# Topological and Semantic Graph-based Author Disambiguation on DBLP Data in Neo4j

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Abstract-In this work, we introduce a novel method for entity resolution author disambiguation in bibliographic networks. Such a method is based on a 2-steps network traversal using topological similarity measures for rating candidate nodes. Topological similarity is widely used in the Link Prediction application domain to assess the likelihood of an unknown link. A similarity function can be a good approximation for equality, therefore can be used to disambiguate, basing on the hypothesis that authors with many common co-authors are similar. Our method has experimented on a graph-based representation of the public DBLP Computer Science database. The results obtained are extremely encouraging regarding Precision, Accuracy, and Specificity. Further good aspects are the locality of the method for disambiguation assessment which avoids the need to know the global network, and the exploitation of only a few data, e.g. author name and paper title (i.e., coauthorship data).

Keywords—disambiguation; entity resolution; semantic networks; topological similarity; link prediction; bibliometrics; graph-based database; Neo4j; NoSQL Database; co-authorship network; social network analysis

### I. INTRODUCTION

The diffusion of online social networks with ubiquitous access and redundant data can be a challenge for using additional information in order to prevent ambiguity. *Entity Resolution (ER* is the task of identifying and linking different manifestations of real-world objects, compensating for the lack of data quality, such as incorrect or missing data or attributes change over time. ER is essential for several applications, starting with simple de-duplication tasks. For instance, for a company or for a political party, which rely on a database of people who declared their interest in a product/service/activity or were automatically added to the

list, to promote or send an advertisement to a de-duplicated set of people could be an economic advantage. More complex applications include, among others, recommender systems, social network analysis, and digital library management for *research bibliometrics*. In the latter, authors and other inventory metadata should be unambiguously identified and referred to the organisation/topic/journal context related to their production.

*Disambiguation* is a solution to the Entity Resolution problem, recognising and clustering such different object manifestations in groups corresponding to the same object, i.e. identifying which representation objects are different phenotypes of the same real object. Disambiguation is, in fact, the task of identifying entities referring to the same object in a set of candidates [1], [2].

*Link Prediction* (LP) [3] is a method establishing the strength of ties in a graph, e.g. a social network [4] or a bibliographic database. The more the strength, the more robust the ties among potential collaborators, e.g. co-authors.

*Topological similarity* is a suitable candidate method for link prediction. We hypothesise that authors with many *common co-authors* are similar [5], [6]. In fact, if anyone looks at himself as if he was another person, it is easy to guess that a proper evaluation function for similarity will give a high evaluation to such two ambiguous candidates (i.e., him as an observer and him as observed).

In this project we propose a new approach for link prediction using topological (e.g. Adamic, Common Neighbours) and semantic similarity (e.g. Confidence, PMI and PMING). We aim to predict future links or infer existing unknown links from a social network on Neo4j as a graphbased database. The workflow for the experimentation, performed on DBLP, includes the following phases: import DBLP in Neo4j, import information about links (e.g. authorship, publication), import useful metadata (e.g. year of publication), link prediction through graph-based data query, result evaluation. The main idea is that it is useful for link prediction to use a graph-based database in order to quickly perform queries on the links on common-neighbours, in a much more efficient way than on SQL-based databases, or even edges lists, especially for long paths.

Furthermore, our experiments apply, to bibliometric analysis, previous models for semantic similarity and link prediction, stating that it is possible to generalize semantic similarity under the assumption that similar concepts co-occur in documents/databases indexed by a search engine, and that the information on common-neighbours of commonneighbours (up to a maximum path length of three) are effective and efficient for link prediction. Both semantic and topological similarity measures make profit from suboptimal results of computations, where approximations to evaluate frequencies and probabilities can be used to calculate semantic proximity or distance. Which measure to use, and how to optimize the extraction and the utility of the extracted information, are open issues to which we contribute with our results.

In the following sections, we will define and explain the Entity Resolution problems of data quality, consider topological similarity for link prediction as a potential disambiguation method and expose our experiments in the realm of bibliographic data using DBLP [7] in Neo4j [8]. We will use a 2-steps traversal disambiguation with topologicalsimilarity-based link prediction, then discuss the results of our preliminary experimentation phase and present conclusions about the proposed approach.

# II. DATA QUALITY AND DISAMBIGUATION

Widely recognised properties for data quality include the following [9]:

- *Relevance*. Data meet the needs for which they are collected.
- *Accuracy*. Data cannot be protected against every error, but the grade of accuracy of the primary variables of interest can be defined and evaluated.
- *Timeliness*. Concerns about how current does the information need to be, in order to make predictions.
- *Comparability*. Defines if it is appropriate to compare several databases to facilitate data use in modeling statistical estimators.
- *Coherence*. Data are logically interconnected and consistent.
- *Completeness*. No records are missing; no records have missing elements.

Unfortunately, many organisational data do not meet these requisites. In the case of bibliometric research data, poor data quality can be due to situations such as:

• *Incorrect data:* values are recorded incorrectly in the data entry phase, e.g. typographical or spelling mistakes, or information is incorrect, e.g. the wrong

postal code in a postal address.

