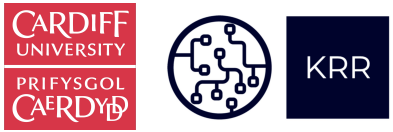
ASPEN: ASP-Based System for Collective Entity Resolution

Zhiliang (Leon) Xiang, Meghyn Bienvenu, Gianluca Cima,
Víctor Gutiérrez Basulto, Yazmín Ibáñez-García



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Background

Entity Resolution (ER)

- **Entity resolution (ER):** identify **different constants** denoting **the same thing**

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- **Central task** in **data quality**, **long-standing challenge**

  erroneous/missing values, syntactic variants

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  Example 1: medical database

  J. Smith is allergic to *ibuprofen*, ***John Smith*** is allergic to *aspirin*

  Example 2: bibliographical database

  Zhiliang Xiang has a paper in *KR*, ***Zhiliang Xiang*** has a paper in *Politics*

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Entity Resolution (ER)

In **database (DB) context**, many approaches: **ML**, **probabilistic**, **logic**

A recent ER framework: LACE

A Logical Approach to Collective Entity Resolution

[Bienvenu et al. PODs 2022, KR&IJCAI 2023]

- **declarative:** logical **rules** and **constraints**
- **collective: interdependencies**, *doctor* merges trigger hospital merges, vice versa
- **explainable**: "**why** are *J. Smith* and *John Smith* deemed to be the **same** patient?"

LACE specification

Album

id	artist	title	barcode
ab1	a3	Born to Die	22334455
ab2	a2	Born to DIe (de)	
ab3	a1	Born to DIE	22334455
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Artist

id	name	born year
a1	Lana Del Rey	21/6/1985
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A **LACE specification Σ** over **database D** takes the form **(*H* , *S* , *C*)**

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H: hard rules indicate **mandatory** merges

- $Album(x,a,t,\mathbf{b}) \wedge Album(y,a',t',\mathbf{b}) \wedge \mathbf{t \approx t'} \Rightarrow Eq(x,y)$

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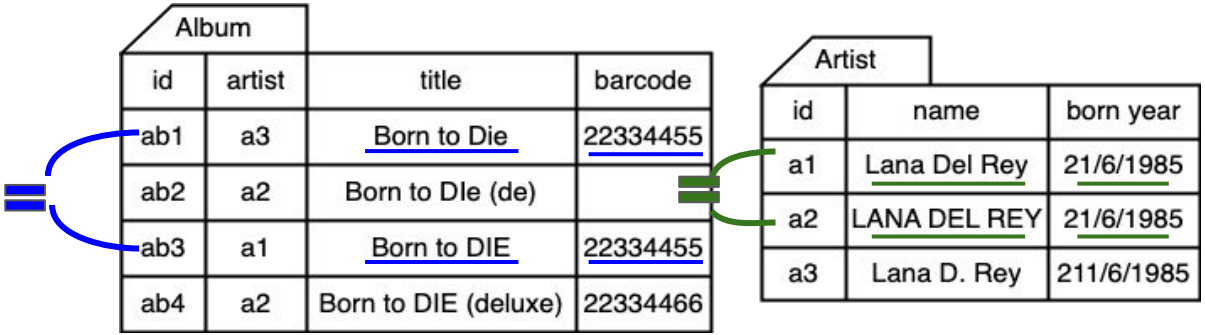

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- *Album(x,a,t,**b**) ∧ Album(y,a',t',**b**) ∧ **t≈t' =>** Eq(x,y)*

S: soft rules indicate **likely** merges

- *Artist(x,n,**b**) ∧ Artist(y,n',**b**) ∧ **n≈n' ~>** Eq(x,y)*
- *Album(x,**a**,t,b) ∧ Album(y,**a**,t',b') ∧ **t≈t' ~>** Eq(x,y)*

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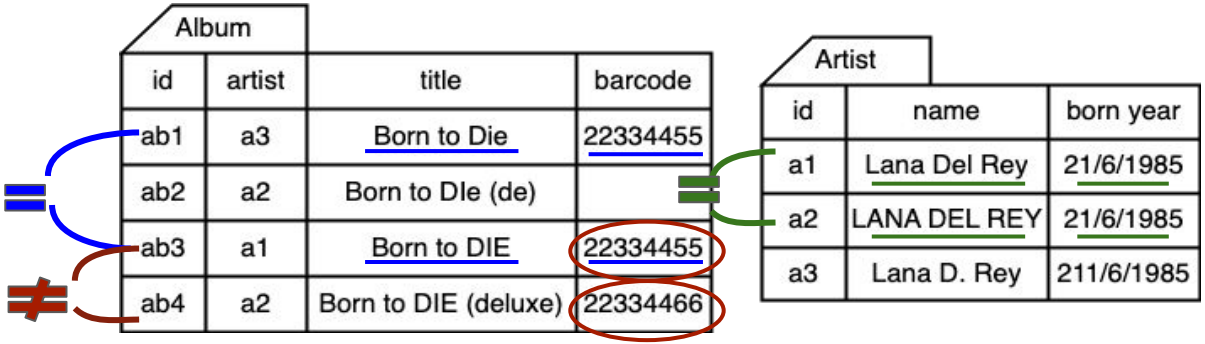

