



# Big Data & Analytics

## Lecture 2: Info-Economy & Data value model

# The economics of “bits vs. atoms”

Statement question: in a digital world, from where come the value?

- Reach doesn't mean richness
- Data Island doesn't become information continents
- There are information even in the data scarcity

# The economics of “bits vs. atoms”

## Richness vs Reach: paradox I. Value from quantity

### Richness of information

- The amount of information that can be transmitted
- The degree to which it can be tailored
- The level of interactivity of the message



### Reach

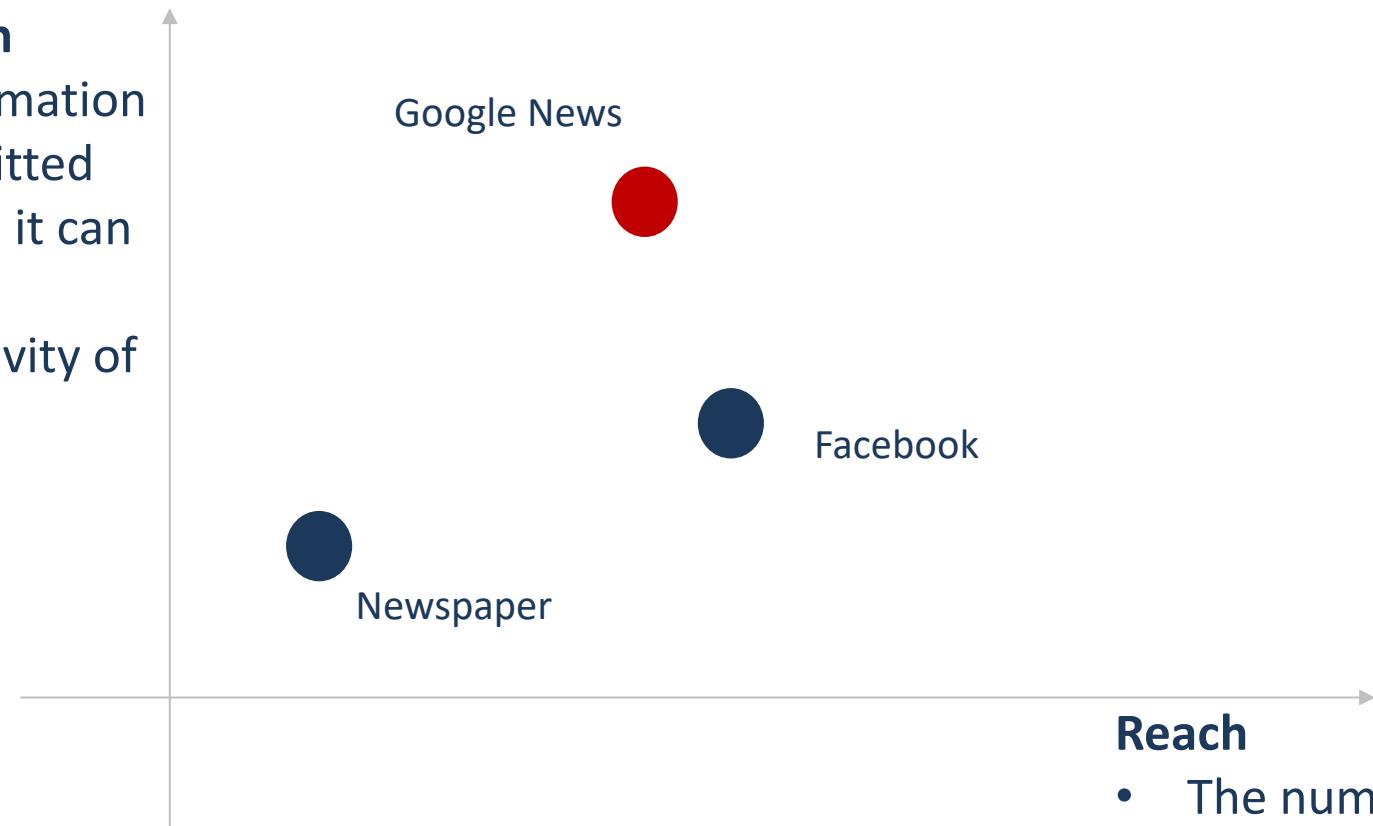
- The number of possible recipients of the message

# The economics of “bits vs. atoms”

## Richness vs Reach: paradox 2. Value from intermediaries

### Richness of information

- The amount of information that can be transmitted
- The degree to which it can be tailored
- The level of interactivity of the message



### Reach

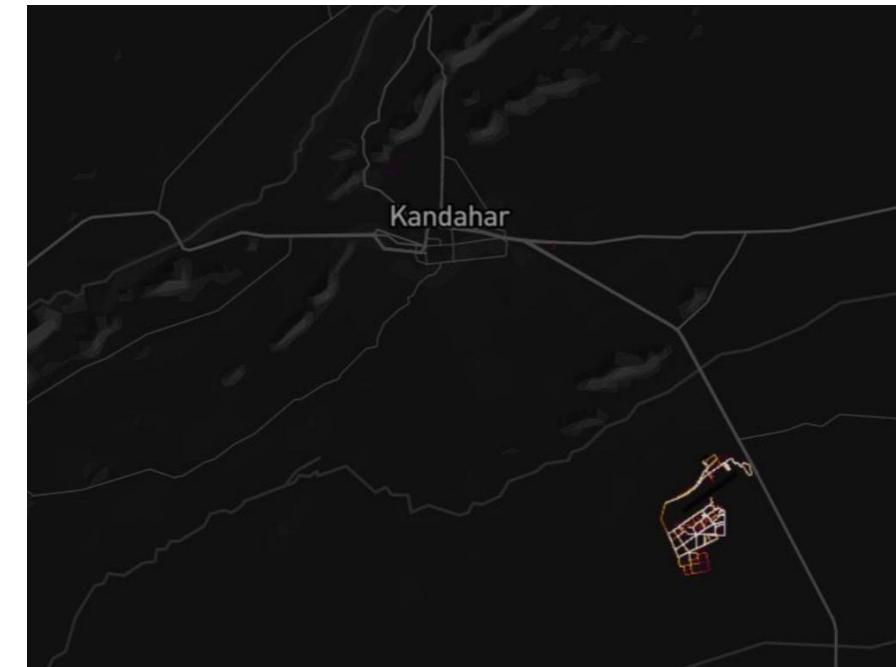
- The number of possible recipients of the message

# The economics of “bits vs. atoms”

Richeness vs Reach: paradox 3. Value from scarcity



Strava running Heat Map: Milano



Strava running Heat Map: Kandahar

# The economics of “bits vs. atoms”

Statement question: in a digital world, from where come the value?

