Efficient Algorithms for Frequently Asked Questions

6. Worst-Case Optimal Join Algorithms

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What Makes a Join Algorithm Optimal?

Terminology

- Join = FAQ where all variables are free, i.e., no marginalisation
- Conjunctive query (CQ) = FAQ over the Boolean semiring
- Query output = Listing representation of all tuples in the query answer

We can reason about two types of output sizes for a join Φ

- Instance output size: The size of Φ's output for a specific input
- Worst-case output size: The maximum size of Φ 's output for any input

Running time of optimal join algorithms is proportional to

Input size (IN) plus output size (OUT) (Instance Optimality)

• Input size plus worst-case output size (Worst-Case Optimality)

Agenda for this Lecture

- 1. Instance optimality for free-connex acyclic CQs: Yannakakis's algorithm
 - Runtime becomes O(IN*OUT) for arbitrary acyclic CQs
 - · This works for semirings with constant-size elements, e.g., sum-product
- 2. Worst-case optimality for arbitrary joins: LeapFrog TrieJoin algorithm
 - · This only works when all variables are free, so no CQs
 - Instance optimality for cyclic joins not possible (unless P=NP)
- 3. Mainstream join algorithms are suboptimal for cyclic joins
- 4. Efficient processing of CQs with large output size

Next lecture: Deriving worst-case optimal size of join output

using Yannakakis Algorithm

1. Computing Acyclic Conjunctive Queries

$$\Phi() = \bigvee_{(x_1, \dots, x_5) \in \prod_{i \in [5]} \mathsf{Dom}(X_i)} \psi_{12}(x_1, x_2) \wedge \psi_{23}(x_2, x_3) \wedge \psi_{34}(x_3, x_4) \wedge \psi_{15}(x_1, x_5)$$

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A join tree for Φ:

$$\begin{array}{c} \psi_{12}(x_1, x_2) \\ / \\ / \\ \psi_{23}(x_2, x_3) \ \psi_{15}(x_1, x_5) \\ | \\ \psi_{34}(x_3, x_4) \end{array}$$

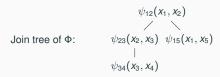
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$$\begin{array}{cccc}
\psi_{12}(x_1, x_2) \\
& \swarrow \\
\psi_{23}(x_2, x_3) & \psi_{15}(x_1, x_5)
\end{array}$$

$$\downarrow \\
\psi_{34}(x_3, x_4)$$

We repeat how Φ can be evaluated efficiently on the next slide.



$$ψ_{12}(x_1, x_2)$$

Join tree of Φ: $ψ_{23}(x_2, x_3) ψ_{15}(x_1, x_5)$
 $ψ_{34}(x_3, x_4)$

 $@\psi_{34}$ Send up its x_3 -values:

$$V_{34\to23}(x_3) = \bigvee_{x_4} \psi_{34}(x_3, x_4)$$

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 $@\psi_{23}$ Send up its x_2 -values that are paired with x_3 common to $V_{34\to23}(x_3)$ and ψ_{23} :

$$V_{23\to12}(x_2) = \bigvee_{x_3} \psi_{23}(x_2, x_3) \wedge V_{34\to23}(x_3)$$

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 $@\psi_{15}$ Send up its x_1 -values:

$$V_{15\to 12}(x_1) = \bigvee_{x_5} \psi_{15}(x_1, x_5)$$

$$ψ_{12}(x_1, x_2)$$

/ \

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 $@\psi_{12}$ Is there a pair (x_1, x_2) of ψ_{12} with x_1 also in $V_{15\rightarrow 12}$ and x_2 also in $V_{23\rightarrow 12}$?

$$\Phi() = \bigvee_{x_1, x_2} \psi_{12}(x_1, x_2) \wedge V_{15 \to 12}(x_1) \wedge V_{23 \to 12}(x_2)$$

$$\Phi() = \bigoplus_{\mathbf{x}} \bigotimes_{S \in \mathcal{E}} \psi_S(\mathbf{x}_S) \text{ with acyclic hypergraph } \mathcal{H} \text{ and join tree } \mathcal{T}$$

Yannakakis's algorithm uses a bottom-up evaluation strategy over the join tree

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Pick a leaf $\psi_L(\mathbf{x}_L)$ with parent $\psi_P(\mathbf{x}_P)$ in \mathcal{T} Propagate information from leaf to parent and remove the leaf from \mathcal{T} Marginalise out variables of the leaf that are not in parent

$$V_{L\to P}(\mathbf{x}_{L\cap P}) = \bigoplus_{i\in L\setminus P: x_i} V_L(\mathbf{x}_L)$$
$$V_P(\mathbf{x}_P) := V_P(\mathbf{x}_P) \otimes V_{L\to P}(\mathbf{x}_{L\cap P})$$

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3. Marginalise out remaining variables and output at root from view $V_R(\mathbf{x}_R)$

$$\Phi()=\bigoplus_{\mathbf{x}_{R}}V_{R}(\mathbf{x}_{R})$$

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$$\Phi()=\bigoplus_{\mathbf{x}_{R}}V_{R}(\mathbf{x}_{R})$$

Time complexity: Linear in the size of the input factors (after sorting them)

$$\Phi(\mathbf{x}_{[f]}) = \bigoplus_{(x_{f+1}, \dots, x_n)} \bigotimes_{S \in \mathcal{E}} \psi_S(\mathbf{x}_S), \text{ where } X_1, \dots, X_f \text{ are free variables}$$

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The output size may be non-linear in the size of the input

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The output size may be non-linear in the size of the input

Adaptation of Steps 2 and 3: do NOT marginalise out free variables

2. We marginalise out $L' = (L \setminus P) \setminus [f]$ and keep $P' = P \cup (L \cap [f])$

$$V_{L o P'}(\mathbf{x}_{L \cap P'}) := \bigoplus_{i \in L': x_i} V_L(\mathbf{x}_L)$$

