Indexing the Positions of Continuously Moving Objects

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Why Moving Objects?

- Position-aware, online, moving objects are enabled by the following trends.
  - Miniaturization of electronics
  - Advances in positioning systems (e.g., GPS, assisted GPS, ...)
  - Advances in wireless communications

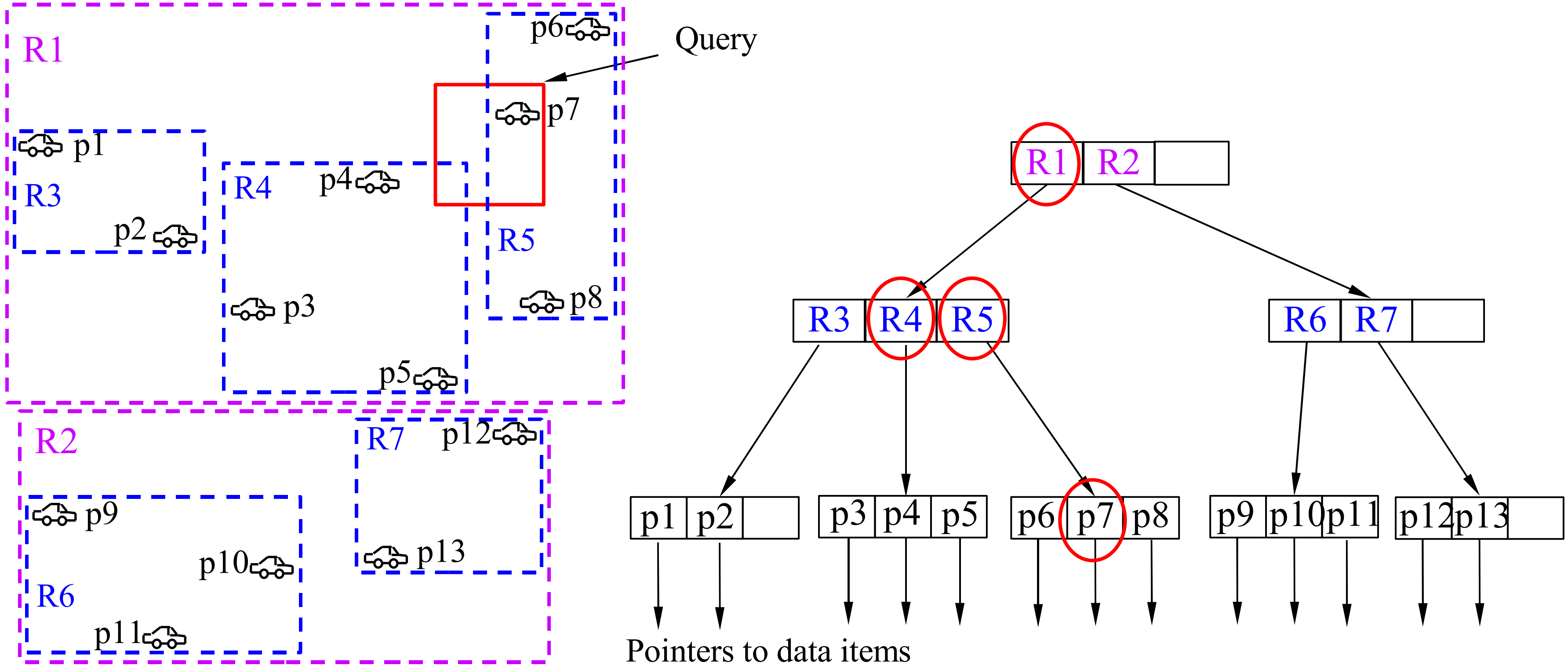
- Examples of position-aware online moving objects
  - GPS-enabled mobile-phones, as well as diverse types of personal digital assistants (online "cameras," "wrist watches," etc.).
    - The coming years will witness very large quantities of these.
  - Vehicles, including cars, public transportation, recreational vehicles, sea vessels, airplanes, etc.
- Sensor-networks also generate MO data
  - Monitoring of any kind-of continuous variables, e.g., temperature, pressure

Outline

- Motivation
- Background: R-tree
- Problem definition
  - Data and queries
- Structure and algorithms of the TPR-tree
- Insertion example
- Summary

