

Query Optimization

How to design a Meta-Algorithm that designs algorithms

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Why Query Optimization TODAY?

- DB systems nowadays are expected to be comprehensive **BI** platforms
 - **learn** from data, make business **decisions**
- Modern queries are getting **incredibly complex!**
 - Auto-generated by **AI Agents** or higher-level languages
- Query Optimizers are now the **bottleneck..**

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 - *"Explain this!" "Can you **fix** it by the morning?!"*
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- Only a **Rigorous Theory** can give you that
 - LLMs can't (yet)
 - They can still be *part of* the pipeline but *cannot replace* it

(Futuristic) Terminology

Query

ANY Question/Problem about the input data

Query Plan

ANY Algorithm

Statistics

ANY Prior Knowledge about the input data

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Examples:

Input:

Query / Problem
(+ Statistics)



Output:

Query Plan / Algorithm

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Shortest-path problem

⇒

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Output:

Query Plan / Algorithm

Floyd-Warshall algorithm

Examples:

Input:

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Shortest-path problem

A matrix product $A \times B \times C \times D$
& dimensions

$\Rightarrow$

$\Rightarrow$

$\Rightarrow$

Output:

Query Plan / Algorithm

Floyd-Warshall algorithm

$A \times ((B \times C) \times D)$

Examples:

Input:

Query / Problem
(+ Statistics)

Shortest-path problem

A matrix product $A \times B \times C \times D$
& dimensions

“Given a graph of size N,
how many 6-cycles are there?”

Output:

Query Plan / Algorithm

Floyd-Warshall algorithm

$A \times ((B \times C) \times D)$

An algorithm matching the
state-of-the-art *human-designed* algorithm

Challenges

1. Accurate **cost estimation** of query plans
 - *How does the optimizer know the complexity of Floyd-Warshall?*
2. **Vastness of the space** of query plans
 - *How can the optimizer stumble upon Floyd-Warshall out of all possible algorithms?*

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3. Emerging applications leading to **new query classes**

- *"Great job about shortest paths!"*
- *"Now when can your optimizer do my tax return?!"*

Outline

- Start with a (relatively) simple class of queries
 - **Research Thread 1:** Using **Information Theory** for
 - Provably Accurate **Cost Estimation**
 - **Designing** Optimal **Query Plans**
- Expanding the class of queries
 - **Research Thread 2:** Using **Algebra** for
 - **Amplifying** the Power of **Query Languages**
 - **Re-using** Algorithms in **Different Applications**

Research Thread 1

An **Information-Theoretic** Framework
for Query Optimization

Conjunctive Queries (**CQs**)

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- **Input**

- A set of *variables* $\mathbf{X}$
- A set of *relations* $R_1(\mathbf{X}_1), \dots, R_k(\mathbf{X}_k)$
- A *query* $Q(\mathbf{X}) = R_1(\mathbf{X}_1) \wedge \dots \wedge R_k(\mathbf{X}_k)$

Conjunctive Queries (**CQs**)

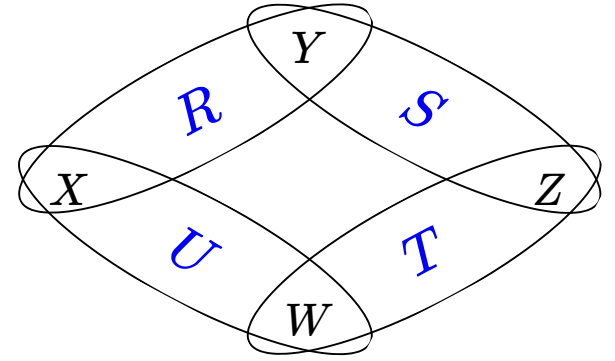
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- **Target**

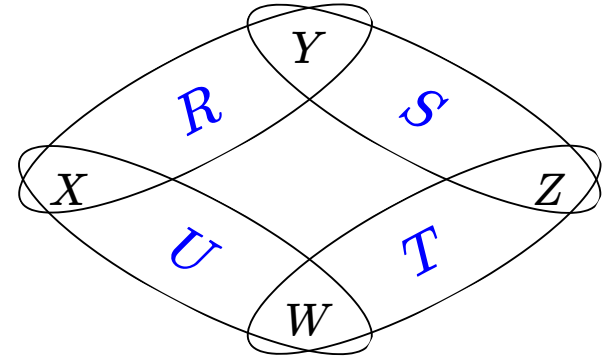
- Compute $Q(\mathbf{X})$

Conjunctive Queries (**CQs**) - Example



$$Q(X, Y, Z, W) = R(X, Y) \wedge S(Y, Z) \wedge T(Z, W) \wedge U(W, X)$$

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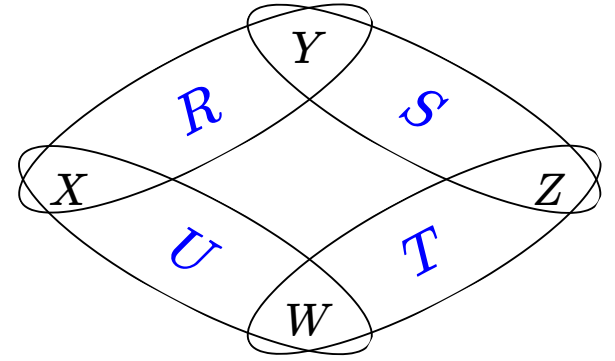
<i>R</i>	
<i>X</i>	<i>Y</i>
1	<i>p</i>
1	<i>q</i>
2	<i>p</i>

<i>S</i>	
<i>Y</i>	<i>Z</i>
<i>p</i>	3
<i>q</i>	4
<i>q</i>	5

<i>T</i>	
<i>Z</i>	<i>W</i>
3	<i>i</i>
5	<i>i</i>
5	<i>j</i>

<i>U</i>	
<i>W</i>	<i>X</i>
<i>i</i>	1
<i>j</i>	1
<i>k</i>	2

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- **Variants**

- *Detection*: Does G contain P ?
- *Counting*: How many occurrences of P does G contain?
- *Listing*: List all occurrences
- ...

CQs are a *Vast* Generalization of GPM

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- $R_1, \dots, R_k$ are not necessarily binary relations
 - *Hypergraphs*
- We could have many *statistics* besides N
 - *Functional dependencies*, e.g. city $\rightarrow$ country in R(city, country, company)
 - *Degree statistics*, e.g. average or max number of cities per country
 - *Correlation* among data columns
 - ...

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- **Non-combinatorial:**

- Triangle $\Rightarrow O(N^{\frac{2\omega}{\omega+1}})$
- 4-cycle $\Rightarrow \tilde{O}(N^{\frac{4\omega-1}{2\omega+1}})$
- 5-clique $\Rightarrow O(N^{\frac{\omega}{2}+1})$
- ...

