Automated Observatory Contributors' Handbook

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Big Data for All

We want to make sure that every individual research, artists, professional, NGO, small and large organization can take equal benefit in the era of big data from artificial intelligence.

Big data creates injustices, because it is the big corporations, big government agencies and the biggest, best endowed universities that can finance long-lasting, comprehensive data collection. Big data, and large, well-processed, tidy and imputed datasets allow them to unleash the power of machine learning and AI. They create algorithms that decide the commercial success of your product, your artwork, gives them a competitive edge against smaller competitors and helps them evade regulations.

We are looking for partners to develop our technological solution in financially sustainable way with bringing more and more relevant, curated open data to light. Our Product/Market Fit was validated in the world's 2nd ranked university-backed incubator program, the Yes!Delft AI Validation Lab. We are currently developing this project with the help of the JUMP European Music Market Accelerator program.

How We Add Value To Your Data?

Many countries in the world allow access to a vast array of information, such as documents under freedom of information requests, statistics, datasets. In the European Union, most taxpayer financed data in government administration, transport, or meteorology, for example, can be usually re-used. More and more scientific output is expected to be reviewable and reproducible, which implies open access.

We create high value key business indicators, policy evaluation indicators, scientific proofs require the combination of matching, well formatted, and verified, controlled pieces of data. It comes from a verified and legal source, with information about use rights and its complete history. We do not deal in blood diamonds.

Adding metadata exponentially increases the value of dataDid your region added a new town to its boundaries – how do you adjust old data? Can I practically combine satellite sensory data with my organization records? And do I have the right? Metadata logs the history of the data, gives instructions who to reuse it in indicators, sets the terms of use. We automate this boring and labor-intensive process applying the FAIR data concept.

Data is only potential information, raw and unprocessed.How I translate dollars to euros correctly? Are millions adjusted for billions? Some of our indicators go through more than 10,000 processing steps. If your team does this in a spreadsheet or statistical software, there is no way it will be faultless - or that senior staff can verify it.

Data curationData sits in every government data warehouse (you can reuse it!), scientific journal, library, your sales records, in sensors. Not having access to it due to budgetary or legal constraints is an absolute barrier, but not being able to correctly assemble it into reliable information can keep its value low.

- In the **??**. Open Data chapter we investigate why not even those organizations, like the European Commission, use open data in their own data dissemination practices, who make them at least legally available. The idea of open data is that it can reduce your material data costs, because

it gives you access to data that was created at your tax expense by governmental agencies or universities. The problem main problem with *open data* is that while it is legally accessible, and often cost-free, it in most cases not findable, and not even accessible directly. While the EU has policies since 2003 about making taxpayer funded data reusable, it did not make much technical steps to make this a reality. Reusability of governmental data and scientific data is a right, but not a practical possiblity for most users.

- In the **??**. FAIR Data and the Added Value of Rich Metadata we introduce how we apply the concept of FAIR (**f**indable, **a**ccessibe, **i**nteroperable, and **r**eusable of digital assets) in our APIs. Metadata does not relate to material data acquistion costs, but in fact, it is probably even more important: it is responsible for your non-billable hours, or the uncredited working hours in academia. Poor data documentation, lack of reproducible processing and testing logs, inconsistent use of currencies, keywords, and storing messy data makes reusability impossible. Organization pay many times for the same, repeated work, because these boring tasks, which often comprise of tens of thousands of microtasks, are neglected. Our solution creates automatic documentation and metadata, if necessary, to your own historica internal data or acquisitions from data vendors. We apply the more general Dublin Core and the more specific, mandatory and recommended values of DataCite for datasets – these are new requirements in EU funded research from 2021. But they are just the minimal steps, and there is a lot more to do to create a diamond ring from an uncut gem.
- In the **??**. Application: Automated Data Observatories chapter we provide further technical information about our application. We use open-source software and open data. The applications are hosted on the cloud resources of Reprex, an early-stage technology startup currently building a viable, open-source, open-data business model to create reproducible research products. Our development team works on an open collaboration basis. Our indicator R packages, and our services are developed together with rOpenGov.
- See **??**. Service Design and Business Case Development we lay out our ideas about finding a suitable business model for data sharing, and shared research activities that maintains the fairly shares the exponential value added from data integration across various business, policy, and academic partners.
- The **??**. Data Curators chapter we give information for prospective curators. See also our get inspired and your first contribution subchapters.

Big Data For All

Machine learning and AI gives a competitive edge for large companies and governments that can exploit it. But training algorithms requires much, uniformly formatted, high quality data, and algorithms come with many potential side effects.

Trustworthy AIWe help deploying reliable AI that is under human supervision, and algorithms that will not turn against your organization, or engage in discriminative, unlawful, or counterproductive behavior. We automate data and metadata management, documentation, verification, because computers are much better than humans in these boring tasks; humans must increasingly focus on oversight of too much data.

Open collaboration for data treasuresWe use the agile open collaboration project methodology of open source software development to make sure that large universities, consultancies, citizen scientists, individual artists and small NGOs can share the research budget, data assets and research of big data, and remain competitive against big tech and large organizations.

Data-as-Service.Most organizations cannot afford to build an in-house data science and data engineer team, or they do not even have in-house market research or IT. Instead of burdening your team with manual data downloads and ad hoc data manipulations, we offer you subscription for curated open and proprietary processed data. We keep all your data assets tidy, documented, and easy to use.

Automated Data ObservatoriesData sits in every government data warehouse (you can reuse it!), scientific

journal, library, your sales records, in sensors. Not having access to it due to budgetary or legal constraints is an absolute barrier, but not being able to correctly assemble it into reliable information can keep its value low. Our observatories are built around open collaborations of scientific, business, public and NGO policy partners.

Automated Data Observatories

We are working around the open collaboration concept, which is well-known in open source software development and reproducible science, but we try to make this agile project management methodology more inclusive, and include data curators, and various institutional partners into this approach. Based around our early-stage startup, Reprex, and the open-source developer community rOpenGov, we are working together with other developers, data scientists, and domain specific data experts in climate change and mitigation, antitrust and innovation policies, and various aspects of the music and film industry.

Green Deal Data Observatoryis a modern reimagination of existing 'data observatories'; currently, there are over 70 permanent international data collection and dissemination points. One of our objectives is to understand why the dozens of the EU's observatories do not use open data and reproducible research. We want to show that open governmental data, open science, and reproducible research can lead to a higher quality and faster data ecosystem that fosters growth for policy, business, and academic data users. Find it on the web and on social media: the Green Deal Data Observatory on Linkedin and the Green Deal Data Observatory on Twitter, and join our contributor team.

Digital Music Observatoryis a fully automated, open source, open data observatory that creates public datasets to provide a comprehensive view of the European music industry. It provides high-quality and timely indicators in all four pillars of the planned official European Music Observatory as a modern, open source and largely open data-based, automated, API-supported alternative solution for this planned observatory. The insight and methodologies we are refining in the DMO are applicable and transferable to about 60 other data observatories funded by the EU which do not currently employ governmental or scientific open data. Find it on the web and on social media: the Digital Music Data Observatory on Linkedin and the Digital Music Data Observatory on Twitter and join our contributor team.

is the first offspring of the Economy Data Observatory incubator. See further details in **??** Competition Data Observatory Chapter. We would like to create early-warning, risk, economic effect, and impact indicators that can be used in scientific, business and policy contexts for professionals who are working on re-setting the European economy after a devastating pandemic and in the age of AI. We would like to map data between economic activities (NACE), antitrust markets, and sub-national, regional, metropolitan area data. See the prototype on the web.

The Economy Data Observatory works now as an incubator for economy-focused data observatories. Find it on the web and on social media: Economy Data Observatory on Linkedin; Economy Data Observatory on Twitter. Join our contributor team!

Chapter 1

Open Data

In the EU, open data is governed by the Directive on open data and the re-use of public sector information - in short: Open Data Directive (EU) 2019 / 1024. It entered into force on 16 July 2019. It replaces the Public Sector Information Directive, also known as the *PSI Directive* which dated from 2003 and was subsequently amended in 2013.

- Open Data - The New Gold Without the Rush
- Open Data is Like Gold in the Mud Below the Chilly Waves of Mountain Rivers

Poor quality, needs reprocessingOpen data quality is usually poor. You even need to reprocess datasets of statistical organizations or official data observatories.

Undocumented, no reuse informationThe most open data is impossible to find or reuse because of the lacking administrative, descriptive and processing metadata.

Data is only potential information, raw and unprocessed.Open data is always messy. If you make the many hundred, thousand, or ten thousand little steps to clear it manually, than your work will be error-prone, and very difficult for internal or external auditors to check.

Data curationData sits in every government data warehouse (you can only legally reuse it), scientific repositories, libraries, your sales records, in sensors. Our automated data observatories help them bringing up to the sunlight.

The EU has an 18-year-old open data regime, and it makes public taxpayer-funded data in the values of tens of billions of euros per year; the Eurostat program alone handles 20,000 international data products, including at least 5,000 pan-European environmental indicators.

As open science principles gain increased acceptance, scientific researchers are making hundreds of thousands of valuable datasets public and available for replication every year.

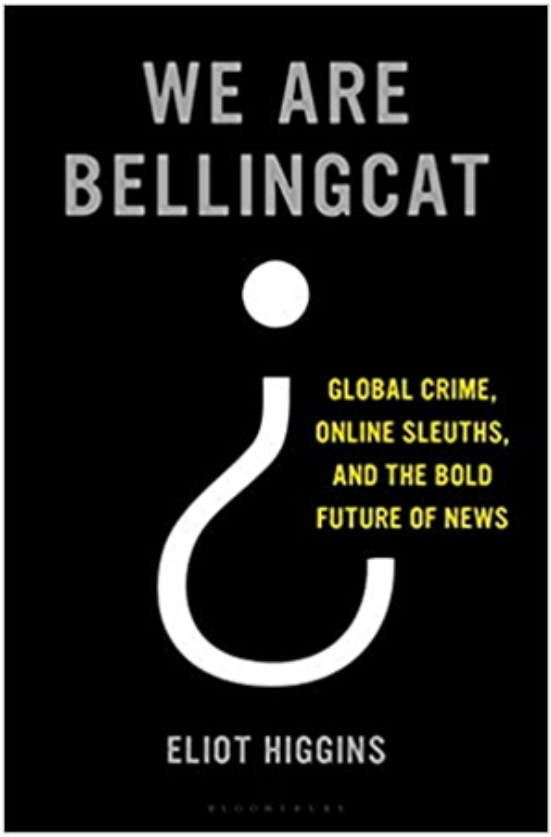
The EU, the OECD, and UN institutions run around 100 data collection programs, so-called 'data observatories' that more or less avoid touching this data and buy proprietary data instead. Annually, each observatory spends between 50 thousand and 3 million EUR on collecting untidy and proprietary data of inconsistent quality, while never even considering open data.

The problem with the current EU data strategy is that while it produces enormous quantities of valuable open data, in the absence of common basic data science and documentation principles, it seems often cheaper to create new data than to put the existing open data into shape.

This is an absolute waste of resources and efforts. With a few R packages and our deep understanding of advanced data science techniques, we can create valuable datasets from unprocessed open data. In most domains, we can repurpose data originally created for other purposes at a historical cost of several billions of euros, converting these unused data assets into valuable datasets that can replace tens of millions' worth of proprietary data.

What we want to achieve with this project – and we believe such an accomplishment would merit one of the first prizes - is to add value to a significant portion of pre-existing EU open data (for example, available on data.europa.eu/data) by re-processing and integrating them into a modern, tidy database with an API access, and to find a business model that emphasises a triangular use of data in 1. business, 2. science and 3. policy-making. Our mission is to modernize the concept of `data observatories`.

OSINT & Open-Sour



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Stunt Geolocation - Ver

MH17 Russia

Examining the MH17 La

Investigathon MH17

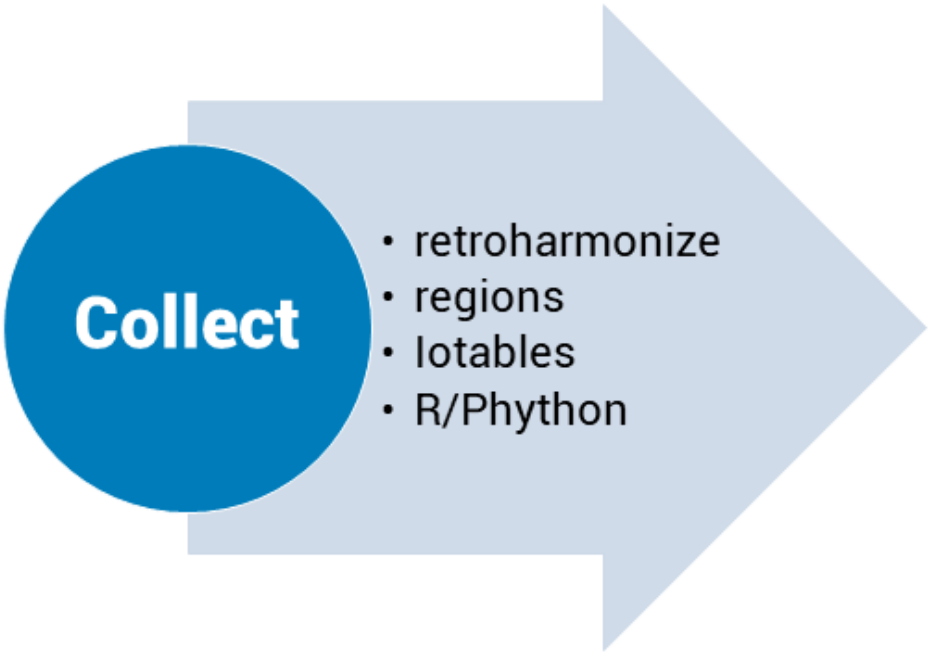
Investigathon - War and
Investigations

MH17 Russia

Geolocating the June Ru
Millerovo

1.1 How We Add Value to Open Data

While the EU announces every year that again billions and billions of worth data became “open” again, this is not gold. At least not in the form of nicely minted gold coins, but in gold dust and nuggets found in the muddy banks of chilly rivers. There is no rush for it, because panning out its value requires plenty of hard work. We are trying to automate this work to make open data useable at scale, even in trustworthy AI solutions.



Our retroharmonize, regions and iotables software has e
The users are potential collaborators to pan out more op

Most open data is not public, it is not downloadable from the Internet – in the EU parlance, "open" only means a legal entitlement to get access to it. And even in the rare cases when data is open and public, often it is mired by data quality issues. We are working on the prototypes of a data-as-serve and research-as-service built with open-source statistical software that taps into various and often neglected open data sources.

We are in a prototype phase in June, but we hope that we will have a well-functioning service by the time of the conference, because we are working only with open-source software elements; our technological readiness level is already very high. The novelty of our process is that we are trying to further develop and integrate a few open-source technology items into a technologically and financially sustainable data-as-service and even research-as-service solutions.

