European Commission

DEDS

European Joint Doctorate in
Data Engineering for Data Science (DEDS)

Doctoral Project Plan[1]
Synopses-Driven Data Integration and Federated Learning

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1 Project Summary

The term Big Data refers to data sets that are too large or complex to be dealt with by traditional data processing software. In particular, Big Data captures to 4 dimensions: Velocity, Variety, Veracity, and Volume. This large quantity of data available nowadays has a lot of statistical and business value, therefore their analysis is of core importance for business decision-making. Nevertheless, the data involved in those processes contains a lot of sensitive information regarding individuals (e.g. health sector). There is therefore also the need to guarantee the privacy of the individuals while being able to extract insights and patterns from the data.

Data Integration is the set of processes to gather and bridge data from heterogeneous sources together in order to have a unified view. The premise of data integration is to make data more freely available and easier to consume and process by systems and users. Research on Data Integration started more than 50 years ago [18, 32] but as we entered the Big Data era, new challenges arose, which include scaling [16] data integration while guaranteeing the privacy [51, 22] of the individuals involved in the datasets. Over the last decade new techniques have been applied for improving computational performance, consisting of the use of parallelizing the computation by using big data processing platforms [16], or algorithmically, namely using summarization techniques [8], used for approximate fast and approximate querying, improving the performance of Machine Learning processes [23, 1, 27] as well as in some data integration scenarios. Despite the progress made, it is difficult to combine efficiency (the integration is completed with no, or very few, errors), computational performance and privacy altogether [26].

Machine Learning and Data Integration have really close relationship [15]. In particular, it is possible to leverage the first to improve the performance of the second and vice-versa. An evolving branch of Machine Learning (ML) is Federated Learning (FL), which consists in building a model in a federated setting (when the data is distributed across different data owners) and model in a collaborative way, without moving the data to a central server. This new technique is a good match with the need of privacy in ML nowadays. Despite its advantages, there are a lot of open problems in FL [28]. In particular, data in FL needs to be pre-processed (e.g. align the schemas, record linkage) in order to start the training process. This would require the data to move out of the edge-devices, therefore threatening privacy.

This Ph.D. aims to explore algorithms, data structures and ML for scaling Data Integration tasks while guaranteeing privacy and achieving good performance, tailored to the Federated Learning pre-processing workflow.

2 Scientific Content of the Doctorate Project

2.1 Background

2.1.1 Data Integration

Data Integration (DI) is the practice of consolidating data from disparate sources into a unified view. It has been studied since the birth relational databases. It is characterized by three main steps:

1. **Schema alignment**, a process that takes as input a set of different schemas on the same domain an outputs a *mediated schema*, an *attribute matching* and a *schema mapping*.
2. **Record linkage**, also referred as entity resolution, computes a partitioning of the set of records from different datasets, such that each partition identifies the records that refer to a distinct entity.
3. **Data fusion** aim is to identify which are the best records to represent a specific entity, when a source provide conflicting values.

2.1.2 Federated Learning

FL is a ML approach where a model is trained across multiple decentralized data owners. Each data owner trains a local model and then, either in a centralized, decentralized or heterogeneous approach, build a global model. It differs from a distributed machine learning as the data is not expected to be identically distributed. Besides the advantage of having a distributed computation, guaranteeing more efficiency, it gained a lot of popularity due to the fact that data is not exchanged between the parts involved, thus guaranteeing privacy.

It has gained a lot of popularity both in research and industry, in particular in transportation [17], Industry 4.0 [45] and digital health [40].

2.1.3 Differential Privacy & Synopses for Big Data

Differential Privacy (DP) is a technique for sharing datasets' information without compromising the privacy of the individuals. The idea is to add noise to the data such that the new distribution is close to the real one, but not equal.