ω is the Matrix Multiplication exponent

[Alon, Yuster & Zwick-**Algorithmica'79**]

[Yuster & Zwick-**SODA'04**]

[Dalirrooyfard et al-**STOC'19**]

[Dalirrooyfard et al-**STOC'24**]

Our Results: A Unified Algorithm, **PANDA**

- subsumes *all known* results
- discovers *new* ones
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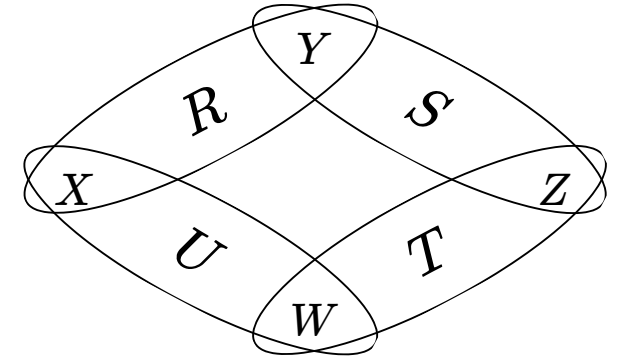
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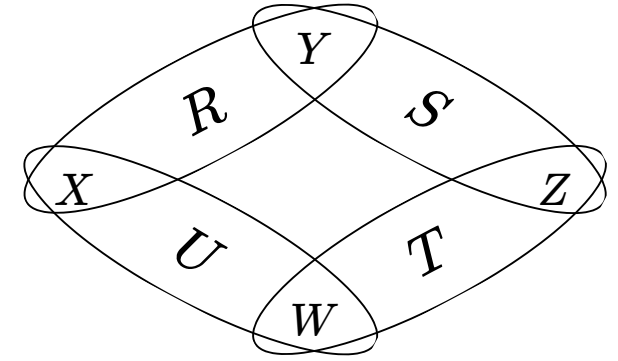
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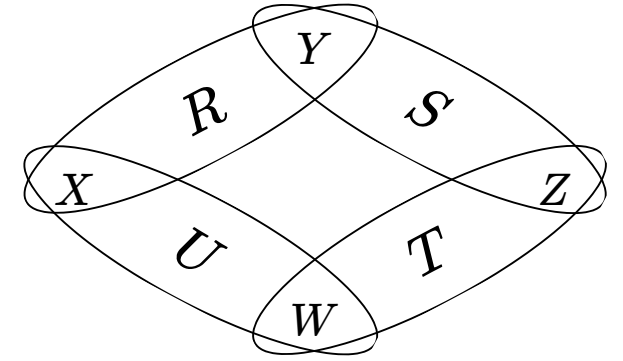
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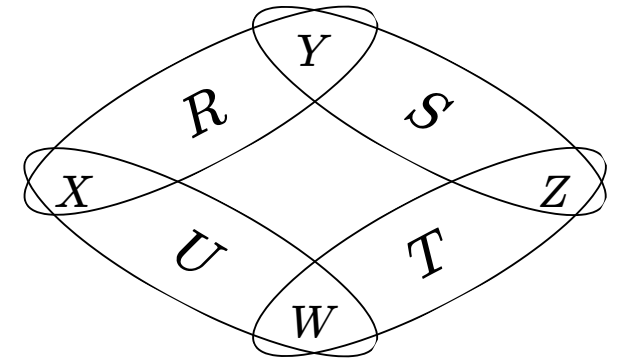
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- **Output:**

- An $O(N^{3/2} \cdot \sqrt{C})$ -time **algorithm**
- An **upper bound**, e.g., $|Q| \leq N^{3/2} \cdot \sqrt{C}$



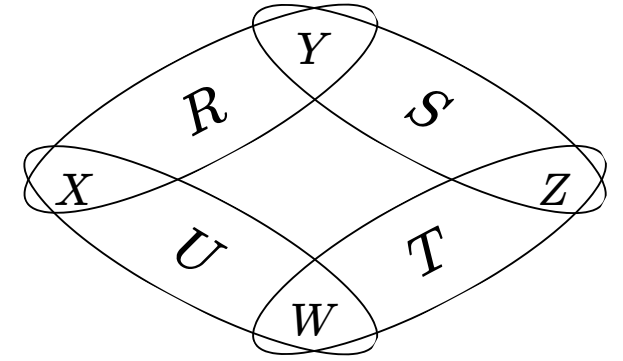
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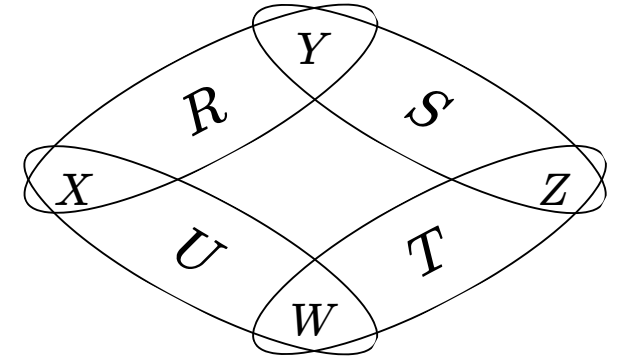
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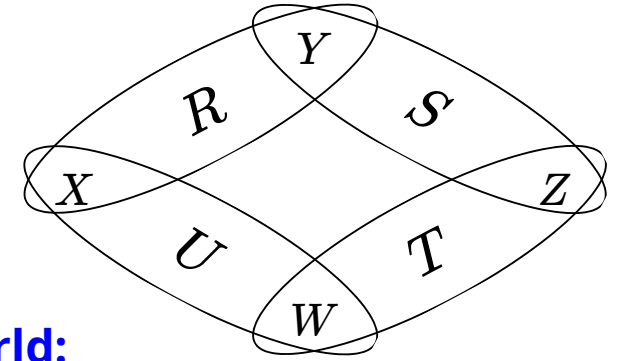
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Information-Theory World:

- maximize $h(XYZW)$
- over all "entropies" h
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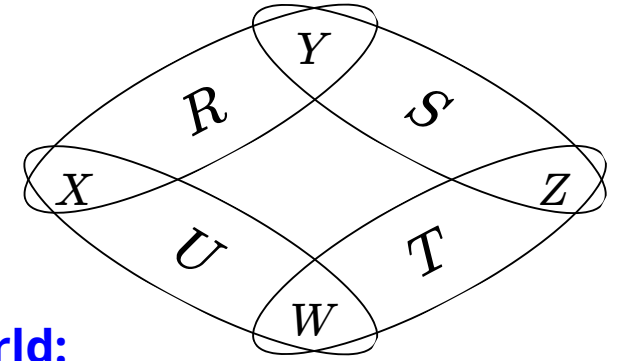
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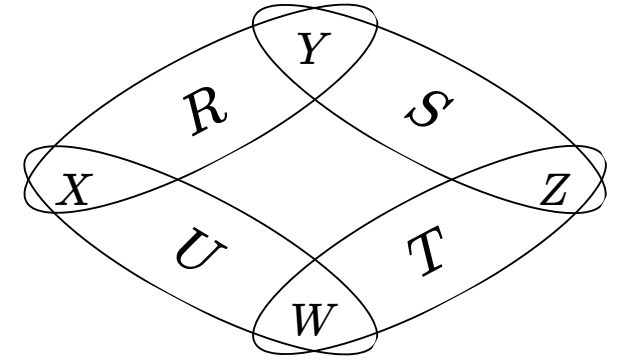
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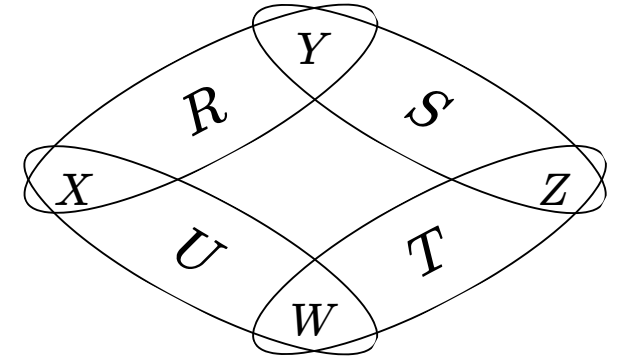
- maximize $h(XYZW)$
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- subject to statistics:
 - $h(XY), h(YZ), h(ZW), h(WX) \leq \log N$
 - $h(X|W) = 0$
 - $h(W|X) \leq \log C$
 - ...



