GORC: A large contextual citation graph of academic papers

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Abstract

We introduce the Semantic Scholar Graph of References in Context (GORC),1 a large contextual citation graph of 81.1M academic publications, including parsed full text for 8.1M open access papers, across broad domains of science. Each paper is represented with rich paper metadata (title, authors, abstract, etc.), and where available: cleaned full text, section headers, figure and table captions, and parsed bibliography entries. In-line citation mentions in full text are linked to their corresponding bibliography entries, which are in turn linked to in-corpus cited papers, forming the edges of a contextual citation graph. To our knowledge, this is the largest publicly available contextual citation graph; the full text alone is the largest parsed academic text corpus publicly available. We demonstrate the ability to identify similar papers using these citation contexts and propose several applications for language modeling and citation-related tasks.

1 Introduction

Academic literature graphs (e.g. the Semantic Scholar literature graph (Ammar et al., 2018), the Microsoft Academic Graph (Shen et al., 2018), AMiner’s Open Academic Graph (Tang et al., 2008), the Web of Science,2 and others) describe connections between academic entities such as papers, authors, and institutions. An important use of these resources is in defining citation graphs, which are collections of academic publications represented as nodes connected by directed citation edges. Citation graphs provide a way to detect trends in scientific publishing and measure the speed and trajectory of research progress.

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1The corpus can be accessed by following the instructions provided at https://github.com/allenai/s2-gorc/.

2https://www.webofknowledge.com/

They have widespread applications for bibliometric analysis and science-of-science studies.

One limitation of traditional citation graphs is the lack of full text citation context associated with each citation edge. This limits the ability to perform certain types of analyses, such as studying how or why a paper cites another paper. Unlike traditional citation graphs, contextual citation graphs make apparent the textual contexts for each citation. Contextual citation graphs are useful for a variety of research tasks, such as identifying similar papers (Kanakia et al., 2019; Eto, 2019; Haruna et al., 2018; Small, 1973), paper-level citation recommendation (Bhagavatula et al., 2018; Liu et al., 2015; Yu et al., 2012), in-line citation recommendation (Jeong et al., 2019; Huang et al., 2015; He et al., 2010), categorizing citation intent (Cohan et al., 2019; Teufel et al., 2006), paper summarization (Cohan and Goharian, 2015; Mitrovic and Müller, 2015; Qazvinian and Radev, 2008; Teufel et al., 2006), citation analysis (Asatani et al., 2018; Jurgens et al., 2018, 2016; Ding et al., 2014), and more (Trujillo and Long, 2018;
Valenzuela et al., 2015; Caragea et al., 2014; Athar and Teufel, 2012).

Few contextual citation graphs are publicly available. The ACL Anthology Network (AAN)\(^3\) (Radev et al., 2009) is one such contextual citation graph built from the ACL Anthology corpus (Bird et al., 2008), consisting of 24.6K papers manually augmented with citation information. CiteSeer (Giles et al., 1998) provides a large corpus consisting of 1.0M papers with full text and bibliography entries parsed from PDFs.\(^4\) Saier and Färber (2019) introduces a contextual citation graph of approximately 1.0M arXiv papers with full text LaTeX parses where citations are linked to papers in the Microsoft Academic Graph.

We release the Semantic Scholar GORC dataset, a large contextual citation graph consisting of 81.1M papers across broad domains of science. Each paper node contains metadata and abstracts derived from trusted sources such as academic publishers and literature archives like PubMed and arXiv. Of these, 73.4M papers have publisher-provided abstracts, and 27.6M papers have parsed and linked bibliography entries, forming 380.5M citation edges. Around 156.5M of these citation edges are supported by citation contexts in parsed full text. Notably, we release full text PDF parses for 8.1M papers with open access status. Of these, 1.5M papers also have full text LaTeX parses from which we have extracted, in addition to citations and references, the source text of tables and mathematical formulas.

