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# Large-scale Machine-Learning analysis of scientific PDF for monitoring the production and the openness of research data and software in France

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**Abstract.** There is today no standard way to reference research datasets and software in scientific communication. Emerging editorial workflows and supporting infrastructures dedicated to research datasets and software are still poorly adopted in current publishing practices and are highly fragmented. To better follow the production of research datasets and software, we present a text mining method applied to scientific publications at scale and implemented at the French national level. Our approach relies on state-of-the-art Machine Learning and document engineering techniques to ensure reliable accuracy across multiple research areas and document types. The annotations produced by our system are used by the French Open Science Monitor (BSO) platform to follow the production and the openness of research datasets and software in the context of the French second National Plan for Open Science. The source code and the data of the French Open Science Monitor, as well as all the associated tools and training data, are all available under open licenses.

**Keywords:** research data, research software, open access, open science, scientometrics

# 1 Introduction

## 1.1 Motivations

Research datasets and software are today core elements of the research activities. 90-95% of researchers in the US and the UK rely upon software, and more than 60% would be unable to continue working if such software stopped functioning (Philippe et al., 2019). Nearly half of the researchers commonly use data generated by other scientists (Science staff, 2011) and the vast majority of researchers support data sharing (Tenopir et al., 2015). The critical role of research data and software is today broadly acknowledged, in particular for improving the reuse, the reproducibility and the transparency of research results (Laurinavichyute et al., 2022).

Following several recommendations such as the San Francisco Declaration on Research Assessment, pro-active policies to enforce higher standards of openness and visibility for all research results have been introduced in the last years. Significant national open science policies are currently implemented. Recently, the U.S. OSTP (White House Office of Science and Technology Policy) launched the Year of Open Science to advance national open science policies across the federal US government in 2023 (House, 2023; Nelson, 2022). This new policy introduces in particular a mandate for free, immediate public access to government-funded research to take effect by the end of 2025, including research datasets, and the development of key performance indicators.

Another example is the French National Plan for Open Science, a long-term, forerunner effort supported by 5 million euros annual budget in 2018-2021 to promote every aspects of Open Science in France. Under this framework, a public dashboard to follow the Openness of scientific publication with key performance indicators has been developed and deployed already since 2019, called the French Open Science Monitor (BSO - Baromètre de la Science Ouverte). This plan was extended in a second phase in 2022-2024 with an

increased budget to 15 million euros per year, giving additional attention to the openness of research datasets and software.

To evaluate, adapt and maximize the adoption of these policies, their effects must be measured. Monitoring tools and dashboards are crucial to follow the evolution of practice regarding openness and sharing of research datasets and software. However, in contrast to the well-established practice of citing scholarly publications, the visibility of these research products is considered largely insufficient and challenging.

(Park et al., 2018) shows that most data citations are informal (mentions without cross-reference with a bibliographical section and without identifiers) and found mostly in footnotes, acknowledgements or supplementary materials sections of research articles. Similarly, software are not cited in scholarly publications in a consistent and easily readable manner (Howison & Bullard, 2016). Multiple initiatives took place in the last decade to address this issue, in particular focusing on improving research datasets and software cataloging (Elger et al., 2016; Garijo et al., 2019), standards for data citation and software citation (Katz et al., 2021; Silvello, 2018) and advocacy efforts. The main advocacy effort regarding dataset and software identification is currently focusing on using PIDs similar to the successful Crossref DOIs for the research publications.

The usage of PID, combined with PID authority agencies and infrastructures, offers indeed a comprehensive technical solution for the identification and the citation of any research entities in scholar communication (Cousijn et al., 2019; Juty et al., 2020). However, (Du et al., 2022) failed to observe any usages of PID associated to software when they exist in random samples of software mentions from recent articles on COVID-19. Regarding dataset citations, (He & Han, 2017) report that less than 10% of publications that include data mentions contain any PID. According to the study of (Macgregor et al., 2022), PID associated to data have a much more limited awareness among researchers as compared to publication PID. With their current adoption and impact, PID cannot provide today realistic

measurements of the usage, creation and sharing of research data and software.

One immediately available alternative to PIDs for datasets and software is to rely on a text mining approach to automatically detect their mentions in scholarly full texts and their role in the described research work. If the corpus of scientific full texts is comprehensive enough, this approach can provide a realistic snapshot of the actual practices regarding research datasets and software at a given time. Such continuous source of data could then lead to trustful indicators for monitoring the impact of open science policies with limited latency.

For extending the French Open Science Monitor (BSO) platform (Bracco et al., 2022) to measure the openness of research datasets and software, we implemented a large text mining pipeline applied to a comprehensive corpus of scientific publications including at least one author with a French affiliation. After describing how we created this corpus and harvested full texts, we will show that recent advances in scientific text mining make fine-grained extraction approaches effective. Our models capture reliably research datasets and software mentions directly from the full text publications, but also characterize these mentions in term of usage, creation and sharing. Finally we will present the indicators developed from these text mining results and how they are integrated in the French Open Science Monitor infrastructure and dashboards, offering at the same time country-wide measurements and custom monitors at the level of an institution or a scientific field.

## **1.2 The French Open Science Monitor**

The French Open Science Monitor<sup>1</sup>, also called BSO for *Baromètre de la Science Ouverte*, is a tool for steering the public policy introduced by the first French National Plan for Open Science (MESR, 2018). A first version was released in 2019 providing a collection of measurements and dashboards on the rate of Open Access publications produced by

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<sup>1</sup><https://frenchopensciencemonitor.esr.gouv.fr>

all public French research entities (Jeangirard, 2019). In 2021, the new version of BSO was extended to better encompass the field of health, with additional information on the openness of clinical trials and observational studies.

Following efforts initiated by the University of Lorraine in 2020, the national monitor also offers tools and training materials to support the publication by individual institutions of their own Open Science monitor from the national data.

While opening scientific publications is a crucial aspect of Open Science, other research outputs need to be considered. The follow-up second Plan for Open Science (MESR, 2021), which started in 2022, includes a particular focus on research datasets and software, supporting numerous projects and initiatives to broaden their openness. Although the French Open Science Monitor is updated every year (Bracco et al., 2022), measurements related to research datasets and software were not covered yet and required specific indicators.

### **1.3 Quality criteria for Open Science indicators**

Before discussing existing works and describing our approach, we introduce the main quality criteria that we think should be considered when designing open science indicators. We also highlight some of the main challenges associated to these quality criteria when applied to research datasets and research software.

- **Coverage:** Ideally the indicators should cover all the research outputs of interest in the context of Open Science policies. This is very challenging for research datasets and software, because, to a large extent, they are not identified nor indexed as traditional scholarly articles. A high coverage is however mandatory to create reliable estimates that are inclusive for all scientific fields and all types of institutions.
- **Accuracy:** Indicators should be reliable, in particular avoiding false positive and duplicates. This criteria supposes thorough and reproducible evaluations in term of standard accuracy metrics (e.g. precision, recall, F1-score) and to rely on reliable

authoritative sources.

- **Freshness:** Policy indicators are developed to capture recent changes in publishing practices. The data acquisition underlying these indicators must reduce as much as possible delays between actual publication dates and measurements.
- **Adaptability to different geographical and organizational levels:** To exploit indicators, we expect that further analyses are possible at lower levels of granularity than the sole national level. Deriving indicators at the level of geographical areas and at the level of individual organizations (universities, research institutes, research laboratories) are requirements for the proper study and adaptation of an Open Science policy.
- **Adaptability to different research domains:** Practices vary significantly from one research domain to another. The volume of scientific production is also specific to research areas, and one field could be entirely diluted and invisible within global indicators. Following the evolution of indicators by scientific and technical domains is a key requirement.
- **Fairness:** Indicators should maintain consistency in terms of domains and languages. As much as possible, we want to avoid exclusion of some research areas and languages. This aspect is challenging for example with Social Sciences and Humanities, where publications are more incompletely referenced by large bibliographical index, and frequently published in languages other than English.
- **Understandability and interpretability:** Indicators should present measurements easy to understand for researchers and for the public. For example, if expressed as a percentage, the indicator maximum value (100%) should be clear and correspond directly to a goal of the evaluated public policy.
- **Consistency maintained over time:** Indicators produced for a given year must



be directly comparable with the indicators from previous years, in order to follow correctly the evaluation of research activity over time. The consistency should be valid in terms of measurement methodology, corpus, and presentation.

- **Independence and trustfulness for the researchers:** to maximize trust by researchers, public indicators should preferably be independent from proprietary resources and interests. Open source, open data and open access documentation are therefore to be prioritized. In addition, we think methods and data sources for creating the indicators should be fully documented to meet this criterion.

## **1.4 Existing Open Science indicators for research datasets and software**

To our knowledge, there are currently only two examples of deployed Open Science monitors related to research data and software, one part of the OpenAire infrastructure and the PLOS Open Science indicators. We discuss these two examples based on the quality criteria presented in the previous section.

### **1.4.1 OpenAire**

OpenAire is an infrastructure dedicated to open science and mainly funded by EU Horizon 2020 and Horizon Europe programs. Among other services, OpenAire developed the Open Science Observatory<sup>2</sup> to better understand the European open research landscape. The service includes dashboards related to publications, datasets and software.

Relatively to datasets, if we focus on France, this observatory references only 958 datasets affiliated to an organization in the country for the period 2014-2023, with 373 reported as Open Access (as of May 2023). It also reports 16,863 Open Access datasets in the country's repositories (for reference, there are a total of 42M item registered on DataCite

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<sup>2</sup><https://osobservatory.openaire.eu>

worldwide). Similarly, 533 software are affiliated to an organization in France, with 111 identified as Open source. As visible, the coverage is extremely limited. Coverage of research domains is similarly incomplete and not consistent.

The method for generating the indicators is currently not documented, beyond an indication that it relies on the OpenAire Research graph. This includes a “PID graph” aggregating open metadata databases such as CrossRef, PubMed or arXiv, but we were not able to find additional information about the involved “intelligent linking”. We assume dataset and software metadata sources mainly correspond to those implementing manual references via PID with sufficient metadata, such as parsed affiliations. As such, we think the OpenAire Observatory illustrates the limit of an approach relying on PID and on manual referencing for research datasets and software. All in all, it lacks transparency and might be more a proof of concept than a usable service.

As a result, such fragmentary coverage leads to biased and unreliable indicators. Under these conditions, we think that the published dashboards are counter-productive. Publishing aggregated dashboards on so little and non-representative data can lead to the disengagement of the public for the tool, false interpretation, wrong public policy decisions and inability to assess public the application of Open Science policies.

#### **1.4.2 PLOS Open Science indicators**

In late 2022, and with an update in March 2023, PLOS published a series of open science indicators (Public Library of Science, 2023). These indicators are evaluated on the 71,109 PLOS research articles published during the 4 year period from January 2019 to December 2022. Three main indicators are provided: the rates of research data sharing per article, the rate of code sharing per article and rate of preprints associated to a published article. The PLOS method relies on DataSeer text mining tools (“DataSeer project”, 2019–2023).

As compared to the OpenAire dashboards, the PLOS Open Science indicators correspond

to a significantly higher quality considering the criteria we introduced in section 1.3. The corpus is well delimited and the indicators are regularly updated. The text mining process is comprehensive because applied to all the publications. The indicators can be adapted by geographical areas and institutions. The relative ratios over time are easy to interpret and directly capture the relevant output for PLOS Open Science policy.

However, in terms of scale, diversity and complexity, the PLOS collection is narrow in comparison with the national ambition of the BSO. These indicators only cover one publisher and are mostly limited to the Life Science domain. In addition, the extraction process took advantage of the Data Availability statements exceptionally present in all PLOS publications over the considered period, and of the existing JATS XML format, which is easier to process than PDF.

Finally, although the text mining tools from DataSeer are open source and documented, their training data and Machine Learning models are currently not open. The trustfulness criteria for the researchers is impacted by the limitation for reproducing the annotations used to derived the indicators.

