

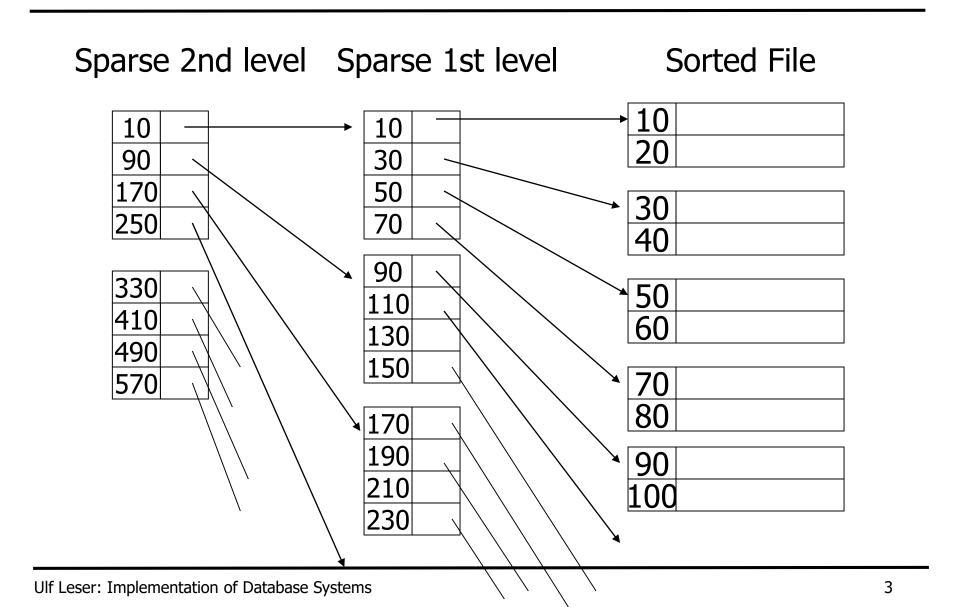
Datenbanksysteme II: B / B+ / Prefix Trees

Ulf Leser

Content of this Lecture

- B Trees
- B+ Trees
- Index Structures for Strings

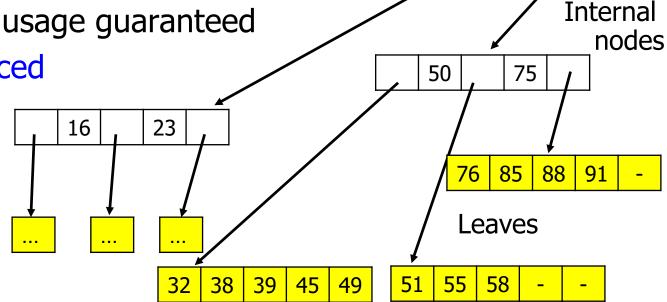
Recall: Multi-Level Index Files



B-Trees (\neq binary tree)

- B-Tree is a multi-level index with variable number of levels
 - Many variations: B/B+/B*/B++/BB...
- Height adapts to table size
- Fan-out depends on block size
- Designed for block-wise access
- >50% space usage guaranteed
- Always balanced

R. Bayer, E. McCreight. Organization and Maintenance of Large Ordered Indexes. Acta Informatica, 1972



Root node

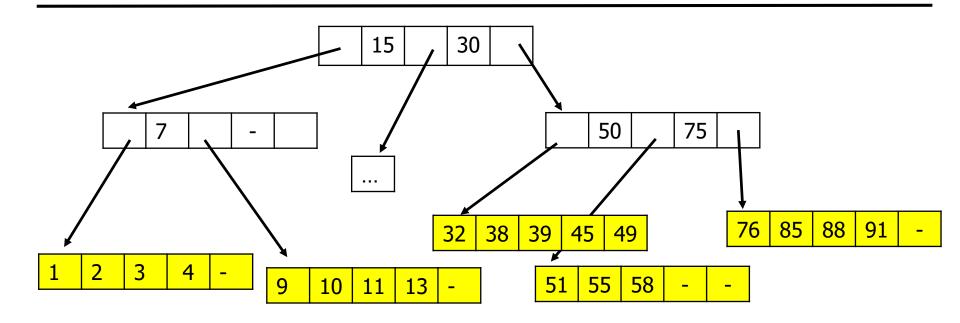
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Formally

- Assume index on primary key (no duplicates)
- Internal nodes contain pairs (key, TID) and block pointer
- Leaf nodes only contain (key, TID)
- Assume: Internal nodes can hold 2k triples plus 1 ptr
- Guarantee: Internal node contains between k and 2k triple
 - This includes [k+1, 2k+1] pointers to subtrees
 - Condition: Subtree left of pair (v,TID) contains only and all keys y<v
 - Condition: Subtree right of pair (v,TID) contains only and all keys y>v
 - Triples are sorted: v_i < v_{i+1}
 - Exception: Root node
 - Thus, B-trees use always at least 50% of allocated space

Searching B-Trees



Find 9

- 1. Start with root node
- 2. Follow p₀
- 3. Follow p₁
- 4. Scan leaf found

Find 60

- 1. Start with root node
- 2. Follow p₂
- 3. Follow p₁
- 4. Scan leaf not found

How much IO?

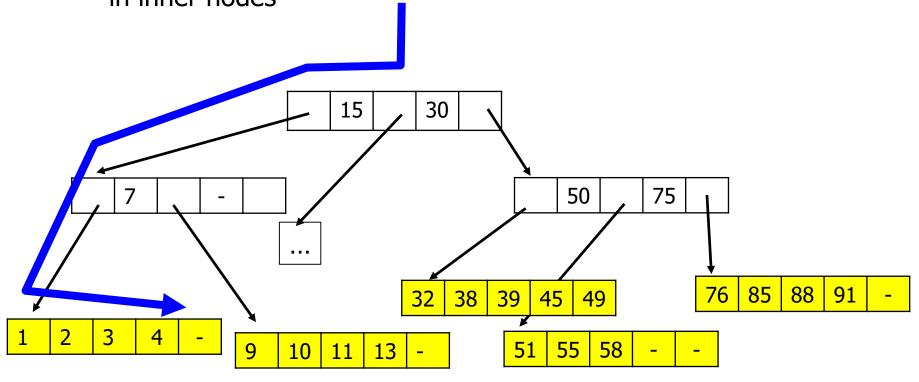
- B-trees are always balanced (how? Wait)
 - All paths from root to a leaf are of equal length
- Assume n keys; let r=|key|+|TID|+|pointer|
- Best case: All nodes are full (2k keys)
 - We have b~n/2k blocks
 - Actually a little less, since leaves contain no pointers
 - Height of the tree h~log_{2k}(b)
 - Search requires between 1 and log_{2k}(b) IO
- Worst case: Every nodes contain only k keys
 - We need b∼n/k blocks
 - Height of the tree $h \sim \log_k(b)$
 - Search requires between 1 and log_k(b) IO