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- $Album(x,\mathbf{a},t,b) \wedge Album(y,\mathbf{a},t',b') \wedge \mathbf{t \approx t'} \rightsquigarrow Eq(x,y)$

C: constraints enforce **consistency**: $Album(\mathbf{x},a,t,\mathbf{b}) \wedge Album(\mathbf{x},a',t',\mathbf{b'}) \wedge \mathbf{b \neq b'} \Rightarrow \bot$

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- ***Eq/2*** is **reflexive**, **symmetric** and **transitive**, induce ***equivalence relation E***
  - Evaluate rule bodies on **induced database D_E**
  - Construct **step-by-step**
  - **Solution** for *(D,Σ)* is an **equivalence relation *E*** *(over constants in D)*, s.t. **D_E satisfies H and C**

Multiple solutions -> focus on the best ones, (**set-inclusion**) **maximal solution**

Computational problems in LACE

Main decision problems:

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Goal: develop ASP-based system as implementation

ASP-Based System to ER

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- **Similarity atom** expanded with an **extra argument** denoting **threshold**

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{eq(X,Y)}:- album(X,A,T,B), album(Y,A',T',B'), eq(A,A'), ***sim(T,T',S), S>=90****.*

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- Axiomatise ***eq*/2**:

Reflexivity: *eq(X,X) :- album(X,A,T,B).* **Symmetry:** *eq(X,Y) :- eq(Y,X).*

Transitivity: *eq(X,Y):- eq(X,Z), eq(Z,Y).*

Reasoning using ASP Encoding

Use the **ASP encoding** of a LACE specification (***H*** **,** ***S*** **,** ***C***), we can:

- Test **solution existence**, **generate one** or **more** if exist
- Generate **maximal solution** (s) with **set preference**
- Compute **possible merges** with brave reasoning
- Compute **certain merges**?

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  - Meta programming *[Gebser et al, TPLP'2011]*
  - WASP *[Alviano et al, AIJ'2023]*

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- Compute **possible/certain merges** (brave reasoning/?)

Transform **ASP encoding** to compute **approximate** set of **certain**/**possible** merges

Π_2^p-c NP-c

- **Lower bound (LB):** drop ***S*** and ***C***
- **Upper bound (UB)**: drop ***C***, “harden” ***S***

polynomial, with **unique** stable model!

Important ingredient: similarity facts

- **Not present** in **database**
- **Similarity measure**: call an external **scoring** function (e.g. edit distance) to compare constants and apply **threshold**
- **Naive**: score **all pair** of constants (quadratic), **infeasible** as data scales up

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Similarity computation

Observation:

E.g. *eq(X,Y):- album(X,**A**,T,B), album(Y,**A'**,T',B'), **eq(A,A')**, **sim(T,T',S), S>=90**.*

only need to compare similarity of ***titles*** of those albums have the **same artist**.

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Intuition:

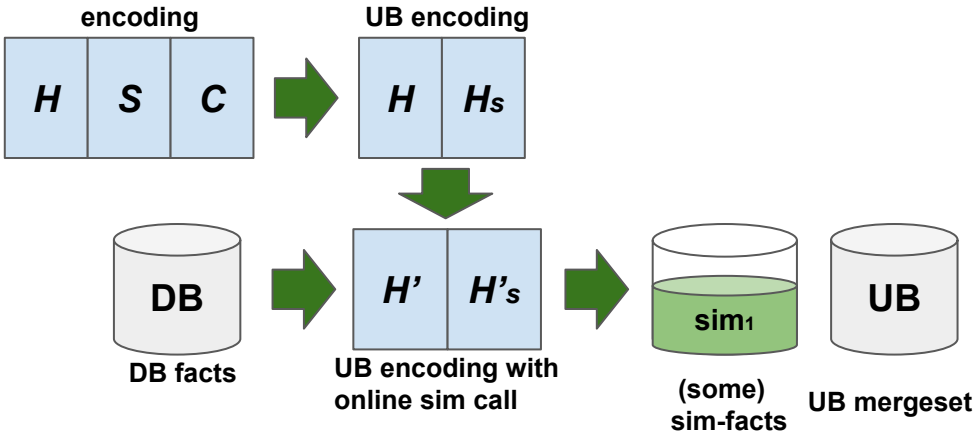
- take into account **structure of an encoding**
- compare all those may actually be **useful**, so that we can use the output to **compute all possible mergesets**!

