

# The Semantic Scholar Open Data Platform

Rodney Kinney, Chloe Anastasiades, Russell Authur\*, Iz Beltagy, Jonathan Bragg, Alexandra Buraczynski, Isabel Cachola\*, Stefan Candra, Yoganand Chandrasekhar, Arman Cohan\*, Miles Crawford\*, Doug Downey, Jason Dunkelberger, Oren Etzioni, Rob Evans, Sergey Feldman, Joseph Gorney, David Graham, Fangzhou Hu, Regan Huff, Daniel King\*, Sebastian Kohlmeier\*, Bailey Kuehl, Michael Langan, Daniel Lin, Haokun Liu\*, Kyle Lo, Jaron Lochner, Kelsey MacMillan, Tyler Murray, Chris Newell, Smita Rao, Shaurya Rohatgi\*, Paul Sayre, Zejiang Shen\*, Amanpreet Singh, Luca Soldaini, Shivashankar Subramanian\*, Amber Tanaka, Alex D. Wade\*, Linda Wagner\*, Lucy Lu Wang\*, Chris Wilhelm, Caroline Wu, Jiangjiang Yang, Angele Zamarron, Madeleine Van Zuylen\*, Daniel S. Weld

Allen Institute for Artificial Intelligence

Seattle, Washington

{rodneyk, dougd, danw}@allenai.org

## Abstract

The volume of scientific output is creating an urgent need for automated tools to help scientists keep up with developments in their field. Semantic Scholar (S2) is an open data platform and website aimed at accelerating science by helping scholars discover and understand scientific literature. We combine public and proprietary data sources using state-of-the-art techniques for scholarly PDF content extraction and automatic knowledge graph construction to build the Semantic Scholar Academic Graph, the largest open scientific literature graph to-date, with 200M+ papers, 80M+ authors, 550M+ paper-authorship edges, and 2.4B+ citation edges. The graph includes advanced semantic features such as structurally parsed text, natural language summaries, and vector embeddings. In this paper, we describe the components of the S2 data processing pipeline and the associated APIs offered by the platform. We will update this living document to reflect changes as we add new data offerings and improve existing services.

## 1 Introduction

Semantic Scholar<sup>1</sup> (S2), was launched in 2015 by the Allen Institute for Artificial Intelligence<sup>2</sup> (AI2) to help scholars combat information overload and more efficiently discover and understand the most relevant research literature. Through a growing number of partnerships with scientific publishers and preprint services, Semantic Scholar has built a comprehensive and open corpus of scientific publications as a public service. While the Semantic Scholar website provides

many features, such as automatically-generated author pages, personalized libraries, and paper recommendations, most of the site’s data and functionality is also available via data download, open-source libraries, and API services.

In this paper, we overview the primary technology used to build the corpus, and the API services and downloads we provide to access it. We hope that the resources described in this article can further accelerate a variety of work that depends critically on high-quality scholarly data. Research into scientific NLP and science of science benefit directly from such resources. More generally, we are enabling the development of new applications that help scientists discover and understand the literature of their field. The need for timely and comprehensive scholarly data has become more imperative since the 2021 sunset of the Microsoft Academic Graph (MAG) (Sinha et al., 2015), which was long a standard source for scholarly data in the community.

The remainder of the paper proceeds as follows. In Section 2, we give an overview of the data and services that comprise the platform. In Section 3, we describe the platform’s data processing pipeline. In Section 4, we describe our public APIs and downloadable datasets. In Section 5, we discuss related work. In Section 6, we conclude and discuss future work.

## 2 Platform Overview

The purpose of the Semantic Scholar Open Data Platform is to build and distribute the Semantic Scholar Academic Graph, or S2AG (pronounced "stag"). S2AG is a disambiguated, high-quality, bibliographic knowledge graph. The nodes of S2AG represent papers, authors, venues, and academic institutions. The edges represent papers written by an author, papers cited by another paper, papers published in a venue, and authors affiliated with an institution. S2AG is built by ingesting a variety of data sources into our data

