Entity Resolution of Publication Data

Github link

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2. Abstract

In this project, we explore the development of data engineering and ML pipelines, with a specific emphasis on constructing an Entity Resolution (ER) pipeline for deduplicating research publication datasets.

The initial phase involves acquiring the datasets and transforming them from TXT to CSV format. Subsequently, we proceed to create a local entity resolution pipeline designed to merge related entities.

In the final stage, we were hands-on PySpark framework to reimplement our local pipeline on top of a data-parallel computation framework. We also evaluate the scalability of the module through comprehensive testing.

3. Quick Overview and User Instruction

3.1. Installation

The prerequisites in addition to the python packages are

> spark == 3.5.0 scala == 2.12.x graphframes == 0.8.3-spark3.5-s_2.12

graphframes can be installed by running `pyspark --packages graphframes:graphframes:0.8.3-spark3.5-s_2.12` and moving those jars to path-to-spark-home/libexec/jars

```
cd path-to-this-project
pip install -e .
```

3.2. Sample to Run Exercise

part1/2/3

```
from erp import part1, part2, part3
part1() # cleaned data stored in "data"
part2() # results of all methods stored in "method_results.csv"
part3() # scability test
```

3.3. Quick Project Overview

The project involves implementing an Entity Resolution Pipelining on citation networks from ACM and DBLP datasets.

3.3.1. Data Source

The project starts with two large dataset text files you need to download:

- [DBLP-Citation-network V8]
- [ACM-Citation-network V8]

(Can be found here)

Make sure to save these in the local `data` folder.

Below is the structure of the project:

- 📁 **project**
  - 📁 **erp**: Contains Python scripts for the entity resolution pipeline.
  - 📁 **data**: Stores datasets and instruction files.
  - 📁 **results**: Contains results of the entity resolution pipeline process.
  - 📄 `.gitignore`
  - 📄 `requirements.txt`
  - 📄 `setup.py`
  - 📄 `README.md`
  - 📄 `sample.py`

3.3.2. erp Folder

The erp folder contains scripts for the entity resolution pipeline with specific configurations:

- **Preparing Data**: Run `erp.preparing.prepare_data("path_to_txt_file")` for both text files. This will clean and extract the relevant data (1995-2004 citations by "SIGMOD" or "VLDB" venues). The resulting csv files will show in `data` folder.
- **Running Pipeline**:
  - Local Version : Run `erp.ER_pipeline(databasefilename1, databasefilename2, ERconfiguration, baseline=False, cluster=True,matched_output="path-to-output-file", cluster_output="path-to-output-file", isdp=False)` (in `erp/main.py`)
  - DP Version: Run `erp.ER_pipeline(databasefilename1, databasefilename2, ERconfiguration, baseline=False, cluster=True, matched_output=F"path-to-output-file", cluster_output="path-to-output-file", isdp=True)` (it calls `ER_pipeline_dp` in `erp/dperp.py`)
- **Configuration Options**:
  - `blocking_method` (String): Methods to reduce execution time `{“Year”, “TwoYear”, “numAuthors”, “FirstLetterTitle”, “LastLetterTitle”, "FirstOrLastLetterTitle", “authorLastName”, “commonAuthors”, “commonAndNumAuthors”}` .
  - `matching_method` (String): Algorithms for entity matching `{"Jaccard", "Combined"}` .
  - `clustering_method` (String): Altogirthm for clustering {"basic"}.
  - `threshold` (float): A value between 0.0-1.0 for the matching similarity threshold.
  - `output_filename` (String): path and file name of clustering results to be saved.

Selected Functions in local pipeline

- Blocking: `erp.blocking(df1,df2,blocking_method)`
  - Parameters:
    - df1,df2 (pandas.DataFrame) : input databases
    - blocking_method(str) : {“Year”, “TwoYear”, “numAuthors”, “FirstLetterTitle”, “LastLetterTitle”, “authorLastName”, “commonAuthors”, “commonAndNumAuthors”}
- Matching: `erp.matching(blocking_df,similarity_threshold, matching_method)`
  - Parameters:

        - blocking_df(pandas.DataFrame)
        - similarity_threshold (float from 0.0 to 1.0)
        - matching_method (String) : {"Jaccard", "Combined"}
- Clustering: `erp.clustering(matched_entities, df1, df2, clustering_method)`
    - Parameters:
        - matched_entities(pandas.DataFrame)
        - df1,df2 (pandas.DataFrame) : input databases
        - clustering_method (String) :{'basic'}

Selected Configuration

ERconfiguration:

```
{
  "matching_method": "Combined",
  "blocking_method": "FirstOrLastLetterTitle",
  "clustering_method": "basic",
  "threshold": 0.7,
  "output_filename": "clustering_results_local.csv"
}
```

- This folder also contains `dperp.py` , which serves as a reimplementation of the local entity recognition pipeline within the Apache Spark framework.