Example

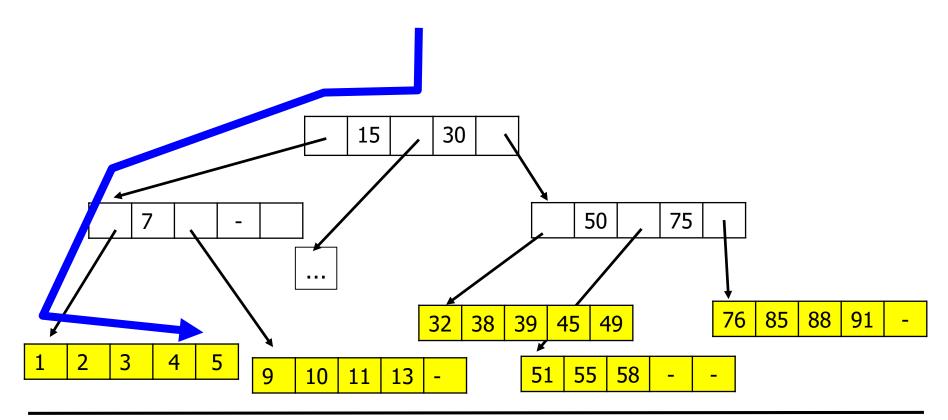
- Assume |key|=20, |TID|=16, |pointer|=8, block size=4096
 r=44
- Assume n=1.000.000.000 (1E9) records
- Gives between 46 and 92 index records per block
- Hence, we need 5 or 6 IO
 - Essentially all data is in the leaves
 - Very small chances to find key earlier
- Caching the first two levels (between 1+46 and 1+92 blocks), this reduces to 3 or 4 IO

- In B-Trees, we always insert into a leaf
- We insert 5 (assume: 2*k=2)

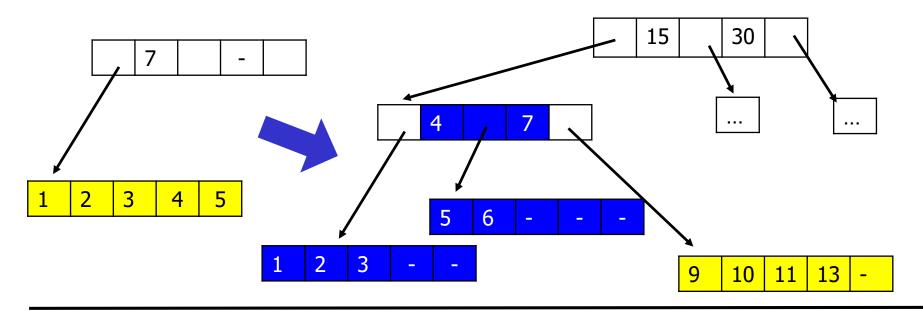
For ease of exposition, we assume 2-5 keys in leaves and 1-2 keys in inner nodes



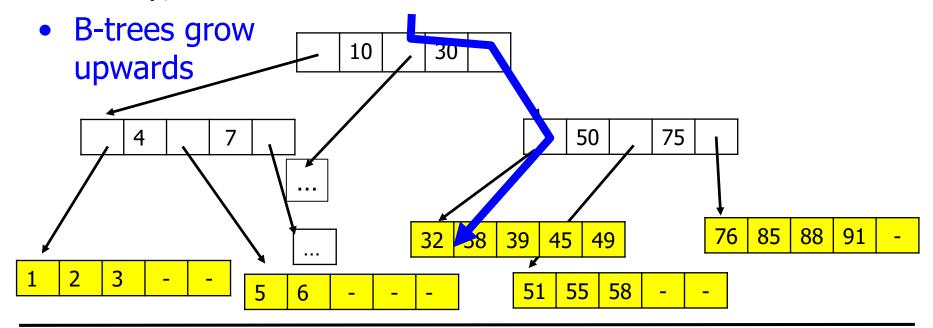
- We insert 6
- Block is full we need to split



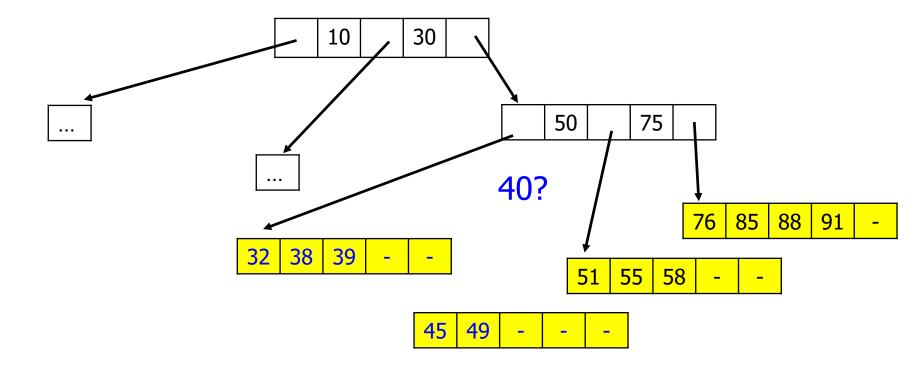
- Split overflow block and propagate median upwards
 - All values from old node plus new value minus median are evenly split between two new nodes
 - − Thus, each has ~k keys
 - Median is pushed up to parent node and inserted there



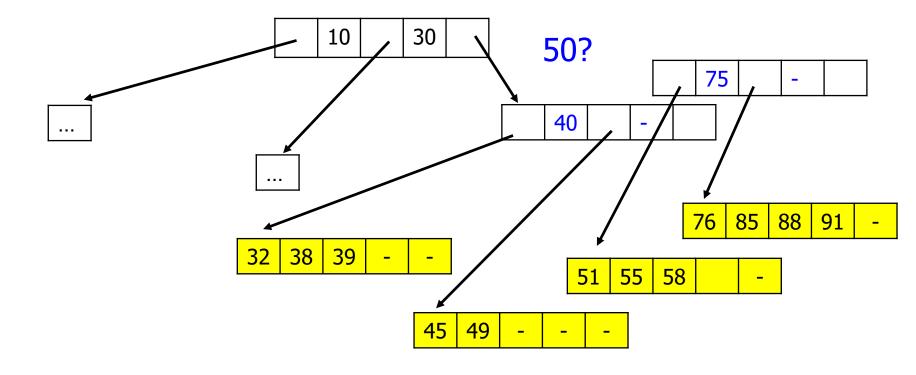
- We insert 40
 - Block is full split and propagate 40, the median
- Propagating upwards leads to overflow in parent(s)
 - Split in the same way as leaves
- Finally, the root note overflows



