A Graph-Theoretic Fusion Framework for Unsupervised Entity Resolution

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Entity Resolution

Text Records	Identical Entity
Les Celebrites 160 Central Park S New York French	√
Les Celebrites 155 W. 58th St. New York City French (Classic)	
Palm 837 Second Ave. New York City Steakhouses	×
Palm Too 840 Second Ave. New York City Steakhouses	

Two examples from the restaurant dataset.

Previous Work

- **Distance-based Methods**
  - Edit Distance, TF-IDF
  - Simple and scalable, but not effective enough
- **Learning-based Methods**
  - Learn a distance metric
  - Model ER as a classification task and apply SVM
  - Require considerable amount of training data
- **Crowd-based Methods**
  - CrowdER, TransM, TransNode, GCER, ADC, Power+
  - Achieve state-of-the-art accuracy but require human intervention

Our Objective

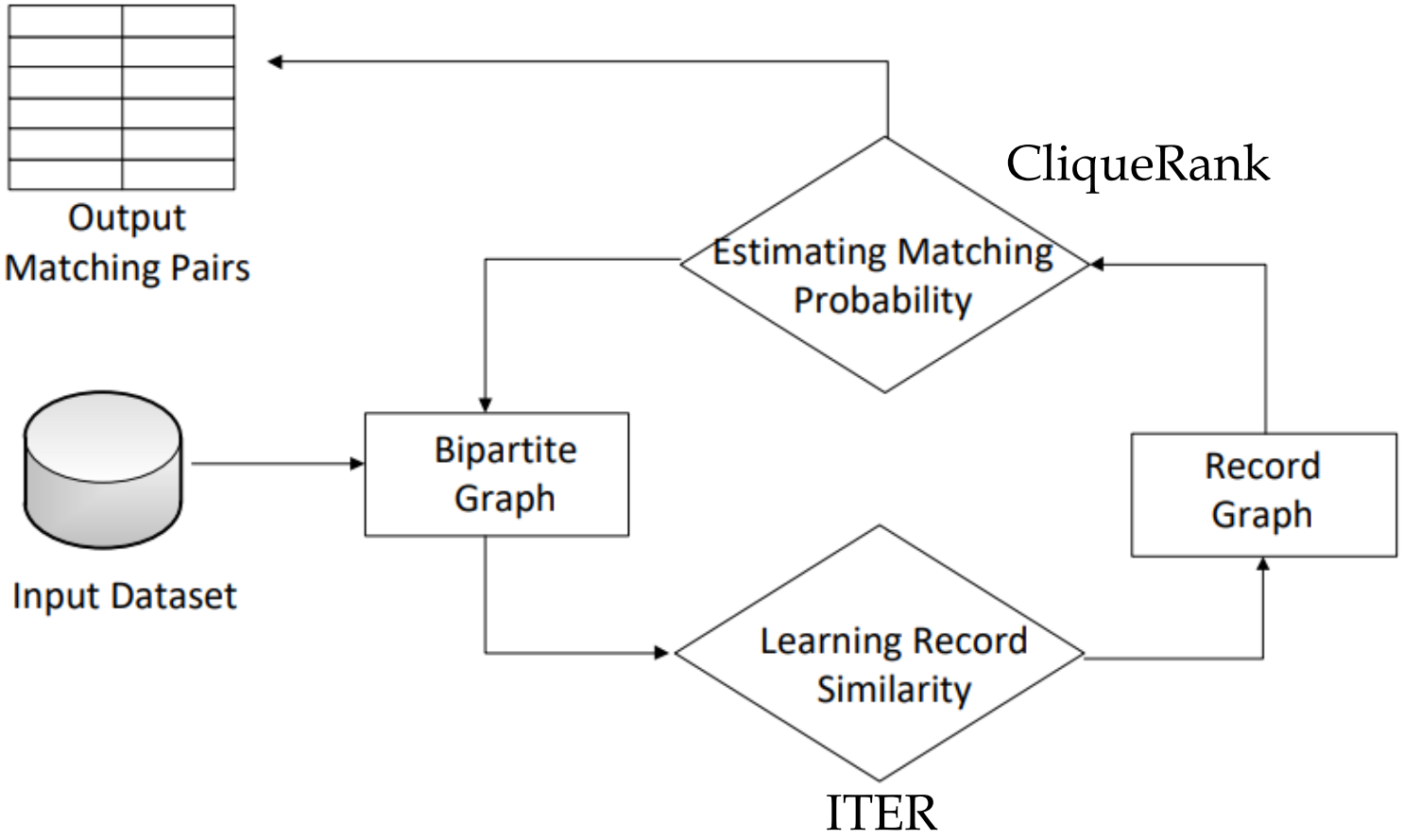
- **Propose an unsupervised approach**
  - More accurate when compared with distance-based methods
  - Require no training/labeling efforts when compared with learning-based methods
  - Require no human intervention and financial cost when compared with crowd-based methods

