

The role of Privacy Enhancing Technologies in future Trusted Smart Statistics

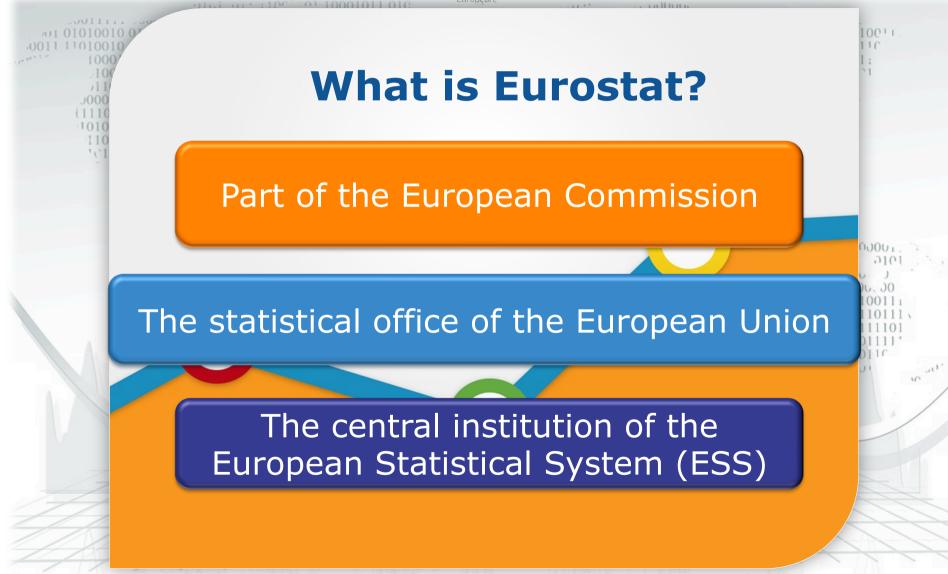
Fabio Ricciato, Eurostat, Unit B1 'Methodology & Innovation in Official Statistics'

fabio.ricciato@ec.europa.eu

CYD Conference on PET 4. November 2020







Eurostat

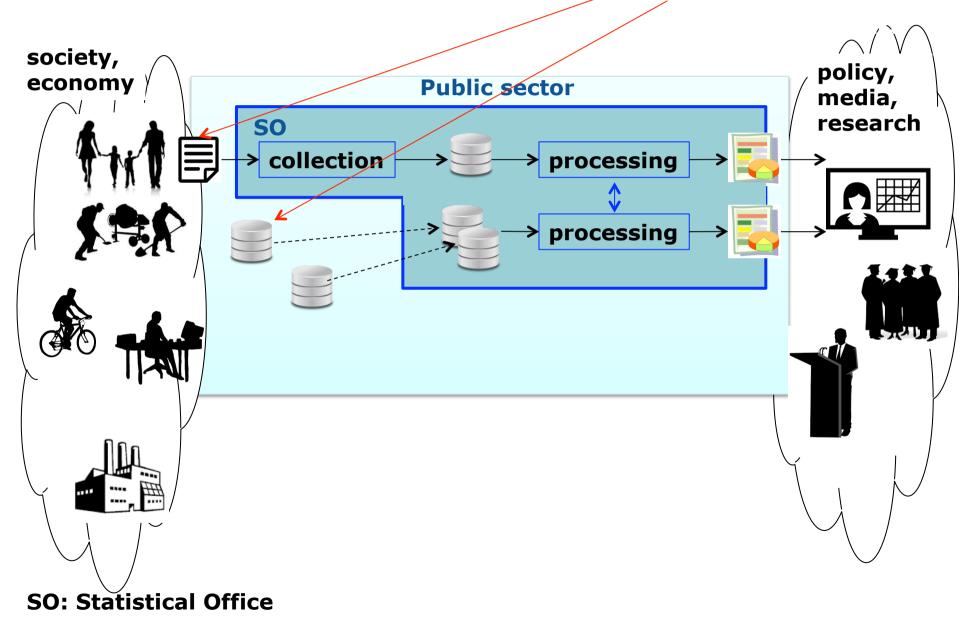
Official Statistics

The role of official statistics is to describe quantitatively the economy, the society and the environment