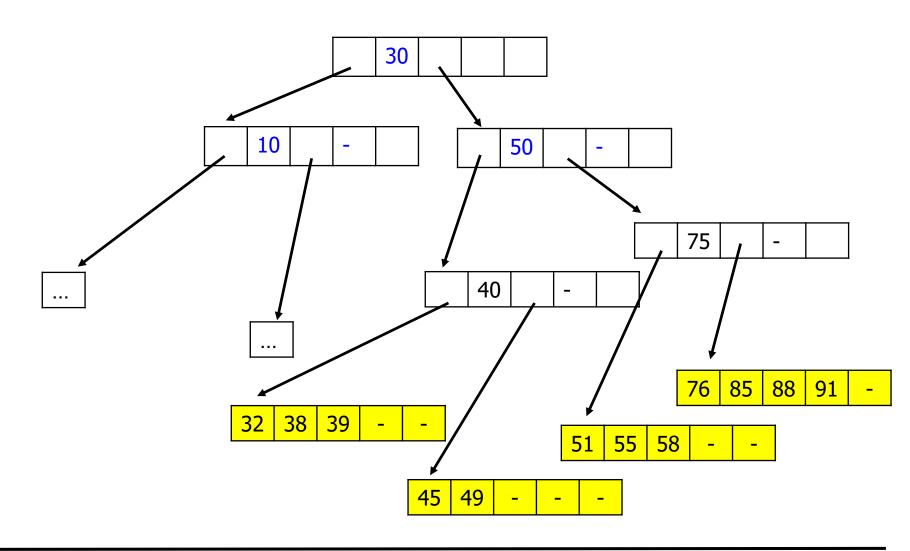
Intermediate 1



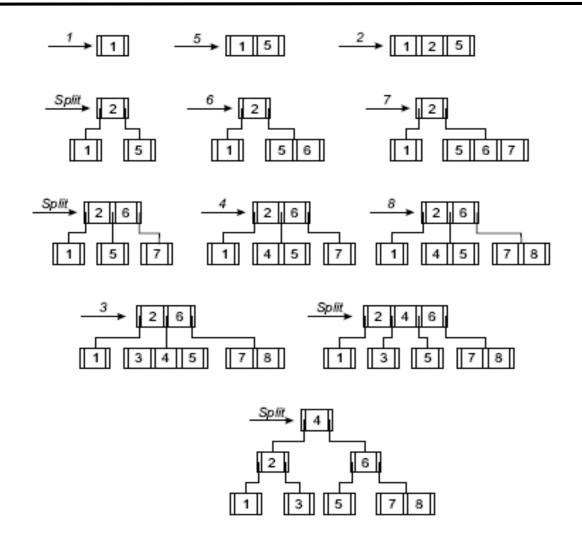
Intermediate 2



Final Tree



Longer Sequence of Insertions

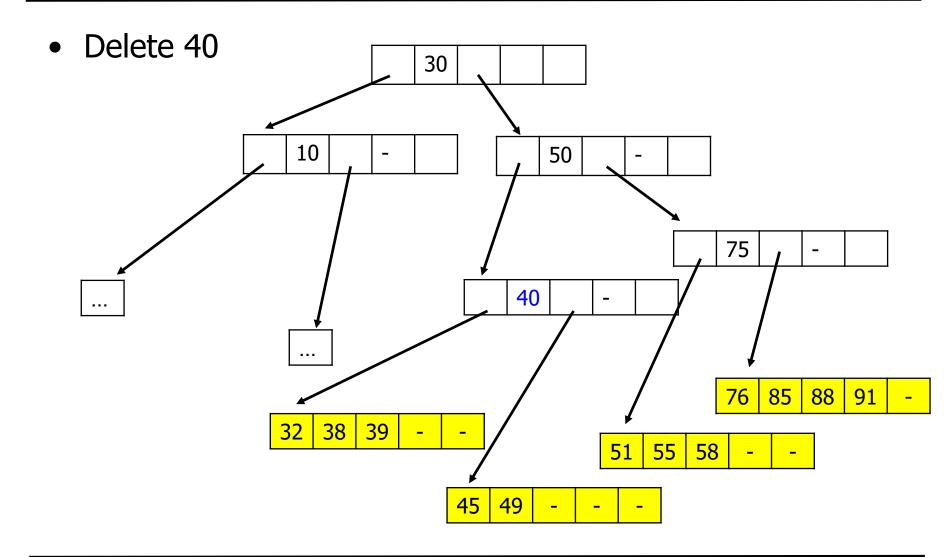


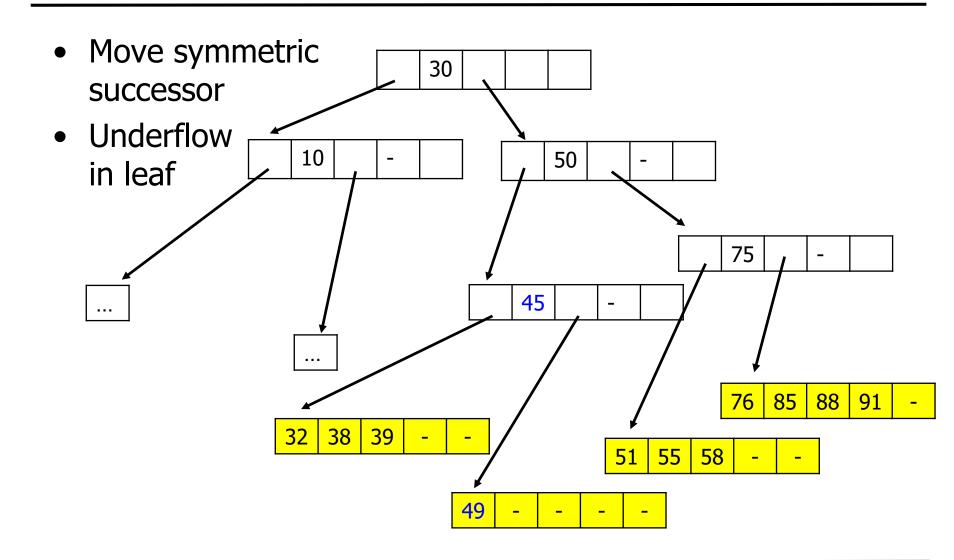
How much IO?

