Artificial Intelligence applied to enviromental monitoring

Technical challenges and limitations of environmental AI

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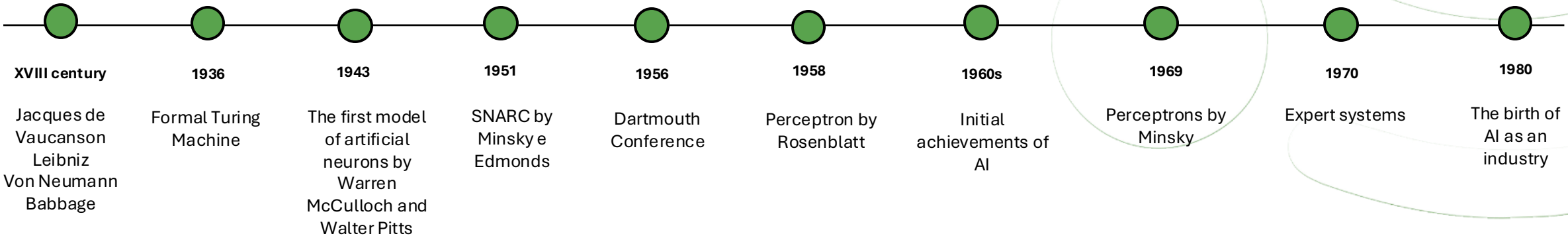
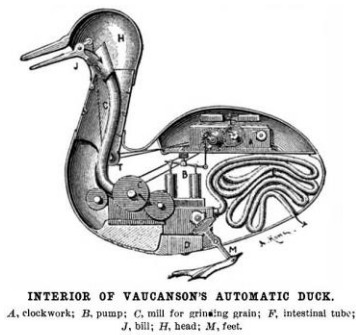
Module 1: AI and Data

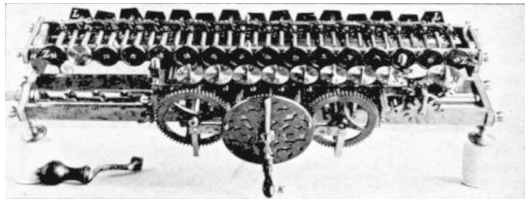
Historical perspective



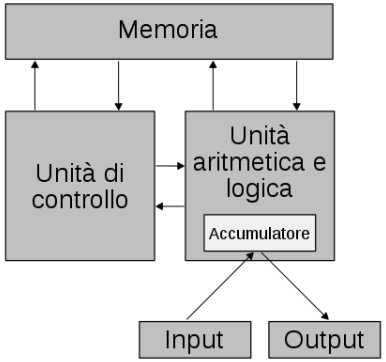
AI Ethics



The *Digesting Duck* by Jacques de Vaucanson (1738)

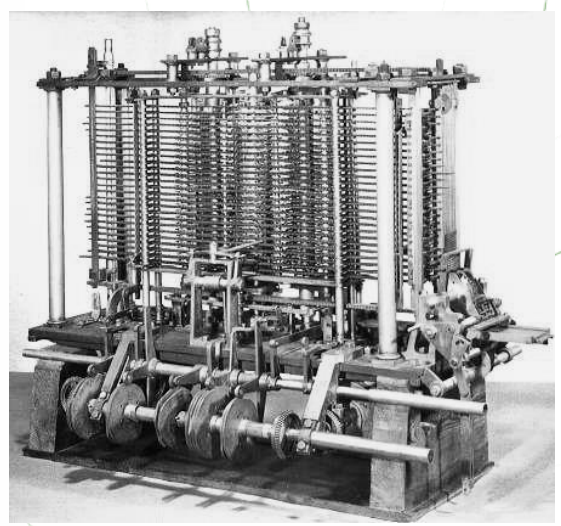


Calculus ratiocinator By Leibniz



Von Neumann architecture

Charles Babbage's Difference Engine



Charles Babbage's Analytical Engine

- These figures allow us to refer to the tradition of formalist research.
- This tradition helps us understand how artificial performance is part of human practice.
- In particular, through the projects of mathematician Charles Babbage, we see the human tendency to self-imitate using machines.
- Mathematician Ada Lovelace, in 1840, recognized the potential of Babbage's Analytical Engine.
- Lovelace was interested in the machine's ability to process symbols that could represent all objects.
  She was the first to foresee the advent of a form of Artificial Intelligence.
- Artificial Intelligence was possible, but it was not yet clear how to achieve it.

ARTIFICIAL INTELLIGENCE

=

THE SCIENCE THAT ADDRESSES THE PROBLEM OF HOW TO REPRESENT AND BUILD KNOWLEDGE

Data as the foundation

- Artificial Intelligence relies on large volumes of data.
- Data fuels machine learning models: **more data → better accuracy**.
- **Raw data → Information → Knowledge → Automated decisions**
- AI doesn't just analyze data — it transforms it into **intelligent actions** (e.g., predictions, recommendations, classifications).

Definition of data

Data are **original representations** — that is, not yet interpreted — **of a phenomenon, event, or fact**, conveyed through symbols, combinations of symbols, or any other expressive form associated with a medium

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⇩

Data are representations of events or facts:

– **Not interpreted (original)**
– **Expressed through symbols (or combinations of symbols)**
– **Stored or conveyed on some medium (expressive form)**

Structured data vs Unstructered data

Structured data refers to data that follows a predefined and expected format → as a table in a database, with columns for name, date, temperature — each entry follows a set structure

VS

Unstructured data lacks a predefined format (e.g.Podcast, video files…)

Quality of data

HOW GOOD IS THIS DATA?

What makes data "High quality"?

- **Accuracy**
- **Consistency**
- **Timeliness**
- **Completeness**
- **Spatial and temporal resolution**
- **Metadata and documentation**

Data Quality and validation according to ISTAT

According to ISTAT, the final output of a statistical survey can be broken down into **three levels of information**:

- **Microdata** = individual data points
- **Macrodata** = statistical summaries
- **Metadata** = documentation about the data

Together represent the **statistical information** produced by a survey.
That's why ISTAT refers not just to **data quality**, but more broadly to the **quality of information >** we must define what "quality" means at **each of the three levels** — individual data, aggregated results, and metadata.

