Data Infrastructure

Lecture 1: Data & Data Management

Federica Bazzocchi
10/04/2026

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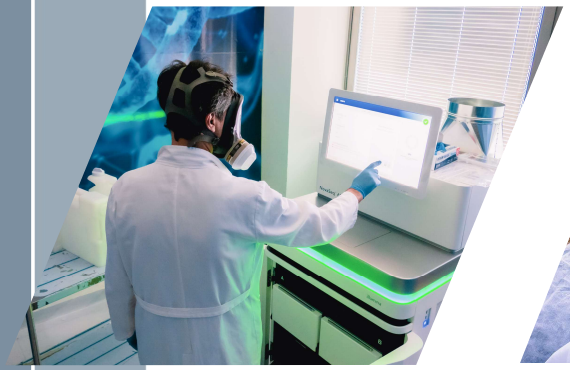
Brief introduction to Data Infrastructure section:

- Welcome
- Goals
- Calendar
- Topics and Organization

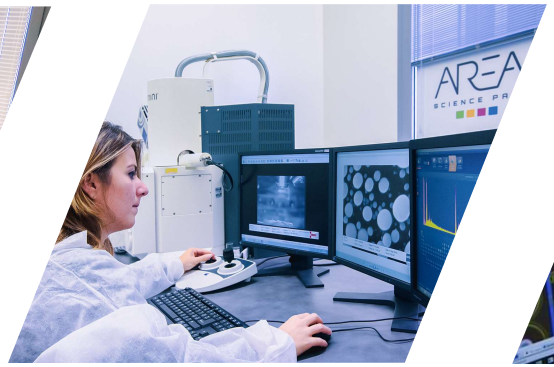
Welcome

- Few words about you
- My contact: Federica.Bazzocchi@areasciencepark.it
- My institute: RIT@AreaScience Park

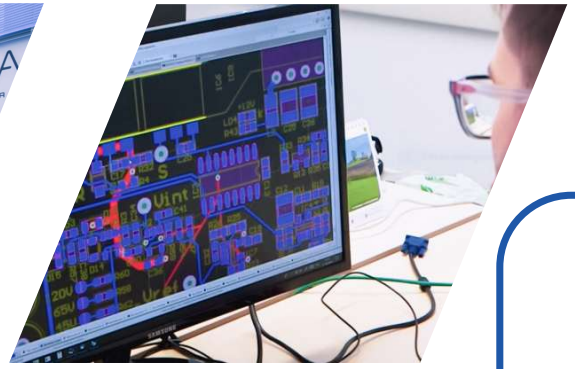
Three laboratories active in creating an **integrated system** of research infrastructures and platforms.



GENOMICS AND EPIGENOMICS LABORATORY
LAGE



ELECTRON MICROSCOPY LABORATORY
LAME



DATA ENGINEERING LABORATORY
LADE

DATA INFRASTRUCTURE

DATA MANGEMENT AND DATA CURATION

DATA SCIENCE

Welcome

- @LADE we host students'internship and have different possibilities for undergraduated and graduated fellowhips! (if interested ask me!)
- We organize together with SISSA a **Master in Data Management and Curation** ! The pilot edition is finishing but the next one will start on September 2026
- The new call opened on 1st of April and will close on 30th of June!

Learning Goals

- Master FAIR Principles & Open Science
- Curate and Preserve Research Data
- Navigate Legal & Ethical Data Management requirement
- Understand AI Fundamentals and Applications
- Implement FAIR-by-Design Workflows and pipelines
- Develop Comprehensive DMPs
- Manage Metadata Effectively
- Utilize Data Management Tools & Technologies
- Perform Foundational Data Analysis
- **Operate as a Data Professional:** Like Data Steward, Data Engineer or Research Data Manager

Master in Data Management and Curation (MDMC)

Goals

- Introduce/review the concepts of data management
- Discuss the concepts of data infrastructure and storage ecosystem
- Present some examples/tools and some parallelism between research and enterprise approach
- Data infrastructure sustainability
- Discuss some specific examples: OFED and ORFEO data monitoring

Calendar :

Timetable	10-apr	13-apr	17-apr	20-apr	24-apr	27-apr	04-may	?-may
10:15-12:00	presence		presence		presence		presence	?
11:15-13:00		presence		presence		presence		

Topics:

- (Research) Data Management and tools
- Large scale data infrastructure and hardware/software stack for large data management
- Parallel and distribute storage
- Cloud storage and associated services

Organization:

- Frontal lessons
- Active participation from you
- Interactive session on an example of data management in material science: OFED and its services
- Seminar to discuss of an example of data management: …to be defined!

LECTURE 1 OUTLINE:

- Some Reflexion on Data
- Research Data Management
- Data Management in the AI Era
- Introduction to Data Infrastructure

REFLEXION ON DATA

WHAT IS

DATA

?

https://www.menti.com/alqg3o2yxp2e

WHAT IS DATA ?

My old (ingenuous) BIAS as young physics' student (that I am not anymore) and science enthusiast (that I still am)

- Data is a results of a measurement;
- It is objective;
- It is quantitative;
- It is related to a physical law/phenomena;
- It is analyzed by mean of statistics and is used to validate a/make prediction by a (analytical) mathematical model.

DATA is a wider concept

- "Data is any set of characters that has been gathered and translated to some purpose, usually analysis. It can be any character, including text and numbers, pictures, sound, or video"
  (https://www.computerhope.com/jargon/d/data.html)
- "Data is information that has been translated into a form that is efficient for movement or processing“
  (https://searchdatamanagement.techtarget.com/definition/data)
- · "Data is a collection of facts, such as numbers, words, measurements, observations or even just description of things"
  (https://www.mathsisfun.com/data/data.html)

DATA journey

- The word “data” derives from the Latin word “datum” (singular), which means the “thing given”
- A **data** can be defined as a fundamental unit of **raw unstructured information**, represented in different form that can be transferred and then **recorded, processed, analyzed** and then **interpreted**.
- 19000 B.C-**calculation**- Ishango bone (baboon tool) : the first **mathematical data** (intended as information registered)
- I640s –**medical data-** John Graunt started collecting information regarding deaths in London (number of death, mortality rate per age, causes)
- 1880s-**data processing-** the German-American statistician Herman Hollerith had the idea of using punch cards in writing and processing data. With this invention Hollerith helped the American government complete the US census within the same year.
- 1928 – **magnetic tape**- German engineer Fritz Pfleumer patented a magnetic tape that he used to replace wire recording for storing data.
- 1960s – **relational database** – idea introduced by the computer scientist Codd
- 1990s **–** Internet and then Google **– the rise of big data**

DATA is raw and processed information

From my slides 2025

Key Characteristics

- Primality – A data point on its own is neutral and meaningless without context.
- Representation – expressed in different formats (numerical, textual, binary, images, sound signals)
- Storage – It can be recorded on physical or digital media.
- Processing and Analysing –extraction of useful information
- Transferability –data pipeline- It can be transmitted and exchanged between systems, individuals, or devices.

Kind of Data

- Observational: real-time captures (e.g. brain images, survey data)
- Experimental: from experimental results (e.g. from lab equipment)
- Simulation: generated from test models (e.g. economic or climate models)
- Derived or compiled: resulting from processing or combining 'raw' data (e.g. compiled databases, text mining, aggregate census data) ·
- Reference or canonical: collection of datasets, usually published and curated (e.g. gene databanks, crystallographic databases)

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"If you don't look back at your training programs from a year ago and feel a little bit embarrassed, you aren't learning enough."

Supposed to be by Dan John (fitness trainer) but many coaches took it

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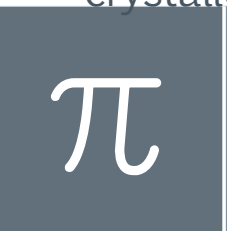
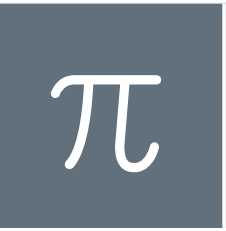


Types of Data

- Structured Data: Organized in tables or databases (e.g., name, age, address).
- Unstructured Data: Texts, images, videos, audio, without a predefined structure.
- Semi-structured Data: JSON, XML, which have some organization but are not as rigid as relational databases.
- Qualitative vs. Quantitative Data: Words vs. numbers.

Data Sources

- Data are not only created anymore to write scientific papers or doing analysis, but they are created with the notion of being reused in different contexts which is revolutionary in many disciplines;
- Data are produced by almost everything
- Advanced statistical methods (machine learning/deep learning) are required and have allowed to detect the patterns and correlations hidden in the data



DATA-CENTRIC WORLD

In 2006, mathematician Clive Humby coined the phrase "**data** is **the new oil**."

Forbes

INNOVATION

Data Is The New Oil -- And That's A Good Thing

By Kiran Bhageshpur , Forbes Councils Member.
for Forbes Technology Council, COUNCIL POST | Membership (fee-based)

Nov 15, 2019, 08:15am EST

INNOVATION

Data Is The New Business Fuel, But It Requires Sound Risk Management

By Morgan Palmer , Former Forbes Councils Member.
for Forbes Technology Council, COUNCIL POST | Membership (fee-based)

Apr 28, 2022, 08:00am EDT

Why Are We Moving Towards A Data-Centric World?

Ian Gerald King · Follow
4 min read · Feb 23, 2017

CYBERSECURITY

We need a new era of data responsibility

Jan 21, 2018

#ETHOS-AIOPENMIND

OpenAI sotto accusa: Britannica denuncia uso illecito dei dati

Marzo 20, 2026

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A parentheses

- Data intended as digital recorded infomation is a technical concept and is processed /analyzed by highly specialized techniques and professionals (data scientists, data and AI engineers)

- Nevertheless our society is so data-centered (and data-obsessed) that also humanities/social studies are interested in the influence of data for our society. They enter into the dialogue about DATA and their own studies are influenced by DATA.

LECTURE/PRESENTATION/TALK

Mellon Sawyer Seminar Series: Catastrophe, Data, and Transformation (Dagomar Degroot and Jessica Otis)

Sponsored by Center for Spatial and Textual Analysis (CESTA)

May 21st, 2024 | 6 min read Arts & Humanities

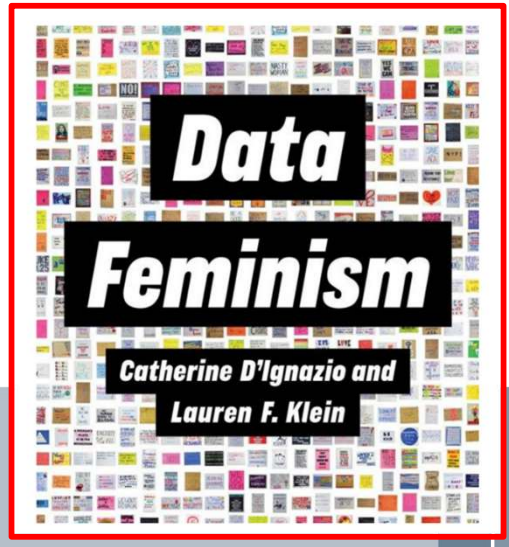
Lectures explore data's place in the humanities

A seminar series takes a humanistic approach to extracting meaning from the numbers that saturate our world.

