# A Worst-Case Optimal Multi-Round Algorithm for Parallel Computation of Conjunctive Queries

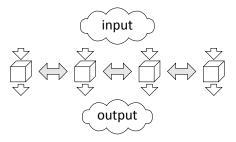
Bas Ketsman & Dan Suciu

## Topic of the Talk

How to compute multi-joins (over graphs) ...

$$(x, y, z) \leftarrow R(x, y), S(y, z), T(z, x)$$

... in a multi-round shared nothing cluster setting ...



... with communication cost that is worst-case optimal?

Worst-case optimality:

• **Output size:** AGM bound [Atserias, Grohe & Marx 08] query output =  $m^{\rho^*}$ .

Lower-bound on worst-case running-time

Optimal sequential algorithms: (w.r.t running-time)

Leapfrog-trie-join, NPRR, Generic Join

# Introduction (2)

Worst-case optimal communication cost:

- Load = maximal amount of messages received by any server in any communication round
- Lowerbound

load  $\geq \frac{m}{p^{1/\rho^*}}$ . [Koutris, Beame & Suciu 16]

 Optimal parallel algorithms: (w.r.t communication cost) [Koutris, Beame & Suciu 16]

Ad-hoc algorithms for chains, stars, simple cycles

## Main Result

A parallel algorithm exists for computing join queries over graphs using only a constant number of rounds and

 $\mathsf{load} \leq \tilde{\mathcal{O}}(\textit{m}/\textit{p}^{1/\rho^*}).$ 

## Query/schema restrictions:

- Arity at most two
- No projections
- No self-joins

## **Essentially optimal:**

- Up to a poly-log factor
- Data-complexity

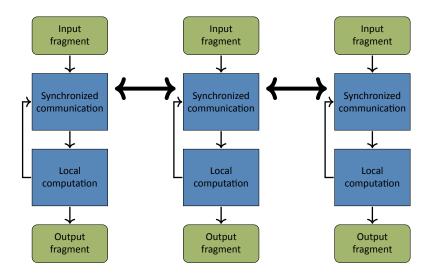
## The Model

Lowerbound and Hypercube ( $ho^*$  and  $au^*$ )

Main Result by Example

Summary & Future Work

# Massively Parallel Communication Model: [Koutris, Suciu 2011]



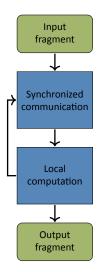
## The Model

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# Lower-Bound [Koutris, Beame, Suciu 2016]



For a constant-round algorithm to be correct for given query on every instance

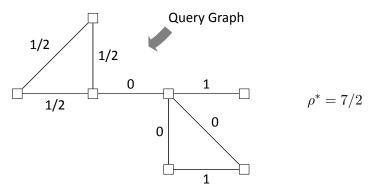
worst-case load is  $\geq rac{m}{p^{1/
ho^*}}$ 

(assuming equi-sized relations)

Through AGM bound

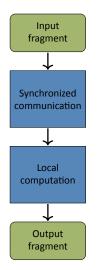
# $\rho^*$ = Fractional Edge Covering Number

 $R_1(x, y), R_2(y, z), R_3(z, x), R_4(z, u), R_5(u, w), T_6(u, t), T_7(t, s), T_8(s, u)$ 



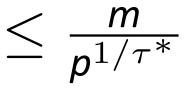
- Objective function: Assign a positive weight to every edge
- ► Constraint: Every vertex incident to sum of weights ≥ 1
- Optimization goal: Minimize total sum of assigned weights

# Hypercube (= shares algorithm)



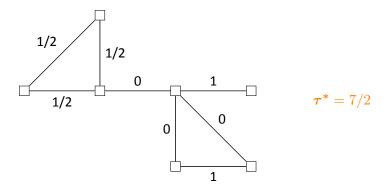
## = Single-round hash-join algorithm Introduced by [Afrati, Ullman, 2010]

## If database has no skew, runs with load:



(w.h.p. and ignoring poly-log factor) [Beame, Koutris, Suciu 2013]

# $au^*$ = Fractional Edge Packing Number



- Objective function: Assign a positive weight to every edge
- ► Constraint: Every vertex incident to sum of weights ≤ 1
- Optimization goal: Maximize total sum of assigned weights

**Solution is tight** if satisfies = rather than  $\leq$  or  $\geq$ .

For general hypergraphs: No clear relation between  $\tau^*$  and  $\rho^*$ !

