Efficient Rank Join with Aggregation Constraints

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Outline

- Introduction
- Aggregation Constraints
- Deterministic Optimization
- Probabilistic Optimization
- Empirical Results

Top-k Query Processing

- Top-k query [Ilyas et al., CSUR'11]
  - Information retrieval, recommender system and etc.
  - Extremely fruitful area with lots of interesting work
- Rank join [Ilyas et al., VLDB'03, Natsev et al., VLDB'01]
  - Well studied top-k operator in the DB community with many applications
    - Multi-criteria selection
    - Information retrieval
    - Data mining

Rank Join Operator

- Rank join
  - Extremely useful for building preferred packages of items
  - **Travel Planning**: a package of one museum & one restaurant

Museum

Location	Rating
a	5
a	5
b	4.5
a	4.5
b	3.5

$$\bowtie_{Museum.Location = Restaurant.Location}$$

Order By

$Museum.Rating + Restaurant.Rating$

Keep top-k

Restaurant

Location	Rating
c	4.5
b	4.5
b	4.5
a	3
a	3

Limitation of Rank Join Operator

- Aggregation constraints
  - Constraints on **attribute values of each join result**
  - Extremely common for applications such as travel packages, course recommendations and etc.

Museum

Location	Cost	Rating
a	13.5	5
a	15	5
b	10	4.5
a	15	4.5
b	5	3.5

$\bowtie$

$Museum.Location = Restaurant.Location$

Order By

$Museum.Rating + Restaurant.Rating$

Keep top-k

Restaurant

Location	Cost	Rating
c	50	4.5
b	20	4.5
b	10	4.5
a	5	3
a	10	3

Constrained by

$Museum.Cost + Restaurant.Cost \leq 50$

Review of Existing Rank Join Algorithms

- Existing algorithms [Ilyas et al., VLDB'03] [Schnaitter and Polyzotis, PODS'08]
  - ***Settings***: Tuples in each table pre-sorted based on the score attribute(s)
  - Threshold-based algorithm
    - Accessing tuples iteratively from each table
    - Determine a upper bound after a new tuple is accessed
    - Stop if the current top-k results of accessed tuples are better than the upperbound
- Cruxes of the rank join algorithms
  - ***Item accessing strategy*** (Round Robin/Adaptive)
  - ***Bounding schemes*** (Corner Bound/FR(*) Bound)
  - Significantly affect the performance of the underlying rank join algorithms

Review Existing Rank Join Algorithms

- Performance of rank join algorithm
  - Number of items accessed
  - In memory computation cost
- Rank join algorithms with FR(*) bounding scheme is **Instance Optimal** [Schnaitter and Polyzotis, PODS'08]
  - Within a broad class of algorithms, the # of items accessed is always bounded by a constant factor compared with other algorithm
- Instance optimality alone doesn't guarantee ***good overall performance!*** [Finger and Polyzotis, SIGMOD'09]
  - In memory computational cost may dominate the cost

Leveraging Existing Rank Join Algorithms

- How to support aggregation constraints?
  - A naive solution: post-filtering
  - Threshold-based algorithm
    - Accessing tuples iteratively from each table
    - Determine a upper bound after a new tuple is accessed
    - Stop if seen top-k results of accessed tuples, **which satisfies all aggregation constraints**, are better than the upper bound
- How good is this naive algorithm?
  - **Instance Optimal !** (Proof in the paper)
  - **Yet bad empirical performance**
    - In memory processing cost is high

Optimization Opportunity (i)

Museum

	Location	Cost	Rating
t_1:	a	13.5	5
t_2:	a	15	5
t_3:	b	10	4.5
t_4:	a	15	4.5
t_5:	b	5	3.5

Restaurant

	Location	Cost	Rating
t_6:	c	50	4.5
t_7:	b	20	4.5
t_8:	b	10	4.5
t_9:	a	5	3
t_{10}:	a	10	3

