Deep and Collective Entity Resolution in Parallel

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Deep and Collective Entity resolution (ER)

- Identify whether two tuples in a dataset refer to the same real-world entity
- It has been a longstanding challenge to improve the accuracy of ER

Deep and collective ER by unifying logic rules and ML models

Deep ER (Recursion)		*Collective ER*		*Unifying Logic and ML*
Identify new matches by *making use of matches deduced earlier*	+	Collectively correlate information *across multiple tables*	+	Benefit from both and improve the accuracy by *unifying the two methods*

Matching Rules with mL (MRLs)

MRL φ: $X \longrightarrow l$

Precondition X:
A conjunction of *predicates* over a database schema $\mathcal{R}$
$p ::= R(t) \mid t.A = c \mid t.A = s.B \mid \mathcal{M}(t[\bar{A}], s[\bar{B}])$

Consequence l:
An *id predicate* t.id$=s$.id or
an *ML predicate* $\mathcal{M}(t[\bar{A}], s[\bar{B}])$.

- Extend matching dependencies by embedding with *well-trained ML classifiers* as ML predicates
- t.id $= s$. id : the entities represented by t and s match, then refer to the same entity

Deep and Collective ER

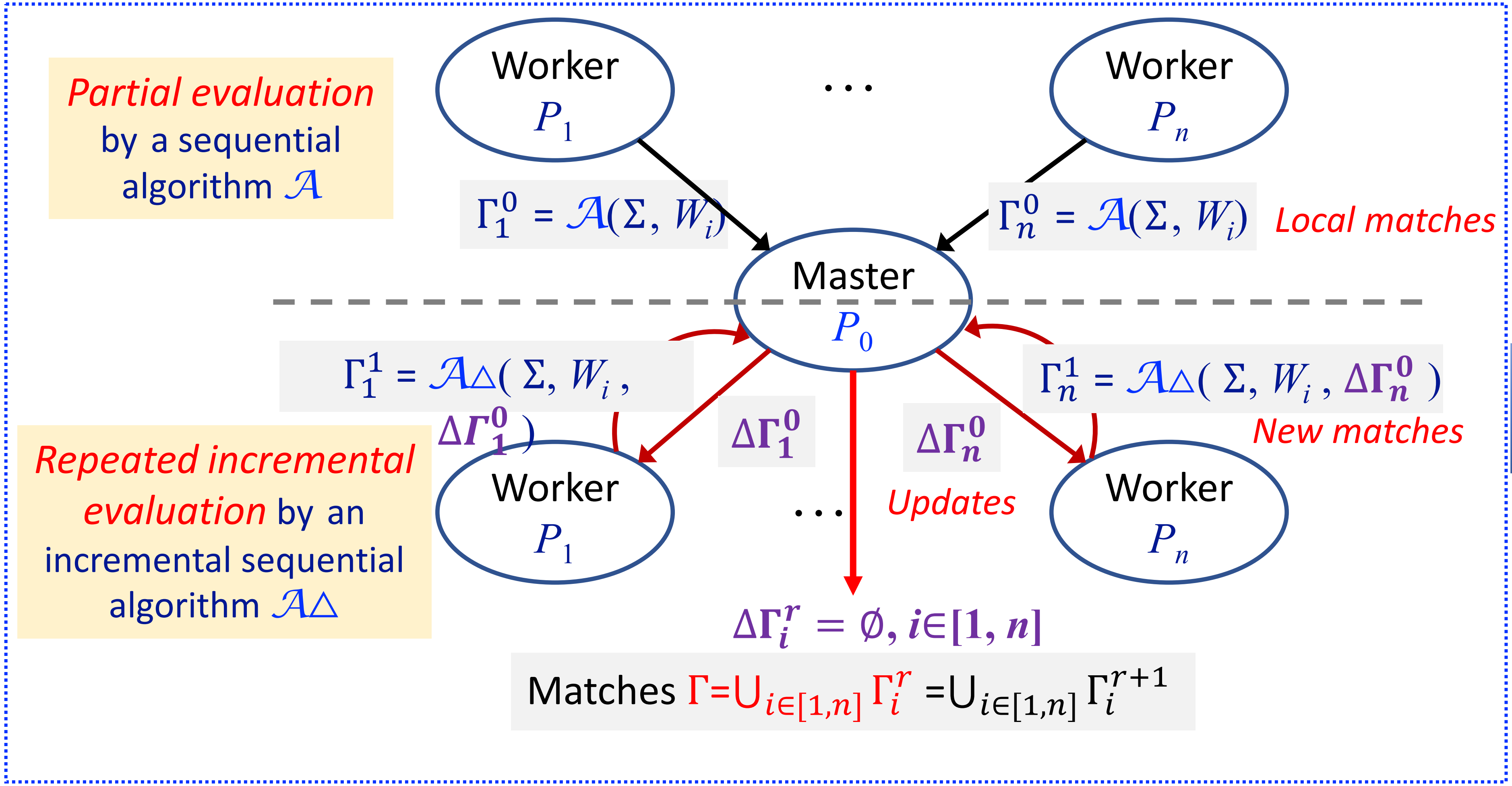
- Deduces a set Γ of *matches and validated ML predications* by applying MRLs in Σ
- Modeled as an extension of the *chase* with MRLs, with the *Church-Rosser* property