#### For simple graphs:

- Optimal half-integral fractional edge packings exist (using only weights 1, 1/2 and 0)
- ►  $\tau^* \leq \frac{|vars(Q)|}{2} \leq \rho^*$  (assign weights 1/2 to all vertices)

$$\blacktriangleright \ \tau^* + \rho^* = |\mathsf{vars}(\mathcal{Q})|$$

## The Model

Lowerbound and Hypercube ( $ho^*$  and  $au^*$ )

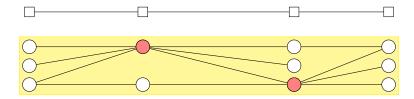
Main Result by Example

Summary & Future Work

## **Heavy-Hitter Configurations**

## **Example Query:**

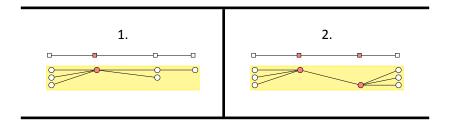
$$(\mathbf{x}, \mathbf{y}, \mathbf{z}) \leftarrow \mathbf{R}_1(\mathbf{x}, \mathbf{y}), \mathbf{R}_2(\mathbf{y}, \mathbf{z}), \mathbf{R}_3(\mathbf{z}, \mathbf{u})$$



**Heavy-hitter**: value with degree  $> \delta$  (in some direction)

Skew: some heavy-hitter exists

**Heavy-hitter configuration**  $(\delta, H)$ : A skew threshold value  $\delta$  + labeling of query variables with "heavy" (H) or "light" (others).



**Matching instance**  $I_{(\delta,H)}$  = induced subinstance where heavy variables have only the heavy values, light variables only the light values.

## **Evaluation strategy:**

Compute Q in parallel over all instances  $I_{(\delta, H)}$  using the same p servers.

For Fixed  $\delta$ :

Claim: 
$$\bigcup_{H \subseteq vars(Q)} Q(I|_{(\delta,H)}) = Q(I).$$

As the number of configurations depends on Q, maximal load  $\leq \max_{H} \{ \max \text{ maximal load to compute } Q \text{ on } I_{(\delta,H)} \}.$ 

(ignoring constants)

## Preprocessing:

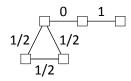
 Identify where skew is Heavy-hitters and degrees of heavy-hitters.

## Algorithm:

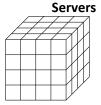
- 1. Break skewed instance in understandable pieces
- 2. Divide and Conquer strategy to deal with skew
- 3. Solve remaining (skew-free) problem with Hypercube

# The Algorithm by Example

## **Example query**

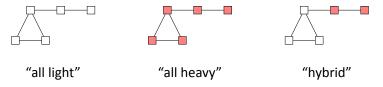


$$\bullet \ \tau^* = \rho^* = |\mathsf{vars}(\mathcal{Q})|/2$$



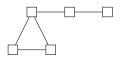
Threshold value: 
$$\delta = \frac{m}{p^{1/|\text{vars}(\mathcal{Q})|}}$$

## Do computation for each heavy-hitter configuration in parallel



# The Algorithm by Example: "All light"





## Use the Hypercube algorithm

- Due to tightness:  $\tau^* = \rho^* = |\text{vars}(\mathcal{Q})|/2$
- ► non skewed means: degree  $\leq \delta = \frac{m}{p^{1/|vars(Q)|}} = \frac{m}{p^{1/(2\tau^*)}}$
- Hypercube ensures load  $\leq \frac{m}{p^{1/\tau^*}} = \frac{m}{p^{1/\rho^*}}$ .