Spatial Indexing With the R-Tree

- Example



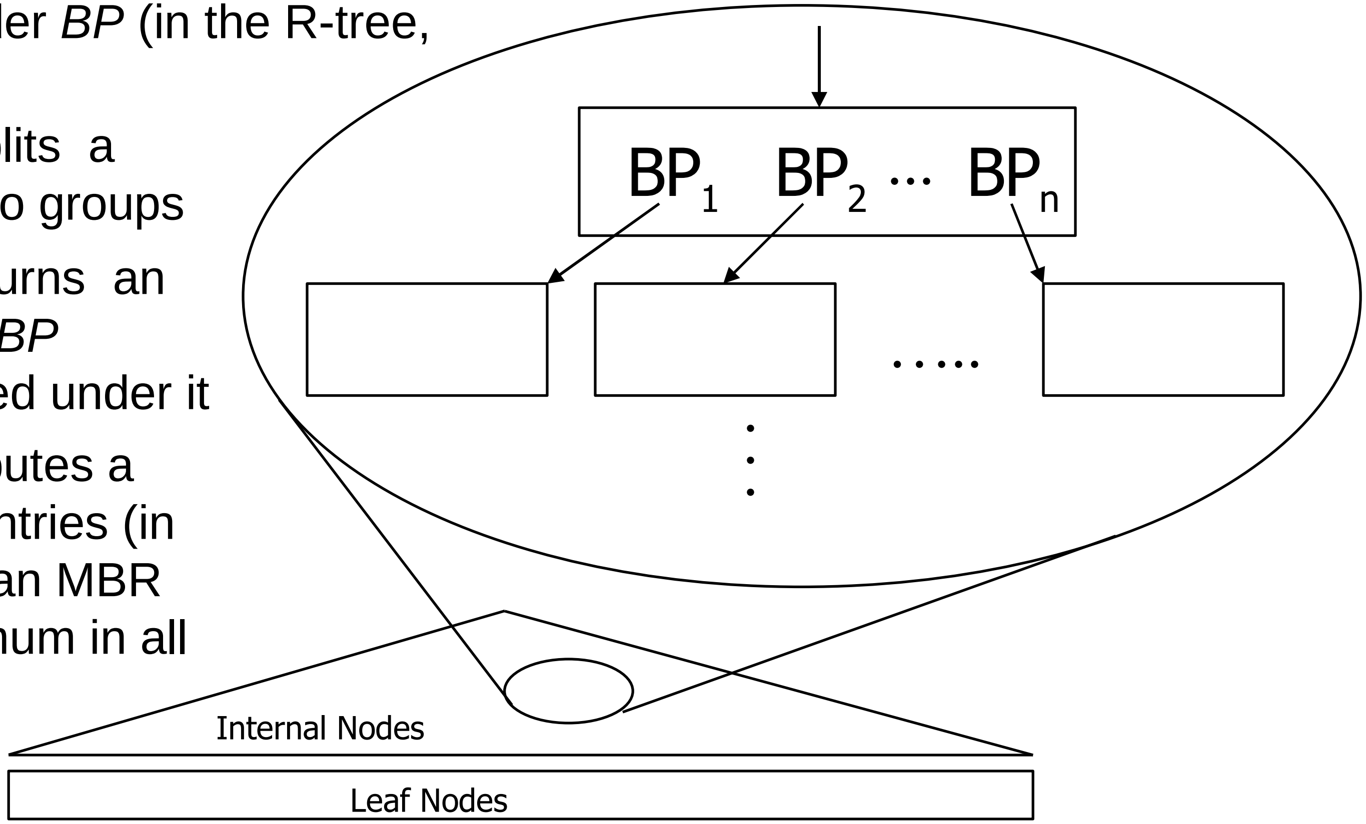
Grow-Post trees

Grow-Post trees: generalized R-tree-type indexes

Bounding predicate (*BP*) = *something that describes entries in a subtree*

Building blocks of algorithms:

- **Consistent**(*BP*, *Q*) – returns *true* if results of query *Q* can be under *BP* (in the R-tree, MBR intersects *Q*)
- **PickSplit**(*node*) – splits a page of entries into two groups
- **Penalty**(*BP, E*) – returns an estimate how "worse" *BP* becomes if *E* is inserted under it
- **Union**(*node*) – computes a BP of a collection of entries (in the R-tree, computes an MBR – minimum and maximum in all dimensions)

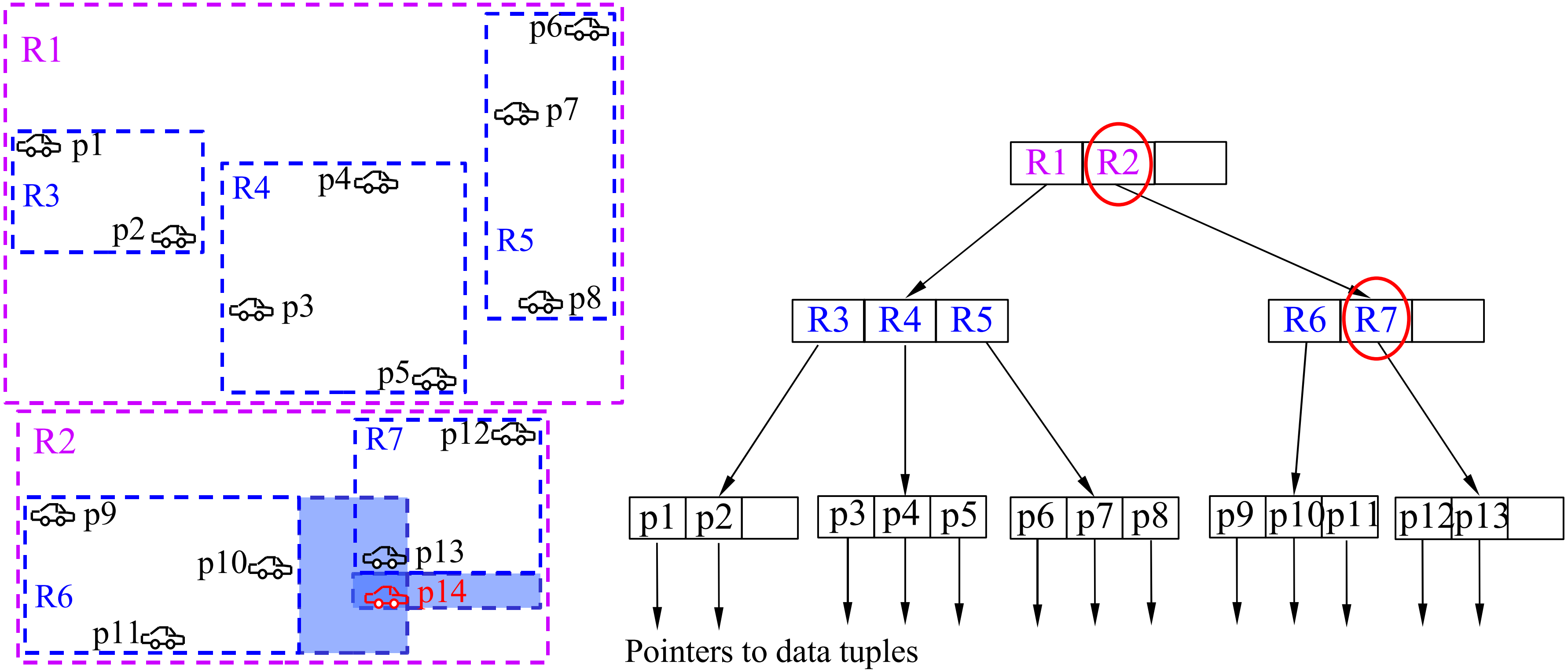


Insertion

- *Insert*(*E*)
  - *leaf* = *ChoosePath*(*E*, *root*)
  - Insert *E* into *leaf*
  - *PropogateUp* (*leaf*)
- *ChoosePath*(*E*, *node*)
  - **If** *node* is leaf, **return** *node*.
  - From all entries in *node,* choose entry *<MBR, ptr>* with the smallest **Penalty (***MBR, E***).**
  - *ChoosePath*(*E*, *ReadNode*(*ptr*)).
- *PropogateUp*(*node*)
  - **If** *node* is overfull, call **PickSplit(***node***)** to produce *n1* and *n2*, replace *node's* old entry in its parent by *e1* = **Union(***n1***),** *e2* = **Union(***n2***)**, call *PropogateUp*(*node's* parent)
  - **Else if** *e* = **Union(***node***)** is different from *node's* old entry in its parent, replace the old entry with *e,* call *PropogateUp*(*node*'s parent).
- Create a new root with two entries whenever a root is split.

Heuristics for **Penalty**

- Heuristics of *least area enlargement* and *smallest area* are used in the R-tree's **Penalty**.



