DAF: Data Acquisition Framework to Support Information Extraction from Scientific Publications

Muhammad Asif Suryani[1,2][a], Steffen Hahne[1][b], Christian Beth[1][c], Klaus Wallmann[2][d]
and Matthias Renz[1][e]

[1] *Institute of Informatik, Christian-Albrechts-Universität zu Kiel, Kiel, Germany*

[2] *GEOMAR Helmholtz Centre for Ocean Research Kiel, Kiel, Germany*

Keywords: Information Extraction, Data Acquisition, Research Data Management, Scientific Publication, Marine Science.

Abstract: Researchers encapsulate their findings in publications, generally available in PDFs, which are designed primarily for platform-independent viewing and printing and do not support editing or automatic data extraction. These documents are a rich source of information in any domain, but the information in these publications is presented in text, tables and figures. However, manual extraction of information from these components would be beyond tedious and necessitates an automatic approach. Therefore, an automatic extraction approach could provide valuable data to the research community while also helping to manage the increasing number of publications. Previously, many approaches focused on extracting individual components from scientific publications, i.e. metadata, text or tables, but failed to target these data components collectively. This paper proposes a Data Acquisition Framework (DAF), the most comprehensive framework to our knowledge. The DAF extracts enhanced metadata, segmented text, captions and content of tables and figures respectively. Through rigorous evaluation on two distinct datasets from the Marine Science and Chemical Domain we showcase the superior performance compared of the DAF to the baseline PDFDataExtractor. We also provide an illustrative example to underscore DAF's adaptability in the realm of research data management.

1 INTRODUCTION

Researchers disseminate their findings through scientific publications, most notably in the form of PDF documents. These PDFs are primarily created for platform-independent viewing and printing and serve as repositories of valuable knowledge across diverse domains (Inc., 2006). However, their primary design for human readability poses a significant challenge when it comes to automatically extracting structured information for further analysis or data management tasks. These publications contain valuable insights generally presented in various components, i.e., text, tables, and figures. The presented information in these components is generally densely linked among the structural components and exhibits diverse characteristics. Generally, context elaboration is given through plain text, while numerical and graphical results are expressed in tables and figures respectively. Open access to scientific publications and extracting the relevant data component is a core interest of research communities in order to learn from previous findings and acquire new insights from the data to instigate data-driven research activities (Martinez-Rodriguez et al., 2020), (Swain and Cole, 2016).

There has been a substantial increase in publications over the last decades. With the widespread use of computational methods and the volume and reliability of scientific publications, they can be viewed as a manifestation of Big Data (Jinha, 2010), (Taylor-Sakyi, 2016). Hence, the surge in scientific publications in every domain makes it difficult for researchers to seek valuable information from these documents (Zhu and Cole, 2022). Facing the massive volume of publications, manually extracting information from them is not a favourable solution, as it is only feasible for small document corpora. In order to support research activities in every domain, automatic infor-

[a] https://orcid.org/0000-0003-1669-5524
[b] https://orcid.org/0009-0008-6434-4001
[c] https://orcid.org/0000-0003-3313-0752
[d] https://orcid.org/0000-0002-1795-376X
[e] https://orcid.org/0000-0002-2024-7700

Suryani, M., Hahne, S., Beth, C., Wallmann, K. and Renz, M.
DAF: Data Acquisition Framework to Support Information Extraction from Scientific Publications.
DOI: 10.5220/0012260300003598
In *Proceedings of the 15th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2023) - Volume 1: KDIR*, pages 468-476
ISBN: 978-989-758-671-2; ISSN: 2184-3228

mation extraction approaches are getting increasingly involved in knowledge discovery and support research data management activities (Swain and Cole, 2016).

Scientific publications are generally well-written for human readers but do not support automatic extraction. Besides, an important aspect is that publications are highly dependent on the templates of their respective publishers, which is an essential factor to be considered in the automatic information extraction process. Hence, to automatically identify and extract relevant textual, quantitative information, many factors have to be taken into account, such as layout analysis, writing styles, variations of expressions or units, numerical features, and graphical information (Foppiano et al., 2019), (Zhu and Cole, 2022).

Therefore, the automatic extraction of targeted information from scientific publications is a worthy idea, which is suitable for researchers to strive for their desired information by minimizing manual interventions. The automatic extraction will help in making relevant information available digitally. Initially, numerous studies targeted the extraction of metadata and bibliographic information from publications, i.e. DOI, title, authors, journal, abstract, keywords and references, respectively (Martinez-Rodriguez et al., 2020). Recently, applications have been introduced, which focused on the full plain-text from research publications (Suryani et al., 2022).

Subsequently, in addition to focusing on metadata and plain-text, it is necessary to incorporate tables and figures into information extraction spectrum. This inclusion will provide access to a wider range of data, facilitating data-driven research activities.

