Non-Standard-Datenbanken und Data Mining

Probabilistic Spatio-Temporal Databases and Streams

Prof. Dr. Ralf Möller

Universität zu Lübeck

Institut für Informationssysteme

Acknowledgments

Presentation slides are largely taken from

Location-aware Query Processing and Optimization: A Tutorial

Mohamed F. Mokbel

Department of Computer Science and Engineering, University of Minnesota, Minneapolis, MN, USA

mokbel@cs.umn.edu

Walid G. Aref

Department of Computer Science, Purdue University, West Lafayette, Indiana, USA.

aref@cs.purdue.edu

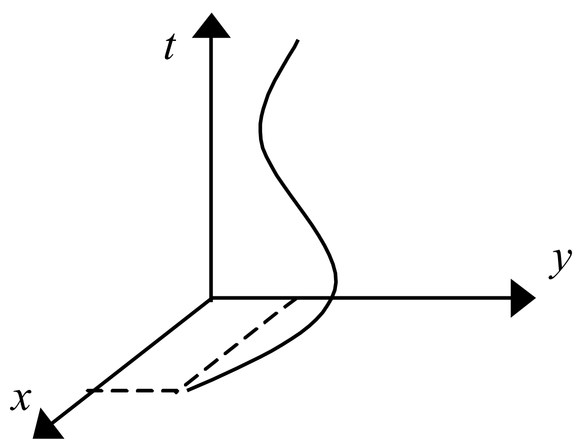
Some slides (indicated) were produced by George Kollios

Slides have been modified or extended. Faults are mine!

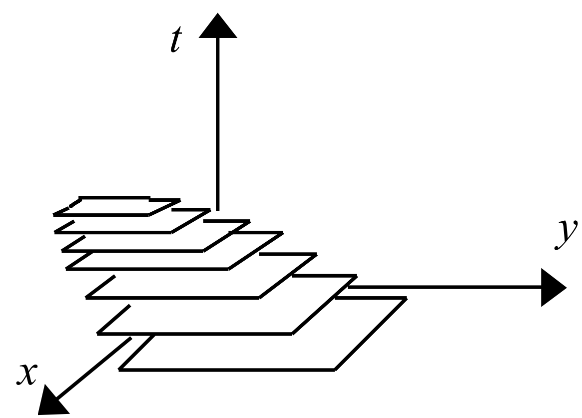
Mohamed F. Mokbel, Thanaa M. Ghanem, and Walid G. Aref. Spatio-temporal Access Methods. IEEE Data Engineering Bulletin, 26(2):40-49, June 2003.

Spatio-Temporal Objects

- Moving points (extent does not matter)
  - Each object is modeled as a point (e.g., moving vehicles in a GIS based transportation system)
- Moving regions (extent matters)
  - Each object is represented by an MBR, the MBR can change as the object moves (e.g., thunderstorm, noise)



(a)
a moving point



(b)
a moving and shrinking region

Location-aware Queries

Continuously report the number of cars on freeway 71-75

- *Type:* Range query
- *Time:* Present
- *Duration:* **Continuous**
- *Query:* Stationary
- *Objects:* Moving

What are my nearest McDonalds for the next hour?

- *Type:* Nearest-neighbor query
- *Time:* **Future**
- *Duration:* **Continuous** / **Snapshot**
- *Query:* Moving (reference rectangle)
- *Objects:* Stationary (McDonalds)

Send E-coupons to all cars that I am their nearest gas station

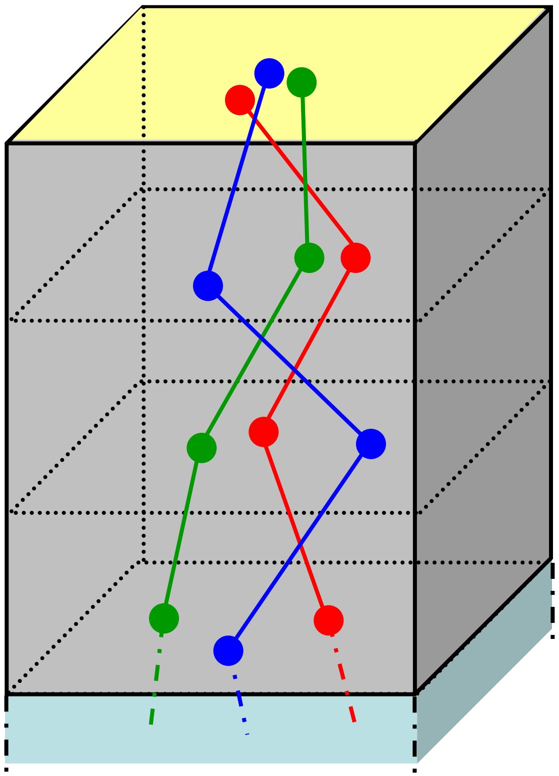
- *Type:* Reverse NN query
- *Time:* **Present**
- *Duration:* **Snapshot**
- *Query:* Stationary (gas station)
- *Objects:* Moving

What was the closest distance between Taxi A & me yesterday?

- *Type:* Closest-point query
- *Time:* **Past**
- *Duration:* **Snapshot**
- *Query:* Moving
- *Objects:* Moving

Snapshot Querying the Past

- Examples:
  - **Temporal** Dimension:
    What was the location of a certain object from 7:00 AM to 10:00 AM yesterday?
  - **Spatial** Dimension:
    Find all objects that were in a certain area at 7:00 AM yesterday
  - **Spatio-temporal** Dimension:
    Find all objects that were close to each other from 7:00 AM to 8:00 AM yesterday

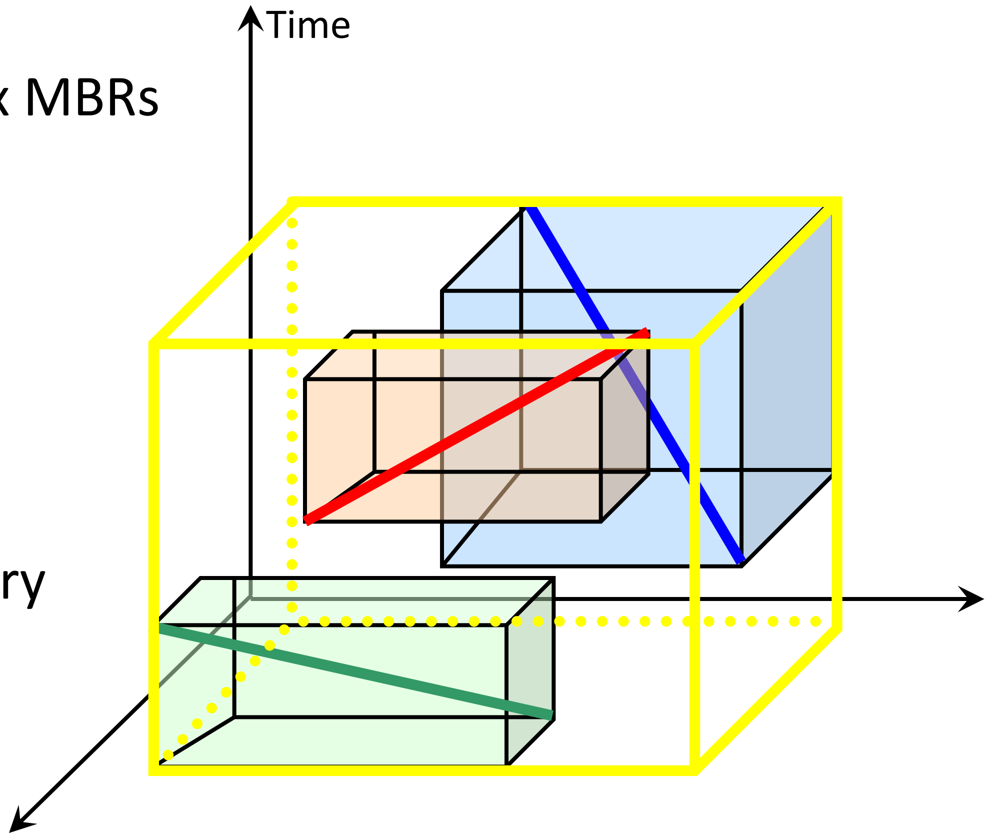


- Features:
  - Large number of historical trajectories
  - Persistent read-only data
  - Query spatial and/or temporal dimensions

Indexing the Time Dimension

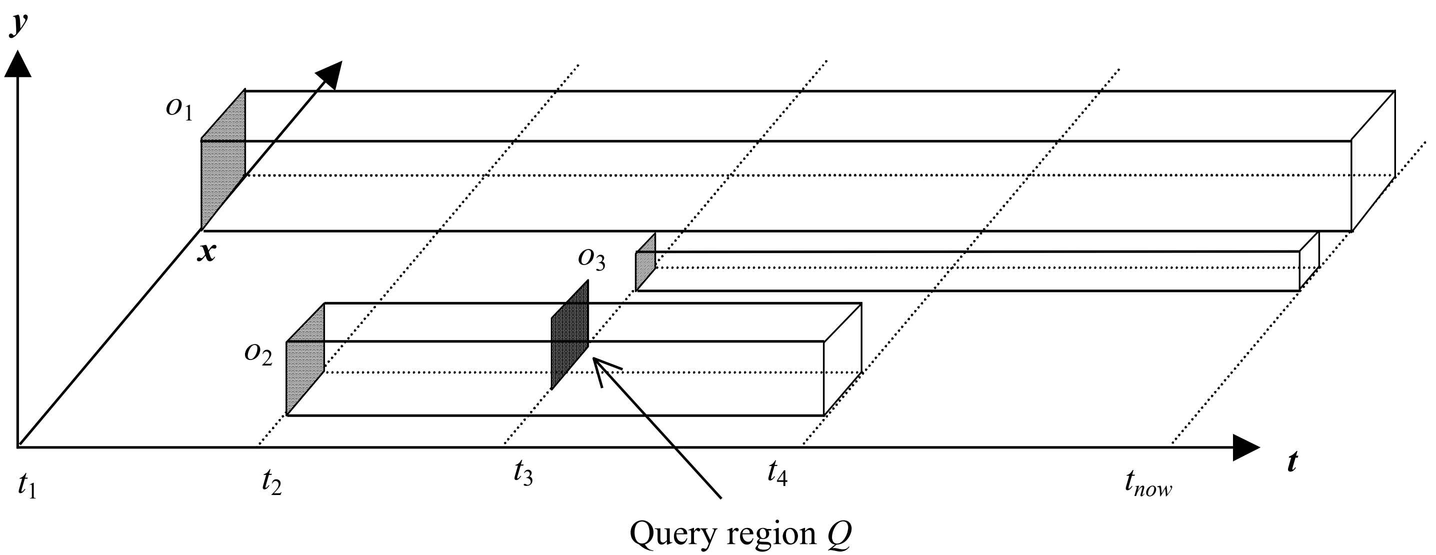
Historical trajectories are represented by their three-dimensional Minimum Bounding Rectangle (MBR)

- 3D R-tree can be used to index MBRs



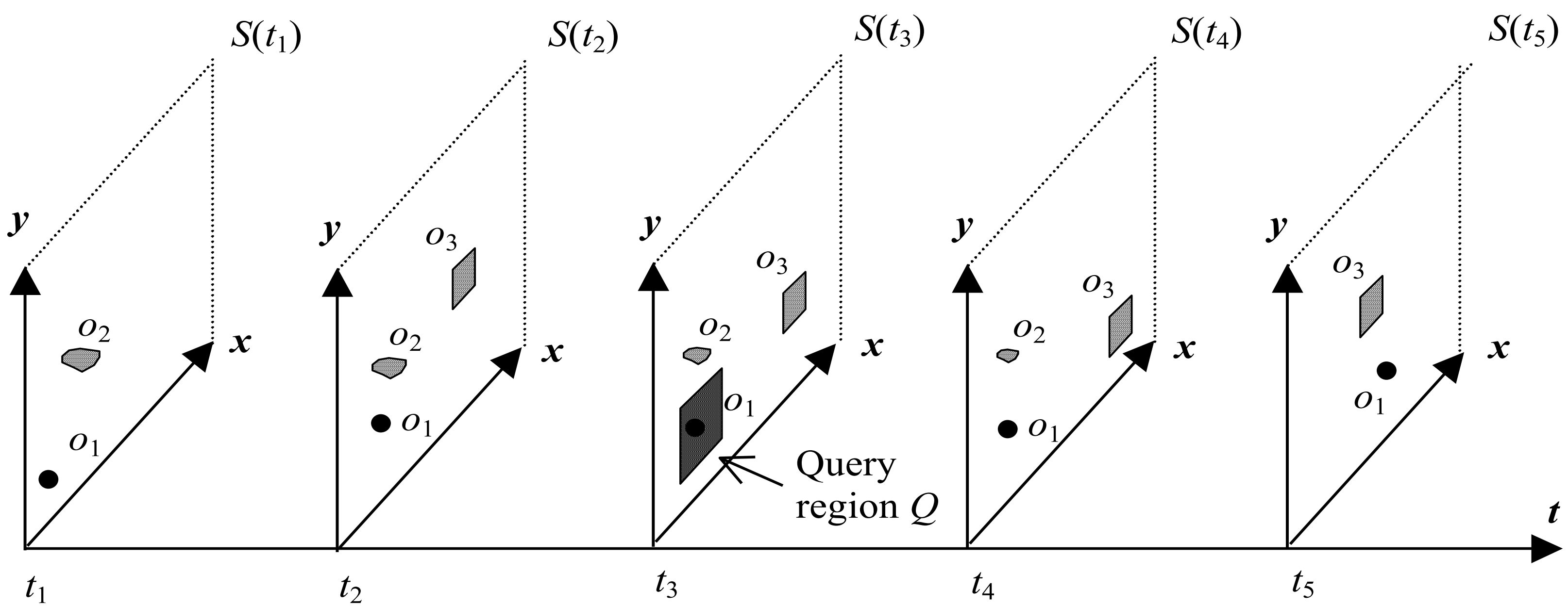
- Technique simple and easy to implement
- Does not scale well
- Does not provide efficient query support for snapshot queries (aka timestamp queries)

3D R-Tree



No correlation to objects on the slides before the previous slide

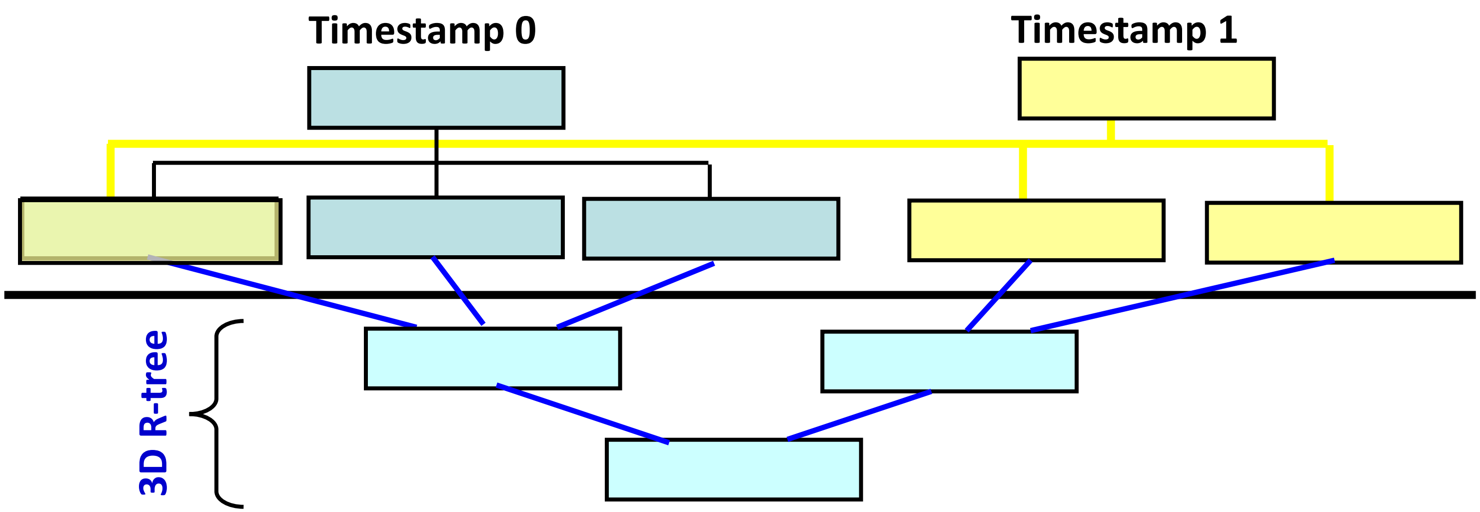
Modeling Evolution: Historical R-Trees



Snapshot query

Multi-Version Index Structures (MVR-Trees)

- Maintain an R-tree for each time instance (aka historical r-tree, HR-tree)
- R-tree nodes that are not changed across consecutive time instances are linked together (remove redundancies: MVR-tree)



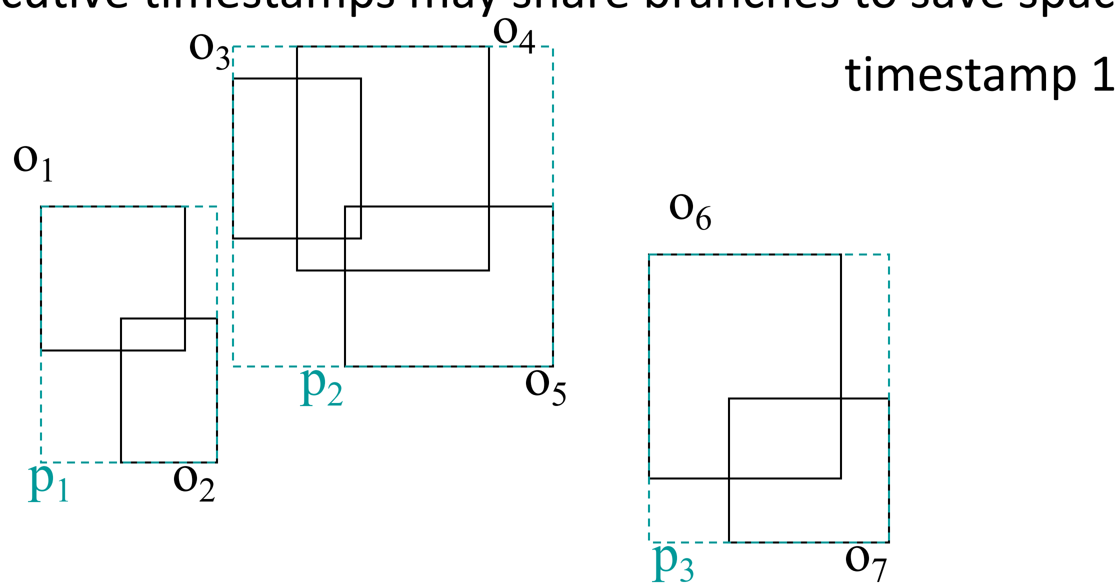
- A multi-version R-tree can be combined with a 3D-R-tree to support interval queries (combination is called MV3R-Tree)

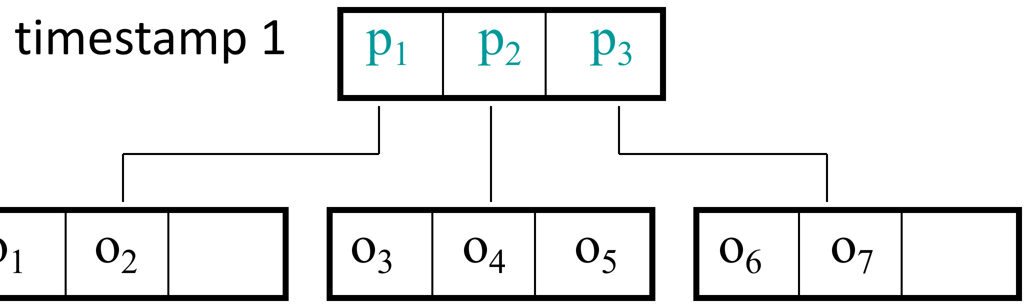
Yufei Tao and Dimitris Papadias. MV3R-Tree: A Spatio-temporal Access Method for Timestamp and Interval Queries. In Proc. VLDB-01, pp. 431-440, 2001

Historical R-trees (HR-trees)

An R-tree is maintained for each timestamp in history.