# The Algorithm by Example: "All heavy"



#### **Broadcast all relations**

- A value is heavy if degree  $> \delta = \frac{m}{p^{1/|vars(Q)|}}$ .
- An heavy attribute has  $\leq p^{1/|vars(Q)|}$  heavy values.
- ► A heavy relation has  $\leq p^{2/|vars(Q)|}$  heavy tuples.
- ► Every server receives at most  $p^{2/|vars(Q)|}$  tuples.

► 
$$p^{2/|\operatorname{vars}(\mathcal{Q})|} \leq \frac{m}{p^{2/|\operatorname{vars}(\mathcal{Q})|}} = \frac{m}{p^{1/p^*}}$$
 due to  $m \geq p^2$ .

(ignoring the constants)

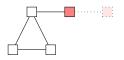
# The Algorithm by Example: "Hybrid"



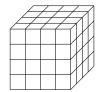
## Step 1: Broadcast heavy relation

• As before: load  $\leq \frac{m}{p^{1/\rho^*}}$  due to  $m \geq p^2$ .

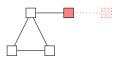
**Refocus:** 



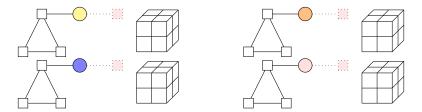
► Solution can be easily extended.



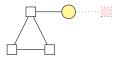




## Step 2: Assign group of servers to every heavy value



## Combination of outputs = complete output



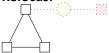


 size of group p' = p<sup>(|vars(Q)|-1)/|vars(Q)|</sup> (because ≤ p<sup>1/|vars(Q)|</sup> heavy values)

Step 3: Semi-join reduce involved relations

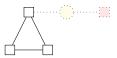
 reductions are cheap: 2 rounds and load ≤ m/p' ≤ m/p<sup>1/ρ\*</sup> (because we have > 2 light variables)

## Refocus:





 Output for simpler query can be translated to output for original query by simply adding to every tuple the locally known heavy value





## Step 4: Hypercube

- ► degrees  $\leq \frac{m}{p^{1/|\text{vars}(\mathcal{Q})|}} = \frac{m}{p'^{1/(|\text{vars}(\mathcal{Q})|-1)}} \leq \frac{m}{p'^{1/|\text{vars}(\mathcal{Q}')|}} = \frac{m}{p'^{1/(2\tau^*(\mathcal{Q}'))}}$
- ► Hypercube guarantees load  $\leq \frac{m}{p^{1/\rho^*(Q')}} \leq \frac{m}{p^{1/\rho^*(Q)}}$

#### done

## Sometimes more complex: algorithm uses up to 9 rounds

## The Model

Lowerbound and Hypercube ( $ho^*$  and  $au^*$ )

Main Result by Example

Summary & Future Work

Every conjunctive query without self-joins, that is full, over relations with arities at most two can be computed in 9 rounds with load  $\leq \tilde{\mathcal{O}}(\frac{m}{\rho^{1/\rho^*}})$ .

## **Essentialy optimal**

 $\rho^*$  seems the right way to express optimality for the communication cost of distributed query evaluation algorithms, at least when relation arities do not exceed two.

# Does an algorithm exist with worst-case optimal load $m/p^{1/p^*}$ for queries over relations with arbitrary-arities?

- ► relation between edge cover / packing unclear in general
- half-integral edge cover/packing does not always exist
- queries exist where  $\tau^* > \rho^*$

 $R_1(x_1, y_1, z_1), R_2(x_2, y_2, z_2), S_1(x_1, x_2), S_2(y_1, y_2), S_3(z_1, z_2).$ 

 $\Rightarrow$  Hypercube cannot be used even when there is no skew

# Is $m/p^{1/\rho^*}$ a tight lower bound for joins over arbitrary-arity relations?

Are the 9 rounds essential?

## What if queries have existential quantification (projections)?

What if the database has dependencies?

Thank you!