We decided to take a new, modern approach to the 'data observatory' concept, and modernize it with the application of 21st century data and metadata standards, the new results of reproducible research and data science. See **??**. Service Design and Business Case Development

1.2 Research Automation

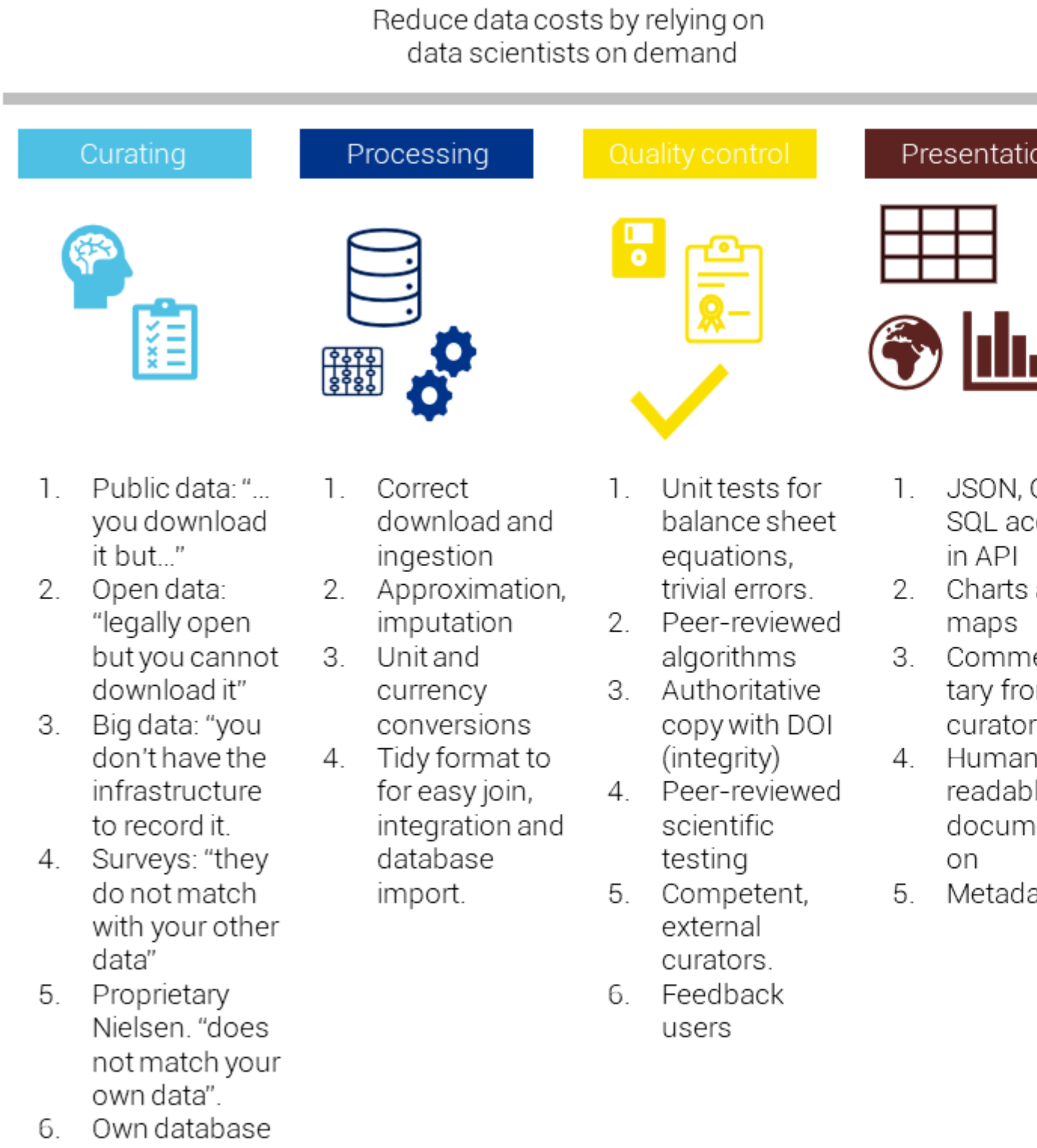
1. Our **curators** help finding the best available information source. This is often open data, which is not equal to public data. Open data is a governmental or scientific data source which you can legally access. It is almost never available for direct download and requires much processing. You could probably do this in Excel -– if the data were not in various `sql`, `pdf`, `sav`, `csv`, `tsv`, `xls` and various other file formats.
2. **We process the data**: Yes, anybody can convert from millions of euros to euros in a spreadsheet, tons to kilograms, maybe even ounces to grams, but many unit conversions are error-prone if done by humans. Not everybody can make valid currency translations (*When do I use year-end USD/EUR rate? Today's EUR/GBP? Or GBP/EUR? Annual average rate?*) We do this processing in a way that conforms to the tidy data definition, which allows easy integration, joining, and importing of data into your database. While the unit conversions can be automated in Excel or PowerBI, the data tidying requires a more programatic approach.
3. **Quality control**: Our data goes through dozens of computer logical checks (*Do assets and liabilities match? Do dollar and euro amounts lead to the same result?*) Our algorithms go through automated and human statistical peer-review, and are open to your experts for checking, because transparency and openness allow for the best quality control. This unit testing is not really possible in Excel or Power BI, not to mention the senior supervision of such tasks. To maintain data integrity, we place an authoritative copy with a digital object identifier in the Zenodo scientific data repository. We place both our algorithms and our methods into peer-reviewed scientific publications, and our data products are checked and improved by competent experts in the field.
4. **We produce** the data and its visualization in easy to reuse, machine-readable, platform-independent formats. Just like that, `csv`, `json`, `jpg`, `png`, `doxc`, `epub`, `pdf`, `pptx`, `odt`, `sav`, you name it, we do it.

Reproducible research is a scientific concept that can be applied to a wide range of professional designations, such as accounting, finance or the legal profession. We are applying this concept to Evidence-based, Open Policy Analysis and Professional Standards in Business, including, for example, reproducible finance in the investment process or reproducible impact assessment in policy consulting. Based on computational reproducibility we believe that the following principles should be followed:

- **Reviewability** means that our application's results can be assessed and judged by our user's experts, or experts they trust.
- **Reproducibility** means that we provide data products and tools that allow the exact duplication of our results during assessments. This ensures that all logical steps can be verified.
- **Confirmability** means that using our applications findings leads to the same professional results

as other available software and information. Our data products use the open-source statistical programming language R. We provide details about our algorithms and methodology to confirm our results in SPSS or Stata or sometimes even in Excel.

- **Auditability** means that our data and software is archived in a way that external auditors can later review, reproduce and confirm our findings. This is a *stricter form of data retention* than most organizations apply because we do not only archive results step-by-step but all computational steps – as if your colleagues would not only save every step in Excel but also their keystrokes. Read more about this topic here.


Reduce data costs by relying on data scientists on demand
Curating
Processing
Quality control
Presentatic
1. Public data: "... you download it but..."
2. Open data: "legally open but you cannot download it"
3. Big data: "you don't have the infrastructure to record it.
4. Surveys: "they do not match with your other data"
5. Proprietary Nielsen. "does not match your own data".
6. Own database
1. Correct download and ingestion
2. Approximation, imputation
3. Unit and currency conversions
4. Tidy format to for easy join, integration and database import.
1. Unit tests for balance sheet equations, trivial errors.
2. Peer-reviewed algorithms
3. Authoritative copy with DOI (integrity)
4. Peer-reviewed scientific testing
5. Competent, external curators.
6. Feedback users
1. JSON, C SQL ac in API
2. Charts maps
3. Comme tary fro curator
4. Human readabl docum on
5. Metada

1.2.1 Reproducible Research

Reproducible research is a scientific concept that can be applied to a wide range of professional designations. We are applying this concept to Evidence-based, Open Policy Analysis and Professional Standards in Business, for example, reproducible finance in the investment process or reproducible impact assessment in policy consulting. Based on the computational reproducibility we believe that the following principles should be followed.

- **Reviewability** means that we are providing data products and tools that allow the exact duplication of our results during assessments. This ensures that all logical steps can be verified. Reproducibility ensures that there is no lock-in to our applications. You can always choose a different data and software vendor or compare our results with them.
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- **Confirmability** means that using our applications findings leads to the same professional results as other available software and information. Our data products use the open-source statistical programming language R. We provide details about our algorithms and methodology to confirm our results in SPSS or Stata or sometimes even in Excel.
- **Auditability** means that our data and software is archived in a way that external auditors can later review, reproduce and confirm our findings. This is a *stricter form of data retention* that most organizations apply because we do not only archive results step-by-step but all computational steps – as if your colleagues would not only save every step in Excel but also their keystrokes. While auditability is a requirement in accounting, we are extending this approach to all the quantitative work of a professional organization in an advisory or consulting capacity.
- **Reviewable findings**: The descriptions of the methods can be independently assessed, and the results judged credible. In our view, this is a fundamental requirement for all professional applications. CEEMID's music data is used to settle royalty disputes in judicial procedures, or in grant and policy design. We believe that the future European Music Observatory should aim at the same bar, making its data & research products open for challenges in the publicity of science, courts, and professional peers.
- **Replicable findings**: We are presenting our findings and provide tools so that our users or auditors or external authorities can duplicate our results.
- **Confirmable findings**: The main conclusions of the research can be obtained independently without our software because we describe in detail the algorithms and methodology in supplementary materials. We believe that other organizations, analysts, statisticians must come to the same findings with their own methods and software. This avoids lock-in and allows independent cross-examination.
- **Auditable findings**: Sufficient records (including data and software) have been archived so that the research can be defended later if necessary or differences between independent confirmations resolved. The archive might be private, as with traditional laboratory notebooks. See Open collaboration with academia, auditors, and industry.

These computational requirements require a data workflow that relies on further principles.

- **Record retention**: all aspects of reproducibility require a high level of standardized documentation. The standardization of documentation requires the use of standardized metadata, metadata structures, taxonomies, vocabularies.
- **Best available information / data universe**: the quality of the findings, their confirmation and auditing success will improve with better data and facts used.

- **Data validations**: The quality of the findings will greatly depend on the factual inputs. While the reproducible findings may have many problems, inputting erroneous data or faulty information will likely lead to wrong conclusions, and in all cases will make confirmation and auditing impossible. Especially when organizations use large and heterogeneous data sources, even small errors, such as erroneous currency translations or accidental misuse of decimals, units can cause results that will not pass confirmation or auditing.

Chapter 2

FAIR Data and the Added Value of Rich Metadata

Adding metadata exponentially increases the value of dataDid your region added a new town to its boundaries – how do you adjust old data? Can I practically combine satellite sensory data with my organization records? And do I have the right? Metadata logs the history of the data, gives instructions who to reuse it in indicators, sets the terms of use. We automate this boring and labor-intensive process applying the FAIR data concept. We provide you with polished data, or we process your uncut dataset diamonds to shape.

We are providing a comprehensive, automated solution to problems that are not so much related to the data itself, but the information, documentation of the data, i.e. the metadata, and the structure how the data is stored. These problems create countless non-billable hours in professional services, or daunting extra work in research institutions that do not result in credited publications and other research output. These problems should be eliminated or handled by computers. We believe that the most value in our research automation comes from the documentation automation, which adds automatically rich descriptive, administrative and processing metadata to your data assets.

Lack of clarity with respect to: - The legal consequences of reusing a dataset. Do licensing restriction apply? What are the correct attributions to creators, contributors, publishers? - Who checked the reliability of the dataset? Did it change? - It is unclear what is the content of a data file. Who used it, who controlled it, does it need further work? The description is missing or difficult to use. There are no systematic keywords applied to the files, data, and it is impossible to run a search on your computer that will deliver the right asset. - Is this the latest verion of the dataset? Is there a new version available somewhere? Did somebody recast the data, did corrections take place? This can be particularly labor intensive to check if you use external data sources.

The lack of reusability: - If you open a dataset, you need to make several moves with your mouse or apply several keystrokes (all error-prone and generate new supervisory, control taks) before you can start analyzing or visualizting the data. Generally, as soon as you need to use a mouse, plenty of new work and cost is generated. - What are the units or currency rates used? Is the data expressed in euros, milions of euros? Do you need to translate dollars to euros on the average rate, the spot rate? What is the functional currency of the problem? - The data cannot be easily imported, further processing is needed before you can add it a relational database. Tidy data can be imported without further work. - The data has many versions in your organization. - Corrections were not logged, and before using it or handing it over to a client, all verification processes must be repeated, even though they may have been done several times in the past.

Potential mistakes during use: - Wrong currency translations, or wrong type of financial data merged. - Annual, year end data divided by annual, middle of the year data. - Accidentally units recorded in

thousands of euros and euros are mixed up. - During tidying a digit is entered accidentally to the keyboard. Or a field is erased.

Some of these problems are controled by database schemas, but database schemas are rigid and most workers do not like to work with them. We use different schemas that are not as strict as schemas applied in databases, and we use automation software that applies these schemas to documents and data has been created by your colleagues in the past without reference to schemas. We apply instead the FAIR Data concept stands for **f**indable, **a**ccessibe, **i**nteroperable, and **r**eusable of digital assets, for example, when we re-create a missing codebook to a survey documentation that was carried out years ago.

The problem with Open Data is that while it is legally *accessible*, and often cost-free, it in most cases *not findable*, and not even accessible directly. While the EU has policies since 2003 about making taxpayer funded data reusable, it did not make much technical steps to make this a reality. Reusability of governmental data and scientific data is a right, but not a practical possiblity for most users. The data may sit in various historical file formats, without documentation.

Interoperability means that you can use governmental open data, scientific open data, your own system's data, your membership organizations shared resources, and data subscriptions together. A special case of lack of interoperability when you do not know if you are facing a legal risk from using a data resource.

In our experience, in most research-driven organizations, such as consultancies, law firms, university research groups, NGOs and public policy bodies, reusability is mainly limited by poor data documentation, and sometimes by the use of of obsolete proprietary file formats. Documentation in the short run is not always a necessity, and it belongs to the non-billable hours, or among the tasks that do not really count in a researchers' promotion. The poor documentation however makes it extremely demanding to re-use a data or document a few years from now. From 2021, if you apply for Horizon Europe funding, your research output must meet basic findability and reusability criteria.

- Our data comes with metadata that meets the requirements of two metadata standards, the more general Dublin Core and the more specific, mandatory and recommended values of DataCite for datasets. We go even further, we add rich processing metadata beyond these requirements. These are not only nice to have: from 2021, if you apply for Our solution can automate this process, and besides making you compliant, it adds a lot of value to your own data management.
- We are making our data-as-service APIs FAIR by automatically adding to our data standardized metadata that fulfills the mandatory requirements of the Dublic Core metadata standards and at the same time the mandatory requirements, and most of the recommended requirements of DataCite.
- Furthermore, we apply the tidy data concept to our partners data assets. The tidy data principle applies a certain structure to datasets that facilitates immediate use and reuse.

2.1 FAIR

In 2016, the **FAIR Guiding Principles for scientific data management and stewardship** were published in *Scientific Data*. The authors intended to provide guidelines to improve the **F**indability, **A**ccessibility, **I**nteroperability, and **R**euse of digital assets. The principles emphasize machine-actionability (i.e., the capacity of computational systems to find, access, interoperate, and reuse data with none or minimal human intervention) because humans increasingly rely on computational support to deal with data because of the increase in volume, complexity, and creation speed of data.

A practical "how to" guidance to go FAIR can be found in the **Three-point FAIRification Framework**.

Findable

The first step in (re)using data is to find them. Metadata and data should be easy to find for both humans and computers. Machine-readable metadata are essential for automatic discovery of datasets and services, so this is an essential component of the **FAIRification process**.

F1. (Meta)data are assigned a globally unique and persistent identifier

F2. Data are described with rich metadata (defined by R1 below)

F3. Metadata clearly and explicitly include the identifier of the data they describe

F4. (Meta)data are registered or indexed in a searchable resource

Accessible

Once the user finds the required data, she/he/they need to know how can they be accessed, possibly including authentication and authorisation.

A1. (Meta)data are retrievable by their identifier using a standardised communications protocol

A1.1 The protocol is open, free, and universally implementable

A1.2 The protocol allows for an authentication and authorisation procedure, where necessary

A2. Metadata are accessible, even when the data are no longer available

Interoperable

The data usually need to be integrated with other data. In addition, the data need to interoperate with applications or workflows for analysis, storage, and processing.

I1. (Meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation.

I2. (Meta)data use vocabularies that follow FAIR principles

I3. (Meta)data include qualified references to other (meta)data

Reusable

The ultimate goal of FAIR is to optimise the reuse of data. To achieve this, metadata and data should be well-described so that they can be replicated and/or combined in different settings.

