Synopses-Driven Data integration & Federated Learning

Doctorate Project Plan Presentation

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Contents

Privacy

- Big data $\rightarrow$ various challenges in data management
- Privacy breaches over the last decade
  - Need of new regulation $\rightarrow$ GDPR
  - Increase of work in the research fields
    - **Privacy Preserving Big Data Mining/Analytics**
    - **Privacy Preserving Data Synthesis/Release**
    - **Privacy Preserving Machine Learning**
    - **Federated Learning**

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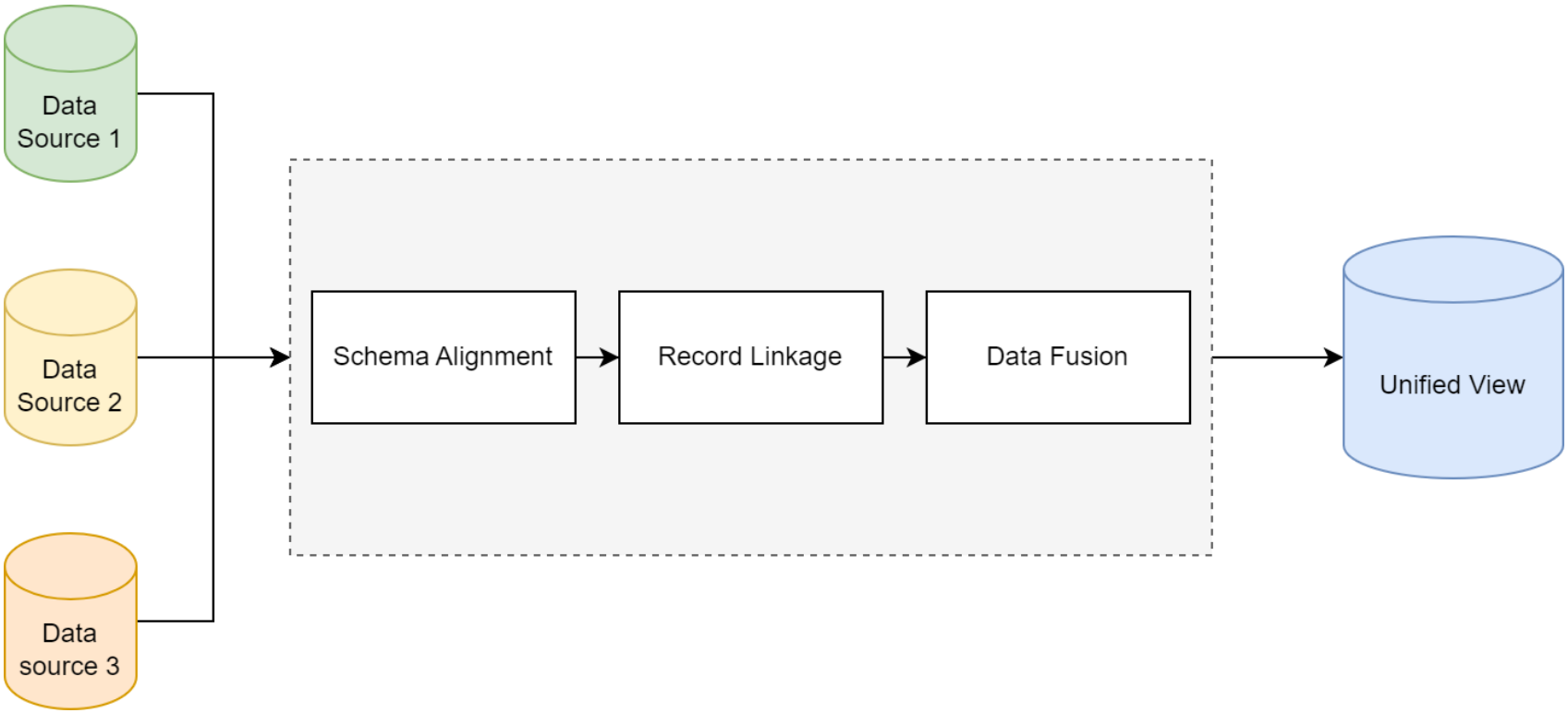
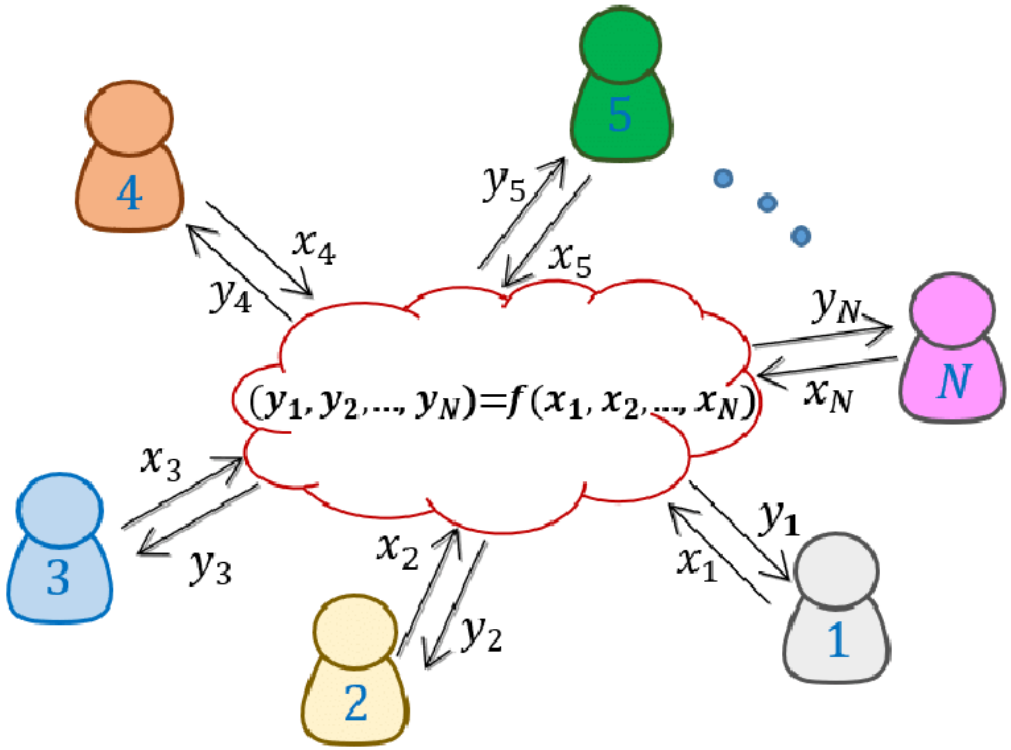
Data Integration

