Chap3#1: Privacy Preservation in Machine Learning #1

February 4, 2023

Devesh C Jinwala,
Professor, SVNIT and Adjunct Prof., CSE, IIT Jammu

Department of Computer Science and Engineering,
Sardar Vallabhhai National Institute of Technology, SURAT

Chap 2: ML Applications in Security: Topics to study

- Privacy Preservation, What is Privacy? Data Privacy. Machine Learning in Privacy Preservation: Four Main stakes to Privacy preservation in ML. Two principle approaches: (a) Augmenting the ML techniques with the conventional approaches in the domain of privacy preservation to achieve privacy viz. Homomorphic Encryption, Secret Multiparty Computations, Zero Knowledge Proofs, Perturbation techniques (e.g. differential privacy) Anonymization techniques (e.g.)k-Anonymity, l-Diversity) (b) ML-specific approaches like Federated Learning OR Ensemble Learning. Homomorphic Encryption Algorithms and the associated mathematics. Ethical issues and Law for data / process privacy : GDPR, Alexa, other relevant applications [6 hours]

ML Paradigms for Privacy Preservation

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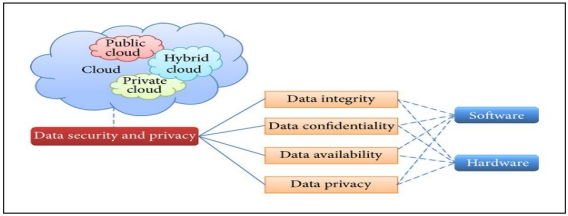

Figure: Data Security Attributes and Privacy

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  - where one stores the data, whether or not it is encrypted, who has access to it, and how one determines who is an authorized user.

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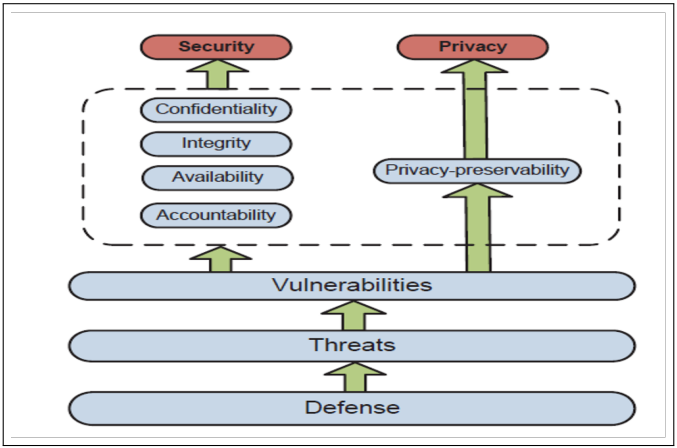

Figure: Data Security Attributes and Privacy [1]

[1] Ref: Z. Xiao et al, IEEE CS & T, April 2012

Data Privacy means ?

Multiple privacy goals

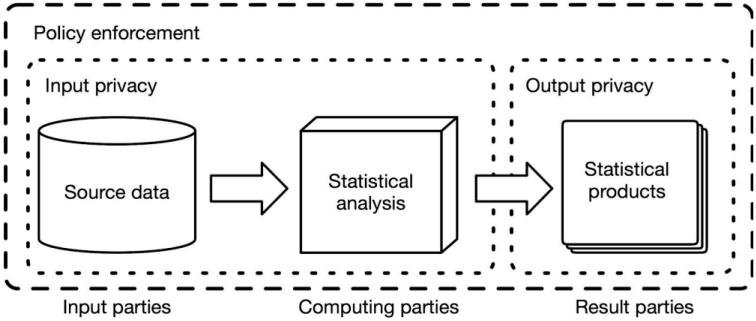

Figure 4: How multiple privacy goals co-exist in a system

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[1] Src: BigData UN Global Working Group Report

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- an example.....
  - Governor of Massachusetts was identified using apparently anonymized health data records containing only his birth date, gender, and ZIP code in a study done by Latanya Sweeney.....

Source: "Law, Ethics & Science of Re-identification Demonstrations". Bill of Health: Examining the Intersection of Health Law, Biotechnology and Bioethics, Petrie Flom Center at Harvard University. Retrieved 2021-06-12.

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Hence, the ML algorithms used, must be privacy preserving.

Four Main stakes to Privacy preservation

There are four main stakes to privacy preservation in general:

- Privacy of the input data, input queries , web search queries
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We examine one of these viz. Privacy of Computations in greater detail shortly hereafter seeing main stakes to Privacy preservation in ML

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- Privacy of the output data
  - the assurance that the output of a model is only accessible to the client whose data is being inferred upon.
- Privacy of the model
  - rhe assurance that a hostile party will not be able to steal the model
- Data privacy in training
  - the assurance that a malicious party will not reverse-engineer the training data - although gathering information about training data and model is more difficult than that for the data.