 $V_{P'}(\mathbf{x}_{P'}) := V_P(\mathbf{x}_P) \otimes V_{L o P'}(\mathbf{x}_{L \cap P'})$

3. Marginalise out non-free variables and output at root from view $V_R(\mathbf{x}_R)$

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$$\Phi(\mathbf{x}_{[f]}) = \bigoplus_{i \in R \setminus [f]: x_i} V_R(\mathbf{x}_R)$$

Question: Since $P' \supseteq P$, $V_{P'}$ may be larger than the input, yet how much larger?

$$\Phi(x_1, x_4) = \bigvee_{(x_1, \dots, x_5) \in \prod_{i \in [5]} \mathsf{Dom}(X_i)} \psi_{12}(x_1, x_2) \wedge \psi_{23}(x_2, x_3) \wedge \psi_{345}(x_3, x_4, x_5)$$

$$\Phi(\textit{\textbf{X}}_{1},\textit{\textbf{X}}_{4}) = \bigvee_{(\textit{\textbf{X}}_{1},...,\textit{\textbf{X}}_{5}) \in \prod_{i \in [5]} \mathsf{Dom}(\textit{\textbf{X}}_{i})} \psi_{12}(\textit{\textbf{X}}_{1},\textit{\textbf{X}}_{2}) \wedge \psi_{23}(\textit{\textbf{X}}_{2},\textit{\textbf{X}}_{3}) \wedge \psi_{345}(\textit{\textbf{X}}_{3},\textit{\textbf{X}}_{4},\textit{\textbf{X}}_{5})$$

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$$\begin{array}{c|cccc} \psi_{12} & X_1 & X_2 \\ \hline a_0 & b_0 \\ a_1 & b_1 \end{array}$$

$$\begin{array}{c|ccccc} \psi_{345} & X_3 & X_4 & X_5 \\ \hline c_1 & d_1 & e_1 \\ c_2 & d_2 & e_1 \\ c_2 & d_3 & e_1 \\ & \cdots & \cdots & \cdots \\ c_2 & d_N & e_1 \\ \hline \end{array}$$

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$$V_{12} = X_1 = X_2 = A_0 = A$$

$$V_{345 o 234} egin{array}{cccc} X_3 & X_4 \ \hline c_1 & d_1 \ c_2 & d_2 \ c_2 & d_3 \ & \cdots & \cdots \ c_2 & d_N \ \end{array}$$

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A join tree for Φ:

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345}(x_3, x_4, x_5)$$

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$$V_{345\to 234}$$
 X_3
 X_4
 C_1
 C_2
 C_2
 C_3
 C_4
 C_2
 C_3
 C_4
 C_5
 C_7
 C_8
 C_9
 C

$$\Phi(x_1, x_4) = \bigvee_{(x_1, \dots, x_5) \in \prod_{i \in [5]} \mathsf{Dom}(X_i)} \psi_{12}(x_1, x_2) \wedge \psi_{23}(x_2, x_3) \wedge \psi_{345}(x_3, x_4, x_5)$$

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A join tree for Φ : $\psi_{12}(x_1, x_2)$

Problem: Intermediate results are of quadratic size!

Reducing the Size of Intermediate Results

Consider again the following join tree and factors:

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345}(x_3, x_4, x_5)$$

$$\begin{array}{cccc}
\psi_{12} & X_1 & X_2 \\
\hline
 & a_0 & b_0 \\
 & a_1 & b_1
\end{array}$$

$$\psi_{23} = \begin{array}{cccc} X_2 & X_3 \\ \hline b_0 & c_0 \\ b_1 & c_1 \\ b_2 & c_2 \\ b_3 & c_2 \\ & \cdots & \cdots \\ b_N & c_2 \end{array}$$

$$\begin{array}{c|ccccc} \psi_{345} & X_3 & X_4 & X_5 \\ \hline c_1 & d_1 & e_1 \\ c_2 & d_2 & e_1 \\ c_2 & d_3 & e_1 \\ \cdots & \cdots & \cdots \\ c_2 & d_N & e_1 \\ \end{array}$$

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Consider again the following join tree and factors:

No tuple (b_i, c_2) of ψ_{23} is in the join result: ψ_{12} has no matching tuple

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Reducing the Size of Intermediate Results

Consider again the following join tree and factors:

No tuple (b_i, c_2) of ψ_{23} is in the join result: ψ_{12} has no matching tuple

Tuple (a_0, b_0) of ψ_{12} is **not** in the join result: ψ_{345} has no matching tuple

These are examples of dangling tuples

Adaptation: remove all dangling tuples at each factor before we do the join

Fully reduce input factors along a join tree $\ensuremath{\mathcal{T}}$

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- 1. Initialisation: Create a view $R_S(\mathbf{x}_S) = \psi_S(\mathbf{x}_S)$ for every $S \in \mathcal{E}$
- 2. Remove dangling tuples bottom-up

In bottom-up traversal of \mathcal{T} , filter each node ψ_{P} using its child ψ_{C}

Remove tuples from R_P with no match in R_C

$$R_P(\mathbf{x}_P) := R_P(\mathbf{x}_P) \otimes \mathbf{1}_{\bigoplus_{i \in C \setminus P: x_i} R_C(\mathbf{x}_C)}$$

Indicator $\mathbf{1}_{\Psi}$: Returns $\mathbf{1}$ if $\Psi \neq \mathbf{0}$ and $\mathbf{0}$ otherwise

