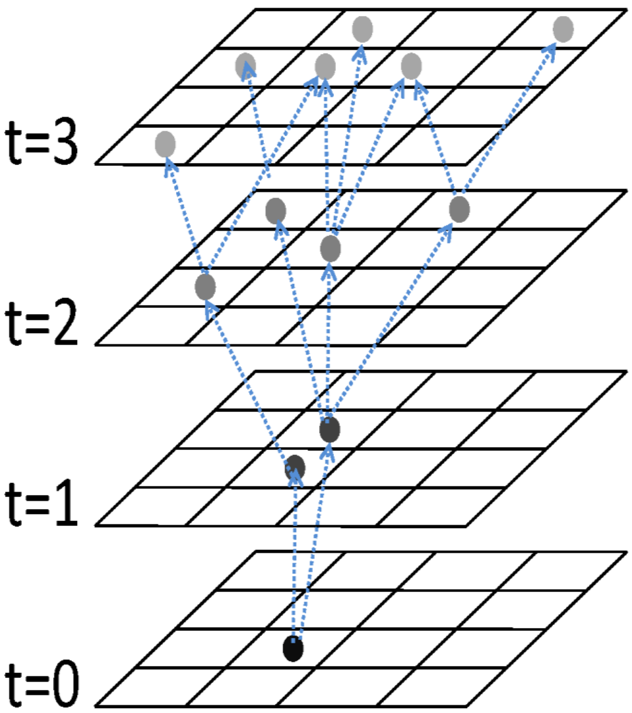
What is uncertain Spatio-Temporal Data?

- Existing works
  - Bound the set of possible (location,time) pairs of an object between observations
  - e.g. by modeling knowledge about maximum speed
  - Allows to make statements like „its possible that o intersects some query window Q“
  - But how likely is this event?



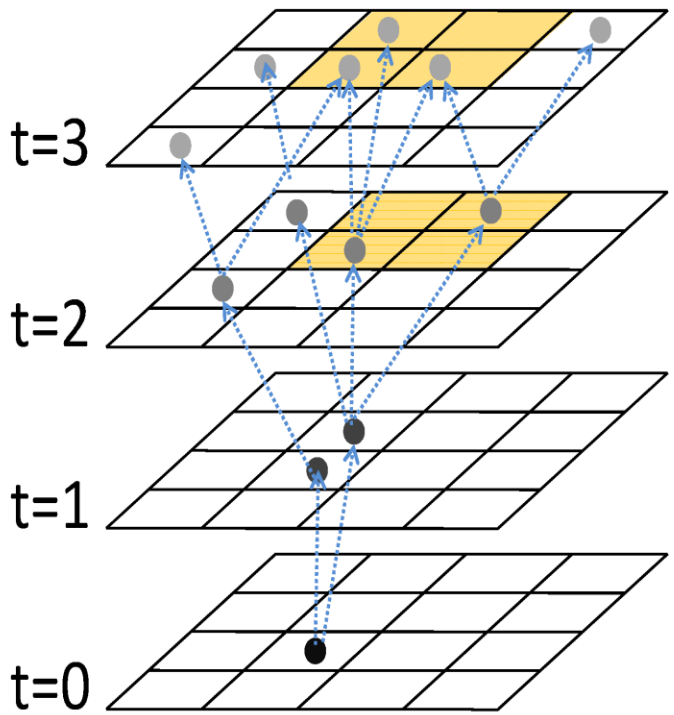
Modeling Spatio-Temporal Uncertainty

- The position of an object o a some time t is a random variable
- The trajectory of o follows a stochastic process, i.e. a family of random variables o(t)



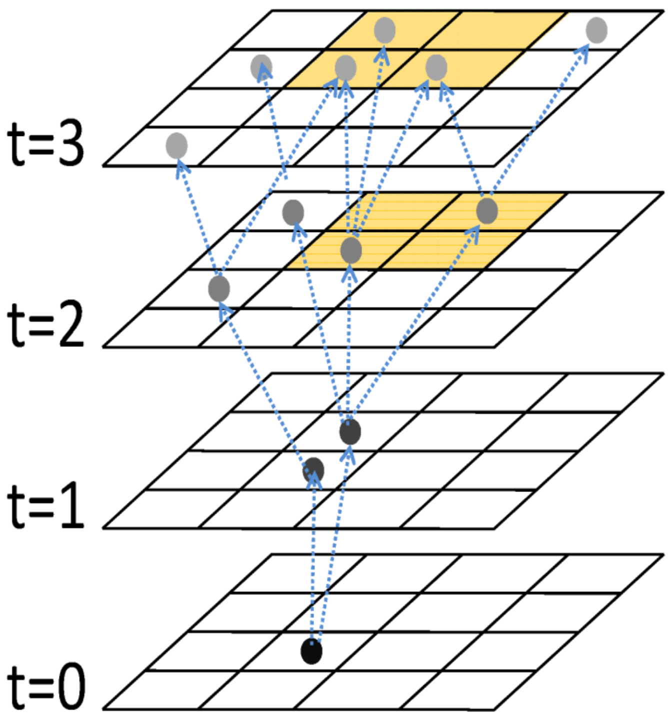
Modeling Spatio-Temporal Uncertainty

- The position of an object o a some time t is a random variable
- The trajectory of o follows a stochastic process, i.e. a family of random variables o(t)
- Given a predicate φ, the event that o satisfies φ is a random event.