The General Idea

- **In the traditional unsupervised methods**
  - Step 1: Craft a distance measure between two records
  - Step 2: Tune a threshold such that two records with similarity score higher than the threshold are considered as the same entity

- **We are motivated to improve these two steps by**
  - Proposing ITER algorithm to learn record similarity
  - Proposing CliqueRank to estimate the likelihood of two records referring to the same entity
  - Iteratively Reinforcing these two components

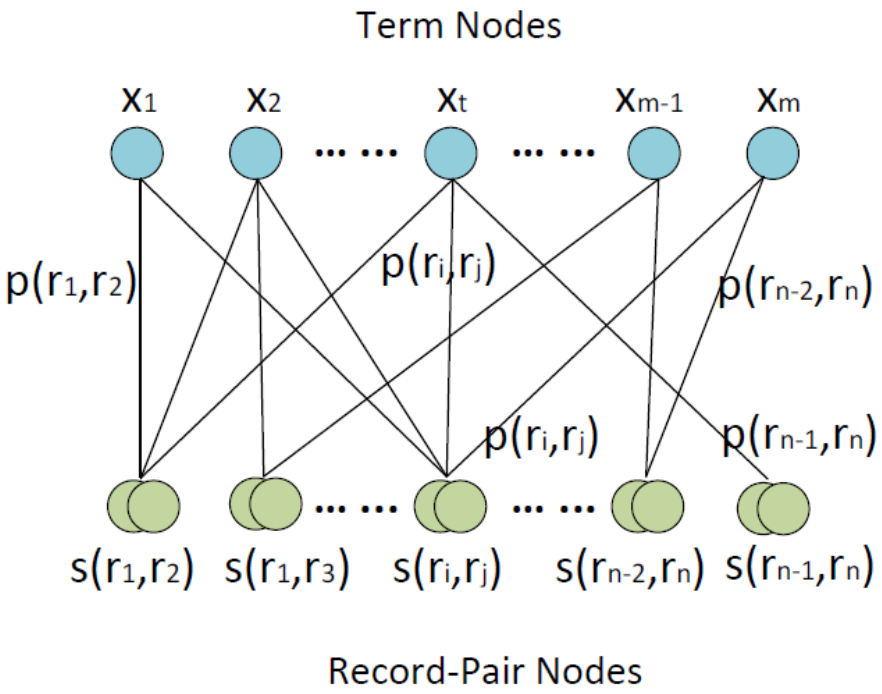
Unsupervised Fusion Framework



ITER Algorithm

- **If a term only occurs in a group of matching records, then we consider the term as highly discriminative**
  - Examples include product models for electronic devices or telephone numbers for restaurant.
  - These terms have low term frequency and may not be emphasized by TF-IDF
- **If a term is shared by many non-matching records, its weight will be punished**