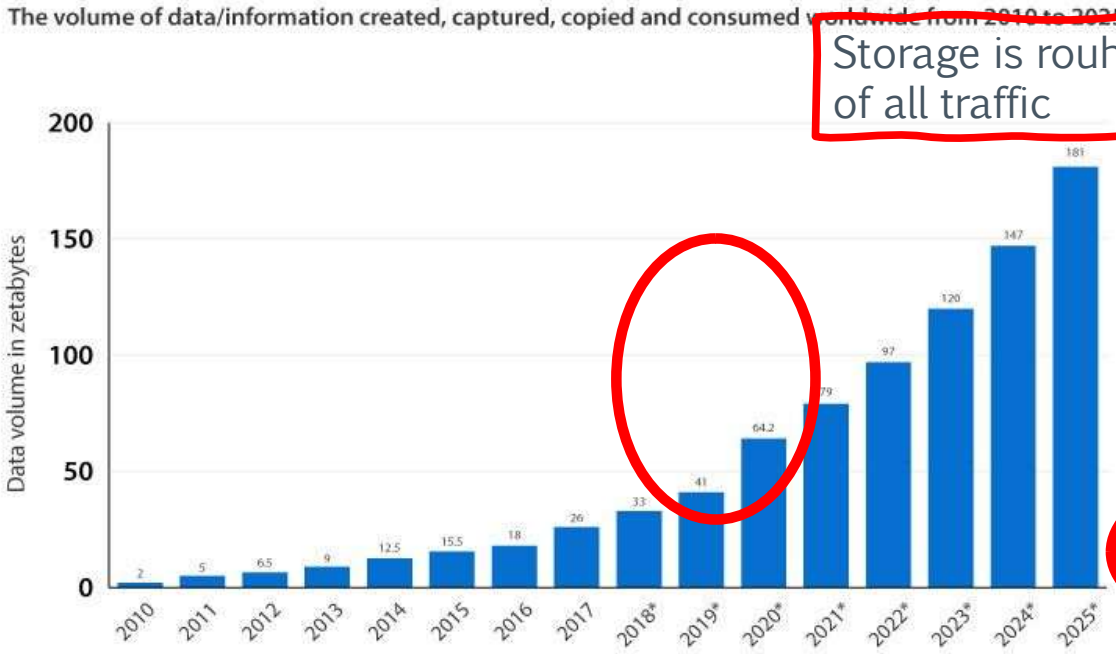
WHAT IS DATA ETHICS?

Data ethics encompasses the moral obligations of gathering, protecting, and using personally identifiable information and how it affects individuals.

"Data ethics asks, 'Is this the right thing to do?' and 'Can we do better?'" Harvard Professor Dustin Tingley explains in the Harvard Online course Data Science Principles.

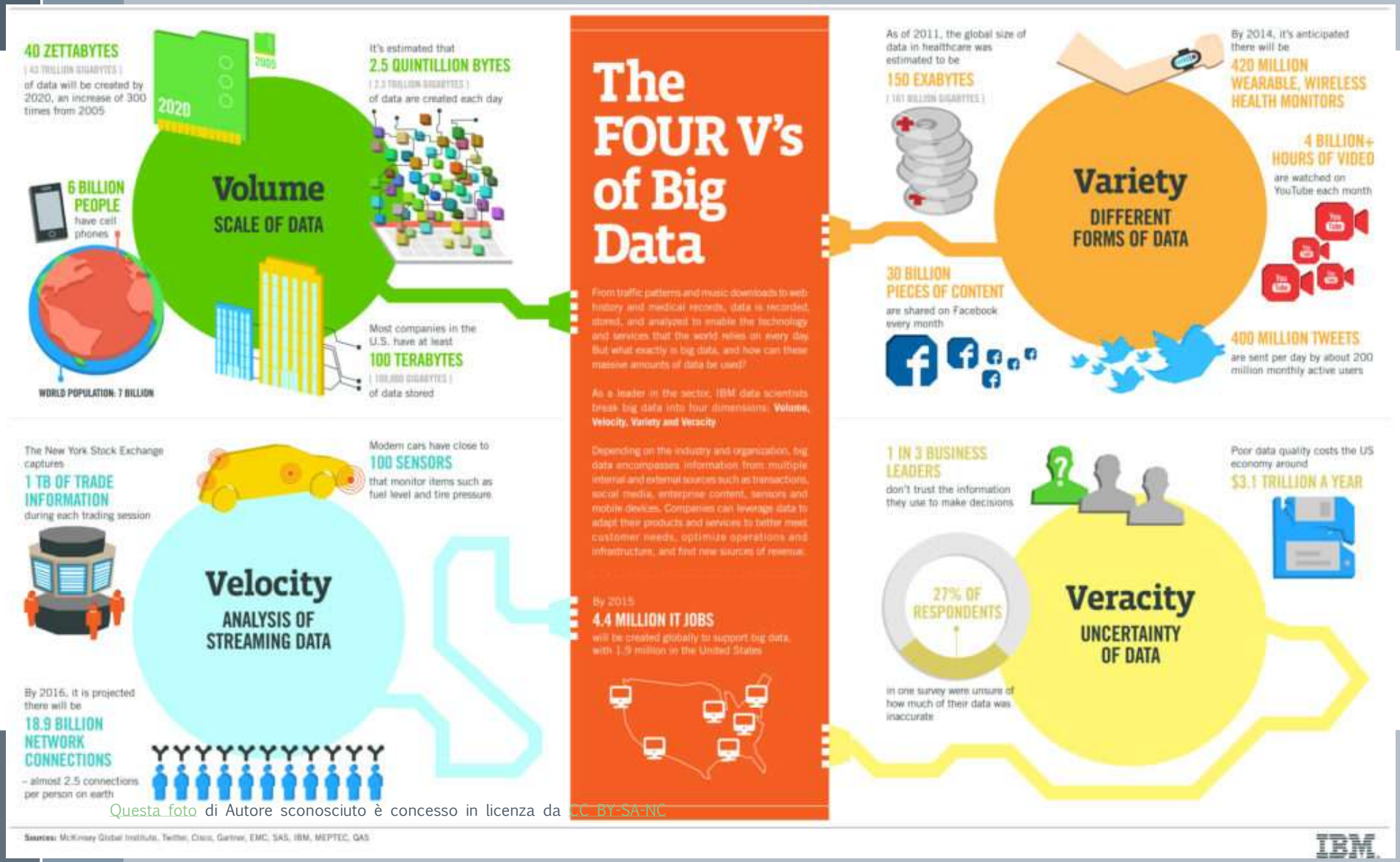


DATA explosion in the last decades



Storage is rouhghly 10% of all traffic

Year	World Storage Size (Exabytes)
1986	2.6 EB
1993	15.8 EB
2000	54.5 EB
2007	295 EB
2014	5000 EB
2020	6800 EB



HOW WE MANAGE THIS

HUGE AMOUNT OF DATA

?

WHERE WE STORE THIS

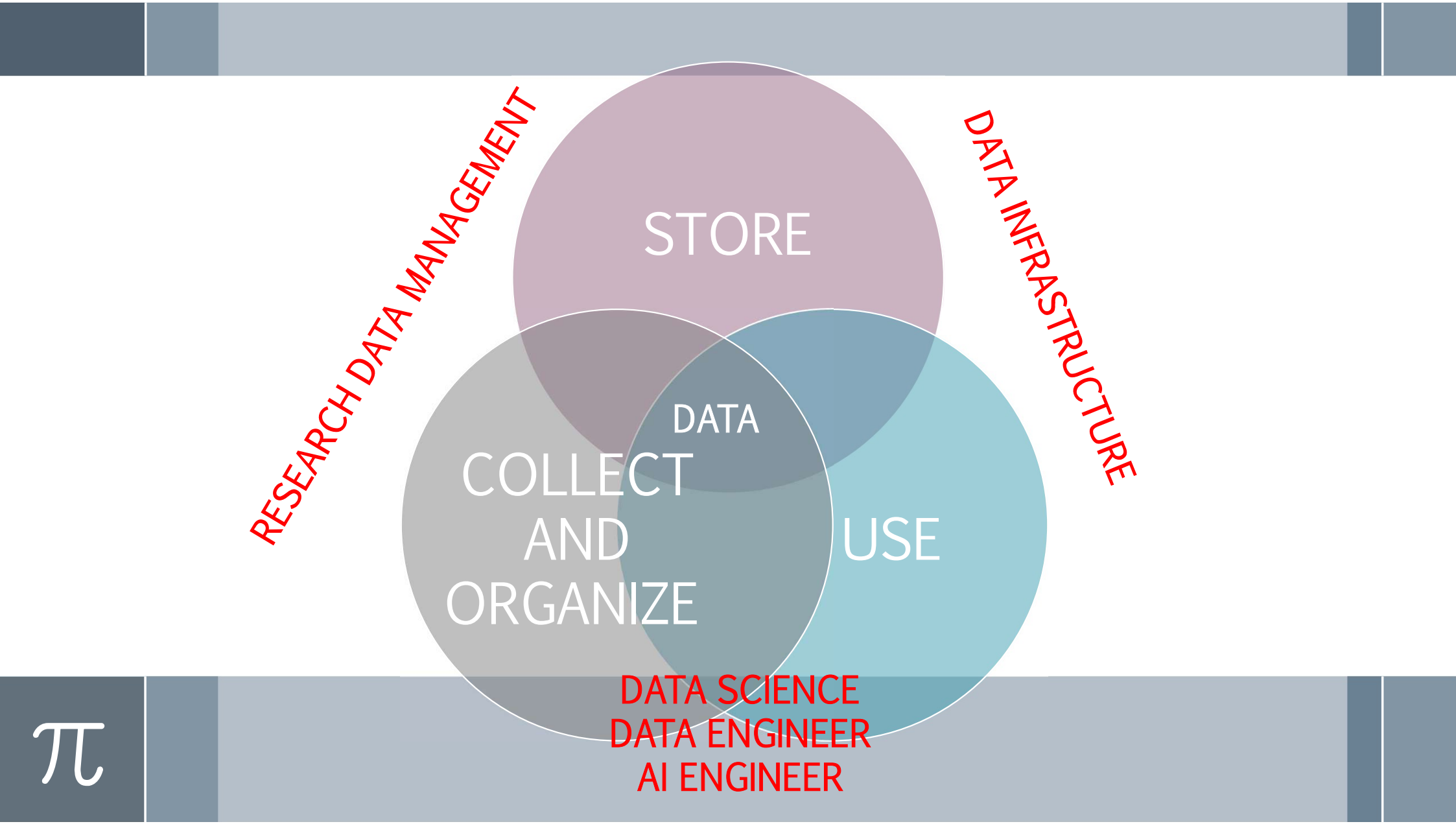
HUGE AMOUNT OF DATA

?

HOW WE USE (AND WHAT WE MAY DO WITH) THIS

HUGE AMOUNT OF DATA

?


RESEARCH DATA MANAGEMENT
DATA INFRASTRUCTURE
STORE
DATA
COLLECT
AND
ORGANIZE
USE
DATA SCIENCE
DATA ENGINEER
AI ENGINEER

DATA is raw and processed information

From my slides 2025

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DATA $\neq$ **INFORMATION**

DATA is raw and processed values, it becomes INFORMATION when it is enriched by metadata

If we take the general definition

INFORMATION= DATA + MEANING

Data may be seen as raw and processed substrate, to which we add metadata to get information

What is «information»?