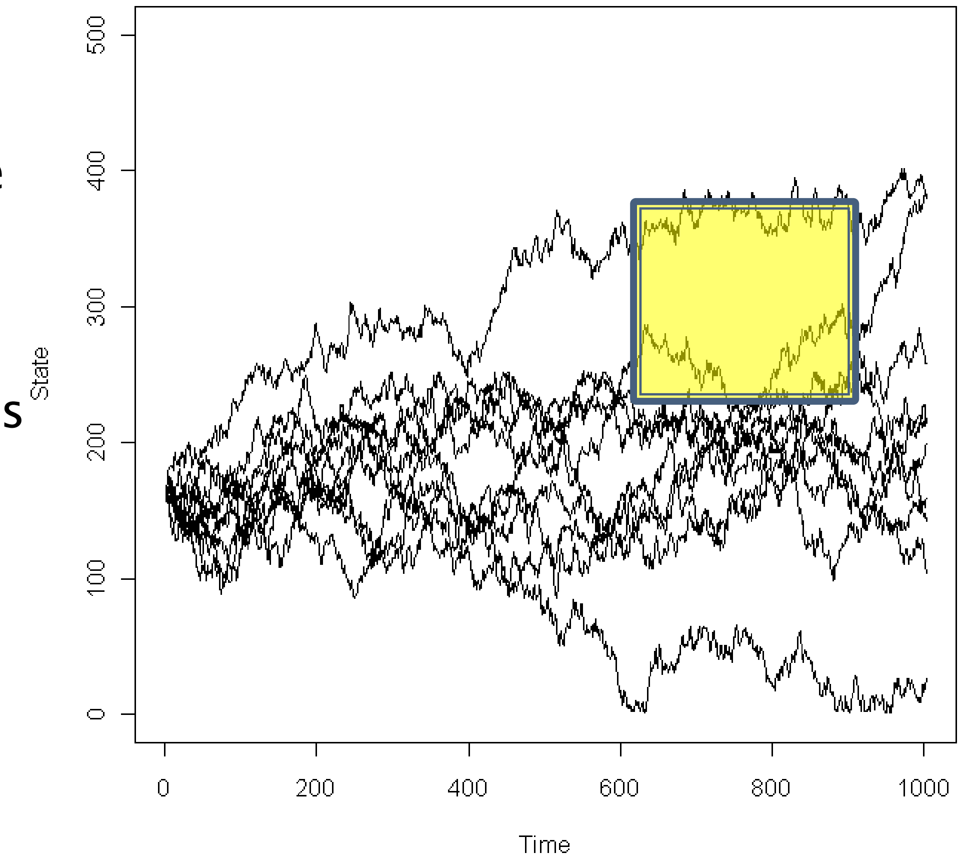
Markov-Chain Model

- Assumes discrete state space S and discrete time space T
- Given the position of an object o at time t=i, the position at t=i+1 is conditionally independent of t=i-1
- Transition probabilities stored in a (sparse) |State|x|State| matrix M(o,t), called transition matrix
- M(o,t)[i,j] is the probability that object o will transition to state j at time t+1, given o is located at state i at time t
- Use sparse matrix operations for efficient implementation



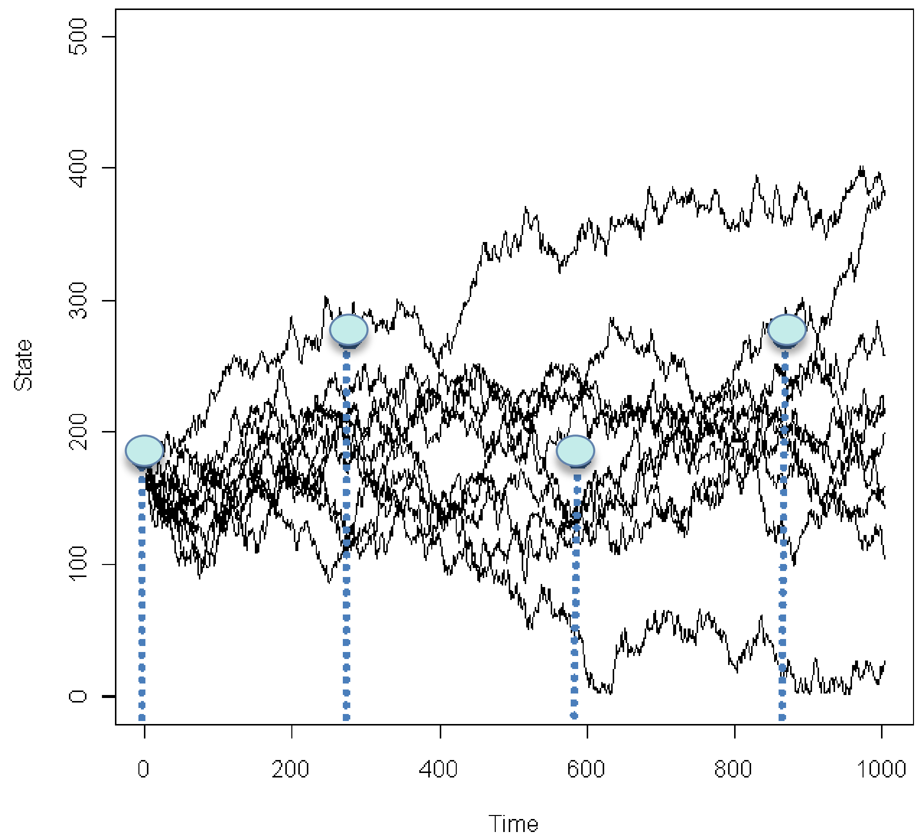
State of the art

- Monte-Carlo
  - Given a single observation, use the model to sample possible worlds.
  - The fraction of such worlds satisfying the query predicate is an unbiased estimator of the true probability.



State of the art

- Monte-Carlo
  - Problem:
    - Cannot handle multiple observations
    - Most samples will miss further observations
    - Expected number of samples to aquire a „good“ sample grows exponentially



Paradigm for Query Processing in probabilistic databases

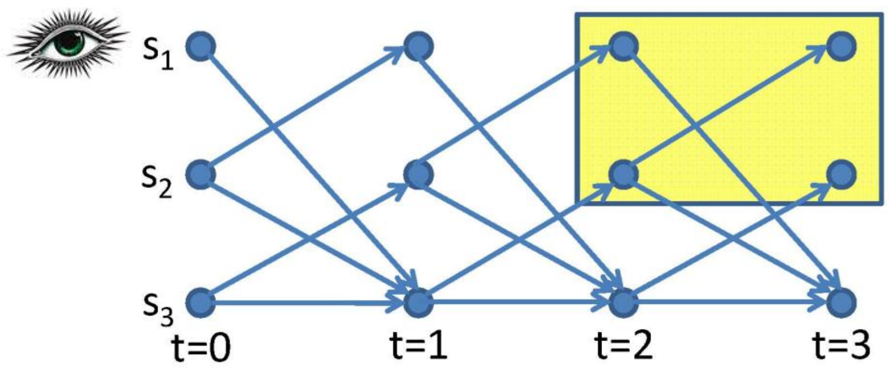
- Given a probabilistic database representing a exponential number of possible worlds.
- Given some query predicate φ, identify a polynomial set of disjunctive classes of possible worlds that are equivalent with respect to φ.
- Perform query processing using these classes.
- In the following, this paradigm will be used to answer probabilistic window queries such as *Return for each object* $o \in DB$ the probability $P(o, \blacksquare)$ that o intersecets a given spatial query window at any time within a given query time interval.