- Value came from taking right decisions
- Decisions are supported by knowledge
- Knowledge come from Informations
- Informations are derived from data
- **So, does value come from data ?**

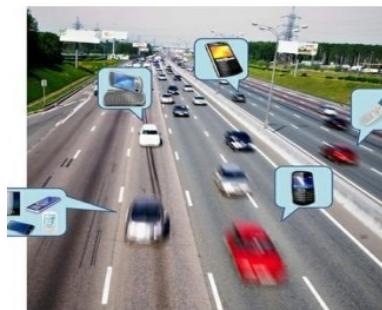
# **From Data to Decision**

## A difficult journey



# From Data to Decision

## A real world example



Computing



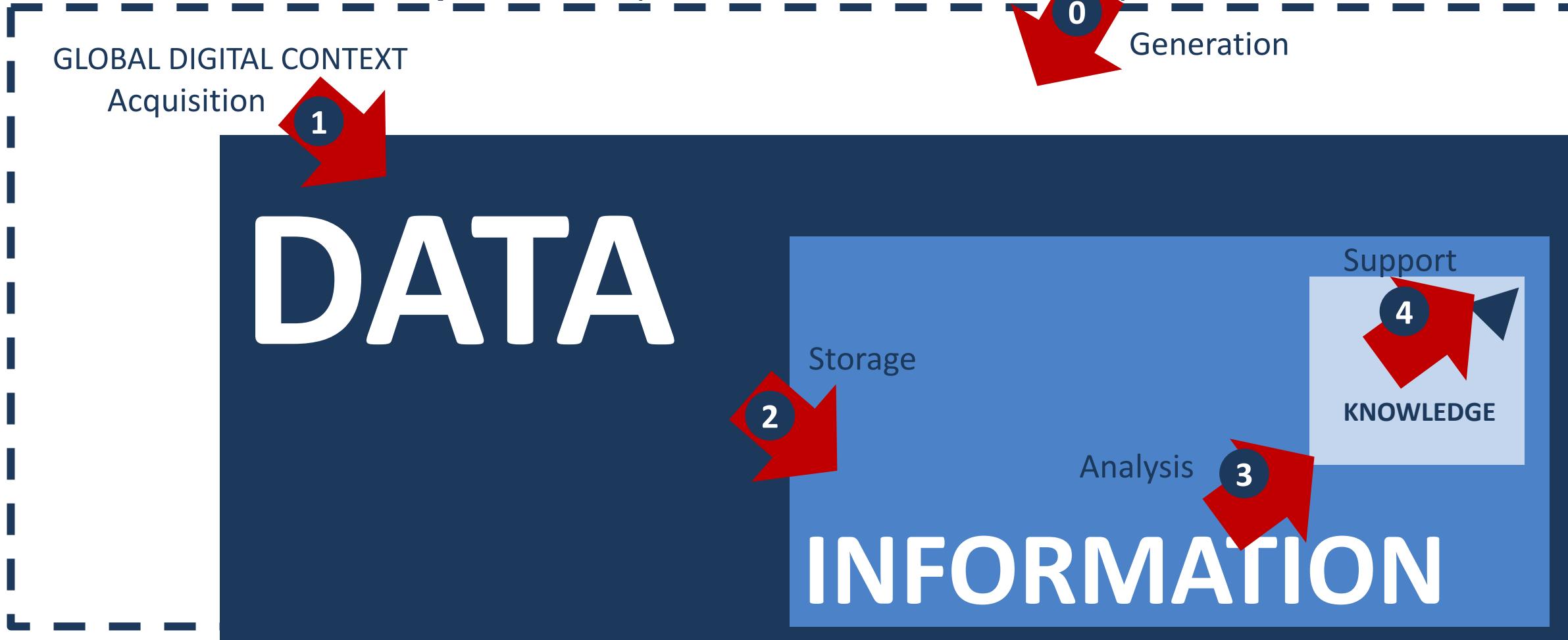
Sensing



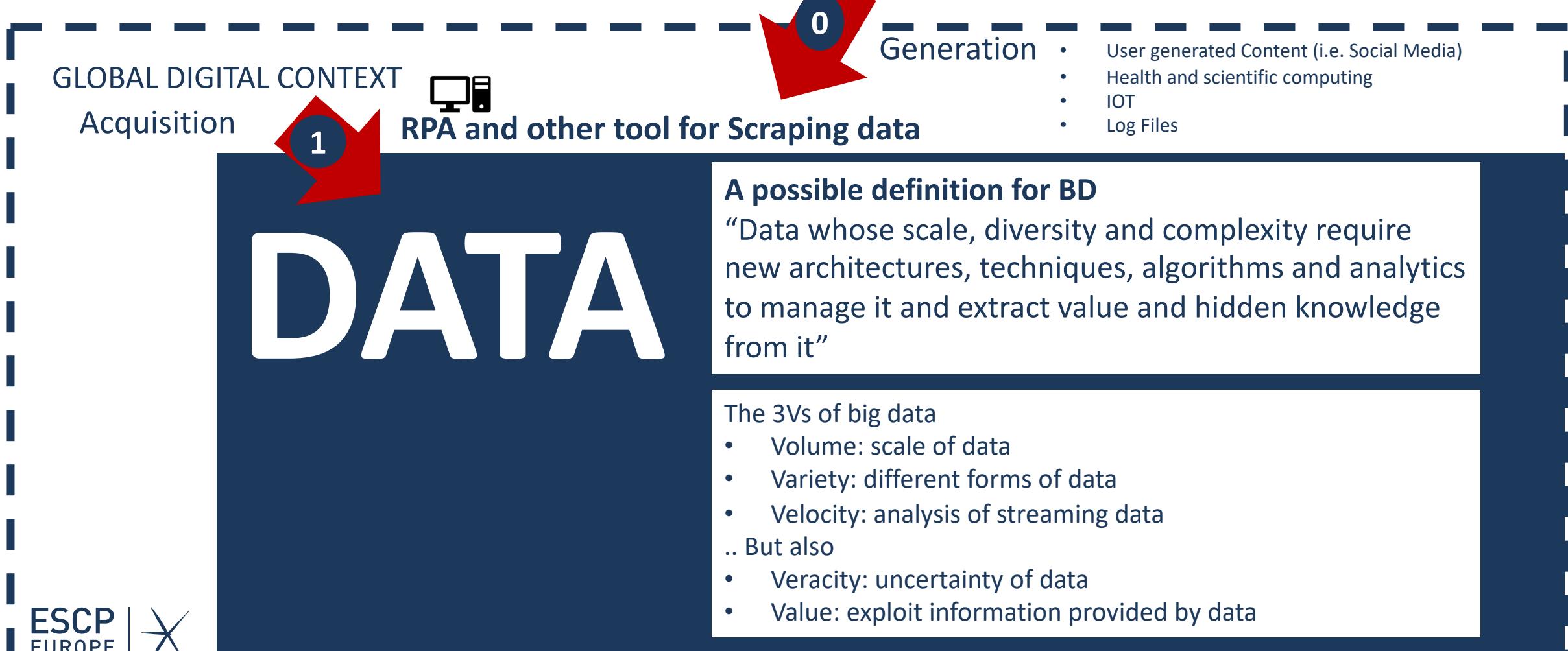
Real time traffic info

# Data Value Model

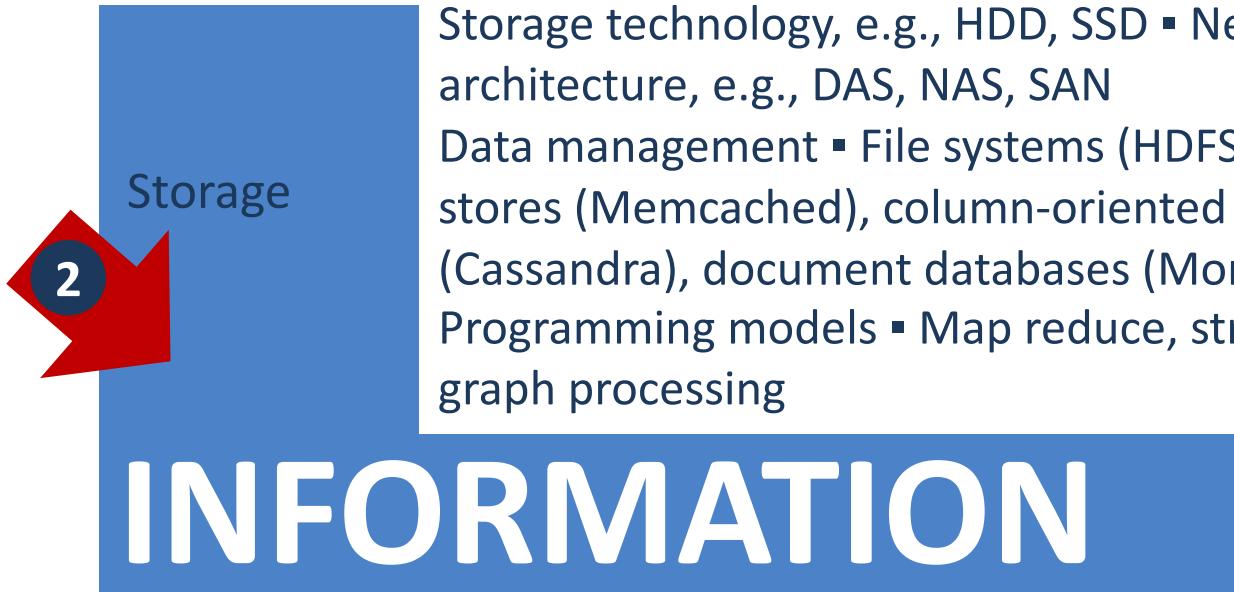
Value come from process (extended value chain)



