Datenbanksysteme II: Set Containment Join

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Set Containment Join

Definition 1 (Set containment join). *Given two relations R, S with set-valued attributes $R.a$ and $S.b$, a set-containment join $R \bowtie_{\subseteq} S$ returns all pairs $(r, s), r \in R, s \in S$ where $r.a \subseteq s.b$.*

Job ID	*Required skills*
r1	{Java,C++}
r2	{Java,C++,SQL,EJB}
r3	{Java,C++,EAI}
r4	{Java,SOA}
r5	{Cloud}

$\bowtie_{\subseteq}$

Applicant ID	*Qualifications*
s1	{Java}
s2	{Java,C++,SOA}
s3	{Java,C++,SQL,EAI}
s4	{C++,EJB}
s5	{Java,EAI,EJB}
s6	{C++,SQL,EJB}

Set Containment Join

JID	*Required skills*
r1	{Java,C++}
r2	{Java,C++,SQL,EJB}
r3	{Java,C++,EAI}
r4	{Java,SOA}
r5	{Cloud}

$\bowtie_{\subseteq}$

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s1	{Java}
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s3	{Java,C++,SQL,EAI}
s4	{C++,EJB}
s5	{Java,EAI,EJB}
s6	{C++,SQL,EJB}

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Job ID	*AppID*	*Required skills*
r1	s2	{**Java,C++**, SOA}
r1	s3	{**Java,C++**,SQL,EAI}
r3	s3	{**Java,C++**,SQL, **EAI**}
r4	s2	{**Java,** C++, **SOA**}

SQL Formulation [BMGT15]

Requires

Skill	Course
Systems	RDBMS-1
Systems	OS
Databases	RDBMS-1
Databases	RDBMS-2

Passes

Student	Course
Ana	RDBMS-1
Ana	OS
Peter	RDBMS-1

```
select P1.Student, R1.Skill
from Passes as P1, Requires as R1
where not exists (select R2.Course
                  from Requires as R2
                  where R1.Skill = R2.Skill
                  and not exists (select P2.Course
                                  from Passes as P2
                                  where P2.Student=P1.Student
                                  and P2.Course=R2.Course));
```

NF2 Formulation

Requires

Skill	Course*
Systems	{RDBMS-1,OS}
Databases	{RDBMS-1, RDBMS-2}

Passes

Student	Course*
Ana	{RDBMS-1, OS}
Peter	{RDBMS-1}

```
SELECT  student, skill
FROM    requires R, student S
WHERE   S.course ⊆ R.course;
```

Computing SCJ – The Early Years [HM03, MGM03]

Job ID	*Required skills*
r1	{Java,C++}
r2	{Java,C++,SQL,EJB}
r3	{Java,C++,EAI}
r4	{Java,SOA}
r5	{Cloud}

Job ID	*Req.*
r1	C++
r1	Java
r2	C++
r2	EJB
r2	Java
r2	SQL
r3	C++
r3	EAI
r3	Java
…	…

A-ID	*Qual.*
s1	Java
s2	C++
s2	Java
s2	SOA
s3	C++
s3	EAI
s3	Java
s3	SQL
s4	C++
s4	EJB
…	…

- Build on normalized model
- Sort by ID and skills
- Sort-merge join, hash-join, partitioning etc.
  - Followed by postprocessing or group-by \ having
- Problem: Much unnecessary work (no early pruning)

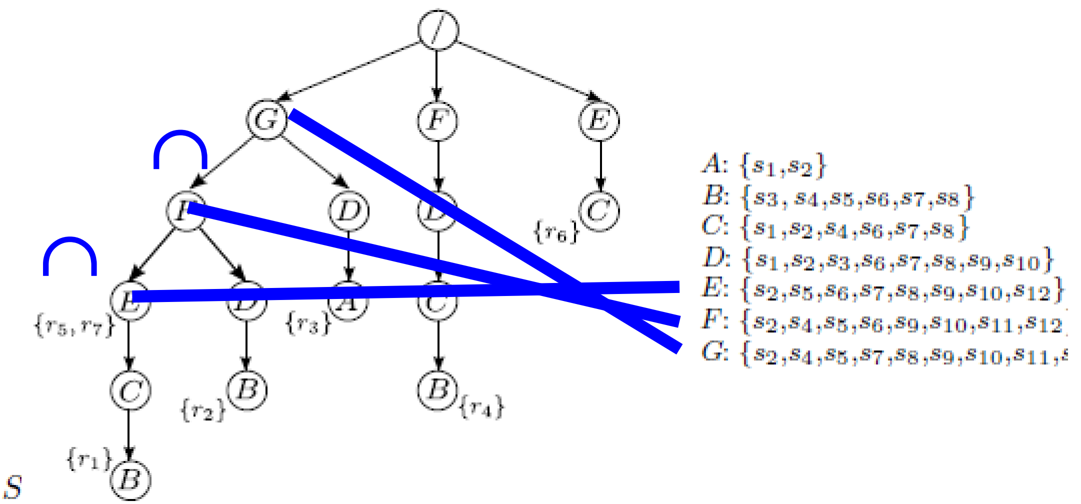
PRETTI: Prefix Tree for R / Inverted Index for S [JP05]

r_1: $\{G, F, E, C, B\}$
r_2: $\{G, F, D, B\}$
r_3: $\{G, D, A\}$
r_4: $\{F, D, C, B\}$
r_5: $\{G, F, E\}$
r_6: $\{E, C\}$
r_7: $\{G, F, E\}$

(a) left-hand collection R

s_1: $\{D, C, A\}$
s_2: $\{G, F, E, D, C, A\}$
s_3: $\{D, B\}$
s_4: $\{G, F, C, B\}$
s_5: $\{G, F, E, B\}$
s_6: $\{F, E, D, C, B\}$
s_7: $\{G, E, D, C, B\}$
s_8: $\{G, E, D, C, B\}$
s_9: $\{G, F, E, D\}$
s_{10}: $\{G, F, E, D\}$
s_{11}: $\{G, F\}$
s_{12}: $\{G, F, E\}$