Apply this Paradigm to Markov-Chains

- For window queries, we only need to consider the follow classes:
  - The class of worlds that intersect the window – regardless of their state.
  - For the remaining worlds, one class s_i for each spatial state

Example

$$M(o,t) = M = \begin{pmatrix} 0 & 0 & 1 \\ 0.6 & 0 & 0.4 \\ 0 & 0.8 & 0.2 \end{pmatrix}$$



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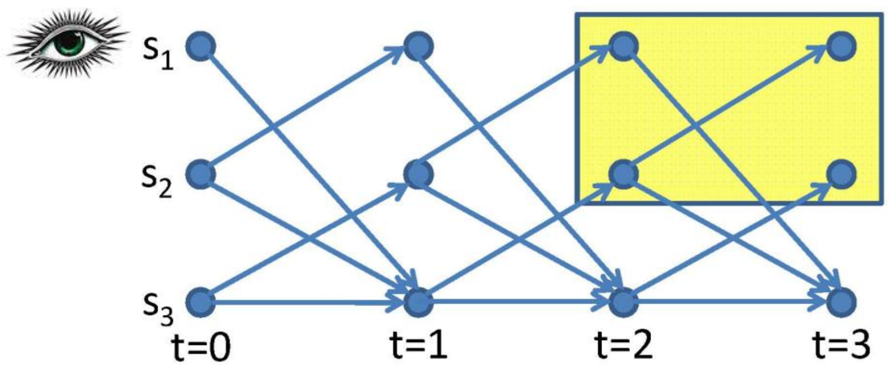

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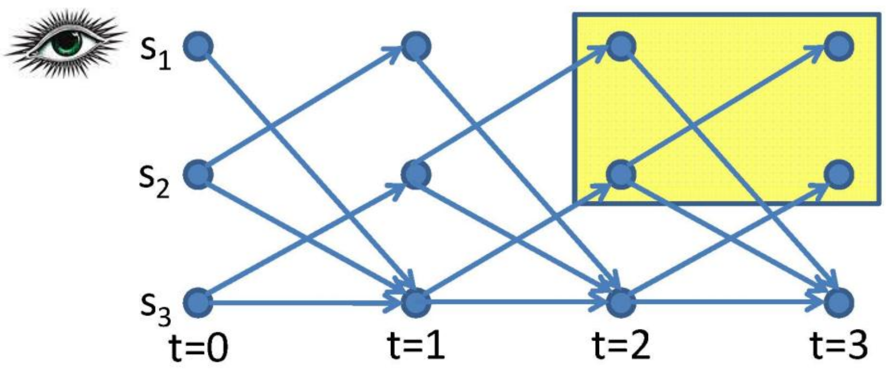

$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

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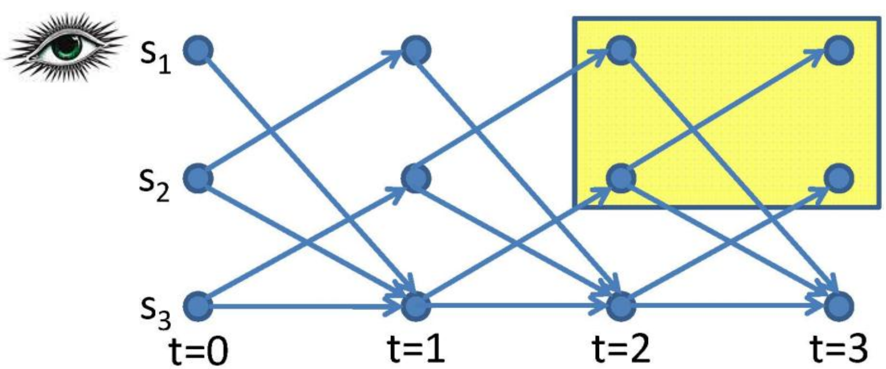

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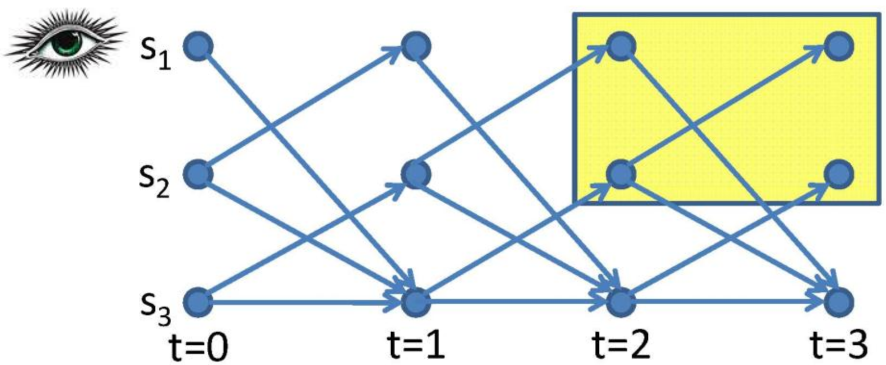
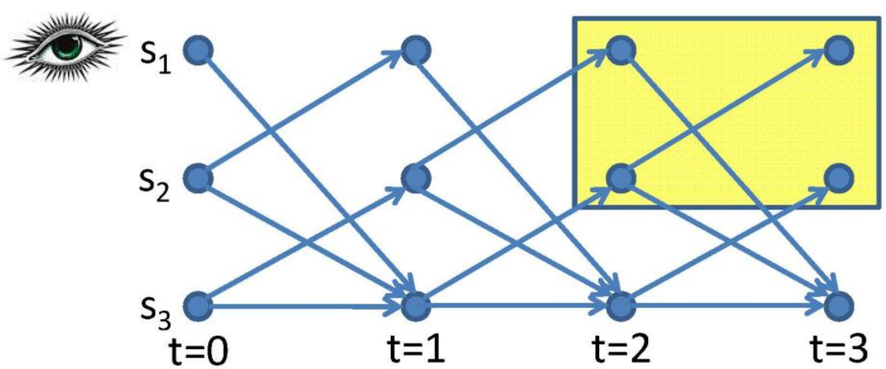


$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \quad \begin{pmatrix} 0 \\ 0.8 \\ 0.2 \end{pmatrix} \quad \begin{pmatrix} 0.48 \\ 0.1 \\ 0.42 \end{pmatrix}$$

Example

$$M = \begin{pmatrix} 0 & 0 & 1 \\ 0.6 & 0 & 0.4 \\ 0 & 0.8 & 0.2 \end{pmatrix}$$

$$M^- = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0.6 & 0 & 0.4 & 0 \\ 0 & 0.8 & 0.2 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad M^+ = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0.4 & 0.6 \\ 0 & 0 & 0.2 & 0.8 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$



