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Big Data Privacy by Design Computation Platform

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Resumo

Vivemos na era das grandes quantidades de dados (Big Data). Os dados pessoais dos utilizadores, em particular, são necessários para o desenvolvimento, funcionamento e melhoria constante dos serviços disponíveis na Internet, nomeadamente o Google, Facebook, WhatsApp, Spotify, entre tantos outros. Muitas vezes, a recolha e o uso dos dados pessoais não são explícitos para os utilizadores, embora a sua utilização seja central para o modelo de negócios de muitas empresas. No entanto, o direito à privacidade de cada indivíduo tem de ser respeitado. De que forma podem estas duas necessidades conflituantes ser reconciliadas, ou seja, como podemos construir sistemas de *Big Data* que respeitem a privacidade do utilizador? O objetivo deste trabalho é desenhar e implementar uma "prova de conceito" de uma plataforma para realizar computações que preservem a privacidade dos utilizadores. Pretende-se disponibilizar um método de simples utilização para a implementação de técnicas de preservação da privacidade. Este sistema pode ser utilizado para encapsular algoritmos que permitam, por exemplo, monitorizar os sinais vitais dos pacientes (sem os expor a outras pessoas), produzir recomendações em tempo real com base na localização (mas sem a divulgação da mesma), entre outros. Assim, esta "prova de conceito" implementa versões de algoritmos de aprendizagem automática que preservem a privacidade, e fornece um referêncial que permita uma melhor compreensão das relações e benefícios criados com o uso de técnicas de preservação de privacidade.

Abstract

We live in the age of Big Data. Personal user data, in particular, are necessary for the operation and improvement of everyday Internet services like Google, Facebook, WhatsApp, Spotify, etc. Many times, the capture and use of personal data are not made explicit to the users, but they are central to the business model of the companies. However, the right to privacy of each individual has to be respected. How can these two conflicting needs be reconciled, i.e. how can we build useful Big Data systems that are respectful regarding user privacy? The goal of this work is to design and implement a "proof-of-concept" of a platform for performing privacy-preserving computations, providing an easy-to-use method to implement privacy-preserving techniques. This system could be used to encapsulate algorithms that can, for example, monitor the vital signs of patients (without exposing the data to other people), produce real-time recommendations based on location (without disclosing the location to others), etc. This proof-of-concept implemented privacy-preserving versions of Machine Learning (ML) algorithms and compares them against a baseline reference, allowing a better understanding of the trade-offs of using privacy-preserving technology.

Palavras-Chave
Keywords

Palavras-Chave

Preservação de Privacidade em Computações
Aprendizagem Automática
Extração de Dados
Grandes Quantidades de Dados
Processamento de Dados
Computação Multi-Entidade Segura

Keywords

Privacy-preserving Computations
Machine Learning
Data Mining
Big Data
Data Processing
Secure Multi-Party Computations

Acknowledgements

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List of Acronyms

BARD Big dAta pRivacy by Design platform

CRISP-DM Cross Industry Standard Process for Data Mining

DM Data Mining

DP Differential Privacy

DT Decision Trees

EMR Electronic Medical Records

ED Euclidean Distance

ENISA European Union Agency for Network and Information Security

EU European Union

FN False Negative

FP False Positive

FE Functional Encryption

FHE Fully Homomorphic Encryption

GC Garbled Circuits

GDPR General Data Protection Regulation

HE Homomorphic Encryption

***k*-M** k-Means

***k*-NN** k-Nearest Neighbors

LR Logistic Regression

ML Machine Learning

MUX Multiplexer

OT Oblivious Transfer

PHE Partially Homomorphic Encryption

PII Personally Identifiable Information

PPDM Privacy-Preserving Data Mining

PPML Privacy-Preserving Machine Learning

RBF Radial Basis Function

SMPC Secure Multi-Party Computations

STPC Secure Two-Party Computations

SVM Support Vector Machines

TN True Negative

TP True Positive

1 Introduction

With the so-called "Big Data revolution", vast amounts of data are now being analyzed and processed by companies that take advantage of the enormous quantities of information that is generated every day[1]. The Big Data and Business Analytics market reflects this growth rate, expecting to hit the $210 billion mark in the year 2020[2]. Through this data processing, meaningful information can be obtained to improve existing systems or to discover new approaches in business models. An example is the deployment of Data Mining (DM) algorithms by companies to better understand their customers and to devise better recommendation systems, in order to surpass their competitors in customer satisfaction. Another example lies in the field of healthcare, where it can be beneficial to match patient records from different hospitals in order to identify inefficiencies and develop best practices [41].

Data often contain Personally Identifiable Information (PII) of individuals, such as health records or daily routines. This kind of data cannot be freely processed because that leads to breaches of private information, such as the AOL Search Leak[3] or the Microsoft Hotmail privacy breach[4]. Due to these type of breaches, consumers show an increasing concern in the privacy threats posed by them [13]. The privacy of an individual may be violated due to, for example, unauthorized access to personal data, or the use of personal data for purposes other than the ones for which data were collected.

To deal with the privacy issues in DM, a sub-field known as Privacy-Preserving Data Mining (PPDM) has been gaining attention over the last years [18]. The goal of PPDM is to guarantee

[1] http://www.vcloudnews.com/every-day-big-data-statistics-2-5-quintillion-bytes-of-data-created-daily/

[2] https://www.idc.com/getdoc.jsp?containerId=prUS42371417

[3] https://www.networkworld.com/article/2185187/security/15-worst-internet-privacy-scandals-of-all-time.html

[4] https://www.networkworld.com/article/2185187/security/15-worst-internet-privacy-scandals-of-all-time.html

the privacy of sensitive information, while, at the same time, preserving the utility of the data for DM purposes [2]. This can be achieved by using one or more privacy-preserving techniques, such as Differential Privacy (DP) [19] or Secure Multi-Party Computations (SMPC) [18].

Machine Learning (ML) algorithms in the context of Big Data processing are also producing significant results, so it is possible to gather knowledge from datasets in order to predict future *labels* (i.e. classes of data) or *clusters* (i.e. groups of related data) as new data are acquired. An example application of ML algorithms in DM is *Classification* [38]. In Classification, a training set is processed in order to create a classifier for data, and then that classifier is used to predict class labels for new data. These applications show a great impact in the field of medicine as mentioned above. For example, DeepMind (Google) building ML algorithms to process admissions in hospitals[5], and with Watson (IBM) assisting medical personnel to consider treatment options for their patients[6]. Some examples of ML algorithms include Decision Trees (DT), k-Nearest Neighbors (k-NN), and Support Vector Machines (SVM) [38].

By combining ML algorithms and privacy-preserving techniques, it is possible to create DM processes that not only allow for knowledge learning on large datasets but also help maintain a level of privacy that is desirable by individuals and that complies with the applicable legislation [18].

1.1 Contributions

The main contribution of this thesis is the design and creation of a proof-of-concept platform for privacy-preserving distributed ML computations. Since the platform has its foundations on privacy-preserving techniques, it addresses satisfactorily the privacy demands that individuals want for their data. We show a possible usage for this platform in the field of healthcare, detailing the typical scenario of privacy-preserving processing of Electronic Medical Records (EMR) in Section 4.2. We also present in Section 4.1 the possible applications of the developed

[5] https://deepmind.com/applied/deepmind-health/
[6] https://www.mskcc.org/about/innovative-collaborations/watson-oncology

solution in a business environment.

We provide a detailed comparison of four ML algorithms: DT, SVM, k-Means (k-M) and Logistic Regression (LR), combined with two privacy-preserving techniques: Garbled Circuits (GC) and Homomorphic Encryption (HE), allowing us to understand what is the right combination for each ML algorithm, depending on the context of data and on the operations done by the algorithms. More details can be found in Chapter 5.

With our work, we aim to give individuals a ML platform without them having to build their own, meaning fewer maintenance costs derived from maintaining code developed or dedicated servers.

This thesis is part of a larger project developed in Altran (Big dAta pRivacy by Design platform (BARD)), and the implementation was done by a team of developers. We detail in Section 3.4 what were our contributions to the project, and what results were developed in BARD and are presented in this thesis for completeness purposes.

1.2 Outline

The remainder of this thesis is structured as follows. In Chapter 2 we present an overview on the related work about the Privacy-Preserving Machine Learning (PPML) paradigm. Chapter 3 presents the project from Altran that this thesis is a part of. In Chapter 4 we discuss the implementation specifications of the platform. Chapter 5 presents the results obtained with the implementation. Finally, in Chapter 6 we wrap up the thesis with the conclusions and propose directions for future work.

2 Related Work

This Chapter provides an overview of the concepts relevant to privacy-preserving data processing. We start by defining Data Security and Data Privacy, in sections 2.1 and 2.2 respectively, and describe the differences between them. Section 2.3 presents the concepts of data processing and Data Mining (DM), gives an overview of the Cross Industry Standard Process for Data Mining (CRISP-DM) model and defines the attack models that can be assumed when developing a Privacy-Preserving Data Mining (PPDM) solution. For developing a PPDM algorithm, we can implement one or more of the privacy-preserving techniques briefly presented in Section 2.4. We present Privacy-Preserving Machine Learning (PPML) in Section 2.5. Finally, in Section 2.6 we discuss known use cases that show what can be achieved.

2.1 Data Security

Data Security refers to protective digital measures that are applied to prevent unauthorized access to computers, databases, and websites that store data, as well as to prevent data destruction or alteration.

2.1.1 Data Security Principles

We define here the core security principles widely accepted in the literature, often known as the CIA triad: *Confidentiality*, *Integrity*, and *Availability* [33].

- *Confidentiality* is defined as the property of data, and of services that process such data, that prevents them from being accessed by unauthorized entities.

- *Integrity* is defined as the property of data, and of services that process such data, that prevents them from being modified in an unauthorized or undetected manner.
- *Availability* is defined as the property that access to data, and services that process such data, is always possible when needed by the authorized parties and in a timely manner.

For applying Data Security measures, various technologies can be implemented:

- *Data backups* ensure that data that have been lost can be recovered. This technique is a standard procedure for most companies, since the permanent loss of crucial data can seriously cripple a company's business.
- *Data erasure*, in contrast to backups, is a technique to permanently delete data from a hard drive or other digital media, to ensure that no sensitive data are leaked when a company wants to permanently remove an asset from usage, or when they required to do so by court order.
- *Data encryption*, or disk encryption, refers to techniques that allow a user to encrypt data in a disk, such that the disk remains protected and cannot be decrypted by an unauthorized party.
- *Identity-based security* is a method to limit the access to data such that only a user that has been authenticated and has permission to access a piece of data can do so.

These techniques offer ways to protect data, but sometimes this is not enough. Usually, due to programming bugs in the system, vulnerabilities occur in the software, allowing unauthorized parties to bypass these techniques and get access to data that should be confidential.

2.1.2 Examples of Data Security Breaches

Data Security breaches refer to attacks, usually through unauthorized access, to systems that contain private data. These attacks are commonly made by organized hacker groups to gain

leverage against companies or to make a profit by selling the data in the black market. Next, we present some recent examples of Data Security breaches.

- *Sony Pictures hack*[1]. In 2014, a hacker group leaked confidential data from Sony Pictures in an attempt to gain leverage with the company to make it comply to their demands. The hacker group threatened to commit acts of terrorism in theaters if Sony released a movie related to the North Korean leader.
- *Ashley Madison data breach*[2]. In 2015, a group of hackers stole user data from the adultery website Ashley Madison, and threatened to release usernames and Personally Identifiable Information (PII) if the website was not shut down.
- *Yahoo! data breach*[3]. In 2016, Yahoo! reported two separate data breaches occurring in 2014 and 2013, of over 1.5 billion user accounts, including Yahoo! email access, which in turn can reveal bank and family details as well as passwords for other services.

2.2 Data Privacy

Data Privacy, also referred to as Information Privacy, is the relationship between the collection and dissemination of data, and the legal issues surrounding them. It refers to the measures taken in providing individuals with defenses for their personal data.

Privacy can be defined as the ability or right that an individual has of protecting his/her personal information and extends the ability or right to prevent invasions on the personal space of said individual [4]. Privacy is an important field in information security because it gives an individual his/her personal space and defines his/her personal private information, giving the individual the right to decide which information is for sharing and which should be kept confidential. The right to privacy also limits the access that other entities, being them the government or private companies, have to personal data.

[1] https://www.washingtonpost.com/news/the-switch/wp/2014/12/18/the-sony-pictures-hack-explained/

[2] http://fortune.com/2015/08/26/ashley-madison-hack/

[3] https://www.theguardian.com/technology/2016/dec/14/yahoo-hack-security-of-one-billion-accounts-breached

One of the prime examples of Privacy applied to information technology problems is related to Electronic Medical Records (EMR) [41]. These records must be handled with extra care because they contain a large number of sensitive information about patients. The Patient Record Systems should be able to disclose information only to selected personnel. However, not all the information about the patient should be disclosed, only what is necessary to proceed in helping the patient. This example illustrates the tension between having access to the data, which can be useful, but at the same time keeping them closed to other users.

2.2.1 Privacy Protection Principles

New concepts have arisen in recent years for privacy protection principles [19]. Their definitions are as follows:

- *Unlinkability* is defined as the property that ensures privacy-relevant data cannot be linked across domains that are constituted by a common purpose and context. In other words, multiple actions from the same user/entity cannot be linked together.

- *Transparency* is defined as the property that ensures all privacy-relevant data processing can be understood and reconstructed at any time. Transparency has to cover not only the actual processing but also the planned processing and after processing to fully know actions and entities involved. Transparency is related to the principles concerning openness and it is a prerequisite to accountability. The individual must know and understand how his/her private data is being handled.

- *Intervenability* is defined as the property that ensures mediation is possible concerning privacy-relevant data processing, in particular by the people whose data is being processed. Intervenability is related to the rights of an individual, in a way that the owner of privacy-relevant data must have the means to rectify or erase said data.

2.2.2 European Union Legislation

It is also important to mention in the context of this work the current legislation in the European Union (EU) regarding data protection.

The Data Protection Directive[4] is the current law regarding privacy in the EU and is in force since 1995. More recently, a replacement has been proposed and accepted in the EU, the General Data Protection Regulation (GDPR)[5], that will take effect in May 2018. Both these laws are advised by European entities, namely the European Union Agency for Network and Information Security (ENISA)[6] for the GDPR, and the Article 29 Data Protection Working Party[7] for the Data Protection Directive.

According to ENISA, EU data protections law applies to any processing of personal data [18]. This personal data are defined as any information related to an identified or identifiable natural person. In the context of Big Data analytics, the focus is more on indirect identification, which translates into three different approaches:

- The possibility of isolating some or all records which identify an individual in a dataset.
- The linking of at least two records concerning the same individual in the same database or in different databases.
- The possibility to infer the value of an attribute in a dataset from the value of other attributes.

Another important cornerstone of GDPR is the principles relating to data quality:

- The *fairness principle* requires that personal data should never be processed without the individual actually being aware of it.

[4] http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:31995L0046
[5] http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.L_.2016.119.01.0001.01.ENG&toc=OJ:L:2016:119:TOC
[6] https://www.enisa.europa.eu/
[7] http://ec.europa.eu/newsroom/just/item-detail.cfm?item_id=50083

- The *purpose limitation principle* implies that data can only be collected for specified, explicit and legitimate purposes.
- The *data minimization principle* states that data processed should be the one which is strictly necessary for the specific purpose previously determined by the data controller.

These three principles together mandate that data processing must be done with the consent of the subject, informing the subject of what is the purpose of the processing, and do not deviate from this purpose without informing the subject.

Finally, and also important to mention in the context of this work, are the rights of the data subject according to the GDPR. There are two important rights that a subject has: the *right of access* and the *right to object*. The *right of access* ensures that any data subject is entitled to obtain from the data controllers communication of the data that is subjected to processing and to know the logic involved in any processing of data concerning him/her. This is particularly relevant in the context of Big Data analytics because it limits technological lock-ins and other competition impediments, and it enhances transparency and trust between users and service providers. The *right to object* ensures that data subjects have a right to revoke any prior consent, and to object to the processing of data relating to them, giving them the power to remove himself completely or partially to any data processing mechanisms using their personal data.

2.2.3 Examples of Data Privacy Breaches

In recent years we can find a number of attacks made to systems that handle personal information. Next are some relevant examples regarding Data Privacy breaches.

- *Massachusetts GIC medical encounter database*[8]. In 1997, a researcher from Carnegie Mellon University linked the anonymized database (which contained birth date, sex, and ZIP code) with voter registration and was able to link medical records with individuals.

[8] https://techpinions.com/can-you-be-identified-from-anonymous-data-its-not-so-simple/7627

- *AOL search data leak*[9]. In 2006, AOL released to the general public a text file containing search keywords from a large amount of users, intended for research purposes. The users were not identified, but PII was present in many of the queries. These queries contained a user *id* attributed by AOL, and an individual could be identified and matched to their account and search history using such information when combined with "voting lists".

- *Netflix Prize*[10]. In 2007, Netflix created a contest to improve their recommendation system. To do that, they released a training dataset, with all the personal information regarding customers removed and customer *ids* replaced by randomized *ids*. Later, it was shown that this was not enough when a group of researchers linked public information in another movie-rating website (IMDb) with the released dataset and were able to partially de-anonymize the training dataset, compromising the identity of some users.

- *Target Pregnancy Leak*[11]. In 2012, Target, an American retail company, started merging data from user searches and demographics data in order to learn when their customers were pregnant, to approach them with a specific advertisement. This constituted a clear violation of private sensitive information about their customers and their private life.

2.3 Privacy Implications of Personal Data Processing

Data processing is the conversion of raw data to meaningful information through a process, where operations are performed on a given set of data to extract the required information. Data is manipulated to produce results that lead to a resolution of a problem or improvement of an existing situation.

DM is the process of discovering interesting patterns and knowledge from large amounts of data [32]. We describe the DM process according to the widely used CRISP-DM model [63] (Figure 2.1), in which the process is separated into six major phases, as described next.