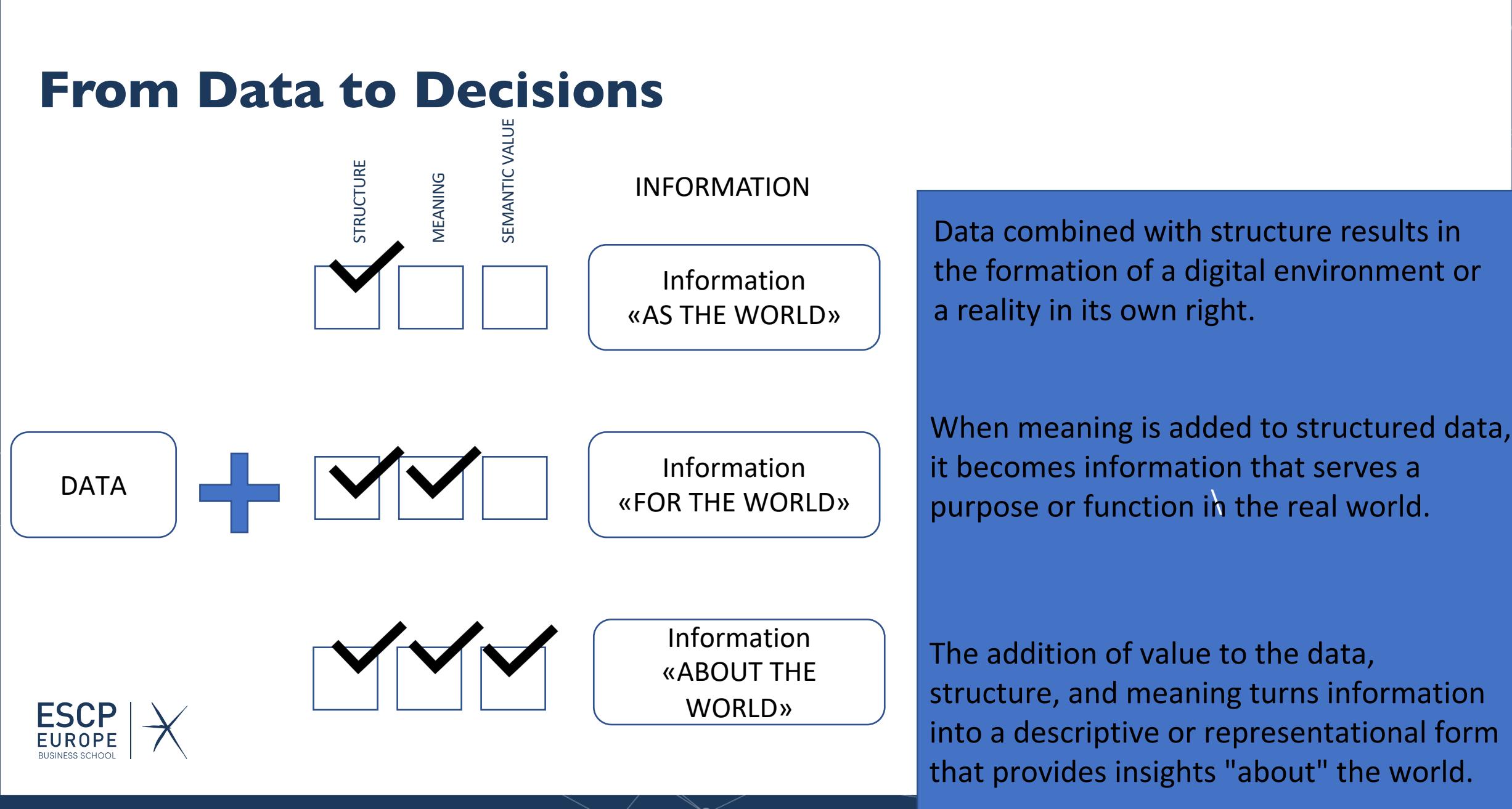
# From Data to Decisions



# From Data to Decisions



# From Data to Decisions



# From Data to Decisions

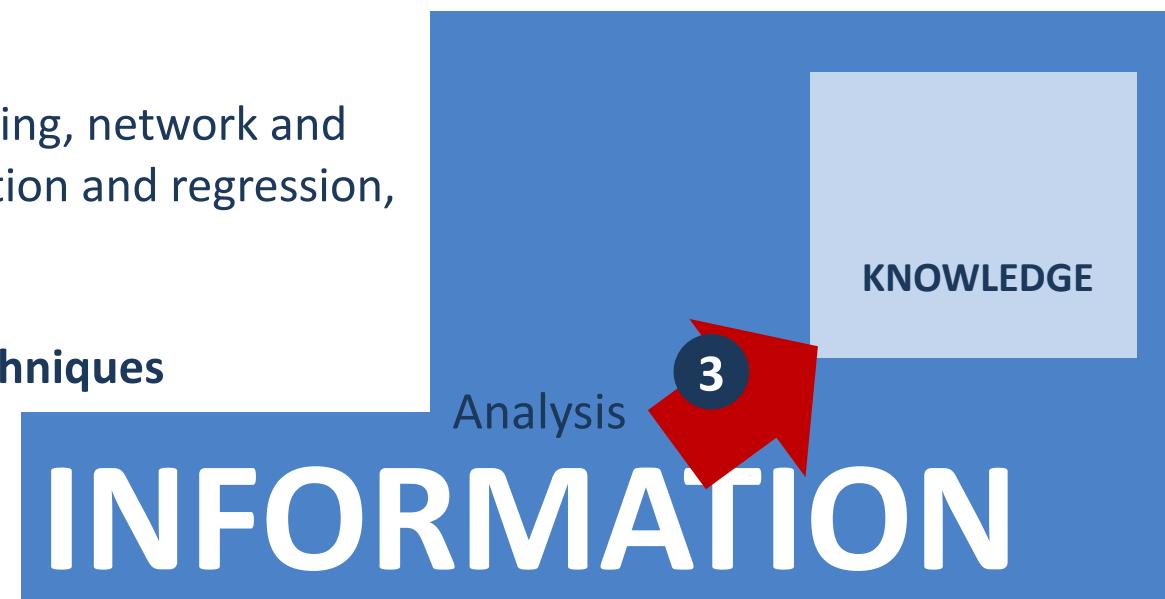
## Objectives

Descriptive analytics, predictive analytics, prescriptive analytics

## Methods

Statistical analysis, data mining, text mining, network and graph data mining , Clustering, classification and regression, association analysis

Diverse domains call for customized techniques



 BI tools, Analytics

# From Data to Decisions

## DESCRIPTIVE ANALYTICS

■ *Descriptive analytics* report on what happened in the past. The format may be a standard report, a dashboard or scorecard (as in this simulation) or an alert. Although there are not normally statistical relationships in descriptive analytics, an analyst can segment the data and explore differences across segments. This simulation primarily uses descriptive analytics, which are sometimes also called *business intelligence*.

## Three Types of Analytics

## PREDICTIVE ANALYTICS

■ *Predictive analytics* make use of statistical models on past data to predict the future. Once a model is created that fits past data well, we can use it to predict what may happen in the future, given no major changes in assumptions or relationships. The forecasting exercise in this simulation is an example of predictive analytics.

## PRESCRIPTIVE ANALYTICS

■ *Prescriptive analytics* are models or analyses that inform people how best to perform a specific task in their jobs. It is an analytics-based recommendation for action. The recommendation might involve the best price to charge for a product, the optimal level of inventory to hold, or the treatment for a particular patient's disease. There are no prescriptive analytics in this simulation.

# From Data to Decisions

## DESCRIPTIVE ANALYTICS

- **Sales analysis:** Descriptive analytics can be used to analyze sales data to identify trends, patterns, and areas of growth or decline. This can help food and beverage companies to understand consumer preferences and make informed decisions about product development, marketing, and distribution.
- **Customer segmentation:** Descriptive analytics can be used to segment customers based on demographics, purchasing behavior, and other factors. This can help food and beverage companies to target specific groups of customers with tailored products and promotions.
- **Inventory analysis:** Descriptive analytics can be used to analyze inventory data to identify patterns in stock levels, stock turnover, and demand forecasting. This can help food and beverage companies to optimize inventory management and reduce costs.
- **Quality control:** Descriptive analytics can be used to analyze quality control data to identify trends and patterns in product defects, and to identify areas for improvement in the production process.
- **Supply chain analysis:** Descriptive analytics can be used to analyze data from the supply chain, including suppliers, logistics, and distribution. This can help food and beverage companies to identify bottlenecks and inefficiencies in the supply chain and take action to improve performance..

## EXAMPLE

Customer lifetime value (CLV) of their customers. CLV is a metric that quantifies the total value that a customer is expected to bring to a business over their lifetime. The formula for calculating CLV is:

$CLV = (\text{Average Purchase Value}) \times (\text{Number of Purchases per Year}) \times (\text{Average Retention Time in Years})$

# From Data to Decisions

## PREDICTIVE ANALYTICS

- **Sales forecasting:** Predictive analytics can be used to analyze historical sales data and identify patterns that can be used to forecast future sales. This can help food and beverage companies to make informed decisions about production, inventory management, and marketing.
