LD Connect: A Linked Data Portal for IOS Press Scientometrics

Zilong Liu[1(✉)⋆], Meilin Shi[1⋆], Krzysztof Janowicz[1], Blake Regalia[1], Stephanie Delbecque[2], Gengchen Mai[1,3], Rui Zhu[1], and Pascal Hitzler[4]

[1] STKO Lab, UC Santa Barbara, Santa Barbara, California, USA
{zilongliu,meilinshi,janowicz,regalia,gengchen_mai,ruizhu}@ucsb.edu
[2] IOS Press, Amsterdam, NL
s.delbecque@iospress.nl
[3] Department of Computer Science, Stanford University, Stanford, California, USA
maigch@cs.stanford.edu
[4] Data Semantics Lab, Kansas State University, Manhattan, Kansas, USA
hitzler@k-state.edu

Abstract. In this work, we describe a Linked Data portal, LD Connect, which operates on all bibliographic data produced by IOS Press over the past thirty-five years, including more than a hundred thousand papers, authors, affiliations, keywords, and so forth. However, LD Connect is more than just an RDF-based metadata set of bibliographic records. For example, all affiliations are georeferenced, and co-reference resolution has been performed on organizations and contributors including both authors and editors. The resulting knowledge graph serves as a public dataset, web portal, and query endpoint, and it acts as a data backbone for IOS Press and various bibliographic analytics. In addition to the metadata, LD Connect is also the first portal of its kind that publicly shares document embeddings computed from the full text of all papers and knowledge graph embeddings based on the graph structure, thereby enabling semantic search and automated IOS Press scientometrics. These scientometrics run directly on top of the graph and combine it with the learned embeddings to automatically generate data visualizations, such as author and paper similarity over all journals. By making the involved ontologies, embeddings, and scientometrics all publicly available, we aim to share LD Connect services with not only the Semantic Web community but also the broader public to facilitate research and applications based on this large-scale academic knowledge graph. Particularly, the presented scientometric system generalizes beyond IOS Press data and can be deployed on top of other bibliographic datasets as well.

Keywords: LD Connect · Knowledge Graphs · Ontology Engineering · Document Embeddings · Knowledge Graph Embeddings · Scientometrics.

⋆ Both authors contributed equally to this work.

1 Introduction

Knowledge graphs are playing an increasingly important role in academic search engines, and they serve as data backbones for data analytics at publishers and funding organizations. For example, Semantic Scholar provides a REST API[5] to facilitate author and paper lookup, conference peer review service, etc., based on its academic literature graph. SPECTER [3], a method for embedding scientific papers based on paper IDs, titles, and abstracts, has also been implemented in Semantic Scholar as a public endpoint[6] for retrieving embeddings computed for selected papers. However, these academic knowledge graphs suffer from several limitations. First, the access to these large-scale graphs, either via public endpoints or downloadable URLs, is limited. An example is AMiner, which consists of over 130M researchers and 320M publications in total (by the time of writing), has only released parts of its entire graph for the public to download[7] (i.e., 50K entities and 290M links). Second, few academic search engines share documentations about their ontologies, which hinders the semantic interoperability across different academic knowledge graphs. Third, spatial and temporal information is often unavailable in these graphs. For instance, while the data schema of Microsoft Academic Graph[8] contains affiliation information with geocoded outputs as `Latitude` and `Longitude`, no additional spatial contexts (e.g., the country of an affiliation) are provided nor visualization. Similarly, there is a lack of annotations about when a publication was received, reviewed, and accepted to support knowledge discovery during the entire publication process. Fourth, while pre-trained document embeddings such as SPECTER[9], are shared for academic knowledge graphs such as Semantic Scholar, these embeddings are learned from titles and abstracts instead of the full text of publications. Additionally, no knowledge graph embeddings trained on these graphs have been publicly available yet. Finally, the dataset and scientometric portal presented here are, while restricted to a single publisher, not merely a data export or service, but form the deployed data backbone of an academic publisher since several years, thus offering additional insights into the usage of bibliographic knowledge graphs in commercial practice.