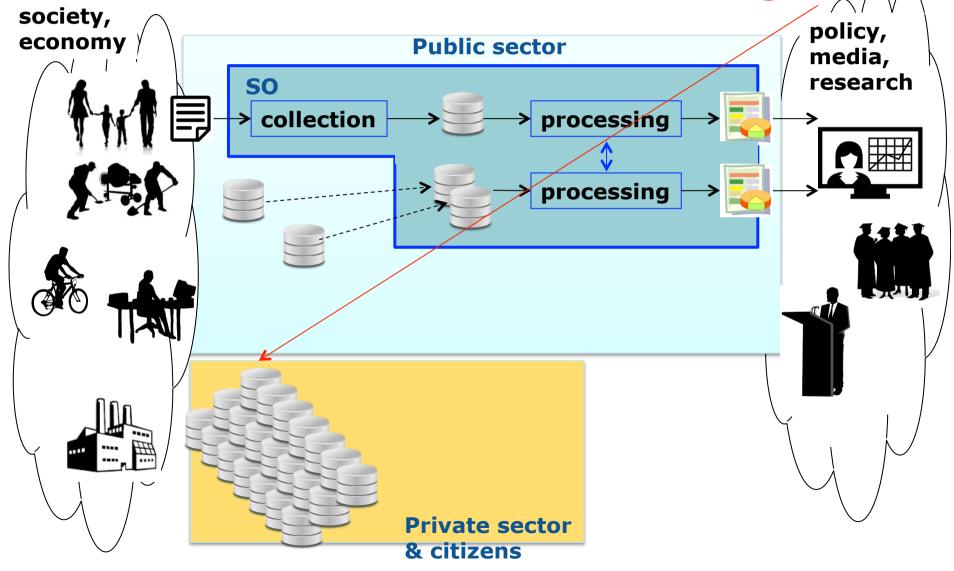


European Commission

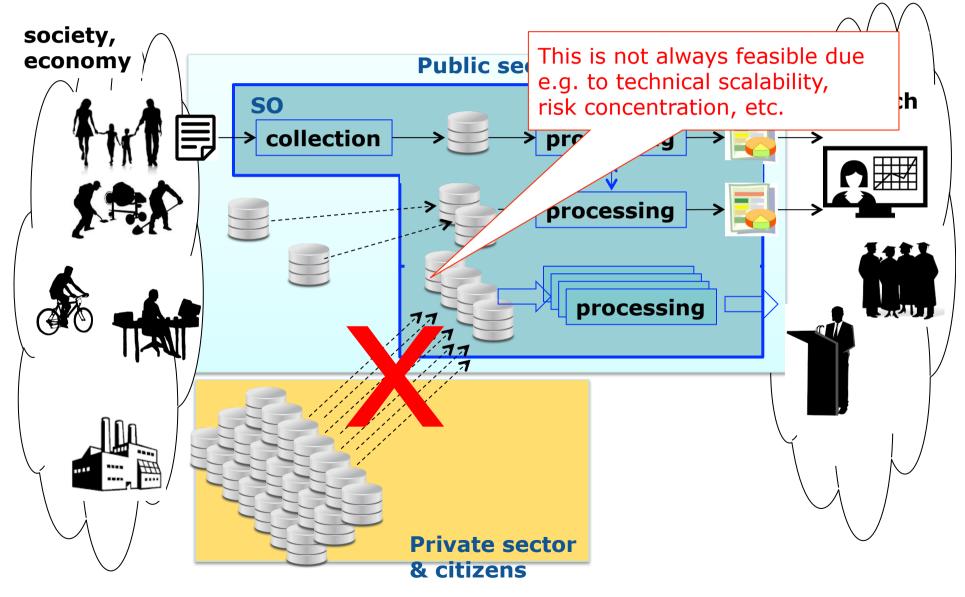
Official Statistics based on survey data and administrative data