3.3.3. Results Folder

- The steps above will produce the results. They are saved according to your `output_filename` configuration. In our ERconfiguration shown above, it will be saved as `clustering_results_local.csv` within the `results` folder.
- This folder contains all the results that are calculated and used in part 2 and part 3.

3.3.4. Data Folder

The data folder includes the prepared and cleaned datasets and additional samples:

- `citation-acm-v8_1995_2004.csv` : ACM citation network dataset.
- `dblp_1995_2004.csv` : DBLP citation network dataset.
- `DIA_2023_Exercise.pdf` : Project instruction file.

Note: Check `requirements.txt` for compatibility before running the code.

4. Data Acquisition and Preparation (Part 1)

In this section, we acquire datasets related to research publications. These datasets, available in text format, can be reached by clicking here.

As a prerequisite for Entity Resolution and Model Training, we have generated a dataset containing the following attributes:

- Paper ID, paper title, author names, publication venue, year of publication
- Publications published between 1995 and 2004
- Publications from VLDB and SIGMOD venues

We utilized Pandas DataFrame, to convert the datasets from TXT to CSV. Our code iterates through the text file, extracting entries separated by double newlines and filtering based on the specified criteria. The resulting cleaned dataframes are exported to the local `data` folder.

> The code for this section can be found in the file named `preparing.py` under the function called `prepare_data` . Additionally, the resulting CSV files are available in the local `data` folder with the suffix `__1995_2004.csv` .

5. Entity Resolution Pipeline (Part 2)

We aim to apply an entity resolution pipeline to the aforementioned datasets, following the scheme depicted below:

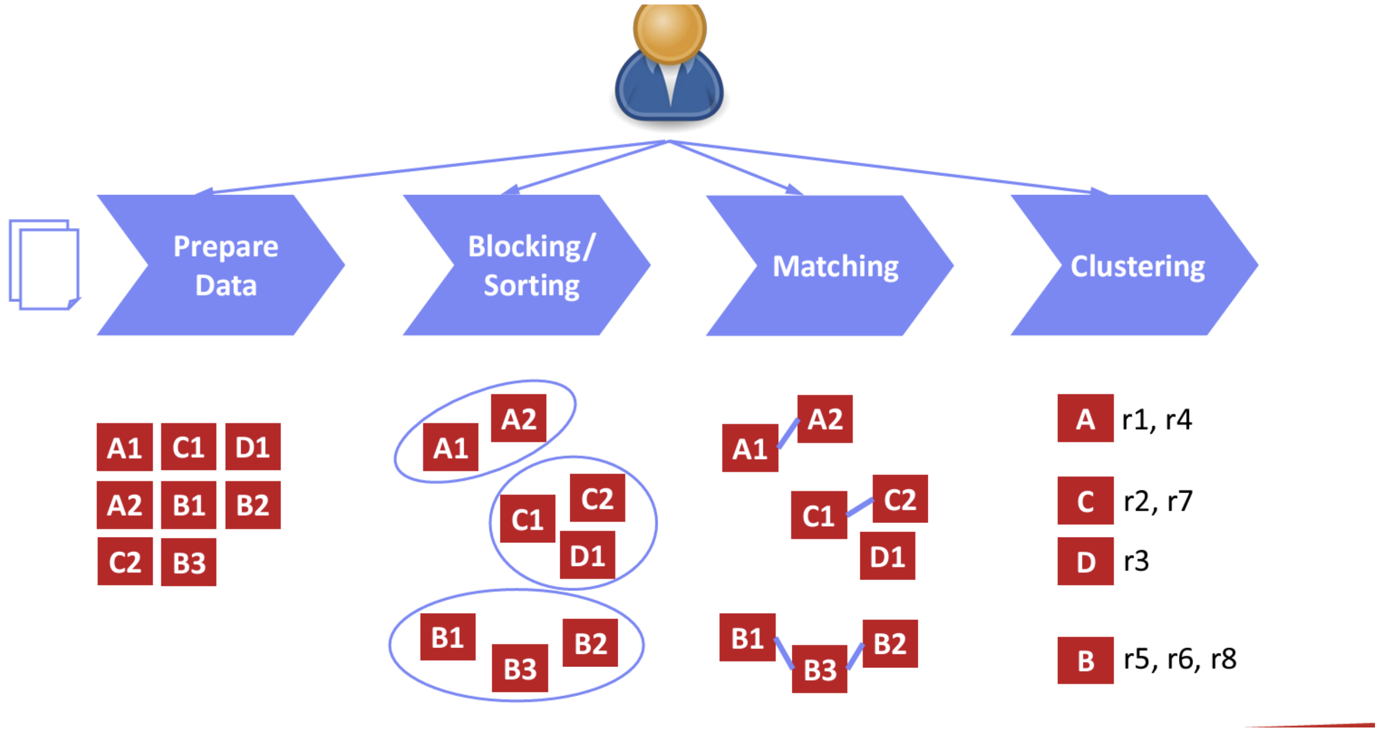


Image Source: Prof. Matthias Boehm, Data Integration and Large-Scale Analysis Course, TU Berlin.

5.1. Prepare Data

Continuing from the previous section, we employ various data-cleaning techniques. This step converts all characters to lowercase, ensures uniformity, and eliminates special characters, retaining only alphanumeric characters, spaces, and commas. This process standardizes and cleans the textual data for easier comparisonmand analysis.

> The code for this part is available in the file named `preparing.py` under the function called `prepare_data` .

5.2. Blocking

Blocking is employed to reduce the number of comparisons by using effective partitioning strategies. In each 'bucket', we run the comparisons (see the section below). Our blocking is achieved through partitioning based on attributes:

1. **Year:** Articles that were published in the same year would be in the same bucket.
2. **Two Year:** Articles that were published in the same year or in the adjacent year would be in the same bucket.
3. **Num Authors:** Articles with a similar number of authors (up to 1 difference) would be in the same bucket.
4. **Common Author:** Articles with at least one common author would be in the same bucket.
5. **Num Authors and Common Author:** Articles with at least one common author and a similar number of authors (up to 2 differences) would be in the same bucket.
6. **First Letter:** Articles with the same first letter of the title would be in the same bucket.
7. **First or Last Letter:** Articles with the same first letter or the last letter of the title would be in the same bucket.
8. **Last Name:** Articles with at least one author with a common last name would be in the same bucket.

> The code for blocking is in the file named `matching.py` , with functions named `blocking` and `create_xBlocking` , where x is the respective blocking method. (see selected functions for more detail to use them.)

5.3. Matching

Before discussing comparison methods, some terms related to our pipeline are introduced:

- Baseline - We establish a baseline by comparing every pair between datasets, given a certain similarity function applied. This is our 'ground truth'.
- Matched Entities - Our matched entities are generated by comparing each pair within a bucket, with the same similarity function applied to the respective baseline.

Jaccard - The Jaccard similarity function is employed to measure the extent to which two sets share common elements. It does so by calculating the ratio of the shared elements to the total elements in both sets. Thresholds of 0.5 and 0.7 are used in the comparison of the 'paper title' attribute.

Combined - This function calculates a combined similarity score between two papers based on their titles and author names. It utilizes Jaccard similarity for title comparison and, if available, trigram similarity for author name comparison. The final combined similarity score is a weighted sum of title and author name similarities, with 70% weight is assigned to the title and 30% to the author names. If author names are missing for either paper, the function defaults to using only the Jaccard similarity of titles.

For the blocking methods mentioned above:

Jaccard similarity function with **Year** partitioning identifies matching articles with similar titles published in the same year.

Jaccard and **Two-year** partitioning identifies matching articles with similar titles published in the same year or in the adjacent year.

Jaccard and **Num Authors** partitioning identifies matching articles with similar titles and a similar number of authors.

Jaccard and **First Letter** partitioning identifies matching articles with similar titles and the same first letter of the paper title.