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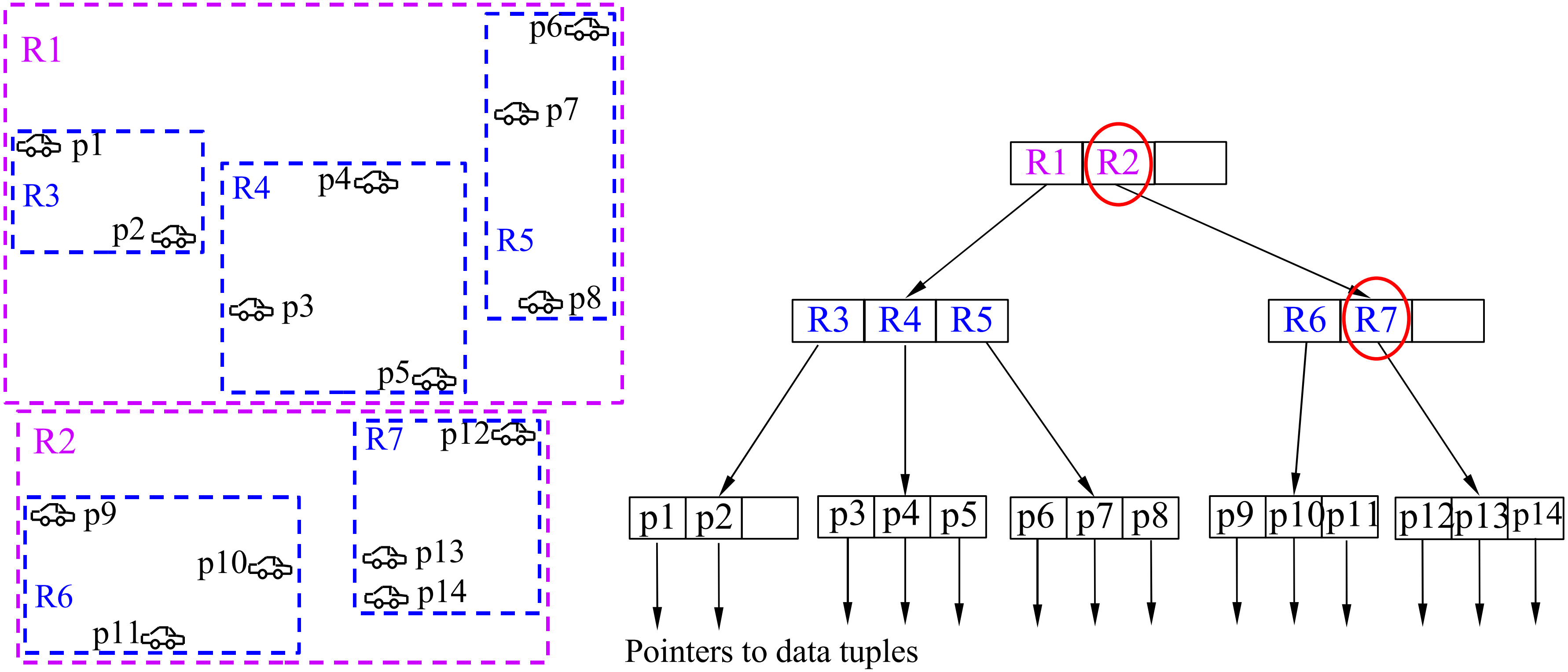

Comments on R-Trees

- Works well for 2 - 4 D datasets. Several variants (notably, R^+ and R*-trees) have been proposed; widely used
- Supports a wide variety of queries
  - Point / range queries
  - Spatial join queries [Brinkhoff et al., 1993]
  - Direction, topological, distance queries [Papadias et al., 1995]
  - k- Nearest neighbor queries [Roussopoulos et al., 1995]

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Problem Statement

We address the problem of indexing the ever-changing current and predicted future positions of point objects moving in one, two, and three-dimensional space.

- Indexing challenges specific to MOs
  - continuous change of positions – extrapolation between the last update and the current time must be supported
  - hyper-dynamic workloads – high-rates of updates

Modeling Continuous Movement

- In conventional databases, data is assumed constant unless explicitly modified.
- With continuous movement, this is problematic.
  - Too frequent updates
  - Outdated, inacurate data

Modeling Continuous Movement

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  - Outdated, inacurate data
- Instead of storing position values, we store positions as functions of time, yielding *time-parameterized* positions.
  - We use linear functions to capture the present and future positions.

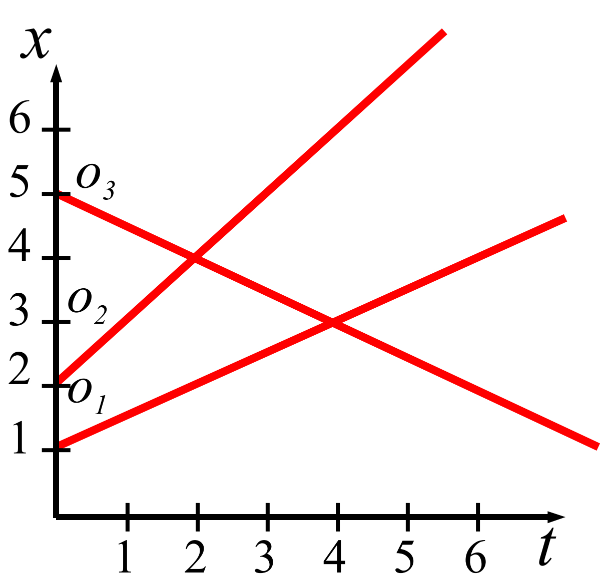
$$\bar{x}(t) = \bar{x}(t_0) + \bar{v}(t - t_0), \quad \text{where } t \geq \mathit{now}$$

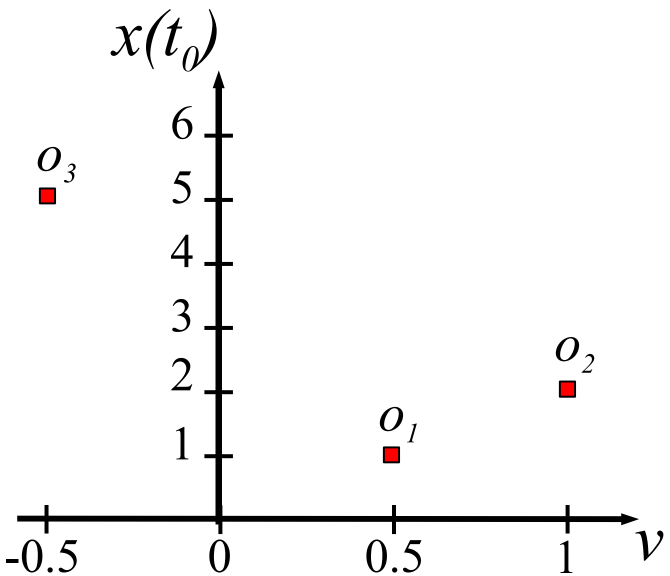
  - Updates are less frequent
  - Tentative future queries are supported
  - For example, given t_0, the current and anticiapted, future position of a two-dimensional point can be described by four parameters.

