# ORLF: A Flexible Framework for Online Record Linkage and Fusion

El Kindi Rezig
Purdue University
erezig@cs.purdue.edu

Eduard C. Dragut
Temple University
edragut@temple.edu

Mourad Ouzzani, Ahmed K. Elmagarmid
Qatar Computing Research Institute
{mouzzani, aelmagarmid}@qf.org.qa

Walid G. Aref
Purdue University
aref@cs.purdue.edu

***Abstract*—With the exponential growth of data on the Web comes the opportunity to integrate multiple sources to give more accurate answers to user queries. Upon retrieving records from multiple Web databases, a key task is to merge records that refer to the same real-world entity. We demonstrate *ORLF* (Online Record Linkage and Fusion), a flexible query-time record linkage and fusion framework. *ORLF* deduplicates newly arriving query results jointly with previously processed query results. We use an iterative caching solution that leverages query locality to effectively deduplicate newly incoming records with cached records. *ORLF* aims to deliver timely query answers that are duplicate-free and reflect knowledge collected from previous queries.**

## I. Introduction

The sheer amount of information on the Web has triggered the emergence of a vast array of applications that integrate data from multiple Web sources to answer users' queries. This has brought along new data curation challenges. Data across different Web sources contains multiple anomalies, such as missing data, inconsistent data, and oftentimes the same real world entities, e.g., a company, a person, or a book, is represented differently by different Web sources.

Web applications often require duplicate-free data and error-free representation of entities. The former goal is achieved through Record Linkage (RL) while the latter is achieved through Data Fusion. Record Linkage and Data Fusion (RL&F) are two well-studied problems [2], [4]. While significant effort has been dedicated to solve them, little work has been conducted to perform them at query time. Online RL&F differs from its offline counterpart in the following aspects: (i) the entire data cannot be obtained all at once, e.g., usually only through restricted Web query forms, (ii) since it runs at query time, it has to be performed relatively fast; and (iii) multiple query submissions may be needed to acquire enough evidence about an "ideal" representation of an entity.

We introduced the algorithmic infrastructure of *ORLF* in [7]. The proposed infrastructure allows seamless application of RL&F over live data coming from multiple Web sources. *ORLF* leverages previously submitted queries to perform RL&F on query results. As a result, the more queries *ORLF* processes, the better the query results are likely to be. To achieve this goal, *ORLF* uses a caching system that serves two main purposes: (i) storing fused records of entities seen so far from previous queries and (ii) allowing a fast lookup at query time to identify relevant entities in the cache and update them with newly arriving query records. We developed a new record indexing data structure to obtain a fast lookup time. The index, which is based on the $B^{ed}$-tree index [10], is used to index the cache records and to answer top-k similarity queries. We implemented a software framework for online RL&F that incorporates these algorithmic features and a number of additional ones.

In this demo, we will walk the audience through the following key features of *ORLF*:

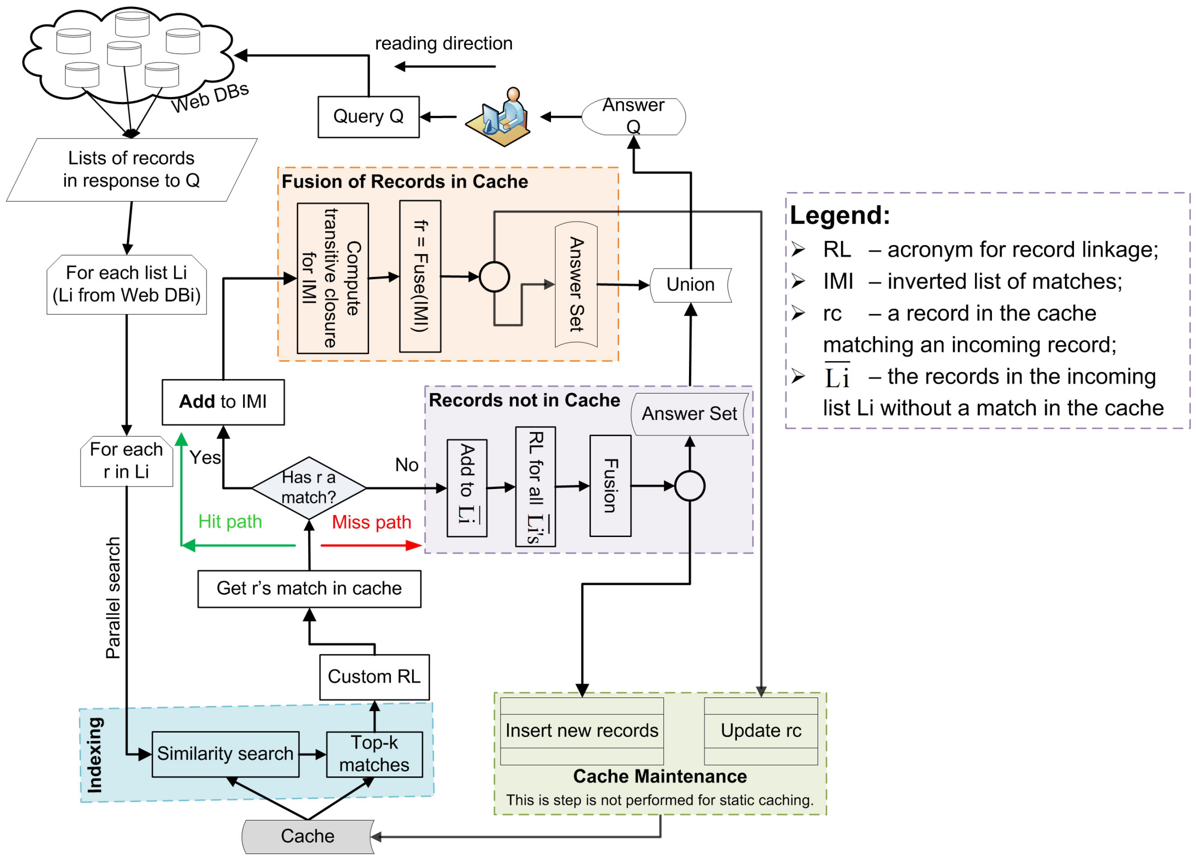
- An end-to-end framework to support RL&F at query time.
- The ability to seamlessly customize our framework by plugging in specific RL and data fusion algorithms. This feature is important because most RL&F algorithms are data-specific.
- A visually rich user interface that allows monitoring the quality of the data in the cache over time.
- We prepared several scenarios from five domains, such as restaurant, hotel and books, to demonstrate that the quality (cached results include previous knowledge about entities) and efficiency (cached results reduce the number of unnecessary RL&F operations) of RL&F greatly benefit from query locality.

## II. System Description

We show the functioning of *ORLF* in Figure. 1. After obtaining the query results from the Web databases, *ORLF* first attempts to match them to cached records. If a match is found in the cache for an incoming record $r$ (the Hit path), $r$ is fused jointly with its matching cache record. If a match is not found in the cache for $r$ (the Miss path), *ORLF* adds $r$ to a miss list $\bar{L}_i$. Once all records have been consumed, *ORLF* applies a record linkage and fusion process on $\bar{L}_i$ and appends the result to the cache. To support these two paths, we introduce several key components.

### A. ORLF Components

**Caching Policy:** We implemented in *ORLF* three caching policies to support multiple application settings. The caching policies dictate the cache record update behavior of *ORLF* upon processing new queries: *dynamic* - all the records in the cache are subject to updates, *static* - records in the cache are read-only, and *static with in-place updates* - is similar to the static one except that a subset of the cache records are allowed to be updated until they reach a desired "cleaning factor".



Web DBs
reading direction
Query Q
Answer Q
Lists of records in response to Q
Fusion of Records in Cache
Compute transitive closure for IMI
fr = Fuse(IMI)
Answer Set
Union
Legend:
➢ RL – acronym for record linkage;
➢ IMI – inverted list of matches;
➢ rc – a record in the cache matching an incoming record;
➢ $\overline{\text{Li}}$ – the records in the incoming list Li without a match in the cache
For each list Li (Li from Web DBi)
Add to IMI
Records not in Cache
Answer Set
For each r in Li
Yes
Has r a match?
No
Add to $\overline{\text{Li}}$
RL for all $\overline{\text{Li}}$'s
Fusion
Hit path
Miss path
Get r's match in cache
Parallel search
Custom RL
Indexing
Similarity search
Top-k matches
Insert new records
Update rc
Cache Maintenance
This is step is not performed for static caching.
Cache

Fig. 1: Query answering using RL&F with iterative caching.