Not a easy definition…

«Information is data that has been processed into a form that is meaningful to the recipient.» (Davis, Olson, 1985, p. 200)
«Data are the raw material that is processed and reworked to generate information.» (Silver, Silver, 1989, p. 6)
«Information equals data plus meaning.» (Checkland, Scholes, 1990, p. 303)
«Information consists of data that have been interpreted and understood by the message recipient.» (Lucey, 1991, p. 5)
«Data must be interpreted or manipulated [to] become information.» (Warner, 1996, p. 1)

Filosofia dell'informazione, L. Floridi

WHAT IS METADATA?

- Data describing other data
- It provides information about the content, i.e., an image may include metadata describing the picture size, colour depth, image resolution, creation date...
- It describes individual files, single objects, or complete collections

WWW.FLICKR.COM/PHOTOS/CENTRALASIAN/8071729256/

What do you think of
when I say "metadata"?

THE IMPORTANCE OF BEING METADATA

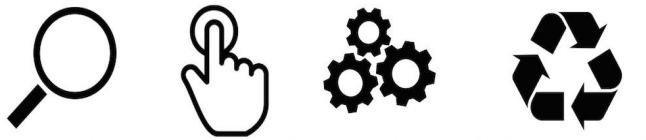
- Gives the context, gives meaning to the data
- Ensures that resources will "survive" continuing to be findable and accessible in the future
- Is searchable, aiding the identification and retrieval of resources
- Helps users in managing, mantaining, and preserving digital collections
- Supports archiving, security, and authentication of data

WHAT MAKES METADATA GOOD?

- Be complete and consistent ! (collect all metadata)
- If exist, use standards, if not exist define ad hoc schema and gives it a URI
- Controlled vocabularies for unambiguous keywords, define crosswalks when needed
- Persistent identifiers (DOIs)
- Clearly stated data limitations
- Explanation for appropriate reuse (indicate licences etc)
- Machine readable (interoperability)

(GOOD) METADATA HAVE A CORE ROLE IN FAIR PRINCIPLES

Findable Accessible Interoperable Reusable



F

F1: **(Meta) data** are assigned globally unique and **persistent identifiers**
F2: Data are described with rich metadata
F3: Metadata clearly and explicitly include the **identifier of the data** they describe
F4: **(Meta)data are registered** or indexed in a searchable resource

A

A1: **(Meta)data** are **retrievable** by their identifier using a standardised communication 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 should be accessible** even when the data is no longer available

I

I1: **(Meta)data** use a formal, accessible, shared, and **broadly applicable language** for knowledge representation
I2: **(Meta)data use vocabularies** that follow the FAIR principles
I3: (Meta)data include qualified references to other (meta)data

R

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**

http://www.nature.com/articles/sdata201618

Which metadata FAIR principles are referring to?

F

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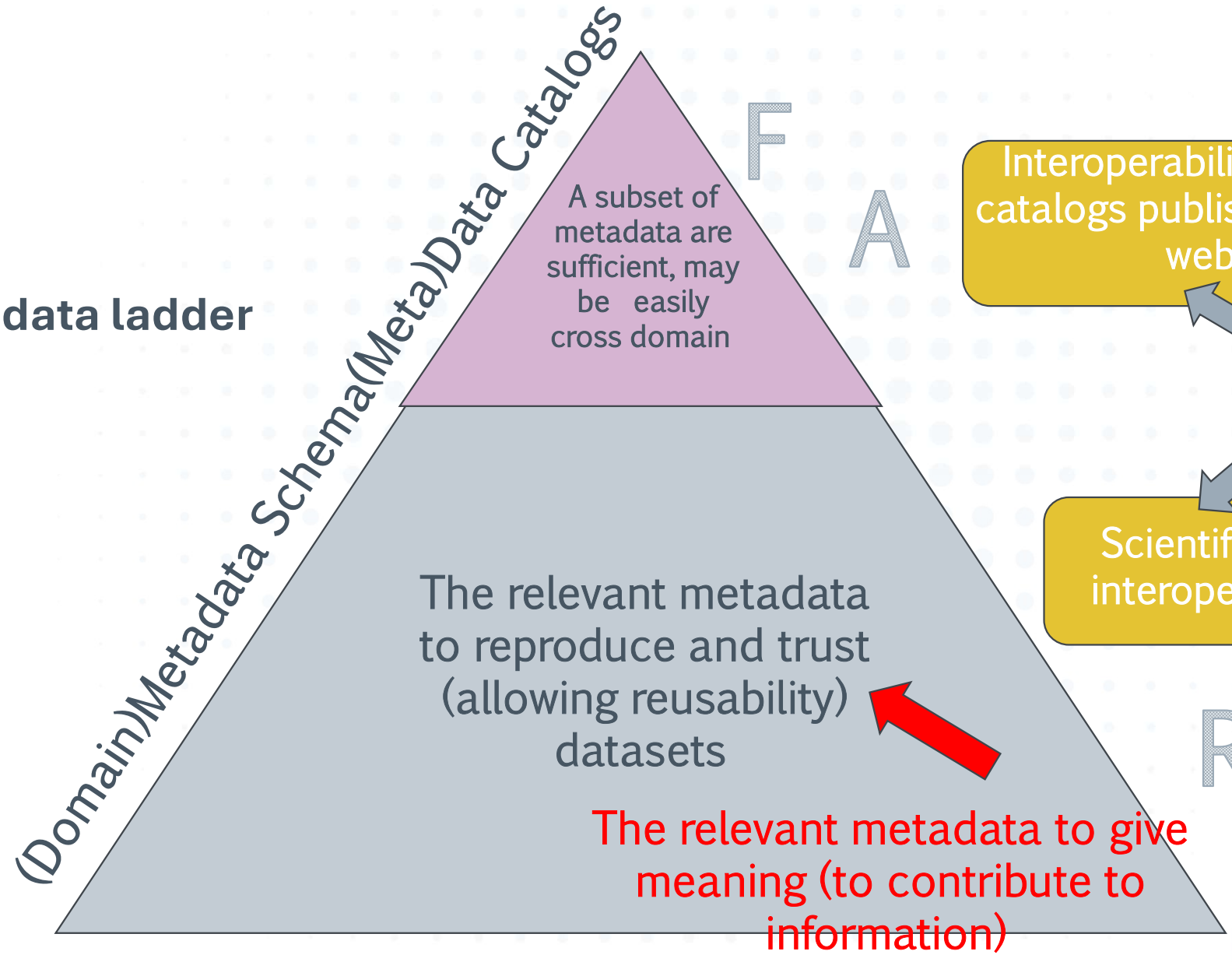
Metadata ladder



Suppose to have

7
10
15
8
16

data.csv

- On zenodo
- It has a doi (F)
- It is open with ccby (AR)
- I may access it using Zenodo API (I)

Do I satisfy FAIR principles?

Do I know to what this numbers refer to?

They could be

- Temperature degrees recorded at 7am in spring in Trieste
- Sons' ages of a (large) family
- Hours at which I record a specific parameter/event (headache occurence for examples)
- Kms run per day

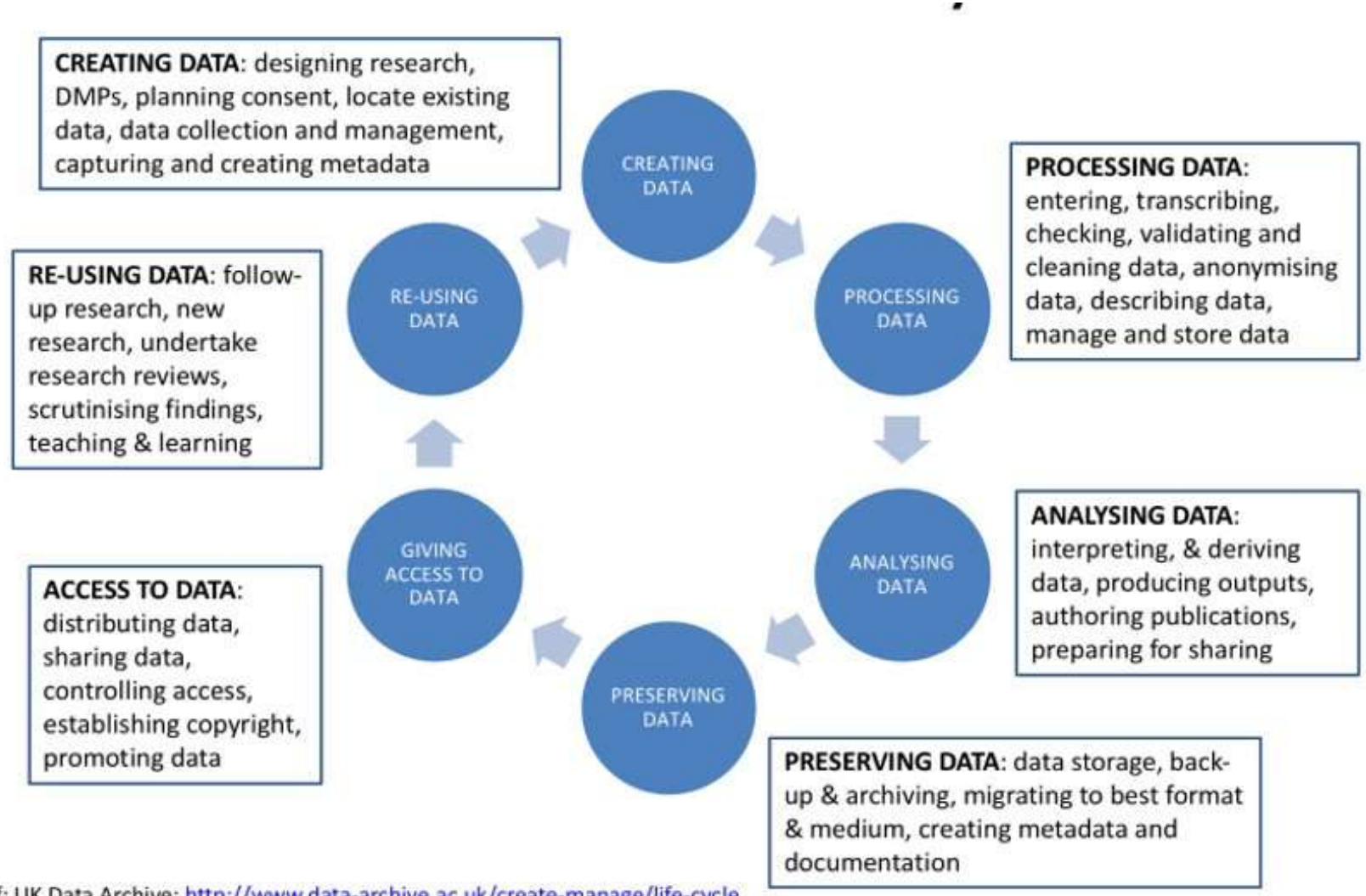
RESEARCH DATA MANAGEMENT

BIG DATA IN SCIENCE

- Data growing exponentially, in all sectors and therefore also in all science ·
- All science is becoming data-driven and this is happening very rapidly
- Data becoming increasingly open/public
- A scientific revolution in how discovery takes place => a rare and unique opportunity
- Data have to be managed adequately

Cross domain/context problem!