But, before attempting to understand each of these let us pause for a moment and try to understand the taxonomy of approaches to privacy preservation in ML

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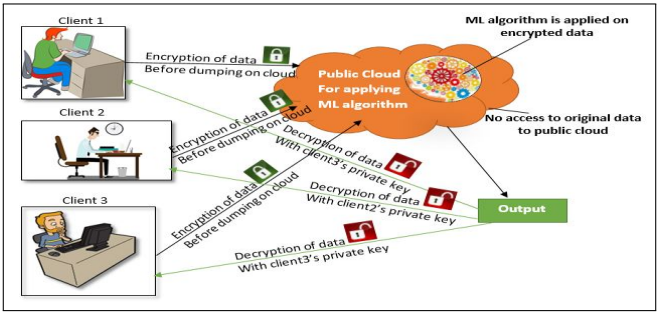

Figure: Privacy Preserving ML

Src: https://www.analyticsvidhya.com/blog/2022/02/privacy-preserving-in-machine-learning-ppml/

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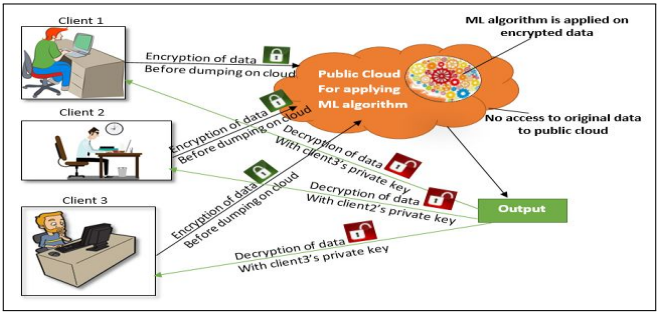

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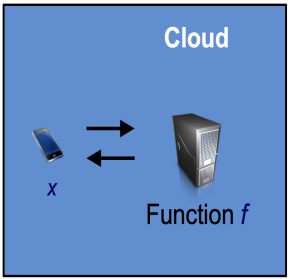
  - ML-specific approaches like Federated Learning OR Ensemble Learning - the Privacy-Preserving Techniques - modifying the conventional ML training methods to keep user data private.

Augmenting ML for Privacy Preservation: Homomorphic Encryption

Issues in outsourcing computations



- Privacy
  - Cloud should not learn anything about x

- Verifiability
  - Cloud cannot cheat i.e., return an incorrect answer without being detected

Figure: Outsourcing Computations [1]

[1] Src: Vinod Vaikunthnathan

Why privacy of computations:1 ?

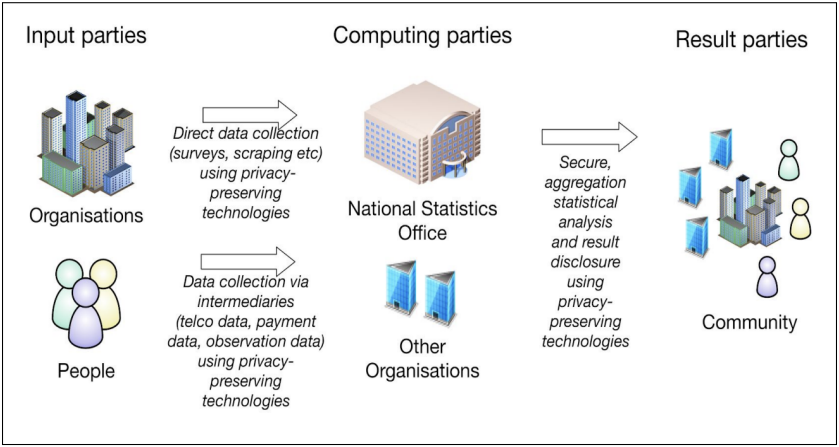


Figure: Privacy-preserving statistics workflow for a single Statistics Office [1]

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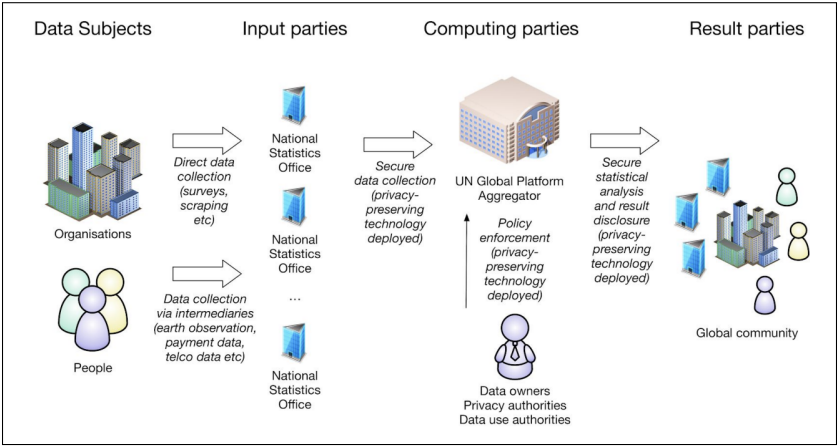