ITER Algorithm



$$x_t = \sum_{i \neq j} \frac{p(r_i, r_j) s(r_i, r_j)}{P_t}$$

$$s(r_i, r_j) = \sum_{t \in r_i \wedge t \in r_j} norm(x_t)$$

ITER Algorithm

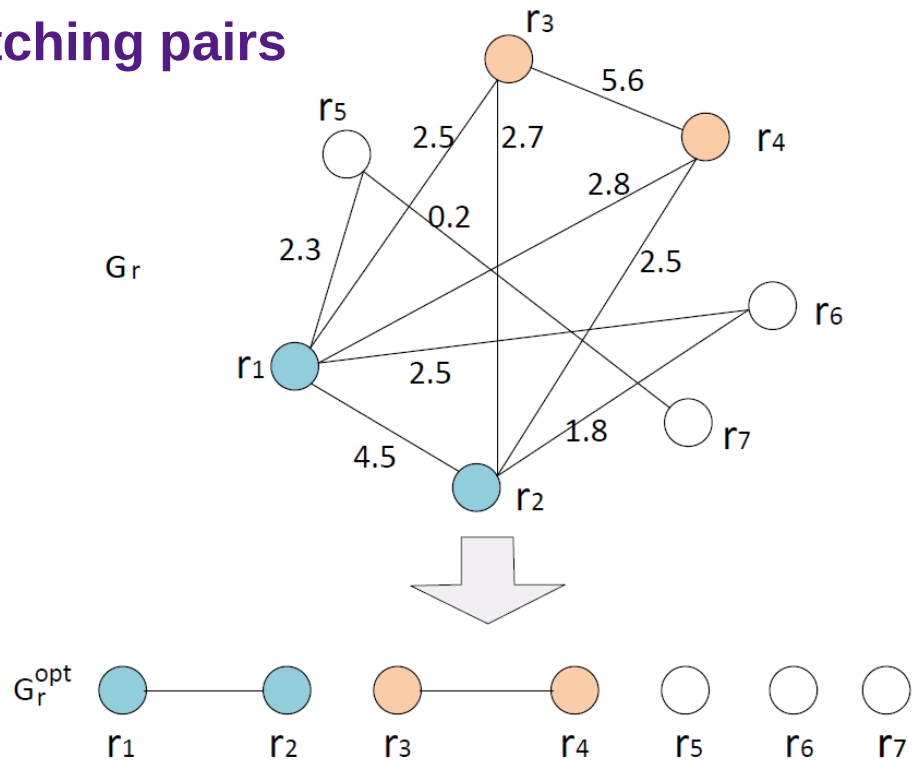
Algorithm 1: ITER Algorithm

Input: Bipartite graph structure with edge weight $p(r_i, r_j)$;
Output: Node salience x_t and record pair similarity score $s(r_i, r_j)$;

1. Randomly initialize x_t in $(0, 1)$;
2. **while** x_t does not converge **do**
3. **for** each record pair (r_i, r_j) **do**
4. Set its weight $s(r_i, r_j) \leftarrow \sum_{t \in r_i \wedge t \in r_j} x_t$;
5. **for** each term t **do**
6. Set its weight $x_t \leftarrow \sum_{i \neq j} \frac{p(r_i, r_j) s(r_i, r_j)}{P_t}$;
7. Set $x_t = 1/(1 + \frac{1}{x_t})$
8. **return** x_t and $s(r_i, r_j)$

CliqueRank Algorithm

- Given Gr, our goal is to identify matching probability.
- Ideally, the probability should be 1 for matching pairs and 0 for non-matching pairs



CliqueRank Algorithm

- **Random-Walk based interpretation**
  - **Ideally, if r_i and r_j refer to different entities, they should be located in different cliques and not reachable from each other**
  - **Otherwise, if we start a random walk from one record r_i, it will be very likely to visit the other record r_j within certain number of steps**

Random-Surfer Sampling

Algorithm 2: Random-Surfer Sampling (RSS)