With these limitations in mind, this paper presents LD connect, a Linked Data portal that serves, retrieves, visualizes, and analyzes IOS Press bibliographic data. More specifically, we introduce the construction of an academic knowledge graph using a newly designed (but aligned) ontology, the implementation of document embedding and knowledge graph embedding techniques, and the design of a scientometric system to support visualization and analysis of bibliographic data.

[5] https://www.semanticscholar.org/product/api
[6] https://github.com/allenai/paper-embedding-public-apis#specter
[7] https://www.aminer.cn/knowledge_graph
[8] https://docs.microsoft.com/en-us/academic-services/graph/reference-data-schema
[9] https://github.com/allenai/specter

All resources in this paper, including a version of the datasets and pre-trained embeddings, underlying ontology, and scientometrics, are publicly available on GitHub[10] with detailed documentation.

The remainder of this paper is organized as follows. Sec. 2 provides an overview of LD Connect with the underlying ontology. Sec. 3 explains the need of embedding representation for both documents and knowledge graphs, and elaborates how they are generated. Sec. 4 demonstrates how IOS Press scientometrics are developed to answer identified competency questions for bibliographic analysis. Finally, Sec. 5 concludes the paper, and discusses future directions of improving and adopting LD Connect to other academic related datasets.

2 LD Connect

The ontology of LD Connect can be considered as an extension of the Bibliographic Ontology (BIBO)[11]. First, publications (`iospress:Publication`) are categorized as articles (`iospress:Article`) and chapters (`iospress:Chapter`), and contributors (`iospress:Contributor`) of a publication are categorized as authors (`iospress:Role.Author`) and editors (`iospress:Role.Editor`). Using list properties of container membership in RDF, the order of authorship in a paper is expressed as `rdf:_0`, `rdf:_1`, `rdf:_2`, etc. During bibliographic data triplification, since multiple Uniform Resource Identifiers (URIs) are assigned to a contributor for all contributed publications, co-reference resolution is performed to learn weights for matching contributors, and `owl:sameAs` relations are established among those URIs which indicate the same contributor based on whether their information, including first names, last names, and affiliations, is significantly similar. The same process is applied to one affiliation (`iospress:Organization`) shared by multiple contributors based on affiliation names and associated contributors. Fig. 1(a) and Fig. 1(b) show ontology fragments of `iospress:Publication` and `iospress:Contributor`, respectively.

In addition, during the triplification process, spatial and temporal information is automatically generated and integrated into the knowledge graph. Affiliations are geocoded with Geocoding API provided by Google Map to fetch their geographic information. The ontology follows the OGC GeoSPARQL standard[12] to generate affiliation geometry. In addition, we provide spatial contexts about affiliations, including cities (`iospress-geocode:city`), countries (`iospress-geocode:country`), postal codes (`iospress-geocode:postalCode`), regions (`iospress-geocode:region`), and zones (`iospress-geocode:zone`). We also include rich temporal information about a publication such as its received date (`iospress:publicationReceivedDate`), accepted date (`iospress:publicationAcceptedDate`), preprint date (`iospress:publicationPreprintDate`), and publication date (`iospress:publicationDate`).

[10] `https://github.com/stko-lab/LD-Connect`
[11] `http://bibliontology.com/specification.html`
[12] `https://www.ogc.org/standards/geosparql`

A statistical summary about these main classes is listed in Tab. 1. By the time of writing, there are over 100K articles, 530K contributors, and 60K geocoded locations in LD Connect linked by 11M relations, and these numbers are still growing as the dataset gets updated. It contains all papers published at IOS Press over the past 35 years.

Table 1. An overview of LD Connect as of 12/06/2021.