In Section 2, we define terms and concepts used throughout the paper. In Section 3, we describe the construction of the graph. In Section 4, we provide summary statistics and a description of the dataset format. In Section 5, we evaluate the data quality. In Section 6, we discuss some potential applications of GORC. In Section 7, we discuss related work.

2 Background

In this work, we distinguish between bibliography entries and in-line citations. A bibliography entry is an item in a paper’s bibliography that refers to another paper. It is represented in a structured format that can be parsed for paper-identifying features such as Title, Authors, Year, and Venue or Journal, and for journal articles, the Volume, Issue, and Pages. Also commonly represented are unique document identifiers such as the Document Object Identifier (DOI), arXiv identifier, or PubMed identifier. Common formats for bibliography entries are MLA, APA, Vancouver-, and Chicago-style, among others, which are different ways of representing these various features for document identification.

There is often variation in the representation of certain fields. For example, Authors can include the first names of each author or only their first initials. In many scientific domains, journal publications are the norm, whereas conference proceedings dominate in fields such as Computer Science; conference proceedings tend to lack journal-related features such as Volume, Issue, and Pages. Bibliography entry demarcation also varies between different formats. In some cases, each entry is preceded by a citation marker (e.g. “[1]” or “[ABC2019]”) that is used throughout the text of the paper to denote in-line citations.

An in-line citation is a mention span within the paper’s abstract or body text that refers to one of the entries in its bibliography.

“In Figure 3, we show the relationship between A and B.”

http://aan.how/

\(^3\)The RefSeer dataset (Huang et al., 2015) is an example of a dataset of citation contexts derived from CiteSeer. It can be found at https://psu.app.box.com/v/refseeer.
where Figure 3 refers to a plot displayed on a separate page. These in-line references can be important for understanding the relationship between text and objects within the paper.

In GORC, we resolve links between in-line citations and bibliography entries, identify links between bibliography entries and other papers within the corpus, and extract and resolve in-line references within each paper (see Figure 1). Links between bibliography entries and other papers are traditionally found in other citation graphs. The addition of inline citation-bibliography links within the paper full text allows for retrieval of citation context and provides a more granular and contextual understanding of the relationship between two papers.

3 Graph construction

GORC is constructed using data from the Semantic Scholar literature corpus (Ammar et al., 2018). Papers in Semantic Scholar are derived from numerous sources: obtained directly from publishers, from resources such as the Microsoft Academic Graph, from various archives such as arXiv or PubMed, or crawled from the open Internet.

To create GORC, we:

1) Construct paper clusters using paper metadata derived from various sources,
2) Process PDFs and LaTeX sources to derive clean full text, in-line citations and references, and bibliography entries,
3) Select the best metadata and full text parses for each paper cluster,
4) Filter out paper clusters with insufficient metadata or content, and
5) Resolve bibliography links between paper clusters in the corpus.

Details for each of these steps are provided below.

3.1 Paper clustering

Starting from 356.3M paper entries from Semantic Scholar, we construct paper clusters based on title similarity and overlap between associated DOIs and PDFs. Some paper entries are metadata only; for example, publishers provide titles, authors, and abstracts for papers. Other paper entries are crawled from sources such as arXiv or PubMed, where metadata has been extracted from the paper landing page, and an associated PDF has been downloaded.

Clustering is necessary to reduce redundancy in the final corpus. For example, we may have several paper entries corresponding to the same paper, where the entries are different versions of an arXiv pre-print, along with a camera-ready version derived from conference proceedings. To avoid duplicates, we join these paper entries into one paper cluster, and select the most representative metadata and PDF for full text processing. We cluster papers based on logic used by Semantic Scholar (Ammar et al., 2018), resulting in 176.7M paper clusters. We comment on this clustering problem further in Appendix A.

Canonical values for metadata fields such as title and author are then selected for each paper cluster based on source trust and majority voting. If metadata comes directly from publishers (gold metadata) and are associated with a PDF, we trust and select those metadata values. In cases where no gold metadata values are available, we use majority voting among the papers in the cluster to select metadata values. Metadata fields for which we derive best values are title, author, year, venue, abstract, identifiers (DOI, PubMed, PubMed Central (PMC), arXiv, and ACL Anthology), and associated PDF. Details for voting logic are provided in Appendix B.