1. Construct a record graph G_r based on $s(r_i, r_j)$;
2. **for** each edge $(r_i, r_j) \in G_r$ **do**
3. $\quad c_1 \leftarrow 0; \quad c_2 \leftarrow 0$
4. $\quad$ **for** $m \leftarrow 1; m \leq M/2; m++$ **do**
5. $\quad\quad c_1 \leftarrow c_1 + RandomWalk(r_i, r_j)$;
6. $\quad$ **for** $m \leftarrow 1; m \leq M/2; m++$ **do**
7. $\quad\quad c_2 \leftarrow c_2 + RandomWalk(r_j, r_i)$;
8. $\quad p(r_i, r_j) \leftarrow (c_1 + c_2)/M$;
9. **return** $p(r_i, r_j)$;

Random Walk Algorithm

Algorithm 3: RandomWalk($start$, $target$)

1. $cur \leftarrow start$;
2. **for** $s \leftarrow 1; s \leq S; s++$ **do**
3. pick a random value $b \in (0, 1)$;
4. $s'(cur, target) \leftarrow (1 + b) \cdot s(cur, target)$;
5. $next \leftarrow$ pick a node from neighbors of cur based on the new transition probability $p_b(r_i \rightarrow r_j)$;
6. **if** $next == target$ **then**
7. **return** 1;
8. **if** edge $(next, target) \notin G_r$ **then**
9. **return** 0;
10. $cur \leftarrow next$;
11. **return** 0;

To handle large cliques

$$p(r_i \rightarrow r_j) = \frac{s(r_i, r_j)^\alpha}{\sum_{r_j \in O(r_i)} s(r_i, r_j)^\alpha},$$

To champion edge with high score

For early termination

CliqueRank Algorithm

- Iterative sampling is slow, and we switch to matrix operation

- M_t be the matrix with reaching probability from r_i to r_j with 1 step

$$M_t[i,j] = p(r_i \rightarrow r_j)$$

- M_t^S be the matrix with reaching probability from r_i to r_j with S steps

$$M_t^S = \underbrace{M_t \times M_t \times \ldots \times M_t}_{S-1 \text{ times of operation } \times}$$

- The random surfer algorithm essentially estimates such probability

CliqueRank Algorithm

- We make customizations to the RSS algorithm
- $M_b[i,j]$ be the initial transition probability matrix

$$p_b(r_i \rightarrow r_j) = \frac{(1+b)^{\alpha} s(r_i,r_j)^{\alpha}}{norm(r_i,r_j)}.$$

- $M_n[i,j]$ is set to 1 if r_i to r_j are connected in Gr
- Finally, we can define the reaching probability with S steps

$$M_t^S = \begin{cases} M_b & \text{if } S = 1 \\ M_t \times (M_t^{S-1} \odot M_n) & \text{if } S > 1 \end{cases}$$

Benchmark Datasets

- **Restaurant**
  - 858 non-identical restaurant records.
  - Each record contains the information of restaurant name and address.
- **Product**
  - 1081 records from the abt website and the other 1092 records from the buy website.
  - Each product record contains its name and descriptive information.
- **Paper**
  - 1865 non-identical publication records.
  - Each record has a cluster id and its textual information consists of authors, title, publication venue and year.

Experimental Setup

- **For the three datasets, we use the same setting of parameters**
  - $\alpha=20$
  - $S=20$
  - $\eta=0.98$
  - 5 iterations between the reinforcement of ITER and CliqueRank
- **Eigen library is used to boost matrix multiplication**

  http://eigen.tuxfamily.org/index.php?title=Main Page

Experiment & Analysis

- **Accuracy**

	Restaurant	Product	Paper
String-distance based approaches			
Jaccard	0.836	0.332	0.792
TF-IDF	0.871	0.658	0.821
Machine-learning based approaches			
Gaussian Mixture Model [5]	0.704	-	-
HGM+Bootstrap [5]	0.844	-	-
MLE [5]	0.904	-	-
SVM [6]	0.922	-	0.824
Crowd-sourcing based approaches			
CrowdER [8]	0.934	0.800	0.824
TransM [10]	0.930	0.792	0.740
GCER [9]	0.930	0.760	0.785
ACD [12]	0.934	0.805	0.820
Power+ [13]	0.934	-	0.820
Graph-theoretic baselines			
SimRank	0.645	0.376	0.730
PageRank	0.905	0.564	0.316
Hybrid	0.946	0.593	0.748
Proposed graph-theoretic fusion framework			
ITER+CliqueRank	0.927	0.764	**0.890**