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$$R_P(\boldsymbol{x}_P) := R_P(\boldsymbol{x}_P) \otimes \boldsymbol{1}_{\bigoplus_{i \in \mathcal{C} \setminus P: x_i} R_\mathcal{C}(\boldsymbol{x}_\mathcal{C})}$$

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3. Remove dangling tuples top-down

Fully reduce input factors along a join tree ${\mathcal T}$

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In bottom-up traversal of \mathcal{T} , filter each node ψ_P using its child ψ_C Remove tuples from R_P with no match in R_C

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Indicator $\mathbf{1}_{\Psi}$: Returns $\mathbf{1}$ if $\Psi \neq \mathbf{0}$ and $\mathbf{0}$ otherwise

3. Remove dangling tuples top-down

In top-down traversal of $\mathcal T$, filter each node $\psi_{\mathcal C}$ using its parent $\psi_{\mathcal P}$ Remove tuples from $R_{\mathcal C}$ with no match in $R_{\mathcal P}$

$$R_{\mathcal{C}}(\mathbf{x}_{\mathcal{C}}) := R_{\mathcal{C}}(\mathbf{x}_{\mathcal{C}}) \otimes \mathbf{1}_{\bigoplus_{i \in P \setminus \mathcal{C}: x_i} R_{\mathcal{P}}(\mathbf{x}_{\mathcal{P}})}$$

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345}(x_3, x_4, x_5)$$

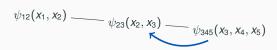
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$$\psi_{23}$$
 X_2 X_3
 b_0 c_0
 b_1 c_1
 b_2 c_2
 b_3 c_2
 \cdots
 b_N c_2

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 & a_1 & b_1
\end{array}$$



$$\begin{array}{c|cccc}
R_{12} & X_1 & X_2 \\
\hline
a_0 & b_0 \\
a_1 & b_1
\end{array}$$

$$\psi_{12}(x_1, x_2) - \psi_{23}(x_2, x_3) - \psi_{345}(x_3, x_4, x_5)$$

$$\begin{array}{c|cccc}
R_{12} & X_1 & X_2 \\
\hline
a_0 & b_0 \\
a_1 & b_1
\end{array}$$

$$\psi_{12}(x_1, x_2) - \psi_{23}(x_2, x_3) - \psi_{345}(x_3, x_4, x_5)$$

$$\begin{array}{c|cccc}
R_{12} & X_1 & X_2 \\
\hline
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\end{array}$$

$$\psi_{12}(x_1, x_2)$$
 $\psi_{23}(x_2, x_3)$ $\psi_{345}(x_3, x_4, x_5)$

$$\begin{array}{c|cccc}
R_{12} & X_1 & X_2 \\
\hline
 & a_0 & b_0 \\
 & a_1 & b_1
\end{array}$$

$$R_{23}$$
 X_2 X_3 $-b_0$ $-c_0$ b_1 c_1 b_2 c_2 b_3 c_2 \cdots b_N c_2

$$\psi_{12}(x_1, x_2)$$
 $\psi_{23}(x_2, x_3)$ $\psi_{345}(x_3, x_4, x_5)$

$$\begin{array}{c|cccc}
R_{12} & X_1 & X_2 \\
\hline
 & a_0 & b_0 \\
 & a_1 & b_1
\end{array}$$

$$R_{23}$$
 X_2 X_3 $-b_0$ $-c_0$ b_1 c_1 $-b_2$ $-c_2$ $-b_3$ $-c_2$ $-b_N$ $-c_2$

$$\psi_{12}(x_1, x_2) - \psi_{23}(x_2, x_3) - \psi_{345}(x_3, x_4, x_5)$$

$$\begin{array}{cccc} R_{12} & X_1 & X_2 \\ \hline a_0 & b_0 \\ a_1 & b_1 \end{array}$$

$$\psi_{12}(x_1, x_2) - \psi_{23}(x_2, x_3) - \psi_{345}(x_3, x_4, x_5)$$

$$\begin{array}{c|cccc}
R_{12} & X_1 & X_2 \\
\hline
 & a_0 & b_0 \\
 & a_1 & b_1
\end{array}$$

Consider again the previous join tree and factors:

$$\psi_{12}(x_1, x_2) - \psi_{23}(x_2, x_3) - \psi_{345}(x_3, x_4, x_5)$$

Only tuples remain that contribute to at least one tuple in the join result

Adaptation of Step 1: initialise views as fully reduced

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Size of intermediate results is bounded by product of input size and output size

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Time complexity: Linear in the product of input size and output size (after sorting)

Adaptation of Step 1: initialise views as fully reduced

Size of intermediate results is bounded by product of input size and output size

Time complexity: Linear in the product of input size and output size (after sorting)

For free-connex acyclic CQs, the algorithm is instance-optimal:

Time complexity is linear in the sum of input size and output size (after sorting)

- 1. Bottom-up *local* computation in time proportional to IN
 - · Pick one node with free variables as root
 - The nodes with free variables form a connected subtree in the join tree
 - Values for free variables pushed up when these variables are also in parent

We are now left with a reduced join tree only over free variables

2. We can now join all the remaining factors in time proportional to OUT

2. Computing Joins using LeapFrog TrieJoin

Beyond Acyclicity

Various applications call for cyclic joins

- graph problems, e.g., looking for cyclic patterns in networks, social media
- Typical cyclic queries: loops, triangles, Loomis-Whitney
- Compute the factors representing the bags in hypertree decompositions

Surprisingly, mainstream join algorithms are sub-optimal for cyclic joins

- nested-loops join, hash join, sort-merge join, [your favourite join algorithm]
- Sub-optimal: It takes asymptotically more time than worst-case join size
- We will see this by means of an example later in this lecture

