ON THE USE OF ARXIV AS A DATASET

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ABSTRACT

The arXiv has collected 1.5 million pre-print articles over 28 years, hosting literature from scientific fields including Physics, Mathematics, and Computer Science. Each pre-print features text, figures, authors, citations, categories, and other metadata. These rich, multi-modal features, combined with the natural graph structure—created by citation, affiliation, and co-authorship—makes the arXiv an exciting candidate for benchmarking next-generation models. Here we take the first necessary steps toward this goal, by providing a pipeline which standardizes and simplifies access to the arXiv’s publicly available data. We use this pipeline to extract and analyze a 6.7 million edge citation graph, with an 11 billion word corpus of full-text research articles. We present some baseline classification results, and motivate application of more exciting generative graph models.

1 INTRODUCTION

Real world datasets are typically multimodal (comprised of images, text, and time series, etc) and have complex relational structures well captured by a graph. Recently, advances have been made on models which act on graphs, allowing the rich features and relational structures of real-word data to be utilized (Hamilton et al., 2017b,a; Battaglia et al., 2018; Goyal & Ferrara, 2018; Nickel et al., 2016). Many of these advances have been facilitated by the availability of large, benchmark datasets: for example, the ImageNet (Russakovsky et al., 2015) dataset has been widely used as a community standard for image classification. We believe the arXiv can provide a similarly useful benchmark for large scale, multimodal, relational modelling.

The arXiv is the de-facto online manuscript pre-print service for Computer Science, Mathematics, Physics, and many interdisciplinary communities. Since 1991 the arXiv has offered a place for researchers to reliably share their work as it undergoes the process of peer-review, and for many researchers it is their primary source of literature. With over 1.5 million articles, a large multigraph dataset can be built, including full-text articles, article metadata, and internal co-citations.

The arXiv has been used many times as a dataset. Liben-Nowell & Kleinberg (2007) used the topology of the arXiv co-authorship graph to study link prediction. Dempsey et al. (2019) used the authorship graph to test a hierarchically structured network model. Lopuszynski & Boliowski (2013) used the category labels of arXiv documents to train and assess an automatic text labelling system. Dai et al. (2015) used a subset of the full text available on the arXiv to study the utility of “paragraph vectors” for capturing document similarity. Alemi & Ginsparg (2015) used the full text to evaluate a method for unsupervised text segmentation. Eger et al. (2019) and Liu et al. (2018) built models to predict future research topic trends in machine learning and physics respectively. The arXiv also formed the basis of the popular 2003 KDD Cup (Gehrke et al., 2003), in which researchers competed for the prize of best algorithm for citation prediction, download estimation, and data cleaning.\footnote{https://arxiv.org} \footnote{The data for those challenges are available at http://www.cs.cornell.edu/projects/kddcup/datasets.html}
All these works used different subsets of arXiv’s data, limiting their potential impact, as future researchers will be unable to directly compare their work to these existing results. The goal of this paper is to improve this situation by providing an open-source pipeline to standardize, simplify, and normalize access to the arXiv’s public data, providing a benchmark to facilitate the development of models for multi-modal, relational data.

2 D ATASET

We built a freely available, open-source pipeline for collecting arXiv metadata from the Open Archive Initiative (Lagoze & Van de Sompel 2001), and bulk PDF downloading from the arXiv. Further, this pipeline converts the raw PDFs to plaintext, builds the intra-arXiv co-citation network by searching the full-text for arXiv ids, and cleans and normalizes author strings.

