COLIBRI

Unsupervised Link Discovery Through Knowledge Base Repair

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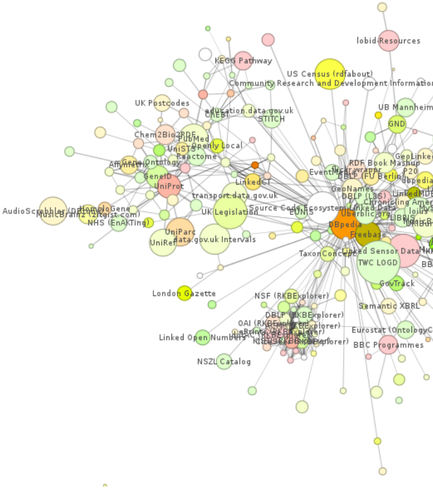
Outline

1. Motivation
2. Approach
3. Evaluation
4. Conclusion and Future Work

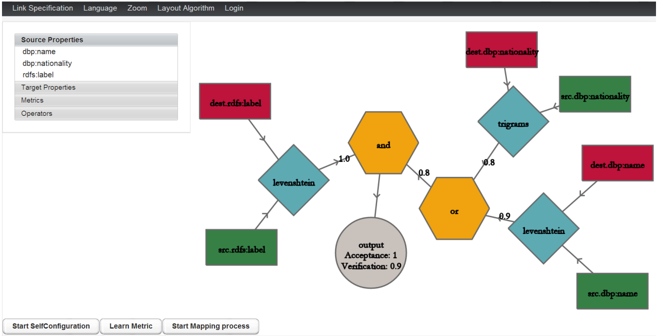
Why Link Discovery?

1. Fourth principle
2. Links are central for
   - Cross-ontology QA
   - Data Integration
   - Reasoning
   - Federated Queries
   - ...



Why is it difficult?

- **Time complexity**
  - Large number of triples
  - Quadratic runtime
- **Complexity of specifications**
  - Combination of several attributes required for high precision
  - Tedious discovery of most adequate mapping
  - Dataset-dependent similarity functions



Solution

1. Use unsupervised link discovery
   - No need for training data
   - Minimizes load on user
2. Combine results of linking tasks over $n > 2$ knowledge bases
   - Make explicit use of the topology of the Data Web
3. Repair noisy data to improve link discovery
   - Address different quality of datasets across the Data Web

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COLIBRI *overview*

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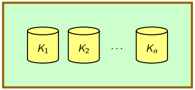

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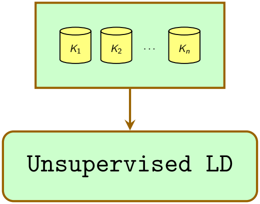

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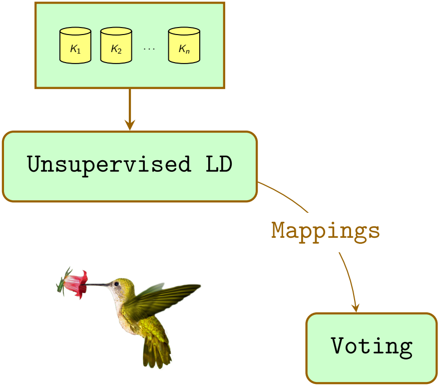

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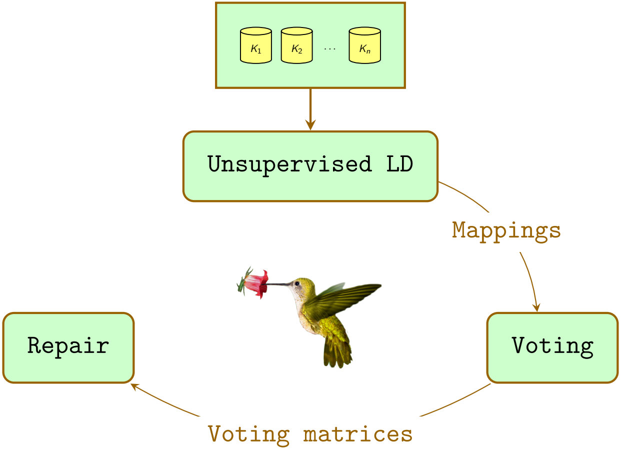