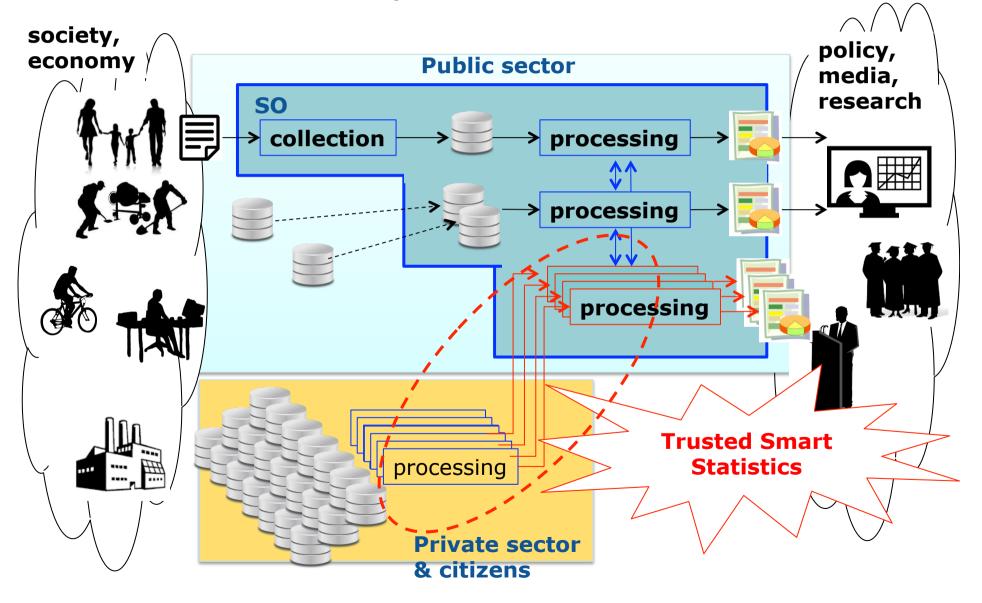
Official Statistics based on survey data and administrative data and now Big Data

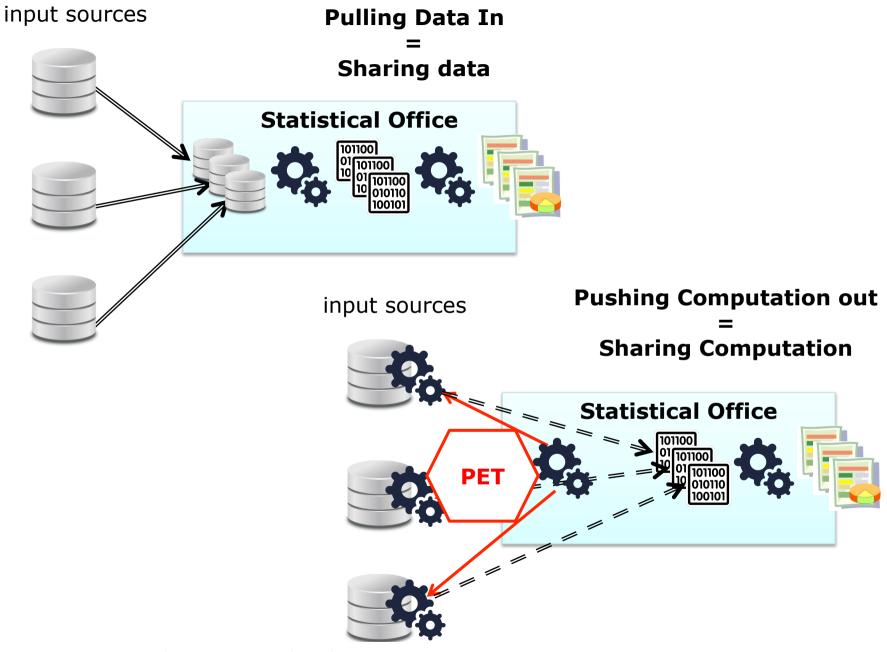


Handling the new in the old way Pull data in



Handle the new in new ways Push computation out (partially)





PET: Privacy Enhancing Technologies

Data and new data



"micro-data"

Name. Gender. Birth date. Marital Status. Residence address. Occupation. Household composition...

Monthly income. Monthly expenditures per good category. Number of touristic trips in a year

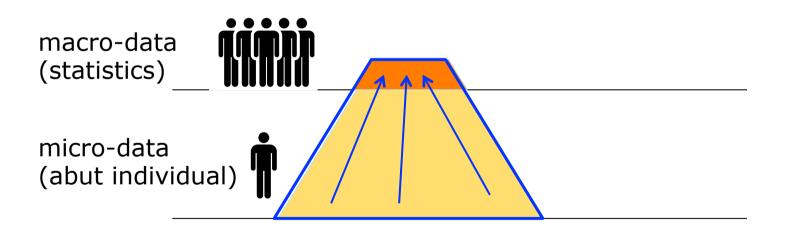
"nano-data"

Your exact location, every second. Every single heart-beat, blood pressure... Every single transaction, purchases, encounter, event involving you... Your current opinion on any single fact...



Official Statistics.