[9] https://techcrunch.com/2006/08/06/aol-proudly-releases-massive-amounts-of-user-search-data

[10] https://www.wired.com/2009/12/netflix-privacy-lawsuit

[11] https://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/#3001668b6668

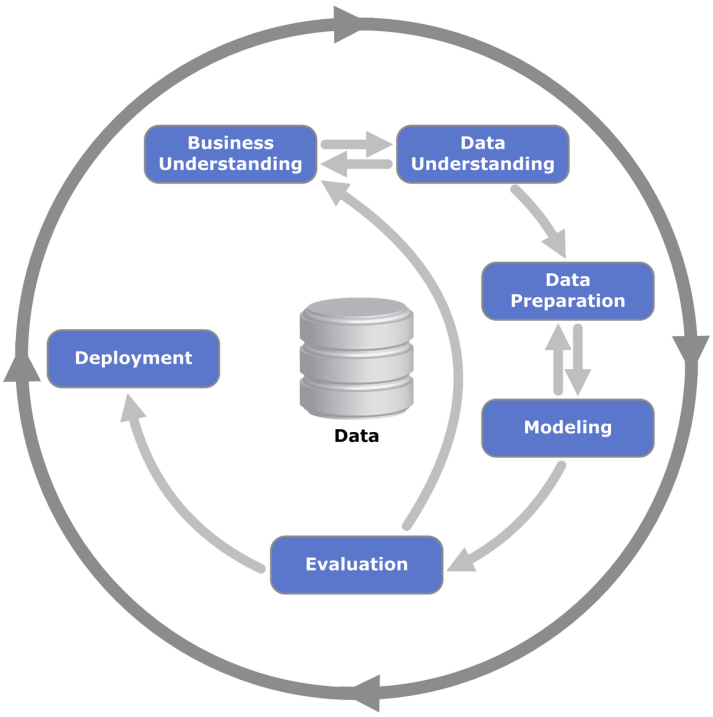


Figure 2.1: Process diagram showing the relationship between the different phases of CRISP-DM [63].

- **Business Understanding:** In this initial phase, the project goals and requirements must be understood from a business perspective and then converted into a DM problem.

- **Data Understanding:** During this phase, an initial data collection is done, followed by a number of activities in order to get familiar with the data, to understand how the data are organized, to identify if the data have quality problems, or even to detect interesting subsets in the data collected.

- **Data Preparation:** This phase covers all the data preparation tasks to construct the final dataset from the initial raw data collected. These tasks include attribute selection, data cleaning, and transformation of data to fit the modeling tools.

- **Modeling:** In this phase, various modeling techniques are selected and applied, and the underlying parameters are calibrated to optimal values. Usually, there are several techniques that can be applied to the same DM problem type, and some of these techniques require specific data formats.

- **Evaluation:** At this point in the DM process, one or more of the models that have been developed are excepted to be of high quality, from a data analysis perspective. These models must be evaluated thoroughly so that they properly achieve the business goals.

- **Deployment:** In this last phase, the knowledge gained by the DM process needs to be organized and presented in a way that the customer can use it. This, of course, depends on the requirements presented at the beginning of the process. An example of a common deployment that results from DM is a simple report on the knowledge obtained.

In the DM process, we must be aware that, sometimes, private information about individuals can be used and it may lead to breaches of privacy. We define this private information as PII [54], i.e. as information that can be used alone or in conjunction with other information to identify, contact, or locate a single person, or to identify an individual in a context.

2.3.1 Attack Models

When considering the security of a system, one must have into account the concepts of threat model, attack model, and type of adversary, to understand how to better implement an efficient and trustworthy security layer. The *honest-but-curious adversary* follows the protocol, but he will try to extract information from his viewpoint to gain some form of advantage or access to confidential information. The *malicious adversary* is one that can deviate from the protocol specification as he desires, and will try to disrupt and/or collect as much information as he can.

Cryptographic attacks are possible whenever a target system relies on cryptography for protection. An attack model is, in terms of cryptanalysis, a classification of cryptographic attacks specifying the type of access the attacker has to a system when attempting to break an encrypted message. We can summarize cryptographic attacks in the following four categories:

- **Ciphertext-only attack:** In this type of attack, the adversary has access only to the ciphertext and has no access to the plaintext. This is the most common type of attack, and it is a requirement for modern ciphers to be resistant to it. An example of a ciphertext-only attack is the brute force attack, where the attacker makes a trial-and-error approach to decrypt the ciphertext.

- **Known-plaintext attack:** In this type of attack, the adversary has access to a number of pairs of plaintext and the corresponding ciphertext.

- **Chosen-plaintext attack:** In this type of attack, the adversary is able to encrypt arbitrary plaintext and have access to the resulting ciphertext, allowing him to make a statistical analysis on the plaintext state space.

- **Chosen-ciphertext attack:** In this type of attack, the adversary is able to choose arbitrary ciphertext and obtain the corresponding plaintext.

When designing privacy solutions using cryptography, protections must be put in place against these kinds of attacks.

2.4 Privacy-Preserving Techniques

In this section, we will describe some of the techniques used in preserving Data Privacy, namely Anonymization, Differential Privacy (DP), Secure Multi-Party Computations (SMPC), Garbled Circuits (GC), Oblivious Transfer (OT), Homomorphic Encryption (HE), and Functional Encryption (FE).

2.4.1 Anonymization

Data anonymization is a type of information sanitization technique that has the final intent of privacy protection. This can be achieved by either removing or encrypting PII from datasets so that the individuals whom the data describes remain anonymous [48].

Anonymization techniques use a variety of approaches, for example, *suppression*, where a piece of information (e.g., name, age) is removed from the dataset; *generalization*, where data is coarsened into less refined sets; *perturbation*, where data is modified by adding noise; and *permutation*, where sensitive associations between entities in the dataset are swapped.

The goals behind anonymization of data are tightly intertwined with the privacy goals we want to achieve for the data being processed. Usually, one or more techniques mentioned above are applied to the data until certain properties are met, for example, *k-anonymity*, *ℓ-diversity* or *t-closeness*:

- *k-anonymity* states that, for each individual whose data is released in some dataset, he must not be distinguishable from at least k individuals that are also present in the release [59].
- *ℓ-diversity* is an extension of *k-anonymity*, and furthers the anonymization of data by reducing the granularity of the data representation such that for any given record, there exist at least ℓ different sensitive attribute values, in addition to the guarantees made by *k-anonymity* [42].
- *t-closeness* is a further refinement of *ℓ-diversity*. It requires that the distribution of a sensitive attribute in any equivalence class is close to the distribution of the attribute in the overall table, effectively limiting the amount of individual-specific information an observer can learn [39].

2.4.2 Differential Privacy

The concept of Differential Privacy (DP) arose due to recent Data Privacy breaches such as the ones mentioned in Section 2.2.3. The security standard for statistical databases, which states that access to a statistical database should not enable an adversary to learn anything about an individual that could not be learned without access, is not achievable because of the existence of auxiliary information, i.e. information available from sources other than the statistical database [23].

DP is a process of maximizing the accuracy of queries in statistical databases while minimizing the chances of identifying its records. The core of the procedure is based on *randomized response* [62], giving the possibility to infer statistical information from the dataset, while still ensuring high levels of privacy.

Detailed information about DP and algorithms designed to achieve it are described in the literature [24].

2.4.3 Secure Multi-Party Computations

Secure Multi-Party Computations (SMPC) (also known as secure computation, multi-party computation, or privacy-preserving computation) is a protocol for different parties to jointly compute a function over their inputs while keeping those inputs private. The problem of computing functions while also preserving the privacy of the inputs is referred in the literature as a SMPC problem [64]. Generally speaking, a SMPC problem deals with computing any probabilistic function on any input, while also ensuring the correctness of the computation. It also guarantees that no more information is revealed to a participant in the computation than what can be inferred from that participant's input and output [29].

A strategy to solve these problems is to trust an external entity (a *trusted third party*), that can mediate the computation. This approach can be risky because it requires a third party that all participants agree to trust, which can sometimes be difficult to find. Sometimes, the data have such high degree of importance to the participants that even disclosing them to a trusted third party is not viable.

When building a SMPC protocol, the most important properties that must be ensured are *input privacy* and *correctness* [28]:

- The *input privacy* property states that no information about the private data held by the parties can be inferred during the execution of the protocol. The only inferences about private data are those that could be inferred from seeing the output of the computation made by the protocol.

- The *correctness* property relates to the existence of malicious parties that could try to deviate from the normal functioning of the protocol. In these cases, the protocol should prevent honest parties to output incorrect results. The approach to implementing the correctness property comes in two alternatives: either the protocol is robust, i.e. it guarantees that the honest parties compute the correct output; or the honest parties abort the computation if they find an error during the execution of the protocol.

The first implementation of secure computation was introduced as Secure Two-Party Computations (STPC) [64]. It is a simplification of the problem of SMPC, and a known protocol for STPC is Yao's GC protocol, which is detailed in Subsection 2.4.5. In STPC, there are only two participants in the computation, and usually one is responsible for starting and encoding the computation mechanism, while the other is responsible for evaluating the computation. In SMPC, the parties have no special roles and, instead, the encoding is shared amongst the parties, by secret sharing, and the evaluation is made by a protocol. An example of a SMPC implementation is the FairplayMP [8].

Some recent implementations of SMPC protocols are based on *Secret Sharing* that allows one party to distribute a secret over a number of parties by distributing shares to each party. Three of the types of secret sharing techniques more commonly used are: Shamir Secret Sharing [55], Additive Secret Sharing and Replicated Secret Sharing.

2.4.4 Oblivious Transfer

Oblivious Transfer (OT) [47] is a protocol in which a sender transfers one of the potentially many pieces of information he has to a receiver but remains oblivious as to what piece has been transferred. Let s^0 and s^1 be two strings held by a sender that wants to transfer one of the strings to a receiver, holding a selection bit b; the protocol allows for only one of the inputs s^b to be transferred; the receiver learns nothing about s^{1-b}, and the sender does not learn b.

An interesting implementation of OT is the one done by Pinkas and Naor [43]. In it, the

authors describe an extension to the basic 1-out-of-2 OT protocol, to a 1-out-of-N protocol, and a k-out-of-N protocol.

The use of OT has been shown as a fundamental cornerstone in modern cryptography [35], and it is an essential building block for communication between parties in a SMPC protocol.

2.4.5 Garbled Circuits

Yao's Garbled Circuits (GC) [65] are a cryptographic protocol that allows two mutually mistrusting parties to evaluate a function over their private inputs without resorting to a trusted third party. In other words, GC allow parties holding inputs x and y to evaluate an arbitrary function $f(x, y)$ without leaking any information about their inputs beyond what is inferred from the function output. The idea behind GC is that one party prepares an encrypted version of a circuit that computes $f(x, y)$ and the other party then computes the output of the circuit without learning any intermediate values.

Some optimizations have been proposed for Yao's GC. Namely, Kolesnikov and Schneider [36] present a technique that eliminates the need to garble XOR gates. Pinkas *et al.* present a technique that reduces the size of a garbled table from four to three ciphertexts [45].

2.4.6 Homomorphic Encryption

Homomorphic Encryption (HE) [50] is a cryptographic technique that allows computations to be carried out over the ciphertexts, so that, when decrypted, the resulting plaintext reflects the computation made. In other words, HE allows to make some computation over the ciphertext, for example, addition, without decrypting it, and the result is the same as making that computation on the plaintext. This is of great importance because it allows chaining multiple services that make computations on a ciphertext, without the need to expose the data to those services.

Homomorphic cryptosystems can be classified into two distinct groups: partially homomorphic cryptosystems and fully homomorphic cryptosystems.

- In Partially Homomorphic Encryption (PHE) only one operation is permitted, for example addition, multiplication or XOR. Some examples of existing partially homomorphic cryptosystems are: ElGamal cryptosystem [26]; Unpadded RSA [51]; and Pailier cryptosystem [44].

- In Fully Homomorphic Encryption (FHE) it is possible to compute two different operations on the ciphertext, namely addition and multiplication. This concept was first introduced in the 1970's [50], and it remained a theoretical result, until recently, when fully homomorphic implementations were developed, for example, Gentry's cryptosystem [27].

2.4.7 Functional Encryption

In Functional Encryption (FE) systems, a decryption key allows a user to learn a specific function of the encrypted data, while also stopping that same user from learning anything more about the encrypted data. In other words, having a secret key only allows for computation of a specific function over the ciphertext [11]. When comparing FE with FHE, the main difference is that, in an FHE scheme, we compute an encryption of $f(x)$ from an encryption of x, whereas in an FE scheme we compute, in the clear, $f(x)$ from an encryption of x. More details can be found in the literature [3].

2.5 Privacy-Preserving Machine Learning

The conjunction between Machine Learning (ML) and privacy-preserving techniques comes from the need to do knowledge learning over large datasets, while also maintaining protection over the privacy of the data, without degrading the quality of data by using anonymization techniques.

In the context of knowledge acquisition, ML techniques come as an important addition to the data processing step. An example of that is the *Classification* method. Classification is described by a two-step process: a classification algorithm is employed to build a classifier for

the data by analyzing a training set made of tuples of data and their associated labels, and then the classifier is used to predict class labels for new data. Due to the large size of the datasets produced in Big Data operations, classification algorithms have a large quantity of data to learn from, making them less prone to erroneous classification of new data.

In the field of ML, we can identify a number of algorithms that can be used in knowledge learning. In Table 2.1, we list some of them, with a brief description, and identify a PPML implementation present in the literature.

Table 2.1: PPML algorithms.

Machine Learning Algorithm	**Short summary**	**Privacy-Preserving Technique**	**Reference**
DT	Protocol for distributed learning of Decision-Tree classifiers.	SMPC	[14]
Naive Bayes	Differentially private naive Bayes classifier. Centralized access to the dataset.	DP	[60]
SVM	Algorithm for Support Vector Machines classification over vertically partitioned data.	SMPC	[67]
k-NN	Nearest Neighbors of records in horizontally distributed data.	SMPC	[56]
k-M	k-Means clustering based on additive secret sharing.	SMPC	[22]
LR	Logistic Regression based on Differential Privacy.	DP	[15]

2.6 Use Cases

In terms of PPML and its applications, it is important to distinguish the context of the data that are being processed. Different data can be subjected to different constraints regarding laws and privacy. Some sensitive data may be only processable in a local environment, while other data can only be processed in a less individualized way. We now detail three relevant and diverse use cases that are bound to different privacy constraints.

- **Health records:** Healthcare systems are one of the examples where vast amounts of data are collected every day. It is relevant to do knowledge learning on patient records, for a better understanding of patients and to improve the healthcare system. Patient records contain very sensitive information about individuals and cannot be processed without the DM system being in compliance with the applicable legislation on Data Privacy. Therefore it is of interest to build privacy-preserving systems for the healthcare system, so that hospitals and other health-related organizations can share and infer knowledge without violating the privacy of their patients.

- **Governance (students and taxes):** A group of researchers made a statistical study in 2015 using SMPC to look for correlations between working during university studies and failing to graduate in time [10]. For this study, it was necessary to link the database of individual tax payments and the database of higher education universities. These types of governmental data are subject to strict legislation and cannot simply be handled without strong privacy guarantees. To solve this problem, a SMPC system was developed and deployed that could assure a level of privacy that would be in compliance with the laws on Data Privacy. The data processing steps were all made using SMPC between three parties, using OT so that each party would not know each other inputs.

  In the end, the study using SMPC was compared with an anonymized study using k-anonymity with $k = 3$. The loss of samples in the latter was 10%-30%, depending on the demographic group, thus suggesting that producing studies on existing databases using SMPC to enforce privacy can give more accurate results than the same study run using k-anonymity measures.

- **Human mobility:** Another subject that provides great challenges in the field of Data Privacy is the mobility traces generated by people when driving, walking, etc. Mobility traces are highly unique so it is possible, even after anonymizing the dataset, to link an individual to his mobility patterns [20]. Since mobility data contains the approximate whereabouts of individuals, it can be used to reconstruct their movements across space and time. Applying privacy-preserving techniques to process this highly sensitive data

can result in robust privacy-compliant geographic-based recommendation systems.

2.7 Summary

The previous Sections provided an overview of the state of the art surrounding privacy-preserving data processing. We started by defining Data Security and Data Privacy in Sections 2.1 and 2.2. We described the concept of DM and data processing, in Section 2.3. In Section 2.4 we described privacy-preserving techniques that can be used to implement a PPML algorithm. We presented ML applied in DM in Section 2.5. Finally, we discussed known use cases that illustrate the benefits of what can be achieved in the field in Section 2.6.

3 BARD

In this chapter, we present the Big dAta pRivacy by Design platform (BARD) project from Altran that this thesis is a part of. In Section 3.1, we present the motivations behind the creation of BARD, and define its objectives in Section 3.2. Section 3.3 presents the architectural specifications of the project. Finally, since the development of this project was a team effort, Section 3.4 details our contributions to BARD.

3.1 Motivation

The idea for this project was motivated by the current growth trend in the Big Data market. The evolution of Big Data the last years, caused by the increasing number of devices connected to the Internet, provided analysts with the data to develop and improve systems in a varied scope of subjects, such as Healthcare and the Automotive Industry. But this data have private information about individuals, and, as we have shown before, processing them without certain precautions leads to breaches of private information. The BARD project contributes to solving this problem, by raising awareness of it and providing solutions in the form of methods and protocols to build privacy-preserving solutions for Big Data systems.

3.2 Objectives

The objectives defined for BARD are described below:

- Define methods to support protection of personal data for harvesting, sharing, querying and processing data assets, and supporting all the decisions to be taken while developing the platform.

- Analyze the effects of the current legislation on the validation of the solution proposed, as it may restrict which technical solutions can be used.
- Conceive a Privacy-by-Design architecture which makes the right balance between the data subject's needs, the data consumer's demands and the legal constraints.
- Develop a Privacy-by-Design platform based on a reference architecture for the entire data flow process, in order to maximize value for both the people and companies.

The expected result of BARD is to produce a platform that provides mechanisms for the protection of personal data, that complies with the current legislation, and that assures Privacy by Design and by Default.