Data Quality and validation according to ISTAT

ISTAT adopts a definition of quality originally proposed by **O. Arkhipoff** in 1986:

"The quality of a product is its ability to meet the guarantees provided by the producer."

These guarantess includes both the **design characteristics and tolerance**

Data Quality and validation according to ISTAT

Design guarantess

1. Timeliness
2. Theoretical relevance
3. Effective relevance
4. Transparency
5. Tolerence

Tolerance guarantess

1. Sampling precision
2. Non-sampling precision

Dimensions of data quality

Dimension	Definition	Defined by
1. Relevance	The extent to which statistics meet the real needs of users.	Eurostat
2. Accuracy	The closeness between statistical estimates and the true values.	Eurostat
3. Timeliness	The delay between the reference period and the availability of data.	Eurostat
4. Punctuality	The degree to which data is released according to the planned schedule.	Eurostat
5. Accessibility	The ease with which users can access the data.	Eurostat
6. Clarity (Transparency)	The clarity of presentation and documentation, enabling users to understand and interpret data.	Eurostat
7. Comparability	The possibility of comparing data across time, regions, or countries.	Eurostat
8. Coherence	The internal consistency of data and its compatibility with other datasets.	Eurostat
9. Completeness	The extent to which required data are available without gaps.	Eurostat
10. Confidentiality Protection	Ensuring the privacy of respondents and secure handling of individual data.	**ISTAT** (added)

Data validation

Data validation involves examining all the characteristics that define the **dimensions of data quality**, and it has two main objectives:

a) To assess whether the **quality of the data is sufficient** for public dissemination.

b) To identify the **most significant sources of error**, and to introduce changes in the production process in order to reduce errors in future surveys.

Four key validation measures:

Facilitating user assessments

Calculating process quality indicators

Conducting consistency studies

Estimating the main components of the error profile

TRANSPARENCY

Data validation

According to a definition provided by **Marescotti (1985)**, **environmental information** has three fundamental characteristics:

1. **Complexity**
2. **Uncertainty**
3. **Conflict**

Data abundance vs data scarcity

- **Data Abundance:**
  When there is a large volume of data available, often from multiple sources, sometimes even overwhelming in size.
  Example: Social media data, satellite imagery, sensor networks producing continuous streams of information.
- **Data Scarcity:**
  When data is limited, either in quantity, quality, or both. This can happen due to cost, accessibility, or rarity of events.
  Example: Rare disease cases, remote environmental measurements, early-stage research data.

Challenges of Big Data:

STORAGE

PROCESSING

NOISE

Challenges of Small Data:

OVERFITTING

LACK OF REPRESENTATIVENESS

Group activity: Exploring data quantity challenges

Group 1

Small Sample Size

- **Scenario:** A city wants to model traffic flow but only has traffic count data from 3 days in a year.
- **Challenge Questions:**
  - What problems might arise using such a small sample?
  - How might this affect the model's reliability and predictions?
  - What strategies could improve data quantity or address this issue?

Group 2

Missing Data

- **Scenario:** A weather dataset has temperature readings for every day, but 20% of the data is missing randomly.
- **Challenge Questions:**
  - How could missing data impact analysis?
  - What are possible risks when building models with this dataset?
  - What are common techniques to handle missing data?

Group 3

Uneven Sampling

- **Scenario:** Environmental sensors are deployed in a forest, but some sensors record data hourly while others record daily.
- **Challenge Questions:**
  - What challenges could uneven sampling frequencies cause?
  - How might this bias the results or the model?
  - How could you standardize or correct this inconsistency?

Group 4

Excessive Data / Overfitting Risk

- **Scenario:** A model uses a very large dataset with thousands of features but limited observations (high dimensionality).
- **Challenge Questions:**
  - What issues can arise from having too many features relative to data points?
  - How can this affect the model's performance?
  - What approaches can reduce this risk?

Bias

The occurrence of distorted outcomes due to human prejudices that alter the original training data or the AI algorithm itself, leading to skewed and potentially harmful outputs

Types of AI bias

- Algorithmic bias
- Cognitive bias
- Confirmation bias
- Exclusion bias
- Measurement bias
- Out-group homogeneity bias
- Prejudice bias
- Recall bias
- Sampling/Selection bias
- Stereotype bias

Algorithms that amplify biases in present data

- Algorithms can not only **absorb** those biases, but actually **amplify** them

How does this happen?

1. **Learning from biased data**
2. **Reinforcing existing trends**
3. **Feedback loops**

Why does this matter?

We risk making inequalities worse

Biases that were once hidden in society can become embedded in technology.

Group activity: Invisible pollution

The problem

After a year of implementation, environmental NGOs and citizen groups noticed something strange. The model consistently reported **lower pollution levels** in certain low-income neighborhoods — despite clear evidence of heavy traffic, industrial activity, and frequent respiratory issues reported by local clinics.

Investigation findandings

- These disadvantaged areas had **fewer air quality sensors**, due to underinvestment.
- Training data was heavily weighted toward **central, wealthier zones**.
- The model assumed that areas with green spaces nearby had low pollution — but failed to account for illegal waste burning or aging heating systems common in poorer districts.
- Complaints from residents were not included in the model's input, as they were seen as "anecdotal" data.

Discussion question

- **What types of bias are present in this case?**
- **How could these biases affect policy and public health?**
- **What changes would you suggest to make the model more fair and accurate?**
- **Can “less data” about an area be considered a form of bias in itself? Why or why not?**
- **How can local communities be involved in improving these models?**

Divide in small teams

- City government
- Data scientists
- Local community representatives
- Environmental health experts

Each group must:

1. Identify their key concern
2. Propose one concrete change to the AI model or the data collection process

How to mitigate bias

At the data level (pre-processing)

- **Data augmentation**: generate new examples for underrepresented groups
- **Resampling**: apply over/undersampling to balance classes/groups
- **Reweighing**: assign different weights to samples based on their group membership

At the model level (in-processing)

- **Fairness-aware algorithms**: models designed to incorporate fairness constraints
- **Fairness regularization**: penalize bias during training

At the output level (post-processing)

- **Equalized odds post-processing**: adjust predictions to reduce bias
- **Threshold optimization** for different groups
- **Reject option classification**: alter decisions in uncertain cases to promote fairness