DATA LIFE CYCLE

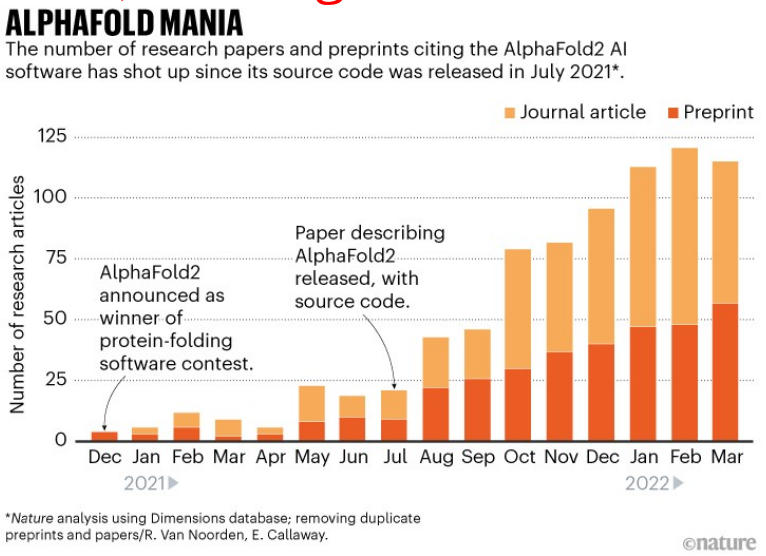


Ref: UK Data Archive: http://www.data-archive.ac.uk/create-manage/life-cycle

NOT – INCREMENTAL CHALLENGES!

- Multi-faceted challenges in the analysis as well
- New computational tools and strategies
- … not just statistics, not just computer science, not just astronomy, not just genomics…
- Science is moving increasingly from hypothesis driven to data-driven discoveries and now to LLM-driven discoveries (think to alphafold/matgen)

AI-agents



AI-<<something>>

SQUIRRELS

- They eat too much at once

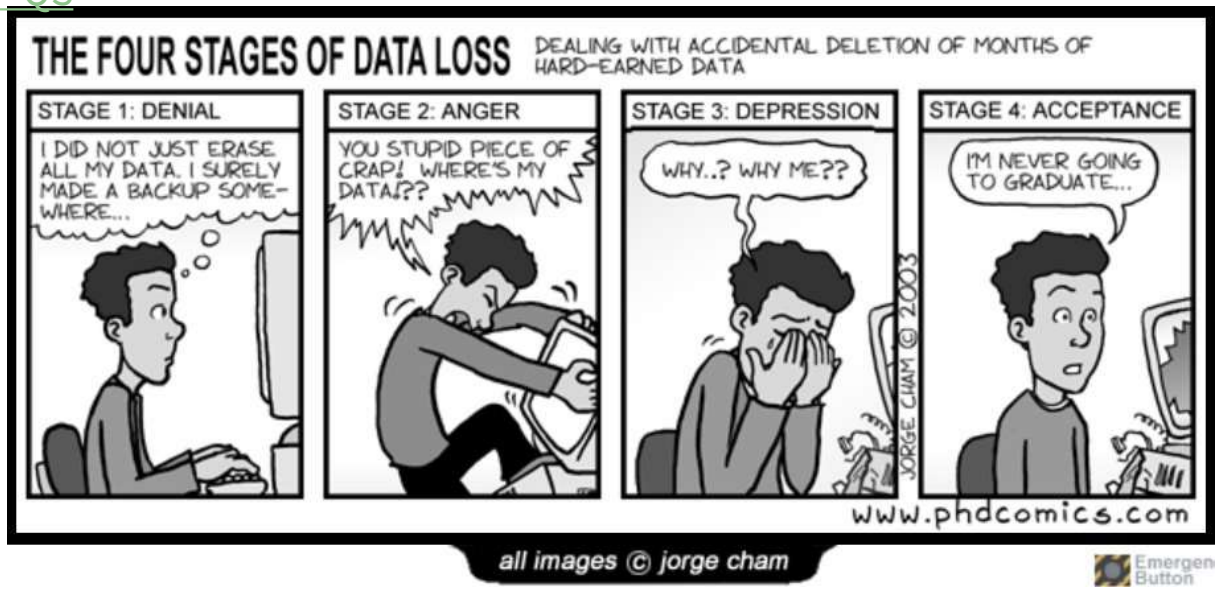
They forget where they store their food

SCIENTISTS ARE LIKE SQUIRELLS

They collect too much data at once

QS World University Rankings by Subject 2015 - challenges and developments - QS

They forget where they stored them!

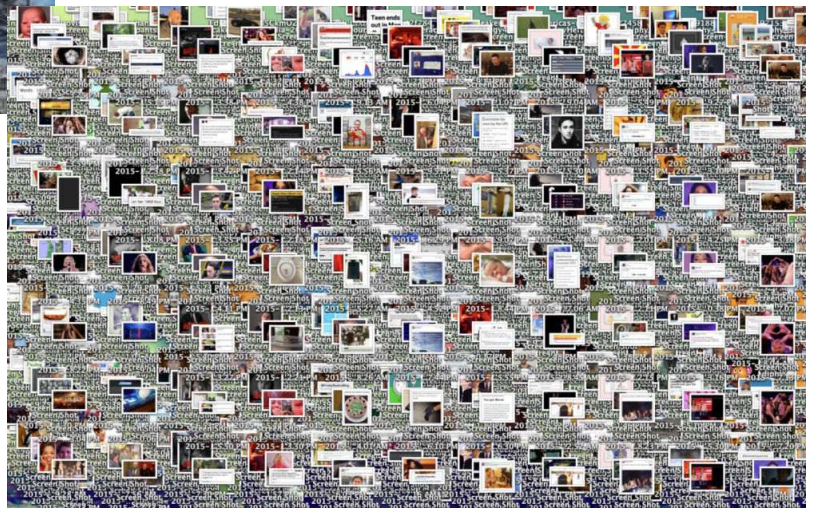


PHD Comics: Stages of Data Loss

DATA SCIENTIST IS THE SEXIEST JOB IN 21st CENTURY?

DATA MINING FOR SURE NOT!!!

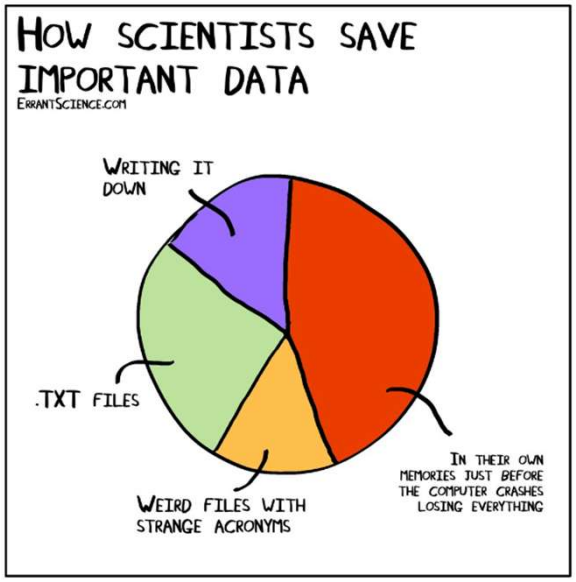
DATA SCIENTIST IS THE SEXIEST JOB IN 21st CENTURY?



DO SCIENTISTS NEED DATA MANAGEMENT?

subject: External hard disk lost
Organization: S.I.S.S.A.
Date: Wed, 4 Jul 2018 13:54:48 +0200
From: Students' Secretariat <XXXX@sissa.it>
To: SISSA Users:;

An external hard disk has been lost, most probably on the 4th floor, black, in a white box.
It contains a lot of work data of a SISSA PhD student.
If you happen to find it, please leave it at the reception desk or at the students' secretariat. Alternatively you can leave it in the Students' Secretariat mailbox in the lower level.