Similarity computation

Phase 1: Compute a **UB encoding** making **online sim calls**

- Transform to **upper bound encoding**
- Make **online calls** to similarity functions

*E.g. eq(X,Y):- artist(X,N,B), artist(Y,N',B), **@sim(N,N')>=95**.*

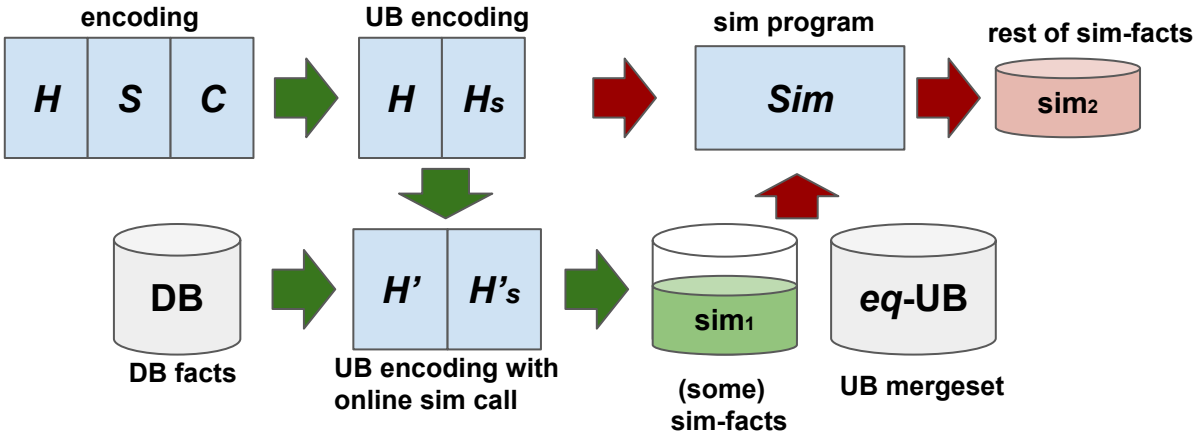


Similarity computation

Phase 1: Compute a **UB encoding** that makes **online sim calls**

Phase 2: **Retrieve** those have **not yet compared** using UB and **similarity program** (another transformation of UB encoding), then **evaluate** and **materialise**

E.g. ***sim(N,N')*** *:- artist(X,N,B), artist(Y,N',B),* ***eq(X,Y)****.*

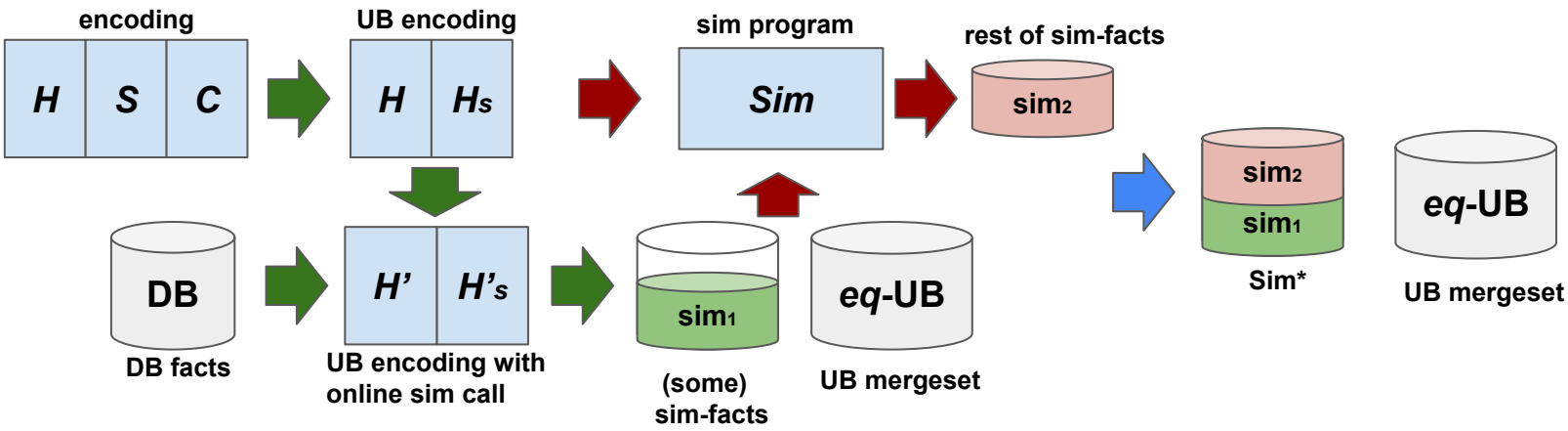


Similarity computation

Final output:

Sim* (Sim-facts required to compute UB) **& UB eq-facts**

Both can be reused later for computation of (diff'nt) mergesets!