2.1 M ETA DATA

Through its participation in the Open Archives Initiative the arXiv makes all article metadata available, with updates made shortly after new articles are published. We provide code for utilizing these public APIs to download a full set of current arXiv metadata. As of 2019-03-01, metadata for 1,506,500 articles was available. For verification and ease of use purposes, we provide a copy of the metadata (less abstracts) on the date we accessed it. An example listing is shown in Figure 1. Each article includes an arXiv id (e.g. 0704.0001) used to identify the article, the publicly visible name of the submitter, a list of authors, title, abstract, versions and category listings, as well as optional doi, journal-ref and report-no fields. Of particular note is the first category listed, the primary category, of which there are 171 at this time. Notice that the list of authors is just a single string of author names, potentially joined with commas or ‘and’s. We’ve provided a suggested normalization and splitting script for splitting these author strings into a list of author names. Additional fields may be present to denote doi, journal-ref and report-no, although these are not validated they can potentially be used to find intersections between the arXiv dataset and other scientific literature datasets. Population counts for the optional fields are shown in Table I.

```json
[{
    'id': '1904.99999',
    'submitter': 'Colin B. Clement',
    'authors': 'Colin B. Clement, Matthew Bierbaum, Kevin P. O’Keefe, and Alexander A. Alemi',
    'title': 'On the Use of ArXiv as a Dataset',
    'comments': '7 pages, 3 figures, 2 tables',
    'journal-ref': '',
    'doi': '',
    'abstract': 'The arXiv has collected 1.5 million pre-prints over 28 years, hosting literature from physics, mathematics, computer science, biology, finance, statistics, electrical engineering, and economics. Each pre-print features text, figures, author lists, citation lists, categories, and other metadata. These rich, multi-modal features, combined with the natural relational graph structure created by citation, affiliation, and co-authorship makes the arXiv an exciting candidate for benchmarking next-generation models. Here we take the first necessary steps toward this goal, by providing a pipeline which standardizes and simplifies access to the arXiv’s publicly available data. We use this pipeline to extract and analyze a 6.7 million edge citation graph, with an 11 billion word corpus of full-text research articles. We present some baseline classification results, and motivate application of more exciting relational neural network models.',
    'categories': ['cs.IR'],
    'versions': ['v1']
}]
```

Figure 1: An example of what the metadata for this very article may look like if it were submitted to the arXiv.
Table 1: Number of articles with the corresponding field populated. Note that the fields id, abstract, authors, versions, and categories are always populated.

| Field         | Count     |
|---------------|-----------|
| id            | 1,506,500 |
| submitter     | 1,491,303 |
| comments      | 1,229,138 |
| doi           | 810,209   |
| journal-ref   | 608,286   |
| report-no     | 154,922   |

2.2 FULL TEXT

One advantage the arXiv has over other graph datasets is that it provides a very rich attribute at each id node: the full raw text and figures of a research article. To extract the raw text from PDFs, we provide a pipeline with two parts. A helper script downloads the full set of PDFs available through the arXiv’s bulk download service. Since arXiv hosts their data in a requester-pay AWS S3 buckets, this constitutes ~ 1.1 TB and ~ $100 to fully download. For posterity, we have provided MD5 hashes of the PDFs at the state of the frozen metagraph extraction. Raw T eX source is also available for the subset of articles that provide it. Second, we provide a standard PDF-to-text converter – powered by pdftotext – to convert the PDFs to plaintext.

Using this pipeline, it is currently possible to extract a corpus of 1.37 million raw text documents. Figure 2 shows an example of the text extracted from a PDF. Though the extracted text isn’t perfectly clean, we believe it will still be useful for many tasks, and hope future contributions to our repository will provide better data cleaning procedures.

The extracted raw-text dataset is ~ 64 GB in size, totaling ~ 11 billion words. An order of magnitude larger than the common billion word corpus (Chelba et al., 2013), this large size makes the arXiv raw-text a competitive alternative to other full text datasets. Moreover, the technical nature of the arXiv distinguishes it from other full text datasets. For example, the T eX data contained in the arXiv presents an opportunity to study mathematical formulae in bulk, as is done in the NTCIR-11 Task: Math-2 (Aizawa et al., 2014).

Figure 2: Example text extracted from this PDF.

Published as a conference paper at ICLR 2019

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A BSTRACT

The arXiv has collected 1.5 million pre-print articles over 28 years, hosting literature from scientific fields including Physics, Mathematics, and Computer Science. Each pre-print features text, figures, authors, citations, categories, and other metadata. These rich, multi-modal features, combined with the natural graph structure created by citation, affiliation, and co-authorship makes the arXiv an exciting candidate for benchmarking next-generation models. Here we take the first necessary steps toward this goal, by providing a pipeline which standardizes and simplifies access to the arXiv’s publicly available data. We use this pipeline to extract and analyze a 6.7 million edge citation graph, with an 11 billion word corpus of full-text research articles. We present some baseline classification results, and motivate application of more exciting generative graph models.

https://arxiv.org/help/bulk_data
10 Version 0.61.1, available on most Debian systems from the apt package poppler-utils
Table 2: Graph statistics for popular citation networks. All but the data for this work (first row) were taken from Table 1 and 2 in Subelj et al. (2014). \( \langle k \rangle \) is the average degree, and \( \alpha_{in} \) and \( \alpha_{out} \) are power law exponents of best fit for the degree distribution. WCC refers to the largest weakly connected components, computed using the python package 'networkx'. The power law exponents \( \alpha_{in}, \alpha_{out} \) were found using the python module powerlaw. When fitting data to a powerlaw, the package discards all data below an automatically computed threshold \( x_{min} \). These thresholds for \( k_{in} \) and \( k_{out} \) were \( x_{min} = 73 \) and \( x_{min} = 59 \) respectively.

