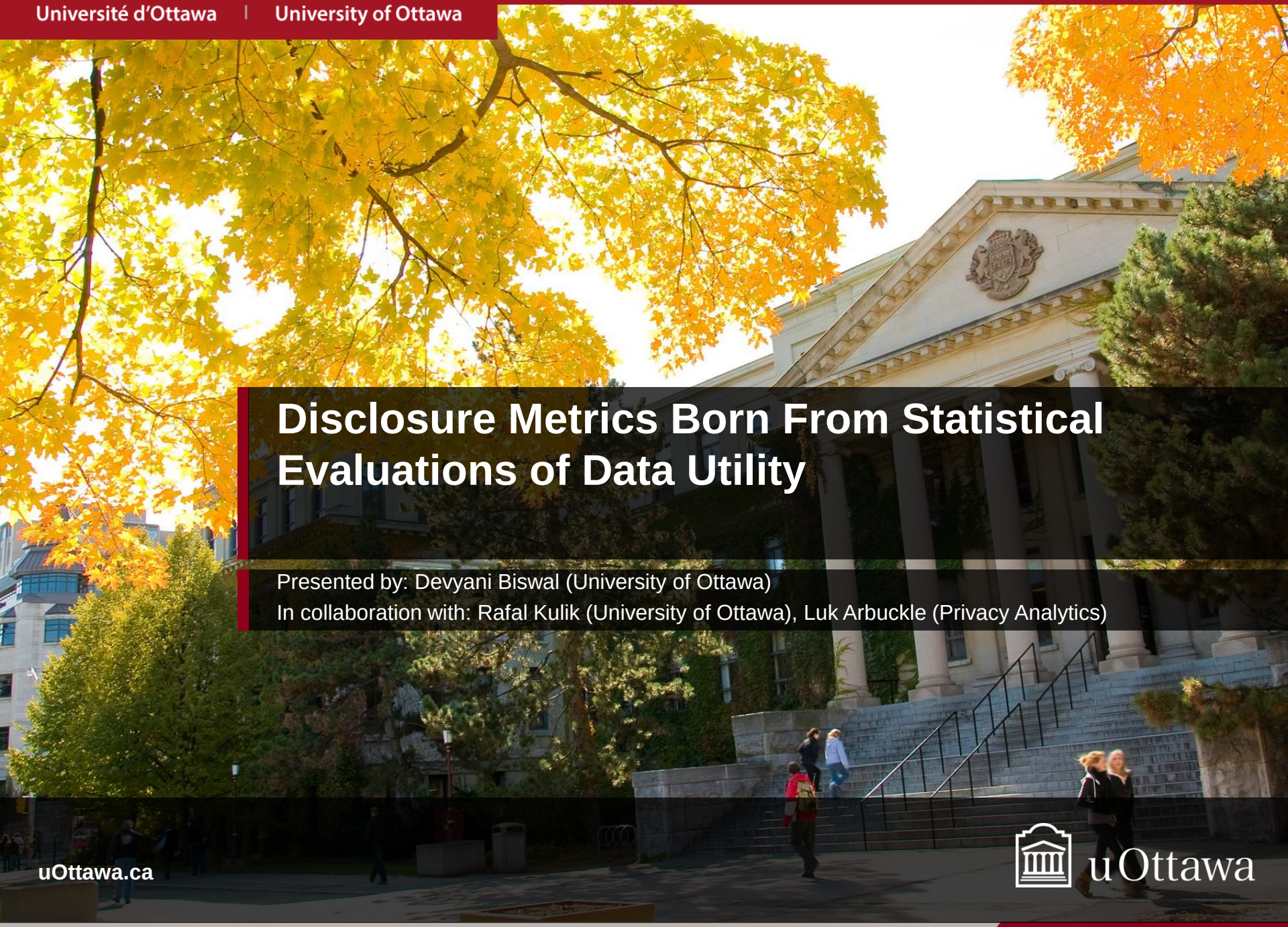


Disclosure Metrics Born From Statistical Evaluations of Data Utility

Presented by: Devyani Biswal (University of Ottawa)
In collaboration with: Rafal Kulik (University of Ottawa), Luk Arbuckle (Privacy Analytics)

