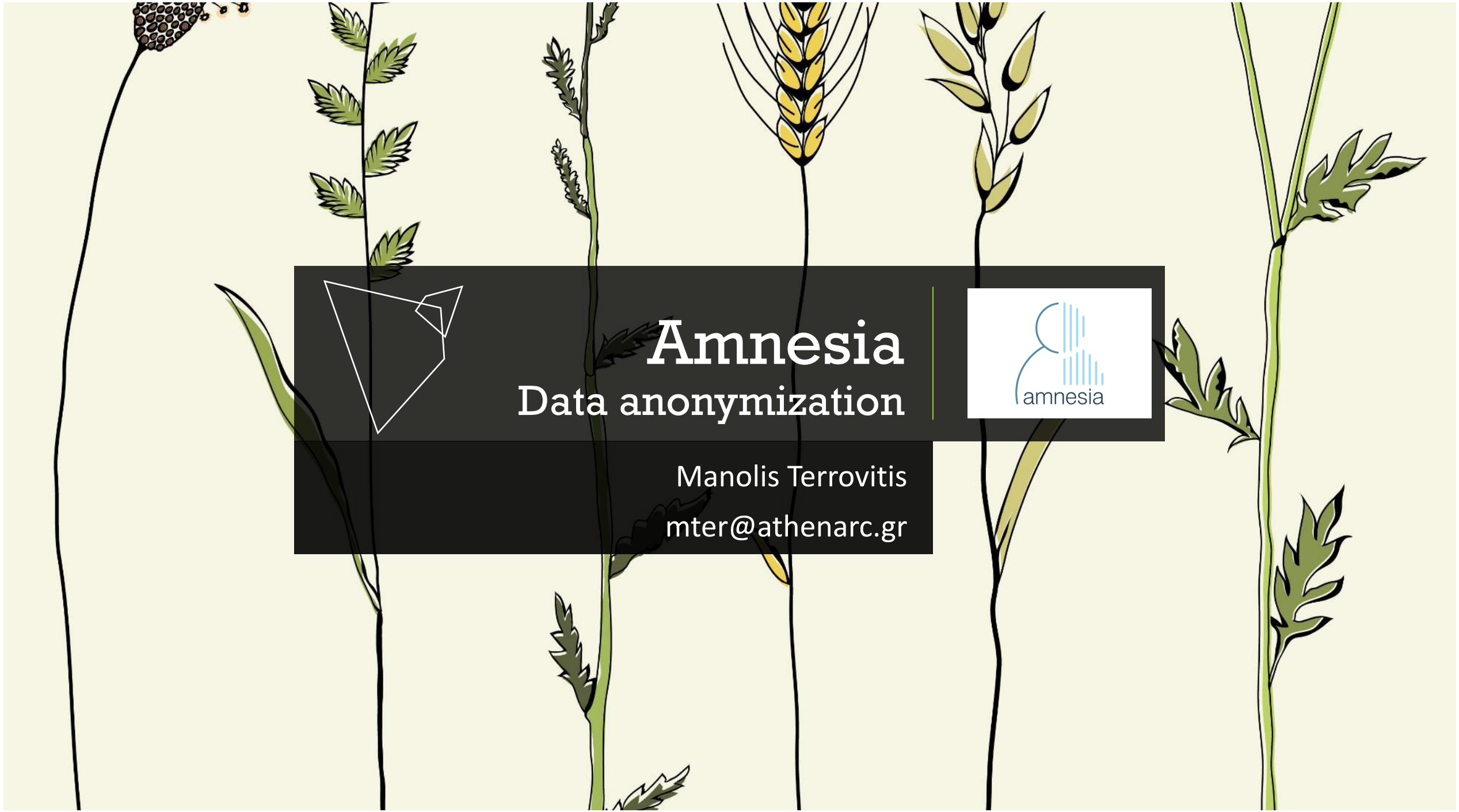

# Amnesia

## Data anonymization

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- GDPR limits the usage of personal data
  - according to law and contracts
  - Consent
  - Can be used for research

- Using Personal data
  - Consent might be refused or withdrawn
  - Difficult to manage
  - Usage for research purposes requires strict internal processes
  - Cannot share with third parties

# Unlock the information

- Research requires statistical information and properties
- Personal identification is not necessary in most fields
- Low reduction in data quality is tolerable
    - Or can be mitigated by using larger amounts of data

- Anonymization unlocks the valuable information in data
  - The anonymized data are **different from the original data.**
  - Anonymization is a one-way transformation of data.
  - Original data cannot be retrieved.
- Pseudonymization is not Anonymization
  - In Pseudonymized data there is a way to retrieve the original data
  - Pseudonymized data are still personal data.
  - The General Court of the EU decided there are cases where pseudonymized can be considered as anonymized (judgment in Case T-557/20).
    - This decision does not cover the dangers we discuss here.