3.2 PDF processing

We process all PDFs from the Semantic Scholar corpus (Ammar et al., 2018) through the following pipeline:

PDF selection We remove PDFs which are less likely to be scientific papers. GROBID is not optimized for processing non-paper scientific documents such as dissertations, reports, slides, etc., and this filtering step is necessary to increase output data quality. See Appendix C for filter details. There are 31.3M PDFs associated with the 176.7M paper clusters of the Semantic Scholar corpus, and 30.5M PDFs were selected for processing based on these filtering criteria.

PDF to JSON We use GROBID4 (Lopez, 2009) to process each PDF: (i) extract the paper’s Title, Authors, Year and Venue, and Abstract, (ii) extract

4GROBID v0.5.5: Tkaczyk et al found that GROBID had the highest out-of-the-box performance in bibliography and citation parsing among 10 available tools (Tkaczyk et al., 2018).
paragraphs from the Body text organized under extracted Section headings, (iii) extract Figure and Table captions, (iv) remove equations, table content, headers, and footers from the body text, (v) extract in-line citations from the abstract and body text, (vi) extract and parse each bibliography entry, identifying its Title, Authors, Year, and Venue, and (vi) link the in-line citation mentions to their corresponding bibliography entries. The resulting parses are expressed in JSON format as described in Appendix E.

**Postprocessing** We postprocess GROBID output using regular expressions to classify the parenthetical citation style of a paper as BRACKET (e.g. [2]), NAME-YEAR (e.g. ABC (2019)), or OTHER (which includes superscripts and other mixed styles). We focus on addressing two types of common errors in GROBID’s in-line citation extractions: (i) false positives resulting from superscripts or equation references being recognized as in-line citations in papers with BRACKET-style citations, and (ii) false negatives resulting from an inability to expand bracket citation ranges (e.g. “[3]-[6]” should be expanded to “[3], [4], [5], [6]” before linking). False positives are detected using regular expressions and removed from the GROBID output. Bracket citation ranges are manually expanded and linked to their corresponding bibliography entries.

### 3.3 LaTeX processing

LaTeX document source is available for a majority of arXiv submissions, and where available, are used to construct a full text parse. We retrieve body text, section headers, figure/table captions, equations, and inline citations and references directly from LaTeX source. Inspired by Saier and Färber (2019), we construct a pipeline that converts LaTeX source into XML documents and then extract structured information from the XML.

Due to direct access to source, the accuracy of citation span, reference, caption, section header, and equation detection, as well as paragraph segmentation is near-perfect. We process 1.5M papers from LaTeX source derived from arXiv, all of which are included as part of GORC.

### 3.4 Corpus assembly

We construct the final corpus by assembling clustered paper metadata with GROBID and LaTeX parse objects. The best metadata is selected for each paper cluster based on logic described in Section 3.1. If a PDF is available for the paper cluster, a GROBID parse was produced, and the PDF is open access, we associate the GROBID parse with the GORC paper object. Open access status is assigned if a paper is derived from arXiv, ACL Anthology, the open access subset of PubMed Central, and/or associated with an open-access DOI in the Unpaywall database. If the PDF is not open access, we only include the bibliography from the GROBID parse in GORC. If arXiv LaTeX source is available for the paper cluster, we also associate the LaTeX parse with the GORC paper object.

### 3.5 Paper cluster filtering

We further filter paper clusters to remove papers with (i) no title, (ii) no authors, (iii) fewer than 100 characters of abstract and body text, and (iv) where English is not the primary language. The first three filters remove papers that provide little value for a contextual citation graph and for which we cannot provide bibliography-paper linking. The English language filter is meant to reduce parsing errors and restricts the corpus to the subset of scientific literature that is well represented in Semantic Scholar. All filters are applied in series.

