Finding Top-k Min-Cost Connected Trees in Databases

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IEEE 23rd International Conference on Data Engineering



- Meyword Search in Relational Databases
 - Database Graph, Query, and Answer
 - The Hardness of This Problem
- 2 Our New Parameterized Solutions
 - Finding Top-1 Answer
 - Finding Top-k Answers
- 3 Existing Solutions
 - Other Graph-Based Solutions
- Experimental Studies
 - Some Representative Experimental Result.



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Weighted Database Graph G(V, E, W)

Node set V

• Nodes - tuples in database, |V| = n

Edge set E

 Edges - foreign key references between tuples, |E| = m

Edge Weight *W*

- Edge weight $w_e((v, u)) = \log_2(1 + \max\{d_v, d_u\})$ $(d_x - \text{degree of node } x)$
- The lower, the tighter
- Intuition: the relationship between one node and the others is distributed

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Query and Answer

Query

- I keywords p_1, p_2, \cdots, p_I
- or I subsets $V_1, V_2, \cdots, V_I \subseteq V$ (V_i contains keyword p_i)

Answer

- Connected subtree T in G containing the I keywords
- or Group Steiner tree T, s.t. $V(T) \cap V_i \neq \emptyset$ $(i = 1, \dots, l)$

Objective

- Cost of answer T: $s(T) = \sum_{(u,v) \in E(T)} w_e((u,v))$ (linear combination of node/edge weight)
- Output answers T_1, \dots, T_k , with top-k minimum costs

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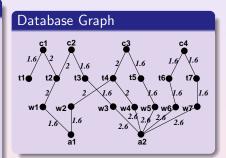
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(Top-k) Minimum Group Steiner Tree Problem

Database

Aut	Author			
AID	N	ame		
a1		Jim		
a2	F	Robin		
Citation				
Cite Cited				
t1 t2				
t3		t2		
t5		t4		

Pap	oer Pap	er–A	utho
PID	Title	PID	AID
t1	Keyword Search on RDBMS	t2	a1
t2	Steiner Problem in DB	t4	a1
t3	Efficient IR-Query over DB	t3	a2
t4	Online Cluster Problems	t4	a2
t5	Keyword Query over Web	t5	a2
t6	Query Optimization on DB	t6	a2
t7	Parameterized Complexity	t7	a2



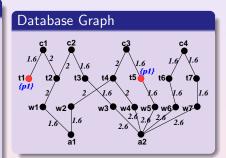
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Database

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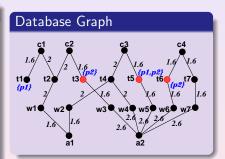
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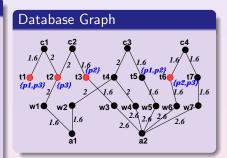
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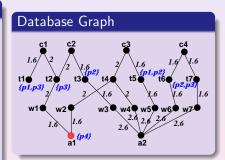


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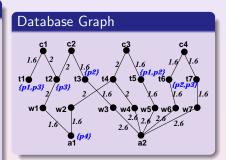


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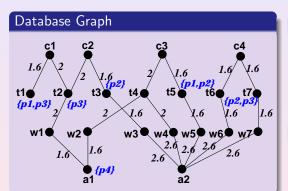
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Query





Node sets containing keywords:

$$V_1 = \{t1, t5\}, V_2 = \{t3, t5, t6\},\$$

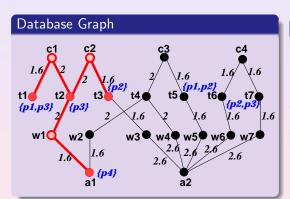
 $V_3 = \{t1, t2, t6\}, \text{ and } V_4 = \{a1\}.$

Answer T

- Jim (a₁) writes a paper, t₂, which is cited by two papers, t₁ and t₃.
- Cost: $s(T_1) = 10.8$