\* Work done while at the Allen Institute for AI

<sup>1</sup><https://semanticscholar.org>

<sup>2</sup><https://allenai.org>

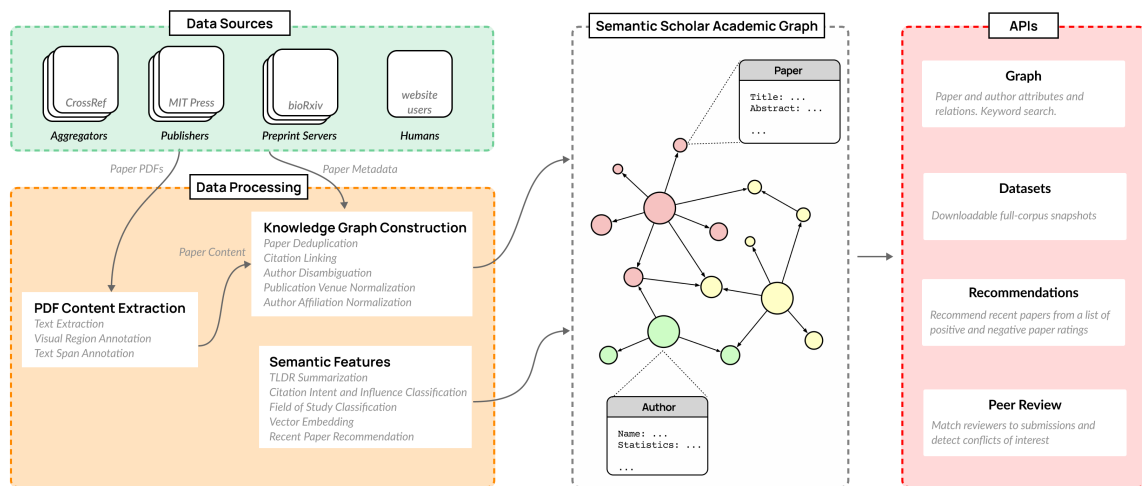


Figure 1: Illustration of the Semantic Scholar platform

processing pipeline, and is distributed via a variety of publicly-available APIs and datasets, as illustrated in Figure 1.

The work we describe here is an update of a previous version of the Semantic Scholar data pipeline described in Ammar et al. (2018). The core structure of the graph (authors, papers and their relationships) is the same, although the components that build the knowledge graph have been refined. The entity extraction and linking described in Ammar et al. (2018) have been deprecated in favor of the semantic features described below.

Table 1 summarizes the overall size of S2AG as of January 2023.<sup>3</sup> S2AG covers many natural, physical, and social sciences. Table 2 summarizes the number of paper records in different academic fields of study. Some papers are assigned to multiple fields, whereas many are unclassified (“n/a”), due to lack of sufficient information.

### 3 Data Processing Pipeline

At the core of Semantic Scholar lies a sophisticated data processing pipeline that continually ingests documents and metadata from numerous sources, extracting full text and metadata from PDFs, normalizing and disambiguating authors, institutions, and venues, classifying each paper’s field of study, generating a textual summary of its key results, and more.

The pipeline builds S2AG by ingesting academic paper metadata and PDF content from a variety of *Data Sources*. A *PDF Content Extraction* system extracts structured data from unstructured PDFs. The extracted content, along with structured metadata from the input sources, is processed by a series of *Knowledge Graph Construction* systems that build S2AG. A set of models add *Semantic Features* to the graph, such as

<sup>3</sup>We are populating the author-affiliation links at the time of writing, so we have given the expected eventual number.

paper summarization and vector embeddings.

Many components of our pipeline are available as open software or models. Table 3 provides a high-level summary alongside links to publicly available code, models and datasets, where applicable. Many of these also have an associated published research article, to which we refer readers seeking further details.

#### 3.1 Data Sources

The pipeline has more than 50 input sources. They include non-profit organizations such as Crossref, preprint servers such as arXiv, academic publishers through negotiated agreements, and our own internet web crawler. Sources may provide metadata in the JATS<sup>4</sup> format, or a variety of proprietary formats. Data may be pushed or pulled via FTP, fetched via an API, or downloaded in bulk via HTTP. Most sources are updated daily. An important additional source is human-created data. Users of the web site can claim the identity of an author in our corpus and manually curate the papers associated with that author. Our team also makes manual corrections in response to email requests from users. The first task of the pipeline is to fetch the latest data from each source and parse it into a normalized format. Sources typically provide limited information about a paper in structured form: typically the title, author names, venue, and date, often linked to a PDF file.