A subsequent 95.5M paper clusters were filtered out based on the aforementioned criteria and removed from the corpus. The distribution for the filtered papers is given in Table 1. We note that a large number of paper clusters are filtered out; 80.0M of these filtered clusters have no associated text and do not provide significant value to our dataset in their current state.

| Filter       | Number of papers |
|--------------|------------------|
| No title     | 20.4K            |
| No authors   | 331.1K           |
| < 100 chars  | 80.0M            |
| Not English  | 15.2M            |

Table 1: Post-processing data quality filters for papers

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7Unpaywall 2019-04-19 data dump
8We use the clid2 tool for language detection with a threshold of 0.9 over the English language score.
3.6 Bibliography-paper linking

Each bibliography entry in both GROBID and LaTeX parses are then linked to the most similar papers in the corpus. For linking, we score each bibliography entry and paper cluster pair using a similarity score computed between their titles. Each title is first normalized (i.e. white spaces stripped, lower-cased, special characters removed) and represented by its character 3-grams. The similarity score $S_{title}$ is then computed as the harmonic mean between a Jaccard index and a containment metric:

$$S_{title} = \frac{2 \times J \times C}{J + C}$$

(1)

where the Jaccard index $J$ and containment metric $C$ are computed from the $n$-grams of the two titles $N_1$ and $N_2$ as:

$$J = \frac{|N_1 \cap N_2|}{|N_1 \cup N_2|}$$

$$C = \frac{|N_1 \cap N_2|}{\min(|N_1|, |N_2|)}$$

For each bibliography entry, the bibliography-paper pair with the highest similarity score (above 0.8) is output as the correct link. Otherwise, the bibliography entry remains unlinked. We perform an evaluation of linking performance in Section 5.

4 GORC dataset

The resulting dataset consists of 81.1M papers. For these papers, our PDF coverage is approximately 35.6%, or 28.9M PDFs. These PDFs are processed using the pipeline discussed in Section 3.2. The vast majority of these PDFs are successfully processed using GROBID, and we extract bibliography entries for 27.6M of 28.9M PDFs. Approximately 8.1M of the 28.9M PDFs have open access status, and we provide the full text for this open access subset. LaTeX parses are further provided for the 1.5M papers for which LaTeX source is available through the arXiv pre-print server. We resolve 380.5M bibliographic links between papers, 156.5M of which are supported by in-line citation contexts.

Paper and identifier coverage for GORC are provided in Table 2. Full-text statistics are provided for GROBID and LaTeX parses in Table 3. On average, LaTeX parses contain significantly more paragraphs of body text, largely due to the greater proportion of math, physics, and computer science papers in arXiv that incorporate proofs, and the near perfect preservation of paragraph breaks in LaTeX files. We speculate that differences in bibliography entry and linking counts between the GROBID and LaTeX parses are due to the differences in field representation between the two sub-corpora.

The basic format for each GORC paper object is given below, with structured representations provided for GROBID and LaTeX parses:

```json
{
    paper_id: paper_id
    metadata: {
        title: title
        authors: [author1, author2, ...]
        year: year
        ...
    }
    grobid_parse: {...}
    latex_parse: {...}
}
```

| Statistic                  | GROBID | LaTeX |
|----------------------------|--------|-------|
| Paragraphs (abstract)      | 1.1    | 0.2   |
| Paragraphs (body)          | 9.9    | 93.3  |
| Inline cite spans (abstract) | 0.7  | 0.0   |
| Inline cite spans (body)   | 45.2   | 46.8  |
| Bib. entries (OA subset)   | 27.6   | 21.9  |
| Linked bibs (OA subset)    | 19.3   | 6.8   |
| Bib. entries (All)         | 21.7   | -     |
| Linked bibs (All)          | 13.8   | -     |

Table 2: Statistics on paper provenance.