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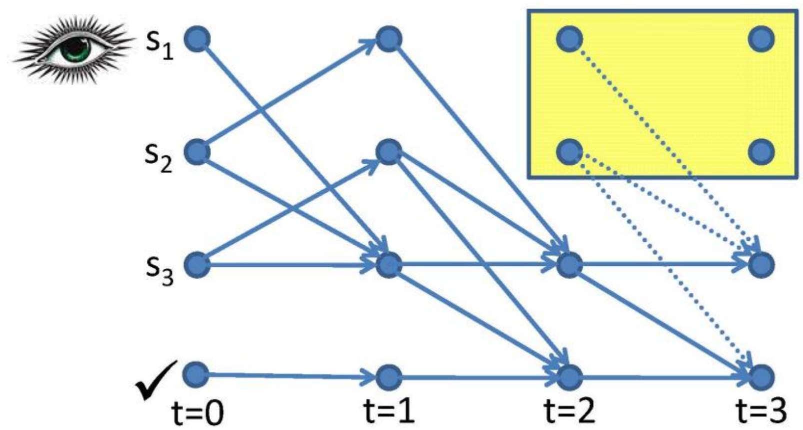

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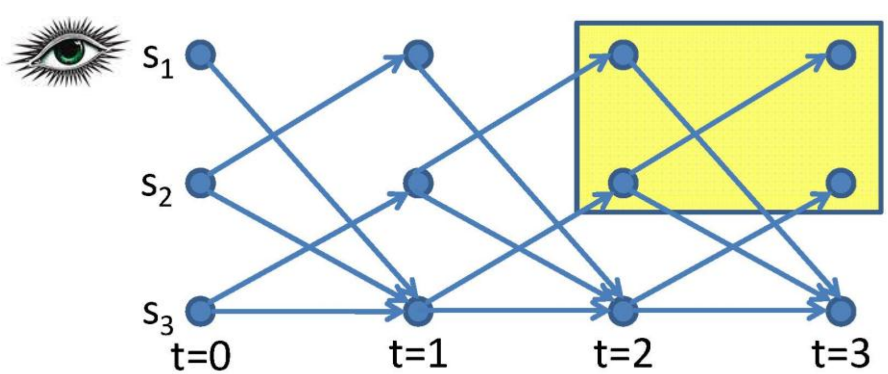

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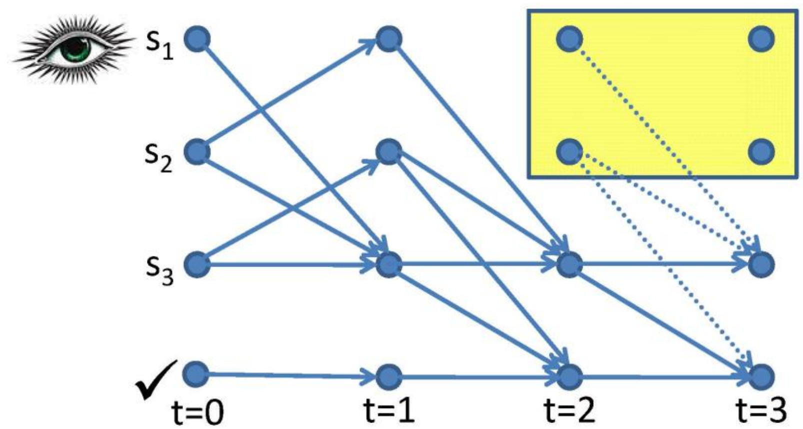

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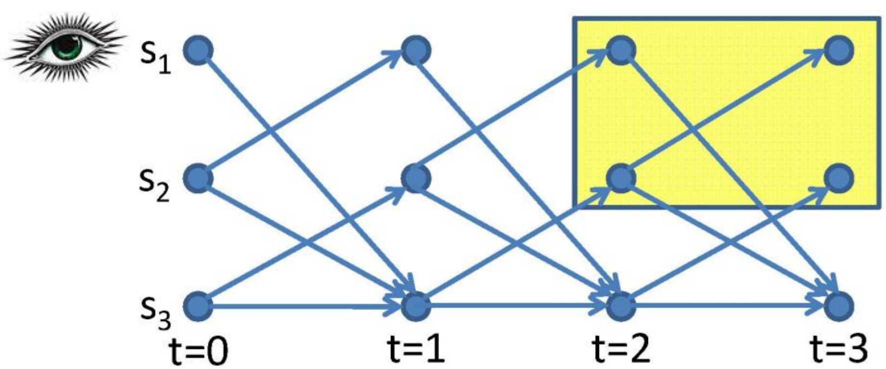

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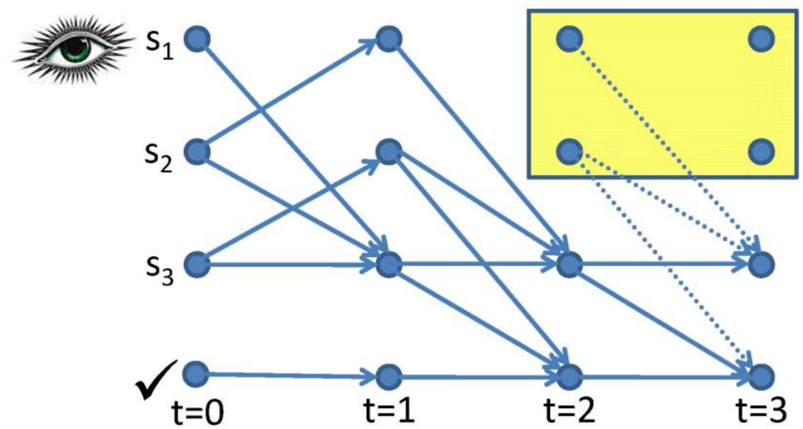

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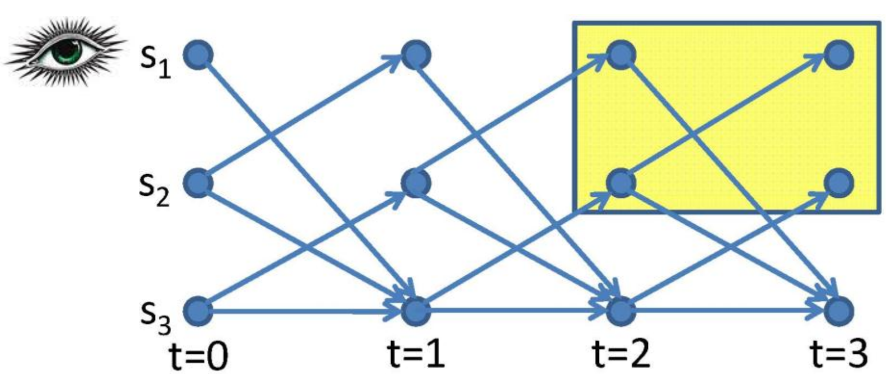