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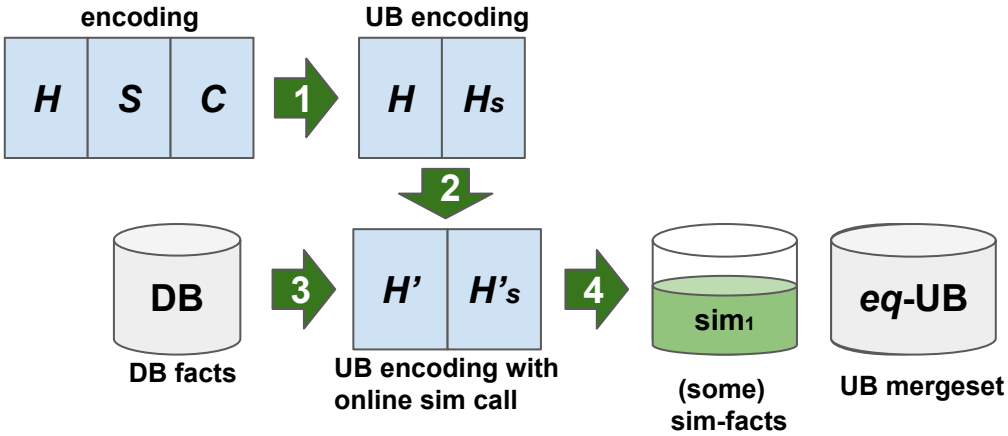

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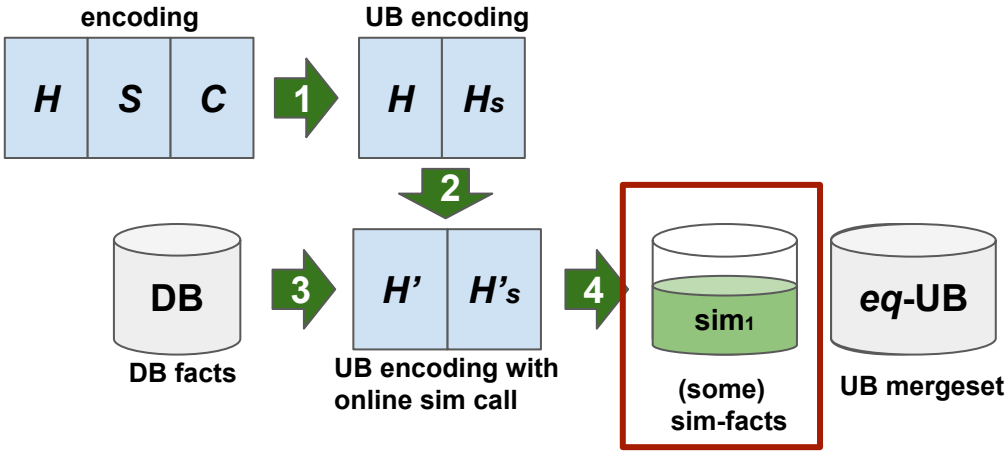

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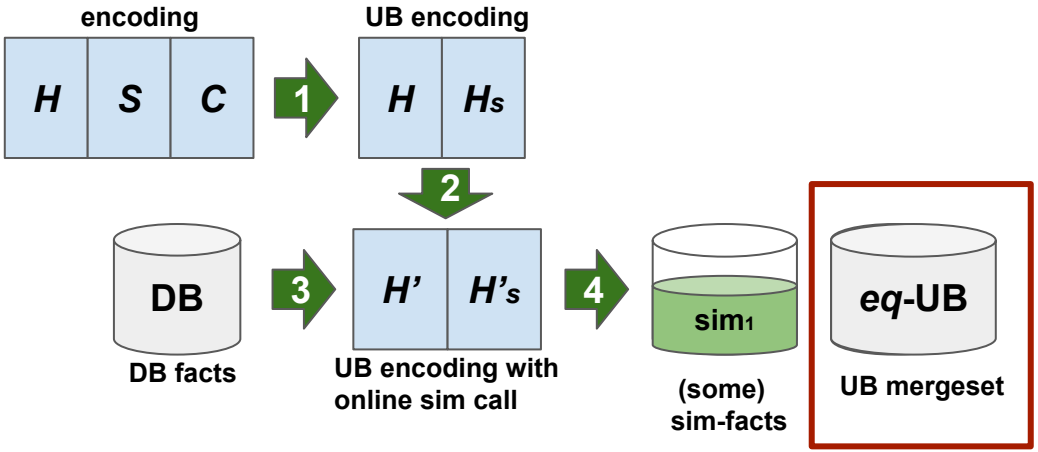