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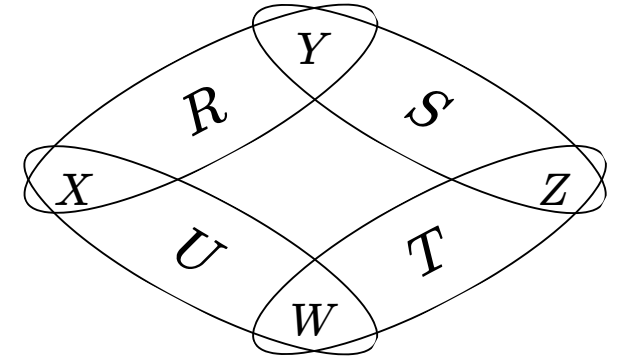
R	
X	Y
1	p
1	q
2	p

S	
Y	Z
p	3
q	4
q	5

T	
Z	W
3	i
5	i
5	j

U	
W	X
i	1
j	1
k	2

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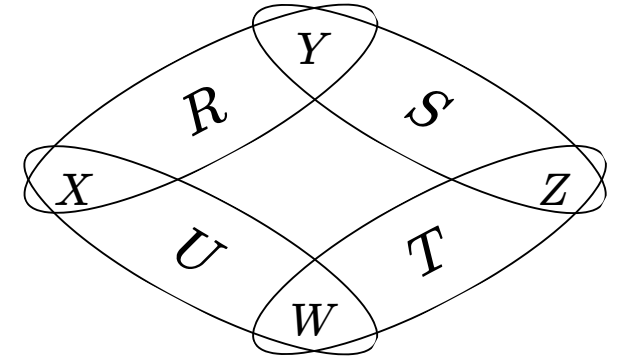
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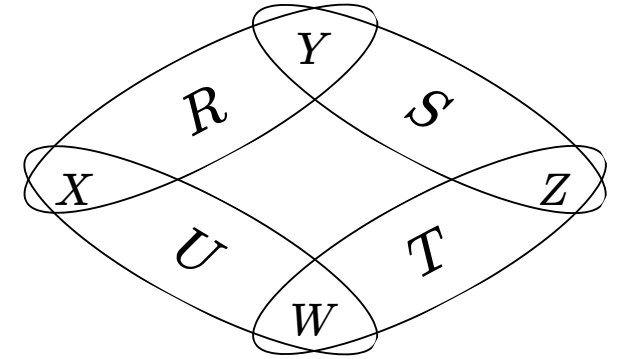
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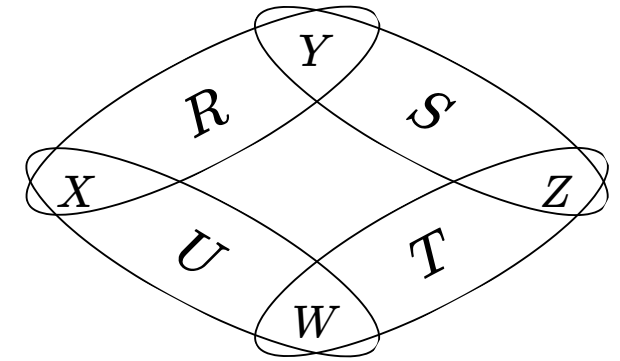
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<i>T</i>		
<i>Z</i>	<i>W</i>	
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5	<i>i</i>	1/3
5	<i>j</i>	1/3

<i>U</i>		
<i>W</i>	<i>X</i>	
<i>i</i>	1	2/3
<i>j</i>	1	1/3
<i>k</i>	2	0

<i>Q</i>				
<i>X</i>	<i>Y</i>	<i>Z</i>	<i>W</i>	
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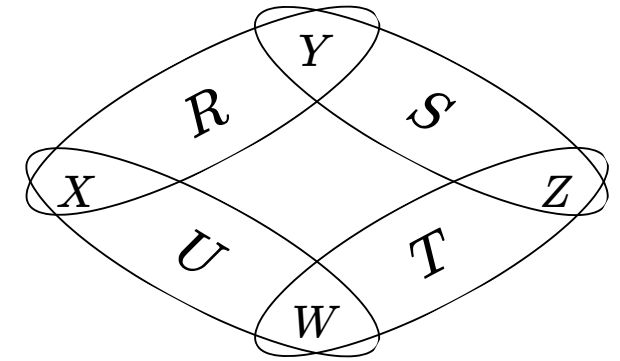
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1	q	5	j	$1/3$

Database World:

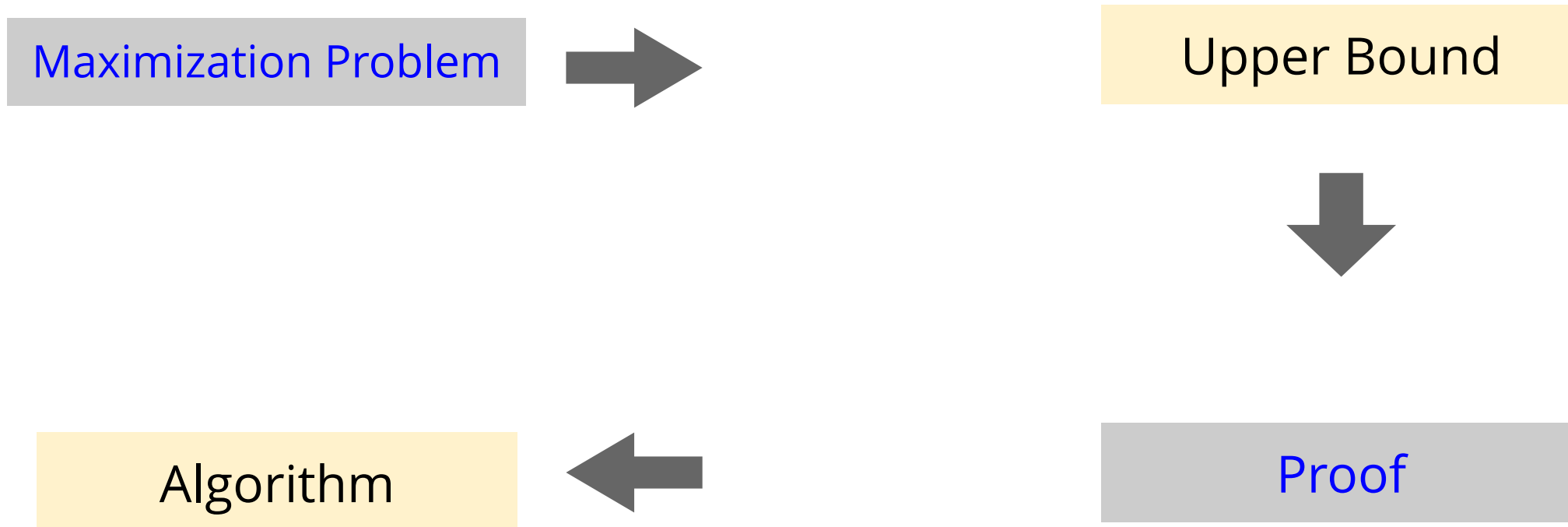
- $|Q|$
- $|R| \leq N$
- $W \rightarrow X$
- $\text{maxdeg}(W|X) \leq C$
- ...