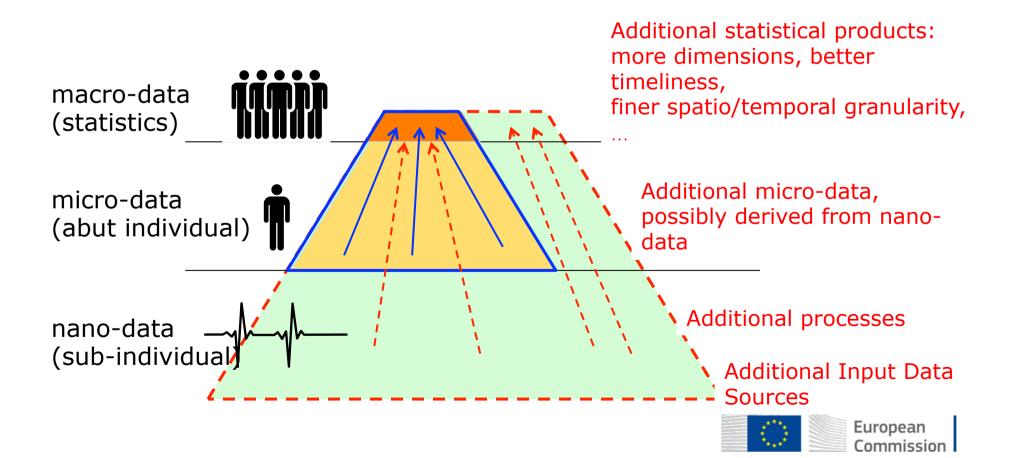
- The ultimate goal of Official Statistics is to produce macro-data (statistics) from input micro-data
 - Collection of micro-data as ancillary task

