

pyCANON: A Python library to check the level of anonymity of a dataset

JUDITH SÁINZ-PARDO DÍAZ (sainzpardo@ifca.unican.es)

Instituto de Física de Cantabria (IFCA), CSIC-UC

Motivation

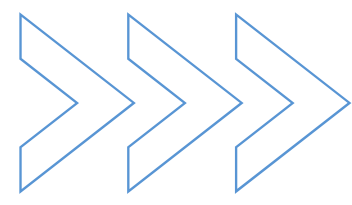
The unstoppable improvements in data analysis techniques for knowledge extraction and decision-making make necessary the evolution of techniques for the secure publication of data. Moreover, the need for collaboration between different institutions, research centers or companies makes it necessary to be able to share data with certain security guarantees. There are numerous attacks that can be carried out on databases: re-identification, linkage, skewness and semantic attacks among others. For this the implementation of *pyCANON*, a Python library and CLI that can be used to know the level of anonymity of a dataset (and thus publish or share it while being aware of the risks involved), is presented. Nine different techniques will be used for this purpose.

Key concepts

- **Identifiers:** variables that allow a person to be unequivocally identified (e.g. name, ID number, email).
- **Quasi-identifiers (QI):** set of variables accessible to an attacker that allow to identify an individual (e.g. city, sex, age).
- **Sensitive attributes (SA):** variables that contain information that must not be disclosed (e.g. diseases, political opinion).
- **Equivalence class (EC):** partition of a database in which all the quasi-identifiers have the same value. Users in the same EC are all indistinguishable with respect to the QI.

| Name | Age | Sex | ZIP code | Stroke |
|---------|-----|-----|----------|--------|
| Alice | 32 | F | 28105 | Yes |
| Bob | 37 | M | 28305 | No |
| Charles | 44 | M | 28520 | Yes |
| Dianne | 25 | F | 28025 | No |

Table 1. Simple example of a database with one identifier, three QI and one SA.



| Name | Age | Sex | ZIP code | Stroke |
|------|----------|-----|----------|--------|
| * | [25, 35) | F | 28**5 | Yes |
| * | [25, 35) | F | 28**5 | No |
| * | [35, 45) | M | 28*** | No |
| * | [35, 45) | M | 28*** | Yes |

Table 2. Anonymized version of Table 1.

- **Linkage attack:** consists of combining at least two anonymized databases in order to reveal the identity of some individuals.
- **Re-identification attack:** occurs when the anonymization process is reversed.
- **Homogeneity attack:** occurs when all the values for a SA in an EC are identical.
- **Background knowledge attack:** the adversary has some foreknowledge about the target of the attack.
- **Skewness attack:** can occur when a SA is not really frequent in the whole database, but it is extremely frequent in an EC.
- **Similarity attack:** may occur when the values of a SA in an EC are different but semantically similar.
- **Inference attack:** consists of applying data mining techniques to extract information from a database.

Anonymity tools implemented

pyCANON allow to check the following nine anonymization techniques:

- **k-anonymity.**
- **(α ,k)-anonymity.**
- **ℓ -diversity.**
- **Entropy ℓ -diversity** (more restrictive than ℓ -diversity).
- **Recursive (c, ℓ)-diversity.**
- **t-closeness.**
- **Basic β -likeness.**
- **Enhanced β -likeness** (more robust privacy than basic β -likeness).
- **δ -disclosure privacy.**

| Technique | Principal attack which prevents | | | | | | |
|----------------------------------|---------------------------------|-------------------|-------------|------------|----------|------------|-----------|
| | Linkage | Re-identification | Homogeneity | Background | Skewness | Similarity | Inference |
| k-anonymity | ✓ | ✓ | | | | | |
| (α ,k)-anonymity | ✓ | ✓ | ✓ | | | | |
| ℓ -diversity | | | ✓ | ✓ | | | |
| Entropy ℓ -diversity | | | ✓ | ✓ | | | |
| Recursive (c, ℓ)-diversity | | | ✓ | ✓ | | | |
| t-closeness | | | | | ✓ | ✓ | |
| Basic β -likeness | | | | | ✓ | | |
| Enhanced β -likeness | | | | | ✓ | | |
| δ -disclosure privacy | | | | | ✓ | | ✓ |

Table 3. Anonymization techniques and principal attacks that prevent.

Impact

GOAL: given a dataset, a list of QI and a list of SA, check for which parameters the aforementioned techniques are satisfied.

pyCANON helps to detect failures in the anonymization process.

Allows to know how different properties scale as a function of others. Example: evolution of t and $\log(\beta)$ when varying k (for t -closeness, basic β -likeness and k -anonymity respectively).