$^{'}$ Answer T_2

- Jim (a₁) writes a
 paper, t₂, which is cited
 by t₃; the author of t₃,
 Robin (a₂), writes
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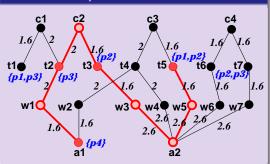
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Hardness Results

The Hardness of (Top-k) Minimum Group Steiner Tree Problem

- NP-Complete
- Harder than Undirected Minimum Steiner Tree Problem
- Equivalent to Directed Minimum Steiner Tree Problem
- ullet NP-Hard to find $(1+\epsilon)$ -approximation for any fixed $\epsilon>0$
- ullet NP-Hard to find $(1-\epsilon)\log I$ -approximation for any fixed $\epsilon>0$

Summary of Our Solution

Two Steps

- Optimal top-1 answer with the minimum cost
- Approximate top-k answers

Parameterized Complexity

- Time complexity: $O(3^l n + 2^l((l + \log n)n + m))$
- Space complexity: $O(2^l n)$
- (For fixed I) Time complexity: $O(n \log n + m)$
- (For fixed I) Space complexity: O(n)
- Efficient because: n (the number of tuples) is large; m (the number of foreign keys) is large; l (the number of keywords) is small



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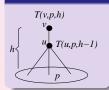
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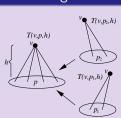
Optimal Substructure $T(v, \mathbf{p}, h)$

Subtree $T(v, \mathbf{p}, h)$: (i) rooted at node $v \in V$; (ii) with height $\leq h$; (iii) containing a set of keywords \mathbf{p} ; (iv) with the minimum cost.

Tree Grow Case



Tree Merge Case



Dynamic Programming Equation

$$\begin{array}{l} \mathsf{Tree} \ \mathsf{Grow} \colon \mathsf{T}_{\mathsf{g}}(v,\mathbf{p},h) = \\ \min_{u \in N(v)} \{(v,u) \oplus \mathcal{T}(u,\mathbf{p},h-1)\} \end{array}$$

$$\begin{array}{l} \text{Tree Merge: } T_m(\nu, \textbf{p}_1 \cup \textbf{p}_2, \textit{h}) = \\ \min_{\textbf{p}_1 \cap \textbf{p}_2 = \emptyset} \{ \textit{T}(\nu, \textbf{p}_1, \textit{h}) \oplus \textit{T}(\nu, \textbf{p}_2, \textit{h}) \} \end{array}$$

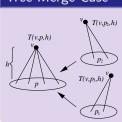
(\oplus : merge two trees into a new tree)

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Tree Grow Case T(v,p,h) V = T(u,p,h-1)

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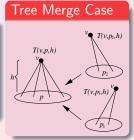
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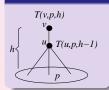
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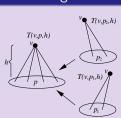
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(\oplus : merge two trees into a new tree)

Dynamic Programming Equation

- $T(v, \mathbf{p}, h) = \min\{T_g(v, \mathbf{p}, h), T_m(v, \mathbf{p}, h), T(v, \mathbf{p}, h-1)\}$
- $T(v, \mathbf{p}, 0) = 0$, for v containing keywords \mathbf{p}

Naive Dynamic Programming Algorithm

- Compute $T(v, \mathbf{p}, h)$ in the ascending order of h
- Optimal top-1 answer: $\min_{v \in V} \{ T(v, \{\mathbf{p}_1, \dots, \mathbf{p}_l\}, n) \}$
- Time complexity: $O(3^l n^2 + 2^l nm)$
- Space complexity: $O(2^l n^2)$

Speedup of Dynamic Programming

Main Idea

- Reduce the search space of dynamic programming
- 2 Speed up the computation of dynamic programming equation

Complexity

- Time complexity: $O(3^l n + 2^l ((l + \log n)n + m))$
- Space complexity: $O(2^l n)$