Information-Theory World:

- $h(XYZY) = \log |Q|$
- $h(XY) \leq \log N$
- $h(X|W) = 0$
- $h(W|X) \leq \log C$
- ...

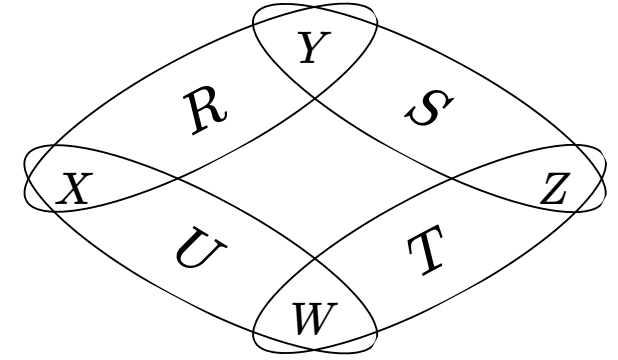
[..., AGM08, GLVV'12, ANS'17, JRR'21, ANOS'24, ...]

Framework Overview



Framework Overview

- *maximize $h(XYZW)$*
- *over all **"entropies"** h*
- *subject to statistics:*
 - $h(XY), \dots \leq \log N$
 - $h(X|W) = 0$
 - $h(W|X) \leq \log C$



$$\begin{aligned} |Q| &\leq N^{3/2} \cdot \sqrt{C} \\ \underbrace{2h(XYZW)}_{=\log |Q|} &\leq \underbrace{h(XY)}_{\leq \log N} + \underbrace{h(YZ)}_{\leq \log N} + \underbrace{h(ZW)}_{\leq \log N} + \underbrace{h(X|W)}_{=0} + \underbrace{h(W|X)}_{\leq \log C} \end{aligned}$$

- $S(Y, Z) \rightarrow S^h(Y) \cup S^\ell(Y, Z) \quad // \sqrt{N/C}$
- $R(X, Y) \bowtie S^\ell(Y, Z) \rightarrow P^\ell(X, Y, Z)$
- $P^\ell(X, Y, Z) \bowtie U(W, X) \rightarrow Q^\ell(X, Y, Z, W)$
- $S^h(Y) \bowtie T(Z, W) \rightarrow P^h(Y, Z, W)$
- $P^h(Y, Z, W) \bowtie U(W, X) \rightarrow Q^h(X, Y, Z, W)$

- $h(YZ) \rightarrow h(Y) + h(Z|Y)$
- $h(XY) + h(Z|Y) \rightarrow h(XYZ)$
- $h(XYZ) + h(W|X) \rightarrow h(XYZW)$
- $h(Y) + h(ZW) \rightarrow h(YZW)$
- $h(YZW) + h(X|W) \rightarrow h(XYZW)$

Interest within **Different Communities**

- **Theory & Algorithms**

- Invited *Plenary Talk* at **STOC 2018**
- Invited to JACM
- Invited to TheoretiCS

- **Information Theory**

- AAIT (Algorithmic Aspects of Information Theory) Seminar
- Dagstuhl Seminar 22301

- **DB Systems**

- **ACM SIGMOD 2025 Best Paper Award**
- ACM SIGMOD 2024 *Research Highlight Award*

- **DB Theory**

- ACM PODS 2024 & 2025 *Distinguished Paper Awards*

Practical Impact

[Haozhe Zhang, Christoph Mayer, Mahmoud Abo Khamis, Dan Olteanu, Dan Suci - **SIGMOD 25 Best Paper Award**]

- **Q1:** How accurate is our framework in predicting true output sizes?
 - **Competitors:** a wide range of size estimators
 - Open-source & commercial, ML-based, etc..
 - **Benchmarks:** IMDB JOB, STATS, Subgraph Matching (DBLP)
 - **Accuracy:** Our framework can be **orders of magnitude** more accurate
 - **Resources:** Comparable **low time and space**

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 - **Accuracy:** Our framework can be **orders of magnitude** more accurate
 - **Resources:** Comparable **low time and space**
- **Q2:** How much does a typical optimizer benefit from our size estimator?
 - Postgres produces query plans as good as those based on **true sizes**

Key Takeaways So Far...

- PANDA is a Meta-Algorithm that **automatically generates** algorithms for CQs
- **Recovers or improves** upon known hand-written algorithms
- Rooted in **information theory**
- Has **applications** in DB systems

Research Thread 2

Using **Algebra** to Amplify the Power
of Query Languages & Algorithms

Motivation

Math	PL
Algebraic Abstraction T	Template T
Parameterized Algorithm by T	Templated Library
$\text{Algo}_1 + \text{Algo}_2 + \dots \Rightarrow \text{Algo}<\mathbf{T}>$	$\text{fun}_1 + \text{fun}_2 + \dots \Rightarrow \text{fun}<\mathbf{T}>$
Generalize proofs	Reuse code

Functional Aggregate Queries (**FAQ**)

[M. Abo Khamis, Hung Ngo, Atri Rudra - PODS'16 Best Paper - PODS'26 ToT]

Functional Aggregate Queries (**FAQ**)

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- A *unified query language* that captures many problems across different domains
 - Databases
 - CQs, #CQs, QCQs
 - Linear Algebra
 - Matrix Chain Multiplication
 - Tensor Computations
 - Probabilistic Graphical Models (PGMs)
 - MAP queries
 - CSP
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- A *unified algorithm* for FAQs, called **InsideOut**