Case study: 4 dimensional enviromental-monotoring at ECMWF

A standard method to estimate observational bias in satellite observations is to monitor first-guess departures for a certain period of time

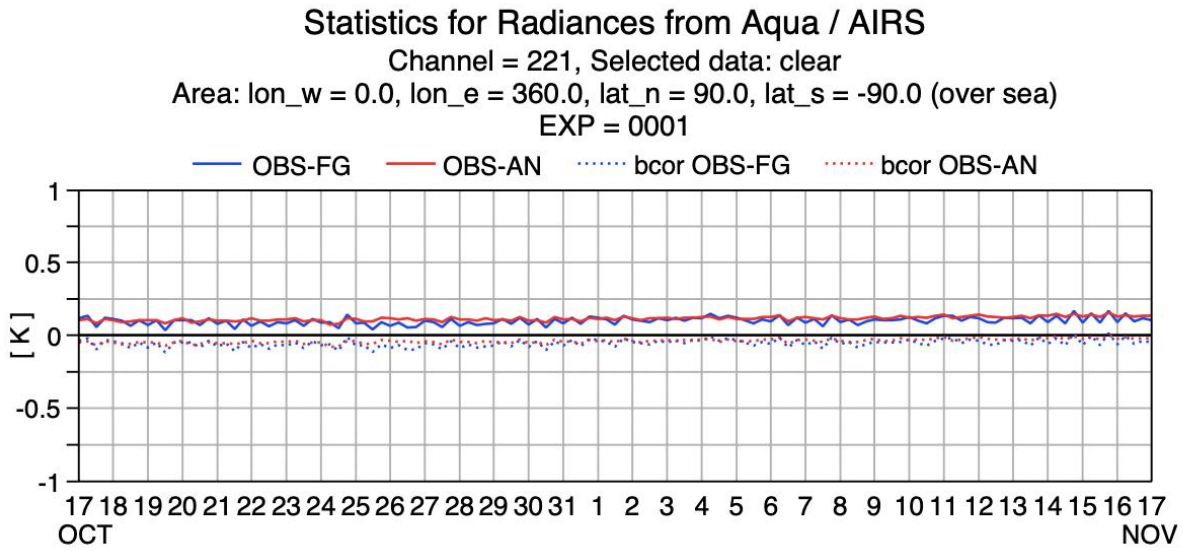


Figure 1: AIRS monitoring.

Case study: 4 dimensional enviromental-monotoring at ECMWF

- Use clear-sky data to isolate systematic differences
- Differences caused by:
  - Observation errors (e.g. radiative transfer)
  - Model errors (minimized near radiosonde data)

AIRS CO_2 Channel

- Bias: small and stable → easy to correct
- CO_2 signal ≈ bias magnitude → risk of removing real signal or misinterpreting bias

Case study: 4 dimensional enviromental-monotoring at ECMWF

Bias in CO_2 estimates due to cloud detection issues

- Cloud detection for AIRS radiances generally works well
- However, assumption of no systematic errors fails in tropical convective regions
- Thin cirrus clouds (allowing atmosphere/surface visibility) are hard to detect
- Large systematic errors in background water vapor profiles affect lowest peaking longwave channels (water vapor sensitive)

BREAK

Module 2: Enviromental data

Enviromental data analysis

- It focuses on collecting and interpreting **data** related to the enviroment
- It includes data about air, water, soil and ice to assess enviromental health
- Key steps in data analysis include collection, inspection, cleaning, trasformation and modeling
- The goal is to understand the impact of human activites on the enviroment