We next discuss a worst-case optimal join algorithm: LeapFrog TrieJoin

- Runtime proportional to the size of the join output (proof in paper)
- Recall: Join output size $O(N^{\rho^*})$; ρ^* is the fractional edge cover number
- We later show that $O(N^{\rho^*})$ is worst-case optimal join size

LFTJ: The LeapFrog TrieJoin Algorithm

State-of-the art worst-case optimal join (WCOJ) algorithm

- Available at http://arxiv.org/abs/1210.0481
- Variants implemented in commercial and open-source query engines
- LFTJ can be orders of magnitude faster for cyclic queries on large datasets than existing commercial and open-source query engines
- Adapting an existing engine to support joins worst-case optimally requires significant design changes

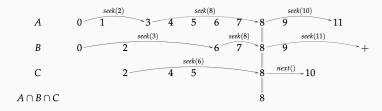
Join of Unary Factors: Standard Approach

Compute the join of unary factors (intersection): $\Phi(x) = A(x) \otimes B(x) \otimes C(x)$

Α	0	1		3	4	5	6	7	8	9		11
В	0		2				6	7	8	9		
С			2		4	5			8		10	
$A \cap B \cap C$									8			

- Standard approach (for sorted factors): multi-way sort-merge join
- Iterators over the three factors proceed in lockstep to find common values
- · Each iterator scans the entire list
- Time to compute: proportional to the sizes of the lists

Join of Unary Factors: Leapfrogging



Complexity: let $N_{min} = \min\{|A|, |B|, |C|\}$ and $N_{max} = \max\{|A|, |B|, |C|\}$. Then leapfrog join runs in time $\Theta(N_{min}(1 + \log(N_{max}/N_{min})))$.

- Leapfrog Join: Multi-way sort-merge join using smart seeks instead of scans
- Seeking m keys amongst N possible keys in ascending order has amortised complexity O(1 + log(N/m)) as for balanced search tree data structures

Linear Iterator

We navigate a unary factor using an iterator that sees it as an ordered list.

The linear iterator interface:

int key()	Returns the key at the curre	ent iterator position

next() Proceeds to the next key

seek(int seekKey) Positions the iterator at a least upper bound for seekKey

i.e., the least key \geq seekKey, or move to end if no such key exists.

The sought key must be \geq the key at the current position.

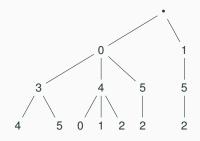
bool atEnd() Returns true if the iterator is at the end.

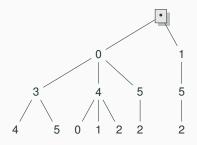
Trie Presentation of Factors With Non-Unary Arity

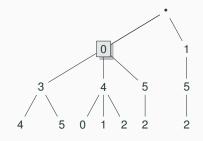
R(x, y, z)	
(0,3,4)	
(0,3,5)	
(0,4,0)	
(0,4,1)	
(0,4,2)	



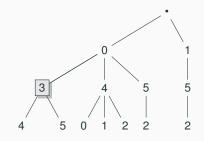




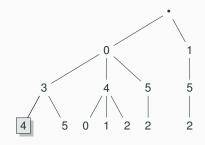




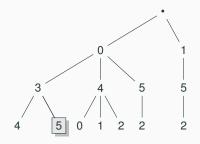
Call: open()



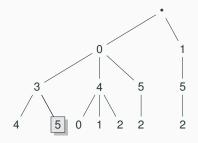
Call: open()



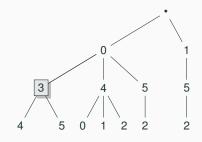
Call: open()



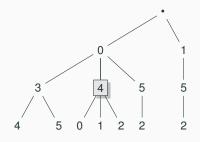
Call: next()



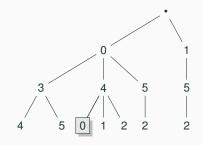
Call: atEnd() true



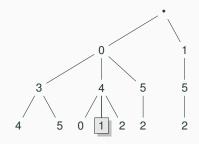
Call: up()



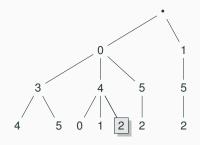
Call: next()



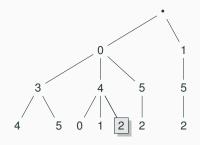
Call: open()



Call: next()



Call: next()



Call: atEnd() true and so on

Trie Iterator

We navigate a factor using an iterator that sees it as a trie.

The trie iterator interface:

void open()

void up()	Return to the parent key at the previous depth			
int key()	Returns the key at the current iterator position			
next()	Proceeds to the next key			
seek(int seekKev)	Positions the iterator at a least upper bound for seekKey			

i.e., the least key > seekKey, or move to end if no such key exists.

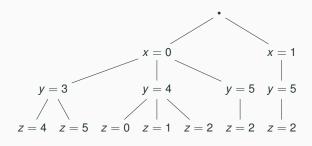
The sought key must be \geq the key at the current position.

Proceed to the first key at the next depth

bool atEnd() Returns true if the iterator is at the end.

Binding Trie: Variables Mapped to Values During Trie Traversal

- The variables of a factor are bound to values following a backtracking search
- Satisfying assignments are emitted when leaves are reached
- Consider our trie below for factor R(x, y, z)

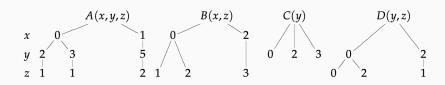


Execution Strategy of LeapFrog TrieJoin

- Choose a global and total variable ordering for all factors
- · Each factor is traversed following this variable ordering
- Backtracking search through binding trie to find result tuples
 - Example join: R(a, b) * S(b, c) * T(a, c) under variable ordering: [a, b, c]
 - Leapfrog join for a occurring in both R and T
 - For each such a, leapfrog join for b occurring in S and Ra
 - For each such b, leapfrog join for c occurring in S^b and T^a
- The result is presented as a non-materialised view using a trie iterator

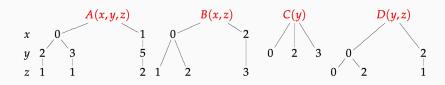
LeapFrog TrieJoin in Action: Example (1/7)

Tree join example



LeapFrog TrieJoin in Action: Example (2/7)

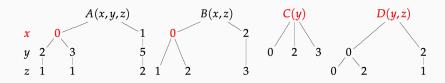
Tree join example



Position iterators at root of trees.