3.3 Architecture

We now present the architectural specifications of BARD. The Cross Industry Standard Process for Data Mining (CRISP-DM) model described in Figure 2.1 was used as a baseline to represent the data life cycle. BARD focuses on Data Quality (e.g.: cleaning, annotation), Data Representation (e.g.: anonymization, ciphering) and Data Processing (e.g.: computation on ciphertext).

The *Data Quality* step refers to the transformation of raw input data into a structured, consistent, and, whenever possible, complete representation. An important aspect to mention in this step is that the data must be processed in plaintext by a trusted entity, meaning that this is done by the data owner or an entity in which the data owner trusts and has explicit permission to perform the operations. The *Data Representation* step refers to the protection of Personally Identifiable Information (PII) contained in the data. This data should be: integrated using privacy-preserving data integration techniques; aggregated using anonymization techniques; and represented using either hashing techniques or homomorphic cryptosystems. The *Data Processing* step is done in two different approaches. On one hand, Secure Multi-Party Computations (SMPC) techniques, such as Garbled Circuits (GC) or

Homomorphic Encryption (HE), are performed over the data. On the other hand, Machine Learning (ML) algorithms, adapted to work with hashed or encrypted data, are used in performing knowledge learning.

We now describe the internal components of a BARD solution. As stated in the objectives (Section 3.2), the main goal of BARD is to produce a platform that will provide mechanisms so that companies can perform privacy-preserving computations for ML algorithms, that are respectful of user privacy, and comply with the legislation. A representation of a solution is described by the following components:

- **A dataset** to train the ML algorithms, or the values representing the already trained algorithms.
- **A sample** or a set of samples that represent the user inputs, to be predicted.
- **Prediction algorithms** that depend on the ML algorithms and the privacy-preserving techniques chosen.
- **A set of toolkits** for each of the techniques used.

These components altogether allow the user of the platform to perform privacy-preserving ML over data of his own choosing. In Figure 3.1 we present the architecture for BARD, showing the components and steps that were taken in the design and implementation of the platform.

3.4 Our Contributions to BARD

Our contributions to BARD project were the development of a solution using the toolkit VIPP for privacy-preserving computations using GC. This includes the development of a baseline system, the adapted algorithms, the testing of the various toolkits and the actual development of the final solution with GC.

As mentioned in 1.1, this thesis is part of a project, and the development of the solution was done by a team. Some of the results shown in this thesis are presented for completeness only,

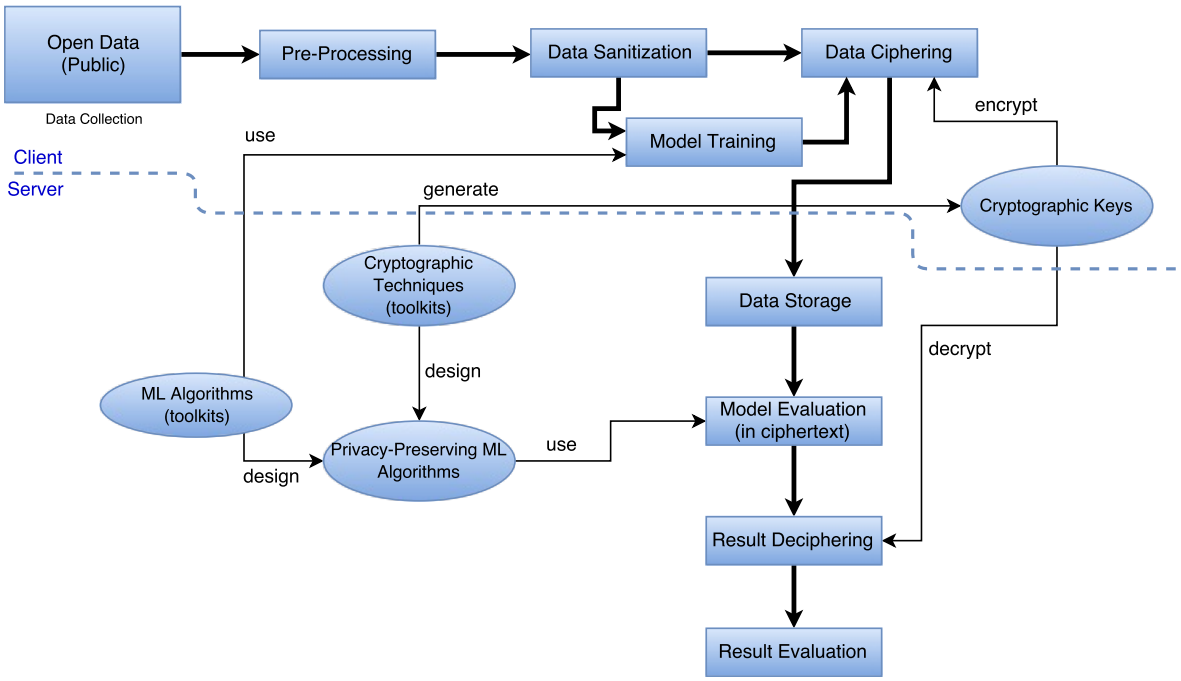


Figure 3.1: Platform architecture for BARD.

as they were developed by the BARD team at Altran. Those results are presented in Sections 5.5.3 and 5.5.4, for the results obtained using HE and Logistic Regression (LR), and for the results using HE and Support Vector Machines (SVM), respectively, and Sections 5.6.3 and 5.6.4 for the communication costs of using Partially Homomorphic Encryption (PHE) and Fully Homomorphic Encryption (FHE). All the remaining results were obtained by the author of this dissertation.

3.5 Summary

In this chapter, we discussed the project from Altran that this thesis is a part of. We explained the motivations behind its creation in Section 3.1, and its objectives in Section 3.2. We detailed the architecture of BARD in Section 3.3. Finally, we identified our individual contributions to the project in Section 3.4.

4 Implementation

When building a platform for Privacy-Preserving Machine Learning (PPML), we must go beyond the traditional steps in data processing mentioned in Section 2.3 and in Figure 2.1, and also have an increased care when preprocessing data to incorporate the cryptographic techniques.

This Chapter describes the work that was done in implementing a PPML platform. In Section 4.3, we start off with a description of the structure we followed in implementing and evaluating the platform. In Section 4.4, we offer a description of the datasets chosen to test our platform. Then, we explain the preprocessing that was done to those datasets, in Section 4.5. Section 4.6 presents the baseline implementation of the chosen Machine Learning (ML) algorithms, resorting to a widely used ML toolkit for Python. In Section 4.7, we present the cryptographic protocols used, why we used them, and how we implemented them, mentioning which toolkits were used. For understanding the applicability of the solution developed, we detail in Section 4.2 a use case for our implementation. Finally in Section 4.1 we present a possible usage for our implementation, in the form of a toolkit that could be used in a business environment.

4.1 Platform

In Figure 4.1 we present the conceptual view of our platform. The *data resources* represent the datasets that are used in the classification process. The data processing itself is done using the combination of ML algorithms and cryptographic techniques for performing privacy-preserving computations. The Application Programming Interface (API) layer abstracts details and provides the operations of the platform itself, which allow a simplified building of applications and data visualizations. The use-cases describe the various subjects

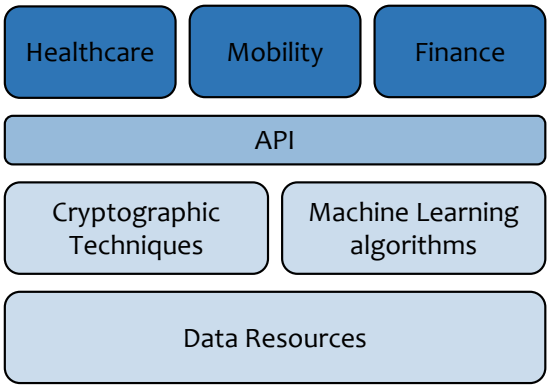


Figure 4.1: Conceptual view of the platform.

that can be addressed using this platform, and allow us to place it in real-world scenarios that have high impact and demand in Big Data operations. More use-cases are possible beyond Healthcare, Mobility and Finance, as the platform is designed for general use.

Joining the algorithms and techniques described in the previous sections, we propose now the creation of a platform that would allow developers to create, implement, and expand the existing components.

- What ML algorithm to use.
- What privacy-preserving technique to use.
- The dataset to process.
- Inspect the resulting data.

Finally, we now present how BARD could be implemented in a business scenario. The users, in this case, the companies that profit from using BARD to do knowledge learning, provide the dataset to train the model or select an existing model already trained with publicly available data, and provide the sample to be evaluated. A team of developers, that could be outsourced or part of the company, maintain the toolkit and develop new functionalities (new ML algorithms, new privacy-preserving techniques, etc.). A central repository, that contains

ML models trained *a priori* for different types of data context (healthcare, income, etc.). In Figure , we present a context diagram for BARD.

4.2 Use Case: Healthcare

As mentioned in Section 2.6, healthcare systems generate vast amounts of data every day. Processing this data can be beneficial for both the health institution (hospitals, clinics) and for the patients. However, the usage of Electronic Medical Records (EMR) cannot be freely done by institutions without the consent of the patients and in compliance with data protection legislation. As a result, this processing is performed *in-house*, with only a few exceptions[1]. The problem is that developing and/or maintaining a Data Mining (DM) infrastructure in an institution amasses costs that it may not be willing to support.

Our contribution to mitigating this standoff between the gains and costs of DM EMR is to provide a product that removes the costs of maintenance and development from the institutions, while at the same time provides enough privacy guarantees to comply with existing legislation.

We now describe a typical use case scenario for privacy-preserving processing of EMR.

- **Description:** Design and implementation of a platform to process EMR in order to improve treatments and diagnoses, while maintaining identities private. This is achieved by training models using these data and then predict medical conditions for future patients. All the computations should be done resorting to privacy-preserving techniques.
- **Actors involved:** Healthcare institutions, patients, medical staff.
- **Preconditions:** Access to data and to EMR of patients. Consent from each patient regarding the processing of his/her data.
- **Basic Flow:**

[1] https://www.reuters.com/article/us-health-medicalrecords-sharing/few-u-s-hospitals-can-fully-share-electronic-medical-records-idUSKCN1C72UV

1. The institution supplies the platform with data to train the models for one or more ML algorithms. This training must be done in an encrypted and/or anonymized domain.
2. A new patient arrives at the institution and it is asked if he/she consents to the use of the platform to speed up his/her diagnosis, including consent to data collection and data processing. If the patient agrees, the process can continue.
3. Patient data are collected by the medical staff, including his/her symptoms, medical history, etc.
4. These data are supplied to the platform, and the platform performs one or more predictions, depending on the number of models the platform has, using privacy-preserving techniques to do so.
5. The platform informs the doctor of what are the prediction results.
6. The doctor decides on the appropriate medical action, taking into account his medical background and the information supplied by the platform.

- **PostConditions:** The platform has received data from the institution. The platform has trained different instantiations of ML algorithms. The platform successfully predicted the labels for the new samples.

4.3 Structure

The process of implementing and testing a PPML platform can be achieved in a number of steps. The plan we designed was composed of three steps, each with three processes that are repeated for all steps.

- **Step 1**: Use a toolkit (*scikit-learn*) to implement baseline versions of the chosen ML algorithms. Each of the processes were performed in black boxes[2] supplied by the toolkit:

[2] A black box is a device, system or object which can be viewed in terms of its inputs and outputs, without any knowledge of its internal workings.

1. Compute the model using the training set.

2. Use the model to predict the labels of the testing set.

3. Evaluate the performance of the model by comparing predicted labels with the real ones.

- **Step 2**: Write scripts implementing the ML algorithms that explicitly contain all the equations for the processes described above.

- **Step 3**: Rewrite the scripts from Step 2 using cryptographic techniques to perform the necessary computations, that add protections for all the processes described above.

It is important to mention that the processes in Steps 2 and 3 where implemented in reverse order, not only because training is more complex that prediction, which in turn is more complex that evaluation, but also because this new ordering better matches the purpose and logic of implementing them using cryptographic techniques for privacy-preserving purposes. Figure 4.2 presents a visual representation of the structure we followed, and show what was left for future work.

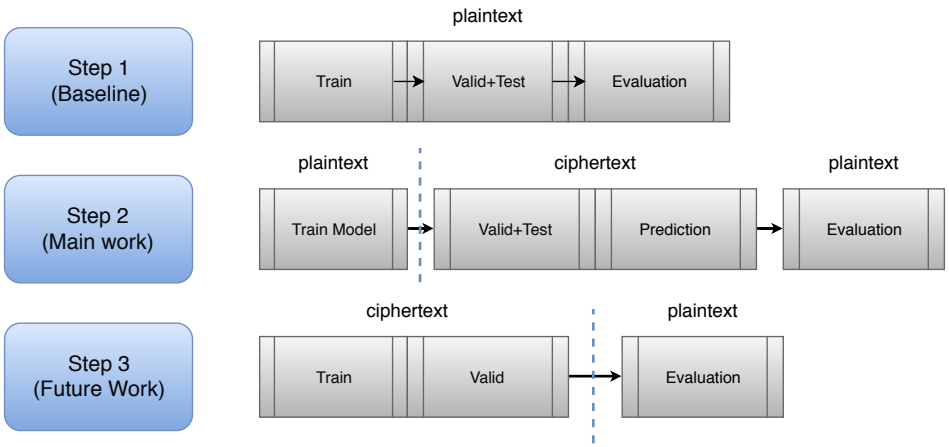


Figure 4.2: Steps and Processes of the implementation.

4.4 Datasets Used

For running the experiments, we used datasets that are normally considered in the literature, namely the *Breast Cancer Wisconsin Diagnostic* dataset[3], the *Pima Indians Diabetes* dataset[4], the *Credit Approval* dataset[5], and the *Adult Income* dataset [6]. Table 4.1 presents a brief description of each dataset, and the number of features after the preprocessing techniques presented in Subsection 4.5.

Table 4.1: Datasets used in the evaluation of BARD.

Dataset	**Subject**	**Instances**	**#Features**	**#Features after one-hot encoding**
Pima Indians Diabetes	HealthCare	768	8	8
Breast Cancer Wisconsin	HealthCare	569	30	30
Credit Approval	Finance	690	15	51
Adult Income	Governance	48842	14	108

4.5 Data Preprocessing

Although our data is obtained from publicly available data sources, some preprocessing on the data is still required. For example, the existence of categorical data, that some ML algorithms cannot process directly, must be addressed. We now describe some of the techniques we used in the data preparation phase for the datasets described in Table 4.1.

- **One-hot Encoding**[34] was initially used in digital circuits in order to determine the state of a state machine without using a decoder. The binary code is converted in a group of bits in which only one bit can have the value high (1), and all the others low (0). In ML, we apply this technique to deal with the problems created in using datasets with categorical (or nominal) data. Most ML algorithms require numerical representations in the data. A solution can be to assign an integer number to each different value present in the data, but this leads to the model assuming a natural ordering between

[3] https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)
[4] https://archive.ics.uci.edu/ml/datasets/pima+indians+diabetes
[5] http://archive.ics.uci.edu/ml/datasets/credit+approval
[6] https://archive.ics.uci.edu/ml/datasets/adult

categories that may not exist. Using one-hot encoding in categorical data allows us to circumvent this problem, creating additional binary variables for each unique value, e.g., if a variable describing pets has the values "dog", "cat" and "fish", after encoding, three more variables will be added to the dataset, each representing a possible value. Then, a high (1) will be placed on the binary variable that represents the original value, and low (0) on all the others. Using the pets example, if the original value was "dog", the resulting three binary variables will be high on the binary variable representing "dog", and low on the other two, i.e. "dog" becomes $(1, 0, 0)$.

- **Feature Scaling** is a technique to normalize the range of data. For some ML algorithms, having a broad range of values in one of the features may cause this feature to govern the modeling. There are different ways of achieving this, for example, *rescaling*, where the range of values is scaled to a target range (usually $[0, 1]$ or $[-1, 1]$), or *standardization*, where the features are rescaled so that they have the properties of a standard normal distribution, i.e. mean average equal to 0 and standard deviation equal to 1.

In our implementation, we used one-hot encoding in the *Adult Income* dataset and in the *Credit Approval* dataset. These two datasets contain categorical features that required the use of encoding to be processed by the ML algorithms.

In the *Adult Income* dataset, we have multiple examples of categorical features, namely the *work-class*, *education*, *marital-status*, *occupation*, *relationship*, *race*, *sex* and *native-country*. These were all encoded so that only numerical features remained, causing a large growth on the number of features, going from the initial 14 to 108. In the *Credit Approval* dataset, we encoded all the non-numerical features, changing the number of features from 15 to 51. Feature scaling was used in all of the datasets, in order to reduce the errors caused by wide ranges. We used rescaling of all values to numbers between 0 and 1.

Besides the techniques mentioned above, it was also necessary to deal with the missing values that existed in the datasets. So, for the numerical features, we replaced those missing values

with the median of the other existing values. In the case of the categorical features, the missing values are considered as another valid value for that feature, in order to make the calculation of one-hot encoding to the whole dataset easy.

Finally, for our setup we required a validation and a testing set, which some of the datasets did not contain originally. We divided those datasets into training, validation and testing sets, using a proportion of 70/15/15, respectively. In the cases where a testing set already existed, the validation set was created from the training set, and forced to have the same size as the testing set.

4.6 ML Algorithms

The baseline approach consists of setting up reference values so that meaningful comparisons can be achieved. For understanding the overhead created by privacy-preserving technologies, we implemented the baseline using the publicly available ML toolkit for Python, *scikit-learn*[7].

In order to understand and explain what was done and why, next we detail the ML algorithms that were implemented in the baseline and in Section 4.7.

4.6.1 Decision Trees

Decision Trees (DT) [46] are a decision support tool that uses a tree-like graph to represent decisions and possible outcomes of those decisions. It is an algorithm that is composed of conditional control sequences. DT learning uses DT as a predictive model for classification. These DT are composed of nodes and leaves. The nodes represent decisions to take, or more specifically, thresholds that a feature is compared against in order to decide which branch of the tree to follow. The leaves represent class labels.

To build a DT classifier there are a number of algorithms that can be used, each with different approaches and benefits. Examples include ID3, C4.5, C5.0 and CART [58]. These algorithms

[7] http://scikit-learn.org

focus on maximizing one or more metrics, such as Gini impurity or information gain [52].

