ArXiv Text Classification in PySpark

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***Abstract*—This final project will be an exploration of the arXiv open dataset metadata. ArXiv is an organization that seeks to increase access to scholarly papers across a range of academic disciplines. According to their website they host and make available over 1.9 million academic papers on Physics, Mathematics, Computer Science, Quantitative Biology, Quantitative Finance, Statistics, Electrical Engineering, and Economics. This paper will demonstrate text classification of academic paper's using the metadata from the arXiv open dataset and PySpark.**

Keywords—Big Data, NLP, PySpark, Machine Learning, UMD.

I. Introduction

ArXiv is a frequent access point for Machine Learning literature, as can be attested to by the author of this work, who has utilized this resource frequently for reference to pivotal machine learning papers as well as the latest in state-of-the-art ML research. In keeping with the culture of open access in machine learning, arXiv has made available a dataset including 1.9 million academic papers hosted through their service. The author will utilize the arXiv dataset to explore natural language processing at scale through the classification of academic papers into their academic disciplines [1].

II. Motivation

This problem and dataset were selected because they offer the opportunity to explore how a common machine learning task scales to Big Data and challenging subject matter. The language used in academic research papers is appreciably different from that of Yelp reviews, IMDB movie ratings, and tweets. Researchers writing about niche subjects often use words or phrases that are uncommon, which presents a challenge to shallow statistical language models. In addition, the size of the dataset offers an opportunity to explore how text preprocessing steps like tokenization and word or phrase counting can be sped up by distributed computing systems. Finally, while the present classification task is somewhat trivial, the insights learned from these algorithms, the representations that they can learn, and how to apply them to massive datasets is not. It is undeniable that NLP is a difficult domain, requiring huge datasets and colossal models, and the necessity for distributed computing in NLP will only continue to increase.

III. Dataset

While arXiv makes available full academic papers as full-text or PDF's, this data includes images, mathematical formulas, and other features which would require special attention, considerable time investment to perform feature selection, and compute resources which are all outside of the scope of this project. Instead, the author chose to implement the project using features found in the open arXiv dataset's metadata, the details of which can be found below.

A. Metadata

The ArXiv open dataset metadata is offered as a JSON file which includes a number of useful features for machine learning tasks including dates, authors, title, category id, abstract, and the publishing journal of the academic paper [2]. The problem that this work is exploring is a supervised text classification, so the title, abstract, and category id are the features of interest. The 'categories' feature is presented as a list of codes representing a number of academic sub-disciplines. The 'title' and 'abstract' features are unstructured text.

B. Pre-processing

In the interest of producing a feasible demonstration, the author elected to collapse the subcategory codes into one category feature representing the academic discipline. This was accomplished by generating regular expressions that matched all subcategory codes to a broader parent category and then using PySpark to find and replace the subcategories with their parent category. The result being that each paper is assigned one of nine labels:

- Physics
- Astronomy
- Mathematics
- Statistics
- Economics
- Computer Science
- Electrical Engineering
- Biology
- Finance

Finally, these labels are provided a numeric index value using PySpark's StringIndexer.

The unstructured text in the 'title' and 'abstract' features were combined to create one text feature which was treated with some sanitization. All text was lowercased, punctuation

category	count
PHYS	863455
MATH	436451
CS	320574
ASTRO	261725
STAT	35601
EESS	24893
BIO	23087
FIN	8838
ECON	3485

Figure 1 Dataset class distribution

removed, and the most common English stop words like ‘and’, ‘but’, and ‘the’ were striped from the text. The hypothesis being that these features are so common in the English language that rather than helping to disentangle the representation of each of our classes in high dimensional space they would instead just add noise [5]. Finally, these features were converted into a vector representation of either term frequency or term frequency inverse document frequency.

C. *Data Exploration*

An initial analysis of the dataset revealed that most of the papers fall under the Physics, Astronomy, Computer Science, and Mathematics disciplines, and there were many fewer papers from disciplines like Economics and Finance. This is somewhat to be expected given that arXiv began as an archive of Physics research [1].