- *Missing data*: values are not recorded, e.g. missing university department and address information, when only the name of the academy is given.
- Attributes change over time, e.g. an author changing affiliation, or an institute changing the name, as happened in last five years in Italian universities, where faculties were eliminated as institution level, and departments changed names and sometimes merged.
- *Irrelevant data:* relevant information is submerged in poorly structured data, e.g. poor or diverse data formatting.
- *Imprecise data:* information is not recorded at the desired level of granularity, making a wrong use of a proper format, e.g. name and surname inverted, wrong level on the specificity of the affiliation (for example confusing laboratory or research group, a department with faculty or university).

Furthermore, acronyms, abbreviations, and data truncation, among others for space limitations, can vary from publication to publication. Translations can also introduce issues, e.g. original name versus English name, or different translations of the same institutional name. Although most authors indicate their affiliation with an English name, translation from the original entity name may not be univocal, and therefore difficulties may arise to credit the same institution for publications in which it was indicated with different names.

An excellent approach to the solution will include prevention, detection and repair of disambiguation [10]–[12]. Henk Moed [13] assesses that the best disambiguation method is the human manual one.

#### III. TOPOLOGICAL SIMILARITY FOR LINK PREDICTION

Common Neighbours-based (CN) rankings (e.g. Jaccard, Adamic-Adar) [14], [15] represent a class of similarity measures for link prediction, which efficiently assess the likelihood of a new link based on the neighbours frontier of the already existing nodes [16]. The CN similarity measures are more performant than others (e.g. preferential attachment, path-based distances [17]–[21]) in link prediction [22], [23], but they present the drawback of returning a large *0-tail*: a zero-rank value is given to all the links of pair of nodes, which have no common neighbours. Even if the rating is equal to *0*, such links may be potentially suitable for link prediction [24], [25].

Let a training network G=(V,A) at time t, with N nodes and undirected arcs  $A \subseteq VxV$ , and let a given test network G'=(V,A'), where G' is an extension of G at time t+k and  $A \subseteq A'$ . The classic link prediction problem is to rank with a function r(G) the set of potential links  $A_{pot}$  which could appear in *G*', such that the new links  $A_{new}$  are ranked first. A perfect rank function (Kendall 1938) would return all the  $A_{new}$  links in the first  $/A_{new}/$  ranking positions:

$$KtA = \frac{1}{|A_{pot}| - 1 - |A_{new}|} * \sum_{l=|A_{new}|}^{|A_{pow}| - 1} (r_l - |A_{new}| + 1)$$
(1)

We provide here the definition of three commonneighbours-based similarity measures  $\Phi$ : the simple Common Neighbours (CN), the Adamic-Adar (AA), and the Pointwise Mutual Information (PMI) [26].

Given two papers *p1* and *p2* of authors *a1* and *a2*:

- \$\overline{\Phi\_1} = CN(a1,a2)\$ is a simple query in Cypher, the Neo4j query language, which counts the number of elements in the path like the following:
   match
   p=(a1:Author)-[\*..2]-(a2:Author)
   where a1.AuthorName="a1.name" and
   a2.AuthorName="a2.name"
   return p as path;
   (2)
- $\Phi_2 = PMI(j1, j2) = log[p(j1, j2)(p(j1)p(j2)]$  (3)
- $\Phi_3 = AA(a1,a2) = Sum(1/log[degCN(a1,a2)])$  (4)

Note that (3) is originally a semantic similarity measure [27], [28] of which we provided a novel topological definition in a graph.

#### IV. TWO-STEPS TRAVERSAL DISAMBIGUATION

Assume to start from a bipartite graph *authors-papers-authors* (see Fig.1), where authors may be ambiguous or partially disambiguated: this is the typical situation of a bibliographic database like the public DBLP Computer Science database when a new article is indexed. There can be specific information indicating an author identifier or, more likely, such information is not present. In particular, DBLP is extremely poor of information about the content of the papers.

The hypothesis is to have two authors a1 and a2 of two different papers p1 and p2: we aim to evaluate through each paper the similarity of the two authors, i.e. the likelihood that a1 and a2 are the same person (i.e., a1==a2). This problem is present only if a1 and a2 have similar names, or the same name or abbreviation, i.e. a1.fullName==a2.fullName or a1.abbreviatedName/Surname==a2.abbreviatedName/Surna me.

The two-steps traversal consists of 3 phases:

- *Phase 1:* starting from the node *a1*, evaluate her co-authors *a1*<sub>1</sub>...*a1*<sub>n</sub> for her paper *p1*.
- *Phase 2:* from the node *a2*, evaluate her coauthors *a2*<sub>1</sub>...*a2*<sub>n</sub> for her paper *p2*.
- Phase 3: the similarity measure Φ is applied to p1 and p2, i.e. to the occurrences of authors and coauthors of p1 and p2.

