Knowledge discovery through text-based similarity searches for astronomy literature

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Abstract

The increase in the number of researchers coupled with the ease of publishing and distribution of scientific papers (due to technological advancements) has resulted in a dramatic increase in astronomy literature. This has likely led to the predicament that the body of the literature is too large for traditional human consumption and that related and crucial knowledge is not discovered by researchers. In addition to the increased production of astronomical literature, recent decades have also brought several advancements in computer linguistics. Especially, the machine aided processing of literature dissemination might make it possible to convert this stream of papers into a coherent knowledge set. In this paper, we present the application of computer linguistics techniques on astronomy literature. In particular, we developed a tool that will find similar articles purely based on text content from an input paper. We find that our technique performs robustly in comparison with other tools recommending articles given a reference paper (known as recommender system). Our novel tool shows the great power in combining computer linguistics with astronomy literature and suggests that additional research in this endeavor will likely produce even better tools that will help researchers cope with the vast amounts of knowledge being produced.

1. Introduction

Since the inception of writing, human knowledge has steadily increased as has the number, and size, of published works. The output of the scientific community has doubled every nine years over the past decades [Bornmann and Mutz, 2015].

The computing and internet revolution has made the publication and dissemination of these works easy and with the advent of open access channels pluralistic. In the physical sciences the public repository arXiv has provided open access to almost the entire corpus of publications since 1992.

Given the rise of publications each year and the fixed capacity of a human to process information either we shall narrow the specialization range in each field to limit the breadth of the necessary knowledge base or have new tools that filter the available publications.

In astronomy, the NASA Astrophysics Data System (ADS) [Kurtz et al., 2000] has provided access (in addition to many other accomplishments such as digitizing old articles) to this large amount of literature with a search interface that captures the traditional way of accessing information (name of first author and year) extremely well. Newer iterations of this system (Chyla et al., 2015) have started to branch out and allow not only search algorithms but provide certain bibliometric statistics as well as a recommender system (named “Suggested Articles”). This recommender system is based on citations, text similarity and co-reading (as described on the ADS 2.0 website and suggested in Henneken and Kurtz, 2010; Kurtz, 2011). Such recommender systems will be a first step to tackle a world in which the scientific literature has massively outgrown the memory capacity of human brains.

In this paper, we present a new method for article recommendations starting from a reference article or text. We employ the techniques of text similarity and specifically avoid citations. This strict abstention from citation was chosen due to the fact that citations are influenced by many factors and may not provide an unbiased link between publications (several examples in van Welzel et al., 2014).

In Section 2 we describe the data acquisition, initial vetting and processing. Section 3, describes the method used and some statistics arising. An overview of the framework used in this work and its application to several example papers in in Section 4. Caveats and possible improvements are discussed in Section 5 and we
conclude with an outlook to the future in Section 6.

2. Data Processing

For our initial raw corpus, we considered all papers submitted to *arXiv*. Using the bulk data access\(^1\) we downloaded the entire corpus. After a series of operations (discarding any non-latex submissions), we arrived at individual source directories (a total of 1 145 992). This work focuses currently on the field of astronomy. For *arXiv* entries until 2007-01-01 this can be filtered on the id itself (the id starts with ‘astro-ph’). For later entries we harvested the meta data through the OAI protocol for metadata harvesting (OAI-PMH) and then selected all *arXiv* entries that had astro in the subject node of the metadata. This as well as the ‘astro-ph’ selected papers amount to a total corpus of 187 531 papers.

In each source compilations, we tried to identify the main tex file by requiring a single valid \texttt{\begin{document}} clause and processed this further with \texttt{latexparse} to a single document that would contain all relevant text content. Not all entries had a uniquely identifiable main tex-file resulting in a total of 178 756 papers.

The resulting tex-files were further processed removing the most common environments:

- figure
- table
- align
- equation
- thebibliography
- deluxetable
- picture
- subequations

Then we removed any text before the first section command or if this was not present any text before end abstract. If neither of these criteria were met, we discarded the file, resulting in 176 979 articles.

The final step of the raw reduction process was the removal of latex commands using the opendetex software\(^2\).

