Space Adaptation: Privacy-preserving Multiparty Collaborative Mining with Geometric Perturbation

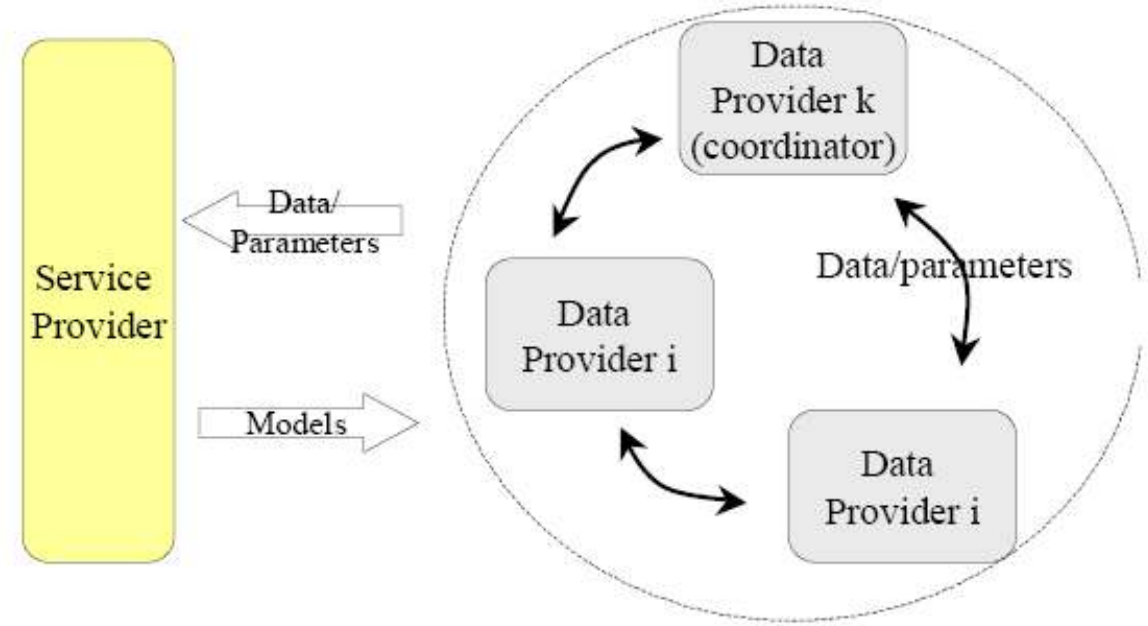
Keke Chen Ling Liu

Outline

- Introduction
  - Service-based collaborative mining
  - Privacy issues
- Geometric perturbation
  - Concept
  - Challenges in service based collaborative mining
- Space Adaptation Protocol

Introduction

- Service-based multiparty collaborative mining



- Privacy issues in this paradigm
  - The shared data may contain sensitive information that is important to the owner
- The goal
  - Find the model without leaking the sensitive information to *any of the involved parties*.
- Assumption:
  - Data are encrypted in transmission.
  - Semi-honest parties, without collusion.

Geometric Data Perturbation

- G(X) = RX + T + D
  - X: dataset
  - R: “random rotation matrix”
  - T: “random translation matrix”
  - D: random noise, for perturbing distances

  Gi represents the parameters (R,T,D),
  Gi(X) is the perturbed data

- Particularly good for many classification models
  - Models trained with perturbed data keep similar prediction accuracy
  - kNN, kernel methods, SVMs, linear classifiers, and more

When it goes to multiparty…

- Each party has its own secret G_i
  - Different G_i → different data space
  - But mining can be only done on a unified space
  - So we need to ***securely unify these G_i to G_t***

- Potential attacks
  - The revealed information is valuable, only when
    - the data owner is identified, given $G_i(X)$ or $G_t(X)$
    - when $G_i(X)$ or $G_t(X)$ is known, X can be estimated precisely
  - Privacy threats from
    - Other curious data providers
    - Curious service provider

Space Adaptation (SA)

- SA is one of the approaches unifying Gi
  - Utilize the fact that geometric transformations are transformable to each other
  - The "space adaptor": transform Gi to Gt
    - Gt(X) = $S_{i \to t}$(Gi(X)), S is the space adaptor, Gt is the unified perturbation
    - Each party knows Gt, and thus holds $S_{i \to t}$, Gi, and Gi(X)

Space Adaptation

- Protocol
  - Prevent service provider identifying source
    - Shuffle perturbed data between data providers
  - Prevent data provider breaching privacy from the received perturbed data
    - Locally optimized Gi [Chen&Liu SDM07]
  - Ignore the details …

Evaluation

- Source identifiability

  π = Pr(source is identified)

- Normalized privacy guarantee
  - Maximum privacy guarantee bi
  - Locally optimized privacy guarantee ρi
  - Normalized privacy guarantee: ρi/bi

- Overall risk of privacy breach for DPi

  For DP j receiving perturbed data from DP i

  risk: 1* (1- ρi/bi)

  For service provider

  risk: 1/n * (1- ρi'/bi)

  ρi' is the privacy guarantee of Gt to Xi

Conclusion

- Properties of geometric perturbation
- SA protocol considers
  - Source identifiability
  - attacks to the perturbed data
- Future work
  - Remove the semi-honest assumption
- Contact the authors
  - Keke Chen (kekechen@cc.gatech.edu)
  - Ling Liu (lingliu@cc.gatech.edu)