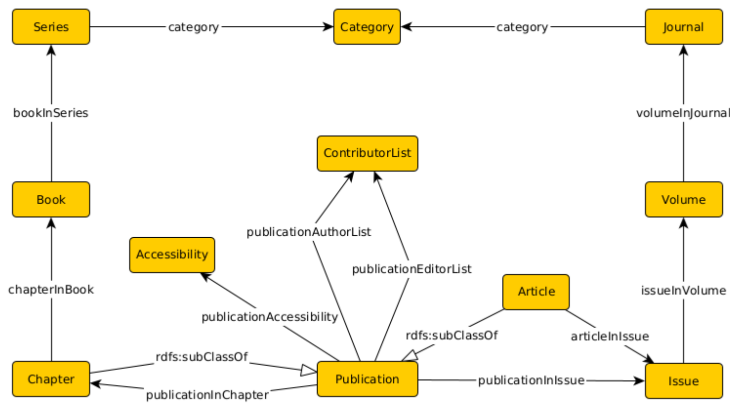
Class	Number of Instances
iospress:Category	9
iospress:Series	44
iospress:Journal	133
iospress:Volume	2687
iospress:Issue	9732
iospress:Chapter	49874
iospress:Article	106131
iospress:Contributor	531126
iospress:Organization	547014
iospress:GeocodedLocation	60284

LD Connect is also made available via a SPARQL endpoint[13] for semantic search and more complex queries. The following SPARQL query shows an example of retrieving relevant information about papers whose first author is from affiliations located in China. The returned results include corresponding paper titles, associated keywords, publication years, journals, first authors, and their affiliations. At an academic publisher, such queries can be used to compare and potentially adjust the composition of editorial boards of journals to keep them geographically representative with respect to the locations of authors.

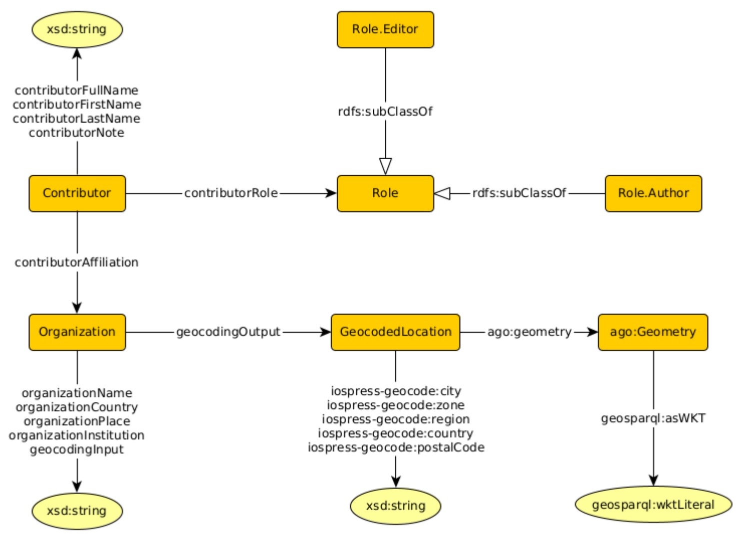
```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX iospress: <http://ld.iospress.nl/rdf/ontology/>
PREFIX iospress-geocode: <http://ld.iospress.nl/rdf/geocode/>

select ?title (group_concat(?keyword; separator=',')
       as ?keywords) ?year ?journal ?first_author_name ?org_name
{
    ?paper iospress:publicationTitle ?title;
           iospress:publicationIncludesKeyword ?keyword;
           iospress:publicationDate ?date;
           iospress:articleInIssue/iospress:issueInVolume/
           iospress:volumeInJournal ?journal;
           iospress:publicationAuthorList ?author_list.
    ?author_list rdf:_0 ?first_author.
    ?first_author iospress:contributorFullName ?first_author_name;
                  iospress:contributorAffiliation ?org.
```

[13] http://ld.iospress.nl/sparql



(a) Main classes and their relations to model `Publication`.



(b) Main classes and their relations to model `Contributor`.