These unprocessed data and metadata already allow for some interesting statistics to study publication behaviour. As *arXiv* has already shown\(^4\) there is a roughly linear increase in astronomy papers. The number of authors also is an important metric to understand the culture of a field. Here often people turn to the average number of authors as a measure (e.g. Aboukhalil, 2014). While this is a useful statistics, it is heavily biased towards the few papers with extreme number of authors. Figure\(^3\) shows that the general number of authors remains relatively low but there is a very small number of papers with increasingly extreme number of authors (only 0.5% of papers have more than one hundred authors).

2.1. Natural Language Processing

These raw texts are ready for natural language processing and the following steps use the Natural Language ToolKit (NLTK; Bird et al., 2009) tools extensively.

The first step in this process is to break the text into individual words using \texttt{NLTK.tokenize(words)}, which splits into individual words and removes all punctuation - except the period (which is treated as a single word at this step).

The next process is to remove stop words such as *these, those, am, is, are* (using the english stop words defined in \texttt{NLTK.corpus.stopwords}).
The final step of processing is to lemmatize the words, which is the process of grouping together the different inflected forms of a word so it can be analyzed as a single item. For this process we use the tool `nltk.wordnet.morphy` to bring the words back to their original forms (galaxies maps to galaxy, expanding maps to expand, etc.). We discard words that do not have a corresponding entry in the dictionary provided (WordNet; Fellbaum, 1998).

After this final step we are left with a corpus consisting of 176,881 documents.

3. Method

In this work, we will entirely rely on the bag-of-words technique (Harris, 1954), that disregards grammar and word order, treating the document just as a collection of words. The features that we use for our analysis are several statistics based on word frequency. For all feature extraction tasks, we relied on `scikit-learn` (Pedregosa et al., 2011).

The first step for any of these methods is building a vocabulary of unique words. This is helped by the fact that we transformed our document removing any stop words and transforming the words to their simplest form.

This vocabulary consists of \( \approx 32,000 \) words. This is only slightly larger than the \( \approx 20,000 \) (Goulden et al., 1990) words a well educated native speaker knows and much lower than the \( \approx 170,000 \) words in the Oxford English dictionary (Simpson and Weiner, 1989). Our vocabulary can then be used to vectorize (feature extract) the documents to vectors the size of the dictionary (in our case \( \approx 32,000 \)).

The simplest case is the use of a binary statistics for feature extraction which will only encode if a word is present or not present. This statistics can give a rough overview of the content but will de-weight more frequently used words and thus possible shift the inferred topic of the document in statistical analysis.

The first statistics we have performed on the corpus of documents is a simple count vectorization (using `scikit-learn.feature_extraction.CountVectorizer`). This count measures allows us to quantify the growth of literature since the conception of arXiv. Figure 2 shows, that while the growth in document size (using the processed document word counts as a proxy) has been maybe a factor of 1.5 over the last decade, astronomical literature in total has grown exponentially (see Figure 3) over the same period. This given measure of “word count”, however, has several drawbacks, the most important one being that it increases with document length and thus does not give a useful measure for word importance.

The last vectorization technique is a natural extension of the word counts that aims at emphasizing a word’s importance in text - thus ideal for assessing content of a paper. In the following, we will use the moniker “term” and “word” interchangeably as our analysis uses only one-word terms (unigrams). The term frequency \( tf(t, d) \) method normalizes the simple word count by the number of words in the document. This relies on the assumption that the importance (or weight) of a term in documents is proportional to this term frequency (Luhn, 1957). In addition to term frequency, we want to quantify the information content a specific term carries. Sparck Jones (1972) have introduced the concept of inverse document frequency \( idf(t, d) \). We use
the inverse document frequency given in scikit-learn is log \( \frac{n_d}{df(d,t)} \), where \( n_d \) is the total number of documents and \( df(d,t) \) is the number of documents containing the given term. The combination of both measures gives the well established \( t f(t,d) \times id f(t,d) \) (henceforth TFiDF) measure which weights terms highly that have a high information content due to their rarity. This measure is used in several machine learning tasks including finding similar texts.

4. Similarity in papers

We explore how the TFiDF statistics can lead to knowledge discovery.