## **2 Identification of countrywide research publications**

We emphasized in section 1.3 the importance of the coverage and freshness criteria to produced meaningful indicators. The examples of the OpenAire and PLOS indicators illustrate the challenge of addressing these criteria.

In this section, we explain how the corpus of French research publication is created. Identifying in a reliable and comprehensive manner the global set of French research publications is the mandatory basis for developing targeted indicators. A detailed presentation of the approach is given in (Bracco et al., 2022).

In 2018 and 2019, the following two principles have been established when launching the

French Open Science Monitor project:

1. The French research publication corpus is defined as all the publications with at least one author with a French affiliation.
2. The French Open Science Monitor is a sovereign tool to steer public policies, it is independent from proprietary database and providers, therefore the project only uses open data for creating the reference set of French research publication.

The first principle supposes to be able to access the affiliation information of every authors for all the publications. However, open bibliographic databases such as Crossref and PubMed lack metadata related to publication country and affiliations. To solve this limitation without relying on proprietary data such as Web of Science (WoS) and Scopus, the French Open Science Monitor has developed an original data ingestion and extraction pipeline running every year (Bracco et al., 2022):

1. Start with all CrossRef DOI for a given publication time range.
2. Collect additional open metadata relative to each DOI, from several sources:
  - harvest at scale and parse every HTML landing pages associated to a DOI to extract additional affiliation raw strings,
  - harvest repositories metadata (PubMed, HAL),
  - when the full-text is available, use GROBID (“GROBID”, 2008–2023) to extract affiliations metadata.
3. Use an in-house open source affiliation matcher (L’Hôte & Jeangirard, 2021) to detect affiliation countries from raw affiliation strings.

This approach appears to be highly competitive and reliable when compared to proprietary data such as WoS and Scopus, while relying only on transparent open data sources. Studying French publications in 2019, (Chaignon & Egret, 2022) shows that the open-data

method implemented by the French Open Science Monitor (BSO) is able to identify the largest share of French publications as compared to the combined aggregated corpus of Scopus, Web of Science (WoS), HAL archive, the Astrophysics Data System Abstract Service (ADS), PubMed and Microsoft Academic Graph (MAG).

Table 1: Share of the different sources in the overall French publication aggregated corpus (total of 167,412 publications) for the year 2019, as reported by (Chaignon & Egret, 2022).

	Scopus	WoS	HAL	ADS	PubMed	MAG	<b>BSO</b>
<b>Share of total (%)</b>	67	58	38	9	29	61	<b>92</b>

(Chaignon & Egret, 2022) further indicates that the approach used by the French Open Science Monitor effectively identifies the vast majority of publications with a persistent identifier (DOI) for Open Science monitoring. Table 1 reports the coverage estimated by this study.

### 3 Full text harvesting

Once the bibliographical set of French publications has been created, the next step is to harvest the largest possible amount of full texts to apply text mining.

In the case of Open Access publications, we identify one or more possible download URL using Unpaywall, which is broadly acknowledged as the most advanced database for this purpose (Else, 2018). Table 2 presents the proportion of Open and Closed Access publication for the complete BSO collection (2013-2021) as of year-end 2022. We also indicate the number for the first considered publication year (2013) and the last one (2021) to illustrate the current Open Access dynamic.

Despite the presence of one or several direct full text access URL, around 15% of downloads fail. Main failure reasons include broken link, IP blocking after a threshold of down-

Table 2: Number of publications in the French Open Science Monitor with Open Access (OA) and Closed Access (CA) shares with associated download rates of full texts (PDF), as of year-end 2022.

<b>Publication periods</b>	<b>2013-2021</b>	<b>2013</b>	<b>2021</b>
Overall # publications in BSO	1,426,140	143,095	160,217
- # succesful dowload	908,567	85,914	103,211
- % succesful dowload rate	63.7	60.0	64.4
# OA publications	773,753	61,849	107,722
- # succesful downloads	660,501	52,549	85, 073
- % succesful dowload rate	85.4	85.0	79.0
Number of CA publications	652,387	81,246	52,495
- # succesful dowmloads	248,066	33,365	18,138
- % succesful dowmload rate	38.0	41.1	34.6

loads, or Cloudflare challenges to block machine-based download. The usage of robust web harvesting techniques (rotating HTTP header, support of simple Cloudflare challenges, random delays, bulk download of the full arXiv collection, etc.) only partially mitigates the risk of failed downloads.

For closed access publications, programmatic download of PDF documents depends on the nature of the contractual agreement with individual publisher for Text and Data Mining (TDM) application, leading to complex and time-consuming contractual negotiations. Even when such a contractual agreement exists, implementing it can be costly. Most publishers have set procedures and technical constraints to control or even discourage this type of projects. Moreover, such a contract may not be renewed, thus not guaranteeing the sustainability of the approach over time for closed publications. Our full text harvesting currently includes Elsevier and Wiley TDM web services.

Table 2 further summarizes the success rate of the harvesting of full text documents realized in 2022.

## 4 Machine Learning for mention detection and characterization

As discussed in the section 1.1, PID and metadata driven approach related to research datasets and software cannot lead currently to realistic evaluations and indicators due to low adoptions and lack of awareness. In contrast, automatic recognition of these mentions from full texts potentially offers a factual and comprehensive approach, directly usable to estimate quantitatively these research outputs.

### 4.1 Advantages of text mining publications

We think that mining research datasets and software mentions in scientific publications can provide solutions for most of the quality criteria for indicators introduced in section 1.3:

- In terms of **coverage and freshness**, a corpus of scientific publications can offer a trustful snapshot of the scientific production if the text mining is applied to a very significant amount of scientific publications. First the ratio of Open Access publications has now reached more than 50% of the all publications. Second, copyright exception for text mining for subscription-based publications makes it possible to harvest legally a large corpus of closed-access publications. Accessing a comprehensive corpus close to completeness is thus realistic.
- When enough training data is available, the **accuracy** of modern machine learning techniques, in particular based on a Deep Learning architecture, has improved significantly. We will see that large scale datasets of manually annotated research datasets and software mentions have been recently released, and we can expect reaching a satisfactory level of accuracy;
- The **adaptability** to different geographical and organizational levels and different

scientific and technical domains have already been addressed with high reliability at the level of publications in the previous version of the French Open Access Monitor (Bracco et al., 2022).

- With respect to **fairness**, the systematic application of text mining on a comprehensive corpus can cover research domains where awareness of metadata and PID referencing is very low, because online access to full-texts publications is today a universal practice, avoiding their exclusions.
- **Consistency**: an automated text mining solution can be re-applied to a full corpus regularly, including back files, and produce consistent indicators over any period. The process is independent from a manual referencing of research datasets and software that could happen to already published articles, certain research fields, from certain publishers and is applied to all types of publications.
- **Independence and trustfulness**: we think that this criteria can be fulfilled if the software used to obtain these indicators are open source, publicly documented and transparently evaluated.

The first text-mining approaches for capturing information on data and software have been rule-based techniques. We discuss in the next section their different limitations.

## 4.2 Limitation of rule-based tools

In the context of Open Science and bibliometrics, some pattern matching tools have been developed to capture statements about data and software openness in a given corpus. For example, (Larregue et al., 2020) uses keyword matching applied to the data availability statements and obtained an approximation of the data sharing status for 7,394 COVID-19 articles deposited on medRxiv. However, data sharing statements are, to a very large extent, not limited to data availability statements (Park et al., 2018), COVID-19 articles are not representative of general data sharing practices (Sevryugina & Dicks, 2022) and



keyword matching is far from a state of the art automation technique. Such a work can be seen as a one shot exercise for reporting interesting results in a limited scope, but not as a method that can be generalized and re-used for mining data usage in full texts.

A more general purpose tool, ODDPub (Riedel et al., 2020), has been developed to detect open data statements in full texts and applied at scale to 2.75 million articles on PubMed Central XML publications (Serghiou et al., 2021). It implements a rule-based approach for capturing open data statement patterns. ODDPub yields global information about openness of data and software used in a document. The rules have been developed for biomedical literature. However, we think ODDPub has underlying limitations for the production of data and software Open Science indicators and these limitation can be generalized to other similar pattern matching tools:

- ODDPub produces information about *openness statements* related to data and software used in the work described in a publication. The tool does not produce more fine-grained information about their re-use, production and sharing. The global volume of novel data and code is unknown. This makes impossible to estimate the key ratio of created data and software openly shared, which is the measurement that Open Science policies need to monitor and maximize.
- Rule-based approaches are useful when no training data is available or when transparency for auditing error is relevant, but they are technically outdated. They perform with lower accuracy and portability to other domains than modern machine learning when quality training data is available (Chiticariu et al., 2010; Trienes et al., 2020). We will see that such quality training data exists today for software and dataset mentions.
- Reported ODDPub F1-scores are 0.73 for data openness recognition and 0.64 for code openness recognition at document level. As indicated in (Lafia et al., 2022), performance metrics for the open code detection are unreliable because of a lack of

data for significant evaluation (open code in the evaluation data was found in only 11 publications<sup>3</sup>). ODDPub was designed to be part of a workflow including a manual validation step. In this context, accuracy of the automated step can be balanced to ensure an expected quality level. However, for a fully automated text mining at scale, the reported accuracy values are more challenging.

- ODDPub often has no clear distinction between code and data - including in the evaluation data of the tool. Data present on a GitHub repository for example will often be classified as open software.
- ODDPub produces global screening information about openness at document level, but the tool does not have the technical capacity to identify mentions (dataset and software names), nor to provide usable information at software and dataset levels (dataset and software attributes and mention contexts). We think that the level of complexity of the rules required to extract mentions and mention-level characterizations would make the approach very hard and time-consuming to extend to such recognition, if doable.

### **4.3 Machine Learning for mention detection and characterization**

The automatic recognition approach raises crucial challenges that are necessary to tackle and evaluate rigorously for a valid application:

- processing PDF as input for ensuring coverage, freshness and fairness,
- accuracy and sparsity to address accuracy and trustfulness,
- robustness, speed and production-level technical capacities for supporting freshness, consistency and accuracy requirements.

We discuss these three points in the next sections.

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<sup>3</sup>It means for example that one additional example of open code will increase or decrease the reported F1-score by around ten percents.

### **4.3.1 Processing PDF as input**

To perform text mining on scientific articles, we cannot assume the availability of clean and structured text. The most widespread and easily available scientific publication format is raw PDF, a presentation-oriented format that destroys the semantics and the original structure of data, introducing noise in text encoding and text order stream. This format raises issues for text mining applications, both in terms of significant source of errors and technical feasibility (Westergaard et al., 2017).<sup>4</sup>

Often presented as an alternative, publisher structured XML including the text body is text-mining friendly, but they have limited availability. First, XML are costly to produce, many small, medium and academic publishers do not have the resources today to produce formats beyond PDF. Second, recent publications are critical for developing Open Science indicators, but the availability of XML is delayed and uncertain as compared to PDF (e.g. for conference proceedings or preprints initially in PDF). Third, accessing XML versions often require additional subscription-based API services even when the Open Source PDF version is available. Last, processing XML only would create a strong dependency on publishers. Even when available, XML full-texts are in a variety of different native publisher XML formats (Bretel et al., 2010), often incomplete and inconsistent from one to another, involving the development of many custom parsers when considered at scale.

Thus, supporting PDF by using a layout-aware parsing and conversion tool appeared very early as a key requirement for any scalable scientific text mining task.

### **4.3.2 Accuracy and sparsity**

Accuracy of the recognition of software and dataset mentions from within scholar full texts is challenging, firstly due to the high sparsity of these mentions. This work requires the

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<sup>4</sup>From one of the author of (Westergaard et al., 2017), an effort to apply text mining to 15 million scientific articles, “We probably spent more computational resources teasing the text out of PDFs and beating it into shape than we spent on the actual text mining.” (McKenzie, 2017)

application of state-of-the-art ML methods to millions of published PDFs across different scientific domains, where dataset and software mentions only represent a few relevant tokens out of several thousands in each document.