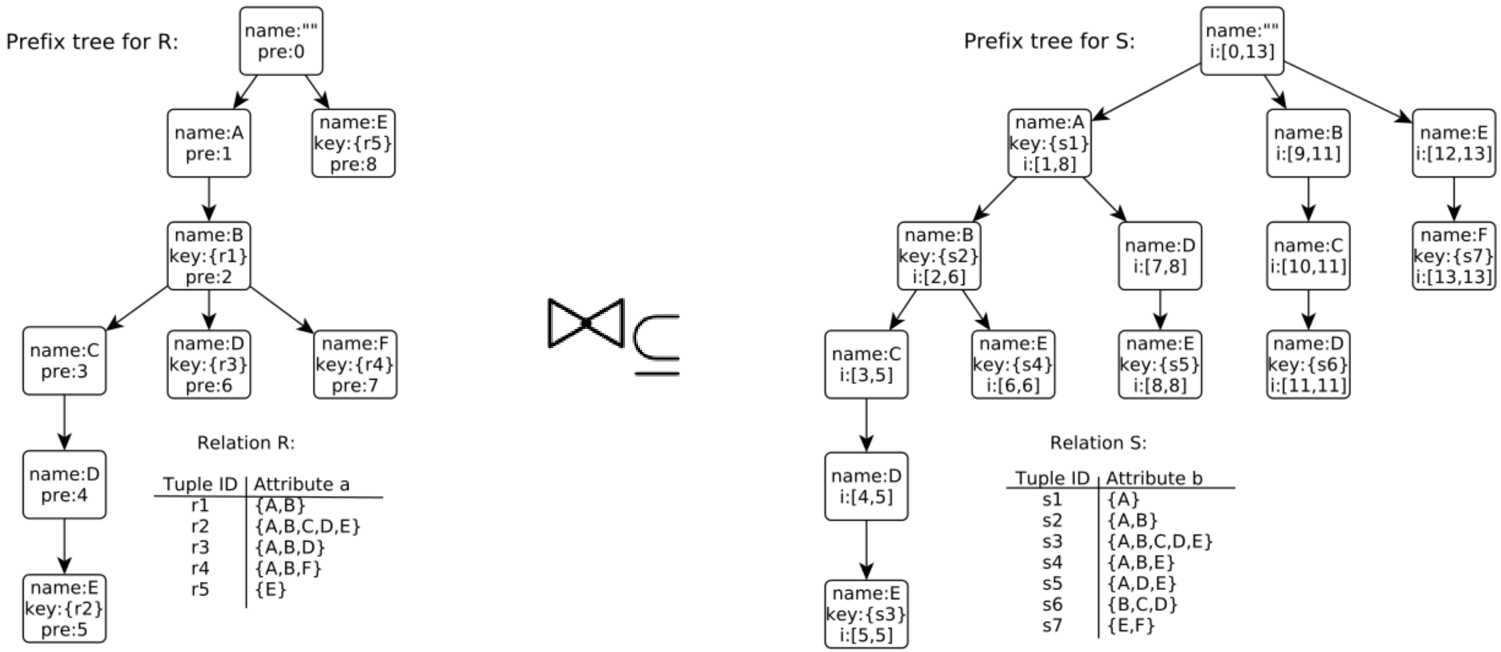
(b) right-hand collection S



(a) prefix tree T_R (b) inverted index I_S

- Traverse PT(R) and look up lists in II(S)
- Progressively compute list intersections from II(S)
- Output Cartesian products when matches are found
- Problem: Still redundant work regarding II(S)
  - Many occurrence of E, F, …

PIEJoin: Use Two Prefix Trees



Relation R:

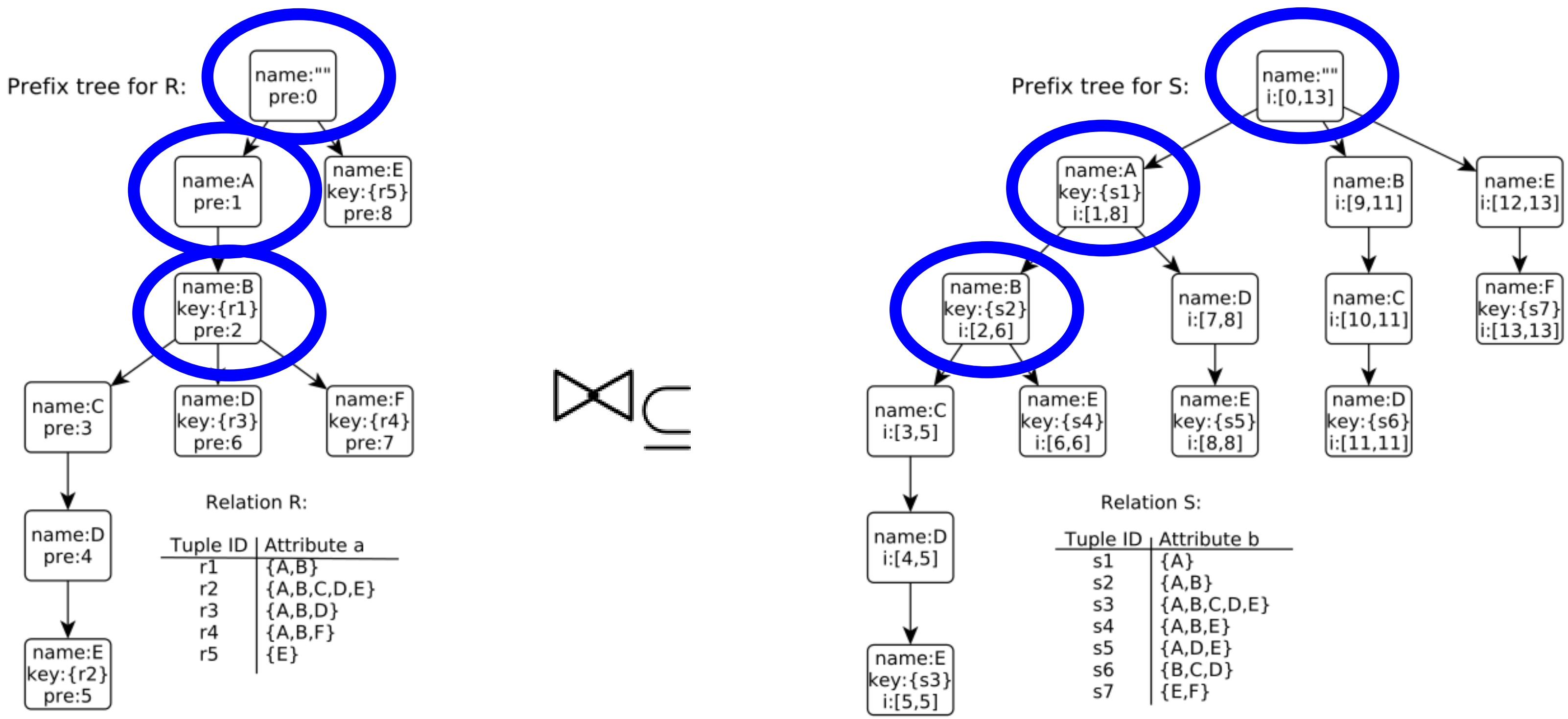
Tuple ID	Attribute a
r1	{A,B}
r2	{A,B,C,D,E}
r3	{A,B,D}
r4	{A,B,F}
r5	{E}

Relation S:

Tuple ID	Attribute b
s1	{A}
s2	{A,B}
s3	{A,B,C,D,E}
s4	{A,B,E}
s5	{A,D,E}
s6	{B,C,D}
s7	{E,F}

- Fix an arbitrary order of elements (frequency, alphabetical)
- Traverse both trees simultaneously
- When finding a key in R, “extract” matching keys in S

Traverse …



Relation R:

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r2	{A,B,C,D,E}
r3	{A,B,D}
r4	{A,B,F}
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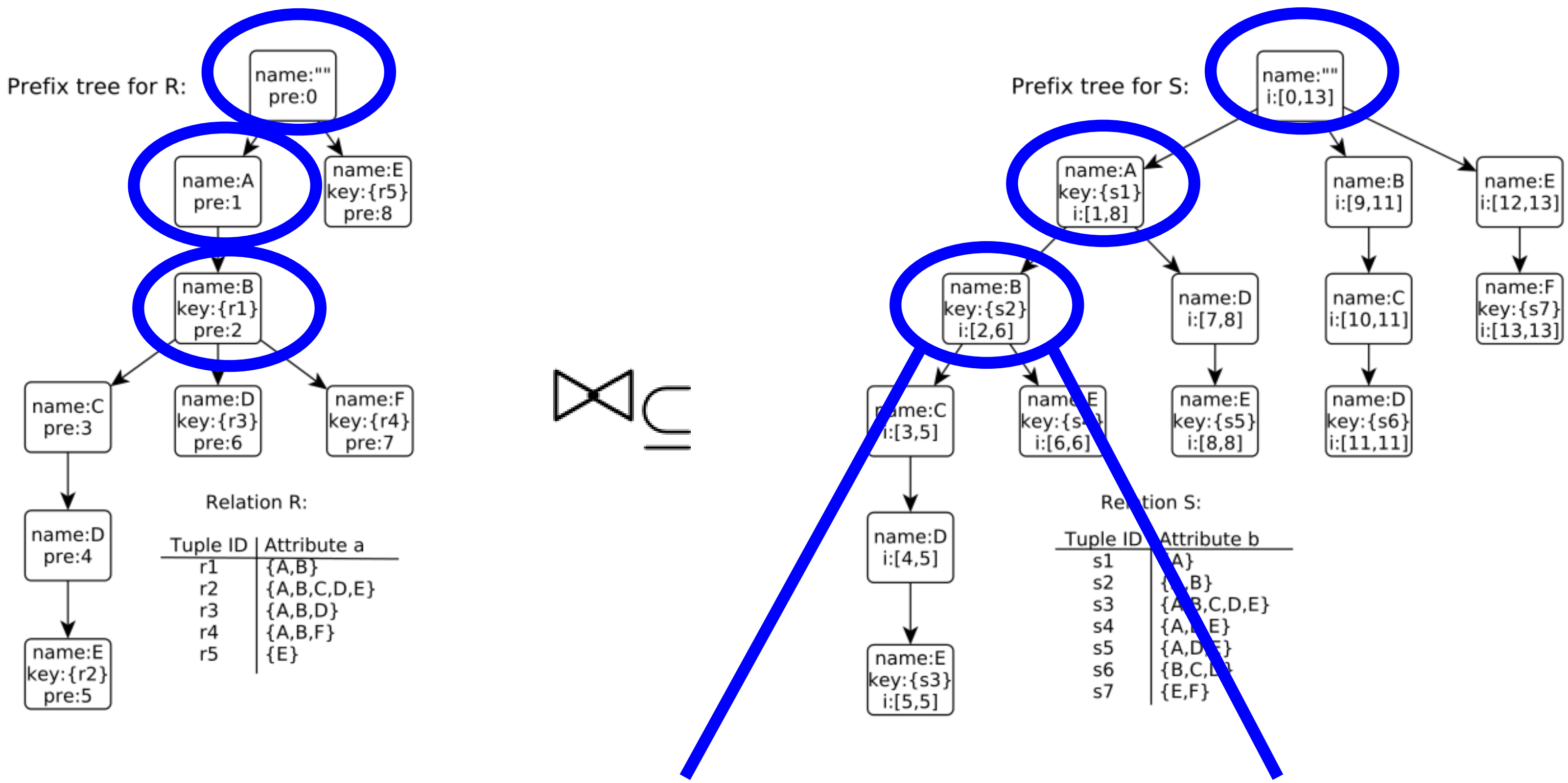
Relation S:

Tuple ID	Attribute b
s1	{A}
s2	{A,B}
s3	{A,B,C,D,E}
s4	{A,B,E}
s5	{A,D,E}
s6	{B,C,D}
s7	{E,F}

Problem P1: When Match Found: Quickly Find all Keys in Subtree



Relation R:

Tuple ID	Attribute a
r1	{A,B}
r2	{A,B,C,D,E}
r3	{A,B,D}
r4	{A,B,F}
r5	{E}

Relation S:

Tuple ID	Attribute b
s1	{A}
s2	{A,B}
s3	{A,B,C,D,E}
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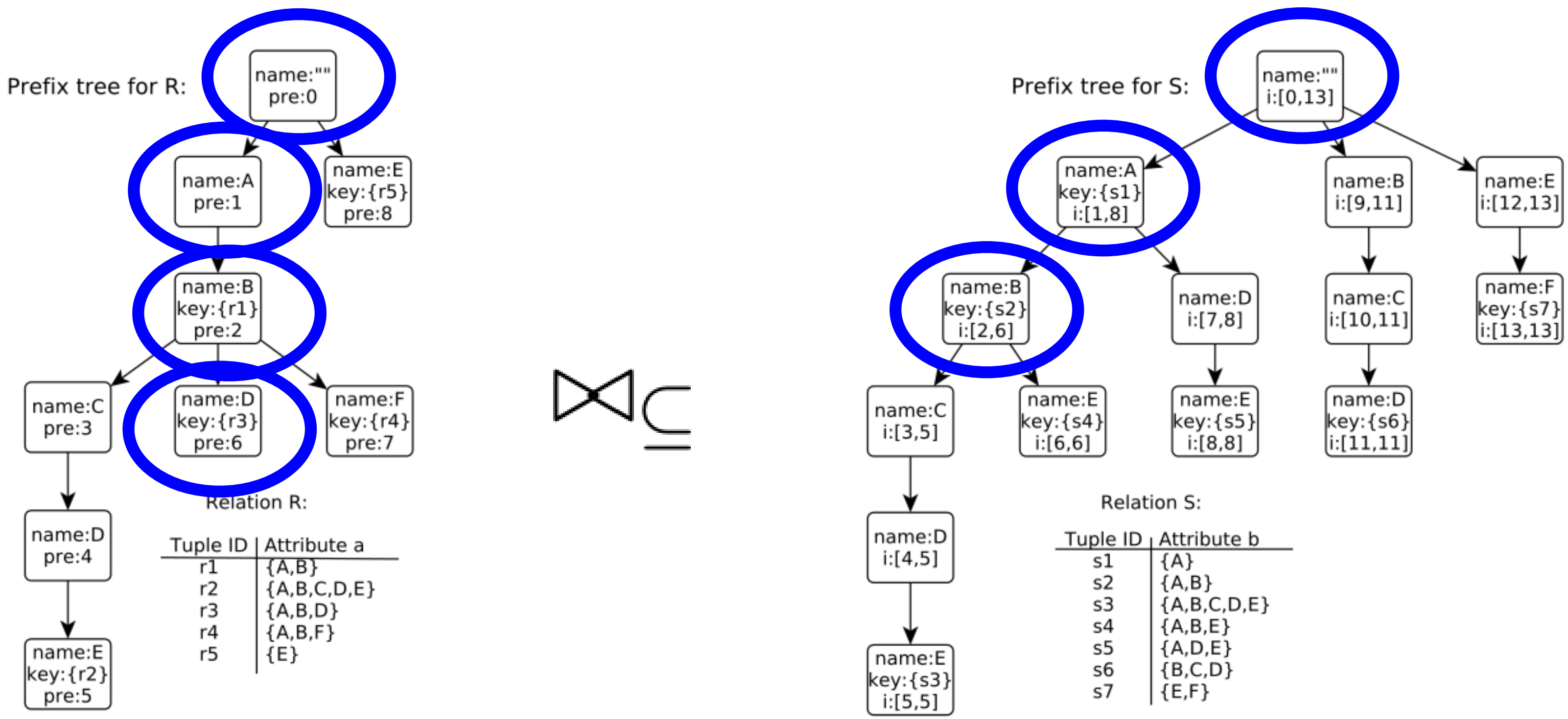
s5	{A,D,E}
s6	{B,C,D}
s7	{E,F}