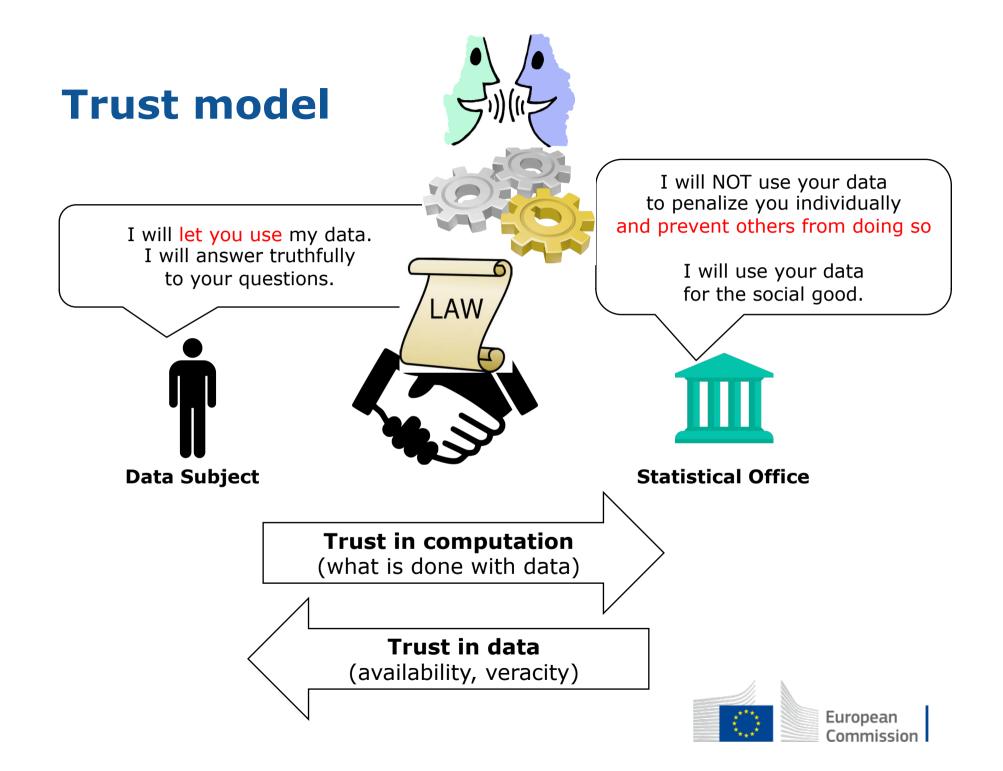




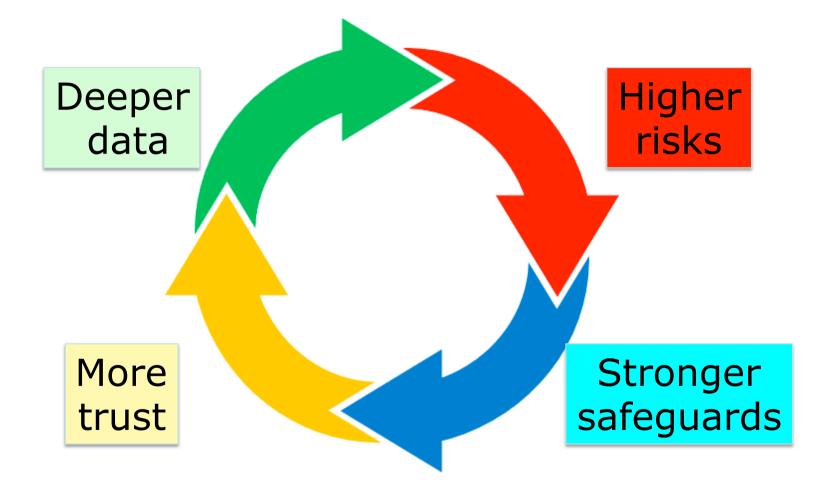
Official Statistics. Augmented

• Availability of new (deep, nano) data sources as opportunity to extend & empower Official Statistics



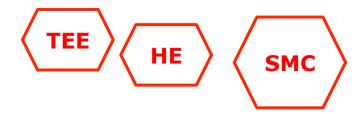


Smart & Trusted

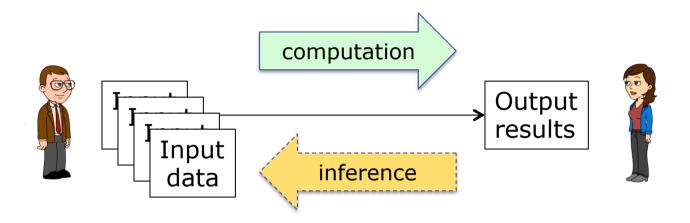


• Input Privacy vs. Output Privacy





Input privacy problem: enabling forward computation (from closed input)



Output privacy problem: preventing backwards inference

(from disclosed output)



SMC: Secure Multi-party Computation SDC: Statistical Disclosure Control

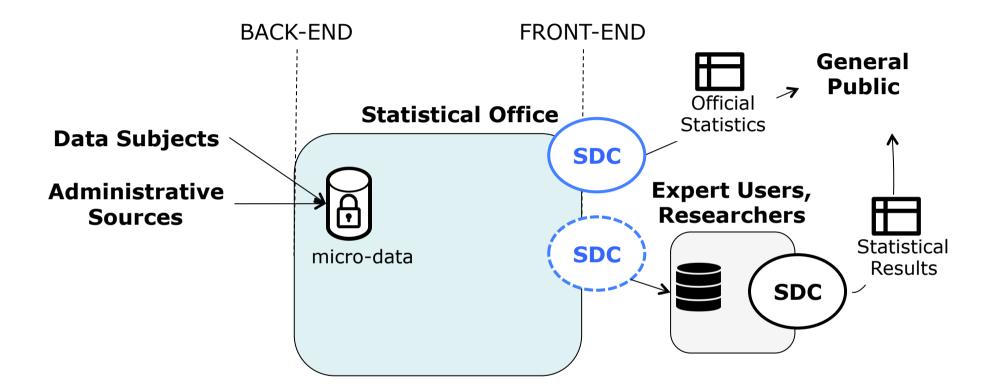
TEE: Trusted Execution Environment HE: Homomorphic Encryption DP: Differential Privacy

Output Privacy: Statistical Disclosure Control (SDC)