More specifically, it guarantees that any sequence of outputs (response to a query) is equally likely to occur, independent of the presence or absence of any individual in the dataset. The main advantage of DP is that it is robust against membership and information inference attacks, i.e. when an attacker is able to de-anonymize an anonymized dataset via linkage attacks. A good example of de-anonymization attack is the one proposed by Narayanan et.al. [33] where from an anonymized dataset of Netflix subscribers' viewing history, they de-anonymized it through a linkage attack with the Internet Movies Database, revealing the users' apparent political preferences and other sensitive information.

Synopses or summaries are a set of technique and probabilistic data structures to compute compact description of big datasets. These methods compute lossy, compact summaries of data, from which it is possible to carry out interactive analyses and queries. They have been used extensively for streaming data, now gaining popularity also in ML and FL.

2.2 State of the Art

2.2.1 Privacy-aware Data Integration in the Big Data Era

Privacy in the context of data management has gained a lot of popularity over the last decade, as public awareness about issues in management sensitive data increased. Due to this, privacy

became of central importance in the field of Big Data Management, analytics and processing.

In the particular case of DI, privacy-preserving techniques has been used extensively in literature, especially for record linkage. In particular, differentially-private record linkage and cryptography has been used extensively [29, 49, 7, 31, 22, 35, 4, 31]. As regards schema matching and data fusion, there are fewer works on guaranteeing privacy, most of the work is based on guaranteeing efficiency, by using both rule-based and learning-based approaches [43, 42, 44].

Schema matching. Schema matching aligns attributes and data types. It is one of the oldest problems studied for data integration and the traditional approaches consist in extracting knowledge according to a predefined schema. They can be categorized as it follows:

- **Schema-level matchers**, where only the metadata is considered (e.g. column labels, data-types). Linguistic matching is mostly used here (stemming, tokenization, etc.) [2].
- **Instance-level matchers**, where the content of the columns is used for matching by using probabilistic approaches [46, 11] or rule-based approaches.
- **Hybrid matchers** that combine the two matchers just described.

In schema matching the problem of *volume* have to be taken into account only in few specific cases, for example when we consider millions sources from the web [38], but not in typical DI scenarios, where the number of sources is limited. Universal Schema [42] has revolutionized schema alignment. It consists in extracting (subject, predicate, object) triples, where the predicate can be any word or phrase from texts and instead of outputting mappings between predicates, it adds inferred triples. This is done through matrix factorization [42], while recently it is improved by using Recurrent Neural Networks [9, 34].

For what we know so far, there is no work in literature regarding privacy-aware schema matching, due to the fact that most of the techniques are based on the schemas' metadata. Nevertheless, if Instance-level approaches are used, it may be useful to use techniques for guaranteeing the privacy of the individuals, e.g. differential privacy.

Record linkage. Record Linkage, also called Entity Resolution, consists in finding records, among different data sources, that refers to the same real world entity. It is the most important problem in integrating data from different sources.

Generally, it proceeds in three steps:

1. **blocking records** that are likely to be a match;
2. **compare pairs of records** in order to decide if it's a match;
3. **clustering records** according to the previous step's results.

Approaches consisted mostly in rule-based techniques [18, 19] for the first two steps, while for clustering either rule-based or optimizing a particular objective function [25].

Recently, supervised learning approaches (e.g. Support Vector Machines, Decision Trees, Random Forest) showed to obtain high precision and recall [10], at the cost of generating training labels, i.e. to obtain a precision and recall of 99% on linking a pair of datasets, 1.5M training labels are required [13].

Performance and efficiency is not only the main concern of Record Linkage. In a real-world scenario, the data involved in the linkage may be sensitive, and methods to guarantee the privacy of the individuals is a major concern. Privacy-Preserving Record Linkage (PPRL) identifies the set of techniques that aim to link different datasets in a privacy-preserving manner. Initially, Secure Multiparty Computation (SMC) techniques were used, in particular, the Paillier crypto-system [36]. These protocols are reliable and very effective, with the downside of a very prohibitive computational cost. In order to improve performance, by applying secure

transformations to the data [3], such as embedding records to different spaces and then mining them with differential privacy. This comes with the cost of having less accurate results.