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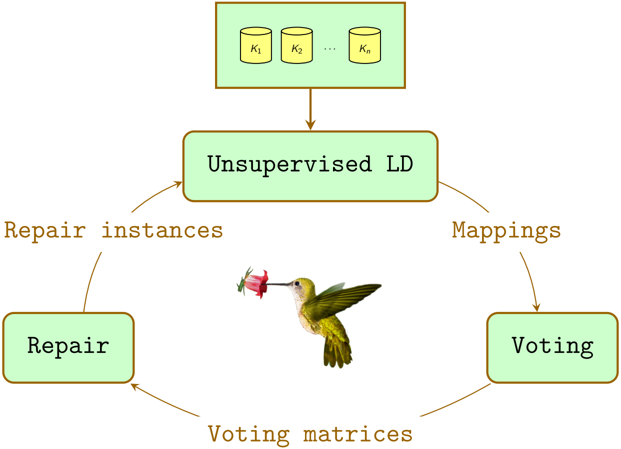
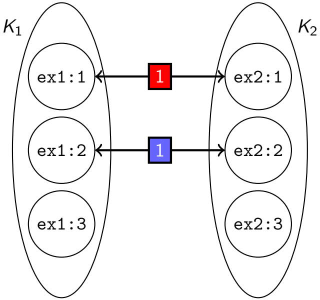


Key Concepts

- Mapping matrix
  - $M_{12} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$

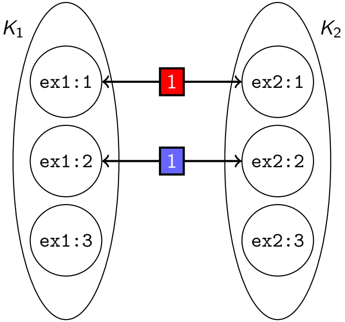


Key Concepts

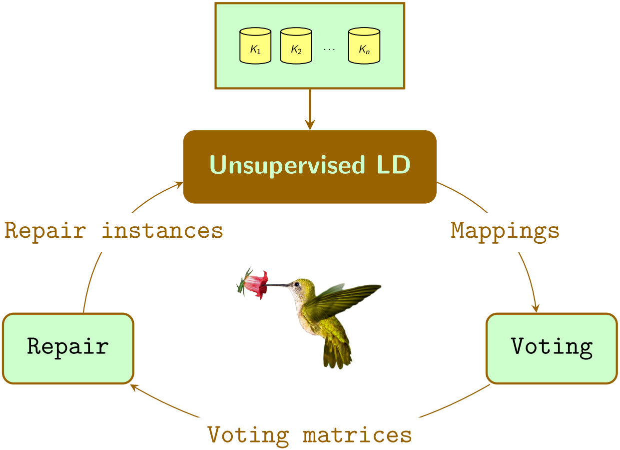
- Pseudo-F-measure as objective function
- $\mathcal{P}(M_{ij}) = \frac{|links(K_i,M_{ij})|+|links(K_j,M_{ij})|}{2|M_{ij}|}$
- $\mathcal{R}(M_{ij}) = \frac{|links(K_i,M_{ij})|+|links(K_j,M_{ij})|}{|K_i|+|K_j|}$
- $\mathcal{F}_\beta = (1+\beta^2)\frac{\mathcal{P}\mathcal{R}}{\beta^2\mathcal{P}+\mathcal{R}}$

Example:

- $\mathcal{P}(M_{12}) = 1$
- $\mathcal{R}(M_{12}) = \frac{2}{3}$
- $\mathcal{F}_1(M_{12}) = \frac{4}{5}$

