Lecture Notes on

Artificial Intelligence for Games

Summer Semester 2020

Spatial Management for Games

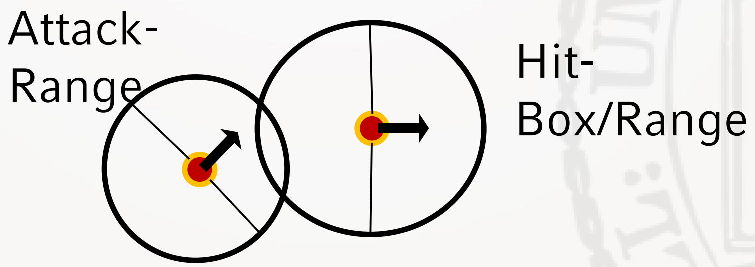
https://moodle.lmu.de/course/view.php?id=6799

https://uni2work.ifi.lmu.de/course/S20/IfI/AI4G

https://www.dbs.ifi.lmu.de/cms/studium_lehre/lehre_master/art20/index.html

Spatial Management in Games

- majority of games takes place in a spatial environment (2D/3D maps, …)
- transition models, agent control and transmission protocols require spatial query processing:
    - Which other game entities are within interaction range? (AoI = Area of Interest)
    - Support collision detection and area intersections (pre-filtering)
        - Which other game entity is closest?
        - Does a player enter the agro-range of an opponent?



Spatial Management for Games

- for small game worlds with limited game entities
  => organize spatial position in a list
- process queries by sequential scans
- with high query frequencies and large numbers of moving objects query processing becomes expensive
  example: 1000 game entities in one zone, 24 ticks/s
  - ⇒ naive AoI computation requires 11988000 distance computations per second

$$\left(\frac{1000 * 999}{2} \cdot 24 = 11988000\right)$$

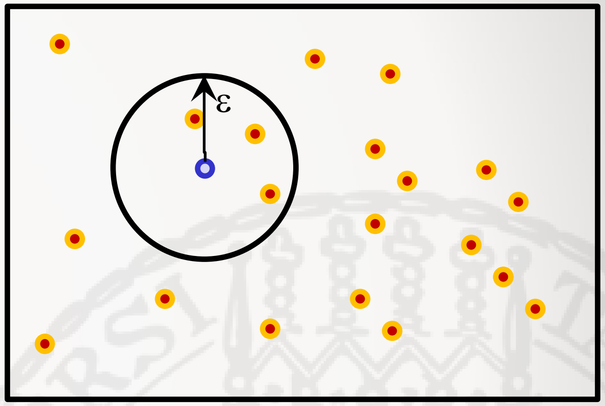
- **conclusion**: the cost for spatial query processing strongly increases with the size of the game state
  (number of potential interacting entities grows quadratic)

Spatial Queries (1)

Here spatial queries w.r.t Euclidian distance in IR^2

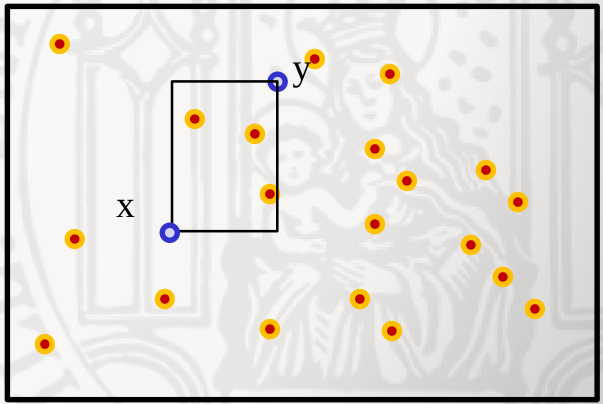
- ε-Range Queries

$$RQ(q,\varepsilon) = \left\{v \in GS \middle| \sqrt{(q_1 - v_1)^2 + (q_2 - v_2)^2} \leq \varepsilon\right\}$$



- Box-Query

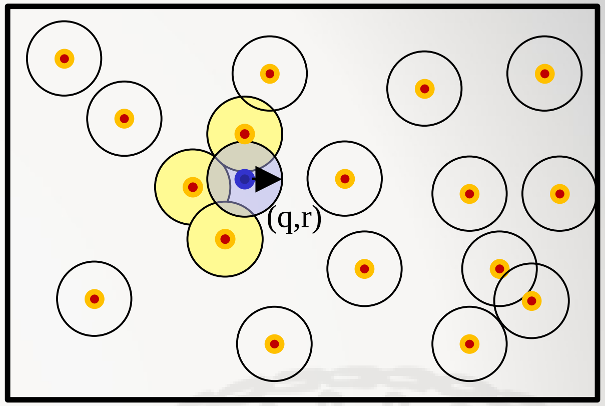
$$BQ(q,\varepsilon) = \{v \in GS | x_1 \leq v_1 \leq y_1 \wedge x_2 \leq v_2 \leq y_2\}$$