Generally, the PPRL protocols proposed for secure two-party private record linkage are not able to meet the following three requirements altogether, without making strict assumptions: (1) **full end-to-end privacy**, (2) **perfect precision and recall** for the matching records and (3) **sub-quadratic computational complexity** [26, 24]. Moreover, multi-party PPRL is a more realistic scenario and only in the last years it has been tackled, with still limited results [48, 49, 47].

Data Fusion. Data fusion resolves conflicts between different data sources, namely, for each entity choose the best record to represent it. Access to highly accurate data is critical for industry applications, such as knowledge graph search, so data fusion is often an important step in data integration.

The main methods for data fusion are rule-based [14] and also data-mining based [37]. Graphical models are also used in this context [20] as well as semi-unsupervised approaches [41].

Privacy-preserving data fusion has not been studied deeply in literature. There are a few context specific works, for example [12] identifies privacy issues and future research directions for data fusion in Internet-Of-Things and [21] which focuses on Differential Privacy in the context of Cyber-Physical Systems.

2.2.2 Federated Learning

Federated Learning (FL) has been proposed by Google [30]. The idea is to build a global ML model from datasets that are distributed across edge devices, without moving the data. An unbalanced and non-IID (identically and independently distributed) data partitioning across a massive number of unreliable devices with limited communication bandwidth was introduced as the defining set of challenges [28]. Privacy is one of the essential properties of FL. Many techniques exist in literature (e.g. Secure Multiparty Computation, homomorphic encryption), but **Differential Privacy** represents *de facto* standard for Privacy in many areas (querying, synthetic data generation, etc.) as it guarantees a better computational performance rather than cryptographic approaches.

FL can be categorized as it follows:

- **Horizontal Federated Learning**. Horizontal FL refers when the federated datasets share the same feature space (the column names) but not the sample space (rows). This system assumes that all the participants are honest and security against an honest-but-curious server [50]. Usually, the learning steps in this system are: (1) each data owner *trains a local model* then the (2) *gradients are sent* to the central server, which applies a (3) *secure aggregation*. Finally, the (4) *model updates* computed by the central server are sent back to the data owners and their local models get updated.
- **Vertical Federated Learning**. Vertical FL is applicable when the datasets share the sample ID space, but the features are different. In this scenario, data pre-processing is required, in particular *schema alignment* and *entity resolution*. These phases require exchanging data with a third party to do the pre-computation, therefore security is more difficult to guarantee in this case.

2.2.3 Future Directions

FL is getting more and more used in many areas, in particular in the health care [6, 5, 39]. Despite the fact that FL brought us new hope for the of data privacy in Artificial Intelligence,

various challenges needs to be addressed [28]. In particular, FL applications usually require engineers to align and link the datasets manually. Therefore, it would be critical to work on new methods to automate and scale the data preparation steps while guaranteeing the privacy.

2.3 Project Objectives

The goal of this PhD can be divided in two main objectives. The first is to develop Privacy Preserving DI algorithms to improve the computational performance with respect to state-of-the-art algorithms, by also extending to a multi-party scenario. The second objective is to experiment those algorithms in the FL process, namely alignment the schemas of the datasets and linking the records to in particular in the DI phase and observe how the performance of the learned models changes, with respect to FL solutions that does not align the data.

Briefly, our objectives are:

1. **O1.** Provide Privacy Preserving DI solutions (i.e. schema alignment and PPRL) by tackling the computational performance limitations presented above and extending them to multi-party scenarios.
2. **O2.** Prototype a DI plugin to integrate to the FL data integration phase, with the aim of improving the learned models' performance.