This paper introduces the Data Acquisition Framework (DAF), an extensive and comprehensive solution, which offers a potential solution to manage the growing volume of scholarly work. DAF focuses on extracting enriched metadata, segmenting textual content, and extracting the tables and figures including their respective captions. The outcome of DAF's rigorous evaluation on two distinct datasets, drawn from the fields of Marine Geology and Chemistry, highlights its superiority over the baseline method. Our contributions can be summarized as follows:

1. We propose a comprehensive Data Acquisition Framework (DAF) capable of extracting the structural components, i.e., text, tables and figures, without template dependency.
2. We propose Document OPTICS, which provides the document's structural topology and instigates an enhancement in traditional metadata.
3. DAF also presents captions for tables and figures.
4. DAF is evaluated on two diverse dataset and achieve better results than comparable approach.
5. We also showcase a potential information modelling use-case to highlight the efficacy of DAF.

2 RELATED WORK

From scientific publications, extracting structured information is pivotal for data-driven applications and knowledge discovery. This section offers a comprehensive overview of both individual extraction modules and entire frameworks, where the focus is on various facets of data extraction, metadata, textual content, images, and tables.

2.1 Data Extraction Packages

Researchers have primarily focused on extracting metadata from scientific publications, e.g. DOIs, authors, titles, and venues. This extracted information is utilized in various potential applications, such as Bibliographic Networks, Recommendation Systems and Heterogeneous Information Networks (HINs) (Kreutz and Schenkel, 2022), (Yadav et al., 2019), (Guerra et al., 2018).

Rcrossref (Chamberlain et al., 2023) and fulltext (Chamberlain, 2019) are modules in R that extract metadata from scientific publications online. Both modules cover numerous publishers and provide, DOI, title, authors, journals, abstracts, etc. as dataframe. PDFminer.six (PDFminer,) is a community-maintained version of PDFminer, that offers a range of extraction capabilities from metadata to structural extraction. Apache Tika (Contributors, b), a Java library, which is also available as a Python package, which extracts metadata and plain-text from publications. The output from Tika covers a relatively high number of structural features besides metadata.

For text extraction from publications, there are numerous libraries in different environments, but for brevity we only cover the most recent ones. PDFminer.six (PDFminer,) is a Python library capable of extracting text from PDFs and it is the most used module for text extraction. Tika (Contributors, b) and PDFBox (Contributors, a) are Java libraries - also available in Python - are suitable for text extraction. Slate (Slate, 2022) is a Python library, that supports text extraction by the use of PDFminer. Textract (Textract, 2023) is also a Python library that extracts text from different file formats.

At the time of writing there exist only few packages suitable for image extraction. In addition to metadata and text extraction, PDFminer.six (PDFminer,) also offers image extraction. PyMuPDF

(PyMuPDF, 2023), a Python library that extracts images from PDFs using coordinates and provides output in PNG format.

There are many approaches available that extract tables from scientific publications. Among them, two stand out. Tabula (Tabula, 2023), a Java library also available in Python that provides an interface for the table extraction by pages and also supports coordinate base access. Camelot (Camelot, 2023) is a Python library capable of extracting tables from scientific publications. It provides two different extraction approaches, i.e. lattice and stream, which is useful for different table layouts. Moreover, it supports extraction by coordinates and provides output in CSV format and have been used in studies recently (Peña et al., 2023). Similarly it is the best performing table extraction among several packages (Mehta, 2019).

2.2 Extraction Frameworks

By focusing on data extraction from scientific publications, numerous frameworks have emerged to tackle the challenge of transforming unstructured content into structured data, facilitating subsequent tasks. These frameworks range from extracting bibliographic details to capturing text, tables, and specialized domain-specific information. Here for simplicity the approaches could be categorized for true digital and scanned documents respectively.

GROBID is an open-source machine learning library in Java for extracting, parsing, and restructuring raw documents into structured XML/TEI encoded documents based on conditional random fields (CRF). The primary functionality of GROBID is to extract bibliographic information from scientific publications and also to be able to extract text as well as tables. It also has various extensions i.e. grobid-quantities and entity fishing, which performs various NLP tasks (Lopez, 2009),(Foppiano et al., 2019), (Entity-Fishing, 2023).

Chemdataextractor (Swain and Cole, 2016) is a framework, that aims for publications from the chemical domain. It captures relevant information from various data components of scientific publications and PDFminer.six was utilised for the text extraction process. Subsequently to enhance the extraction process PDFDataExtractor was proposed (Zhu and Cole, 2022), it targets various aspects of information extraction considering scientific publications. PDFDataExtractor for text extraction also uses PDFminer.six and for metadata extraction they use a rule based approach considering a set of templates from domain-specific journals. The output of the framework is supposed to be passed to Chemdataextractor for relevant NLP tasks. Recently, in Marine Geology domain, a framework was proposed that extracts the plain-text from scientific publications by using PDFminer.six and capable of extracting measurements and relevant oceanographic and spatial information (Suryani et al., 2022).

