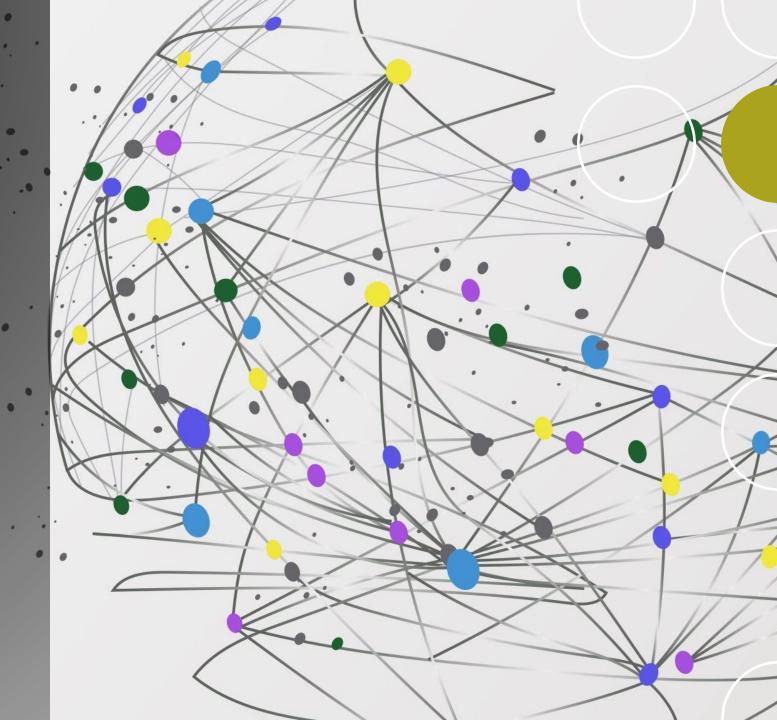
A Data Anonymisation Case Study



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Overview

The Problem Data Anonymisation Considerations The Solution Methods K-anonymity Calculation Sharing of the Anonymized Data Looking Forward

The Problem

- Protecting the privacy of the customers
- Maximizing the useful information that can be given to the CEO and government research teams



The CEO



The Government



The Data



The CEO wants to:

- Use her customer's data
- Pass this data to research teams
- Investigate the travel habits of people with the Wanderlust gene
- Potentially increase the insurance policy for customers with the gene

The government wants to:

- Investigate people with the Wanderlust gene
- Check for educational or geographical similarities

The data includes:

- Personal info
- Geographical info
- Identification numbers
- Social habits
- Genomic info for the Wanderlust gene

Data Sharing Considerations



Benefits of data sharing:

Enable the community to confirm published results.

Avoids duplicating work

Reduces cost

Facilitates further analysis on the same dataset

Encourages collaborative work



Issues of data sharing:

Data privacy

- Confidentiality
- Ideas could be stolen
- Malicious misuse of data
- Accidental misuse of data

The Solution

Data anonymisation:

 The process of cleaning personal identifiers within a dataset that could potentially identify unwilling individuals

Removal of direct identifiers

 Taking out values in the data that could identify a specific individual

Pseudonymisation

Replacing personal, identifiable data with artificial identifiers

Banding

 Classifying data into buckets with numeric ranges or representative categories

Aggregation

 Gathering data to express in a broader, summarised form

K-anonymity

- First described by Latanya Sweeney in 1998.
- It tells us the likelihood of individuals being identified from other individuals within the dataset via the combination of quasi-identifiers.
- Each record should be similar to at least k-1 other records based on the potentially identifiable variables (quasi-identifiers).

Direct -identifiers

- Can directly identify an individual
- Ex: name

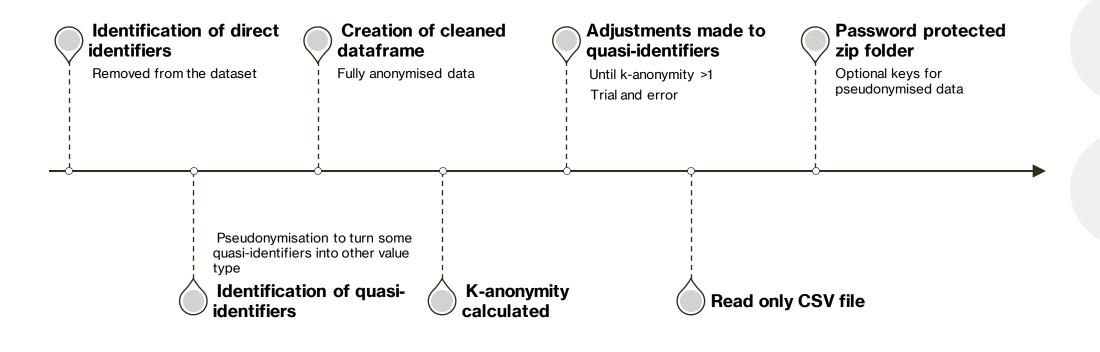
Quasi-identifiers

- Can indirectly identify an individual through combination
- Ex: country of birth