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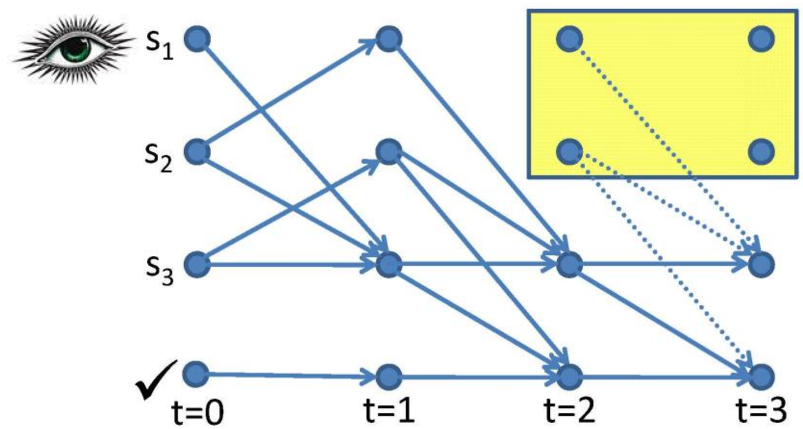
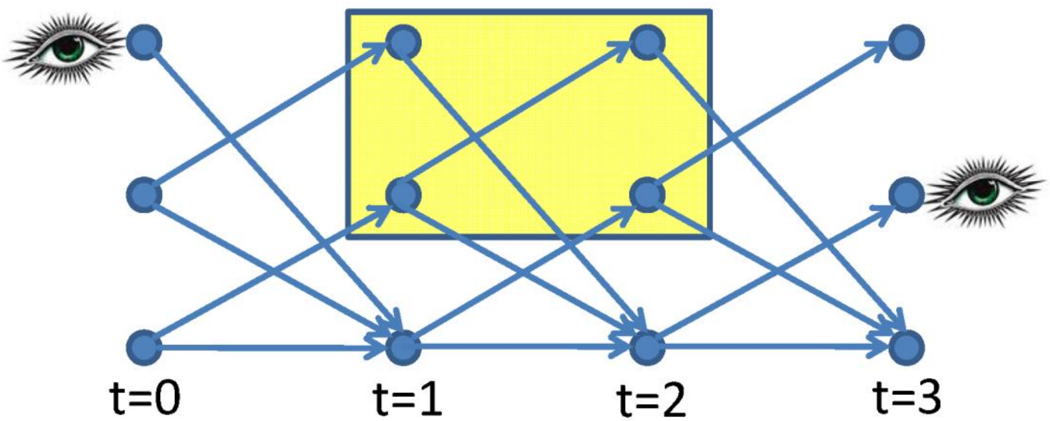


$$\begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} \quad \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \end{pmatrix} \quad \begin{pmatrix} 0 \\ 0 \\ 0.2 \\ 0.8 \end{pmatrix} \quad \begin{pmatrix} 0 \\ 0 \\ 0.04 \\ 0.96 \end{pmatrix}$$

$$P(\blacksquare) = 0.96$$

Multi-Observation-Case: Example



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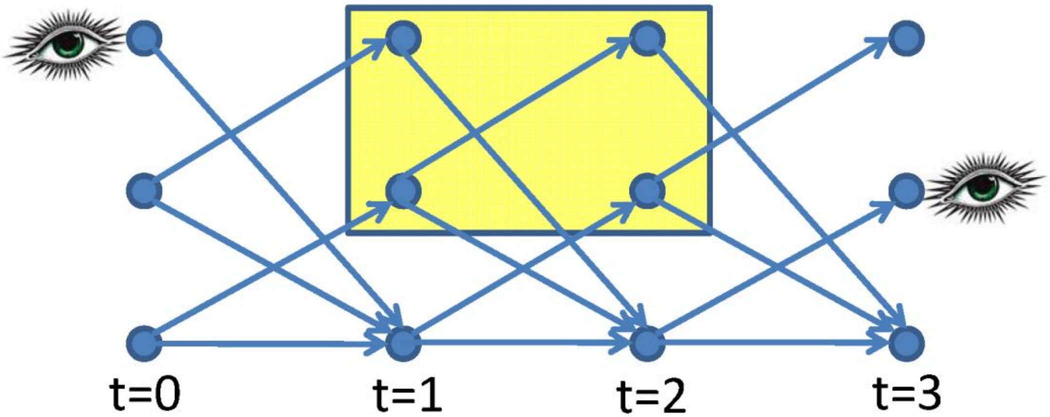
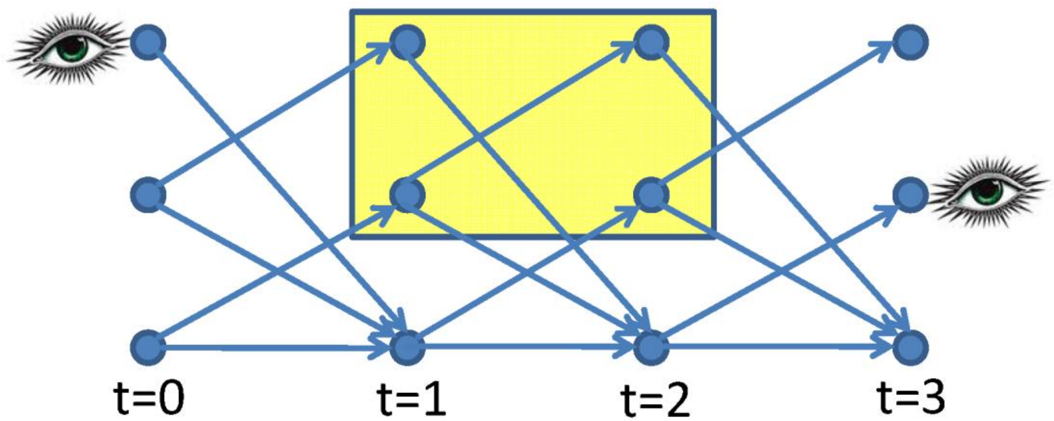


- We need to track where true hit worlds are located
  - 2*|S| classes of equivalent worlds
  - One class S_i– corresponding to worlds where o is located in state S_i, and o has not intersected the window
  - One class S_i+ corresponding to worlds where o is located in state S_i, and o has not intersected the window

Multi-Observation-Case: Example



$$\begin{matrix} S_1 - \\ S_2 - \\ S_3 - \\ S_1 + \\ S_2 + \\ S_3 + \end{matrix} \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