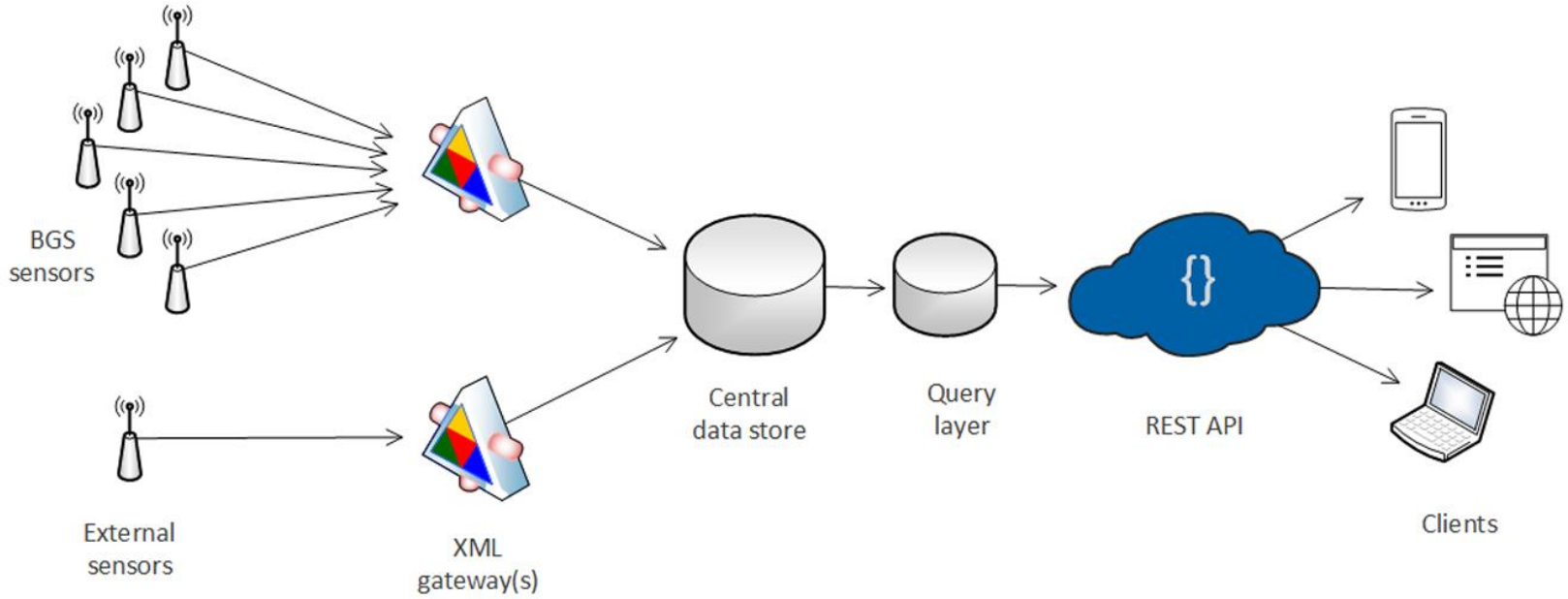
Dan Hammer

Data Science for the Environment

Types of environmental data

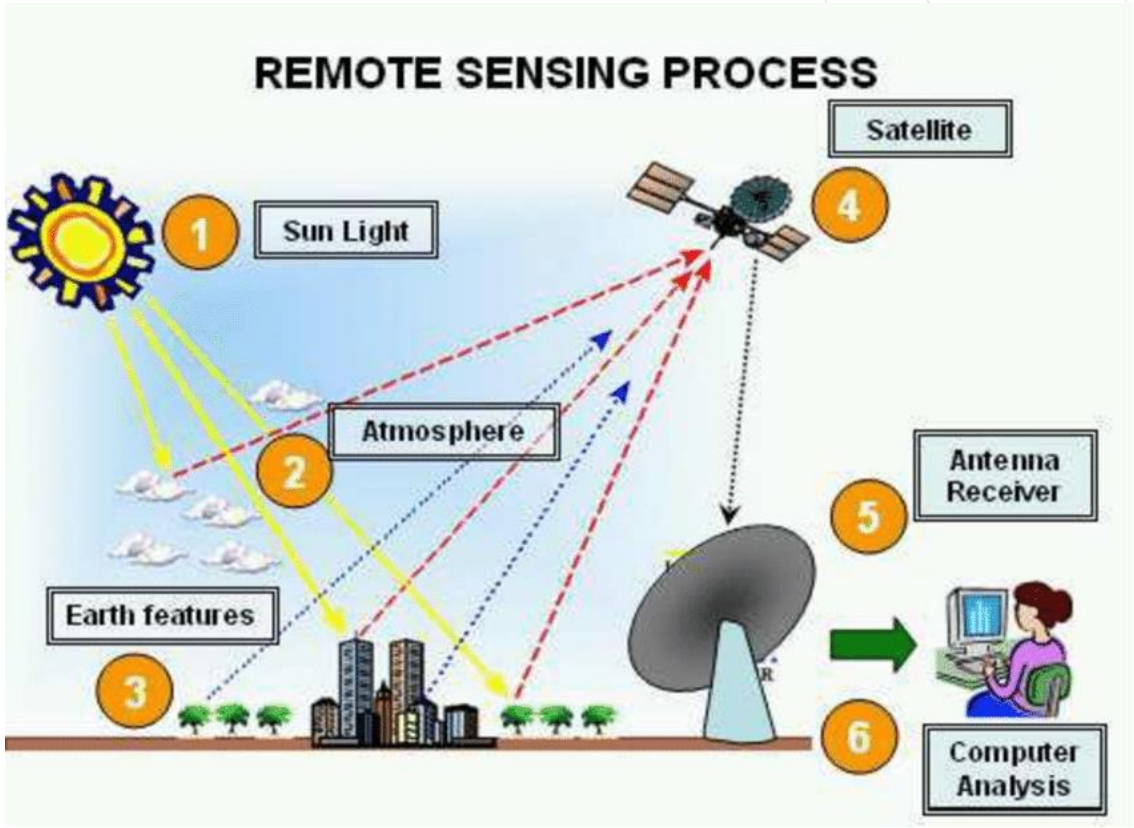
- Sensor data (e.g., air quality, temperature)
- Remote sensing (e.g., satellite imagery)
- Crowdsourced data (e.g., citizen science)
- Historical datasets (e.g., weather archives)
- Model-generated data

Sensor data



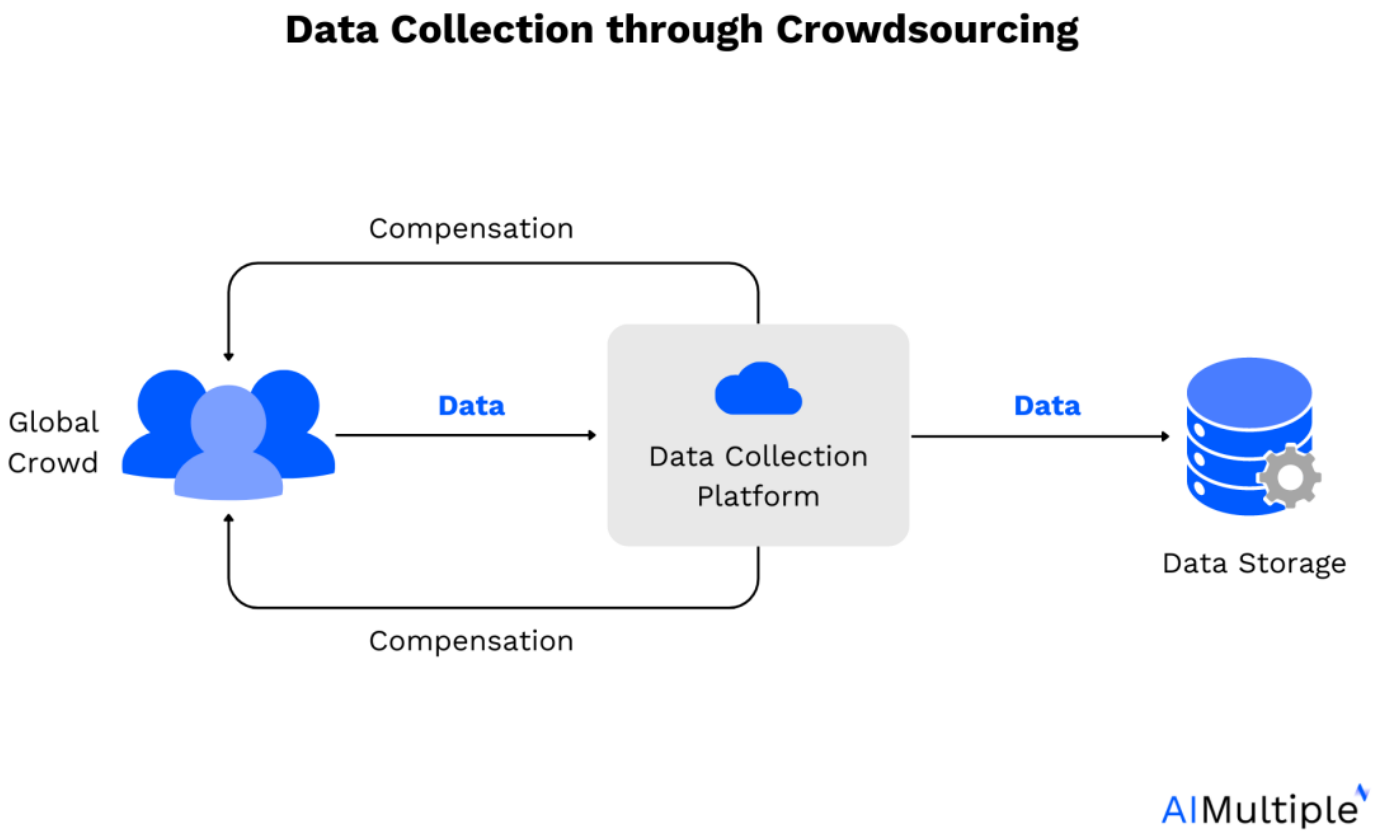
For example: air quality, temperature, humidity, noise levels