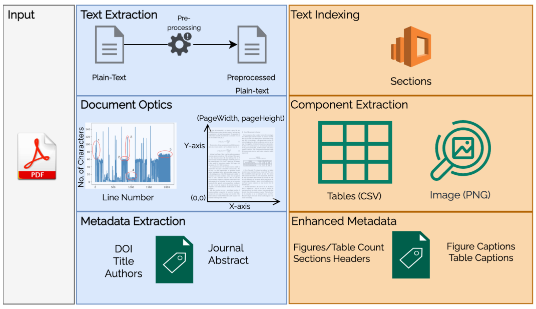


Figure 1: Block Diagram of DAF Framework.

Furthermore, numerous approaches specialize in information extraction from scanned documents i.e. receipts, forms and letters rather than true PDFs. BROS (Hong et al., 2022) is a pre-trained language model that extracts relevant information from images of receipts and forms and DocFormer is a transformer base model which aims to extract various aspects from scanned documents i.e. Dates (Appalaraju et al., 2021).

3 DATA ACQUISITION FRAMEWORK (DAF)

This section presents Data Acquisition Framework (DAF) in Figure 1. In the following, the individual modules will be elaborated thoroughly.

3.1 Document OPTICS Component Segmentation

In order to gain a high extraction accuracy of tables and figures, the framework utilises the “Document OPTICS” layout analysis approach. The document OPTICS layout analysis provides a topological summary of a document before initiating the extraction process. This approach of detecting data components refers to the OPTICS (Ankerst et al., 1999) algorithm. OPTICS (Ordering Points to Identify the Clustering Structure) is a density based algorithm for finding clusters in spatial data. The algorithm dynamically takes into account the average distance of all points distances to each other within a cluster. It can detect clusters with different densities. The densities and distances of the points will then be plotted as a bar chart, which is known as the characteristic OPTICS

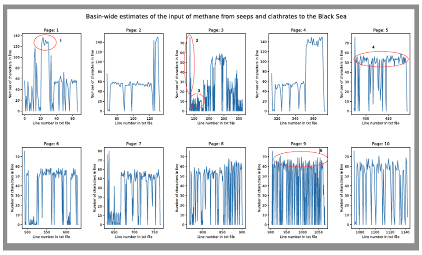


Figure 2: Number of chars per text line for extracted text of (Kessler et al., 2006) per page.

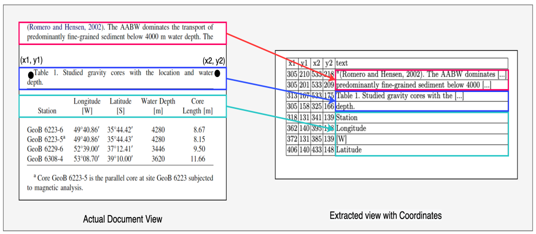
plot. Analyzing the OPTICS plot, one can identify data clusters. Data points, which belong to the same cluster have on average the same height in the plot.

The same accounts for the plot of line lengths of the extracted PDF text on Figure 2. It catches the eye that there are regions on Figure 2 with a low average line length and as well regions with an on average higher line length, which could be a cluster considering OPTICS. These regions, which on average share the same height, belong to the same data component in the publication. For lines with a low height this will most likely be a table, because the table columns text is extracted row by row from the PDF file.

Moreover, Figure 2 showcases the document OPTICS of a publication (Kessler et al., 2006). Several components are marked with red ovals. The first one is the abstract, since it is at the beginning of the document and has an average line length of 100 chars per line and second is a table caption, as it spreads over two columns, like the most captions do and it is followed by several short lines. The short lines marked with a red oval for number three is text belonging to a table, which is extracted column by column, row by row. The fourth one is double column text: it has on average 65 chars per line and final one indicates references, which have on average plus ten higher number of chars per line than the plain-text.

Using this characteristic of the publication text, text lines can be grouped in to component and non-component lines. This text segmentation is later used for component extraction and PDF layout analyzer of PDFminer (Shinyama, 2013) was used to extract the coordinates of the horizontal text lines in the document and horizontal text lines and their corresponding coordinates extraction is called "coordinates file". A snippet of the coordinates file is shown in Figure 3.

As described earlier, the document OPTICS layout analysis is used for text segmentation where text is segmented into different groups/components. The coordinates file is segmented into components by applying the document OPTICS to the coordinates file's "text" column. The result is a list of lists, where every list includes text lines, their corresponding coordinates and indices respectively.


(Romero and Hensen, 2002). The AABW dominates the transport of predominantly fine-grained sediment below 4000 m water depth. The

(x1, y1) (x2, y2)

Table 1. Studied gravity cores with the location and water depth.