| Dataset  | \( N_{nodes} \)   | \( N_{edges} \)   | \( \langle k \rangle \) | \( \alpha_{in} \) | \( \alpha_{out} \) | % WCC   |
|---------|------------------|------------------|----------------------|-----------------|-----------------|--------|
| arXiv   | \( 1.35 \times 10^6 \) | \( 6.72 \times 10^6 \) | 9.933                | 2.93            | 3.93            | 62     |
| WoS     | \( 1.40 \times 10^5 \) | \( 6.4 \times 10^5 \)   | 9.11                 | 2.39            | 3.88            | 97     |
| CiteSeer| \( 3.84 \times 10^5 \) | \( 1.74 \times 10^5 \)   | 9.08                 | 2.28            | 3.82            | 95     |
| KDD2003 | \( 3.34 \times 10^4 \) | \( 4.21 \times 10^5 \)   | 24.50                | 2.54            | 3.45            | 99.6   |

2.3 Co-Citations

While the arXiv does not currently publicly provide an API to access co-citations, our pipeline allows a simple but large co-citation network to be extracted. We extracted this network by searching the text of each article for valid arXiv ids, thereby finding which nodes should be linked to a given node in the co-citation network. We provide a compressed binary of the resulting network at the repository, so that researchers can study it directly, and avoid the difficulty of constructing it themselves. Table 2 summarizes the size and statistical structure of our co-citation network, compared with other popular citation networks. Subelj et al. (2014) also studied data from the arXiv, but as indicated in the bottom row of Table 2, it used only the 34,546 articles from the 2003 KDD Cup challenge.

Table 2 reports standard statistics for the co-citation network. Our arXiv co-citation network contains \( O(10^5) \) nodes, an order of magnitude larger than the \( O(10^5) \) nodes in the other citation networks. The exponents of best fit for the degree distributions \( \alpha_{in} \) and \( \alpha_{out} \) are consistent with the existing citation networks Subelj et al. (2014), as it the degree \( \langle k \rangle \), 62% of the nodes are contained in the largest weakly connected component, while 31% of the nodes are fully isolated – meaning their in-degree \( k_{in} \) and out-degree \( k_{out} \) are zero. Recall that our arXiv co-citation network only contains publications which have been posted on the arXiv; a given paper which cites papers published elsewhere – and not on the arXiv – will have \( k_{out} = 0 \) in this set, which is an explanation the large number of isolated nodes.

Beyond constructing and analyzing a co-citation network, the arXiv dataset can be used for many tasks, such as relationally powered classification, author attribution, segmentation, clustering, structured prediction, language modeling, link prediction and automatic summary generation. As a basic demonstration, in Table 3 we show some baseline category classification results. These were obtained by training logistic regression on 1.2 million arXiv articles to predict in which category (e.g. cs.Lg, stat.ML) a given article resides. See Appendix A for a detailed explanation of the experimental setup. Titles and abstracts were represented by vectors from a pre-trained instance \(^{12}\) of the Universal Sentence Encoder of Cer et al. (2018). We see that including more aspects of each document (titles, abstracts, fulltext) and exposing their relations via co-citation leads to better predictive power. This is only scratching the surface of possible tasks and models applied to this rich dataset.

3 Conclusion

As research moves increasingly towards structured relational modelling (Hamilton et al. 2017\(^{13}\); Battaglia et al. 2018), there is a growing need for large-scale, relational datasets with rich annotations. With its authorship, categories, abstracts, co-citations, and full text, the arXiv presents an exciting opportunity to promote progress in relational modelling. We have provided an open-source repository of tools that make it easy to download and standardize the data available from the arXiv. Our preliminary classification baselines support the claim that each mode of the arXiv’s feature set

\(^{11}\) As part of one of the tagged releases: https://github.com/mattbierbaum/arxiv-public-datasets/releases

\(^{12}\) From https://tfhub.dev/google/universal-sentence-encoder/2
Table 3: Baseline classification performance on a holdout set of 390k articles. Titles and abstracts were embedded in a 512 dimensional subspace using the Universal Sentence Encoder, and trained on 1.2 million articles with logistic regression. ‘All’ refers to the concatenation of titles, abstract, fulltext, and co-citation features. ‘All - X’ refers to the ablation of feature X from ‘All.’ Top n is the classification accuracy testing when the correct class is in the top n most confident predictions. Detailed explanation of the features and methods can be found in Appendix A.