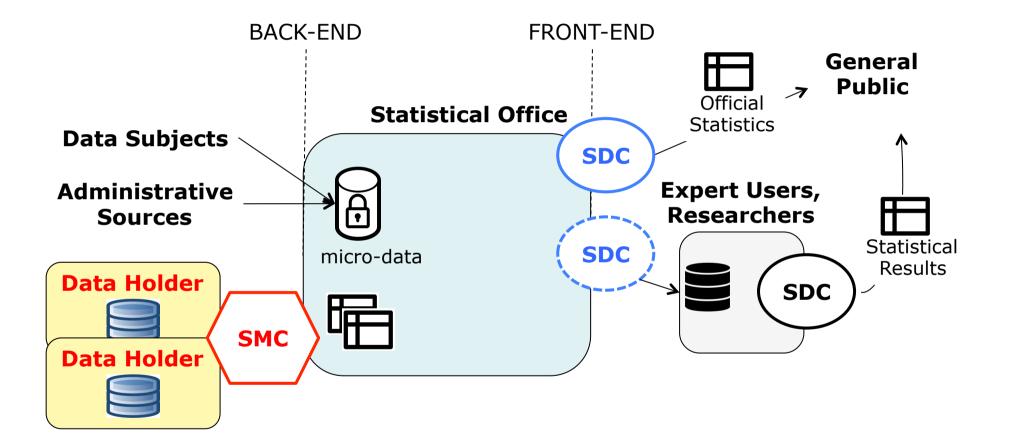
- Suppression (e.g. cell deletion, column removal)
- Add noise, perturbation, rounding

			Average	1—	SDC			Town	Count all	Count sick	Average Income Average
Town	Count all	Count sick	Income			· ,/	╞	Town	Count all	Count sick	Income
							╞				
Smallville	5	1	51					Smallville	6	2	59
Midpoli	85	7	40678					Midpoli	88	7	40401
argetown	5777	45	89					Largetown	5773	44	89
	$\langle $							me	7own 	Sick	
Name	Age	Gend	er Ind	come	Town	Sick		SDC >-	Largetown	1	
									Largetown	0	
Eva	23	F		10	Smallville	1		100	Smallville	1	
Fabio	38	M	7	30	Largetown			23	Midpoli	0	
Elisa	78	F		100	Largetown	1		40000	Midpoli	0	
Oscar	32	M		23	Midpoli	0		30	Largetown	0	
Michail	38	M	4	0000	Midpoli	0					
Anna	24	F	×	11	Largetown	0					
											ropean mmission

SDC on the front-end



SMC on the back-end



SDC: Statistical Disclosure Control

SMC: Secure Multi-Party Computation

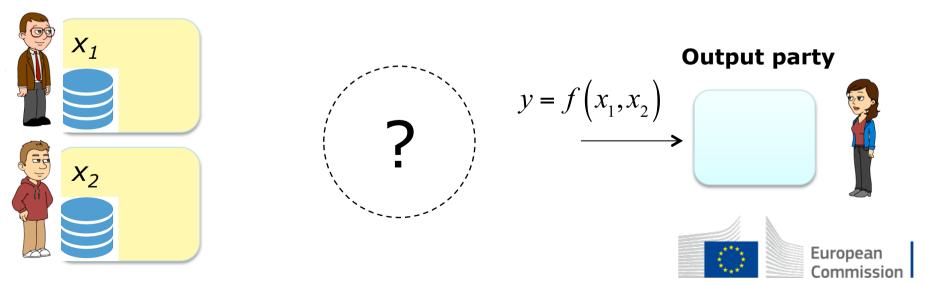
• Input Privacy approaches for multiple input parties



Input Privacy problem

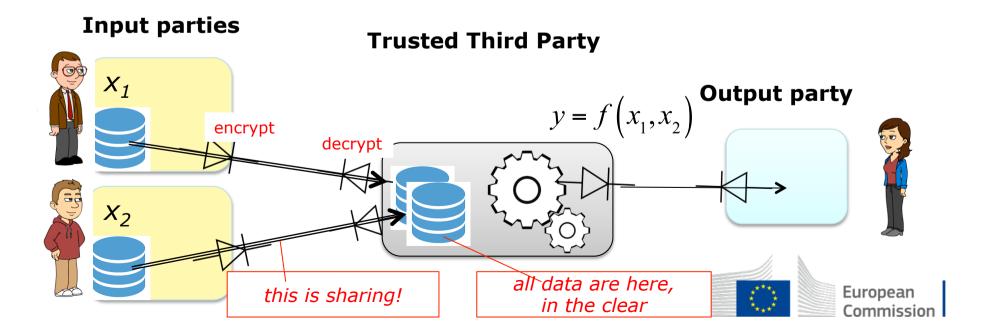
- Marc and Bob (the input parties) agree to let Anne (output party, or result party) learn the result y=f(x1,x2)
- But nobody wants to share their input to any other...