Agenda

- Background
- Privacy Models
- Empirical Results
- Ongoing Research

Context and Motivation

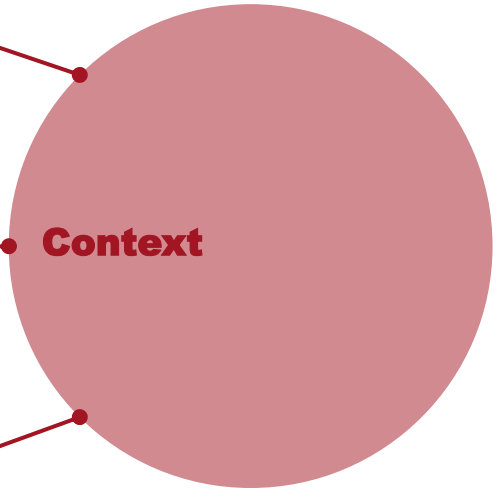
BACKGROUND

Context

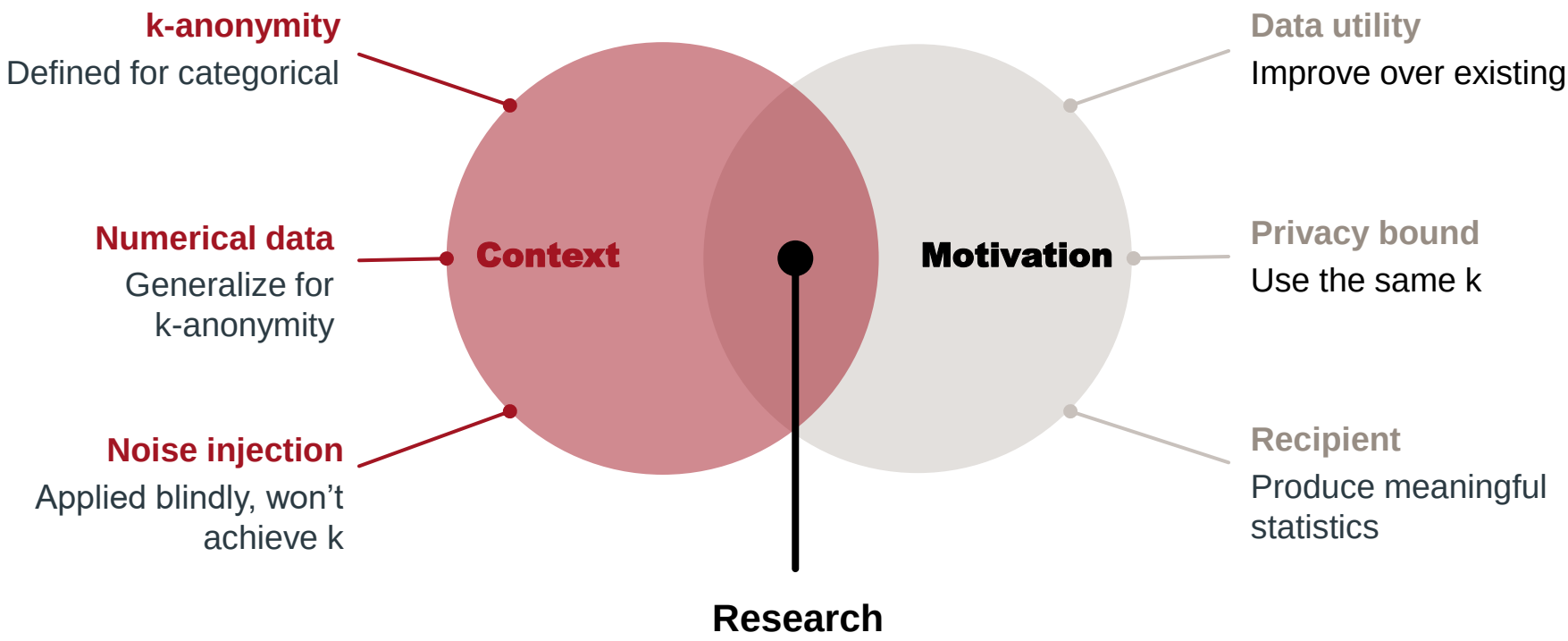
