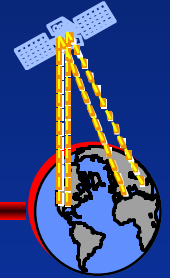


Nearest Neighbor Queries

Nick Roussopoulos
Stephen Kelley
Frederic Vincent

University of Maryland
May 1995

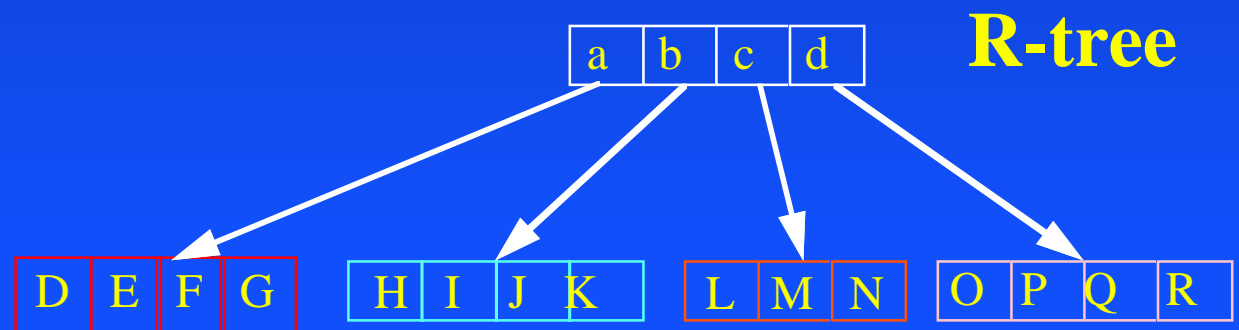
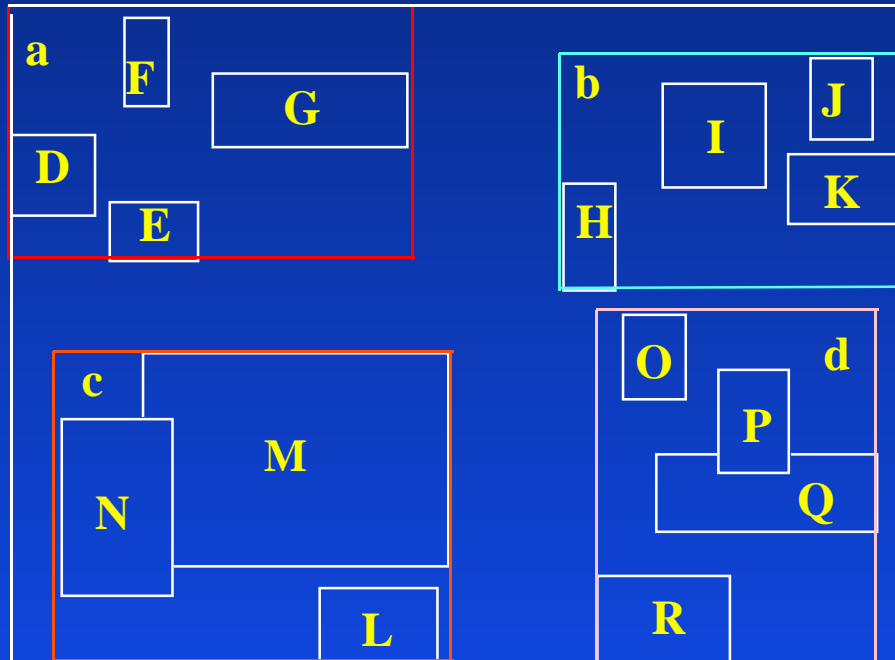
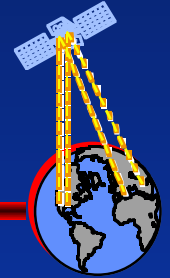
Problem / Motivation



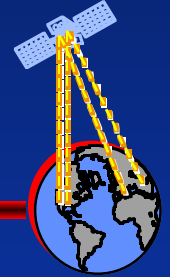
Given a point in space, find the k NN

- classic NN queries *(find the nearest 5* French restaurants)*
- bounded queries *(gas stations between 10 and 15 mile range)*
- spatial joins combined with NN
(3 NN restaurants to each movie theater)
- useful to formulate queries when exact location specification is hard *(astrophysics)*
- combined with other geographic relationships and spatial predicates
(5 NN cities west of Mississippi)
(NN houses on lots larger than 2 acres)
- Furthest Neighbors and other distance ordering functions

