Chap3#4: Anonymization and Randomization based approaches #1

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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(HE Algorithms and the associated mathematics), Secret Multi-party Computations, Zero Knowledge Proofs, Anonymization techniques (e.g.)k-Anonymity, l-Diversity) Perturbation techniques (e.g. differential privacy) (b) ML-specific approaches like Federated Learning OR Ensemble Learning. Ethical issues and Law for data / process privacy : GDPR, Alexa, other relevant applications [6 hours]

Reviewing the theme of ML Paradigms for Privacy Preservation

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
- Privacy of the computations
- Privacy of the output data, web search query results
- Data Privacy General Regulations, Data protection strategies, processes and principles

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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

Four Main stakes to Privacy preservation in ML

There are four main stakes to privacy preservation in general:

- Privacy of the input data
  - the assurance that other parties, including the model developer, will not be able to see a user's input data
- 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.

Privacy Preserving Machine Learning: How to achieve?

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  - anonymization techniques like k-Anonymity and l-Diversity
  - 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: Anonymization Methods

Anonymization Methods: Background

Anonymization method

- mainly applied to the databases, to preserve the privacy while mining the data.

	Non-Sensitive Data			Sensitive Data	
#	**Zip**	**Age**	**Nationality**	**Name**	**Condition**
1	13053	28	Indian	Kumar	Heart Disease
2	13067	29	American	Bob	Heart Disease
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Figure: Data with a hospital

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- Let us look at an example.....

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Data leak!

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1	John	13053	28	American
2	Bob	13067	29	American
3	Chris	13053	23	American

Voter List

Figure: Data published but leaks

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- The attacker can join them with other sources and identify individuals.

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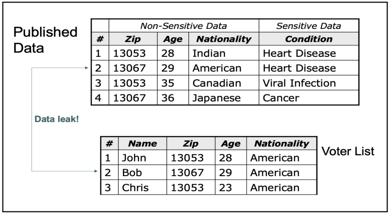

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Hence the need for anonymization methods

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- here, we have a 4-anonymized table

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Techniques for Anonymization

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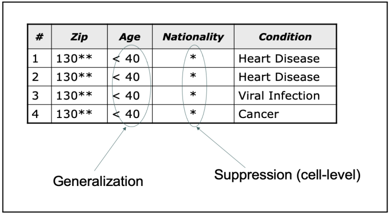
  - Data not released at all
  - Can be Cell-Level or (more commonly) Tuple-Level

Data Generalization

- is the process of creating a broader categorization of the data in a database,



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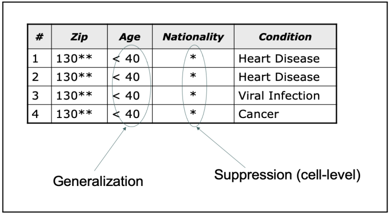

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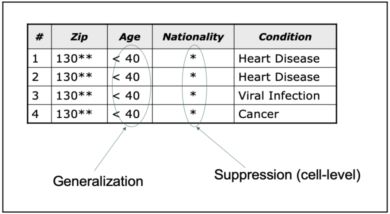

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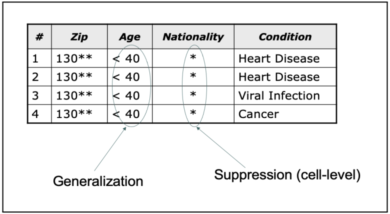

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3	130**	< 40	*	Viral Infection
4	130**	< 40	*	Cancer

Figure: Data Generilization/Suppresion

In Data Suppression certain values of the attributes are replaced by an asterisk '*'. All or some values of a column may be replaced by '*'.

Src: Prof B. Aditya Prakash, IITB and CMU

Anonymization Methods: Generalization Hierarchies

- Data owner defines how values can be generalized

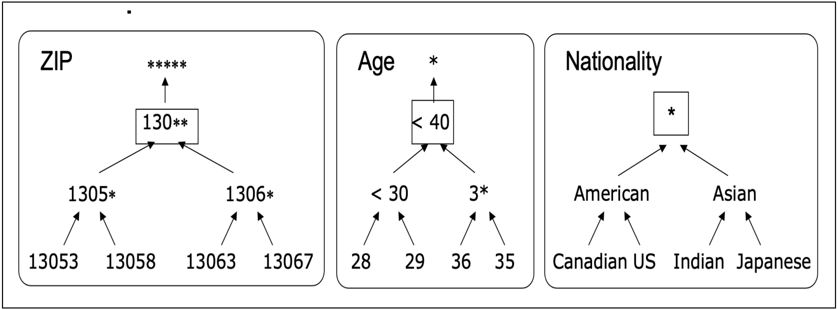

Figure: Data Generilization Hierarchies

Src: Prof B. Aditya Prakash, IITB and CMU

Anonymization Methods: Generalization Hierarchies

- Data owner defines how values can be generalized
- A table generalization is created by generalizing all values in a column to a specific level of generalization

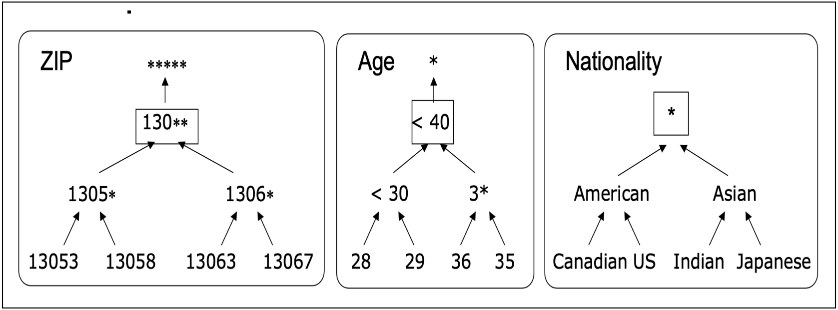

Figure: Data Generilization Hierarchies

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- There are many k-anonymizations – which one to pick?