Remote sensing data



For example: satellite images, aerial photos, radar scans

Crowdsourced data



For example: citizen science contributions, mobile apps, social media reporting

Historical dataset

U.S. Department of Commerce
National Oceanic & Atmospheric Administration
National Environmental Satellite, Data, and Information Service
Current Location: Elev: 1518 ft. Lat: 33.4191° N Lon: -111.8444° W
Station: **EAST MESA, AZ US USC00022782**

Record of Climatological Observations
These data are quality controlled and may not be identical to the original observations.
Generated on 05/03/2021

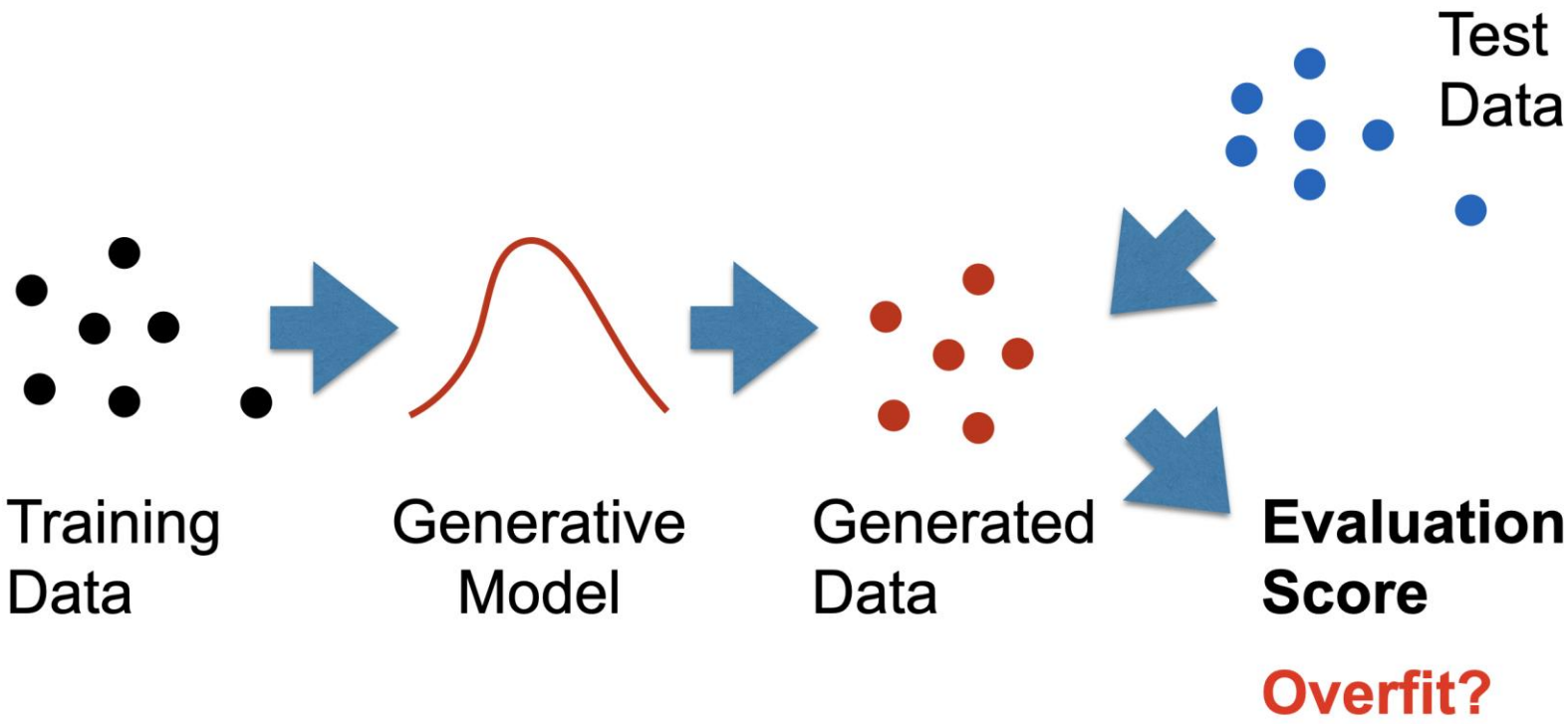
National Centers for Environmental Information
151 Patton Avenue
Asheville, North Carolina 28801