- **Customer behavior prediction:** Predictive analytics can be used to analyze customer data, such as demographics and purchase history, to predict future purchasing behavior. This can help food and beverage companies to target their marketing efforts more effectively and improve customer retention.
- **Inventory optimization:** Predictive analytics can be used to analyze historical inventory data and demand trends to predict future demand and optimize inventory management. This can help food and beverage companies to reduce inventory costs and improve delivery times.
- **Quality control:** Predictive analytics can be used to analyze data from quality control processes to identify patterns and predict potential issues, allowing for proactive maintenance and reducing downtime.
- **Supply chain optimization:** Predictive analytics can be used to analyze data from suppliers and logistics to predict future demand, identify potential disruptions and optimize the entire supply chain.

## EXAMPLE

One common method for forecasting demand is the time-series analysis method, which uses historical data to identify patterns and trends that can be used to predict future demand.

One example of a formula for this method is the Exponential Smoothing (ETS), which can be used to forecast future demand for a product.

The formula for ETS is:

$$F(t+1) = \alpha y(t) + (1-\alpha)F(t)$$

where  $F(t+1)$  is the forecast for the next period,  $F(t)$  is the forecast for the current period,  $y(t)$  is the actual demand for the current period, and  $\alpha$  is a smoothing constant between 0 and 1 that represents the weight given to the most recent demand data.

# From Data to Decisions

## PRESCRIPTIVE ANALYTICS

- **Sales optimization:** Prescriptive analytics can be used to analyze sales data, customer behavior, and market trends to recommend specific actions that will optimize sales and improve performance.
- **Inventory management:** Prescriptive analytics can be used to analyze inventory data, demand patterns, and logistics information to recommend specific actions that will optimize inventory management and reduce costs.
- **Quality control:** Prescriptive analytics can be used to analyze quality control data and predict potential issues. It can then recommend specific actions to prevent or mitigate those issues, such as adjusting production processes or implementing new quality control measures.
- **Supply chain optimization:** Prescriptive analytics can be used to analyze data from suppliers and logistics to predict future demand and potential disruptions. It can then recommend specific actions to optimize the supply chain, such as identifying new suppliers or adjusting logistics routes.
- **Marketing:** Prescriptive analytics can be used to analyze customer data, market trends, and sales data to recommend specific actions that will optimize marketing efforts and improve customer retention.

## EXAMPLE

One example of a formula for this optimization is the **Linear Programming (LP) method**, which can be used to find the optimal prices for a set of products given certain constraints such as production costs, competition, and customer demand.

The LP problem can be formulated as:

Maximize:  $P = \sum(P_i * X_i)$

subject to:  $\sum(C_i * X_i) \leq B$

(production costs)  $\sum(D_i * X_i) \leq D$

(demand)  $X_i \geq 0$  (non-negativity)

Where P is the total revenue,  $P_i$  is the price of product i,  $X_i$  is the quantity of product i,  $C_i$  is the production cost of product i, B is the total budget for production costs,  $D_i$  is the demand for product i and D is the total demand.