$$x(t_0), y(t_0), v_x, v_y$$

Modeling Continuous Movement

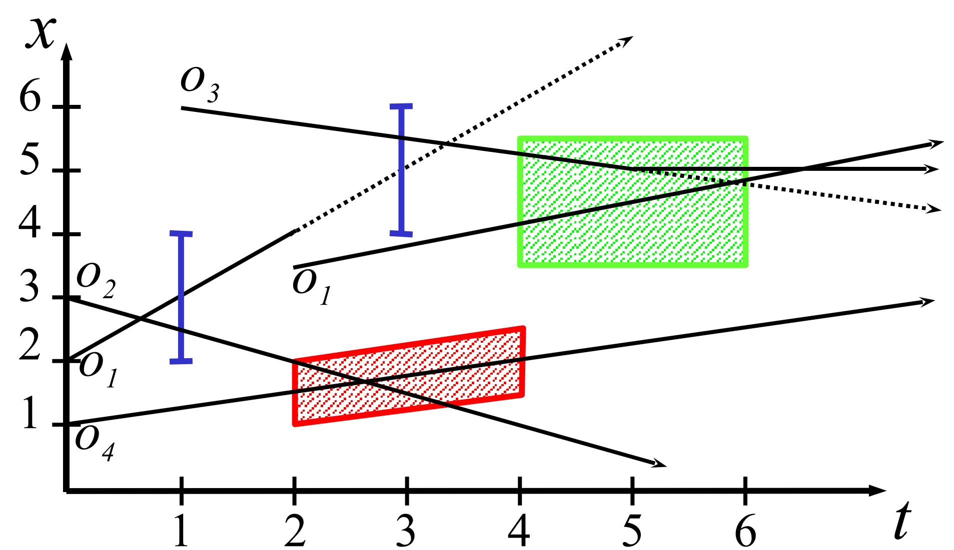
- Three ways to think about continuously moving points in *d*-dimensional space:
  - Lines in (*d*+1)-dimensional space
    - *d* spatial dimensions and 1 time dimension
  - Points in 2*d*-dimensional space
    - *d* spatial and *d* velocity dimensions (function parameters: $\bar{x}(t_0), \bar{v}$)
  - Time-parameterized points in *d*-dimensional space





Queries

- **Type 1**: objects that intersect a given rectangle at t
- **Type 2**: objects that intersect a given rectangle sometime from t_1 to t_2
- **Type 3**: objects that intersect a given moving rectangle sometime between t_1 and t_2



- We can expect, that most queries will be consentrated in the sliding window [CT, CT+*W*], i.e. $CT \le t, t_1, t_2 \le CT + W$

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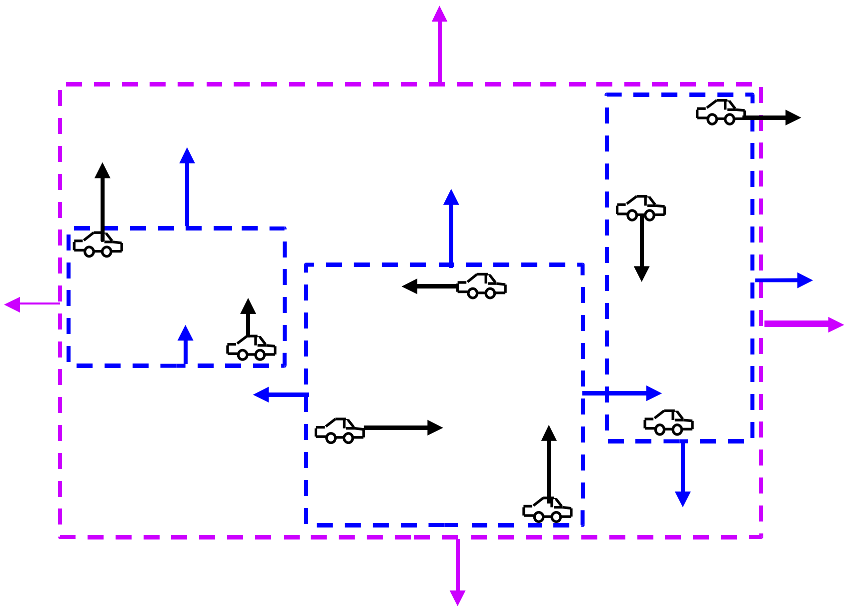
Time-Parameterized Rectangles

- The TPR-tree is based on the R-tree.
- Moving points are bounded with *time-parameterized* rectangles.
  - Are bounding from *now* on.
  - The R-tree allows overlap.
- The tree employs *conservative bounding rectangles.*



$$\text{Union}(node):$$

$$x_i^{\min}(t_c) = \min\{o.x_i(t_c) \mid o \in node\}$$

$$x_i^{\max}(t_c) = \max\{o.x_i(t_c) \mid o \in node\}$$

$$v_i^{\min} = \min\{o.v_i \mid o \in node\}$$

$$v_i^{\max} = \max\{o.v_i \mid o \in node\}$$

Entry Structure, Querying

- Do we need to store t_c in each entry?
  - No – we use one common reference time t_r (the same for data points):

$$x_i^{\min} = x_i^{\min}(t_r) = x_i^{\min}(t_c) + v_i^{\min}(t_r - t_c)$$

$$x_i^{\max} = x_i^{\max}(t_r) = x_i^{\max}(t_c) + v_i^{\max}(t_r - t_c)$$

- Entry structure: <*TPBR, ptr*>
- *TPBR* = *MBR*,*VBR* = $(x_1^{\min}, x_1^{\max}, x_2^{\min}, x_2^{\max}), (v_1^{\min}, v_1^{\max}, v_2^{\min}, v_2^{\max})$

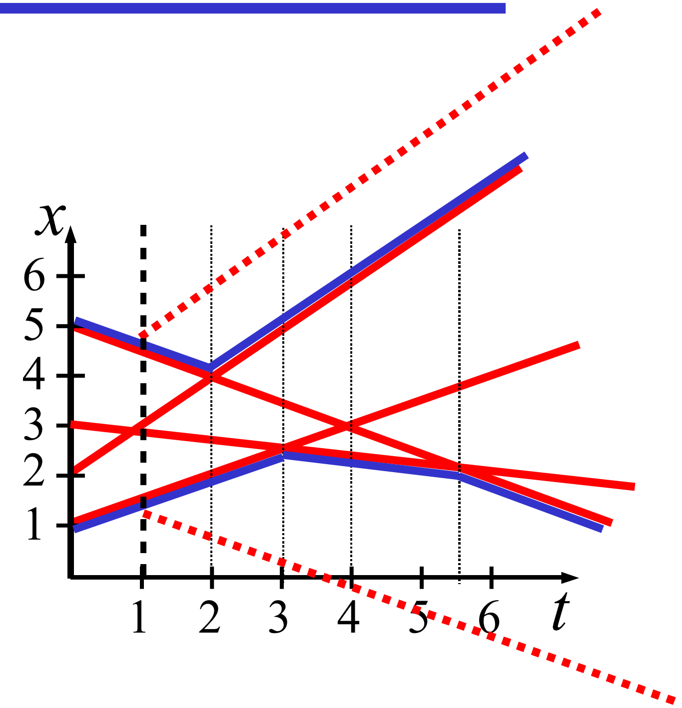
- At any $t > CT$ we can get a valid R-tree: TPR-tree*(t)* = R-tree

$$x_i^{\min}(t) = x_i^{\min}(t_r) + v_i^{\min}(t - t_r)$$

$$x_i^{\max}(t) = x_i^{\max}(t_r) + v_i^{\max}(t - t_r)$$

Tightening

- Ideally, bounding rectangles should be always minimal.
  - Excessive storage cost