**Record Lookup:** *ORLF* has two processing paths for the incoming query records: the *Hit path* and the *Miss path* (Figure 1). Upon processing an incoming record $r$, *ORLF* attempts to find a record that is similar to $r$ in the cache, so that they can be cleaned collectively. We developed an indexing data structure based on the B$^{ed}$-tree index [10] to support fast (approximate) record search (see [7] for details) in the cache. The index is used to retrieve the $k$ most similar records to $r$.

**Custom RL:** The set of the top-k records returned by the index needs to be further filtered out using a matching function. We implemented three domain-specific matching functions (Section III-A). Users however can input their matching algorithm in the form of a Java code to perform *Custom RL*. The function takes as input two records and returns $True$ if they match (refer to the same entity), and $False$ otherwise.

**Handling Non-Matching Records:** When the top-k records for $r$ do not include any matching record, $r$ is processed in the *Miss path*. The incoming records that do not have a match in the cache are stored in a data structure $\bar{L}_i$, where $i$ is the source index. RL&F are performed across the records in $L_k$ where $1 \leq k \leq N$, $N$ is the number of data sources. The resulting fused records are appended to the cache.

**Fusion:** The fusion procedure $fuse$ is an input to the *ORLF* system. Users are allowed to feed *ORLF* their own data fusion algorithms (in the form of a Java procedure). *ORLF* has a default fusion procedure which uses majority voting as the fusion criterion. The input of $fuse$ is a collection of records and the output is one fused record.

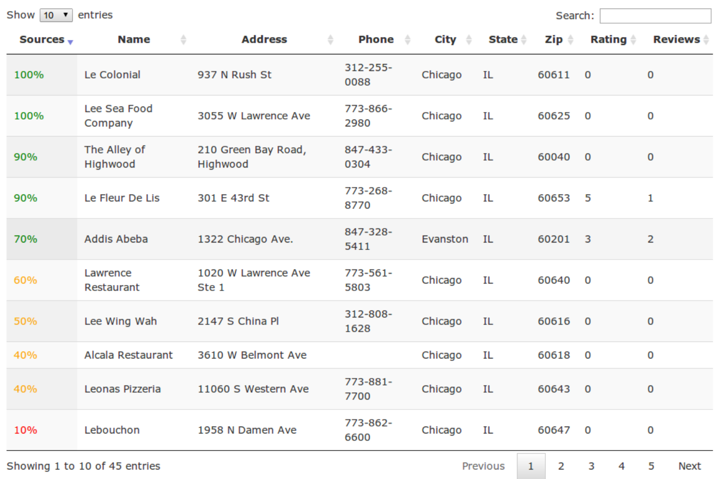
***ORLF* Dashboard:** The dashboard allows users to view and edit the cache configuration. It also provides users with statistics such as the current size of the cache and the average query hit ratio (ratio of records returned by the query that were matched to cache records). The dashboard offers users intuitive visualizations to better understand the state of the cache. For example, Figure 2b shows a heatmap of cached entities over a time window: the darker the entry, the more frequently that entry was matched to query results. This information is useful to assess the effectiveness of the cache in terms of how frequently it matches query results. Figure 2a shows an example visualization of the cache table, the attribute "sources" contains the ratio of sources that contributed in fusing the cache record.

## *B. ORLF User Input*

*ORLF* accepts four types of user inputs: (1) Schema-related files; (2) Cache warm up; (3) Record matching procedure; and (4) Fusion procedure.

**Schema-Related Files:** *ORLF* returns an answer to a query $Q$ over a target schema $T$. Users input two sets of XML files: the source and target schema and the correspondences between their elements.

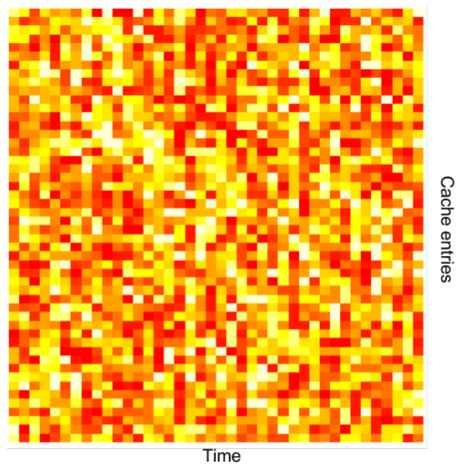
**Cache Warm up:** Users may choose to bootstrap the system with a set of queries that are posted to *ORLF* to populate the cache initially. This input is optional.