Fig. 1. An overview of the ontology behind LD Connect. Edges with filled arrows are object/datatype properties, and edges with open arrow heads represent subclass relations. All classes and properties without any prefix are in the namespace `iospress`: <`http://ld.iospress.nl/rdf/ontology/`> .

```
    ?org iospress:geocodingInput ?org_name ;
                 iospress:geocodingOutput/
                 iospress-geocode:country ?org_country.
    bind(year(?date) as ?year)
    values ?org_country {"China"@en}
} group by ?title ?year ?journal ?first_author_name ?org_name
```

3 Embeddings

In order to capture both semantic and structural knowledge about IOS Press publications, we take advantages of unsupervised embedding learning techniques, such as document embeddings [16,12] and knowledge graph embeddings [1,5] that encode each document and each entity in the graph as high dimensional embeddings, respectively. More details about the generation of both embeddings can be found in our paper [13].

3.1 Document Embeddings

To fill the gap of missing semantic properties of publications in LD Connect, we adopt the Distributed Bag of Words (PV-DBOW) [12] model, which is a specific version of the Doc2Vec model that encodes the full text bodies of documents (e.g., conference papers, journal articles, book chapters) from IOS Press into document embeddings.

PV-DBOW uses the maximum log likelihood (MLE) as its training objective. Given a document d_i represented as a sequence of words, i.e., $d_i = \{w_1, w_2, ..., w_T\}$, PV-DBOW aims at optimizing the joint probability distribution of each word given d_i, as shown in Eq. 1.

$$\sum_{t=1}^{T} \log p(w_t|d_i) \tag{1}$$

In the generation pipeline, the full text bodies of documents are first extracted from their corresponding PDF files. Text preprocessing steps such as tokenization, lemmatization, and stop word removal are carried out before texts are fed into the PV-DBOW model. Note that although there are more advanced text embedding techniques such as ELMo [17] and BERT [4], we selected PV-DBOW because 1) PV-DBOW is a rather simple but widely used neural network architecture that can be re-trained in a short amount of time, which is favored by LD Connect given its fast evolving nature and updates, and 2) implementation of PV-DBOW is highly reproducible for commercial production.

3.2 Knowledge Graph Embeddings

While document embeddings provide semantic knowledge about publications, structural knowledge is also needed to understand the relations among entities in LD Connect, such as journals, authors, and affiliations. Therefore, we utilize the knowledge graph embedding technique, TransE [1], to encode each entity and relation in LD Connect into a high dimensional vector space. Given one triple (h_i, r_i, t_i) in LD Connect, TransE encodes both entities and relations into the same embedding space - $\mathbf{h_i}, \mathbf{r_i}, \mathbf{t_i}$ - so that relation embedding $\mathbf{r_i}$ is treated as a translation operation from the head entity embedding $\mathbf{h_i}$ to the tail entity embedding $\mathbf{t_i}$. A plausibility scoring function $f_{TransE}(\cdot,\cdot,\cdot)$ is defined for each triple as shown in Eqn. 2, where triples that exist in LD Connect receive lower plausibility scores, and those that do not exist receive higher scores.

$$f_{TransE}(h_i, r_i, t_i) = \parallel \mathbf{h_i} + \mathbf{r_i} - \mathbf{t_i} \parallel \tag{2}$$

Similar to the reason why we use PV-DBOW, we choose to use TransE because it is more efficient to train, easier to interpret, and it has rather acceptable performance compared with other counterparts such as TransH [20], TransR [5], R-GCN [19], and TransGCN [2].

4 IOS Press Scientometrics

Scientometrics refers to the study of measuring and analyzing scholarly literature [8]. Research in scientometrics ranges from the study of growth and development in publications of a specific journal [11] to quantitatively characterizing the scientific output of a scholar [7], to designing a framework for measuring spatial and temporal citation patterns of both publications and researchers [6]. The large amount of structured bibliographic data provided by LD Connect enables knowledge discovery and data-driven analysis in studying the science of science. Our previous work have demonstrated prototypes of scientometric systems that use similar extended BIBO ontologies based on data from one journal published by IOS Press, or data enriched with research topics, expertise, and geographic information of institutions [15,9,10].