Traverse …



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Relation S:

Tuple ID	Attribute b
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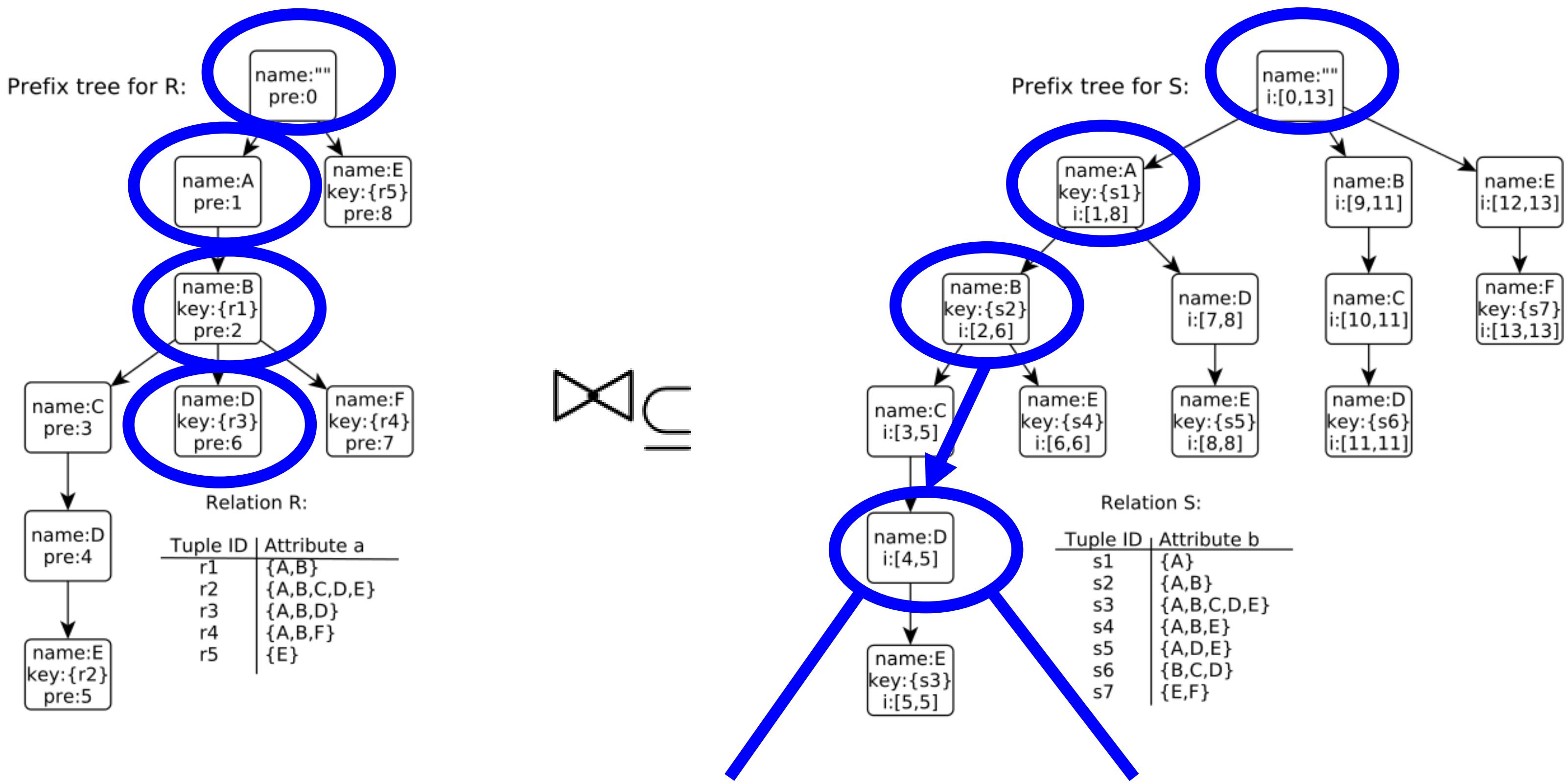
Problem P2: Find all „D"'s in Subtree below {A,B}



Relation R:

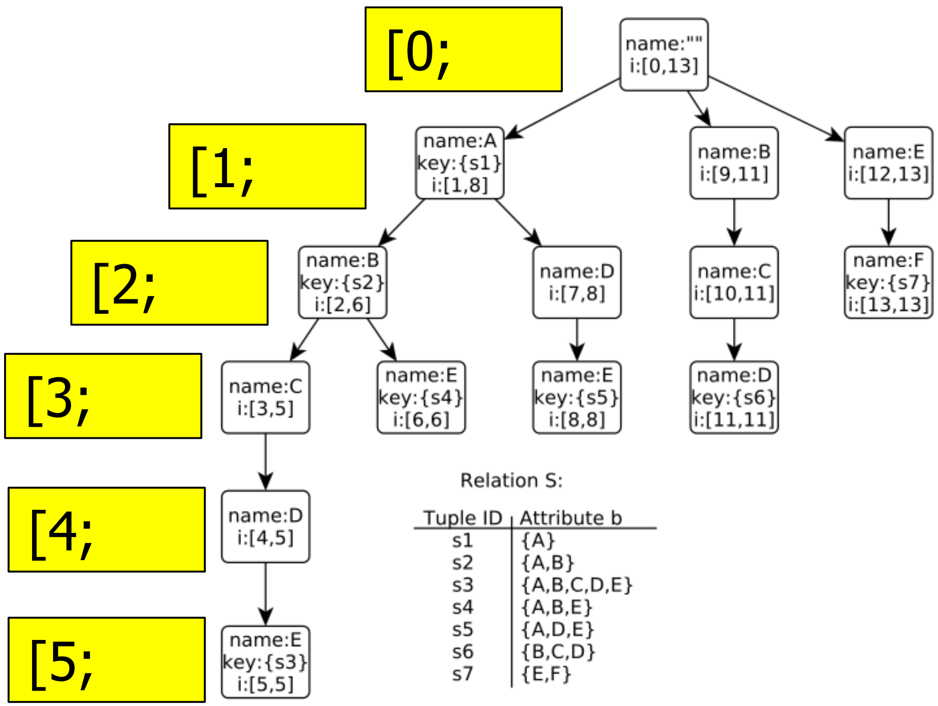
Tuple ID	Attribute a
r1	{A,B}
r2	{A,B,C,D,E}
r3	{A,B,D}
r4	{A,B,F}
r5	{E}

Relation S:

Tuple ID	Attribute b
s1	{A}
s2	{A,B}
s3	{A,B,C,D,E}
s4	{A,B,E}
s5	{A,D,E}
s6	{B,C,D}
s7	{E,F}