Considering the Softcite dataset version 1.0 (Du et al., 2021), the 4,971 full-texts contain a total of around 46 million tokens, but only 15,280 tokens are relevant as a software mention. Around one token is positively labeled for each 3,000 “negative” tokens, with a ratio as low as one token per 17,500 tokens for *publishers* and *URL* fields. An Imbalance Ratio value above 500 is usually already considered to be extreme (Lee & Deleris, 2020). With the higher observed Imbalance Ratio here, from 1:3,000 to 1:17,500, an ML approach to finding new unseen software mentions can be very challenging.

### **4.3.3 Robustness, speed and production-level capacities**

Given the technical environment of the French Ministry of Higher Education and Research, which is operating the French Open Science Monitor, and the volume of full texts downloaded reported in section 3, the following technical constraints needed to be covered:

- scaling to at least 1 million PDF in manageable time and standard computing infrastructure,
- secure storage for harvested full texts,
- repeatable processing every year for the complete corpus,
- high robustness to avoid service failure, in particular in the common case of ill-formed and corrupted PDF,
- fully automated process for deployment on a Kubernetes cloud.

## 4.4 Research software

Automatic recognition of software mentions has attracted a lot of interest in parallel with the development of research software citation advocacy in the last decade. (Krüger & Schindler, 2020) presents these first approaches, based mainly on gazetteers and rules. Machine Learning promises significantly higher accuracy and coverage, but appeared however first limited by the lack of manually annotated training data necessary for reliable models - the largest public dataset until 2020 being limited to only 85 annotated documents (Duck et al., 2015). With the development of large annotated gold corpus, the Softcite dataset (Du et al., 2021), 4,971 articles in Life Sciences and Economics (4,093 software mentions), and the SoMeSci dataset (Schindler et al., 2021), 1,367 articles in Life Sciences (3,756 software mentions), Deep Learning approaches have been recently possible for this task.

### 4.4.1 Prior work

To our knowledge, three systems have used modern Deep Learning techniques and the recent large annotated gold corpora for software mention recognition. (Lopez et al., 2021), (Schindler et al., 2022) and (Istrate et al., 2022). All are using fine-tuned SciBERT models (Beltagy et al., 2019).

The *Softcite software mention recognizer* (Lopez et al., 2021) is the earliest published system and was developed in parallel with the creation of the Softcite dataset. The system includes a variety of models trained with the Softcite dataset. The training uses sampling techniques to increase the number of negative examples for mitigating the problem of mention sparsity. The best model is a SciBERT model, with a CRF activation layer, fine-tuned with the positive examples of the Softcite dataset and additional negative examples selected with a technique called active sampling. The training set uses a 1:20 ratio (20 paragraphs without annotations for one paragraph with at least one annotation). With the

Softcite dataset, it corresponds to around 2000 positive paragraphs and 40K negative paragraphs. The model has been evaluated on full paper content for 20% of the annotated articles. Additional entity disambiguation is used to filter out false positives and document-level mention propagation is used to increase recall. Input of the service can be PDF or various publisher XML formats.

The *SoMeSci recognizer* (Schindler et al., 2022) is trained with the SoMeSci dataset (Schindler et al., 2021), which is smaller and limited to Life Sciences, but has a more comprehensive set of annotations than (Du et al., 2021), including relationships between mentioned software entities. The model uses a more complex architecture to also predict these relationships. Training and evaluation are realized with the annotated corpus, which only includes the positive sentences (sentences with at least one software mention) for 787 PLoS articles, method sections for 480 PLoS articles (a total of around 3,200 paragraphs) and complete content for 100 articles. The distribution of software mentions is thus oversampled as compared to the actual distribution. The system supports JATS XML documents as input.

The *CZI recognizer* (Istrate et al., 2022) is the latest published system, but also the simplest, with a more limited scope. It is a SciBERT model fine-tuned with the Softcite dataset (Du et al., 2021). The trained model used software name and version information and does not cover the other annotated attributes available in the dataset (url, publisher). The model is only trained and evaluated on the annotated examples of the dataset, which are all positive paragraphs (the paragraphs with at least one software mention). The model can then be used in a pipeline starting from XML documents as input, relying on *GNU parallel* command lines.

#### **4.4.2 Comparing model predictions with real mention distributions**

The accuracy and sparsity aspect is important to stress when comparing these tools. While software mentions are extremely sparse in actual scholarly full texts, they are represented

in either every paragraph (Istrate et al., 2022) or in around one third of the paragraphs (Schindler et al., 2022) of their training data. According to our evaluations, this leads to model unrealistic ratio of software mentions. These models tend to predict software mentions in many sentences/paragraphs, leading to a very high amount of false positives. Because these models also report evaluation scores produced on partitions of the annotated data, the reported evaluations present similarly unrealistic figures, over-representing expected software mentions. The invalid evaluation of a model for an unbalanced classification problem after sampling the training data is a known issue discussed in (Vandewiele et al., 2021).

Table 3: Reported scores, reproduced scores and benchmark scores against an holdout set of full papers for three Deep Learning software mention recognizers.

Software mention recognizer	F1-score on annotated corpus as reported in original publication	F-1 score on annotated corpus, reproduced	<b>F1-score on holdout set</b> (full article content)	Note
CZI recognizer	92.0	85.5 <sup>a</sup>	<b>56.3<sup>a</sup></b>	(software name and version only)
SoMeSci recognizer	88.3	84.0 <sup>b</sup>	<b>62.4<sup>b</sup></b>	("Application" name only)
Softcite recognizer (using around 40K negative sampling examples)	-	82.3	<b>79.1</b>	(software name, version, publisher, url)

<sup>a</sup> Fork for reproduced cross-evaluation and Softcite holdout evaluations available at <https://github.com/kermitt2/software-mention-extraction-czi>

<sup>b</sup> Fork for reproduced SoMeSci cross-evaluation and Softcite holdout evaluations available at <https://github.com/kermitt2/SoMeNLP>

Table 3 illustrates the issue of training and predicting with very different mention distributions. We indicate reported scores based on cross-evaluation on the annotated corpus (all

over-representing mentions) and our reproduced scores in the first two columns. In the third column, we report realistic evaluation scores on the full content of a set of annotated articles (the softcite holdout set, 20% of the Softcite articles).

This shows that a parser like (Istrate et al., 2022) trained on unrealistic over-sampled distributions will perform with much lower accuracy when applied to real full documents, producing a high rate of false positive. For this reason, in (Istrate et al., 2022), manual corrections have been realized at very large scale on the extracted results.

We think that a similar observation applies to (Schindler et al., 2022). The recognizer is trained and evaluated on the SoMeSci corpus. This corpus is over-representing software mentions due its construction. However, differences in the definitions of "software mentions" between the SoMeSci and the Softcite datasets challenge the validity of this evaluation. False positives can be the consequence of the broader definition of "software mentions" in SoMeSci as compared to Softcite, and not only due to very high ratio of software mentions in the training data of the SoMeSci recognizer.

To address false positives, (Lopez et al., 2021) has explored several sampling ratios and techniques to adapt the model to the actual extremely sparse distribution of mentions. With F1-score around 80% on actual mention distribution and full article content, the results do not require manual corrections for tasks which are robust enough to cope with some uncertainty, like statistical analysis, indicators or knowledge base construction.

#### **4.4.3 Production considerations**

The Softcite software mention recognizer (Lopez et al., 2021) has the advantage of being integrated with GROBID to allow the processing of PDF documents, while the other tools work with XML full text inputs and would require further development to support PDF parsing and structuring.

GROBID is used for parsing, extracting, and structuring the content of scientific articles in



PDF, but also to drive entity recognition in relevant sections. This tool provides in particular clean text paragraphs, solving issues like character encoding, character composition, hyphenation, reading order, identification of reference markers, footnotes, headnotes, tables and figures, which improve any subsequent text mining process. In addition, GROBID parses bibliographical references, match them to CrossRef DOI and identifies citation contexts in the text body associated to dataset and citation mentions.

The Softcite software mention recognizer includes production-ready releases, with docker images, REST API service and a python client for parallel processing. It is thus ready to deploy in the existing cloud-based BSO infrastructure and service pipeline. The system also includes a web GUI console for the service that display annotations on PDF for easy visual inspection.

We have therefore chosen to extend the system of (Lopez et al., 2021) for the production of the French Open Science indicators, considering its accuracy, the support of PDF and its engineering maturity. Improvements to the system developed in this work includes: a new extended and enriched Softcite corpus, refinement of software types and relationships, automatic characterization of mention context in term of usage/creation/sharing and some improvement of models using LinkBERT fine-tuning (Yasunaga et al., 2022).

#### **4.4.4 Data model and training data**

**Definition** A “software” entity can be defined as *a collection of computer programs that provides the instructions for telling a computer what to do and how to do it*. In the present work, we mostly reused existing annotation guidelines and tried to follow consensus on the definition of “software”. We consider as software: programs, packages, scripts, plug-ins, workflow scripts, API, OS, programming environments, macros and embedded software. We exclude databases, models (simulation, machine learning), algorithms/methods, programming languages and file formats.

Mentions are however often ambiguous. For example, it is quite frequent that the name of an algorithm and its implementation (as software) are used in papers in an interchangeable manner. The mention to all these entities should be interpreted in context, checking if the statement refers to the software implementation of an algorithm. Similarly, mentions to devices, databases, models, etc. require to check in context if the mention actually refers to the software part of these entities or not.

For a more detailed discussion and more examples, see the *Annotation Guidelines* coming with the public dataset (Howison et al., 2023).

A software mention contains at least a software substantive, which could be a proper name or an implicit name like *script*, *program*, etc., and optional attributes. In our framework, we considered as attributes: URL, publisher (organization or individual which publishes the software), version, programming language and one or several bibliographical references.

In order to characterize software contributions in research papers, we need to identify precisely the created software parts. For example when a script is developed and should be run in a particular environment, we distinguish the script as one sharable software component distinct from its software environment. For this, we introduce a typing for software mention:

- **standalone software:** a software expressed in the mention context without dependency to another software and which does not require code.
- **software environment:** a software requiring some code/scripts to realize the research task, expressed in the mention context with or without dependency to another software.
- **named software component:** a named software depending on another software environment to run, the software environment being expressed in the mention context.
- **implicit software component:** an unnamed software depending on another soft-

ware environment to run, the software environment being expressed in the mention context, and where the software referring expression is a generic term for program. such as *program, code, script, macro, package, library, etc.*

**Annotations** The Softcite dataset is encoded in TEI XML (TEI Consortium, 2010). In its first version, software mentions were all encoded as standalone software. To produce indicators on software and code sharing associated to research works, we extended the annotations for refining the type of the software mentions and to encode the dependencies between mentioned software. With the additional dependency annotations between software, the new Softcite dataset version is comparable to SoMeSci in term of annotation comprehensiveness, with the benefit of a larger amount of annotated documents and a coverage not limited to Life Science. Like the previous versions of the Softcite dataset, the additional annotations have been produced in parallel by 2 annotators and a reconciliation phase has been realized by a curator for all cases of disagreements.

Table 4 presents some statistics about this new revised version (2.0) of the Softcite dataset. A significant amount of software mentions have been broken down into software parts to encode their relationships.

Table 4: Annotation overview for the Softcite corpus version 1.0 and 2.0.

Softcite dataset version	v1.0 (2020)	v2.0 (2023)
number of documents	4,971	4,971
software name (total)	4,093	5,134
- environment	-	1,089
- component	-	88
- implicit	-	106
version	1,258	1,478
publisher	1,111	1,311
URL	172	231
programming language	-	71

The latest version of the Softcite dataset is available on Zenodo (Howison et al., 2023).

#### **4.4.5 Evaluation**

The following tables present the evaluation of the two main models involved in the identification of software mentions, based on version 0.7.2 of the Softcite software mention recognizer and the updated version 2.0 of the Softcite dataset.