FAQ: Before and After

FAQ: Before and After

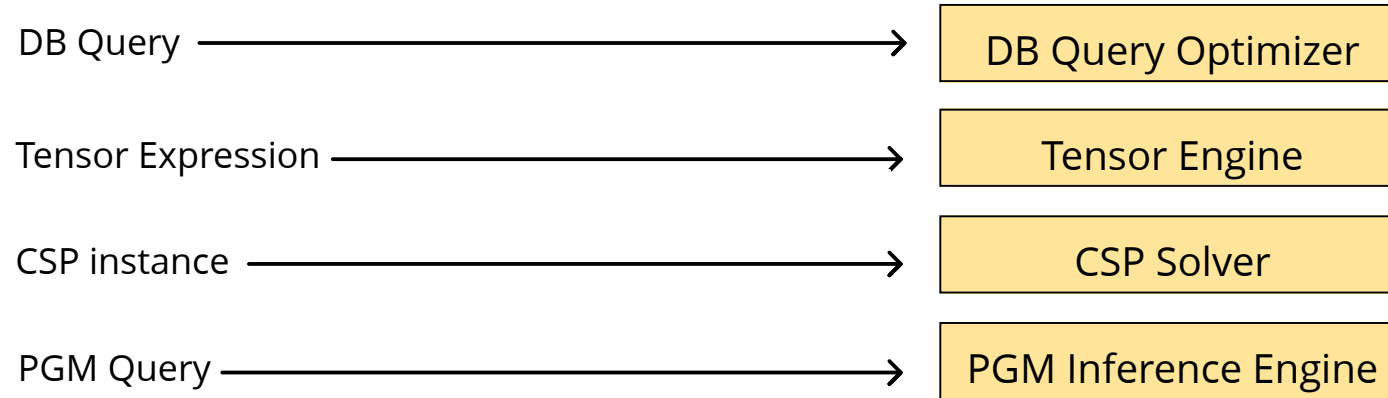
DB Query

Tensor Expression

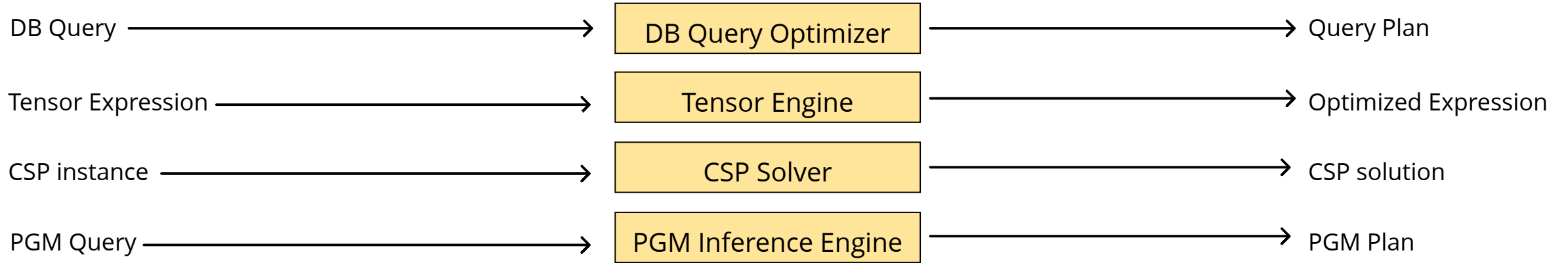
CSP instance

PGM Query

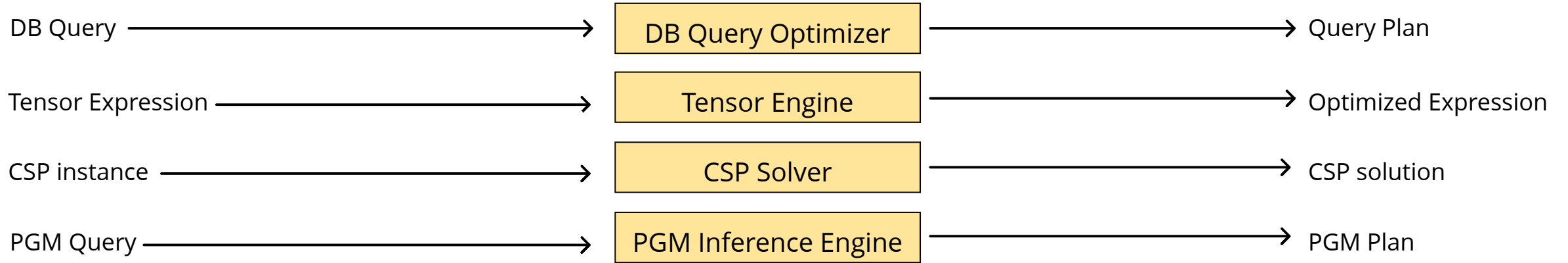
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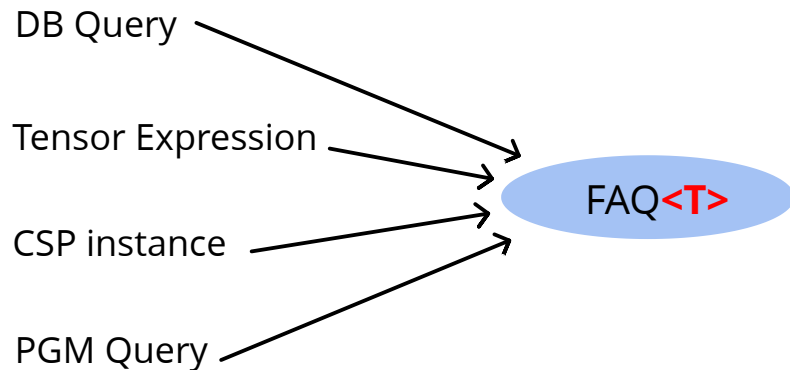
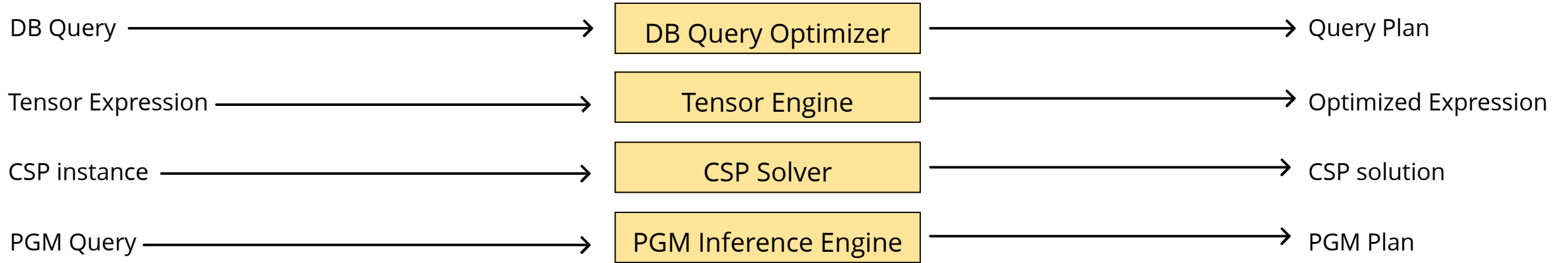
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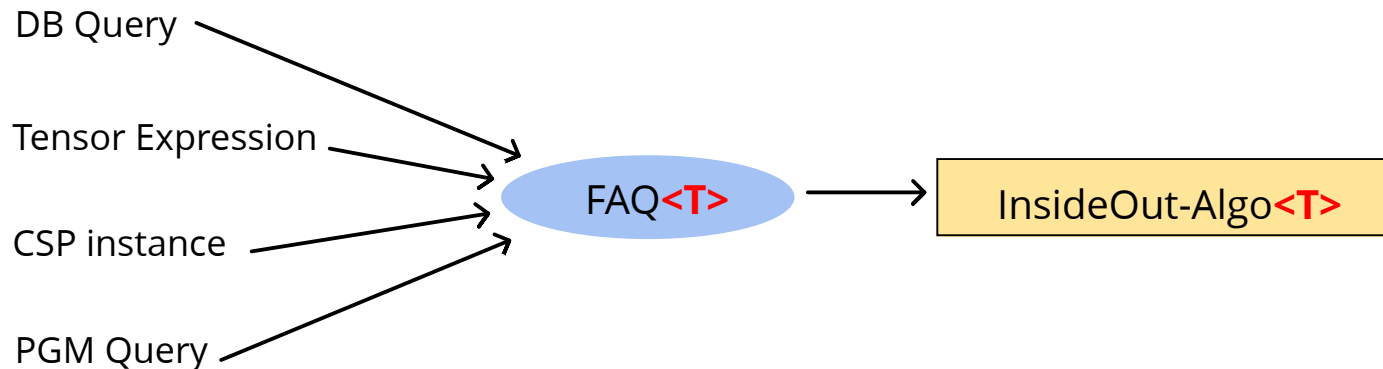