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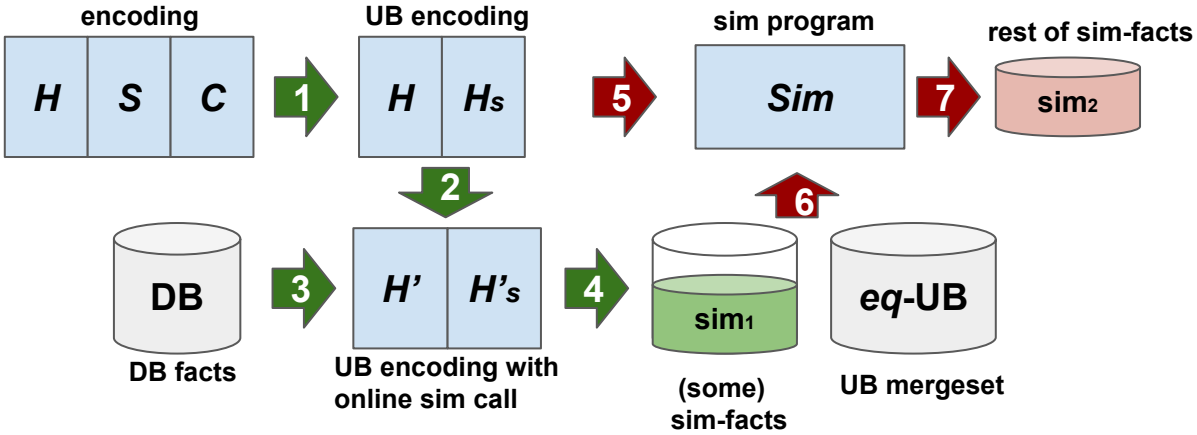

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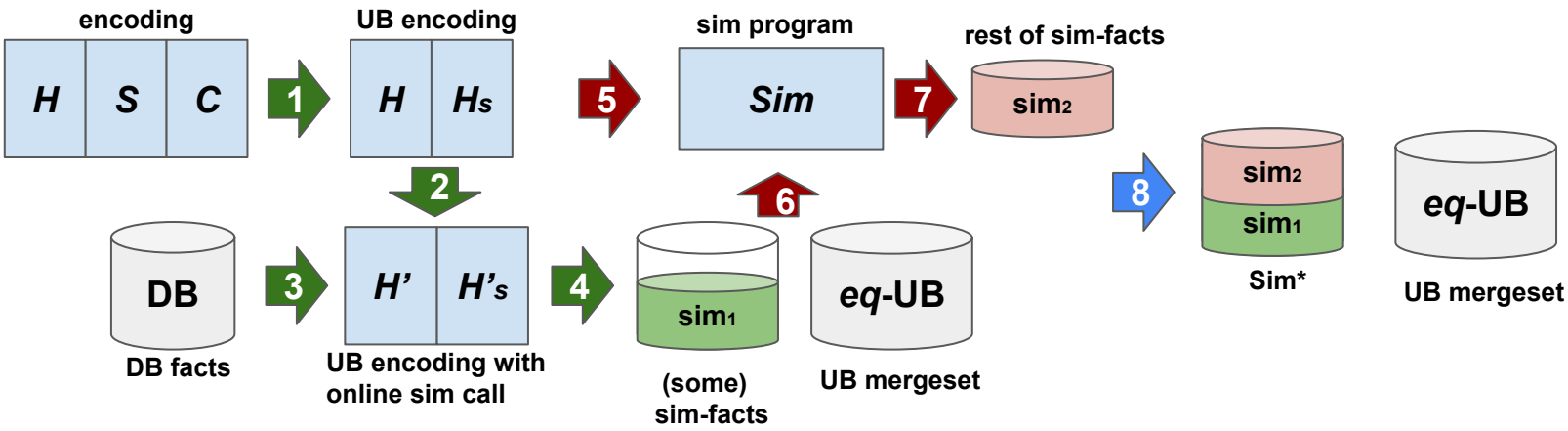
Final output:

Sim* (all those may actually be **useful** to compute mergesets) **&** **UB eq-facts**

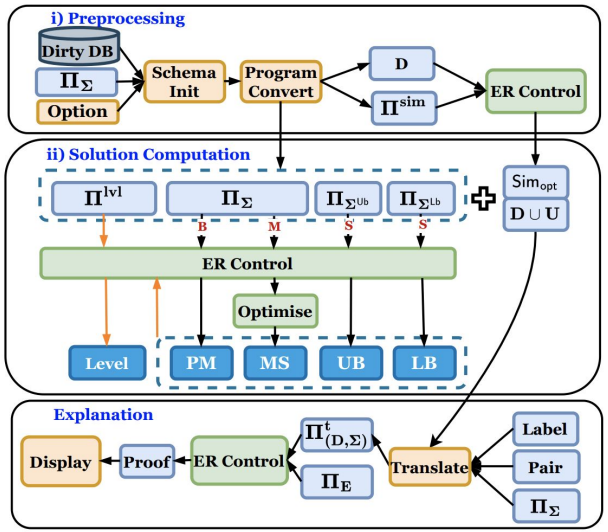
Both can be reused later for computation of (diff'nt) mergesets with proved correctness!