PIEJoin: Jump the Queue

Use preorder indexing of PT(S) to solve both problems (with a few lookups)



Relation S:

Tuple ID	Attribute b
s1	{A}
s2	{A,B}
s3	{A,B,C,D,E}
s4	{A,B,E}
s5	{A,D,E}
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s7	{E,F}

PIEJoin: Jump the Queue

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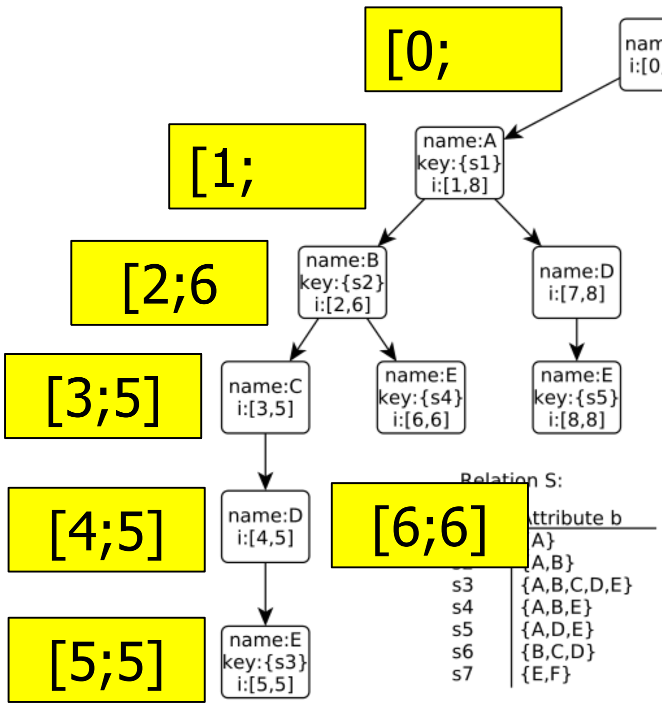
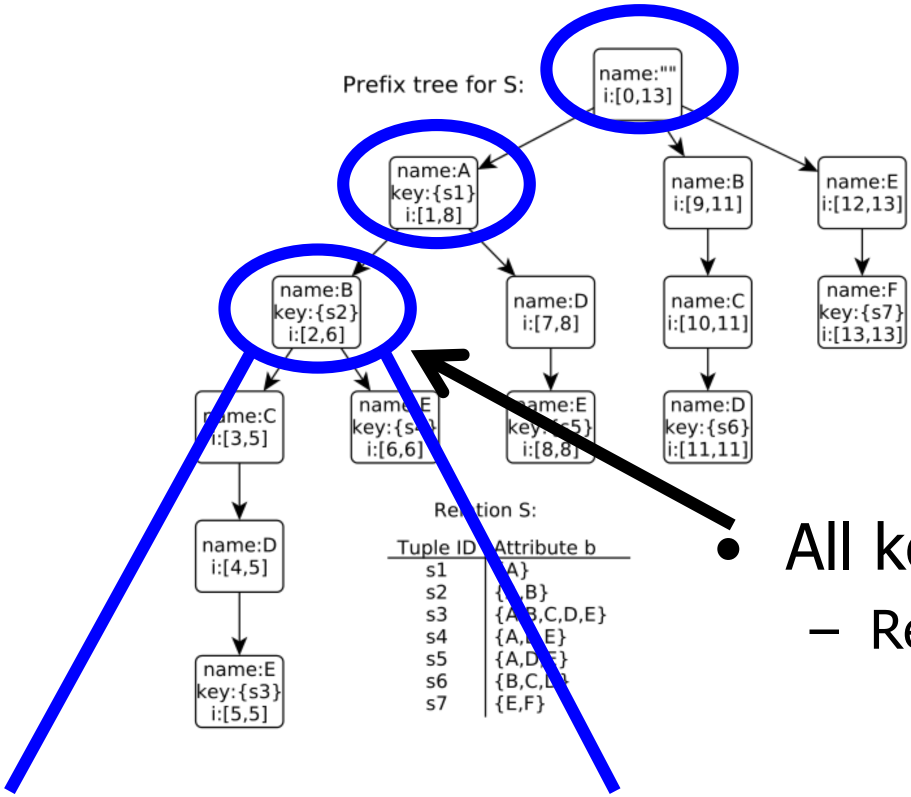


- All nodes p below a node n: p.pre>n.pre and p.post≤n.post
  - Build two lists sorted by pre/post
  - Finding all p: 2*log(|R|)+list intersection

P1: Find all Keys in Subtree

Use Preorder indexing to solve both problems
(with a few lookups)

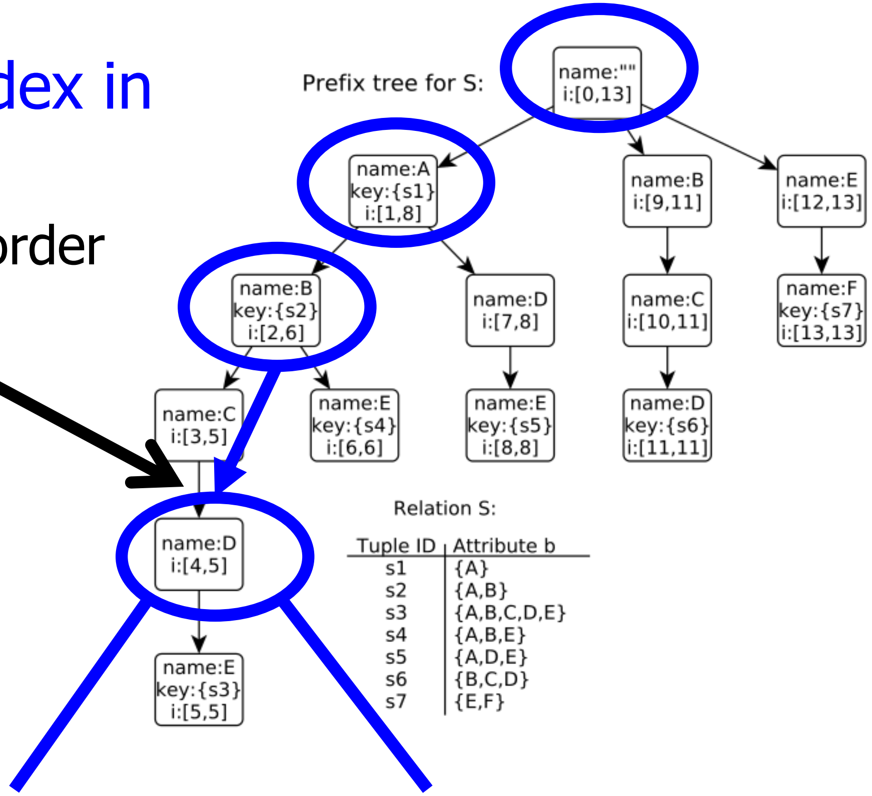


- All keys with preorder index in [2,6]
  - Requires index preorder -> keys

P2: Find All Occurrence of Search Key

Use Preorder indexing to solve both problems
(with a few lookups)

- All nodes with preorder index in [2,6] and label "D"
  - Requires index label -> preorder



