

USING KD-LAPLACE TO TRAIN PRIVACY-PRESERVING CLUSTER ALGORITHMS ON DISTRIBUTED K-DIMENSIONAL DATA

by

Tjibbe van der Ende

in partial fulfillment of the requirements for the degree of

Master of Science
in Software Engineering

at the Open University, faculty of Management, Science and Technology
Master Software Engineering
to be defended publicly on Day Month DD, YYYY at HH:00 PM.

Student number: 852372917
Course code: IMA0002
Thesis committee: Dr. Ir. Mina Sheikhalishahi (chairman), Open University
Dr. Ir. Clara Maathuis (supervisor), Open University

CONTENTS

1	Introduction	1
2	Literature review	4
2.1	Differential privacy	5
2.2	Clustering	10
2.3	Literature review	16
3	nD-Laplace	25
3.1	2D-Laplace	25
3.2	3D-Laplace	30
3.3	nD-Laplace	34
4	Attacks on privacy	47
4.1	Membership inference attacks	47
4.2	Reconstruction attack	49
4.3	Attack evaluation	50
5	Methodology	51
5.1	Research design	51
5.2	Data collection	56
5.3	Data analysis	59
6	Results	60
6.1	Cluster utility	61
6.2	Mechanism utility	67
6.3	Privacy	71
6.4	Dimensionality	77
6.5	Shape	78
7	Discussion	80
8	Conclusion	81
Bibliography		i
Hyperparameters		xi
.1	K-Means	xi
Theory		xiii
.2	Big O Notation	xiii
Results		xiv
.3	Cluster utility	xiv
.4	Mechanism utility	xx

1

INTRODUCTION

Data has become an increasingly important part of our daily lives, and its applications are continuously growing. Personal and sensitive information, such as scrolling through Facebook or Instagram, is often sourced from various structured and unstructured data origins. As many businesses see the potential of data [noa, b], the urgency of protecting sensitive information also increases. This development is why there have been several regulations regarding data and privacy. Therefore, the European Union created the GDPR [noa, a], and the United States created the privacy act [Division, 2007]. For instance, the GDPR describes in article 34 that data should always be stored in an " incomprehensible way for unauthorized people.". Due to these regulations, it is challenging for companies to store and analyze data to gain insights.

A method for gaining insights into data is using unsupervised machine learning. It can be used to find a structure or pattern in uncategorized data [Dridi, 2021]. Clustering is a type of unsupervised learning commonly applied to group similar data points and reveal patterns and structures [Dridi, 2021]. Cluster algorithms need to be trained on an adequate amount of historical data, so the data needs to be stored and processed in an accessible location.

A common solution for hiding data from unauthorized access is encryption. Although this method is widely used for databases, it is unsuitable for data analysis. The data is unreadable for examination, and it adds communication overhead [Liu et al., 2022]. For this reason, researchers have explored methods for anonymizing data to protect the privacy of individuals [Sweeney, 2002]. But, this can still reveal much information about a person, as the range of possible values is limited. A more effective way to preserve privacy is by using differential privacy. This method controls the amount of noise using a privacy budget [Dwork, 2006]. Due to the configurability of this mechanism, it is a popular method for privacy-preserving clustering . In recent years, the method was extended to add noise locally before sending it to a central server and called Local Differential Privacy (LDP) [Kaisiviswanathan et al., 2010]. Although this method reduces privacy leakage risks because no plain data is stored on the server, the amount of data is limited in the local view. This makes the noise more significant, impacting the data utility [Yang et al., 2020].

source

RELATED WORK

Tell something about other mechanisms

The difficulty in preserving utility for clustering while preserving privacy is a well-known problem in the literature. A study that focuses on preserving the cluster shapes sends the feature's distance information to the server instead of the feature value [Sun et al., 2019]. Their method works on multiple cluster algorithms, compared to other studies focusing on a single cluster algorithm. But, their method leaks distance information, another study aimed to improve this by using a distance-aware randomization algorithm Xia et al. [2020]. An extension of this study aimed at reducing the difference between actual and perturbed values [Huang et al., 2021]. Both studies focus on K-means and LDP but do not have direct support for other algorithms.

Due to the inflexibility and lack of practical testing in the current literature, developing a solution closer to practical applicability becomes essential. Our research incorporates realistic attacks and datasets to test privacy and utility to bridge this gap and move towards a practically deployable LDP mechanism. Therefore, the overarching goal of this thesis is to develop a privacy framework that facilitates secure training of cluster algorithms on distributed n-dimensional data.