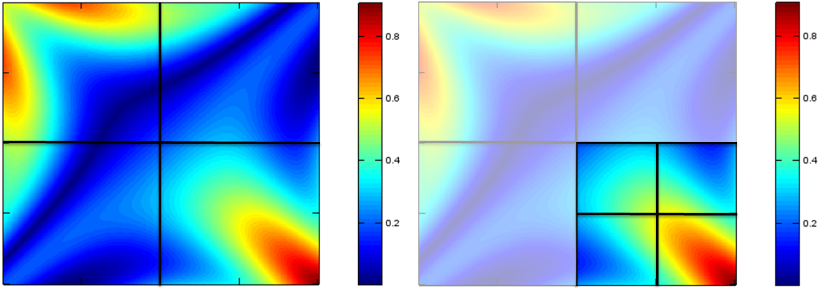


Step 1: Unsupervised Link Discovery



Step 1: Unsupervised Link Discovery

- Link all pairs (K_i, K_j) using any unsupervised link discovery approach
- Here, EUCLID
  - Specifications are points in a similarity space
  - Find accurate specification by using hierarchical grid search
  - Detect specification which maximizes $\mathcal{F}_\beta$



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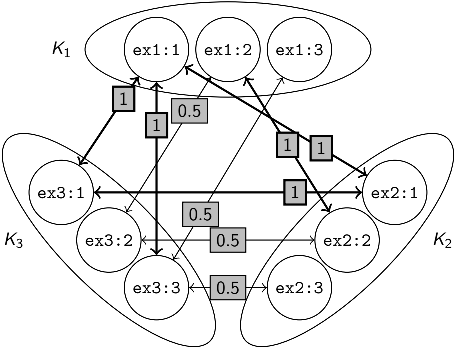
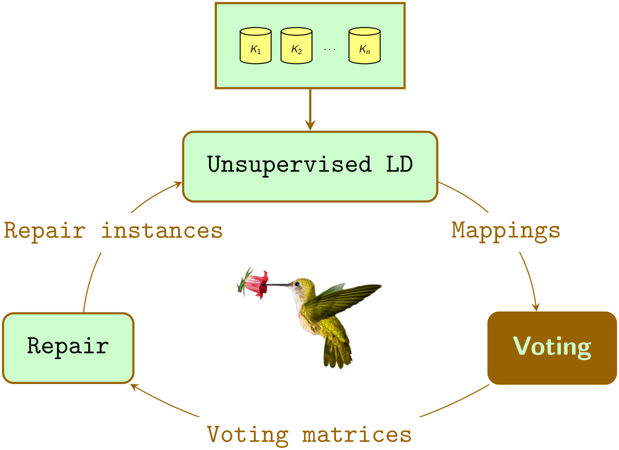


Step 2: Voting



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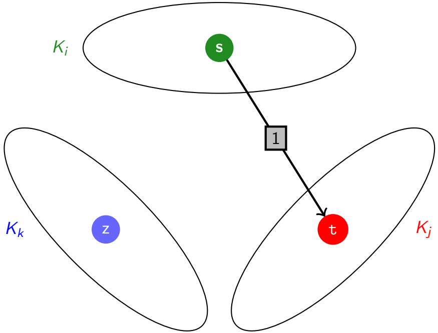

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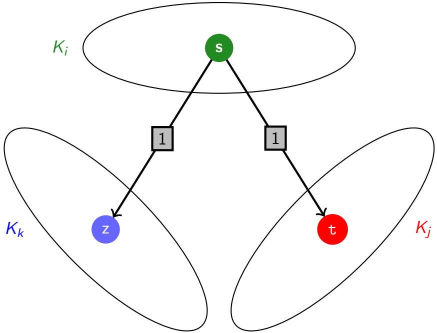

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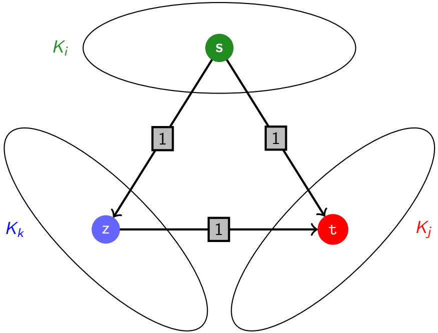