| Sources | Name | Address | Phone | City | State | Zip | Rating | Reviews |
|---|---|---|---|---|---|---|---|---|
| 100% | Le Colonial | 937 N Rush St | 312-255-0088 | Chicago | IL | 60611 | 0 | 0 |
| 100% | Lee Sea Food Company | 3055 W Lawrence Ave | 773-866-2980 | Chicago | IL | 60625 | 0 | 0 |
| 90% | The Alley of Highwood | 210 Green Bay Road, Highwood | 847-433-0304 | Chicago | IL | 60040 | 0 | 0 |
| 90% | Le Fleur De Lis | 301 E 43rd St | 773-268-8770 | Chicago | IL | 60653 | 5 | 1 |
| 70% | Addis Abeba | 1322 Chicago Ave. | 847-328-5411 | Evanston | IL | 60201 | 3 | 2 |
| 60% | Lawrence Restaurant | 1020 W Lawrence Ave Ste 1 | 773-561-5803 | Chicago | IL | 60640 | 0 | 0 |
| 50% | Lee Wing Wah | 2147 S China Pl | 312-808-1628 | Chicago | IL | 60616 | 0 | 0 |
| 40% | Alcala Restaurant | 3610 W Belmont Ave |  | Chicago | IL | 60618 | 0 | 0 |
| 40% | Leonas Pizzeria | 11060 S Western Ave | 773-881-7700 | Chicago | IL | 60643 | 0 | 0 |
| 10% | Lebouchon | 1958 N Damen Ave | 773-862-6600 | Chicago | IL | 60647 | 0 | 0 |

Showing 1 to 10 of 45 entries

(a) The Cache Table



(b) The Cache Heatmap

Fig. 2: Dashboard: Visualization of the cache content and an example heatmap of cache entries, entries with more frequent query hits are color-coded with a darker colors

**Record Matching Procedure:** *ORLF* requires a pair-wise record matching function in order to classify a record pair as a match or a mismatch. Since record matching functions are highly domain-dependent, *ORLF* allows users to write their own Java code to perform record matching. This function is used to remove false positive record matches from the top-k result set returned by the index data structure for an incoming record. The following is the signature of the function **compare**:

```
Boolean compare(Record target_record)
```

Function **compare** is a non-static member function of the class **Record**. It returns *True* if the calling record matches **target_record**, and *False* otherwise.

**Fusion procedure:** *ORLF* also gives users the flexibility to plug in their own fusion procedure. The fusion operation is performed for each list of matching records. The signature of the function **fuse** is:

```
Record fuse(Collection<Record> records)
```

**fuse** is a non-static member function of the class **Record**. It fuses the calling record with a collection of **records** and returns the fused record. *ORLF* provides three fusion algorithms: (i) default, based on majority voting, (ii) Solaris' ACCU fusion algorithm [6], and (iii) LTMinc [11].

## III. Demonstration Overview

In this demonstration, the audience will experience two different usage scenarios using three datasets.

### A. Datasets

While *ORLF* works directly with Web databases, we will use three pre-crawled datasets to avoid connectivity issues during the demonstration. These datasets are: (1) **Restaurants:**[1] We crawled 9 Web databases that provide information about restaurant listings in the metropolitan Chicago area, US, such as Yelp (10,115 records), YellowPages (7,798 records) and Yahoo (10,820 records); (2) **Book Author:**[2] This dataset is crawled from abebooks.com. It consists of 1,263 book entities, 2,420 book-author facts, and 48,153 claims from 879 book seller sources; and (3) **Flight:**[2] This dataset contains flight data from 38 sources.

### B. Demonstration Scenarios

We will showcase two demonstration scenarios: (1) an interactive demonstration in which we walk the audience through the core features of the *ORLF* system and (2) a scenario where users can set up *ORLF* for a particular application domain.

*1) Scenario I: A Walk-through of the Core Features of ORLF:* The audience will interact with *ORLF* at multiple levels, namely: (1) Record Linkage and Fusion procedures editor; (2) Warming up the cache; (3) Experimenting with different cache configurations, presenting their impact on the data quality of the query results; and (4) Monitoring the state of the cache.

**(1) Plug-and-Play Record Linkage and Fusion:** We will demonstrate multiple custom RL&F algorithms through the *ORLF* RL&F rule editor. The audience will select from three fusion algorithms, namely, majority voting (the default fusion), the Solaris' fusion algorithms [6] and the LTM and LTMinc fusion algorithms [11]. The audience will also have the opportunity to contrast the outcome of the fusion algorithms in *ORLF* on different datasets.