| Statistic                  | GROBID | LaTeX |
|----------------------------|--------|-------|
| Paragraphs (abstract)      | 1.1    | 0.2   |
| Paragraphs (body)          | 9.9    | 93.3  |
| Inline cite spans (abstract) | 0.7  | 0.0   |
| Inline cite spans (body)   | 45.2   | 46.8  |
| Bib. entries (OA subset)   | 27.6   | 21.9  |
| Linked bibs (OA subset)    | 19.3   | 6.8   |
| Bib. entries (All)         | 21.7   | -     |
| Linked bibs (All)          | 13.8   | -     |

Table 3: Extraction/Linking statistics over 27.6M PDFs and 1.5M LaTeX source parses. All reported values are average over all papers, with the OA subset consisting of 8.1M PDFs and 1.5M LaTeX sources.
The GORC file format is discussed in detail with examples in Appendix E.

5 Evaluation

We evaluate the quality of paper clustering, canonical metadata selection, and bibliography linking by sampling a subset of the corpus and annotating the results. We do not perform a detailed evaluation of in-line citation detection or bibliography parsing as these tasks are dependent on GR O B I D and have been independently evaluated (Lopez, 2009; Tkaczyk et al., 2018).

For paper clustering, we sample 500 paper clusters randomly, restricting to those with PDFs. Within each sampled cluster, we determine whether the canonical title and authors (selected based on logic described in Section 3.1) match the title and authors in the selected canonical PDF. For bibliography linking, we randomly sample GORC papers (500 GR O B I D PDF parses and 100 LaTeX parses) and select one random linked bibliography entry from each sampled paper (while avoiding selecting multiple entries linked to the same paper). We then determine whether the title and authors in the bibliography entry agree with the title and authors of the linked paper. Results for all evaluation are provided in Table 4 and evaluation criteria are detailed in Appendix D.

| Evaluated task                  | Title | Authors |
|---------------------------------|-------|---------|
| Paper clustering                | 0.93  | 0.89    |
| Bibliography linking (GR O B I D)| 1.00  | 0.96    |
| Bibliography linking (LaTeX)    | 1.00  | 0.92    |

Table 4: Accuracy of paper clustering and bibliography linking for titles and authors for sampled evaluation sets.

6 Example use cases

Below, we discuss some potential applications for this corpus.

6.1 Paper representations

The GORC dataset is predicated on the idea that access to papers with citation contexts may provide insights that we are unable to gain from paper-to-paper citation graphs alone. Paper embeddings trained on citation contexts may allow insight into the organization and overlap of paper topics.

![Embeddings for arXiv papers (6 ML categories)](image)

Figure 2: Visualization of word2vec embeddings associated with six arXiv categories related to Machine Learning. Example papers from two randomly selected sub-regions A and B are given in Table 5.

| Region A | Title                                                                 |
|----------|-----------------------------------------------------------------------|
| cs.LG    | “On Unifying Deep Generative Models”                                  |
| cs.LG    | “PixelGAN Autoencoders”                                               |
| stat.ML  | “Learning Disentangled Representations with Semi-Supervised Deep Generative Models” |
| cs.LG    | “Denoising Criterion for Variational Auto-Encoding Framework”         |
| cs.CV    | “Variational methods for conditional multi-modal deep learning”       |

| Region B | Title                                                                 |
|----------|-----------------------------------------------------------------------|
| cs.CL    | “TransA: An Adaptive Approach for Knowledge Graph Embedding”         |
| cs.CL    | “An Interpretable Knowledge Transfer Model for Knowledge Base Completion” |
| cs.AI    | “TorusE: Knowledge Graph Embedding on a Lie Group”                    |
| cs.CV    | “Image-embodied Knowledge Representation Learning”                    |
| stat.ML  | “Neural Embeddings of Graphs in Hyperbolic Space”                     |

Table 5: Sampled top papers in clusters from t-SNE embedding space in Figure 2. Region A consists of papers related to deep generative models; region B consists of papers concerned with graph representation learning.

We train word2vec (Mikolov et al., 2013) paper embeddings over the full text of all GORC papers, replacing all inline citation spans with unique paper identifiers, allowing us to generate embeddings of papers in the context of their mentions. We train a word2vec skip-gram model...
with window size 8 and minimum word frequency 2, generating 300-dimensional vectors for all in-vocabulary paper identifiers.