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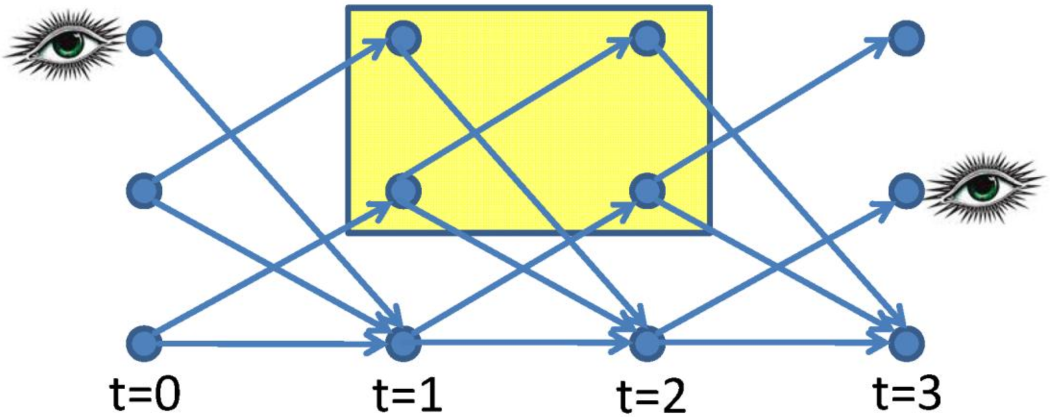

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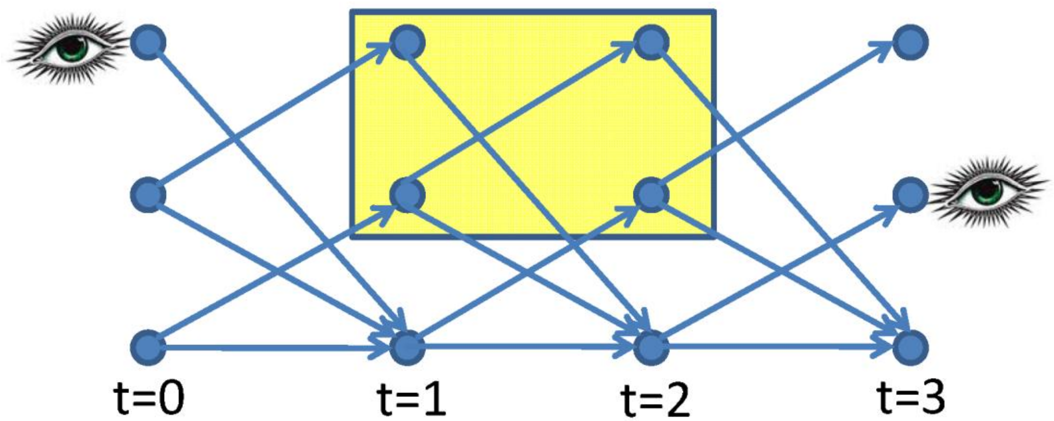

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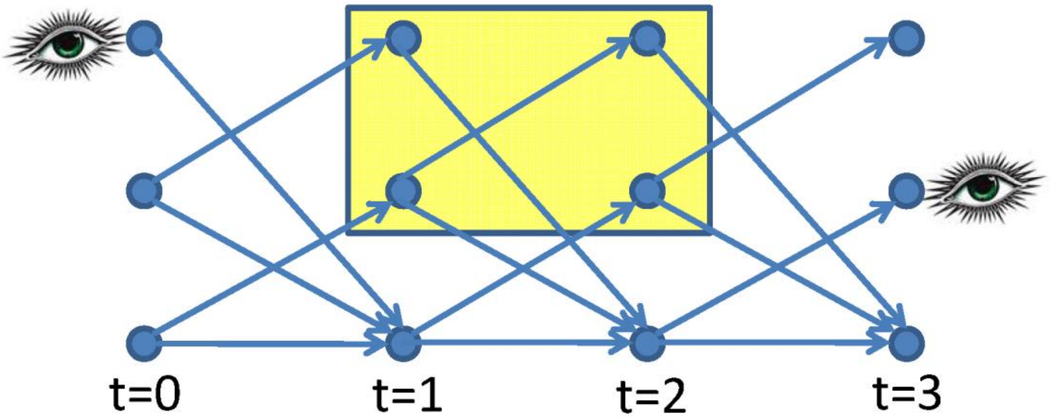

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Add knowledge to the model: Bayesian Approach

$$P(\blacksquare \mid \cdot) \overset{?}{=}$$

$$\begin{matrix} S_1 - \\ S_2 - \\ S_3 - \\ S_1 + \\ S_2 + \\ S_3 + \end{matrix} \begin{pmatrix} 0 \\ 0.16 \\ 0.04 \\ 0.48 \\ 0 \\ 0.32 \end{pmatrix}$$

Add knowledge to the model: Bayesian Approach

$P(\blacksquare \mid$  $) = \dfrac{P(}{}$  $\mid \blacksquare) * P(\blacksquare)$ / $P($  $)$

$$\begin{matrix} S_1 - \\ S_2 - \\ S_3 - \\ S_1 + \\ S_2 + \\ S_3 + \end{matrix} \begin{pmatrix} 0 \\ 0.16 \\ 0.04 \\ 0.48 \\ 0 \\ 0.32 \end{pmatrix}$$

Add knowledge to the model: Bayesian Approach

$P(\blacksquare \mid$  $) = \dfrac{P(}{}$  $\mid \blacksquare) * P(\blacksquare)$ / $P($  $)$

$= P(\blacksquare \wedge$  $)$ / $P($  $)$

$$
\begin{matrix} S_1 - \\ S_2 - \\ S_3 - \\ S_1 + \\ S_2 + \\ S_3 + \end{matrix}
\begin{pmatrix} 0 \\ 0.16 \\ 0.04 \\ 0.48 \\ 0 \\ 0.32 \end{pmatrix}
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$$P(\blacksquare \mid \text{👁}) = \frac{P(\text{👁} \mid \blacksquare) * P(\blacksquare)}{P(\text{👁})}$$