Origin Dynamic Programming Equation

$$\begin{array}{rcl} \mathcal{T}(v,\mathbf{p},0) &=& 0 \text{ for } v \text{ containing keywords } \mathbf{p}, \\ \mathcal{T}(v,\mathbf{p},h) &=& \min\{\mathsf{T_g}(v,\mathbf{p},h),\mathsf{T_m}(v,\mathbf{p},h),\mathcal{T}(v,\mathbf{p},h-1)\}, \\ \text{where } \mathsf{T_g}(v,\mathbf{p},h) &=& \min_{u\in\mathcal{N}(v)}\{(v,u)\oplus\mathcal{T}(u,\mathbf{p},h-1)\}, \\ \mathsf{T_m}(v,\mathbf{p}_1\cup\mathbf{p}_2,h) &=& \min_{\mathbf{p}_1\cap\mathbf{p}_2=\emptyset}\{\mathcal{T}(v,\mathbf{p}_1,h)\oplus\mathcal{T}(v,\mathbf{p}_2,h)\}. \end{array}$$

Presence of Height h

- Promising the correctness
- Size of the search space: $O(n^22^l)$
- Serving as an order to compute $T(v, \mathbf{p}, h)$



Origin Dynamic Programming Equation

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Simplified Dynamic Programming Equation

```
\begin{array}{rcl} T(v,\mathbf{p},0) & = & 0 \text{ for } v \text{ containing keywords } \mathbf{p}, \\ T(v,\mathbf{p},h) & = & \min\{T_{\mathbf{g}}(v,\mathbf{p},h),T_{\mathbf{m}}(v,\mathbf{p},h),T(v,\mathbf{p},h-1)\}, \\ \text{where } T_{\mathbf{g}}(v,\mathbf{p},h) & = & \min_{u \in \mathcal{N}(v)}\{(v,u) \oplus T(u,\mathbf{p},h-1)\}, \\ T_{\mathbf{m}}(v,\mathbf{p}_1 \cup \mathbf{p}_2,h) & = & \min_{\mathbf{p}_1 \cap \mathbf{p} \geq \emptyset}\{T(v,\mathbf{p}_1,h) \oplus T(v,\mathbf{p}_2,h)\}. \end{array}
```

Absence of Height *h*

- Still promising the correctness
- Size of the search space: $O(n2^{l})$
- Need to find another order to compute $T(v, \mathbf{p})$



Simplified Dynamic Programming Equation

$$\begin{array}{rcl} \mathcal{T}(\boldsymbol{\nu},\boldsymbol{p}) & = & 0 \text{ for } \boldsymbol{\nu} \text{ containing keywords } \boldsymbol{p}, \\ \mathcal{T}(\boldsymbol{\nu},\boldsymbol{p}) & = & \min(\mathsf{T}_{\mathsf{g}}(\boldsymbol{\nu},\boldsymbol{p}),\mathsf{T}_{\mathsf{m}}(\boldsymbol{\nu},\boldsymbol{p})), \\ \text{where } \mathsf{T}_{\mathsf{g}}(\boldsymbol{\nu},\boldsymbol{p}) & = & \min_{\boldsymbol{u}\in\mathcal{N}(\boldsymbol{\nu})}\{(\boldsymbol{\nu},\boldsymbol{u})\oplus\mathcal{T}(\boldsymbol{u},\boldsymbol{p})\}, \\ \mathsf{T}_{\mathsf{m}}(\boldsymbol{\nu},\boldsymbol{p}_1\cup\boldsymbol{p}_2) & = & \min_{\boldsymbol{p}_1\cap\boldsymbol{p}_2=\emptyset}\{\mathcal{T}(\boldsymbol{\nu},\boldsymbol{p}_1)\oplus\mathcal{T}(\boldsymbol{\nu},\boldsymbol{p}_2)\}. \end{array}$$

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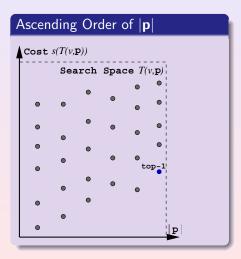
The Order to Compute $T(v, \mathbf{p})$