Station	Longitude [W]	Latitude [S]	Water Depth [m]	Core Length [m]
GeoB 6223-6	49°40.86′	35°44.42′	4280	8.67
GeoB 6223-5[a]	49°40.86′	35°44.43′	4280	8.15
GeoB 6229-6	52°39.00′	37°12.41′	3446	9.50
GeoB 6308-4	53°08.70′	39°10.00′	3620	11.66

[a] Core GeoB 6223-5 is the parallel core at site GeoB 6223 subjected to magnetic analysis.

Actual Document View

x1	y1	x2	y2	text
305	210	533	218	"(Romero and Hensen, 2002). The AABW dominates [...]
305	201	533	209	predominantly fine-grained sediment below 4000 [...]
313	167	533	175	Table 1. Studied gravity cores with the [...]
305	158	325	166	depth.
318	131	341	139	Station
362	140	395	148	Longitude
372	131	385	139	[W]
406	140	433	148	Latitude

Extracted view with Coordinates

Figure 3: Actual Paper and Coordinate view of Table (Riedinger et al., 2005).

3.2 Caption Extraction

In scientific publications, captions an essential element to support the extraction and indexing of figures, tables and information linking between various data components. The caption extraction flow is illustrated and the detailed routine is presented in Algorithm 1.

As captions are extracted sequentially page by page. First the publication text is split in to pages and each page is divided into paragraphs (text blocks). Depending on the caption layout different extraction approaches may apply. For horizontal captions, if any text block's first line matches a figure/table caption it is afterwards checked if it was matched at the beginning of the line to minimize false positives. False positives occur through inlined figure/table references. Considering vertical captions, all vertically depicted words in the PDF will result in text blocks whose lines are all of length one. Given the former it is first checked whether all lines are of length one. If so, the block is joined, reversed and checked if it is equal to "Table" or "Figure" from line nine to eleven. When this case applies, this match is joined with the before block and checked if it matches the rules for caption layout. Afterwards up to 20 text blocks (caption text) can be appended. The result of the extraction is a JSON file carrying captions for every page.

3.3 Figure and Table Extraction

The overall process of table and figure extraction is showcased in Figure 4. Both modules are based upon Document OPTICS text segmentation prior applied to the coordinates file and the captions extracted from the plain-text. The idea behind the extraction of figures and tables is to extract the top left and bottom right coordinates from the components text lines. The coordinates equal the maximum plane of the component inside the PDF and can afterwards passed to the extraction mechanism.

Algorithm 1: Caption Extraction.

```
Input : Text $t$
ft_captions, pages = $\emptyset$, $t$.splitByPage()
foreach $page \in pages$ do
    $\mathcal{P}$ = page.splitToParagraphs()
    for $i \in \{0 \dots |\mathcal{P}| - 1\}$ do
        cm = lambda x: caption_match(x)
            // lambda x:returns python re match object
        if $cm(\mathcal{P}_i) \wedge cm(\mathcal{P}_i).startPosition() == 0$ then
            ft_captions.add($\mathcal{P}_i$)
        if $all(map(len(line)=1, \mathcal{P}_i))$ then
            cap$_{kw}$ = reverse(join($\mathcal{P}_i$))
            if $cap_{kw} \in \{Table, Figure\}$ then
                cap$_{num}$ = $\mathcal{P}_{i-1}$
                if $cm(cap_{kw} + cap_{num})$ then
                    caption = Caption($\mathcal{P}_i$)
                    ft_captions.add(caption)
```

3.3.1 Tables

For the extraction, the coordinates file, captions and the PDF file is required. The coordinates file's text lines are segmented in to tables by utilizing the OPTICS layout analysis and regular expressions to filter noise. Afterwards, every page's caption is evaluated for horizontal or vertical table captions. For every horizontal caption, the caption is searched in the coordinates file to retrieve its starting index. In this case the starting index is the top left coordinate of the table and can be returned from the coordinates file. As well, the starting index allows to select the correct table from the segmented tables.

For table captions, there accounts the layout rule, that a table caption must always be written on top of the table. Therefore the starting index of the first table caption line must be smaller than the first line of the table group and higher than the last line index of the prior table group. After selecting the correct group, in order to extract the table with camelot by coordinates xy1 and xy2 coordinates have to be retrieved. The top left coordinates can be taken from the caption as mentioned earlier. The bottom right coordinates can be retrieved from searching the maximum x2 and y2 coordinates from the selected table group. These coordinates are then passed to camelot module, which extracts the table in CSV format.

For every vertical table caption it is important to mention again, that vertical table's text lines are all of length one. Therefore it is not possible to find the caption's starting index as it is done for the horizontal captions. First all white-space is removed from the caption. If one text line equals the letter "T" and its predecessors equal the rest of the caption the starting index of the caption is found and likewise the xy1 coordinates. With the starting index, the table group is selected and from the table group the maximum span is retrieved. Later on, the page is rotated by 90 degrees and the coordinates are passed to camelot module for extraction.