Trees at consecutive timestamps may share branches to save space.

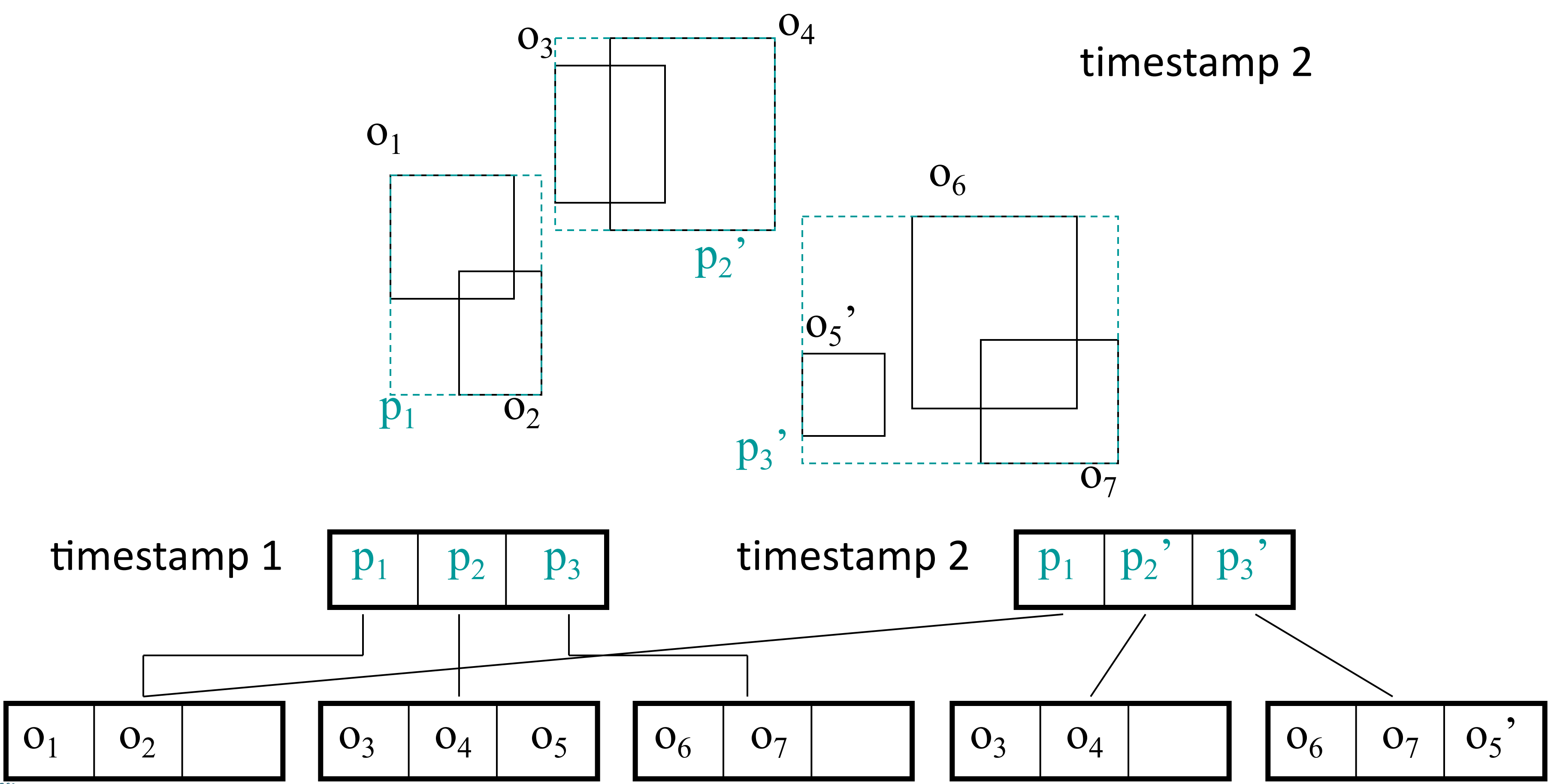




Historical R-trees

An R-tree is maintained for each timestamp in history.

Trees at consecutive timestamps may share branches to save space.



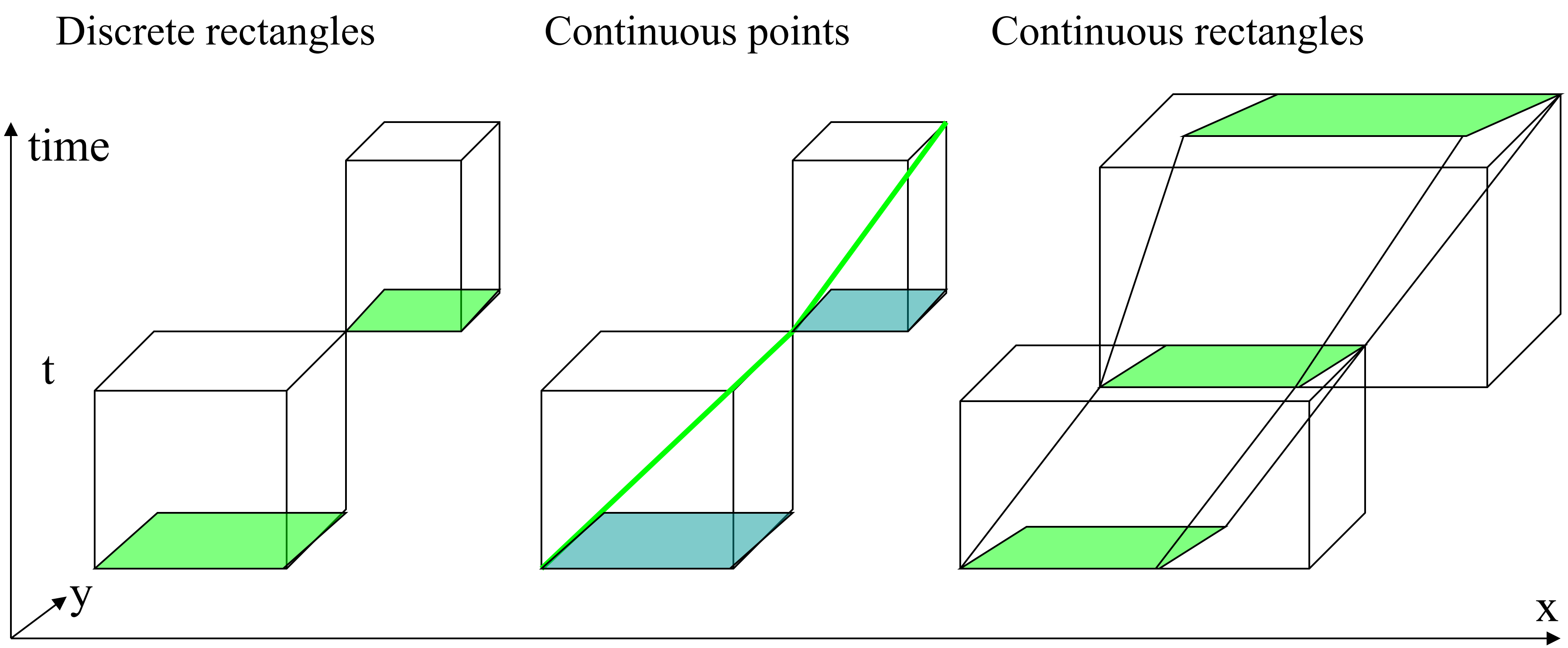
UNIVERSITÄT ZU LÜBECK
INSTITUT FÜR INFORMATIONSSYSTEME

Building a 3D R-tree on the Leaves of the MVR-tree

- Size of the 3D R-tree is much smaller than a complete 3D R-tree as the number of leaf nodes is significantly lower than the number of actual objects.
- Long interval queries can be processed with auxiliary 3D R-trees

Rectangles

Problem of indexing any type of moving objects can be reduced to indexing discrete rectangles



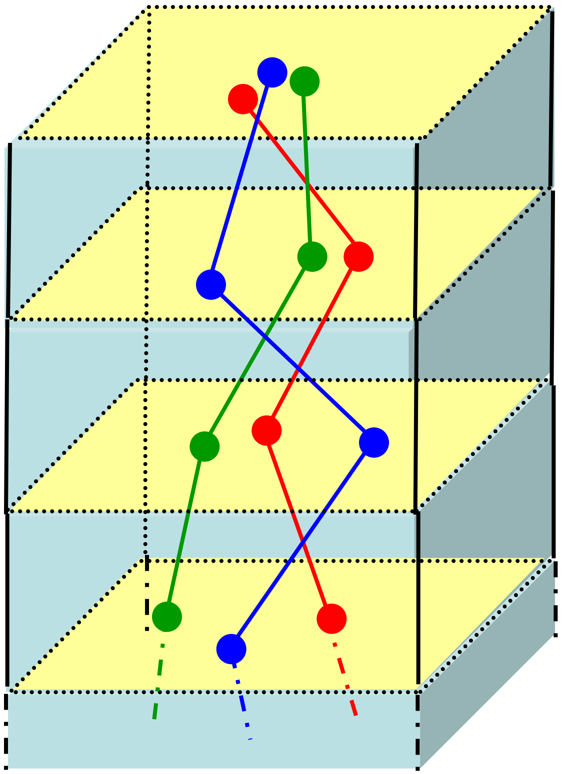
Optimization

- If N objects move with linear functions of time:
- Minimize total volume by splitting in equidistant points
- Given K splits you can decide the best splits in O(K log N) time.

Yufei Tao and Dimitris Papadias. MV3R-Tree: A Spatio-temporal Access Method for Timestamp and Interval Queries. In Proc. VLDB-01, pp. 431-440, **2001**

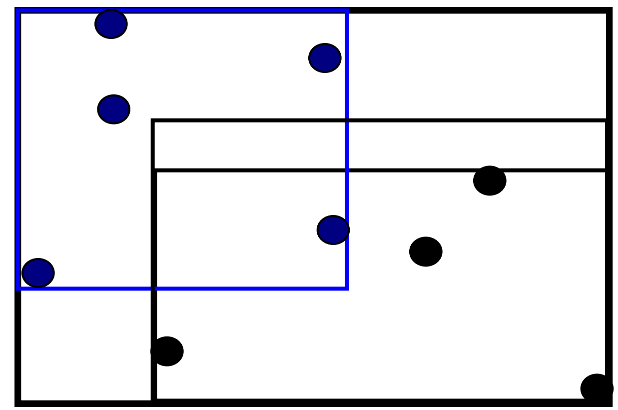
Querying the Present

- Time is always NOW
- Example Queries:
  - Find the number of objects in a certain area
  - What is the current location of a certain object?
- Features:
  - Continuously changing data
  - Real-time query support is required
  - Index structures should be update-tolerant
- Present data is always accessed through continuous queries

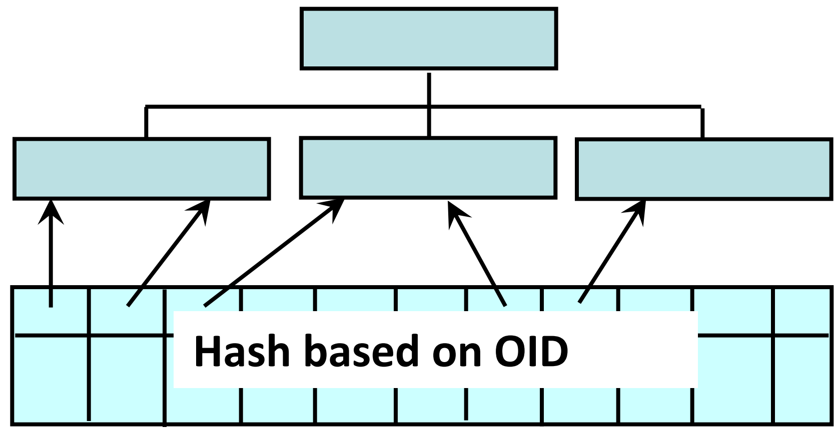


Updating Index Structures

- Traditional R-tree updates are *top-down*
- Updates translated to delete and insert transactions



- To support frequent updates:
  - Updates can be managed “inline” without the need for deletion or insertions
  - *Bottom-up* approaches through auxiliary index structures to locate the object identifier



Non-Standard-Datenbanken und Data Mining

Probabilistic Spatio-Temporal Databases and Streams

Prof. Dr. Ralf Möller

Universität zu Lübeck

Institut für Informationssysteme

Informatik M.Sc.: Vertiefung Data Science und KI

UNIVERSITÄT ZU LÜBECK

Studienplan Master Informatik

ENTWURF !!

gültig ab WS 2019/20

Version Dez 2018

Fach-Sem.	Kernbereich Informatik	KP	Prüf	Fachübergr. Bereich	KP	Prüf
1+2	Basismodul Theoretische Informatik CS4000 Algorithmik (WS) oder CS4020 Spezifikation und Modellierung (SS)	6	1	mindestens 1 LM aus		
	Basismodul Praktische Informatik CSxxxx Learning Based Programming (SS) oder CS4150 Verteilte Systeme (WS)	6	1			
	Basismodul Technische Informatik CS4160 Echtzeitsysteme (WS) oder CS4170 Parallelrechnersysteme (SS)	6	1			
2 + 3	3 Vertiefungsmodule a 12 KP aus folgender Liste	36	3	CS5840 engl. Seminar (WS+SS)	4	0
	CS4501 Algorithmik, Logik und Komplexität CS4502 Parallele und verteilte Systeme CS4503 Ambient Computing und Anwendungen CS4504 Cyber Physical Systems CS4505 Systemarchitektur CS4506 Sicherheit von Daten und Kommunikation CS4507 Softwareverifikation CS4508 Datenmanagement CS4509 Internet-Technologien CS4510 Signalanalyse CS4511 Lernende Systeme CS4512 Bildgeb. Systeme und inverse Probleme CS4513 Web und Data Science CS4520 Fallstudie zur prof. Produktentwicklung			EC4001 Allgemeine BWL (WS)	4	0
				EC4010 Wirtschaftsrecht (WS oder SS)	4	0
				PS5810 Wissenschaftl. Lehrtätigkeit (WS+SS)	4	0
				EC4008 Entrepreneurship und Innovation (WS)	4	0
4	CS5990 Masterarbeit Informatik mit Kolloquium	30				

kanonische Vertiefungen / **individuell**

Fach-Sem.	Bioinformatik	KP	Prüf	SW-Systems-Eng	KP	Prüf	Data Science & KI	KP	Prüf	individuell	KP	Prüf
1+2	CS4441 Molek. Bioinformatik (CS4440 WS) Model. bio. Systeme (MA4450 WS)	8	1	CS5170 HW-SW Codesign (WS)	4	1	CS5130 Foundations of Ontologies and Databases (WS)	6	1	Basismodul	6	1
	CS5549 Projektpraktikum Bioinformatik (WS)	4	0	CS4507 SW-Verifikation I Model Check. (CS4138 WS) Runtime Ver. (CS4139 SS)	6	0	CS5450 Maschinelles Lernen (WS)	4	1			
2+3	CS4410 Neuroinformatik (CS4405 SS) Computer Vision (CS4250 SS)	8	1	CS4507 SW-Verifikation II Model Check. (CS4138 WS) Runtime Ver. (CS4139 SS)	6	1	CS5020 Alg. Lernen und kausale Inferenz (SoSe)	6	1	Vertiefungsmodul	12	1
	LS3151 Molekularbiologie (SS)	4	1	CS4130 Web. Info.sys (SS) oder CS4150 Verteilte Sys. (WS)	6	1	CS5131 Web Mining Agents (SoSe)	8	1	Wahlpflichtbereich Kernbereich Informatik 10-14 Fachübergreifend 0-4	14	2
	CS5400 Aktuelle Themen Bioinformatik (WS+SS)	8	1	CS4212 Aktuelle Themen SSE (WS)	4	1	CSxxxx Aktuelle Themen Data Science & KI (WS oder SS)	4	1			
				CS5490 Projektprakt. SSE (WS+SS)	6	0	CSxxx Projektprakt. Web- und Data Science (WS od. SS)	[illegible]	0			

Wichtige Hinweise:

* im Kernbereich Informatik sollte im 1. FS für jeden der 3 Bereiche Theor., Prakt. und Techn. Informatik das entsprechende Basismodul (abhängig ob WS oder SS) gehört werden; bis Ende des 2. FS muß für jeden dieser Bereiche ein LZF erworben sein (Eignungsfeststellung).
* Im Vertiefungsbereich 1. und 2. FS hängt die Reihenfolge der Module vom Studienbeginn (WS oder SS) ab - diese sind unabhängig voneinander, das gilt auch für Teilmodule der Form I + II
* mindestens 1 Seminar im Umfang von 4 KP muss gewählt werden: CS5840 oder im Rahmen eines Vertiefungs- oder Anwendungsfachsmoduls mit 4 KP Seminaranteil

Summe	KP	Prüf
Kernbereich Informatik	84	6
Fachübergr. Bereich	4	0
Bioinformatik	#	4
SW-Systems-Eng	#	4
Data Science & KI	32	5
individuell	32	4

Informatik B.Sc.: Vertiefung Web und Data Science

UNIVERSITÄT ZU LÜBECK

Studienplan Bachelor Informatik

ENTWURF !!