k-anonymity
Defined for categorical

Numerical data
Generalize for k-anonymity

Noise injection
Applied blindly, won't achieve k



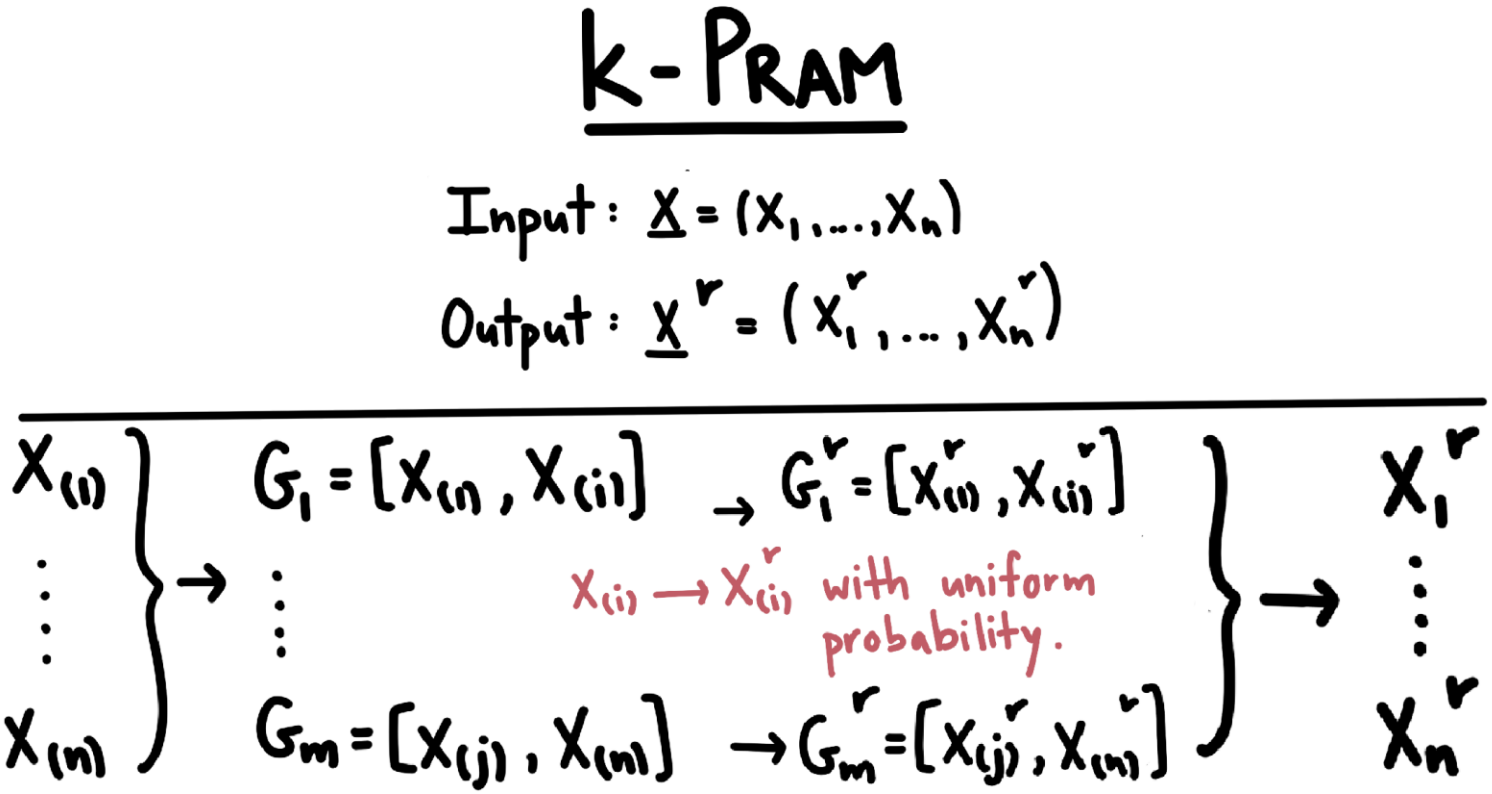
Context and Motivation