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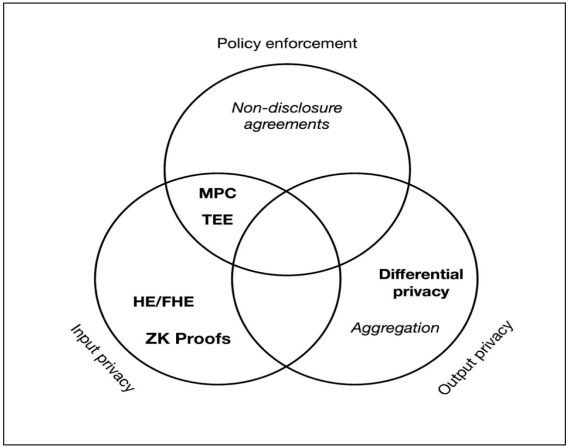
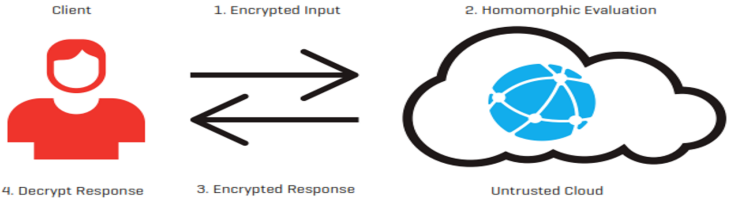


Figure: Venn diagram showing which privacy goals are fulfilled by which privacy techniques. [1]

[1] Src: BigData UN Global Working Group Report

Outsourcing computations: Requirements

Figure 1: A natural application of fully homomorphic encryption is outsourcing computation to an untrusted third party, such as the cloud.



Such a scenario might arise when a client lacks the computational resources to carry out the computation, and thus, needs to delegate the computation to a potentially untrustworthy party. In the simplest example of outsourcing computation using the fully homomorphic encryption scheme (FHE), the client first encrypts the input using the FHE scheme, then sends the ciphertexts to the cloud, which performs the computation homomorphically. Finally, the client receives the encrypted response and decrypts it to learn the result of the computation.

Figure: Outsourcing Computations [1]

[1] CACM

Outsourcing computations: Using Homomorphic Encryption

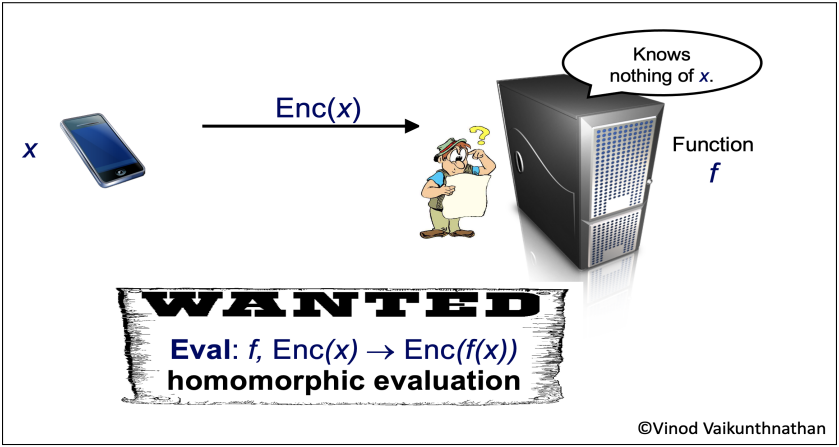


Figure: Outsourcing Computations [1]