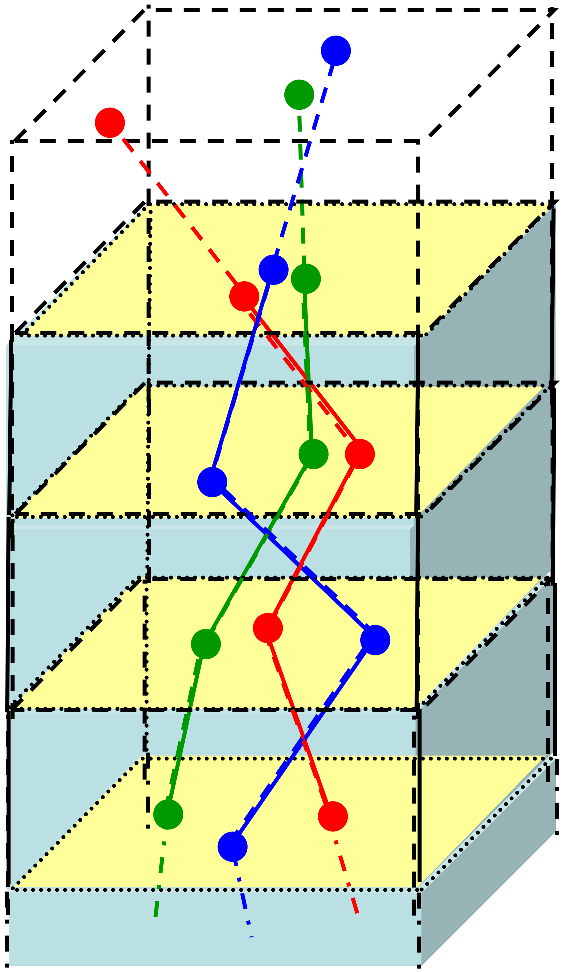
gültig ab WS 2019/20

Version Dez 2018

Fach-Sem.	KP	Kernbereich Informatik	KP	Prüf	Mathematik	KP	Prüf	Fachübergr. Bereich	KP	Prüf	Bioinformatik	KP	Prüf	SW-Systems-Eng	KP	Prüf	Web and Data Sc.	KP	Prüf	Individuell	KP	Prüf	Prüf
											kanonische Vertiefungen									individuell			
		Kernbereich Informatik	101	13	Mathematik	32	5	Fachübergr. Bereich	11	0	Bioinformatik	36	8	SW-Systems-Eng	36	7	Web and Data Sc.	36	7	Individuell	36	5-9	9
1	30	CS1000 Einführung in die Programmierung	10	1	MA1000 Lin. Algebra u. Disk. Strukturen 1	8	1				CS1400 Efg in die Bioinformatik	4	1	CS1900 Efg in SSE	4	1	CS1800 Efg in Web und Data Science	4	1	CSxxx Efg in ...	4		1
					MA2000 Analysis 1	8	1																
2	30	CS1001 Algorithmen und Datenstrukturen	8	1	MA1500 Lin. Algebra u. Disk. Strukturen 2	8	1				LS2500 Grundlagen der Biologie	4	1	CS3050 Codierung und Sicherheit	4	1	CS3050 Codierung und Sicherheit	4	1				1
		CS1201 Technische Grundlager	6	1	MA2500 Analysis 2	4	1													Wahlpflicht Modu 32			
3	30	CS1202 Technische Grundlager	6	1				CS2450 Werkzeuge für wiss. Arbeiten	2	0	LS1100 Allge. Chemie	4	1	CS3052 Progr.spr. und Typsysteme	4	1	CS3052 Progr.spr. und Typsysteme	4	1	aus den Bereich			1
		CS1002 Einführung in die Logik	4	1																Informatik			
		CS2000 Theoretische Informat	8	1																Mathematik			
		CS2300 SW-Engineering	6	1																Medizinische Informatik			
4	30	CS2301 SW-Engineering Prakti	6	0	MA2510 Stochastik 1	4	1				MA1600 Biostatistik 1	4	1	CS3051 Parallel-verarbeitung	4	1	CSxxxx Logikprogrammierung	4	1	Naturwissenschaften			1
		CS2100 Rechnerarchitektur	4	1																Technik			
		CS2150 Betriebssysteme und Netze	8	1																Fachübergreifend			
		CS2700 Datenbanken	4	1																			
5	33	CS3000 Algorithmendesign	4	1				CS3702 Ba-Seminar Informatik	4	0	MA3400 Bio-mathematik	4	1	CS3250 Sichere SW	8	1	CS3130 Nonstandard-DBs und Data Mining	8	1				1
		CS3010 Mensch-Computer-Interaktion	4	1				CS3701 Ba-Projekt Informatik	5	0	ME1500 Grundlagen der Physik	4	1	CS3060 Ba-Projekt-Erweiterung	4	0	CS3250 Sichere SW	8	1				1
											CS3100 Signal-verarbeitung	8	1	CS3201 Usability Engineering	4	1							1
6	27	Wahlpflicht Informatik	8	1-							LS3100 Molekular-genetik	4	1	CS2101 Eingebett. Systeme	4	1	CSxxxx Web Technologies	4	1				1
		CS3990 Bachelorarbeit	12																				1
		Kolloquium	3																				

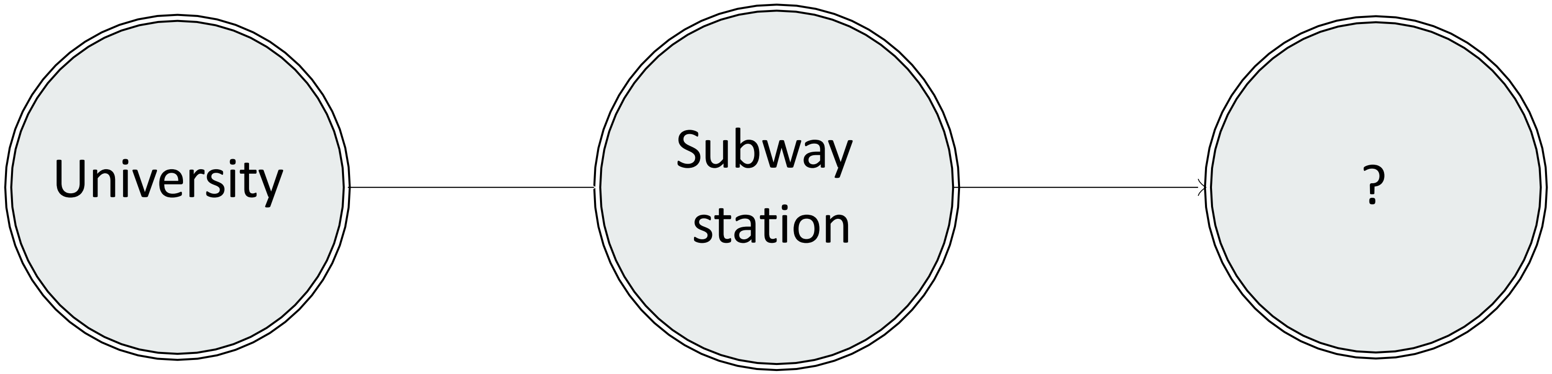
Querying the Future

- Examples:
  - *What will my nearest restaurant be after 30 minutes?*
  - *Does my path conflict with any other cars for the next hour?*
- Features:
  - Predict the movement through a velocity vector
  - Prediction could be valid for only a limited time horizon in the future
- Methods:
  - Dynamic Bayesian networks
    - Hidden Markov models
    - Kalman Filters
  - Others …



Example: Location Prediction

Location prediction seems to be a simple task in some cases:

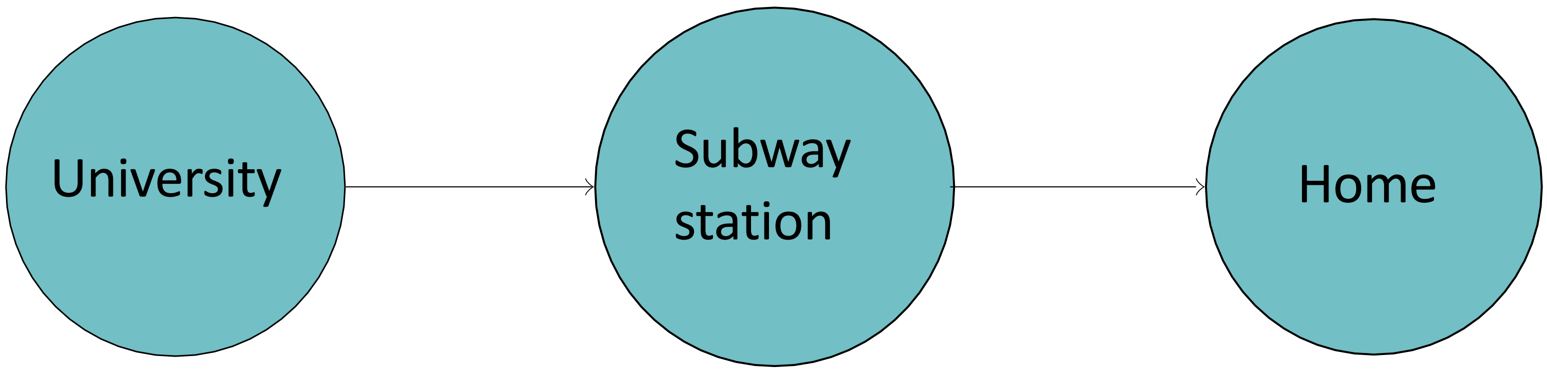


Jonas Lüthke. Location Prediction Based on Mobility Patterns in Location Histories. Master thesis, TU Hamburg-Harburg, **2013**

https://www.ifis.uni-luebeck.de/~moeller/publist-sts-pw-and-m/source/papers/2013/luethke13.pdf

Location Prediction - Approach

Location prediction seems to be a simple task in some cases:



Previous observations can enable an educated guess

Example: Location History Data

Cabspotting data set:

- GPS coordinates collected from 563 cabs in San Francisco over 30 days
- Interval between measurements < 60seconds
- Ten taxis selected for testing (with regard to measurement density, measurement errors)

- Spatial probability distribution could be estimated from this (e.g., GMM)
- *Spatiotemporal* probability distribution is needed

Delay Embedding

Embed location time series in $2m$-dimensional space using a delay v:

- Time series is iteratively sampled using delay time v
- Every m subsequent locations are combined into one vector (*delay vector*)

Starting from each location x_n, combine x_n with m subsequent locations if they were observed at a time interval v

$$\boldsymbol{x}_n = (x_n^1, x_n^2) \text{ location data points, index } n \in \{1, \ldots, N\}$$

$$\boldsymbol{\delta}_n = [x^1_{n-(m-1)}, x^2_{n-(m-1)}, x^1_{n-(m-2)}, x^2_{n-(m-2)}, \ldots, x^1_n, x^2_n]$$

For example: $m = 2 : \boldsymbol{\delta}_n = [x^1_{n-1}, x^2_{n-1}, x^1_n, x^2_n]$

Note: Prior sampling with delay v is omitted for simplification

Delay Embedding – Benefits

- Euclidean distance is a measure for similarity between subsequences
- Similar subsequences are close in embedding space
- Density is a measure for likelihood of a subsequence
- Mobility patterns can be extracted in terms of density

Prediction Approach

Learn mobility patterns from large amount of history data:

- Delay embedding to map mobility patterns to density
- Density estimation based on embedding space

$$P(X_t = x, X_{t-1}, \ldots, X_{t-(m-1)})$$

- Derive conditional distribution

$$P(X_t = x | X_{t-1}, \ldots, X_{t-(m-1)}) = \alpha \, P(X_t = x, X_{t-1}, \ldots, X_{t-(m-1)})$$

Predict location given the last $m - 1$ locations (current context):

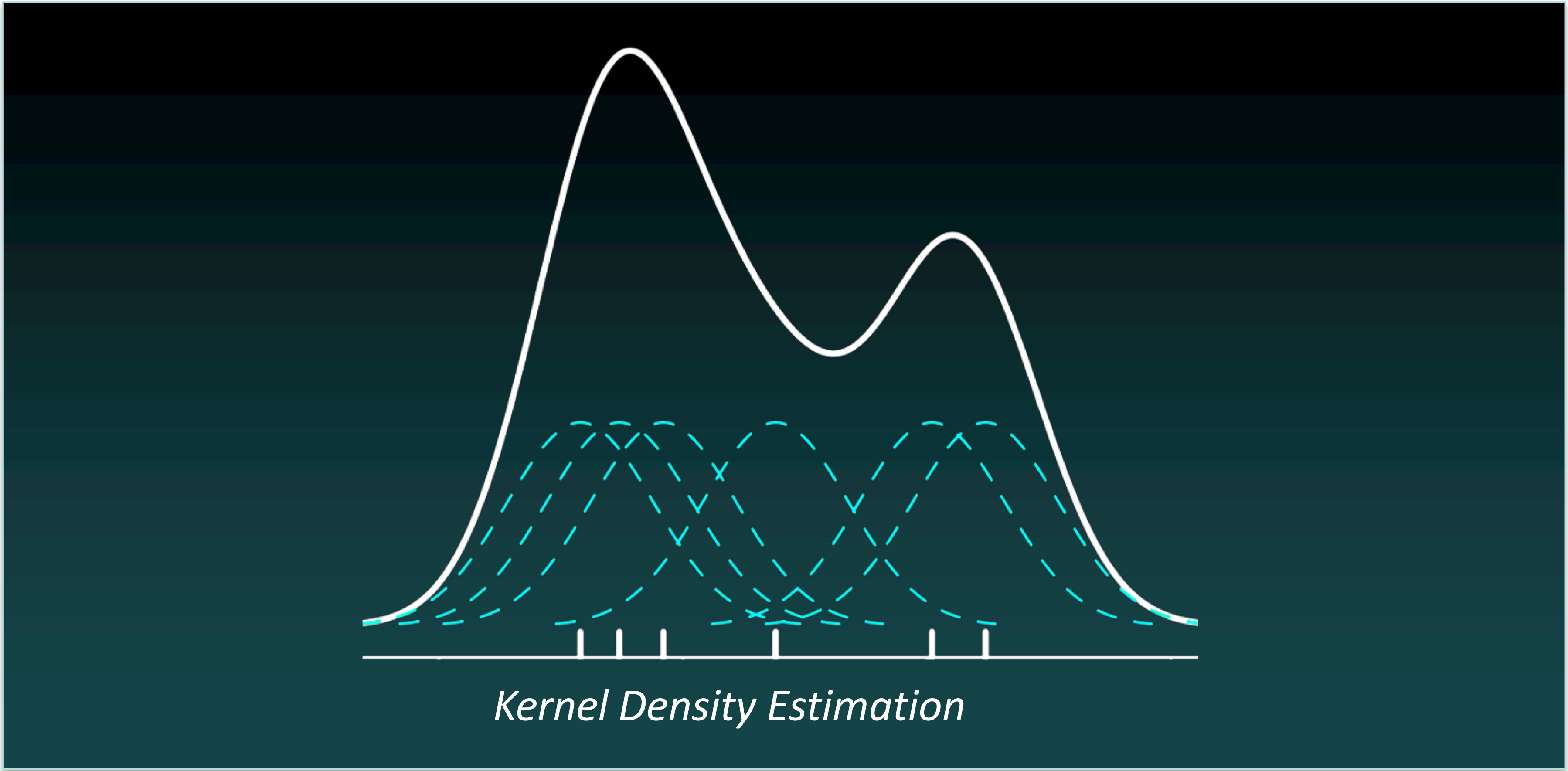
- Maximization of probability density
  to obtain most likely location (MLL problem)

$$x^* = \underset{x}{\operatorname{argmax}} \, P(X_t = x, X_{t-1}, \ldots, X_{t-(m-1)})$$

What about m=2?