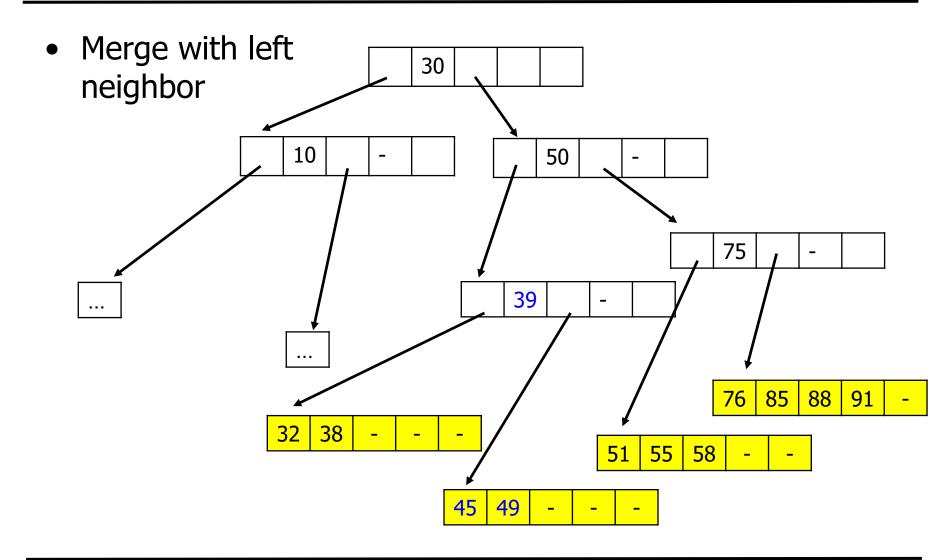
- Let h be height of B-tree
- Cost for searching leaf node: h IO
- If no split necessary: Total IO cost = h+1 (writing)
- If split is necessary
 - Worst case up to the root
 - We assume we cached ancestor blocks during traversal
 - We thus need to read them once and write them once
 - Total cost: (h+2)+2(h-1)+1 = 3h+1
 - At lowest level, we need to split and thus write 2 blocks
 - This is repeated at all parent levels
 - Finally, we need to create new root node

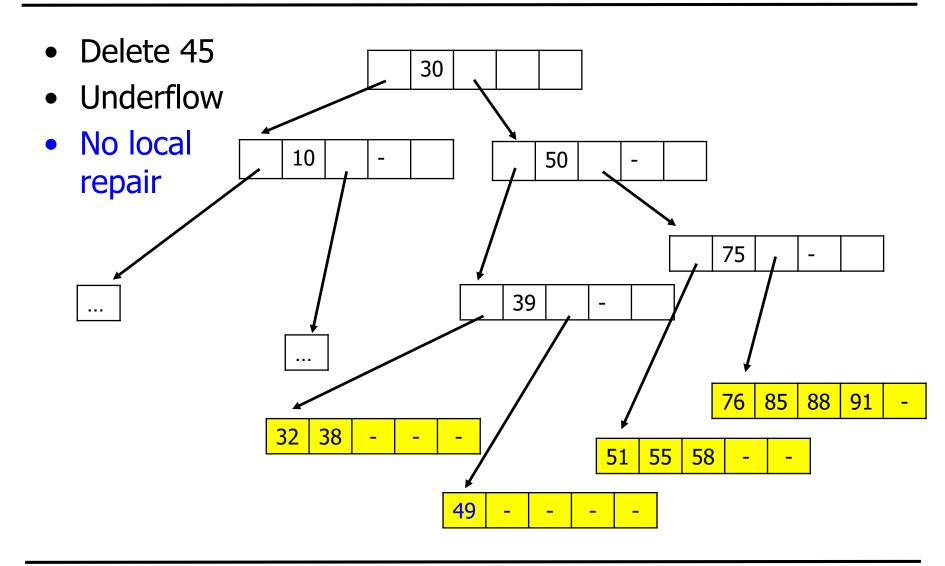
Deleting Keys

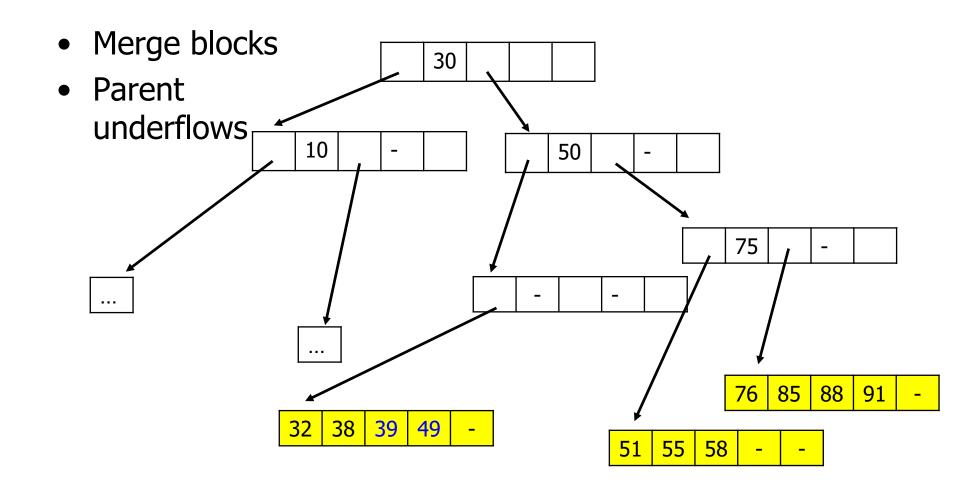
- If found in internal node
 - Choose smallest value from right subtree and replace deleted value
 - This value must be in a leaf
 - Recall search trees: symmetric predecessor (or successor)
 - Delete value in leaf and progress
- If found in leaf
 - Delete value
 - If blocks underflows (<k keys), choose one of neighboring blocks
 - Must have the same parent node
 - If both blocks together have more than 2k records: Distribute values evenly; adapt between-key in parent node
 - Otherwise merge blocks
 - One block with all leaf-records plus the median in parent
 - Remove middle value in parent block which now might underflow
 - Might work recursively up the tree