[1] Src: Vinod Vaikunthnathan

Outsourcing computations Privately

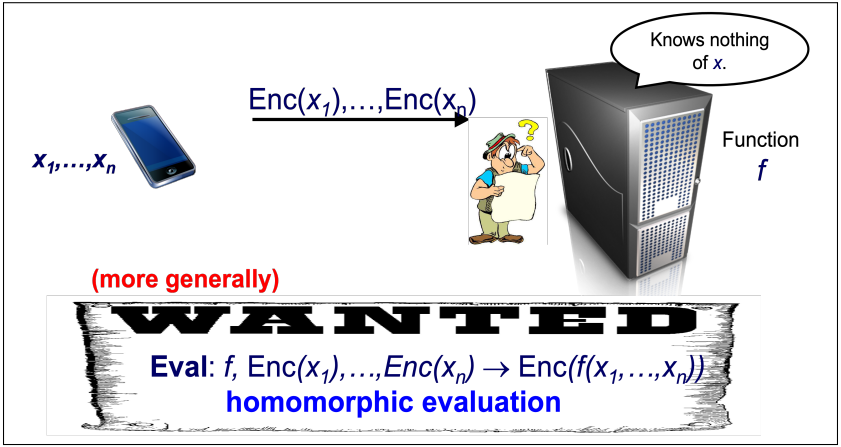


Figure: Outsourcing Computations Privately

Outsourcing computations Privately

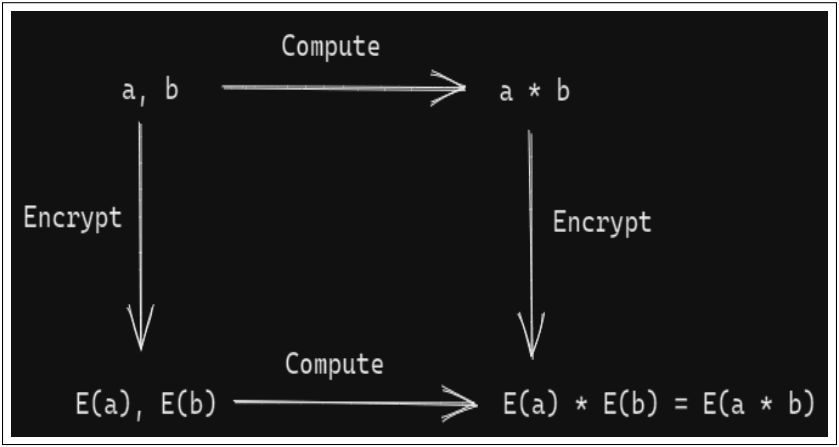


Figure: Outsourcing Computations Privately [1]

[1] Src: Vinod Vaikunthnathan

Outsourcing computations: Is Privacy Preserved?

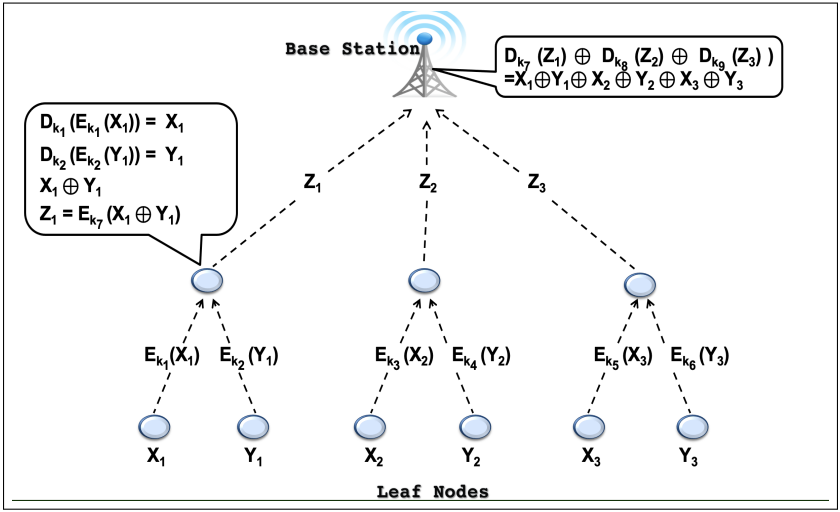


Figure: Coventional Encryption: Is Privacy preserved ?

Outsourcing computations : Is Privacy Preserved?

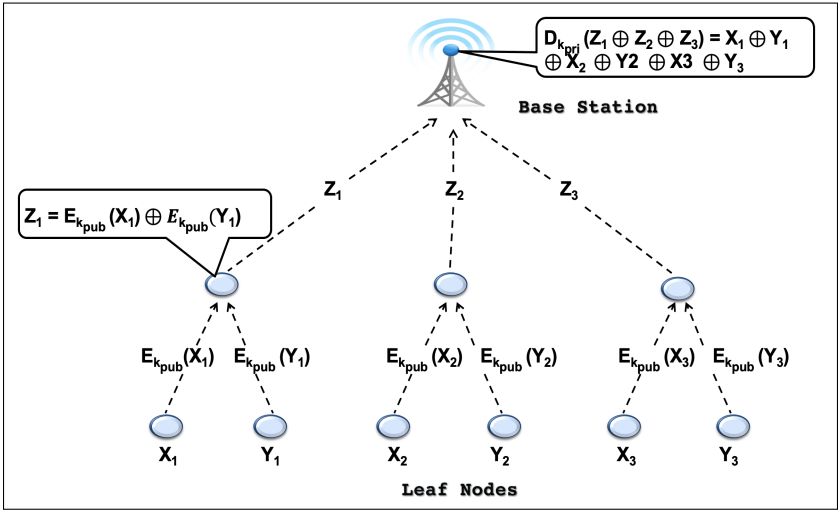


Figure: Outsourcing Computations Privately

Homomorphic Encryption Algorithms

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