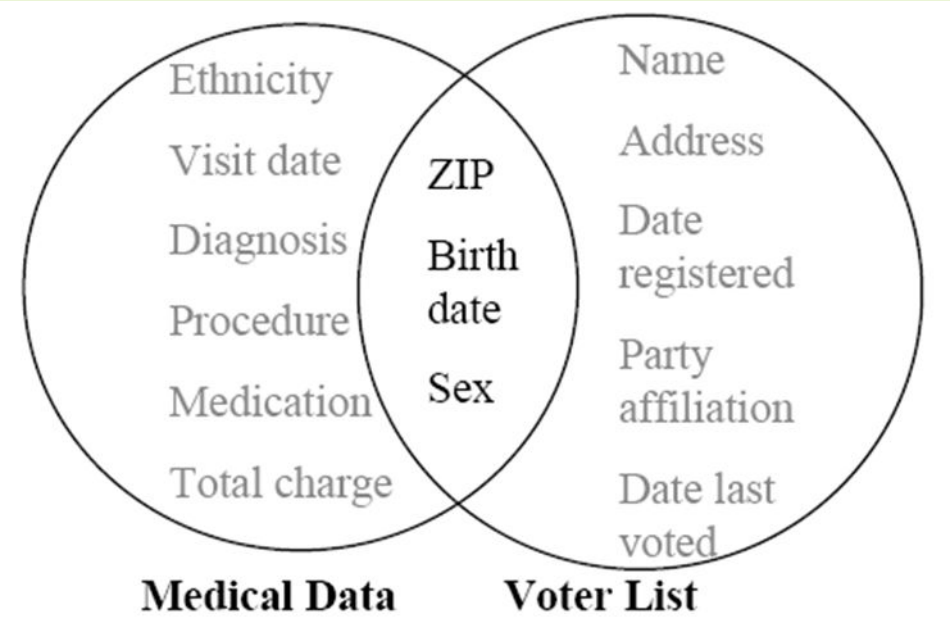
# Why Anonymize?

- Anonymized data are outside the scope of GDPR
- Anonymization provides a statistical guaranty about the risk of information leakage
- It is the most suitable way to give information to third parties, without revealing personal data

# When to anonymize

- When you are a practitioner, and you want to share data with researchers and third parties without compromising the privacy of the user
  - After the data is anonymized, you do not need consent
- When you want to give data to recipients you do not fully trust
  - Encryption will reduce the risks of data leaks to unauthorized third parties, it will do nothing for untrusted recipients
- When you want to openly publish data and you are not fully aware of the audience
- When reduction in information quality is acceptable