3.3.2 Figures

In general there are mostly two types of figures included in a scientific publication: Portable Network Graphic (PNG) or graphical based formats (PDF/SVG). Regarding graphical based formats, the xy-ticks of a diagram or plot can be extracted by PDFminer. In the document OPTICS plot those ticks appear as a region with on average low line lengths and could be wrongly identified as a table. Just as in the table extraction module, every figure's caption index is retrieved from the coordinates file in order to use it for the group selection. Generally, figure captions are located below the figure. For the group selection the figure caption index must be greater than the last group's line index and smaller than the first line of the next group's index. Later on, the maximum xy-span is selected from the group in the same way as retrieving the maximum span from the table group.

In order to be able to extract graphical based figures, all PDF pages need to be converted to PNGs. Afterwards the xy-span of the PDF images and the coordinates file is obtained. This is necessary to convert the coordinates obtained from the figure group (PDFminer coordinates) to PNG coordinates. Along with the converted coordinates the graphical based image can be cut out from the original PDF page, that was converted to PNG.

3.4 Section Extraction

The section extraction module extracts the text of the publications segmented in to its section structure. Initially, the section modules gets passed the plain-text, where all lines non-text-lines (figures, tables, etc.) have been removed by the prior modules. The next step is to parse the text for its sections. Essential for the extraction accuracy is the correct parsing for section titles. This is done by regular expressions. The routine iterates over all text paragraphs and checks if the first line matches a section title. If this is the case, the title is inserted in to a dictionary. Otherwise, the text of the paragraph is appended to the values of the

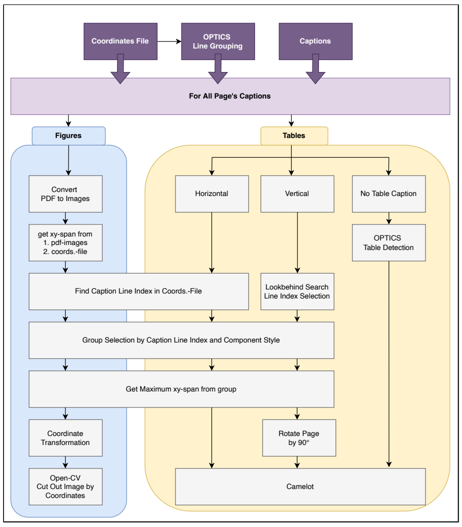

Coordinates File
OPTICS Line Grouping
Captions
For All Page's Captions
Figures
Tables
Convert PDF to Images
get xy-span from 1. pdf-images 2. coords.-file
Horizontal
Vertical
No Table Caption
OPTICS Table Detection
Find Caption Line Index in Coords.-File
Lookbehind Search Line Index Selection
Group Selection by Caption Line Index and Component Style
Get Maximum xy-span from group
Coordinate Transformation
Rotate Page by 90°
Open-CV Cut Out Image by Coordinates
Camelot

Figure 4: Table and Figure Extraction Flow Diagram.

last key inserted. Moreover, auxiliary sections like ”Appendix” or ”Acknowledgements” are appended in section dictionary. Likewise the section’s sentences are pre-processed, cleaned and matched for certain patterns defined by regular expressions. Making use of the NLP library spaCy (Honnibal et al., 2020), the text is parsed into sentences. Finally the abstract and references are inserted at their respective positions in the dictionary.

3.5 Metadata Extraction

This section briefly explains the metadata extraction process of Data Acquisition Framework. Generally, metadata features can be located on the first page of a publication. The following list provides an overview:

- **DOI:** The framework first looks for the DOI in the metadata file generated by the Tika module, or, if not found, it tries to locate the DOI within any line on the first page using a regular expression.
- **Citation/Dates:** both can also be found by substring match for ”citation”, ”received” or ”accepted” keywords.
- **Affiliations** can be found by searching variations of ”University of” in different languages with a regular expression.
- **Abstract** For abstracts, the text is divided at the position of ”Abstract” keyword and afterwards again it is divided at the position of ”Introduction” keyword and the text between the keywords is separated. From the given data it is experienced, that the average length of abstract ranges from 300 to 600 words. Each paragraph is added to the string, which will in the end be the abstract, while it is not longer than 600 words. The word limit is especially helpful for abstracts, which are not written in a single paragraph. Therefore all the abstract layouts are covered. Regarding the text line length condition, the most abstracts’ length span over two columns and layouts can differ. Therefore only if two-thirds of the text blocks lines are longer than 80 characters, then the text block is accounted as an abstract paragraph. For abstracts, which are written in single column layout the char limit is 65 characters per line.
- **Title:** First the framework tries to extract it from the Tika metadata file, otherwise searches it on the first page of publication. The title is mostly written on the top of the first page after journal name and citation, but before the authors, abstract and keywords. In most cases it is the only paragraph left after everything else was separated.