LeapFrog TrieJoin in Action: Example (3/7)

Tree join example

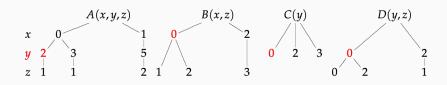


open() iterators for trees that bind x.

Join for $A(x, _{-}, _{-}), B(x, _{-})$ finds x = 0.

LeapFrog TrieJoin in Action: Example (4/7)

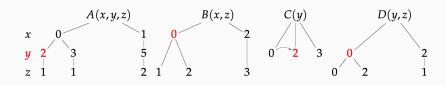
Tree join example



open() iterators for trees that bind y.

LeapFrog TrieJoin in Action: Example (5/7)

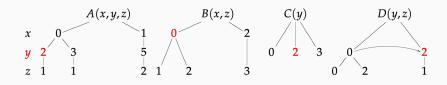
Tree join example



seek(2) on C iterator

LeapFrog TrieJoin in Action: Example (6/7)

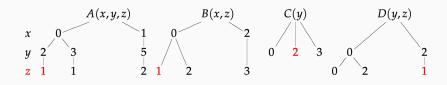
Tree join example



seek(2) on D iterator; join for $A(0,y,_)$, C(y), $D(y,_)$ finds y=2

LeapFrog TrieJoin in Action: Example (7/7)

Tree join example



open() on iterators for z

join for A(0,2,z), B(0,z), D(2,z) produces z = 1: emit (0,2,1)

3. Suboptimality of Mainstream Join Algorithms

The Triangle Join on Factors with Heavy and Light Values

Each input factor has size 2m + 1, the output factor has size 3m + 1.

Values a_0 , b_0 , c_0 are *heavy* in the input factors, all other values are *light* Ideally, a join algorithm takes time proportional to the input and output sizes.

How would existing join algorithms compute this query?

Mainstream Join Algorithms Compute One Join at a Time

Traditional join: Join two of the three factors, then join in the remaining factor

$$\Phi'(\mathbf{X}_{1}, \mathbf{X}_{2}, \mathbf{X}_{3}) = \psi_{12}(\mathbf{X}_{1}, \mathbf{X}_{2}) \otimes \psi_{13}(\mathbf{X}_{1}, \mathbf{X}_{3})$$

$$\Phi(\mathbf{X}_{1}, \mathbf{X}_{2}, \mathbf{X}_{3}) = \Phi'(\mathbf{X}_{1}, \mathbf{X}_{2}, \mathbf{X}_{3}) \otimes \psi_{23}(\mathbf{X}_{2}, \mathbf{X}_{3})$$

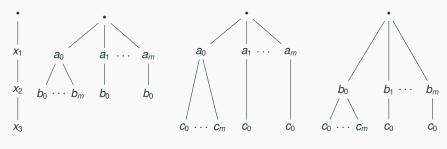
$$\psi_{12}$$

• Φ' takes quadratic time to compute: It has $(m+1)^2 + m$ tuples

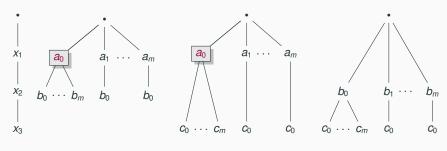
$\psi_{12}({\color{red} \textbf{\textit{X}}_1},{\color{red} \textbf{\textit{X}}_2})$		$\psi_{13}(\mathbf{x_1}, \mathbf{x_3})$		$\Phi'(x_1,x_2,x_3)$		
<i>a</i> ₀		a ₀		a ₀	<i>b</i> ₀	<i>c</i> ₀
a_0	20	a ₀	00	a_0	b_0	
a_0	b _m	a_0	· · ·	a_0	b_0	Cm
			C _m			
a ₁	<i>b</i> ₀	<i>a</i> ₁	<i>c</i> ₀	a ₀	b _m	<i>C</i> ₀
	<i>b</i> ₀		<i>C</i> ₀	a_0		c_0
am	<u>b</u> 0	a _m	<i>C</i> ₀	a_0	<i>b</i> _m	<i>c</i> ₀
				a ₁	<i>b</i> ₀	<i>C</i> ₀
					b_0	<i>c</i> ₀
				am	b_0	C ∩

• This behaviour happens regardless of which two factors we join first

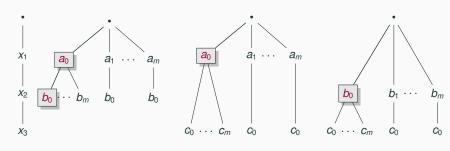
This is not optimal: The intermediate result is larger than the final join result