$$= \frac{P(\blacksquare \wedge \text{👁})}{P(\text{👁})}$$

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

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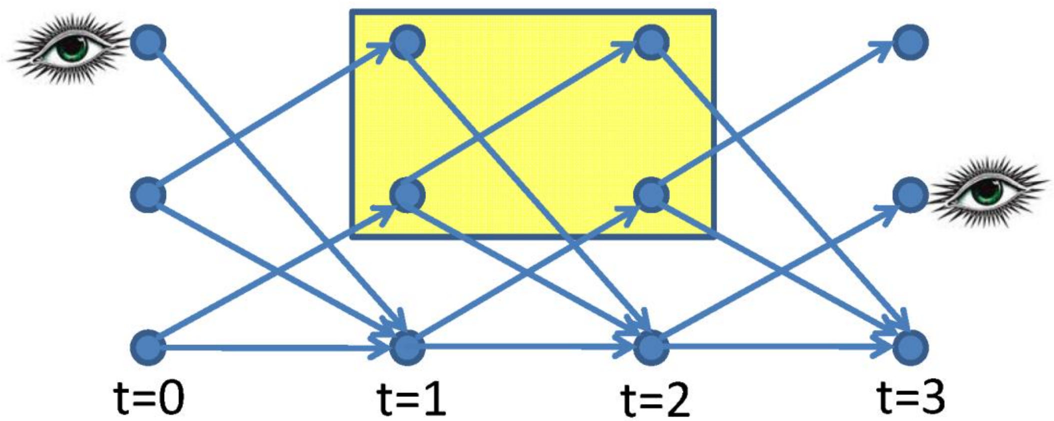
$$= \frac{P(\blacksquare \wedge \text{👁})}{P(\text{👁} \wedge \blacksquare) + P(\text{👁} \wedge \neg \blacksquare)}$$

$$= \frac{0}{0 + 0.16} = 0$$

Multi-Observation-Case: Example



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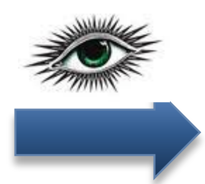
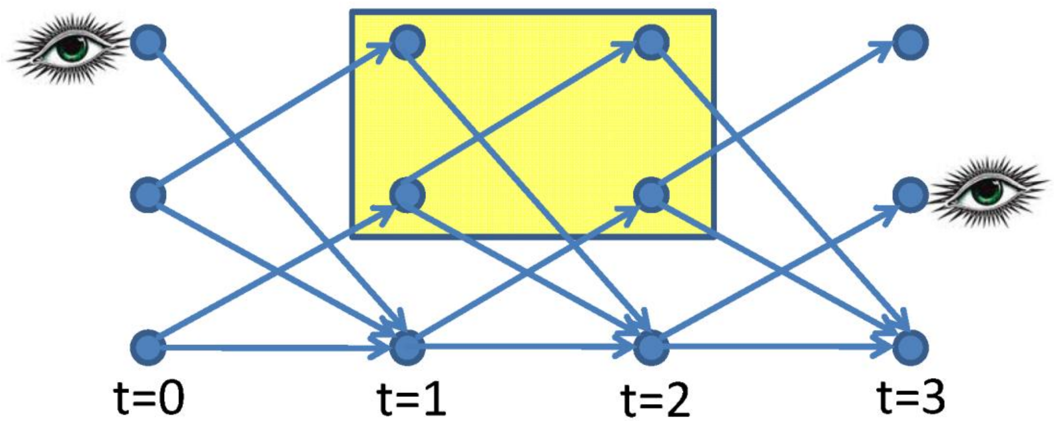


$$\begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

Multi-Observation-Case: Example



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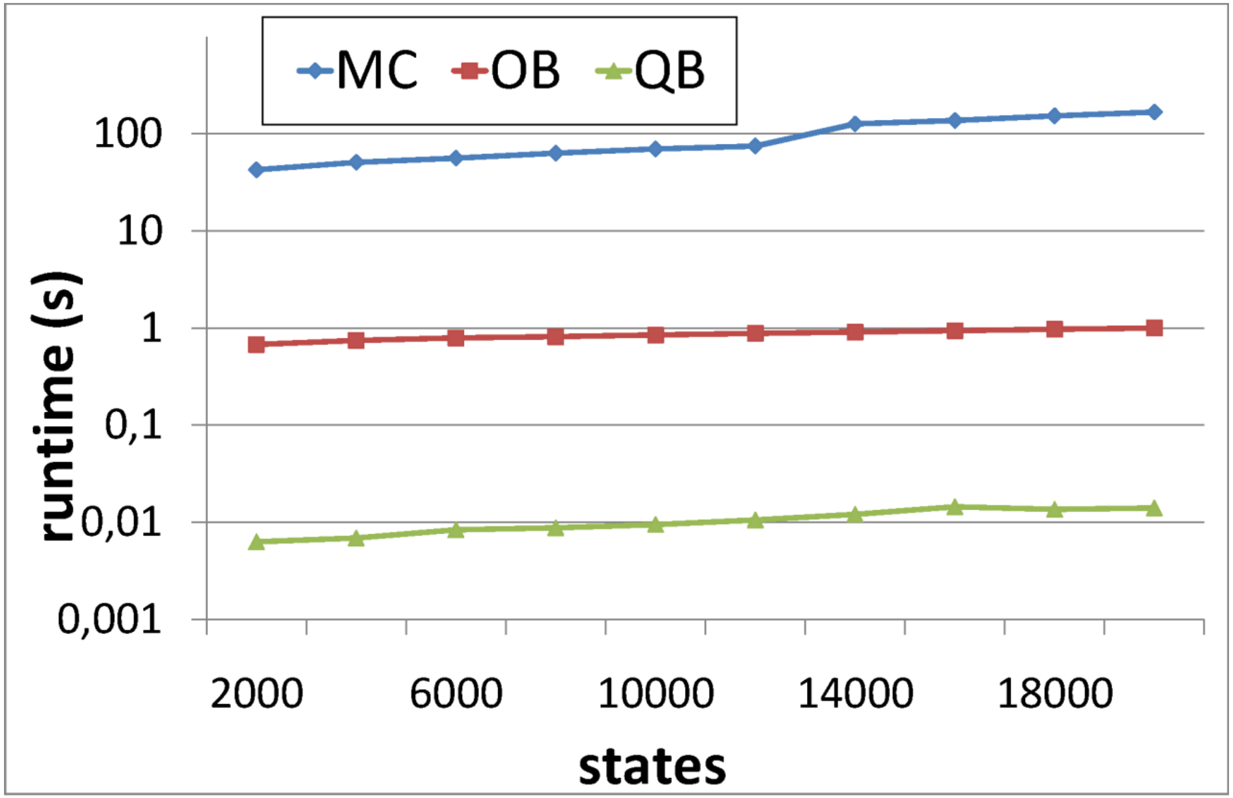
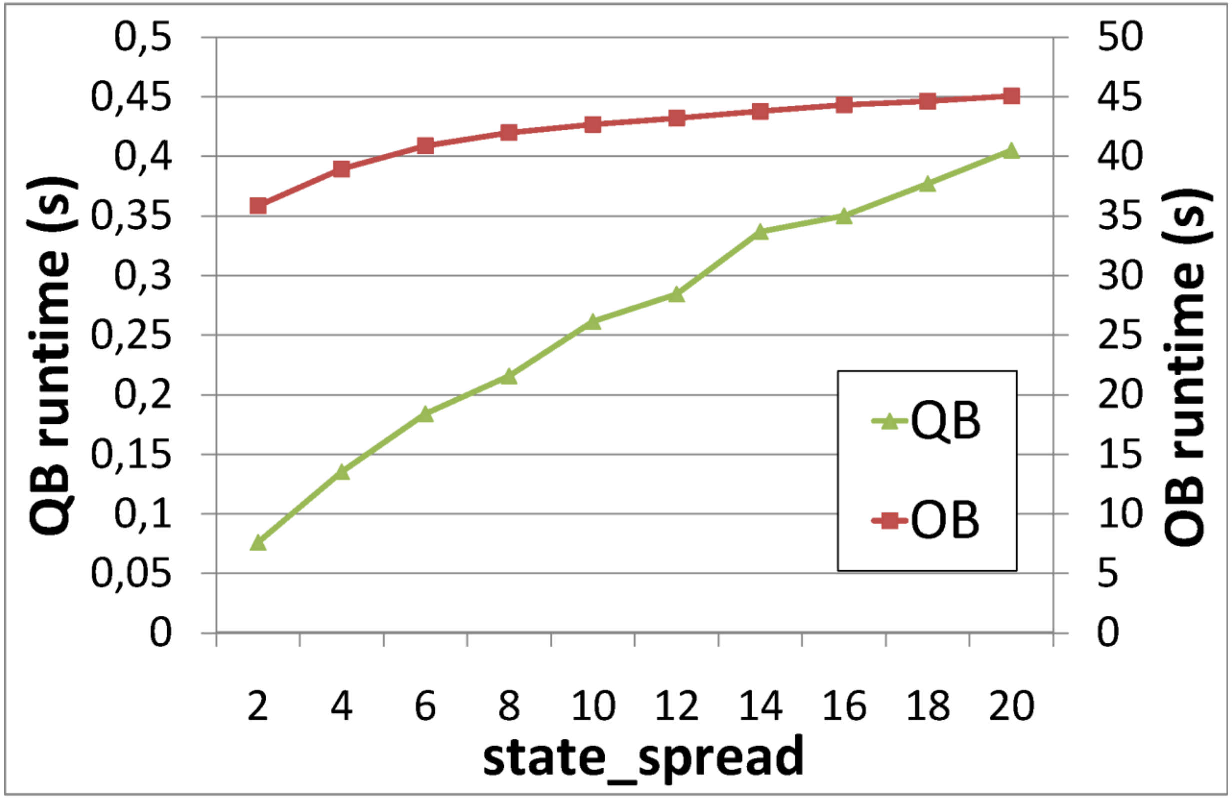
Experimental Evaluation