4 EXPERIMENTAL RESULTS

This section presents a comprehensive experimental evaluation of the Data Acquisition Framework.

4.1 Dataset

For the experimental evaluation of DAF, we considered two distinct dataset. Firstly, we replicated the dataset used in evaluating the PDFDataExtractor framework from the Chemical Domain, which comprises of 100 full publications collected from five chemical domain journals. The second dataset was gathered from the field of Marine Science comprises of 700 full papers from various journals, maintaining the same criteria as the PDFDataExtractor module i.e. Elsevier Journal Publications only. It is important to note that PDFDataExtractor strongly relies on templates, unlike our proposed framework (Zhu and Cole, 2022). Hence, to highlight DAF’s flexibility, we also processed research reports from Marine Science expeditions.

4.2 Chemical Domain Results

In this regard, initially we replicated the results collected by PDFDataExtractor on chemical domain publications and process similar papers using our module. For the sake of generality, we adhered to the evaluation criteria defined by the PDFDataExtractor framework (Zhu and Cole, 2022). Typically, the evaluation process is manual, making it a semi-manual process overall. The results for the metadata

Table 1: Results Chemical Domain Publications (Metadata).

Framework	Metadata														
	DOI			Title			Abstract			Authors			Journal		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
PDFDataExtractor	0.928	0.966	0.944	0.925	0.944	0.932	0.854	0.862	0.852	0.466	0.527	0.480	0.244	0.528	0.304
DAF	1.0	0.950	0.974	1.0	0.950	0.975	0.932	0.588	0.715	1.0	0.916	0.956	1.0	0.950	0.974

Table 2: Results of Chemical Domain Publications (Paper Content).

Framework	Captions and Content												Body			References		
	Figure Caption			Figure Content			Table Caption			Table Content			Sections			References		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
PDFDataExtractor	0.811	0.840	0,818	-	-	-	-	-	-	-	-	-	0.650	0.905	0.746	0.566	0.694	0.588
DAF	0.952	0.927	0.939	0.484	0.948	0.641	0.969	0.969	0.969	0.839	0.894	0.866	0.968	0.634	0.766	1.0	0.690	0.816

extraction task is compiled in Table 1 indicating that DAF performs well overall. Table 2 presents the results collected considering the content of the papers. Hence, DAF is able to cover a broader spectrum of data components from publications in comparison to PDFDataExtractor, The "-" signs in tables indicates that the system was unable to extract the respective content. The final results indicate that our framework perform better in comparison to the baseline.

During the evaluation, it has been experienced that PDFDataExtractor is unable to process a good set of papers. In contrast, DAF was able to successfully process all the provided files. For simplicity , we abbreviated Precision, Recall, and F1-Score as P, R, and F1, respectively in corresponding tables.

4.3 Marine Science Results

Similarly, papers from the Marine Science domain is processed using both the PDFDataExtractor and DAF. The outcomes of the metadata extraction are presented in 3, which emphasises the effectiveness of our proposed framework. Moreover, Table 4 highlighted the results for the content of the papers. For tables evaluation we followed: headers of the tables and data in columns remain intact and no rows were lost. Additionally, tables in Marine Science papers typically contain diverse numerical expressions and spatial data.

4.4 IODP Results

International Ocean Discovery Program (IODP) is global scientific research program that conducts expeditions at various oceanographic locations and reports of these expeditions are available in their publication portal[1]. These reports are in PDFs, but not follow the standard publication formats. Generally, these report comprise of text, tables, figures. So, we processed these reports with both frameworks. DAF was able to extract the IDs, titles, authors, source, table captions and table content respectively, but PDFDataExtractor framework was unable to process even a single report. The gathered results are presented in Table 5, indicating the DAF's ability to process PDF files in general with fewer template dependency in comparison to PDFDataExtractor.

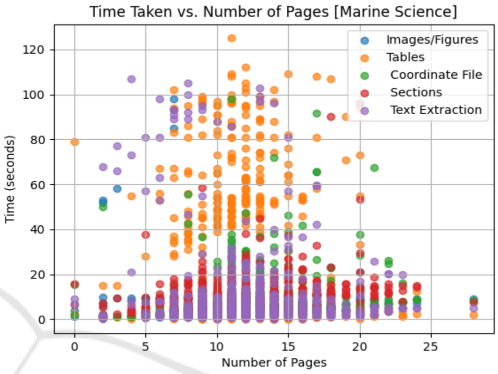


Figure 5: Number of Pages and Time plot.

4.5 Overall Results

This sections discusses the overall performance of DAF. We presented the response time of DAF for individual components with respect to number of pages shown in Figure 5. For table detection, we evaluated our coordinate based approach to base camelot module on Marine Science publications and results are presented in Figure 6. Our approach detects 1241 table instances out of 700 files, which is inline with the actual number of 1255 and base camelot detects 4782 instances. For Chemical domain publications, there are 144 tables are in actual and our approach detect 128 table instances, beside, base camelot module detects 440 table instances.