#### 3.2 PDF Content Extraction

We augment the structured metadata by parsing the unstructured information in a paper’s PDF into structured form, resulting in fine-grained information about the complete text. A critical output of our PDF content extraction is a structured bibliography from which we can construct the citation graph. Other important out-

<sup>4</sup><https://jats.nlm.nih.gov/>

Nodes	
paper	205M
author	80M
publication venue	550k
academic institution	*100k
Edges	
citation	2.4B
paper-author	580M
paper-venue	40M
author-affiliation	*100M

\* = anticipated in 2023

Table 1: Approximate size of S2AG.

puts include section headers, paragraphs, figures and tables, and inline references to figures, tables, and bibliography entries. PDFs are fundamentally a print-format specification, and extracting structured information from them is difficult and subject to errors. Nevertheless, they are the de-facto representation of a paper’s official content, and we have invested heavily in our extraction technology. There are three steps to PDF content extraction: *Text Extraction*, *Visual Region Annotation*, and *Text Span Annotation*.

*Text Extraction* is the process of converting the set of commands that indicate where characters should appear on the page into plain text, i.e., inferring word boundaries and word order. For this, we use existing open-source toolkits, including pdfalto,<sup>5</sup> PDFPlumber,<sup>6</sup> and/or PDFMiner.<sup>7</sup>

It is possible to extract decent-quality content using only the plain text from the Text Extraction step. For this, we have used Grobid<sup>8</sup> as well as our own extractor called ScienceParse.<sup>9,10</sup> Our latest pipeline uses visual recognition, described below, to improve the quality of the extraction.

The *Visual Region Annotation* step first generates a visual image for each page, using poppler.<sup>11</sup> Within each page, we run an object detection model<sup>12</sup> from the LayoutParser (Shen et al., 2021) library which identifies bounding boxes and labels each one with visual layout categories such as figure, table, paragraph. The code, model, and data are available at <https://github.com/Layout-Parser/layout-parser>.

*Text Span Annotation* is the process of giving semantic labels to tokens from the Text Extraction step.

<sup>5</sup><https://github.com/kermitt2/pdfalto>

<sup>6</sup><https://github.com/jsvine/pdfplumber>

<sup>7</sup><https://github.com/pdfminer/pdfminer.six>

<sup>8</sup><https://github.com/kermitt2/grobid>

<sup>9</sup><https://github.com/allenai/science-parse>

<sup>10</sup><https://github.com/allenai/spv2>

<sup>11</sup><https://poppler.freedesktop.org/>

<sup>12</sup>EfficientDet (Tan et al., 2020) model trained on PubLayNet (Zhong et al., 2019)

Field of Study	Count
n/a	60.0M
Medicine	31.8M
Biology	20.4M
Physics	11.6M
Engineering	10.2M
Computer Science	9.7M
Chemistry	9.1M
Education	7.4M
Materials Science	7.4M
Environmental Science	7.0M
Economics	6.2M
Psychology	6.2M
Agricultural and Food Sciences	5.9M
Business	5.6M
Mathematics	3.7M
History	3.4M
Political Science	2.9M
Art	2.8M
Geology	2.6M
Sociology	1.4M
Philosophy	1.4M
Law	1.1M
Linguistics	1.1M
Geography	350k

Table 2: Paper records in S2AG for different academic fields

For this, we use the I-VILA model trained on the S2-VL dataset, both introduced in Shen et al. (2022), to tag tokens with categories such as title, author name, section header, body text, figure caption, bibliography, etc. The code, model, and data are available at <https://github.com/allenai/VILA>.

Visual Region and Text Span annotations are converted into structured data (e.g., section headers are associated with section content, figures are associated with their captions, and bibliography entries are decomposed into their constituent elements) using the PaperMage library, which makes its code, models and data available at <https://github.com/allenai/papermage>. The final output of the PDF extraction pipeline is a structured data object suitable for encoding in JSON format. It includes core metadata such as title, authors, and abstract, as well as the full body text with detailed structural information about the text.