R-trees

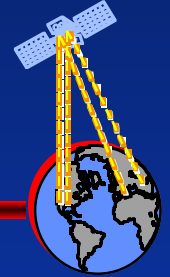


Need for Formalization of NN Queries

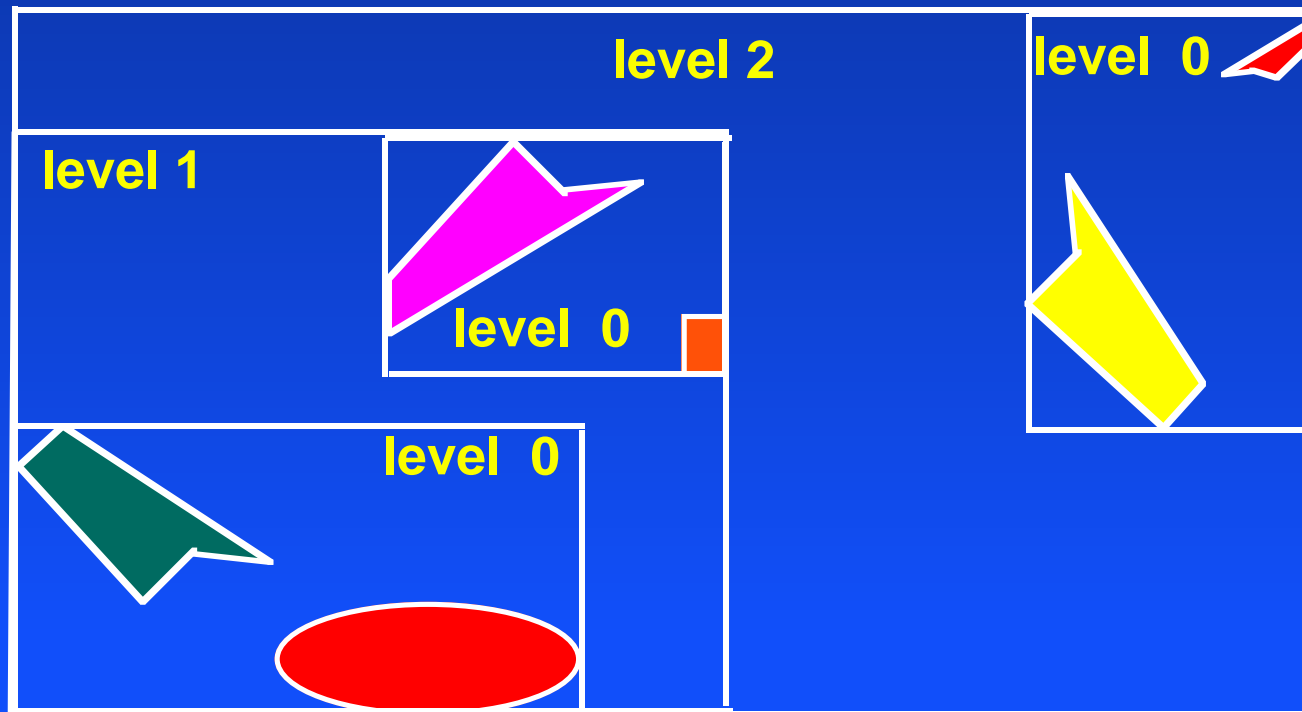


- No formalism for NN search
- No metrics for ordering and pruning the search
- R-trees only for overlap/containment queries
- R-tree based spatial joins used only overlap/containment predicates

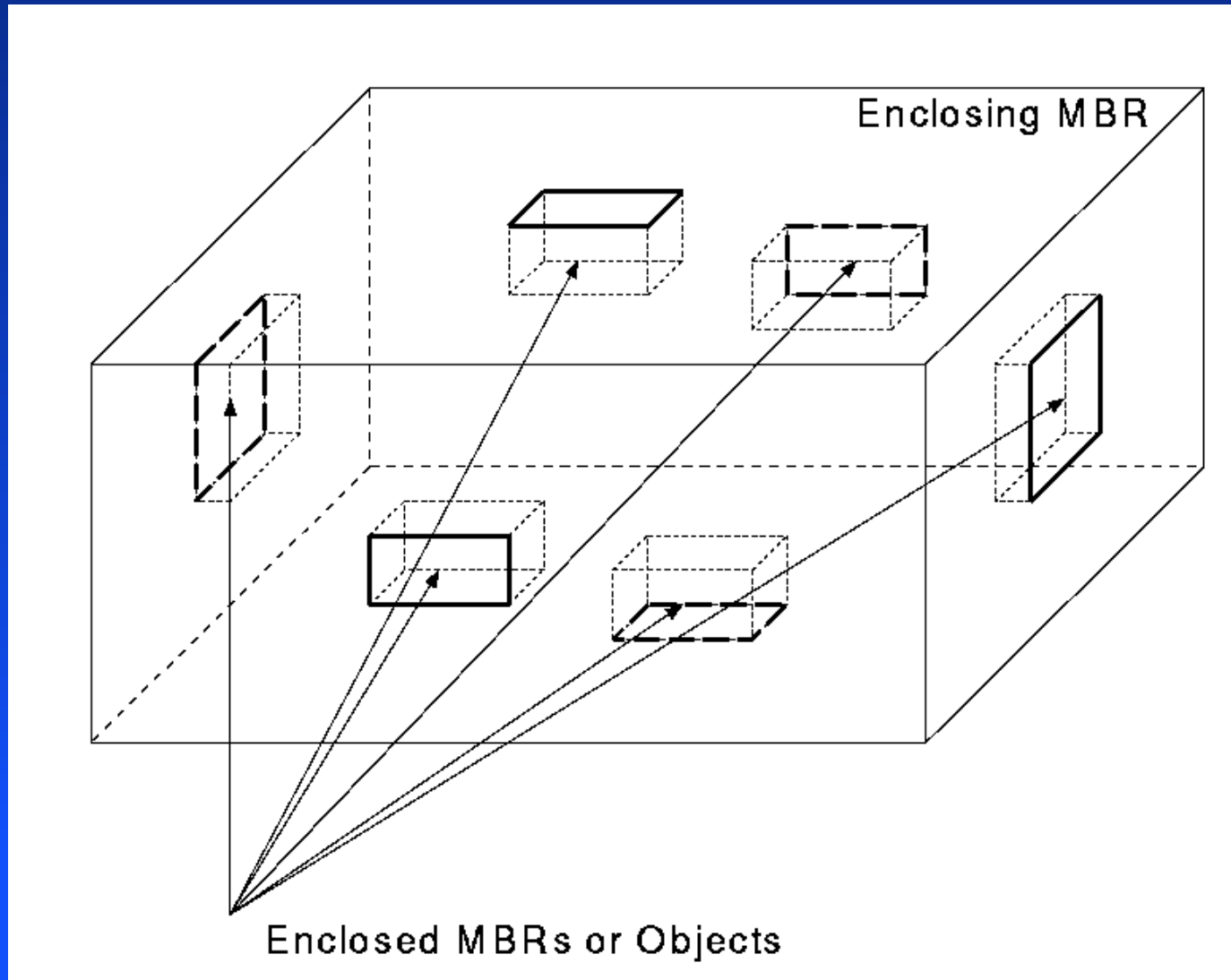
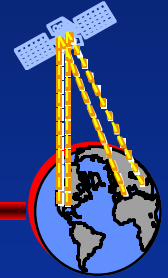
The MBR Face Property