Marconi: scratch is almost full – quota imposed

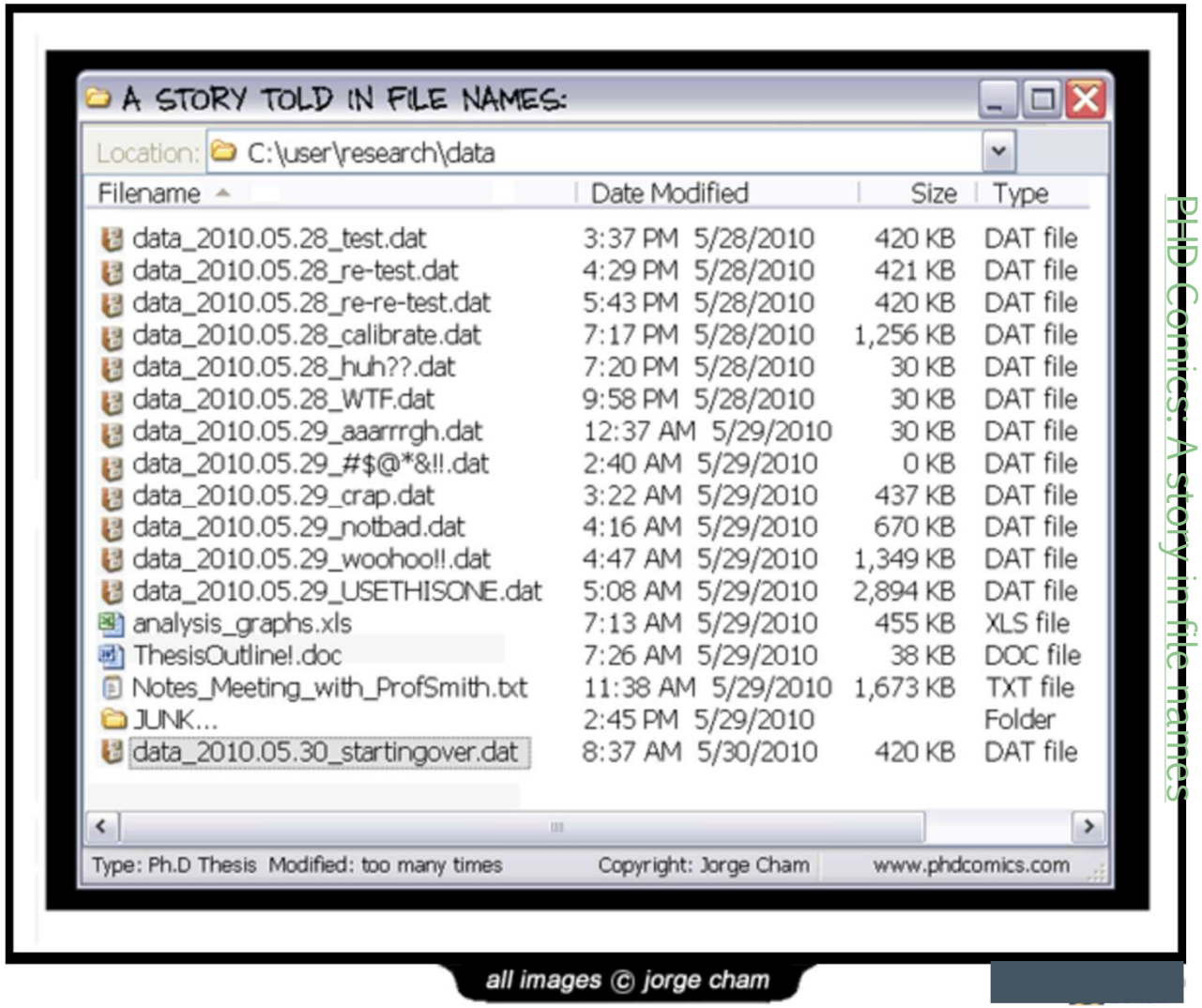
16 May 2024

Dear Marconi Users,

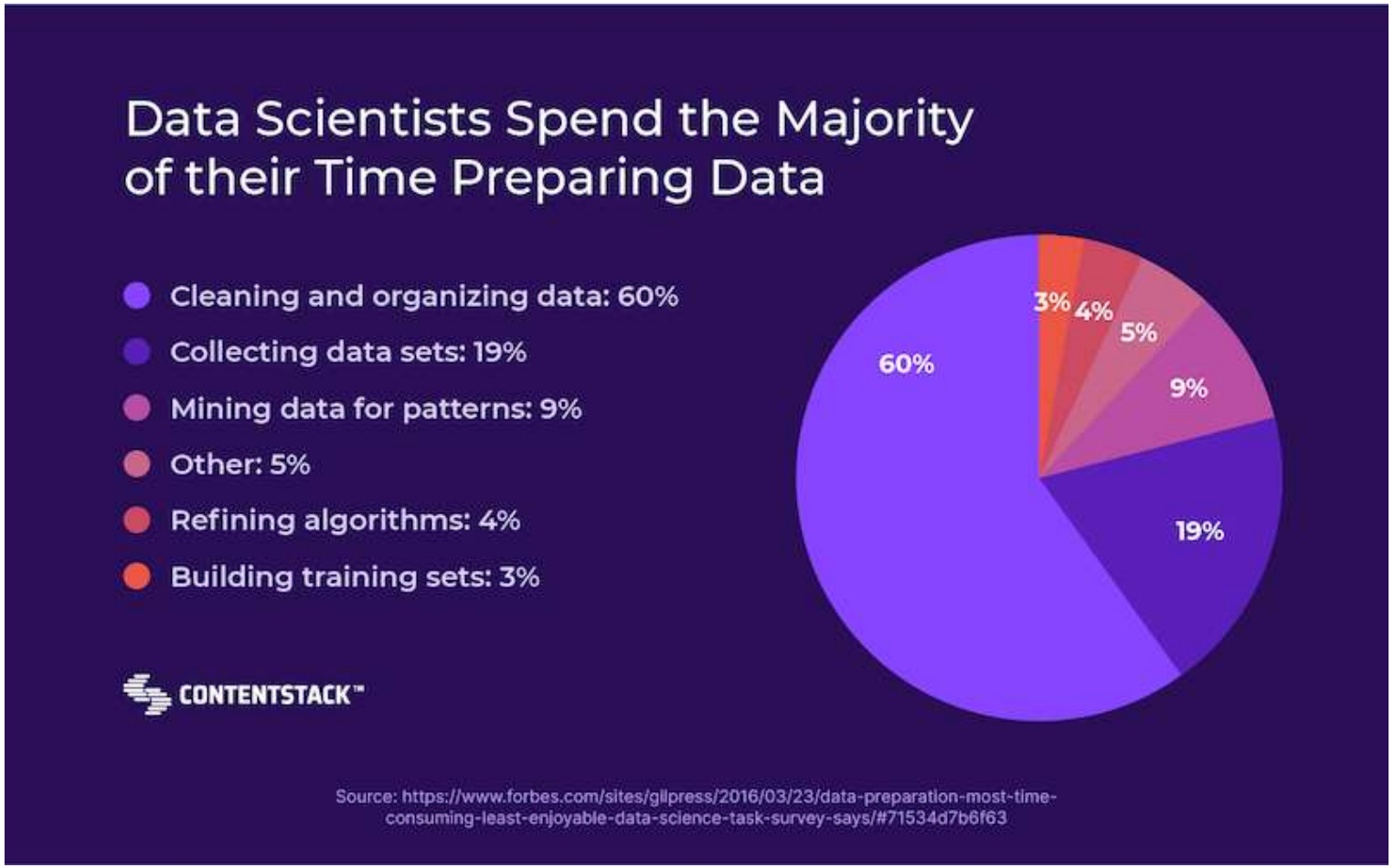
we inform you that the scratch space has reached the occupation of more than 87% today. This may cause malfunctions to the filesystems. To avoid reaching a 100% occupancy, we temporarily set a quota of 20 TB on the scratch folder of each user. We encourage you to clean your scratch folders by removing useless data or by moving data to work and dres spaces. We will inform you as soon as normal occupancy will be restored and the quota removed.

Best regards,
HPC User Support @ CINECA

DO SCIENTISTS NEED DATA MANAGEMENT?



DO SCIENTISTS NEED GOOD DATA MANAGEMENT?



DATA MANAGEMENT ROLE IN SCIENCE

› "*Research cannot flourish if data are not preserved and made accessible. All concerned must act accordingly*".

› "*Data management should be woven into every course in science, as one of the foundations of knowledge*"

'Editorial: Data's Shameful Neglect'

(**10 September 2009**) in Nature 461, p. 145, doi:10.1038/461145a.

What is Research Data Management (RDM)?

Data management refers to all aspects of creating, housing, delivering, maintaining, and archiving and preserving data. It is one of the essential areas of responsible conduct of research

Ensures data integrity, accessibility, and compliance with regulations

Supports reproducibility, transparency, and long-term usability of research outputs

Increasingly, universities and research center now encourage all researchers (including postgraduate students) to undertake data management plans (DMPs) at the start of their research project

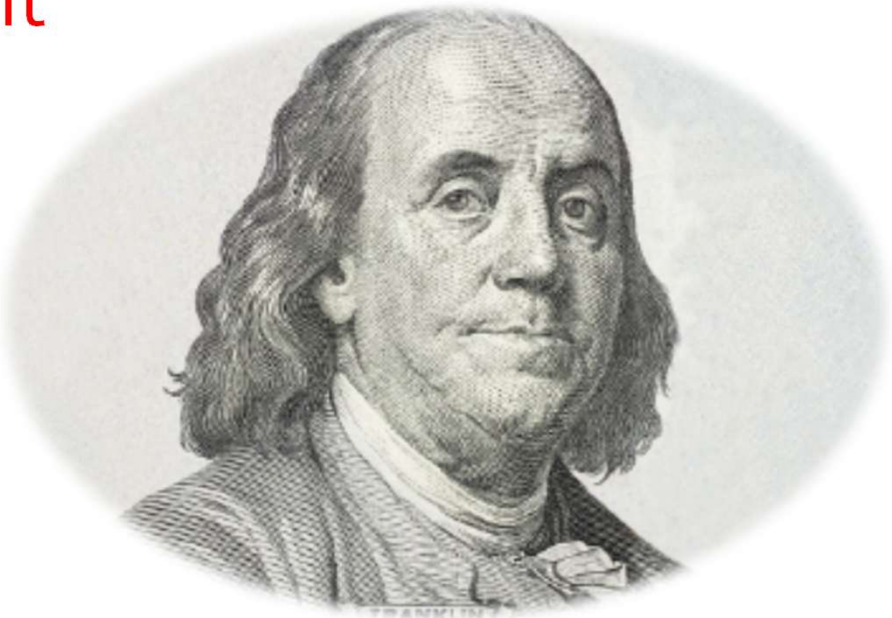
Before starting a new research project, Principal Investigators (PIs), research teams, and postgraduate students must address issues related to data management

EU-funded projects require a data management plan

Why is RDM Important?

- Enhances data quality and integrity
- Facilitates data reuse and collaboration
- Complies with funding agency and institutional policies
- Prevents data loss and ensures long-term preservation
- A good data management allows progress in research in a more direct way, without reinventing the wheel each time, both locally and within the community

“If you think ~~education~~
data management is expensive,
Try ~~ignorance~~ without it”



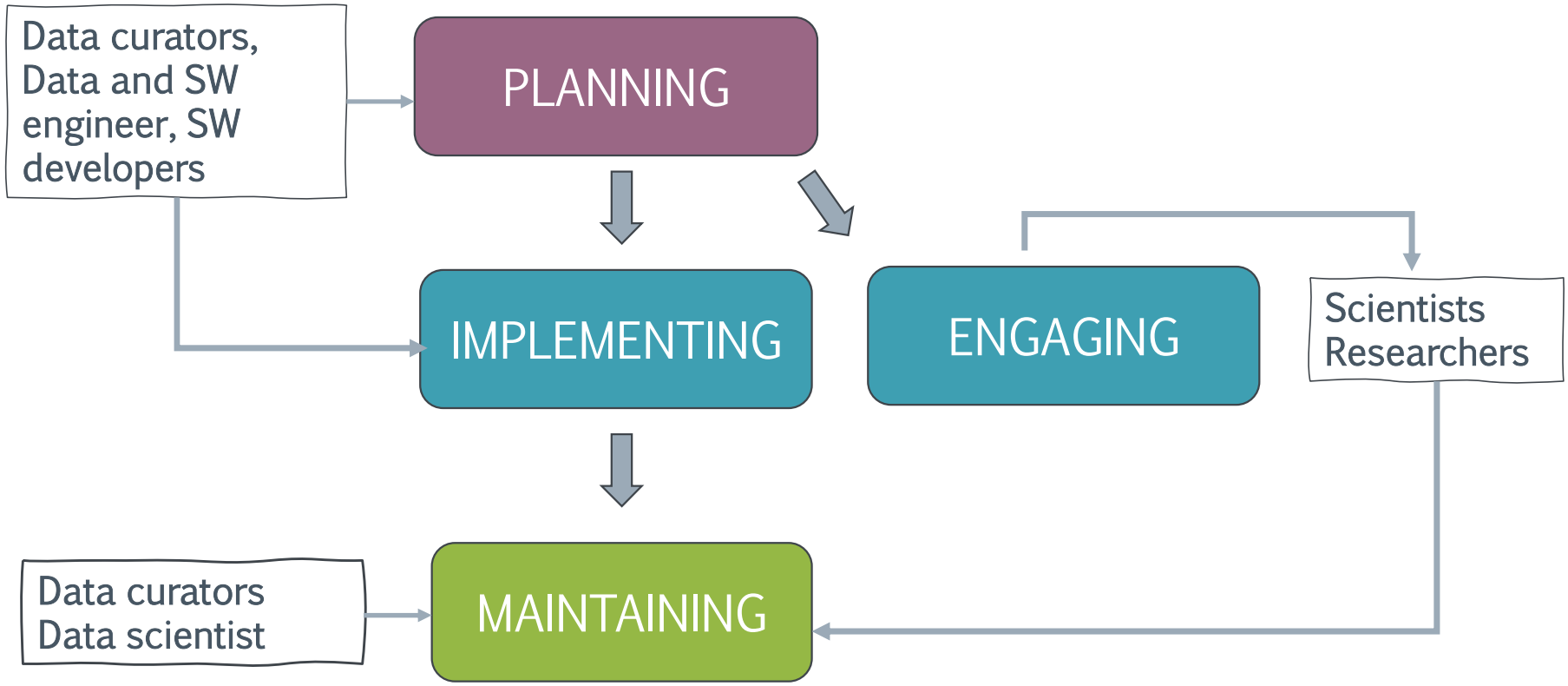
Benjamin Franklin

Data Management Priorities

- A higher degree of interoperability is required to overcome the huge fragmentation;
- Data scientists have to face too much detail in an increasingly complex data and tool landscape;
- Data scientists need wide scale data tracing and reproducibility mechanisms to facilitate trust and verification;
- Improved ways are needed to automatically create scientific annotations to capture and exploit knowledge