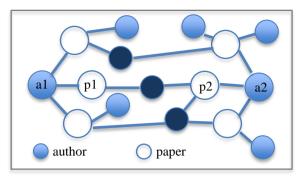


Fig. 1: Two-steps disambiguation: two-steps(a1,a2)= $\Phi(p1,p2)$ , where p1 is a paper of a1and p2 is a paper of a2, and  $\Phi$  is a similarity measure

Please note that, for the nature of the similarity measures presented in section III, paper nodes without common neighbours will have similarity equal to 0, for the phenomenon of the 0-tail [24].

Moreover, concerning classical Link Prediction (LP), the similarity of the two ambiguous candidates a1 and a2 is not directly calculated with  $\Phi(a1,a2)$ , but applying the measure to the papers of a1 e a2. The two-steps traversal consists in navigating the path *author-paper-author* two times.

It is noticeable that the two-steps evaluation requires only local visits to the graph between a1 and a2, being very efficient.

All the  $\Phi_i$  topological similarity measures for LP have been slightly modified so that the function excludes the initial authors from the neighbour count of p1 and p2.

For our experiments, we chose the graph-based database Neo4j as a proper NoSQL database for quick path traversal queries. The main program has been developed in C# using Neo4j APIs. As a dataset, a dump of the online Computer Science Database DBLP has been imported in Neo4j.

As an ambiguous author name, we chose to use the Chinese name *Chen LI*. LI is among the most frequent surnames in China, and Chen Li is among the most ambiguous names in DBLP, present with 24 versions, 23 of which are disambiguated with an identifier (see Fig.2), and 1 is a big furball of ambiguous LIs. The total amount of papers written by all the Chen LIs in DBLP is 72295.

Chen Li
Chen Li 0001
University of California, Irvine, CA, USA
Chen Li 0002
South China University of Technology, Guangzhou, China
Chen Li 0003
New York University, Courant Inst. of Mathematical Sciences
Chen Li 0004
Purdue University
Chen Li 0005
Beijing Information Technology Institute, Beijing, China
Chen Li 0006

Fig. 2: A subset of the Chen LIs in DBLP

The disambiguation classification of DBLP has been used as a Ground Truth, while our algorithm does not include any knowledge about the identifiers of the Chen LIs.

Noticeable that the database also presents a particular case of a paper co-authored by two different Chen LIs, one of whom is ambiguous and the other disambiguated, providing a further detail in the Ground Truth.

In our experiments, all the pairs of papers written by Chen LI have been evaluated, producing a similarity assessment for each pair of candidate Chen LIs. The similarity measures  $\Phi_i$  applied are  $\Phi_1$ =Common Neighbours (CN),  $\Phi_3$ =Adamic-Adar (AA), and  $\Phi_2$ =Pointwise Mutual Information (PMI), which are among the most performant for Link Prediction.

A rating of the pairs of authors have been obtained, where the value of  $\Phi$  is considered positive (i.e. a1==a2) if greater than a threshold  $\rho$ . In the baseline experiment,  $\rho=0$ . Comparing the resulting classification with the DBLP Ground Truth (i.e. disambiguated Chen LIs with identifiers), we verified the classes of *True Positive (TP)*, *False Positive (FP)*, *True Negative (TN)*, and *False Negative (FN)* and from the count of such classes, we calculated the evaluation metrics of *Precision, Accuracy, Specificity* and *Sensitivity*.

## II. DISCUSSION OF RESULTS

Experimental results are very good for Precision, Accuracy and Sensitivity. The experimented similarity measures all have good results: AA and CN have excellent performances, while PMI shown to be less performant, still obtaining Precision around 70% and Accuracy around 80%.

It is noticeable that the negative rate includes the 0-tail, for the cases where two papers of the same author do not have common co-authors: in such cases, the value of the similarity measures based on common neighbours is equal to 0, therefore affecting the false negative classification. The 0-tail is particularly visible in the evaluation of Sensitivity, i.e. Recall, i.e. True Positive rate=TP/(TP+FN), where the FN classification influences the total value. On the other hand, the positive classification is exact and performant (Specificity, i.e. True Negative rate=TN/(TN+FP)is greater than 0.95% for all the similarity measures), because of a low FP count. The only errors are on the papers in common for the Chen LIs who co-authored the same paper.

The result of the direct application of our approach leads to partitioning the ambiguous set of candidate authors in clusters of common authors. In order to avoid such partitions, a solution may be to apply a transitive closure of the relation *"is the same author"* obtained by the disambiguation method or to use a significative third category of data (i.e. metadata, e.g., affiliation, publication, year) to reduce the false negatives.

#### VI CONCLUSIONS

We introduced a novel local method in bibliometrics for authors disambiguation, applying topological similarity measures on a graph-based database in its implementation on DBLP data on Neo4j. Among the definition of the used topological similarity measures, we included a new topological definition of the Pointwise Mutual Information, initially a semantic similarity measure.

Experiments have shown very encouraging results: a deepening study is in course.

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