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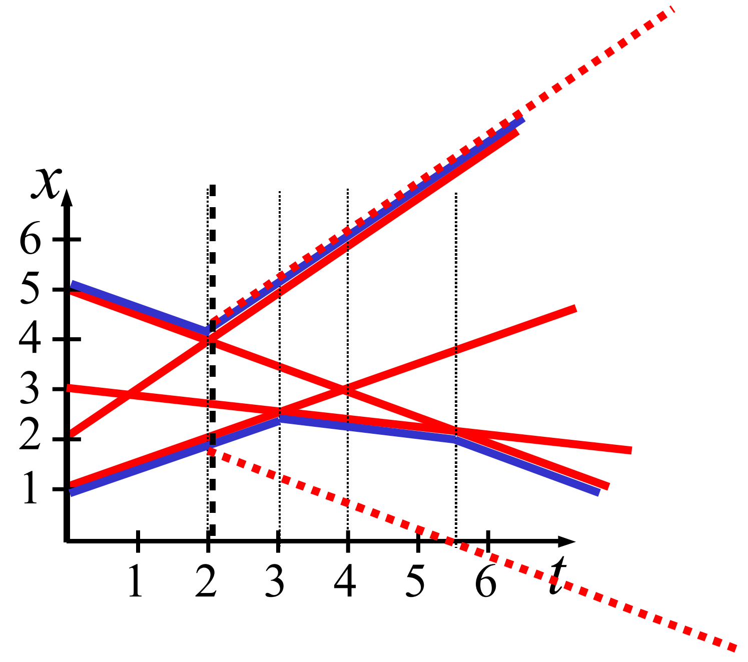
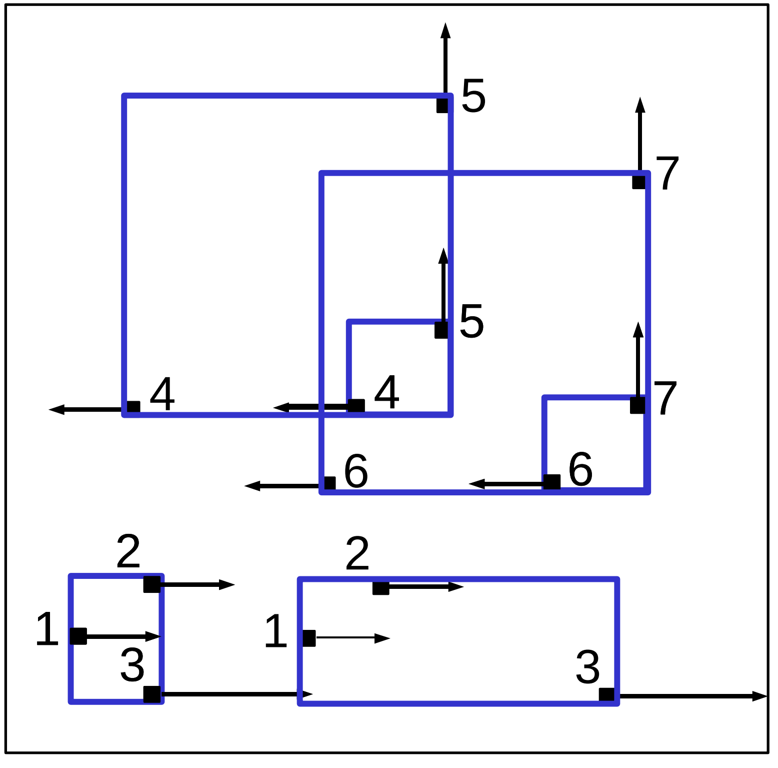
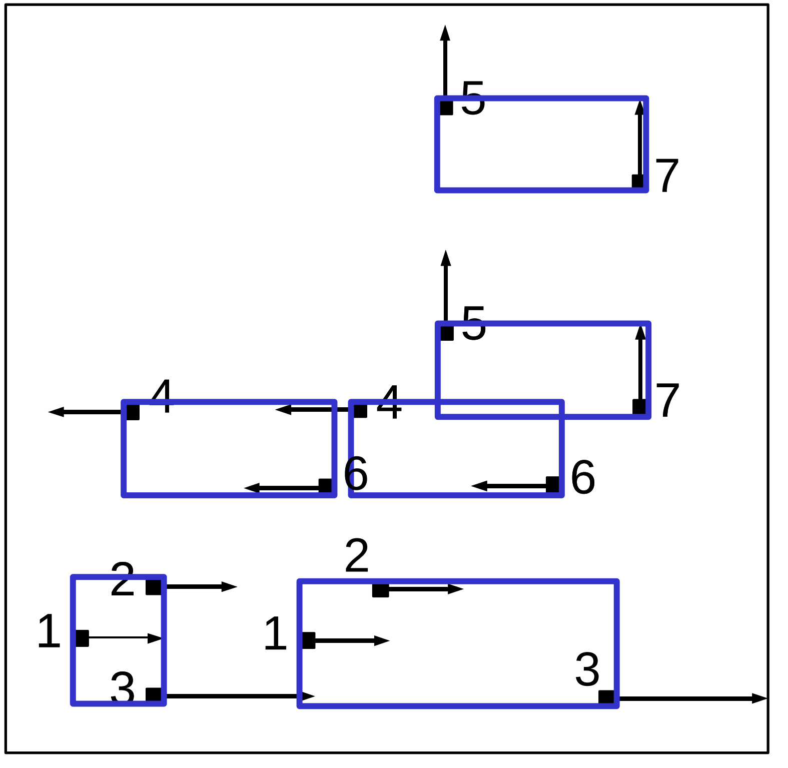


- TPBRs are ”*tightened*” (i.e., recomputed) whenever a bounded node is modified

Insertion: Grouping Points

- How to group moving points (**Penalty** and **PickSplit**)?
  - The R-tree's algorithms minimize characteristics of MBRs such as area, overlap, and margin.
  - How does that work for moving points?