Constraint

$SUM(Cost) \leq 20$

Top-2 results

$\{ t_3, t_8 \} : 9$

$\{ t_1, t_9 \} : 8$

$Upperbound : 8$

- Number of tuples kept for each relation
  - Museum : 5
  - Restaurant : 4
- Number of ***join probes*** performed (Round Robin)
  - 20

Optimization Opportunity (ii)

- Deterministic optimization

Museum

	Location	Cost	Rating
t_1:	a	13.5	5
t_2:	a	15	5
t_3:	b	10	4.5
t_4:	a	15	4.5
t_5:	b	5	3.5

Restaurant

	Location	Cost	Rating
t_6:	c	50	4.5
t_7:	b	20	4.5
t_8:	b	10	4.5
t_9:	a	5	3
t_{10}:	a	10	3

Constraint

$$SUM(Cost) \leq 20$$

Top-2 results

Deterministic tuple pruning can save many unnecessary join probes during the query processing

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- Aggregation Constraints
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- Probabilistic Optimization
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Aggregation Constraints

- Aggregation constraint definition
  - Let A be an attribute, λ be a constant value, θ be a comparison operator and AGG be an aggregation function {MIN,MAX,SUM}
  - Primitive aggregation constraint (PAC)

$$pac ::= AGG(A)\ \theta\ \lambda$$

  - Aggregation constraint (AC)

$$ac ::= pac \mid pac \wedge ac$$

Museum

	Location	Cost	Rating
t_1:	a	13.5	5
t_2:	a	15	5
t_3:	b	10	4.5
t_4:	a	15	4.5
t_5:	b	5	3.5

Restaurant

	Location	Cost	Rating
t_6:	c	50	4.5
t_7:	b	20	4.5
t_8:	b	10	4.5
t_9:	a	5	3
t_{10}:	a	10	3

Constraint

$SUM(Cost) \leq 20$

Top-2 results

$\{ t_3, t_8 \}$

$\{ t_1, t_9 \}$

Problem Definition

- **Rank Join with Aggregation Constraints**
  - Given a set of relations **R**, a join condition **jc**, a monotonic score function **S** and an aggregation constraint **ac**
  - Find top-k join results which satisfy **ac**

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Deterministic Optimization (i)

- Basic properties of aggregation constraints
  - When AGG is MIN and θ is ≥, the corresponding PAC can leverage on **direct-pruning**.
    - If a tuple **t** doesn't satisfies the PAC, **t** can be directly pruned

Example (i)

Museum

	Location	Cost	Rating
t_1:	a	13.5	5
t_2:	a	15	5
t_3:	b	10	4.5
t_4:	a	15	4.5
t_5:	b	5	3.5

Restaurant

	Location	Cost	Rating
t_6:	c	50	4.5
t_7:	b	20	4.5
t_8:	b	10	4.5
t_9:	a	5	3
t_{10}:	a	10	3

Constraint

$$MIN(Rating) \geq 4$$

Top-2 results

Deterministic Optimization (i)

- Basic properties of aggregation constraints
  - When AGG is MAX and θ is ≥, the corresponding PAC is **monotone**.
    - If a tuple **t** satisfies the PAC, join results of **t** with any tuple also satisfy the PAC
  - When AGG is SUM and θ is ≤, the corresponding PAC is **anti-monotone**.
    - If a tuple **t** doesn't satisfy the PAC, join results of **t** with any tuple also don't satisfy the PAC

Deterministic Optimization (i)

- Basic properties of aggregation constraints

AGG\θ	≤	≥	=
MIN	monotone	direct-pruning	monotone after pruning
MAX	direct-pruning	monotone	monotone after pruning
SUM	anti-monotone	monotone	c-anti-monotone

Pruning based on investigating each individual tuple

Deterministic Optimization (ii)

- Subsumption-based Pruning (Motivation)

Museum

	Location	Cost	Rating
t_1:	a	13.5	5
t_2:	a	15	5
t_3:	b	10	4.5
t_4:	a	15	4.5
t_5:	b	5	3.5

