# Synthetic Data

IOM/Microsoft collaboration Prepared by the Counter-Trafficking Data Collaborative (CTDC)

2024-02-28



## What are synthetic data?

- Synthetic data are **artificial data** generated from real data
- It cannot be linked back to the original data (including cases), so we can ensure data confidentiality and privacy.
- The statistical properties and relationships from the original data are preserved in synthetic data.
- The advantages of synthetic data over other forms of data are, e.g.,
  - Aggregate data: Researchers can no longer make connections between traits
    - Example: The Global Estimates of Modern Slavery
  - K-anonymized data: The redaction of outliers can lead to significant data loss
    - Example: CTDC data pre-2021



## Example: Raw Data vs. K-anonymized Data

Raw D	ata	Anonymiza	tion						
Gender	Age	Age isForcedLabour							
Female	19	1							
Male	18	1							
Male	20	1							
Male	37								
Female	35								
Female	31								

K-anonymized Data (k = 2)

Gender	AgeBroad	isForcedLabour	k
Female	18-20	1	1
Male	18–20	1	2
Male	18–20	1	2
Male	30-38		1
Female	30–38		2
Female	30–38		2

### Example: Synthetic Data vs. K-anonymized Data

#### Synthetic Data 🥐

Gender	AgeBroad	isForcedLabour
Female		
	18–20	1
Male		
	30-38	
		1
Male	18–20	1
Male	18–20	1
Female	30–38	
Female	30–38	

isForcedLabour k Gender AgeBroad  $\frac{18}{20}$ Male 2 18-20 1 Male 18-20 1 2 Male 30 38 Female 30-38 2 Female 30-38 2

K-anonymized Data (k = 2)

\*Both datasets are generated from the same raw data. For CTDC, k = 10.

#### Overcoming challenges with synthetic data

#### Problem – Then

- CTDC's previous solution was labour-intensive and partner reliant
- K-anonymization results in the loss of potentially useful data
- Risk of re-identification and reprisals
- Market providers were **expensive**

#### Solution – Now

- Microsoft Research's solution automatically prevents the publication of rare attributes
- **Preserves** the statistical properties and relationships in the original data
- Differential privacy guarantees against any privacy attacks
- Open-source

### Synthetic Data Timeline and achievements

	2019 TAT Accele program	erator	<b>2021</b> Released the <u>Global</u> <u>Synthetic Dataset</u>						
2017 CTDC launch		2020 Publish with M Researc privacy data so	ed a <u>paper</u> icrosoft ch on the -preserving <u>lution</u>	<b>2022</b> Released the <u>Global</u> <u>Victim-Perpetrator</u> <u>Synthetic Dataset</u>					

## Synthetic Data Tech Against Trafficking Accelerator Program

- Tech Against Trafficking invited IOM's CTDC to participate the 2019 Accelerator Program.
- The partnership focused on 3 workstreams:
  - 1. Privacy-preserving mechanism: Develop a solution for analyzing case data while protecting victim privacy.
  - 2. Data standards: Address data standards/consistency related to victim case management.
  - **3.** Stakeholder engagement: Maximize utility and impact of the CTDC platform.
- IOM has benefitted from substantial in-kind support from Microsoft Research to support CTDC.



#### Microsoft Research's Synthetic Data Showcase

- Synthetic Data Showcase can automatically generate 3 elements:
   i) a synthetic data, ii) aggregate data, and iii) data dashboards.
- The tool provides 2 approaches to create anonymous datasets:
   i) differential privacy and ii) k-anonymity.

Select

Prepare

• The tools are available with **command-line** options in Python/Rust or a locally run **web application** using Javascript and Web Assembly.

MIGRATION

Synthesize

Navigate

## Synthetic Data Showcase Free-to-use web application

Prepare the sensitive data behind your synthetic dataset. Transform until each individual is resented by a single row of discrete attribute values. All data and processing remain local to your web browser.	Prepare	Select	Synthesize	Navigate		
Open sensitive data file () clean_nonk_pdata_stata.csv ~	Prepare t presented by	he sensitive da a single row	ata behind your syn of discrete attribut web	thetic dataset. Transf e values. All data and browser.	form until each individual is d processing remain local to yo	our
clean_nonk_pdata_stata.csv 🗸						
clean_nonk_pdata_stata.csv 🗸	<sup>7</sup> Open sensit	ive data file 🕖	)			
clean_nonk_pdata_stata.csv 🗸	<sup>5</sup> Open sensit	ive data file 🕕	)			
	<sup>2</sup> Open sensit	ive data file U	)			
	Open sensit	ive data file () nonk_pdata_stata	) a.csv 🗸			



#### Global Synthetic Dataset (2021) You can download data, codebook, and data dictionary



#### Global Victim-Perpetrator Synthetic Dataset (2023) You can download data, codebook, and data dictionary

Privacy-preserving data on victims of trafficking assisted by IOM and their accounts of perpetrators. Protected via differential privacy with ε = 12.