# From Data to Decisions

*RED = UNKNOWN*  
*BLUE = KNOWN*

Descriptive

$$F(\Delta X) = \Delta Y$$

Predictive

$$F(\Delta X) = \Delta Y$$

Prescriptive

$$F(\Delta X) = \Delta Y$$

## Philosophical Reflection

It's no more a matter of REALITY it's a matter of CORRELATIONS

We are no more driven by REALITY but by possible REALITIES that emerge from correlations

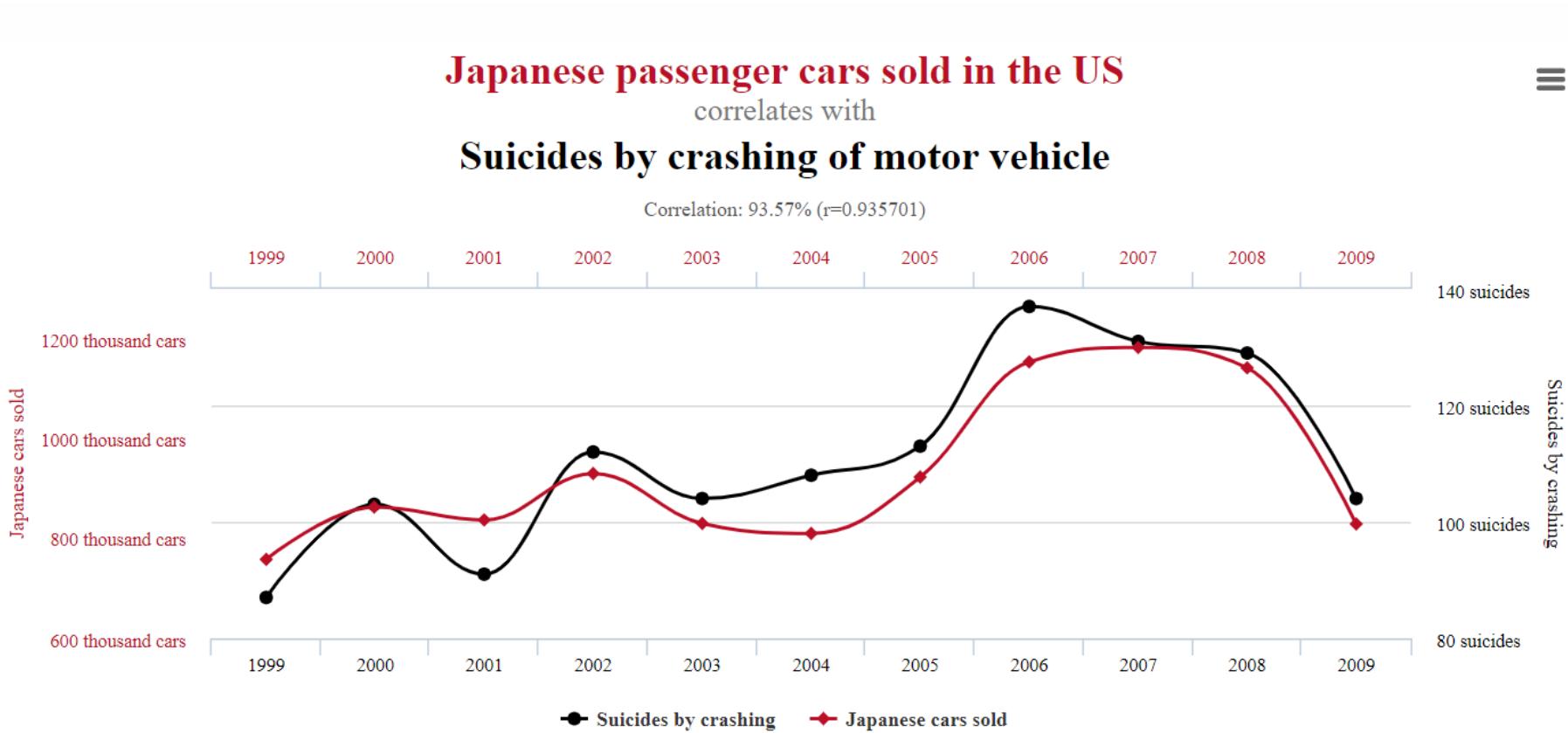
But what about spurious correlations?

# From Data to Decisions

RED = UNKNOWN  
BLUE = KNOWN

## Philosophical Reflection

But what about spurious correlations? CORRELATION AND CAUSALITY ARE DIFFERENT THINGS!



Data sources: U.S. Bureau of Transportation Statistics and Centers for Disease Control & Prevention

[tylervigen.com](http://tylervigen.com)

Spurious Correlations (tylervigen.com)

# From Data to Decisions

- Machine learning: collection of techniques for understanding the structure of data and learning patterns in them (broad definition) and that require:
  1. A function that maps well-defined inputs to well-defined outputs: classification & prediction
  2. Large, digital, clean data sets must exist and contain input-output pairs
- More data, higher accuracy (especially with deep learning)
- Training of the algorithm occurs on past input-output decisions made by individuals => *risk of mimicking and perpetuating human biases (e.g. no hires of women)*

Support

4



KNOWLEDGE

# Foundation crisis in the Digital Age

## Digital disruption debunked

Ubiquitous integration of digital technology in daily routines

Technology's seamless blend with daily life (are you that are scrolling the Instagram story on the Smart Phone or is Smart Phone that is guiding you in doing that?)

In the rapidly evolving digital landscape, we are confronted with a triad of crises that challenge the very fabric of our societal, cultural, and political structures.