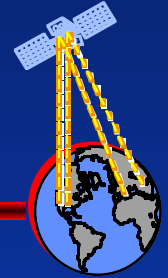
Lemma: Every face of any MBR contains at least one point of an actual spatial object



The MBR Face Property in 3-d



NN Metrics



- $\text{MINDIST}(P,R)$: the shortest distance from P to R

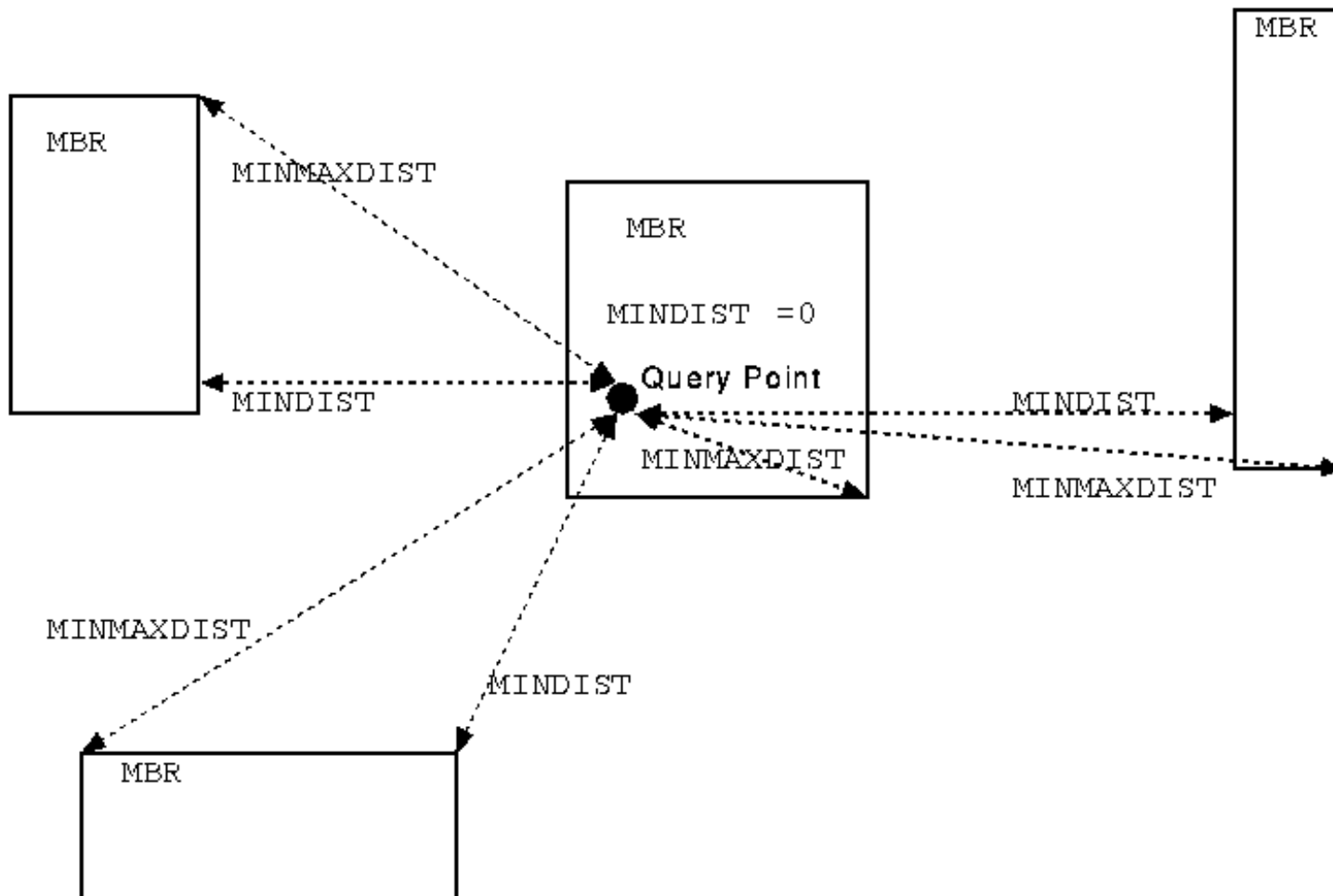
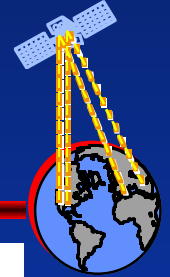
Theorem: Any object O in R has distance from P that is at least as large as MINDIST

- $\text{MINMAXDIST}(P,R)$ the minimum over all dimensions distance from P to the furthest point of the closest face of the R