Insertion in the TPR-Tree

- The bounding rectangle characteristics (area, overlap, and margin) are functions of time.
- The goal is to minimize these for all time points from *now* to *now+H.*
  - Minimizing the characteristics for time *now* + *H/2* does not work (e.g., the area of a conservative bounding rectangle is not linear).
- We use the regular R*-tree algorithms, but all bounding rectangle characteristics are replaced by their *integrals*.

$$\int_{now}^{now+H} A(t)\,dt,$$ where *A*(*t*) is, e.g., the area of an MBR

What *H* to use?

- Intuitivly: we want *H* to be equal to the time during which queries will see the node that we consider modifying:
  - *H* depends on the update rate, and on how far queries may reach into the future (*W*)
  - Experiments show that *H* = *UI* + *W* consistently gives good query performance (*UI* – average update interval)
  - The system can track *UI* automatically (*How*?)
  - *W* is usually smaller than *UI*
    - can be tracked automatically too

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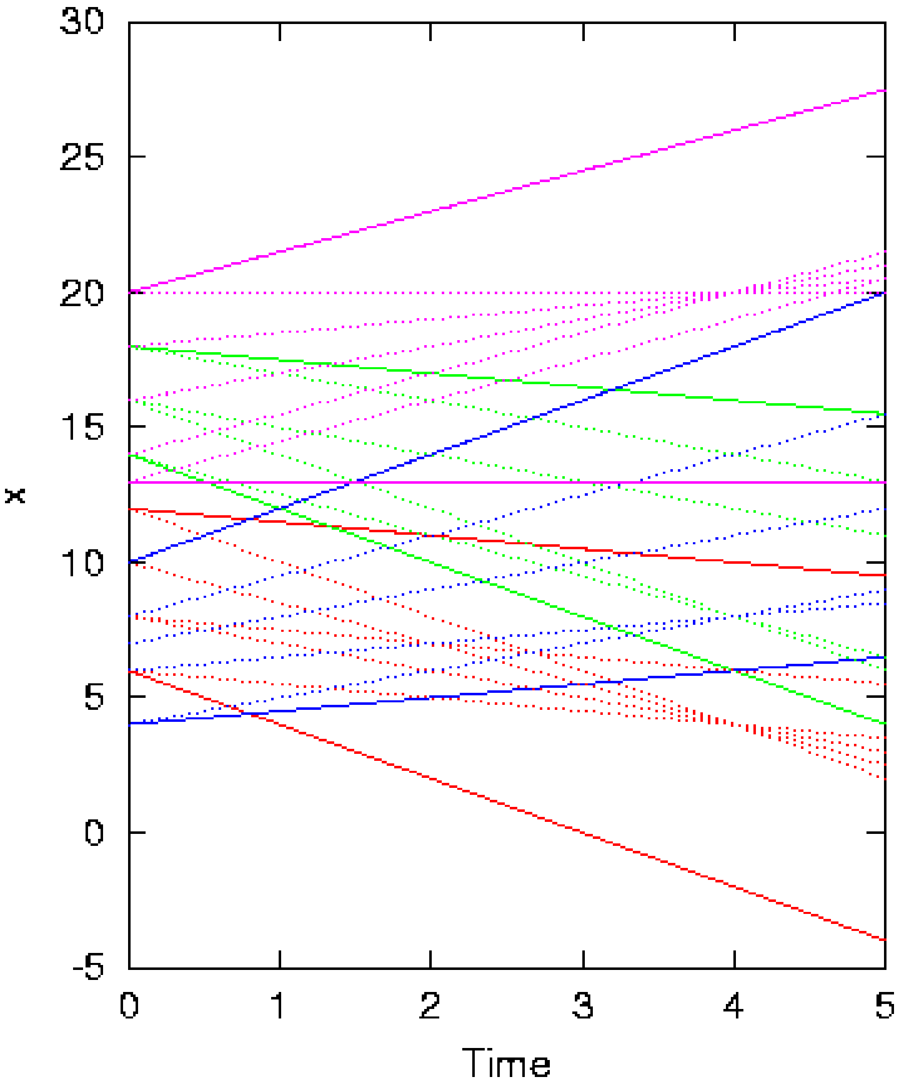
Example I

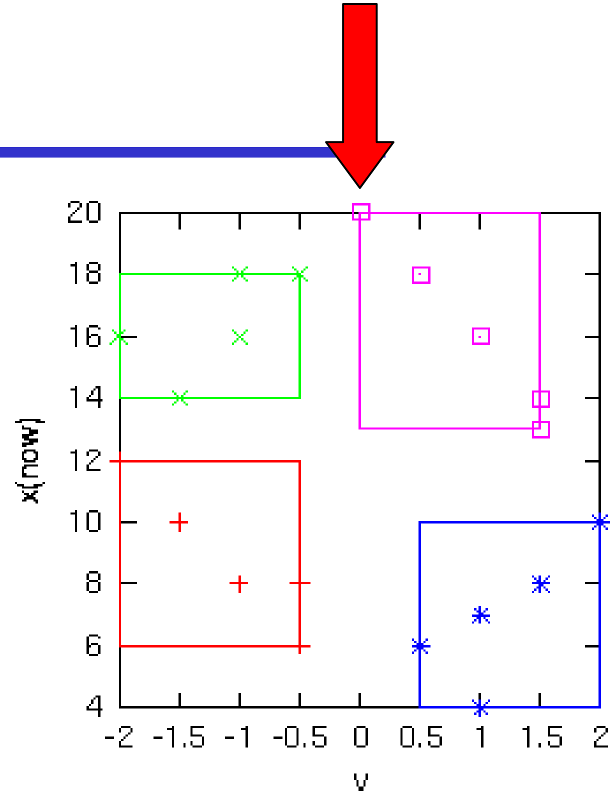
- We illustrate the working of the TPR-tree by means of an example.
  - The subsequent figures are generated automatically, by the index code used for performance experiments.

- Data
  - 20 one-dimensional points are used.

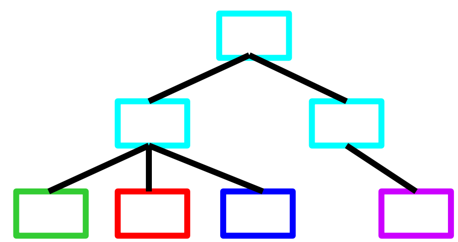
- Index Parameters
  - Page size = 64 (5 entries in leaf nodes and 3 in non-leaf nodes).
  - H = 8.