Input parties



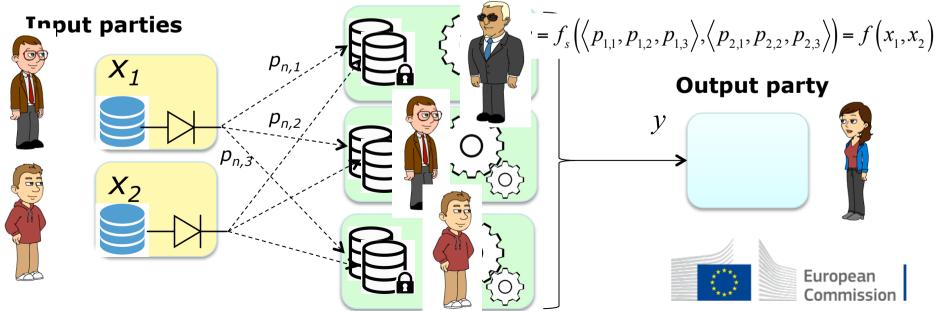
Trusted Third Party (TTP)

- Wih a Trusted Thid Party (TTP) ...
 - data sharing still occurs towards the TTP
 - risk concentration: TTP gets all the data
 → single point of (trust) failure
 - a single entity trusted by all parties might not exist



Secure Multi-Party Computation (SMC)

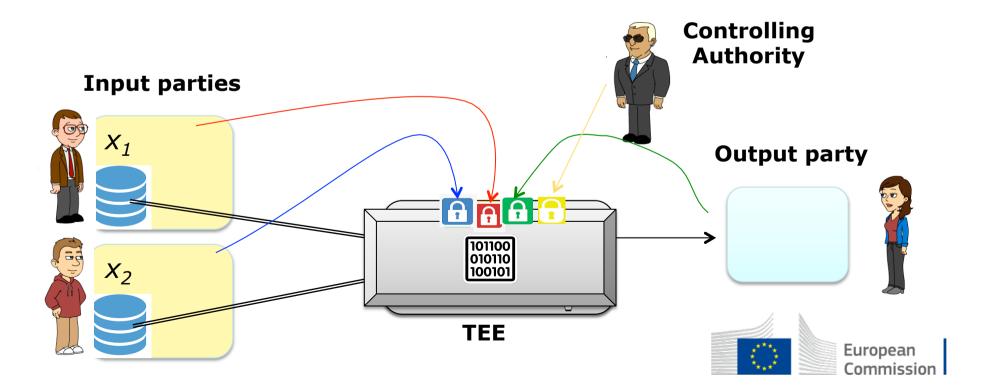
- Each element of secret input x_n is transformed into K "shares" $p_{n,1}, p_{n,2} \dots p_{n,k}$ that are distributed to different computing parties
 - no single party holds "the data"
- The computation on secret shares
 - is distributed (shared) among the computing parties
 - returns the same output value that would be obtained from the input data (homomorfism)
- The computing parties need to be trusted collectively, not individually