Data Integration is the process of bringing different disparate sources into a unified view



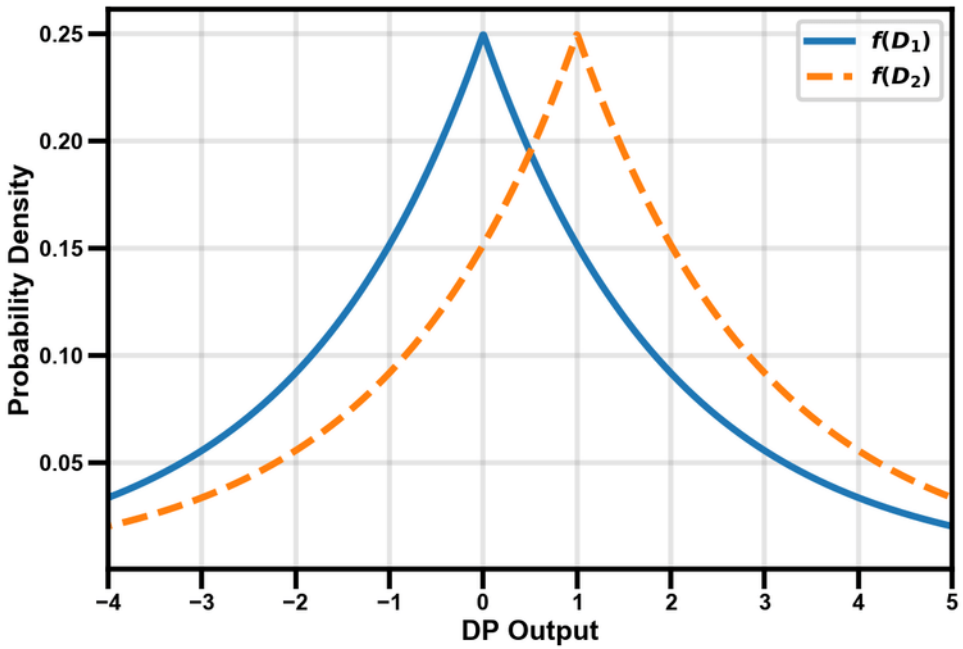
Secure Multi-Party Computation

- Models for parties to jointly compute a function over their input while keeping those inputs private
- Sub-field of cryptography



Differential Privacy

- State-of-the-art standard for Big Data Analytics/Machine Learning
- Learn nothing about an individual while learning useful information about the population



Privacy-Preserving Schema Alignment

Parties learn no information regarding other parties' schemas, except for the matching attributes

- A basic approach is to use encrypted hashes [16]
- Other approaches use *probabilistic* [12] or *data summaries* [6]

Takeaways

- Very limited research for privacy-preserving schema alignment
- exploring DP and the usage of data summaries for matching schema is an open research question

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Privacy-Preserving Record Linkage

During the RL phase, parties only learn the set of matching records

- Works can be grouped into 4 categories:
  - Masking/Embedding
  - SMC/Cryptography
  - Differential Privacy
  - Hybrid

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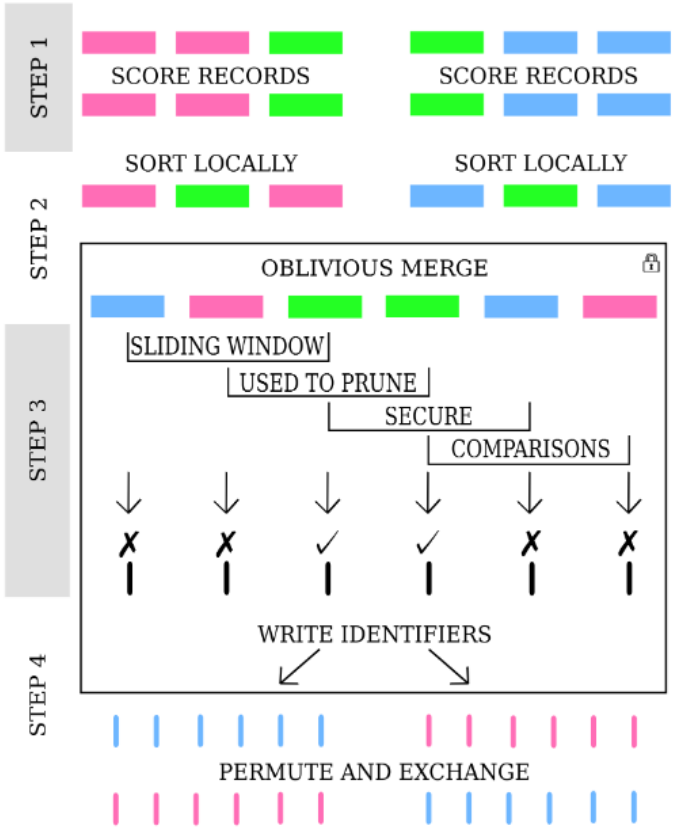
Masking and Embedding

- Masking: usage of probabilistic data structures → **Bloom Filters** [7, 17]
  - Frequency attacks [3, 5, 4, 14]
- Embedding: map records to a space
  - Euclidean/Complex Spaces [19, 16] → limited accuracy
  - Distributed Representation of Tuples [8]: promising approach for linkage quality