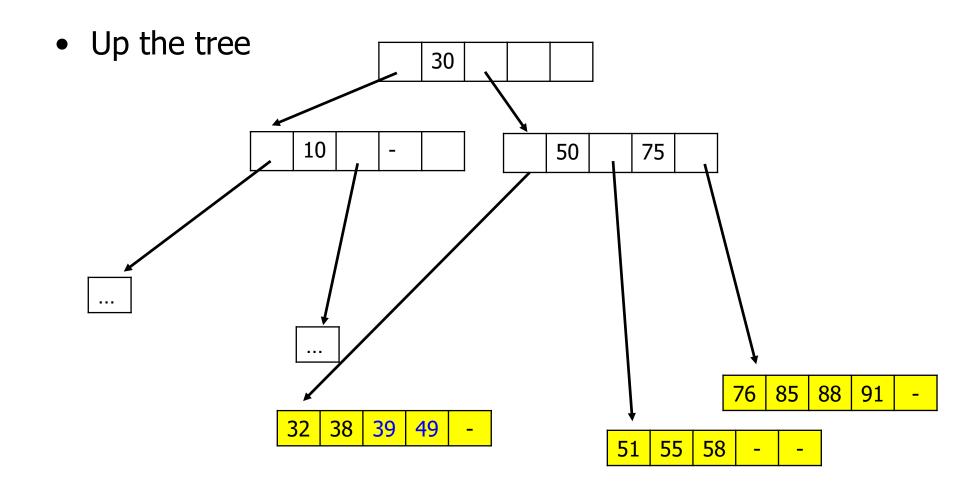












How much IO?

- Going down costs h IO
 - If key found in leaf, it costs h to read and 1 to write
 - If found in internal node, we still have to read h blocks to choose replacement value from leaf
- If no underflow, total cost is h+1
- If local underflow (with merge), total cost is ~h+4
 - Checking left and right neighbor, writing block and chosen neighbor, writing parent
- If blocks underflow until root, total cost is at most 4h-2
 - If left and right neighbors have to be checked at each level

B-trees on Non-Unique Attributes

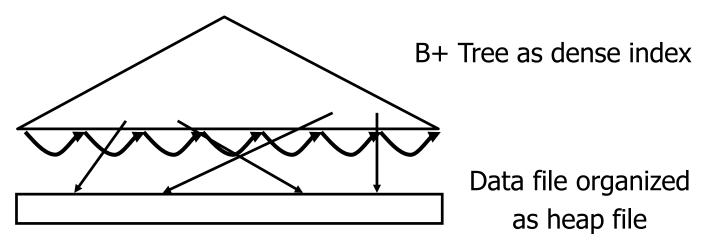
- If duplicates exist ...
- Option 1: Compact representation
 - Store (value, TID₁, TID₂, ... TID_n)
 - Difficult— internal nodes don't have fixed number of pairs any more
 - Requires internal overflow blocks
- Option 2: Verbose representation
 - Treat duplicates as different values
 - Constraints on keys change from "<" to "≤"
 - Extreme case: Generates a tree although a list would suffice
- Better: B+ trees

Content of this Lecture

- B Trees
- B+ Trees
- Index Structures for Strings

B+ Trees

- Internal nodes contain only values and pointers
 - Values demark borders between subtrees
 - Concrete values in inner nodes need not exist as keys only signposts
- Leaves are chained for faster range queries



Operations

Searching

- Essentially the same as for B trees
- But will always go down to leaf marginally more IO
 - Chance to find key in inner node is "exponentially" small

Insertion

- Essentially the same as for B trees
- When block is split, no value moves upwards
 - Parent block still changes new signpost
 - Typical choice: avg(v_{median-1}, v_{median+1})

Deletion

- Deletion in internal node cannot occur
- When blocks are merged, no values are moved up
 - But signposts in parent node are deleted as well

Advantages

- More pointes in inner nodes higher fan-out less IO
 - No TIDs in internal nodes more space for pointers
 - Reduced height (base of log() changes)
- Can achieve smooth balancing: Chose signposts carefully
 - Choose such that future inserts are evenly distributed
- Linked leaves
 - Faster range queries traversal need not go up/down the tree
 - Optimally, leaves are in sequential order on disk
 - Than a B+ tree also supports fast sorted scans

B* tree: Improving Space Usage

- Can we increase space usage guarantee beyond 50%?
- Don't split upon overflow: Move values to neighbor blocks as long as possible
 - More complex operations, need to look into neighbors
 - We only split when all neighbors and the current block is full
- When splitting, make three out of two
 - We only split when all neighbors are full choose one
 - Generate three new blocks from the two full old ones
 - Each new block has 4/3k keys: Guaranteed 66% space usage
- Knuth, D. E.: The Art of Computer Programming, Volume III: Sorting and Searching Addison-Wesley, 1973

B+ Trees and Hashing

- Hashing faster for some applications
 - Can lead to O(1) IO
 - Assumes good hash function
 - Requires domain knowledge
- B+ trees
 - Very few IO if upper levels are cached
 - Adapts to skewed (non-uniformly distributed) data
 - Domain-independent
 - Also supports range queries

Loading a B+ Tree

What happens in case of

create index myidx on LARGETABLE (id);

Loading a B+ Tree

What happens in case of

```
create index myidx on LARGETABLE ( id);
```

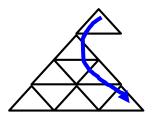
- Naïve: Record-by-record insertion
 - Each insertion has 3h+1 ~ log_k(b) block IO
 - Altogether: $\sim n*log_k(b)$
- Blocks are read and written in arbitrary order
 - Very likely: bad cache-hit ratio
- Space usage will be anywhere between 50 and 100%
- Can't we do better?