#	Zip	Age	Nationality	Condition
1	13053	< 40	*	Heart Disease
2	13053	< 40	*	Viral Infection
3	13067	< 40	*	Heart Disease
4	13067	< 40	*	Cancer

2-minimal Generalizations

#	Zip	Age	Nationality	Condition
1	130**	< 30	American	Heart Disease
2	130**	< 30	American	Viral Infection
3	130**	3*	Asian	Heart Disease
4	130**	3*	Asian	Cancer

#	Zip	Age	Nationality	Condition
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2	130**	< 40	*	Viral Infection
3	130**	< 40	*	Heart Disease
4	130**	< 40	*	Cancer

NOT a 2-minimal Generalization

Figure: K Minimum Generalization

Anonymization Methods: K-minimal Generalizations

- There are many k-anonymizations – which one to pick?
- Intuitively one that does not generalize the data more than needed (decrease in utility of the published dataset!)

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Anonymization Methods: K-minimal Generalizations

- There are many k-anonymizations – which one to pick?
- Intuitively one that does not generalize the data more than needed (decrease in utility of the published dataset!)
- K-minimal generalization: A k-anonymized table that is not a generalization of another k-anonymized table

#	Zip	Age	Nationality	Condition
1	13053	< 40	*	Heart Disease
2	13053	< 40	*	Viral Infection
3	13067	< 40	*	Heart Disease
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NOT a 2-minimal Generalization

Figure: K Minimum Generalization

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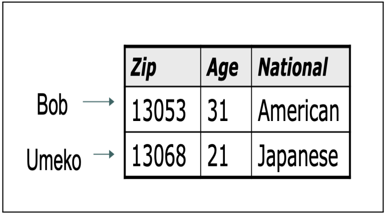

Figure: KAnonymity Attack

k-Anonymization Attack

Original Data →

	Non-Sensitive Data			Sensitive Data
#	**ZIP**	**Age**	**Nationality**	**Condition**
1	13053	28	Russian	Heart Disease
2	13068	29	American	Heart Disease
3	13068	21	Japanese	Viral Infection
4	13053	23	American	Viral Infection
5	14853	50	Indian	Cancer
6	14853	55	Russian	Heart Disease
7	14850	47	American	Viral Infection
8	14850	49	American	Viral Infection
9	13053	31	American	Cancer
10	13053	37	Indian	Cancer
11	13068	36	Japanese	Cancer
12	13068	35	American	Cancer

Figure: KAnonymity Attack

k-Anonymization Attack

4-anonymized Table

	Non-Sensitive Data			Sensitive Data
#	***ZIP***	***Age***	***Nationality***	***Condition***
1	130**	< 30	*	Heart Disease
2	130**	< 30	*	Heart Disease
3	130**	< 30	*	Viral Infection
4	130**	< 30	*	Viral Infection
5	*1485**	*> = 40*	*	*Cancer*
6	*1485**	*> = 40*	*	*Heart Disease*
7	*1485**	*> = 40*	*	*Viral Infection*
8	*1485**	*> = 40*	*	*Viral Infection*
9	130**	3*	*	Cancer
10	130**	3*	*	Cancer
11	130**	3*	*	Cancer
12	130**	3*	*	Cancer

Umeko Matches here (rows 1–4)

Bob Matches here (rows 9–12)

Figure: KAnonymity Attack

k-Anonymization Attack

4-anonymized Table

	Non-Sensitive Data			Sensitive Data
#	**ZIP**	**Age**	**Nationality**	**Condition**
1	130**	< 30	*	Heart Disease
2	130*			Heart Disease
3	130*			Viral Infection
4	130**	< 30	*	Viral Infection
5	*1485**	*> = 40*	*	*Cancer*
6	*1485**	*> = 40*	*	*Heart Disease*
7	*1485**	*> = 40*	*	*Viral Infection*
8	*1485**	*> = 40*	*	*Viral Infection*
9	130**	3*	*	Cancer
10				Cancer
11	130			Cancer
12	130**	3*	*	Cancer

Umeko Matches here

Umeko has Viral Infection!

Bob Matches here

Bob has Cancer!

Figure: KAnonymity Attack

k-Anonymization Limitation

- Basic Reasons for leak – Sensitive attributes lack diversity in values - Homogeneity Attack

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k-Anonymization Limitation

- Basic Reasons for leak – Sensitive attributes lack diversity in values - Homogeneity Attack
- Attacker has additional background knowledge - Background knowledge Attack
- Hence a new solution has been proposed in-addition to k-anonymity – l-diversity