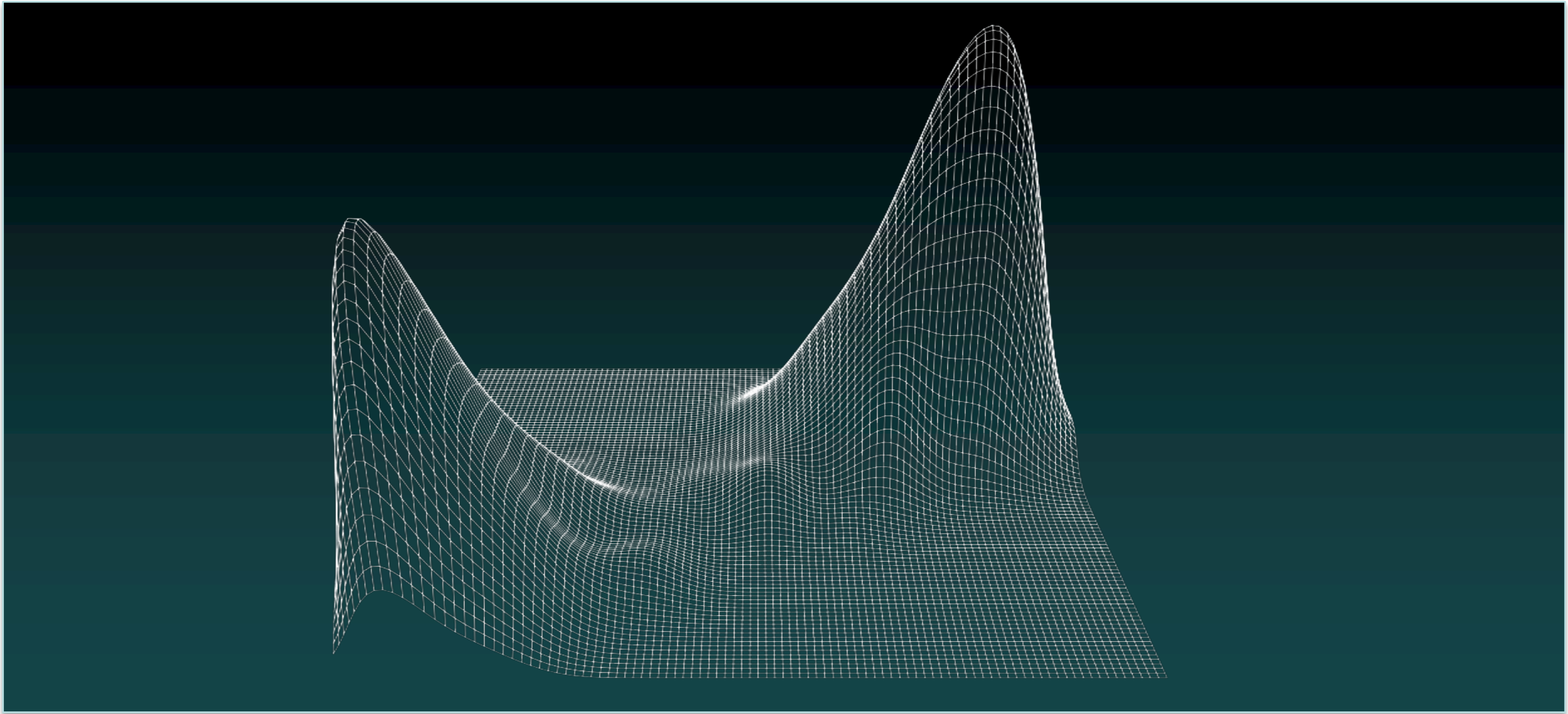
Assuming ($m - 1$)-th order Markov process

Density Estimation



Optimization problem:
Minimize distance between estimated and unknown underlying distribution (AMISE, asymptotic mean integrated square error)

Gaussian Mixture Models



$$P(\mathbf{x}) = \sum_{m \in M} \omega_m N(\mathbf{x} \mid \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m)$$

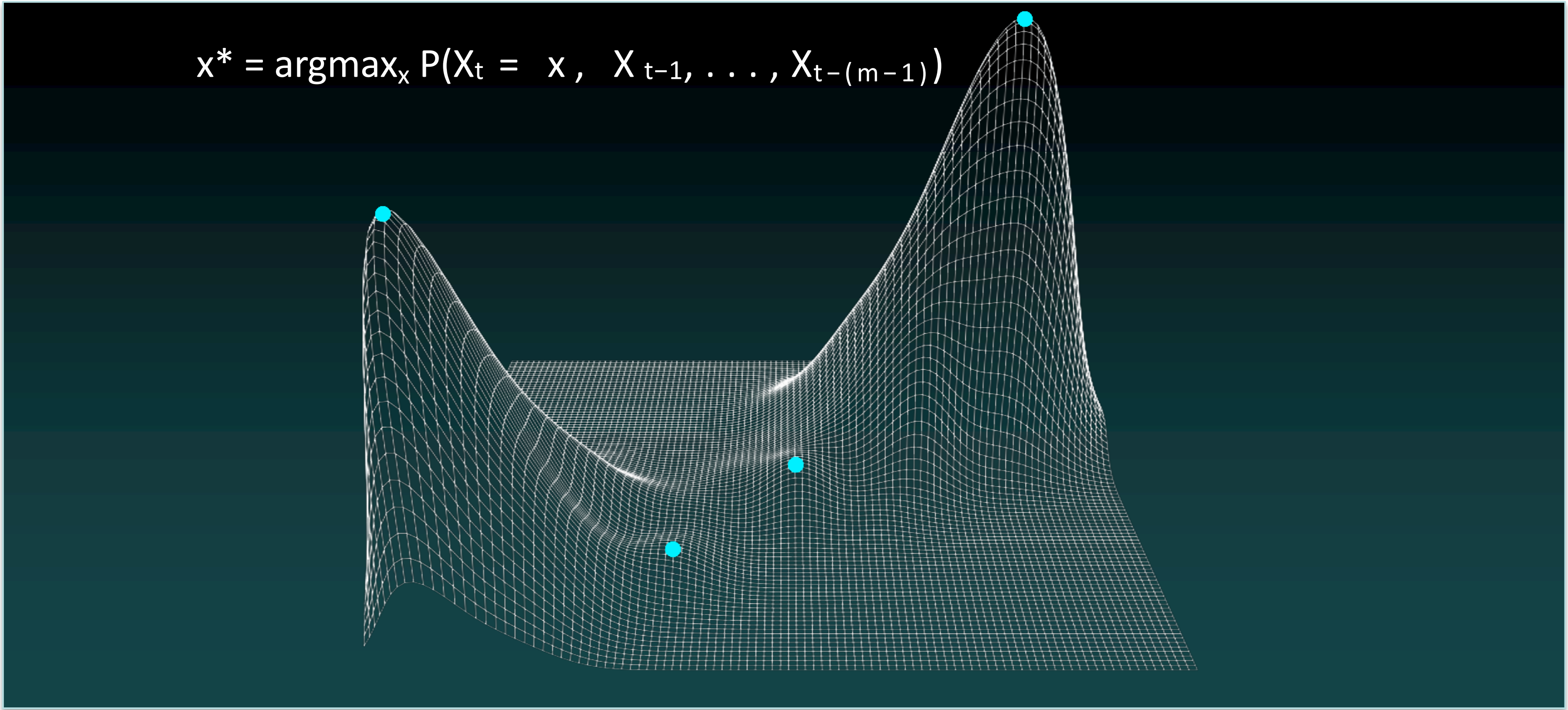
Online Kernel Density Estimation

- Incremental - can be updated as new data arrives
- Uses compression to keep memory footprint small

Christoph Heinz, Kernel Density Estimation over Data Streams, Dissertation Philipps-Universität Marburg, **2007**

Matej Kristan, Aleš Leonardis, and Danijel Skočaj. 2011. Multivariate online kernel density estimation with Gaussian kernels. Pattern Recogn. 44, 10-11, 2630-2642, **2011**

Solving MLL: Mode Finding

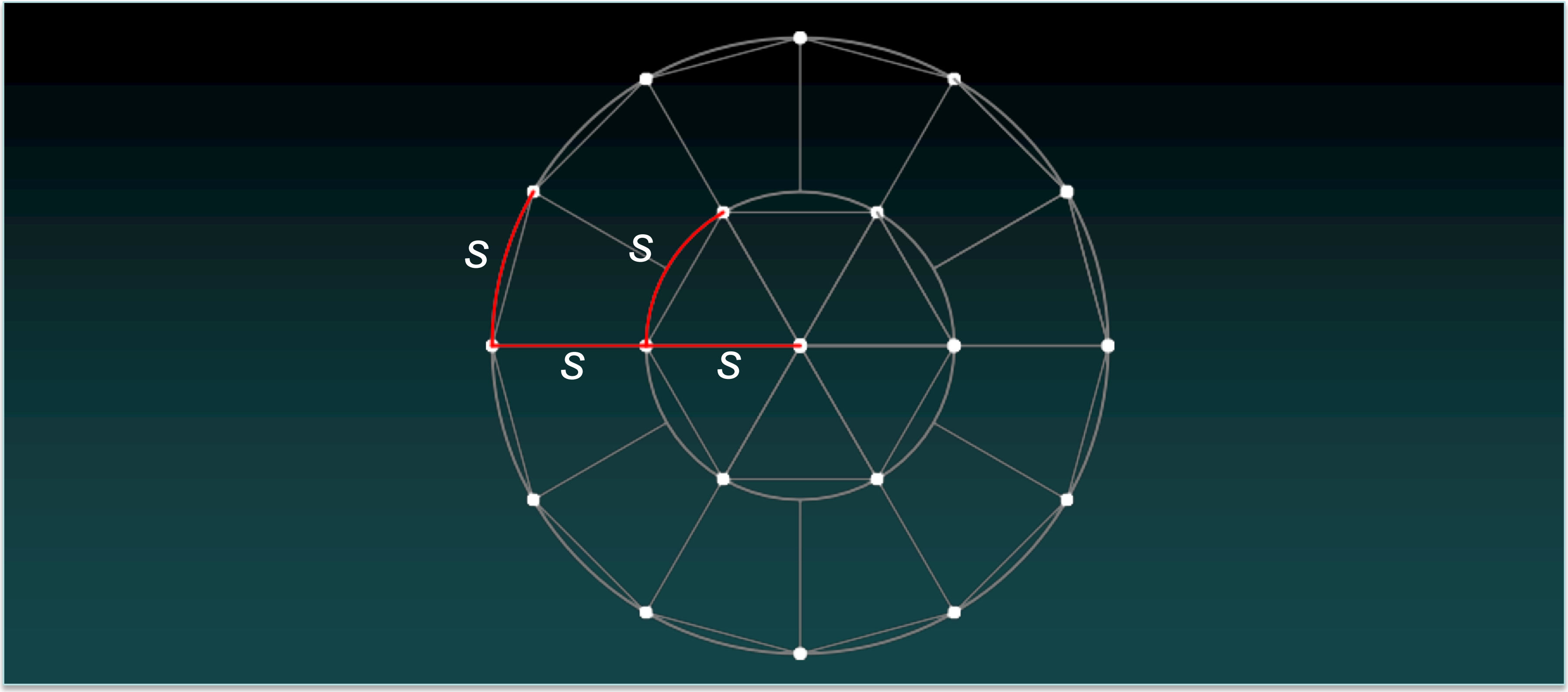


- Use hill-climbing search to find position of maximum
- Starting points?

Miguel Á. Carreira-Perpiñán. 2000. Mode-Finding for Mixtures of Gaussian Distributions. IEEE Trans. Pattern Anal. Mach. Intell. 22, 11, 1318-1323, **2000**

Starting Points for Maxima Search

- Define search region around last observed location
- If radius large enough, all relevant maxima are found

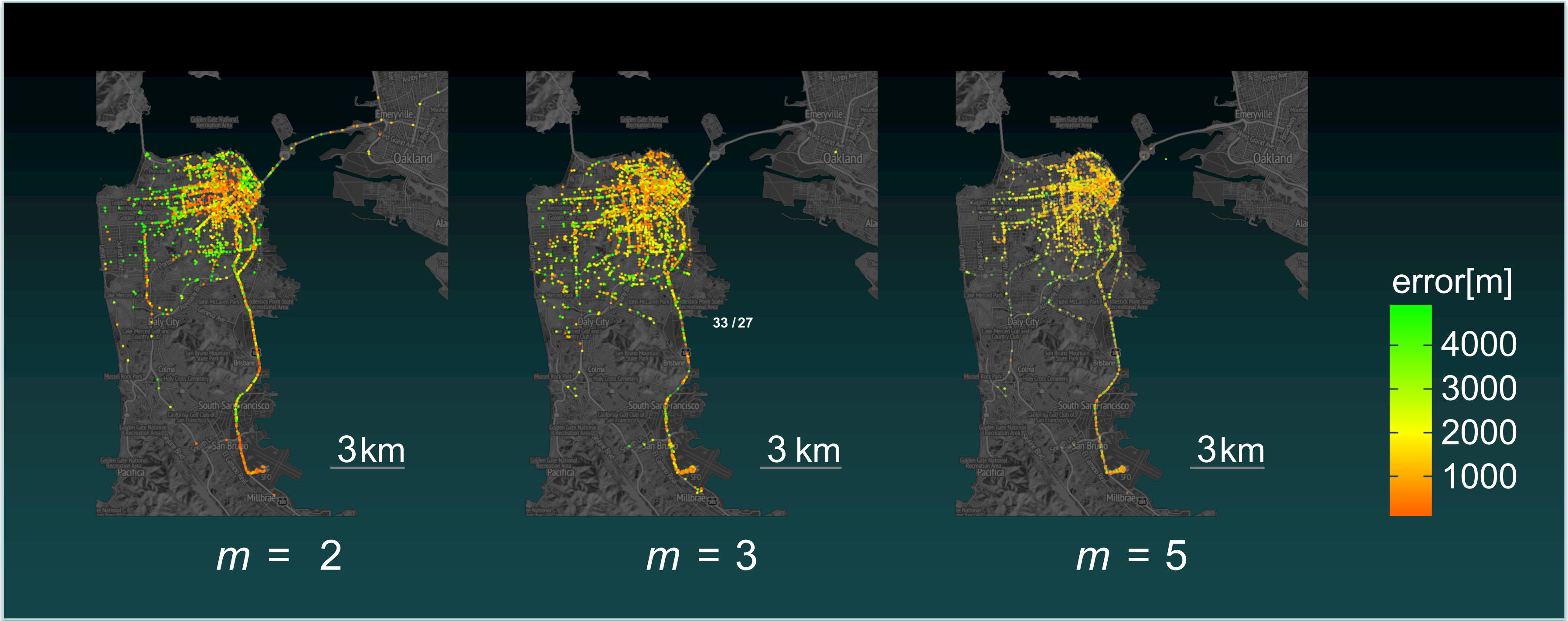


Summary - Prediction

- Delay embedding:
  Map mobility patterns to density
- Density estimation:
  Assigns probability to each possible location sequence
- Mode finding:
  Searches the most likely future location

Test Results

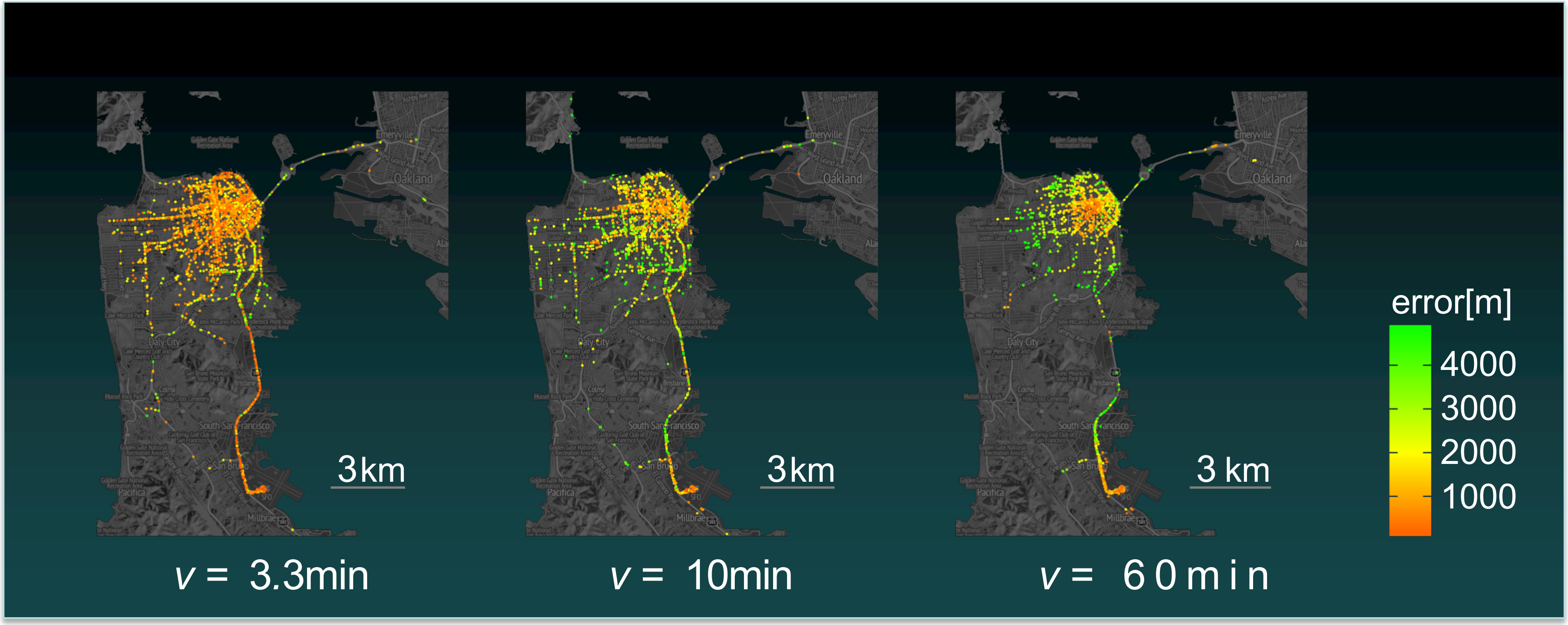
Varied m, fixed v = 6min:



Accurate predictions are more uniformly distributed for m = 3 and m = 5.

Test Results

Varied v, fixed $m = 3$:



Accurate predictions are increasingly clustered as v increases.