Restaurant

	Location	Cost	Rating
t_6:	c	50	4.5
t_7:	b	20	4.5
t_8:	b	10	4.5
t_9:	a	5	3
t_{10}:	a	10	3

Constraint

$$SUM(Cost) \leq 20$$

Top-2 results

Pruning based on comparing tuples

Deterministic Optimization (ii)

- **pac-Dominance Relationship**
  - Comparing two tuples w.r.t. a single PAC
  - Given two tuples t, t' from the same relation **R**
  - t pac-dominates t' (or t $\succcurlyeq_{pac}$ t'), if
    - for any tuple t'' which can join with t' without violating pac
    - **t'' can also join with t without violating pac**
- For the common scenario where we have one aggregation constraint per attribute
  - **Sufficient** and **necessary** conditions for determining pac-dominance relationship of each possible aggregation constraint

Deterministic Optimization (ii)

- Example
  - Consider AGG is SUM, and θ is ≥, t $\succcurlyeq_{pac}$ t' iff.
    - t, t' has the same join attribute value
    - Either
      - t satisfies the PAC
      - Or t.A ≥ t'.A
- Similar conditions can be derived for other aggregation constraints (details in the paper)

Quasi-order:
reflexive, transitive
~~anti-symmetric~~

	Location	# of Review	Rating
t_1:	a	15	5
t_2:	a	9	5
t_3:	a	8	4.5
t_4:	a	8	4.5
t_5:	a	5	3.5

# of Review ≥ 10

Top-1

Deterministic Optimization (ii)

- **Tuple Subsumption**
  - Let $ac = pac_1 \land \ldots \land pac_m$ be the aggregation constraint
  - t subsumes t' (or $t \succcurlyeq t'$) if
    - score of t is larger than or equal to t'
    - for all pac in ac
      - $t \succcurlyeq_{pac} t'$

Deterministic Optimization (ii)

- **Theorem 1:**
  - A tuple t from relation R can be directly dropped iff. t is subsumed by at least k other tuples in R
- *Small improvement*: after we have found k' join result which are guaranteed to be the top-k' results (k' < k)
  - A tuple t from relation R can be directly dropped iff. t is subsumed by at least **k - k'** other tuples in R
  - Adaptive subsumption based pruning

Optimized Algorithm for Rank Join with Aggregation Constraints

- Procedure kRJAC
  1. Access new items from each relation
  2. **Using the basic property of aggregation constraints to prune tuples which are not promising**
  3. **Use subsumption based pruning to further prune away unpromising tuples**
  4. If a new tuple isn't pruned, join it with accessed tuples from other relations
  5. Update upperbound threshold and check the stopping criteria

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Probabilistic Optimization

- Rank join algorithms with deterministic pruning can save lots of in memory computations
  - Can we further speedup the algorithm?
- Utilize a probabilistic procedure inspired by the previous work on probabilistic top-k algorithms [Theobald et al., VLDB'04]
  - Don't need 100% guarantee that the returned top-k results are actual top-k results
  - Stop the algorithm once we can guarantee the current top-k results are correct with a certain confidence threshold

Probabilistic Optimization

- Let $ac = pac_1 \wedge \ldots \wedge pac_m$ be the aggregation constraint
- Let *jc* be the join condition
- Given a set *s* of tuples, consider the join result of s
  - The probability of it satisfying *jc* can be estimated using existing work in RDBMS [Lipton et al., SIGMOD'90], let it be P_{jc}
  - For common data distributions such as uniform and exponential, the probability of the join result of s satisfying each *pac* can also be estimated (details in the paper), let it be P_{pc}