4.6 Information Modelling

To demonstrate efficacy of DAF, we presented a complex use-case which could facilitate research data

[1] http://publications.iodp.org

Table 3: Results of Marine Science Publications (Metadata).

Framework	Metadata														
	DOI			Title			Abstract			Authors			Journal		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
PDFDataExtractor	1.0	0.958	0.978	0.924	0.923	0.923	0.931	0.506	0.656	0.937	0.253	0.399	0.965	0.547	0.698
DAF	0.996	0.988	0.992	1.0	1.0	1.0	0.917	0.930	0.923	0.999	0.975	0.987	1.0	0.984	0.992

Table 4: Results of Marine Science Publications (Paper Content).

Framework	Captions and Content												Body			References		
	Figure Caption			Figure Content			Table Caption			Table Content			Sections			References		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
PDFDataExtractor	0.972	0.936	0.954	-	-	-	-	-	-	-	-	-	0.883	0.865	0.874	0.321	0.127	0.182
DAF	0.980	0.930	0.954	0.994	0.829	0.903	0.997	0.980	0.988	0.921	0.945	0.933	0.997	0.674	0.804	0.997	0.977	0.987

Table 5: Results of IODP Expedition Reports.

Framework	Metadata												Caption and Content					
	E-DOI			Title			Authors			Source			Table Caption			Table Content		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
PDFDataExtractor	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DAF	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.985	1.0	0.993	0.730	0.902	0.807

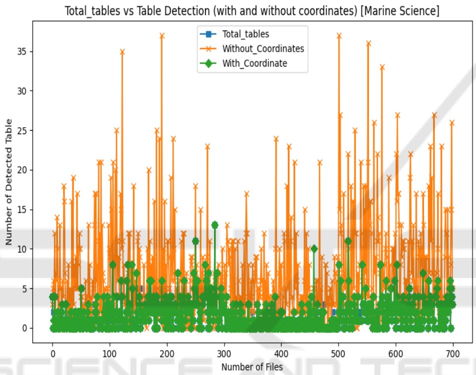


Figure 6: Table Detection for Marine Science.

management. We segregated a set of publications from Marine Science carrying spatial coordinates in tables i.e. latitude and longitude. These coordinates are being represented in degrees/decimals and could be a perfect case to demonstrate the usefulness of extracted information. Out of 700 files 73 publications are carrying spatial coordinates in tables. Among these tables, there are total 2092 location instance were observed and 1855 of them are the expressions that could lead to true spatial coordinates. In this exercise, 237 location instances were missed/extraction anomalies, which rather indicates encoding issues. For example: degree sign were converted to “0” / “8” and minute sign was converted to “1”.

5 CONCLUSIONS

The Data Acquisition Framework (DAF) significantly broadens the scope of information extraction by encompassing more data components from scientific publications by showcasing its potential to adhere diverse information extraction in comparison to baseline. Its hybrid approach to tackle metadata proved successful as indicated by the gathered results. For extracting captions, tables and sections, DAF also highlights its authority, leveraging document OPTICS and coordinate files. However, there is room for enhancement in figure extraction, currently the system is not able to group multiple figures under a single caption. Experimental results have demonstrated that DAF exhibits minimal template dependency and excels in precise data extraction from various components as revealed in information modelling.

Moreover, the possible enhancements in DAF may include precise caption-to-image mapping, challenge of associating non-graphical figures with their respective captions. Additionally, the framework could include the extraction of mathematical formulas, preserving their integrity during extraction and conversion to LaTeX code. Such enhancements would be particularly valuable in applications related to the natural sciences. Furthermore, DAF presents exciting opportunities for future research. It could serve as a candidate for creating an image data repository by extracting images from publications. Additionally, the extracted data from tables could contribute to the development of a Knowledge Graphs, Recommender Systems for scientific publications, encompassing both metadata and paper content. Hence, the publications in this regard are a horizon of information, DAF could be a step towards extraction of relevant information for the knowledge discovery and research data management tasks.

ACKNOWLEDGEMENTS

This work was supported by the Helmholtz School for Marine Data Science (MarDATA) partially funded by the Helmholtz Association (grant HIDSS-0005).

REFERENCES

Ankerst, M., Breunig, M. M., Kriegel, H.-P., and Sander, J. (1999). Optics: Ordering points to identify the clustering structure. *ACM Sigmod record*, 28(2):49–60.

Appalaraju, S., Jasani, B., Kota, B. U., Xie, Y., and Manmatha, R. (2021). Docformer: End-to-end transformer for document understanding. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 993–1003.

Camelot (2023). camelot. [Online; accessed: March 21, 2023].

Chamberlain, S. (2019). fulltext: Full text of 'scholarly' articles across many data sources. R package version 1.4.0.