1860 synthetic records matching the query "gender:Female & IP\_RecruiterBroker:1 & UN\_COE\_Region:Europe"



Created using synthetic data showcase. Synthetic counts are calculated over synthetic microdata. Aggregate counts are precomputed for short combinations of attributes. Both datasets preserve privacy by design.

 +
 89%

 Microsoft Power BI
 <</td>
 1 of 2

Perpetrator' characteristics, e.g.,

Role

- Region of citizenship
- Victimperpetrator relationship
- Pay money
   Victim's
- characteristics, e.g.,
- Type of exploitation
- Region of exploitation and citizenship

#### Global Synthetic Dataset (2024) You can download data, codebook, and data dictionary



**Protecting over** 206K actual trafficked persons assisted by CTDC partners from 2002 to 2022 via differential privacy.

(?)

About synthetic data

Sector

93.3K

57.2K

10.9K

37.6K

9.9K

8.2K

7.1K

Мар

No data

S Reset page + 89%

Ē

[ ]

7

% of total

% of total

61%

37%

7%

61%

16%

13%

11%

List

Microsoft Power BI

## Synthetic Data Relevance to stakeholders

- More data (that are published safely) can enable more effective research and scalable responses.
- Victim-perpetrator relationships and victims' characteristics can help advance the understanding of risk factors for vulnerability.
- The technology can be used by any stakeholder who wants to collect and publish sensitive data while protecting individual privacy.
- Synthetic data, if well used, can strengthen the evidence base on human trafficking and help address this grave human rights violation.



## Want to know more?

- Take this free and self-paced e-learning course on <u>"Standardized</u> <u>Human Trafficking Survivor Data Management"</u>
- Visit the <u>CTDC</u> website
- Read/consult this joint IOM-UNODC report (2023), "Leveraging Administrative Data to Strengthen the Response to TIP (ICSTIP)" and guidance



### Appendix: Different forms of data

Туре	Definition					
Raw data	Data collected on <i>data subjects</i> and <b>not processed</b> .					
Partially	Data modified only marginally by removing direct identifiers					
de-identified data	(e.g., name, ID number, IP address).					
Aggregate data	Data combined and presented in a summarized format in the					
	form of statistics, etc. (e.g., Global Estimates 2022).					
K-anonymized	Data modified by removing direct identifiers, reducing details					
data	(e.g., 23 becomes 18–24), and <b>redacted outliers</b> (e.g., <i>k</i> = 10).					
Synthetic data	Data that are artificially created rather than obtained through					
	direct measurement, but the statistical properties and					
	relationships from the original data are preserved.					

#### Appendix: Synthesizing data with full k-anonymity (Microsoft)

#### Step 1

	ATTI	RIBUTES	S/COLU	MNS									
row ID	Α	В	С	D									
1	a1	b1	c1	d1									
2	a2	b2	c1	d1									
3	a1	b2	c2	d1									
4	a2	b1	c1	d2									
5	a2	b2	c3	d1									
6	a1	b1	c3	d1									
7	a1	b2	c1	d2									
r													

#### Step 2

	ATTRIBUTES/COLUMNS												
ID	А	В	С	D									
1	a1	b1	c1	d1									
3	a1	b2	c2	d1									
6	a1	b1	c3	d1									
7	a1	b2	c1	d2									
/	al	DZ	CI	uz									

	ATTRIBUTES/COLUMNS											
ID	Α	В	С	D								
1	a1	b1	c1	d1								
7	a1	b2	c1	d2								

Step 3

Step 4

	ATTRIBUTES/COLUMNS											
ID	Α	В	С	D								
1	a1	b1	c1	d1								

															_								
	value of	from		rel.	cumu.	RAND		value of	frog	rel.	cum.	RAND		value of	frog	rel.	cumu.	RAND	Wa	ممياط م	at in a	uda att	ributo [
	attribute	ireq	•	freq.	freq.	[0,1]		attribute	ireq.	freq.	freq.	[0,1]		attribute	ireq.	freq.	freq.	[0,1]	vve	could no	ot inci	ude att	indute E
	a1		4	0.25	0.25	0.1	1	b1	2	0.29	0.29			b1	1	0.5	0.5						
	b1		3	0.19	0.50		]	c1	2	0.29	0.57	0.6											
	c1		4	0.25	0.69		]	d1	3	0.43	1			d1	1	0.5	1	0.75					
	d1		5	0.31	0.94		]			_						_							
-	total	1	6				-	total	7					total	2								
															_	-							
	new1	a1						new1	a1		c1		$\rightarrow$	new1	a1		c1	d1	ne	w1 <mark>a1</mark>	NUL	_ c1	d1
																			ne	w2 NULL	b1	c1	d1

\* "freq." stands for frequency. "rel." stands for relative. "cumu." stands for cumulative.