Jaccard and **Last Letter** partitioning identifies matching articles with similar titles and the same last letter of the paper title.

Jaccard and **First or Last Letter** partitioning identifies matching articles with similar titles and the same first or last letter of the paper title.

Jaccard and **Authors last name** partitioning identifies matching articles with similar titles and the author's last name.

Jaccard and **Common Authors** partitioning identifies matching articles with similar titles and the same authors.

Jaccard and **Num of Authors** partitioning identifies matching articles with similar titles and the difference between their numbers of authors are smaller than 2.

Jaccard and **Num of Authors and Common Author** partitioning identifies matching articles with similar titles and at least one common Author with the difference between their numbers of authors smaller than 3.

Likewise, the **Combined** similarity will yield results for the different blocking methods, with the only difference being that it takes into account the number of authors in the comparison.

> The code for this part is available in the file named `matching.py`, with function `matching(blocking_results, similarity_threshold, matching_method, outputfile)` similarity functions named `calculate_x_similarity`, where x is the respective similarity method. CSV files for each similarity function and blocking method will be exported to a local `results` folder.

By testing various combinations, we obtained results that can be seen here, with a screenshot displayed below:

Blocking method	Matching Method	Baseline Execution Time	Blocking Execution Time	Matching Execution Time	Execution Time	Similarity Threshold	Pairs In Baseline	Pairs In Blocking	TP	FN	FP	Precision	Recall	F1 Score
TwoYear	Jaccard	0.73	0.03	0.13	0.16	0.5	2007	1813	1813	194	0	1.0	0.9033383158943697	0.9492146596858639
commonAuthors	Jaccard	0.73	0.8	0.0	0.8	0.5	2007	1701	1701	306	0	1.0	0.8475336322869955	0.9174757281553398
Year	Jaccard	0.73	0.03	0.07	0.1	0.5	2007	1749	1749	258	0	1.0	0.8714499252615845	0.9313099041533547
LastLetterTitle	Jaccard	0.73	0.07	0.15	0.22	0.5	2007	1876	1876	131	0	1.0	0.9347284504235177	0.9662631985578161
numAuthors	Jaccard	0.73	0.52	0.56	1.08	0.5	2007	1944	1944	63	0	1.0	0.968609865470852	0.9840546697038723
FirstOrLastLetterTitle	Jaccard	0.73	0.12	0.17	0.29	0.5	2007	1976	1976	31	0	1.0	0.9845540607872446	0.992216921918152
FirstLetterTitle	Jaccard	0.73	0.08	0.08	0.16	0.5	2007	1864	1864	143	0	1.0	0.9287493771798705	0.9630586411779902
commonAndNumAuthors	Jaccard	0.73	0.77	0.0	0.77	0.5	2007	1673	1673	334	0	1.0	0.833582461385152	0.9092391304347825
authorLastName	Jaccard	0.73	0.48	0.01	0.49	0.5	2007	1805	1805	202	0	1.0	0.8993522670652716	0.9470094438614901
TwoYear	Jaccard	0.71	0.05	0.12	0.16	0.7	1818	1715	1715	103	0	1.0	0.9433443344334433	0.9708463062553071
commonAuthors	Jaccard	0.71	0.63	0.0	0.63	0.7	1818	1610	1610	208	0	1.0	0.8855885588558856	0.9393232205367561
Year	Jaccard	0.71	0.05	0.06	0.11	0.7	1818	1673	1673	145	0	1.0	0.9202420242024203	0.9584646233171011
LastLetterTitle	Jaccard	0.71	0.08	0.14	0.21	0.7	1818	1752	1752	66	0	1.0	0.9636963696369637	0.9815126050420168
numAuthors	Jaccard	0.71	0.5	0.46	0.95	0.7	1818	1771	1771	47	0	1.0	0.9741474147414741	0.9869044302033992
FirstOrLastLetterTitle	Jaccard	0.71	0.12	0.17	0.29	0.7	1818	1811	1811	7	0	1.0	0.9961496149614961	0.9980710939652797
FirstLetterTitle	Jaccard	0.71	0.08	0.04	0.12	0.7	1818	1745	1745	73	0	1.0	0.9598459845984598	0.9795116474880718