Spatial Queries (2)

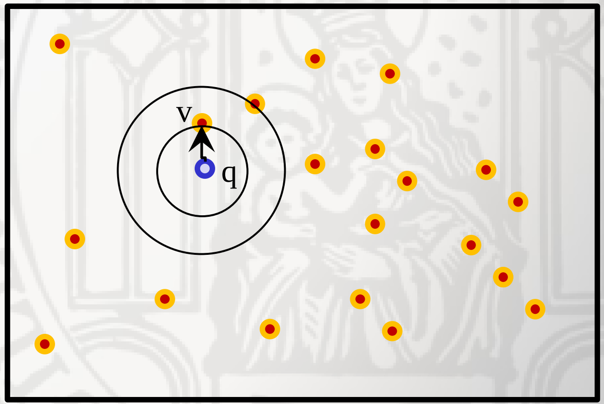
- Intersection Query

$IQ(q,r) =$
$\left\{(v,s) \in GS \times \mathbb{R} \middle| \sqrt{(q_1 - v_1)^2 + (q_2 - v_2)^2} \le r + s\right\}$



- Nearest Neighbor Query

$NN(q) =$
$\left\{v \in GS \middle| \forall x \in GS: \sqrt{(q_1 - v_1)^2 + (q_2 - v_2)^2} \le \sqrt{(q_1 - x_1)^2 + (q_2 - x_2)^2}\right\}$



Efficiency Tuning for Spatial Queries

methods to reduce the number of considered objects (pruning)
- distribute the game world (zoning, instancing, sharding, …)
- index structures (BSP-Tree, KD-Tree, R-Tree, Ball-Tree)

reduce the number of spatial queries
- reduce query ticks
- spatial publish subscribe

efficient query processing
- nearest-neighbor queries
- ε-range Join (simultaneously compute all AoIs)

Sharding and Instantiation

- copying a region for a specific group
- any number of the same region exists
- instances and shards part of game design (e.g., limiting the number of players for a quest)
  but: The more players are in an instance, the less performance issues in the open world.

Complications:

- does not solve the underlying problem (no connected game world)
- storing local game states, even if there are no more players in the instance

  => instance management can cause additional expenses
  (worst case: 1000 parallel game states for 1000 players)

Zoning

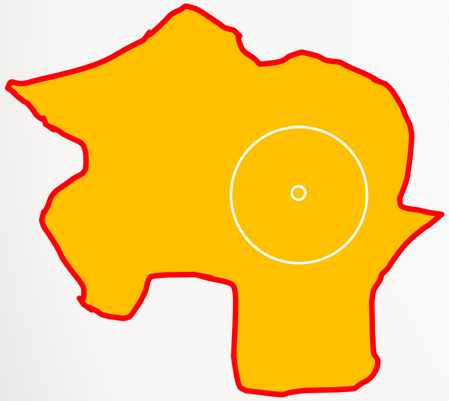
- splitting the open world into several fixed areas
- only objects in the current zone need to be considered for a query
- does not only partition space, but also the game state
- makes it easier to distribute the game world onto several computers

problems:

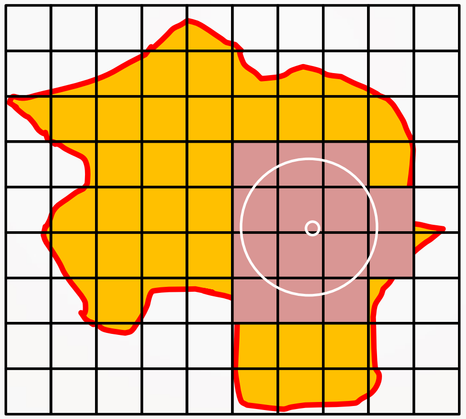
- objects of bordering zones need to be considered
- uneven distribution of players