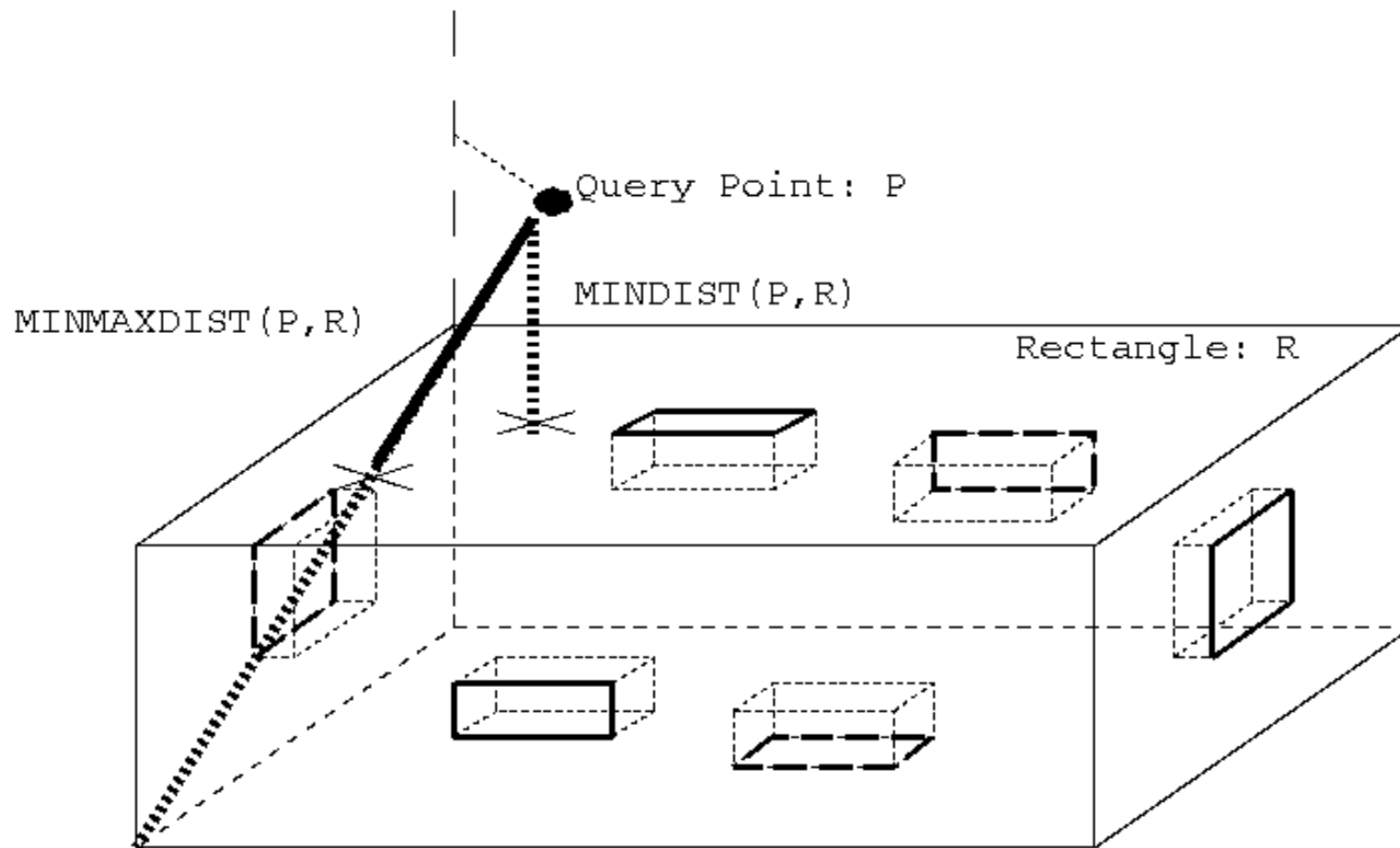
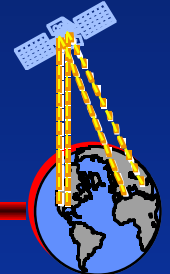
Theorem: There exists at least one object within R with distance \leq to MINMAXDIST

$$\text{MINDIST}(P,R) \leq \text{NN}(P) \leq \text{MINMAXDIST}(P,R)$$

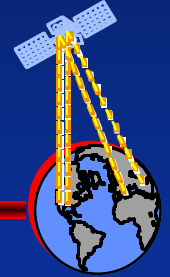
MINDIST & MINMAXDIST



MINDIST & MINMAXDIST in 3-d



NN Branch-and-Bound Algorithm



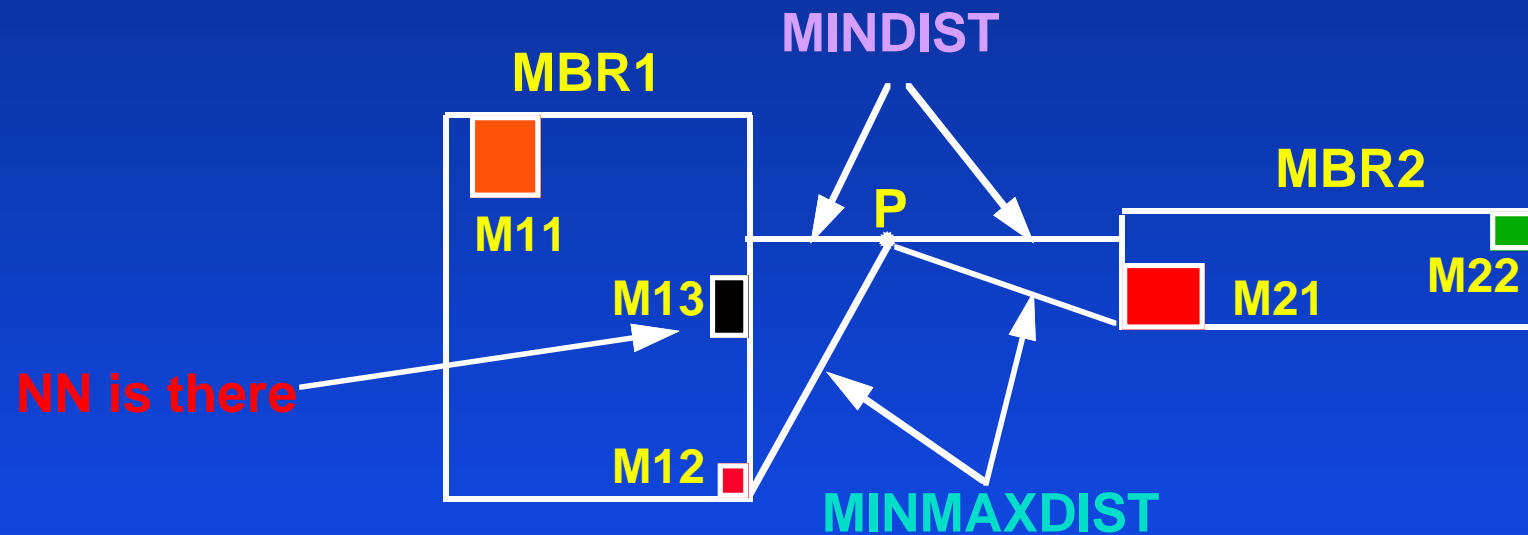
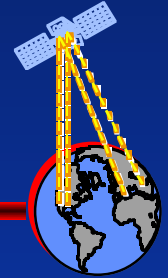
Ordering search alternatives