No formal privacy guarantee

SMC and Cryptography

- Two main relevant works
- [1] uses commutative encryption
- [13] represent one the state-of-the-art works



→ Still computationally expensive

Differential Privacy

- [2] introduce the use of DP in RL
  - The idea is to generate a base for a euclidean space that is DP
  - Prefix mining algorithm: extract the top-k frequent n-grams, then add Laplace noise to the counts
- [18] use Randomized Response to perturb the BFs

Research Questions

As embedding and DP were explored, a research question would be to use modern embedding technologies (deep learning) and DP

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Hybrid

- Combining k-anonymity and SMC [10]
- Combining DP and SMC [11, 9, 15]

→ k-anonymity doesn't guarantee a good level of privacy
→ DP+SMC provides a good level of privacy, still improvements to reduce the number of comparisons are needed

Research Questions

1. How DP affects synopses-driven algorithms for mining the structure of federated datasets?
2. With regards to Record Linkage, privacy-preserving technologies have been studied extensively, but
   - Hybrid approaches are still limited due to the expensive SMC computations $\rightarrow$ improvements in the private blocking/indexing algorithms are possible
   - deep learning embeddings brought the democratization of RL to a new level $\rightarrow$ can DP be applied to learning word embeddings in a federated scenario?

Idea - Schema Alignemnt

- Use DP mechanisms on sketching algorithms like
  - MinHash
  - Qgram sketches
- experiment utility/privacy tradeoff

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Idea II - Schema Alignment

- [12] use undirected graphs representation of tables (node=entropy of column, edge=MI between two columns), then run a graph matching algorithm
- Private Synthetic Data generation makes use of Bayesian Networks (BN) [20]
- BN estimates the full distribution of a dataset, graphically as a DAG
- **Experiment with the graph matching approach with the DP BN graph**

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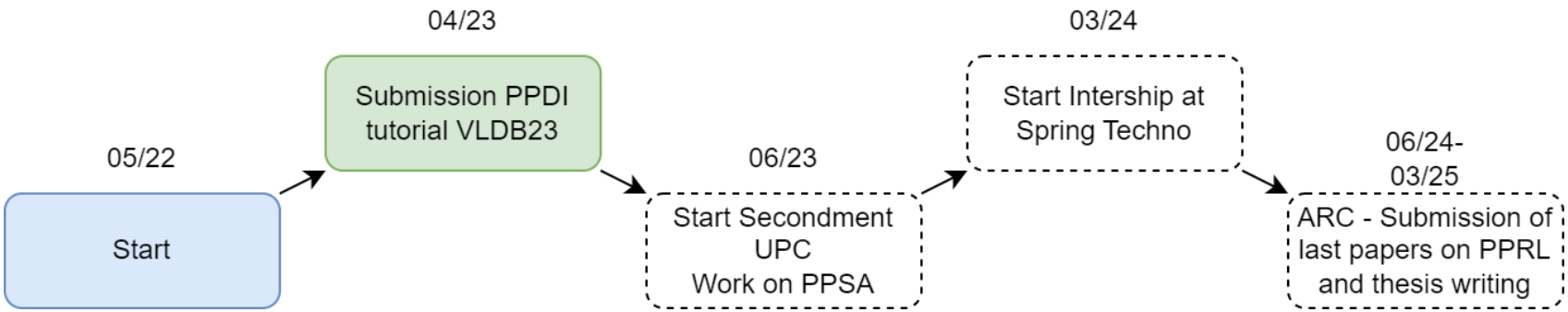
Idea III - Record Linkage

- [15] use a private indexing algorithm that distributed the DP noise to the leaves
  - It is worth investigating and experimenting with more advanced indexing algorithms
- Outstanding results of DL embeddings for RL [8]
  - Study the applicability of DP on Deep Learning word embeddings to support RL and Schema Alignment

Timeline


05/22
Start
04/23
Submission PPDI tutorial VLDB23
06/23
Start Secondment UPC
Work on PPSA
03/24
Start Intership at Spring Techno
06/24-03/25
ARC - Submission of last papers on PPRL and thesis writing

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