R1. (Meta)data are richly described with a plurality of accurate and relevant attributes

R1.1. (Meta)data are released with a clear and accessible data usage license

R1.2. (Meta)data are associated with detailed provenance

R1.3. (Meta)data meet domain-relevant community standards

The principles refer to three types of entities: data (or any digital object), metadata (information about that digital object), and infrastructure. For instance, principle F4 defines that both metadata and data are registered or indexed in a searchable resource (the infrastructure component).

2.2 The Dublin Core

Contributor	An entity responsible for making contributions to the resource.
Coverage	The spatial or temporal topic of the resource, the spatial applicability of the resource, or the jurisdiction under which the resource is relevant.
Creator	An entity primarily responsible for making the resource.
Date	A point or period of time associated with an event in the lifecycle of the resource.
Description	An account of the resource.

Format	The file format, physical medium, or dimensions of the resource.
Identifier	An unambiguous reference to the resource within a given context.
Language	A language of the resource.
Publisher	An entity responsible for making the resource available.
Relation	A related resource.
Rights	Information about rights held in and over the resource.
Source	A related resource from which the described resource is derived.
Subject	The topic of the resource.
Title	A name given to the resource.
Type	The nature or genre of the resource.

2.3 DataCite

We use all mandatory DataCite metadata fields, and many of the recommended and optional ones.

Identifier	An unambiguous reference to the resource within a given context. (Dublin Core item), but several identifiders allowed, and we will use several of them.
Creator	The main researchers involved in producing the data, or the authors of the publication, in priority order. To supply multiple creators, repeat this property. (Extends the Dublin Core with multiple authors, and legal persons, and adds affiliation data.)
Title	A name given to the resource. Extends Dublin Core with alternative title
subtitle, translated Title, and other title(s)	
Publisher	The name of the entity that holds, archives, publishes prints, distributes, releases, issues, or produces the resource. This property will be used to formulate the citation, so consider the prominence of the role. For software, use Publisher for the code repository. (Dublin Core item.)
Publication Year	The year when the data was or will be made publicly available.
Resource Type	We publish Datasets, Images, Report, and Data Papers. (Dublin Core item with controlled vocabulary.)

2.3.1 Recommended

Subject	The topic of the resource. (Dublin Core item.)
Contributor	The institution or person responsible for collecting, managing, distributing, or otherwise contributing to the development of the resource. (Extends the Dublin Core with multiple authors, and legal persons, and adds affiliation data.) When applicable, we add Distributor (of the datasets and images), Contact Person, Data Collector, Data Curator, Data Manager, Hosting Institution, Producer (for images), Project Manager, Researcher, Research Group, Rightsholder, Sponsor, Supervisor
Date	A point or period of time associated with an event in the lifecycle of the resource, besides the Dublin Core minimum we add Collected, Created, Issued, Updated, and if necessary, Withdrawn dates to our datasets.
Language	A language of the resource. (Dublin Core item.)
Alternative Identifier	An identifier or identifiers other than the primary Identifier applied to the resource being registered.
Related Identifier	An identifier or identifiers other than the primary Identifier applied to the resource being registered.
Size	We give the CSV, downloadable dataset size in bytes.
Format	We give file format information. We mainly use CSV and JSON, and occasionally rds and SPSS types. (Dublin Core item.)
Version	The version number of the resource.
Rights	We give standards rights description with URLs to the actual license. (Dublin Core item.)
Description	Recommended for discovery.(Dublin Core item.)
GeoLocation	Similar to Dublin Core item Coverage
Funding Reference	We provide the funding reference information when applicable. This is usually mandatory with public funds.
Related Item	We give information about our observatory partners' related research products, awards, grants (also Dublin Core item as Relation.) We particularly include source information when the dataset is derived from another resource (which is a Dublin Core item.)

2.4 Processing Metadata

Value Type	We observe actual, missing, imputed, estimated values.
Method	If the value is estimated, we provide modelling information.

Unit	We provide the measurement unit of the data (when applicable.)
Frequency	We provide the measurement frequency of the data in a more practical format than the Dublin Core and DataCite descriptive dates.
Related Item	We give information about the software code that processed the data (both Dublin Core and DataCite compliant.)

2.5 Tidy Data

A dataset is a collection of values, usually either numbers (if quantitative) or strings (if qualitative). Values are organised in two ways. Every value belongs to a variable and an observation. A variable contains all values that measure the same underlying attribute (like height, temperature, duration) across units. An observation contains all values measured on the same unit (like a person, or a day, or a race) across attributes.

It is often said that 80% of data analysis is spent on the cleaning and preparing data. And it's not just a first step, but it must be repeated many times over the course of analysis as new problems come to light or new data is collected. The tidy data principle applies a certain structure to datasets that facilitates immediate use and reuse.

The principles of tidy data provide a standard way to organise data values within a dataset. A standard makes initial data cleaning easier because you don't need to start from scratch and reinvent the wheel every time.

Tidy data is a standard way of mapping the meaning of a dataset to its structure (. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types.

In tidy data we need a way to describe the underlying semantics, or meaning, of the values displayed in the table:

- Every column is a variable.
- Every row is an observation.
- Every cell is a single value.

2.6 Messy data

Real datasets can, and often do, violate the three precepts of tidy data in almost every way imaginable – this particulary true of open data, even when it is released by statistical bodies. The most typical errors:

- Column headers are values, not variable names.
- Multiple variables are stored in one column, for example, the number of item purchased and the price of the item.
- Variables are stored in both rows and columns, for example, the columns are organized by income level groups.
- Multiple types of observational units are stored in the same table. For example, names of musicians and their songs.
- A single observational unit is stored in multiple tables.

While messy data almost always can be tidied, if you do this in a spreadsheet application manually, it is almost impossible not to make a mistake. Spreadsheet applications do not check the tidyness of the data, and do not record the logs of your manual tidying efforts. Unless every single mouseclick, drag and drop is recorded, the work is impossible to validate. However, we believe that data should never

be manipulated with a mouse. Computer algorithms should be deployed in a way that our their tidying efforts are reproducible and logged.

Chapter 3

Trustworthy AI

Trustworthy AIWe help deploying reliable AI that is under human supervision, and algorithms that will not turn against your organization, or engage in discriminative, unlawful, or counterproductive behavior. We automate data and metadata management, documentation, verification, because computers are much better than humans in these boring tasks; humans must increasingly focus on oversight of too much data.

Human agency and oversight	AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches
Technical Robustness and safety	AI systems need to be resilient and secure. They need to be safe, ensuring a fall back plan in case something goes wrong, as well as being accurate, reliable and reproducible. That is the only way to ensure that also unintentional harm can be minimized and prevented.
Privacy and data governance	besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be ensured, taking into account the quality and integrity of the data, and ensuring legitimised access to data.
Transparency	the data, system and AI business models should be transparent. Traceability mechanisms can help achieving this. Moreover, AI systems and their decisions should be explained in a manner adapted to the stakeholder concerned. Humans need to be aware that they are interacting with an AI system, and must be informed of the system's capabilities and limitations.

Diversity, non-discrimination and fairness	Unfair bias must be avoided, as it could have multiple negative implications, from the marginalization of vulnerable groups to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle.
Societal and environmental well-being	AI systems should benefit all human beings, including future generations. They should consider the environment, including other living beings, and their social and societal impact should be carefully considered.
Accountability	Mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes.

Chapter 4

Application: Automated Data Observatories

This year's EU Datathlon includes three challenges. We are contesting all three of them with the same technology and knowledge management, but with different data used in a wide range of knowledge domains.

4.1 Data Acquisition and Processing

We access various open governmental and open scientific sources programatically. Our programs are mainly written in the R language, but we have a growing body of software written in Python, too. We thrive to be open for both R and Python developers, and as much as possible, exploit the synergies between the more statistically oriented R language and the more general application-oriented Python. We welcome curators and developers in both languages.

An important aspect of our quality control is that our processing code is open and peer-reviewed. Our observatories are turning the peer-reviewed statistical software of the rOpenGov community into a continuous data-as-service product. This means that we are creating collector software that is making reproducible data assets, mainly business and policy indicators. Then we are running this software daily in the cloud, and place the new data acquisitions' authoritative copies into a scientific repository for data integrity purposes, then upload it to our API, describe it in our long form documentation, and eventually blog about the newsworthy finds on our Front-end Websites.

The entire research automation system is maintained by Reprex, a Dutch research automation startup, in open collaboration with rOpenGov and other developers.

4.2 Data Integrity: Authoritative Copies

We rely on a data repository to keep a final, authoritative copy of our data assets and visualizations. This repository is independent from us.

Zenodo is a semi-endorsed EU solution, originating from CERN. In the last EU budget period all EU-funded research was supposed to deposit data there, although this requirement was not often enforced. Manual deposition is in working order, and we can very easily retrieve our own data in various versions. It is also free data storage.

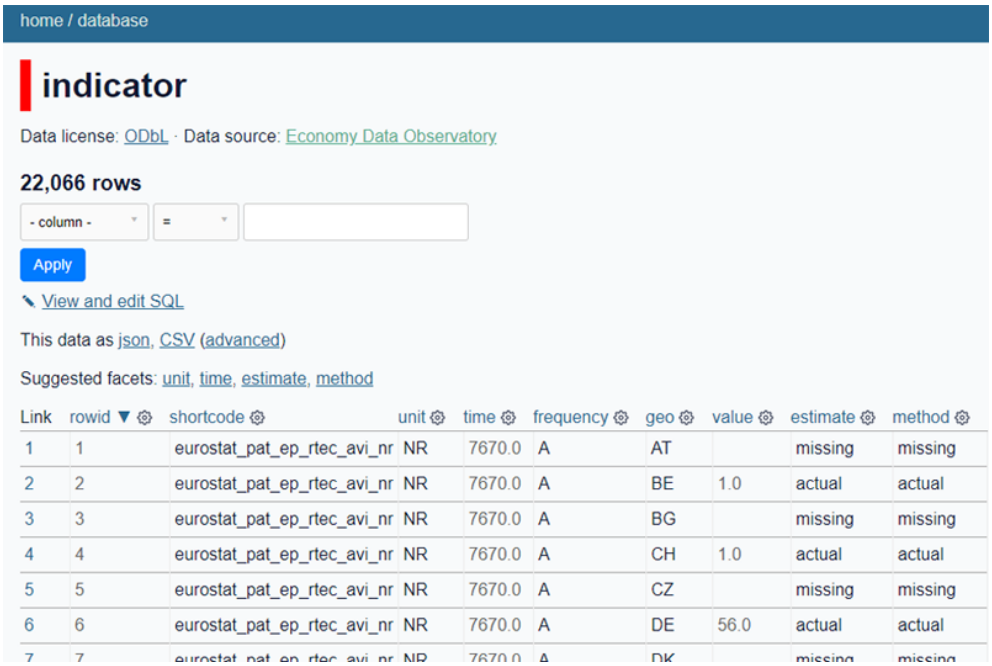
The Zenodo API is not very well documented, particularly for R. But it is supported both in Python and R. We have a tutorial and code on how to deposit our assets programatically via the Zen4R package. It is a bit difficult to use - it mimics "true" object-oriented programming relying on R6 classes, which is extremely rarely used by R programmers.

The Dataverse is much better served, the API is better documented, and technically we could even set up our own instance (new dataverses can be installed.) The best instance is of course the original Harvard Dataverse. Currently Dataverse has no support on CRAN - the R package was just kicked out of CRAN, and it is buggy, but it can be fixed. Should there be a need, we can make a connector to Dataverse, too.

4.3 Automated Data Observatory API

Our observatories APIs are Datasette instances. It is a lightweight, Python-based application that turns a SQLite database into a powerful API. Our developer, Botond Vitos manages our APIs.

The indicator table contains the actual values, and the various estimated/imputed values of the indicator, clearly marking missing values, too.


home / database

indicator

Data license: ODbL · Data source: Economy Data Observatory

22,066 rows

- column - = Apply

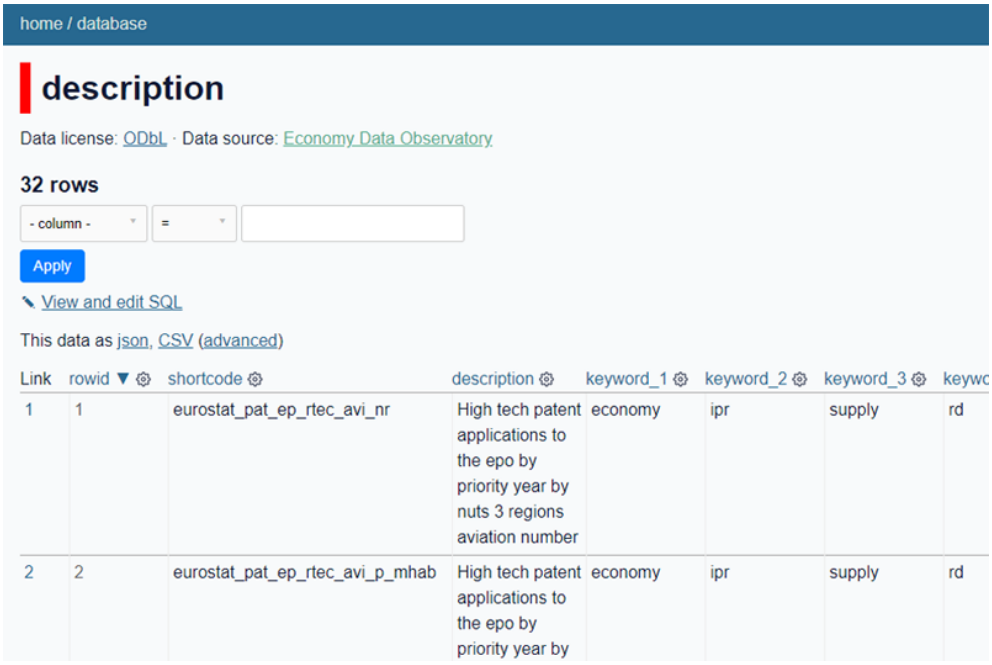
View and edit SQL

This data as json, CSV (advanced)

Suggested facets: unit, time, estimate, method

Link	rowid	shortcode	unit	time	frequency	geo	value	estimate	method
1	1	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	AT		missing	missing
2	2	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	BE	1.0	actual	actual
3	3	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	BG		missing	missing
4	4	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	CH	1.0	actual	actual
5	5	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	CZ		missing	missing
6	6	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	DE	56.0	actual	actual
7	7	eurostat_pat_ep_rtec_avi_nr	NR	7670.0	A	DK		missing	missing

The descriptive metadata is contained in the **description** tables.