Test Result Analysis

- Algorithm is based on *sequential correlation* in data (delay embedding)
- Locations in taxi data only correlated if part of same trip
- For each trip the client defines new destination
- Recurring similar location sequences only observed when limiting time span to average trip time
- Else prediction falls back to $m = 2$

Similar Approaches:

- Song et al. - Markov predictor
- Scellato et al. - Nonlinear predictor

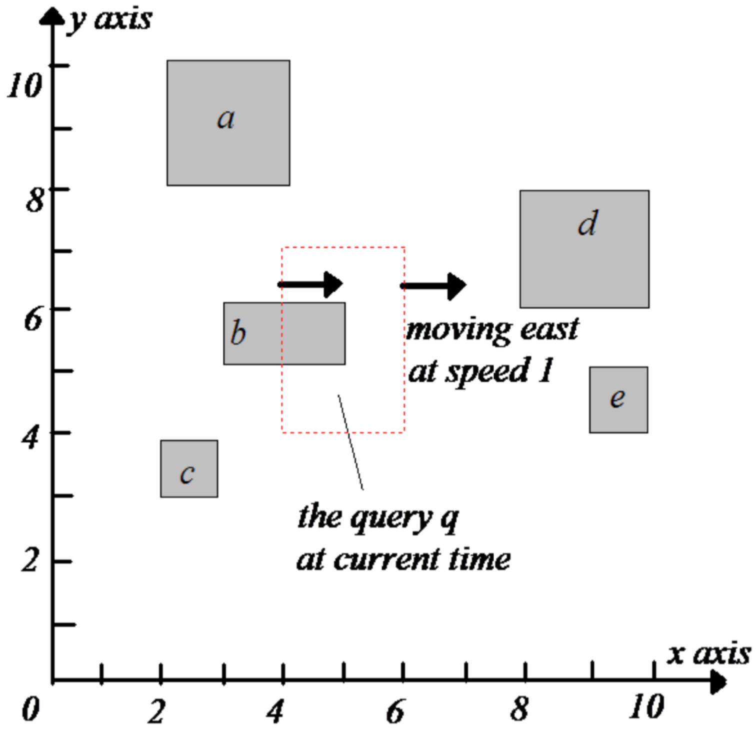
L. Song, D. Kotz, R. Jain, and X. He, Evaluating location predictors with extensive with mobility data, In Proc. IEEE Computer and Communications Societies, pp. 1414-1424, **2004**

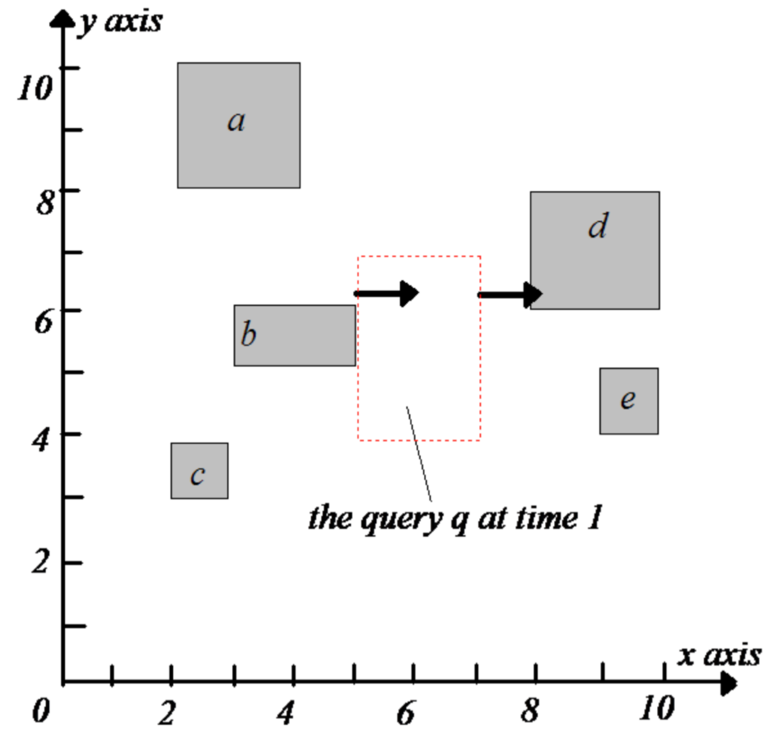
S. Scellato, M. Musolesi, C. Mascolo, V. Latora, and A. T. Campbell, NextPlace: a spatio- temporal prediction framework for pervasive systems, In: Proc. Pervasive Computing, **2011**

Duality Transformation: Avoid 3D-Rtrees?

- A linear trajectory in two-dimensional space can be transformed into a point in another *dual* two-dimensional space
- Trajectory: $x(t) = vt + a$ ➔ Point: (v,a)
- Embedding in more dimensions
- All queries will need to be transformed into the dual space

Time Parameterized Queries





- Result={b}
- Conventional Query

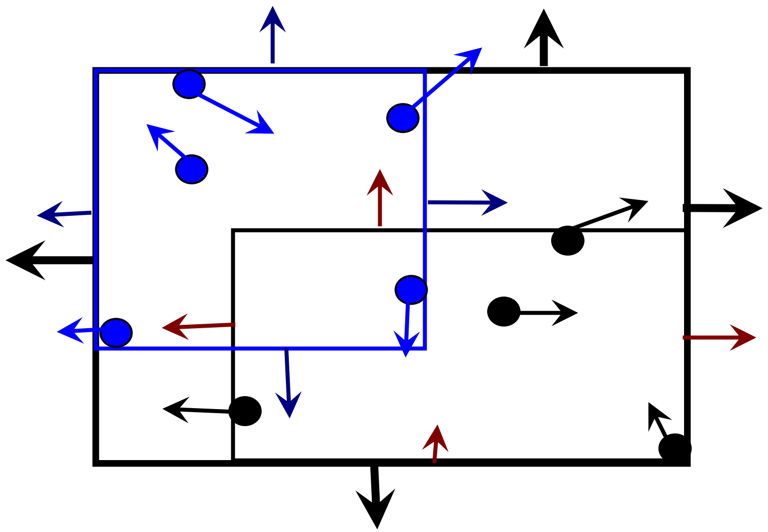
- At time 1 b would be the nearest neighbor, after that time the results expire and d would be the new nearest neighbor
- Time Parameterized Query

Time Parameterized queries (TP queries)

- Whenever a query is issued, a TP returns
  - The actual result that satisfies the corresponding spatial query.
  - The validity period/expiration time of the result.
  - The change that cause the expiration of the results
- Can be used for prediction

Time-Parameterized Data Structures

- The Time-Parameterized R-tree (TPR-tree) consists of:
  - Minimum bounding rectangles (MBR)
  - Velocity bounding rectangles (VBR)



- A bounding rectangle with MBR & VBR is guaranteed to contain all its moving objects as long as they maintain their velocity vector

- Optimization: Minimize area of the bounding rectangle

- Time-Parameterized Bounding Rectangles (TPBRs) for answering TP queries

Indexing Past, Present, and Future

- A unified index structure for both past, present, and future data
- Makes use of the partial-persistent R-tree for past data and the TPR-tree for current and future data

Katerina Raptopoulou, Michael Vassilakopoulos, and Yannis Manolopoulos..
Efficient processing of past-future spatiotemporal queries. In Proc. ACM
Symposium on Applied Computing (SAC '06). ACM, pp. 68-72, 2006

Outline

- Location-aware Environments
- Location-aware *Snapshot* Query Processing
- Location-aware *Continuous* Query Processing
- Scalable Execution of Continuous Queries
- Location-aware Query Optimizer
- Uncertainty in Location-aware Query Processing

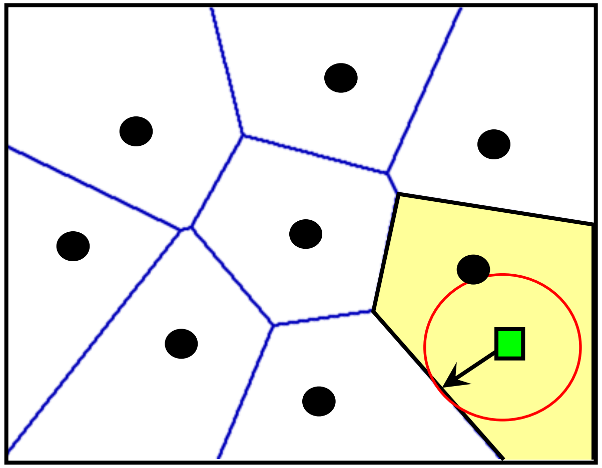
Approaches

- *Straightforward Approach*
  – Abstract the continuous queries to a series of snapshot queries evaluated periodically (and possibly incrementally)
- *Result Validation*
- *Result Caching*
- *Result Prediction*
- *Incremental Evaluation*

Result Validation

- Associate a *validation* condition with each query answer

- *Valid time (t):*
  - The query answer is valid for the next *t* time units
- *Valid region (R)*
  - The query answer is valid as long as you are within a region *R*

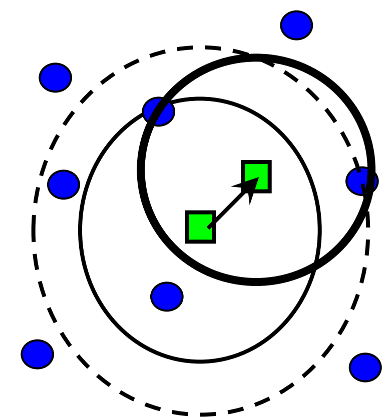


- It is challenging to maintain the computation of valid time/region for querying *moving objects*
- Once the associated validation condition expires, the query will be *reevaluated*

Caching the Result

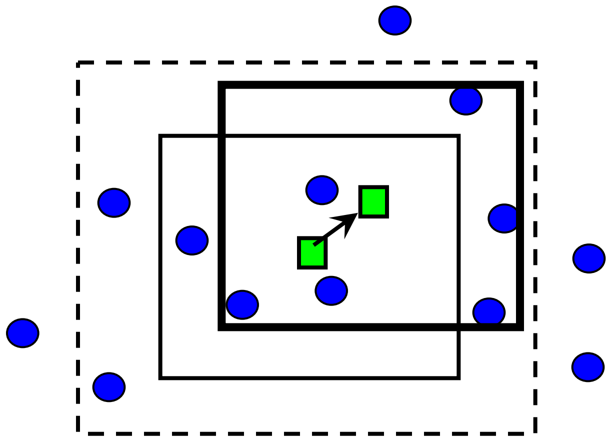
- *Observation:* Consecutive evaluations of a continuous query yield very similar results

- *Idea:* Upon evaluation of a continuous query, retrieve more data that can be used later



- *K-NN query*
  - Initially, retrieve more than k

- *Range query*
  - Evaluate the query with a larger range

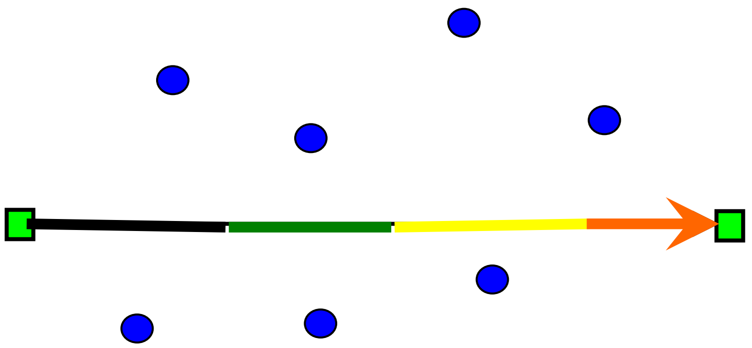


- How much do we need to pre-compute?
- How do we do re-caching?

Predicting the Result

- Given a future trajectory movement, the query answer can be pre-computed in advance

- The trajectory movement is divided into N intervals, each with its own query answers A_i



Nearest-Neighbor Query

- The query is evaluated once (as a snapshot query). Yet, the answer is valid for longer time periods

- Once the trajectory changes, the query will be reevaluated

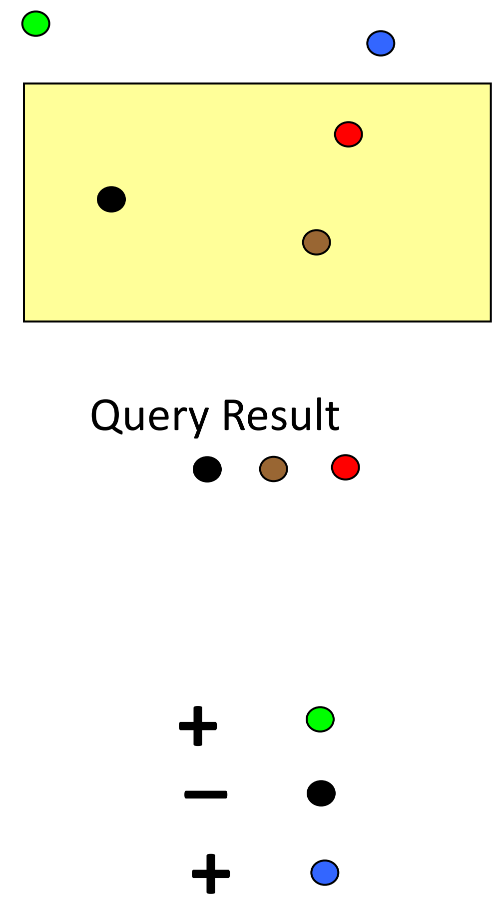
Incremental Evaluation

- The query is evaluated only once. Then, only the *updates* of the query answer are evaluated

- There are two types of updates. *Positive* and *Negative* updates

- Only the objects that cross the query boundary are taken into account

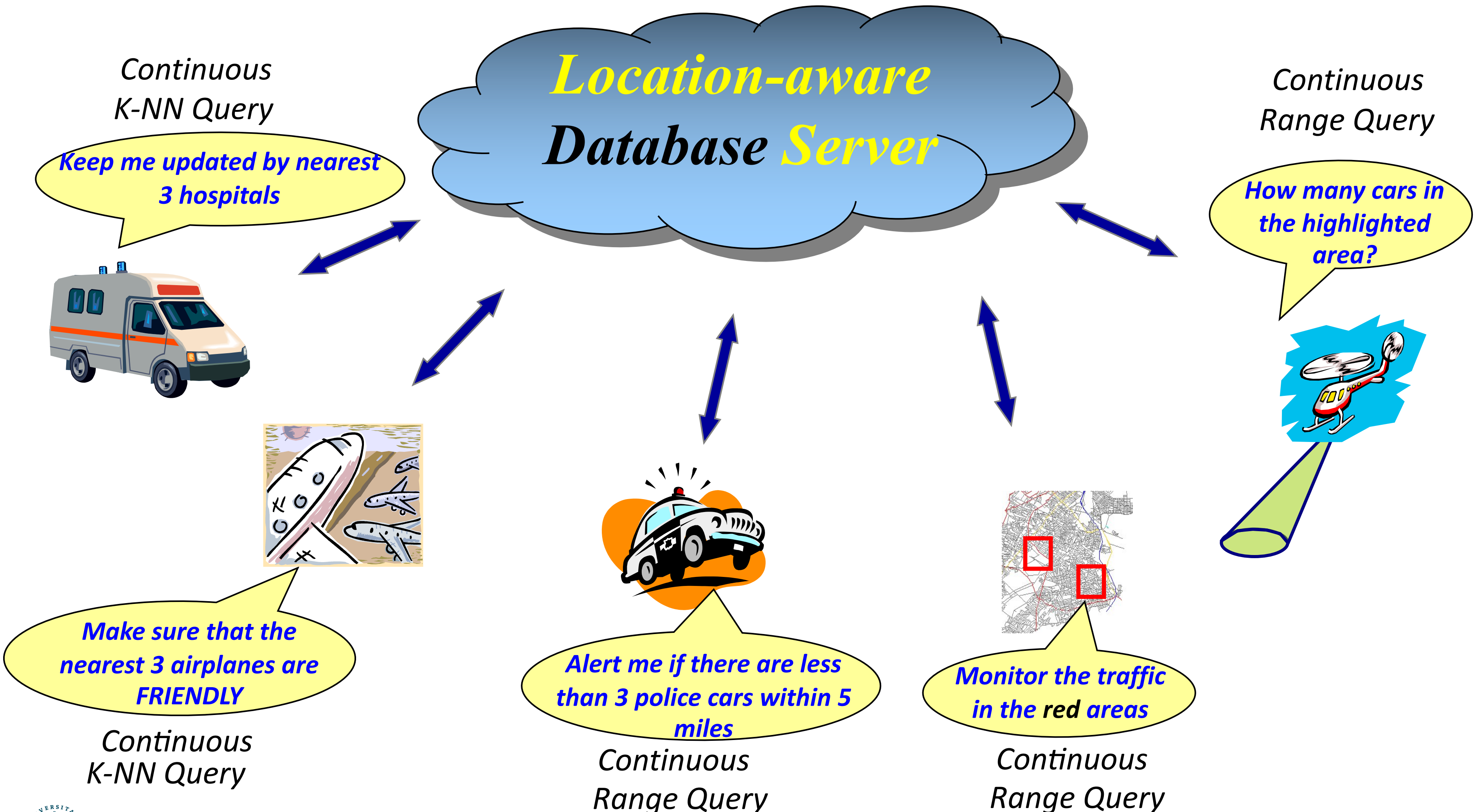
- Need to continuously listen for notifications that someone cross the query boundary



Outline

- Location-aware Environments
- Location-aware *Snapshot* Query Processing
- Location-aware *Continuous* Query Processing
- Scalable Execution of Continuous Queries
  - Location-aware Centralized Database Systems
  - Location-aware Distributed Database Systems
  - Location-aware Data Stream Management Systems
- Location-aware Query Optimizer
- Uncertainty in Location-aware Query Processing

Queries as Data – Motivation



Main Concepts

Continuous queries last for long times at the server side

- → While a query is active in the server, other queries will be submitted
- ❑ *Shared execution among multiple queries*