Micro-Zoning

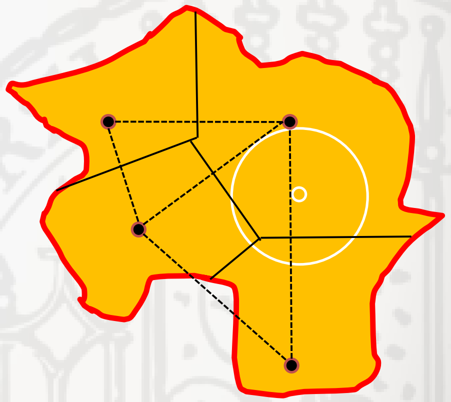
- game world is partitioned into several small areas (micro zones)
- only game entities within the actual micro zone are being managed
- only micro zones that intersect the AoI are relevant
- sequential search within the region
- zones can be created with different methods (grids, Voronoi-cells, …)



zoning



micro zoning (grid-based)



micro zoning (Voronoi based)

Spatial Publish-Subscribe

- combination of micro-zoning and a subscriber systems
- game entities are registered in their current micro zone (publish)
- game entities subscribe to the information of all micro zones that intersect their AoI (subscribe)
- list of all game entities within AoI is created by merging all entries of subscribed micro zones

Advantages:

- objects close by can be determined efficiently
- changes can be passed on to subscribers
  (no regular queries necessary)

Micro Zoning and Spatial Publish-Subscribe

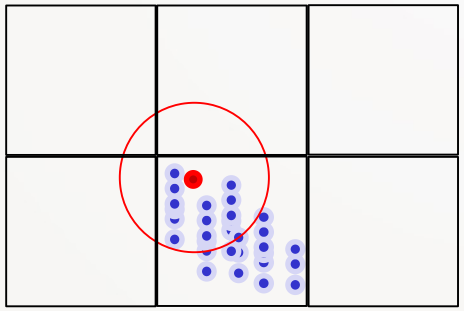
Disadvantages:

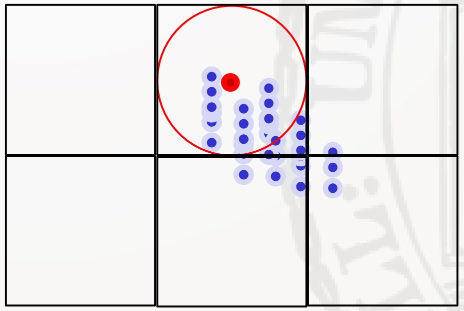
- even micro zones can be overcrowded

  ⇒ the larger the area, the higher the number of contained entities
- overhead for changing zones increases if zones are too small

  ⇒ the smaller the zone, the more zones are traversed
- location of zone borders may lead to extreme fluctuations of observed objects.
- high rates of change extremely increase overhead.

  ⇒ many subscribe- and unsubscribe-operations inhibit the system



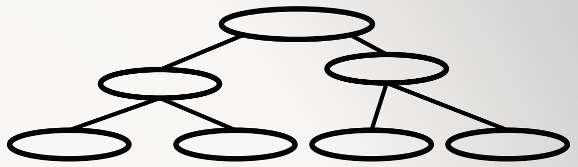


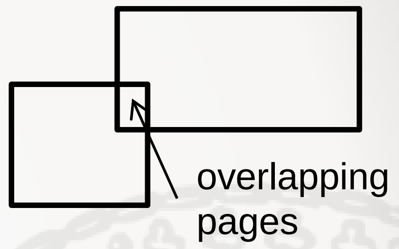
Classic Index Structures

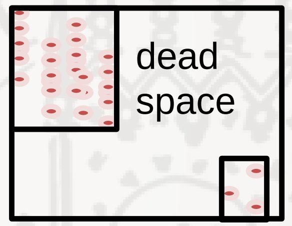
- managing spatial objects can also be done via spatial search trees
- search trees tailor their region pages (zones) to data distribution
- one maximally filled region pages/zone is guaranteed
- reducing the number of objects in question increases search performance
- adjusting the search tree causes calculation effort
- adaption via recursive partition of space (Quad-Tree, BSP-Trees)
- adaption via distribution of data to minimal surrounding page regions

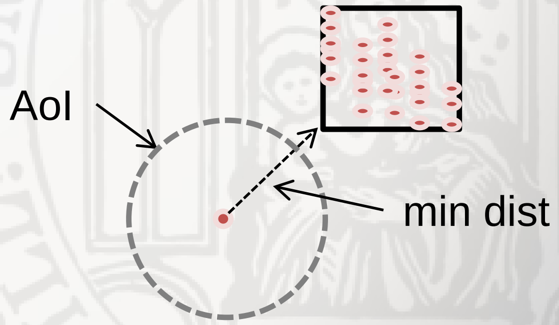
Important Features of Search Trees

- **region page**: surrounding approximation of several objects
- **balancing**: addressing different path lengths, from root to leaf notes, of branches
- **page capacity**: minimum and maximum number of objects within a region page
- **overlap**: intersecting regions between pages
- **dead space**: space without region pages/objects
- **pruning**: exclusion of all objects within one region page via testing for region pages