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- $V_{ij} = \frac{1}{n-1}\left(M_{ij} + \sum_{\substack{k=1\\k\neq i,j}}^{n} M_{ik}M_{kj}\right)$

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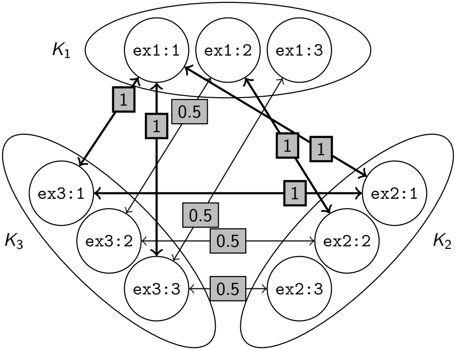

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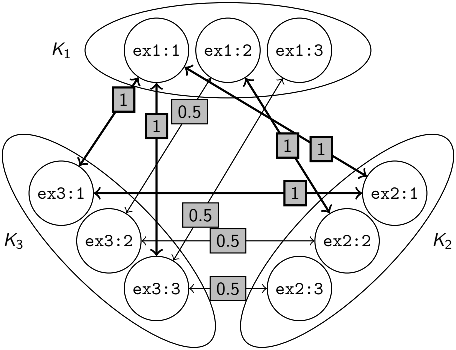

$$V_{12} = \begin{pmatrix} 1 & 0 & 0.25 \\ 0 & 0.625 & 0 \\ 0 & 0 & 0.125 \end{pmatrix}$$

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- Voting matrices
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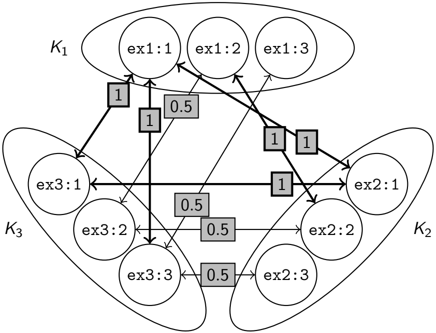
  - $V_{23} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.25 \end{pmatrix}$
- Post-processed matrices
  - $\tilde{V}_{12} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0.625 & 0 \\ 0 & 0 & 0.125 \end{pmatrix}$



Step 2: Voting

- Assume links in $\tilde{V}_{ij}$ to be correct
- $\tilde{v}_{ij} = 1 \rightarrow$ All matrices agree on how to link (K_i, K_j)
  e.g., $\tilde{V}_{12}(\texttt{ex1:1}, \texttt{ex2:1})$
- For all $\tilde{v}_{ij} < 1$ assume either
  1. *Missing links*
     e.g., $\tilde{V}_{12}(\texttt{ex1:3}, \texttt{ex2:3})$ not contained in M_{12}
  2. *Weak links*
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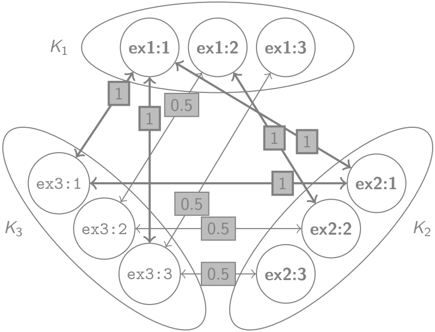

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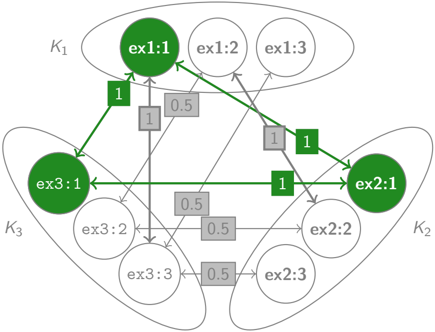