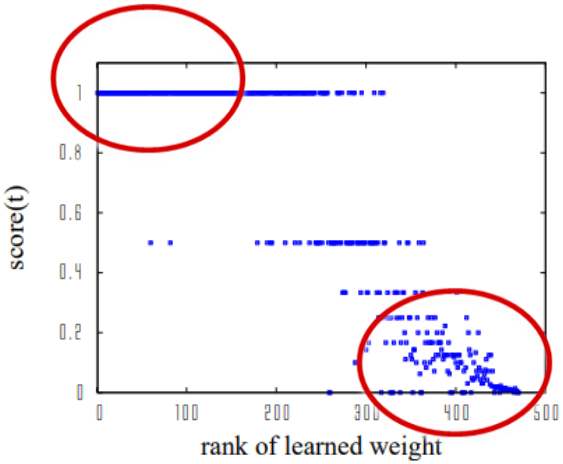
Experiment & Analysis

- **Efficiency**

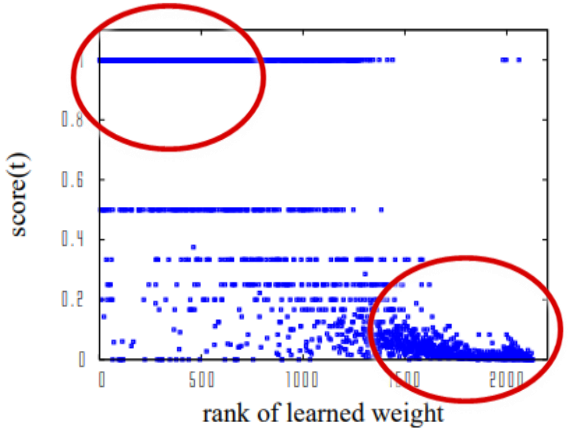
	Restaurant	Product	Paper
Number of nodes in G_r	858	2173	1865
Number of edges in G_r	5,320	151,939	980,780
Total running time	1.1min	21.6min	24.2min
Running time for ITER	3sec	20sec	58sec
Speedup compared to RSS	1.3x	1.5x	60x

Experiment & Analysis

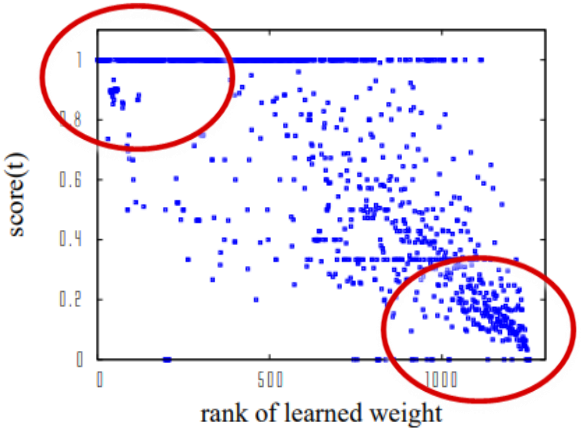
- **Effectiveness of Learned Term Weights**



(a) Restaurant



(b) Product



(c) Paper

ground-truth score: $score(t) = \frac{\sum_{t \in r_i \wedge t \in r_j} I(r_i, r_j)}{P_t}$