Requirements for Games

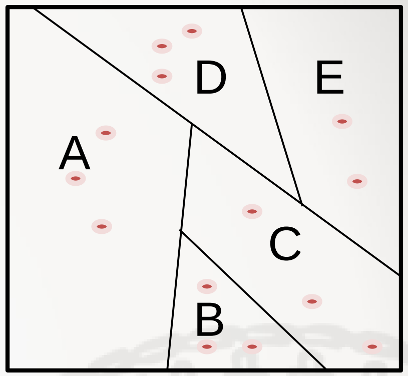
- generally the whole tree is stored within main memory
- high volatility, i.e. every change of a game entity's position
  - dependent on the game, up to one change per tick per entity
  - trees might degenerate in their structure/costly balancing required
- many queries per time unit
- support for multiple queries during one tick
- objects have either 2 or 3 dimensions
- objects have volume (spatial extension, hitbox, ...)

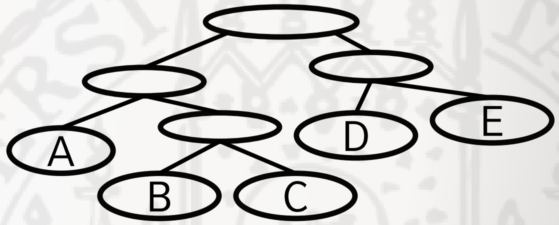
conclusions:

- data structures optimizing page accesses are ill suited (tree is stored in main memory)
- **runtime increase for query processing must compensate for the time for index creation/update**

Binary Space Partitioning Trees (BSP-Tree)

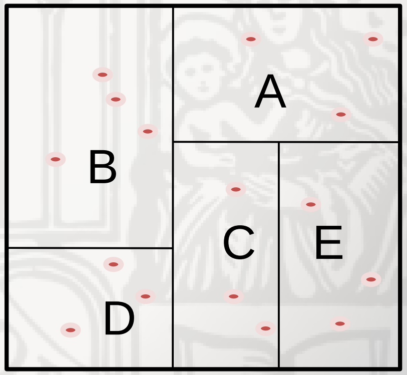
- root contains the whole data space
- every inner node has two successors
- data objects are stored in leaf nodes





most popular type: kD-tree

- max. page capacity are M entries
- min. page capacity are M/2 entries
- at overflow => splitting w.r.t. an axis
- axis for the split changes after every split
- data is distributed 50%-50%
- at deletion: merge sibling nodes



Binary Space Partitioning Trees (BSP-Tree)

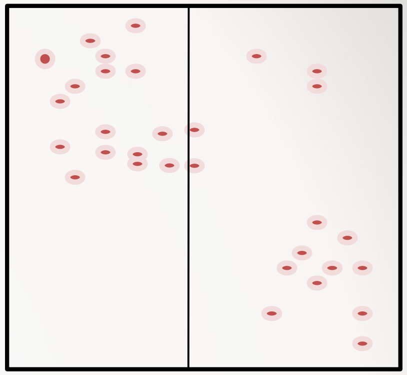
problem with dynamic behavior:

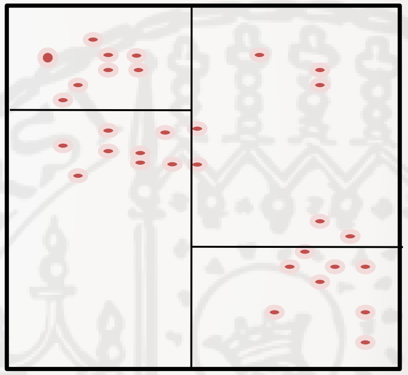
- no balancing (tree might degenerate)
- rebalancing is possible but very expensive