The ASPEn system

Input:

- Database, ASP Encoding
- Options specify desired output



Output:

- Merge lower/upper bound (LB/UB)
- Exact set of possible merge (PM)
- **Fixed # of** maximal solutions (**MS**, with asprin *[Brewka et al. AAAI'2015]*)
- Graphical explanation of a possible merge (s) (xclingo *[Cabalar et al. ICLP'2020]*)

Experimental setup

Datasets:

- 2 **single-table benchmarks** (DBLP-ACM, CORA)
- 4 **multi-table datasets** IMDB (movie), (**synthetic duplicates**) MUSIC, Pokemon

Rules and constraints:

- **Handcrafted**
- #Rule: 9 to 57
- #Constraint: 1 to 8

Name	#Rec	#Rel	#At	#Ref	#Dup
Dblp	5k	2	5^b	0	2.2k
Cora	1.9k	1	17	0	64k
Imdb	30k	5	22	4	6k
Mu	41k	11	72	12	15k
MuC	41k	11	72	12	15k
Poke	240k	20	104	20	4k

Experimental setup

- **Quality measure**: **F1/ Precision/ Recall**
- **Efficiency**: **Running times** / **Memory usage** (sim computation)

Experimental setup

- **Environments**: *clingo 5.5 Python API, a single 3.8GHz AMD Ryzen Threadripper 5965WX core and 128 GB of RAM*
- **Quality measure**: **F1/ Precision/ Recall**
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Experiment 1: Sim computation

- Baseline: **naive computation** of sim
- Consistently **much more memory-efficient**
- **Runtimes** got **twice better** for **larger datasets**

Data	#At	#Cat	t_{cs}	t_{opt}	M_{cs}	M_{opt}	MRed.
Dblp	5	10.2M	**96.3**	531.4	512Mb	256Mb	50
Cora	17	0.8M	**5.49**	932.9	32Mb	4Mb	87.5
Imdb	22	19.6M	**89.5**	598.9	512Mb	128Mb	75
Mu	72	143.6M	**664.03**	772.3	4Gb	256Mb	93.8
MuC	72	147.1M	867.5	**446.4**	4Gb	256Mb	93.8
Poke	104	769.9M	9,419	**4,142**	32Gb	128Mb	99.6

Experiments: Main results

- **Consistently superior quality** compared to baselines (Magellan, JeDAI), **esp. multi-table**
- **Disadvantageous runtime** (*expensive preprocessing*)

Data	Method	F_1	(P / R)	t_o	t_g	t_s
Dblp	Magellan	79.97	89.80 72.08	**1.71**	-	-
	JedAI	95.02	**100** 90.51	49.16	-	-
	LB	46.09	97.10 30.21	531.63	**0.23**	**0.0039**
	MS-1	**96.21**	95.36 97.07	532.17	0.45	0.32
	PM	95.15	92.85 **97.57**	538.5	0.35	6.75
	UB	91.11	85.50 **97.57**	531.41	-	-
Cora	Magellan	79.70	93.09 69.68	131.13	-	-
	JedAI	90.53	95.53 87.72	**40.92**	-	-
	LB	83.57	**99.80** 71.87	1,008	**7.85**	**0.29**
	MS-1	**95.55**	94.25 96.79	1,031	20.88	10.50
	PM	**95.55**	94.25 96.79	1,857.6	20.19	837.58
	UB	87.50	79.66 **97.05**	999.87	-	-

single table

Data	Method	F_1	(P / R)	t_o	t_g	t_s
MuC	Magellan	55.54	97.51 38.83	66.87	-	-
	JedAI	32.75	73.95 21.02	**7.88**	-	-
	LB	53.95	**99.79** 36.97	474.56	**28.01**	**0.062**
	MS-1	**84.10**	88.11 80.44	562.37	113.64	2.33
	PM	83.87	87.59 80.46	893.44	113.26	333.78
	UB	83.55	86.01 **81.24**	446.4	-	-
Poke	Magellan	7.01	3.97 29.74	260.96	-	-
	JedAI	2.1	1.08 46.56	**23.46**	-	-
	LB	28.00	**100** 16.27	4,144	**2.29**	**0.018**
	MS-1	**88.71**	92.88 **84.90**	4,271.8	127.67	2.17
	PM	**88.71**	92.88 **84.90**	4,296	129.04	25.84
	UB	77.00	70.43 **84.90**	4,142	-	-

multi-table

Exp1: Sim computation

- Compared **our sim computation** with the **naive one (commonly used)**

Data	#At	#Cat	t_{cs}	t_{opt}	M_{cs}	M_{opt}	MRed.
Dblp	5	10.2M	**96.3**	531.4	512Mb	256Mb	50
Cora	17	0.8M	**5.49**	932.9	32Mb	4Mb	87.5
Imdb	22	19.6M	**89.5**	598.9	512Mb	128Mb	75
Mu	72	143.6M	**664.03**	772.3	4Gb	256Mb	93.8
MuC	72	147.1M	867.5	**446.4**	4Gb	256Mb	93.8
Poke	104	769.9M	9,419	**4,142**	32Gb	128Mb	99.6