The classification process of a sample in DT is an intuitive method. Each node of the tree has the information on which feature in the sample to compare against the threshold. Classifying a sample in DT is done by traversing the tree starting at the top, comparing the values selected on each node with its respective threshold, and, depending on the result, choosing one child node or the other. When a leaf is reached, a class label is retrieved from the leaf and assigned to the sample, ending the classification process. At each tree node, a decision is computed using:

$$f_{\mathrm{DT}}(x_i) = x_i \overset{?}{\geq} \theta_j \tag{4.1}$$

where x_i is the feature value of interest of the testing sample and θ_j is the decision threshold of node j. If the output is 0, the left hand child is selected; if it is 1, the right hand child is selected.

4.6.2 Support Vector Machines

Support Vector Machines (SVM) [17] are supervised learning models used for classification and regression analysis. A SVM model represents the examples as points in space, mapped so that the margin between the two classes for the data is as wide as possible. The vectors that define this margin, or *hyperplane*, are called support vectors. For classifying new samples, they are mapped in that space and predicts which class they belong to based on which side of the gap they lie.

For calculating the SVM for linear classification, and in the case of a *hard-margin*, i.e. when the training data is linearly separable, we select two parallel hyperplanes so that the distance between them is as large as possible. These hyperplanes can be described by the Equations (4.2).

$$\begin{aligned} \vec{w}.\vec{x} - b &= 1, \\ \vec{w}.\vec{x} - b &= -1 \end{aligned} \tag{4.2}$$

where $\vec{w}$ is the normal vector to each hyperplane, $\vec{x}$ is the training set and b is a scalar number. To maximize the distance between hyperplanes, we minimize the value of $||\vec{w}||$ subject to $y_i(\vec{w} \cdot \vec{x}_i - b) \geq 1$, for $i = 1, \ldots, n$, where the y_i are either 1 or -1, depending on the class label, and n is the number of samples in the training set. In the case where the data is not linearly separable (*soft-margin*), we minimize instead the *hinge* loss function given by the Equation (4.3).

$$f(w, \lambda) = \left[\frac{1}{n} \sum_{i=1}^{n} \max\left(0, 1 - y_i(\vec{w} \cdot \vec{x}_i - b)\right) \right] + \lambda \|\vec{w}\|^2 \tag{4.3}$$

where the parameter λ determines the tradeoff between increasing the margin size and ensuring that the $\vec{x}_i$ lie on the correct side of the margin.

For SVM non-linear classification, we use a *kernel trick* [53], in which the dot product is replaced by a non-linear kernel function. The most used kernels are:

- Linear: $k(\vec{x_i}, \vec{x_j}) = (\vec{x_i} \cdot \vec{x_j})$
- Polynomial: $k(\vec{x_i}, \vec{x_j}) = (\vec{x_i} \cdot \vec{x_j})^d$
- Radial Basis Function (RBF): $k(\vec{x_i}, \vec{x_j}) = \exp(-\gamma \|\vec{x_i} - \vec{x_j}\|^2)$

The classification of new samples in SVM is done using the scoring function in (4.4), where each testing sample x is attributed to a prediction label.

$$f_{\text{SVM}}(x) = \sum_{i=1}^{m} \alpha_i K(x_{SV}^{(i)}, x) + b \tag{4.4}$$

where α_i is the coefficient associated with the support vector $x_{SV}^{(i)}$, K is the kernel function chosen, and b is a scalar number.

4.6.3 *k*-Means

k-Means (k-M) clustering [40] is a method commonly used to partition a dataset into k groups. It proceeds by selecting k initial cluster centers (centroids) and then iteratively refine them. This refining is done in two distinct steps:

1. Each instance is assigned to its closest cluster. This is done by calculating the Euclidean Distance (ED) between each instance and each cluster center. Then, the lowest distance indicates which cluster the instance must be assigned to.

2. Each cluster center is updated to be the mean of all the instances assigned to it.

The algorithm stops when the centroids no longer change position. This means that, depending on the data, it is not guaranteed that the optimal solution is found.

The classification of each testing sample is done similarly to step 1., i.e. by computing the ED of the new sample with each centroid, discovering the cluster whose centroid is closest to it. The label of the cluster becomes the predicted label of the sample. Equation (4.5) describes the prediction:

$$f_{\text{k-M}}(x) = \underset{C}{\operatorname{argmin}}\, d_E(x, C_j) \tag{4.5}$$

where C are the centroids of each cluster, x is the testing sample and d_E is the ED.

4.6.4 Logistic Regression

Logistic Regression (LR) [61] is a regression model in which the dependent variable is categorical. This variable is usually binary, i.e. it can only take two values, usually 0 or 1 that represents opposite outcomes such as “win/lose” or “healthy/sick”. This binary logistic model is used to estimate the probability of a binary response based on one or more variables. To define LR, one must begin with the logistic function, which in turn is given by Equation (4.6).

$$\sigma(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}} \tag{4.6}$$

where t is the input. If we express t as $t = \beta_0 + \beta_1 x$, we can write the logistic function as in Equation (4.7).

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \tag{4.7}$$

To classify testing samples we use Equation (4.8) to attribute a prediction label to each sample x.

$$f_{\text{LR}}(x) = \beta_0 + \sum_{i=1}^{m} \beta_i x_i \tag{4.8}$$

4.7 Privacy-preserving Algorithms

In the final step of our implementation, we made adjustments to the evaluation processes of the ML algorithms discussed above, so that we could apply two privacy-preserving techniques, namely Garbled Circuits (GC), described in Section 2.4.5, and Homomorphic Encryption (HE), described in Section 2.4.6. These two techniques offer different means to obtain privacy-preserving computations, and we must consider them when choosing which ML algorithm to use with each cryptographic algorithm. GC builds ciphered Boolean circuits, which means that most of the computations are possible to implement on them. However, arithmetic computations require a large number of logic gates, creating an overhead that makes GC very slow. So, for some of the ML algorithms, we used a HE system, since it offers arithmetic operations as a core operation. Due to these constraints, we decided to adapt the DT and k-M to be evaluated using GC, and SVM and LR to be evaluated using HE.

4.7.1 Garbled Circuits and Decision Trees

The process of evaluating a DT in a privacy-preserving context is similar to evaluating in the usual manner, as described in Section 4.6.1. The main differences are the use of ciphered Boolean circuits instead of operations, i.e. basic operations such as additions, comparisons, are replaced with logic gates, and the evaluation of the DT involves evaluating every single node in it. Although the use of GC effectively hides the DT evaluation process from unwanted parties, it does not hide the sparseness of the DT, which could leak some relevant information about the original data, meaning that the use of expanded DT is preferable for preserving privacy.

In Figure 4.3 we show how the computations are done inside each node of the DT. Each node contains the *featureID*, the ID of the feature to be selected from the sample to be classified, and the *threshold*, the value that is compared against the selected feature and that decides which branch of the tree to follow next. The first Multiplexer (MUX) gate selects from the sample the feature to be compared. The greater-than gate compares the selected feature with the threshold. Then, the value from the comparison (0 or 1) is used as a selection bit in the second MUX to choose the *next_featureID* and *next_threshold* for the next node in the tree.

It is also important to mention that the trees that we used are always complete, i.e. the number of nodes n is always the maximum possible, and it can be defined as $n = 2^{h+1} - 1$, where h is the *height* of the tree. We can see in Figure 4.4 the implications of this expansion of the binary trees.

In Figure 4.4(a) we have a binary DT with $height = 3$ and with different path lengths to the leaves, depending on the branch of the tree taken, but on the tree in Figure 4.4(b), all paths have the same length. With this, we can effectively hide the sparseness of the tree, which could leak relevant information about the original data. However, this solution increases exponentially the total amount of nodes that need to be evaluated, and that decreases performance significantly, as we will see in Chapter 5.

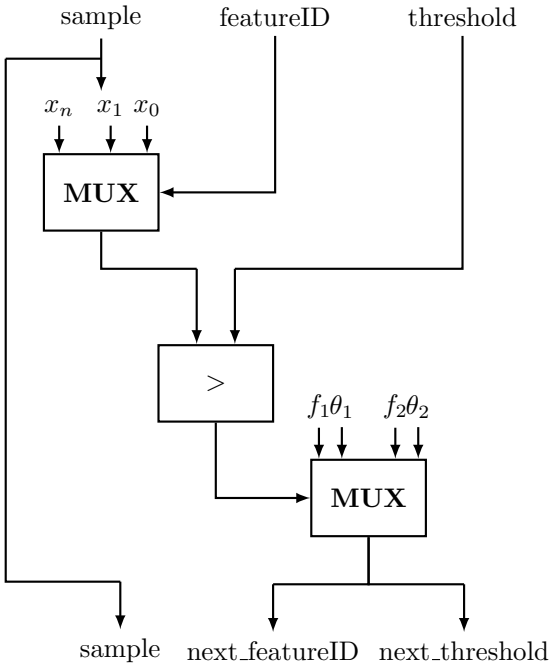


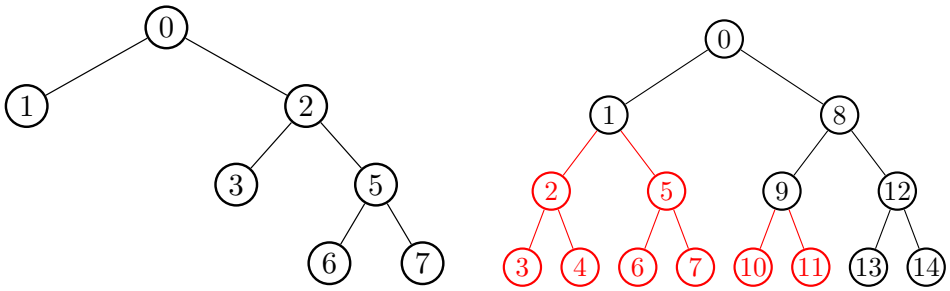
Figure 4.3: Boolean circuit of each node in a DT.

4.7.2 Garbled Circuits and *k*-Means

As in the previous section, evaluating the *k*-M algorithm in a privacy-preserving manner is similar to evaluating it in the usual manner. We took the operations in the prediction step and transformed them into Boolean circuits, with logic gates such as multiplexers, adders, etc.

In Figure 4.5 we show how we designed the circuit to represent the *k*-M prediction. The d_E blocks represent the operations to calculate the ED between the sample and each centroid provided by the *k*-M model. The ARGMIN block determines which of the ED is the smallest.

As shown in the results in Section 5.5.2, there is an exponential decrease in performance when the number of clusters increases or the sample has a larger number of features. This is caused by the multiplications necessary for computing the ED. Usually, this is a reason to use HE instead, but the algorithm to implement comparisons using HE is very complex to implement and requires considerable computational power [9].



(a) Original DT. (b) Complete DT.

Figure 4.4: Expansion of binary trees.

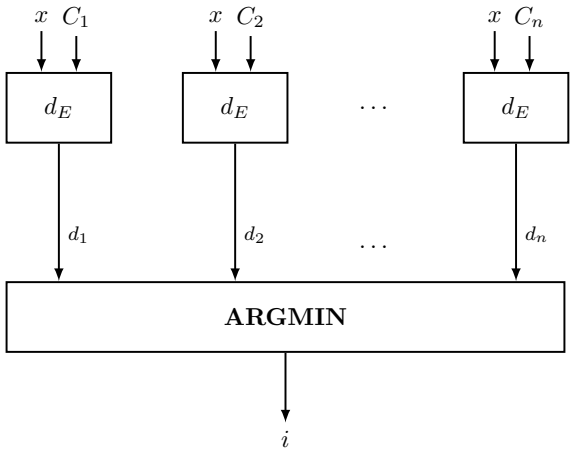


Figure 4.5: Boolean Circuit of the prediction of the k-M algorithm.

4.7.3 Homomorphic Encryption and Logistic Regression

For the LR algorithm, in order to use a Fully Homomorphic Encryption (FHE) system, the prediction function described in (4.8) must be converted to:

$$f_{FHE}(x) = D_k\left(E_k(\beta_0) + \sum_{i=0}^{m} E_k(\beta_i) \cdot E_k(x_i)\right) \tag{4.9}$$

where E_k represents the encryption operation and D_k represents the decryption operation using the key k. Converting Equation (4.9) to be computed using a Partially Homomorphic Encryption (PHE) system is straightforward, but this can only be done under two assumptions: 1) the data to be evaluated (x) and the model parameters ($\beta_0, \beta_1, \ldots, \beta_m$) must come

from two different parties, and 2) the owner of the model parameters must be the one processing the data. Under these assumptions, the linear prediction function for a multiplicative PHE system becomes:

$$f_{PHE}(x) = D_k\left(E_k(\beta_0) \cdot \prod_{i=1}^{m} E_k(x_i)^{\beta_i}\right) \tag{4.10}$$

4.7.4 Homomorphic Encryption and Support Vector Machines

For the SVM algorithm, we only considered the linear kernel, as it simplifies the scoring function. The Equation (4.4) is then simplified to the following:

$$f(x) = \sum_{i=1}^{m} \alpha_i x_{SV}^{(i)} x + b = \sum_{i=1}^{m} \alpha_i \sum_{j=1}^{n} x_j x_{SV}^{(i,j)} + b \tag{4.11}$$

To compute this function using a FHE system, we must convert it to:

$$f_{FHE}(x) = D_k\left(\sum_{i=1}^{m} E_k(\alpha_i) \cdot \sum_{j=i}^{n} E_k(x_j) \cdot E_k(x_{SV}^{(i,j)}) + E_k(b)\right) \tag{4.12}$$

where E_k represents the encryption operation and D_k represents the decryption operation using the key k. Like in the previous Subsection, converting it to be computed using a PHE system is equally straightforward, but this must be done under the same two assumptions: 1) the data to be evaluated (x) and the model parameters (α_i,$x_{SV}^{(i,j)}$,b) must come from two different parties, and 2) the owner of the model parameters must be the one processing the data. Under these assumptions, the scoring function for a multiplicative PHE system becomes:

$$f_{FHE}(x) = D_k\left(\prod_{i=1}^{m}\left(\prod_{j=1}^{n} E_k(x_i)^{x_{SV}^{(i,j)}}\right)^{\alpha_i} \cdot E_k(b)\right) \tag{4.13}$$

4.8 Summary

In this Chapter, we discussed the implementation of a privacy-preserving ML platform. We started by describing the datasets chosen to evaluate the platform in Section 4.4, and then we explained the preprocessing step in Section 4.5. Section 4.6 presented the implementation of

the baseline for the chosen ML algorithms. In Section 4.7, we detailed which cryptographic protocols we used, why we used them, and how we implemented them, mentioning which toolkits were used. For understanding the uses of the solution developed, we detailed in Section 4.2 a use case for our implementation, and finally in Section 4.1 we presented a possible usage for our implementation, in the form of a toolkit that could be used in a business environment.

5 Evaluation

In this Chapter we describe the experiments that were conducted regarding the implementation of Machine Learning (ML) algorithms using privacy-preserving techniques made to prove the concept of the platform. In Section 5.1, we present the metrics used in the experiments. Section 5.2 describes the setup that was used to run the experiments, as well as the toolkits used and the parameters chosen for those toolkits. In Section 5.3, we present the best baseline results obtained for the datasets in question and in Section 5.4 we compare those results with the ones obtained using the toolkits. In Section 5.5, we present the execution times for the combinations of ML algorithms and privacy-preserving techniques that were implemented, and in Section 5.6 we present the communication costs for those combinations. Finally, in Section 5.7 we make some final observations about the obtained results.

5.1 Evaluation Metrics

To evaluate our implementation, a set of metrics was considered, namely: *accuracy*, *precision*, *recall*, and *F-measure*. For the definition of the metrics, we need to define the events that can occur when making predictions, shown in Table 5.1 below.

Table 5.1: Binary confusion matrix.

		Real label	
		+1	-1
Predicted label	+1	True Positive (TP)	False Positive (FP)
	-1	False Negative (FN)	True Negative (TN)

Accuracy is defined as how much of the measurements of a value differ to the real value. In our implementation, it represents how many times the predictions calculated by the ML generated

models match the class of the testing samples. In mathematical terms, it is represented by:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.1}$$

Precision is defined by the fraction of relevant instances among the retrieved instances. *Recall* is defined by the fraction of relevant instances that have been retrieved over the total of the relevant instances.

$$precision = \frac{TP}{TP + FP} \tag{5.2}$$

$$recall = \frac{TP}{TP + FN} \tag{5.3}$$

F-measure is a measure of the accuracy of a test. It considers both the precision and the recall of the test to compute the score:

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{5.4}$$

Besides these metrics, we also used additional ones in order to understand how much the computational overhead due to the use of cryptography influences the system. We compared the *results* obtained by the privacy-preserving versions of ML algorithms with the ones obtained using the baseline. We also take into account the *execution times* of the system, which shows the overhead caused by the additional computational cost added by cryptography. Finally, we also show the increase in communication costs that happen when cryptography is involved, as all values must be represented by ciphertext, instead of plaintext integer or float values.

5.2 Experimental Setup

All the experiments were performed using a machine with an Intel Core i5-4300M CPU @2.60Gz with 3MB L3 cache memory and 12 GB RAM memory.

For obtaining the experimental results, we started by applying the preprocessing techniques

mentioned in Section 4.5 to the datasets described in Table 4.1. As described before, all datasets that were composed of a single file were split into three sets: training, validation and testing sets, with the proportion 70/15/15. Each ML model was trained using the training set, the best model configuration was chosen using the validation set, and the model performance was evaluated using the testing set.

Taking into account that the baseline implementation was done using *scikit-learn*, we could not explicitly observe the operations done in the toolkit since they were made in a "black box" mode. This could lead to an inability to distinguish prediction errors caused by the privacy-preserving systems and caused by the implementation of the prediction equations. To solve this problem, we implemented the evaluation prediction processes of the ML algorithms without using the toolkit, i.e. directly from the algorithm equations. We successfully recreated the prediction processes by retrieving from the toolkit the specifications for each ML model.

- For the Decision Trees (DT), we needed to retrieve all of the model, i.e. the binary tree, so that we could traverse it according to each testing sample, comparing the feature with the threshold of each node, and choosing which branch of the tree to follow, until a label is reached.