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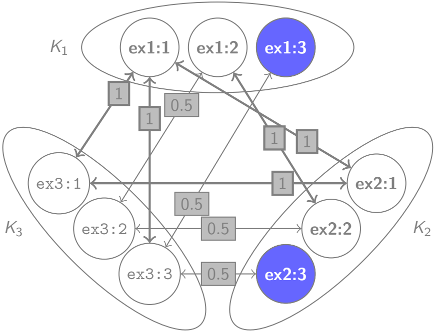

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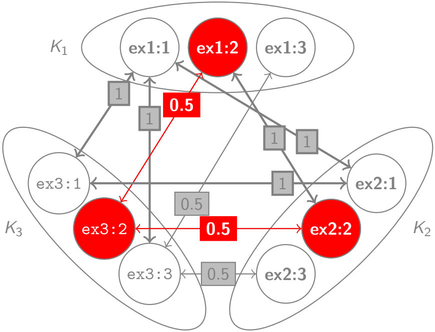

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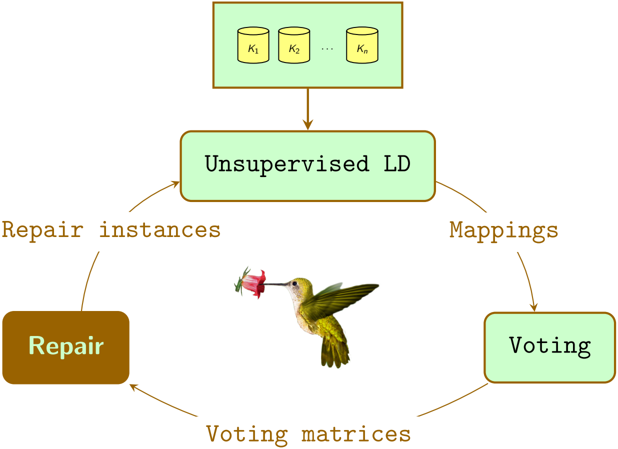

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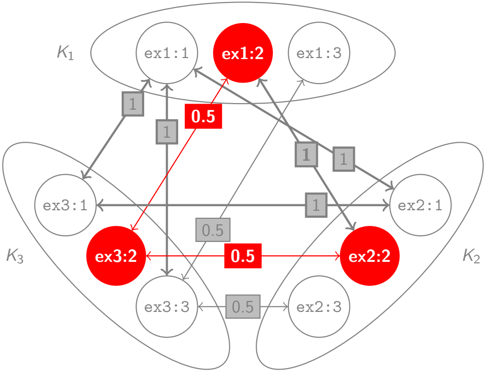
$$\tilde{V}_{12} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0.625 & 0 \\ 0 & 0 & 0.125 \end{pmatrix}$$

- **Goal**: Repair instance data so as to improve $\tilde{v}_{ij} < 1$
- Link to be repaired is (`ex1:2`, `ex2:2`).
- Reason for this link:
  - rs = `ex1:2` and
  - rt = `ex3:2`.
- Computing *average similarity*:
  - $\bar{\sigma}$(`ex1:2`) = 0.75 while
  - $\bar{\sigma}$(`ex3:2`) = 0.5.
- Colibri overwrite the values of `ex3:2` with those of `ex1:2`.



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$$\tilde{V}_{12} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \color{red}{0.625} & 0 \\ 0 & 0 & 0.125 \end{pmatrix}$$

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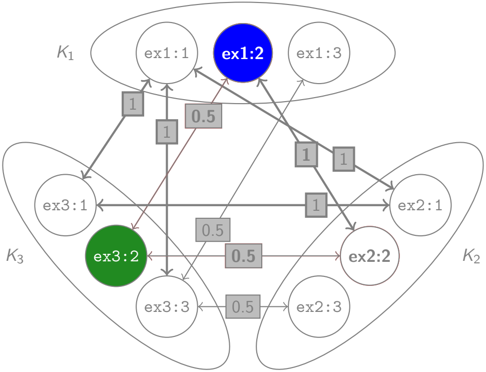