Probabilistic Optimization

- Assume all PACs and the join condition are mutually independent

$$P_{jc \wedge ac} = P_{jc} \times \prod_{pac \in ac} P_{pc}$$

- Let N be the estimated number of possible join results which are better than the current top-k result [Theobald et al., VLDB'04]
    - based on histogram
- The probability of having a future join result which is better than current top-k result can be estimated as

$$P = 1 - (1 - P_{jc \wedge ac})^N$$

- We stop the algorithm if $P \leq \varepsilon$

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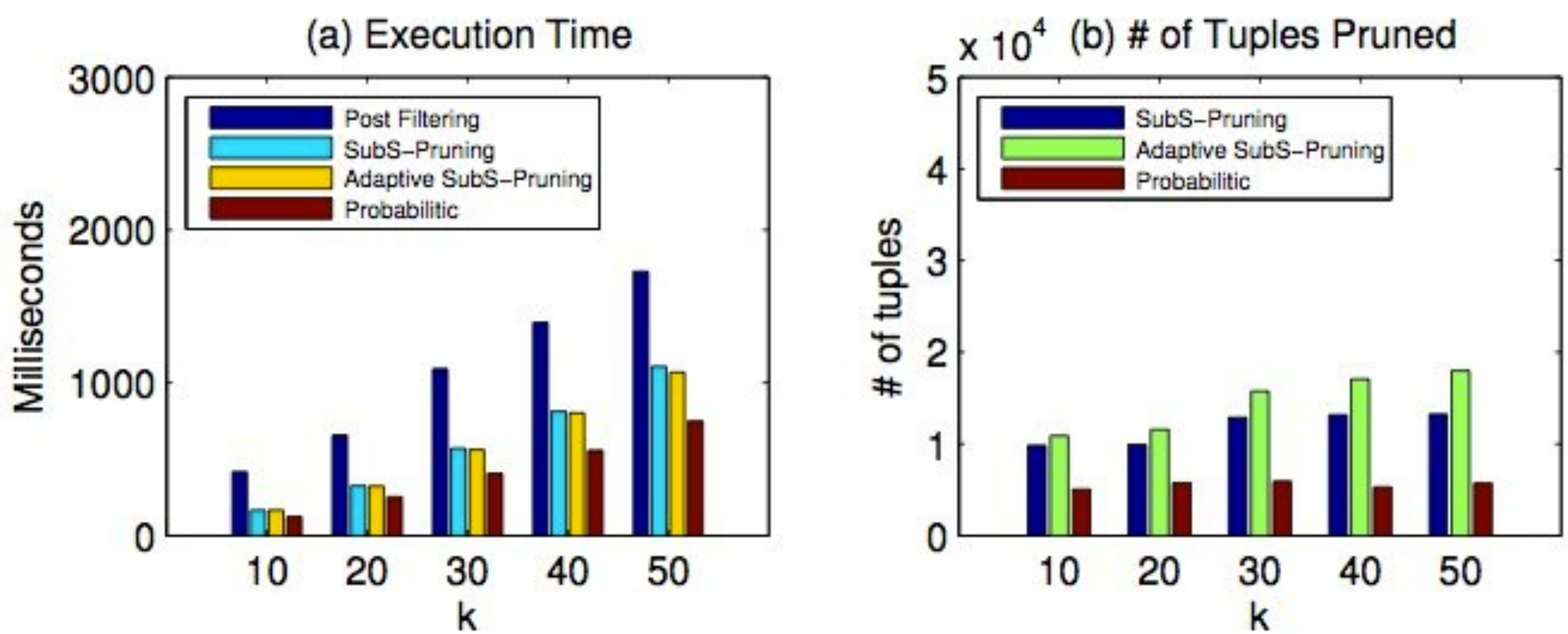
Data Setting

- Consider synthetic two relation datasets
  - For join attribute, the join selectivity fixed at 0.01
  - For other attributes, we consider two settings
    - Uniform attribute value distribution
    - Exponential attribute value distribution
    - Values are normalized to [0,1]