- In the case of Support Vector Machines (SVM), we retrieved from the toolkit all the coefficients needed to compute Equation (4.4), namely the support vectors $x_{SV}^{(i)}$, the α_i coefficients for each support vector, the kernel function $k(\vec{x_i}, \vec{x_j})$ that was used (linear or polynomial), the exponent for the polynomial kernel if needed, and the scalar value b.

- For k-Means (k-M), we just required from the toolkit the centroids for each cluster, as well as the prediction labels associated with each one. The classification of each testing sample was done by discovering which centroid was closest to it.

- In Logistic Regression (LR), we extracted the $\beta = (\beta_0, \beta_1, ..., \beta_n)$ that appear in Equation (4.8). β_0 is the intercept from the linear regression, and β_i are each regression coefficient that are multiplied by each feature of the sample.

5.2.1 Baseline Parameters

The following parameters are the ones used in the *scikit-learn* toolkit.

For the experiments with DT, we tested the values for *max_depth* of 5%, 10%, 20%, 50%, 100%, 200%, and 500% of the total number of features, and the values for *min_samples_leaf* of 0.001%, 0.002%, 0.005%, 0.01%, 0.02%, 0.05%, 0.1%, 0.2%, 0.5%, 1%, 2% and 5% of the total number of training samples.

For the experiments with SVM, we used *kernel* values of *linear*, *poly* and *rbf*. For all kernels, we used C values of 2^{-10}, 2^{-6}, 2^{-2}, 2^{2}, 2^{6} and 2^{10}. For the polynomial kernel, we used *degree* values of 2, 3 and 4. For the Radial Basis Function (RBF) kernel, we used γ values of 2^{-9}, 2^{-5}, 2^{-1}, 2^{1} and 2^{3}.

For the experiments with k-M, we tested with a variable number of clusters, i.e. with *num_clusters* values of 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100.

For the experiments with LR, we used the *liblinear* solver with C values of 2^{-10}, 2^{-6}, 2^{-2}, 2^{2}, 2^{6} and 2^{10}.

These variations on parameters allowed to train models with all possible configurations without the need to specifically adapt the parameters to the different datasets.

5.2.2 Garbled Circuits toolkits and parameters

For the experiments with Garbled Circuits (GC), we used the toolkit developed by VIPP group from the University of Siena[1]. This toolkit was not our first choice since it has known issues in computation times, but the other toolkits that we tested contained limitations that we could not overcome, as stated below:

- **ABY[21]:** We found it impossible to define gate-to-gate wires, and that removed the ability for fine control on how to use and combine wires.

[1] http://clem.dii.unisi.it/~vipp/index.php/home

- **JustGarble[7]:** This toolkit could not be fully compiled due to conflicts with current versions of the GNU gcc compiler.
- **Ciphermed[12]:** This toolkit is efficient for small DT, but is exponentially slower for larger trees (above 10 nodes).
- **TinyGarble[57]:** The current version of this toolkit does not support the open source synthesis tool (Yosis[2]) recommended by the authors, and only supports a paid one.
- **CompGC[30]:** The implementation of all the examples of ML algorithms in this toolkit are hardcoded, making it extremely difficult to adapt to our needs.

In the experiments using GC, we tested values of 8, 12, 16, 20 and 24 bits for the numeric precision of the data and model parameters. This will be reflected in the circuit size and the accuracy of the results. Larger values were not considered because 24 bits are already sufficient for an exact representation of the input values and model parameters.

5.2.3 Homomorphic Encryption toolkits and parameters

For the experiments using Partially Homomorphic Encryption (PHE), we implemented our own version of the Paillier cryptosystem [44]. We decided to do this way instead of using an existing toolkit because it was simple to implement and because it provided a good learning experience on the inner workings of a cryptographic system.

For the experiments using Fully Homomorphic Encryption (FHE), we used the HElib toolkit [31]. Two methods were considered in the implementation, method M1: multiply and sum arrays without packing, and method M2: use coefficient packing, invert and multiply polynomials, that was inspired in a HElib tutorial[3]. It is also important to note that, due to intrinsic limitations in HElib, we had to pre-compute $\alpha_i \cdot x_{SV}^{(i)}$ when evaluating the SVM. However, this does not negatively affect the experiments, since these model parameters are both owned by the same party.

[2] http://www.clifford.at/yosys/
[3] https://mshcruz.wordpress.com/2016/09/27/scalar-product-using-helib/

For the experiments using PHE, we used the values of 128, 256, 512, 1024 and 2048 bits (NBits) for the length of the cryptographic keys.

For the experiments using FHE, no parameter search was made, since adequate default values were pre-determined for most parameters, and we chose a large enough number for the modulus ($(2^{15})^4 = 2^{60}$). Changing these parameters should not affect the obtained predicted labels in any way, although they may have minimal effects on the actual output of the evaluation functions of LR and SVM algorithms. The values considered are too large to affect the results and correspond to a cryptographic security factor.

5.3 Experimental Results - Baseline

We now show the experimental results obtained by applying different ML algorithms to the datasets mentioned above. In each Subsection below, for each dataset, we present the different ML algorithms and parameters. The results shown in the following tables are the ones obtained in the testing sets using the parameters that provided the best accuracy or F-Measure results with the validation set. We also present results found in the literature, for comparison.

5.3.1 *Pima Indians Diabetes* Dataset

We present the best baseline results obtained in the testing set for the *Pima Indians Diabetes* Dataset in Table 5.2. We can see that our results are comparable to the ones found in the literature.

Table 5.2: Baseline results. *Pima Indians Diabetes* Dataset. "A" represents Accuracy, "F" represents F-Measure.

ML algorithm	**DT**	**k-Means**	**LR**	**SVM**		
				Linear	Poly	RBF
Baseline	A: 73.04% F: 63.53%	A: 72.17% F: 52.94%	A: 75.65% F: 58.82%	A: 75.65% F: 61.11%	A: 76.52% F: 59.70%	A: 77.39% F: 62.86%
Literature	A: 75.39%[5] F: -	A: 73.7%[25] F: -	A: 77.95%[5] F: -	A: - F: -	A: - F: -	A: 80.2%[1] F: -

5.3.2 *Breast Cancer Wisconsin Diagnostic* Dataset

We present the best baseline results obtained in the testing set for the *Breast Cancer Wisconsin Diagnostic* Dataset in Table 5.3. As we see, our baseline results are, again, close to the ones found in the literature.

Table 5.3: Baseline results. *Breast Cancer Wisconsin Diagnostic* Dataset. "A" represents Accuracy, "F" represents F-Measure.

ML algorithm	**DT**	**k-Means**	**LR**	**SVM**		
				Linear	Poly	RBF
Baseline	A: 92.94% F: 90.91%	A: 91.76% F: 90.91%	A: 95.29% F: 93.75%	A: 94.12% F: 92.06%	A: 94.12% F: 92.31%	A: 94.12% F: 92.06%
Literature	A: 95.13%[6] F: 94.88%[6]	A: 92.79%[4] F: -	A: 93.50%[49] F: -	A: - F: -	A: 97.54%[66] F: -	A: 97.13%[6] F: 96.25%[6]

5.3.3 *Credit Approval* Dataset

We present the best baseline results obtained in the testing set for the *Credit Approval* Dataset in Table 5.4. We obtained results that are similar to the ones found in the literature.

Table 5.4: Baseline results. *Credit Approval* Dataset. "A" represents Accuracy, "F" represents F-Measure.

ML algorithm	**DT**	**k-Means**	**LR**	**SVM**		
				Linear	Poly	RBF
Baseline	A: 78.64% F: 75.00%	A: 83.50% F: 81.32%	A: 85.44% F: 84.21%	A: 85.44% F: 84.54%	A: 85.43% F: 83.87%	A: 84.47% F: 83.33%
Literature	A: 85.5%[5] F: -	A: 86.3%[25] F: -	A: 87.9%[16] F: -	A: 86.2%[5] F: -	A: 84.8%[16] F: -	A: 85.5%[5] F: -

5.3.4 *Adult Income* Dataset

We present the best baseline results obtained in the testing set for the *Adult Income* Dataset in Table 5.5. We can see that our baseline results are comparable to the ones found in literature, and therefore are a good reference for the privacy-preserving platform.

[4] https://www.linkedin.com/pulse/using-k-means-clustering-tableau-diagnose-breast-cancer-mayand-tiwari

[5] http://docplayer.net/storage/53/32532528/1505920161/lql-Akt2A2T_EvaGfgnQww/32532528.pdf

[6] http://www.dudonwai.com/docs/gt-omscs-cs7641-a1.pdf?pdf=gt-omscs-cs7641-a1

Table 5.5: Baseline results. *Adult Income* Dataset. "A" represents Accuracy, "F" represents F-Measure.

ML algorithm	**DT**	**k-Means**	**LR**	**SVM**		
				Linear	Poly	RBF
Baseline	A: 85.56% F: 67.37%	A: 81.95% F: 55.80%	A: 85.08% F: 66.87%	A: 69.67% F: 57.04%	A: 80.82% F: 65.91%	A: 82.79% F: 61.15%
Literature	A: 82.20%[5] F: -	A: - F: -	A: 80.00%[5] F: -	A: - F: -	A: 84.55%[6] F: -	A: 84.93%[37] F: -

5.4 Experimental Results - Comparison with the Baseline

It is important to mention that, after analyzing the results obtained using the VIPP toolkit to implement GC, we verified that changing the amount of bits for the actual numeric precision of the data and model parameters affects the accuracy of the results. The degree of this error is depicted in Tables 5.6 and 5.7, for the experiments for DT and k-M respectively. It is to be noted that this error is computed versus the baseline prediction results, not the prediction labels from the dataset.

Table 5.6: GC+DT. Average label prediction error when compared with the baseline.

bits	**Pima Indians**	**Breast Cancer**	**Credit Approval**	**Adult Income**
8	1.88%	0.55%	8.70%	0.00%
12	0.00%	0.13%	1.11%	0.00%
16	0.00%	0.13%	0.31%	0.00%
20	0.00%	0.13%	0.31%	0.00%
24	0.00%	0.13%	0.31%	0.00%

Table 5.7: GC+k-M. Average label prediction error when compared with the baseline.

bits	**Pima Indians**	**Breast Cancer**	**Credit Approval**	**Adult Income**
8	2.03%	3.07%	0.05%	0.02%
12	0.39%	0.85%	0.00%	0.00%
16	0.29%	0.72%	0.00%	0.00%
20	0.29%	0.72%	0.00%	0.00%
24	0.00%	0.00%	0.00%	0.00%

By observing these tables, we can conclude that the loss of prediction performance caused by using the privacy-preserving versions of the ML algorithms is not relevant, as long as at least 16 bits are used to represent the data. Since both DT and k-M only output an integer representing the label, and not a real number, the visible effect of changing the number of

bits is minimal.

After analyzing the results obtained using the PHE and FHE systems, we verified that all predicted labels and almost all function evaluation outputs match the baseline. The few examples when an exact match does not happen come mostly from the SVM scoring evaluation function implemented in HElib, and are most likely caused by the accumulation of the intrinsic noise generated every time an operation is performed between two ciphertexts. Therefore, we can conclude that our privacy-preserving versions of the ML algorithms using PHE and FHE have no relevant loss of prediction performance.

5.5 Experimental Results - Execution Time

In order to better assess the execution time required by each privacy-preserving version of the different ML algorithms, we will analyze each of the combinations separately. We do not present total execution times for the whole datasets because execution times per sample are independent of the dataset size, and execution times per sample are the expected costs in a real-life scenario where a large computer cluster is available and data samples are supplied in a continuous fashion.

5.5.1 Garbled Circuits and Decision Trees

We present the execution times obtained by using the toolkit to build a GC implementation of DT for all the datasets in the tables below. The results are presented in terms of average pre-computation times per data sample and runtimes per data sample. Table 5.8 presents the average pre-computation times for each data sample for all datasets. We can observe that average pre-computation times are very similar to one another, despite the slight dependence on the size of the GC, which is defined by the numeric precision. This means that pre-computation poses no restrictions regarding the scalability of our approach.

Regarding the runtimes per data sample (Figure 5.1), we can observe that the results obtained dominate over the pre-computation times. Although they scale slightly sub-linearly with the

Table 5.8: GC+DT. Average pre-computation times per data sample, in seconds. All datasets.

dataset	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
Pima	0.219	0.285	0.310	0.344	0.356
Breast	0.205	0.240	0.281	0.325	0.356
Credit	0.224	0.253	0.271	0.290	0.315
Adult	0.233	0.271	0.313	0.355	0.373

Table 5.9: GC+DT. Runtime per data sample, in seconds. *Pima Indians Diabetes* dataset.

DT depth	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
1	0.374	0.502	0.663	0.782	0.901
4	0.457	0.548	0.677	0.888	1.087
6	0.654	0.877	1.051	1.177	1.195
8	1.622	1.689	1.889	2.099	2.180
10	3.469	3.644	3.112	4.300	4.343
12	7.884	9.727	12.459	16.270	17.488
13	16.289	18.353	20.926	25.120	33.508

Table 5.10: GC+DT. Runtime per data sample, in seconds. *Breast Cancer Wisconsin Diagnostic* dataset.

DT depth	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
1	1.015	1.383	1.735	2.082	2.442
3	1.057	1.425	1.804	2.187	2.550
4	1.107	1.533	1.920	2.319	2.724
5	1.307	1.713	2.122	2.665	2.974
6	1.538	2.030	2.522	2.939	3.330
7	1.966	2.393	2.823	3.507	3.787

Table 5.11: GC+DT. Runtime per data sample, in seconds. *Credit Approval* dataset.

DT depth	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	1.598	2.333	2.956	3.591	4.190
5	1.852	2.603	3.295	3.953	4.576
7	2.702	3.600	4.359	5.743	5.848
8	3.365	4.280	6.541	7.337	8.998
9	4.511	6.930	8.202	10.990	12.227

Table 5.12: GC+DT. Runtime per data sample, in seconds. *Adult Income* dataset.

DT depth	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
5	3.777	5.169	6.502	8.171	9.424
6	4.111	5.774	7.074	8.813	10.816
9	9.256	13.864	20.294	24.314	27.236
10	17.167	23.056	30.553	39.114	54.987

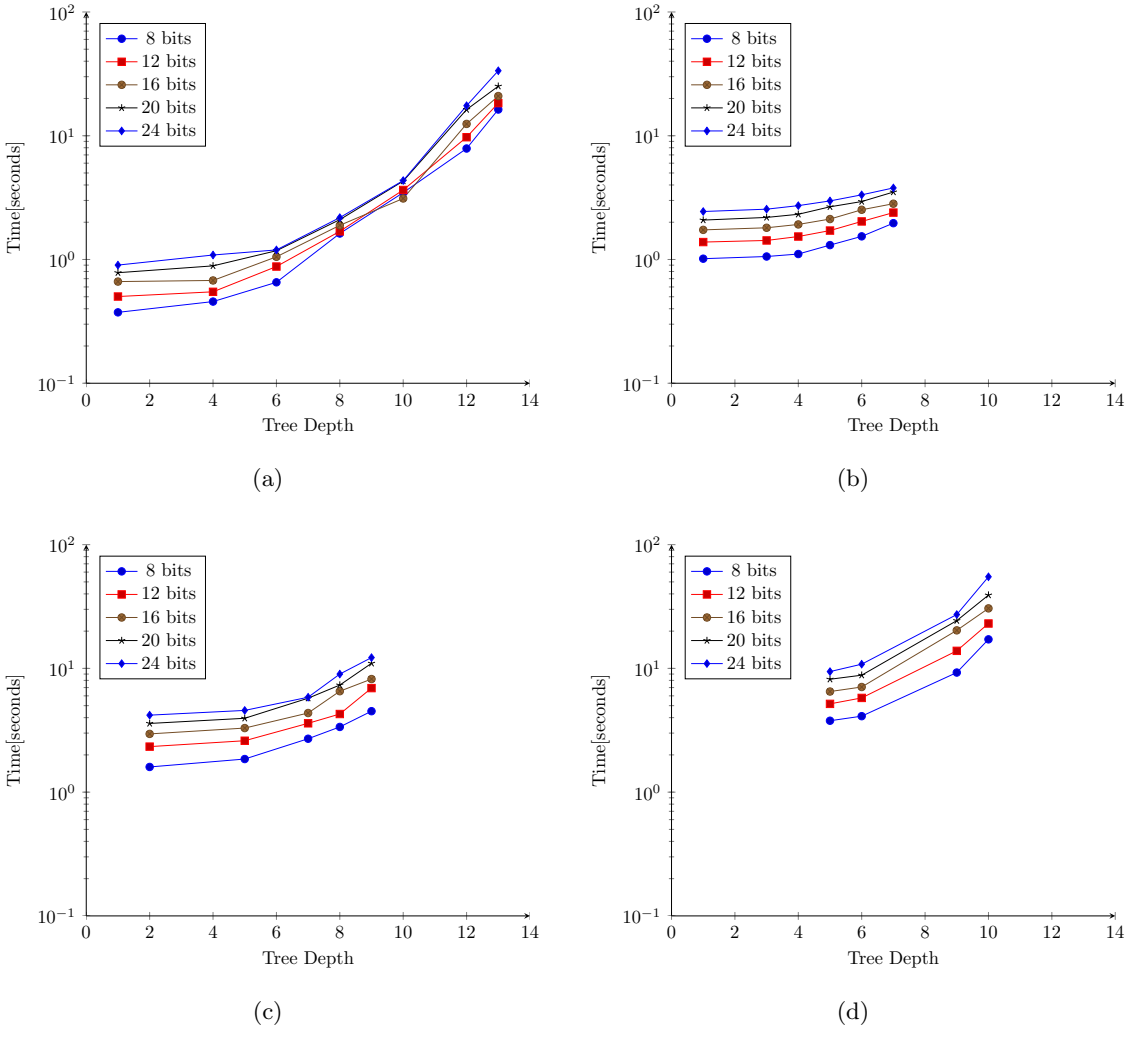


Figure 5.1: GC+DT. Runtime per data sample, in seconds. (a) *Pima Indians Diabetes* Dataset; (b) *Breast Cancer Wisconsin Diagnostic* Dataset; (c) *Credit Approval* Dataset; and, (d) *Adult Income* Dataset.

numeric precision and the number of features, they scale super-linearly with the number of nodes in the DT. This can be a problem in terms of scalability since we are using fully expanded DT, which means that increasing DT depth leads to an exponential increase in the number of nodes.