Decision problem	*Number of relations*	*id predicates* in the Prec.	
Deep and Collective ER	*Unbounded*	Yes	*NP-complete*
Collective ER (*not* Deep)	*Unbounded*	No	*NP-complete*
Deep ER (*not* collective)	Fixed	Yes	PTIME

Parallel fixpoint model

Updated-driven Parallel fixpoint model under BSP model

Partitioned dataset $\mathcal{D}= (W_1, \ldots, W_n)$, distributed to workers $P_1, \ldots, P_n$



Data partitioning strategy

Parallel deduction algorithm

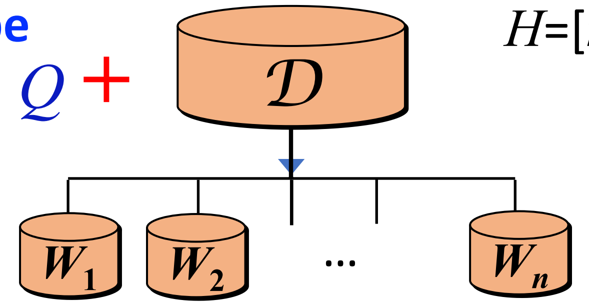
Update-driven fixpoint computation: no communication of raw data

Data partitioning for parallel fixpoint computation

Extend Hypercube (HC) to handle a set of MRLs with *multiple query optimization* (*MQO*)