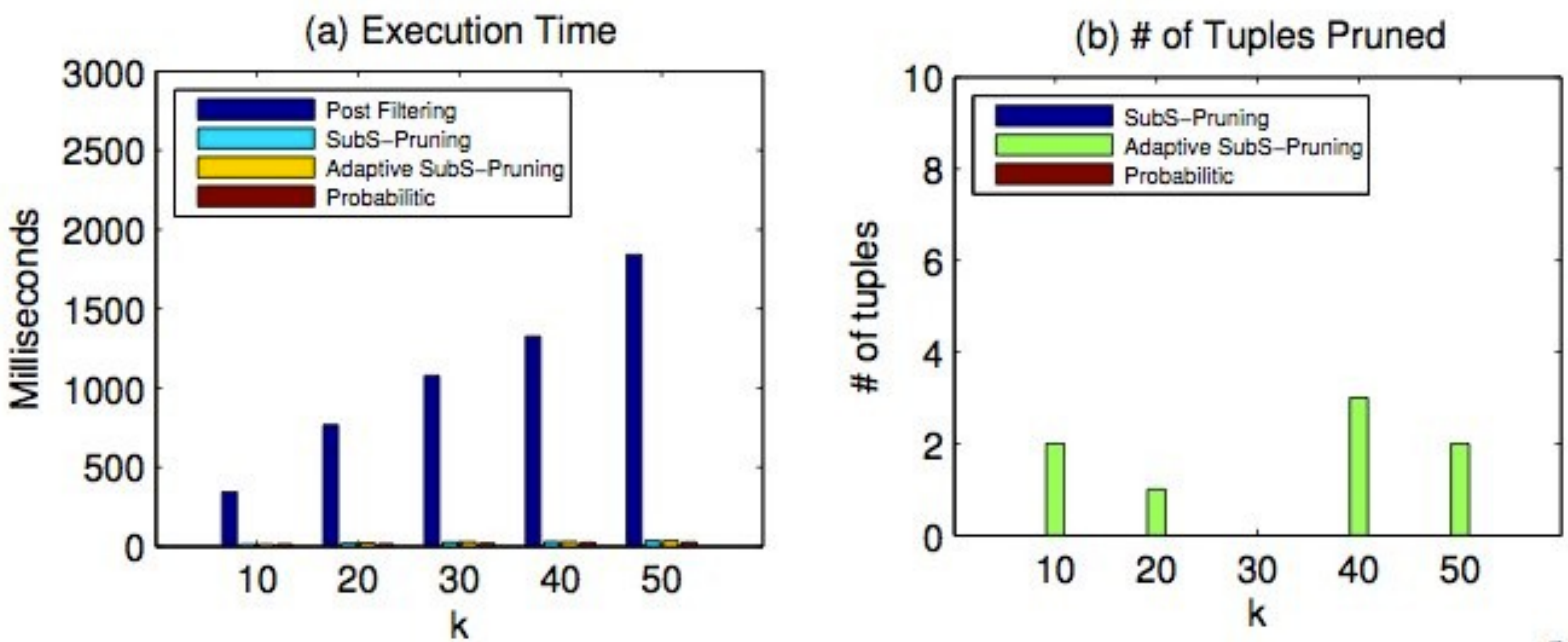
Efficiency Study (Single PAC)