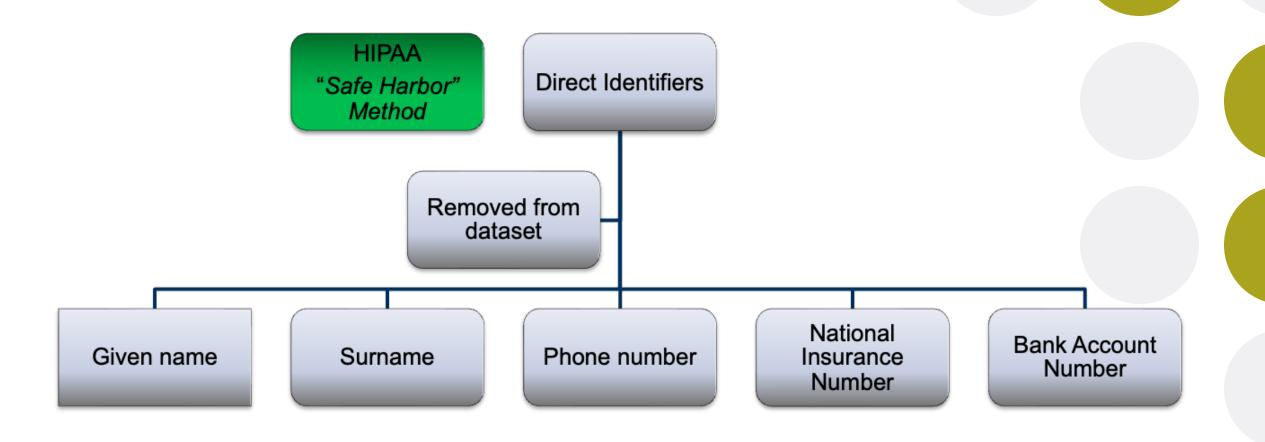
Other values

- Values that are not a direct identifier and are not able to be combined to identify individuals
- Ex: weight and height