For this purpose, we first normalize our document vectors using the euclidean norm \( d_{norm} = \frac{d}{||d||} \) before proceeding further. Leaving us with the entire sparse matrix (which is available upon request). Here, we present an example of such a matrix (with the different document vectors as rows and the columns representing different words/terms):

\[
A_{TFiDF} = \begin{pmatrix}
    \text{star} & \text{model} & \ldots & \text{galaxy} \\
    \text{arXiv} - 1 & 0.021 & \cdots & 0 \\
    \text{arXiv} - 2 & 0 & 0.03 & \cdots & 0 \\
    \vdots & 0.019 & 0.016 & \cdots & 0 \\
    \text{arXiv} - n & 0 & 0 & \cdots & 0.023
\end{pmatrix}
\]

\[\text{TFiDF Similarity} = \frac{\text{cosine distance}}{||d_{norm}||} \]

We simply use the cosine distance by choosing a document that we want to compare and multiplying this with the TFiDF matrix \( v_{\text{similarity}} = A_{TFiDF} \times d_{norm} \) to measure text similarity. An example service that showcases this technique is available at http://opensupernova.org:7071

4.1. Example: SN 1006 companion search

In the following, we will use this approach on a paper that is well known to the author: "Hunting for the Progenitor of SN 1006: High-resolution Spectroscopic Search with the FLAMES Instrument" (Kerzen-dorf et al. 2012). This paper describes the failed attempt to find a surviving companion star (often called donor star) to a supernova (likely caused by a white dwarf) searching in one of the supernova remnants in our Galaxy.

We first measure the most important words to the presented algorithm. For this purpose, we inverse sort our \( v_{\text{similarity}} \) and use the first best 100 matches. We multiply the \( d_{norm} \) and look for the highest entries in the resulting vector which should give us the most important words that the algorithm matches. Figure 5 clearly shows that very relevant words that one would expect when writing a paper about searching for a donor star in a supernova remnant likely caused by a white dwarf.

This might also be obtained by doing the typical manual search technique using the citations to the current paper as well as the references of the current paper. However, we aim to find papers that would not be found using this common technique.

All references of our test paper (12 in total found in our arXiv corpus) have a median similarity of 0.38. Only 3% of papers (see Figure 4) in the astronomy corpus are more similar than this median which suggests that as expected the citations are highly relevant.

All citations to our test paper (30 in total where found in our arXiv corpus) have a median similarity of 0.26 and 5% of papers are more similar than this suggesting that the citations to this article come from a more varied field than the original references (or that references had been forgotten).

Next we test if the algorithm’s top 30 papers (similar to the citations) are in neither citations nor references and compare this to the relevance of the other papers. Figure 5 shows the comparison between the median cosine distance of the cited papers, the median cosine distance of the references and the median top 30 results excluding papers from both of these groups. This demonstrates that such a system can find relevant papers that could easily be missed otherwise.

ADS has recently implemented a similar system (Chyla et al. 2015), however we find that it does not give as relevant matches as the presented algorithm. There are 30% of papers that are more similar to the
document in question compared to the median similarity of the suggested papers. Manual inspection also shows that some of the suggested papers (e.g. “Maps of Dust Infrared Emission for Use in Estimation of Reddening and Cosmic Microwave Background Radiation Foregrounds” by Schlegel et al. [1998]) might be very broadly related but not very relevant. The precise algorithm to determine the suggested papers for ADS is not accessible thus prohibiting a quantitative comparison.

4.2. Example: Globular cluster

The second test paper we use is “A general abundance problem for all self-enrichment scenarios for the origin of multiple populations in globular clusters” by Bastian et al. [2015]. This paper points out a possible flawed explanation for abundance anomalies in globular clusters. The top matching words (see Figure 5) are highly relevant to a topic that discusses anomalous abundances that might be caused by different pollution system to varying degrees due to their yields. The references are more similar compared to the first paper suggesting that this paper is more focused. The same is true for the citations that also come from more similar papers when compared to the citations in the first paper. The comparison of all median similarity numbers, however, shows a similar pattern when compared to the first paper including the dissimilarity of the ADS suggestion algorithm (see Figure 5).