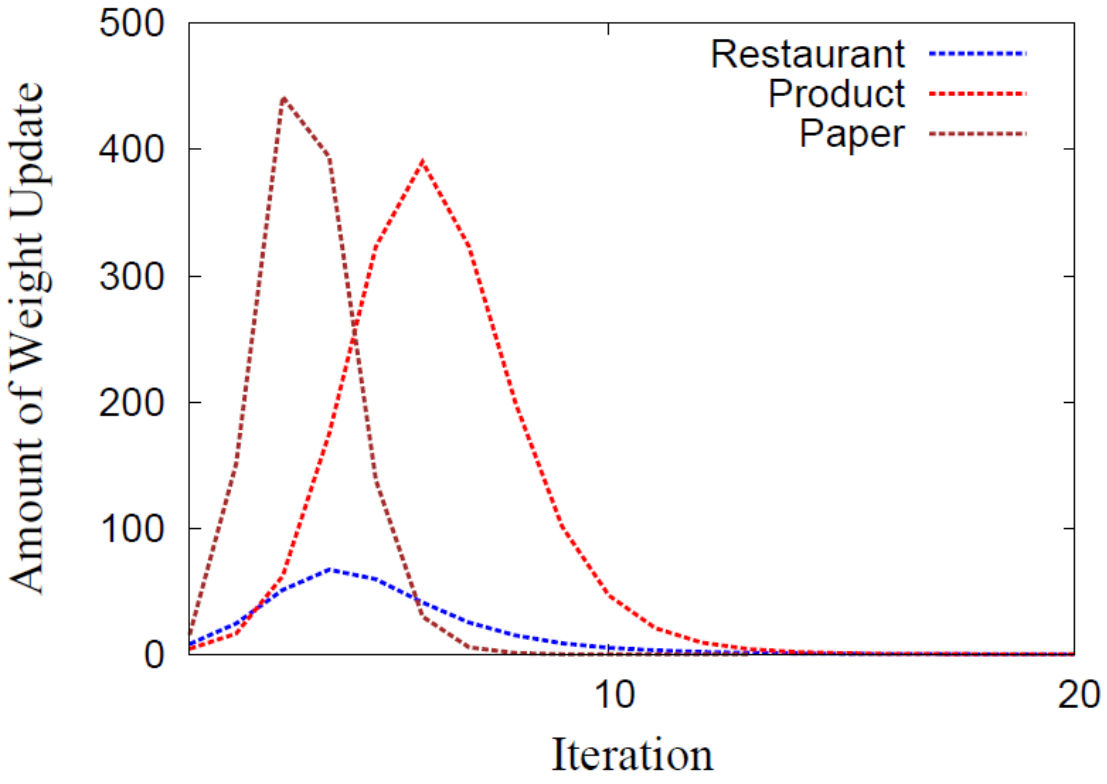
Experiment & Analysis

- **Top-Ranked Terms in the Benchmark Datasets**

Restaurant	coyote, chin's, 702/731-7547, 702/734-0410, 702/791-7111, 3645, 3400, gotham, 2880, arnie, seasons, 12, gramercy, chinois
Product	85w, trackpad, mirroring, magsafe, led-backlit, isight, dis-playport, 5400-rpm, spreadsheets, formulas, dramatically, compromising, multi-angle, 30p, 24mbps, diameter, s320, 7mm
Paper	thurn, wentzel, pachovicz, dzeroski, bloendorn, dze-roski, vafaic, kreusiger, kaufaman, pachowitz, re-ich, dzerowski, weldel, cmu-cd-91-197, jianping, jerzy, janusz, juergen, haleh, cmu-cs-91-197

Experiment & Analysis

- **Convergence of ITER**



Experiment & Analysis

- **Effect of Reinforcement**

	Restaurant		Product		Paper	
Iteration	F1-score	Time	F1-score	Time	F1-score	Time
1	0.916	13	0.543	253	0.844	207
2	0.935	25	0.712	514	0.888	515
3	0.931	39	0.747	768	0.889	819
4	0.931	52	0.754	1027	0.890	1135
5	0.927	64	0.764	1296	0.890	1453

Conclusion

- We propose an unsupervised graph-theoretic framework for entity resolution.
- Two novel algorithms ITER and CliqueRank are proposed, one for term-based similarity and the other for topological confidence. These two components can reinforce each other.
- Experimental results on three benchmark datasets show that our algorithm is accurate

Codes are available at:
https://github.com/uestc-db/Unsupervised-Entity-Resolution

Thank you!

Q&A