Relation S:

Tuple ID	Attribute b
s1	{A}
s2	{A,B}
s3	{A,B,C,D,E}
s4	{A,B,E}
s5	{A,D,E}
s6	{B,C,D}
s7	{E,F}

Trees can be very Space-Consuming

- Efficient implementation
  - Open source
- All based on arrays and integers, no pointers or objects
- See paper

Evaluation

- Comp.: PRETTI [JP05], PRETTI+ [FLH+15], LIMIT+ [BMGT16]
- On-the-fly indexing in main memory
  - All included in measurements
- PRETTI+
  - Use Patricia tree instead of prefix tree (more compact)
- LIMIT+
  - Do not build prefix tree first, but progressively while traversing
    - Large parts of the tree need not be build at all
  - When intermediate lists become very small, stop traversing and directly verify remaining candidates
  - Partition data sets in a clever way to create independent problems leading to shorter ID lists as intermediate results

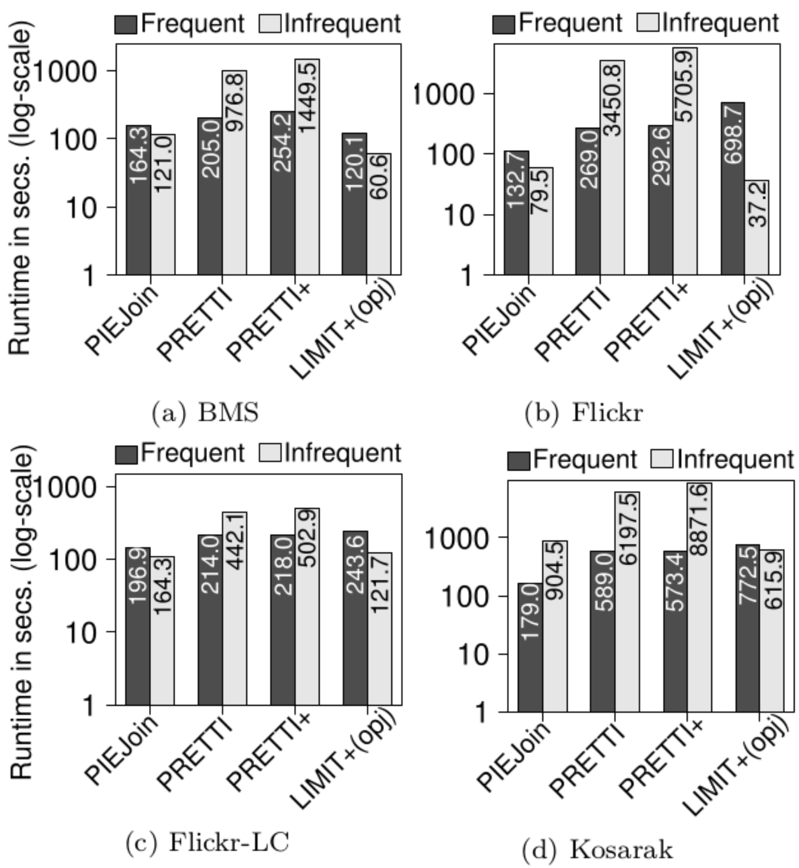
Evaluation

- Eight real-world data sets; non-self-joins in paper
- Some data sets properties
  - Number of sets
  - Number unique elements
    - Fan-Out of prefix trees
  - Average size of sets
    - Depth of prefix trees
  - Skewness of element frequencies
    - Real-world data sets are skewed!
- Parameter: Sort-order (frequent first, infrequent first)
  - Frequent first: Large intermediate sets, quickly shrinking

Data set	Domain size	No. of tuples	Max. set size	Avg. set size	Join cardinality	Size in MB
BMS	1,657	515,597	164	6.53	$3.2 * 10^9$	11.2
Flickr	810,660	1,680,490	102	9.78	$1.6 * 10^9$	79.6
Flickr-LC	618,971	3,546,729	1,230	5.36	$6.3 * 10^9$	132.9
Kosarak	41,270	990,002	2,497	8.10	$5.5 * 10^{10}$	31.6
Netflix	17,770	480,189	17,653	209.25	$1.6 * 10^8$	426.4
Orkut	15,293,693	1,853,285	2,958	57.16	$1.9 * 10^6$	881.7
Twitter	1,318	371,586	687	65.96	$1.2 * 10^8$	82.3
Webbase	15,146,263	168,707	3,842	463.64	$2.3 * 10^7$	709.6

Results

- PIEJoin outperforms PRETTI / PRETTI+ in 7/8 data sets
- LIMIT+ outperforms PIEJoin in 11/16 data sets
- Contradicting [FLH+15], our results indicate that PRETTI is faster than PRETTI+