4.3. Example: ALMA observations of a disk

The last test paper is titled “Unveiling the gas-and-dust disk structure in HD 163296 using ALMA observations” by de Gregorio-Monsalvo et al. [2013]. This paper describes observations of structure around young massive stars. The important words (see Figure 5) again seem highly relevant. Similar to the second paper the citations and references have high similarity numbers that might suggest a narrower focus of this paper. In contrast to the other two example papers in this case the ADS suggestion algorithm also produced a high similarity index. Only three of the papers from the suggestion algorithm could be found the arXiv corpus (compared to the usual six) which might explain this anomaly.

5. Discussion

This test of the use of natural language processing and machine learning tools NLTK, scikit-learn has already shown that even simple techniques result in knowledge discovery. However, there are a number of improvements that can aid in the knowledge discovery part.

Specifically, in the language processing step there are several steps that might be improved in future versions. We remove all words that are not in the English dictionary during our initial run. This already poses some problems in the lemmatization process as the name “Roche” (as in Roche Lobe) is not recognized and is thus removed. This suggests that there is a need to build a domain specific lemmatizer (such as the BioLemmatizer for biology Liu et al. [2012]). In our current approach, we also only consider single words (so called unigrams) but terms like “white dwarf” (bigram) suggest that future iterations of this algorithm might find more relevant results if we treat such bigrams separately. Abbreviations are also commonly used in papers and are most often defined at the beginning of most papers. Thus the expanded word enters the word count only once. However, this leads to a misinterpretation the true importance of the word as all other mentions are discarded.

The next information carrier that is removed are object names which might link papers that are of the same object. However, using this technique, already values a certain type of knowledge above another (any study on the object is valued higher than similar studies on other objects for a given paper). This is especially true in our metric as object names will have a very low document frequency (being only mentioned in few papers) and thus will attain very high values in a TFiDF comparison which might not lead to the desired result.

6. Conclusion

We present a new technique for knowledge discovery by using a text similarity approach to find similar papers to a given reference paper. This technique performs robustly and finds relevant papers that are not discovered via either citations, references or suggestions from ADS. This metric also seems to be a useful tool when studying if a paper is relevant to broader field or addresses some detail in a narrower focus. Similar attempts in other fields (e.g. neuroscience; Achakulvisut et al. [2016]) also suggest that this can be used to provide a powerful method to disseminate papers.

Currently, this allows an additional method to discover knowledge especially when entering a field that one is unfamiliar with (e.g. using this technique for reviews). Our recommendation method might be further improved by linking our algorithm with citation information and using an algorithm like PageRank (popularized by Google; Page et al. [1999]). This will value
highly cited papers more than lower cited ones. While this technique will help in knowledge discovery by finding relevant papers, our future goal is to identify key measurements and statements in each paper. This will allow a scientist to quickly sift through the vast amount of knowledge and identify the relevant paper by the searched quantities (e.g. the most current mass of the proton) before reading the entire paper and critically evaluating the methodology and statistics used.

Such a machinery would be the first instance help scientists to discover sought after knowledge (regardless of bias towards certain authors, etc.) but might also allow for additional services. One of these might be very simple “fact checking” mechanisms that will aid researchers when compiling a paper by providing the most up-to-date quantities and flagging mistakes (similar to a grammar/spelling checker).

Such a machinery has uses far beyond astronomy and astrophysics. However, among the many academic fields, astronomy exposes the vast majority of papers and data in machine readable formats (priv. comm. Christine L. Borgman). This suggests that this field is a good start for the development of such a machinery.

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Figure 5: The TFiDF method applied to three distinct papers (top) “Hunting for the Progenitor of SN 1006: High-resolution Spectroscopic Search with the FLAMES Instrument” (Kerzendorf et al. 2012) (middle) “A general abundance problem for all self-enrichment scenarios for the origin of multiple populations in globular clusters” (Bastian et al. 2015) (bottom) “Unveiling the gas-and-dust disk structure in HD 163296 using ALMA observations” (de Gregorio-Monsalvo et al. 2013). The left plot shows the most important words for matching the first 100 papers while the right plot in each shows the similarity metric applied to several collections associated with these papers.