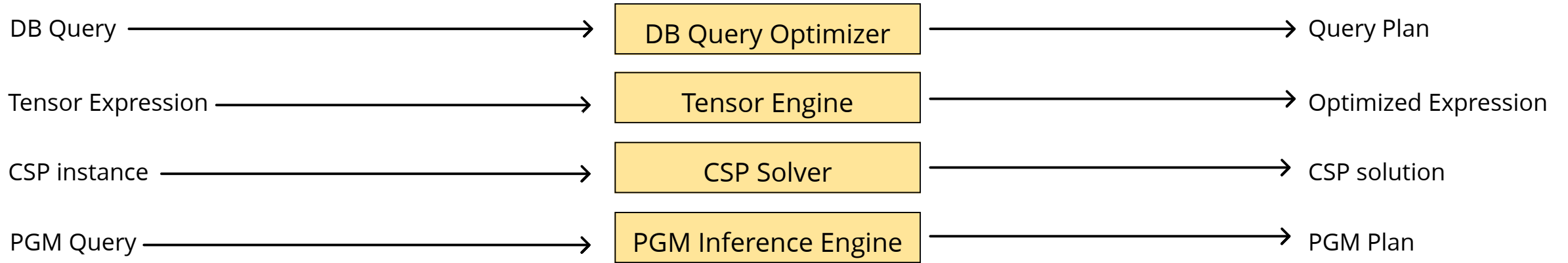
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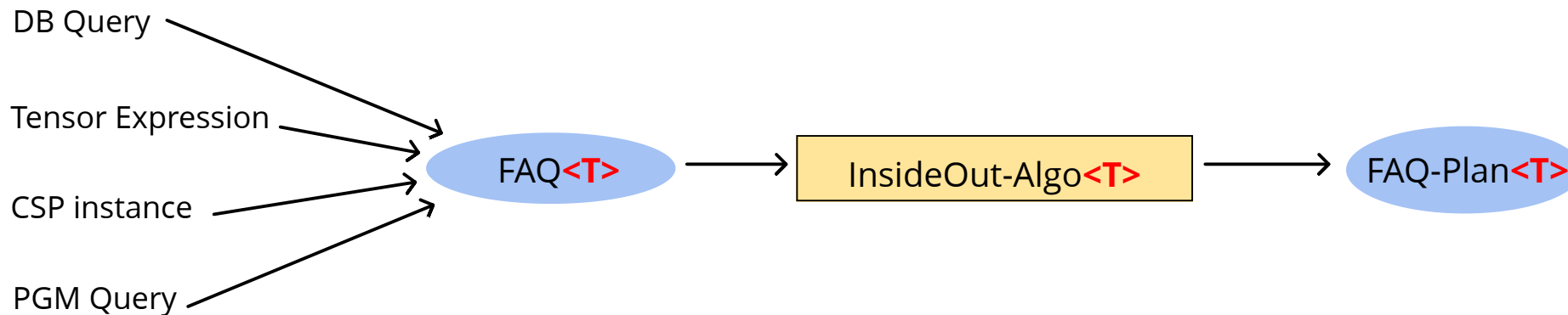
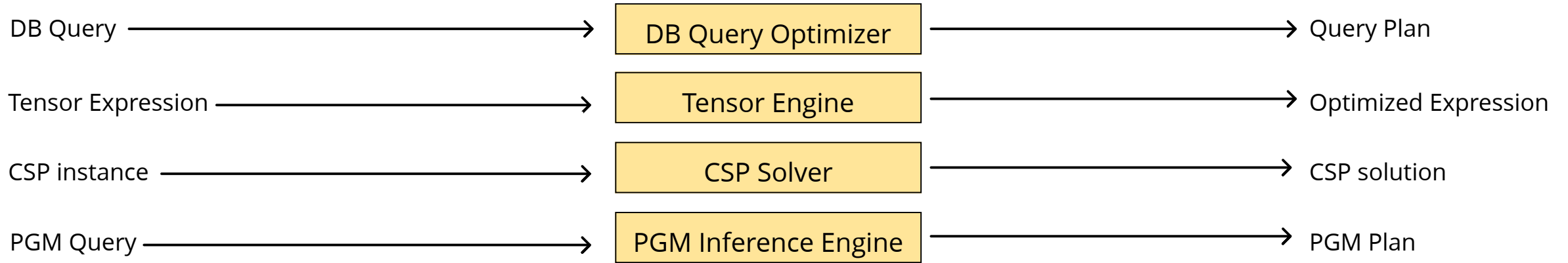
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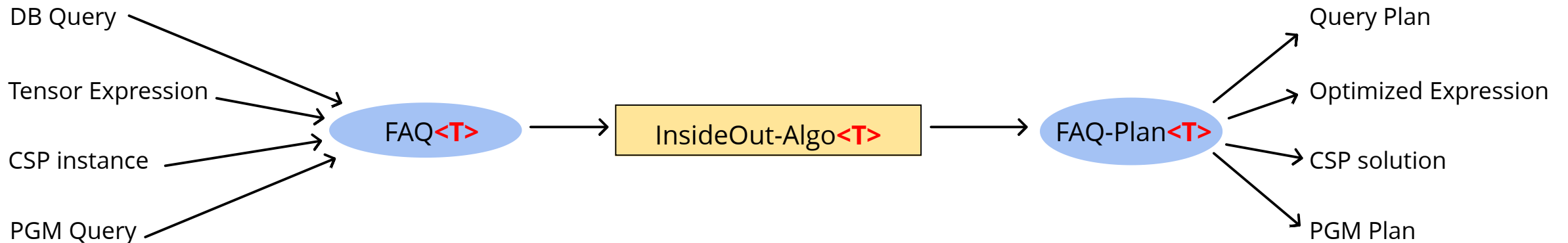
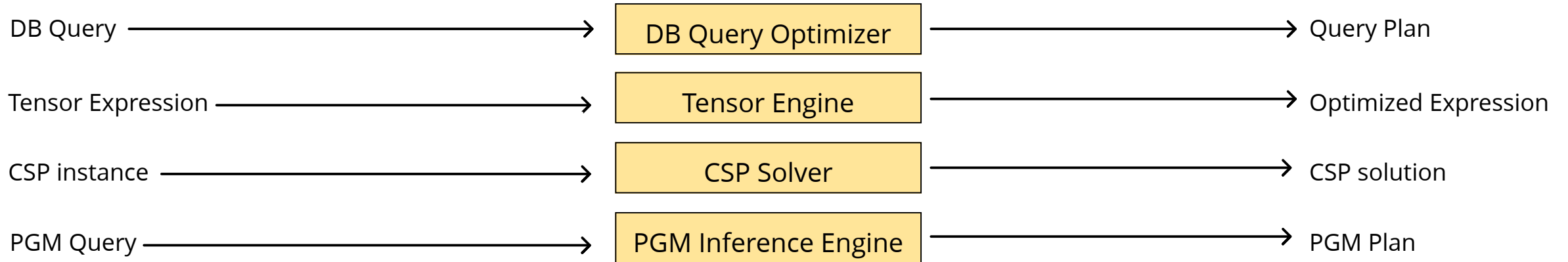
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What is an FAQ?