| Features       | Top 1  | Top 3 | Top 5 | Perplexity |
|----------------|-------|-------|-------|------------|
| Titles (T)     | 36.6% | 59.3% | 68.8% | 12.7       |
| Abstracts (A)  | 46.0% | 70.7% | 79.5% | 7.5        |
| Fulltext (F)   | 64.2% | 79.4% | 85.9% | 4.6        |
| Co-citation (C)| 37.8% | 49.4% | 53.8% | 18.5       |
| All = T + A + F + C | 78.4% | 91.4% | 94.5% | 2.3        |
| All - T        | 77.0% | 90.7% | 94.0% | 2.5        |
| All - A        | 74.7% | 88.3% | 91.9% | 2.8        |
| All - F        | 59.0% | 79.8% | 86.2% | 4.6        |
| All - C        | 75.5% | 89.9% | 93.6% | 2.6        |

allows for greatly improved category inference. More sophisticated models that include relational inductive biases—encoding the graph structures of the arXiv—will improve these results. Further, this new benchmark dataset will allow more rapid progress in tasks such as link prediction, automatic summary generation, text segmentation, and time-varying topic modeling of scientific disciplines.

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Lovro Šubelj, Dalibor Fiala, and Marko Bajec. Network-based statistical comparison of citation topology of bibliographic databases. Scientific reports, 4:6496, 2014.
A Logistic Regression Article Classification Baseline

ArXiv articles are assigned primary categories (e.g. cs.AI is Artificial Intelligence and cs.CC is computational complexity) by the article submitter, which is then confirmed by the ArXiv moderation system. This label can be obtained for each article from the OAI metadata described in the main article, and is the first element of a space-delimited string in the categories attribute. There are, at the time of writing, $L = 175$ possible categories. Since more categories can be added in the future and the metadata can be modified, please consult the frozen metadata file in the github repository releases for these 175 categories. This appendix explains how we developed the article classification baselines using features from the titles, abstracts, full-text, and co-citation network. The code for performing this task can be found in the git repository.

A.1 Building Features

The title, abstract, and full-text of each article is a variable-length string, and each article has both a title and abstract from the OAI metadata, but not all articles have a full-text PDF. In our frozen dataset there are $N = 1,506,500$ articles with metadata, but only 1,357,536 have full-text in the ArXiv. We vectorized each string into 512 dimensions using the pretrained Universal Sentence Encoder substituting zeros for missing full-text.

The intra-ArXiv citation graph can be used via the $N \times N$ co-citation matrix, which is defined as

$$M_{ij} = \begin{cases} 
1 & \text{if article } i \text{ cites article } j \text{ or vice-versa} \\
0 & \text{else}
\end{cases} \quad (1)$$

In order to prevent a leaking of the test set into the training set, using the train/test partition defined below, we omitted citations in $M$ from articles in the training set which connect to the test set, but retained citations in the test set which connect to the training set.

We can also define the $N \times L$ category matrix in the standard one-hot fashion

$$C_{jl} = \begin{cases} 
1 & \text{if article } j \text{ is in category } l \\
0 & \text{else}
\end{cases} \quad (2)$$

Then the co-citation feature matrix is the $N \times L$ matrix product $MC$. Note that this feature uses only nearest-neighbor citation graph relationships. We could include next-nearest neighbor relationships and so on by calculating $MC + aM^2C + bM^3C + \ldots$ for some constants $a$ and $b$. In this paper we only used first order connections via $MC$ as the co-citation feature vectors.

A.2 Training

Using vector embeddings from titles, abstracts, and full-text, and co-citation features as described above, we fed several combinations of these vectors concatenated in the obvious way into the scikit-learn SGD classifier sklearn.linear_model.SGDClassifier. We used the keyword arguments loss='log', tol=1e-6, max_iter=50, and alpha=1e-7 to define the model, which uses 50 epochs, and very small quadratic regularization alpha on the weights and biases.

With the features and model defined, we performed a train/test split by shuffling the data in place randomly, and selecting the first $N_{\text{train}} = 1,200,000$ for training. The remaining $N_{\text{test}} = 306,500$ articles were used to evaluate the accuracy of the trained classification, and the model perplexity as reported in table in the main text.

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2. [https://github.com/mattbierbaum/arxiv-public-datasets/blob/v0.2.0/analysis/classification.py](https://github.com/mattbierbaum/arxiv-public-datasets/blob/v0.2.0/analysis/classification.py)
3. [https://tfhub.dev/google/universal-sentence-encoder/2](https://tfhub.dev/google/universal-sentence-encoder/2)