# Pseudonymization - Link attacks



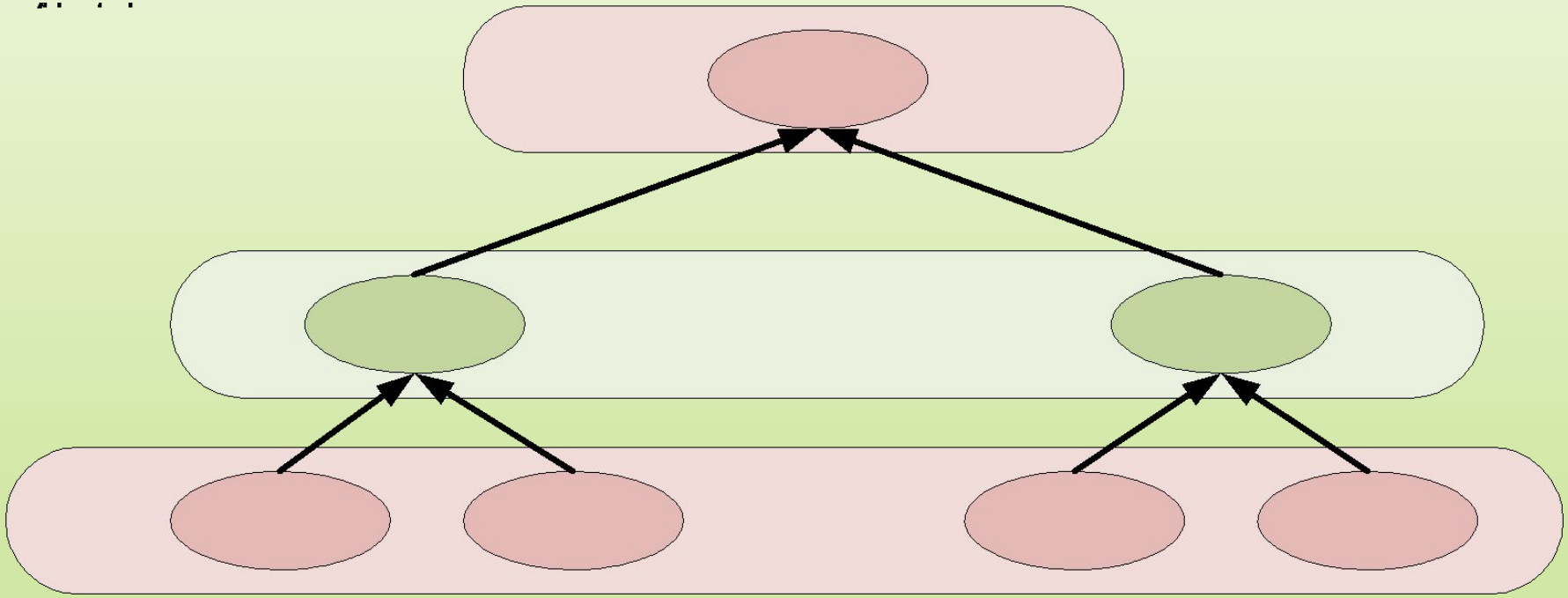
# *k*-anonymity

- Each entry becomes indistinguishable from other *k*-1 entries

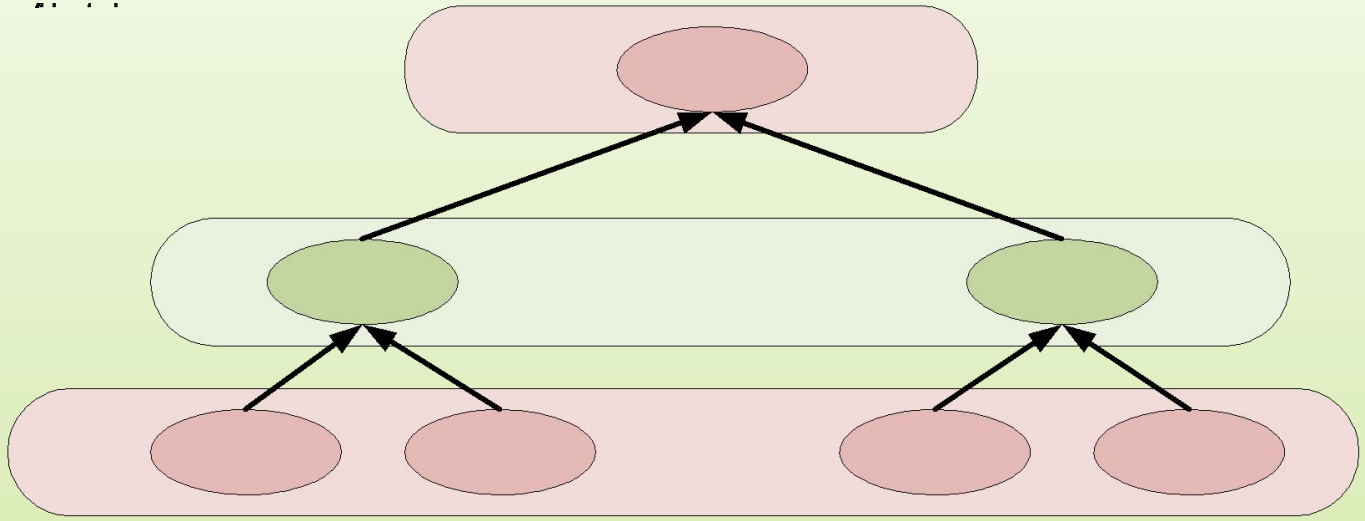
| id | Zipcode | Age | National. | Disease |
|---|---|---|---|---|
| 1 | 13053 | 28 | Russian | Heart Disease |
| 2 | 13068 | 29 | American | Heart Disease |
| 3 | 13068 | 21 | Japanese | Viral Infection |
| 4 | 13053 | 23 | American | Viral Infection |
| 5 | 14853 | 50 | Indian | Cancer |
| 6 | 14853 | 55 | Russian | Heart Disease |
| 7 | 14850 | 47 | American | Viral Infection |
| 8 | 14850 | 49 | American | Viral Infection |
| 9 | 13053 | 31 | American | Cancer |
| 10 | 13053 | 37 | Indian | Cancer |
| 11 | 13068 | 36 | Japanese | Cancer |
| 12 | 13068 | 35 | American | Cancer |