- MINDIST is the most optimistic
- MINMAXDIST is the most pessimistic ever needed be considered

Pruning search alternatives

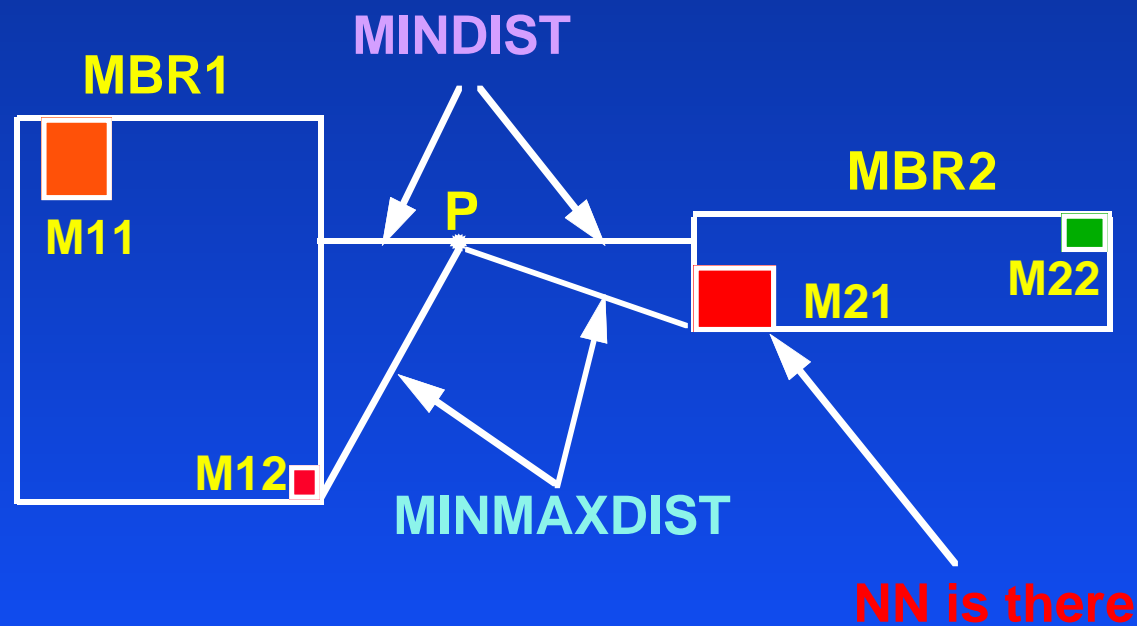
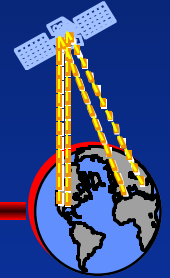
- **downward pruning:** an MBR R is discarded if there exists an R' s.t.
$$\text{MINDIST}(P, R) > \text{MINMAXDIST}(P, R')$$
- **downward pruning:** an object O is discarded if there exists an R s.t.
$$\text{ACTUAL-DIST}(P, O) > \text{MINMAXDIST}(P, R)$$
- **upward pruning:** an MBR R is discarded if an object O is found s.t.
$$\text{MINDIST}(P, R) > \text{ACTUAL-DIST}(P, O)$$

MINDIST vs MINMAXDIST Ordering

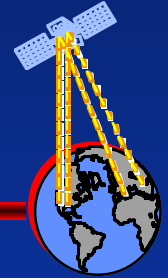


MINDIST leads the search to MBR1 which finds the NN in M13 and prunes MBR2 before visiting it

MINDIST vs MINMAXDIST Ordering

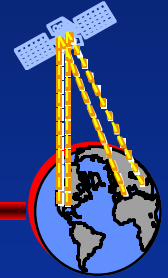


Generalization to k NN



- Keep a sorted buffer of at most k NN
- Pruning is applied according to the furthest NNs in the buffer
- Extra pruning based on additional predicates

IMPLEMENTATION

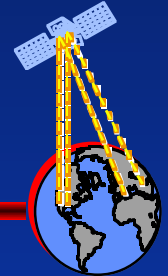


- Extended PSQL syntax
- Uses our version of high performance R-trees
- Also runs on top of ORACLE / INGRES