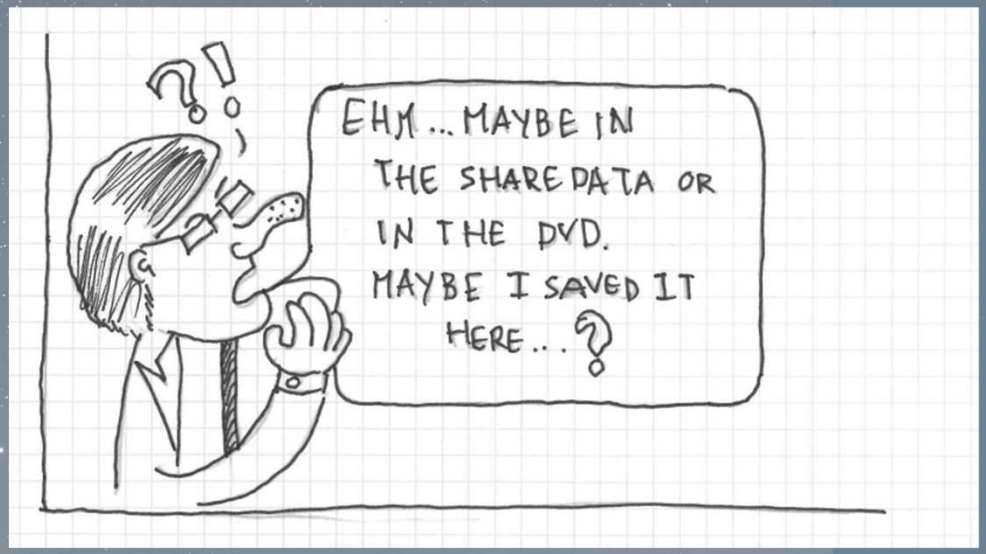
Roles in data intensive science:

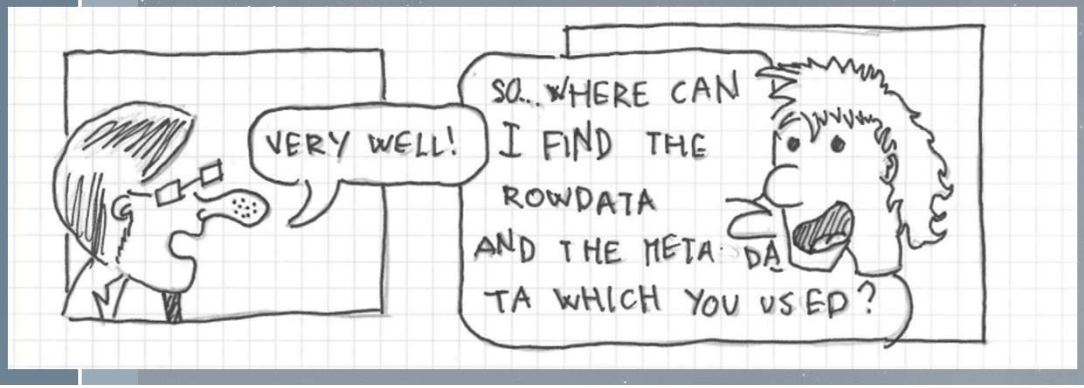
- Scientists/researchers: acquire, generate, analyze, check, organize, format, document, share, publish research data
- Data scientists/users: access, understand, integrate, visualize, analyze, subset, and combine data
- Data engineers: develop infrastructure, standards, conventions, frameworks, data models, Web-based technologies
- Software developers: develop tools, formats, interfaces, libraries, services
- Data curators: preserve data content and integrity of science data and metadata in archives
- Research funding agencies, professional societies, governments: encourage free and open access to research data, advocate elimination of most access restrictions

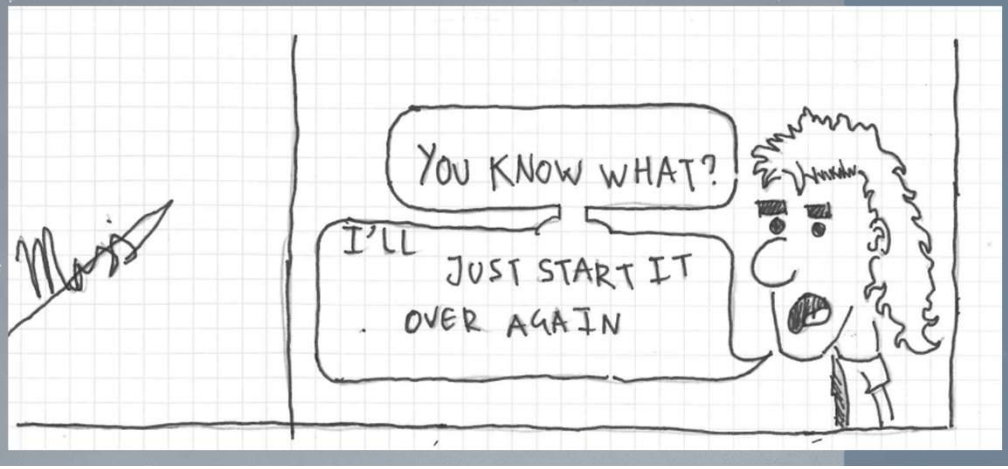


GOOD DATA MANAGEMENT REQUIRES COORDINATION AND COLLABORATION AMONG ALL THE PLAYERS !!!

Scientists need a Data Management Plan







DATA MANAGEMENT PLAN (DMP)

- How will the data be created?
- How will the data be documented?
- Who will access the data?
- Where will the data be stored?
- How will the data be shared?
- How long will the data be preserved?
- Who will back up the data?

A living document updated any time is needed

TOOLS (and guides) TO WRITE A DMP

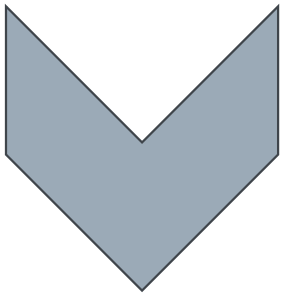
- Each funding agency could require or **recommend a specific** DMP template.
- Your institution could require and **recommend** a DMP template.
- Template could be presented as list of questions in text format or in a **machine-actionable format**.

Brief recap on DMP

DMP is at the heart of fair (FAIR) DATA MANAGEMENT

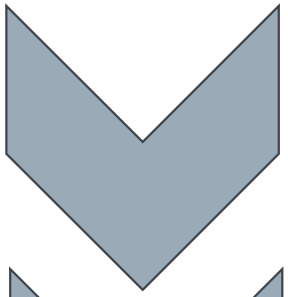
1.1st Generation DMPs (Structured Data):

- In the 1960s, the concept of DMPs began with organizations emphasizing professional training and quality assurance metrics.
- DMPs primarily focused on managing structured data, such as relational databases. (datadiversity.net)



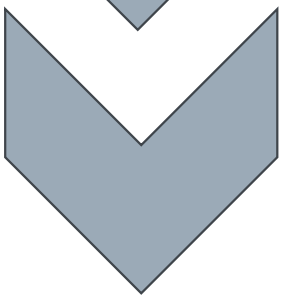
2. 2nd Generation DMPs (Big Data Analytics):

- With the rise of big data, DMPs adapted to handle diverse data types (structured, semi-structured, unstructured). (sparkfish.com)

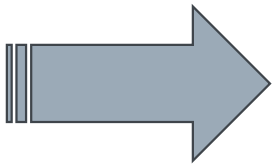


3. Current Trends in DMPs:

- Metadata and FAIR data principles (Findable, Accessible, Interoperable, Reusable) play a crucial role.
- Ensuring data security, confidentiality and ethical compliance remains essential



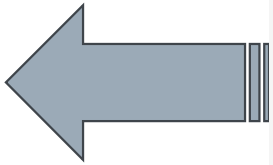
Brief recap on DMP



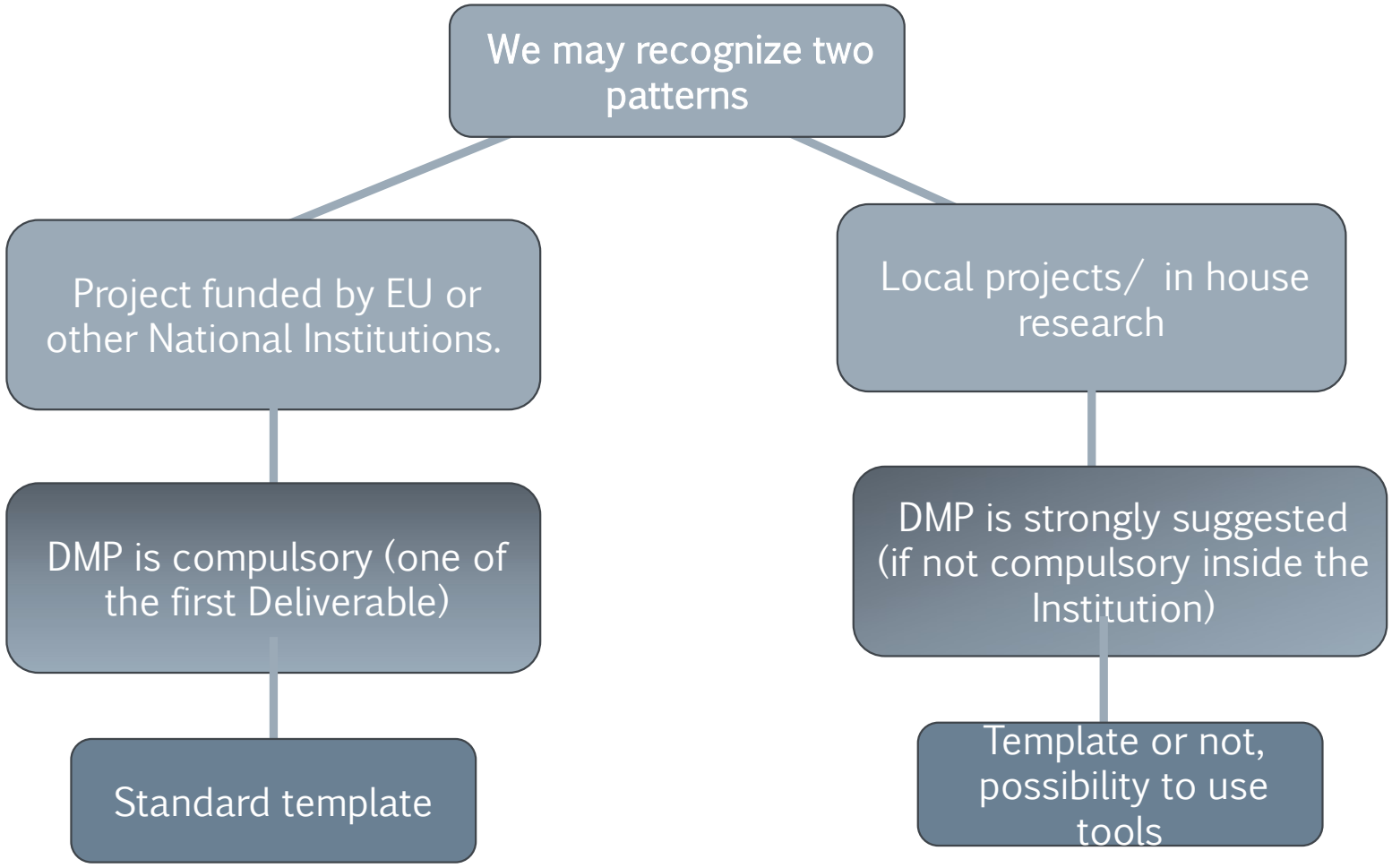
The **Data Management Plan (DMP)** became **mandatory** for all EU projects, including **Horizon Europe** grants (rdm.mpdl.mpg.de)