Figure 2 visualizes a subset of these embeddings, specifically those belonging to papers derived from six categories of arXiv related to Machine Learning. These categories are Artificial Intelligence (cs.AI), Computation and Language (cs.CL), Learning (cs.LG), Computer Vision and Pattern Recognition (cs.CV), Neural and Evolutionary Computing (cs.NE), and Machine Learning (stats.ML). Embeddings from 20,126 papers from these categories are visualized by computing 2-dimensional t-distributed stochastic neighbor embeddings (t-SNE) (van der Maaten and Hinton, 2008).

Table 5 shows samples of papers from two randomly selected regions (A and B) of Figure 2. Although the papers within these regions have a variety of arXiv primary categories, they cluster well by research theme. Region A is represented by papers discussing deep generative models. Region B consists of papers dealing with neural knowledge-graph embedding methods. This demonstrates the ability of word2vec embeddings trained on citation contexts to identify semantically similar papers based on their occurrence in similar contexts.

### 6.2 Pre-trained language models

GORC provides clean full text data for pre-training neural language models for scientific text. PDF is the primary distribution format for scientific literature. PDF parsing is notoriously difficult because PDFs are concerned with visual rather than semantic structure. Because of these and other features unique to scientific publications such as intermingled figures, tables, headers, and footers, and high prevalence of mathematical formulas and special characters, extracted scientific text often suffers from quality issues.

We attempt to offset these issues by extracting and removing figure and table content from the full text. We also attempt to identify in-line citations and references, which may interrupt the textual flow of a paper. Additionally, for LaTeX parses, we identify and extract all equation spans, which allow for mathematical formulas and special characters to be removed fully from the full text. The resulting clean full text is particularly suitable for training neural language models. Conservatively, we estimate that 8.1M full text papers consist of approximately 40B tokens, more than sufficient to train or tune model architectures such as ELMo, BERT, RoBERTa, or GPT2, whose reported training data sizes are given in Table 6. Due to the open access status of full text papers included in GORC, this corpus can serve as a standard benchmark for comparing different models and task performance over scientific text.

| Language model | Training data |
|----------------|---------------|
| ELMo (Peters et al., 2018) | 1BW (800M) Wikipedia (1.9B) WMT 2008-2012 (3.6B) |
| BERT (Devlin et al., 2019) | BooksCorpus (800M) Wikipedia (2.5B) |
| RoBERTa (Liu et al., 2019) | BooksCorpus (800M) CC-News (~3.8B) OpenWebText (~1.9B) Stories (~1.6B) |
| GPT2 (Radford et al., 2019) | Web Text Corpus (~2.8B) |

Table 6: Reported and estimated (several papers report corpus size in terms of bytes) token counts of training data used to train language models.

### 6.3 Other related tasks

The GORC corpus can also be applied to a variety of citation-related tasks, such as citation recommendation (both document-level and in-line), understanding citation intent, or citation-based paper summarization. Because all citations are available jointly with the full text, it is easy to retrieve citation contexts for each cited paper. In-line citation recommendation would be the most straightforward application, where the GORC corpus could be used to generate training data for a recommender model.

The LaTeX subset of the corpus also provides unique opportunities for research. In addition to citations and references, we also extract and parse tables from LaTeX source. There is an opportunity to use these tables for corpus-level results extraction and aggregation. The LaTeX subset also has fine-grained extraction and labeling of mathematical formulas, which can be used to understand proof construction, or to assist in variable co-reference resolution within a paper.

### 7 Related work

The ACL Anthology Network (AAN) (Radev et al., 2009) consists of 24.6K papers from conferences related specifically to computational linguist-
tics. CiteSeer (Giles et al., 1998), consists of 1.0M papers collected primarily via web crawl, without integrating metadata provided by sources outside of the PDF. Both contain full PDF text, citation contexts and bibliography entries. Recently, Saier and Färber (2019) introduces a dataset built using 1.0M arXiv publications using LaTeX source to extract text, citation spans, and bibliography entries, additionally linking papers to entries in the Microsoft Academic Graph. GORC presents a significantly larger dataset of linked papers covering broad domains of science by leveraging PDF parsing in addition to LaTeX source.