Another interesting find was that after removing common English stop words, there were still a considerable number of words that were common across all the papers. These words are essentially filler and aren’t likely to be useful in learning a

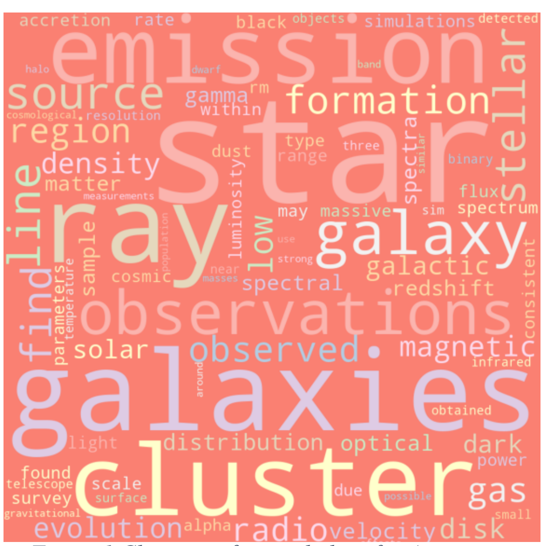

Figure 1 Class specific vocabulary for Astronomy

relationships between the language and vocabulary used in the different disciplines. An exploration of performance changes with and without these common words can be found in *Methods* and *Results*.

Finally, it was reassuring from a classification perspective, to see that the most common words from each of the classes all had what appears to be a unique vocabulary. As you can see in the figure below, the most common vocabulary in the Computer Science discipline does not share much in common with the most common vocabulary in the Astronomy discipline.

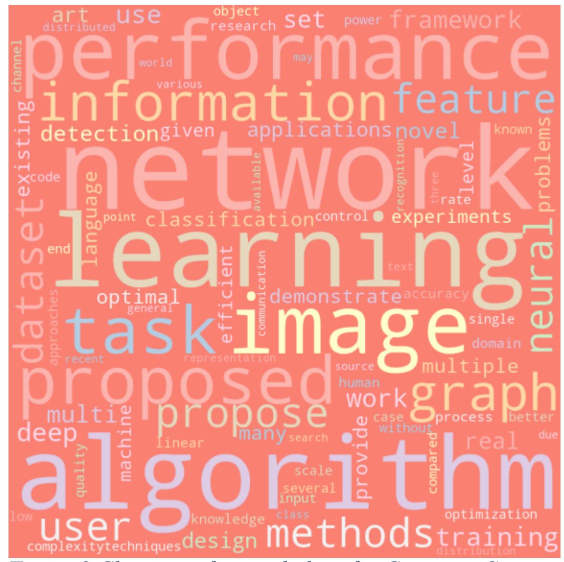

Figure 2 Class specific vocabulary for Computer Science

IV. PySpark

While there are a range of approaches that could be taken in a text classification task, the size of the training dataset presents a challenge to common machine learning libraries for local experimentation. Unstructured text will need to undergo preprocessing and transformation before it can be used for training and on local commodity equipment the strain will be significant. This presents an opportunity to instead take advantage of the speed ups that can be achieved through a distributed computing approach. In this work the author will use PySpark, a Python wrapper of the Spark framework and MLLib, a machine learning framework for Spark systems. PySpark is built around Resilient Distributed Datasets which, amongst other benefits, allow for distribution of memory intensive applications and lazy evaluation which delays execution of intermediate steps until it is necessary [3].

V. Methods

The initial dataset of 1,978,109 samples was split into a training dataset of 1,384,667 samples and a test dataset of 593, 442 samples. 124,484 sample were taken from the training dataset for a validation set and various quantities of the remaining training samples were experimented with for training models.

To arrive at the most performant model possible, a baseline model was created followed by a number of experiments involving the model type, data preprocessing, and the size of the training data.

A. Baseline Model

The baseline model is an implementation of Logistic Regression provided by PySpark's MLLib library. This model is essentially training a separate Logistic Regression classifier for each class in the dataset [4]. This model was chosen for its simplicity and to serve as a benchmark to compare other models to. The model was fitted with a small subset of the data and uses term frequency vectors as features. This experiment was run with common academic stop words included and excluded.