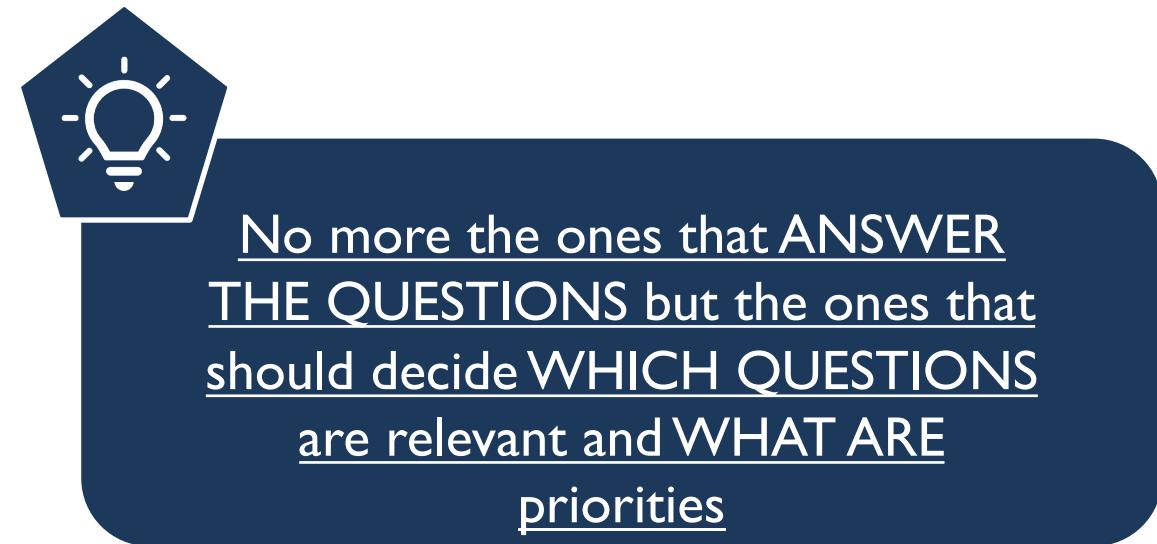
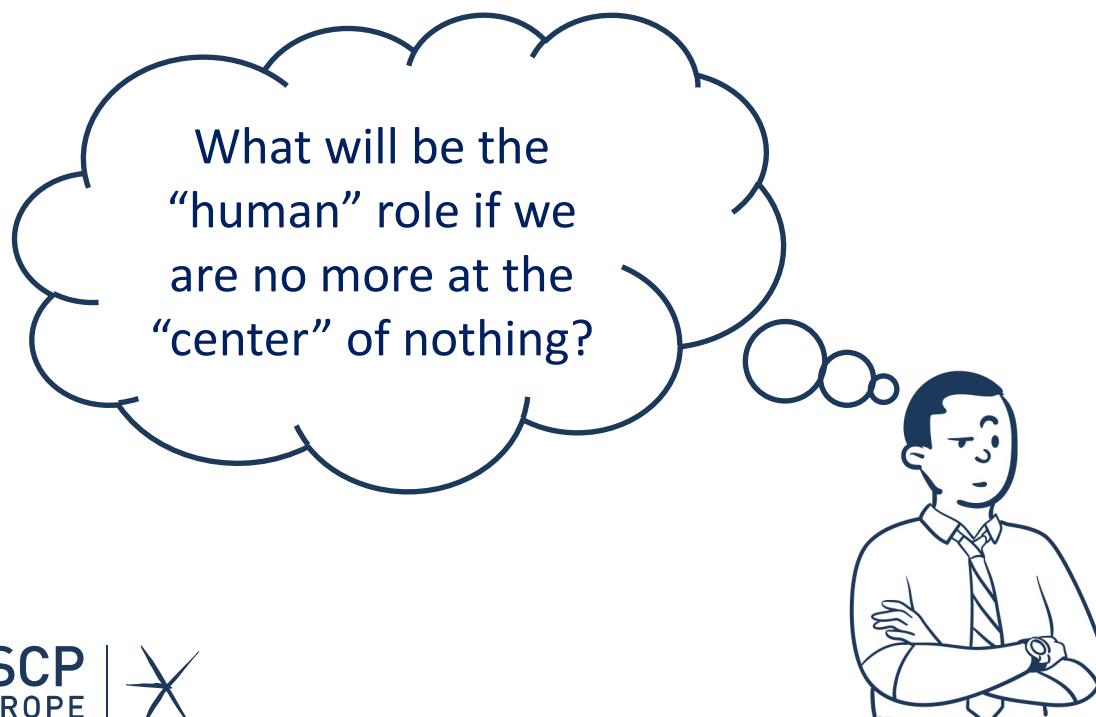
- **Normative (Legal and Ethics crisis)**
- **Epistemological (cultural crisis)**
- **Political (right and roles crisis)**



# The 4 revolutions

## An history of displacement

Humanity's undergone **Copernican**, **Darwinian**, and **Freudian** revolutions, challenging our centrality. Now, the Fourth Revolution, driven by tech and AI, further displaces us from **cognitive** dominance.



Our role is now providing SEMANTICS for a syntactical perfect world.

# The 4 revolutions

## An history of displacement

The displacement of human centrality.

### Copernican Revolution

### Darwinian Revolution

### Freudian Revolution

### Turing/AI Revolution (The 4th)

We are not the center of the universe.

We are not the center of creation.

We are not the center of our own minds (subconscious).

We are no longer the center of intelligence/processing.

### The New Human Role

We stop answering questions and start **\*asking\*** them.

Machine = Syntax (Perfect Logic).  
Human = Semantics (Meaning & Values).

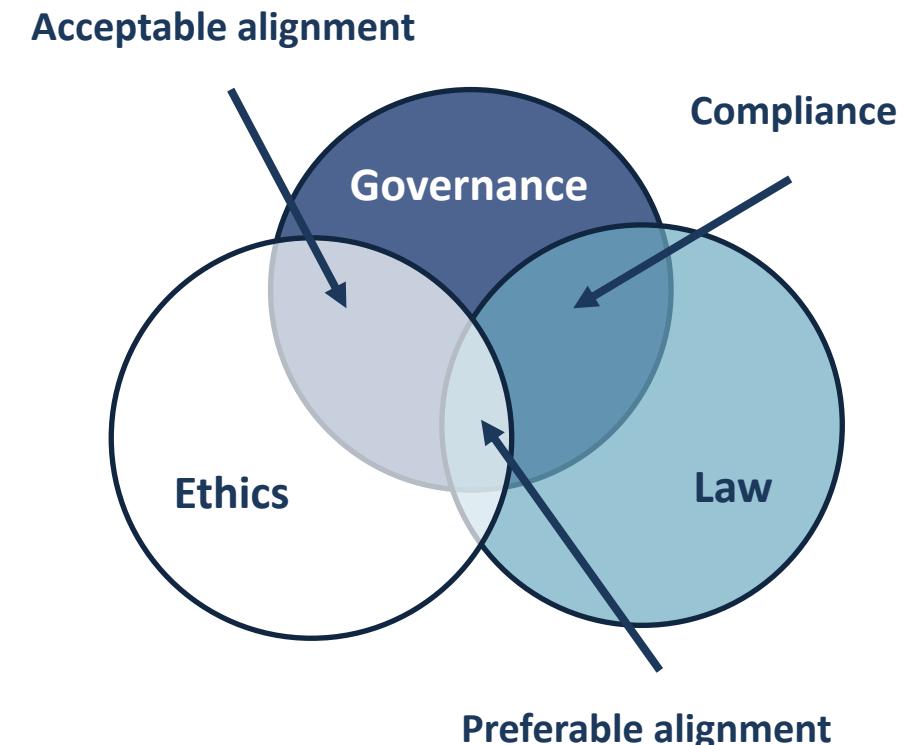
# Beyond the law

## Ethic, governance law and Compliance

- **Law** consists of codified rules enforced by the state
- **Ethics**, which encompasses moral principles guiding what is right or wrong.
- **Governance**, meanwhile, involves mechanisms and processes for regulating and controlling activities, balancing both legal compliance and ethical integrity

Unfortunately, the laws that we have (even the GOOD ONES, like GDPR) are not adequate or no more “in line” with the technological development.