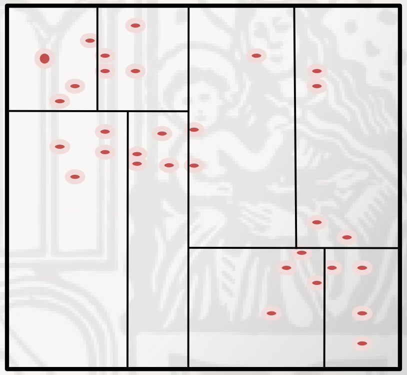
  => high update complexity

Bulk-Load

- **assumption**: all data objects are known
- **creation**: recursively distributing objects with a 50/50 split until every leaf contains less than M objects
- bulk-load always creates a balanced tree
- a data page of a tree of size *h* containing *n* objects contains at least $\left\lfloor \frac{n}{2^h} \right\rfloor$ objects and at most $\left\lfloor \frac{n}{2^h} \right\rfloor$+1 objects

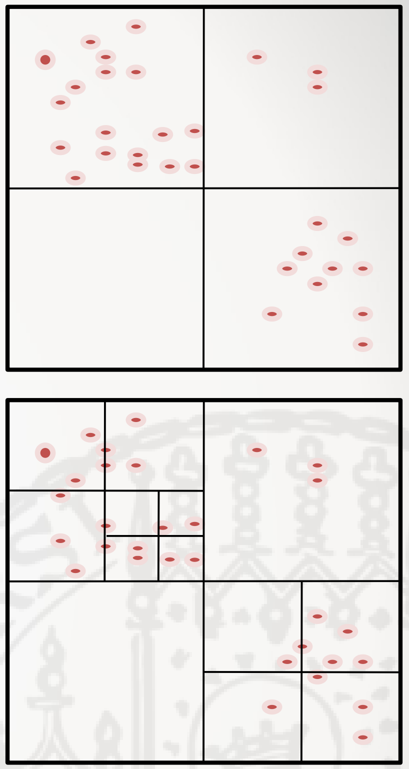


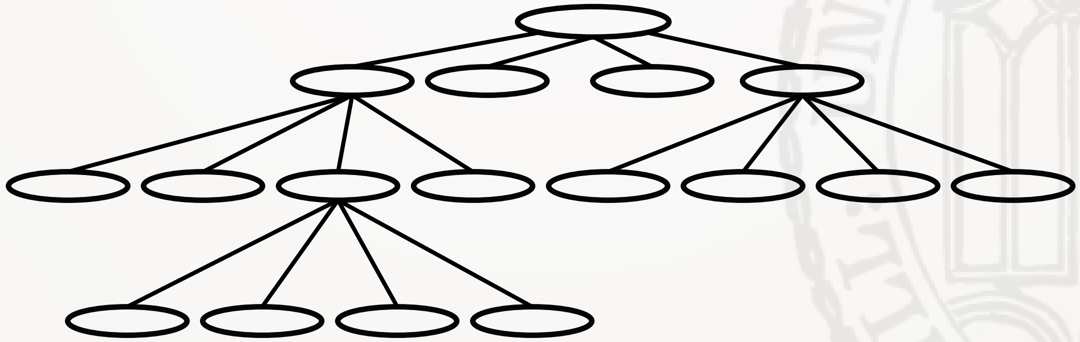




Quad-Tree

- root represents the whole data space
- every inner node has four successors
- sibling nodes split their parents space in four equal parts
- as a rule quad-trees are not balanced
- pages have a maximum filling ratio M, but no minimum
- leaves contain data objects



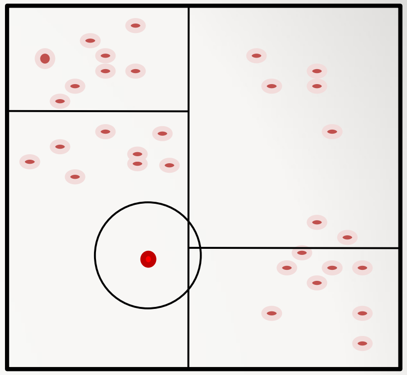


Data Partitioning Index Structures

space partitioning procedures:

- partitioning the data space via dimensional splits
- page regions include dead space

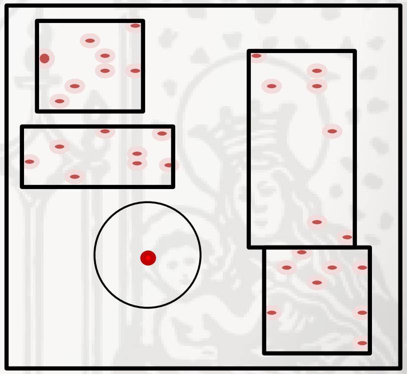
  => potentially bad search performance for spatial queries



range query on BSP-Tree

data partitioning procedures:

- page regions are defined by their minimum bounding region (e.g. rectangles)
- => better pruning performance
- page regions may overlap
  => degeneration w.r.t. overlap
- split- and insert-algorithms minimize:
  - overlap between page regions
  - dead space within pages
  - balancing w.r.t. filling degree



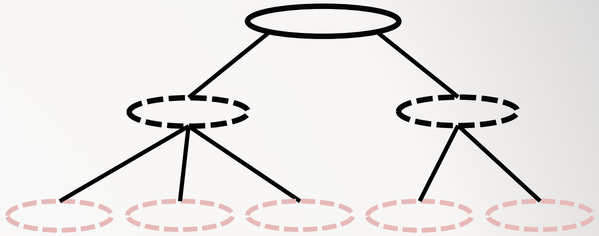
range query on R-Tree

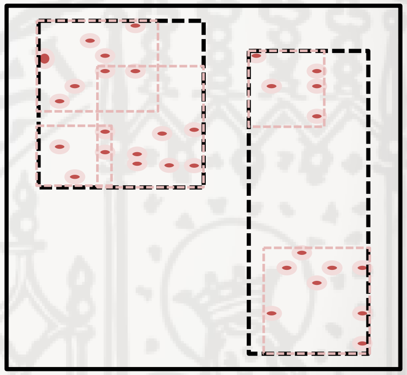
R-Tree

R-Tree structure:

- root encompasses the complete data space and contains a maximum of M entries
- page regions are modeled by minimal bounding rectangles (MBR)
- inner nodes have between *m* and *M* successors (where m ≤ M/2)
- the MBR of an successor node is completely contained within the predecessor's MBR
- all leafs are at the same height
- leafs contain data objects

  possible date objects:
  - points
  - rectangles





Inserting into an R-Tree

object x is to be inserted into an R-tree

due to overlap, there are three possible cases

- Case 1: x is contained the directory rectangle D
  ⇒ Insert x into subtree of D
- Case 2: x is contained in several directory-rectangles $D_1, \dots, D_n$
  ⇒ Insert x into subtree D_i with the smallest area
- Case 3: x is not contained in any directory-rectangle D
  ⇒ Insert x into subtree D which suffers the smallest area increase to contain x (in doubt, choose the one with the smaller area)
  ⇒ extend *D accordingly*

Split-Algorithm within a R-Tree

(for the following we consider the case of inner nodes: objects are MBRs)

node K has an overflow $|K| = M+1$

$\Rightarrow$ divide K into two nodes K_1 and K_2, so that $|K_1| \geq m$ and $|K_2| \geq m$

Basic algorithm in $O(n^2)$

- choose the pair of rectangles (R_1,R_2) with the largest "dead space" within the MBR, in case both R_1 and R_2 fall into Node K_i

  d (R1, R2) := area(MBR(R1∪R2)) - area(R1) - area(R2)

- set $K_1 := \{R_1\}$ and $K_2 := \{R_2\}$
- repeat the following until STOP:
  - all R_i are assigned: STOP
  - if all remaining R_i are necessary to minimally fill the smaller node: assign them all and STOP
  - else, choose the next R_i and allocate it to the node whose MBR will experience the smallest area increase. In doubt, prefer the K_i with the smaller MBR area or rather with fewer entries.

Faster Split Strategy for R-Tree

Linear Algorithm *O(n)*

The linear algorithm is identic to the square algorithm with the exception of choosing the initial pair (R_1,R_2).

Choosing the pair (R_1,R_2) with the *"greatest distance"*, or more precise:

- Identify the rectangle with the lowest maximum value and the rectangle with the largest minimum value, for every dimension (*maximum distance*).
- Normalize the maximum distance in every dimension by dividing it by the sum of the expansions of all R_i in this dimension (*setting the maximum distance in relation to their extension*).
- Choose the pair of rectangles with the greatest normalized distance in all dimensions. Set $K_1 := \{R_1\}$ and $K_2 := \{R_2\}$.

- This algorithm has linear complexity concerning the number of rectangles (*2m+1)* and the number of dimensions d.