Unlike in Horizon 2020, where an opt-out option existed, Horizon Europe no longer allows skipping the DMP requirement. This trend aligns with the goal of making research data **FAIR** (findable, accessible, interoperable, and reusable) across all projects

The huge amount of data produced nowadays in all Sciences requires a deep planning of data management in all projects. Scientific team as well as individual investigator should always start their project with a DMP for sake of (their own) science



Approaches


We may recognize two patterns
Project funded by EU or other National Institutions.
DMP is compulsory (one of the first Deliverable)
Standard template
Local projects/ in house research
DMP is strongly suggested (if not compulsory inside the Institution)
Template or not, possibility to use tools

CHALLENGES IN RDM

Ensuring compliance with evolving data policies

Managing large volumes of diverse data types

Encouraging researchers to adopt best practices

Balancing data security with open access principles

DATA POLICY

A documented set of guidelines for ensuring the proper management of the data in an organization

Establishes who is responsible for data under various circumstances, and specifies what procedures should be used to manage it

Regulated data usage, data sharing, and data citations

Requires synergy of executive committee, finance, IT, management, and other data stewards within the organization

Is a flexible document, which can be changed in response to changing needs of the community

AND….

DATA GOVERNANCE ?

TAKE AT HOME MESSAGE N.1

Data wrangling:

Different formats (often proprietary)

No standardization

Different information

Different units

Incomplete data

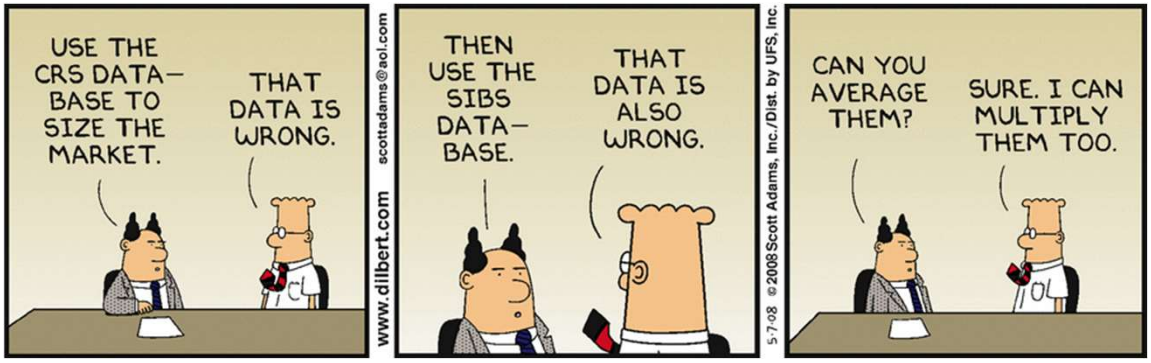
Incompatible data

TAKE AT HOME MESSAGE N.2

Lack of agreement among scientists and IT on how to treat data

Manual metadata registration only at publication time

No clear and common (meta)data models



TAKE AT HOME MESSAGE N.3

Inactivity of scientists:

- Old "handmade" programs
- Pen and copybook
- Data intellectual propriety
- Not familiar with technology
- Sharing data by physical drives (external hard disk, usb pen, ...)
- *"Metadata registration is a waste of time"* (cit.)

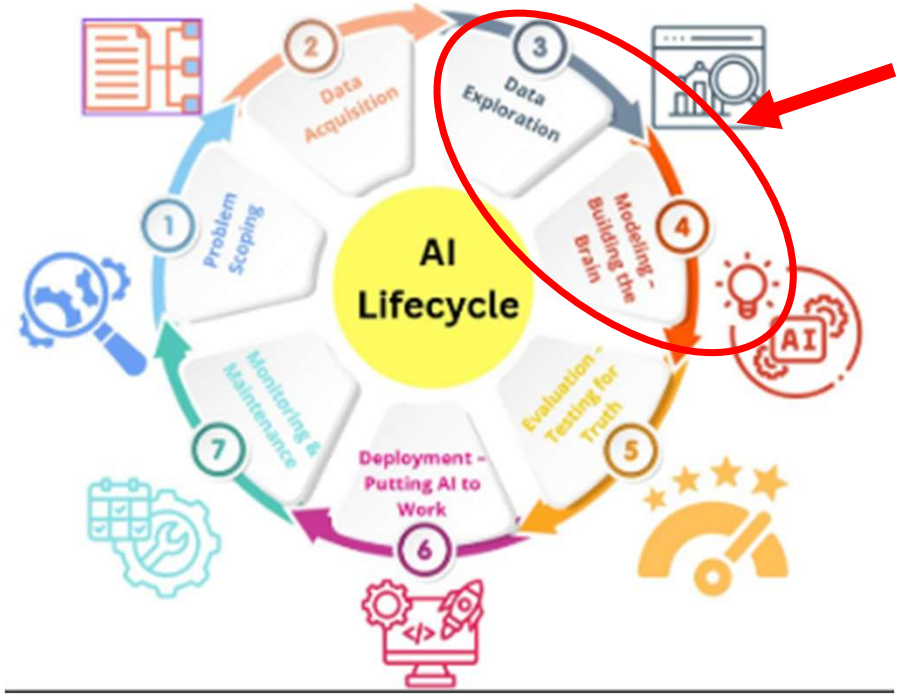
AI AND DATA MANAGEMENT

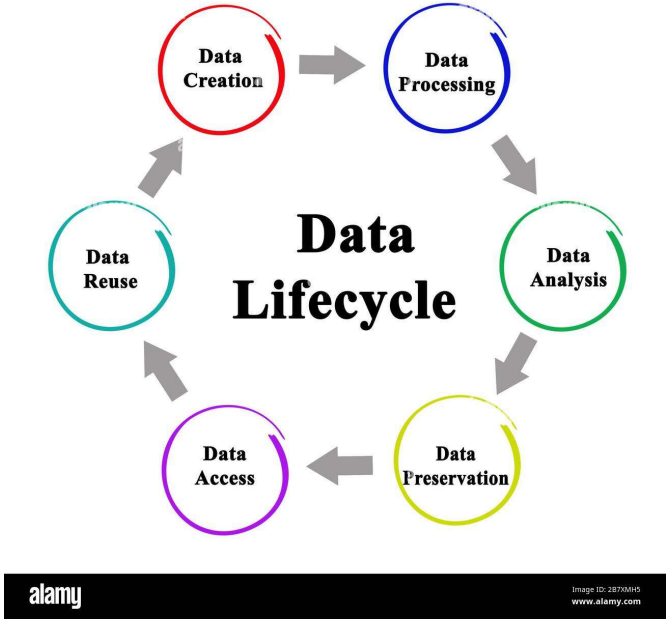
DATA and AI

We may recognize three main level on data management related issues in the AI ecosystem.

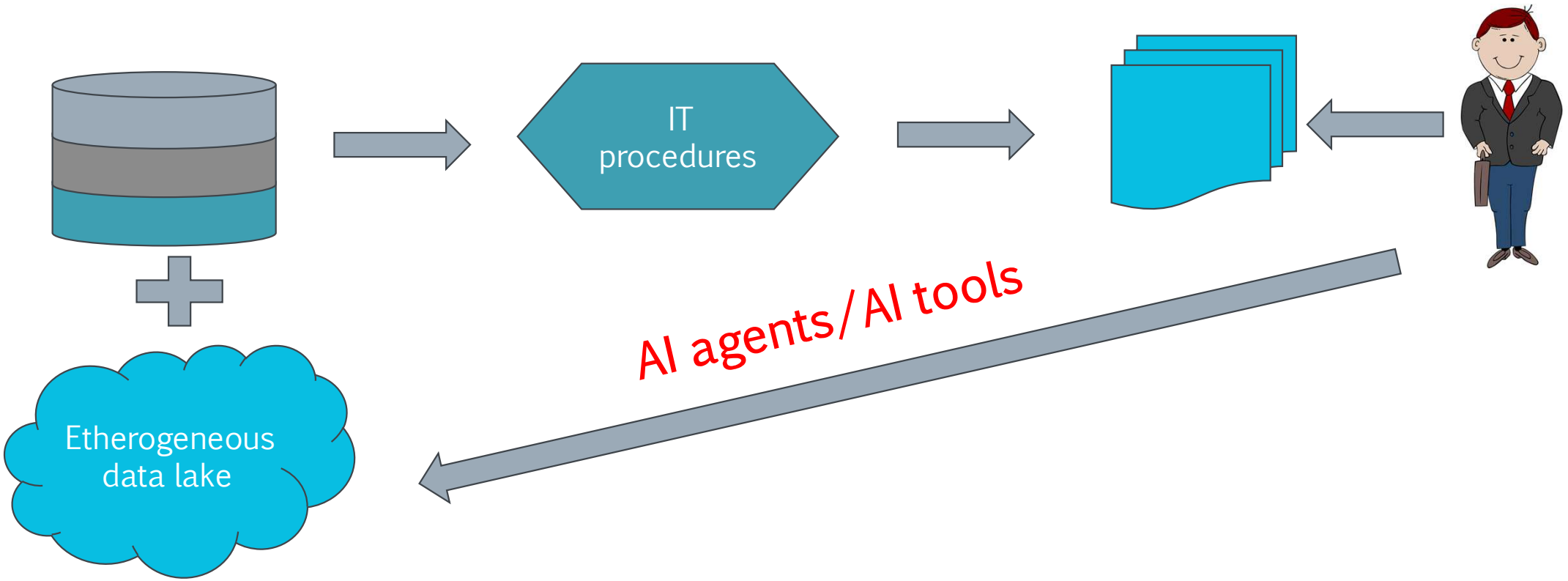
- ❑ DATA to train the models (the «proteins» that build the model)
- ❑ DATA on which AI Agents act to extract «value»
- ❑ DATA to be managed better thanks to AI

DATA that train the models (or used to fine tuning/ RAG)





DATA products



DATA mesh: approach to data management that decentralizes data ownership and governance, enabling more flexible and scalable data integration across an organization.