2.4 Key Methods

We will try to apply the following methods to achieve the project's objectives and ensure the production of high quality results:

- Study the literature review of the current Privacy-Preserving Data Integration techniques and analyze their strengths and weaknesses. This step can be considered continuous over the course of the PhD as more and more scientific content is published continuously at top tier conferences and journals.
- Study Differential Privacy and Synopses in order to understand how to apply them for DI integration algorithms.
- After understanding and analyzing the offerings of current solutions, we will propose algorithms that will use Differential Privacy and Synopses with the aim of obtaining solutions that are computationally performant and differentially private, without losing efficacy (i.e. precision and recall). The goal here is to prototype those solutions in a simulated federated environment.
- Regarding the evaluation of the proposed solutions, appropriate benchmarks will be considered ensuring the correctness of our results.

2.5 Significance and Outcome

Big Data is the core of most businesses nowadays. Data are being generated, analyzed, and used at an unprecedented scale, and data-driven decision-making regards all aspects of society. As the value of data increases when it can be linked with other data, addressing big data integration is critical. Big Data introduced also privacy concerns, that have been dealt with policy regulations (e.g. GDPR).

However, most of the solutions applied now struggle to guarantee good privacy, good efficacy and good computational performance altogether. Moreover, the actual literature made a small use of techniques like Differential Privacy and Synopses, which are de facto standard in other areas (e.g. private data analysis and processing big data streams). The doctoral project will investigate further the application of these techniques to improve the performance of DI algorithms. Finally, these techniques will be applied to FL scenarios, to observe how the

Synopses-driven and differentially-private DI algorithms can improve the quality of the learned models.

The expected outcome of this project includes (1) presentation of our work in top tier conferences and journals, (2) collaboration with other research teams and/or industrial partners (e.g. secondment), to exchange ideas and boost the results of our work, and (3) open-sourcing critical components of our work.

3 Co-supervisors/Candidate Co-operation Agreements

The project will be carried out in three years during which the PhD student will stay in one research institution and one university. During the first and the third year, the candidate will work in Athena Research Center (ARC) under the supervision of Prof. Minos Garofalakis (ARC). During the second year, the program will take place in Universitat Politecnica de Catalunya (UPC) under the supervision of **PLACEHOLDER** (UPC). The project will be a joint work of all parties, hence close co-operation is expected in the following way.

The progress of the project will be validated through frequent meetings between the candidate and his supervisors. The candidate will meet on a weekly basis with his home supervisor and one or two times per month with his host supervisor (the opposite when he will be hosted at UPC). Following typical business practice, the expectations and tasks planned for each meeting will be clearly communicated in advance, with a reasonable notice, both from the supervisors to the candidate and vice-versa. Standard tools of the trade will be used to boost collaboration, such as a shared repository for documents and code artifacts (e.g., Mendeley Library, GitHub, etc.), communication platforms (e.g. Skype, Teams).

4 Work Plan

4.1 Timetable

The PhD is a 3-year-long study, spanning from May 1st, 2022 to February 28th, 2025.

4.2 Thesis Outline

The thesis will be constituted by the research papers that will be written during the whole duration of the project. The thesis report will include (1) an introduction chapter providing background knowledge, motivation, research challenges, objectives and contributions, (2) a chapter about the state of the art (survey paper), (3) one chapter for each published research paper that will include technical details of the implementation, evaluation etc., and (4) a last chapter concluding the work, discussing lessons learned and providing future directions.

4.2.1 Tentative Publication List

The publications that can be considered at the moment of writing the Doctorate Project Plan are the following:

1. A survey paper targeting to illustrate the state of the art of Privacy Preserving Data Integration. Our main contributions will be to initiate a new reader to the field of PPDI, by illustrating the current applied techniques through examples. Comparison of the methods, limitations, research challenges, and future work will also be included.
2. A research and a demo paper about learning for each of the following: (a) Differentially Private and Synopses-driven schema alignment for FL and (b) PPRL for FL and show how it can be used for tracking the patient history.