home / database

description

Data license: ODbL · Data source: Economy Data Observatory

32 rows

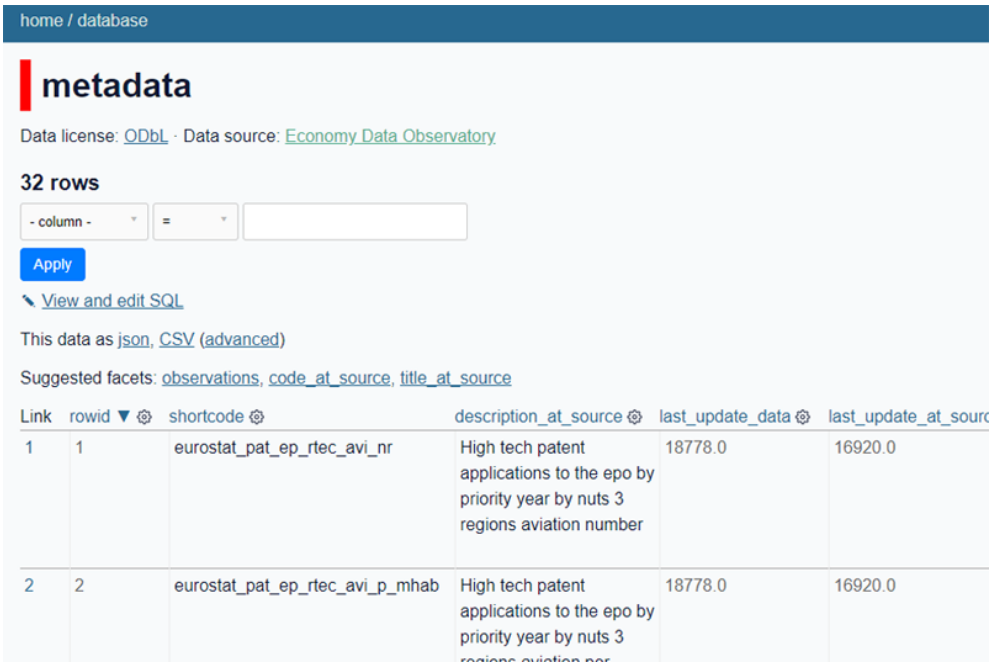
- column - = Apply

View and edit SQL

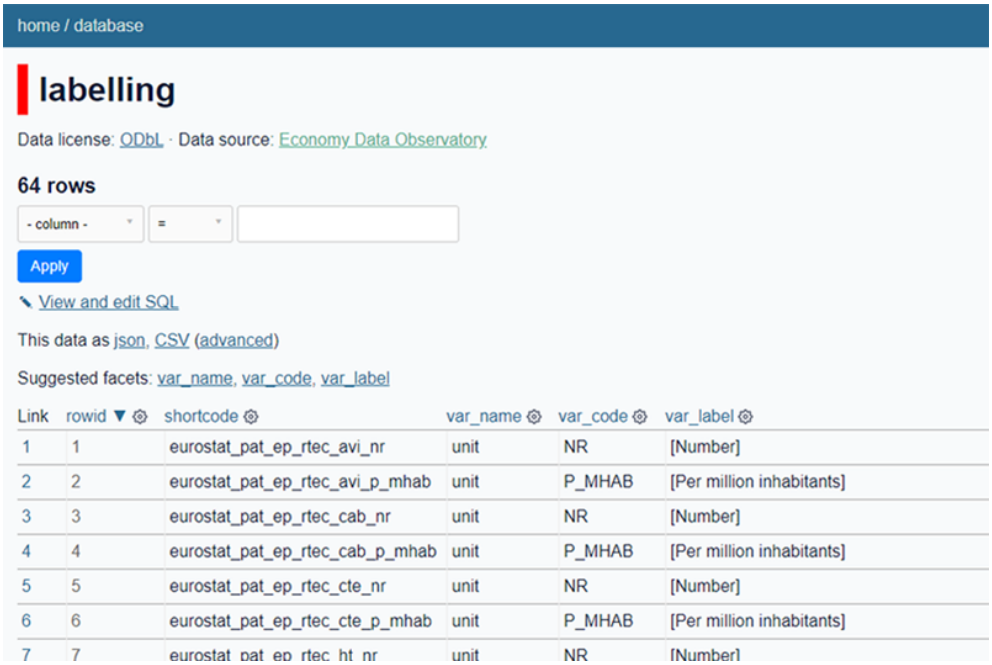
This data as json, CSV (advanced)

Link	rowid	shortcode	description	keyword_1	keyword_2	keyword_3	keywo
1	1	eurostat_pat_ep_rtec_avi_nr	High tech patent applications to the epo by priority year by nuts 3 regions aviation number	economy	ipr	supply	rd
2	2	eurostat_pat_ep_rtec_avi_p_mhab	High tech patent applications to the epo by priority year by	economy	ipr	supply	rd

The data transactional and processing metadata is contained in the **metadata** tables.



The variable labelling and unit labelling information is stored in the **labelling** tables.



Currently our APIs are re-freshed by an R code. We will soon add a Python collector, too.

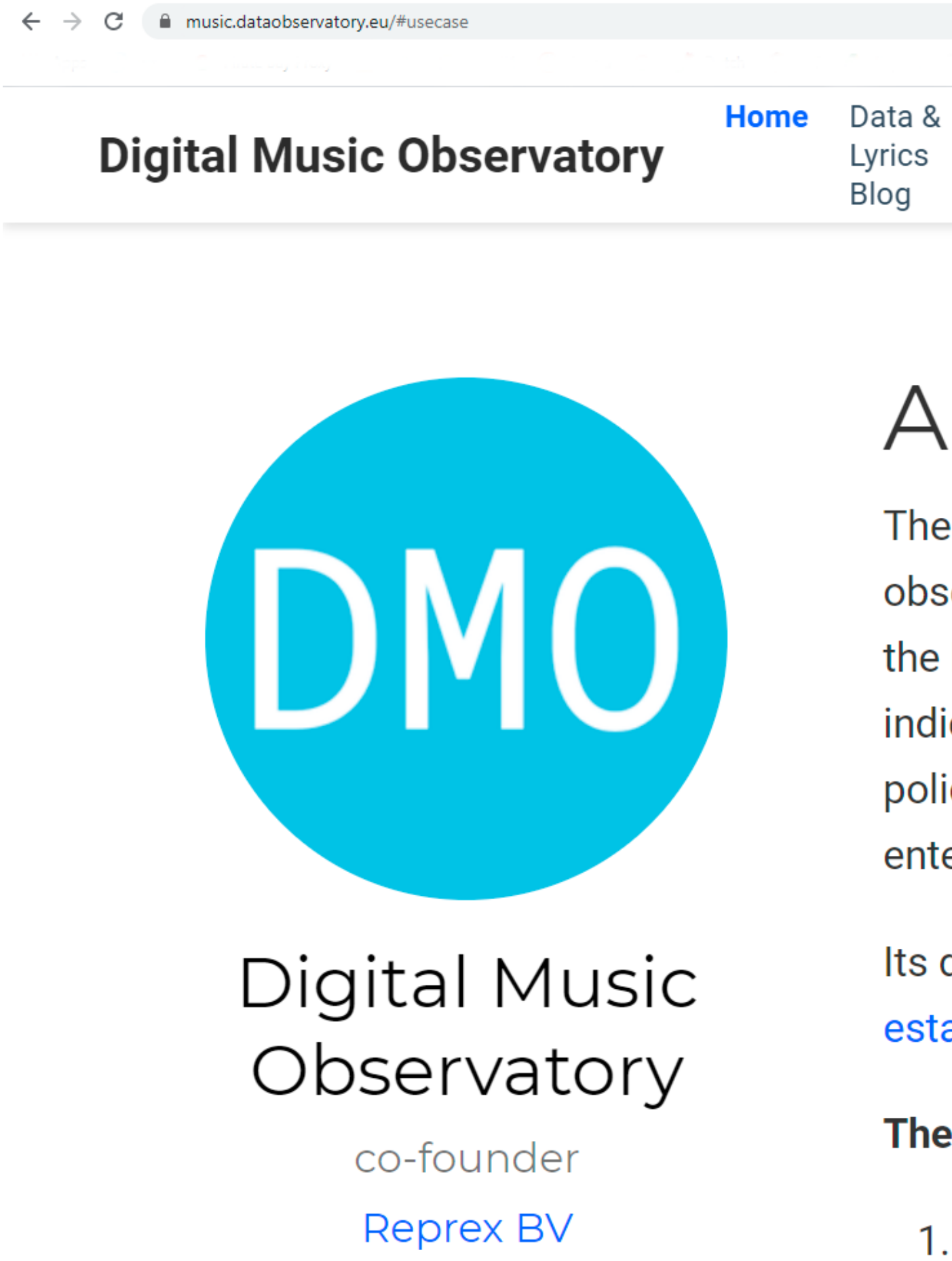
4.4 Long form documentation

Our long-form documentation is based on bookdown, which relies on pandoc, rmarkdown and knitr. This handbook is also created in bookdown.

It is a very mature workflow, it produces a long-form website, and PDF, ePUB or Word versions from the API. The current automation is not operational, as we have recently included the API.

4.5 Front-End Websites

Our observatory's client-facing front end is made by the static website generator hugo, which is programmed in the `go` language. We use the open-source Starter Hugo Academic template of wowchemy. If we win a price, we'll certainly offer them a share!


music.dataobservatory.eu/#usecase
Digital Music Observatory
Home
Data &
Lyrics
Blog
DMO
Digital Music
Observatory
co-founder
Reprex BV
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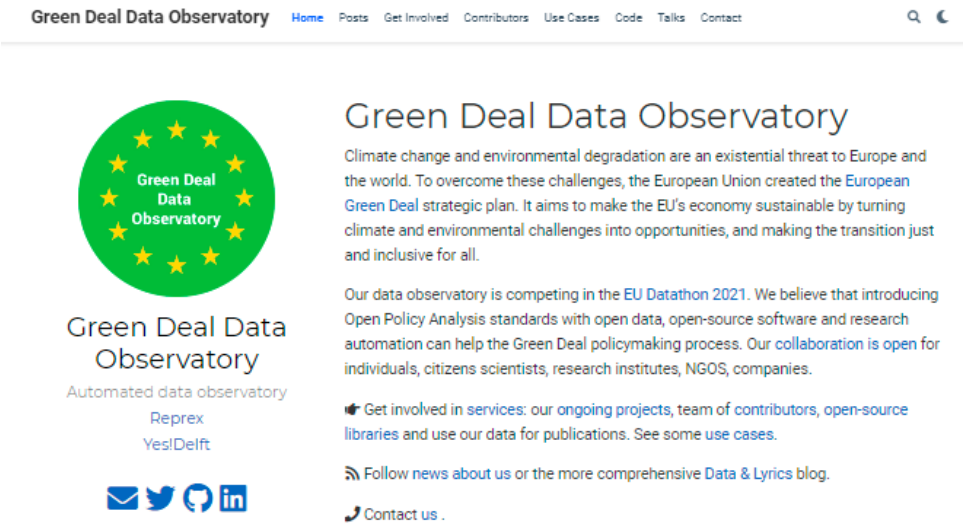
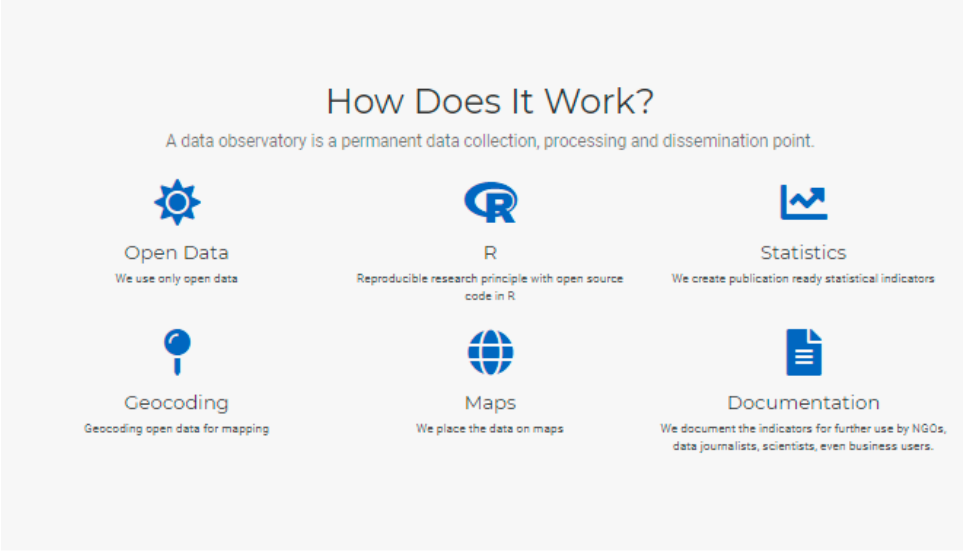
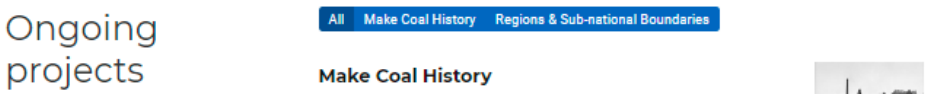
1.

The hugo-bookdown integration is partly supported by the R package blogdown. This is a semi-success, and while academic is a super-popular template, it is getting further and further away from blogdown. The original advantage is that it can be managed in the same workflow as the indicator generation, package documentation, the long-form documentation is a bit gone.







4.6 Research Automation

Because every step of our data acquisition, processing, structuring, and testing is going through machines, it can be replicated any given year, month, day, or hour. Research automation means that we update our data every day (Is there new data at the source? Corrections? Known issues?) and place the current version in an API.

1. **Continous data collection**: Big data sources usually provide the user with a large quantity of insignificant data. Because of the large quantity, the data is usually not available historically:

you capture it today or it is gone. You need to process data in big quantities in order to find signficiant and meaningful information. Most small enterprises and research teams do not have the engineering capactity to organize this. We do continous data collection on all sources to capture the latest updates, or corrections.

2. **Focus on reusability**: In our experience, the resuability of research and consulting work is greatly reduced by two factors, which we resolve with continous data collection and documentation:
    - poor documentation (the bibliography updates and file descriptions are the least priortized tasks)
    - data tables, charts, visualizations became dated then obsolete.
3. From tidy and open data to **data-as-service**: Because all our assets, including key business indicators, policy indicators, scientific replication sets, and their visualizations, as well as maps, are created by open source and reproducible software, the software can run continously. Instead of providing our users with data tables, charts and maps, we provide them with a subsription to the latest data and its latest visualizations.

Chapter 5

Service Design and Business Case Development

We are taking a new and modern approach to the `data observatory` concept, and modernizing it with the application of 21st century data and metadata standards, the new results of reproducible research and data science. Various UN and OECD bodies, and particularly the European Union support or maintain more than 60 data observatories, or permanent data collection and dissemination points, but even these do not use these organizations and their members open data. We are building open-source data observatories, which run open-source statistical software that automatically processes and documents reusable public sector data (from public transport, meteorology, tax offices, taxpayer funded satellite systems, etc.) and reusable scientific data (from EU taxpayer funded research) into new, high quality statistical indicators.

We are building open-source data observatories, which run open-source statistical software that automatically processes and documents reusable public sector data (from public transport, meteorology, tax offices, taxpayer funded satellite systems, etc.) and reusable scientific data (from EU taxpayer funded research) into new, high quality statistical indicators.

We are building various open-source data collection tools in R and Python to bring up data from big data APIs and legally open, but not public, and not well served data sources. For example, we are working on capturing representative data from the Spotify API or creating harmonized datasets from the Eurobarometer and Afrobarometer survey programs.

- Open data is usually not public; whatever is legally accessible is usually not ready to use for commercial or scientific purposes. In Europe, almost all taxpayer funded data is legally open for reuse, but it is usually stored in heterogeneous formats, processed into an original government or scientific need, and with various and low documentation standards. Our expert data curators are looking for new data sources that should be (re-) processed and re-documented to be usable for a wider community. We would like to introduce our service flow, which touches upon many important aspects of data scientist, data engineer and data curatorial work.
- We believe that even such generally trusted data sources as Eurostat often need to be reprocessed, because various legal and political constraints do not allow the common European statistical services to provide optimal quality data – for example, on the regional and city levels.
- With rOpenGov and other partners, we are creating open-source statistical software in R to reprocess these heterogenous and low-quality data into tidy statistical indicators to automatically validate and document it.
- We are carefully documenting and releasing administrative, processing, and descriptive metadata, following international metadata standards, to make our data easy to find and easy to use for data analysts.
- We are automatically creating depositions and authoritative copies marked with an individual digital object identifier (DOI) to maintain data integrity.

- We are building simple databases and supporting APIs that release the data without restrictions, in a tidy format that is easy to join with other data, or easy to join into databases, together with standardized metadata.
- We maintain observatory websites (see: Digital Music Observatory, Green Deal Data Observatory, Economy Data Observatory) where not only the data is available, but we provide tutorials and use cases to make it easier to use them. Our mission is to show a modern, 21st century reimagination of the data observatory concept developed and supported by the UN, EU and OECD, and we want to show that modern reproducible research and open data could make the existing 60 data observatories and the planned new ones grow faster into data ecosystems.