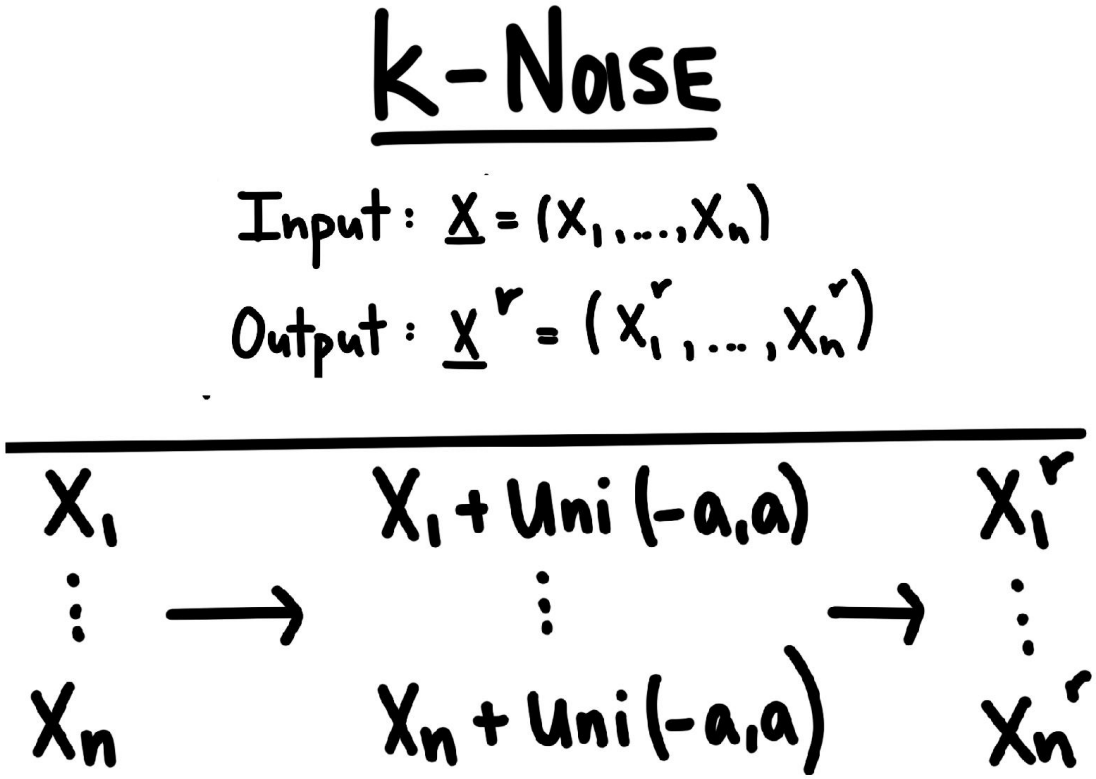
Theoretical

PRIVACY MODELS

Categorical Data



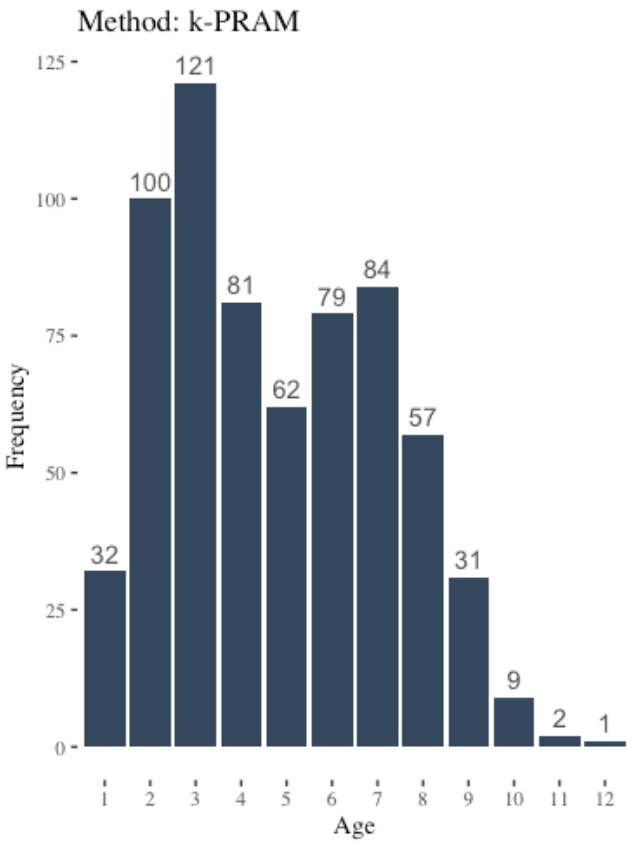
Numerical Data

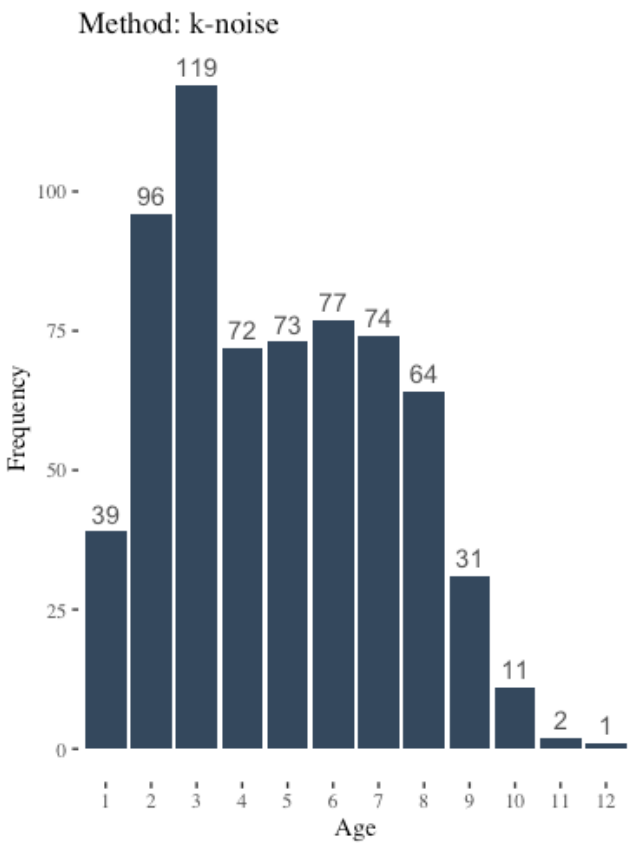


Experiments

EMPIRICAL RESULTS