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 - $Q_3(x, t) = \min_{y,z} W(x, y) + W(y, z) + W(z, t)$ $\mathbf{T} = (\mathbb{R}, \min, +)$

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$$\mathbf{T} = (\mathbb{R}, \min, +)$$

- Matrix Chain Multiplication

- $M[x, t] = \sum_{y,z} M_1[x, y] \times M_2[y, z] \times M_3[z, t]$

$$\mathbf{T} = (\mathbb{R}, +, \times)$$

InsideOut: Variable Elimination on Steroids

$$\varphi(x, t) = \bigoplus_{y, z} \psi_1(x, y) \otimes \psi_2(y, z) \otimes \psi_3(z, t)$$

InsideOut: Variable Elimination on Steroids

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- Eliminate z

$$\blacksquare \varphi(x, t) = \bigoplus_y \psi_1(x, y) \otimes \underbrace{\bigoplus_z \psi_2(y, z) \otimes \psi_3(z, t)}_{\psi_z(y, t)}$$

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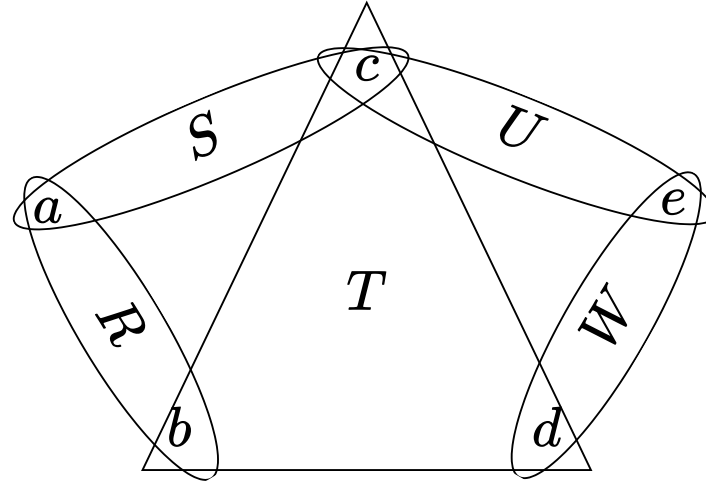
$$\blacksquare \varphi(x, t) = \bigoplus_y \psi_1(x, y) \otimes \psi_z(y, t)$$

- Eliminate y

$$\blacksquare \varphi(x, t) = \underbrace{\bigoplus_y \psi_1(x, y) \otimes \psi_z(y, t)}_{\psi_y(x, t)}$$

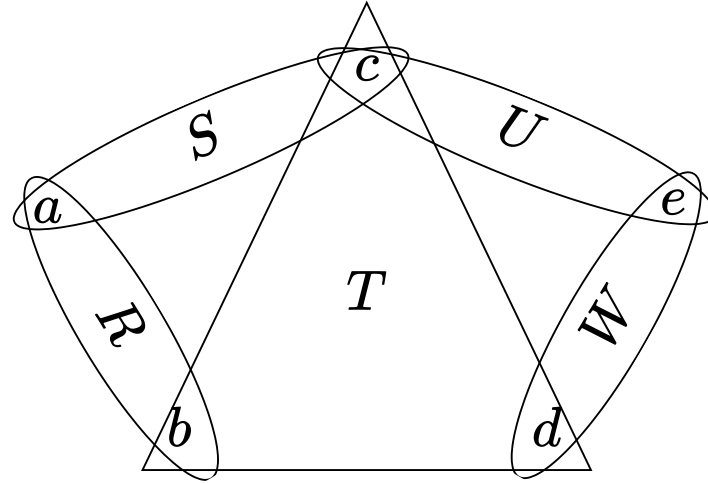
$$\blacksquare \varphi(x, t) = \psi_y(x, t)$$

InsideOut: Variable Elimination on Steroids



$$\varphi(a) = \bigoplus_{b,c,d,e} R(a,b) \otimes S(a,c) \otimes T(b,c,d) \otimes U(c,e) \otimes W(d,e)$$

InsideOut: Variable Elimination on Steroids

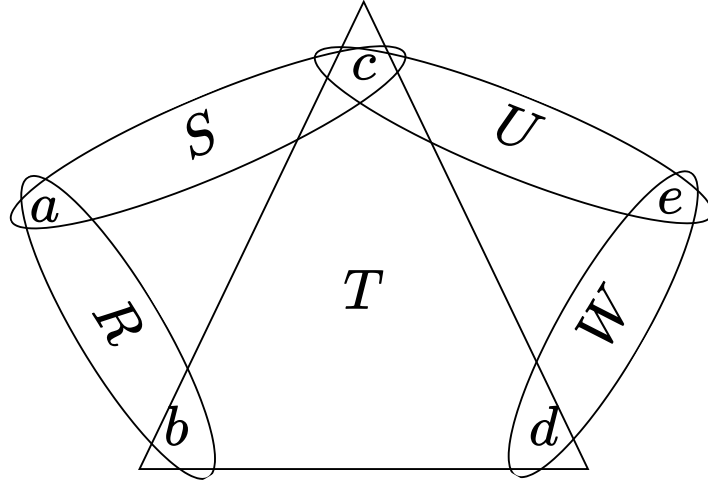


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- Eliminate d

$$= \bigoplus_{b,c,e} R(a,b) \otimes S(a,c) \otimes U(c,e) \otimes \underbrace{\bigoplus_d T(b,c,d) \otimes W(d,e)}_{\substack{\psi_d(b,c,e) \\ O(N^2)}}$$

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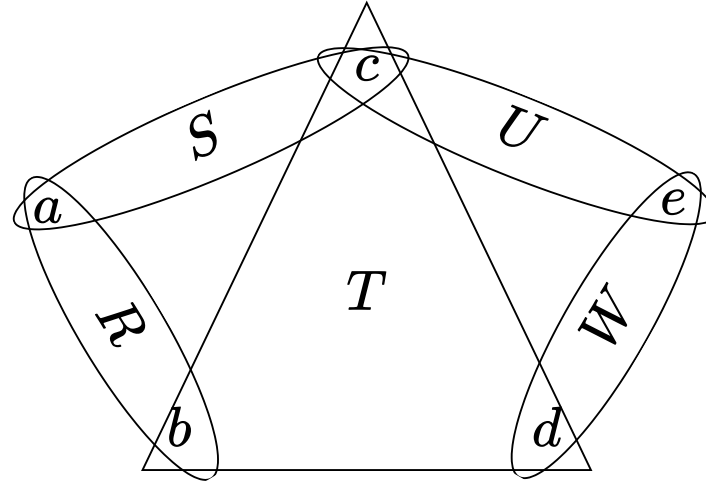


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- Eliminate e **smarter**

$$= \bigoplus_{b,c,d} R(a,b) \otimes S(a,c) \otimes T(b,c,d) \otimes \underbrace{\bigoplus_e U(c,e) \otimes W(d,e)}_{\psi'_e(c,d)} \otimes T'(c,d)$$

$$T'(c,d) := 1_{\exists b : T(b,c,d) \neq 0}$$

$$O(N^{1.5})$$

Practical Impact

- Implemented and **used in production** at
 - [LogicBlox](#)
 - [RelationalAI](#)
- An *essential* part the query optimizer
 - Many real workloads **don't terminate** without it!
 - Breaks down a large query into smaller ones

FAQs are not enough: Enter **Recursion**

Many real-world problems are **circular!**

- Price $\Rightarrow$ Sales $\Rightarrow$ Price...
- ML training: Model1 $\Rightarrow$ Error1 $\Rightarrow$ Model2 $\Rightarrow$ Error2 ...
- LLMs (auto-regression): Token1 $\Rightarrow$ Token2 $\Rightarrow$ Token 3 ...
- **Graphs** (Knowledge Graphs, Social Networks, Semantic Web...)
 - Reachability
 - Shortest Path
 - Pagerank
 - Betweenness Centrality

Datalog^o: FAQs with Recursion

[M. Abo Khamis, Hung Ngo, Reinhard Pichler, Dan Suciu, Remy Wang - **PODS'22 Best Paper** - **JACM'24**]

- Abstract Datalog^o program parameterized by a **semiring**

$$\blacksquare R(X, Y) = E(X, Y) \oplus \bigoplus_Z E(X, Z) \otimes R(Z, Y) \quad (\mathbf{D}, \oplus, \otimes)$$

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$$\blacksquare R(X, Y) = E(X, Y) + \sum_Z E(X, Z) \times R(Z, Y) \quad (\mathbb{N}, +, \times)$$

Recognition of FAQ and Datalog^o

- **Test-of-Time Award** at ACM PODS 2026 (2nd year in a row)
- **Two Best Paper Awards** at ACM PODS 2016 and 2022
- Invitation for a *Plenary Talk* at **STOC 2017** (and again in STOC 2018)
- Two invitations to the **Journal of the ACM** (only one published)
- Two ACM SIGMOD Research Highlight Awards
- Best Dissertation Award at UB 2016

Key Takeaways So Far...