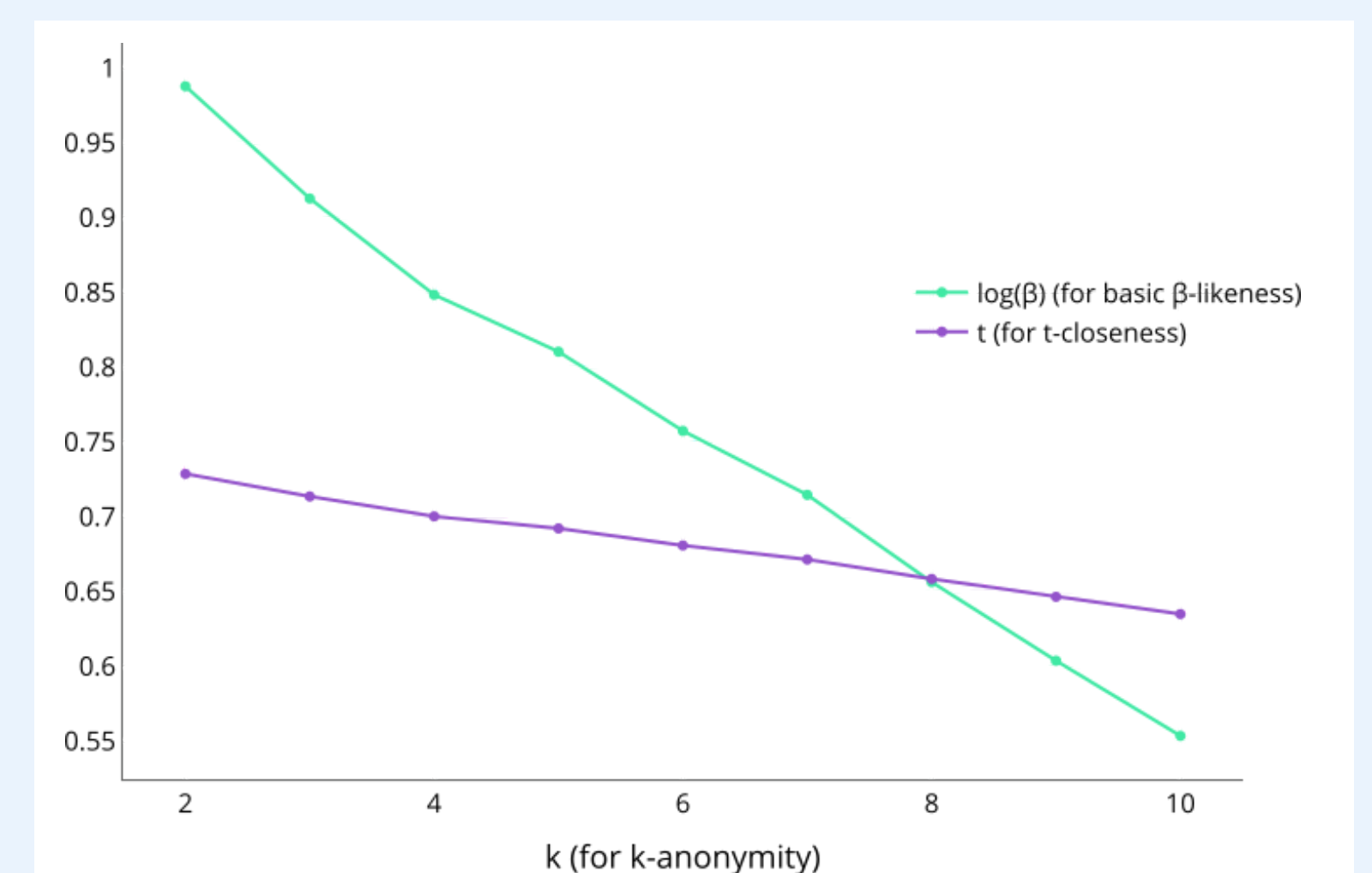


Figure 1. Use example of the *report* package of *pyCANON*.

Evaluate the level of anonymity depending on the selected QI.

Enable data to be published or shared with security guarantees.

Two approaches are allowed in case of more than one SA.

No previous knowledge of Python or anonymity techniques is required.

Customized reports in JSON and PDF formats can be easily obtained as in the following example:

```
import pandas as pd
from pycanon.report import pdf

FILE_NAME = "adult.csv"
DATA = pd.read_csv(FILE_NAME)
QI = ["age", "education", "occupation",
      "relationship", "sex", "native-country"]
SA = ["salary-class"]
FILE_PDF = "report_adult.pdf"
pdf.get_pdf_report(DATA, QI, SA, file_pdf = FILE_PDF)
```

Example code 1. Use example of the *report* package of *pyCANON*.

Documentation:

<https://pycanon.readthedocs.io/>

PyPi (installation):

<https://pypi.org/project/pycanon/>

Preprint: J. Sáinz-Pardo Díaz, Á. López García, "pyCANON: A Python library to check the level of anonymity of a dataset", 2022, <https://arxiv.org/abs/2208.07556>

GitHub repository: <https://github.com/IFCA/pycanon>



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