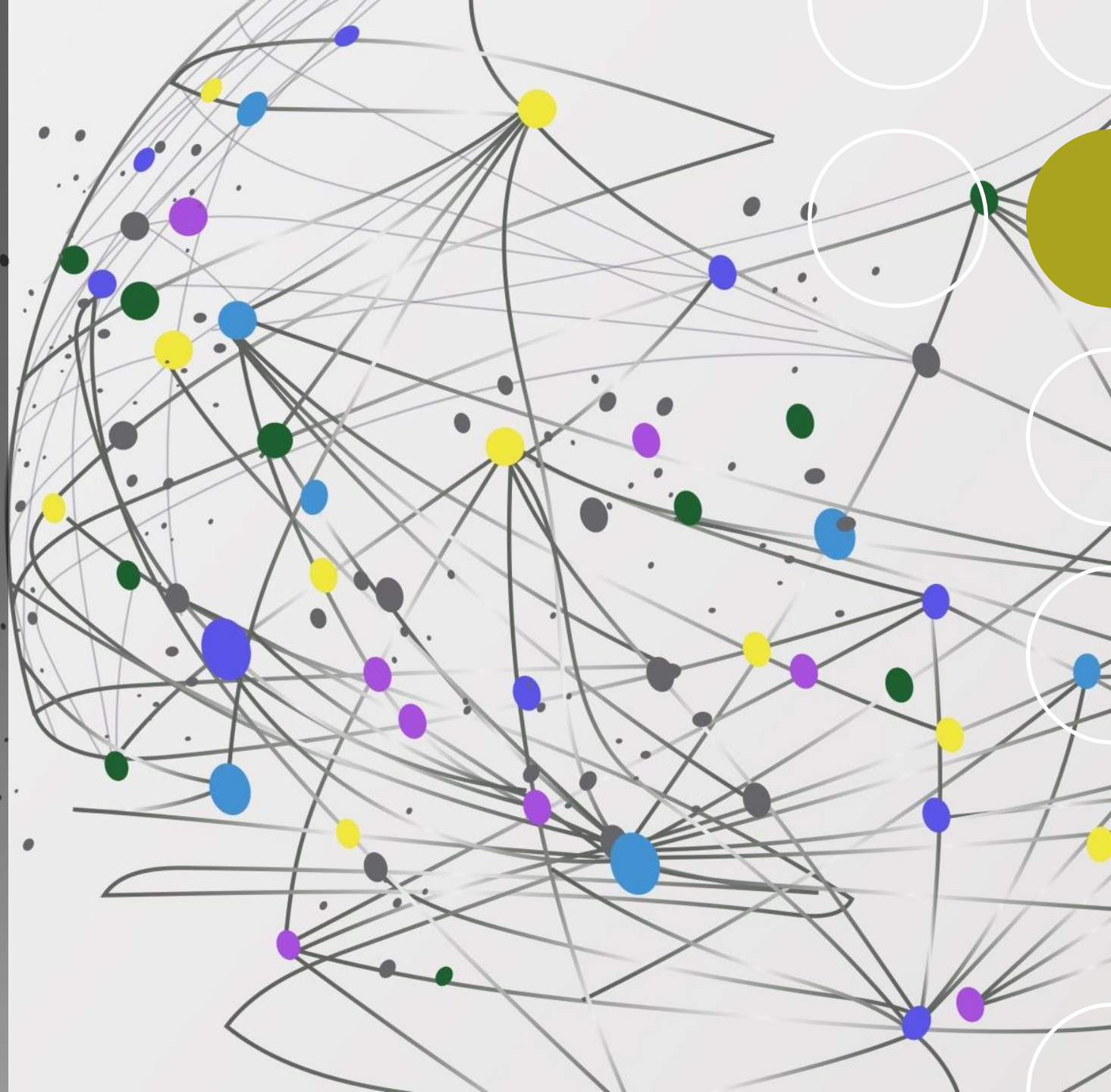


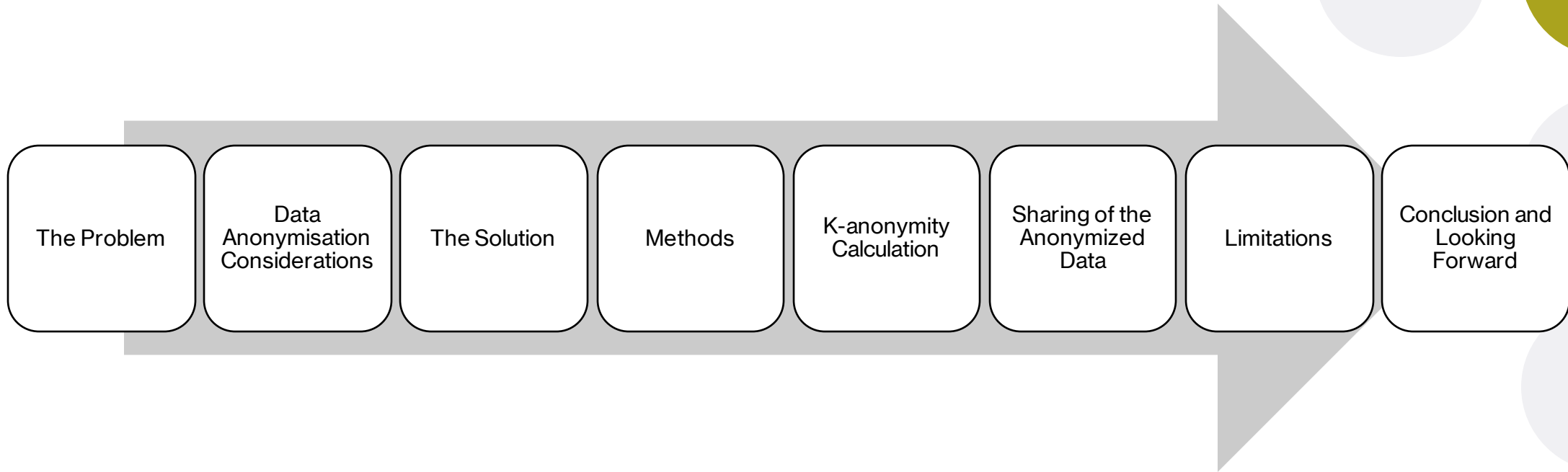
A Data Anonymisation Case Study



Dan Huntley, Divya Shridar,
Nicole Cizauskas, Sreenidhi
Venkatesh



Overview



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 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



The government wants to:

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

The Data



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

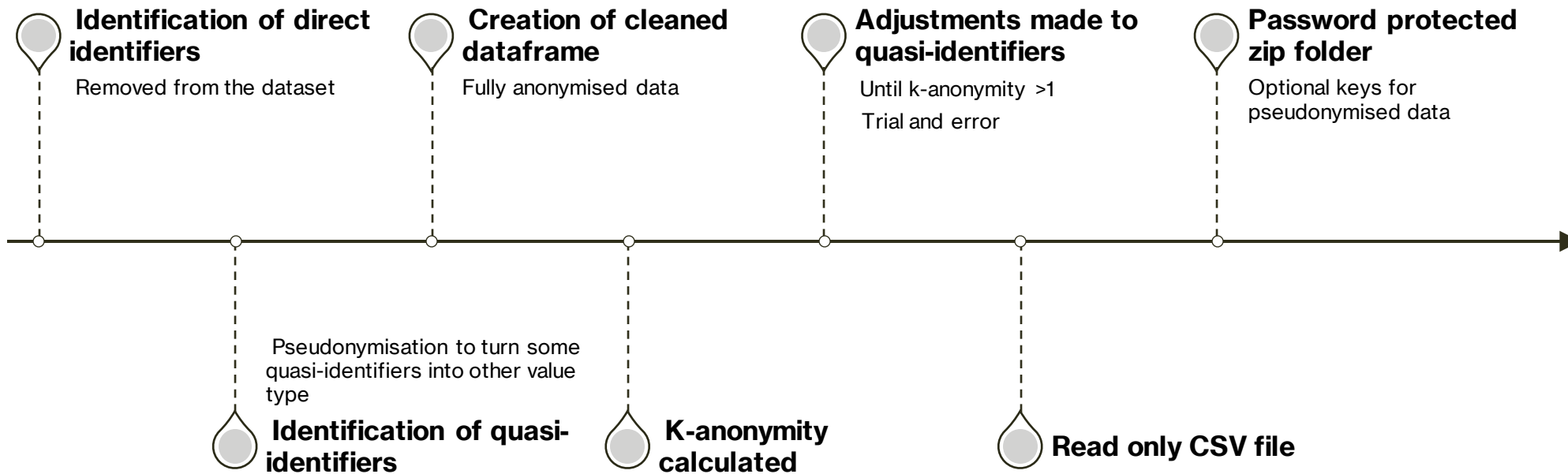
Quasi-identifiers

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

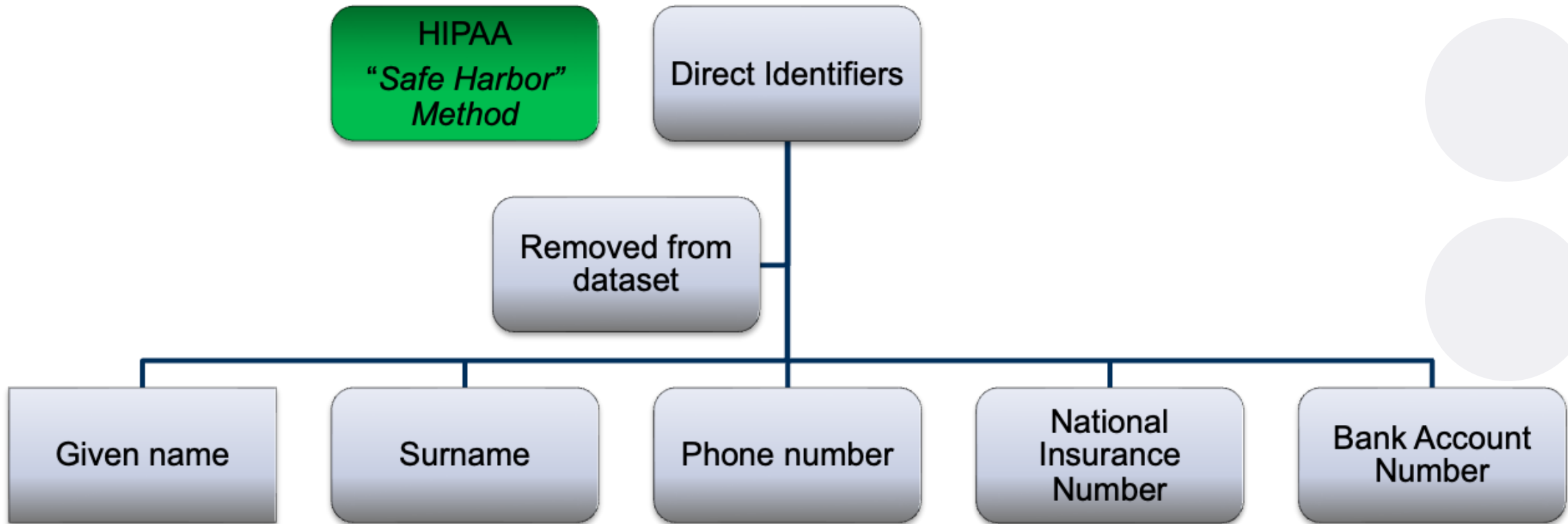
Other values

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

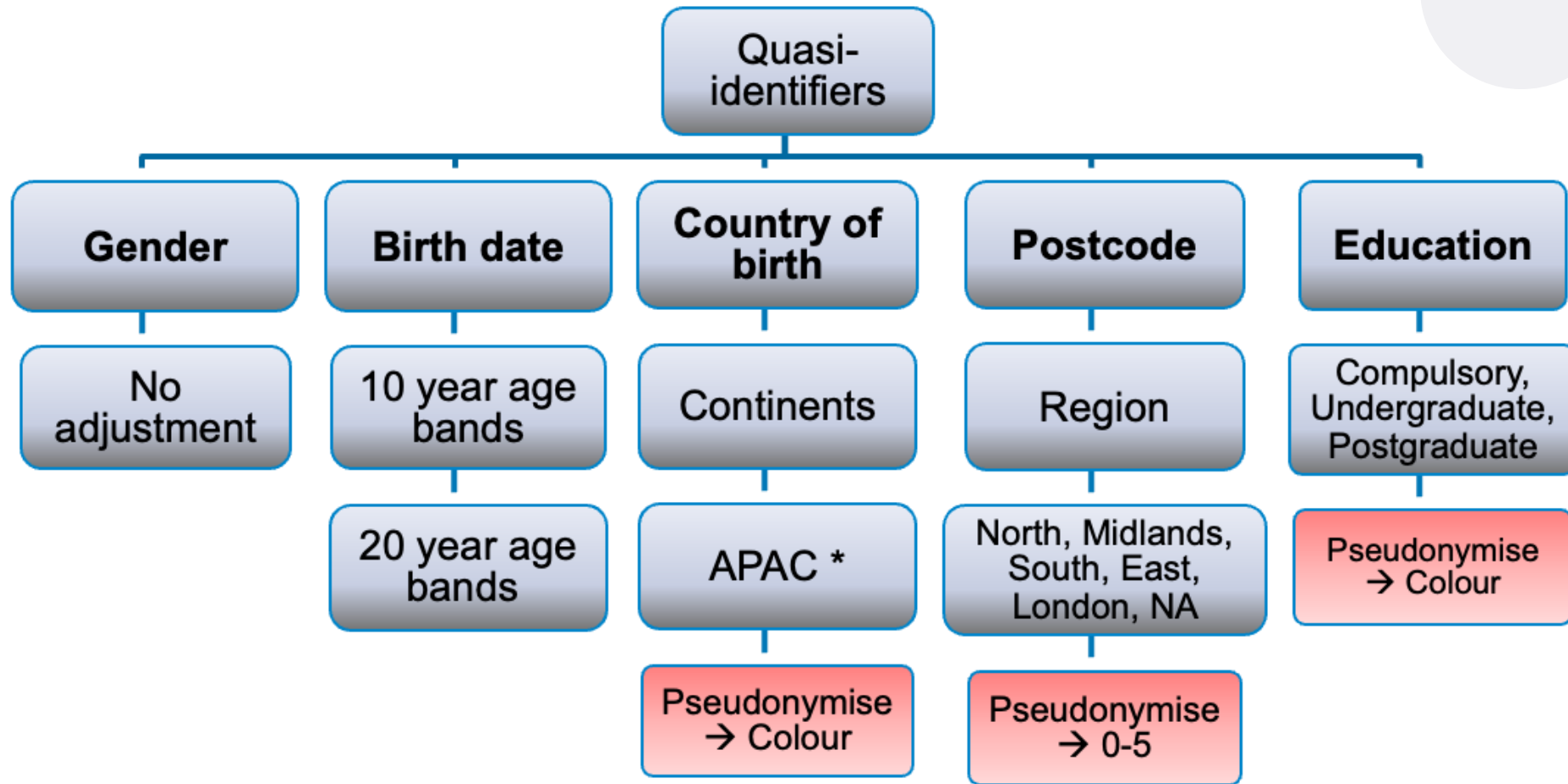
Methods



Direct Identifiers

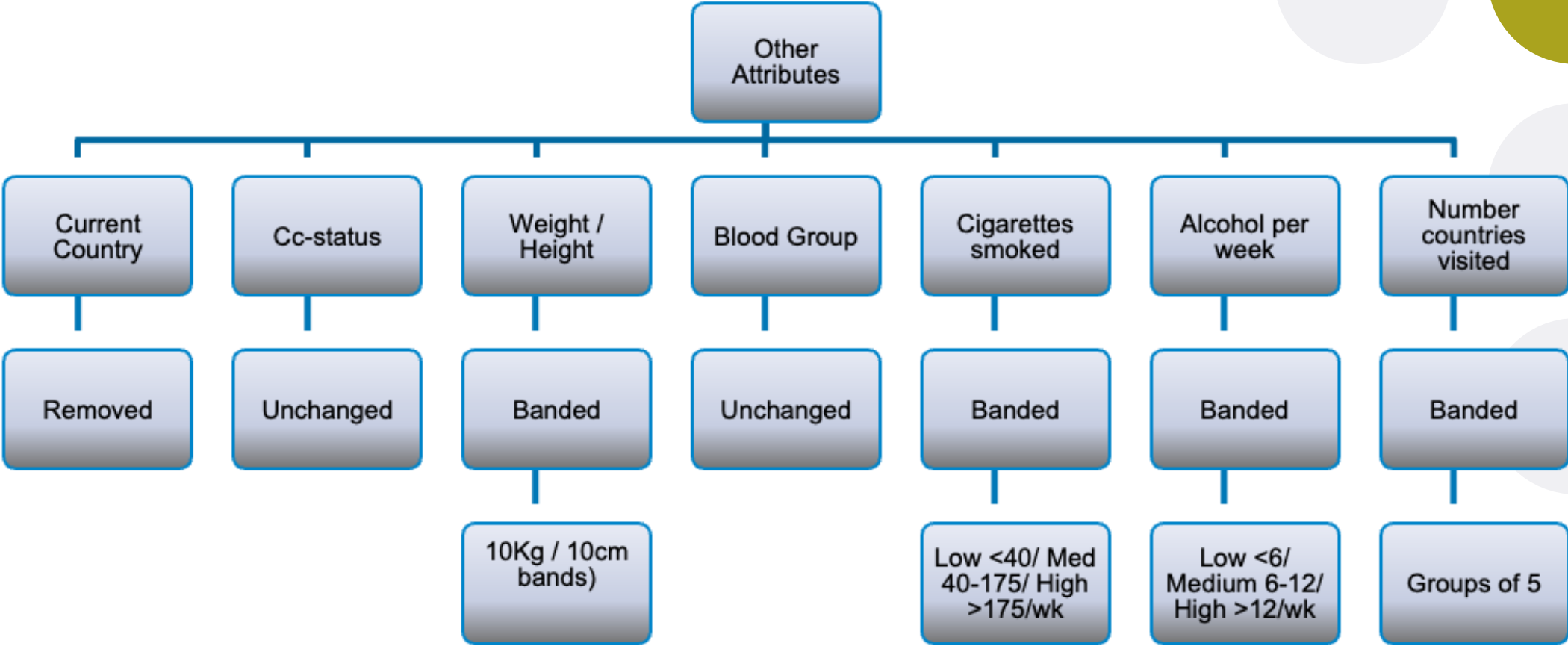


Quasi-identifiers



* APAC - Asia + Oceania + Antartica

Other Values

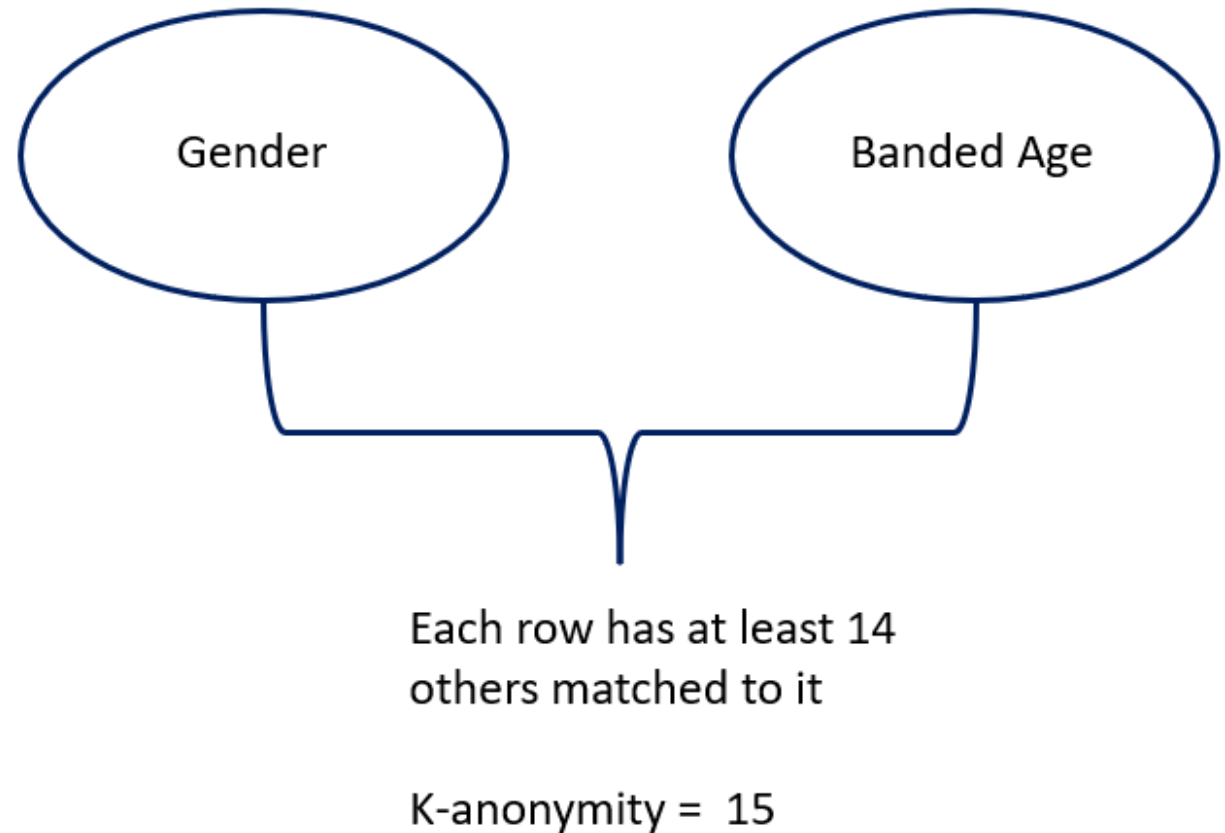