- FAQs are "templated" queries
 - InsideOut is a "templated"-algorithm
 - unifies and generalizes several algorithms in different domains
- Datalog^o are FAQs with Recursion
 - Very expressive
 - But very hard to optimize

Future Directions

Recursion Optimization!

- Recursion is inevitable when modeling problems in the real world
- Yet, we are struggling to automatically generate algorithms for these problems
- because we are struggling to automatically analyze the runtimes of these algorithms

Change is good... if you can keep up!

- Real data is constantly changing, now faster than ever!
- Real-world query evaluation is like shooting a moving target
- Algorithms Community:
 - **Dynamic** Algorithms
- DB Community:
 - **Incremental View Maintenance (IVM)**

Change is good...

if you can keep up!

- State-of-the-art is scattered!
 - Triangle $\Rightarrow O(N^{1/2})$ -updates [\[KNNOZ'20\]](#)
 - 4-path $\Rightarrow O(N^{1/2})$ -updates [\[HHH'22\]](#)
 - 4-cycle
 - Combinatorial: $O(N^{2/3})$ -updates [\[HHH'22\]](#)
 - Non-combinatorial: $O(N^{2/3-\epsilon})$ [\[AS'25\]](#)
 - ...
- Is there a **dynamic** Meta-algorithm?

Conclusion

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- A Query Optimizer is a Meta-Algorithm: Any problem $\Rightarrow$ Algorithm
- Perfect opportunities for cross-community collaboration
 - **Algorithms/Theory**
 - **DB Systems**
 - **DB Theory**

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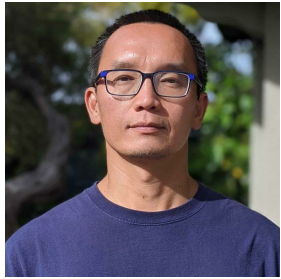
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 - Brings the **bridge**, but needs to **keep up!**

Thank You All!



Hung Ngo



Dan Suciu



Xiao Hu



Dan Olteanu



Chris Mayor



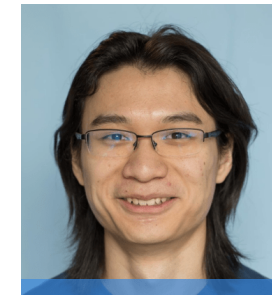
Haozhe Zhang



Atri Rudra



Reinhard Pichler



Remy Wang



Molham Aref

and many more!

Appendix

Appendix A:

PANDA

Appendix B:

FAQ

FAQ<T>: The underlying structure T

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- **T** is a commutative semiring (or multiple semirings)
 - **T** = (*D*, $\oplus$, $\otimes$)
 - Distributive Property:
 - $a \otimes (b \oplus c) = (a \otimes b) \oplus (a \otimes c)$

FAQ<T>: The underlying structure **T**

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 - **T** = (**D**, $\oplus$, $\otimes$)
 - Distributive Property:
 - $a \otimes (b \oplus c) = (a \otimes b) \oplus (a \otimes c)$
- Examples
 - Boolean: ($\mathbb{B}$, $\vee$, $\wedge$)
 - Tropical: ($\mathbb{R} \cup \{\infty\}$, **min**, $+$)
 - Numeric: ($\mathbb{R}$, $+$, $\times$)

Appendix C:

Datalog^o

Datalog^o: Datalog with Semirings

[M. Abo Khamis, Hung Ngo, Reinhard Pichler, Dan Suciu, Remy Wang - PODS'22 Best Paper - JACM'24]

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Terminates *always*!

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Datalog^o: Datalog with Semirings

[M. Abo Khamis, Hung Ngo, Reinhard Pichler, Dan Suciu, Remy Wang - PODS'22 Best Paper - JACM'24]

- Abstract Datalog^o program parameterized by a semiring

$$\blacksquare R(X, Y) = E(X, Y) \oplus \bigoplus_Z E(X, Z) \otimes R(Z, Y) \quad (\mathbf{D}, \oplus, \otimes)$$

- Transitive Closure

$$\blacksquare R(X, Y) = E(X, Y) \vee E(X, Z) \wedge R(Z, Y) \quad (\mathbb{B}, \vee, \wedge)$$

Terminates *always*!

- Shortest Paths

$$\blacksquare R(X, Y) = \min(E(X, Y), \min_Z(E(X, Z) + R(Z, Y))) \quad (\mathbb{R}, \min, +)$$

Terminates *only* on $\mathbb{R}_+$

- Number of Paths

$$\blacksquare R(X, Y) = E(X, Y) + \sum_Z E(X, Z) \times R(Z, Y) \quad (\mathbb{N}, +, \times)$$

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- **Q2:** How do we "fix" non-terminating programs?

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- **Hint:** *p-stability* of the semiring $(D, \oplus, \otimes)$
 - $(D, \oplus, \otimes)$ is *p-stable*:

$$\circ \mathbf{1} \oplus a^1 \oplus a^2 \oplus \dots \oplus a^p = \mathbf{1} \oplus a^1 \oplus a^2 \oplus \dots \oplus a^{p+1}$$

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- Examples

- $(\mathbb{B}, \vee, \wedge)$ is 0-stable:

$$\text{true} = \text{true} \vee a$$

- $(\mathbb{R}_+, \min, +)$ is 0-stable:

$$0 = \min(0, a) \quad \forall a \in \mathbb{R}_+$$

- $(\mathbb{R}, \min, +)$ is NOT *p-stable*

$$0 \neq \min(0, a) \quad \forall a \in \mathbb{R}$$

- $(\mathbb{N}, +, \times)$ is NOT *p-stable*

$$1 \neq 1 + a \quad \forall a \in \mathbb{N}$$

- "*Lifted*" $(\mathbb{N} \cup \{\perp\}, +, \times)$ is 0-stable

$$\perp + a = \perp, \quad \perp \times a = \perp$$

Termination from the Lens of p -stability

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(cycles produce $\perp$)

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Appendix D: Future Directions

Output-Sensitive Meta-Algorithm?

- Runtime in terms of N and **output size OUT**

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- State-of-the-art is *very* scattered!
 - 2-path: $O(N \cdot \text{OUT}^{0.3454} + \text{OUT} + N^{0.8} \cdot \text{OUT}^{0.5436})$ [ABFK'24]
 - Triangle: $O(N^{1.408} + N^{1.222} \cdot \text{OUT}^{0.186})$ [BPWZ'14]
 - Acyclic: $O(N^{0.372} \cdot \text{OUT} + N \cdot \text{OUT}^{0.871})$ [H'24]
 - ...

Datalog^o Analogues of Datalog Problems

- **Data Repair**

- Datalog:

- Add a minimum number of edges to a graph to ensure **reachability**

- Datalog^o:

- Change the weights of edges of a graph to meet certain constraints on **shortest paths**

- **Analyze #Iterations**