RESEARCH OBJECTIVE

Another take on Differential Privacy (DP) is called Geo-indistinguishability (GI) and is specifically used for geographical data [Andrés et al., 2012]. The 2D-Laplace mechanism adds noise to two data points (latitude/longitude) by generating random locations based on the amount of distance. The mechanism is configurable by a privacy budget and holds within a radius of the original location. An extension of this mechanism, called 3D-Laplace, added support for including the altitude to support indoor navigation [Min et al., 2022]. The mechanism has also been extended to nD-Laplace to support n-dimensional data; however, its application focuses entirely on text vectors [Fernandes et al., 2019].

Because the proposed method relies on distance-based considerations, it is plausible that the shape and structure of the data will be preserved during the clustering process. Consequently, we expect this algorithm to perform well for data clustering tasks. To our knowledge, GI has never been previously applied for data clustering. Therefore, the primary research objective of this study is to extend the use of GI to optimize specifically the clustering of data.

This thesis aims at developing a new privacy framework for training cluster algorithms on distributed n-dimensional data. It does so by extending and optimizing the three variants of nD-Laplace to support cluster algorithms. Our contribution to the current literature is as follows:

1. We aim to create a new privacy framework named kd-Laplace using the three variants of Laplace to train privacy-preserving cluster algorithms on distributed n-dimensional data.
2. In addition to K-means, we also demonstrate the working of our method on multiple other cluster algorithms.

3. We introduce different optimization techniques to improve the utility of kd-Laplace using kd-tree.
4. We demonstrate the privacy of kd-Laplace using real-world datasets and attacks.

RESEARCH QUESTION AND METHODS

To reach our goals and objectives, we have formulated the following main question:

"How can the kD-Laplace algorithm be applied in training privacy-preserving clustering algorithms on distributed k-dimensional data?"

Much literature is consulted to answer this research question, and we experiment extensively to gather enough qualitative data. Both external and internal validation methods are employed to assess the utility and privacy of the privacy mechanism. The qualitative data from these experiments are analyzed to compare the different privacy mechanisms and their performance concerning clustering tasks.

ROADMAP

The first chapter is devoted to literature study and review. We explain the various concepts related to clustering and differential privacy. This chapter concludes with a literature review. The second chapter explicitly focuses on the kd-Laplace part, explaining the relevant algorithms and concepts. We then delve deeper into privacy attacks and how they can be evaluated.

The following chapter is dedicated to describing the research itself and the methodology. Subsequently, we present the results, and finally, we conclude with the discussion and conclusions.

2

LITERATURE REVIEW

The current chapter explains the theoretical aspects of the research and evaluates similar and previous studies. First, the concept of Differential Privacy and its various types is explained. Next, we examine cluster algorithms and the methods for evaluating their performance. Regarding the related literature, we first look at studies that have used differential privacy and then the studies that have combined it with cluster methods.

2.1. DIFFERENTIAL PRIVACY

In practice, data is often sent to a central storage point. This requires trust, and because all data is collected in one place, the risk of private data leakage becomes very high. By applying DP, noise can be added to the data to protect it. This principle is illustrated in figure 2.1 with the following actors:

1. Trusted curator: The system that receives data from users. It is assumed in this setting that the system is trustworthy and that the data is securely stored.
2. Adversary: An adversary is someone who uses the data. This could be, for example, a data scientist who wants accurate results or an attacker who wants to obtain as much data as possible.
3. The users are clients (for example, websites or mobile apps) who entrust their data to a central server.

To a certain extent, a user's privacy would be ensured with differential privacy.

Although differential privacy solves privacy problems, it remains challenging to calibrate the mechanism. There is an important trade-off between utility and privacy for the adversary. For example, a data scientist wants accurate data. At the same time, the noise must be sufficient to prevent an attacker from obtaining too much information. For this reason, a few sections will be devoted to outlining the mathematical background of differential privacy. We will examine which factors influence this calibration and whether other methods contribute. Afterward, we will further explain other types of differential privacy (local and geo-indistinguishable) similarly.