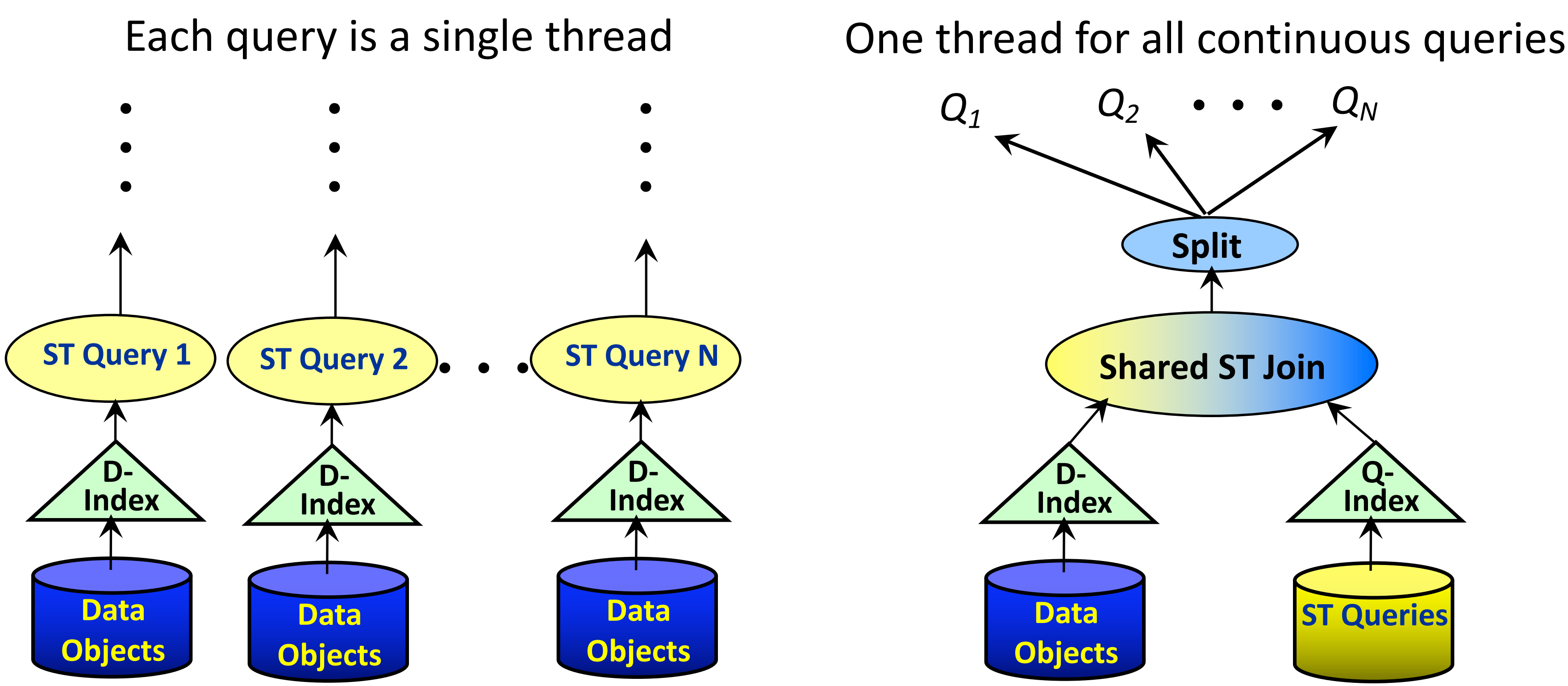
Should we index data OR queries?

- → Data and queries may be stationary or moving
- → Data and queries are of large size
- → Data and queries arrive to the system with very high rates
- ❑ *Treat data and queries similarly*

Queries are coming to data OR data are coming to queries?

- → Both data and queries are subjected to each other
- ❑ *Join data with queries*

Main Concepts (Cont.)

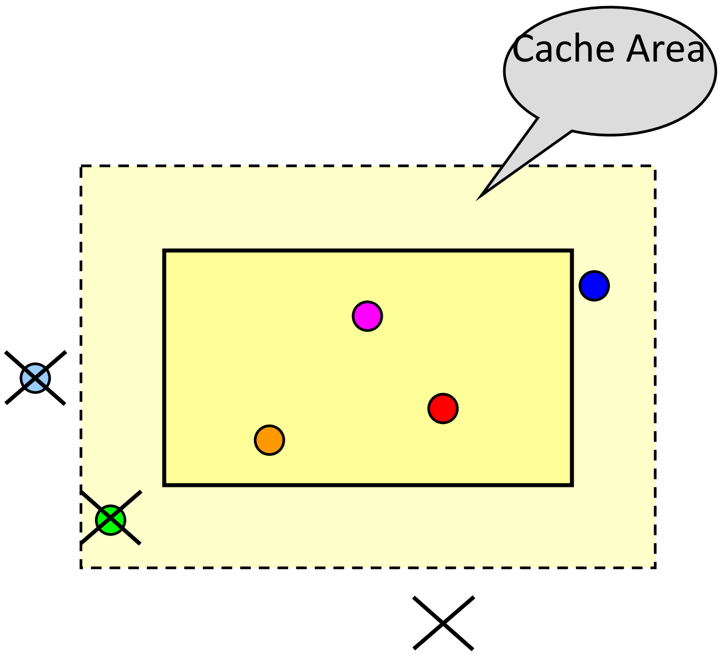


- Evaluating a large number of concurrent continuous spatio-temporal queries is abstracted as a *spatio-temporal join* between moving objects and moving queries

Location-aware Data Stream Management Systems

- Only *significant* objects are stored in-memory

- An object is considered *significant* if it is either in the query area or the cache area



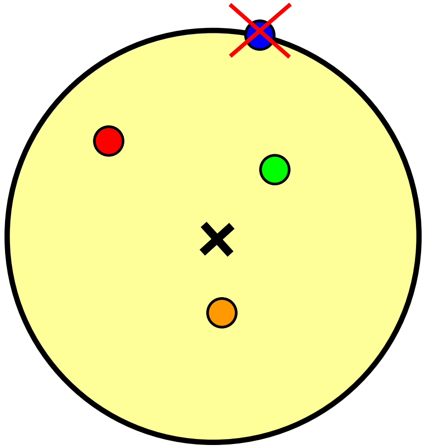
- Due to the query and object movements, a stored object may become *insignificant* at any time

- Larger cache area indicates more storage overhead and more accurate answer

Location-aware Data Stream Management Systems (Cont.)

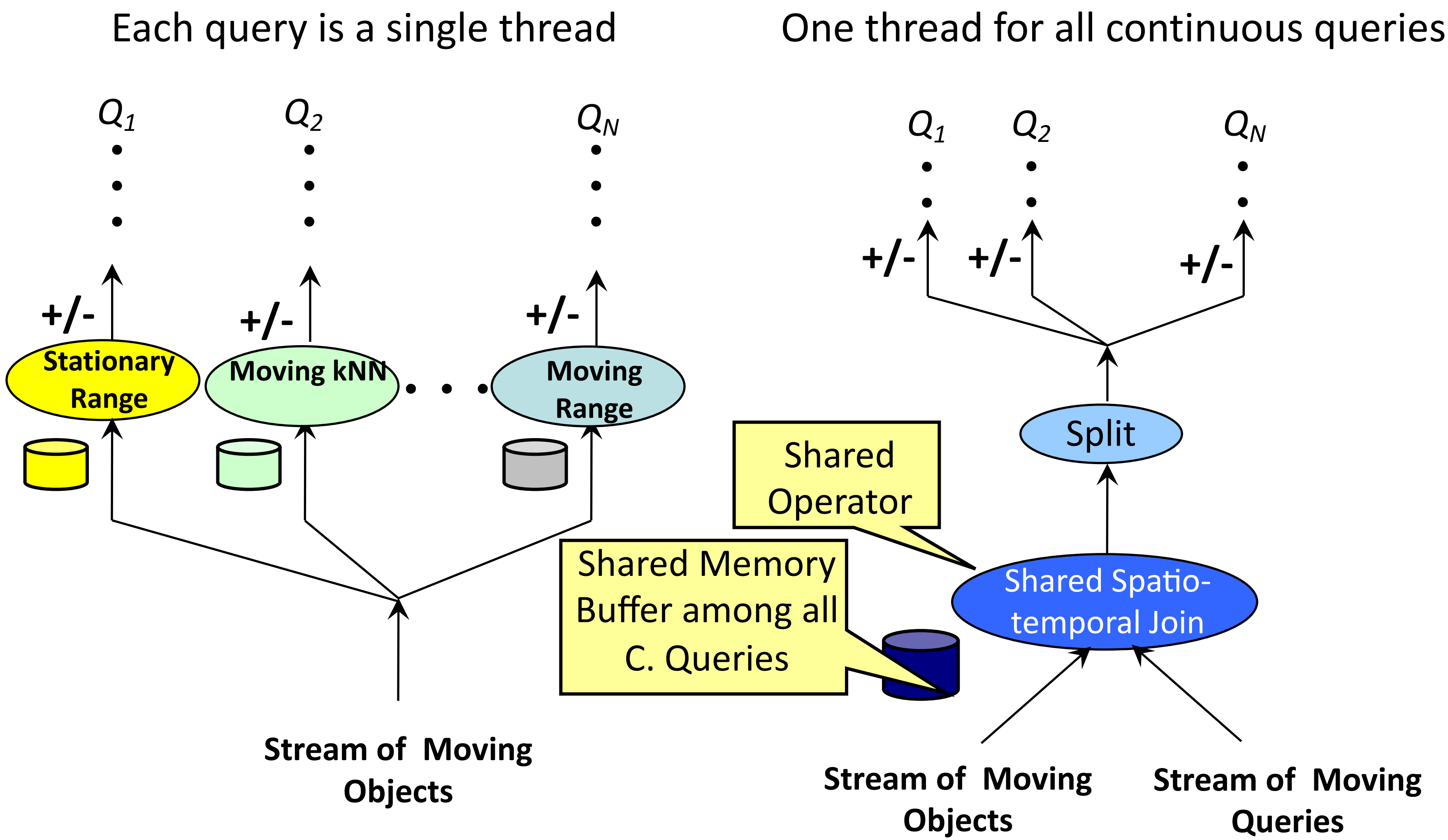
- The first *k* objects are considered an initial answer
- *K*-NN query is reduced to a circular range query

However, the query area may shrink or grow



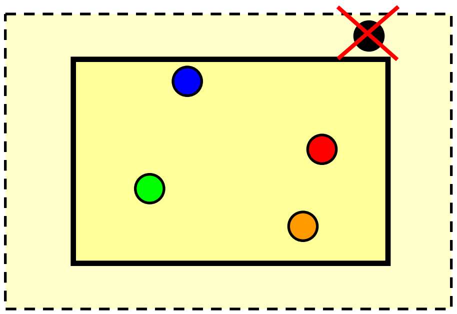
K = 3

Location-aware Data Stream Management Systems (Cont.)

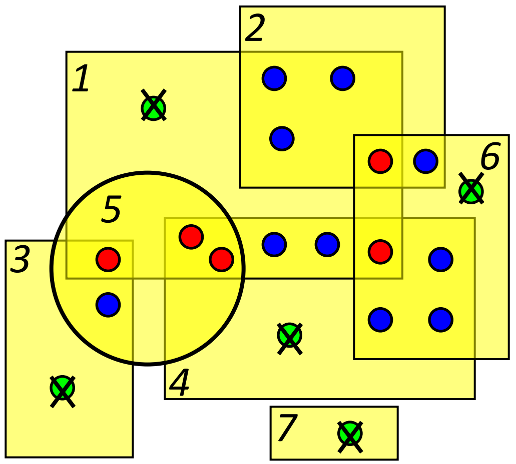


Location-aware Data Stream Management Systems (Cont.)

- Query Load Shedding
  - Reduce the cache area
  - Possibly reduce the query area
  - *Immediately* drop *insignificant* tuples
  - Intuitive and simple to implement



- Object Load Shedding
  - Objects that satisfy less than *k* queries are *insignificant*
  - *Lazily* drop *insignificant* tuples
  - *Challenge I:* How to choose *k?*
  - *Challenge II:* How to provide a lower bound for the query accuracy?



K = 2

Tutorial Outline

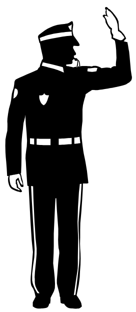
- Location-aware Environments
- Location-aware *Snapshot* Query Processing
- Location-aware *Continuous* Query Processing
- Scalable Execution of Continuous Queries
- Location-aware Query Optimization
- Uncertainty in Location-aware Query Processing

Location-aware Query Optimization

- Spatio-temporal pipelinable query operators
  - Range queries
  - Nearest-neighbor queries
- Selectivity estimation for spatio-temporal queries/operators
  - Spatio-temporal histograms
  - Sampling
- Adaptive query optimization for continuous queries

Spatio-temporal Query Operators

- Existing Approaches are Built on Top of DBMS (at the Application Level)



Continuously report the ***trucks*** in this area

Scalar functions (Stored procedure)

Only produce objects in the

The performance of scalar functions is limited

Engine

SELECT *O. ID*
FROM *Objects O*
WHERE *O.type* = ***truck***
INSIDE ***Area A***

Database Engine

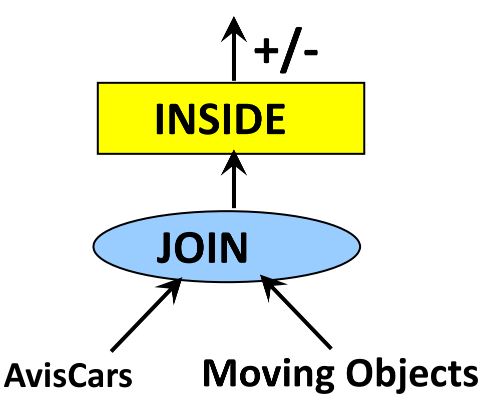
Spatio-temporal Operators

Spatio-temporal Query Operators

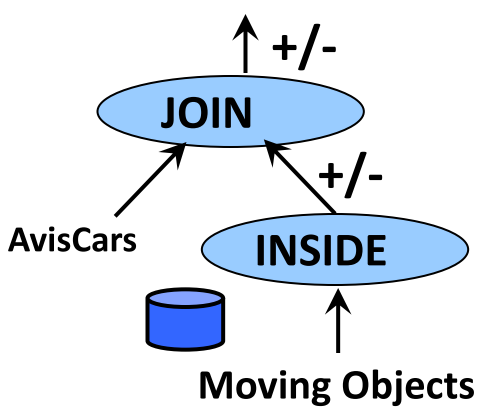
- *“Continuously report the Avis cars in a certain area”*

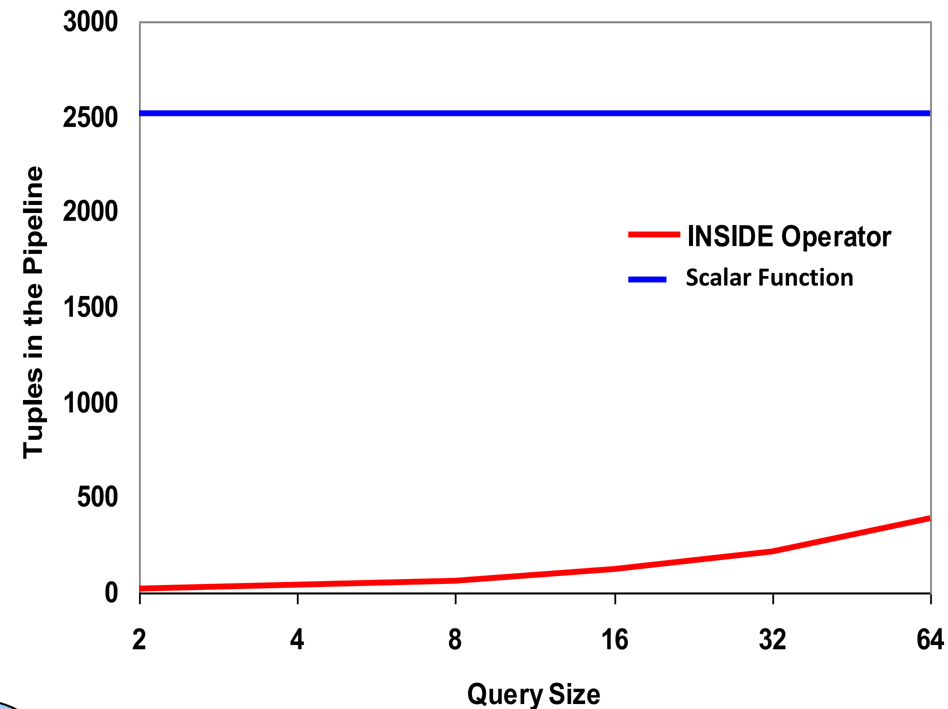
SELECT *M.ObjectID*
FROM *MovingObjects M, AvisCars A*
WHERE *M.ID = A.ID*
INSIDE *RegionR*

Scalar Function



Spatio-temporal Operators

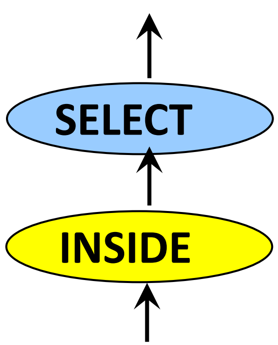


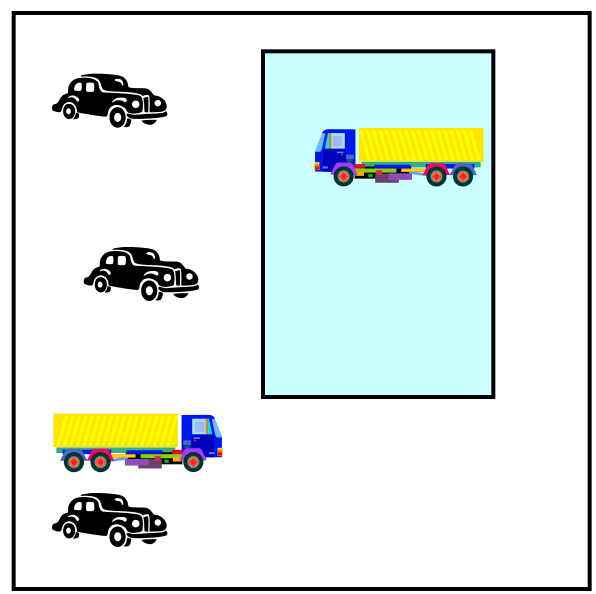


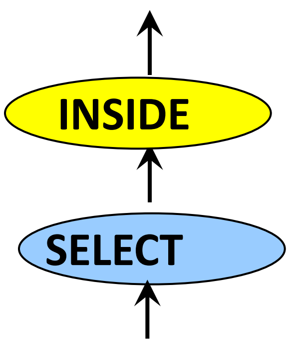
Spatio-temporal Selectivity Estimation

- Estimating the selectivity of spatio-temporal operators is crucial in determining the best plan for spatio-temporal queries