In this section, we present an overview of the current version of the scientometric system *IOS Press scientometrics*[14] built upon LD Connect which contains more enriched journal data and uses a more comprehensive ontology. Developed with JavaScript libraries such as D3.js[15] and Leaflet[16], IOS Press scientometrics consist of seven interactive modules for visual analysis, including *Home*, *Country Collaboration*, *Author Map*, *Author Similarity*, *Paper Similarity*, *Keyword Graph*, and *Streamgraph*. The Semantic Web journal is used as an example to explain how each module helps answer the competency questions listed below.

Q1: What is the spatial coverage of a journal based on the locations of author affiliations? The *Home* module provides an overview of the spatial coverage of the selected journal. A choropleth map displays the countries/regions of author affiliations included in the selected journal. Hovering the mouse over a country/region

[14] http://stko-roy.geog.ucsb.edu:7200/iospress_scientometrics
[15] https://d3js.org
[16] https://leafletjs.com

on the map displays the number of contributing authors. Fig. 2 shows a total of 34 authors from Greece in the Semantic Web journal. The country/region is colored in proportion to the number of contributing authors. Countries/regions with higher than average authors are in darker shades of blue while those with fewer than average are shown in lighter shades.

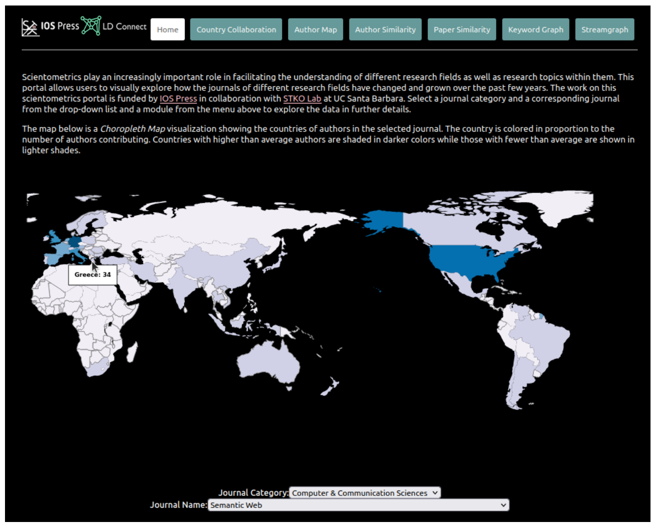
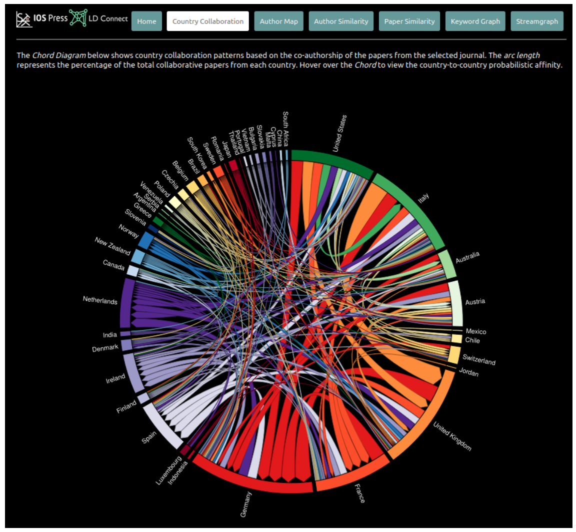


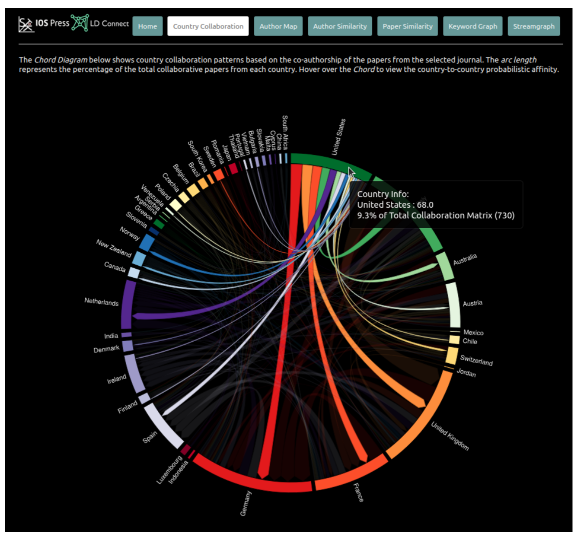
Fig. 2. Spatial coverage of affiliations mentioned in the Semantic Web journal