**Example:** using a law that prescribes rules for using data and enforcing privacy on a DB dealing with an algorithm that has learned from a database but that does not “hold” data



# Beyond the Compliance

## Ethic, governance law and Compliance

Compliance

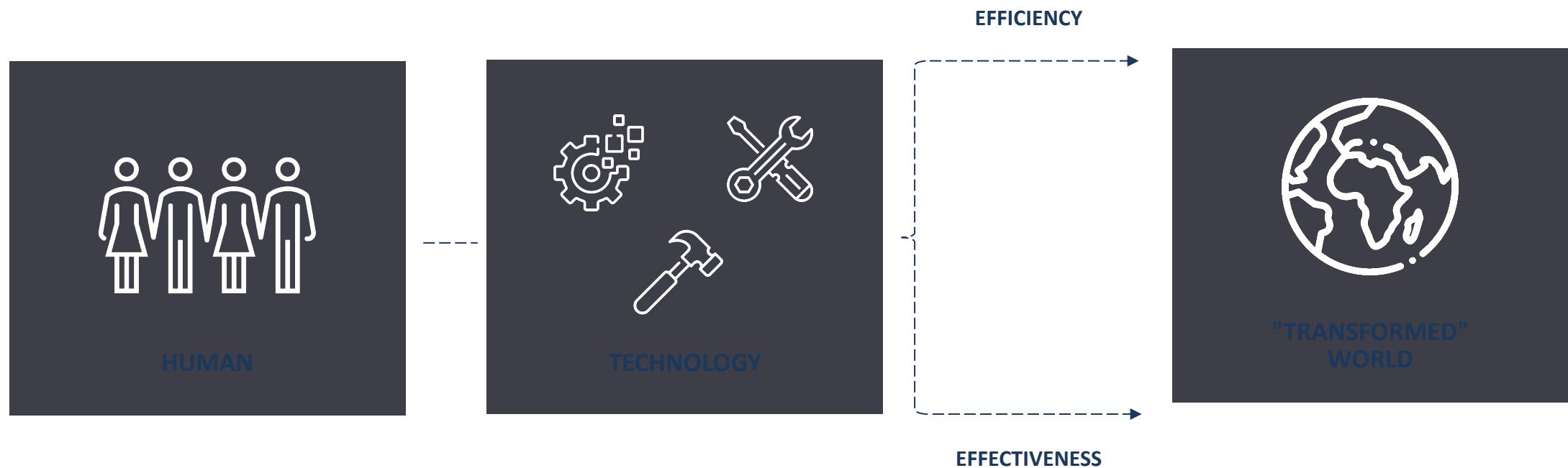
Necessary, but not enough

Ethics

Is the bridge between what is necessary and what need to be done  
for the best and based on that ethics should recommend actions  
or behaviours that are DOABLE

# Digital & AI Ethics : Why?

Because the **nature** of the technologies has changed, and consequently, the **artifacts** they produce have changed, creating new challenges and ethical dilemmas.



# Digital & AI Ethics : Why?

Because of the **consequences** and the **impacts** that the technology produces, affecting privacy, autonomy, and societal well-being, necessitating ethical oversight, and therefore it is necessary to change the perspective with which we 'attribute' purposes and intentions to Technology.



- 01.
- 02.
- 03.

A **means** to an end  
The only purpose is **efficiency** (extension of human capabilities)  
Ethics = The use that is made of it

Intentionality capable of inclining humans toward certain behaviors. It is no longer morally neutral and gains **meaning based on its use**

Technology as an expression of the way a culture organizes itself. Each culture expresses itself through the technological artifacts it produces.

E.g. Nuclear Energy,  
Facial Recognition

# **So, we need ETHICS**

## Digital ethics, furthermore

A new branch of ethics that studies and evaluates moral problems related to **data** (including generation, recording, sharing and use), **algorithms** (including AI, artificial agents, machine learning, and robots) and corresponding **practices** and infrastructures (including responsible innovation, programming, hacking, protocols and professional codes), in order to formulate and support **morally good solutions** (e.g. right conducts or right values).

**And the discussion is open regarding if we need an Hard or a Soft ethics**

...

# So, we need ETHICS

## Digital ethics, furthermore

### Can, May, and Should of

~~ethics~~ can be done, according to e.g. technical and economic consideration (feasible)

- b) What may be done, according to laws and regulations (legal), and
- c) What should be done, according to what is morally good or right (ethical).

### Soft and hard ethics

a) Soft ethics sees ethics as what should be done over and above the law but not against it, or despite its scope.

b) Hard ethics views the role of ethics to be challenging existing laws and informing new ones as they are being formulated.

# Towards a Theory for Digital Ethics

## Ethics by design

Ethics for the digital should be DESIGNED at the correct LoA and adopting the wrong one will result in something ineffective.

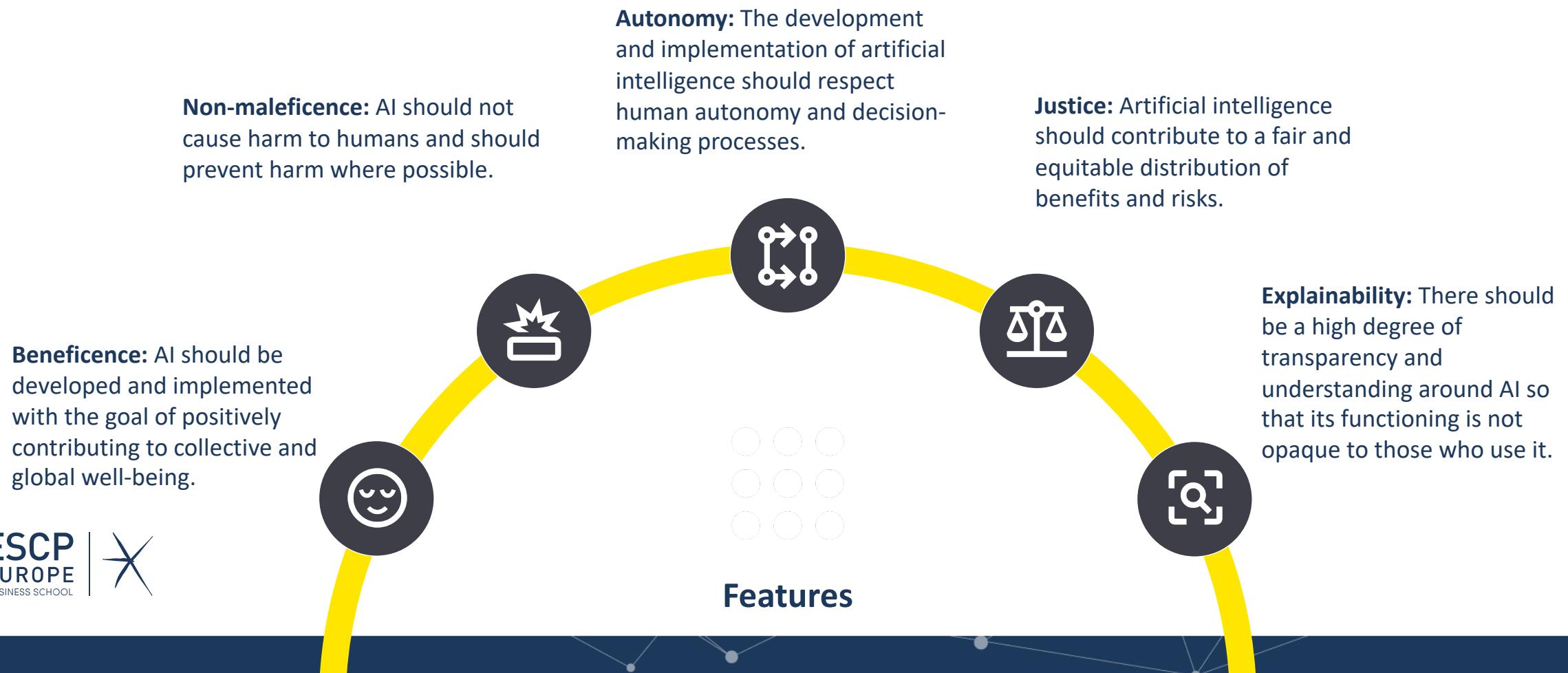
Design of Digital artifact must be done considering the correct LoA of the ethics we want to “apply”