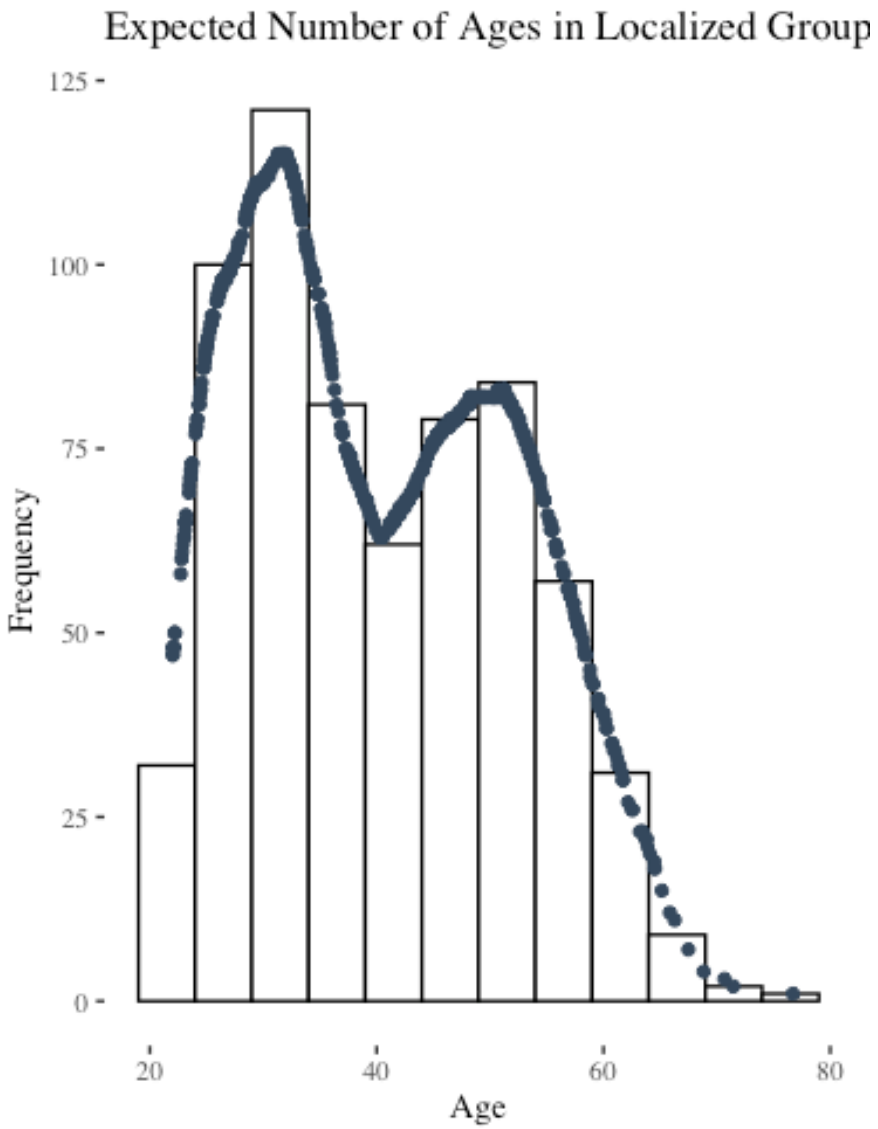
Baseline Level of Privacy





Baseline Level of Privacy

Expected number or records within a neighbourhood of [-2.5,2.5] years of each randomized record in X.