Observation Time Temperature: 1700 Observation Time Precipitation: 1700

Year	Month	Day	Temperature (F)			Precipitation					Evaporation		Soil Temperature (F)					
			24 Hrs. Ending at Observation Time		At Obs.	24 Hour Amounts Ending at Observation Time				At Obs. Time			4 in. Depth			8 in. Depth		
			Max.	Min.		Rain, Melted Snow, Etc. (in)	Flag	Snow, Ice Pellets, Hail (in)	Flag	Snow, Ice Pellets, Hail, Ice on Ground (in)	24 Hour Wind Movement (mi)	Amount of Evap. (in)	Ground Cover (see *)	Max.	Min.	Ground Cover (see *)	Max.	Min.
2016	01	01	65	30	60	0.00												
2016	01	02	71	47	62	0.00												
2016	01	03	73	51	64	0.00												
2016	01	04	64	50	57	0.13												
2016	01	05	59	48	54	0.28												
2016	01	06	58	47	55	0.71												
2016	01	07	55	45	48	0.67												
2016	01	08	52	40	50	0.19												
2016	01	09	57	34	53	0.00												
2016	01	10	55	35	52	0.00												
2016	01	11	60	35	54	0.00												
2016	01	12	65	31	60	0.00												
2016	01	13	67	33	60	0.00												
2016	01	14	63	33	59	0.00												
2016	01	15	60	37	55	0.00												
2016	01	16	61	33	56	0.00												
2016	01	17	66	35	60	0.00												
2016	01	18	70	37	62	0.00												
2016	01	19	67	35	64	0.00												
2016	01	20	68	39	65	0.00												
2016	01	21	70	39	65	0.00												
2016	01	22	75	43	70	0.00												
2016	01	23	73	39	65	0.00												
2016	01	24	65	40	62	0.00												
2016	01	25	66	42	63	0.00												
2016	01	26	67	44	65	0.00												
2016	01	27	70	47	66	0.00												

For example: past weather records, environmental archives, long-term monitoring

Model-generated data



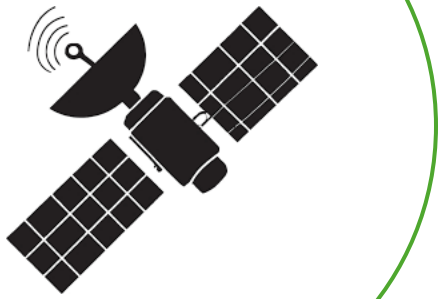
For example: climate models, pollution dispersion simulations, weather forecasts

Enviromental data

Data Type	Source / Origin	Typical Format	Strengths	Limitations
Sensor Data	Ground-based sensors (e.g., temperature, air quality)	Structured (e.g., CSV, time series)	High frequency; real-time; precise local readings	Limited spatial coverage; sensor maintenance needed
Remote Sensing Data	Satellites, drones, aircraft	Semi-structured (e.g., raster images, GeoTIFF)	Wide spatial coverage; frequent global snapshots	Requires specialized processing; may have cloud/noise interference
Crowdsourced Data	Citizens, apps, social media	Unstructured or semi-structured (e.g., text, mobile reports)	Covers gaps in official data; real-time public input	Varies in quality and consistency; can be biased or incomplete
Historical Datasets	Archives, weather stations, long-term monitoring	Structured (e.g., databases, spreadsheets)	Long-term trends; well-documented	Possible gaps or inconsistencies in older data; standard changes over time
Model-Generated Data	Computational simulations and forecasts	Structured (e.g., NetCDF, gridded formats)	Enables prediction; explores hypothetical scenarios	Depends on model assumptions; sensitive to input data quality

Environmental data sources

1



Example: https://modis.gsfc.nasa.gov/

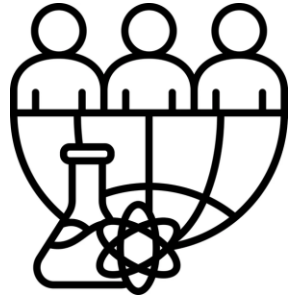
To deepen: https://almanacco.cnr.it/articolo/13371/il-ruolo-dei-satelliti-nella-lotta-al-cambiamento-climatico

2

Example: **https://www.arpae.it/it**

To deepen: https://openaq.org/

3



Example: https://eu-citizen.science/

To deepen: https://www.museonaturalemaremma.it/csi/
https://scistarter.org/
https://www.adventurescientists.org/

Environmental data sources

Source	Description	Data Type	Strengths	Limitations
Satellites	Remote sensing from orbiting platforms (e.g., Sentinel, Landsat, MODIS)	Raster data, images, multispectral	Large-scale coverage; consistent over time; global and repeated observations	Requires complex processing; limited resolution for some applications
Sensors	Ground-based instruments measuring physical parameters (e.g., temperature, air quality)	Time series, structured data	High accuracy; real-time measurements; detailed local information	Limited spatial coverage; maintenance and calibration needed
Citizen Science	Data collected by individuals or communities (e.g., observations, mobile apps)	Text, geolocated points, mixed	Cost-effective; covers data gaps; promotes engagement	Varying quality; subjective reporting; non-standardized formats
Legacy Models / Historical Data	Archived model outputs or old measurement records (e.g., past climate models, weather logs)	Structured datasets, reports	Long time spans; useful for trend analysis and calibration	May use outdated methods; limited metadata; format inconsistencies

Case study: CSI Piedmont

CSI Piemonte specifically focuses on the **collection**, **production**, and **dissemination** of **territorial data**

These data consist of three key components:

1. A **geometric component**
2. An **alphanumeric component**
3. A **relational component**

Quality criteria for territorial and environmental data

CSI considers the **definition and application of a methodology for data quality control** to be of fundamental importance for ensuring the quality of information

↓

Quality is often defined as “fitness for users”

↓

"**Quality**, in an objective sense, is defined as the **set of properties and characteristics** of a product or service that give it the **ability to meet expressed or implied needs**."

Quality criteria for territorial and environmental data

Quality control is based on assessing the fitness of data for the specific application for which it was generated, bearing in mind that:

- The methodology **must be consistent with the logical model** of the database and the objectives of the information system.
- The **technical specifications must incorporate quality control requirements**, not treat them as an afterthought.
- **Automated control procedures should be extensively used**, in order to quickly detect and correct potential errors.

Quality criteria for territorial and environmental data

GLOBAL QUALITY

LOCAL QUALITY

Quality criteria for territorial and environmental data

- **Exhaustiveness**
- **Currency**
- **GenealogY**

- **Metric accuracy**
- **Resolution**
- **Semantic accuracy**
- **Logical/topological consistency**

The procedures for verifying the quality of territorial data

Quality verification by CSI

Geometric data

- Utmost care and precision during acquisition (technique and equipment),
- accuracy in acquiring control points.

Associated data

• type and structure of the data clearly defined (record layout),
• decoding table of values in case of classified associated information,
• legend associating graphic symbol – thematic meaning for information represented graphically. .