| ~~id~~ | Zipcode | Age | National. | Disease |
|---|---|---|---|---|
| ~~1~~ | 130** | <30 | * | Heart Disease |
| ~~2~~ | 130** | <30 | * | Heart Disease |
| ~~3~~ | 130** | <30 | * | Viral Infection |
| ~~4~~ | 130** | <30 | * | Viral Infection |
| ~~5~~ | 1485* | ≥40 | * | Cancer |
| ~~6~~ | 1485* | ≥40 | * | Heart Disease |
| ~~7~~ | 1485* | ≥40 | * | Viral Infection |
| ~~8~~ | 1485* | ≥40 | * | Viral Infection |
| ~~9~~ | 130** | 3* | * | Cancer |
| ~~10~~ | 130** | 3* | * | Cancer |
| ~~11~~ | 130** | 3* | * | Cancer |
| ~~12~~ | 130** | 3* | * | Cancer |

# Data transformation – Full domain generalization



# Full domain



| Age | Place |
|---|---|
| 28 | Greece |
| 33 | Italy |
| 21 | Greece |
| 24 | Greece |
| 37 | Germany |
| 36 | Finland |
| 35 | Germany |

| Age | Place |
|---|---|
| [25-35] | South Europe |
| [25-35] | South Europe |
| [20-25] | South Europe |
| [20-25] | South Europe |
| [35-40] | North Europe |
| [35-40] | North Europe |
| [35-40] | North Europe |