Final Cleaned Dataset

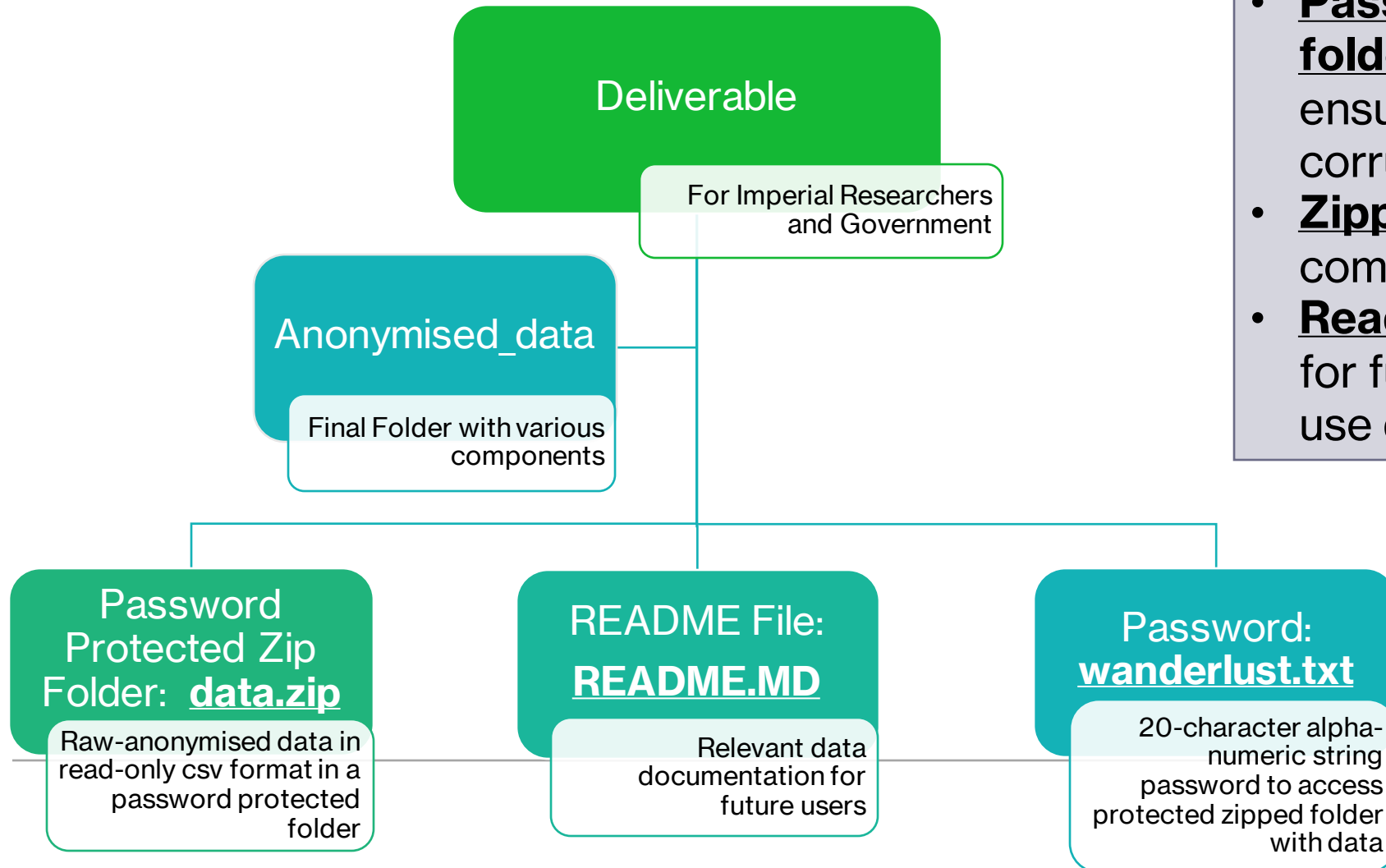
Quasi	Gender	Banded Age					
Formally Quasi	Continent of Birth (colour coded)	Postcode Region (numerical code)	Education Level (banded)				
Other	Wanderlust Gene	Blood Group	Weight (banded)	Height (banded)	Weekly Average Drinks (banded)	Weekly Average Cigarettes (banded)	Number of Countries Visited (banded)

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



Sharing Anonymised Data



- **Used csv files** – 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