### **There are questions that are NECESSARY**

- Who should I be? — ethics of the AGENT (what's my role?)
- What actions should I take? – ethics of the ACTIONS (what's the right things to do?)
- What is the good for the receiver of the action? —ethics of the RECEIVER (What will be the impact of my actions?)

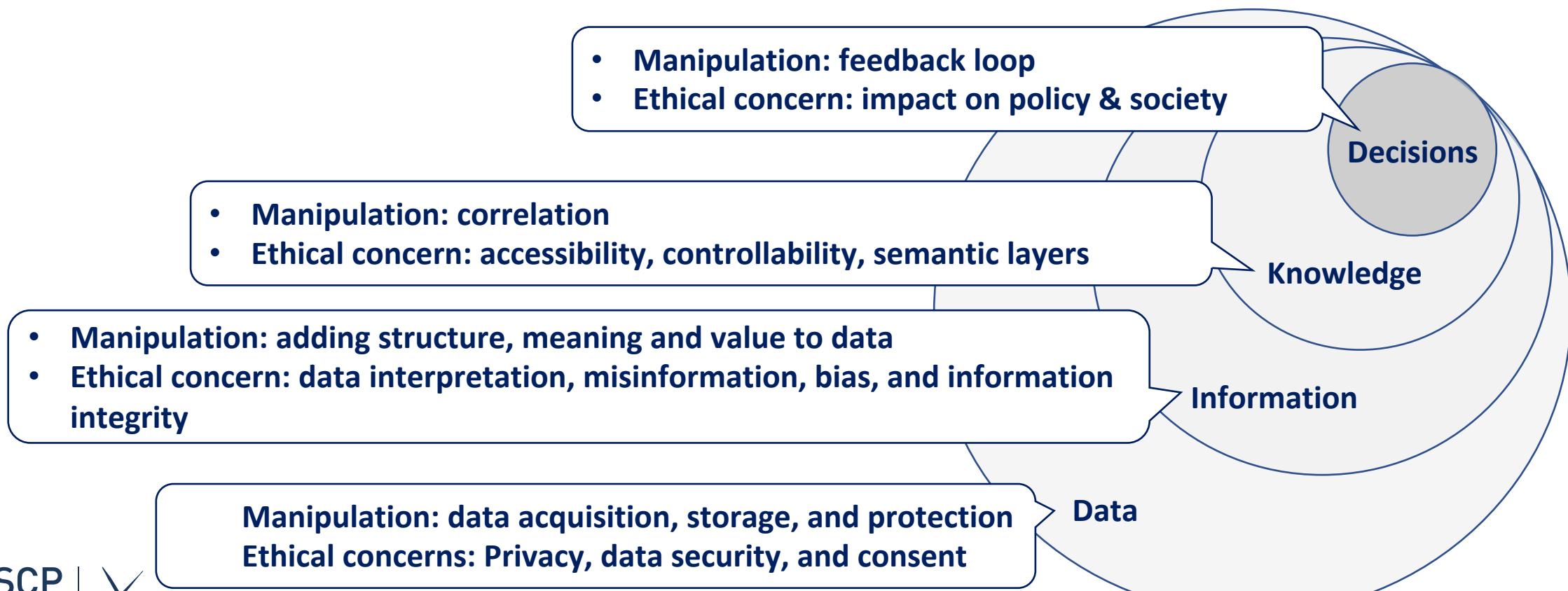
# Towards a Theory for Digital Ethics

In exploring the features and implementation of Digital & AI Ethics we focus on fundamental principles that guide ethical considerations in artificial intelligence. Let's delve into how these principles shape ethical frameworks in AI.



# A first application of the Theory

Ethical concerns across the “information value chain”





# DATA ARE TRANSFORMING BUSINESS MODELS

## Adapt or fail

- Internet is not simply a new channel for customer relationships
- Some industries that are challenged by business model transformation.
  - Music (from selling music to organize live events?)
  - Newspapers (digital advertising, classified ads)
  - Education (like Music?)
  - Car-making
  - Industrial machineries
  - Apparel/sport equipment (e.g. Adidas acquired Runtastic in 2015)
  - Insurance (e.g. «as pay as you drive»)

# DATA ARE TRANSFORMING BUSINESS MODELS

## The big moves

1. From Product to Services, from Ownership to Access
2. Durable Products vs. Services. Differences in revenue model? (Service allows stability of revenues and continuous relationship with customers)
3. Servitization: shift from selling product to selling Product-Service Systems
  - Software (Google docs, Office365)
  - Automotive
  - Aerospace
  - Industrial machineries
  - Tires
  - Apparel (Wearables)
  - Medical systems

# DATA ARE TRANSFORMING BUSINESS MODELS

## The big moves

4. From selling machine to selling services
    - Razor/blades
    - A washing machine requires the following services
      - Selling spare parts profitable for the manufacturer
      - Ordinary maintenance simple, codifiable, it can be done by the customer
      - Repair expensive, difficult to assess for the customer, usually made by affiliated service centers
    - Selling the product and spare parts weakens the incentive of making products reliable, easy to fix, and durable
- A product-as-a-service business model reverses the incentive

# MARKET TRANSFORMATION

## Platform Economy essentials

- Supervised market: operator and at least two group of interests
- Nothing new, at least in Europe
- Metcalfe's Law:  $V=\text{sqrt}(#)$
- Platform / platform of platform
- Fixed costs and different investments
- How it works (e.g Amazon Basics)
  - Identify Buying Behaviour
  - Digitize it
  - Collect data
  - Pull Users into platform
  - New functionalities

# MARKET TRANSFORMATION

## Platform Economy, what's next for F&B?

BOTH SIDE OF THE VALUE CHAIN ARE CURRENTLY TRANSFORMED

- Online marketplaces: Platform economy can be used to create online marketplaces that connect farmers, food producers, and food retailers with consumers. This can increase access to local and specialty foods and reduce costs for farmers and consumers.
- Food delivery: Platform economy can be used to create food delivery platforms that connect restaurants and other food businesses with consumers. This can increase access to a wider variety of food options and reduce delivery times and costs.
- Food traceability: Platform economy can be used to create platforms that track the origin and movement of food products through the supply chain, from farm to consumer. This can increase transparency and food safety, and reduce costs.