- SUM(A) ≥ λ, selectivity 10^{-5}
  - Subsumption-based pruning



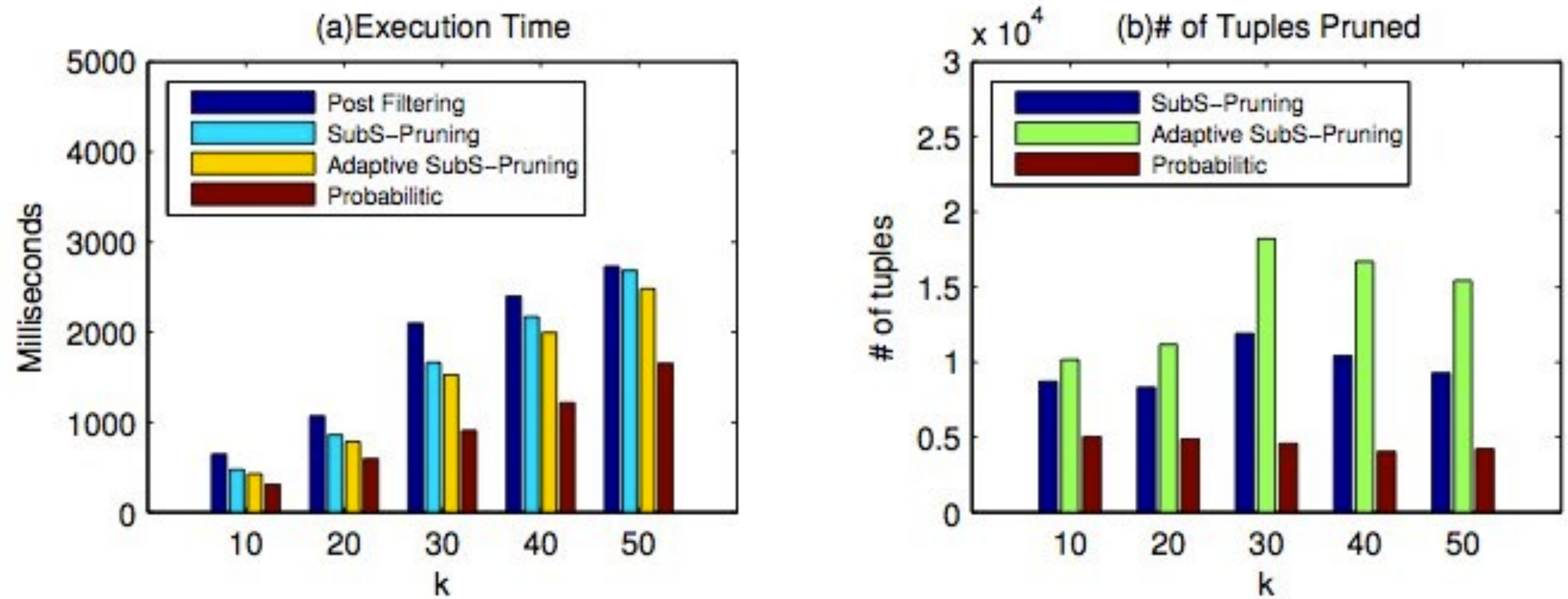
Efficiency Study (Single PAC)

