

Private mouse and keyboard behavioral data

BSc intro

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Introducing myself

Motivation

Key novelty

Timeline



- Hossam Elfar
- Student at the German University in Cairo (GUC).
- Media Engineering and technology (MET).
- hobbies : Playing Chess , Swimming



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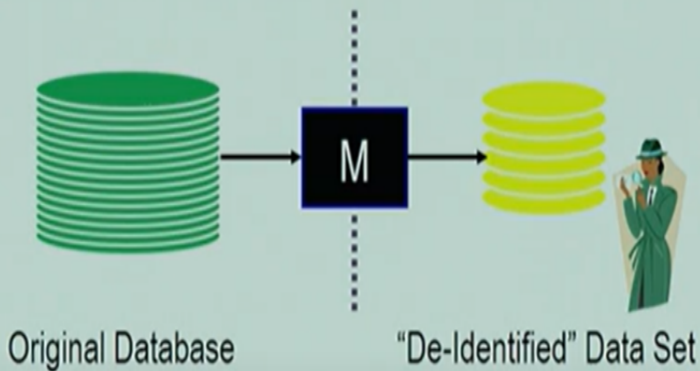
Timeline



Mouse and Keyboard dataset

- Effective behavioural biometrics for data analysis [Hanisch et al., 2021]
- Highly personally sensitive data such as usernames, passwords, banking information, or text messages
- Used as biometrics in active authentication and predicting user's intents [Sun and Upadhyaya, 2015]
- Limited prior work in privacy [Sánchez et al., 2020]

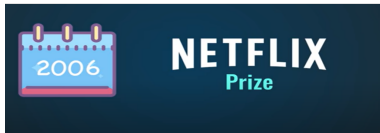




But are these de-identified datasets actually private?

Why anonymisation isn't enough ?

Netflix Prize & Linkage attacks



Source: image from Simply Explained youtube channel



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Differential privacy & remote data science

Our key contributions are two-fold:

We propose the first differential privacy [Dwork, 2008] approach for mouse and keyboard datasets and allow remote processing of mouse and keyboard behavioural data by performing remote data analysis.





(a) Mouse dataset of 20 users

Position : $X \geq 50$, $Y \geq 30$

Does John actually clicks on that position on the screen ?

Probability of people clicking on the position

Dataset \longrightarrow Model \longrightarrow 0.55

Dataset \longrightarrow Model \longrightarrow 0.57
+john

Maybe john
has clicked ?

Plausible deniability





(a) Mouse dataset of 20 users

Position : $X \geq 50$, $Y \geq 30$

Does John actually clicks on that position on the screen ?

Probability of people clicking on the position

Dataset \longrightarrow Model \longrightarrow 0.55

Dataset \longrightarrow Model \longrightarrow ~~0.57~~ 0.88

+john

john has clicked !

Privacy leak !



Privacy Loss

after before

$$\text{Log} (0.57/0.55) = 0.0357$$

$$\text{Log} (0.80/0.55) = 0.357$$

10x the privacy loss if model predicts 0.8!

Differential privacy : Aims to limit this privacy loss!

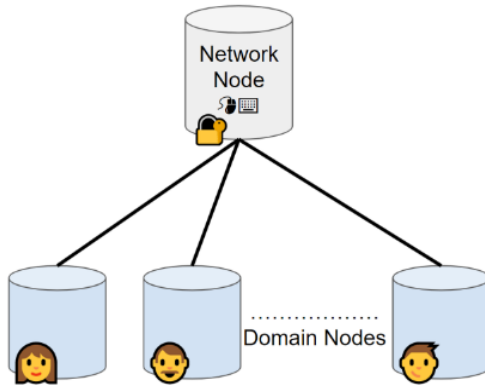
- $\text{Log} (\text{probability after} / \text{probability before}) \leq \epsilon$
Privacy budget
- Smaller budget = more private >>>> Larger budget = Learn more



Remote data science

- Deploy a domain node using HAGrid
- Deploy a network node that collects data from different domain nodes and handles the network requests using PySyft and PyGrid
- Allowing data owners to upload datasets to domain nodes.
- Obfuscating the data once uploaded via differential privacy
- Allow data scientists to log into the network, get a privacy budget, and run machine learning models.





Introducing myself

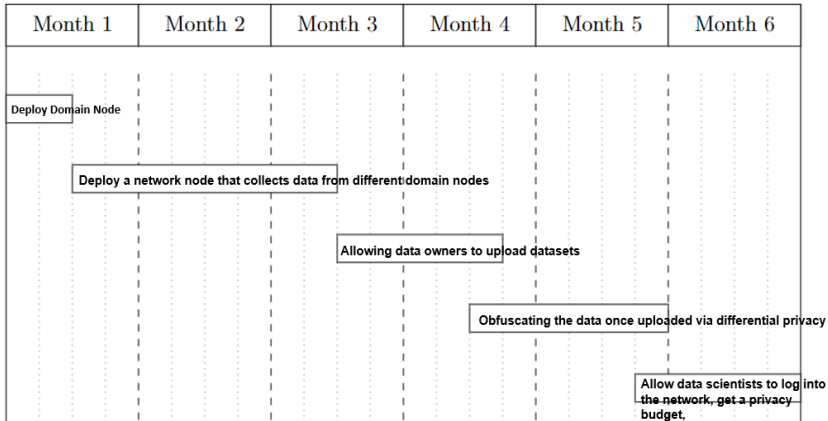
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Schedule with milestones



- C. Dwork. Differential privacy: A survey of results. In *International conference on theory and applications of models of computation*, pages 1–19. Springer, 2008.
- S. Hanisch, P. Arias-Cabarcos, J. Parra-Arnau, and T. Strufe. Privacy-protecting techniques for behavioral data: A survey. *arXiv preprint arXiv:2109.04120*, 2021.
- P. M. S. Sánchez, J. M. J. Valero, M. Zago, A. H. Celdrán, L. F. Maimó, E. L. Bernal, S. L. Bernal, J. M. Valverde, P. Nespoli, J. P. Galindo, et al. Behacom-a dataset modelling users' behaviour in computers. *Data in brief*, 31:105767, 2020.
- Y. Sun and S. Upadhyaya. Secure and privacy preserving data processing support for active authentication. *Information Systems Frontiers*, 17(5):1007–1015, 2015.