commonAndNumAuthors	Jaccard	0.71	0.65	0.0	0.65	0.7	1818	1585	1585	233	0	1.0	0.8718371837183718	0.9315310020570086
authorLastName	Jaccard	0.71	0.45	0.01	0.45	0.7	1818	1704	1704	114	0	1.0	0.9372937293729373	0.9676320272572402
TwoYear	Combined	2.95	0.05	0.56	0.61	0.5	2024	1834	1834	190	0	1.0	0.9061264822134387	0.9507516848107828
commonAuthors	Combined	2.95	0.62	0.02	0.64	0.5	2024	1792	1792	232	0	1.0	0.8853754940711462	0.939203354297694
Year	Combined	2.95	0.05	0.31	0.36	0.5	2024	1764	1764	260	0	1.0	0.8715415019762845	0.9313621964097148
LastLetterTitle	Combined	2.95	0.08	0.65	0.73	0.5	2024	1881	1881	143	0	1.0	0.9293478260869565	0.9633802816901409
numAuthors	Combined	2.95	0.5	2.03	2.54	0.5	2024	1972	1972	52	0	1.0	0.974308300395257	0.9869869869869871
FirstOrLastLetterTitle	Combined	2.95	0.13	0.82	0.95	0.5	2024	1983	1983	41	0	1.0	0.9797430830039525	0.9897679061642125
FirstLetterTitle	Combined	2.95	0.08	0.19	0.27	0.5	2024	1859	1859	165	0	1.0	0.9184782608695652	0.9575070821529745
commonAndNumAuthors	Combined	2.95	0.64	0.01	0.65	0.5	2024	1764	1764	260	0	1.0	0.8715415019762845	0.9313621964097148
authorLastName	Combined	2.95	0.45	0.03	0.49	0.5	2024	1895	1895	129	0	1.0	0.9362648221343873	0.9670834396529727
TwoYear	Combined	3.0	0.05	0.57	0.62	0.7	1784	1693	1693	91	0	1.0	0.9489910313901345	0.9738280126545873
commonAuthors	Combined	3.0	0.69	0.02	0.71	0.7	1784	1639	1639	145	0	1.0	0.9187219730941704	0.9576394975167981
Year	Combined	3.0	0.05	0.31	0.36	0.7	1784	1669	1669	115	0	1.0	0.9355381165919282	0.9666956269910222
LastLetterTitle	Combined	3.0	0.08	0.67	0.75	0.7	1784	1720	1720	64	0	1.0	0.9641255605381166	0.9817351598173517
numAuthors	Combined	3.0	0.5	2.12	2.62	0.7	1784	1751	1751	33	0	1.0	0.9815022421524664	0.9906647807637907
FirstOrLastLetterTitle	Combined	3.0	0.12	0.83	0.95	0.7	1784	1778	1778	6	0	1.0	0.9966367713004485	0.9983155530600786
FirstLetterTitle	Combined	3.0	0.08	0.19	0.27	0.7	1784	1754	1754	30	0	1.0	0.9831838565022422	0.9915206331260599
commonAndNumAuthors	Combined	3.0	0.64	0.01	0.66	0.7	1784	1618	1618	166	0	1.0	0.9069506726457399	0.9512051734273956
authorLastName	Combined	3.0	0.46	0.04	0.49	0.7	1784	1730	1730	54	0	1.0	0.9697309417040358	0.9846328969834945

The best model is based on the combination of the **'First or Last Letter'** blocking and the **Combined** similarity function, for two main reasons:

1. The Combined similarity function has proven to yield more reliable results for matched entities upon close inspection of the data.
2. First or Last Letter Matching has seemed to outperform all the other methods in terms of Precision, Recall and F1 Score, and the execution time reduction is also very significant.

5.4. Clustering

In the final part of the pipeline, we chose to cluster the matched entities.

We use the Numpy package to create a graph, organizing related items into clusters of similar entities in our clustering process (clustering_basic). Each item is represented as a point in the graph. Connections between similar items, as identified in our matching output, are drawn in the graph. We then employ depth-first search (DFS) to traverse these connections, updating values as we explore and contributing to the organization of clusters in the final results.

> The code for clustering is available in the file named `clustering.py` , and The resulting CSV file will be exported to a local directory called "results" with the chosen name (by default: "clustering_results_local.csv").