Time	Plan
Spring 2022	Winter School at ARC Preparation of the two months study plan Literature review of Privacy Preserving Data Integration Summer School at ULB
Milestones	**Submission of two months study plan**
Fall 2022	Participation in 1 PhD courses as shown in the courses' table Preparation of the 11 months study plan Survey the current state of the art in Privacy Preserving DI Summer School at ULB
Milestones	**Submission of 11 months study plan**
Spring 2023	Create an efficient algorithm based of synopses and differential privacy for schema alignment Summer School at UPC
Fall 2023	Participation in 2 PhD courses as shown in the courses' table Design and develop an algorithm for PPRL using synopses and differential privacy
Spring 2024	Prototype a framework for PPDI for Federated Learning systems
Fall 2024	Write the thesis
Milestones	**Submission of the PhD thesis**

3. A research paper about the framework for Privacy Preserving DI for FL systems.

5 Proposed Education and Training Programme

During the PhD studies, it is necessary to have research activities adding up to at least 30 ECTS credits. The ECTS points should be divided between general and research-related courses. Courses can either be taken in National and Kapodistrian University of Athens or in Universitat Politecnica de Catalunya, with conference attendance and other activities contributing as well.

Activity	At	ECTS	Type	Time	Status
Distributed Systems	NKUA	6	General	Autumn'22	Planned
Big Data Management	UPC	6	Project	Autumn'23	Planned
Research Methods	UPC	6	General	Autumn'23	Planned
Winter School (ARC)	ARC	3	Project	Spring'22	Completed
Summer School (ULB)	ULB	3	Project	Spring'22	Mandatory
Winter School (AAU)	AAU	3	General	Fall'22	Mandatory
Summer School (UPC)	UPC	3	General	Spring'23	Mandatory
Conference Attendance	TBD	6	Project	Multiple	Planned
Secondment	SPR	4	Project	Summer'24	Planned
Greek Language course	NKUA	-	Project	Multiple	Planned

6 Knowledge Dissemination and Participation to Scientific Events

We plan to disseminate the product knowledge by publishing papers in top tier conferences, such as ACM SIGMOD, VLDB, IEEE ICDE, EDBT etc. and journals, such as VLDB J., ACM TODS, IEEE TKDE, Information Systems, etc. Moreover, we will pursue opportunities to expose our work to additional outlets (e.g., AI Summit, ACM/IEEE local chapters, meet-ups) through presenting talks and tutorials or giving demonstrations, in order to open a communication channel with the big data engineering, and big data management communities. In this way, we will (a) advertise our work and explore collaboration and exploitation opportunities, and (b) collect valuable feedback that will ameliorate and/or redirect our research.

7 External Co-operation

The doctorate candidate will spend time studying both in Greece and Spain. Furthermore, a secondment of three months will take place, where the candidate will join Spring Techno, where he will work on of a complex Federated Learning scenario with real data. During the following three years, all ESRs will meet in four different winter/summer schools to present their work, receive feedback, exchange ideas, and get exposed to new challenges. During these schools, candidates will have the opportunity to get in touch with academic and non-academic partners, presenting them their findings, reflecting on new opportunities, and opening the way for further collaboration. Finally, the candidate may co-operate with external researchers or research teams, in case that his work can be combined or merged with similar works of others.

8 Agreements on Immaterial Rights to Patents

Patents and immaterial rights will be handled according to general rules applied by Athena Research Center, National and Kapodistrian University of Athens, and Universitat Politecnica de Catalunya.

9 Financing Budget

As regards the long-term career ambitions and objective of the candidate, pursuing a PhD offers This project is one of the 15 ESRs of Data Engineering for Data Science PhD programme, which is funded by the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 955895. The funding covers expenses related to the successful completion of the project, such as work equipment, research experiments, training activities and others that are relevant to the programme.

10 Career Development Plan

After completing the three years programme, the candidate will be an independent researcher, ready to join the academia or pursue a competitive professional career in the industry. During the PhD programme, the candidate will be initiated into research by acquiring competitive research skills, will gain expertise in state-of-the-art technologies, cultivate soft skills, such as communication, presentation and co-operation, and work within a professional environment.

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