

## Pattern Mining and Society: Privacy Issues

- A potential adverse side-effect of data mining—Privacy could be compromised
  - Privacy and accuracy are typically contradictory in nature
  - Improving one often incurs a cost on the other
- Three categories on privacy issues arising out of data mining
  - Input privacy (or data hiding)
    - Distort or hide data to prevent the miners from reliably extracting confidential or private information
  - Output privacy (or knowledge hiding)
    - No disclosure of sensitive patterns or knowledge from datasets
  - Owner privacy
    - Does not allow any party to reliably learn the data or sensitive information that the other owners hold (i.e., the source of the data)

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## **Ensuring Input Privacy**

- Approach 1: Service provider anonymizes user's private information
  - B2B (business-to-business) environment
    - Service provider-to-data miner
  - Do you really trust them?
- Approach 2: Data anonymized/perturbed at the data source itself
  - B2C (business-to-customer) environment: Anonymized likely by a 3<sup>rd</sup>-party vendor
    - Methods: Data perturbation, transformation, or hiding (hide sensitive attributes)
- K-anonymity privacy requirement and subsequent studies
  - k-anonymity: Each equivalent class contains at least k records
  - It is still not sufficient, thus leads to further studies, such as ℓdiversity, t-closeness, and differential privacy

ID	ZIP	Age	Disease
1	61801	45	Heart
2	61848	49	Cancer
3	61815	41	Flu
4	61804	32	Diabetes
5	61802	38	Diabetes
6	61808	39	Flu
ID	ZIP	Age	Disease
1D	ZIP 618**	Age 4*	Disease Heart
1	618**	4*	Heart
1 2	618** 618**	4* 4*	Heart Cancer
1 2 3	618** 618** 618**	4* 4* 4*	Heart Cancer Flu

## Data Perturbation for Privacy-Preserving Pattern Mining

- Statistical distortion: Using randomization algorithms
  - Independent attribute perturbation: Values in each attribute perturbed independently
  - Dependent attribute perturbation: Take care of correlations across attributes
- MASK [Rizvi & Haritsa VLDB'02]
  - Flip each 0/1 bit with a probability p (Note: this may increase a lot of items)
  - $\Box$  Tune p carefully to achieve acceptable average privacy and good accuracy
- Cut and paste (C&P) operator [Evfimievski et al. KDD'02]
  - Uniform randomization: Each existing item in the real transaction is, with a probability p, replaced with a new item not present in the original transaction
  - Methods developed on how to select items to improve the worst-case privacy
  - Experiments show mining a C&P randomized DB correctly identifies 80-90% of "short" (length ≤ 3) frequent patterns, but how to effectively mine long patterns remains an open problem

## Recommended Readings

- R. Agrawal and R. Srikant, Privacy-preserving data mining, SIGMOD'00
- C. C. Aggarwal and P. S. Yu, Privacy-Preserving Data Mining: Models and Algorithms, Springer, 2008
- C. Dwork and A. Roth. The Algorithmic Foundations of Differential Privacy. Foundations and Trends in Theoretical Computer Science. 2014
- A. Evfimievski, R. Srikant, R. Agrawal, and J. Gehrke. Privacy preserving mining of association rules. In KDD'02
- A. Gkoulalas-Divanis, J. Haritsa and M. Kantarcioglu, Privacy in Association Rule Mining, in C. Aggarwal and J. Han (eds.), Frequent Pattern Mining, Springer, 2014 (Chapter 15)
- N. Li, T. Li, S. Venkatasubramanian. t-closeness: Privacy beyond k-anonymity and l-diversity. ICDE'07
- A. Machanavajjhala, D. Kifer, J. Gehrke, M. Venkitasubramaniam, I-diversity: Privacy beyond kanonymity, TKDD 2007
- S. Rizvi and J. Haritsa. Maintaining data privacy in association rule mining. VLDB'02
- J. Vaidya, C. W. Clifton and Y. M. Zhu, Privacy Preserving Data Mining, Springer, 2010