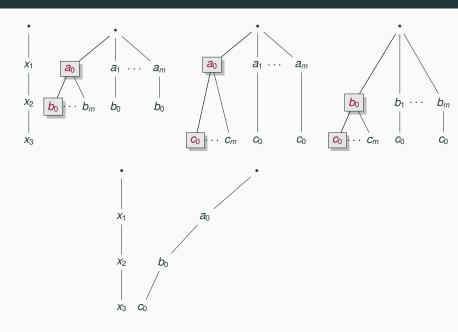


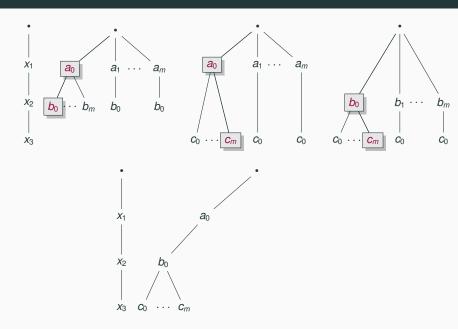




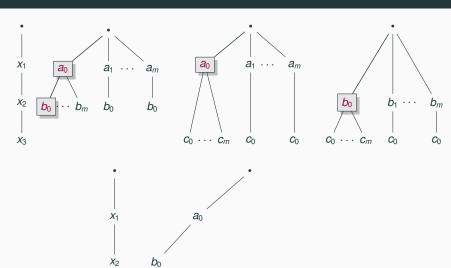


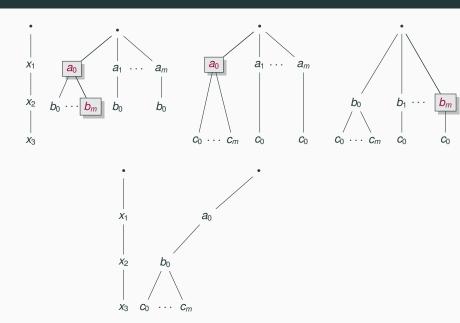


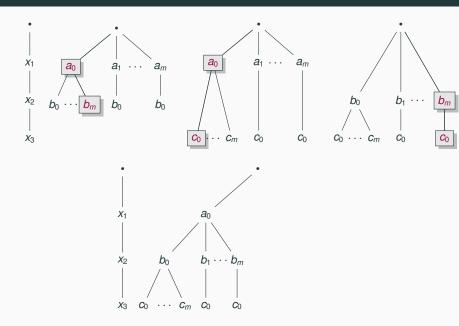


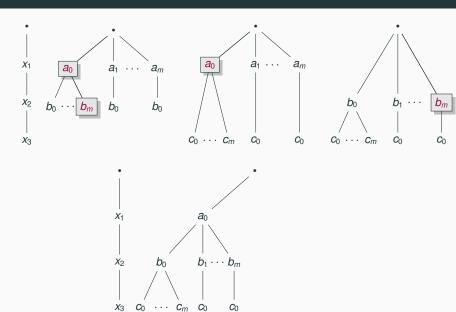


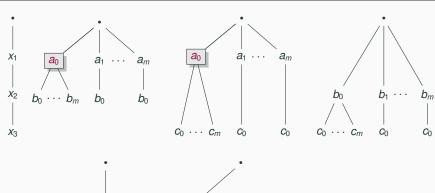
*X*3

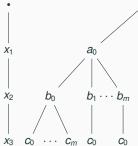


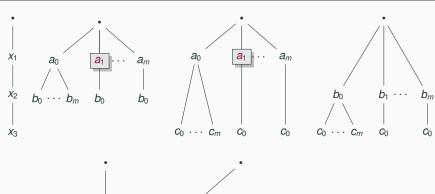


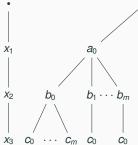


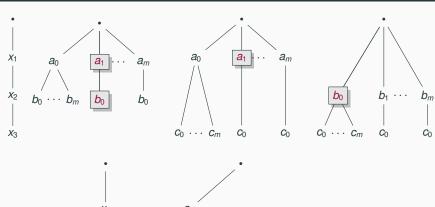


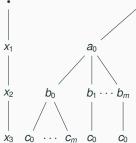


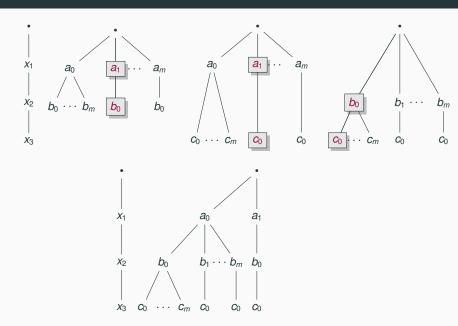








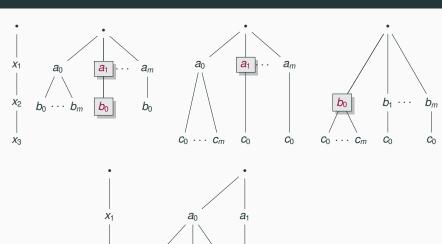




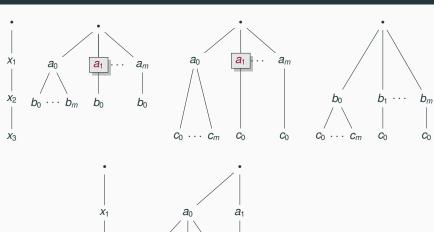
 b_0

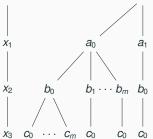
*X*₂

*X*3



 $b_1 \cdots b_m b_0$

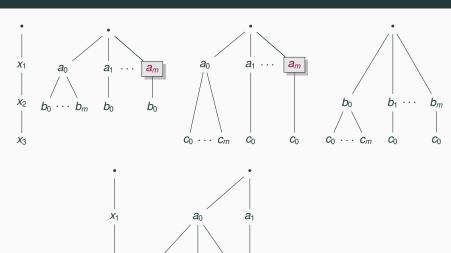




 b_0

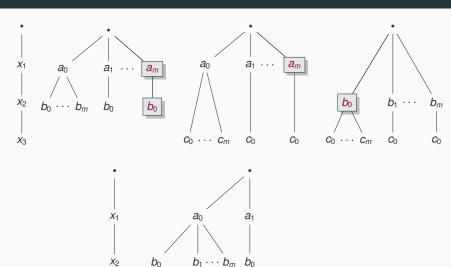
*X*₂

*X*3

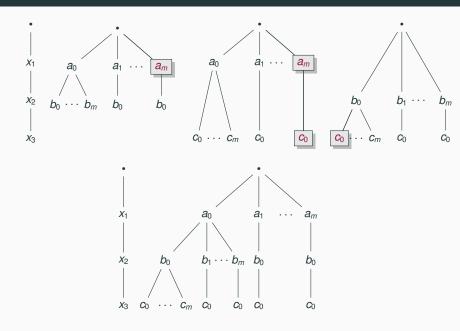


 $b_1 \cdots b_m b_0$

*X*3



LeapFrog TrieJoin Computes All Joins Together in IN + OUT Time



4. Conjunctive Queries with Large Output

Simple Queries May Have Large Output

Output size is not a good measure for the computational effort of a query

Cartesian product $\Phi(x_1,\ldots,x_m)=\psi_1(x_1)\otimes\cdots\otimes\psi_m(x_m)$ has output size N^m

Simple Queries May Have Large Output

Output size is not a good measure for the computational effort of a query

Cartesian product $\Phi(x_1, \dots, x_m) = \psi_1(x_1) \otimes \dots \otimes \psi_m(x_m)$ has output size N^m

Decompose the computational effort into two steps:

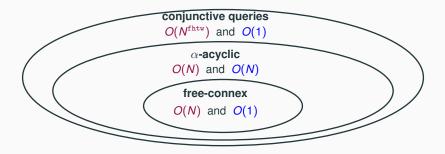
1. Preprocessing step

- · Construct a compact data structure for all tuples in the query result
- · Construction time = true measure of the query's computational effort

2. Enumeration step

- Enumerate the distinct tuples from this data structure one after the other
- Delay: The time needed to return one tuple after returning the previous one
- · Constant delay is as good as enumerating tuples from a listing representation
- One can enumerate top-k tuples in a desired order

Overview of Approaches Covered in Lecture



The above diagram shows preprocessing time and enumeration delay

Two broad strategies:

- 1. All computational effort in the preprocessing step to achieve constant delay