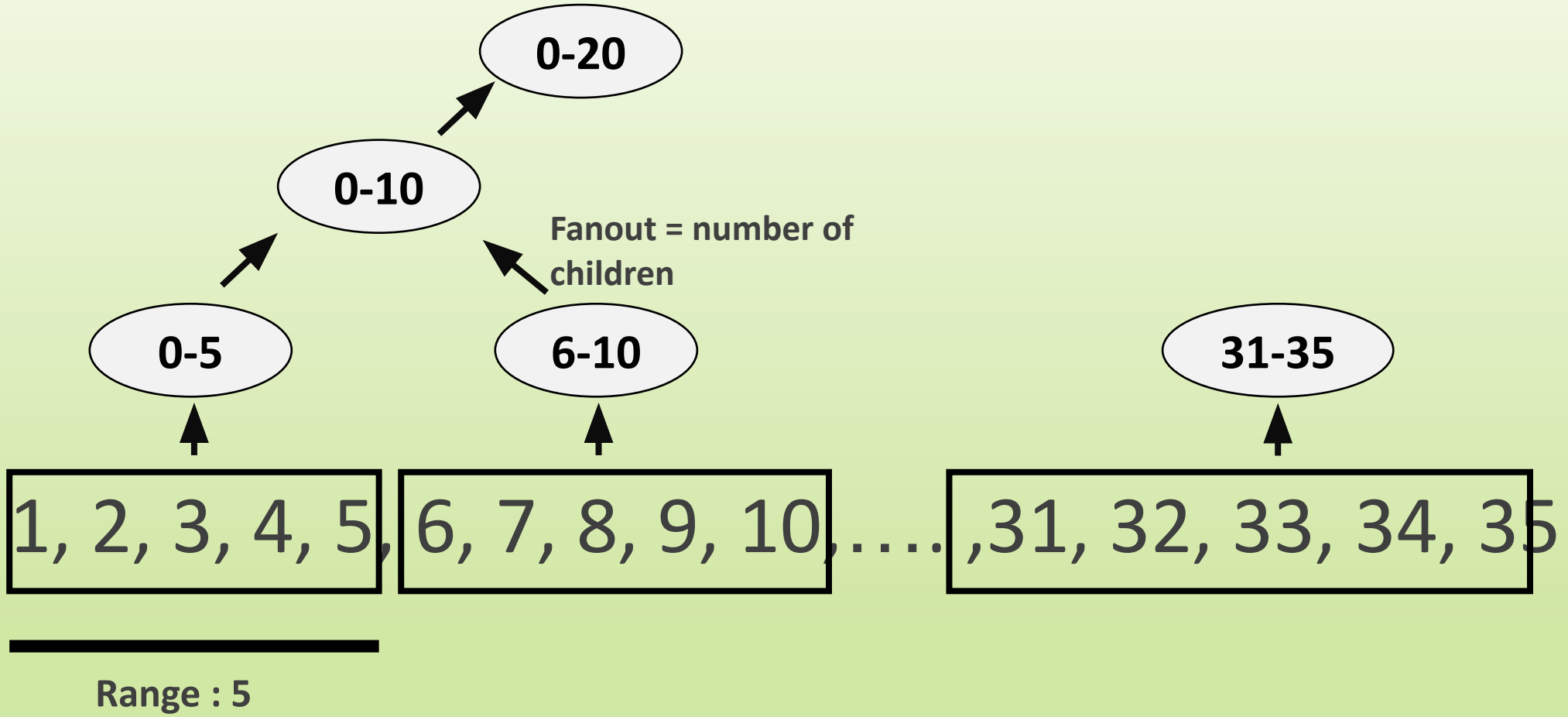
# Local Recoding

- Original values are not globally generalized but only some of subsets of them

| Age | Place |
|---|---|
| 28 | Greece |
| 33 | Italy |
| 21 | Greece |
| 24 | Greece |
| 37 | Germany |
| 36 | Finland |
| 35 | Germany |

| Age | Place |
|---|---|
| [25-35] | South Europe |
| [25-35] | South Europe |
| [20-25] | Greece |
| [20-25] | Greece |
| [35-40] | North Europe |
| [35-40] | North Europe |
| [35-40] | North Europe |

# Amnesia autogenerates hierarchies



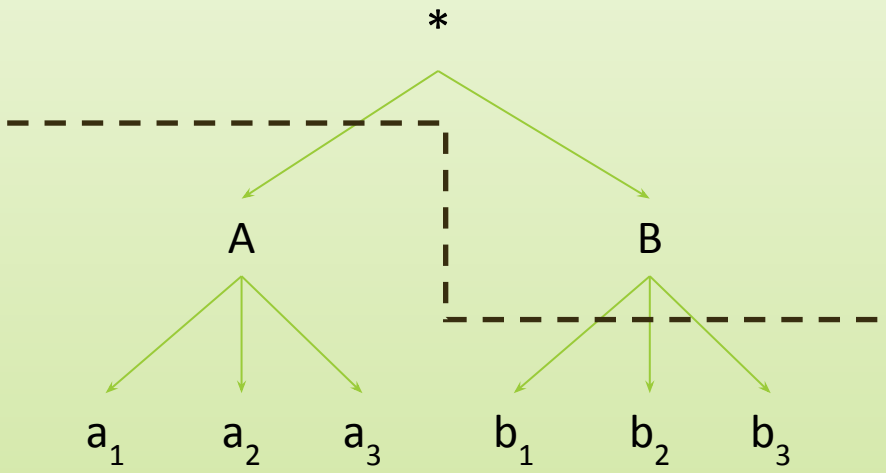
# $k^m$-anonymity – sparse multidimensional data

| | Fruits | Meat | Vegetables | Fish |
|---|---|---|---|---|
| Vassilis | X | X | | |
| Manolis | X | X | X | |
| Eleni | | | X | |
| Maria | | X | X | |
| Kostas | X | | | X |

| | Fruits | Meat | Other food |
|---|---|---|---|
| Vassilis | X | X | |
| Manolis | X | X | X |
| Eleni | | | X |
| Maria | | X | X |
| Kostas | X | | X |

- $2^2$-anonymous
- Any combination of *m* items will not appear less than *k* times