Example II



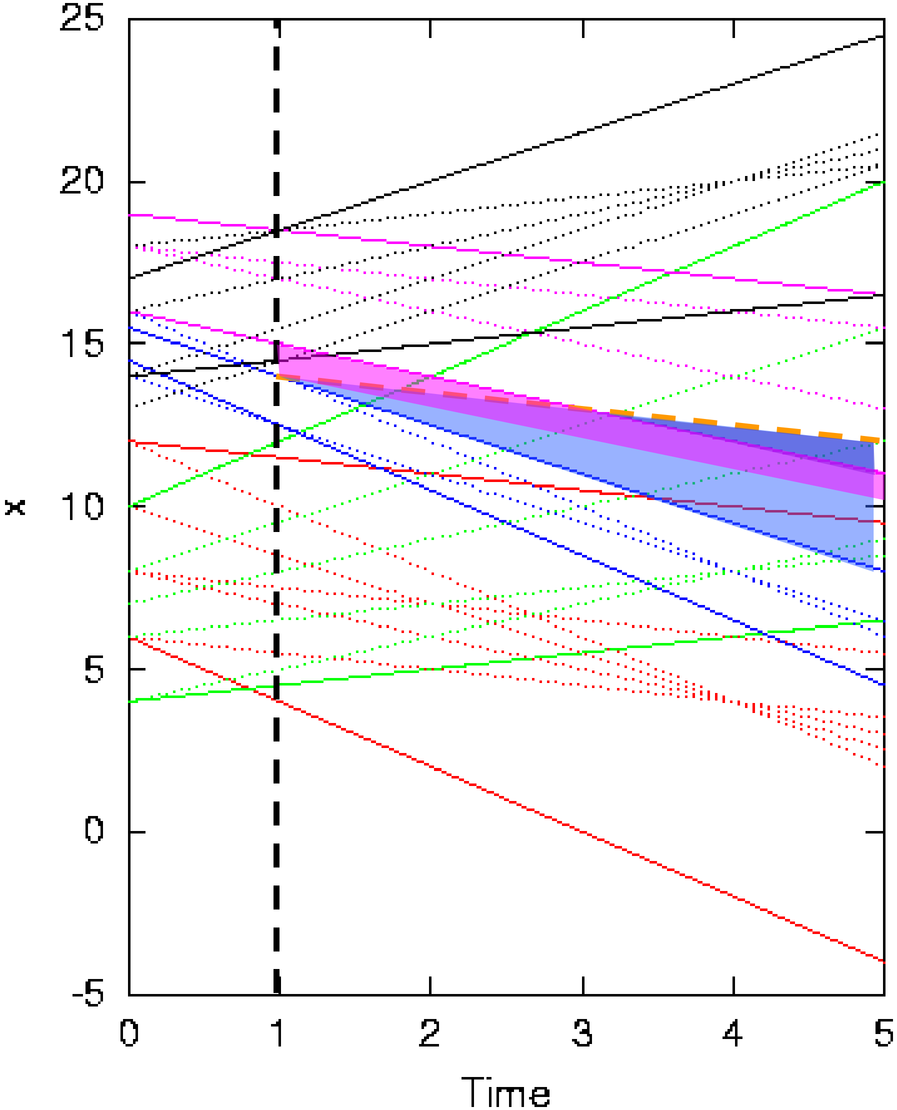


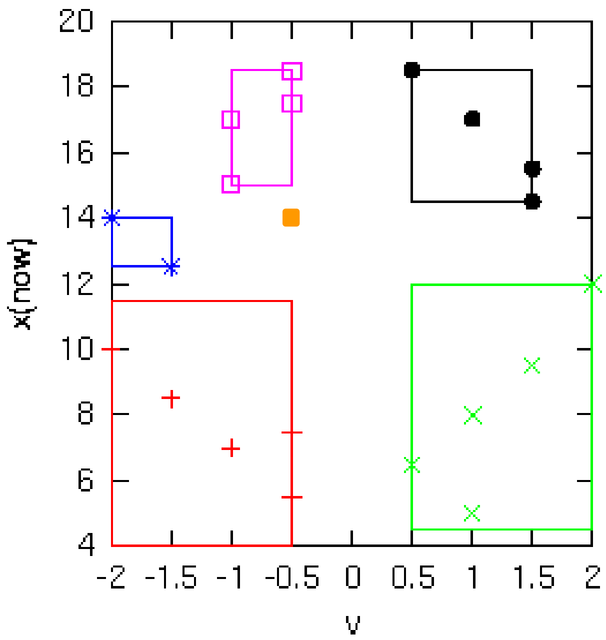
CT = 0



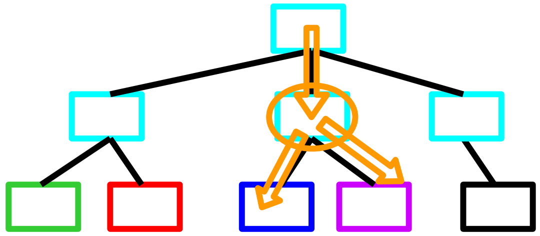
At CT=1, the point at x = 20, *v* = 0 is updated to have x = 18.5, *v* = -0.5.