 - Still lower than materialising the entire query result: $\mathtt{fhtw} \leq \rho^*$
- 2. Distribute the computational effort between preprocessing and enumeration

Strategy 1: All Computational Effort in Preprocessing

Input: FAQ Φ with hypergraph $\mathcal H$ and free variables [f], input factors of size N

Preprocessing Step

- Construct a hypertree decomposition for H in O(N^{fhtw(H,[f])})
 - · Hypertree becomes join tree: each bag is materialised as one factor
 - · Free variables form a connected subtree including wlog the root of the join tree
- Calibrate the factors using a full reducer to remove dangling tuples
- Marginalise out bound (i.e., not free) variables
- Sort factors following an order of free variables compatible with top-down traversal of join tree

Output of preprocessing step:

- · Reduced join tree whose nodes are factors over free variables only
- Expensive and unnecessary: Joining all factors in the reduced join tree
- \Rightarrow Time to compute Φ is $O(N^{\rho^*(\mathcal{H})})$, yet $\rho^*(\mathcal{H}) \geq \text{fhtw}(\mathcal{H}, [f])$

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345}(x_3, x_4, x_5)$$

$\psi_{\rm 12}$	X_1	X_2	
	a ₁	b ₁	
	a_1	b_2	
	a_2	b_1	
	a_2	b_2	
	a_N	b_1	
	a_N	b_2	
	a_N	b_3	

ψ_{345}	<i>X</i> ₃	X_4	<i>X</i> ₅
	C ₁	d_1	<i>e</i> ₁
	C ₁	d_2	e_1
	C 2	d_1	e 1
	<i>C</i> ₂	d_2	e_1
	c_N	d_1	e_1
	c_N	d_2	e_1

Input: join tree and factors as follows, free variables are $\{X_1, X_2, X_3\}$

· Factors are already calibrated

- Factors are already calibrated
- Variables X₄, X₅ are marginalised out

- · Factors are already calibrated
- Variables X₄, X₅ are marginalised out
- · Factors are already sorted appropriately

Strategy 1: All Computational Effort in Preprocessing

Constant-Delay Enumeration of Tuples from Reduced Join Tree

- Variable order (X_1, \ldots, X_f) compatible with top-down traversal of join tree
- · Factors are sorted following this variable order
- For each value x_1 for X_1 , we seek a value x_2 for X_2 , and so on
 - If factors sorted, then all values for X_i are in a contiguous block in factors, given the values for X₁,..., X_{i-1}
 - Since there are no dangling tuples, each value x_i participates in at least one output tuple
- We output a complete assignment $\mathbf{x}_{[t]}$ and backtrack

Why constant delay?