Context-aware citation recommendation is typically posed as an information retrieval problem in which context spans are used in addition to document features such as content and authors to retrieve suitable references during the paper writing process (Jeong et al., 2019; Huang et al., 2015; He et al., 2010). Jeong et al. (2019) use a modified version of the PeerRead dataset (Kang et al., 2018) to generate contextual citations from full text for training an in-line citation recommendation model. Huang et al. (2015) employ the CiteSeer dataset (Giles et al., 1998) that contains citation contexts from over 1M papers. In-line citation recommendation is related to the broader task of suggesting relevant references for an overall document (Bhagavatula et al., 2018; Liu et al., 2015; Yu et al., 2012), with some previous work incorporating citation contexts as training data. Duma and Klein (2014) propose a criterion for evaluating citation prediction that measures how accurately a system can predict a cited paper given a citation context and a masked in-line citation span. The data format for this citation prediction task is similar to what is provided in GORC.

Other tasks that leverage citation contexts are categorizing citation intent (Cohan et al., 2019; Teufel et al., 2006), identifying citation sentiment (Athar and Teufel, 2012), identifying meaningful citations (Valenzuela et al., 2015), extracting key phrases (Caragea et al., 2014), and citation context-based paper summarization (Cohan and Goharian, 2015; Mitrovic and Müller, 2015; Qazvinian and Radev, 2008; Teufel et al., 2006). Citation contexts can also be used for the more general task of identifying similar papers (Kanakia et al., 2019; Eto, 2019; Haruna et al., 2018; Small, 1973). Contextual citation graphs have also been used for bibliometric analysis (Asatani et al., 2018; Jurgens et al., 2018; Trujillo and Long, 2018; Jurgens et al., 2016; Ding et al., 2014).

8 Discussion

We introduce the Semantic Scholar GORC dataset, a large contextual citation graph of 81.1M papers and 380.5M citation edges with associated citation contexts and full text provided from 8.1M open access PDFs and 1.5M LaTeX source files. Instructions for data access are available at https://github.com/allenai/s2-gorc/. The GORC corpus aims to reduce the barrier for NLP research over scientific literature by offering rich reference and citation context-augmented full text from a large number of papers representing a diverse array of scientific fields. We describe some near-term uses for this dataset, including but not limited to training neural language models, citation recommendation, and other citation-related tasks. However, potential applications for this corpus are innumerable, and we encourage researchers to discover novel uses outside of the limited number of ideas proposed above.

Acknowledgements

The authors thank the Semantic Scholar team, Andrew Head, Daniel King, and Bryan Newbold for providing valuable feedback for this project.

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A The paper clustering problem

In academic fields in which pre-print publishing is common (e.g. arXiv), the notion of a paper is somewhat ambiguous. For example, if a published paper differs from its arXiv pre-print (as it often does), are the two documents considered separate papers for the purposes of citation? What about different arXiv pre-print drafts tagged as different versions but under the same arXiv identifier?

In this work, we define a paper to be a cluster of documents, as defined by the author(s) of those documents. For practical concerns in constructing GORC, we further require that one document within the cluster be the canonical document used to represent the paper cluster.

There are issues with defining a paper to be a collection of documents. For example, suppose paper cluster $j$ contains an arXiv draft and a peer-reviewed draft. And suppose paper $i$ contains a citation that critiques the content of the arXiv draft, but the critiqued content was updated in the peer-reviewed draft. If the peer-reviewed draft is chosen as the canonical representation of paper $j$, then the citation context from paper $i$ does not accurately capture the rationale of that reference. While worth noting, we believe such cases are rare and do not affect the vast majority of citation contexts.