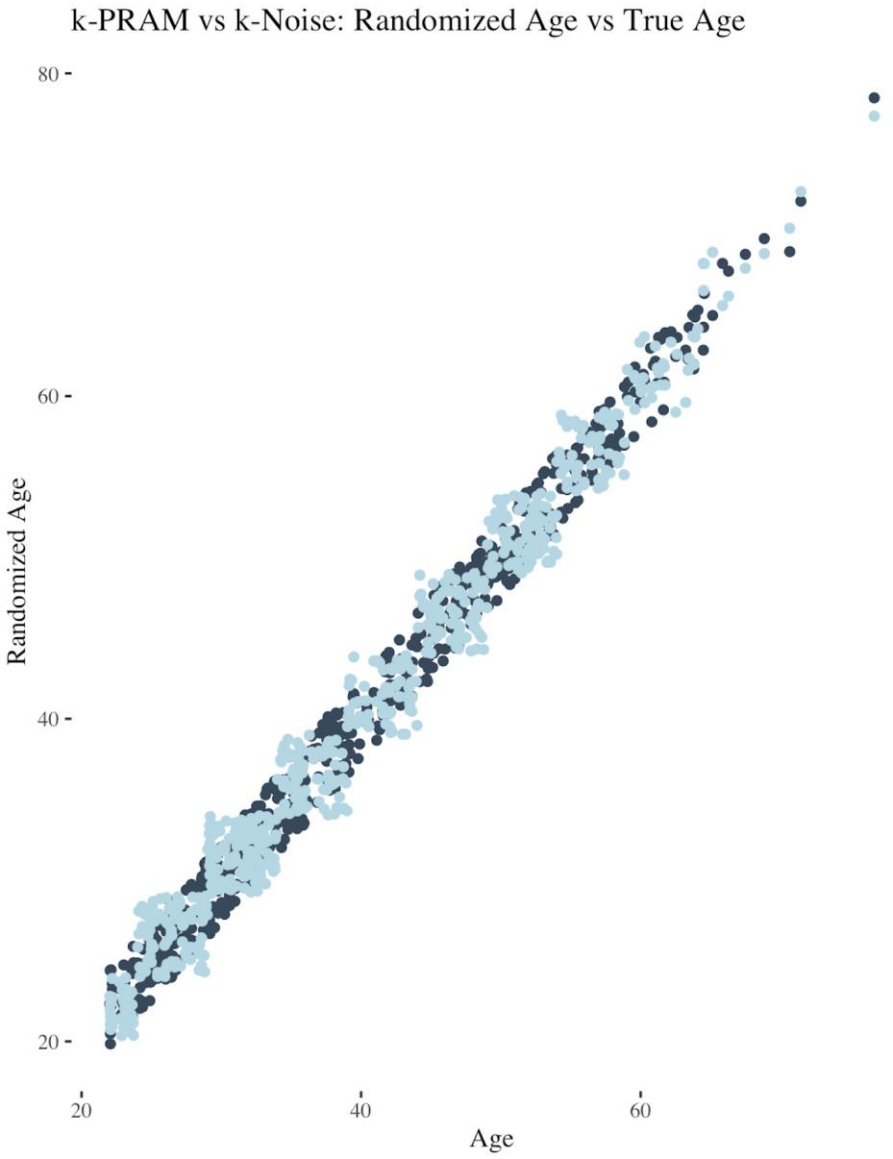
Data Utility Measures

Summary of Utility Estimators			
Method	**Bias**	**Mse**	**Rmse**
k-PRAM	0.076918689	4.368601	2.090120
k-Noise	-0.008230827	2.184711	1.478077