**(2) Warming up the Cache:** We will showcase two methods to warm up the cache: (i) import a clean dataset into *ORLF* and (ii) generate a simulated user query stream to *ORLF* (we explain this procedure in [7]), post them to the sources, collect the query results, apply off-the-shelf RL&F algorithms, and save the outcome into the cache.

**(3) Selecting Cache Configuration:** After the warm up phase, the audience will select the cache configuration, and

[1]http://cis.temple.edu/~edragut/research.htm

[2]http://lunadong.com/fusionDataSets.htm

the eviction policy. The goal is to illustrate the outcome of a query result under different cache configurations.

**(4) Monitoring the State of the Cache:** *ORLF* features a dashboard that shows the audience key insights about the current state of the cache, these include: (i) the usefulness of the cache entries computed so far, expressed in terms of average hit ratio per query; (ii) freshness information of cache records; and (iii) confidence of fused records based on how many sources were involved in fusing them.

*2) Scenario II: Setting up ORLF for a Specific Application Domain:* We will walk the audience through the steps required to set up *ORLF* for a specific application domain. As an example, we will use the **Restaurants** dataset.

**(1) Cache Index:** A key part in setting up the $B^{ed}$-tree-based cache index is the selection of the attributes that are used as a search key in the index. For example, in the restaurant data, we chose the attributes {name, address, phone} to be the search key. After the attribute selection, a few parameters need to be set empirically for the $B^{ed}$-tree index to answer top-k queries. Details on how to tune these parameters can be found in [7], [10].

**(2) Simulated Queries:** In order to simulate the influx of queries faced by search engines, we proposed in [7] a method to generate simulated queries. We will give an overview of the procedure. The stream of generated queries will be used to demonstrate the cache warm up.

**(3) Cache Warm up:** The previously generated queries follow a power-law distribution. The 20% most frequent queries are posted to the Web databases, and their results are cleaned offline using *FRIL* [5].

**(4) Record Matching and Fusion Procedures:** As discussed previously, the record matching and fusion procedures need to be set up depending on the application domain. We will show the audience those functions for the restaurant data.

## IV. Related Work

In this section we give a brief overview of some related systems built to address record linkage and fusion.

NADEEF/ER [3] is a RL system built as an extension of the open-source generalized data cleaning system NADEEF [3]. It leverages *NADEEF*'s programming interface to specify entity resolution rules. Users specify such rules based on their knowledge of the data and NADEEF treats them as black boxes to detect duplicates. We adopt the same idea for specifying the entity matching and fusion functions in *ORLF*. As opposed to *ORLF*, NADEEF/ER requires all the data to be available at once which makes it unsuitable for query-time RL.

Online entity resolution has been addressed in [1], [9], [8]. In [1], the main goal is to reduce the overhead incurred by resolving record pairs. The authors propose a set of semantics that would avoid resolving some pairs altogether as long as the selected semantics constraints are met.

Authors in [9] propose a query-time cleaning algorithm for aggregate queries. The idea is to use a clean sample of the database to estimate the aggregate attribute value.

In [8], record duplicates are identified at query time. The solution employs two classifiers that collaborate with each other iteratively to refine the set of found duplicates.

*ORLF* differs from the above systems in two key aspects: (i) it performs fusion on top of RL and (ii) it harnesses RL&F results from previous queries.

A set of algorithms to perform online data fusion is proposed in [6]. The key idea is to stop querying further data sources that are unlikely to change the decision about the "correct" fused value computed so far. As opposed to *ORLF*, these techniques do not perform record linkage and assume the availability of information about the accuracy of the sources and their copying relationships. Because *ORLF* is orthogonal to the fusion algorithm being used, we have implemented one of these techniques, namely ACCU [6], into our system.

A Bayesian approach to perform data fusion is proposed in [11]. It learns the quality of data sources and incorporates this knowledge in the fusion operation. Because of its stateless nature, the approach falls short in the online setting.

## V. Conclusions

The proposed demonstration brings a new dimension to the tasks of RL and fusion: query time. At its core, *ORLF* leverages query locality, iterative caching, and smart indexing techniques to efficiently deliver duplicate-free and accurate query results. MI'mMoreover, *ORLF* provides users with the ability to use their own record matching and fusion procedures. To showcase its flexibility, the audience will be able to try the system on multiple application domains and with different record matching and fusion algorithms.

## Acknowledgment

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