Range Query



M/RT Browser: <Untitled>

File Edit Search Layer View Conference

LAYERS

Tool

Pattern

Draw

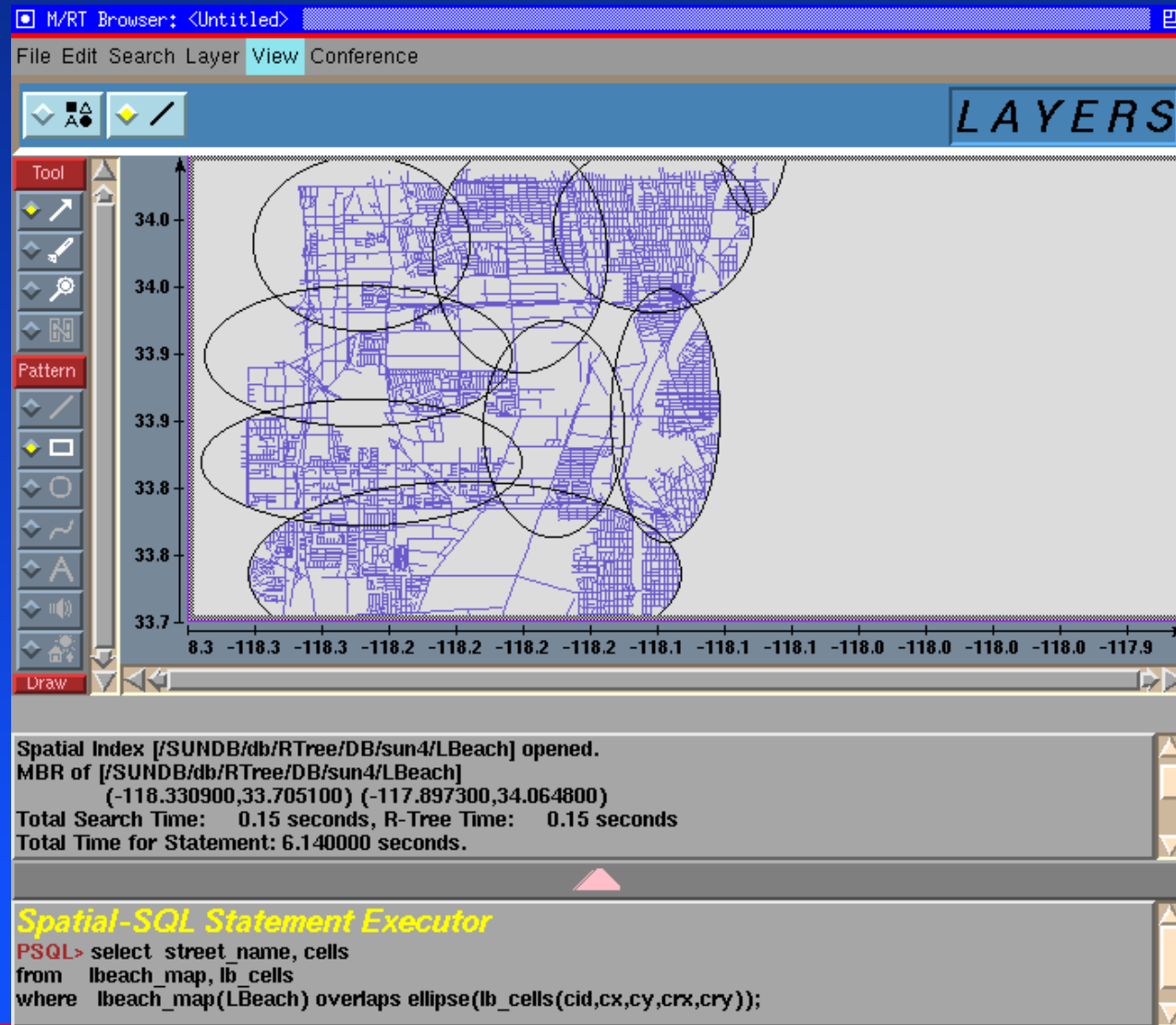
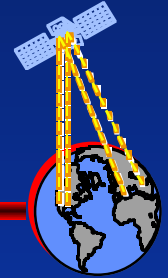
SEARCH WINDOW MBR: [-118.155 33.9144, -118.135 33.9355] HITS: [470] Pages Touched: [27]
 [1] objects clipped.
 Total Search Time: 0.11 seconds, R-Tree Time: 0.09 seconds
 316 row(s) selected

PSQL Results

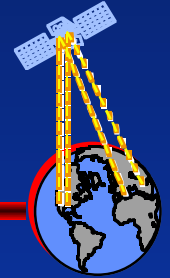
STREET_NAME	STREET
GLENSHIRE	ROAD
BORSON	ST
BORSON	ST
BORSON	ST
BORSON	ST

PSQL> select street_name, street_type
 from lbeach_map
 where street_name < 'M' and
 lbeach_map(LBeach) overlaps rect(' -118.155', '33.9144