The procedures for verifying the quality of territorial data

Procedures for verifying **overall quality**

- **For verifying completeness:** the completeness of the data is checked both for the geometric part and for the data part.
- **For verifying currency:** the indication of the temporal dimension on the data is verified. Data sources may not be directly comparable because the data were collected at different times.
- **For verifying lineage:** the origin of the territorial data is checked. This is derived from the metadata that must accompany the data.

The procedures for verifying the quality of territorial data

Procedures for verifying **local quality**

- **For verifying metric precision (positional accuracy):** the difference between the position of a point represented on the map and its actual position in the geographic reference system is measured.
- **For verifying resolution:** the dimensions of the smallest geographic detail represented are identified.
- **For verifying semantic accuracy:** the correspondence between the qualitative attribute associated with an acquired entity and its actual characterization in the original data is checked.
- **For verifying logical consistency (or congruence):** any inconsistencies in the data are identified, both from the geometric perspective and in the associated data.

BREAK

Module 3: AI ethics

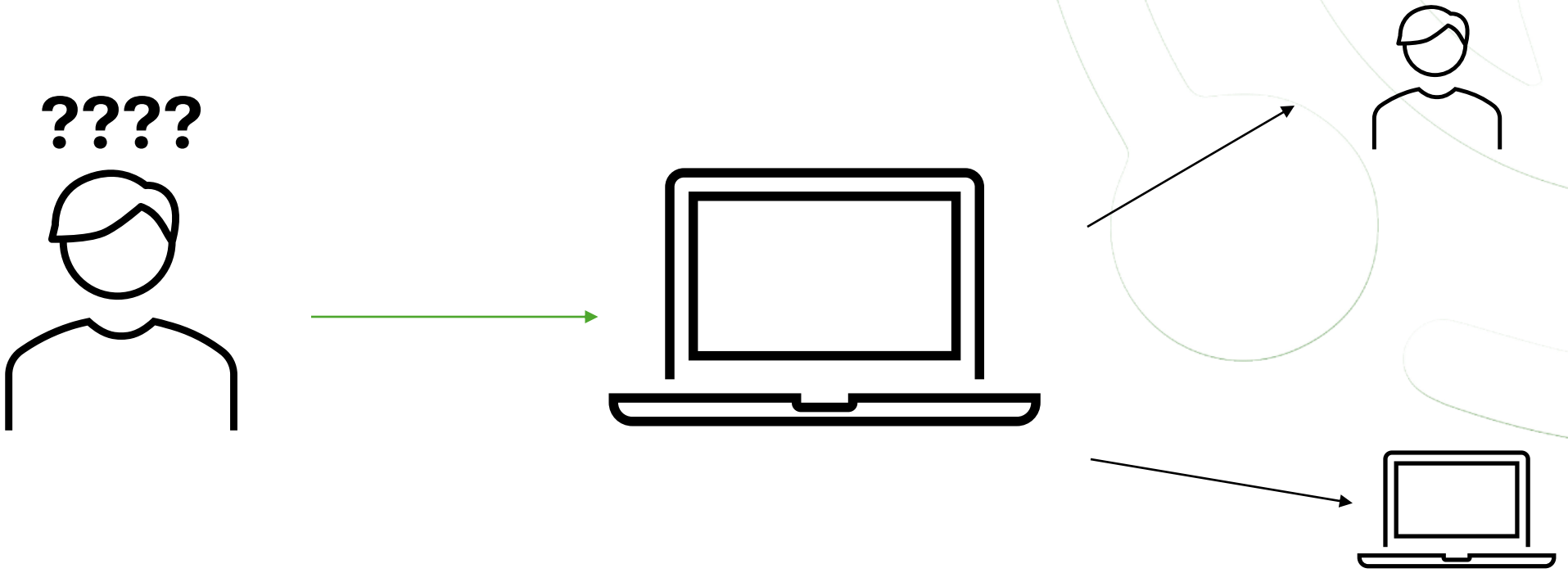
"The real risk of artificial intelligence is not malice, but competence."

Stephen Hawking

AI Ethics

- **Ethics** is the branch of philosophy concerned with judging whether actions are good or bad.
- **AI Ethics** is the branch of technology ethics that specifically focuses on artificially intelligent systems.
- It involves the **creation of a test capable of determining whether decisions made by AI are ethical**.

The imitation game



Purposes of AI

- **Should we give AI a purpose?**
  If so, **what kind of purpose** should that be?
- **How can we define goals** for an AI system in a way it can understand and follow?
- **How can we ensure** those goals are maintained over time, especially as the system evolves or learns?
- **What are the purposes of human beings?**
  And should AI align with them, replicate them, or challenge them?

Friendly Artificial Intelligence

Eliezer Yudkowsky

Artificial intelligence **whose goals are aligned with ours**, based on the principle of **coherent extrapolated volition**.

It means building an AI that does **what we would want it to do**, **if we knew more**, were **more rational**, and had **more time to think**.

AI should help us fulfill our **better, wiser, long-term goals**, —not just our immediate desires or flawed preferences.

Breakdown of the problem:

- Ensuring that AI **understands** our goals
- Ensuring that AI **adopts** our goals
- Ensuring that AI **preserves** our goals

Understanding human goals: solution

Two key problems:

1. **Finding an effective way to encode arbitrary systems of goals and ethical principles** into a machine.
2. **Enabling machines to determine which specific system** of goals or values corresponds to the behavior they observe.

Understanding human goals: solution

- **Inverse Reinforcement Learning (IRL)**
  (Proposed by Stuart Russell)
- This approach expects the AI to **infer something about our goals** by observing the **decisions and actions it takes**.
- In other words, the AI learns what we want by analyzing behavior, rather than being explicitly told.

Adopting our goals: solution

Corrigibility

=

It is possible to give AI a system of goals
that **can be corrected or adjusted** by humans.

Adopting our goals: solution

But are we sure that AI’s goals won’t evolve as its intelligence evolves?

Maintaining goals: the goal preservation problem

- Steve Omohundro and Nick Bostrom argue that we can predict certain **sub-goals** of an AI regardless of its initial goals.
- If a Friendly AI self-improves, can it remain friendly?
- Therefore, it is crucial to clearly define the AI's goals and ensure they are aligned with human values.