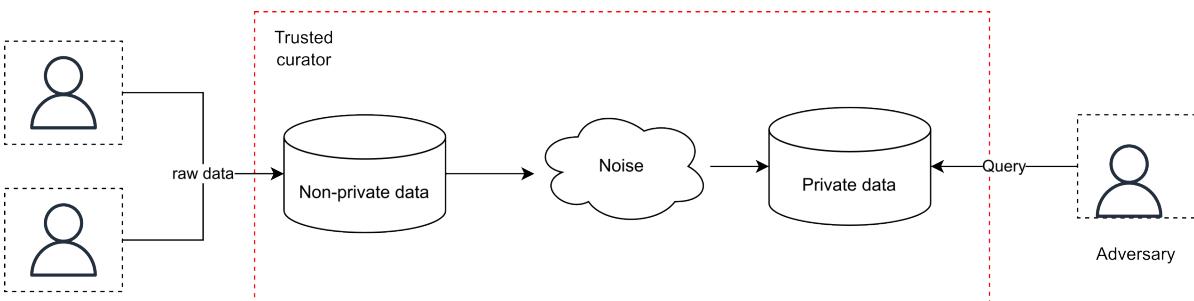


Figure 2.1: General approach for setting up (central) differential privacy.

2.1.1. DEFINITIONS

We examine the different notations and types of differential privacy we consider in this research.

ϵ -DIFFERENTIAL PRIVACY

Dwork et al. formulated the notion of privacy: Participating in a database should not significantly increase the risk of an individual's privacy being compromised [Dwork \[2006\]](#). This is mathematically formulated in the same research named [DP](#). Using the definition of privacy, it is formulated as the maximal possible change when adding or removing a single record [\[Dwork, 2006; Friedman and Schuster, 2010\]](#). This is reflected using the formal mathematical formulation as formulated by Dwork et al:

$$\Pr[K(D_1) \in S] \leq \exp(\epsilon) \times \Pr[K(D_2) \in S] \quad (2.1)$$

So, given a randomization function K , it gives ϵ -differential privacy if dataset D_1 and D_2 are differing at most one element [\[Dwork, 2006\]](#). The ϵ determines the amount of noise (privacy budget) [\[Friedman and Schuster, 2010\]](#). The lower the value of ϵ , the higher the privacy guarantee. In this regard, it is essential for a method that ensures differential privacy to consider this. For this reason, a common way to calibrate the ϵ is to calculate the sensitivity. This value is calculated based on the impact of a function or query on the data. For example, if there is a method called *sum* for the summation of data points, the method's sensitivity is 1. This is because removing one data point would significantly affect the outcome, and ϵ -differential privacy could no longer be guaranteed. It is also mathematically defined by Dwork et al.:

$$\Delta f = \max_{D_1, D_2} \|f(D_1) - f(D_2)\|_1 \quad (2.2)$$

(ϵ, δ) -DIFFERENTIAL PRIVACY

The formal notion of differential privacy has only the privacy budget ϵ as a parameter. This formulation is strict, but most methods relax this a little, with (ϵ, δ) :

$$\Pr[K(D_1) \in S] \leq \exp(\epsilon) \times \Pr[K(D_2) \in S] + \delta \quad (2.3)$$

This equation means the sensitivity (δ) loosens the formal definition of differential privacy. The δ is added to the upper bound of the exponential, so the desired noise can be higher. To some extent, the delta represents the probability of the algorithm leaking information [\[Aitsam, 2021\]](#). With ϵ -differential privacy, there would be no difference in the case of information leakage ($\delta = 0$). However, with (ϵ, δ) -differential privacy, the information can leak up to the probability of delta.

ϵ -LOCAL DIFFERENTIAL PRIVACY

As the name suggests, LDP is executed on the client side instead of on the server (See Figure 2.1). Local differential privacy removes the "trusted" curator (See Figure 2.2), preventing sensitive data leakage even if an attacker gains access to the dataset [Xiong et al., 2020a]. The definition for LDP is the same as for equation 2.3 with $\delta = 0$ being equal to equation 2.1.