Q2: What is the country collaboration pattern based on co-authorship? The *Country Collaboration* module uses a chord diagram to display collaboration patterns based on the co-authorship of the papers from the selected journal. The arc length represents the percentage of the total collaborative papers from each country/region. When hovering the mouse over the arc of a specific country/region, the total number of papers contributed by authors whose affiliations are from that country/region, and its percentage of the total collaborations is displayed. The probabilistic affinity between two countries/regions is shown when hovering the mouse over a specific chord. Fig. 3(a) provides an overview of the collaboration pattern of the Semantic Web journal, and Fig. 3(b) highlights collaborations with the United States.

Q3: How are institutions of all authors geographically distributed on a global/local scale? The *Author Map* module allows users to drag, zoom in or out to see how institutions are clustered, and shows the count of each cluster. Users are able to observe at a local view and investigate further details about the institution of an author. For example, from Fig. 4 we can know that Ludger Jansen was working at Institute of Philosophy in the University of Rostock (when one of his papers



(a) Country Collaboration Overview



(b) Country Collaboration with the United States

Fig. 3. Country collaboration of the Semantic Web journal

was published in the Semantic Web journal), and the address of the institution is August-Bebel-Straße 28, 18051 Rostock, Germany.

Q4: Who are the most similar authors/papers to a selected author/paper? In *Author Similarity* module, similar authors across all journals are found based on the pre-trained knowledge graph embeddings discussed in Sec. 3.2. Cosine

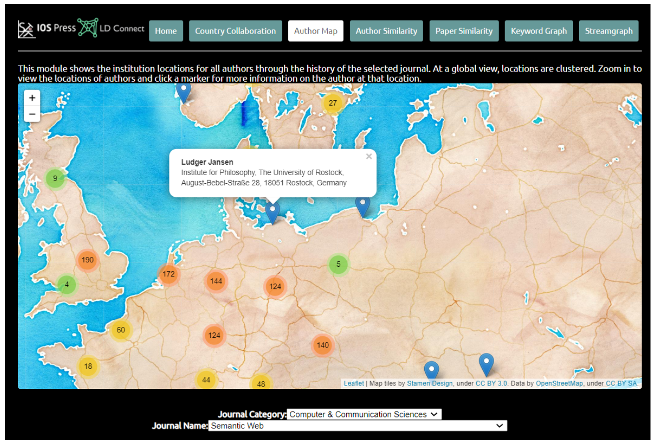
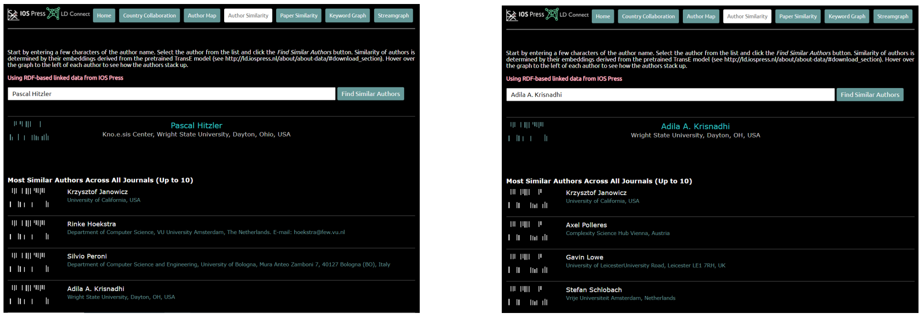


Fig. 4. Map visualization of clusters of author affiliations

similarity between each pair of authors is computed to measure their similarity. The top 20 similar authors are retrieved, along with their institutions, addresses, and first 20 associated knowledge graph embeddings (see Fig. 5(a)). Hovering over stack bars of the selected author enables users to see the actual values of its knowledge graph embeddings. By clicking on one of the similar authors, a follow-your-nose author similarity search will be conducted with the selected author as a new input (see Fig. 5(b)). Similarly, the *Paper Similarity* module provides the functionality of searching for the most similar papers based on the pre-trained document embeddings discussed in Sec. 3.1. For each retrieved paper, its published year, a list of keywords, as well as first 20 corresponding document embedding are visualized (see Fig. 6(a)). Similarly, a follow-your-nose paper similarity search will perform once a similar paper is selected (see Fig. 6(b)).