- For each variable X_i , we need constant time to locate its next value, given values for variables X_1, \ldots, X_{i-1}
- The time to output a tuple is independent of the sizes of the factors

 a_N

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345 \to 23}(x_3)$$

ψ_{12}	<i>X</i> ₁	<i>X</i> ₂	
	a ₁	<i>b</i> ₁	
	a ₁	b_2	
	a_2	b_1	
	a_2	b_2	
		• • •	
	a_N	b_1	
	a_N	b_2	
	a_N	b_3	

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345 \to 23}(x_3)$$

ψ_{12}	X_1	X_2
	a ₁	<i>b</i> ₁
	a ₁	b_2
	a_2	b_1
	a_2	b_2
	a_N	b_1
	a_N	b_2
	a_N	b_3

$$\psi_{12}(x_1, x_2) = \psi_{23}(x_2, x_3) = \psi_{345 \to 23}(x_3)$$

ψ_{12}	<i>X</i> ₁	<i>X</i> ₂
	a ₁	<i>b</i> ₁
	a ₁	<i>b</i> ₂
	a_2	b_1
	a_2	b_2
	a_N	b_1
	a_N	b_2
	a_N	<i>b</i> ₃

$$\psi_{23}$$
 X_2 X_3
 b_1 c_1
 \cdots
 b_1 c_N
 b_2 c_1
 \cdots
 b_2 c_N
 b_3 c_1

$\psi_{ m 345 ightarrow 23}$	<i>X</i> ₃
	C ₁
	C ₂
	c_N

Input: join tree and factors as follows, free variables are $\{X_1, X_2, X_3\}$

Output: (a_1, b_1, c_1)

Input: join tree and factors as follows, free variables are $\{X_1, X_2, X_3\}$

Output: $(a_1, b_1, c_1), \ldots, (a_1, b_1, c_N)$

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Input: join tree and factors as follows, free variables are $\{X_1, X_2, X_3\}$

Output: $(a_1, b_1, c_1), \dots, (a_1, b_1, c_N), (a_1, b_2, c_1), \dots, (a_1, b_2, c_N)$

Input: join tree and factors as follows, free variables are $\{X_1, X_2, X_3\}$

Output: $(a_1, b_1, c_1), \dots, (a_1, b_1, c_N), (a_1, b_2, c_1), \dots, (a_1, b_2, c_N), \dots$

Strategy 2: Linear Preprocessing and Linear Enumeration Delay

We discuss this strategy for α -acyclic CQs that are not free-connex

Preprocessing Step

- Apply a full reducer to remove the dangling tuples
- Sort factors following an order of the free variables compatible with top-down traversal of join tree
- This computation can be done in linear(ithmic) time

Enumeration Step

- Iterate over the possible values x₁ for variable X₁
- Restrict the factors for X_1 to those tuples where $X_1 = x_1$
- Fully reduce all other factors to avoid newly dangling tuples
- Do the previous three steps for the next variable
- When a complete variable assignment is found, output it and backtrack
- This computation can be done in linear time per complete assignment

Fix again join tree and factors as follows, free variables are now $\{\textit{X}_{1},\textit{X}_{3}\}$

Fix again join tree and factors as follows, free variables are now $\{X_1,X_3\}$

• Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3

Fix again join tree and factors as follows, free variables are now $\{X_1,X_3\}$

- Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3
- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

$$\psi_{12}(x_1, x_2) = -\psi_{23}(x_2, x_3) = -\psi_{345}(x_3, x_4, x_5)$$

$$\psi_{12} = \begin{array}{c|ccccc} X_1 & X_2 & & \psi_{23} & X_2 & X_3 & & \psi_{345} & X_3 & X_4 & X_5 \\ \hline a_1 & b_1 & & b_1 & c_1 & & c_1 & d_1 & e_1 \\ a_1 & b_2 & & b_2 & c_1 & & c_1 & d_2 & e_1 \\ a_2 & b_1 & & b_3 & c_1 & & c_2 & d_1 & e_1 \\ a_2 & b_2 & & b_1 & c_2 & & c_2 & d_2 & e_1 \\ & \cdots & \cdots & & b_2 & c_2 & & \cdots & \cdots \\ a_N & b_1 & & \cdots & \cdots & & c_N & d_1 & e_1 \\ a_N & b_2 & & b_1 & c_N & & c_N & d_2 & e_1 \\ a_N & b_3 & & b_2 & c_N & & & c_N & d_2 & e_1 \\ \hline \end{array}$$

• Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3

 C_N

- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

• Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3

 C_N

 C_N

 b_1

 b_2

CN

 C_N

 d_1 e_1

 e_1

 d_2

- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1
 - · remove dangling tuples in other factors

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

- Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3
- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1
 - remove dangling tuples in other factors
 - iterate over all results of $\Phi_3(x_3)=\psi_{12}({\color{red} a_1 \over a_1},x_2)\otimes \psi_{23}(x_2,x_3)\otimes \psi_{345}(x_3,x_4,x_5)$

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

- Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3
- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1
 - remove dangling tuples in other factors
 - iterate over all results of $\Phi_3(x_3) = \psi_{12}(a_1, x_2) \otimes \psi_{23}(x_2, x_3) \otimes \psi_{345}(x_3, x_4, x_5)$

Output: (a_1, c_1)

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

- Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3
- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1
 - remove dangling tuples in other factors
 - iterate over all results of $\Phi_3(x_3) = \psi_{12}(a_1, x_2) \otimes \psi_{23}(x_2, x_3) \otimes \psi_{345}(x_3, x_4, x_5)$

Output: $(a_1, c_1), (a_1, c_2)$

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

- Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3
- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1
 - remove dangling tuples in other factors

Output: $(a_1, c_1), (a_1, c_2), \dots, (a_1, c_N)$

Fix again join tree and factors as follows, free variables are now $\{X_1, X_3\}$

- Preprocessing: Remove dangling tuples, sort ψ_{23} by the free variable X_3
- Iterate over all results of $\Phi_1(x_1) = \bigoplus_{x_2} \psi_{12}(x_1, x_2)$
 - restrict ψ_{12} to fixed value, here a_1
 - remove dangling tuples in other factors
 - iterate over all results of $\Phi_3(x_3) = \psi_{12}(\ \ \, a_1 \ \ \, , x_2) \otimes \psi_{23}(x_2,x_3) \otimes \psi_{345}(x_3,x_4,x_5)$

Output: $(a_1, c_1), (a_1, c_2), \ldots, (a_1, c_N), \ldots$