### 3.3 Knowledge Graph Construction

The output of the PDF processing above, like the structured data in our input sources, consists of plain-string names for real world entities. Those entities include authors, the institutions with which those authors are affiliated, the venues in which the papers were published, and of course, the papers themselves. To build S2AG, we must assign an ID to each real-world entity and associate each plain-string name with the appropriate ID.

*Paper Deduplication* is necessary because we process data from many independent sources. Paper titles are not unique, and can vary in how they are expressed. Authors can release updated versions of a

Task	Model	Datasets	GitHub
Visual Region Annotation	EfficientDet (Tan et al., 2020) via LayoutParser (Shen et al., 2021)	PubLayNet (Zhong et al., 2019)	Layout-Parser/layout-parser
Text Span Annotation	I-VILA (Shen et al., 2022)	S2-VL (Shen et al., 2022)	allenai/VILA
Paper Deduplication	S2APLER	S2APLER	allenai/S2APLER
Author Disambiguation	S2AND (Subramanian et al., 2021)	S2AND (Subramanian et al., 2021)	allenai/S2AND
Affiliation Normalization	S2AFF	S2AFF	allenai/S2AFF
TLDR Summarization	BART (Lewis et al., 2019) with CATTs (Cachola et al., 2020)	SciTLDR (Cachola et al., 2020)	allenai/SciTLDR
Citation Intent Classification	Cohan et al. (2019)	SciCite (Cohan et al., 2019)	allenai/SciCite
Field of Study Classification	S2FOS	S2FOS	allenai/s2_fos
Influential Citation Classification	Valenzuela et al. (2015)	meaningful-citations	-
Paper Embedding	SPECTER (Cohan et al., 2020)	SciDocs (Cohan et al., 2020) & SciRepEval (Singh et al., 2022)	allenai/SPECTER allenai/SciRepEval

Table 3: Selected models and datasets used by the pipeline.

paper with a slightly modified, or almost completely different, title. Our latest paper deduplication model is named S2APLER. It works by grouping papers into blocks using title, such that papers with similar but non-identical titles end up in the same block, then scoring the pairwise similarity of papers in each block with a trained model. The model uses string-similarity features for title, abstract, author names, venue name, etc. The synthetic training dataset uses paper data from authoritative sources that provide either a PDF or a DOI.<sup>13</sup> Paper pairs with matching DOI/PDFs from different sources are used as positive training examples. Pairs with similar titles but non-matching DOI/PDFs are used as negative examples. We make S2APLER available at <https://github.com/allenai/S2APLER>.

*Citation Linking* is the system for finding references to one paper in another paper’s bibliography. We also use the Text Span Annotation output to associate each citation link with the text of the sentence containing the citation. Citation Linking is a very similar problem to paper deduplication, except that instead of scoring the similarity between two papers, we score the similarity between a paper and a bibliography entry produced by the PDF Extraction system. We are using fuzzy text-matching heuristics on title and authors for citation linking, but anticipate that the S2APLER model can eventually be adapted to this problem.

For *Publication Venue Normalization*, we combine

data from Fatcat<sup>14</sup> and MAG to build a comprehensive set of normalized venues. To match normalized venues, we index all known variant titles for the venue, including ISO-4 normalization,<sup>15</sup> in a direct lookup table. We apply regular-expression-based rules to the unnormalized venue strings we obtain from extracted or input sources and look for exact matches in the knowledge base.

In *Author Disambiguation*, we use a system named S2AND, introduced in Subramanian et al. (2021), to assign an ID to each author mention (a name of an author appearing in a particular paper). S2AND operates in three stages: (1) Grouping author mentions into candidate blocks, (2) Scoring similarity between records within a block using a LightGBM model (Ke et al., 2017), and (3) Clustering mentions within a block. The similarity scoring is trained on a large dataset for author disambiguation also introduced in Subramanian et al. (2021). The code, model and dataset for S2AND is available at <https://github.com/allenai/S2AND>.