AI make really operative and sustainable this approach!

- **AI-Powered Data Productization** :AI Agents lower the technical barrier for domain experts by automating the transformation of raw **Data** into **Information**. Through "Text-to-ETL" and automated **Metadata** extraction, agents handle the lifting of documentation, schema definition, and cataloging. This ensures that every domain can produce high-quality, self-describing Data Products without needing a massive team of specialized data engineers (that often was a bottleneck)
- **Federated Computational Governance:** In a decentralized mesh, maintaining global standards is a nightmare. AI Agents act as autonomous "Watchdogs" that perform real-time audits across all domains. They automatically enforce data quality,
- **Semantic Interoperability & Self-Serve Efficiency:** AI Agents may facilitate **Semantic Interoperability** by dynamically mapping different domain ontologies (e.g., linking "Customer" in Sales to "Client" in Support). The streamline self-serve infrastructure by automating resource provisioning through natural language, eliminating the friction between domain teams and the central platform.

It really depends on the model/domain!

Data Management Trends in 2026: Moving Beyond Awareness to Action - Dataversity

Key Takeaways

- ✓ According to our research, most companies have implemented data governance, but at a low maturity. Consequently, data quality remains a top challenge.
- ✓ Companies must adjust to a complex and fragmented AI regulatory landscape with substantial financial penalties, making AI governance essential.
- ✓ In 2026, success in data management depends on knowing best practices in data quality, data governance, AI governance, and data literacy, and how to apply them.
- ✓ The demand for ROI on AI projects relies on strong data management fundamentals, a must for implementation.

AI Data Curation Market Report

Global Market Segmentation & Forecasts 2025 - 2030

Ingestion & Transformation	Quality, Governance & Trust	Knowledge Engineering & Context	Training Data & Enrichment	Discovery & Search
Unstructured Data Ingestion & Extraction	Data Quality, Governance and Observability	GraphRAG & Structured Context	Data Labeling & Training Infrastructure	Enterprise Search
Unstructured Data Preprocessing	Privacy-First Data Curation	Agentic Memory & Long-Term Context	Synthetic Data Generation	Intelligent Search & AI Relevance
Unstructured Data Management	Trusted RAG & Hallucination Control	Agentic Knowledge Engineering	Data-Centric AI & Quality Control	Real-Time RAG & Search
Real-Time Data Frameworks & Streaming ETL	AI Evaluation & Guardrails	Active Metadata & AI Lineage	Multimodal Curation for Physical AI	Data Framework & Orchestration
Multimodal Data Pipelines	-	Master Data Curation	-	Medical Audio Curation

AI Data Curation Market Report

- **Market Shift and Valuation**: The AI industry is experiencing a paradigm shift from model-centric development to the **data "curation" layer**, The global AI Data Curation market is projected to expand significantly, growing from **$82.05 billion in 2025 to $253.23 billion by 2030**.
- **Ingestion & Transformation**: This domain tackles the massive influx of unstructured data, projected to reach 175 zettabytes in 2025. Organizations are transitioning from rigid, batch-based ETL processes to **fluid, real-time, and multimodal data pipelines** that can handle text, image, audio, and video simultaneously.
- **Quality, Governance & Trust**: Often referred to as the "guardrail economy," this sector focuses on making AI safe and compliant with strict regulations like the EU AI Act. Key technologies include real-time data observability, privacy-first anonymization, and **hallucination control** to verify model outputs against trusted source materials.
- **Knowledge Engineering & Context**: This pillar is the foundation for autonomous "Agentic AI," giving AI systems long-term memory and structured reasoning. It relies heavily on **GraphRAG**, which uses knowledge graphs to map relational connections between data entities rather than just searching for similar text.

AI Data Curation Market Report

- **Training Data & Enrichment:** Characterized by the **"Synthetic Pivot."** Because high-quality real-world data is becoming exhausted or legally restricted, the industry is increasingly relying on synthetically generated datasets to train models. This area also includes specialized multimodal curation for physical AI, such as robotics and autonomous vehicles.
- **Discovery & Search:** Representing the "last mile" of information delivery, enterprise search is shifting from traditional keyword matching to **"answer-based" discovery**. RAG-enabled platforms now allow employees and consumers to ask conversational questions and receive summarized answers with citations from the company's internal data.
- **Core Growth Drivers:** This rapid sector expansion is driven by technical imperatives (like managing multimodality), economic realities (such as **avoiding the $12.9 million average enterprise loss caused by "dirty" data errors**), and social factors (like the "Privacy Paradox" and the demand for localized AI in emerging economies).

In summary ...from"Human-in-the-loop" to "AI-on-the-loop."

•**Autonomous Data Operations**: Introduction of **Self-healing pipelines**. AI agents now detect schema changes or data drift and suggest (or apply) fixes without manual intervention.

•**Context Engineering**: Management is no longer just about storing rows; it's about managing the **context** (Metadata) that allows an AI to interpret those rows.

•**Democratization**: By 2026, it is estimated that **75% of data integration flows** are generated by non-technical users via Natural Language Interfaces (Generative Data Engineering).

Challenges in RDM

AI4Knowledge: Shaping the Future of Research Data Systems

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- **Data Growth and Complexity:** exponential growth of data, which is highly heterogeneous and multi-formatted (we already said!)
- **Manual Inefficiencies:** Traditional RDM relies heavily on manual processes that are time-consuming, lack scalability, nd increase the risk of errors, data loss, and inconsistencies.
- **Resource Constraints:** Existing systems often lack intelligent tools for resource allocation, leading to a suboptimal use of time, personnel, and finances.

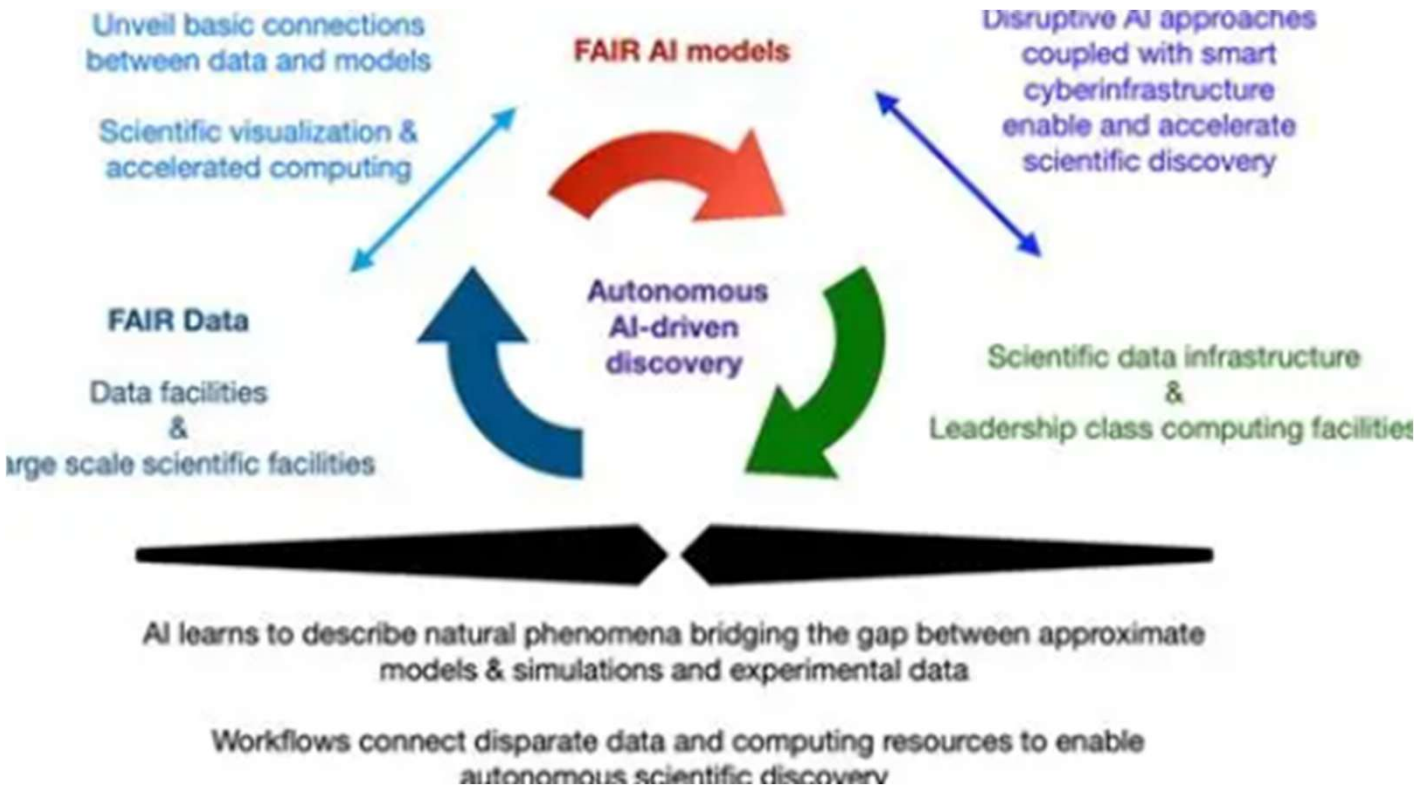
AI Solutions in RDM

- **Classification/Semantic enrichment:** Automates data management by recognizing patterns and tagging both structured and unstructured data
- **Data Quality**: anomaly detection
- **Decision Support Systems (DSS):** Optimizes resource allocation and dynamic planning using predictive models, historical data, and optimization algorithms to avoid bottlenecks.

Outlook and Integration

- **Seamless Integration:** it must be integrated into existing systems without disrupting current workflows, which requires close collaboration between researchers, data scientists, and IT specialists (once more!)
- **Human-AI Collaboration:** user-centered AI that acts as a "co-pilot". Using Explainable AI (XAI) ensures transparency and helps build trust, allowing researchers to focus on high-level analysis rather than administrative tasks.

FAIR data and AI



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FAIR data management and artificial intelligence: CODATA workshop at the University of Minho within Climate-Adapt4EOSC

Addressing FAIR data and AI challenges in research infrastructures

The session explored the evolving challenges of FAIR (Findable, Accessible, Interoperable and Reusable) data management in the context of increasingly complex research data infrastructures and the growing integration of artificial intelligence. Drawing on international best practices and ongoing European initiatives, CODATA provided a structured overview of key issues related to data interoperability, governance frameworks and sustainability.

Particular emphasis was placed on the role of artificial intelligence as an enabler for scalable, reusable and interoperable research infrastructures, while also highlighting the need for robust governance models, transparent workflows and high-quality metadata to ensure trust, reproducibility and long-term value.

KEEP AT HOME MESSAGE FROM LECTURE 1

- **Data management defines how data should be governed:** it sets rules for data quality, security, ownership, and lifecycle, but only a solid infrastructure makes those rules enforceable and operational.
- **Data management ensures data quality, reliability, and reproducibility:** RDM is essential to guarantee reproducible results and scientific discoveries; in enterprise, it ensures accurate, consistent data to support trustworthy analytics and decision-making.
- **Data management enables long-term value, sharing, and compliance**: DM allows data to be reused, shared, and integrated over time, pursuing s collaboration in research and efficiency, compliance and innovation in enterprise environments.