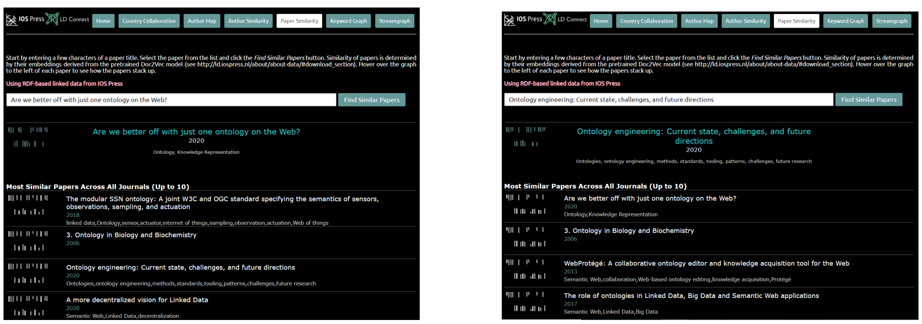
Q5: How are the papers clustered based on similar keywords? The *Keyword Graph* module uses a force-directed graph to show the relationship among papers. Each paper from the selected journal is represented as a node. The nodes are clustered and linked together by shared keywords. Hovering the mouse over a node displays information about the paper, associated keywords, and the number of paper connections. Given the sheer number of keywords, the data have been split by years. In Fig. 7, an example node from the Semantic Web journal in 2016 is displayed.

Q6: What are the research topic trends of a journal across time? The *Streamgraph* module displays the trend of research topics/keywords in the selected journal over time. The top 20 keywords are selected and ranked according to the total number of papers containing the topic keywords. The streamgraph allows users to see the changes in the number of papers under certain topics. When



(a) Search results about *Pascal Hitzler* (b) Search results about *Adila A. Krisnadhi*

Fig. 5. Information display of the selected author and similar authors, including the visualization of their first 20 knowledge graph embeddings.



(a) Search results about *Are we better off with just one ontology on the Web?* (b) Search results about *Ontology engineering: Current state, challenges, and future directions*

Fig. 6. Information display of the selected paper and similar papers, including the visualization of their first 20 document embeddings.

hovering the mouse over a specific keyword on the streamgraph, the information boxes will display author, paper, and year information associated with the selected keyword, as well as its count per year. Clicking on an author will link to its dereferencing interface developed on top of the Phuzzy.link framework [18]. Fig. 8 shows an example of the keyword *Linked Open Data* with a count of 6 in 2016 from the Semantic Web journal.

5 Conclusions and Future Work

In this work, we introduced a Linked Data-driven scientometric system on top of the LD Connect bibliographic knowledge graph that enables users to answer several competency questions by browsing and interacting with the system.