For *Author Affiliation Normalization*, we link to ROR,<sup>16</sup> a registry of persistent identifiers for research organizations. Our linking model is named S2AFF. It first parses unnormalized affiliation strings with a trained NER model into main institute, child institute, and address components. It then fetches the top 100 candidates from a Jaccard-overlap retrieval index and

<sup>13</sup><https://www.doi.org>

<sup>14</sup><https://fatcat.wiki/>

<sup>15</sup>[https://en.wikipedia.org/wiki/ISO\\_4](https://en.wikipedia.org/wiki/ISO_4)

<sup>16</sup><https://ror.org>

ranks them using a pairwise LightGBM model (Ke et al., 2017) trained using internally-gathered human annotations. We make the code and data for S2AFF available at <https://github.com/allenai/S2AFF>. We expect the API to include normalized affiliation links in 2023.

### 3.4 Semantic Features

We now turn to describing the models that provide semantic features on top of the knowledge graph.

#### 3.4.1 TLDR Summarization

To facilitate faster understanding and decision making when scanning lists of papers, we distribute short summaries of scientific papers, or TLDRs, as introduced in Cachola et al. (2020).

Generating TLDRs of scientific papers can be a challenging task that involves high source compression and requires domain-specific expertise. We use a BART (Lewis et al., 2019) model trained with CATTs (Cachola et al., 2020), training on paper titles as a scaffolding task to overcome the problem of limited annotated training data. We trained this model on a combined dataset consisting of examples from SciTLDR (Cachola et al., 2020) and a separately collected set of summaries for biomedical papers from the Semantic Scholar corpus. The code, model, and data are available at <https://github.com/allenai/SciTLDR>.

#### 3.4.2 Citation Intent and Influence Classification

Citations play a critical role in scientific papers, and understanding the intent of a citation is helpful for automated analysis of scholarly literature. We use the model and dataset, called SciCite, introduced in Cohan et al. (2019) to classify each citation into one of three categories: *background information*, *use of methods*, or *comparing results*. The code, model, and data for SciCite are available at <https://github.com/allenai/SciCite>.

We also classify whether each citation is *Highly Influential*. Based on the dataset and findings from Valenzuela et al. (2015),<sup>17</sup> we use a feature-based heuristic: (1) Only citations between papers with no overlapping authors are considered eligible, (2) A citation is classified as Highly Influential if it appears at least three times in a sentence in which no other papers are cited, if the citing sentence contains terms such as "build upon" "following" or "inspired by", or if the citing sentence has references to tables or figures (indicating a direct comparison with the cited work).

#### 3.4.3 Fields-of-Study Classification

Prior to the discontinuation of MAG, Semantic Scholar made use of the fields-of-study classifications that MAG provided, using their level 0 taxonomy. After MAG's deprecation, we deployed our own classification model, adding Education, Law, and Linguistics to the existing MAG list. These additions were based

<sup>17</sup><https://allenai.org/data/meaningful-citations>

on user feedback and comparison to other popular academic data sources such as Dimensions.

We trained our own fields-of-study classifier, named S2FOS,<sup>18</sup> using a multilabel linear SVM using character n-gram TF-IDF representations (the 300k most common character unigrams to 5-grams). For training data, we manually labeled a number of publication venues, and then propagated those labels to all papers published in their respective venues. The code, model, and data are available at [https://github.com/allenai/s2\\_fos](https://github.com/allenai/s2_fos)

#### 3.4.4 Paper Embeddings

Vector representations (embeddings) of papers can be useful in a variety of downstream applications. Our pipeline uses them for author disambiguation and recommendations, and we publish embeddings so that others may use them in their own applications. We produce embeddings using SPECTER (Cohan et al., 2020), which generates document-level embeddings from SciBERT (Beltagy et al., 2019). SPECTER takes the paper title and abstract as input, and is trained to minimize a triplet margin loss that encourages paper pairs with a citation relationship to have more similar embeddings than those without. We evaluated on the SciDocs benchmark, also introduced in Cohan et al. (2020), as well as a newer benchmark SciRepEval (Singh et al., 2022), which increases the number and difficulty of tasks. The code, models, and data for SPECTER are available at <https://github.com/allenai/SPECTER> and for SciRepEval at <https://github.com/allenai/SciRepEval>.

#### 3.4.5 Recent Paper Recommendations

We dynamically train recommendation models to surface relevant new papers to users. Our recommender takes a set of positively- and negatively-annotated papers, and outputs a ranked list of recommended papers. The model generates recommendations in three steps: Ranker Training, Candidate Selection, and Candidate Ranking.