##### **Software mentions and attributes**

Similarly to the work in (Lopez et al., 2021), to evaluate the model on the actual distribution of software mentions in scientific articles, we have reused a *holdout set* containing the complete full text of 20% the Softcite Dataset documents (994 articles). This set reproduces the overall distribution of documents with annotation (29.0%), the distribution between Biomedicine and Economics fields, and the overall distribution of mentions per document. The *holdout set* therefore captures a realistic distribution of software mentions and can be used to produce stable evaluations using different version of the training data. We used the remaining 80% of documents (3,977 articles), divided at paragraph-level into positive (1,886 paragraphs with at least one manual annotation) and negative (612,597 paragraphs without manual annotations). Optimizing the balance between positive and negative sampling, the final model was trained on the 1,886 positive paragraphs of the Softcite dataset and a set a of 50,000 negative paragraphs selected with active sampling as described in (Lopez et al., 2021).

Our best model is a fine-tuned SciBERT base model (Beltagy et al., 2019) with an additional CRF activation layer, which performs slightly but consistently better for this task than a fine-tuned LinkBERT model (Yasunaga et al., 2022).

##### **Software type refinement**

We report the evaluation of our best model for the typing of software mentions, once again

Table 5: Evaluation scores of the fine-tuned SciBERT model for software mention recognition.

	precision	recall	<b>F1-score</b>	support
<b>publisher</b>	75.51	88.80	<b>81.62</b>	250
<b>software</b>	74.01	88.98	<b>80.81</b>	989
<b>url</b>	53.97	82.93	<b>65.38</b>	41
<b>version</b>	83.99	90.81	<b>87.27</b>	283
<b>all (micro avg.)</b>	75.22	89.12	<b>81.58</b>	1563

a fine-tuned SciBERT model with an additional CRF activation layer. This model is applied only to sequences where at least one software mention has been identified previously. The following scores are thus produced using 10-fold cross-validation on a training set based on all the paragraph with at least one annotated software.

Table 6: Evaluation scores of fine-tuned SciBERT model for predicting software mention sub-types.

	precision	recall	<b>F1-score</b>	support
<b>component</b>	71.43	71.43	<b>71.43</b>	7
<b>environment</b>	83.33	83.33	<b>83.33</b>	102
<b>implicit</b>	72.73	57.14	<b>64.00</b>	14
<b>language</b>	100.00	61.54	<b>76.19</b>	13
<b>all (micro avg.)</b>	82.81	77.94	<b>80.30</b>	136

## 4.5 Research datasets

### 4.5.1 Existing work

Similarly to software mentions, data citations are inconsistent, vague, incomplete and indirect (Mooney, 2011). Beyond rule-based method such as ODDPub (Riedel et al., 2020), the limitation of which we have discussed in section 4.2, several works have explored machine learning techniques for the automatic recognition of datasets in technical and scientific documents.

Not going to the level of dataset labeling, (Zhao et al., 2019) relied on fine-tuning BERT and achieved a F1-score of 78.7 for dataset screening on a sentence-level classification task. (Hou et al., 2019) developed automatic extraction of task, dataset, metric and score also by fine-tuning BERT, reaching 67.8 F1-score. In the domain of Machine Learning, NLP and Information Retrieval, (Heddes et al., 2021) investigated BERT and SciBERT models too, reporting F1-score of 0.78 on reused named dataset mention recognition on positive sentences, and 0.73 on a more realistic ratio of positive/negative sentences artificially augmented. (Lafia et al., 2022) experimented on the Social Science domain, identifying automatically 68% of all sentences coded as having data references based on a spaCy NER model. The manually annotated dataset (not made public) was initially obtained by filtering sentences with patterns in a very large corpus of articles.

The Coleridge Initiative held a Kaggle competition on dataset recognition in 2021 in the field of public health and social policies (“Coleridge Initiative - Show US the Data”, 2021). However, we found very hard to rely on the dataset or methods developed for this competition, as further discussed in section 4.5.2.

(Jain et al., 2020) developed SciREX, a dataset of 438 annotated arXiv documents on the Machine Learning domain, with identification of named datasets, among other entities. The reported global F1-score for mention recognition with a BERT-based model is 71.2. Finally, EneRex (Yousuf et al., 2022) is a system for the extraction of various, including technical, facets from scientific publications, again on the Machine Learning field, including *used datasets*. They report F1-scores of 48.6, 63.4 and 66.2 for dataset mention recognition on the EneRex, SciREX and Papers With Code datasets respectively.

We also mention the DataSeer project (“DataSeer project”, 2019–2023), funded by the Sloan Foundation, which focused on a sentence-level classification task related to data and data type prediction. Although the dataset and models of the project were not made publicly available, the development was entirely realized in Open Source.

To our knowledge there is currently no dataset and work with a broad coverage in terms of scientific domains. The existing works usually ignore unnamed mentions of data (with the exception of ODDPub and DataSeer). Although almost all are based upon a fine-tuned BERT, each recognizer greatly depends on domains, definition of datasets and on the distribution of dataset mentions in the training data. These differences make the reported accuracy values impossible to compare, as the distribution of mentions in the evaluation data varies considerably, being not realistic in general.

#### 4.5.2 Data model and training data

Dataset mentions are usually less complex than software mentions, but the exact scope of “research datasets” varies significantly from one existing work to another and needs some clarifications.

**Implicit versus explicit research datasets** Although the production of various data is very common in a scientific work, a large amount of the data discussed in scholarly articles are actually not named, not curated and not shared. For example:

```
The 47 tilapia DNA samples were sent to Beijing Genome Institute (BGI) for 101  
bp paired-end sequencing using Illumina Hiseq 2500. (10.1038/srep14168)
```

The Illumina Hiseq 2500 device produces sequencing data, which are part of the described study. However, this sequencing data is not named and not shared, it remains implicit. Knowledge about the field and the involved devices are necessary to infer that data is produced. We define this sort of research datasets as *implicit datasets*. These data are generally not considered as valuable by the researchers and often not in a sharable state (proprietary format, embedded as project resources). We consider fully automatic recognition of this kind of implicit datasets currently beyond what is feasible given the current existing annotated corpora and machine learning technique accuracy.

In contrast, in this work we focus on *explicitly mentioned datasets*, which we define as:

1. all named datasets,
2. unnamed datasets explicitly mentioned as existing data.

*Explicitly mentioned datasets* are research data identified as such by the authors, discussed and considered valuable with respect to the scientific claims of the publication. They are usually available in a form that makes sharing possible. Datasets related to 2) are unnamed data mentioned as used, produced or shared. They are usually referred to with generic substantive *data* or *dataset*, which can be annotated:

The **data** has been collected by the UN Comtrade organization (<https://comtrade.un.org/>), and cleaned by CEPII. (10.1371/journal.pone.0203915)

All the **data** were recorded after each sub-culture (at 3, 6 and 9 weeks). (10.1038/s41598-018-37335-7)

The **dataset** used in this study consist of natural products that have been tested for in-vitro antiplasmodial activities (NAA) compiled in-house from literature, PhD Theses and public chemical databases. (10.1371/journal.pone.0204644)

Similarly to software, a reference to a named dataset can be ambiguous and should be examined in context. For example, is a mention to a **database** the same as a mention to a dataset? If research data has been loaded and shared via this database, we can consider in general that this data are packaged as a dataset. On the other hand, a “dataset” can exist independently of a database management system and is not ambiguous with respect to its storage and software access environment. So, for deciding if a mention to a database can be considered as a valid dataset mention, one has to clarify if the research work is referring to the data stored in the database or more generally to the software or the service associated to the database.

In addition, we have defined the following main guidelines:



- *Data sharing initiative/project*: we currently exclude the mentions to initiatives, collaborations (HEP or Astronomy) and projects from our dataset extraction. Only mentions to individual research dataset or collection are considered as a “dataset”.
- *Accession number*: the references to an entry in a database, for instance via a unique identifier such as an accession number, is considered as a valid mention to a dataset.

**Training** Developing an annotated corpus of dataset mentions entirely from scratch would not have been possible for this project. The Softcite dataset for example took several years of development and involved a total of 38 different human annotators. To train our dataset mention recognizer, we reused existing annotated corpus, re-annotated them to follow our guidelines and produced some additional annotations for a limited subset.

As noted in section 4.5.1, the datasets of many existing work covering dataset mention recognition have not been made publicly available for reuse. In the case of the Coleridge Kaggle competition (“Coleridge Initiative - Show US the Data”, 2021), we found that the annotations were unreliable, inconsistent and highly incomplete (less than 70 distinct “datasets” annotated only in 8,000 documents). In addition, this effort was realized without a clear definition of a “dataset”. For example, a research initiative name such as ADNI could be labeled as “dataset” even in contexts not related to the datasets produced by this initiative. Unfortunately, the Coleridge dataset makes it impossible to apply state-of-the-art NER techniques without a considerable additional labeling effort and we could use it in a very limited manner, as explained below.

One additional challenge is that, to our knowledge, there is no annotation on a complete full text versions of the annotated articles, well adapted to tackle the sparsity problem on a real distribution. The existing training data are always sets of positive sentences with at least one dataset annotation. In general, there is no guarantee that the rest of these articles do not include other datasets and checking such a large amount of content is

highly time-consuming. To mitigate this issue, we divided the task in two steps, the first one to identify the data sentences in a complete article, and the second one to spot dataset mentions in selected data sentences.

The first step is implemented as data sentence classification model. We used 2,000 positive sentences containing at least one dataset mention and 20,000 negative data sentences without dataset mention from PubMed Central full-texts and from the Coleridge dataset. This combined dataset was used to fine-tune a LinkBERT-base binary classifier.

The second step is the dataset mention recognition in the identified data sentences. To train this model, we use the following resources:

- a re-annotated version of the dataset<sup>5</sup> developed by (Heddes et al., 2021), a set of 6,000 sentences in the IR/ML/NLP domain with 3,684 dataset mentions. We fully reviewed the dataset and re-annotated to follow our dataset annotation principles: it covers now new datasets (not just reused ones) with annotations at individual dataset level, avoid one annotation for a conjunction expression of datasets.
- a set of approx. 1000 sentences from PubMed Central full-texts with at least one dataset mention (named or unnamed datasets) and partial data acquisition device annotations.

These resources were used to train a LinkBERT base model (Yasunaga et al., 2022) with an additional CRF activation layer.

### **4.5.3 Accuracy**

As explained above, the first model is classifying if a sentence introduces a dataset or not. A 10-fold cross-validation on our dataset gives the accuracy presented in Table 7.

Similarly, we evaluate the mention recognition using 10-fold cross-validation on the an-

---

<sup>5</sup>[https://github.com/xjaeh/ner\\_dataset\\_recognition](https://github.com/xjaeh/ner_dataset_recognition)

Table 7: Evaluation scores for first-stage data sentence recognition.

	precision	recall	<b>F1-score</b>	support (10%)
<b>data sentence</b>	93.70	96.21	94.94	200
<b>not data sentence</b>	97.56	95.92	96.73	2000

notated dataset, see Table 8. In the actual application of the models, the second model is applied only to sentences detected as “data sentence”, so the error of the previous model detecting “data sentences” will be propagated to the second model. However, even combining the two error rates, the recognition of mentions of explicit datasets (dataset with names or without name but expressed as dataset or data) appears very reliable with the current amount of training data. This result supports the relevance of these extracted mentions for building indicators.

Table 8: Evaluation scores for dataset mention recognition in predicted data sentences.

	precision	recall	<b>F1-score</b>	support (10%)
<b>named dataset</b>	89.04	89.46	<b>89.24</b>	466
<b>unnamed mentioned dataset</b>	71.85	67.15	<b>69.38</b>	927
data device	51.91	37.94	42.61	97

At this stage, unnamed datasets are harder to recognize and will require additional training data and modeling efforts. We also present for reference the current recognition scores for data device mentions, but their manual annotations are still work-in-progress and very limited. We think that the automatic identification of data acquisition devices or data processing devices could help in the future to spot unnamed and implicit data in a more reliable way.