# Method Description




$c_3 = \{A, b_1, b_2, b_3\}$

# Why Amnesia

- User friendly
- Works locally, no data transfer risk
- Allows users to customize the solution
- The only tool to offer anonymization for set-valued data
- The only tool to support $k^m$-anonymity
- Easy to incorporate to third party information systems

# Statistics

https://amnesia.openaire.eu

- 120k visitors
- 480k page views
- 8.4k downloads

# Status

amnesia

**K-anonymity**

**Km-anonymity**

**Object relational datasets**

**Disk based algorithm**

**API**

ReST and command line API exist to help programmers

**Bugs have diminished**

Queries in helpdesk are less about bugs these days

# Upcoming Amnesia version

## DICOM media

### DICOM media

- DICOM is the international standard for medical images and related information (ISO 12052)
- Radiology, cardiology imaging, and radiotherapy device (X-ray, CT, MRI, ultrasound, etc.)

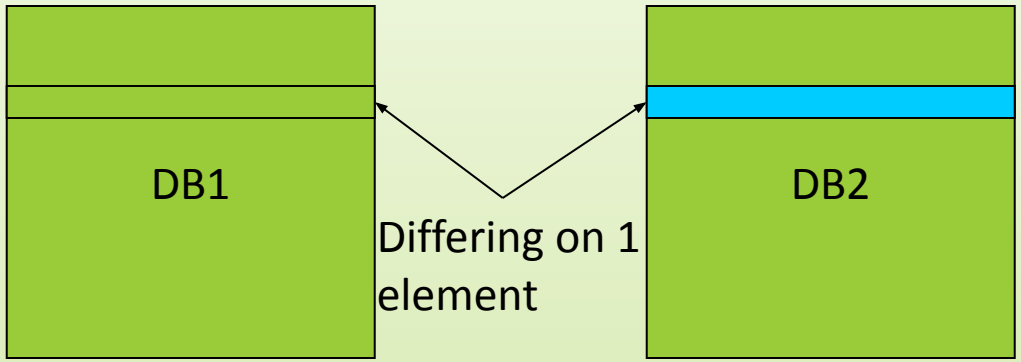
### Metadata anonymization and pseudonymization

- More than 5000 tags
- Amnesia will offer anonymization and pseudonymization of metadata

### User centered approach

- Auto-parse metadata
- Detect non-empty tags
- Remember previous anonymization/pseudonymization processes -TEMPLATES

# Amnesia next steps




$K: \mathcal{D} \rightarrow \mathcal{R}$ ensures $\varepsilon$-DP if for all adjacent datasets $D_1, D_2$ and for all subsets $S$ of $\mathcal{R}$:

$$\frac{\Pr[K(D1) \in S]}{\Pr[K(D2) \in S]} \leq e^{\varepsilon}$$

**Adding differential privacy**

- Stricter, more generic guarantee
- Difficult for non-expert users

**Differential privacy relies on noise addition to mechanisms**

- It guarantees that the impact of each record in an algorithm's output is limited
- It is defined on mechanisms, i.e., algorithms, not on data

**Amnesia will allow differentially private data synthesis**

- Uses will define histograms and aggregates
- Amnesia will create differentially private histograms and will recreate a dataset that supports the DP histogram

# Anonymized vs Synthetic data

- Synthetic data protect user privacy, but they do not provide a guarantee unless coupled with anonymization mechanisms, e.g. differential privacy
- Anonymized data provide a limit in information loss
- Synthetic data need big training sets to perform well
- Anonymized data need a large input dataset to perform well
- Amnesia is a mature tool and has been widely tested

- I expect that anonymization will perform better for low cardinality datasets and synthetic data generators for high dimensional data

# Limitations of Anonymization

**Anonymized data have lost some information**

- The key idea of a good anonymization algorithm is to minimize this loss and limit it in the least important information

**There are gray boundaries between anonymized and pseudo-anonymized data**

**Formal privacy guaranties provide a statistical guaranty for the anonymized data**

- This is only an interpretation of the notion of “privacy”

**It cannot easily be fully automated**

- User input is needed

# Amnesia Limitations

- Users are not familiar with anonymization techniques
- The process is novel and requires effort from the user’s part
- Amnesia cannot decide on privacy parameters
- K-anonymity does not protect from every type of attack

# Thank You

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https://amnesia.openaire.eu