Ranker Training is an extension of Arxiv Sanity.<sup>19,20</sup> From each user's positive/negative annotations, it trains two linear Support Vector Machine models: one from the TF-IDF representations of the annotated papers and one from the SPECTER embeddings. We augment negative user annotations with randomly selected negative examples, the latter having less weight. During Candidate Selection, we use FAISS<sup>21</sup> to search an approximate k-nearest neighbor index of the SPECTER embeddings of ~1M papers published in the last 60 days (refreshed nightly). Finally, for Candidate Ranking we select ~500 papers nearest the centroid of the positively-annotated papers and rank them using the average of the two model scores.

<sup>18</sup><https://blog.allenai.org/9d2f641949e5>

<sup>19</sup><https://arxiv-sanity-lite.com/>

<sup>20</sup><https://github.com/karpathy/arxiv-sanity-lite>

<sup>21</sup><https://github.com/facebookresearch/faiss>

Field of Study	Count
Medicine	2.9M
Biology	2.2M
Physics	1.2M
Computer Science	810k
Mathematics	580k
Psychology	540k
Chemistry	430k
Materials Science	400k
Environmental Science	400k
Engineering	390k
Agricultural And Food Sciences	380k
Education	260k
Business	230k
Economics	210k
Political Science	150k
Geology	110k
Art	50k
Sociology	50k
History	40k
Linguistics	30k
Philosophy	30k
Law	20k
Geography	20k

Table 4: Full-text availability of papers in S2ORC for different academic fields

## 4 APIs and Datasets

The outputs of our data processing pipeline and semantic models are made available through a suite of APIs and datasets described below. Because we develop and refine our models over time, the data served by the APIs may shift, or it may come from a mixture of models as we migrate from one system to its successor. Where appropriate, we will update our live documentation<sup>22</sup> to reflect any changes.

For unauthenticated users, we offer a low volume of API requests and samples of the datasets. For full datasets and high request volumes, we ask that users obtain an authentication key, at no charge, subject to terms of use.<sup>23</sup> To date, we have issued over 700 authentication keys to various partners, for uses varying from student research projects to non-profit organizations to commercial products, serving close to 150 million requests in December 2022.

### 4.1 Graph

The Graph API<sup>24</sup> provides the most current data from the Semantic Scholar Academic Graph. Papers can be retrieved by our internal ID, or by using identifiers from arXiv, PubMed, DOI, and others. Papers can also be retrieved via their bidirectional citation relationship to other papers, or by author. Keyword search, with some filtering options, is available for both papers and authors. We place size restrictions on the number of

<sup>22</sup><https://api.semanticscholar.org/api-docs>

<sup>23</sup><https://www.semanticscholar.org/product/api#Partner-Form>

<sup>24</sup><https://api.semanticscholar.org/api-docs/graph>

search results and encourage users to use the bulk snapshots when retrieving large volumes of data.

### 4.2 Datasets

Download links to monthly snapshots of our knowledge graph can be obtained via our Datasets API.<sup>25</sup> Each dataset is a collection of gzipped JSON files, where records in one dataset refer to records in other datasets by ID. The datasets are:

- `papers`: Core metadata of papers
- `abstracts`: Abstract text for papers, where allowed by licensing
- `authors`: Core metadata of authors
- `citations`: Citation links between papers, with citation context and intent and influential classifications
- `embeddings`: SPECTER embeddings of papers
- `paper-ids`: Mapping between different IDs used to identify a paper. Useful for tracking deduplication between releases.
- `tldrs`: TLDRs for papers
- `publication-venues`: Core metadata for publication venues
- `S2ORC`: Introduced in Lo et al. (2020), S2ORC is the largest publicly-available collection of full text for open-access scientific papers. S2ORC’s full text is annotated with automatically-identified structural and semantic elements of the paper: section headings, paragraphs, bibliography entries, inline citation mentions, table/figure references, etc. Table 4 shows the number of open-access full-text papers broken down by academic field. Since its original release as a static collection, S2ORC has grown in size and is being kept up-to-date as part of our PDF processing pipeline. For further details on S2ORC, we refer the reader to Lo et al. (2020) and documentation at <https://github.com/allenai/s2orc>.