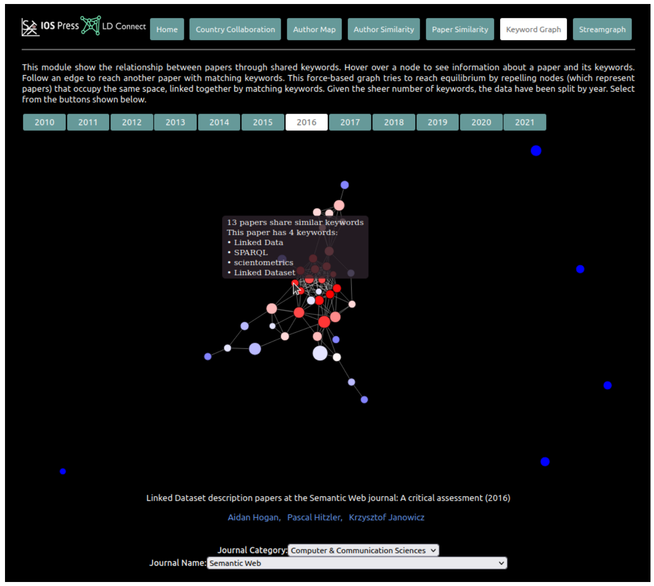


Fig. 7. Keyword graph visualization of the Semantic Web journal in 2016

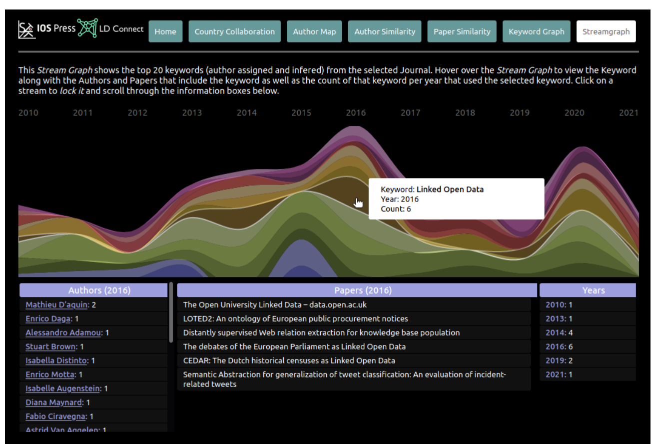


Fig. 8. Streamgraph visualization of top research topics in the Semantic Web journal

The scientometrics showcase the potential to unveil the underlying characteristics of academic literature across space and time, as well as the ability to empower embedding-based similarity search on LD Connect. Being openly and freely available, the system is already in-use at IOS Press where it powers their data backbone, and will be publicly accessible[17] after transforming this prototype into production. At the same time, we aim to increase long-term availabil-

[17] http://ld.iospress.nl/scientometrics/

ity and sustainability of our work in addition to the scientometrics. We have recently switched to an ongoing deployment where almost all steps described in this paper are automated, and therefore, time and costs can be reduced to a minimum. This deployment includes a pipeline that updates both the graph and embeddings when new data come in. We also plan to enrich our graph with more external information. For instance, we will associate contributors with their ORCIDs and include citation data for further bibliographic analysis.

It is worth noting that the scientometric system itself can be used and deployed by other researchers as a resource, such as for recommending reviewers and uncovering potential disparities between the geographic locations of authors versus journal editors. Also, the presented Linked Data-driven scientometrics are not restricted to LD Connect but can be deployed on other RDF-based datasets with minimal adjustments. While future work includes improving scalability of the scientometric system to support queries from journals with a larger volume, we also plan to develop new scientometrics to answer other interesting questions, such as how academic activity and collaboration change across space and time for both individuals and groups of scholars.

The ontology behind LD Connect can be aligned with other open bibliographic ontologies that are commonly in use for academic services, which will facilitate research in ontology alignment to improve semantic interoperability across academic knowledge graphs. Moreover, as a wide variety of spatial and temporal information is integrated with bibliographic data in the knowledge graph construction pipeline, we hope LD Connect highlights the importance of GeoEnrichment in ontology engineering for future research.

In addition to the ontology, a SPARQL endpoint, and open access to both the graph and the scientometrics, LD Connect is the first of its kind that shares both pre-trained document and knowledge graph embeddings, which overcomes copyright limitation to direct access to full text bodies of publications. In the future, we plan to incorporate spatial information in embedding generation by using techniques such as Space2Vec [14] to develop similarity search functions for discovering spatial similarity among entities in LD Connect. Furthermore, both shared embeddings serve as large-scale datasets with a wide diversity of research topics, author contribution, and their relations, opening up a great number of opportunities for research and applications in knowledge graphs, natural language processing, the Semantic Web, and beyond.

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