Bulk-Loads and R-Trees

Advantages :

- faster creation
- structure usually allows for faster query processing

Criteria for optimization:

- greatest possible filling ratio of both sides (low height)
- little overlap
- small dead space

Sort-Tile-Recursive:

- Assembling the R-Tree bottom-up
- No overlap for point objects at leaf level
- Time complexity: *O(n log(n))*

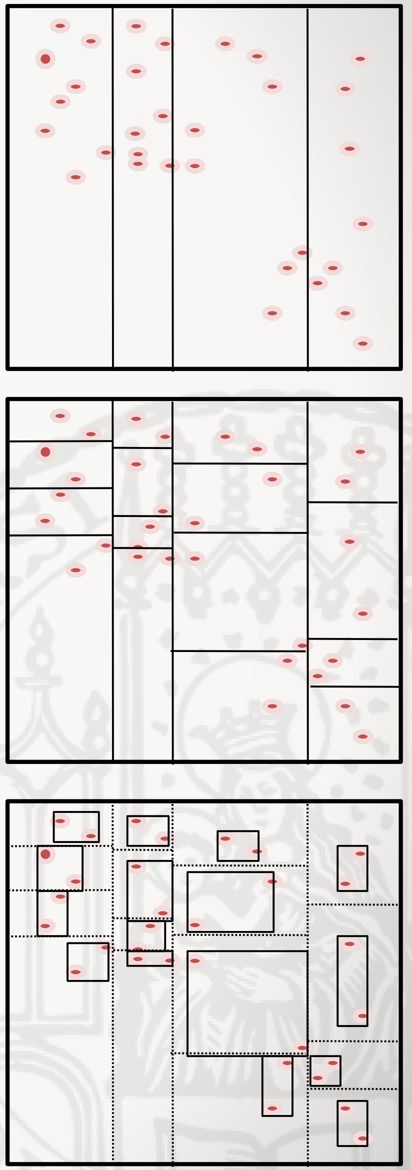
Sort-Tile Recursive

Algorithm:

1. consider n points/rectangles we want to store
2. Calculate the quantile: $q = \left\lceil \sqrt{\frac{n}{M}} \right\rceil$
3. Sort data elements in dimension 1
4. Generate quantile after $q \cdot M$ objects in dimension 1
5. Sort objects of every quantile into dimension 2
6. Generate quantile after M objects in dimension 2
7. Create a MBR around the points within each cell
8. Restart the algorithm with the set of derived MBRs or stop in case of $q < 2$
   (all remaining MBRs fall into the root)

Note:

1. MBRs without overlap are created for points
2. For rectangles overlap may occur
3. For rectangles, calculation of the quantile via minimum values, maximum values or complex heuristics is possible
4. If the number of objects is not sufficient to completely fill all pages, only the last node is not maximally filled.



Deletions in R-Trees

Object x needs to be deleted from the R-Tree.

Delete:

Test page S for underflow after deleting x: $|S| < m$

- If there is no underflow, delete x and STOP
- If there is an underflow, determine which predecessor nodes would have an underflow in case of deletion
  - For every node with an underflow:
    - Delete the under flowed page from its predecessor node.
    - Insert the remaining elements of the page into the R-Tree.
    - In case of the root containing a single child, the child becomes the new root (height is reduced).

Note:

- deletion is not limited to one path with this algorithm
- makes the insertion of a subtree on layer 1 into the R-Tree necessary
- very expensive in worst case

Search Algorithms for Trees

Range Query:

```
FUNCTION List RQ(q,ε):
List  C // list of candidates (MBRs/Objects)
List  Result // list of all objects within ε-range of q
C.insert(root)
WHILE(not C.isEmpty())
   E := C.removeFirstElement()
   IF E.isMBR()
      FOREACH F ∈ E.children()
        IF minDist(F,q) < ε
          C.insert(F)
   ELSE
      Result.insert(E)
RETURN Result
```

Note: BOX and intersection queries follow the same principle.

Nearest Neighbor Queries

NN-query: Top-Down Best-First-Search

```
FUNCTION Object NNQuery(q):
  PriorityQueue  Q // objects/pages to investigate,
  sorted by mindist
  Q.insert(0, root)
  WHILE(not Q.isEmpty())
     E := Q.removeFirstElement()
     IF E.isMBR()
       FOREACH F ∈ E.children()
           Q.insert(mindist(F,q), F)
     ELSE
       RETURN E
```

Notes:

- mindist(R,P) is minimal distance between two points in R and P.
  if R and P are points, mindist = dist
- priority queues are usually implemented via heap-structures
  (cf.heapsort)

Spatial Joins

Idea: Define Joins on spatial predicates.

advantage: Parallel processing of multiple queries.