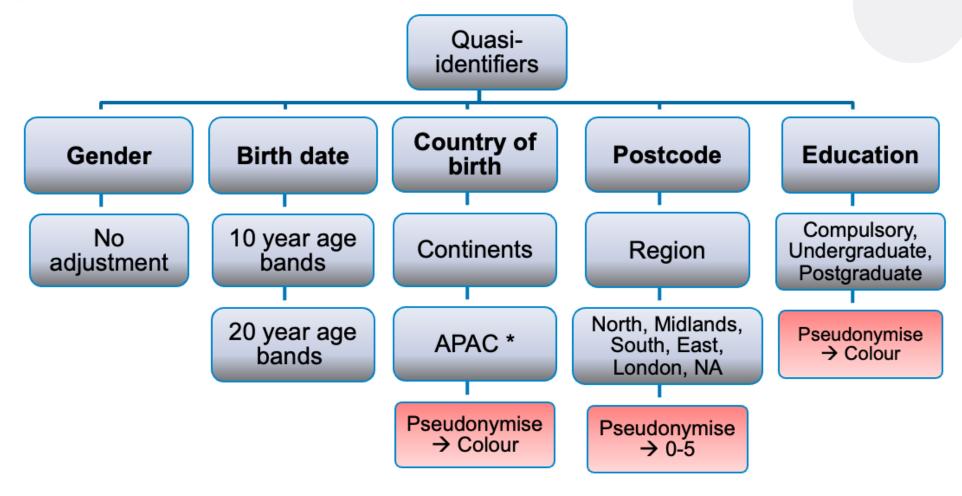
Methods



Direct Identifiers

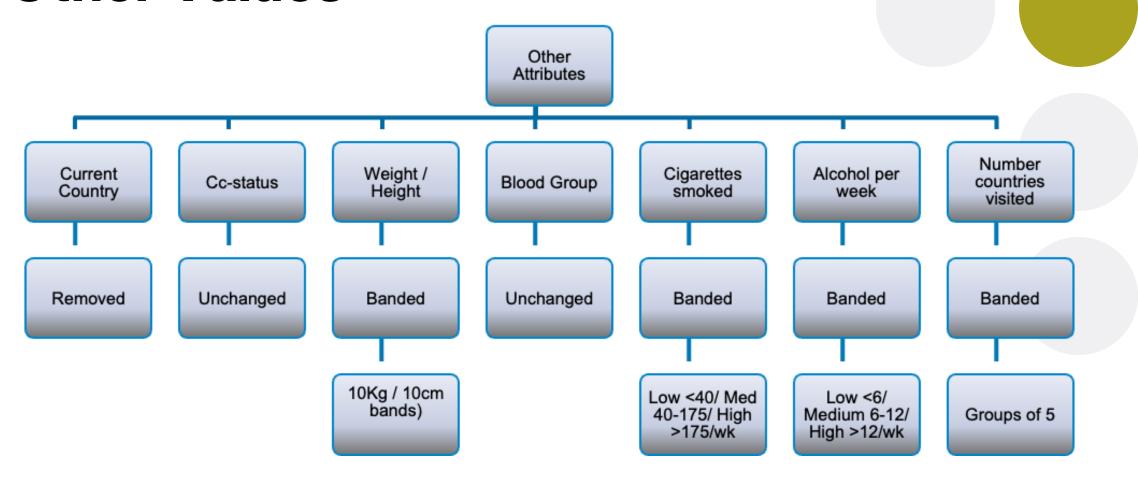


Quasi-identifiers

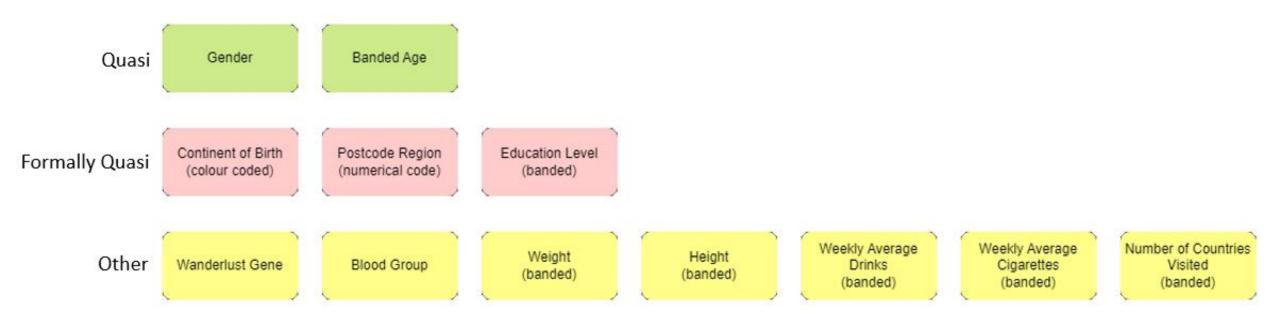


^{*} APAC - Asia + Oceania + Antartica

Other Values

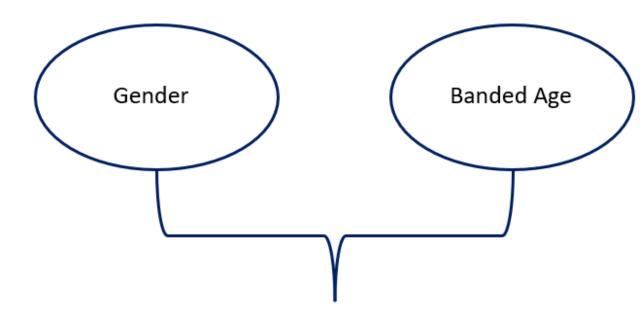


Final Cleaned Dataset



K-anonymity Calculation

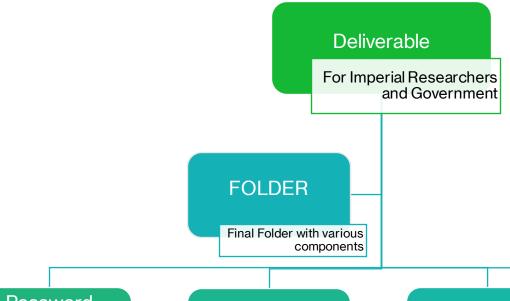
- K-anonymity is calculated by finding the minimum matches of rows of quasi-identifiers
- Our two quasi-identifiers after cleaning the data were gender and banded age
- K-anonymity = 15



Each row has at least 14 others matched to it

K-anonymity = 15

Sharing Anonymised Data



- <u>Used csv files</u> industry standard to share non-complex data
- Password protected zipped folders instead of files – ensures files within are not corrupted
- Zipped folders data is compressed and shareable
- Read-Me file documentation for future users to access and use data

Password Protected Zip Folder: **data.zip**

> Raw-Anonymised Data that is in a password protected folder

README File: **README.ME**

Relevant data documentation for future users

Zipped Folder: **keys.zip**

Keys to de-code variables used in anonymised data

Password: wanderlust.txt

20-character alphanumeric string password to access protected zipped folder with data

Limitations

- Potential over-aggregation of country of birth and postcode data
- Banding reduces specificity of research
- Certain circumstances when other information could be used to identify an individual – extreme outliers
- Still potential for misuse from researchers
- Assumption: only anonymised data set will be published by the government – therefore keys were shared
- Pseudo-anonymisation ratios of different groupings could be used to determine true values

Conclusion and Looking Forward

Challenges

- Lots of trial and error required to reach K > 1
- Difficult to intuitively determine what a quasi-identifier is
 - Especially with medical data
- Difficult to balance needs of CEO researchers and government
- Unsure of which information is valuable to include

Takeaways

- Hashing is best for data with lots of unique values
- Sorting data types (direct, quasi, other) first helps
- Include as much info as you can

References

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