- SUM(A) ≤ λ, selectivity 10^{-5}
  - Anti-monotone & Subsumption-based pruning



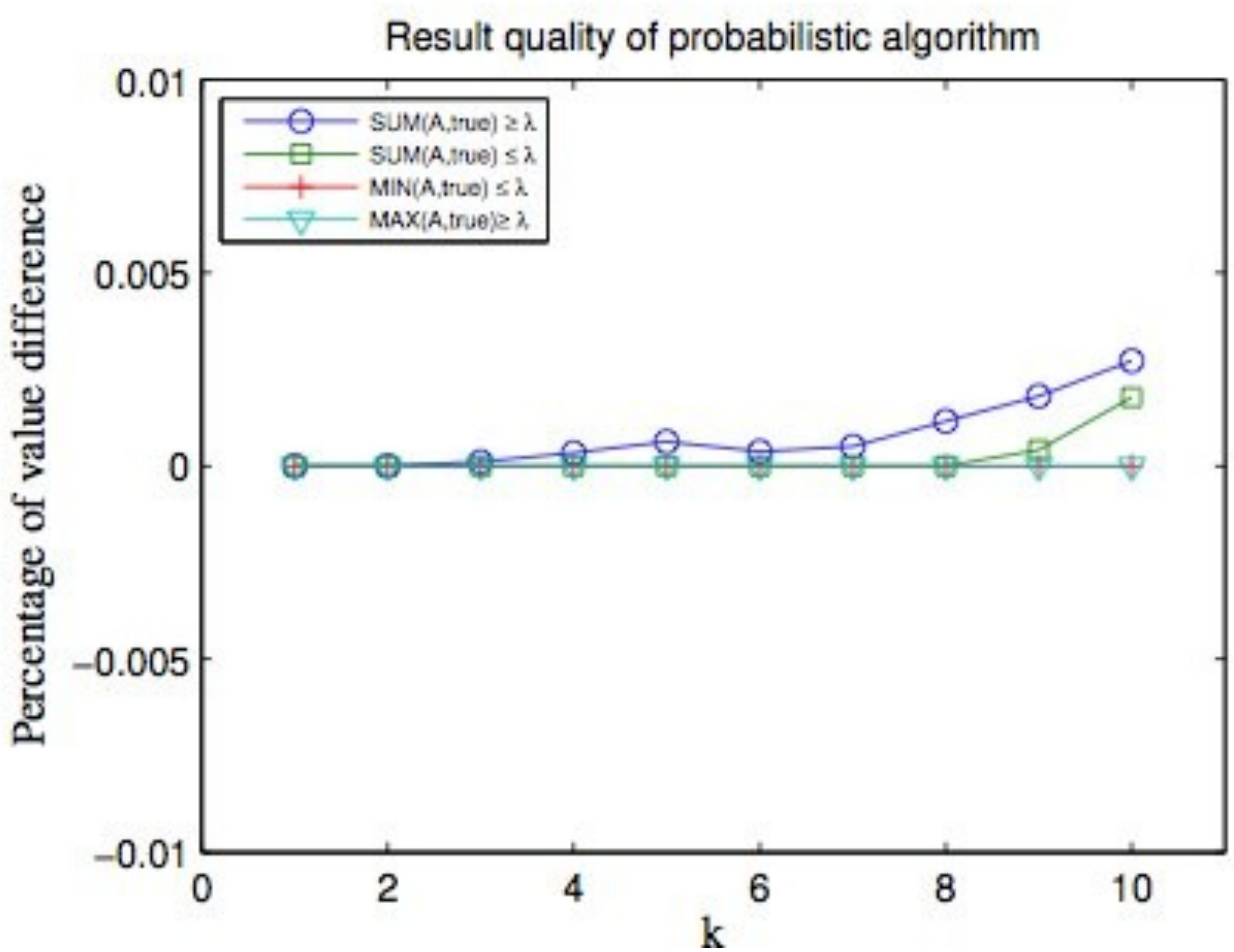
Efficiency Study (Multiple PACs)

- SUM(A) ≥ λ, SUM(B) ≥ λ, overall selectivity 10^{-5}



Quality of Probabilistic Algorithm

- Often much faster than deterministic algorithm
- The value of the top-k result get from the probabilistic algorithm is very close to the exact top-k result



Related Work

- Aggregation constraints
  - Well studied in the database community [Levy et al., VLDB'94][Ng et al., SIGMOD'98][Pei and Han, KDD'00][Ross et al., TCS'98]
  - Allows users to impose application-specific preferences
  - Optimizes the performance of the underlying algorithms

Related Work

- Top-k query processing [Ilyas et al. CSUR'11]
  - Threshold algorithm [Fagin, PODS'01]
- Rank Join
  - Implemented inside RDBMS engines [Ilyas et al., SIGMOD'04, Li et al., SIGMOD'05]
  - Indexing schemes [Tsaparas et al., ICDE'03]
  - Many variations [Martinenghiand and Tagliasacchi, PVLDB'10]

Related Work

- Top-k package recommendation
  - Fixed size package recommendation [Angel et al., EDBT'09]
  - Flexible size package recommendation [Xie et al., RecSys'10] [Parameswaran et al., TOIS'11]
    - The underlying problem is significantly harder
      - Outer join instead of natural/inner join
    - Techniques proposed in this work can still be applied to optimize the performance of the algorithm

Conclusion

- Applications: trip planning and curriculum planning
    - Aggregation constrained top-k query processing
- Naive algorithm works yet high memory computation cost
    - Deterministic optimization: tuple pruning
    - Probabilistic optimization
- Future work
    - Consider flexible size package recommendation under the current framework
    - Broader classes of constraints

Thank you.

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