Goal alignment: the most important problem

- What are the goals of human beings?
- Four guiding principles:
  - **Utilitarianism**
  - **Diversity**
  - **Autonomy**
  - **Legacy**

Human Principles

UTILITARIANISM

Conscious positive experiences should be **maximized** while suffering should be **minimized**.

↓

Challenge: The problem of consciousness — how do we define and measure conscious experiences?

DIVERSITY

A varied set of positive experiences

↓

Has enabled the survival of the species

AUTONOMY

Conscious beings and societies must be free to pursue their own goals.

LEGACY

Ensures compatibility with scenarios that humans consider good.

https://www.moralmachine.net/

AI principles: can human principles align with AI principles?

Six major high-level documents:

- Asilomar AI Principles (2017)
- Montreal Declaration for Responsible AI Development (2017)
- Ethically Aligned Design: A Vision for Prioritizing Human Wellbeing with Autonomous and Intelligent Systems (IEEE, 2017)
- Statement on Artificial Intelligence, Robotics, and Autonomous Systems (EGE, 2018)
- AI in the UK: Ready, Willing and Able? (AIUK, 2017)
- AI Partnership Principles (2018)

AI principles

In 2020, the AI Ethics Guidelines Global Inventory identified **160 proposed principles**

Problem: Overlap and confusion caused by so many guidelines

Overview of the five principles:

1. **Beneficence**
2. **Non-maleficence**
3. **Autonomy**
4. **Justice**
5. **Explainability**

Beneficence

Promote well-being, preserve dignity, and support the planet

- **“The development of artificial intelligence should ultimately promote the well-being of all sentient beings.”** — Montreal Declaration for Responsible AI Development
- **“Common Good”** — Referenced in both **AIUK** and **Asilomar AI Principles**

Non-maleficence

Privacy, security, and capability caution

- It is still unclear whether the people developing these technologies should be encouraged not to do harm,
  or if it is the technology itself that should be prevented from doing harm.
- At the heart of this dilemma lies the issue of **autonomy**.

The power to decide to decide

Establishing a balance between the decision-making power we retain and the power we delegate to artificial agents

- "They must not compromise humans' freedom to establish their own standards and norms." — ESE
- “The autonomous power to harm, destroy, or deceive human beings should never be granted to AI.” — AIUK

Justice

Promote prosperity, preserve solidarity, and prevent inequity

Establishing a balance between the decision-making power we retain and the power we delegate to artificial agents

- “The development of AI should promote justice and strive to eliminate all forms of discrimination.”— Montreal Declaration

Are we (human beings) the patient receiving the "treatment" from AI, which presents itself as the doctor, or are we both?

Explainability

Enabling the other principles through intelligibility and accountability.

Answers the question:
HOW DOES IT WORK?

TRANSPARENCY

The five principles in the six documents

Tabella 4.2 I cinque principi nei sei documenti analizzati e in altri documenti.

	Beneficenza	Non maleficenza	Autonomia	Giustizia	Esplicabilità
AIUK	•	•	•	•	•
Asilomar	•	•	•	•	•
EGE	•	•	•	•	•
IEEE	•	•			•
Montréal	•	•	•	•	•
Partenariato	•	•		•	•
AI4People	•	•	•	•	•
HLEG	•	•	•	•	•
OCSE	•	•	•	•	•
Pechino	•	•		•	•
Rome Call	•	•	•	•	•

Luciano Floridi, «Etica dell'intelligenza artificiale»

Risks

- **Ethical shopping**
- **Ethical bluewashing**
- **Ethical lobbying**
- **Ethical dumping**
- **Ethics evasion**

Ethical shopping

"The malpractice of selecting, adapting, or revising ethical principles, guidelines, codes, frameworks, or similar standards by picking from a variety of available options, in order to give a new veneer to some pre-existing behaviors and thereby justify them retrospectively, instead of implementing or refining new behaviors by comparing them with public ethical standards."

Ethical shopping

Risk of mixing and matching preferred ethical principles, causing incompatibility of standards

+

Risk of reduced competition, evaluation, and accountability

↓

STRATEGY:
Establish clear, shared, and publicly accepted ethical standards

Ethical guidelines for trustworthy AI

In 2021, these guidelines influenced the proposal adopted by the European Commission for an AI regulation, described as the first-ever legal framework on AI.

Ethical bluewashing

"The malpractice of making unfounded or misleading claims regarding ethical values and the benefits of processes, products, services, or other digital solutions in order to appear more ethically sound in the digital realm than one actually is."

Ethical bluewashing

Marketing Practice

Bluewashing + Ethical shopping

=

A public or private actor acquires ethical principles and publicizes them to emphasize their ethical commitment without producing real improvements

↓

STRATEGY:

Transparency and education

(In the long term, certifications for digital products and services are also expected to be established.)

Ethical lobbying

“The malpractice of exploiting digital ethics to delay, revise, replace, or avoid appropriate and necessary legal regulation (or its enforcement) related to the design, development, and implementation of processes, products, services, or other digital solutions.”

Ethical lobbying

Undermines the foundation of ethical self-regulation

↓

And can delay the introduction of necessary regulations

↓

STRATEGY:
Good legislation and effective enforcement

Ethical dumping

"The discontent of (A) outsourcing research activities related to processes, products, services, or other digital solutions to other contexts or locations (for example, from European organizations outside the EU) in ways that would be ethically unacceptable in the original context or location; and (B) importing results of such ethically questionable research activities."

Ethical dumping

Export of Unethical Research Practices

Involves both the export of unethical practices and the unethical import of their results

Ethical dumping may worsen in the near future due to:

1. Impact of digital technologies on healthcare, social services, defense, policing, and security
2. Ease of their deployment and use
3. Strong economic interests

Ethical dumping

STRATEGY

1. **Research ethics:** Control of public funding for research
2. **Consumer ethics:** Establishment of a certification system for products and services

Ethics evasion

“The malpractice of performing less and less ‘ethical work’ in a given context the lower the perceived return of such ethical work in that context.”

Ethics evasion

Applying double standards

STRATEGY:

Address the issue of lack of accountability

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More fairness, less bias, and an ethics of distributed responsibility

THANKS!

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