## 4.6 Characterization of mention contexts

Whether or not a research dataset or software mentioned in an article was used, created and shared is important to monitor the compliance with Open Science policies. We hypoth-

esize here that the wording used to introduce and describe a dataset or software mention can characterize its possible usage, creation and sharing. The sentences containing the mentions are used as classifier input, without additional features. As we observed that the wording used to describe the role of these mentions is very similar for dataset and software, we used the same classifiers for characterizing both research dataset and software mentions.

#### 4.6.1 Training data

The annotated data for training the classifiers are a combination of existing training data and additional manual annotation realized during the project:

- the *used* attribute of the Softcite dataset,
- the corresponding annotations in the SoMeSci dataset,
- a new additional set of 500 contexts manually annotated focusing more on datasets and the minority classes (*created* and *shared*).

Table 9 presents the distribution of classes in this assembled training dataset.

Table 9: Distribution in manually annotated training data of the classes for dataset and software mention characterization.

total contexts	3,643
used	2,774
not used	869
created	338
not created	3,305
shared	266
not shared	3,377

## 4.6.2 Accuracy

The evaluation scores presented in Table 10 are produced using 10-fold cross-validation based on three binary classifiers, one per class used/created/shared. The classifiers are fine-tuned LinkBERT base models (Yasunaga et al., 2022). Binary classifiers for each class perform significantly better than a single multiclass classifier (up to 4 F1-score points).

Table 10: Evaluation scores for dataset and software mention characterization.

	precision	recall	<b>F1-score</b>	support
<b>used</b>	96.83	94.18	<b>95.49</b>	292
<b>not used</b>	84.40	91.09	<b>87.62</b>	101
<b>created</b>	81.08	83.33	<b>82.19</b>	31
<b>not created</b>	98.31	98.04	<b>98.18</b>	362
<b>shared</b>	81.82	90.00	<b>85.71</b>	26
<b>not shared</b>	99.35	98.71	<b>99.03</b>	385

## 4.7 Recognition of availability statements

We have extended GROBID to identify data and code availability statements in research publications automatically. We define a data and/or code availability statements as a standalone section of a research publication (with a section title and one or several paragraphs) describing how the data and code involved in the research work can or cannot be accessed. Availability statements usually appear in the front page of an article or at the end as a annex, but we also considered positions inside the main body, which is not rare with preprints. We did not put any constraints on the section title associated to “data availability statements”. 95 articles out of the 520 training articles of the GROBID `segmentation` model have been further annotated with data availability section markups. This GROBID model is used to segment the main zone of a scientific article, such as header, body, bibliographical section, acknowledgement or funding. The data availability section is then structured and identified as such in the file TEI result file (TEI Consortium, 2010).

To cover the whole spectrum of possible difficulties, we evaluated the reliability of recognition on two set of high quality publisher publications and on one set of preprints:

- a set of 1000 random PLOS articles in PDF and JATS XML (2003-2022) containing 779 data and code availability statement markup information
- a set of 984 random eLife articles in PDF and JATS XML (from the complete eLife collection) containing 585 data availability statements markup information
- a set of 2000 random bioRxiv articles, which have been reviewed and completed manually, containing 473 data availability statements

Table 11 presents an evaluation of the accuracy of the data and code availability statement recognition in a end-to-end scenario with PDF as input.

Table 11: Evaluation scores for the automatic identification of Data Availability Statements. Datasets are available at <https://zenodo.org/record/7708580>.

collection	precision	recall	<b>F1-score</b>	support
PLOS 1000 articles	99.57	89.73	<b>94.4</b>	779
eLife 984 articles	96.62	92.82	<b>94.68</b>	585
bioRxiv 2000 articles	82.7	78.25	<b>80.41</b>	473

On recent publications (2020 and after), we observed that the presence of data availability sections is correctly recognized in nearly all PLOS and eLife documents. On the other hand, preprint data availability statements can be challenging to identify because they can appear in non-usual positions in the article. They can also be introduced by a large variety of section titles depending on the described data. In peer-reviewed publisher versions, we generally observe a high regularity and very high precision similar to PLOS/eLife articles.

## 4.8 Architecture of the mention recognizers

The dataset and software mention extraction processes are very similar and share a common software architecture summarized in Figure 1.

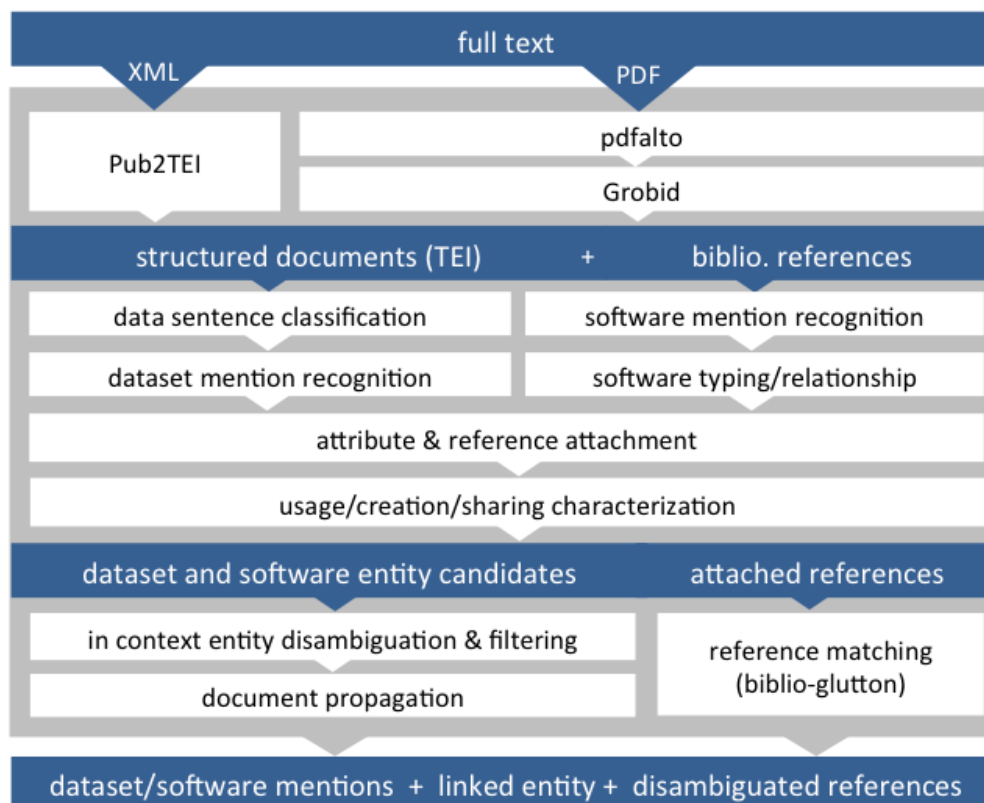


Figure 1: Overview of the dataset and software mention recognition process.

We expect input full texts to be in PDF formats, but a large range of publisher XML formats are also supported. PDF are first parsed with the Open source PDF parser library *pdfalto* (“pdfalto”, 2017–2023). Complementary to the support of ALTO output, a modern format for OCR output, pdfalto implements additional features relevant to scientific documents, in particular better handling of multi-column documents, the recognition of superscript/-subscript style and the robust recognition of line numbers for review manuscripts.

GROBID is then applied to structure the raw PDF stream into header, sections, paragraphs, footnotes, etc. Grobid applies in cascade a set of machine learning models to create hi-

erarchical structures, combining text content and layout features (e.g. font and style information, relative positions, SVG objects, etc.). Bibliographical references are also extracted and parsed. If the input is encoded in a publisher XML format, we transform the XML into the same TEI format as produced by GROBID thanks to the Open Source Pub2TEI tool, which support the main XML publisher formats such as JATS, Elsevier, Wiley, etc. We can therefore centralize our document processing across PDF and XML sources.

Mining for specific entities is only relevant to certain textual structures of a scientific document, such as paragraphs, abstracts, figure captions, etc. In the Softcite corpus, we calculated that, on average, 28% of publication content should be filtered out. This includes metadata (author, affiliations), bibliographical sections, table and figure content, formulas, headnotes, page numbers, reference markers, or some editorial annexes (like conflicts of interest). Relying on GROBID not only improves the quality of textual content, but also makes it possible to apply the text mining process to relevant structures only, avoiding possible sources of false recognition.

To identify software names and related attributes, a first mention recognition is applied to relevant textual structures. For identified software names, a second model is then applied to refine the software mention types. For recognizing datasets, two models are applied. A first classification model is applied to every sentences of the relevant textual structures to determine if the sentence is describing a dataset or not. A second model is applied on positive data sentences to identify dataset mention spans and attributes such as URL and bibliographical references. This division of the recognition task into two steps is introduced to mitigate the problem of lack of dataset annotations for complete documents, mentioned in the section 4.5.2.

Attachment of the bibliographical references in the context of the mentions are evaluated and if successful these bibliographical references are fully resolved against CrossRef DOI via the `biblio-glutton` service (“biblio-glutton”, 2018–2023). An entity disambiguation is



realized in context using *entity-fishing* (“entity-fishing”, 2016–2023) for every software mention candidates. If the candidates is significantly more likely scientific entities different from a software, the candidates are discarded to avoid likely false positives. Otherwise, if the software entity is a known disambiguated software present in Wikidata, the entity is linked via the resulting Q Wikidata identifier. Finally a document-level propagation is realized to identify possible overlooked dataset and software name matches in the same article in order to improve recall.

## **5 Application to the French Open Science Monitor**

### **5.1 Monitoring indicators**

To help steer French public policy, we have seen in section 1.3 that our indicators must meet several minimum quality conditions. In particular, indicators must have floors and ceilings that are easy to understand and interpret by the public, with ceiling values as objectives of a policy.

For research publications, the French Open Science Monitor reports the percentage of open access publications of the previous years. Each year the new indicators are recalculated and do not depend on the indicator of the previous years. The openness indicators vary between 0% and 100%, and 100% is the French National Open Science Plan objective for 2030.

For consistency and readability, we consider that the same requirements apply to indicators for research data and software. The mention detection uses the full-text of the publications as raw material. It is therefore straightforward to also propose indicators relating to the proportion of publications. As the methodology is similar for both datasets and software, the proposed indicators will be equivalent, replacing dataset by software.

## Research dataset and software notations and indicators

$n_{publication}$ : number of publications

$n_{text-mined}$ : number of text-mined publications

$n_{use}$ : number of text-mined publications that mention the usage of at least one dataset

$n_{create}$ : number of text-mined publications that mention the usage and the production of at least one of their datasets

$n_{share}$ : number of text-mined publications that mention the usage, the production and the sharing of at least one of their dataset

$$P_{text-mined} = \frac{n_{text-mined}}{n_{publication}} \quad (1)$$

$$I_{naive} = \frac{n_{share}}{n_{publication}} \quad (2)$$

$$I_{use} = \frac{n_{use}}{n_{text-mined}} \quad (3)$$

$$I_{create} = \frac{n_{create}}{n_{use}} \quad (4)$$

$$I_{share} = \frac{n_{share}}{n_{create}} \quad (5)$$

A direct indicator would be, for example, the proportion of publications that share a dataset as given by  $I_{naive}$  (2). This indicator is simple to understand, but has several shortcomings. First, concerning the denominator, not all publications can be analysed by Softcite and DataStet, because the PDF could not systematically be downloaded. It should therefore be replaced by the number of publications that have been processed. Second, we want to have indicators whose upper bound has interpretations matching the objectives of the public policy. For example, if the described research work does not require the use of any datasets or software, the article is not relevant for the sharing ratio. Thus, the notion of a publication that shares a dataset should be clarified as a publication that uses, creates and shares a dataset.