Bulk-Loading a B+ Tree

- First sort records
 - O(n*log_m(n)), where m is number of records fitting into memory
 - Clearly, m>>k
- Insert in sorted order using normal insertion
 - Tree builds from lower left to upper right
 - Caching will work very well
 - But space usage will be only 50%



- Compute structure in advance
 - Every 2k'th record we need a separating key
 - Every 2k'th separating key we need a next-level separating key
 - ...
- Can be generated and written in linear time (after sorting)

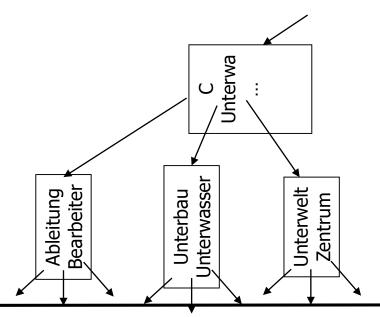


Content of this Lecture

- B Trees
- B+ Trees
- Index Structures for Strings
 - Prefix B+ Tree
 - Prefix Tree
 - PETER
 - PEARL

Prefix B+ Trees

- Consider string values as keys
- Keys for int. nodes: Smallest key from right-hand subtree
 - Leads to internal signposts as large as keys
- Prefix B+ trees Shortest string separating largest key in left-hand subtree from smallest key in right-hand subtree



Advantages: Reduced space,

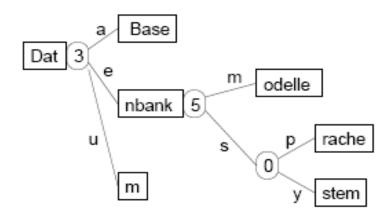
higher fan-out

Disadvantages: Overhead for computing

signpost

Prefix Tree / Patricia tree / Trie

- If we index many strings with many common prefixes
 - ... as in Information Retrieval ...
 - Why store common prefixes multiple times?
- Prefix trees
 - Store common prefix / substring in internal nodes
 - Searching a key k requires at most |k| character comparisons



Indexing Strings

- Prefix trees traditionally are main memory structures
 - How to optimally layout internal nodes on blocks?
 - Not balanced no guaranteed worst-case IO
- More index structures for strings
 - Keyword trees searching for many patterns simultaneously
 - Necessary for joins on strings
 - Persistent keyword trees challenge
 - Suffix trees indexing all substrings of a string
 - Necessary e.g. to search genomic sequences
 - Persistent suffix trees challenge in advancement

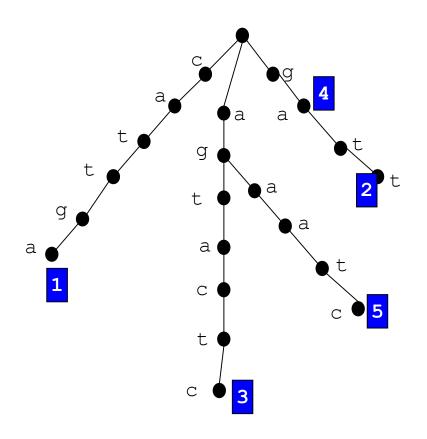
PETER

- Computes joins / search on large collections of long strings much faster than traditional DB technology
- Also handles similarity search / similarity joins
- Open source
 - Rheinländer, A., Knobloch, M., Hochmuth, N. and Leser, U. (2010).
 "Prefix Tree Indexing for Similarity Search and Similarity Join on Genomic Data". SSDBM 2010
- There are many similar index structures
 - PRETTY, PRETTY+, MASSJoin, ...
- Careful: Next results are 13 years old

Prefix-Trees

- Given a set S of strings
- Build a tree with
 - Labeled nodes
 - Outgoing edges have different label
 - Every s∈S is spelled on exactly one path from root
 - Mark all nodes where a string ends
- Common prefixes are represented only once

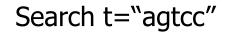
cattga, gatt, agtactc, ga, agaatc

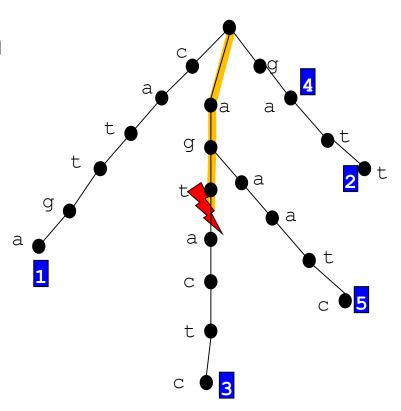


Searching Prefix-Trees

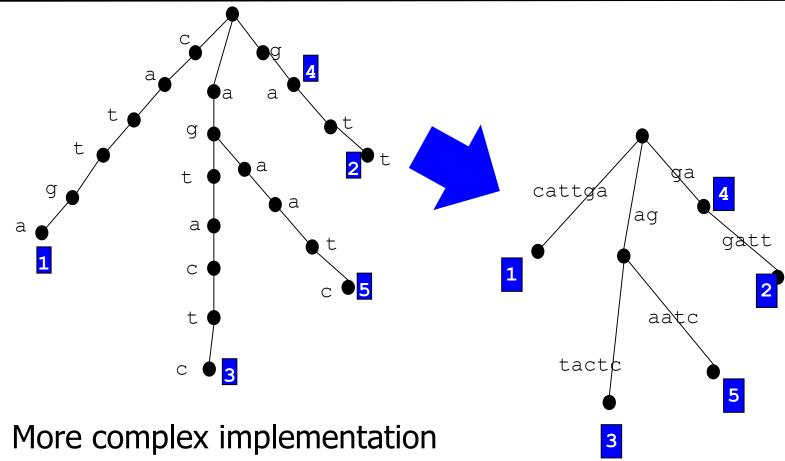
- Search t in S
- Recursively match t with a path starting from root
 - If no further match: t∉S
 - If matched completely: t∈S

- Search complexity
 - Only depends on depth of S
 - Independent from |S|



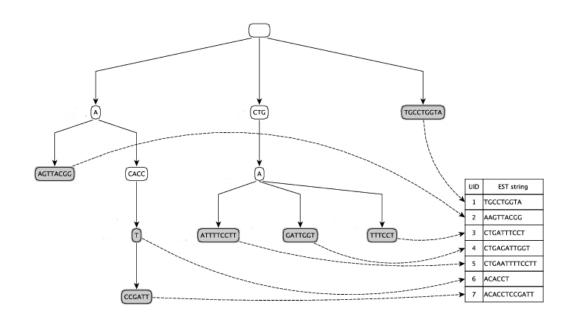


Compressed Prefix Trees (Trie)