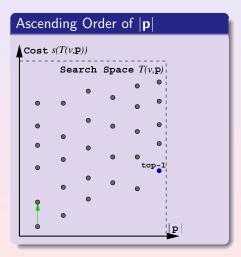
Requirement of the Order to Compute $T(v, \mathbf{p})$

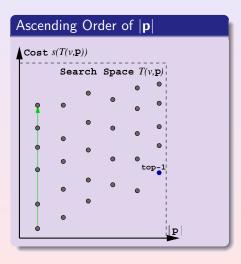
IF $T(v', \mathbf{p}')$ is a subtree of $T(v, \mathbf{p})$, THEN $T(v', \mathbf{p}')$ must be computed earlier than $T(v, \mathbf{p})$.

Two Possible Orders

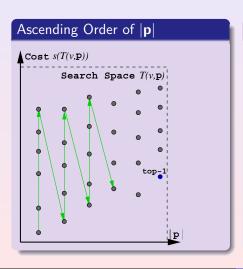
- The ascending order of |p| (size of keywords set p) an unpublished work by Benny Kimelfeld and Yehoshua Sagiv (www.cs.huji.ac.il/~bennyk/papers/steiner06.pdf)
- ② The ascending order of $s(T(v, \mathbf{p}))$ (cost of tree $T(v, \mathbf{p})$) our solution



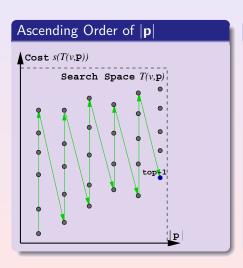




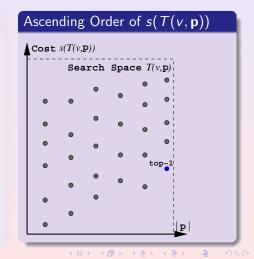
Ascending Order of $s(T(v, \mathbf{p}))$

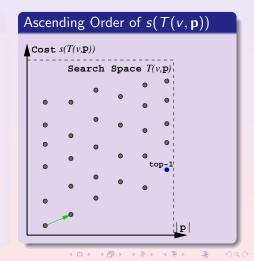


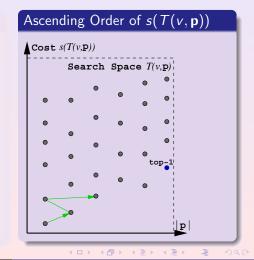
Ascending Order of $s(T(v, \mathbf{p}))$

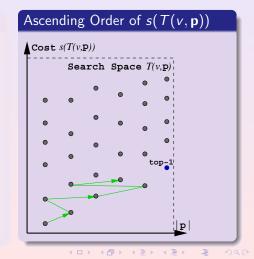


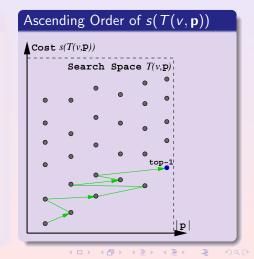
Ascending Order of $s(T(v, \mathbf{p}))$

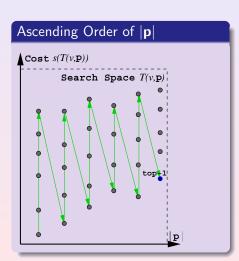


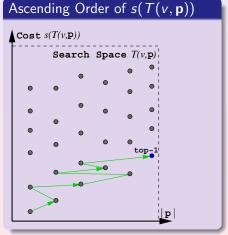












Speedup of Dynamic Programming

Comparing the Two Orders

- In the same search space $\{T(v, \mathbf{p})\}$
- Ascending order of $|\mathbf{p}|$: visiting nearly the whole search space
- Ascending order of $s(T(v, \mathbf{p}))$: following a shortcut to the top-1

Our Second Dynamic Programming Algorithm

- Reduce the search space from $\{T(v, \mathbf{p}, h)\}\$ to $\{T(v, \mathbf{p})\}\$
- Follow the ascending order of $s(T(v, \mathbf{p}))$ to compute the dynamic programming equation of $T(v, \mathbf{p})$
- Visit only the necessary portion of the search space
- Achieve low time / space complexity