We are working around the open collaboration concept, which is well-known in open source software development and reproducible science, but we try to make this agile project management methodology more inclusive, and include data curators, and various institutional partners into this approach. Based around our early-stage startup, Reprex, and the open-source developer community rOpenGov, we are working together with other developers, data scientists, and domain specific data experts in climate change and mitigation, antitrust and innovation policies, and various aspects of the music and film industry.

Our open collaboration is truly open: new data curators, data scientists and data engineers are welcome to join. We develop open-source software in an agile way, so you can join in with an intermediate programming skill to build unit tests or add new functionality, and if you are a beginner, you can start with documentation and testing our tutorials. For business, policy, and scientific data analysts, we provide unexploited, exciting new datasets. Advanced developers can join our development team: the statistical data creation is mainly made in the R language, and the service infrastructure in Python and Go components.

See or share this introduction to the service plans in a blogpost.

5.1 Professional Standards in Business

5.1.1 Key Business Indicators

5.1.2 Business Record Retention

Some of the requirements of reproducible research are usually required by professional standards. For example, various accounting, finance, legal or consulting professional standards call for appropriate documentation and record retention.

5.2 Professional Standards in Policy

5.2.1 Evidence-based, Open Policy Analysis

In the last two decades, governments and researchers have placed a growing emphasis on the value of evidence-based policy. However, while the evidence generated through research to inform policy has become more rigorous and transparent, policy analysis–the process of contextualizing evidence to inform specific policy decisions–remains opaque.

We believe that a modern data observatory must improve how evidence is created and used in policy reports, and pass on the efficiency gains from increasing reproducibility and automation. Therefore, we pledge that the music.dataobservatory.eu will comply with the Open Policy Analysis standards developed by the Berkeley Initiative for Transparency in the Social Sciences & Center for Effective Global Action. These standards are applied by the World Bank.

5.3 Contributors

We are looking for business associates to help our service design into our

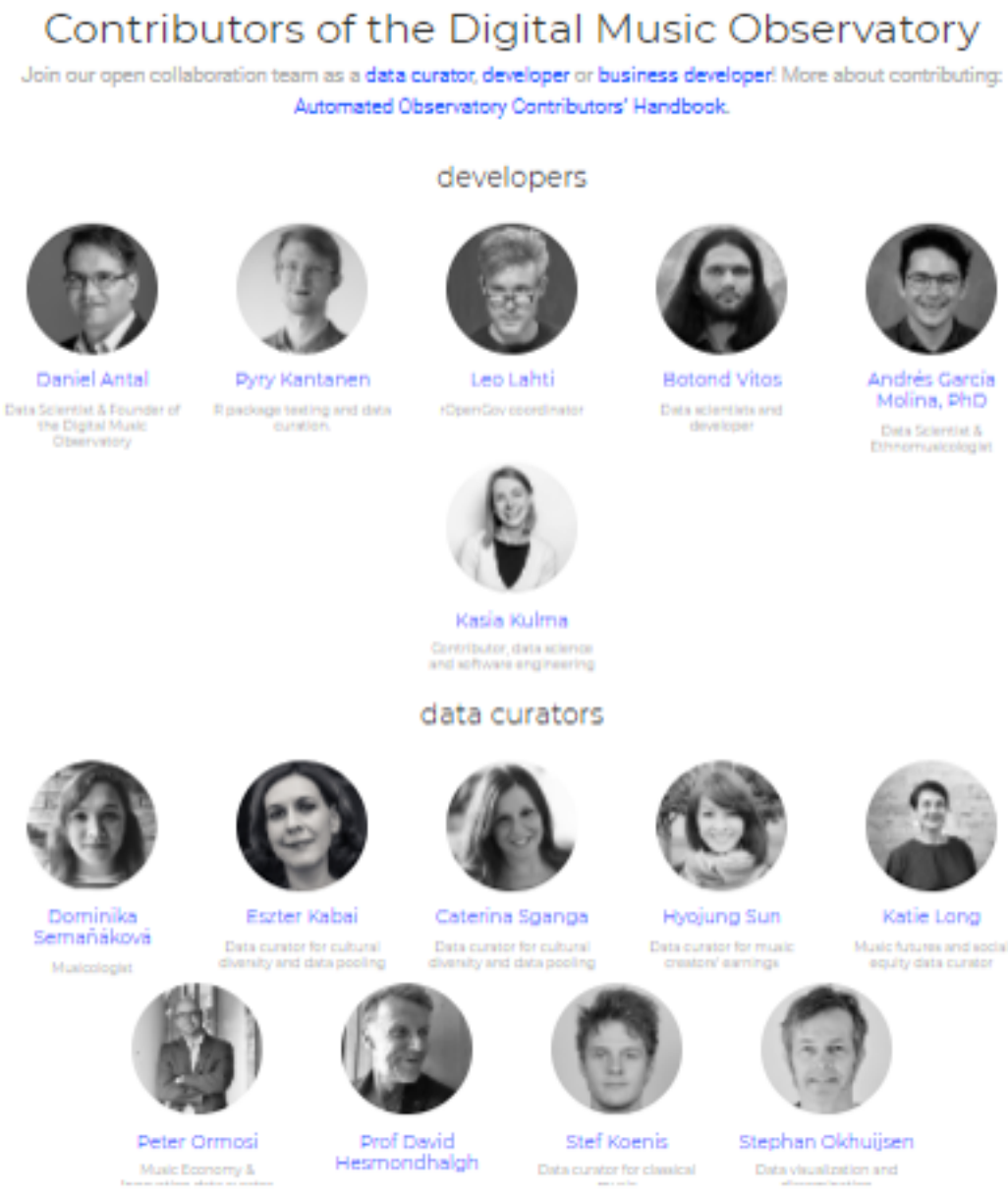


Figure 5.1: Our open collaboration is truly open: new data curators, data scientists and data engineers are welcome to join in.

- Green Deal Data Observatory
- Economy Data Observatory
- Digital Music Observatory

1. Work with governmental or scientific or otherwise open data.
2. Committed to high policy or business professional standards, and by making their work reproducible, they adhere to reviewability, reproducability, confirmability and auditability, regardless if they work, or study for various professsional roles in business, academia, public or non-governmental policy, and data journalism.

   An important aspect of the EU Datathon Challenges is ".. to propose the development of an application that links and uses open datasets [...] to find suitable new approaches and solutions to help Europe achieve important goals set by the European Commission through the use of open data."

Where to find us: - dataobservatory-eu is our private repo collection and private github collaboration platform, but many of our repos are open. Like this one.

- Creative Data Observatories LinkedIn Page. Make sure you follow us, and spread our messages.
- twitter.com/dataandlyrics is our twitter handle for our music-oriented blog. If you are on twitter, please follow us, and retweet our blogposts.
- keybase.io/team/reprexcommunity is our landing page to our otherwise private and invisible internal communication platform. (See more in subchapter**??** of Tools.)

You find more information in the **??** chapter about our topics: What is Open Data?, Reproducible Research, and of course, Get Inspired About Data.

5.4 Passion About Our Topic

- You are passionate about one of our topics, but you do not feel that you have the skills yet to become a data curator or a developer.
- You have a curiosity in the field of economic policies, particularly in computational antitrust, innovation research, and understanding the statistically under-represented micro- and small enterprises, join our Economy Data Observatory as a volunteer.
- You are passionate about environmental research of climate change, designing urban, social and economic mitigation strategies, or undertanding how people think about climate change, join our Green Deal Data Observatory team as a volunteer.
- You want to know how musicians can make a living after the pandemic? How can we make sure that music made by womxn, small country artists or artists of color gets and equal chance? Are you interested in the future of ethical AI and data governance? Join our Digital Music Observatory team as a volunteer.

5.5 Passion For Trustworthy AI, Open Data and Open Source Projects

- You want to learn to write scientifically valid, open source code in R or Python, but you are a beginner. We help you anywhere - you can even start copyediting or technical documentation (it is a must in open source development) and create tutorials for you to interact with our data and products (if if helps you, it will help others.)

- As a business economist or legal professional, you are interested how open data, open source software, research automation and ethical, trustworthy AI products can find their market.
- As a blogger, data journalist or marketeer you would like to help to make open data, and transparent, ethical, open AI more widely known and used.

5.6 Technical Requirements

- Make sure that you read the Contributors Covenant. You must make this pledge to make participation in our community a harassment-free experience for everyone, regardless of age, body size, visible or invisible disability, ethnicity, sex characteristics, gender identity and expression, level of experience, education, socio-economic status, nationality, personal appearance, race, caste, color, religion, or sexual identity and orientation. Participating in our data observatories requires everybody to act and interact in ways that contribute to an open, welcoming, diverse, inclusive, and healthy community. It's better this way for you and for us!
- Give users at least one social media account where they can get in touch with you (any of LinkedIn, Twitter, Academia, SSRN, Google Scholar, or even Facebook.)
- Please, follow us on social media, it really helps us finding new users and showing that we are able to grow our ecosystem.
  - Green Deal Data Observatory on Linkedin and Green Deal Data Observatory on Twitter
  - Economy Data Observatory on Linkedin and Economy Data Observatory on Twitter
  - Digital Music Data Observatory on Linkedin and Digital Music Data Observatory on Twitter
- Please send us back this md file with your data. You can open it with any text editor, but Notepad, TextEdit, Vim and similar clean text editors are the best.
- If you feel you need chatting on onboarding, contact us on Keybase - it's lightweight, discrete, encrypted, your mother, partner and friends are not there, it is free, open source, and can share/exchange files, too. Otherwise in email.

Chapter 6

Data Curators

We are looking for data curators into our

- Green Deal Data Observatory
- Economy Data Observatory
- Digital Music Observatory

1. Work with governmental or scientific or otherwise open data.
2. Committed to high policy or business professional standards, and by making their work reproducible, they adhere to reviewability, reproducability, confirmability and auditability, regardless if they work, or study for various professsional roles in business, academia, public or non-governmental policy, and data journalism.
3. They are interested in helping us with indicator design.
4. Make the authoritative copy of their indicator available on the Zenodo data repository, and keep it up-to-date with our automated observatory's help.

   An important aspect of the EU Datathon Challenges is ".. to propose the development of an application that links and uses open datasets [...] to find suitable new approaches and solutions to help Europe achieve important goals set by the European Commission through the use of open data."

Where to find us: - dataobservatory-eu is our private repo collection and private github collaboration platform, but many of our repos are open. Like this one.

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- keybase.io/team/reprexcommunity is our landing page to our otherwise private and invisible internal communication platform. (See more in subchapter**??** of Tools.)

6.1 Get Inspired

See our first curatorial interviews:

- Economy Data Observatory: New Indicators for Computational Antitrust
- Digital Music Observatory: New Indicators for Royalty Pricing and Music Antitrust

6.1.1 Create New Datasets

Our mission is to create standardized data about a social, economic, or environmental process that does not have standardized, well-processed open data. To be a data curator, you must have a passion for a topic where evidence is hard to find, and you must have the knowledge to assess that the evidence we find in hidden data sources is valid or not.

- This Scientist Stung Himself With Dozens Of Insects Because No One Else Would: The Schmidt Pain Index, as its informally known, runs from 1-4. The common honey bee serves as its anchor point, a solid 2. At the top end of the scale lie the bullet ant and the tarantula hawk (which is neither a tarantula nor a hawk; it's a wasp). Watch the video with Dr. Schmidt, and listen to the whole interview here.
- Big Data Is Saving This Little Bird "We need to improve conservation by improving wildlife monitoring. Counting plants and animals is really tricky business."

6.1.2 Remain Critical

Sometimes we put our hands on data that looks like a unique starting point to create a new indicator. But our indicator will be flawed if the original dataset is flawed. And it can be flawed in many ways, most likely that some important aspect of the information was omitted, or the data is autoselected, for example, under-sampling women, people of color, or observations from small or less developed countries.

- Cathy O'Neil: Weapons of math destruction, which O'Neil are mathematical models or algorithms that claim to quantify important traits: teacher quality, recidivism risk, creditworthiness but have harmful outcomes and often reinforce inequality, keeping the poor poor and the rich rich. They have three things in common: opacity, scale, and damage. https://blogs.scientificamerican.com/roots-of-unity/review-weapons-of-math-destruction/](https://blogs.scientificamerican.com/roots-of-unity/review-weapons-of-math-destruction/)
- Catherine D'Ignazio and Lauren F. Klein: Data Feminism. This is a much celebrated book, and with a good reason. It views AI and data problems with a feminist point of view, but the examples and the toolbox can be easily imagined for small-country biases, racial, ethnic, or small enterprise problems. A very good introduction to the injustice of big data and the fight for a fairer use of data, and how bad data collection practices through garbage in garbage out lead to misleading information, or even misinformation.
- Why The Bronx Burned. Between 1970 and 1980, seven census tracts in the Bronx lost more than 97 percent of their buildings to fire and abandonment. In his book The Fires, Joe Flood lays the blame on misguided "best and brightest" effort by New York City to increase government efficiency. With the help of the Rand Corp., the city tried to measure fire response times, identify redundancies in service, and close or re-allocate fire stations accordingly. What resulted, though, was a perfect storm of bad data: The methodology was flawed, the analysis was rife with biases, and the results were interpreted in a way that stacked the deck against poorer neighborhoods. The slower response times allowed smaller fires to rage uncontrolled in the city's most vulnerable communities. Listen to the podcast here
- Bad Incentives Are Blocking Better Science "There's a difference between an answer and a result. But all the incentives are pointing toward telling you that as soon as you get a result, you stop." After the deluge of retractions, the stories of fraudsters, the false positives, and the high-profile failures to replicate landmark studies, some people have begun to ask: "Is science broken?". Listen to the pdocast *Science is Hard* here
- In Algorithms of Oppression, Safiya Umoja Noble challenges the idea that search engines like Google offer an equal playing field for all forms of ideas, identities, and activities. Data discrimination is a real social problem; Noble argues that the combination of private interests in promoting certain sites, along with the monopoly status of a relatively small number of Internet search engines, leads

to a biased set of search algorithms that privilege whiteness and discriminate against people of color, specifically women of color.

- Christopher Ingraham wrote a quick blog post for The Washington Post about an obscure USDA data set called the `natural amenities index`, which attempts to quantify the natural beauty of different parts of the country. He described the rankings, noted the counties at the top and bottom, hit publish and did not think much of it. Almost immediately he started to hear from the residents of northern Minnesota, who were not very happy that Chris had written, "the absolute worst place to live in America is (drumroll, please) … Red Lake County, Minn." He could not have been more wrong … a year later he moved to Red Lake County with his family.

6.1.3 Your First Data Contribution

Your first contribution can be made without writing a single program code — but if you are experienced in reproducible science, then you can also submit a code that creates your data.

1. Make sure that you read the Contributors Covenant. You must make this pledge to make participation in our community a harassment-free experience for everyone, regardless of age, body size, visible or invisible disability, ethnicity, sex characteristics, gender identity and expression, level of experience, education, socio-economic status, nationality, personal appearance, race, caste, color, religion, or sexual identity and orientation. Participating in our data observatories requires everybody to act and interact in ways that contribute to an open, welcoming, diverse, inclusive, and healthy community. It is better this way for you and for us!
2. Send us a plain language document, preferably in any flavor of markdown (See subchapter **??** in the Tools), or even in a clear text email about the indicator. What should the indicator be used for, how it should be measured, with what frequency, and what could be the open data source to acquire the observations. Experienced data scientists can send us a Jupiter Notebook or an Rmarkdown file with code, but this submission can be a simple plain language document without numbers.
3. Make sure that you have and ORCiD ID. This is a standard identification for scientific publications. We need your numeric ORCiD ID.
4. Make sure that you have a Zenodo account which is connected to your ORCiD ID. This enables you to publish data under your name. If you curate data for our observatories, you will be the indicator's first author, and depending on what processes help you, the author of the (scientific) code that helps you calculate the values will be your co-author.
5. Please, follow us on social media, it really helps us finding new users and showing that we are able to grow our ecosystem.