6. Data Parallel Entity Resolution Pipeline (Part 3)

At the beginning of this stage, we create an Entity Resolution pipeline using Apache Spark. We walk through all the phases of the Entity Resolution pipeline with the structured data frame. We employ a deployment model in our Pyspark environment utilizing a maximum number of local threads specified as local[*]. This deployment configuration enables parallel processing, leading to a substantial reduction in overall runtime. It also has a number of convenient built-in functions, for example, `df.filter` and `df.groupBy` help us with our blocking method.

In this Data Parallel framework, we mainly deploy one matching method (Combined Similarity), two blocking methods (FirstLetterTitle and FirstLetter Matching) and one clustering method (basic clustering with graph).

> You can see the code for this part at `dprep.py`

After using Spark's data frame, we wanted to compare it with our local pipeline (the one we constructed in part 2). The Two ER pipeline is configured as:

```
DEFAULT_ER_CONFIGURATION = {
    "threshold": 0.7,
    "matching_method": "Combined",
    "blocking_method": "FirstLetterTitle",
    "clustering_method": "basic",
    "output_filename": "clustering_results_local.csv",
}
```

The results are quite the same for all the methods we implemented.

	FirstLetterTitle	**FirstOrLastLetterTitle**
Number of differences (dp and local)	0	0
Number of matched pairs	1750	1778

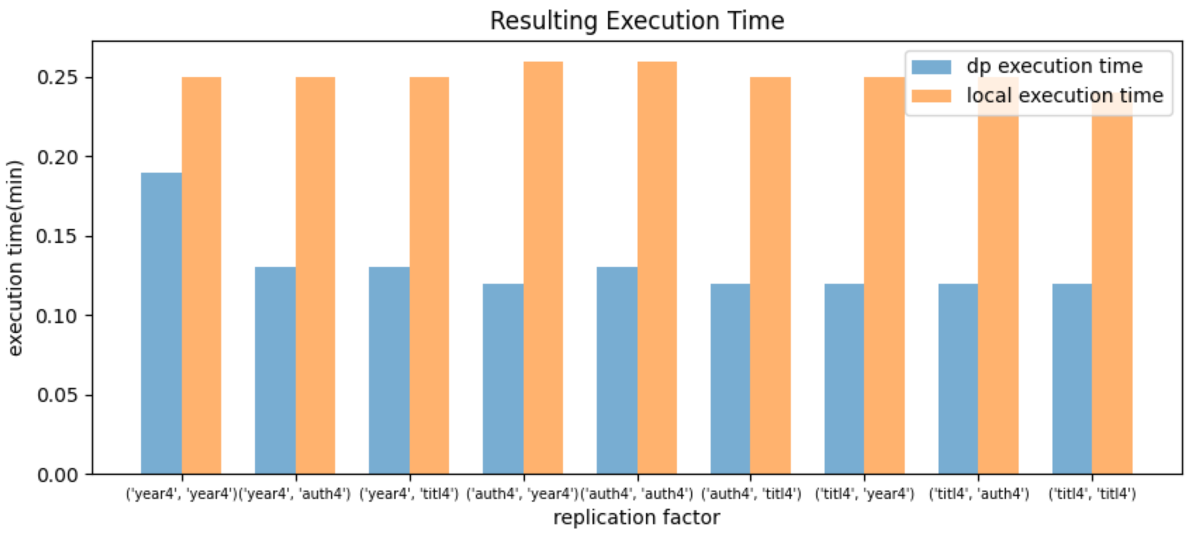
> You can see the code for this part under the function `naive_DPvsLocal` in `main.py`

Given that we have established the reliability of Spark's pipeline, our objective is to evaluate the scalability performance of our pipelines. As a result, we have generated larger datasets with several modifications derived from our initial data.

To investigate the impact on our model, we introduced various alterations to the title, year, and author name. Specifically, for string inputs, we randomly selected n positions within the string and replaced a letter at each position with a randomly chosen alphabet. Moreover, for number inputs, we modified them by either incrementing or decrementing the value by n/2.

> see the function `create_databaseWithChanges`

attached here are our scalability results:



x-asis: Replication factor (first four letter indicates which factor in the original database we choose to modify, and the last letter indicates the value of n), y-axis: Runtime in minutes