SELECT *ObjectID*
FROM *MovingObjects M*
WHERE *Type = Truck*
INSIDE *Region R*

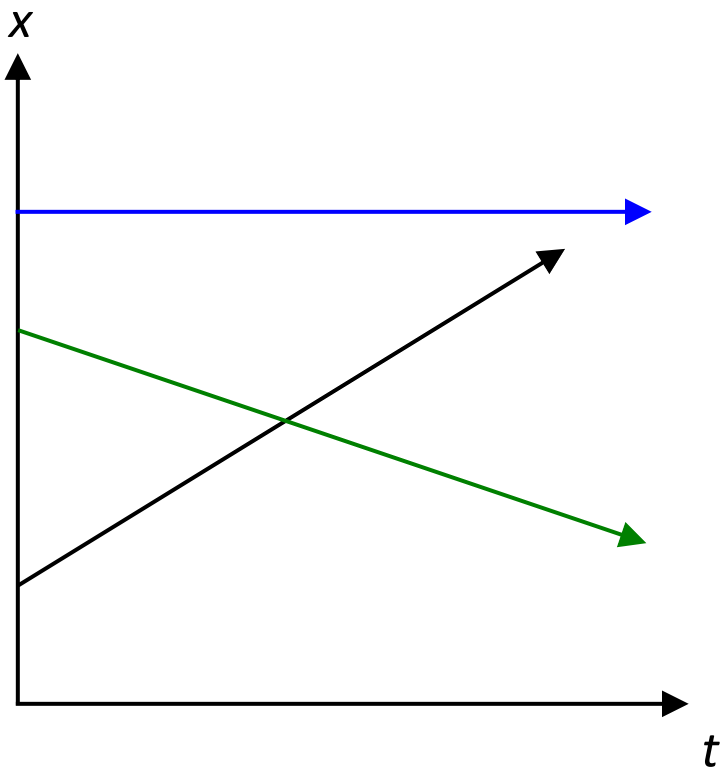


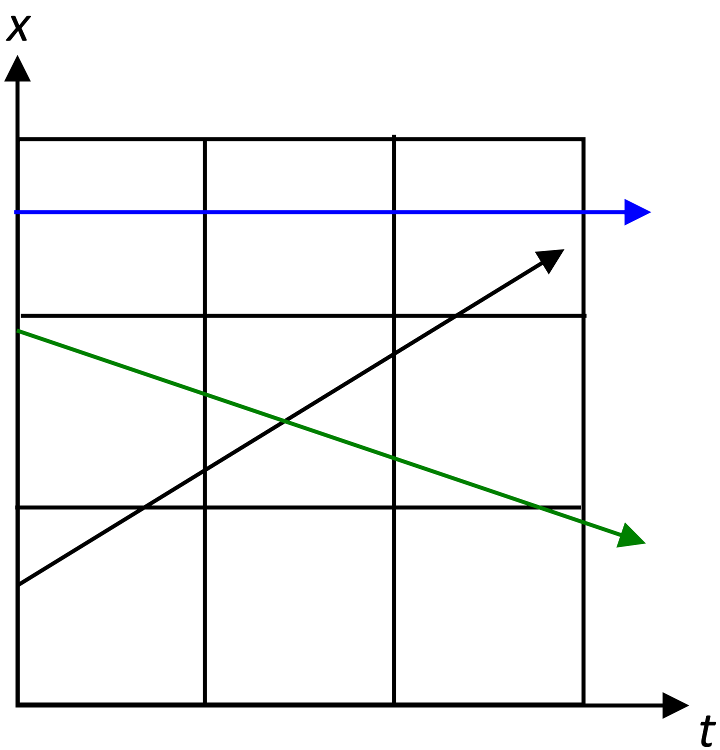




Spatio-temporal Histograms

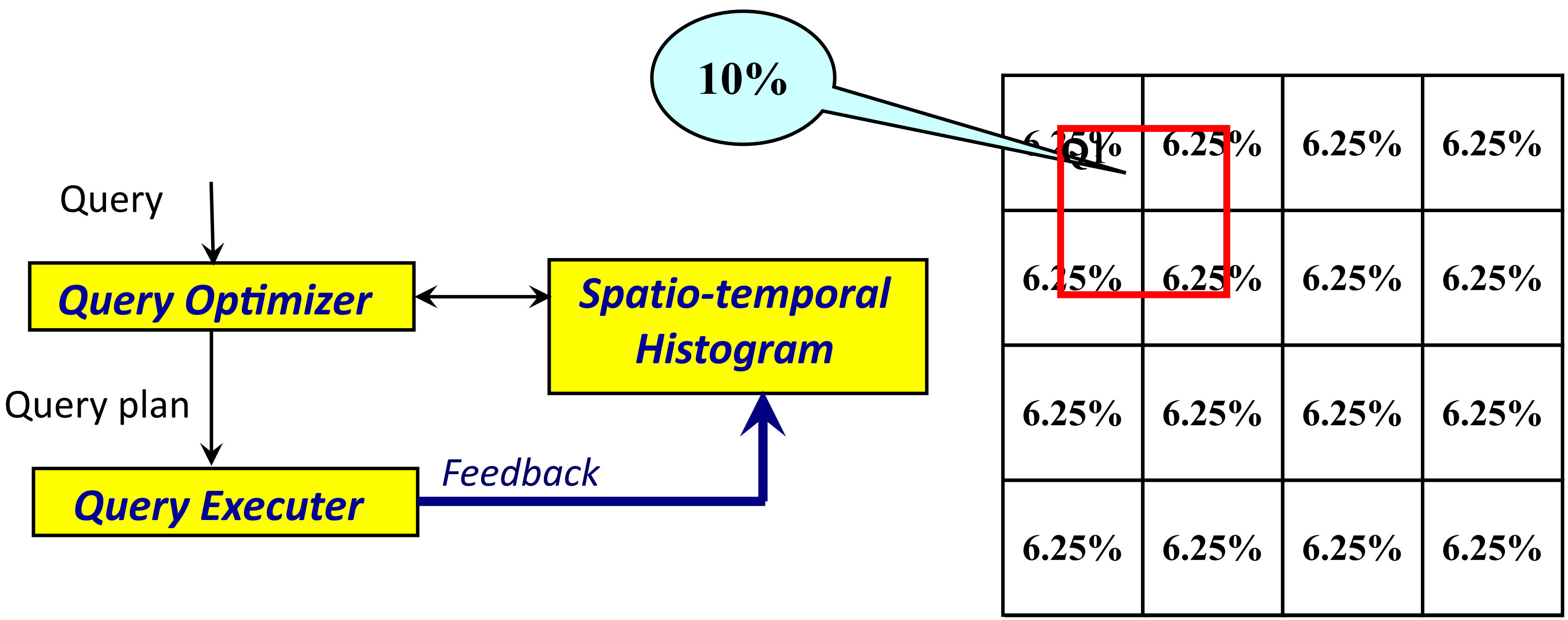
- Moving objects in D-dimensional space are mapped to 2D-dimensional histogram buckets





Spatio-temporal Histograms with Query Feedback

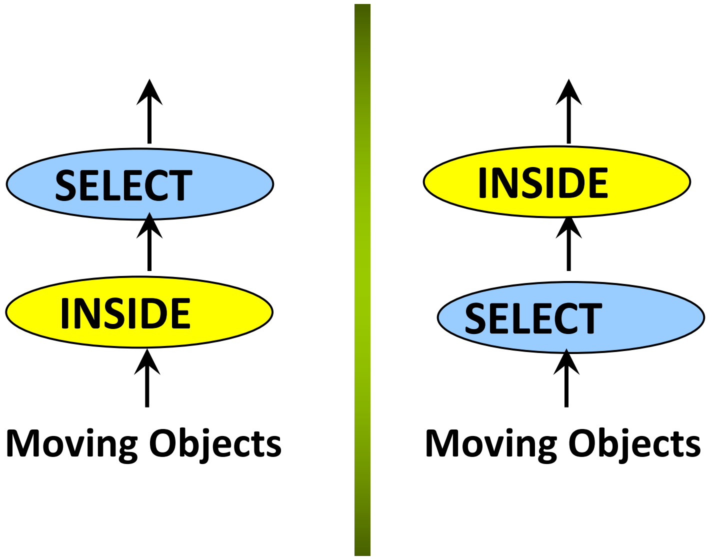
- Estimating the selectivity of spatio-temporal operators is crucial in determining the best plan for spatio-temporal queries



Adaptive Query Optimization

- Continuous queries last for long time (hours, days, weeks)
  - ➔ Environment variables are likely to change
  - ➔ The initial decision for building a query plan may not be valid after a while
- Need continuous optimization and ability to change the query plan:
  - ➔ Training period: Spatio-temporal histogram, periodicity mining
  - ➔ Online detection of changes

SELECT *ObjectID*
FROM *MovingObjects M*
WHERE *Type = Truck*
INSIDE *Region R*



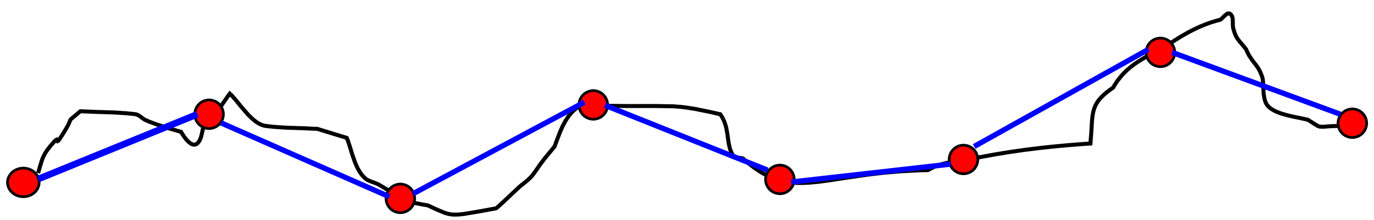
Uncertainty in Moving Objects

- Location information from moving objects is inherently inaccurate

- Sources of uncertainty:
  - Sampling. A moving object sends its location information once every *t* time units. Within any two consecutive locations, we have no clue about the object's exact location
  - Reading accuracy. Location-aware devices do not provide the exact location
  - Object movement and network delay. By the time that a certain reading is received by the server, the moving object has already changed its location

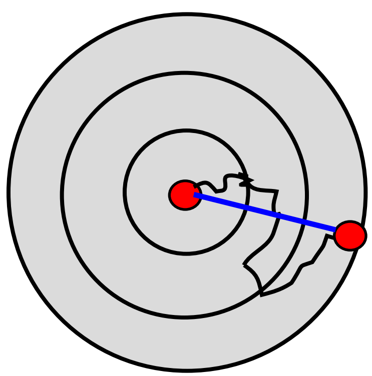
Uncertainty in Moving Objects

- Historical data (Trajectories)



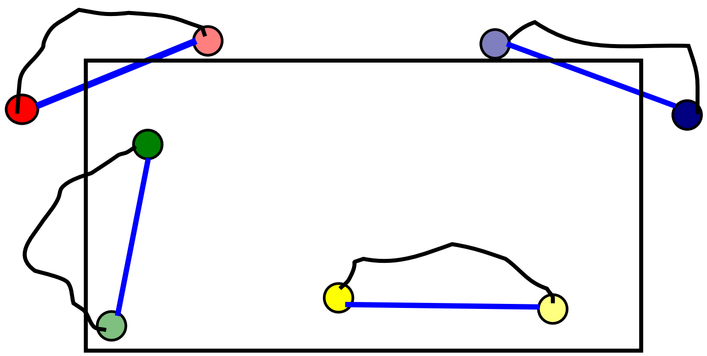
- Current data

$T_0+\epsilon_0$

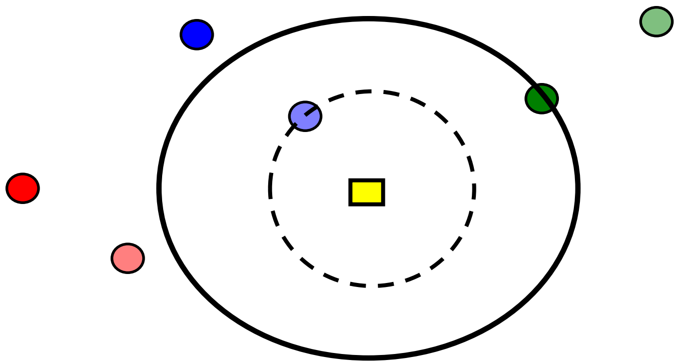


Error in Query Answer

- Range Queries

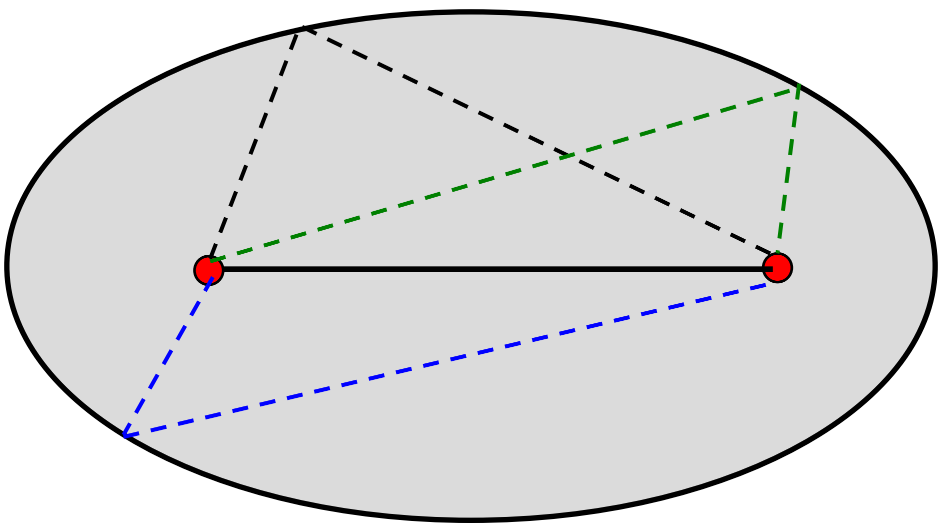


- Nearest Neighbor Queries



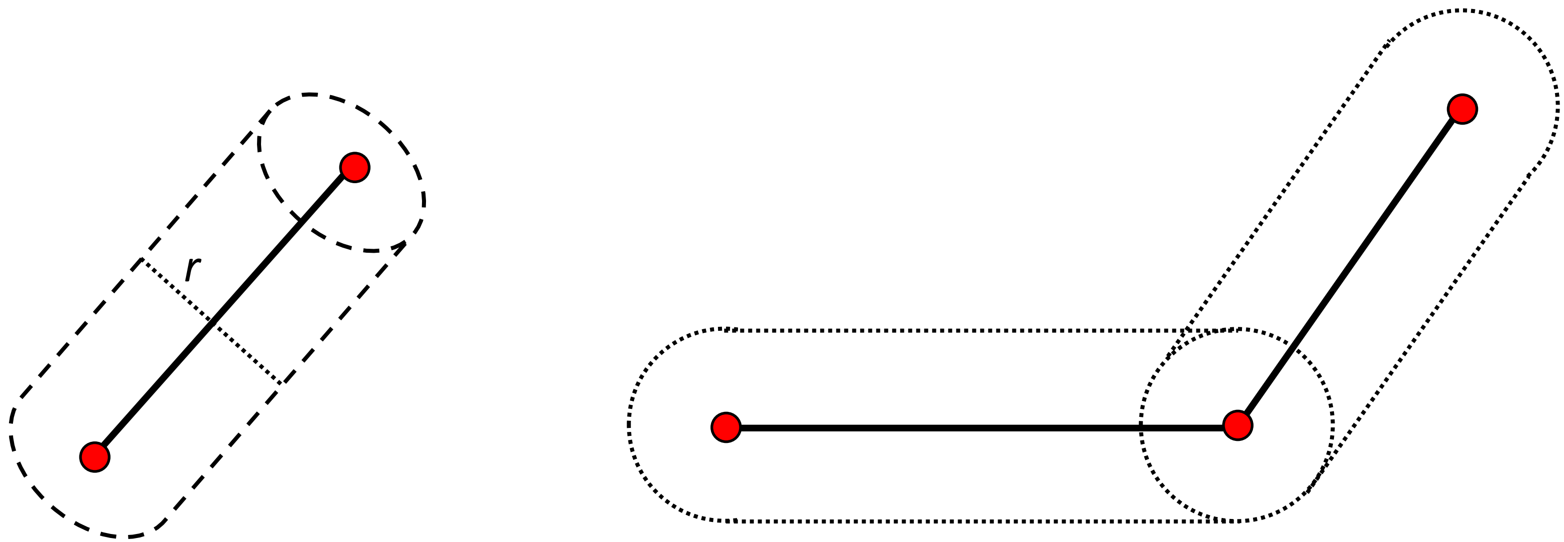
Representing Uncertain Data using Ellipses

- Given :
  - Start point
  - End point
  - Maximum possible speed ➔ Maximum traveling distance S
- If S is greater than the distance between the two end points, then the moving object may have deviated from the given route



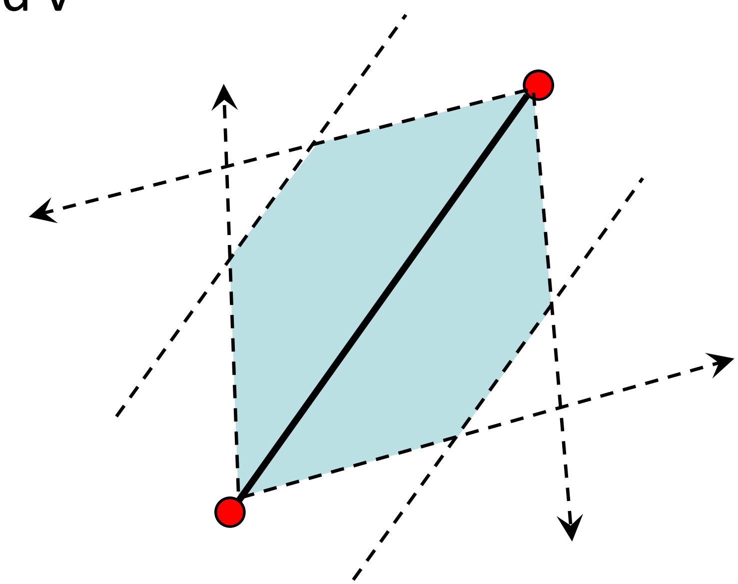
Representing Uncertain Data using Cylinders