5.5.2 Garbled Circuits and *k*-Means

We present the execution times obtained by using the toolkit to build a GC implementation of *k*-M for all the datasets in the tables below. The results are presented in terms of average pre-computation times per data sample and runtimes per data sample. Table 5.13 presents the average pre-computation times for each data sample for all datasets. We can see that average pre-computation times are all very similar to one another despite the slight dependence on the GC size, meaning that it does not impact the scalability of our solution.

Table 5.13: GC+*k*-M. Average pre-computation times per data sample, in seconds.

dataset	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
Pima	0.260	0.283	0.307	0.331	0.339
Breast	0.225	0.251	0.274	0.289	0.301
Credit	0.226	0.249	0.253	0.265	0.272
Adult	0.214	0.214	0.232	0.266	0.262

Regarding the runtimes per data sample (Figure 5.2), we observe again that the results are much larger that the pre-computation times. They scale linearly with the number of features and slightly super-linearly with the number of clusters, none of which compromises the scalability of our approach. However, runtimes scale quadratically with the numeric precision, which is caused by the multiplications required to compute the Euclidean Distance (ED). Although this causes scalability issues for large numeric precision, the results in Table 5.7 show that the loss of accuracy is negligible even when only 12 bits are considered, allowing us to safely ignore this issue. The runtimes per data sample are also considerably large for the instances with a large number of clusters, but in our baseline system, we verified that the best results were always obtained when less than 10 clusters were considered. Even if this was not the case, we could sacrifice a small amount of accuracy by lowering the number

Table 5.14: GC+k-M. Runtime per data sample, in seconds. *Pima Indians Diabetes* dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	0.629	0.848	1.163	1.350	1.533
3	0.813	1.055	1.270	1.494	1.761
4	0.852	1.143	1.429	1.664	1.969
5	0.943	1.246	1.531	1.824	2.066
6	1.140	1.261	1.513	2.266	2.145
7	1.124	1.319	1.620	2.319	2.188
8	1.178	1.339	1.697	2.130	2.337
9	1.227	1.464	2.356	2.178	2.504
10	1.228	1.544	2.439	2.497	3.717
20	1.568	1.896	3.374	3.952	5.751
30	2.142	2.223	3.794	5.315	7.346
40	1.762	3.379	5.099	6.941	9.697
50	1.803	3.670	5.979	8.300	12.376
60	3.005	4.927	7.025	12.218	16.839
70	3.420	5.250	7.616	15.795	19.339
80	3.513	6.187	8.649	15.795	21.302
90	3.490	6.239	12.278	16.691	23.669
100	3.580	7.876	14.497	23.599	32.248

Table 5.15: GC+k-M. Runtime per data sample, in seconds. *Breast Cancer Wisconsin Diagnostic* dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	1.619	2.102	2.788	3.616	3.838
3	1.868	2.451	3.037	3.550	5.674
4	1.800	3.082	3.180	5.028	5.604
5	1.912	2.598	4.760	5.410	7.402
6	2.062	2.707	4.872	5.275	7.951
7	2.351	2.882	5.133	7.149	7.906
8	2.930	2.805	4.978	6.946	9.124
9	2.570	3.917	4.935	7.044	9.136
10	2.291	4.215	5.990	7.349	10.802
20	4.223	6.797	9.580	14.877	25.232
30	5.269	9.234	15.693	24.228	36.767
40	7.126	14.724	25.754	37.984	49.574
50	7.885	14.701	24.245	40.602	67.651
60	9.156	19.862	35.970	56.269	-
70	11.585	23.550	41.306	-	-
80	11.433	23.367	45.067	-	-
90	13.642	27.030	53.124	-	-
100	16.684	32.046	59.372	-	-

Table 5.16: GC+k-M. Runtime per data sample, in seconds. *Credit Approval* dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	2.541	3.652	4.151	5.729	6.837
3	2.615	3.752	5.547	6.369	8.512
4	2.902	3.663	5.934	8.114	9.692
5	3.016	5.036	5.825	8.633	10.725
6	3.129	5.359	7.474	9.820	12.961
7	3.058	5.216	7.463	10.031	16.429
8	3.033	5.360	7.912	11.342	15.633
9	3.082	5.326	8.911	13.911	19.112
10	4.196	6.569	9.412	14.731	18.997
20	6.368	10.641	19.121	28.797	44.666
30	9.060	17.660	28.409	49.931	-
40	11.152	25.673	42.835	-	-
50	14.681	27.539	54.795	-	-
60	18.326	37.088	-	-	-
70	19.318	41.164	-	-	-
80	23.371	56.422	-	-	-
90	27.361	62.862	-	-	-
100	27.908	67.835	-	-	-

Table 5.17: GC+k-M. Runtime per data sample, in seconds. *Adult Income* dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	4.703	5.536	8.098	11.307	13.672
3	4.361	7.535	9.620	14.500	18.896
4	4.396	6.986	10.364	15.635	20.343
5	6.083	8.688	11.681	17.928	25.292
6	5.587	11.307	15.884	23.006	31.464
7	6.441	10.278	15.981	24.306	31.277
8	6.394	10.871	17.157	27.155	38.732
9	8.029	12.958	21.050	32.607	48.497
10	8.706	14.956	24.468	32.010	47.241
20	14.834	24.567	41.386	-	-
30	19.150	39.870	-	-	-
40	27.248	60.023	-	-	-
50	33.243	-	-	-	-
60	42.933	-	-	-	-
70	52.514	-	-	-	-
80	61.952	-	-	-	-
90	-	-	-	-	-
100	-	-	-	-	-

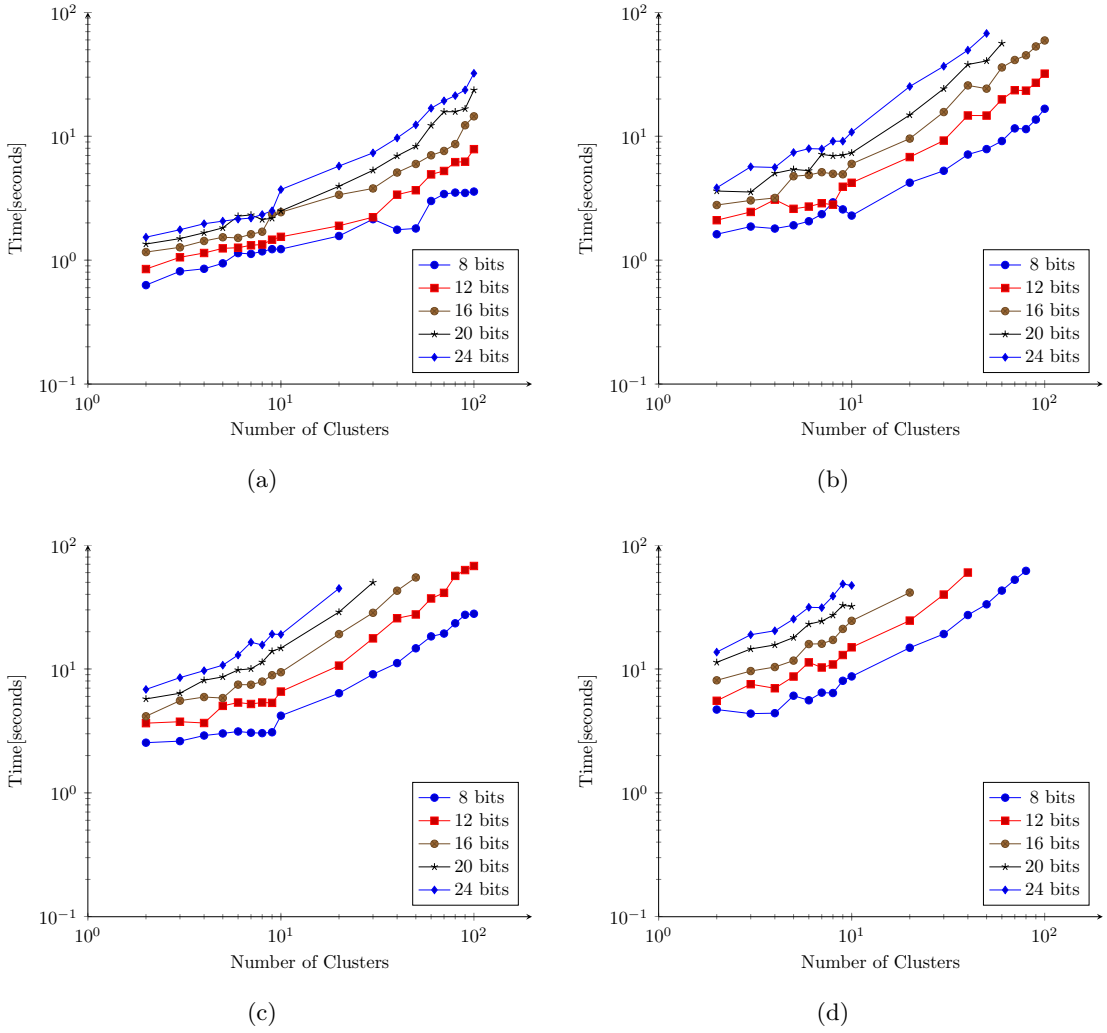


Figure 5.2: GC+k-M. Runtime per data sample, in seconds. (a) *Pima Indians Diabetes* Dataset; (b) *Breast Cancer Wisconsin Diagnostic* Dataset; (c) *Credit Approval* Dataset; and, (d) *Adult Income* Dataset.

of clusters considered in order to obtain much faster runtimes. Finally, it is important to mention that we did not compute all the entries in the tables above because the execution times for the larger datasets were becoming very long as the number of clusters and numeric precision grew and some examples were impossible to run due to insufficient RAM memory.

5.5.3 Homomorphic Encryption and Logistic Regression

As mentioned in Section 3.4, the results presented in this section were developed by other team members in the Big dAta pRivacy by Design platform (BARD) project at Altran, and are presented for completeness purposes.

We present the execution times obtained by using the PHE and FHE systems for all datasets in the tables below. For the FHE system, we present the times for methods M1 and M2 in the same cell, for ease of comparison. The results are presented in terms of execution time per data sample.

Table 5.18: PHE+LR. Execution time in seconds. *Pima Indians Diabetes* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.002	0.001	0.000
256	0.005	0.001	0.000
512	0.014	0.003	0.002
1024	0.035	0.004	0.005
2048	0.168	0.014	0.025

Table 5.19: PHE+LR. Execution time in seconds. *Breast Cancer Wisconsin Diagnostic* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.005	0.002	0.000
256	0.013	0.004	0.000
512	0.024	0.005	0.001
1024	0.100	0.018	0.005
2048	0.570	0.028	0.020

When observing the execution times obtained using PHE (Figure 5.3), we see that a linear

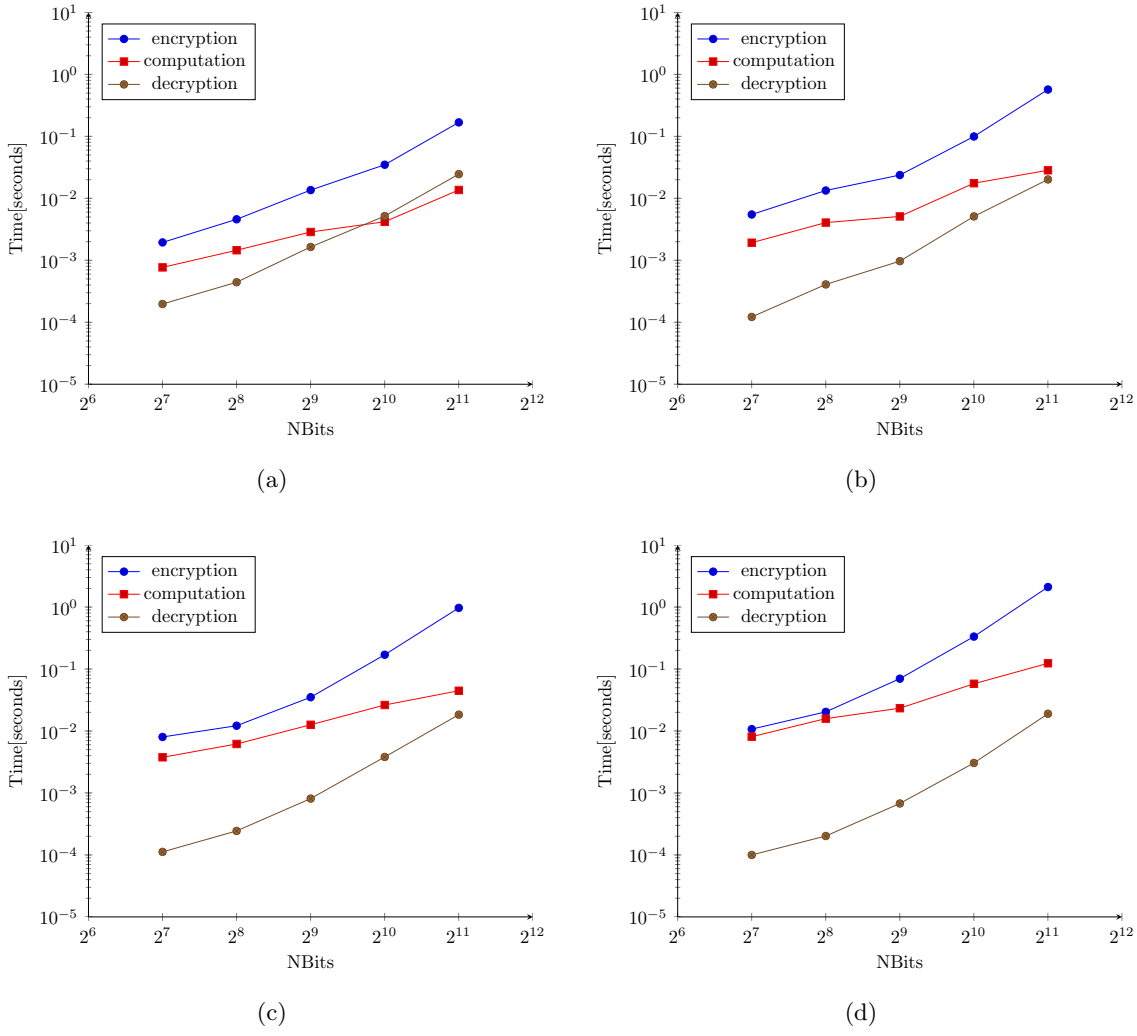


Figure 5.3: PHE+LR. Execution time per data sample, in seconds. (a) *Pima Indians Diabetes* Dataset; (b) *Breast Cancer Wisconsin Diagnostic* Dataset; (c) *Credit Approval* Dataset; and, (d) *Adult Income* Dataset.

Table 5.20: PHE+LR. Execution time in seconds. *Credit Approval* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.008	0.004	0.000
256	0.012	0.006	0.000
512	0.035	0.013	0.001
1024	0.170	0.026	0.004
2048	0.970	0.045	0.018

Table 5.21: PHE+LR. Execution time in seconds. *Adult Income* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.011	0.008	0.000
256	0.020	0.016	0.000
512	0.070	0.023	0.001
1024	0.334	0.058	0.003
2048	2.106	0.124	0.019

increase in encryption and computation times when the number of features in the samples increases, but a constant decryption time, independent of the number of features. We can also observe a linear increase in computation times, and a super-linear increase in encryption and decryption times, when the value of NBits increases. This can cause a problem of scalability, but it can be safely ignored since the execution times per sample are still very small.

Table 5.22: FHE+LR. Execution time in seconds. All Datasets.

dataset	**Execution time / data sample**		
	encryption	computation	decryption
Pima	M1: 2.193 M2: 0.168	M1: 0.049 M2: 0.005	M1: 0.036 M2: 0.036
Breast	M1: 7.494 M2: 0.168	M1: 0.169 M2: 0.005	M1: 0.036 M2: 0.036
Credit	M1: 12.467 M2: 0.180	M1: 0.296 M2: 0.006	M1: 0.038 M2: 0.038
Adult	M1: 24.253 M2: 0.169	M1: 0.590 M2: 0.005	M1: 0.036 M2: 0.036

When analyzing the results obtained using FHE (Table 5.22 and Figure 5.4), we can observe that the packing used by method M2 greatly decreases the encryption and computation times,

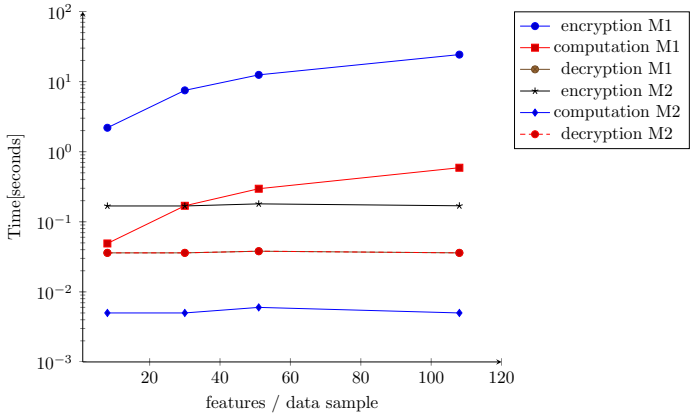


Figure 5.4: FHE+LR. Execution time per data sample, in seconds. All Datasets.

when compared to method M1. We also observe that method M2 makes the encryption and computation times independent from the number of features. Overall, we see that method M2 is much more efficient that method M1, showing the obvious advantage of packing the features for each dataset in a single ciphertext before performing any computation.

When comparing PHE and FHE, we observe that method M2 of FHE has lower execution times than PHE, despite the complexity of the algorithm behind it. The only possible justification for this is the positive effect caused by feature packing, especially due to the gains in encryption time.