B. TFIDF

A similar model to the baseline; an implementation of multinomial Logistic Regression using term frequency inverse document frequency matrices as features instead of term frequency alone. TFIDF considers how often a word occurs in all the documents, reducing the effect of very common words that are not unique to any particular class [5]. This is an alternative approach to removing these common words entirely.

C. Random Forest

A tree-based model that uses an ensemble of models, each built with a subset of the total features. This was selected for contrast against linear models and fitted using term frequency vectors.

D. Naïve Bayes

An alternative probabilistic approach that calculates the posterior probability of a sample belonging to a particular class given the features that it has. This model was fitted using term frequency vectors.

E. Training Size

Finally, the baseline Logistic Regression model was fit with progressively larger training sizes to experiment with the effect on performance that training size would have.

VI. Results

Due to the heavily imbalanced nature of the dataset, it was necessary to select a metric that could accurately reflect the performance of the model on the validation and testing data. F1 score was selected as a metric because it provides a balance between specificity and sensitivity.

The baseline model using simple term frequency vectors was found to be the most performant of the models in the experiments conducted. It was found that removing the most common academic words in the dataset did not have a positive effect on metrics although increasing the size of the training data did increase the F1 score by a small amount. A hyperparameter search was conducted for using cross validation, resulting in a best max_iter at 50, regularization parameter at 0.1, and an elastic net parameter of 0.

Experiment	F1 Score
Baseline LR	0.867
LR w/o common vocab	0.864
LR – Class Balanced Dataset	0.828
TFIDF	0.855
Naïve Bayes	0.846
Random Forest	0.301

Figure 3 Experiment Results

	precision	recall	f1-score	support
PHYS	0.91	0.95	0.93	181614
MATH	0.88	0.91	0.89	91576
CS	0.83	0.88	0.85	67249
ASTRO	0.96	0.89	0.93	54919
STAT	0.69	0.39	0.49	7479
EESS	0.52	0.11	0.18	5340
BIO	0.72	0.38	0.50	4748
FIN	0.72	0.40	0.51	1833
ECON	0.55	0.03	0.06	713
accuracy			0.89	415471
macro avg	0.75	0.55	0.59	415471
weighted avg	0.89	0.89	0.88	415471

Figure 5 Best LR: validation results

	precision	recall	f1-score	support
PHYS	0.91	0.95	0.93	258901
MATH	0.88	0.91	0.89	131055
CS	0.83	0.88	0.85	96214
ASTRO	0.96	0.89	0.93	78245
STAT	0.69	0.39	0.50	10877
EESS	0.55	0.12	0.20	7521
BIO	0.71	0.37	0.48	6934
FIN	0.72	0.39	0.50	2647
ECON	0.45	0.02	0.05	1048
accuracy			0.89	593442
macro avg	0.75	0.55	0.59	593442
weighted avg	0.89	0.89	0.88	593442

Figure 4 Best LR: test results

VII. Conclusion

While these results are not even in the ballpark of state of the art, it is clear that modest performance in text classification can be achieved using simple and explainable models and methods. However, even these simple models would be unfeasible on large text datasets without the help of Big Data frameworks like Spark and Hadoop. The arXiv dataset, at nearly 2 million rows, is a struggle for some commodity hardware. The lazy evaluation offered by Spark prevented the inevitable out of memory errors that would have occurred otherwise and made it possible to train a simple but effective model [3].

References

[1] "About arxiv," *arXiv*. [Online]. Available: https://arxiv.org/about/. [Accessed: 13-Dec-2021].

[2] "ArXiv Bulk Data Access," *arXiv*. [Online]. Available: https://arxiv.org/help/bulk_data. [Accessed: 13-Dec-2021].

[3] "RDD Programming Guide," *RDD Programming Guide - Spark 3.2.0 Documentation*. [Online]. Available: https://spark.apache.org/docs/latest/rdd-programming-guide.html. [Accessed: 13-Dec-2021].

[4] "Logistic regression," *Wikipedia*, 03-Dec-2021. [Online]. Available: https://en.wikipedia.org/wiki/Logistic_regression. [Accessed: 13-Dec-2021].

[5] "TF–IDF," *Wikipedia*, 18-Sep-2021. [Online]. Available: https://en.wikipedia.org/wiki/Tf%E2%80%93idf. [Accessed: 13-Dec-2021].