We therefore propose to monitor the modified key indicator  $I_{share}$  (5). Publications that do

not create a dataset are however also meaningful to understand which proportion of the publications is relevant for data sharing. Therefore, we propose to complete the analysis with the two additional indicators  $I_{use}$  (3) and  $I_{create}$  (4).

These three indicators  $I_{use}$ ,  $I_{create}$  and  $I_{share}$ , correspond to a funnel analysis. They give a global and separated view of all relevant cases: the bottom of the funnel corresponds to the shareable data, which is actionable and which we want to increase. The other two are more descriptive, but will provide insights for understanding the practices regarding data, particularly by breaking them down by subject area.

The three indicators can be further broken down by metadata facets of the publications: year of publication, disciplines, publishers, etc.

We supplement these indicators by providing also the ratio of publications where an explicit Data Availability Statement section has been recognized in the full text. Although Data Availability Statements offer no guarantee of actual sharing for various reasons (Gabelica et al., 2022), it allows the tracking of the evolution of adoption of this practice.

## 5.2 Infrastructure and runtime

Figure 2 outlines the overall automated processing of the full texts part of the BSO platform. After the harvesting phase of PDF documents, several machine learning modules are applied in parallel to extract structured information from the full text: GROBID, Softcite and DataStet. The different extracted mention annotations and metadata are analyzed and aggregated by a Python module to produce the indicators at document level. This module feeds an Elasticsearch instance, used to export a public data dump and as back-end for the different BSO related dashboards.

All the modules are deployed on a managed Kubernetes cluster provided by the public cloud OVHcloud. Unfortunately, the cloud provider did not make available GPU at the time of the run. We used 5 servers with 16 CPU 240GB RAM and 5 servers with 32 CPU

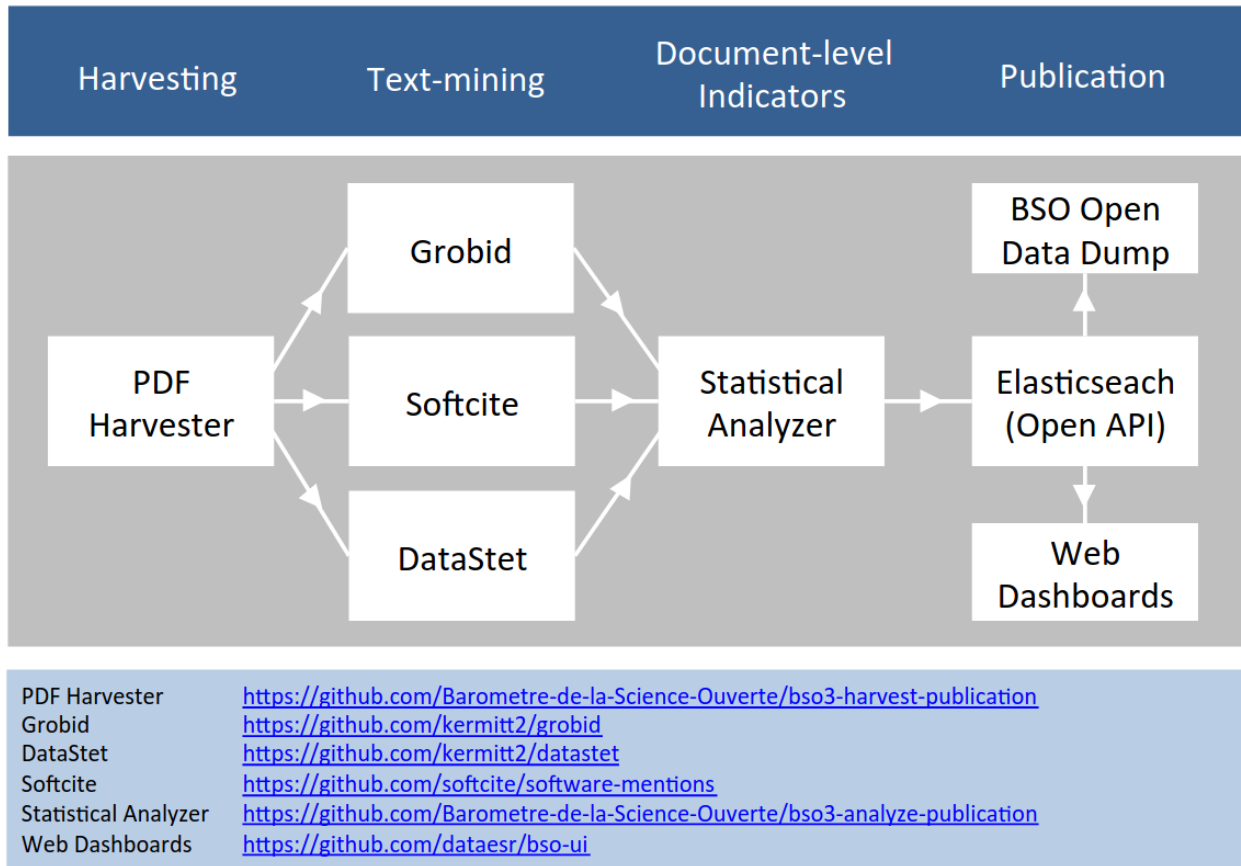


Figure 2: Global overview of the text-mining data flows

120GB RAM to deploy the GROBID, Softcite and DataStet services. An extra server is used to orchestrate all the service calls. Processing around 700k publications took about one month, longer than initially expected. To avoid delaying the scheduled release date of the new Monitor version, we did not process 100% of the downloaded publications as shown by Table 12 - something we expect to solve in the next year version by adjusting our computing capacities. For this reason, we currently present these new indicators on research datasets and software as *beta*. All the data resources are stored on secured cold storage, representing a total of 1.86TB.

### 5.3 Dataset and software mention extraction

Table 12 presents statistics on the number of documents processed by the text mining modules and the total of extracted mentions in the BSO published in early 2023 (period 2013-2021).

Table 12: Statistics on the proportion of text-mined publications in the French Open Science Monitor corpus covering 2013-2021.

	Publications 2013-2021		
	# documents	share (%)	# mentions
Full corpus	1,426,140	100.0	
Full texts downloaded	908,567	63.7	
Processed with GROBID	743,700	52.1	
Processed with Softcite	742,289	52.0	3,567,547
Processed with DataStet	621,306	43.6	5,607,080

Producing document-level indicators as defined in 5.1 is interesting in term of interpretability, but also for the sake of reliability. As the number of extracted mentions increases for one document, the number of observations for producing the indicators also increases.

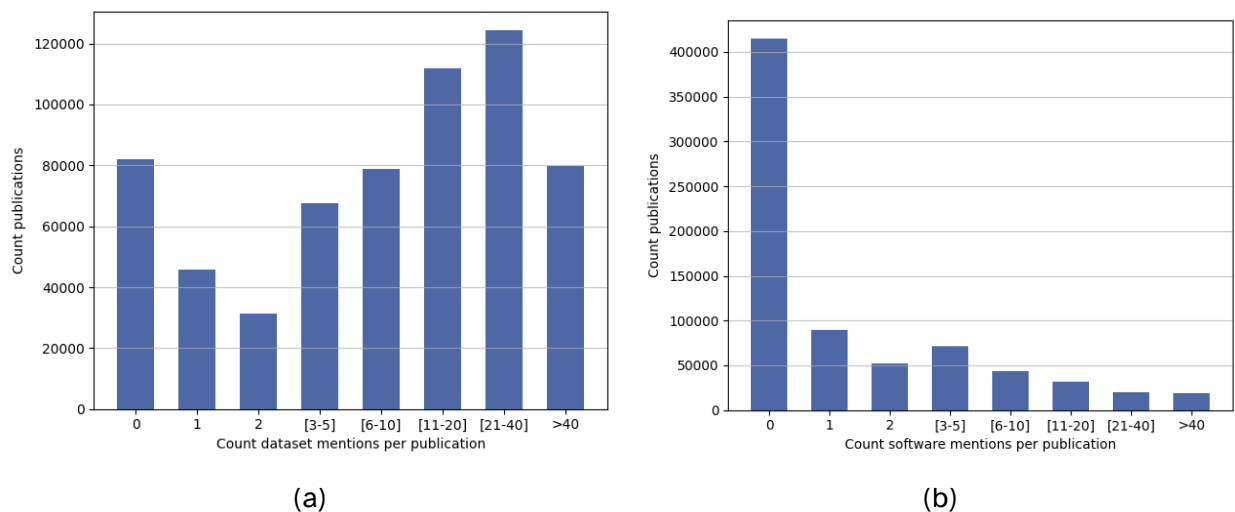


Figure 3: Distribution of documents by number of extracted mentions in the French Open Science Monitor corpus covering 2013-2021, for (a) datasets and (b) software.

Figure 3 shows the distribution of documents by number of extracted mentions. We see that for datasets, 462,486 documents have three or more extracted mentions (85% of all documents having at least one dataset mention), and for software 185,710 documents (56% of all documents having at least one software mention). Considering for instance an error rate at mention level at 15-20%, when several mentions are extracted this error rate follows a polynomial reduction. Several mentions similarly classified (as used/created/shared) consolidates the document-level indicator at higher certainty levels.

## 5.4 French Open Science Monitor indicators and dashboards

The first step of the funnel analysis described in section 5.1 focuses on the use of data in research works. Figure 4(a) shows that the majority of the publications is mentioning the use of data. It also reveals a positive trend over time, with almost 80% of processed publications mentioning the use of data for the publication year 2021.

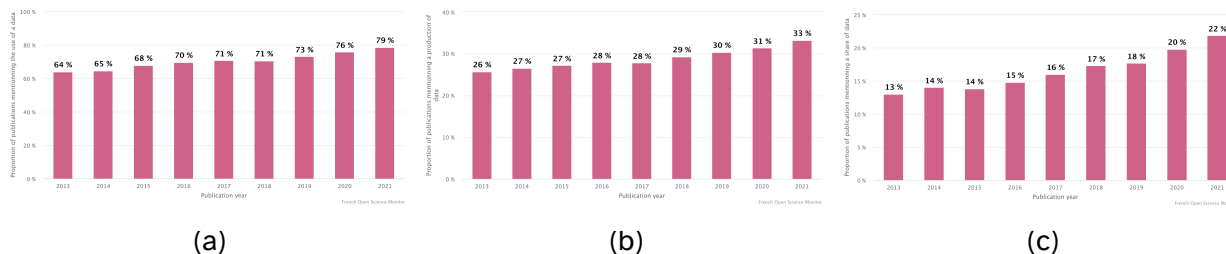


Figure 4: (a) Proportion of publications in France that mention the use of data. (b) Proportion of publications in France that mention having produced data. (c) Proportion of publications in France that mention the sharing of their data.

The second step of the funnel analysis focuses on the production of research data 4(b). It analyses, among the text-mined publications that mention the use of data, the proportion of the publications that also mention the production of data. Around one third of the text-mined publications mention having produced their data, and again the trends goes upwards over time.

The last step of the funnel analysis focuses on the sharing of the produced data 4(c). This indicator goes from 13% for the publications published in 2013 to 22% for the publications published in 2021.

The same funnel analysis conducted for research data is applied for software and code, present on Figure 5, showing lower ratio in all categories.

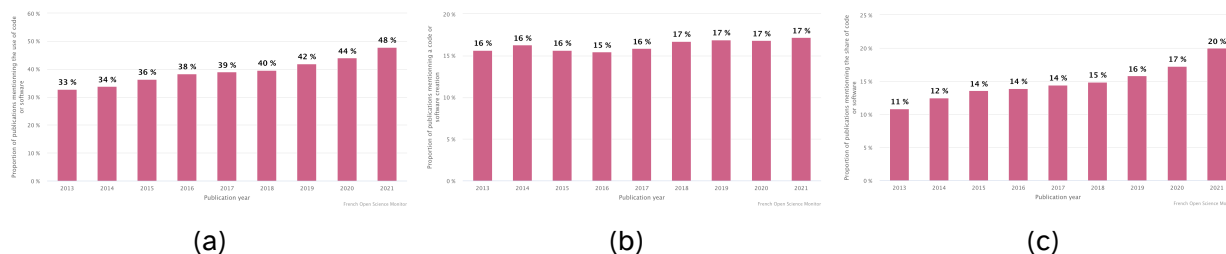


Figure 5: (a) Proportion of publications in France that mention the use of code or software. (b) Proportion of publications in France that mention having created code or software. (c) Proportion of publications in France that mention the sharing of their code or software.