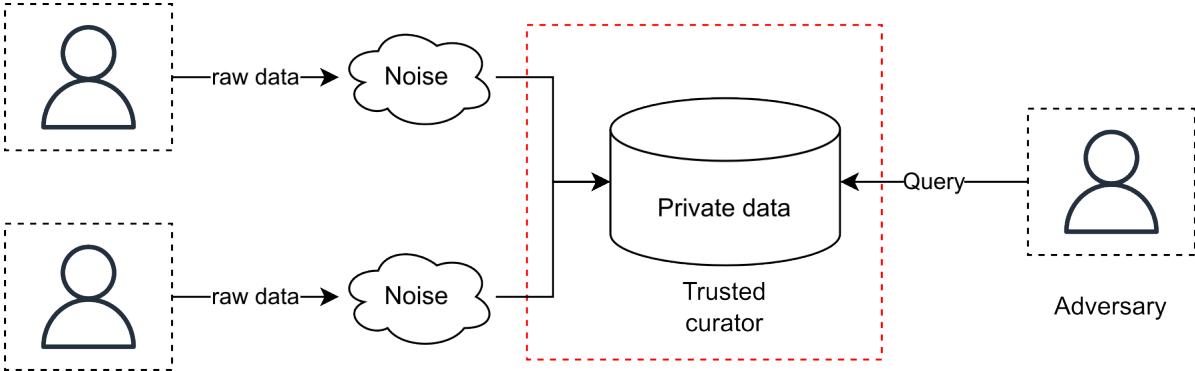


Figure 2.2: Local differential privacy, which moves the noise-adding step to the client-side.

Local differential privacy has two different frameworks. It can be set up as interactive or non-interactive [Xiong et al., 2020a]. Where interactive can be distinguished as either sequentially interactive or fully interactive¹:

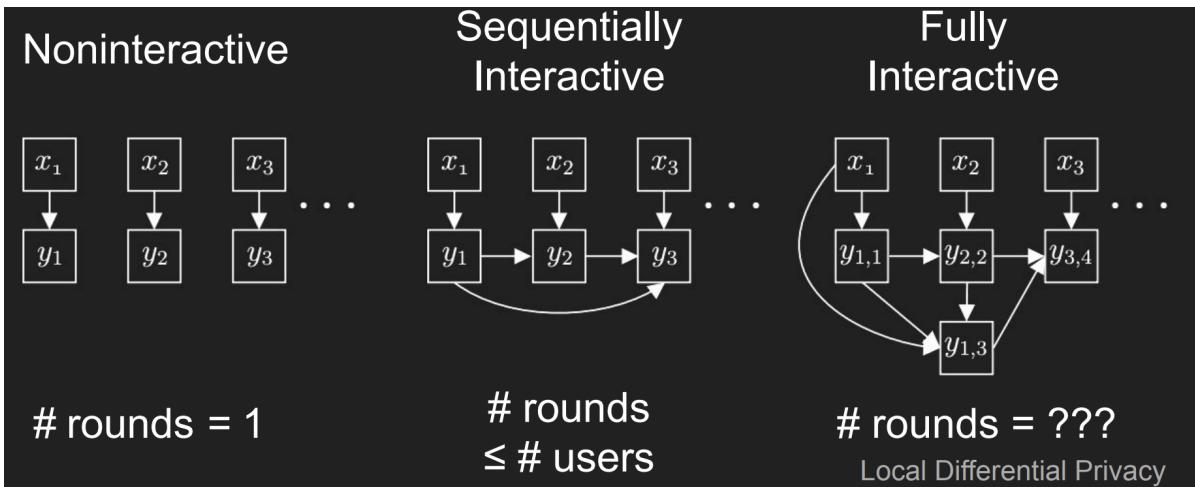


Figure 2.3: Non-interactive versus sequentially interactive versus fully interactive local differential privacy [Joseph et al., 2019]

In the non-interactive framework, the privacy mechanism operates on a single data instance (e.g., users' smartphones) without requiring interaction with other clients or between data points. This interaction means that each data point is perturbed independently, and the privacy guarantees are achieved without communication or coordination between the data points. In the interactive framework, the privacy mechanism involves a process of iterative interactions between users and clients. Each data point considers other data points' responses to determine its own perturbation or privacy level. The interactions can

¹Image source: https://www.majos.net/focs_19_talk.pdf

occur through a communication channel, where data points exchange information with each other or a trusted mediator. The iterative nature of the interactive framework allows for refining and improving the privacy guarantees based on the global knowledge of the data set.

In figure 2.3, the different interactive types are visualized, where the most notable difference is the around of rounds [Xiong et al., 2020b]. A sequentially interactive framework passes at most one message between data points. A fully interactive framework could provide an unknown and unlimited amount of messages between data points. The interactive framework has unlimited access to other data points, which is most suitable for practical appliances [Xiong et al., 2020b]. The practical applications are better because the data points' mutual correlation also contributes to utility [Wang et al., 2020].

ϵ -GEO-INDISTINGUISHABILITY

The last and most important type of differential privacy for this study is GI. GI can be applied to preserve privacy using a differential privacy method specific to spatial data [Andrés et al., 2012]. Consider a local-based system (LBS) that provides a map service to its users (e.g., Google Maps). The users can query the LBS for a route from their current location to a destination. Instead of the exact (private) location, the LBS should only receive an approximate location enough to provide the service at an adequate level. This approximation happens entirely locally, so no central server exists.