M*{cs,opt}** - memory usage, ***MRed. - memory reduction %
t*{cs,opt}** - running times, ***#Cat - no. cross product of constants

Exp1: Sim computation

- Compared **our sim computation** with the **naive one (commonly used)**
- Consistently **much more memory-efficient**

Data	#At	#Cat	t_{cs}	t_{opt}	M_{cs}	M_{opt}	MRed.
Dblp	5	10.2M	**96.3**	531.4	512Mb	256Mb	50
Cora	17	0.8M	**5.49**	932.9	32Mb	4Mb	87.5
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M*{cs,opt}** - memory usage, ***MRed. - memory reduction %
t*{cs,opt}** - running times, ***#Cat - no. cross product of constants

Exp1: Sim computation

- Compared **our sim computation** with the **naive one (commonly used)**
- Consistently **much more memory-efficient**
- **Running times** got **twice better** for **larger datasets**

Data	#At	#Cat	t_{cs}	t_{opt}	M_{cs}	M_{opt}	MRed.
Dblp	5	10.2M	**96.3**	531.4	512Mb	256Mb	50
Cora	17	0.8M	**5.49**	932.9	32Mb	4Mb	87.5
Imdb	22	19.6M	**89.5**	598.9	512Mb	128Mb	75
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M*{cs,opt}** - memory usage, ***MRed. - memory reduction %
t*{cs,opt}** - running times, ***#Cat - no. cross product of constants

Exp2: Main results

- Compared **MS-1** with **2 rule-based baselines** (Magellan/JedAI) in DB community

Data	Method	F_1	(P	R)	t_o	t_g	t_s
Dblp	Magellan	79.97	89.80	72.08	**1.71**	-	-
	JedAI	95.02	**100**	90.51	49.16	-	-
	LB	46.09	97.10	30.21	531.63	**0.23**	**0.0039**
	MS-1	**96.21**	95.36	97.07	532.17	0.45	0.32
	PM	95.15	92.85	**97.57**	538.5	0.35	6.75
	UB	91.11	85.50	**97.57**	531.41	-	-
Cora	Magellan	79.70	93.09	69.68	131.13	-	-
	JedAI	90.53	95.53	87.72	**40.92**	-	-
	LB	83.57	**99.80**	71.87	1,008	**7.85**	**0.29**
	MS-1	**95.55**	94.25	96.79	1,031	20.88	10.50
	PM	**95.55**	94.25	96.79	1,857.6	20.19	837.58
	UB	87.50	79.66	**97.05**	999.87	-	-

single table

Data	Method	F_1	(P	R)	t_o	t_g	t_s
MuC	Magellan	55.54	97.51	38.83	66.87	-	-
	JedAI	32.75	73.95	21.02	**7.88**	-	-
	LB	53.95	**99.79**	36.97	474.56	**28.01**	**0.062**
	MS-1	**84.10**	88.11	80.44	562.37	113.64	2.33
	PM	83.87	87.59	80.46	893.44	113.26	333.78
	UB	83.55	86.01	**81.24**	446.4	-	-
Poke	Magellan	7.01	3.97	29.74	260.96	-	-
	JedAI	2.1	1.08	46.56	**23.46**	-	-
	LB	28.00	**100**	16.27	4,144	**2.29**	**0.018**
	MS-1	**88.71**	92.88	**84.90**	4,271.8	127.67	2.17
	PM	**88.71**	92.88	**84.90**	4,296	129.04	25.84
	UB	77.00	70.43	**84.90**	4,142	-	-

multi-table

Exp2: Main results

- Compared **MS-1** with **2 rule-based baselines** (Magellan/JedAI) in DB community
- **Consistently superior quality** compared to baselines **esp. multi-table**

Data	Method	F_1	(P / R)	t_o	t_g	t_s
Dblp	Magellan	79.97	89.80 / 72.08	**1.71**	-	-
	JedAI	95.02	**100** / 90.51	49.16	-	-
	LB	46.09	97.10 / 30.21	531.63	**0.23**	**0.0039**
	MS-1	**96.21**	95.36 / 97.07	532.17	0.45	0.32
	PM	95.15	92.85 / **97.57**	538.5	0.35	6.75
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single table