As explained in section 4.7, we also tracked the proportion of publications that include a data and code availability statement section. As show in Figure 6, the upward trend is very strong, as this indicators goes from only 1% in 2013 to 21% in 2021.

## 5.5 Local versions of the Open Science Monitor

One of the objectives of the French Open Science Monitor is to provide all research institutions with a local version of the indicators. Similarly as for measuring the openness of research publications on the existing dashboard, the new indicators can be bounded to datasets and software produced by the researchers affiliated with a particular organization.

Not requiring any coding skills, more than 40 French research institutions have published their local monitor with the dataset and software indicators, as of May 2023. This capacity of simple customization has led to the creation of a French Open Science Monitor user

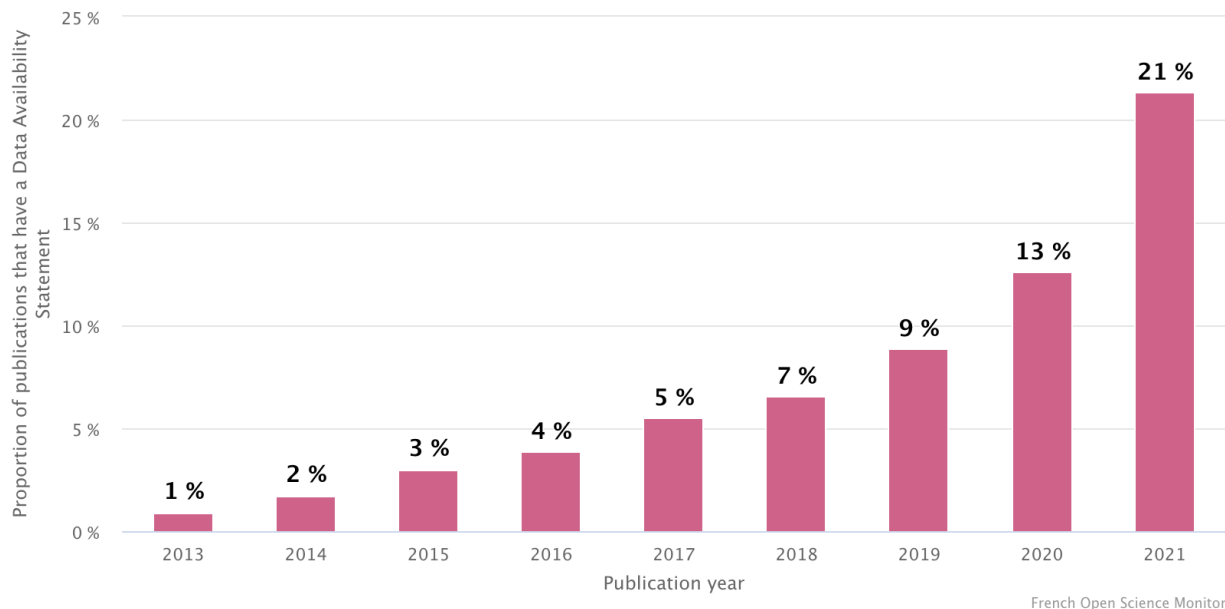


Figure 6: Proportion of publications in France including a Data Availability Statement.

group with more than 200 members.

## 6 Limitations and future work

**Corpus completeness** Several factors currently limit the completeness of our text mining processing framework:

- The creation of the country-wide corpus of publications is only covering articles with DOIs.
- In the current first version of the Monitor, around two thirds of the full texts have been successfully harvested.
- Only English content is currently supported by Softcite and DataStet.

We are aware that these factors, combined together, specifically impact certain scholar fields like Law, Social Science and Humanities. These fields have a lower adoption of DOIs, Open Access and publish more frequently in French.



We expect to increase both the coverage of publication by improving our affiliation matching and by further extending the collection to publications without DOI. The French monitor corpus already contains PhD thesis and all the documents indexed on the French open repository HAL, regardless of the presence of a DOI. These documents could potentially be analyzed to detect datasets and software mentions.

The effort required to the support of the French language by Softcite and DataStet will also be evaluated. Accordingly, a plan for producing additional training data in French will be planned for the next year.

**Performance across domains** Research dataset and software mention recognizers are currently limited by the relatively poor multidisciplinary coverage of the training data. (Lopez et al., 2021) shows that the recognition performance for software mention falls by around 15 points F1-score on an entirely new scientific domain.

To mitigate this issue, we have started new round of manual annotations on multiple domains with systematic model retraining and evaluation. We already observed that, as the global corpus grows, the required number of annotated documents to cover a new domain decreases. We think that we can realistically expect a relatively uniform accuracy of the recognizer across all scholar fields in the mid term.

**Large-scale research entity disambiguation** Recognizing dataset and software entities could make it possible to foresee indicators centered that are not only centered on documents, but also on global production of research datasets and software and their reuse. By recognizing and reporting data and software reuse among a large corpus of publications over time, researchers could receive credit and acknowledgement for the impact of their datasets and software. Such credit can be strong incentive for researchers to open their data and software, as well as producing better datasets and software over time. However dataset and software-level indicators presuppose that we are able to disam-

biguate different mentions of the same dataset and software entity. This task is complicated because software names tend to be very ambiguous and research datasets are mostly unnamed. In addition, no reference database of research software with uniform metadata exists today. We have started to explore mention disambiguation at scale, including referencing when possible datasets with DataCite entries and software with Software Heritage entries and we will assess the feasibility of dataset and software-level indicators in the future BSO.

**Local Open Science Monitor** Automatic affiliation-level identification is harder than country identification. Moreover, smaller institutions might not gather enough publications for the minority categories *production* and *sharing* on datasets and software for reliable trends over time. In order to partially mitigate these issues, the BSO includes the possibility to create local monitors based on a list of DOIs, which is relevant for institutions collecting the list of all their researcher publications for general reporting and evaluation purposes.

**Covering dataset repositories** While datasets associated to an existing publication are particularly important in the context of Open Science and scientific quality, other types of datasets might be developed without mentions in published research works. Some of them can simply be deposited on research dataset repositories. We think that an additional indicator following the global production of deposited datasets would complement the BSO and help to understand and drive research practices. However, poor affiliation metadata associated to datasets in repositories is an additional challenge. We are currently working on such an additional indicator, which is expected to be on air in the next BSO version.

## 7 Conclusion

The French Open Science Monitor shows, first, that quality indicators can rely on open bibliographical data only. Being independent from proprietary databases is an advantage in term of public trust, sovereignty and sustainability. Beyond research publications, our platform also demonstrates that reliable indicators on datasets and software openness can be developed thanks to modern text mining techniques at a large scale. This approach does not depend on the adoption of PID for these research products, which is currently too limited.

Even if indicators are estimates and not exact absolute values, we think that the relative trends over several years are reliable. First as the indicators are produced under the same conditions over time, consistent global trends are captured. Second, several mentions identified in the same document lead to very reliable document-level measurements because the global error rate margin is significantly reduced. Rather than perfect absolute measurements, reliable trends are enough to start following the impact of Open Science policies and adapt effort accordingly.

We expect that these techniques will also help us to explore other research measurements in the next version of the Monitor. Dataset and software-level citations and impact in particular can pave the way to new incentives to recognize and improve the production of datasets and software by scientists.

## References

- Beltagy, I., Lo, K., & Cohan, A. (2019). Scibert: A pretrained language model for scientific text.
- Biblio-glutton. (2018–2023). <https://github.com/kermitt2/biblio-glutton>

- Bracco, L., L'Hôte, Anne, Jeangirard, Eric, & Torny, Didier. (2022). Extending the open monitoring of open science: A new framework for the French Open Science Monitor (BSO). <https://hal.archives-ouvertes.fr/hal-03651518>
- Bretel, F., Lopez, P., Medves, M., Monteil, A., & Romary, L. (2010). Back to meaning - information structuring in the PEER project. *TEI Conference*. <https://inria.hal.science/inria-00537302>
- Chaignon, L., & Egret, D. (2022). Identifying scientific publications countrywide and measuring their open access: The case of the French Open Science Barometer (BSO). *Quantitative Science Studies*, 3(1), 18–36. [https://doi.org/10.1162/qss\\_a\\_00179](https://doi.org/10.1162/qss_a_00179)
- Chiticariu, L., Krishnamurthy, R., Li, Y., Reiss, F., & Vaithyanathan, S. (2010). Domain adaptation of rule-based annotators for named-entity recognition tasks. *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*, 1002–1012.
- Coleridge initiative - show us the data. (2021). <https://www.kaggle.com/competitions/coleridgeinitiative-show-us-the-data>
- Cousijn, H., Feeney, P., Lowenberg, D., Presani, E., & Simons, N. (2019). Bringing citations and usage metrics together to make data count. *Data Science Journal*, 18(1), 9. <https://doi.org/http://doi.org/10.5334/dsj-2019-009>
- Dataseer project. (2019–2023). <https://github.com/dataseer>
- Du, C., Cohoon, J., Lopez, P., & Howison, J. (2021). Softcite dataset: A dataset of software mentions in biomedical and economic research publications. *Journal of the Association for Information Science and Technology*, 72(7), 870–884. <https://doi.org/10.1002/asi.24454>
- Du, C., Cohoon, J., Lopez, P., & Howison, J. (2022). Understanding progress in software citation: A study of software citation in the CORD-19 corpus. *PeerJ Computer Science*, 8, e1022. <https://doi.org/10.7717/peerj-cs.1022>

- Duck, G., Kovacevic, A., Robertson, D. L., Stevens, R., & Nenadic, G. (2015). Ambiguity and variability of database and software names in bioinformatics. *Journal of biomedical semantics*, 6(1), 29.
- Elger, K., Biskaborn, B. K., Pampel, H., & Lantuit, H. (2016). Open research data, data portals and data publication—an introduction to the data curation landscape. *Polarforschung*, 85(2), 119–133.
- Else, H. (2018). The rise and rise of unpaywall. *Nature*, 560(7718), 290–291.
- Entity-fishing. (2016–2023). <https://github.com/kermitt2/entity-fishing>
- Gabelica, M., Bojčič, R., & Puljak, L. (2022). Many researchers were not compliant with their published data sharing statement: A mixed-methods study. *Journal of Clinical Epidemiology*, 150, 33–41. <https://doi.org/10.1016/j.jclinepi.2022.05.019>
- Garijo, D., Osorio, M., Khider, D., Ratnakar, V., & Gil, Y. (2019). Okg-soft: An open knowledge graph with machine readable scientific software metadata. *2019 15th International Conference on eScience (eScience)*, 349–358. <https://doi.org/10.1109/eScience.2019.00046>
- Grobid. (2008–2023). <https://github.com/kermitt2/grobid>
- He, L., & Han, Z. (2017). Do usage counts of scientific data make sense? an investigation of the dryad repository. *Library Hi Tech*, 35(2), 332–342. <https://doi.org/10.1108/LHT-12-2016-0158>
- Heddes, J., Meerdink, P., Pieters, M., & Marx, M. (2021). The automatic detection of dataset names in scientific articles. *Data*, 6(8). <https://doi.org/10.3390/data6080084>
- Hou, Y., Jochim, C., Gleize, M., Bonin, F., & Ganguly, D. (2019). Identification of tasks, datasets, evaluation metrics, and numeric scores for scientific leaderboards construction. *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 5203–5213. <https://doi.org/10.18653/v1/P19-1513>