Users can define a privacy radius r around their location x . A fake location z is generated within this radius based on the Euclidean distance d .

The amount of noise within r depends on the privacy budget ϵ . The privacy budget is based on the privacy level l , combined with r to obtain ϵ using the formula $\epsilon = \frac{l}{r}$.

Calculating the privacy budget is illustrated in the figure below:

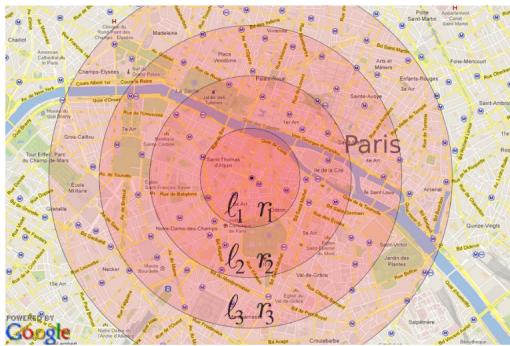


Figure 2.4: Visualisation of radius r with l to provide Geo-indistinguishability mechanism [Andrés et al., 2012]

The formula for GI to measure if an algorithm preserves ϵ -geo-indistinguishability can be expressed as:

$$K(x)(y) \leq e^{\epsilon * d(x, x')} K(x')(y) \quad (2.4)$$

K is a probability method reporting $x, x' \in X$ as $z \in Z$. The intuition for this definition is that it displays the distinguishability level between two secret locations/points x and x' [Chatzikokolakis et al., 2015]. An extension of this is called d_x -privacy, a more general notation of distance-aware differential privacy. Therefore, their definition for GI is d_2 -privacy, but is essentially the same as the proof provided for GI.

2.1.2. MECHANISMS

This section explains the various mechanisms used to achieve differential privacy. The different mechanisms are not limited to the type of DP; some can be applied to multiple types.

RANDOMIZED RESPONSE MECHANISM

The random response method is relatively simple and was first applied in 1965 by Warner et al. It was originally used to mask individuals' answers by randomly switching them with predictable randomness [Warner, 1965]. Therefore, the method is mainly used for categorical data. This method satisfies its own set of requirements for LDP [Xiong et al., 2020a], which differs from the formal definition that was mentioned earlier

Since then, it is still one of the better-known methods, and larger organizations such as Google have used it [Erlingsson et al., 2014]. They have named their extension RAPPOR and expanded it with bloom filters to be able to collect numerical data as well. It is possible to ensure ϵ -differential privacy, and it is also possible to preserve LDP [Xiong et al., 2020a].

LAPLACE MECHANISM

The method that was initially proposed in the differential privacy paper by Dwork et al. is the Laplace algorithm [Dwork, 2006]. Therefore, the method configures the ϵ and δ . A shorthand definition is provided by Rey et al. [Xiong et al., 2020a]:

$$M(f(x), \epsilon) = f(x) + (Z_1, \dots, Z_d) \quad (2.5)$$

The mechanism is based on the Laplace distribution with scale $\lambda f / \epsilon$, where λf is the same as in equation 2.2. Therefore, the Laplace mechanism is tightly linked to the definition of DP [Dwork, 2006]. In addition to this, it is also suitable for preserving LDP [Xiong et al., 2020a]. One disadvantage is that sensitivity is always required, and this parameter can sometimes be difficult to configure. Especially when there is no clear function and the entire dataset is perturbed. This can make finding the right balance between ensuring privacy and utility challenging.

To this end, the sensitivity can be calculated in two forms: global and local. Global sensitivity is independently calculated over two different datasets and is part of the original definition of DP [Dwork, 2006]. Usually, this is not the desired situation since local sensitivity always has more context of the dataset in question [Nissim et al., 2007]. As a result, the trade-off for noise is much more precise, and the balance between utility and privacy is much better. The definition of local sensitivity is the following [Nissim et al., 2007].

$$LS(f, x) = \max_{x' : d(x, x') \leq 1} |f(x) - f(x')| \quad (2.6)$$

A methodology to calculate the local sensitivity is using the smooth sensitivity method, proposed by the same authors [Nissim et al., 2007]. This method aims at smoothing out the local sensitivity by focusing on reducing the noise without the risk of revealing more information. Because it calculates many different configurations, a disadvantage of this method is that it can be computationally expensive. Also, the introduction of this method makes Laplace preserve (ϵ, δ) -DP instead of pure ϵ -DP.