Example III



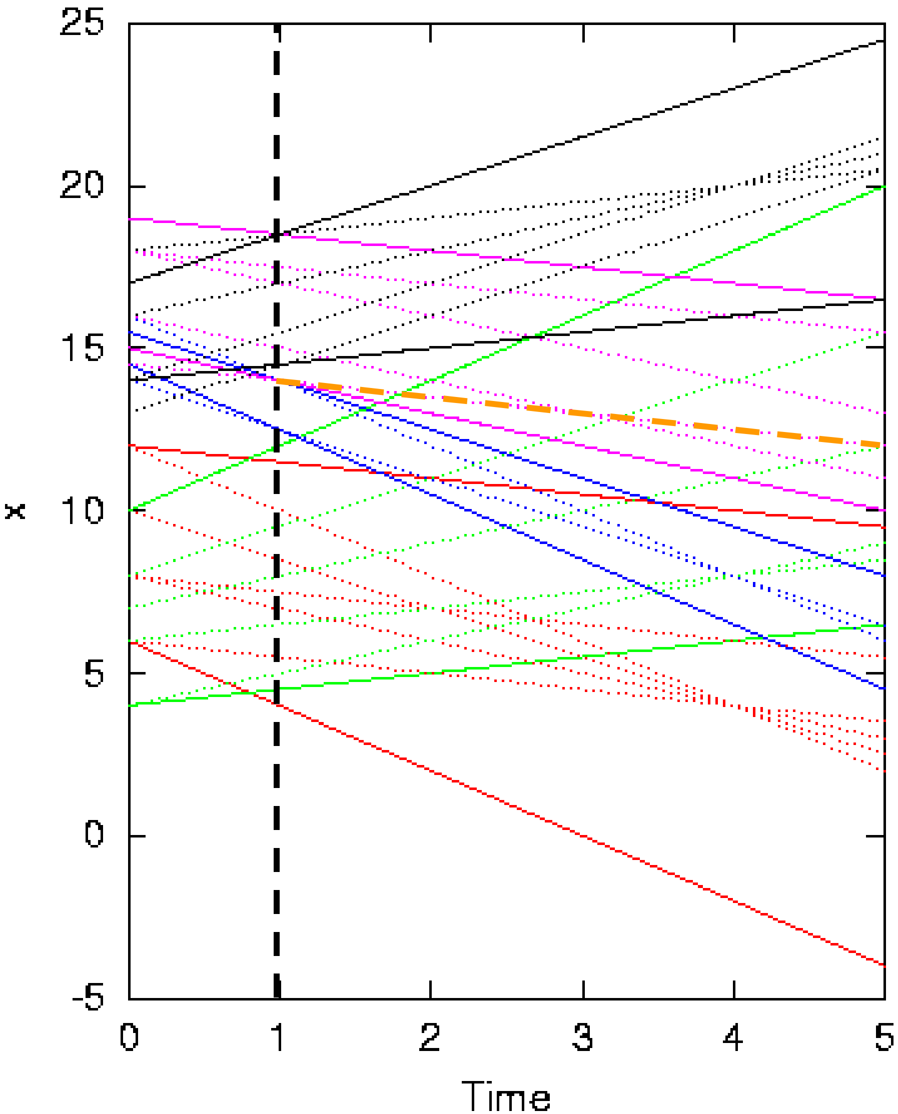


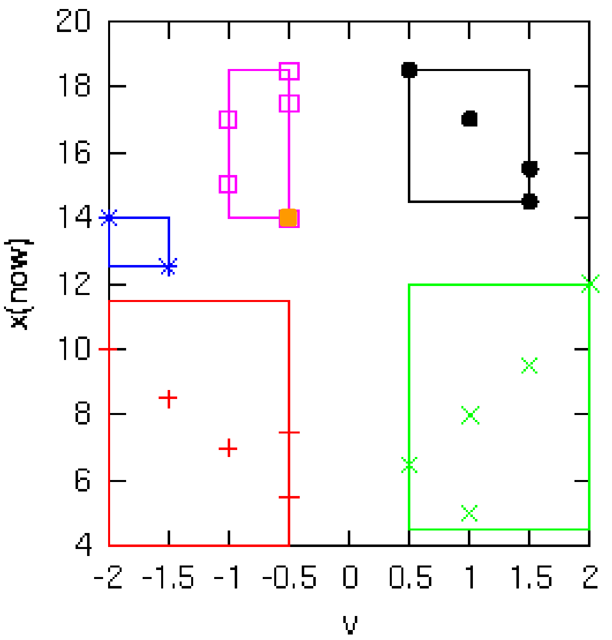
CT = 1



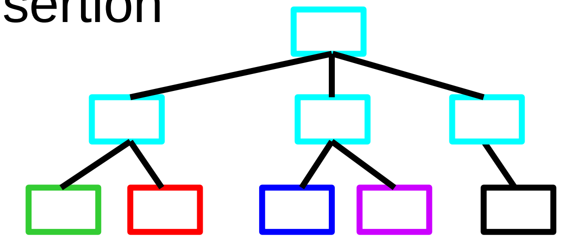
Inserting a moving point at position 14 with v = –0.5.

Example IV



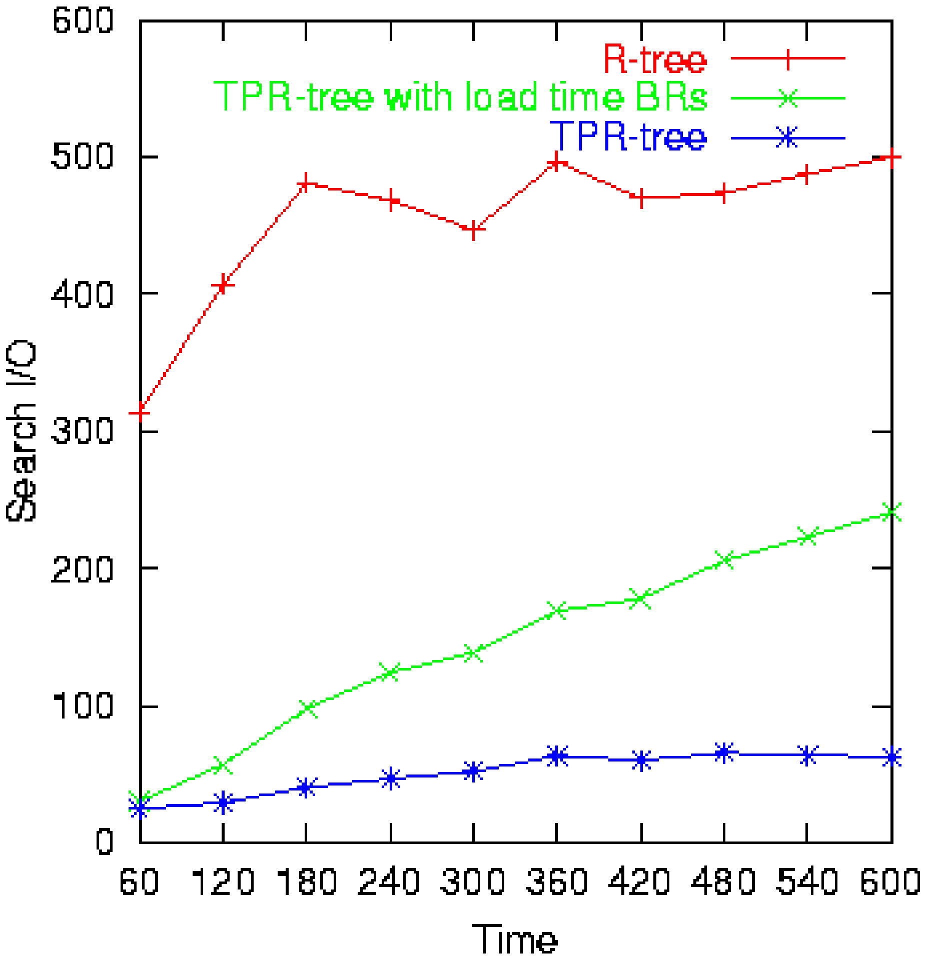


After insertion



What about Expanding BRs?

- Will the expanding TPBRs ruin the performance?
- That's what the experiments show:
  - Settings:
    - objects update only once per hour!
    - 2D data, with *W* = 40.
  - Due to the constant influx of updates, the performance of the TPR-tree does not degrade after reaching a certain level.



Summary

- The TPR-tree indexes the current and predicted future positions of moving objects.
  - The TPR-tree is based on the proven, widely used R-tree technology
  - The tree extends the R*-tree by introducing conservative, time-parameterized bounding rectangles, which are tightened regularly.
  - The tree’s algorithms use integrals of area, overlap, etc.
  - The tree can be tuned to take advantage of a specific update rate and querying window length.
  - Other types of queries that are supported by the R-tree can be supported by the TPR-tree, e.g., nearest-neighbor queries.