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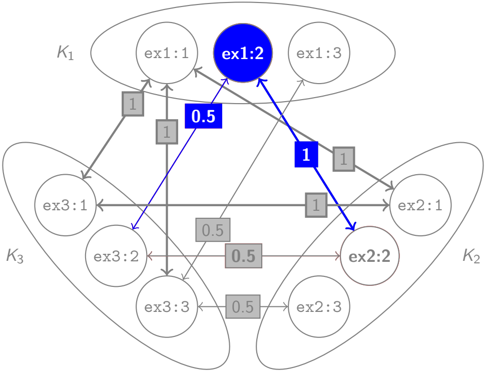

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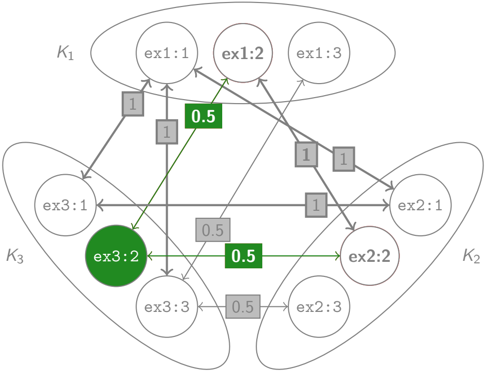

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Benchmark Generation Approach

- So far, no benchmark for linking $n > 2$ knowledge bases
- Benchmark generation approach (Ferrara et al., 2011)
- Generated $m - 1$ copies of initial dataset K_1
- Alteration operators:
  - Misspellings
  - Abbreviations
  - Word permutations
- Alteration strategy:
  - Pick random resource according to alteration probability
  - Pick random operator

Experimental Setup

- Datasets:
  - Two synthetic datasets (OAEI2010)
  - Three real-world datasets (Koepcke et al., 2010)
- COLIBRI:
  - Maximal number of iterations $= 10$
  - Number of knowledge bases $= \{3, 4, 5\}$
  - Alteration probability $ap = \{10\%, 20\%, \ldots, 50\%\}$
  - Repeat each experiment 5 times

Experimental Results (synthetic dataset)

KBs	F_{EUCLID}	F_{COLIBRI}	Runtime (sec)	Repaired links
3	0.89	0.98	0.4	43
4	0.90	1.00	0.9	35
5	0.88	1.00	1.3	34

- Restaurant dataset
- Average values after 10 iterations
- Alteration probability $ap = 50\%$

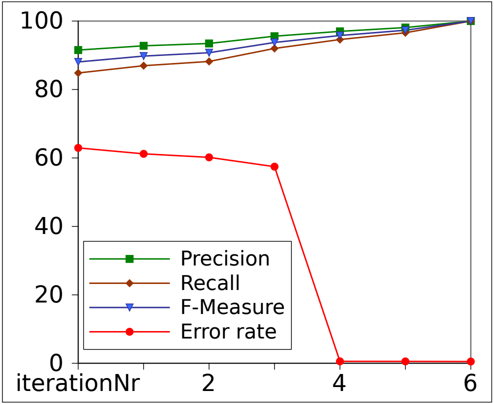
Experimental Results (real-world dataset)

KBs	F_{EUCLID}	F_{COLIBRI}	Runtime (sec)	Repaired links
3	0.86	0.98	81.8	300
4	0.85	0.99	160.4	150
5	0.84	0.88	246.8	60

- Amazon dataset
- Average values after 10 iterations
- Alteration probability $ap = 50\%$

Results on the Restaurants dataset

- Alteration probability $ap = 50\%$
- Knowledge bases = 5



Full results at:
https://github.com/AKSW/LIMES/tree/master/evaluationsResults/colibri

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Conclusion and Future Work

- **Conclusion**
  - Presented COLIBRI
  - Improved F-measure of EUCLID up to 14%
- **Future Work**
  - Evaluation on other datasets
  - Interactive scenarios (i.e., consult user before dataset repair)
  - Combination with other unsupervised solutions (e.g., EAGLE)

Thank You!

Questions?

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