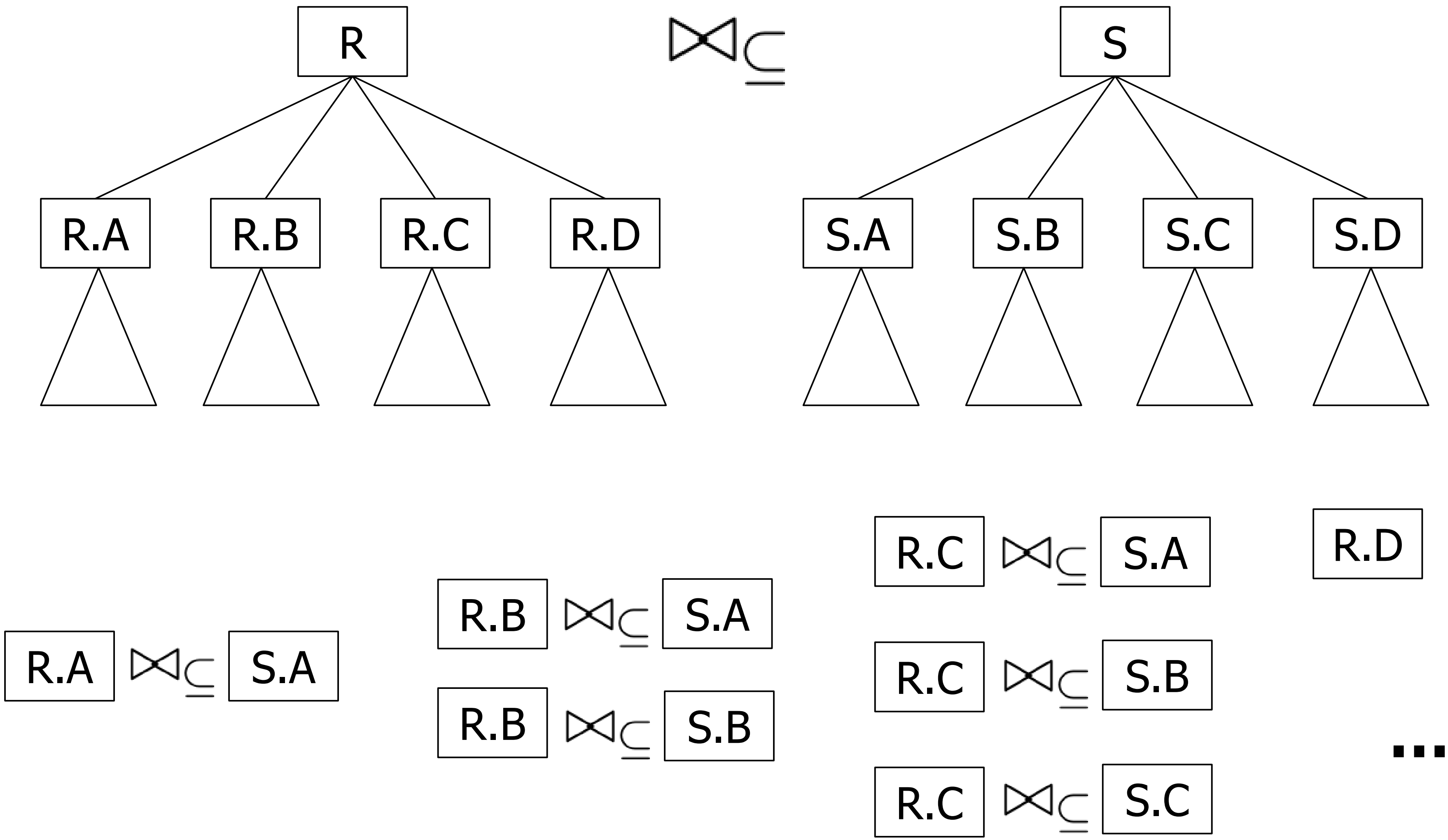


Intermediate Result

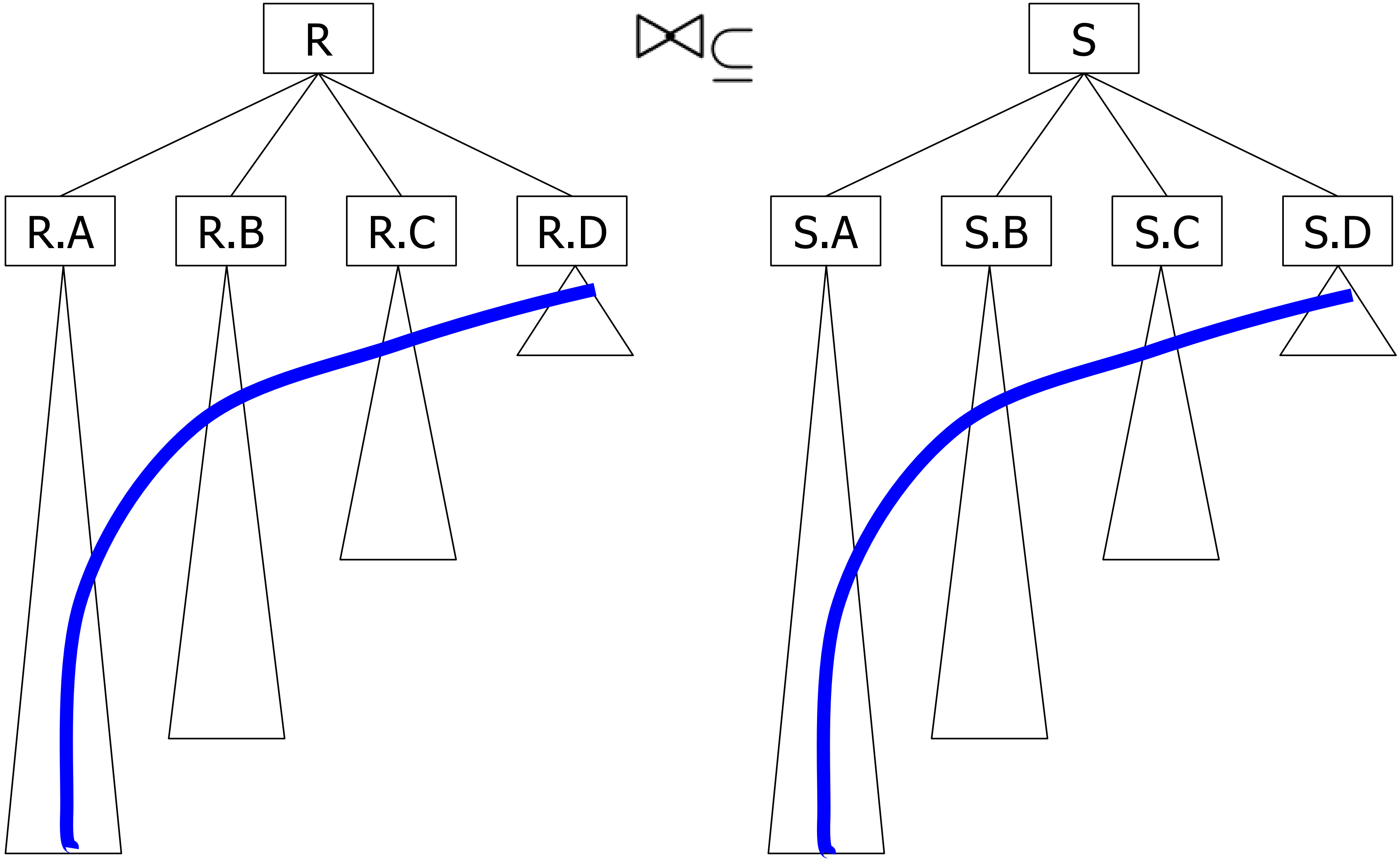
- PRETTI / PRETTI+ very sensitive to sort order
  - Because only one prefix tree is used
- LIMIT+ is the overall fastest method
  - But no orders-of-magnitude differences to PIEJoin
- LIMIT+ also fastest in RxS: 5x PIEJoin, 50x PRETTI
- PIEJoin has lowest memory footprint (factors 2-20)

- Natural next step: Partitioning and parallelization

Partitioning SCJ on Prefix Trees

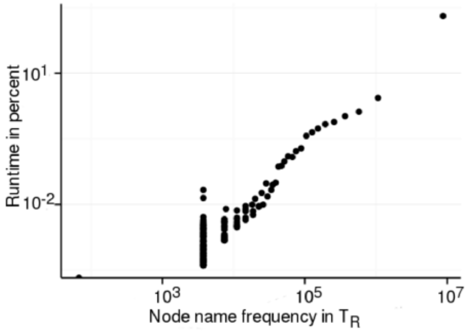


Mind the Data: Partitioning SCJ on Prefix Trees

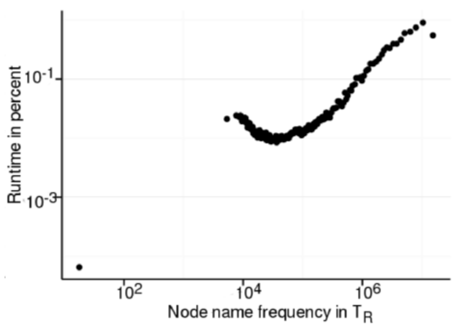


Parallelization Issues

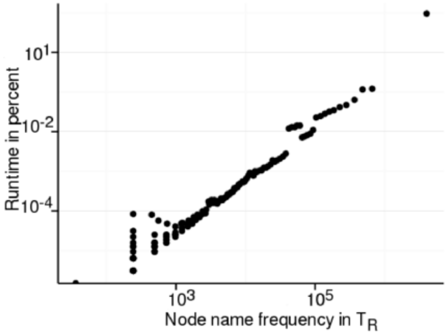
- Different sub-trees have largely different sizes
  - Different sub-tree-joins need largely different run times
  - Stragglers – bad scalability
- Concrete behavior depends on frequencies of sub sets
  - Fortunately, element frequency does roughly correlate to work load