- Different kinds of edges/nodes

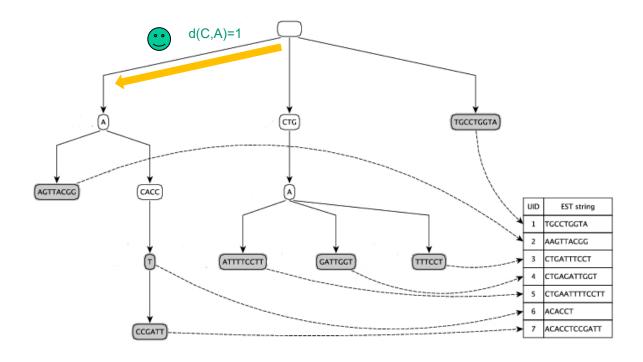
Prefix Trees over Large Strings

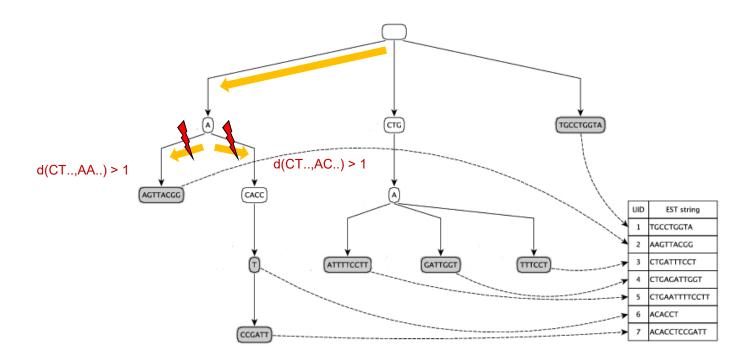


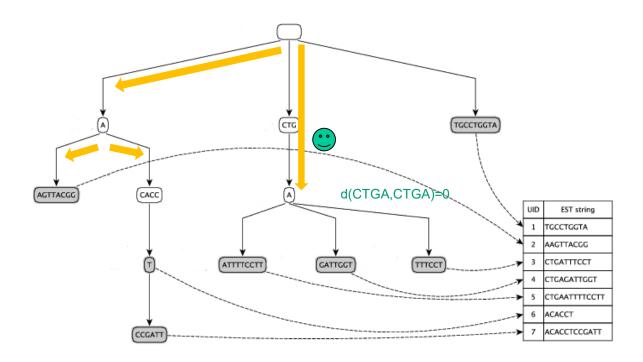
- Unique suffixes are stored (sorted) on disk
- Tree of common prefixes is kept in main memory
 - Most failing searches never access disc
 - At most one disc IO per search
 - [If tree fits in main memory]

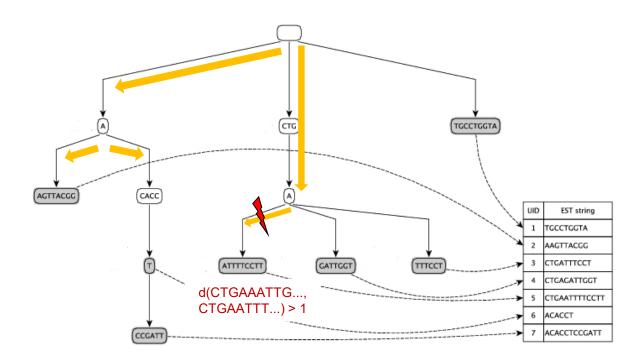
Similarity Search on Prefix-Trees

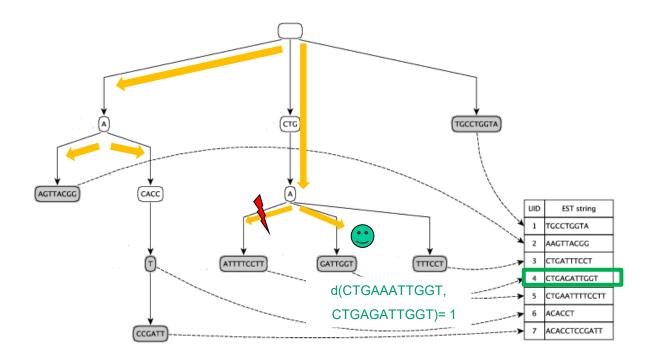
- In similarity search, a mismatch doesn't mean that t∉S
- Several mismatches might be allowed
 - Depending on error threshold
 - Depending on similarity function
- Idea
 - Depth-first search on the tree as usual
 - Keep a counter for the n# of errors occurring in the prefix so far
 - If counter exceeds threshold stop search in this branch
 - Pruning: Try to stop earlier by clever "guessing"

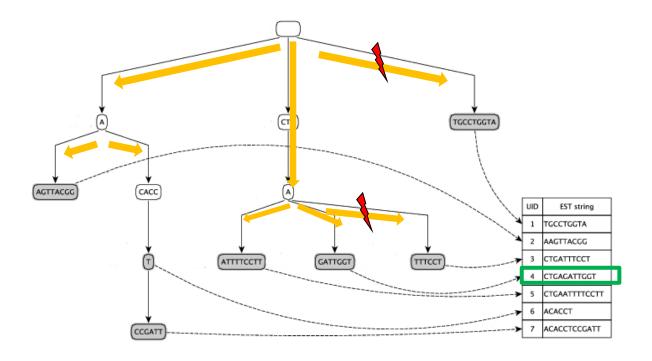






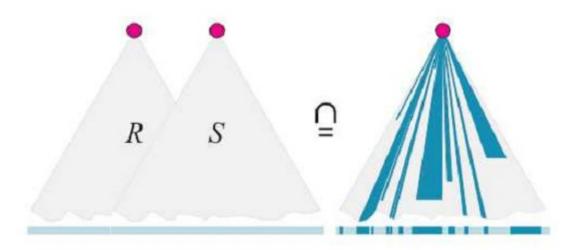






(Similarity) Joins on Prefix Trees

- We compare growing prefixes with growing prefixes
- Exact and similarity join
- Essentially: Compute intersection of two trees
 - Only labeled nodes are interesting
- Traverse both trees in parallel
 - Upon (sufficiently many) mismatches, entire subtrees are pruned



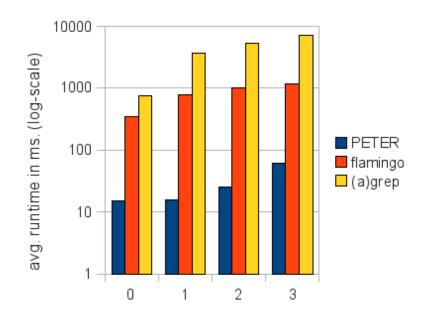
Evaluation

Set	# EST strings	avg. string length	min/max length	# tree nodes	# ext. suffixes
T_1	307,542	348	14/3,615	589,062	293,764
T_2	736,305	387	12/3,707	1,482,709	689,590
T_{2a}	368,152	382	12/2,774	711,632	352,872
T_{2b}	184,076	385	22/2,774	349,329	177,846
T_{2c}	92,038	383	25/2,774	171,964	89,198
T_{2d}	46,019	381	28/2,774	84,954	44,716
T_{2e}	23,009	373	31/ 878	42,375	22,366
T_3	10,000	536	16/3,707	16,310	8,774
TX	5,000,000	359	14/3,247	10,478,214	4,834,231