Spatial Join with Elliptical Cells



EXPERIMENTS

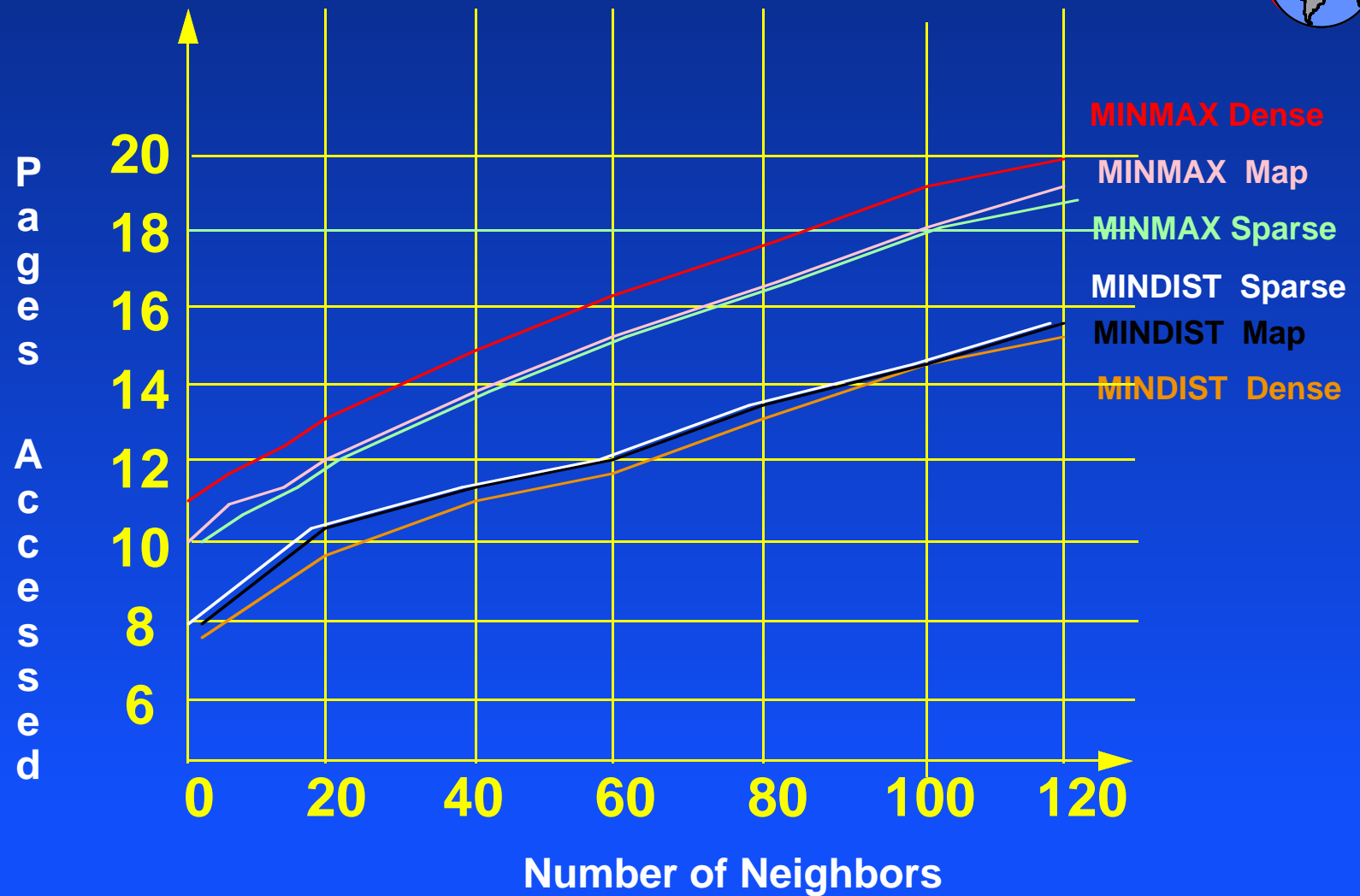
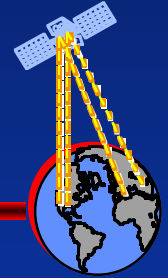


- TIGER data sets of Long Beach, CA and Montgomery County, MD
- International Ultraviolet Explorer (IUE)
- Synthetic data sets 1K-256K points
- Data sets were sorted according to their Hilbert order and R-trees were packed using [Rous+Leif1985],[Kame+Falo1993]
- Achieved the “maximum” performance for R-tree overlap, containment and NN searches

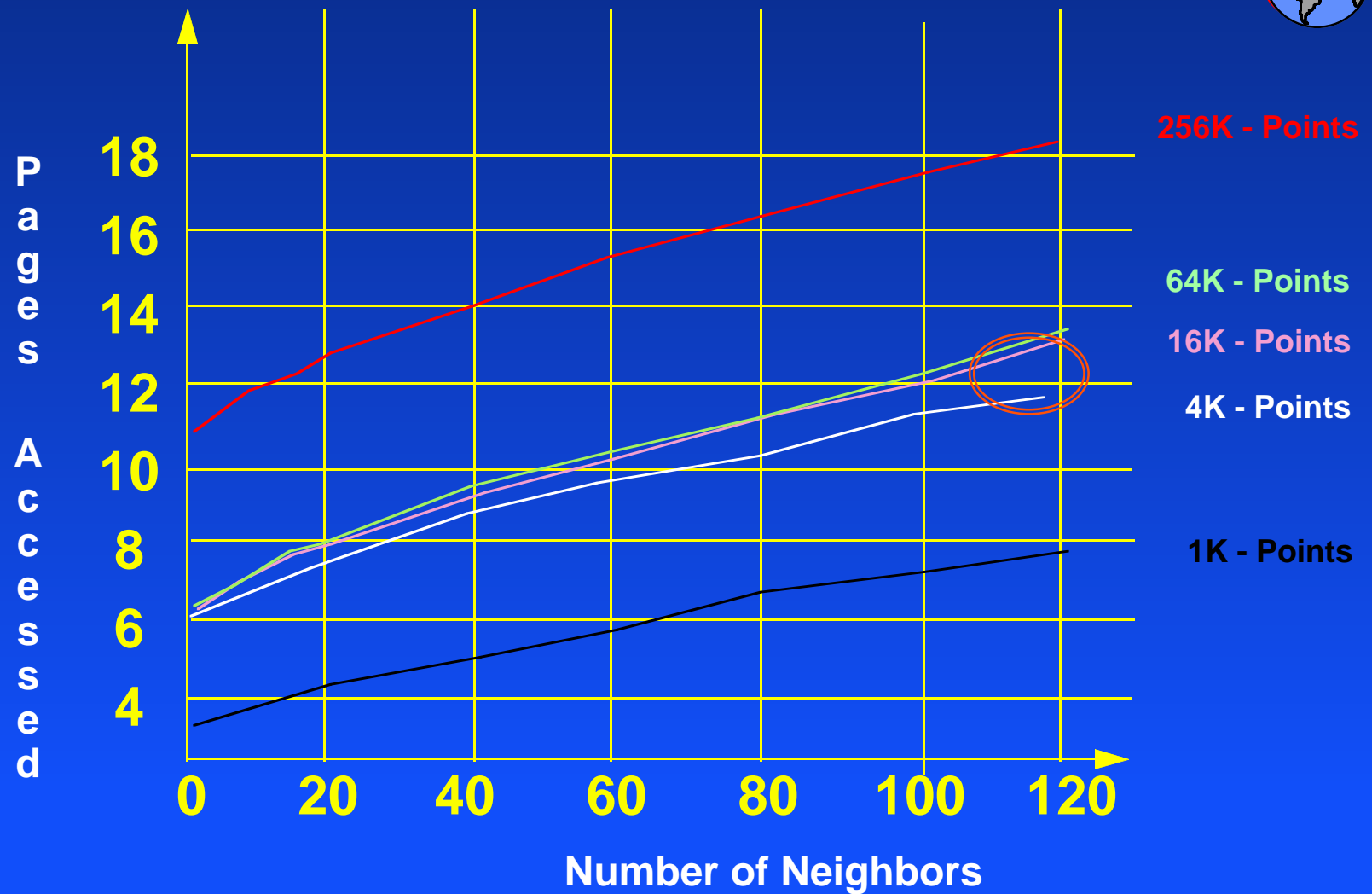
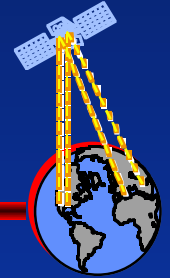
Comparisons