### 4.3 Recommendations

The Recommendations API<sup>26</sup> generates recommendations, selected from papers published within the past 60 days, based on positive/negative paper annotations. The caller provides at least one paper ID as a positive example, and any number of paper IDs as negative examples. The response is a relevance-ordered list of recently-published papers and their metadata.

### 4.4 Peer Review

The Peer Review API<sup>27</sup> supports the process of peer reviewer matching and conflict of interest detection.<sup>28</sup>

<sup>25</sup><https://api.semanticscholar.org/api-docs/datasets>

<sup>26</sup><https://api.semanticscholar.org/api-docs/recommendations>

<sup>27</sup><https://api.semanticscholar.org/api-docs/peer-review>

<sup>28</sup><https://blog.allenai.org/24ab9fce2324>

Resource	URL	Article Count	Access	Services
Aminer	aminer.org	321.5M	open	D*
arXiv	arxiv.org	2M	open	D**,F,S
BASE	base-search.net	180.5M	open	S
CORE	core.ac.uk	207.3M	open	D*, S
Dimensions	app.dimensions.ai	123.8M	subscription	D, F, M, S
Google Scholar	scholar.google.com	?	-	-
The Lens	lens.org	240.4M	subscription	D, M, S
Meta	-	-	terminated 3/31/22	-
Microsoft Academic	-	-	terminated 12/31/21	-
OpenAlex	openalex.org	205.2M	open	D, F, M
PubMed Central	ncbi.nlm.nih.gov/pmc/	7.5M	open	D**,F,P,S
ResearchGate	researchgate.net	135.0M	-	-
Scopus	scopus.com	84.0M	subscription	F, M, S
<b>Semantic Scholar</b>	<b>semanticscholar.org</b>	<b>205M</b>	<b>open</b>	<b>D, F, M, P, S, T</b>
Web of Science Core	webofknowledge.com	83.2M	subscription	F, M, S

Key: D=data download; F=field-of-study classification; M=advanced metadata; P=semantically parsed text; S=title and abstract search; T=natural language summarization  
\*=data more than a year stale; \*\*=restricted fields of study  
Article count does not include patents or datasets.

Table 5: Comparison of leading scholarly data providers

Users, such as journal editors or conference organizers, can upload information about potential reviewers (their Semantic Scholar author ID) and paper submissions (title, abstract, and list of authors, including Semantic Scholar author ID). The Peer Review API returns conflict-of-interest (COI) and matching scores for all reviewer-submission pairs. The COI score is a binary indicator saying whether the reviewer has co-authored with any of the submission’s authors in the past. The reviewer match score is as the average SPECTER distance between submission and the three most similar papers written by the reviewer.

## 5 Related Work

Table 5 summarizes major providers of scholarly data along three key dimensions: comprehensiveness, access, and services offered. Some providers, such as Google Scholar, do not offer any programmatic services at all. Others, such as MAG, have been discontinued. The major open provider of parsed content, PubMed Central, is not cross-disciplinary. Other providers require a subscription. Semantic Scholar is unique in providing a comprehensive and open knowledge base with the widest array of services.

## 6 Conclusion and Future Work

We have described the Semantic Scholar data platform, which offers code bases, data sets, and APIs covering scientific literature. The Semantic Scholar Academic Graph (S2AG) consists of hundreds of millions of pa-

pers and billions of citation links, created by a state-of-the-art PDF extraction and knowledge graph normalization pipeline described in this paper. The platform also offers semantic features such as summarization, vector embeddings and recommendations.

In the future, we hope to expose selected semantic features as services, for users to apply to their own data. We hope to add richer semantic labels to our full-text annotations. We plan to add more personalized functionality, such as access to library content and reading history. We will expand our tools for collecting human data corrections, and possibly collect automated annotations from external collaborators. Of course, we will continue to improve our existing knowledge graph construction and semantic feature models. We hope that providing these resources will enable application development and research using scholarly data to promote the advancement of science globally.

## Acknowledgements

The Semantic Scholar Open Data Platform, including S2AG and various dataset and API offerings, is the product of years of work by members of the Semantic Scholar team. The authors of this paper have all contributed directly to the creation and continued maintenance of this platform, including software and model development, data curation, evaluation, design, product management, and more.

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