Hypercube

Q +



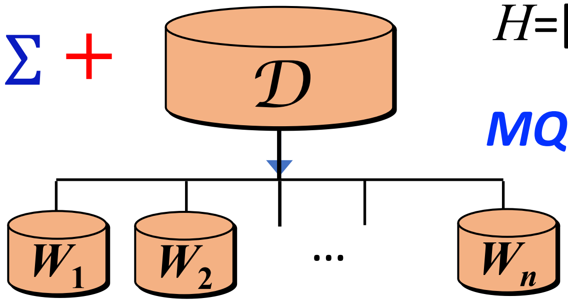
$H=[n_1]\times\cdots\times[n_l]$

A CQ query Q can be answered *locally*

$Q(\mathcal{D})=\bigcup_{i\in[1,n]} Q(W_i)$

HyPart

Σ +



$H=[n_1]\times\cdots\times[n_l]$

MQO

$\mathcal{D}\models\Sigma$ *can be verified locally*

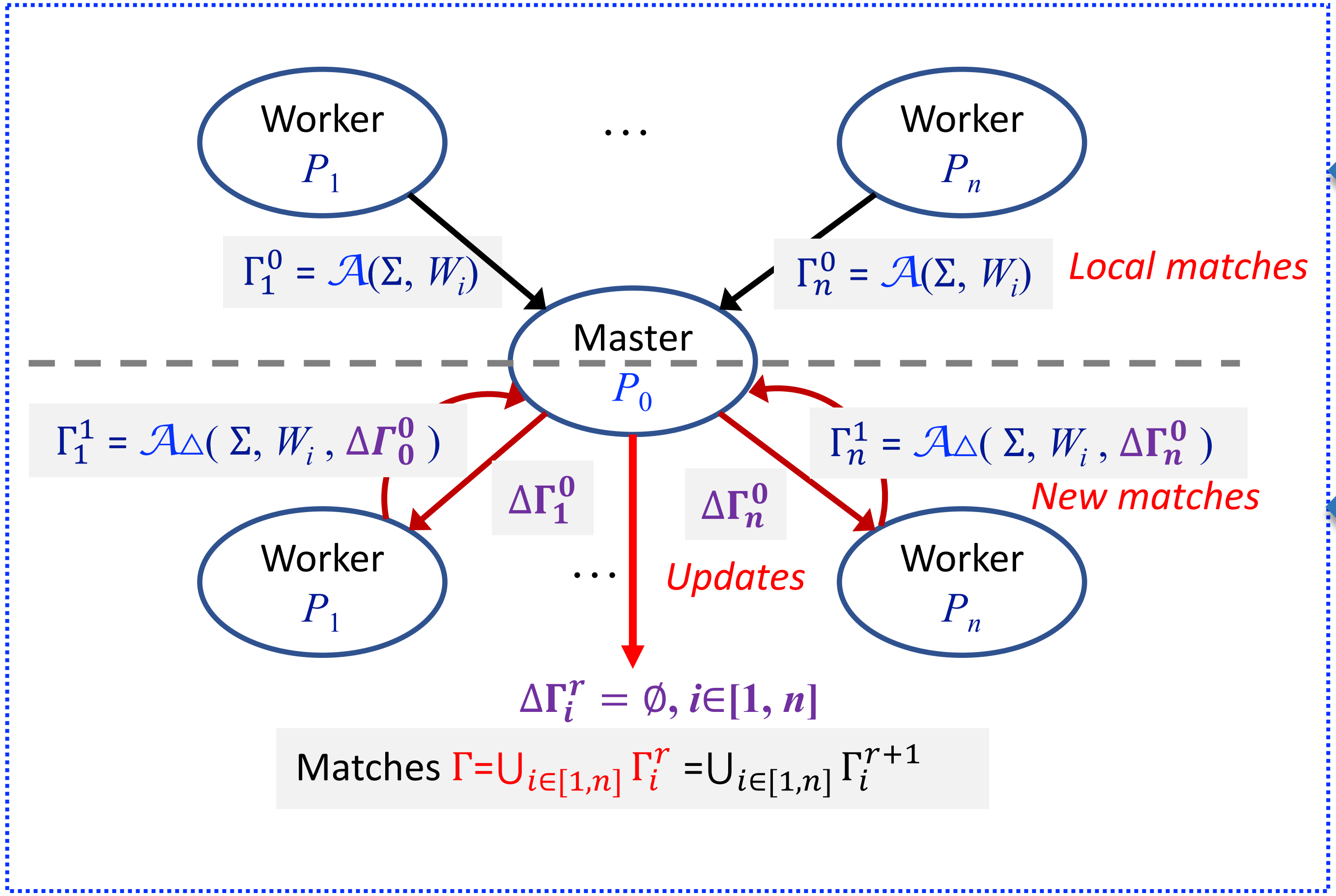
$\mathcal{D}\models\Sigma$ iff $W_i\models\Sigma$, $i\in[1,n]$

- Partition the data with the *minimum hash function computation* (*NP-complete*)

An *heuristic partitioning algorithm* HyPart */A strategy to assign the hash functions*

Reduce the *computation* cost	Reduce the *communication* cost	Improve the performance
Reuse the hash function computations as much as possible	Send a tuple with the same hash functions *to the same worker* for different rules	Using *MQO* to *find the common predicates* of MRLs

A Parallel scalable deduction algorithm



Partial evaluation by Deduce ($\mathcal{A}$)

Deducing matching in Γ *for each MRL and each of its valuations*

Repeated incremental evaluation by IncDeduce ($\mathcal{A}\triangle$)

Incrementally expand Γ by using an *update-driven* strategy

Optimization to speed up the process

Avoid to store all intermediate results and *reduce the repeated valuations*

Parallelly scalable: the more processors are used, the faster the algorithms run

Experimental results

- Using *five real-life Datasets* and synthetic datasets, compared with *eight state-of-the-art* baselines

Accuracy

- ***23% and 38% more accurate*** than ML and logical methods for ER, resp.
- outperforms deep ER and collective ER by 21% and 32%, resp.

Efficiency

- ***505s on datasets of 30M tuples*** using 16 machines.
- faster than 7 out of 8 state-of-the-art ER baselines.

Scalability

- ***Parallelly scalable*** with the number n of processors used: 3.56 times faster when n increases from 4 to 32

Models and Algorithms for Deep and Collective ER by unifying logic and ML