- Optimistic vs pessimistic ordering
- Scalability in the number of NN
- Scalability in the size of the index

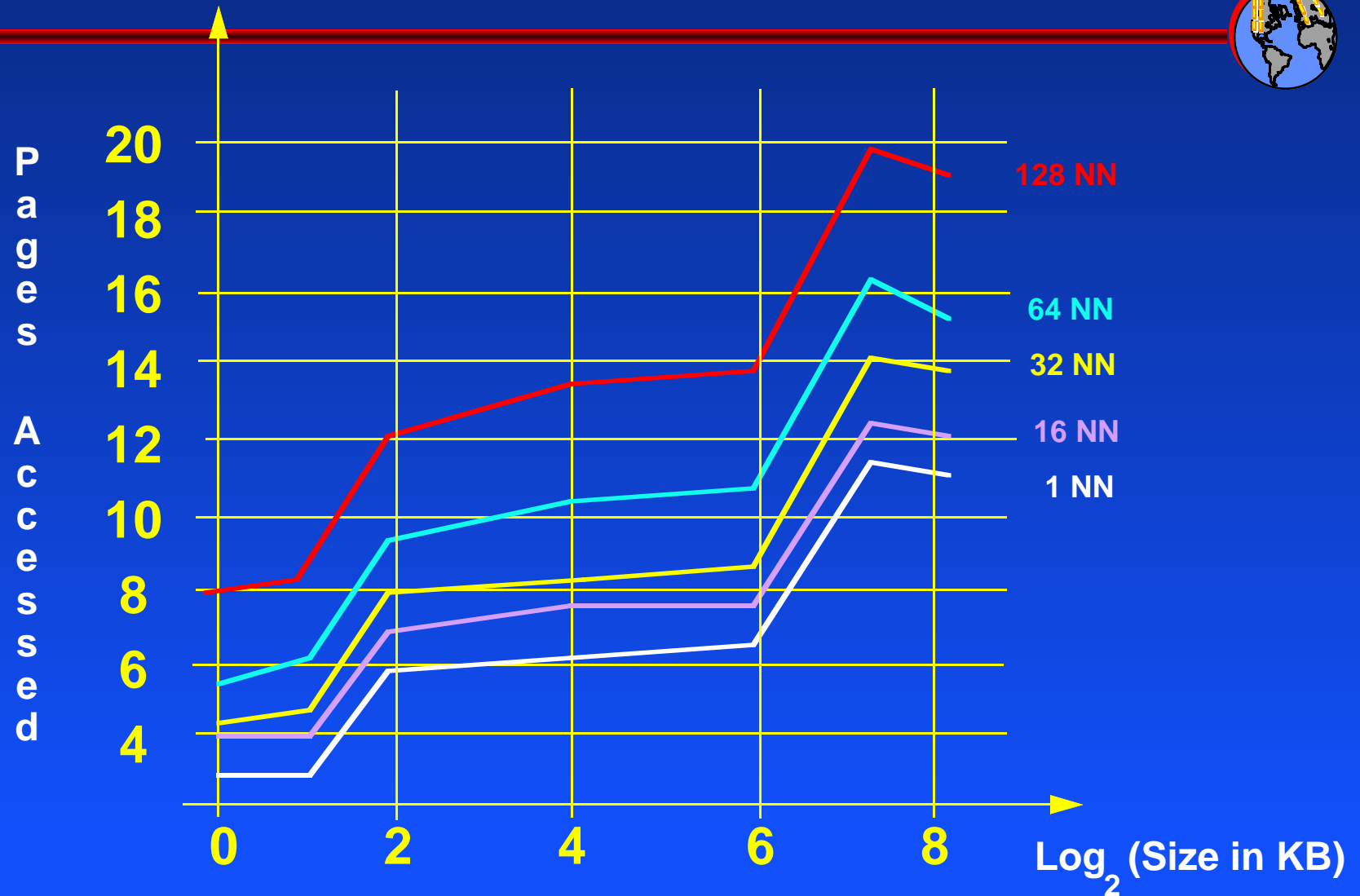
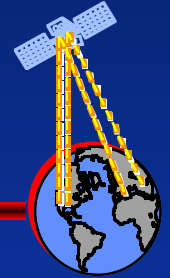
Optimistic vs. Pessimistic Ordering & Scalability in NN - Long Beach Map



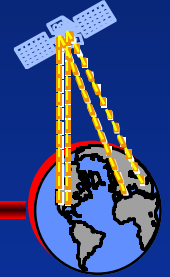
Size Scalability - Synthetic Data



Size Scalability - Synthetic Data



CONCLUSIONS



- **Branch-and-bound NN search algorithm**
- **Formalized and provided metrics for directing NN search**
- **The optimistic MINDIST metric performed better in our experiments but this is related to the construction of the R-trees**
- **Generalized and displayed the versatility of k NN search**