- Given:
  - Start and end points
- Constraint:
  - An object would report its location only if it is deviated by a certain distance r from the predicted trajectory



Representing Uncertain Data in Road Networks

- Given:
  - Start and end points
- Constraints :
  - Deviation threshold r
  - Speed threshold v

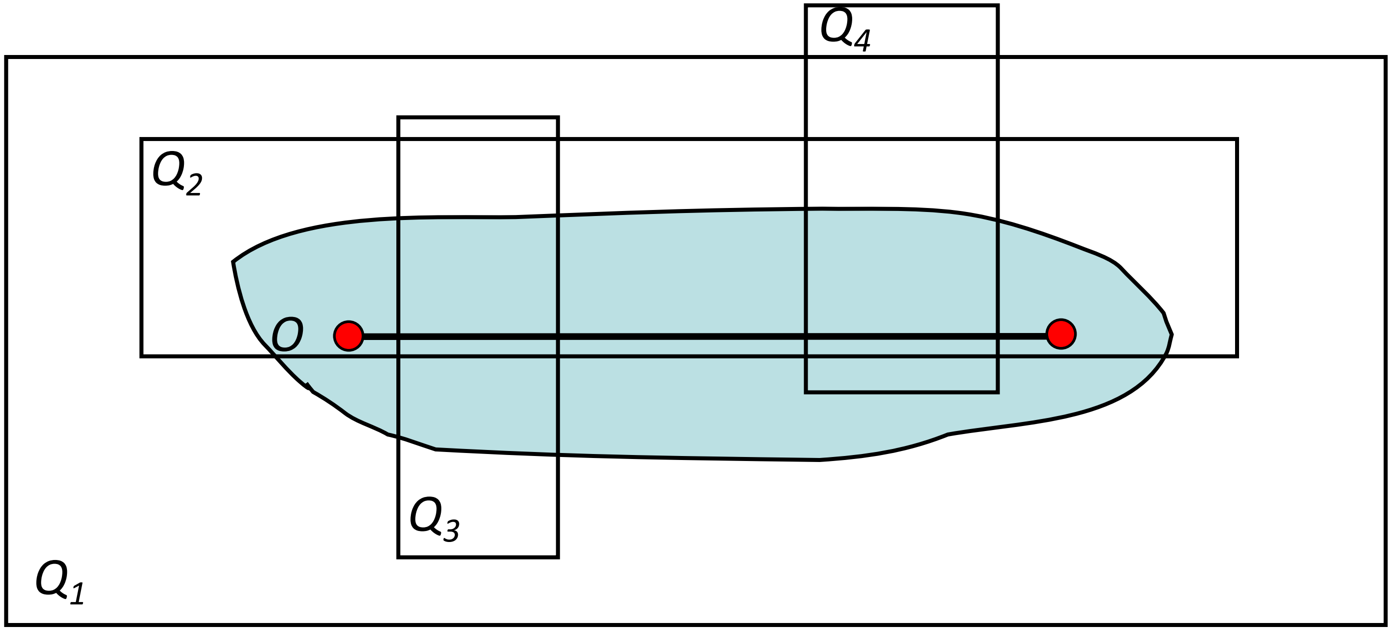


Querying Uncertain Data Uncertain Keywords

- KEYWORDS:
  - Probability: *possibly, definitely*
  - Temporal: *sometimes, always*
  - Spatial: *somewhere, everywhere*

- *Examples:*
  - *What are the objects that are possibly sometimes within area R at time interval T?*
  - *What are the objects that definitely passed through a certain region?*
  - *Retrieve all the objects that are always inside a certain region*
  - *Retrieve all the objects that are sometimes definitely inside region R*

Querying Uncertain Data Uncertain Keywords (Cont.)



- *Object O is definitely always in Q_1*
- *Object O is possibly always in Q_2*
- *Object O is definitely sometimes in Q_3*
- *Object O is possibly sometimes in Q_4*

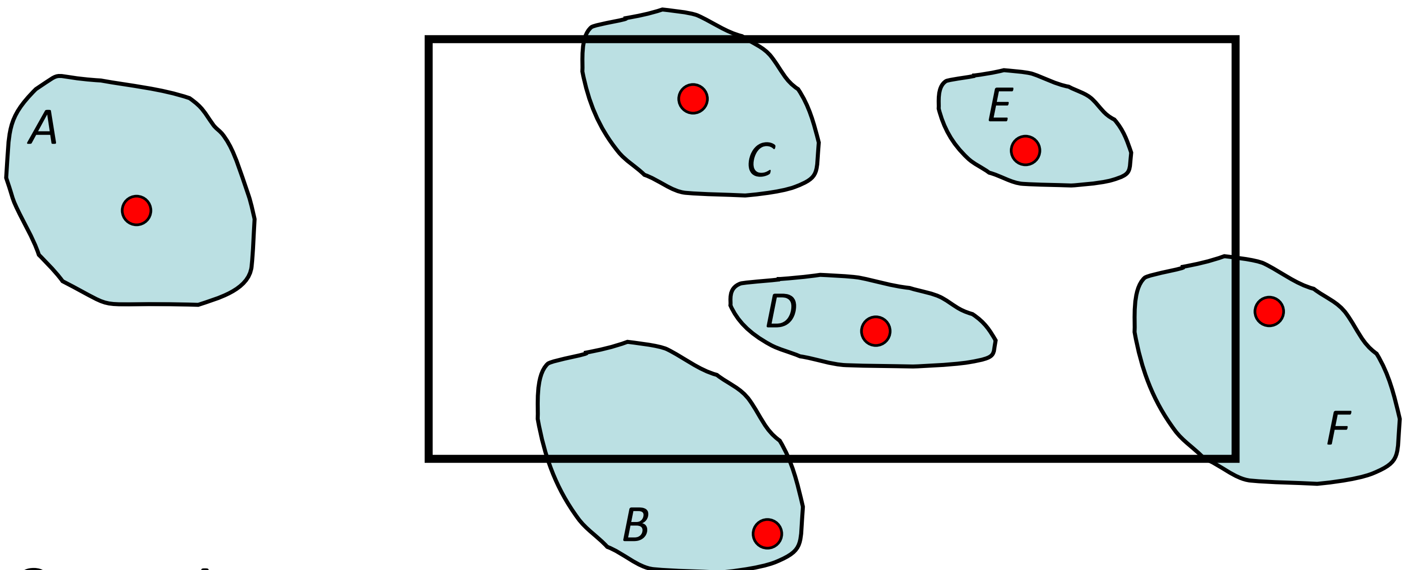
Querying Uncertain Data Probabilistic Queries

- With each query answer, associate a probability that this answer is true

- The answer set of a query Q is represented as a set of tuples <ID, p> where ID is the tuple identifier and p is the probability that the object ID belongs to the answer set of Q

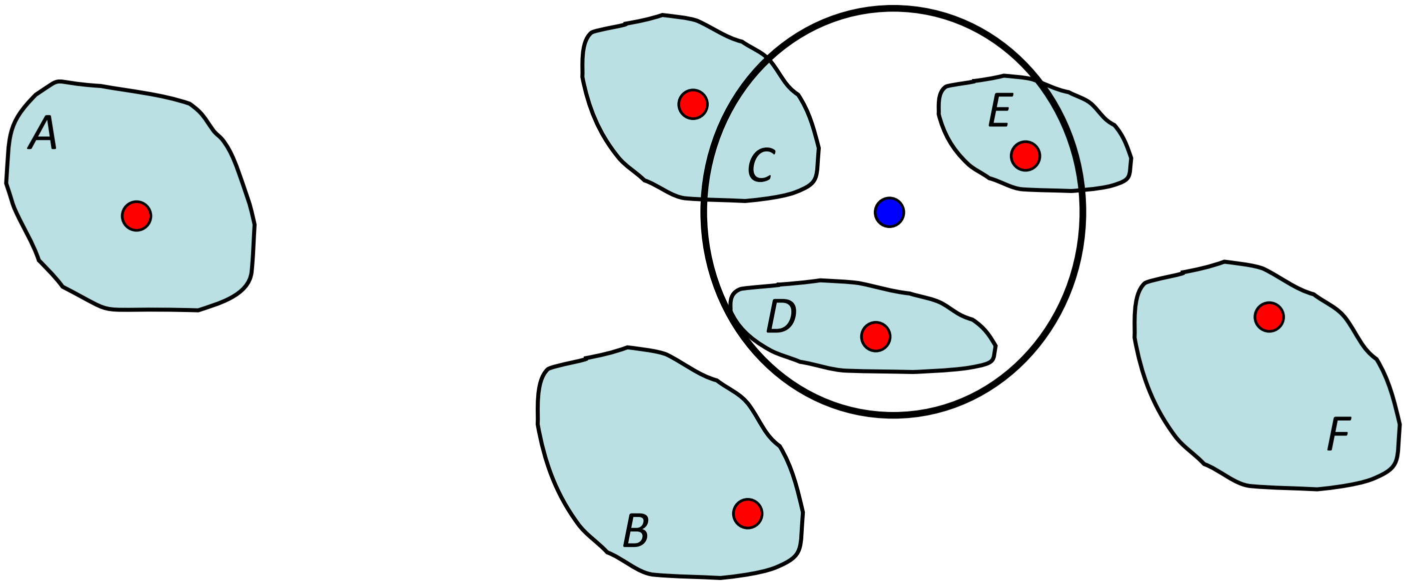
- Assumptions:
  – Objects can lie anywhere uniformly within their uncertainty region

Querying Uncertain Data Probabilistic Range Queries



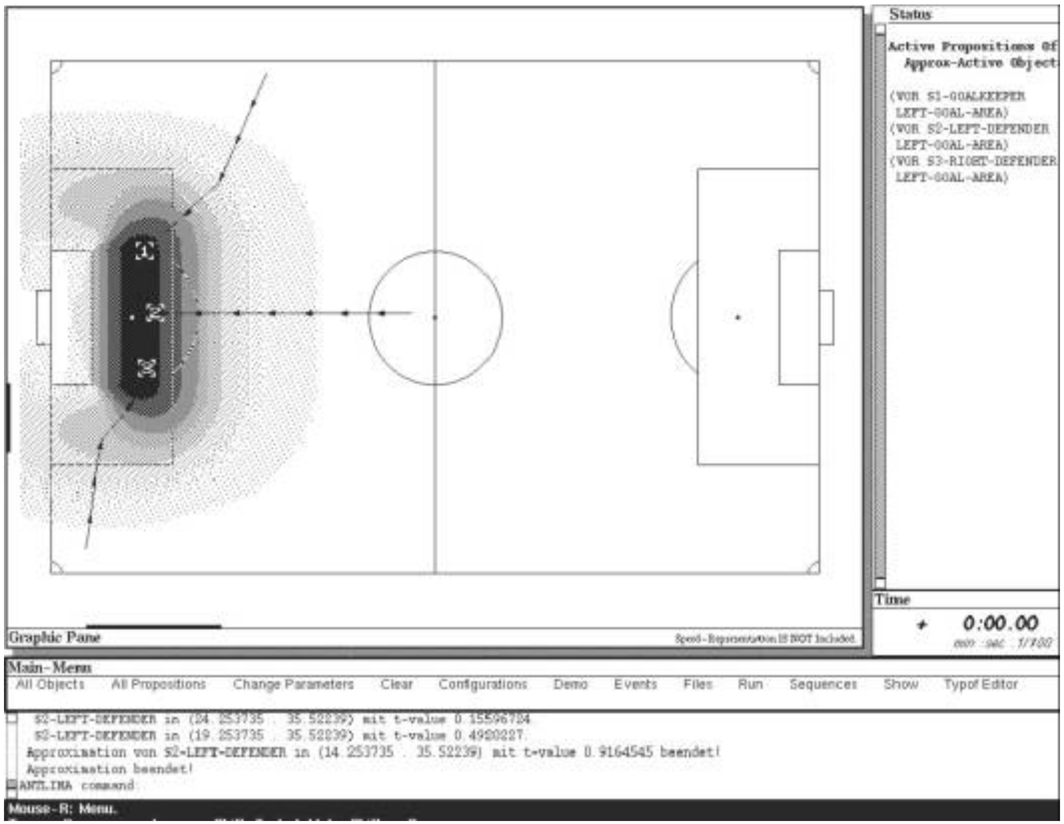
- Query Answer:
  - (B, 50%)
  - (C, 90%)
  - D
  - E
  - (F, 30%)

Querying Uncertain Data Probabilistic NN Queries



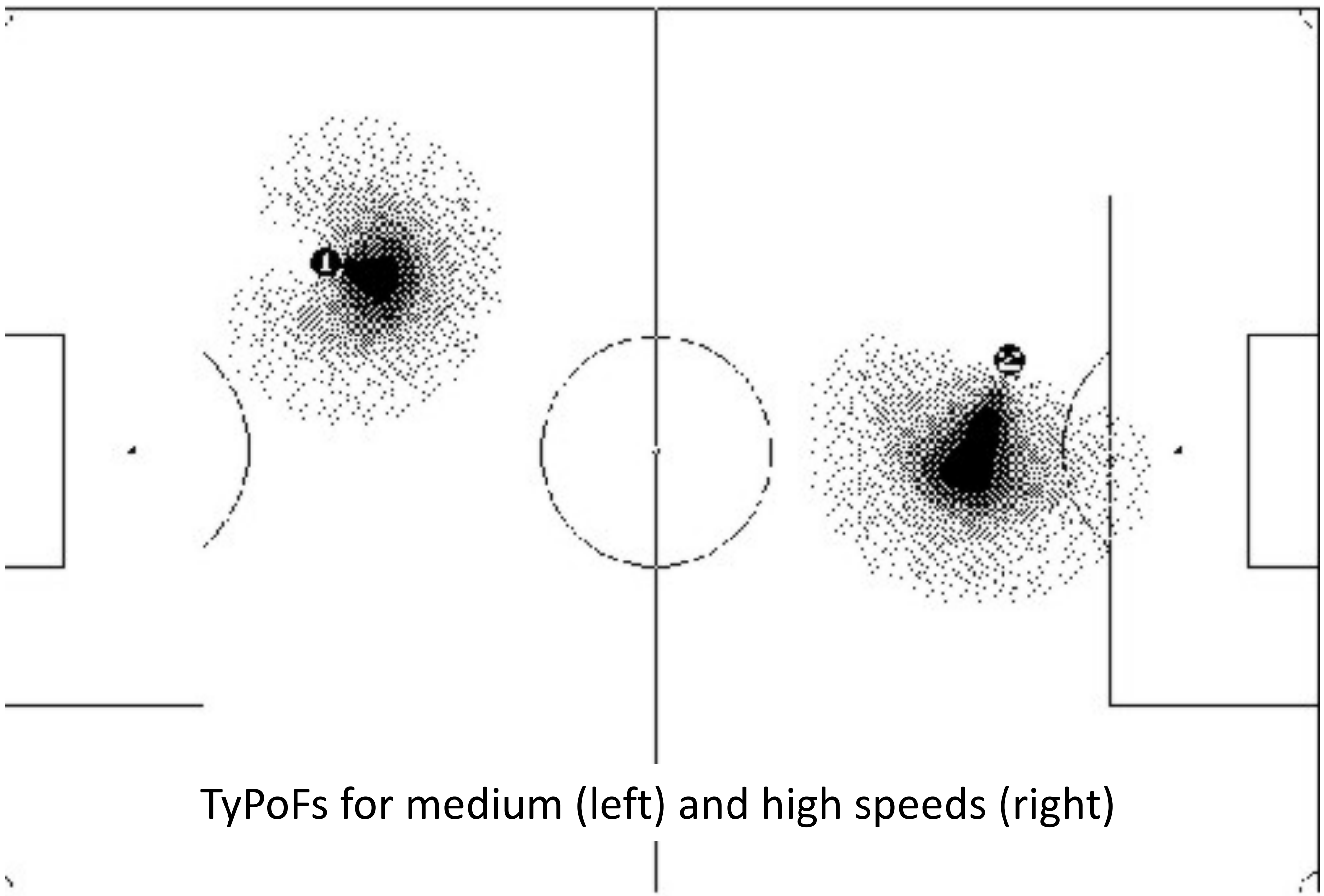
- Query Answer (k=1):
  - (C, p_1)
  - (D, p_2)
  - (E, p_3)

Typicality Potential Fields (TyPoFs)



‘Spieler vor dem Strafraum’

Typicality Potential Fields



TyPoFs for medium (left) and high speeds (right)

J.R.J. Schirra: Bildbeschreibung als Verbindung von visuellem und sprachlichem Raum – Eine interdisziplinäre Untersuchung von Bildvorstellungen in einem Hörermodell. Dissertation. Infix, St. Augustin, **1994**

Summary

- Location-aware Environments
- Location-aware *Snapshot* Query Processing
- Location-aware *Continuous* Query Processing
- Scalable Execution of Continuous Queries
- Location-aware Query Optimizer
- Uncertainty in Location-aware Query Processing

Open Research Issues: Location Privacy

YOU ARE TRACKED… !!!!

"New technologies can pinpoint your location at any time and place. They promise safety and convenience but threaten privacy and security"

Cover story, IEEE Spectrum, July 2003

Spatio-Temporal Data Mining

- Mining the history ➔ Predicting the future
- Online outlier detection for moving objects
- Suspicious movement in video surveillance
- Analysis of tsunami, hurricanes, or earthquakes
- Phenomena detection and tracking