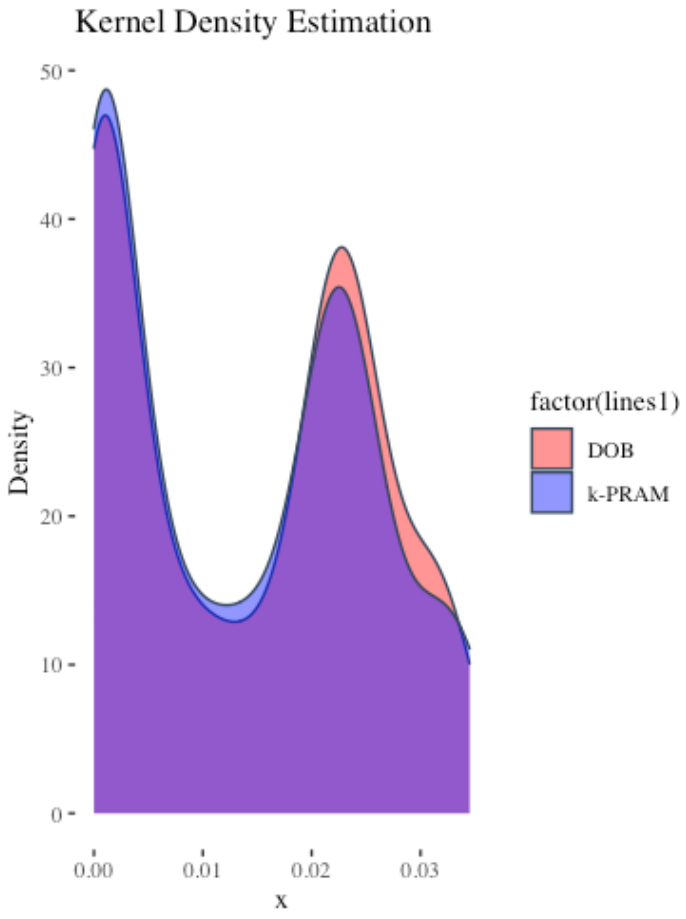
Data Utility Visual

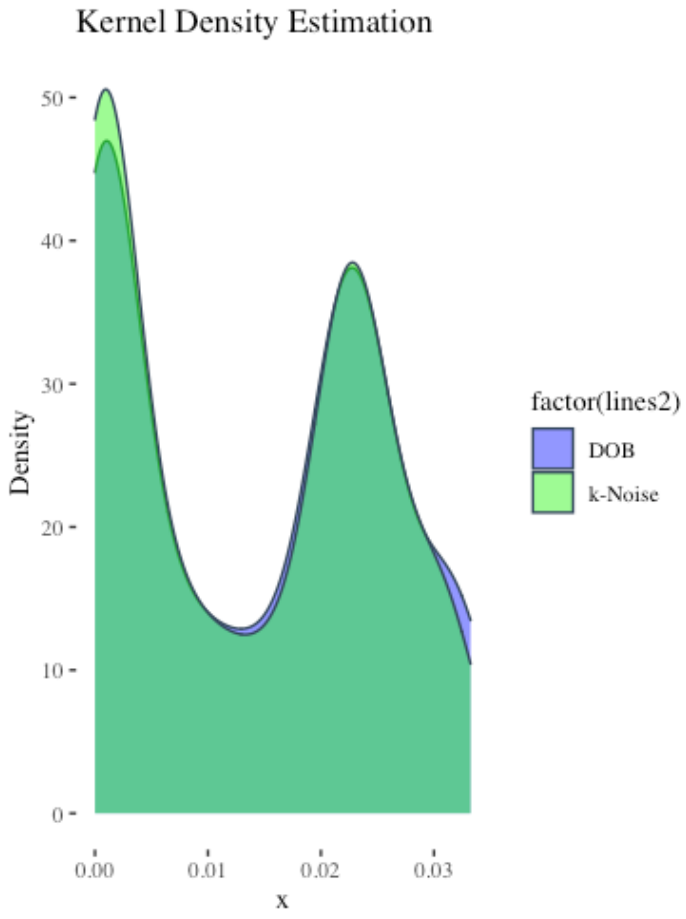
The clustered scatter plot represents k-PRAM randomized individuals.

The bias calculated is visibly noticeable when comparing the two methods against the true value.