Example: *ε-Range-Join*

Let G and S sets of spatial objects $G,S \subseteq D$, let *dist: $D\times D \rightarrow IR$ be a distance function and $\varepsilon \in IR$*. Then, the ε-range join between G and S is defined as:

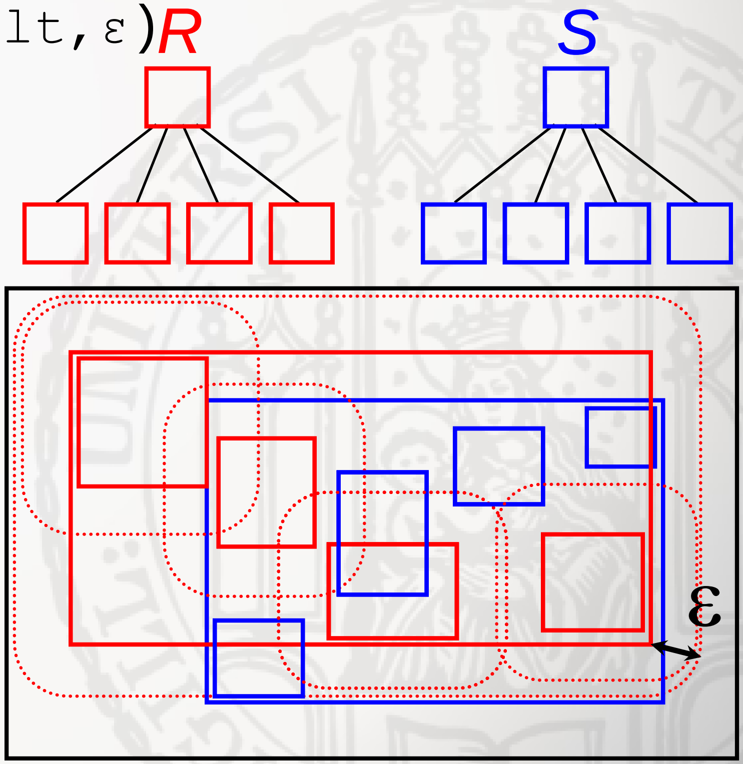
$$S \underset{dist(s,r)< \varepsilon}{\bowtie} G = \{(g,s) \in G\times S \mid dist(g,s) \leq \varepsilon\}$$

Remark: The objects within the area of interest (AoI) for each entity can be determined with a single ε-range-join.

R-tree Spatial Join (RSJ)

Algorithm:

```
FUNCTION rTreeSimJoin (R, S, result, ε)
  IF R.isDirectoryPage() or S. isDirectoryPage()
   FOREACH r ∈ R.children()
      FOREACH s ∈ S.children()
         IF minDist(r,s) ≤ ε
            rTreeSimJoin(r,s,result,ε)
 //R,S are data pages (leaves)
  ELSE
    FOREACH p ∈ R.points
      FOREACH q ∈ S.points
       IF dist(p,q) ≤ ε
         result.insertPair(p,q)
RETURN  result
```



Problems of Data Volatility

Problems caused by spatial movement of all objects:

In games the majority of objects move several times per second.

- changing position by deleting and inserting
  - dynamic changes may negatively influence data structures
    (miss-balance, more overlap, overfilling a micro-zone)
  - changes cause big overhead
    (search for object, follow up inserts, underflow- and overflow-handling)
- changing position via dedicated operations
  - expansion of page regions: page overlap may extremely increase
    (only possible in cases of data partitioning)
  - moving objects between page regions:
    - *might have a negative instance to tree balance*
    - *overflow or underflow possible*

Conclusion: dynamic calculation either has a huge computational overhead or might degenerate data structures.

Throw-Away Indices

Idea:

- For highly volatile data changing existing data structures is more expensive than rebuilding with bulk load.
- Similar to the game state, use 2 index structures:
  - Index I_1 represents positions of the last consistent tick and is used for query processing
  - Index I_2 is created simultaneously:
    - Created via Bulk-Load: little concurrency, but fast creation, good structure
    - Dynamic creation: higher calculation effort and possibility of worse structure, but potential creation for every new position
  - At the start of the new tick, I_2 is used for query processing, I_1 is deleted and subsequently build on the new positions.

Conclusion: Use a tree if time for tree creation and query processing on the tree is faster than brute force query processing.

Game Design

- Spatial problems are very dependent on Game-Design:
- number and distribution of spatial objects
- number and distribution of players
- environmental model, fields, 2D or 3D
    (3D Environment does not necessitate 3D-Indexing)
- movement type and speed of objects

Literature and Material

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