- Green Deal Data Observatory on Linkedin and Green Deal Data Observatory on Twitter
- Economy Data Observatory on Linkedin and Economy Data Observatory on Twitter
- Digital Music Data Observatory on Linkedin and Digital Music Data Observatory on Twitter
- – Please send us back this md file with your data. You can open it with any text editor, but Notepad, TextEdit, Vim and similar clean text editors are the best.

You can stop here if you do not have programming experience. If you do, please go on with the next steps:

6. Without programming experience your first indicator should be uploaded manually to Zenodo, and we will help automating the new versions. This will mean, for example, the upload of a simple, csv version of an Excel table, and filling in some important information about the contents of the table.
7. With some level of R or Python programming experience, we ask you to create a Github repo where you store your indicator. We will help you with tutorials, program codes, or applications to automate your data publication on Zenodo. In this case, make sure that you also have a Sandbox Zenodo

account. There is no undo button on Zenodo. If you are tinkering with automatically publishing data, practice first in the sandbox, which is a practicing clone of Zenodo with undo button. (To avoid accidents, you need to have a completely different account with different credential on the real and the sandbox practice repository.)

8. Experienced programmers are welcome to participate in our developer team, and become contributors, or eventually co-authors of the (scientific) software codes that we make to continuously improve our data observatories. All our data code is open source. At this level, you are expected to be able to raise and/or pick up and solve an issue in our observatory's Github repository, or its connecting statistical repositories.

Our data is mainly processed in R language software, and sometimes in Python language software. If you are experienced with R bookdown, R Shiny or working in the hugo language, then you are welcome to join our developer team in non-curatorial roles.

6.2 Indicator Design

We are committing ourselves in the final deliverable to follow the indicator design principles set out by Eurostat: (**???**) to create high-quality, validated indicators that receive appropriate feedback from users, i.e. music businesses, their trade associations and policy-makers.

What are the characteristics of a good indicator? Based on the above-mentioned Eurostat expectation, we formulated it for our observatories in this way.

- `Relevance`: Indicators must 'meet the users' needs'; if they do not measure anything useful to policymakers, the public or researchers, they will probably not be widely used. Indicators should also be unambiguous in showing which direction is 'desirable'.
- `Accuracy and reliability`: Indicators must 'accurately and reliably portray reality'; an inaccurate indicator can lead to erroneous conclusions, steer the business or policy making process in the wrong direction or let negative effects go undetected.
- `Timeliness and punctuality`: Indicators must be released at a time that is relevant to the end user. If we cannot produce an accurate indicator in a timely manner, we should aim to create a leading indicator that is sooner available and with relatively high accuracy correlates with the indicator that is not available on time.
- `Coherence and comparability`: Indicators should be 'consistent internally, over time and comparable between regions and countries. This is particularly relevant for indicators used for policy monitoring and assessment, and in international business planning and assessment.
- `Accessibility and clarity`

Examples for indicators in our Digital Music Observatory:

- Indicators that were used with all known royalty valuation methods (**?**), for both author's and neighbouring rights, and fulfill the IFRS fair value standards, incorporated in EU law and the recent EU jurisprudence (**??**).
- Indicators that can be used for calculating damages, or calculating the value of the value gap (**??**).
- Indicators that quantify the development needs of musicians and can set objective granting aims and grant evaluations (**?**).
- Understanding how music is taxed, how music contributes to the local and national GDP, and how music creates jobs directly, indirectly and with induced effects (**?**).
- Providing detailed comparison of the differences of music audience among countries.
- Measuring exporting success on streaming platforms, and preparing better targeting tools.

6.2.1 Creation and Quality Control of Indicators

An indicator values are created if we the data curator has some, preferably at least 20 observation values available in data table that confirms the tidy data principles, i.e. each variable is in exactly one column of the table, and each observation is in one row of the table.

Each indicator should be described in a clear, English language text, describing the meaning of the variables, the source of the observations, and other important information about the processing, refreshing, extending of the dataset.

We are safeguarding the quality of the indicators with various reproducible research methods. Depending on the data scientific level of the curator, we either take over the quality control mechanism, or cooperate with the curator. But the main inputs for quality control should be described by the data curator.

- **Unit testing**: Unit tests are simple, numerical test that avoid logical errors in an indicator. Shall we exclude zero values? Negative values? Do percentages must add up to 100? Some of our indicators go through more than 60 unit tests. We ask your help to get us going, and we will take care of the usual suspects: wrong currency translations, wrong decimal places (thousand, million units), etc.
- **Missing data treatment**: No real life dataset is complete, but many statistical and AI methods cannot handle missing values. Therefore, we make an effort to *impute* with an estimated value the missing values. Imputation is sometimes self-understanding, but sometimes it is a very tricky business, particularly when the data has several dimensions (particularly time or geographical dimension.) We want to agree with the curator because some data may be missing, and how best to handle it. For simple, two dimensional datasets, by default, we use linear approximation, forecasting and backcasting of the values, and in small datasets the last observation carry forward or the next observation carry backwards methods. May compromise the data? Let us know.
- **Testing against peer-reviewed results**: Often we know that after making various computations with a data, we must achieve an already known value. For example, the various components of the GDP in economics must add up with a pre-defined precision. Certain inputs must match a scientifically valid result. If you know of such tests, let us know, and let us include them in the unit-testing processes.
- **Peer-reviewed data manipulation code**: Whenever we re-organize, impute, or otherwise change the original data, we do it only with algorithms that went through scientific peer-review as algorithms. If there is a bug or something to improve in the way we handle the data, our code transparency makes it likely to come out.
- **Peer-reviewed data application**: We encourage our curators, particularly academics, to send the indicators created with the help of our research automation to various forms of scientific peer review, to make sure that the data is valid, useful… and to bring credits to the curators.
- **Authentic copies**: We are placing each new version of the indicators values into Zenodo, a data repository that keeps authentic copies, versions, and assigns them digital object identifiers (DOIs). This makes sure that whenever our curators' data is re-used, and incorrectly manipulated by a business, scientific or policy user, we can detect such manipulation.

You can see this dataset here, which was used in this high-profile scientific publication.

6.3 Authentic Depositions of Indicators

We designed a workflow that helps our curators to put their indicator tables to Zenodo. In many cases, particularly if they do EU-funded research, this is also usually a grant requirement. At the same time, we place the indicator to our database, and make it available on our data observatory's API.

With low-frequency data, such as annual data tables, we place all copies to Zenodo first, and then to the data API. In these cases, each new version of the indicator values (containing a new year, a new

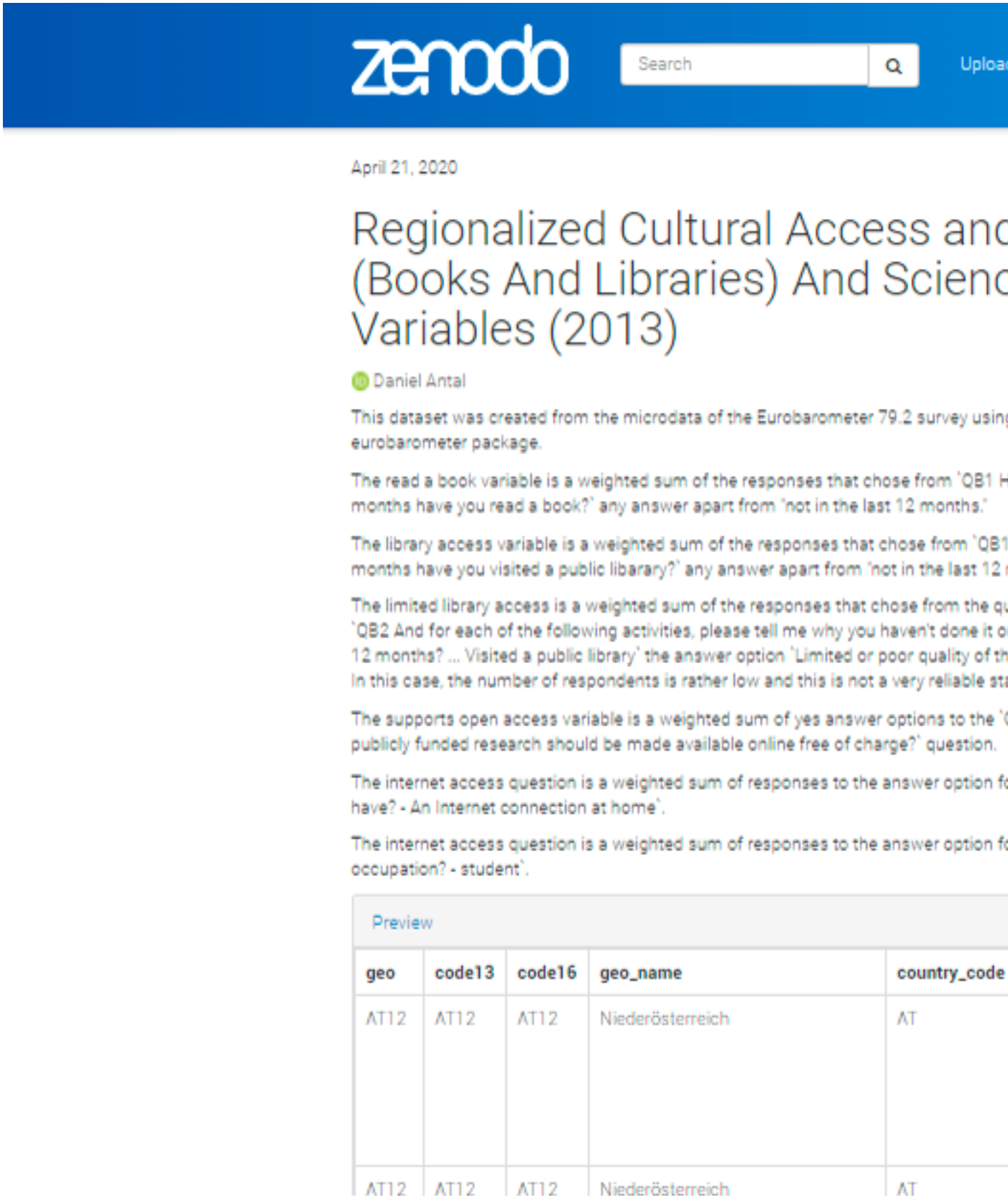


Figure 6.1: Zenodo Deposition Example

estimation, or a new country, a new observation unit) will have a new DOI version.

With high-frequency data, such as data tables that are refreshing daily or several times a day, we do not think that authentic versioning is useful. In such cases, we create an authentic version at a pre-agreed time frequency, for example, monthly.

6.3.1 How to Add your Existing Zenodo Depositions to Our Observatory

If you have a relevant dataset on Zenodo that should be featured in one of our observatories, or you are just uploading a new dataset, you should send it to our observatory `communities`. Communities are just collections that make your data easier to find and cite.

On your new or existing deposition, go to Edit, and you will find `Communities` right after `Files` and above `Upload Type`.

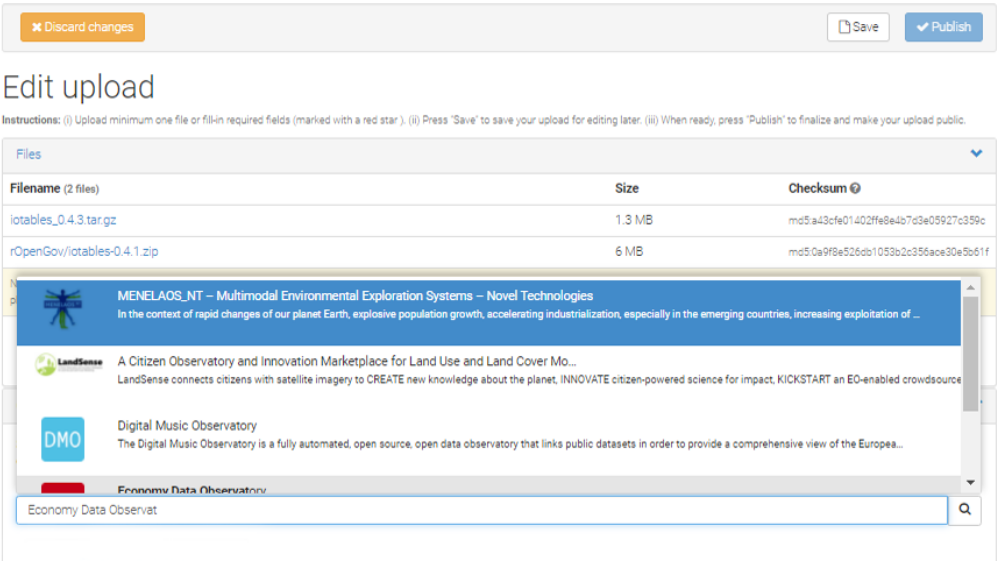


Figure 6.2: How to Add your Existing Zenodo Depositions to Our Observatory?

If you want to be featured regularly in our observatories, your data should conform our database schema. In this case, we will help you maintaining the timeliness of your data – basically we will together keep your dataset growing, expanding, and be available via our API, too. (See an example here. We will add a tutorial on this shortly to our blog.)

6.3.1.1 Digital Music Observatory

You can deposit your data, or search for new, exciting data on Zenodo itself to our music observatory on zenodo.org/communities/music_observatory.

6.3.2 Green Deal Data Observatory

You can deposit your data, or search for new, exciting data on Zenodo itself to our green deal data observatory on zenodo.org/communities/greendeal_observatory.

6.3.2.1 Economy Data Observatory

You can deposit your data, or search for new, exciting data on Zenodo itself to our green deal data observatory on zenodo.org/communities/economy_observatory/.

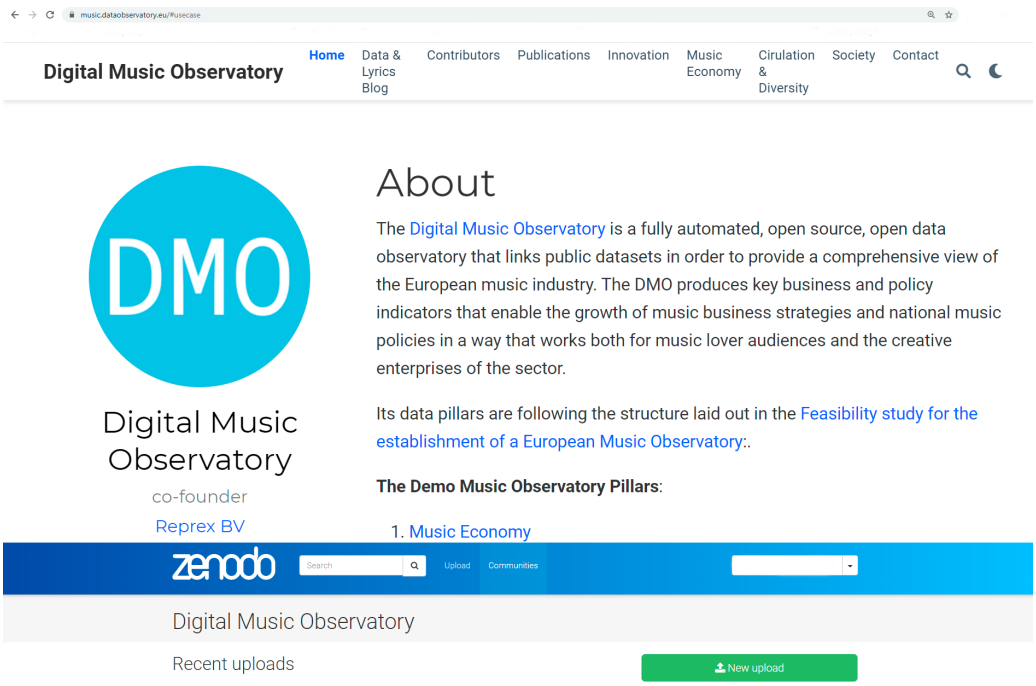


Figure 6.3: Deposit Data, Curate Data on Zenodo for the Digital Music Observatory