Data Utility Densities

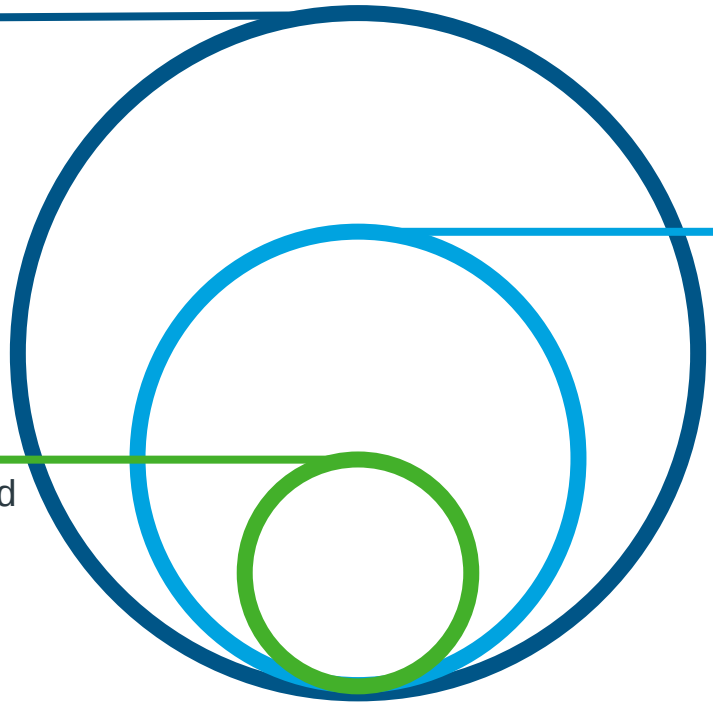




Ongoing research

Multidimensional

Extend to handle correlations, sparsity, etc.



Distributions

Impact on data utility from different noise profiles

Adaptive

Localized noise injection based on empirical distribution