5.5.4 Homomorphic Encryption and Support Vector Machines

Again, as mentioned in Section 3.4, the results presented in this section were developed by other team members in the BARD project at Altran, and are presented for completeness purposes.

We present the execution times obtained by using the PHE and FHE systems for all datasets in the tables below. Once again, for the FHE system, we present the times for methods M1 and M2 in the same cell, for ease of comparison. The results are presented in terms of execution time per data sample for the PHE case, and execution time per sample and support vector for the FHE case.

Table 5.23: PHE+SVM. Execution time in seconds. *Pima Indians Diabetes* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.001	0.033	0.000
256	0.001	0.054	0.000
512	0.005	0.096	0.001
1024	0.024	0.221	0.003
2048	0.185	0.747	0.025

Table 5.24: PHE+SVM. Execution time in seconds. *Breast Cancer Wisconsin Diagnostic* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.002	0.026	0.000
256	0.005	0.043	0.000
512	0.018	0.085	0.001
1024	0.093	0.213	0.003
2048	0.572	0.663	0.019

Table 5.25: PHE+SVM. Execution time in seconds. *Credit Approval* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.003	0.026	0.000
256	0.008	0.042	0.000
512	0.030	0.084	0.001
1024	0.155	0.208	0.003
2048	0.964	0.593	0.019

Table 5.26: PHE+SVM. Execution time in seconds. *Adult Income* Dataset.

NBits	**Execution time / data sample**		
	encryption	computation	decryption
128	0.007	0.317	0.000
256	0.016	0.492	0.000
512	0.066	1.051	0.001
1024	0.344	2.504	0.003
2048	2.057	6.982	0.019

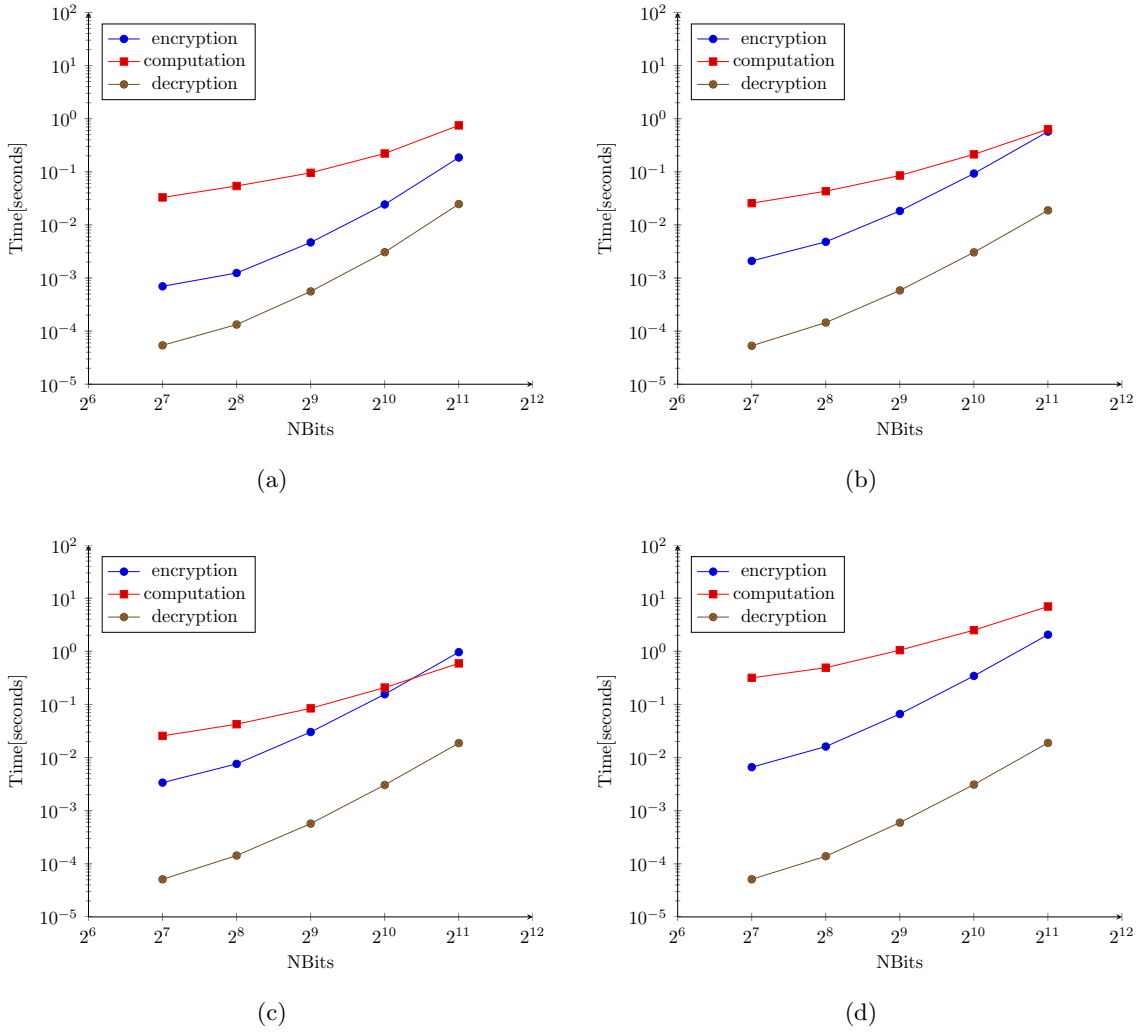


Figure 5.5: PHE+SVM. Execution time per data sample, in seconds. (a) *Pima Indians Diabetes* Dataset; (b) *Breast Cancer Wisconsin Diagnostic* Dataset; (c) *Credit Approval* Dataset; and, (d) *Adult Income* Dataset.

When observing the execution times obtained using PHE (Figure 5.5), we can see that computation times have a significant overhead for small amounts of number of features and number of Support Vectors, as they only affect the results in the *Adult Income* Dataset, where they seem to have a linear dependency. We also observe a linear increase in encryption times with increasing the number of features and a linear increase in computation times with increasing NBits. Finally, we can see that decryption times are constant with increasing number of features and number of Support Vectors, but we verify that there is a slightly super-linear increase in encryption and decryption times with increasing NBits. This can cause a problem of scalability, but it can be safely ignored since the execution times per sample are still very small.

Additionally, for SVM we obtained similar encryption times to the ones obtained for LR, which is not surprising since the encryption is only done on one side of the protocol (due to the way the Paillier cryptosystem works). Also, we can observe that decryption times are comparable in both cases, as decryption only occurs once, when all operations have been performed.

Table 5.27: FHE+SVM. Execution time in seconds. All Datasets.

dataset	**Execution time / data sample**		
	encryption	computation	decryption
Pima	M1: 1.127 M2: 0.231	M1: 0.104 M2: 0.199	M1: 0.058 M2: 0.052
Breast	M1: 4.100 M2: 0.233	M1: 0.359 M2: 0.200	M1: 0.058 M2: 0.053
Credit	M1: 5.892 M2: 0.235	M1: 0.615 M2: 0.201	M1: 0.059 M2: 0.053
Adult	M1: 11.895 M2: 0.232	M1: 1.296 M2: 0.199	M1: 0.057 M2: 0.053

When observing the execution times obtained using FHE (Table 5.27 and Figure 5.6), we can see similar results to those obtained for LR. In particular, we see that the packing used by method M2 greatly decreases the encryption and computation times, when compared with method M1, as well as making the encryption and computation times independent from both the number of features and the number of Support Vectors. We can also observe that the

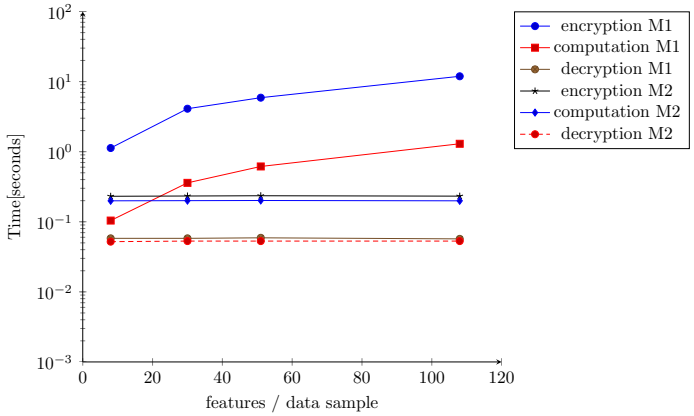


Figure 5.6: FHE+SVM. Execution time per data sample, in seconds. All datasets.

decryption times are independent of the method used, the number of features and the number of Support Vectors.

Once again, we can see that the method M2 is much more efficient than method M1, showing the obvious advantage of packing the features for each dataset in a single ciphertext before performing the computation.

When comparing PHE and FHE, unlike what was observed for LR, here the former has lower execution times that the latter. Even considering the feature packing of method M2, the fact that many multiplications have to be made (one for each Support Vector) overwhelms FHE when compared with PHE for evaluating an SVM.

5.6 Experimental Results - Communication Cost

As we will see in this Section, the communication cost is primarily defined by the cryptographic techniques considered and only secondarily by the ML algorithms. We will focus on the former and address each of the specifics of the latter as needed. Given that cryptographic keys only need to be sent once and the ciphertext containing the desired result also only needs to be sent once, the bulk of the communication cost comes from the transmitting and receiving ciphertexts containing the actual data values. Since the amount of bytes sent by one of the parties is equal to the amount received by the other, and vice-versa, we will only present

costs from one of the parties. We also do not present total communication costs for the whole datasets because communication costs per sample are independent of the dataset size, and communication costs per sample are the expected costs in a real-life scenario where a large computer cluster is available and data samples are supplied in a continuous fashion.

5.6.1 Garbled Circuits and Decision Trees

We present the communication costs obtained by using a GC implementation of DT for all datasets in the tables below. We present results in terms of average amount of bytes per data sample sent during pre-computation, received during pre-computation and sent during runtime, and the number of bytes per data sample received during runtime by the GC evaluator.

Table 5.28: GC+DT. Average amount of bytes per data sample (in kB) sent during pre-computation (PC-S), received during pre-computation (PC-R) and sent during runtime (R-S) by the GC evaluator. All datasets.

dataset	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
Pima	PC-S: 1.055 PC-R: 2.342 R-S: 8.441	PC-S: 1.583 PC-R: 3.513 R-S: 12.662	PC-S: 2.110 PC-R: 4.685 R-S: 16.883	PC-S: 2.638 PC-R: 5.856 R-S: 21.104	PC-S: 3.166 PC-R: 7.027 R-S: 25.324
Breast	PC-S: 1.055 PC-R: 2.342 R-S: 31.656	PC-S: 1.583 PC-R: 3.514 R-S: 47.483	PC-S: 2.110 PC-R: 4.685 R-S: 63.311	PC-S: 2.638 PC-R: 5.856 R-S: 79.139	PC-S: 3.165 PC-R: 7.027 R-S: 94.967
Credit	PC-S: 1.055 PC-R: 2.342 R-S: 53.815	PC-S: 1.583 PC-R: 3.514 R-S: 80.722	PC-S: 2.110 PC-R: 4.685 R-S: 107.628	PC-S: 2.638 PC-R: 5.812 R-S: 134.536	PC-S: 3.166 PC-R: 7.027 R-S: 161.444
Adult	PC-S: 1.055 PC-R: 2.342 R-S: 113.961	PC-S: 1.583 PC-R: 3.514 R-S: 170.940	PC-S: 2.110 PC-R: 4.685 R-S: 227.919	PC-S: 2.638 PC-R: 5.855 R-S: 284.901	PC-S: 3.166 PC-R: 7.027 R-S: 341.881

In Table 5.28, we can see that all communication costs per data sample increase linearly with the variables of interest. Both the number of bytes sent and received by the GC evaluator during pre-computation depend only on the numeric precision, and the amount of bytes sent during runtime depends only on the numeric precision and the number of features.

Regarding the amount of bytes per data sample received during runtime (Tables 5.29, 5.30,

Table 5.29: GC+DT. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Pima Indians Diabetes* Dataset.

DT	**numeric precision**				
depth	8 bits	12 bits	16 bits	20 bits	24 bits
1	23.542	34.941	46.339	57.743	69.137
4	90.858	131.485	172.120	212.741	253.369
6	321.667	462.496	603.318	744.170	885.012
8	1244.83	1786.52	2328.19	2869.91	3411.55
10	4937.70	7082.78	9227.74	11372.8	13517.9
12	19708.8	28267.3	36825.7	45384.2	53942.9
13	39403.7	56513.5	73623.3	90733.1	107843

Table 5.30: GC+DT. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Breast Cancer Wisconsin Diagnostic* Dataset.

DT	**numeric precision**				
depth	8 bits	12 bits	16 bits	20 bits	24 bits
1	85.280	127.547	169.814	212.084	254.348
3	175.738	261.128	346.551	431.980	517.377
4	296.296	439.239	582.210	725.153	868.094
5	537.460	795.483	1053.44	1311.47	1569.51
6	1019.83	1507.91	1996.08	2484.10	2972.24
7	1984.46	2932.86	3881.12	4829.36	5777.78

Table 5.31: GC+DT. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Credit Approval* Dataset.

DT	**numeric precision**				
depth	8 bits	12 bits	16 bits	20 bits	24 bits
2	193.908	289.759	385.628	481.480	577.331
5	889.564	1323.15	1756.74	2190.37	2623.99
7	3274.64	4866.18	6457.81	8049.41	9640.96
8	6454.73	9590.25	12725.9	15861.4	18997.0
9	12815.1	19038.6	25262.1	31485.6	37709.3

Table 5.32: GC+DT. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Adult Income* Dataset.

DT	**numeric precision**				
depth	8 bits	12 bits	16 bits	20 bits	24 bits
5	1843.72	2753.97	3664.21	4574.43	5484.64
6	3485.83	5205.30	6924.63	8643.95	10363.3
9	26476.2	39523.2	52569.9	65617.1	78663.8
10	52751.1	78743.8	104736	130729	156721

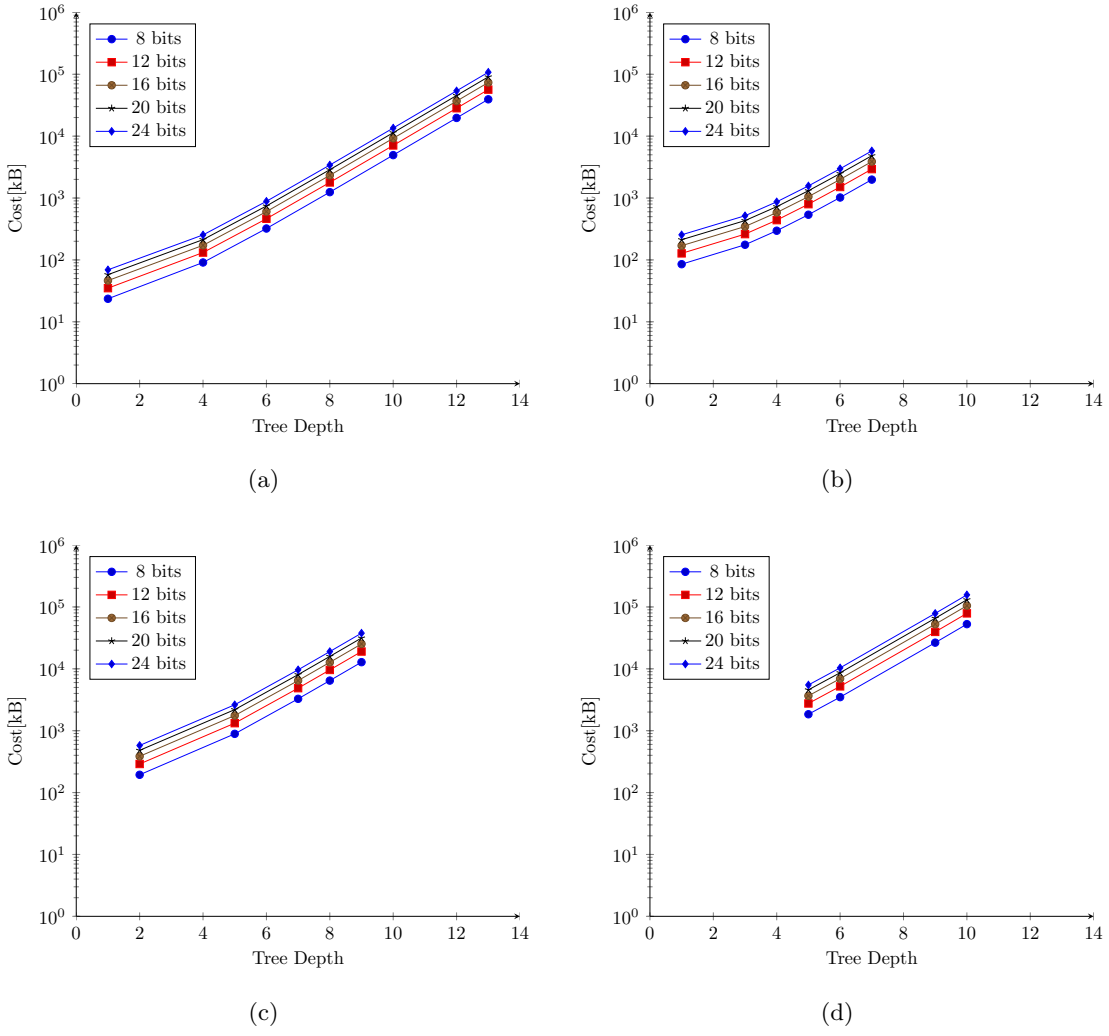


Figure 5.7: GC+DT. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. (a) *Pima Indians Diabetes* Dataset; (b) *Breast Cancer Wisconsin Diagnostic* Dataset; (c) *Credit Approval* Dataset; and, (d) *Adult Income* Dataset.

5.31, 5.32, and Figure 5.7), they depend linearly on the numeric precision, on the number of features and on the number of DT nodes, and therefore do not compromise the scalability of our approach. For larger DT, the communication cost gets considerably large, but it can be easily minimized by using the original DT instead of the fully expanded ones.