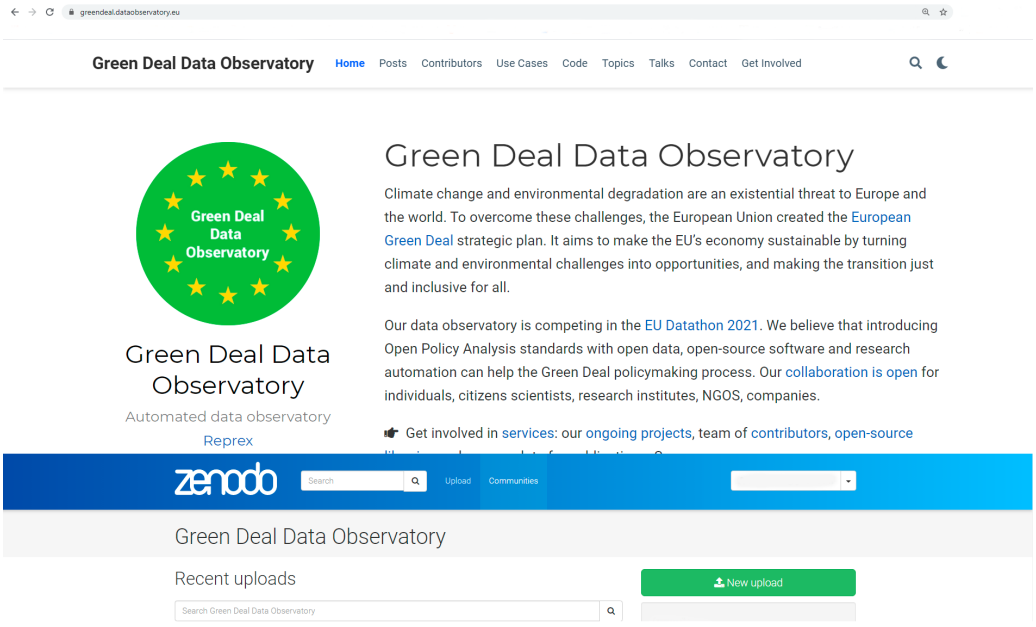


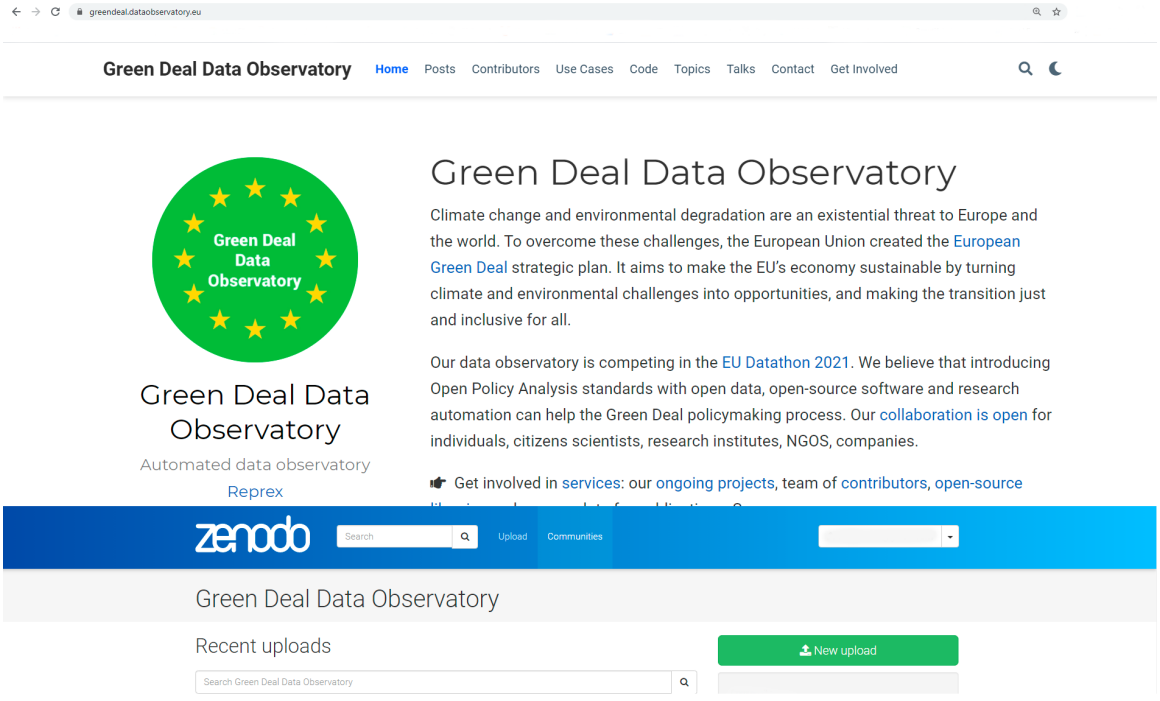
Figure 6.4: Deposit Data, Curate Data on Zenodo for the Green Deal Data Observatory

Chapter 7

Green Deal Indicators

Climate change and environmental degradation are an existential threat to Europe and the world. To overcome these challenges, the European Union created the European Green Deal strategic plan. It aims to make the EU's economy sustainable by turning climate and environmental challenges into opportunities, and making the transition just and inclusive for all.

Our data observatory is competing in the EU Datathon 2021. We believe that introducing Open Policy Analysis standards with open data, open-source software and research automation can help the Green Deal policymaking process. Our collaboration is open for individuals, citizens scientists, research institutes, NGOS, companies.



Please, follow us on social media, it really helps us finding new users and showing that we are able to grow our ecosystem: the Green Deal Data Observatory on Linkedin and the Green Deal Data Observatory on Twitter.

7.1 Curators

- Karel Volckaert: Credibility is Enhanced Through Cross Links Between Different Data from Different Domains
- Suzan Sidal: We Need More Reliable Datasets on the Urban Heat Resilience and Disaster Risk Reduction

See our inspirational examples and Your First Data Contribution in the **??** chapter.

7.2 Aggregating Count Data

`We need to improve conservation by improving wildlife monitoring. Counting plants and animals is really tricky business.`

> The marbled murrelet is an enigma. It wasn't until the 1970s that biologists discovered where the chunky brown-and-white bird made its home, and even then it was by accident: A tree-climber found a murrelet chick at the top of a redwood. Most other bird habitats had been mapped for centuries. But who would have thought to look for a sea bird's nest miles away in the middle of an old-growth forest? And it's elusive. California birders can go a lifetime without seeing one. Every day at the break of dawn, the murrelet zips down from the redwood forest hills, where it lives, to the ocean, where it feeds. It then returns under the cover of darkness. Using remote acoustic sensors and machine learning to analyze the audio, biologists are now better able to track populations of species that were previously hard to monitor. With a threatened species like the marbled murrelet, that can make a huge difference. The better the data on its population and nesting patterns, the better our understanding of how its habitat is threatened, and the more effective conservation efforts can be.

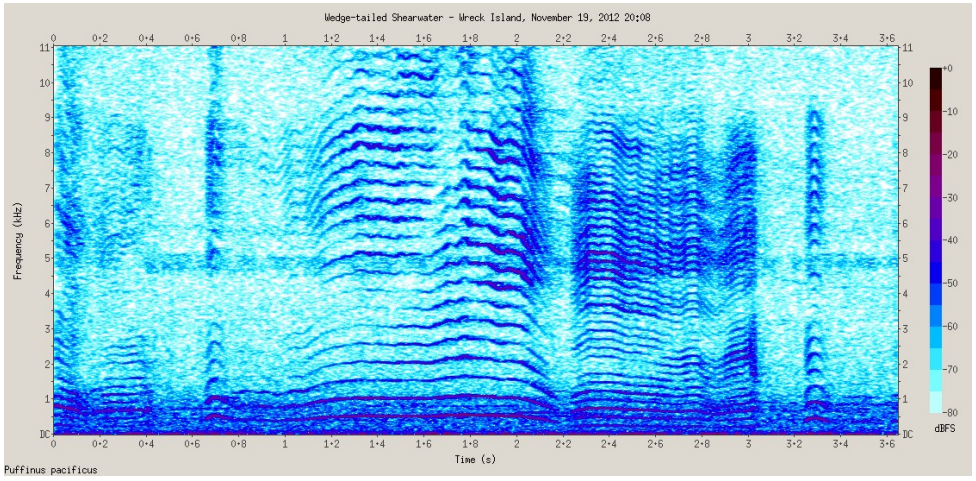


Figure 7.1: Soundscape of the Wedge-Tailed Shearwater from the Acoustic Metrics database

Big Data Is Saving This Little Bird -listen to the interview here. *The illustration is taken from Jody Avirgan's blogpost.*

To analyze governmental, social data with ecological data, we need to place them on the same map. Biostatisticians, ecologists often work with count data – counting trees, birds, various species. We need to aggregate count data over the same maps that statisticians use to count people, measure the GDP or make environmental and urban planning.

This knowledge is also very important for small area statistics that we apply in Social Attituted to Climate Change

7.3 Social Attituted to Climate Change

what do people think about climate change in Europe and other parts of the world? Do they believe that the climate is changing? How? What they think about the causes? Do they report that they change their behavior? Teach their children to do so?

Please take a look at our blogpost Is Drought Risk Uninsurable? as an example.

As a data curator:

- You identify openly accessible surveys that are harmonized (use standardized questions.) In our tutorial we projected the public opinion data from Eurobarometer 90.2 (fieldwork: October-November 2018.) on the municipal map of Belgium
- Tell us which question items would be good candidates to report. We used the answers to the multiple choice question `QB1 Do you think that the following extreme weather events are due to climate change?` We highlighted areas where people find it more likely to be exposed to `Droughts and wildfires`
- How we should calculate the indicator? Take a certain answer and average it over a region? Weight the answers? How?
- You write at least 1-2 unit tests: what must we check when the calculation is over. No negative numbers? Number of regions must up to 265?

If you write R code, you can get involved in our suvey harmonization and regional coding efforts.

See our tutorial:

Regional Geocoding Harmonization Case Study - Regional Climate Change Awareness Datasets

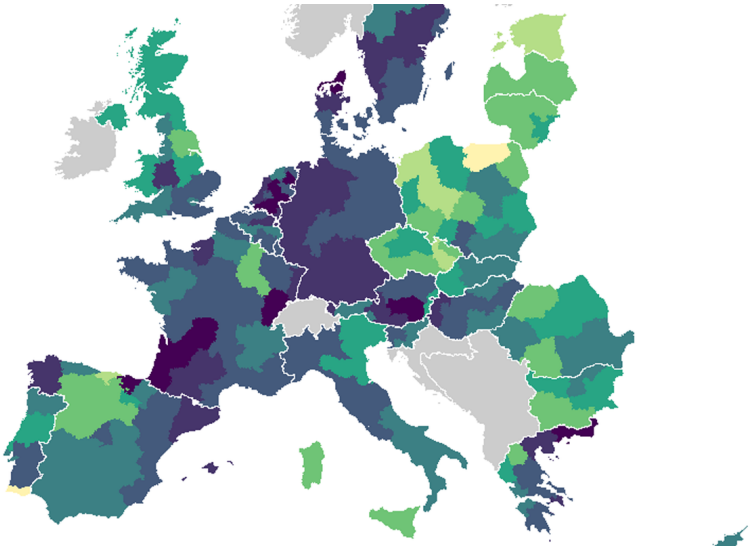


Figure 7.2: Regional attituteds to climate change, from our survey regionalization tutorial

7.4 Environmental Impact Indicator for Economic Activities

Our iotables package practically implements The Eurostat Manual of Supply, Use and Input-Output Tables with real life data and in R, and it is checked against the published results from Jörg Beutel (the author of this excellent manual), the Spicosa Project Report, and official UK statistical tables.

We used it to calculate the effects of cultural activities on various economies, but this methodology is particularly well-suited to measure the effects, or predict the effects of policy changes on greenhouse gas or pollutant emissions.

As a data curator:

- You identify openly accessible surveys data that can contains environmental effects for industries (Eurostat publishes them for many pollutants and greenhouse gases from the European Environmental Data.)
- Tell us which particular data table would be good candidate to report. Give us ideas how to bridge various problems. (The SIOT matrix must be 60x60 or 64x64), sometimes industries must be added together.
- If you write R code, we help you make the calculation yourself, if not, we'll take over.

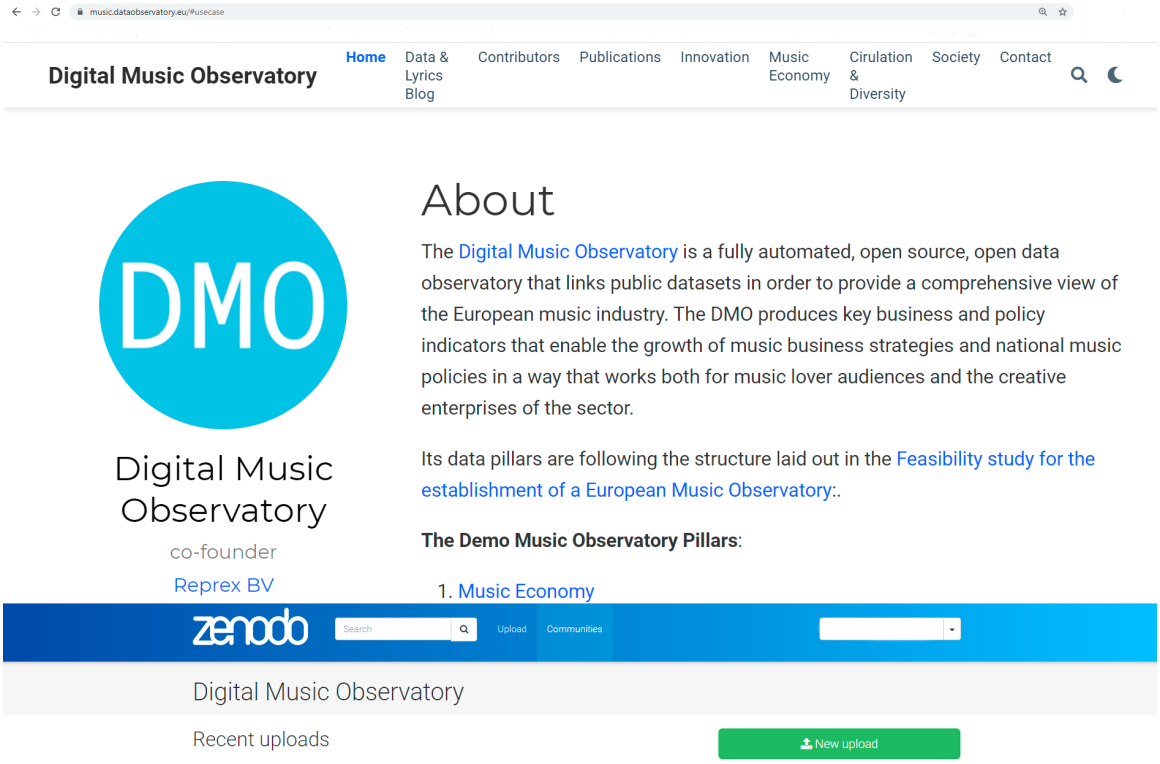
- Please assess the results with us, and let's publish them regularly. (Some EU member states update their SIOTs every year, others every 5 years, but pollutant data may be available annually.)

7.5 Sensory Data Measuring Climate Change Physical Affects

Chapter 8

Digital Music Observatory

The Digital Music Observatory is a fully automated, open source, open data observatory that creates public datasets to provide a comprehensive view of the European music industry. It provides high-quality and timely indicators in all four pillars of the planned official European Music Observatory as a modern, open source and largely open data-based, automated, API-supported alternative solution for this planned observatory. The insight and methodologies we are refining in the DMO are applicable and transferable to about 60 other data observatories funded by the EU which do not currently employ governmental or scientific open data.