- House, T. W. (2023). Fact sheet: Biden-harris administration announces new actions to advance open and equitable research [Accessed on May 17th, 2023]. <https://www.whitehouse.gov/ostp/news-updates/2023/01/11/fact-sheet-biden-harris-administration-announces-new-actions-to-advance-open-and-equitable-research/>
- Howison, J., & Bullard, J. (2016). Software in the Scientific Literature: Problems with Seeing, Finding, and Using Software Mentioned in the Biology Literature. *Journal of the Association for Information Science and Technology*, 67(9), 2137–2155. <https://doi.org/10.1002/asi.23538>
- Howison, J., Lopez, P., Du, C., & Cohoon, H. (2023). Softcite dataset version 2. <https://doi.org/10.5281/zenodo.7995565>
- Istrate, A.-M., Li, D., Taraborelli, D., Torkar, M., Veytsman, B., & Williams, I. (2022). A large dataset of software mentions in the biomedical literature. <https://arxiv.org/abs/2209.00693>
- Jain, S., van Zuylen, M., Hajishirzi, H., & Beltagy, I. (2020). Scirex: A challenge dataset for document-level information extraction. *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*.
- Jeangirard, E. (2019). Monitoring Open Access at a national level: French case study. *ELPUB 2019 23rd edition of the International Conference on Electronic Publishing, Academic publishing and digital bibliodiversity*. <https://doi.org/10.4000/proceedings.elpub.2019.20>
- Juty, N., Wimalaratne, S. M., Soiland-Reyes, S., Kunze, J., Goble, C. A., & Clark, T. (2020). Unique, persistent, resolvable: Identifiers as the foundation of fair. *Data Intelligence*, 2(1-2), 30–39.
- Katz, D., Chue Hong, N., Clark, T., Muench, A., Stall, S., Bouquin, D., Cannon, M., Edmunds, S., Faez, T., Feeney, P., Fenner, M., Friedman, M., Grenier, G., Harrison, M., Heber, J., Leary, A., MacCallum, C., Murray, H., Pastrana, E., ... Yeston, J. (2021). Recognizing

- the value of software: A software citation guide [version 2; peer review: 2 approved]. *F1000Research*, 9(1257). <https://doi.org/10.12688/f1000research.26932.2>
- Krüger, F., & Schindler, D. (2020). A Literature Review on Methods for the Extraction of Usage Statements of Software and Data. *Computing in Science Engineering*, 22(1), 26–38. <https://doi.org/10.1109/MCSE.2019.2943847>
- Lafia, S., Fan, L., & Hemphill, L. (2022). A natural language processing pipeline for detecting informal data references in academic literature. *Proceedings of the Association for Information Science and Technology*, 59(1), 169–178. <https://doi.org/https://doi.org/10.1002/pr2.614>
- Larregue, J., Vincent-Lamarre, P., Lebaron, F., & Larivière, V. (2020). Covid-19: where is the data? <https://doi.org/10.5281/zenodo.2585783>
- Laurinavichyute, A., Yadav, H., & Vasishth, S. (2022). Share the code, not just the data: A case study of the reproducibility of articles published in the journal of memory and language under the open data policy. *Journal of Memory and Language*, 125, 104332. <https://doi.org/https://doi.org/10.1016/j.jml.2022.104332>
- Lee, J., & Deleris, L. (2020). Sequencing, combining and sampling classifiers to help find needles in haystacks. *24th European Conference on Artificial Intelligence, ECAI*.
- L'Hôte, A., & Jeangirard, E. (2021). Using elasticsearch for entity recognition in affiliation disambiguation. <https://arxiv.org/abs/2110.01958>
- Lopez, P., Du, C., Cohoon, J., Ram, K., & Howison, J. (2021). Mining software entities in scientific literature: Document-level NER for an extremely imbalance and large-scale task. *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, 3986–3995. <https://doi.org/10.1145/3459637.3481936>
- Macgregor, G., Lancho-Barrantes, B. S., & Pennington, D. R. (2022). Exploring the concept of pid literacy: User perceptions and understanding of persistent identifiers in support of open scholarly infrastructure. *arXiv preprint arXiv:2211.07367*.

- McKenzie, L. (2017). Want to analyze millions of scientific papers all at once? here's the best way to do it. *Science*. <https://doi.org/10.1126/science.aan7139>
- MESR. (2018). National Plan for Open Science. [https://cache.media.enseignementsup-recherche.gouv.fr/file/Recherche/50/1/SO\\_A4\\_2018\\_EN\\_01\\_leger\\_982501.pdf](https://cache.media.enseignementsup-recherche.gouv.fr/file/Recherche/50/1/SO_A4_2018_EN_01_leger_982501.pdf)
- MESR. (2021). 2nd National Plan for Open Science. [https://cache.media.enseignementsup-recherche.gouv.fr/file/science\\_ouverte/20/9/MEN\\_brochure\\_PNSO\\_web\\_1415209.pdf](https://cache.media.enseignementsup-recherche.gouv.fr/file/science_ouverte/20/9/MEN_brochure_PNSO_web_1415209.pdf)
- Mooney, H. (2011). Citing data sources in the social sciences: Do authors do it? *Learned Publishing*, 24(2), 99–108. <https://doi.org/https://doi.org/10.1087/20110204>
- Nelson, A. (2022). Memorandum for the heads of executive departments and agencies - ensuring free, immediate, and equitable access to federally funded research [Accessed on May 17th, 2023]. <https://www.whitehouse.gov/wp-content/uploads/2022/08/08-2022-OSTP-Public-Access-Memo.pdf>
- Park, H., You, S., & Wolfram, D. (2018). Informal data citation for data sharing and reuse is more common than formal data citation in biomedical fields. *Journal of the Association for Information Science and Technology*, 69(11), 1346–1354. <https://doi.org/https://doi.org/10.1002/asi.24049>
- Pdfalto. (2017–2023). <https://github.com/kermitt2/pdfalto>
- Philippe, O., Hammitzsch, M., Janosch, S., van der Walt, A., van Werkhoven, B., Hettrick, S., Katz, D. S., Leinweber, K., Gesing, S., Druskat, S., Henwood, S., May, N. R., Lohani, N. P., & Sinha, M. (2019). softwaresaved/international-survey: Public release for 2018 results. <https://doi.org/10.5281/zenodo.2585783>
- Public Library of Science. (2023). PLOS Open Science Indicators. <https://doi.org/10.6084/m9.figshare.21687686.v2>
- Riedel, N., Kip, M., & Bobrov, E. (2020). Oddpub - a text-mining algorithm to detect data sharing in biomedical publications. *Data Science Journal*, 19(1), 42. <https://doi.org/http://doi.org/10.5334/dsj-2020-042>



- Schindler, D., Bensmann, F., Dietze, S., & Krüger, F. (2021). Somesci- a 5 star open data gold standard knowledge graph of software mentions in scientific articles. *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, 4574–4583. <https://doi.org/10.1145/3459637.3482017>
- Schindler, D., Bensmann, F., Dietze, S., & Krüger, F. (2022). The role of software in science: A knowledge graph-based analysis of software mentions in PubMed Central. *PeerJ Computer Science*, 8, e835. <https://doi.org/10.7717/peerj-cs.835>
- Science staff. (2011). Challenges and opportunities. *Science*, 331(6018), 692–693. <https://doi.org/10.1126/science.331.6018.692>
- Serghiou, S., Contopoulos-Ioannidis, D., Boyack, K., Riedel, N., Wallach, J., & Ioannidis, J. (2021). Assessment of transparency indicators across the biomedical literature: How open is open? *PLoS Biol*, 19(3), e3001107. <https://doi.org/https://doi.org/10.1371/journal.pbio.3001107>
- Sevryugina, Y. V., & Dicks, A. J. (2022). Publication practices during the covid-19 pandemic: Expedited publishing or simply an early bird effect? *Learned Publishing*, 35(4), 563–573. <https://doi.org/https://doi.org/10.1002/leap.1483>
- Silvello, G. (2018). Theory and practice of data citation. *Journal of the Association for Information Science and Technology*, 69(1), 6–20. <https://doi.org/https://doi.org/10.1002/asi.23917>
- TEI Consortium (Ed.). (2010). Guidelines for electronic text encoding and interchange. <https://www.tei-c.org/P5>
- Tenopir, C., Dalton, E. D., Allard, S., Frame, M., Pjesivac, I., Birch, B., Pollock, D., & Dorsett, K. (2015). Changes in data sharing and data reuse practices and perceptions among scientists worldwide. *PLOS ONE*, 10(8), 1–24. <https://doi.org/10.1371/journal.pone.0134826>

- Trienes, J., Trieschnigg, D., Seifert, C., & Hiemstra, D. (2020). Comparing Rule-based, Feature-based and Deep Neural Methods for De-identification of Dutch Medical Records. *Proceedings of the 1st ACM WSDM Health Search and Data Mining Workshop (HSDM2020)*.
- Vandewiele, G., Dehaene, I., Kovács, G., Sterckx, L., Janssens, O., Ongenae, F., De Backere, F., De Turck, F., Roelens, K., Decruyenaere, J., Van Hoecke, S., & Demeester, T. (2021). Overly optimistic prediction results on imbalanced data: A case study of flaws and benefits when applying over-sampling. *Artificial Intelligence in Medicine*, 111, 101987. <https://doi.org/10.1016/j.artmed.2020.101987>
- Westergaard, D., Stærfeldt, H.-H., Tønsberg, C., Jensen, L. J., & Brunak, S. (2017). Text mining of 15 million full-text scientific articles. <https://doi.org/10.1101/162099>
- Yasunaga, M., Leskovec, J., & Liang, P. (2022). Linkbert: Pretraining language models with document links. *Association for Computational Linguistics (ACL)*.
- Yousuf, R. B., Biswas, S., Kaushal, K. K., Dunham, J. W., Gelles, R., Muthiah, S., Self, N., Butler, P., & Ramakrishnan, N. (2022). Lessons from deep learning applied to scholarly information extraction: What works, what doesn't, and future directions. *ArXiv*, [abs/2207.04029](https://arxiv.org/abs/2207.04029).
- Zhao, H., Luo, Z., Feng, C., Zheng, A., & Liu, X. (2019). A context-based framework for modeling the role and function of on-line resource citations in scientific literature. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 5206–5215.

**Data and software availability** The data resulting from this work are publicly available on the French Ministry of Higher Education and Research open data portal: dataset, <https://doi.org/10.57745/456JF7> (DOI validation currently pending).

Softcite corpus version 2.0 is available at Zenodo, <https://doi.org/10.5281/zenodo.7995565>. The revised manually annotated corpus of dataset mentions at sentence level is available

at Zenodo, <https://doi.org/10.5281/zenodo.8033739>. The annotated corpus of mention context characterizations is available at Zenodo, <https://doi.org/10.5281/zenodo.8033868>. Datasets relative to Data Availability Statement recognition are part of the Grobid annotated data (available at <https://github.com/kermitt2/grobid>) and evaluation datasets are available at Zenodo, <https://zenodo.org/record/7708580>.

The source code used for the French Open Science Monitor is available on GitHub under the organization <https://github.com/Barometre-de-la-Science-Ouverte>, under MIT or Apache 2 licenses. The web dashboards of the monitor are available at <https://github.com/dataesr/bso-ui>.

The source code, documentation and releases of the following tools are available under Apache 2 licenses (except when indicated) as indicated below:

- Softcite software mention recognizer: <https://github.com/softcite/software-mentions>
- DataStet: <https://github.com/kermitt2/datastet>
- Grobid : <https://github.com/kermitt2/grobid>
- Pub2TEI: <https://github.com/kermitt2/Pub2TEI> (MIT)
- entity-fishing: <https://github.com/kermitt2/entity-fishing>
- biblio-glutton: <https://github.com/kermitt2/biblio-glutton>
- pdfalto: <https://github.com/kermitt2/pdfalto> (GPL-2.0)

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