Chamberlain, S., Zhu, H., Jahn, N., Boettiger, C., and Ram, K. (2023). rcrossref: Client for various 'crossref' 'apis'. https://docs.ropensci.org/rcrossref/, https://github.com/ropensci/rcrossref.

Contributors, G. Apache pdfbox - a java pdf library. https://pdfbox.apache.org/. [Online; accessed: February 20, 2023].

Contributors, G. Apache tika - a content analysis toolkit. https://tika.apache.org/. [Online; accessed: February 20, 2023].

Entity-Fishing (2016–2023). entity-fishing. https://github.com/kermitt2/entity-fishing.

Foppiano, L., Romary, L., Ishii, M., and Tanifuji, M. (2019). Automatic identification and normalisation of physical measurements in scientific literature. In *Proceedings of the ACM Symposium on Document Engineering 2019*, pages 1–4.

Guerra, J., Quan, W., Li, K., Ahumada, L., Winston, F., and Desai, B. (2018). Scosy: A biomedical collaboration recommendation system. In *2018 40th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, pages 3987–3990. IEEE.

Hong, T., Kim, D., Ji, M., Hwang, W., Nam, D., and Park, S. (2022). Bros: A pre-trained language model focusing on text and layout for better key information extraction from documents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 10767–10775.

Honnibal, M., Montani, I., Van Landeghem, S., and Boyd, A. (2020). spaCy: Industrial-strength Natural Language Processing in Python.

Inc., A. S. (2006). *PDF Reference Version 1.7*. 6 edition.

Jinha, A. E. (2010). Article 50 million: an estimate of the number of scholarly articles in existence. *Learned publishing*, 23(3):258–263.

Kessler, J., Reeburgh, W., Southon, J., Seifert, R., Michaelis, W., and Tyler, S. (2006). Basin-wide estimates of the input of methane from seeps and clathrates to the black sea. *Earth and Planetary Science Letters*, 243(3-4):366–375.

Kreutz, C. K. and Schenkel, R. (2022). Scientific paper recommendation systems: a literature review of recent publications. *International Journal on Digital Libraries*, 23(4):335–369.

Lopez, P. (2009). Grobid: Combining automatic bibliographic data recognition and term extraction for scholarship publications. In Agosti, M., Borbinha, J., Kapidakis, S., Papatheodorou, C., and Tsakonas, G., editors, *Research and Advanced Technology for Digital Libraries*, pages 473–474, Berlin, Heidelberg. Springer Berlin Heidelberg.

Martinez-Rodriguez, J. L., Hogan, A., and Lopez-Arevalo, I. (2020). Information extraction meets the semantic web: a survey. *Semantic Web*, 11(2):255–335.

Mehta, V. (2019). Comparison with other pdf table extraction libraries and tools.

PDFminer. pdfminer.six. https://github.com/pdfminer/pdfminer.six. [Online; accessed: December 20, 2022].

Peña, A., Morales, A., Fierrez, J., Ortega-Garcia, J., Grande, M., Puente, I., Cordova, J., and Cordova, G. (2023). Document layout annotation: Database and benchmark in the domain of public affairs. *arXiv preprint arXiv:2306.10046*.

PyMuPDF (2023). Pymupdf. [Online; accessed: March 21, 2023].

Riedinger, N., Pfeifer, K., Kasten, S., Garming, J. F. L., Vogt, C., and Hensen, C. (2005). Diagenetic alteration of magnetic signals by anaerobic oxidation of methane related to a change in sedimentation rate. *Geochimica et Cosmochimica Acta*, 69(16):4117–4126.

Shinyama, Y. (2013). Programming with pdfminer.

Slate (2022). Slate. [Online; accessed: November 07, 2022].

Suryani, M. A., Wolker, Y., Sharma, D., Beth, C., Wallmann, K., and Renz, M. (2022). A framework for extracting scientific measurements and geo-spatial information from scientific literature. In *2022 IEEE 18th International Conference on e-Science (e-Science)*, pages 236–245. IEEE.

Swain, M. C. and Cole, J. M. (2016). Chemdataextractor: a toolkit for automated extraction of chemical information from the scientific literature. *Journal of chemical information and modeling*, 56(10):1894–1904.

Tabula (2023). Tabula. [Online; accessed: February 15, 2023].

Taylor-Sakyi, K. (2016). Big data: Understanding big data. *arXiv preprint arXiv:1601.04602*.

Textract (2023). Textract. [Online; accessed: March 21, 2023].

Yadav, P., Remala, N., and Pervin, N. (2019). Reccite: A hybrid approach to recommend potential papers. In *2019 IEEE international conference on big data (big data)*, pages 2956–2964. IEEE.

Zhu, M. and Cole, J. M. (2022). Pdfdataextractor: A tool for reading scientific text and interpreting metadata from the typeset literature in the portable document format. *Journal of Chemical Information and Modeling*, 62(7):1633–1643.