Music is one of the most data-driven service industries where the majority of sales are already made by AI-driven autonomous systems. We provide a template that enables making these AI-driven systems accountable and trustworthy, with the goal of re-balancing the legitimate interests of creators and consumers. Music, like all creative industries, can create high-value, human jobs in the future that utilize digital skills and human creativity. Within Europe, this new balance will be an important use case of the European Data Strategy and the Digital Services Act.

The DMO places the values of the European Data Strategy at its center: our observatory model allows

the seamless flow of data within the EU and across sectors; it abides by European rules concerning privacy, access, and use; it pools data from a wide range of industries and sectors and makes it available for further research. The music industry is a global industry, and the best known European music scene in the world is the British. Our observatory aims to support a new relationship between the European and the UK music industries while offering international open data products from global sources.

The DMO is a fully-functional service that can function as a testing ground of the European Data Strategy, showcasing the ways in which the music industry is affected by the problems that the Digital Services Act and European Trustworthy AI initiatives attempt to regulate. Our observatory's policy insights also shed new light on important aspects of the Digital Skills and Connectivity agenda of the European Union. As a user-friendly one-stop shop for all things concerning data and the music industry, our DMO provides the foundations for a healthier and accountable European music ecosystem.

Please, follow us on social media, it really helps us finding new users and showing that we are able to grow our ecosystem: the Digital Music Data Observatory on Linkedin and the Digital Music Data Observatory on Twitter.

8.1 Curators

- Eszter Kabai: New Indicators for Royalty Pricing and Music Antitrust
- Dominika Semaňáková: We Want Machine Learning Algorithms to Learn More About Slovak Music

See our inspirational examples and Your First Data Contribution in the **??** chapter.

8.2 Music Economy

8.2.1 Demand Drivers

Our music economy demand drivers are data that are known to be leading indicators to an increase in mechanical copies, streaming subscriptions, public performance use, private copying or illegal use of music.

8.2.2 Supply Indicators

Our Music Economy / Supply indicators are related to the supply of new music.

8.2.3 Price Indicators

8.3 Music Diversity

8.3.1 Gender, Language, Ethnic and Other Inclusion Attributes

8.4 Music Circulation

8.4.1 Market shares

We are developing market share indicators for streaming and broadcast music.

For national, gender or other market share, we need to label both music works and recorded fixations. We use various open source databases, and machine learning algorithms to do prepare the data, but eventually our data goes through human musicology or music journalist curators.

For example, in our case study we were interested in the various definitions of `Slovak market share`, and representation of `female artists.` Both problems require rather challenging labeling.

a) we tried to find a location to the artist / band [you can describe why this is not always straightforward, for example, in the case of dead artists, etc.]
b) our algorithm tried to guess the language of the 10 most popular song titles
c) we checked if the person is on the Wikipedia list of "Slovak male singers", "Slovak female singers", "Slovak bands", or their Czechoslovak versions [who did you decide when somebody was Czechoslovak if they were Slovak]
d) check if there was a Slovak placename mentioned on their bandcamp site
e) check if they are associated with Slovakia on the Musicbrainz open source database
f) if any of the artists released recodings was released in Slovakia
g) if the majority of the artist's released recordings was released in Slovakia

....

Until we got to the human curation.

and eventually we either `considered_slovak` or not somebody in our `write-in database`. We are also developing an `opt-in database`, where artists can give us their own ethnic, local and gender identity, if they wish to, and of course, they can opt-out from our labeling.

We are using Monte Carlo simulation and non-parametric sampling of various broadcast and music streams to get a representation of the music listened to in various cities, regions, countries, and then we apply `national`, `language`, `gender`, `sex`, `locality` and `folksonomy` tags to measure female, Slovak, Estonian, Amsterdam or Welsh market share, recommendation probability, etc.

8.5 Music & Society

8.5.1 Social Attitutes to Music

8.5.2 Participation in Music

Chapter 9

Economy Data Observatory

Big data and automation create new inequalities and injustices and has a potential to create a jobless growth. Our Economy Observatory is a fully automated, open source, open data observatory that produces new indicators from open data sources and experimental big data sources, with authoritative copies and a modern API.

Our observatory is monitoring the European economy to protect the consumers and the small companies from unfair competition both from data and knowledge monopolization and robotization. We take a critical SME-, intellectual property policy and competition policy point of view automation, robotization, and the AI revolution on the service-oriented European social market economy.

We would like to create early-warning, risk, economic effect, and impact indicators that can be used in scientific, business and policy contexts for professionals who are working on re-setting the European economy after a devastating pandemic and in the age of AI. We are particularly interested in designing indicators that can be early warnings for killer acquisitions, algorithmic and offline discrimination against consumers based on nationality or place of residence, signs of undermining key economic and competition policy goals, and generally help small and medium-sized enterprises and start-ups to grow, and the financial sector to provide loanable and equity funds for their growth.


Economy Data Observatory
Home
EDO
Economy Data Observatory
Automated Data Observatory

> An important aspect of the EU Datathon Challenges is ".. to propose the development of an application that links and uses open datasets [...] to find suitable new approaches and solutions to help Europe achieve important goals set by the European Commission through the use of open data."

In the An economy that works for people challenge we are focusing on the Single market strategy, and particular attention to the strategy's goals of 1. Modernising our standards system, 2. Consolidating Europe's intellectual property framework, and 3. Enabling the balanced development of the collaborative economy strategic goals.

Timeline for the Economy Data Observa

2018-2020	Open-source statistical software to manipulate open dat
September 2020	Semi-automated prototype, the Demo Music Observatory is with 60 stakeholders in 12 counties.
October 2020	Observatory product/market fit validation in the world' the Yes!Delft AI+Blockchain validation Lab.
February 2021	The **prototype** automated music observatory is chosen to of our data.
March 2021	On International Open Data Day, our second observatory,
April 2021	Fist use case of the green deal observatory with a Belg competition, competitiveness, innovation, and small- an
May 2021	Launch of our data API, separating the product team to EU Datathon 2021 as **Economy Data Observatory** with daily growing from day one continously, but the application i
June 2021	We solidify the automation between the critical element with unit tests, dissemination in API and automatic doc end of the month. From a technical point of view, we r
July 2021	Via our academic, policy and business partners we inten expect that our data observatory, as a data ecosystem o
August 2021	Based on user feedbacks, we are improving the value pro business users.
September 2021	Finalizing the business model based on a hybrid licensi from this point.
November 2021	Feedback from **EU Datathon 2021**!

9.1 Curators

Peter Ormosi: New Indicators for Computational Antitrust

See our inspirational examples and Your First Data Contribution in the **??** chapter.

9.2 Social Attitutes to Economic Change

what do people think about climate change in Europe and other parts of the world? Do they believe that the climate is changing? How? What they think about the causes? Do they report that they change their behavior? Teach their children to do so?

Please take a look at our blogpost Is Drought Risk Uninsurable? as an example.

As a data curator:

- You identify openly accessible surveys that are harmonized (use standardized questions.) In our tutorial we projected the public opinion data from Eurobarometer 90.2 (fieldwork: October-November 2018.) on the municipal map of Belgium
- Tell us which question items would be good candidates to report. We used the answers to the multiple choice question `QB1 Do you think that the following extreme weather events are due to climate change?` We highlighted areas where people find it more likely to be exposed to `Droughts and wildfires`
- How we should calculate the indicator? Take a certain answer and average it over a region? Weight the answers? How?
- You write at least 1-2 unit tests: what must we check when the calculation is over. No negative numbers? Number of regions must up to 265?

If you write R code, you can get involved in our suvey harmonization and regional coding efforts.

See our tutorial:

Regional Geocoding Harmonization Case Study - Regional Climate Change Awareness Datasets

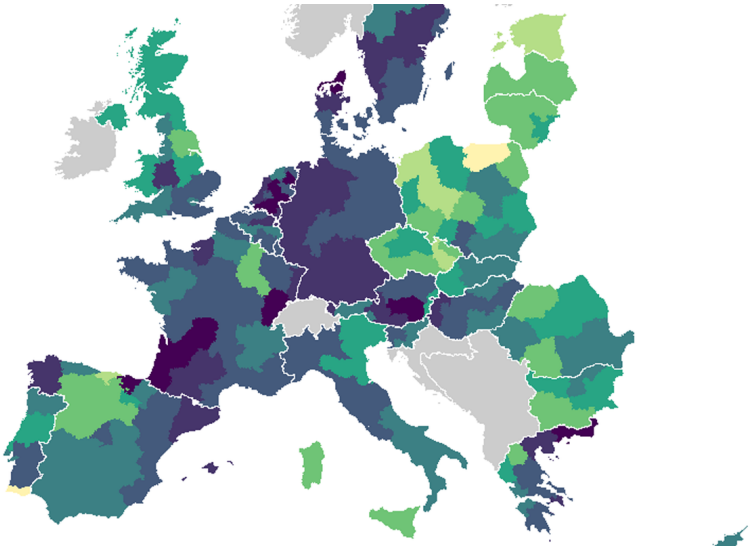


Figure 9.1: Regional attituteds to climate change, from our survey regionalization tutorial

9.3 SME Activity Indicators

9.4 Economic Impact Indicators

Our iotables package practically implements The Eurostat Manual of Supply, Use and Input-Output Tables with real life data and in R, and it is checked against the published results from Jörg Beutel (the author of this excellent manual), the Spicosa Project Report, and official UK statistical tables.

We used it to calculate the effects of cultural activities on various economies, but this methodology is particularly well-suited to measure the effects, or predict the effects of policy changes on greenhouse gas or pollutant emissions.

As a data curator:

- You identify openly accessible surveys data that can contains environmental effects for industries (Eurostat publishes them for many pollutants and greenhouse gases from the European Environmental Data.)
- Tell us which particular data table would be good candidate to report. Give us ideas how to bridge various problems. (The SIOT matrix must be 60x60 or 64x64), sometimes industries must be added together.
- If you write R code, we help you make the calculation yourself, if not, we'll take over.

- Please assess the results with us, and let's publish them regularly. (Some EU member states update their SIOTs every year, others every 5 years, but pollutant data may be available annually.)

9.5 Sensory Data Measuring Changes in Economic Activy

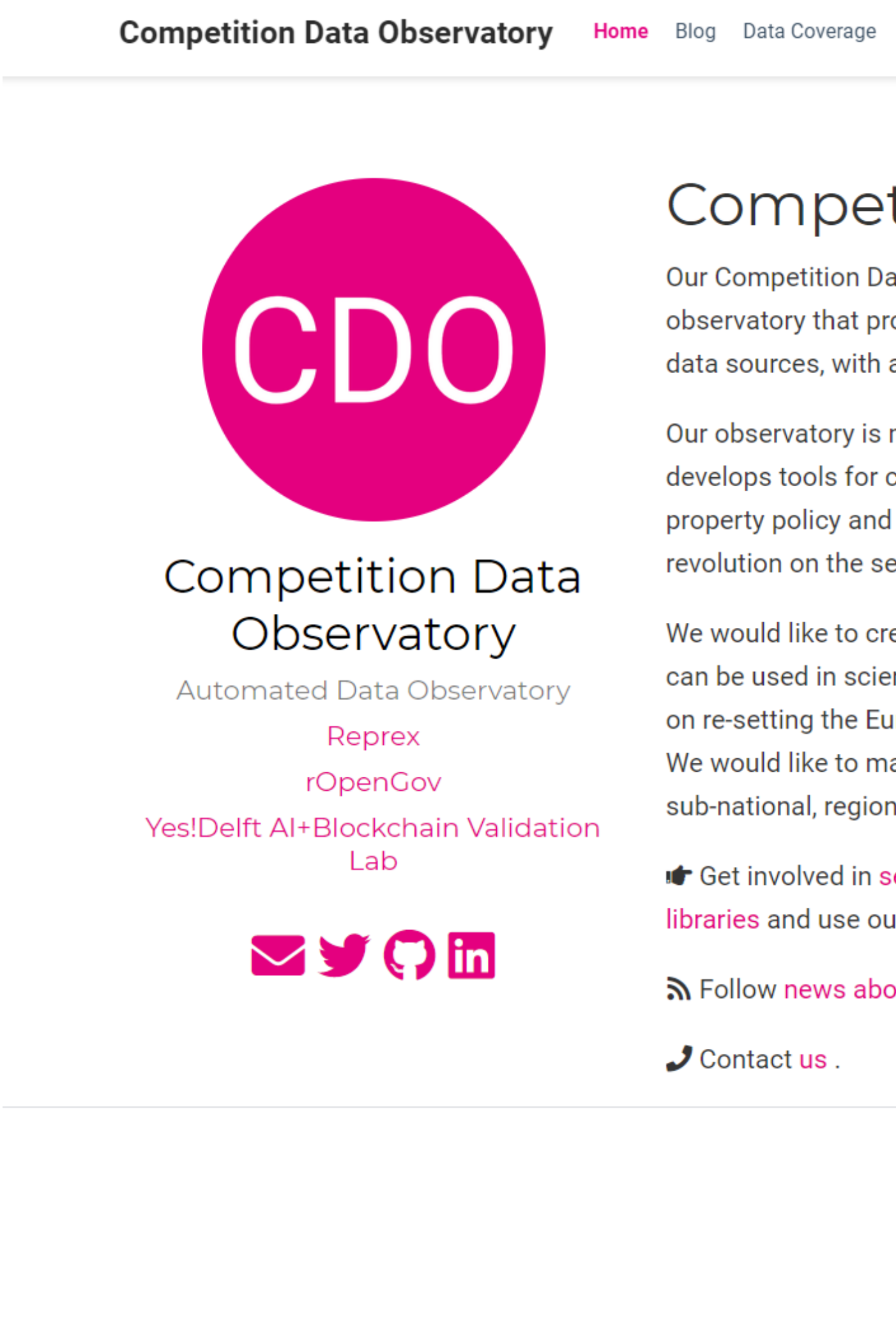
Chapter 10

Competition Data Observatory

Big data and automation create new inequalities and injustices and has a potential to create a jobless growth. Our Economy Observatory is a fully automated, open source, open data observatory that produces new indicators from open data sources and experimental big data sources, with authoritative copies and a modern API.

Our observatory is monitoring the European economy to protect the consumers and the small companies from unfair competition both from data and knowledge monopolization and robotization. We take a critical SME-, intellectual property policy and competition policy point of view automation, robotization, and the AI revolution on the service-oriented European social market economy.

We would like to create early-warning, risk, economic effect, and impact indicators that can be used in scientific, business and policy contexts for professionals who are working on re-setting the European economy after a devastating pandemic and in the age of AI. We are particularly interested in designing indicators that can be early warnings for killer acquisitions, algorithmic and offline discrimination against consumers based on nationality or place of residence, signs of undermining key economic and competition policy goals, and generally help small and medium-sized enterprises and start-ups to grow, and the financial sector to provide loanable and equity funds for their growth.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10.1 Curators

Peter Ormosi: New Indicators for Computational Antitrust

See our inspirational examples and Your First Data Contribution in the **??** chapter.

10.2 Competition

We are seeking API level access to the European Commissions Mergers database, and monitor approved and declined merger requests programatically. These mergers are important cases enough to have a potential impact on the structure of the European economy.

As a data curator, you help us designing datasets

- created from Commission and member state merger decision text databases (we will use NLP extraction from the text of the decisions)
- top-down indicators that show the structural (concentration) changes in the European economy
- connect them to patent databases

These indicators are particularly interestign, because we are trying to connect to databases that fall under the Directive on open data and the re-use of public sector information - in short: Open Data Directive (EU) 2019 / 1024, but programmatic access appears to be problematic. We need to secure reproducible, programmatic access to these important open data sources.

10.2.1 Knowledge Monopolizations, Killer Acquisitions

In killer acquisitions, a large company, for example, in pharmaceutical or technology fiedls, buys a small company, or even a start-up, to avoid disruptive innovation. We are building several types of indicators in this field.

- What type of patents companies hold in smaller entities of mergers and acquisitions? How can we characterize potentially disruptive technology?
- Which economic activities (industries as describe by NACE) are more and less effected?
- How is patent concentration changing?