- Data: Several EST data sets from dbEST
 - Search: All strings of one data set in another data set
 - Join: One data set against another data set
 - Varying similarity thresholds
- (Linear) Index creation not included in measurements

Search: Comparing to Flamingo (2011)

- Flamingo: Library for approximate string matching
 - http://flamingo.ics.uci.edu/
 - Based on an inverted index on q-grams
 - Uses length and charsum filter

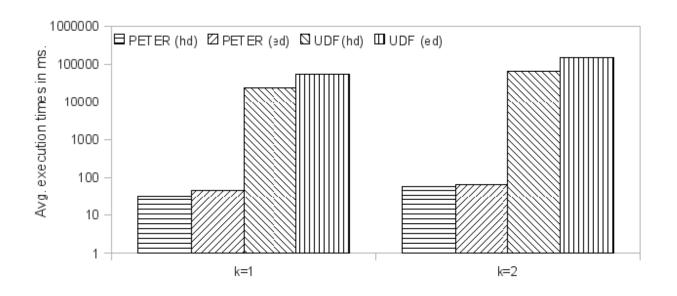


PETER inside a RDBMS

- We integrated PETER into a commercial RDBMS using its extensible indexing interface
 - Joins: table functions
 - Tree stored in separate file, suffixes stored in table
- Hope
 - As search complexity is independent of |S|, ...
 - we might beat B+ trees for exact search on very large and long |S|
 - we might beat hash/merge for exact join of very large data sets
- First hope not fulfilled
 - API does not allow caching of tree index reload for every search
 - Large penalty for context switch through API
 - Especially for JAVA

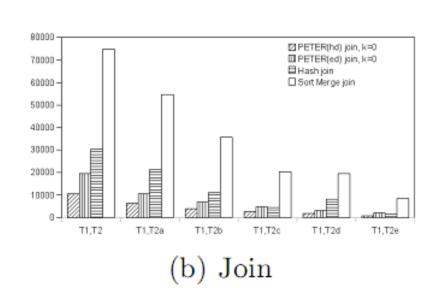
String Similarity Search in a RDBMS

- Peter (behind extensible indexing interface) versus UDF implementing hamming / edit distance calculations
- Difference: 2-3 orders of magnitude, independent of data set, threshold, or search pattern length

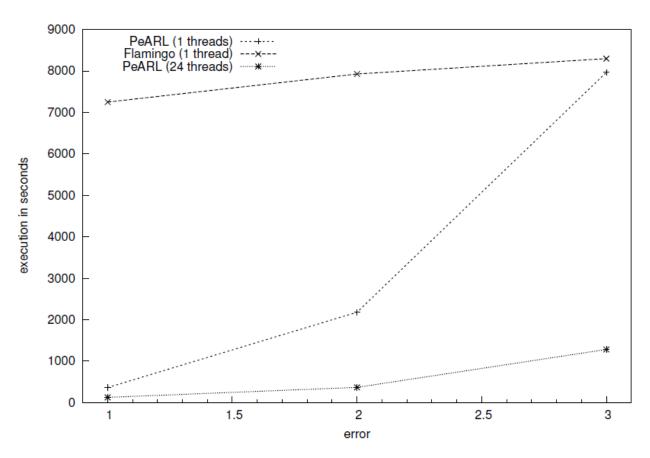


(Similarity) Join inside RDBMS

- PETER (behind extensible indexing interface) versus buildin join (exact join, hash and merge) or UDF
- Similarity join
 - Join T3 with T2e, k=2, inside RDBMS: Stopped after 24 h
 - Same join with PETER: 1 minute
- Exact join
 - For long strings, PETER is significantly faster than commercial join implementations



PEARL: Multi-Threaded PETER



Rheinländer, A. and Leser, U. (2011), "Scalable Sequence Similarity Search and Join in Main Memory on Multi-Cores", HiBB, Bordeaux, France.

Room for Improvement

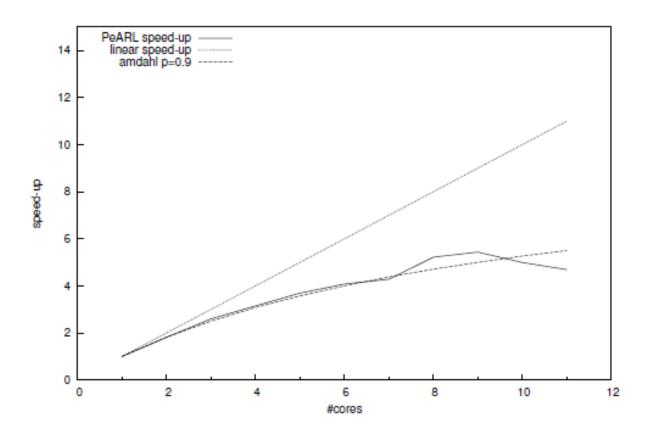


Fig. 7. PeARL speed-up for similarity search on k=2.

Why?

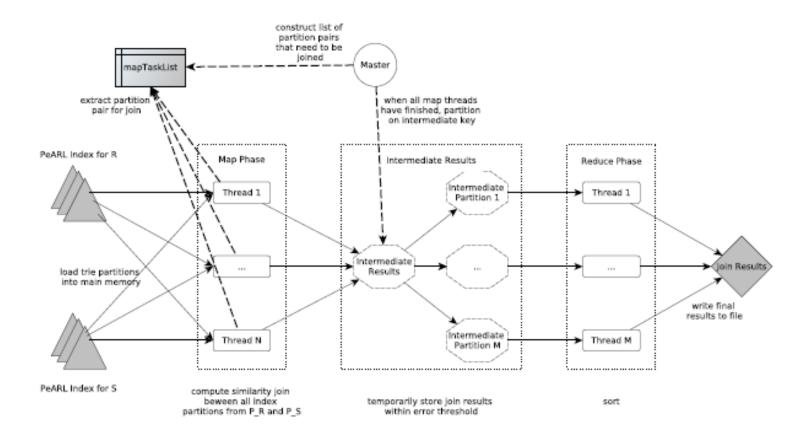


Fig. 2. MapReduce workflow of similarity joins in PeARL.