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Outline

- Meyword Search in Relational Databases
 - Database Graph, Query, and Answer
 - The Hardness of This Problem
- Our New Parameterized Solutions
 - Finding Top-1 Answer
 - Finding Top-k Answers
- 3 Existing Solutions
 - Other Graph-Based Solutions
- 4 Experimental Studies
 - Some Representative Experimental Results

Finding Top-k Answers

A Progressive Method

- Finding $T(v, \{p_1, \dots, p_l\})$'s with top-k minimum costs as the top-k answers
- Advantage I: time / space complexity unchanges
- Advantage II: no sorting is needed

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Other Graph-Based Solutions

1-Star Tree

- Combining I shortest-paths from leaves (containing keywords) to the roots
- \bullet O(I)-approximation for linear cost functions
- BANKS I: Gaurav Bhalotia, et. al., ICDE 2002
- BANKS II: Varun Kacholia, et. al., VLDB 2005

Spanning and Cleanup

- Spanning a set of trees until some of them cover all the / keywords
- O(I)-approximation for linear cost functions
- RIU-E: Wen-Syan Li, et. al., WWW 2001, TKDE 2002

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Experiment Setup

Implementation

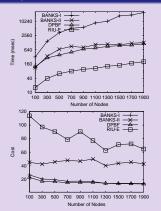
- Compare our solution (DPBF) with: RIU-E, BANKS-I, and BANKS-II
- Implement these algorithms in memory
- Use linear cost function (sum of edge weights)
- Environment: 3.4GHz CPU and 2G memory PC running XP

Datasets - 10 Subsets of DBLP

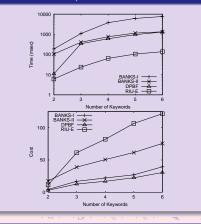
100K (up to 1982), 300K (up to 1987), 500K (up to 1993), 700K (up to 1996), 900K (up to 1997), 1100K (up to 1999), 1300K (up to 2000), 1500K (up to 2001), 1700K (up to 2002), and 1900K (up to 2004)

Some Results

Varying the Size of Database n — 4-Keyword Queries, k = 1



Varying the Number of Keywords I — DBLP 500K, k = 1



Summary

- Model the keyword search problem as the (top-k) minimum group Steiner tree problem.
- Propose a parameterized algorithm for this problem.
 - Bounded time / space complexity
 - ② Efficient in practice
- Support undirected / directed model, node / edge weights, and cost function in the form of linear combination of weights.

Related Work: Other Graph-Based Solutions



BANKS I: Gaurav Bhalotia, et. al.

Keyword Searching and Browsing in Databases using BANKS.

ICDE'02, pages 431-440, 2002.



BANKS II: Varun Kacholia, et. al.

Bidirectional Expansion For Keyword Search on Graph Databases.

VLDB'05, pages 505-516, 2005.



RIU-E: Wen-Syan Li, et. al.

Query Relaxation by Structure and Semantics for Retrieval of Logical Web Documents.

IEEE Trans. Knowl. Data Eng., 14(4):768-791, 2002.



Benny Kimelfeld, et. al.

Finding and Approximating Top-k Answers in Keyword Proximity Search.

PODS'06, pages 173-182, 2006.



Related Work: Database-Based Solutions



Sanjay Agrawal, et. al.

DBXplorer: A System for Keyword-Based Search over Relational Databases

ICDE'02, pages 5-16, 2002.



Vagelis Hristidis, et. al.

Efficient IR-Style Keyword Search over Relational Databases.

VLDB'03, pages 850-861, 2003.



Fang Liu, et. al.

Effective Keyword Search in Relational Databases.

SIGMOD'06, pages 563-574, 2006.



Yi Luo, et. al.

SPARK: Top-k Keyword Query in Relational Databases.

To Appear in SIGMOD'07, 2007.