5.6.2 Garbled Circuits and *k*-Means

We present the communication costs obtained by using a GC implementation of *k*-M for all datasets in the tables below. We present results in terms of the average number of bytes per data sample sent during pre-computation, received during pre-computation and sent during runtime, and the number of bytes per data sample received during runtime by the GC evaluator.

Table 5.33: GC+*k*-M. Average amount of bytes per data sample (in kB) sent during pre-computation (PC-S), received during pre-computation (PC-R) and sent during runtime (R-S) by the GC evaluator. All datasets.

dataset	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
Pima	PC-S: 1.055 PC-R: 2.342 R-S: 8.442	PC-S: 1.583 PC-R: 3.514 R-S: 12.662	PC-S: 2.110 PC-R: 4.685 R-S: 16.883	PC-S: 2.638 PC-R: 5.856 R-S: 21.104	PC-S: 3.166 PC-R: 7.027 R-S: 25.324
Breast	PC-S: 1.055 PC-R: 2.342 R-S: 31.656	PC-S: 1.583 PC-R: 3.514 R-S: 47.483	PC-S: 2.110 PC-R: 4.685 R-S: 63.311	PC-S: 2.638 PC-R: 5.856 R-S: 79.139	PC-S: 3.166 PC-R: 7.027 R-S: 94.967
Credit	PC-S: 1.055 PC-R: 2.342 R-S: 53.815	PC-S: 1.583 PC-R: 3.514 R-S: 80.722	PC-S: 2.110 PC-R: 4.685 R-S: 107.629	PC-S: 2.638 PC-R: 5.856 R-S: 134.536	PC-S: 3.166 PC-R: 7.027 R-S: 161.444
Adult	PC-S: 1.055 PC-R: 2.342 R-S: 113.960	PC-S: 1.583 PC-R: 3.514 R-S: 170.941	PC-S: 2.110 PC-R: 4.685 R-S: 227.921	PC-S: 2.638 PC-R: 5.856 R-S: 284.901	PC-S: 3.166 PC-R: 7.027 R-S: 341.881

In Table 5.33, we can see that all communication costs per data sample increase linearly with the variables of interest. Both the number of bytes sent and received by the GC evaluator during pre-computation depend only on the numeric precision, and the amount of bytes sent during runtime depends only on the numeric precision and the number of features.

Regarding the amount of bytes per data sample received during runtime (Tables 5.34, 5.35,

Table 5.34: GC+k-M. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Pima Indians Diabetes* Dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	309.849	591.326	961.850	1421.45	1970.15
3	456.502	874.347	1425.81	2110.88	2929.57
4	603.113	1157.36	1889.79	2800.34	3889.04
5	749.726	1440.35	2353.72	3489.77	4848.50
6	896.376	1723.41	2817.74	4179.15	5807.92
7	1042.96	2006.43	3281.61	4868.58	6767.40
8	1189.58	2289.42	3745.53	5557.99	7726.80
9	1336.19	2572.47	4209.50	6247.40	8686.30
10	1482.85	2855.49	4673.53	6936.81	9645.61
20	2949.03	5685.65	9312.94	13831.1	19240.0
30	4415.20	8515.81	13952.4	20725.3	28834.3
40	5881.34	11345.9	18592.0	27619.6	38428.7
50	7347.55	14176.2	23231.6	34514.1	48023.0
60	8813.84	17006.3	27871.1	41408.0	57617.9
70	10280.0	19836.4	32510.5	48302.4	67211.9
80	11746.1	22665.5	37510.1	55196.6	76806.3
90	13212.4	25496.9	41789.7	62090.9	86400.4
100	14678.6	28326.8	46429.1	68985.2	95995.1

Table 5.35: GC+k-M. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Breast Cancer Wisconsin Diagnostic* Dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	1160.22	2215.08	3604.00	5326.97	7383.92
3	1706.36	3271.44	5337.51	7904.74	10973.1
4	2252.49	4327.76	7071.10	10482.5	14562.2
5	2798.68	5384.18	8804.74	13060.4	18151.1
6	3344.74	6440.50	10538.2	15638.3	21740.2
7	3890.90	7496.85	12271.9	18215.9	25329.3
8	4437.04	8553.14	14005.4	20793.9	28918.7
9	4983.15	9609.47	15739.1	23371.7	32507.7
10	5529.26	10666.0	17472.6	25949.5	36096.7
20	10990.4	21229.2	34808.3	51728.0	71987.3
30	16451.7	31792.6	52144.1	77506.3	107878
40	21913.0	42356.3	69479.9	103284	143769
50	27374.2	52919.6	86815.3	129062	179660
60	32835.5	63482.7	104151	154841	-
70	38296.9	74046.3	121487	-	-
80	43758.2	84609.9	138822	-	-
90	49219.1	95173.1	156159	-	-
100	54680.5	105737	173494	-	-

Table 5.36: GC+k-M. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Credit Approval* Dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	1972.05	3765.09	6126.07	9054.88	12551.6
3	2899.50	5559.67	9071.71	13435.4	18650.7
4	3827.13	7354.19	12017.0	17815.7	24750.1
5	4754.49	9148.68	14962.5	22196.1	30849.3
6	5682.00	10943.2	17908.1	26576.5	36948.4
7	6609.56	12737.8	20853.7	30956.8	43047.6
8	7536.99	14532.3	23799.2	35337.2	49146.9
9	8464.34	16326.9	26744.6	39717.9	55246.2
10	9391.91	18121.3	29690.1	44098.0	61345.4
20	18666.6	36066.6	59145.0	87901.8	122338
30	27941.7	54011.9	88600.0	131706	-
40	37216.4	71957.2	118055	-	-
50	46491.1	89902.4	147510	-	-
60	55765.9	107848	-	-	-
70	65040.7	125793	-	-	-
80	74315.8	143738	-	-	-
90	83590.5	161683	-	-	-
100	92865.1	179629	-	-	-

Table 5.37: GC+k-M. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. *Adult Income* Dataset.

number clusters	**numeric precision**				
	8 bits	12 bits	16 bits	20 bits	24 bits
2	4174.78	7971.66	12971.1	19173.0	26577.5
3	6136.87	11769.3	19205.7	28445.8	39489.5
4	8098.94	15567.1	25440.1	37718.2	52401.5
5	10061.2	19364.8	31675.0	46990.8	65313.5
6	12023.2	23162.6	37909.2	56263.7	78225.4
7	13985.3	26960.3	44143.4	65536.3	91137.4
8	15947.4	30757.9	50378.0	74808.8	104049
9	17909.6	34555.5	56612.9	84081.3	116961
10	19871.7	38353.1	62847.2	93354.2	129873
20	39493.0	76330.2	125193	-	-
30	59114.1	114307	-	-	-
40	78735.3	152284	-	-	-
50	98356.6	-	-	-	-
60	117978	-	-	-	-
70	137598	-	-	-	-
80	157221	-	-	-	-
90	-	-	-	-	-
100	-	-	-	-	-

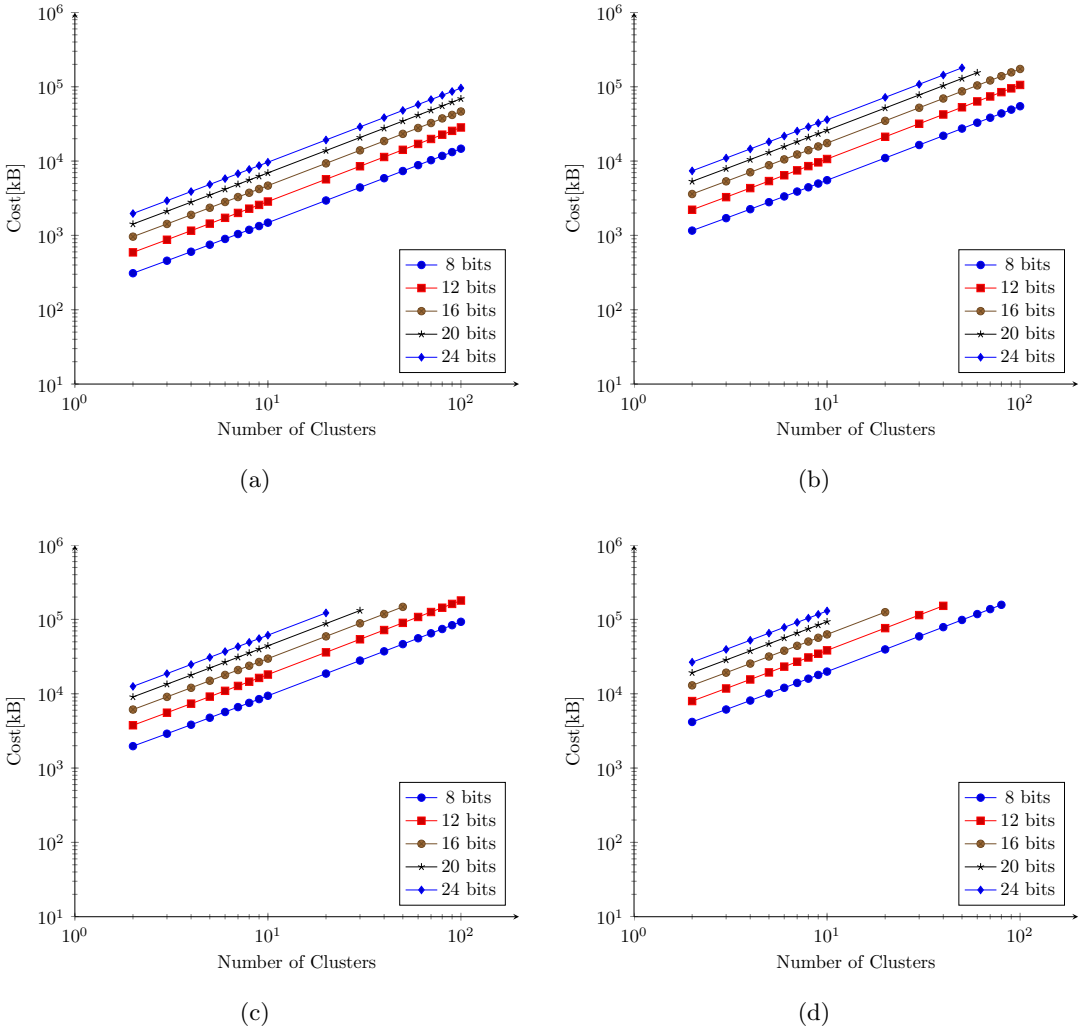


Figure 5.8: GC+k-M. Amount of bytes per data sample (in kB) received during runtime by the GC evaluator. (a) *Pima Indians Diabetes* Dataset; (b) *Breast Cancer Wisconsin Diagnostic* Dataset; (c) *Credit Approval* Dataset; and, (d) *Adult Income* Dataset.

5.36, 5.37, and Figure 5.8), they depend linearly on the number of features and the number of clusters, and quadratically on the numeric precision. However, as we have seen before, the results on Table 5.7 showed that the loss of accuracy is negligible even when only 12 bits are considered, meaning we can easily minimize its effects. Finally, it is important to mention that we did not compute all the entries in the tables above because the execution times for the larger datasets were becoming very long as the number of clusters and numeric precision grew and some examples were impossible to run due to insufficient RAM memory.

5.6.3 Partially Homomorphic Encryption

As mentioned in Section 3.4, the results presented in this section were developed in the BARD project at Altran, and are presented for completeness purposes.

For the PHE systems, both the key size and the ciphertexts size depend only on the number of bits chosen (NBits). For the Paillier cryptosystem in particular, both the public and private keys are composed of two $2 * \text{NBits}$ numbers and any ciphertext is a $2 * \text{NBits}$ number.

Under the assumption that one of the parties owns the data to be evaluated and the other owns the evaluation model and has the computational power to perform the evaluation, we only need to determine the communication cost of transmitting the data to be evaluated from one party to the other. This cost is independent of the ML algorithm considered.

For each of the data samples, each individual feature value needs to be encrypted. The communication cost, in bits, is therefore given by:

$$cost_{comm} = \underbrace{2(2\text{NBits})}_{\text{public key}} + \underbrace{Nn(2\text{NBits})}_{\text{ciphered data}} + \underbrace{2\text{NBits}}_{\text{ciphered result}} \tag{5.5}$$

where N is the number of samples and n is the number of features per sample. As mentioned before, the ciphertexts containing the actual data overwhelm the other contributions. We present the communication costs for the datasets considered in Table 5.38.

As expected, the communication costs increase linearly with increasing NBits, the number

Table 5.38: PHE. Communication costs in kilobytes (kB). All datasets.

NBits	Pima	Breast Cancer	Credit Approval	Adult Income
	cost / sample	cost / sample	cost / sample	cost / sample
128	0.352	1.056	1.728	3.552
256	0.704	2.112	3.456	7.104
512	1.408	4.224	6.912	14.208
1024	2.816	8.448	13.824	28.416
2048	5.632	16.896	27.648	56.832

of samples and the number of features. The communication costs for most datasets are considerably small, around a few megabytes. Even for the larger dataset, the *Adult Income* Dataset, the larger costs are due only to the much higher number of samples considered; the cost per sample is still around a few kilobytes.

5.6.4 Fully Homomorphic Encryption

As mentioned in Section 3.4, the results presented in this section were developed in the BARD project at Altran, and are presented for completeness purposes.

Considering the FHE system used by the HElib toolkit, there was no easy way to precisely compute the total communication cost. The details of the cryptographic key generation process are not included in the toolkit documentation, and both the cryptographic keys and the ciphertexts are represented using their own structure. By printing several examples of cryptographic keys and ciphertexts, we estimated that each key is composed of approximately 400,000 64-bit values (total:$w_{key} \approx 3200\text{kB} = 3.2\text{MB}$) and each ciphertext is composed of approximately 100,000 64-bit values (total:$w_{ciphertext} \approx 800\text{kB} = 0.8\text{MB}$).

Under the assumption that one of the parties owns the data to be evaluated and the other owns the evaluation model and has the computational power to perform the evaluation, we only need to determine the communication cost of transmitting the data to be evaluated from one party to the other. This cost is independent of the ML algorithm considered.

For each of the data samples, each individual feature value needs to be encrypted. The communication cost, in bits, is therefore given by:

$$cost_{comm} = \underbrace{w_{key}}_{publickey} + \underbrace{Nnw_{ciphertext}}_{ciphereddata} + \underbrace{w_{ciphertext}}_{cipheredresult} \tag{5.6}$$

where N is the number of samples and n is the number of features per sample. As mentioned before, the ciphertexts containing the actual data overwhelm the other contributions. We present the communication costs for the datasets considered in Table 5.39.

Table 5.39: FHE. Communication costs in Megabytes (MB). All datasets.

Pima	**Breast Cancer**	**Credit Approval**	**Adult Income**
cost / sample	cost / sample	cost / sample	cost / sample
10.4	28.0	44.8	90.4

Once again, the communication costs increase linearly with increasing NBits, the number of samples and the number of features. However, we can observe the negative effect of the extremely long keys required by the FHE system. The communication costs for all datasets are extremely high. Even if only a single data sample is considered, several megabytes are required for transmitting the corresponding ciphertext.

5.7 Experimental Results - Conclusions

To conclude this chapter, we now make some final observations on the obtained results, analyzing the advantages and disadvantages of our GC and Homomorphic Encryption (HE) approaches.

Although we did not compare the performance of GC and HE directly, for instance by choosing a ML algorithm and implementing it using both privacy-preserving techniques, it is clear that the HE approach is adequate for ML algorithms that rely on arithmetic operations, and the GC approach is adequate for ML algorithms that rely on non-arithmetic operations. An example pointing in this direction is the quadratic increase in runtime verified in the GC+k-M experiments, due to the need to perform multiplications to compute the ED.

An important remark on our experiments with GC is related to our choice to only analyze fully expanded DT instead of the original ones, in order to prevent any information leakage

regarding the shape of the original tree. However, in most cases this causes an exponential growth of the number of nodes with increasing tree depths, leading to proportional increases in both the execution times and the communication costs.

Another important conclusion with our experiments with HE is when each of the techniques should be used. We verified that PHE is, in fact, usable in practice but under some restrictions (e.g.: if there is no need for complex composition of operations and if data is separated between client and server), while FHE is more flexible but still too computationally expensive. However, due to the data packing "trick", FHE can be more efficient than PHE for evaluating some ML algorithms (e.g.: LR).

5.8 Summary

In this chapter, we detailed the experiments that were conducted in implementing our solution. In Section 5.1, we presented the metric used in evaluating the results obtained. Section 5.2 detailed the setup that was used to run the experiments, as well as the toolkits used. In Section 5.3, we presented the baseline results obtained for the datasets in question, and in Section 5.4 we compared those results with the ones obtained using the toolkits. In Section 5.5, we presented the execution times for the implementation, and in Section 5.6 we presented the communication costs for the implementation. Finally, in Section 5.7, we made the final observations on the results obtained.

6 Conclusion

Big data is very useful for the operation and improvement of everyday services, but because data contain private information about individuals, it cannot be freely processed because it leads to breaches of private information. Privacy-preserving processing techniques can be helpful in mitigating this problem.

In this thesis we have presented BARD, a privacy-preserving Machine Learning (ML) platform to provide companies with the means to apply the privacy-preserving paradigm in their Big Data operations. We discussed the existing techniques that provide the level of privacy compliant with the laws in force and matched those techniques with the most commonly used ML algorithms.

We evaluated our solution using publicly available datasets that reflect subjects of relevance. We show that the platform is generic and can be used for other use cases. We compared two privacy-preserving techniques, Garbled Circuits (GC) and Homomorphic Encryption (HE), and identified their limitations, when computing comparisons or arithmetic operations. We were also able to observe the overhead that is caused by these techniques when compared to a baseline that is significant.

With this work, we showed that is possible to provide accurate privacy-preserving ML platforms that achieve a level of privacy compliant with the laws in force while also maintaining the quality of data for knowledge learning.

6.1 Future Work

For future work, we propose the following points to enhance the functionalities of the platform and its performance: extend the platform to work with more ML algorithms (ex: Neural Networks or Naive Bayes), so that the platform can be used for more purposes (ex: Deep Learning); optimize the Secure Multi-Party Computations (SMPC) techniques used, to improve the performance of the platform; implement and test the SMPC techniques using other toolkits, also to improve the performance of the platform.

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