Experimental Evaluation



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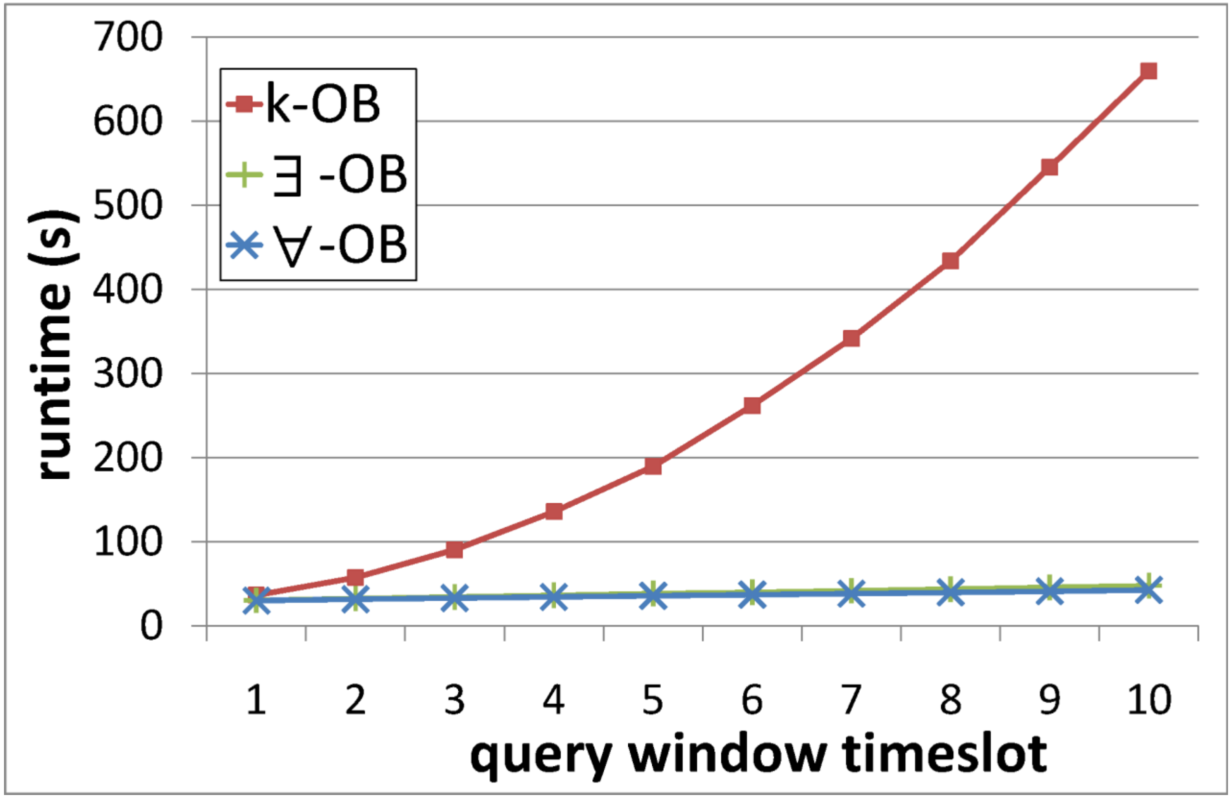

Summary

- In many applications, uncertainty of data is inherent
- Ignoring uncertainty may yield wrong results
- Use stochastic processes to model the movement of objects between observations
- Augment the processes with efficient probabilistic query processing techniques
- Use Bayesian inference to incorporate new observations

Future Work

- Indexing of uncertain spatio-temporal data
- Different query predicates (e.g. Eps-range, kNN, ...)
- Different stochastic processes (e.g. Markov-processes for continuous time)
- Perform real-data experiments, using GPS data to build the Markov-Chain model.

Thank you for listening!