(a) Flickr



(c) Netflix



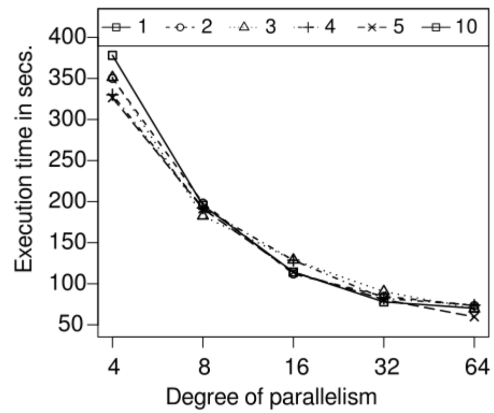
(b) Kosarack

Best we Have so Far

- As always: More partitions create better load balancing yet more overhead
  - E.g. synchronization of result list
  - Parameter rf: Create rf*DOP work groups
    - DOP: Number of available (hardware) threads
- Observation: For large alphabets (>1000), partitioning at level 1 already creates dozens of millions of tasks
  - Too much overhead
- Solution: Sub-tree-joins are adaptively range-partitioned into work groups at level 1 or level 2
  - Most work is done at upper levels – very large list intersections
  - Greedy partitioning – find range with ~1/rf*DOP fraction of work

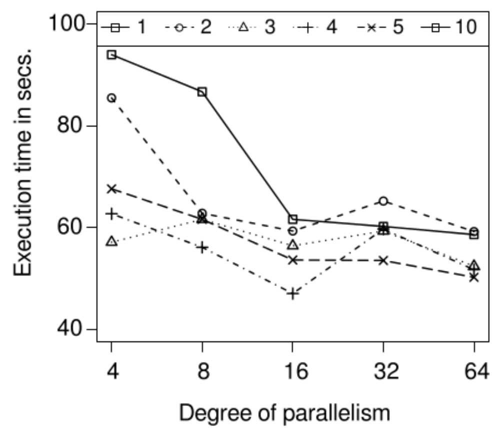
Evaluation

- Sometimes wonderful

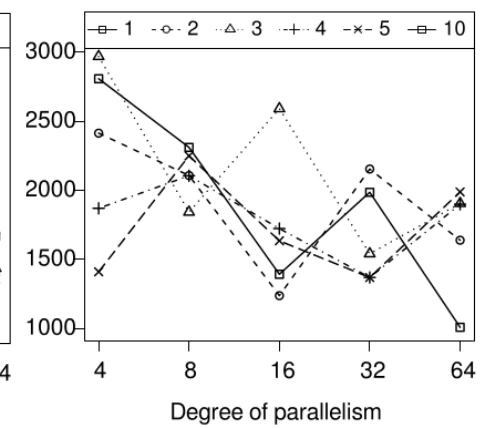


(c) Netflix

- Often ugly



(a) BMS

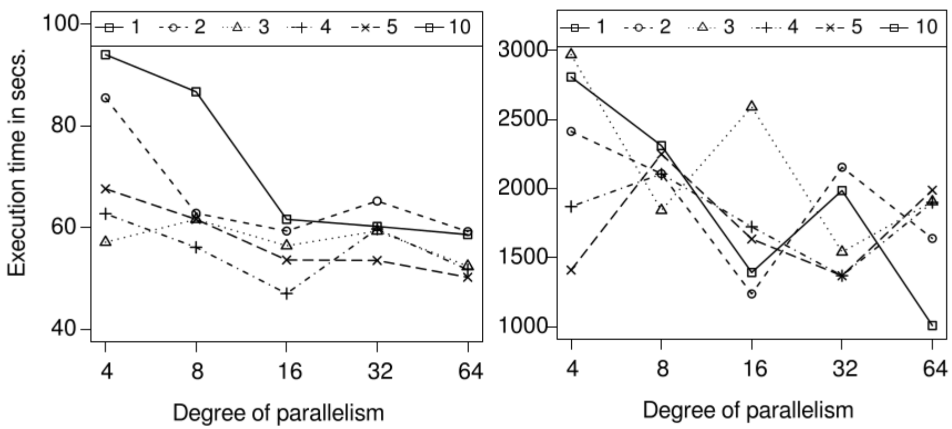


(b) Kosarak

Reasons

- Greedy is not optimal
- Element frequency is not a perfect predictor of work
- Work loads are very heterogeneous
- …

- Often ugly



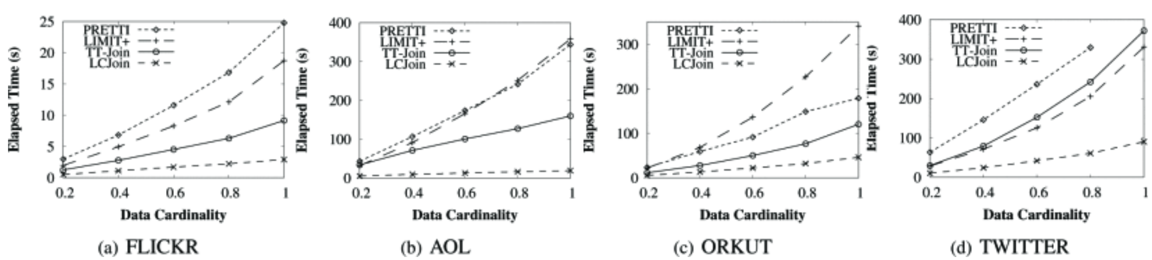
(a) BMS (b) Kosarak

Conclusions

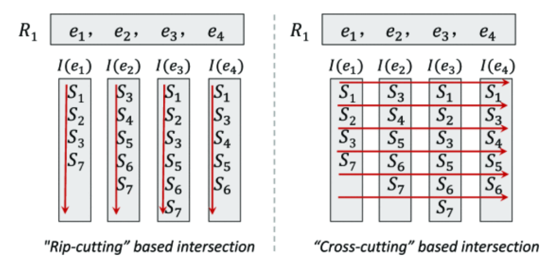
- Set containment join: Operation with many applications
- Parallel PIEJoin: By far the fastest SCJ algorithm so far
  - Efficient basic design + parallelization
  - With 64 threads: Speedup of 30% to 550% compared to LIMIT+
- Further ideas
  - Adaptive, scalable parallelization strategies
    - No fixed "level 2"
    - Better estimation of work
    - Partition the sets, not the items?
  - Given data set characteristics – determine optimal combination of sort-order and algorithm
- Related problem: Set join, Set similarity join

Since 2016

- Tt-Join (2017)
  - Strong set filtering followed by tree-based verification
  - Parallelization based on Map-Reduce paradigm
- LC-Join (2019)
  - Different method to intersect ID lists



(a) FLICKR (b) AOL (c) ORKUT (d) TWITTER



- FreshJoin (2019): Hash-based indexing and filtering

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