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
 - Pseudo-anonymisation – ratios of different groupings could be used to determine true values
 - Still potential for misuse from researchers
-



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

- Devane, H. (2022) *Everything you need to know about K-anonymity, Immuta*. Available at: <https://www.immuta.com/blog/k-anonymity-everything-you-need-to-know-2021-guide/> (Accessed: December 14, 2022).
 - *Data Anonymization* (2022) *Corporate Finance Institute*. Available at: <https://corporatefinanceinstitute.com/resources/business-intelligence/data-anonymization/> (Accessed: December 14, 2022).
 - Ucl (2019) *Anonymisation and Pseudonymisation, Data Protection*. Available at: <https://www.ucl.ac.uk/data-protection/guidance-staff-students-and-researchers/practical-data-protection-guidance-notices/anonymisation-and> (Accessed: December 14, 2022).
 - Sweeney L. K-anonymity: A Model For Protecting Privacy. *International Journal of Uncertainty, Fuzziness and Knowledge Based Systems*. 2002; 10(5): 557-570. <https://doi.org/10.1142/S0218488502001648>
 - El Emam K, Dankar FK. Protecting privacy using k-anonymity. *J Am Med Inform Assoc*. 2008 Sep-Oct;15(5):627-37. doi: 10.1197/jamia.M2716. Epub 2008 Jun 25. PMID: 18579830; PMCID: PMC2528029. doi: [10.1197/jamia.M2716](https://doi.org/10.1197/jamia.M2716)
 - US Department of Health and Human Services. Guidance Regarding Methods for De-identification of Protected Health Information in Accordance with the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule. Available at: <https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html#safeharborguidance> (Accessed: December 14th 2022)
-