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	JedAI	2.1	1.08 / 46.56	**23.46**	-	-
	LB	28.00	**100** / 16.27	4,144	**2.29**	**0.018**
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	PM	**88.71**	92.88 / **84.90**	4,296	129.04	25.84
	UB	77.00	70.43 / **84.90**	4,142	-	-

multi-table

Exp2: Main results

- Compared **MS-1** with **2 rule-based baselines** (Magellan/JedAI) in DB community
- **Consistently superior quality** compared to baselines **esp. multi-table**
- **Disadvantageous runtime** (*expensive preprocessing*)

Data	Method	F_1	(P / R)	t_o	t_g	t_s
Dblp	Magellan	79.97	89.80 / 72.08	**1.71**	-	-
	JedAI	95.02	**100** / 90.51	49.16	-	-
	LB	46.09	97.10 / 30.21	531.63	**0.23**	**0.0039**
	MS-1	**96.21**	95.36 / 97.07	532.17	0.45	0.32
	PM	95.15	92.85 / **97.57**	538.5	0.35	6.75
	UB	91.11	85.50 / **97.57**	531.41	-	-
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	PM	**88.71**	92.88 / **84.90**	4,296	129.04	25.84
	UB	77.00	70.43 / **84.90**	4,142	-	-

multi-table

Exp3: Effect of recursion

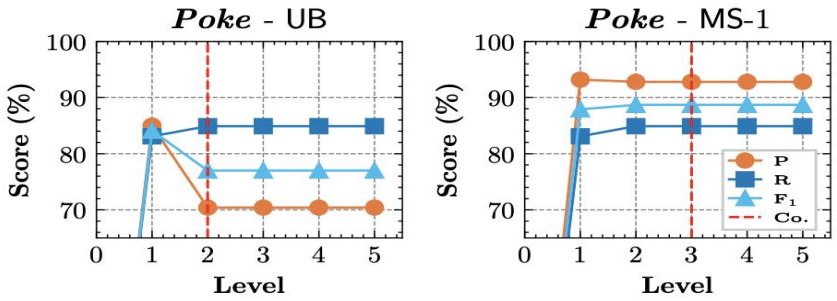
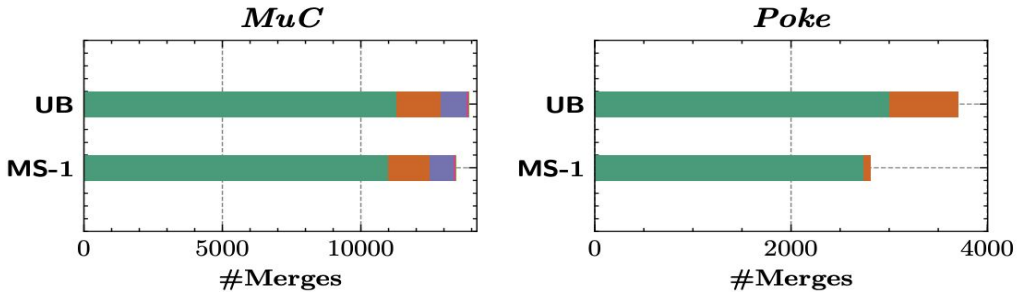


Figure 3: Impact of Recursion on Accuracy



- Most merges in 1st recursion 'level', but **multiple 'levels' to converge**
- **Presence of constraints is crucial** to prevent false positive in the recursive setting

Experiments: scalability & comparison with Datalog

- **Competitive to Datalog engine**, performances trends **differ among datasets**
- **While keeping other 2 factors the same, varying**:
  - **Datasize |D|** -> the **larger** the **slower**
  - **% of duplicates (Du%)** -> the **higher** the **slower**
  - **Similarity thresholds** -> the **lower** the **slower**
- **Grounding times** are more sensitive to **datasize**, **solving times** are more sensitive to **% of duplicates** and **similarity thresholds**

In Arxiv version

Conclusion

- **ASPEn System**, a **declarative**, **collective**, **explainable** solution to **ER** based on **LACE**
- Similarity computation consistently **much more memory-efficient**, more **scalable** to **large datasets**
- Experiment on **complex real-world datasets** shows it is **promising**, achieving **high accuracy** in **real-life ER** scenarios,
- Showcase **ER** as an **exciting** but **challenging** application in the wild for **ASP**

Conclusion

- **ASPEn System**, a **declarative**, **collective**, **explainable** solution to **ER** based on **LACE**
- **Efficiently computable approximations** to possible/certain merges
- Proposed similarity computation consistently **much more memory-efficient**, more **scalable** to **large datasets**
- Experiment on **complex real-world datasets** shows it is **promising**, achieving **high accuracy** in **real-life ER** scenarios
- Showcase **ER** as an **exciting** but **challenging** application in the wild for **ASP**

Thank you for your attention!

repo of the source code/arxiv full detail