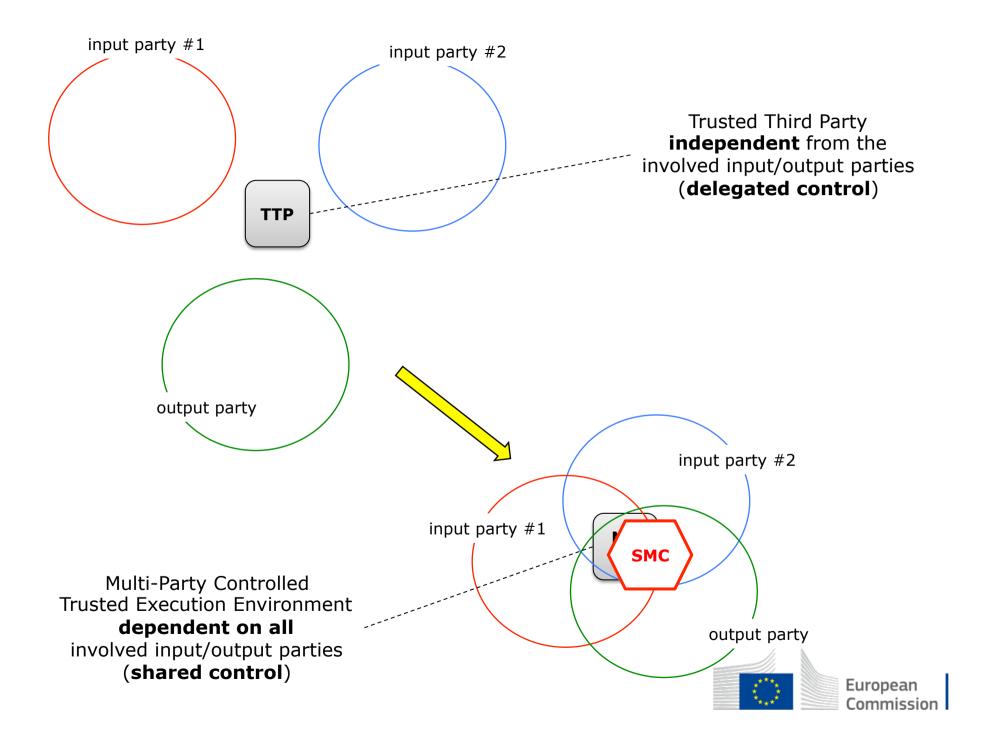


Computing Parties

Multi-Party Controlled Trusted Execution Environment (MPC-TEE)

- Think of a special machine, "trusted" at all layers (software & <u>hardware</u>) to execute/install only code that was jointly authenticated by all involved parties
- TEE separates "ownership" and "control" of the machine





Trust & Control

- Who has control, has to be trusted
- Building trust = engineering <u>credible</u> schemes

for controlling *the use of* data.

- Centralised control \rightarrow single-point-of-trust
- **Shared control** → trust multiple entities <u>collectively</u>, not individually

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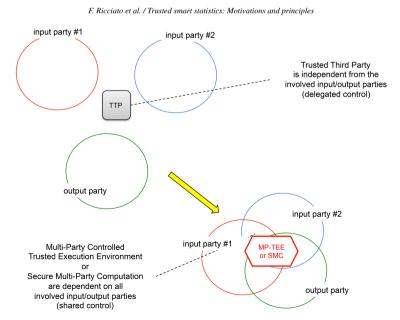


Fig. 3. Delegating control versus sharing control. The Trusted Third Party model (left) all parties must delegate control to an external entity. The technical solutions for Trusted Smart Statistics (like e.g. Multi-Party Controlled TEE or SMC) should instead aim to retain direct (non-exclusive) control among the key stakeholders



• Examples of applications



Application domains

- B2G Data from Private Data Holders (PDH)
 - E.g. merge data from competing Mobile Network Operator (MNO)
- C2G Data from Citizens, Trusted Smart Surveys
 - PET as tool for private computation (similar to Federated Learning concept)
- G2G Data from other public actors
 - Different government agencies, administrative authorities from different countries, etc.



Example#1: Multi-MNO data integration

- Input parties: the 3-5 Mobile Network Operators (MNO) in a same country B2G
- *Privacy of personal data + business sensitivity*
- Output parties: Statistical Office & participating MNOs
- Computation goal: integrate data from individual MNO view without disclosing detailed data to competitors
 - Total counts of inbound roamers^(*)
 - Join spatio-temporal distributions of mobile users across MNO
 - ...



Example#2: Trusted Smart Survey

- Input parties: citizens participating voluntarily to the survey through their mobile devices (several 1000s) C2G
 - passive sensor data and/or active replies to explicit queries
- *Privacy of personal data (possibly very sensitive)*
- Output parties: Statistical Office
- Goal: compute basic aggregate statistics



See e.g. https://ec.europa.eu/eurostat/cros/content/trusted-smart-surveys-possible-application-privacy-enhancing-technologies-official-statistics-short-paper-sis-2020_en



Summary

- Privacy-Enhancing Technologies (PET) will have a role in the context of Trusted Smart Statistics (TSS)^(*)
- PET as tools to improve **trust** by stakeholders (data providers, public) in how data are/will/can be used (for what, how, by whom).
- PET to deliver hard guarantees: make **technically unfeasible**, on top of **legally prohibited**, any deviation from agreed use.
- PET to enable transfer of the strictly necessary information, not whole data.

The GDPR sets out seven key principles:

- · Lawfulness, fairness and transparency.
- Purpose limitation.
- · Data minimisation.
- · Accuracy.
- · Storage limitation.

Accountability.

- Integrity and confidentiality (security)
- (*) *Trusted Smart Statistics: How new data will change official statistics* Data & Policy journal, <u>https://doi.org/10.1017/dap.2020.7</u>

(**) Trusted smart statistics: Motivations and principles. https://ec.europa.eu/eurostat/cros/system/files/sji190584.pdf





Thanks for your attention

fabio.ricciato@ec.europa.eu