B Canonical metadata selection

Canonical values for Title, Authors and other metadata fields are selected from among the papers in a cluster. First, if a cluster contains multiple PDFs, we select one to be canonical. This can occur, for example, for a cluster containing an arXiv pre-print and its eventual camera-ready version. We prioritize selecting PDFs from open access sources and break ties prioritizing PDFs for which there exists richer publisher-provided metadata (e.g. Abstract, Year, Venue, DOI). If the selected PDF is associated with publisher-provided metadata, we select those metadata fields to be canonical. Otherwise, we use majority voting to select canonical metadata fields, and break ties by minimizing the total number of sources from which we select metadata (i.e. if Publisher A provides Title, Authors and Abstract, Publisher B provides Title and Authors, and Publisher C provides Title and Abstract, we’ll prioritize selecting Publisher A over the union of Publishers B and C).

C PDF filters

Prior to running GROBID, we filter out PDFs that (i) produce an error when processed using the Python library PyPDF2, (ii) have greater than 50
pages (more likely to be a dissertation or report), (iii) have page widths greater than page heights (more likely to be slides), and (iv) those which fail to be parsed using pdfalto, the variant of pdftoxml used by GROBID.

Numbers of PDFs removed by these filters are given in Table 7.

| Filter            | Number of PDFs |
|-------------------|----------------|
| PyPDF2 error      | 0.54M          |
| Over 50 pages     | 2.27M          |
| Page width > height | 0.28M        |
| PDFAlto error     | 0.21M          |

Table 7: PDFs filtered out before GROBID processing

D GORC evaluation criteria

Paper cluster quality For each paper cluster, we compare the selected canonical Title and Authors fields with the title and authors of the selected canonical PDF. The Title field is labeled correct if it exactly matches the title seen on the PDF, with some allowance for different capitalization and minor differences in special character representation (e.g. “γ” versus “gamma”) and ignoring whitespace. The Authors field is labeled correct if all authors on the PDF are presented in the correct order, with some allowance for variation in the surface form. This is to avoid penalizing publisher metadata for providing a first initial (instead of the first name) or omitting middle names or titles (e.g. “Dr.”, “PhD”).

Paper-Bibliography linking For each paper-bibliography pair, we compare the selected canonical Title and Authors fields in the parsed bibliography entry to the selected canonical Title and Authors fields of the linked paper cluster. The Title fields are labeled as a match under the same criteria described above for matching paper cluster Title fields and PDF titles. The Authors fields are labeled as a match if there is substantial overlap in the names of the authors. For example, if authors A, B and C are in the bibliography entry and the linked paper cluster has authors A and B, then this is still considered a match. We note that in our evaluation, differences in the two sets of author names primarily stems from incorrectly written bibliography entries or mistakes in publisher-provided metadata.

E GORC data format

An example GORC paper is given below. Select fields are omitted for clarity. An example in-line citation span, bibliography entry and reference entry are shown. The citation span “[Lyons and Waite, 2011]” (line 28) is found in the paragraph text that begins “The solution to this...” (line 23).

```json
{
"paper_id": "104172",
"metadata": {
"title": "Nonlinear inversion...",
"authors": [{
"first": "Gregory",
"middle": ["P."],
"last": "Waite",
"suffix": ""
}],
"abstract": null,
"year": "2016",
"doi": "10.1002/2016jb013287",
"venue": "Journal of Geophysical Research: Solid Earth"
},
"s2_pdf_hash": "73ed8076fc747e77c41845cb5f18b40eece350865",
"grobid_parse": {
"title": "Nonlinear inversion...",
"authors": [...],
"abstract": [],
"body_text": [
{
"text": "The solution to this...",
"cite_spans": [
{ "start": 274, "end": 297, "text": "[Lyons and Waite, 2011]" }
],
"ref_spans": [],
"eq_spans": [],
"section": null
},
"bib_entries": {
"BIBREF9": {
"ref_id": "b9",
"title": "Dynamics of exp...",
"authors": [{"first": "J"}]
},
"fig_entries": {
"FIGREF1": {
"text": "To explore the ful...",
"type": "figure"
}
```
```