2.2. CLUSTERING

This section explains the various cluster algorithms used in the research. Subsequently, we will explain and indicate how the hyperparameters are handled in the research for each algorithm.

2.2.1. TYPES OF CLUSTER ALGORITHMS

Multiple cluster types can be utilized for clustering data [Xu and Tian, 2015]. For this study, we selected the types that use some form of distance for clustering. We explain each cluster type with corresponding cluster algorithms.

PARTITION BASED CLUSTERING

With this type, the data is partitioned and allocated into a fixed amount of clusters. A well-known and popular cluster algorithm is K-means. Based on Loyd et al.'s original method, this algorithm randomly selects k points as cluster centroids [Lloyd, 1982]. Iteratively each data point is assigned to its nearest centroid. It keeps proceeding until the distance between the cluster centroids is optimal. Although K-means serves its purpose well, it requires pre-defining the number of clusters and is sensitive to outliers [Keller et al., 2021]. Therefore, a parameterless alternative to K-means is **Affinity Propagation (AP)** [Frey and Dueck, 2007].

AP is an algorithm that clusters data points by iteratively passing messages between them. Each point sends and receives messages about the attractiveness of other points as cluster centers (exemplars) and the suitability of itself as a center [Keller et al., 2021].

DENSITY BASED CLUSTERING

The data points are partitioned for this clustering type based on nearest neighbors [Fahad et al., 2014]. A region with a high data density is considered a cluster [Xu and Tian, 2015]. A popular density-based cluster algorithm is **Density-based spatial clustering of applications with noise (DBSCAN)**. The method was introduced by Ester et al. and worked by drawing a radius ($radius(\epsilon)$, not to be confused with the privacy budget ϵ) around data points [Ester et al.]. It then groups all points within this radius as clusters. The main advantage is its ability to find arbitrarily shaped clusters and detect outliers [Liu et al., 2012].

Another density-based algorithm is **Ordering Points to Identify Clustering Structure (OPTICS)**, an extension of DBSCAN. This algorithm attempts different $radius(\epsilon)$ values to achieve the best result [Ankerst et al.]. Instead of directly assigning data points to clusters, specific distance calculations are stored in a list. For each data point, it tracks two values: core distance and reachability distance. These values represent the shortest distance to make a data point, p , a core point, and the shortest distance from p to another core point, p' , respectively. A specific ordering is maintained to ensure that clusters with higher density values are processed first. Based on this ordering, the DBSCAN algorithm is constructed hierarchically [Schubert et al., 2017].

HIERARCHICAL CLUSTERING

The name originates from the way hierarchical clustering works. A hierarchy of clusters is generated and merged according to the closeness of data points [Meng et al., 2021]. One of the best known Hierarchical cluster algorithms is **Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH)**. This algorithm works by constructing a tree with nodes (so-called clustering feature) [Zhang et al., 1996]. The algorithm does this iteratively until

a cluster becomes too large or diverse. The algorithm will split again into similar clusters until all data is processed [Zhang et al., 1996].

RESEARCH DIRECTION

Based on the different types of clustering algorithms, we have chosen to apply both partition-based clustering algorithms in this research. K-Means, widely used in the literature, will be utilized alongside the parameterless alternative, AP.

For density-based clustering, we will solely focus on OPTICS in this study. The parameter $radius(\epsilon)$ in DBSCAN is influenced by the data shape, which is further affected by our privacy mechanism. However, as OPTICS automatically determines the $radius(\epsilon)$, the impact of this parameter is less significant, enabling us to emphasize the evaluation of the privacy mechanism itself.

As for hierarchical clustering, we have decided to exclude it from the initial scope of the research. This type of clustering presents substantial differences in its approach compared to the other clustering algorithms. Consequently, we will concentrate on partition-based and density-based clustering methods for the current investigation, ensuring a more cohesive and manageable research scope.

2.2.2. PARAMETER SELECTION

A list of important hyperparameters that can influence the results is provided for each clustering algorithm. Subsequently, we briefly discuss the methods for determining these hyperparameters for the algorithms.

We use the same distance function for all algorithms to have all the algorithms in the same setting. This function will be Euclidean distance, as used for GI.

K-MEANS

The most crucial parameter of the K-Means algorithm is the value of k . This value determines the number of clusters to consider and influences the results by a lot [Ahmed et al., 2020]. The first method is called an "elbow" plot [Kodinariya and Makwana, 2013]. This method finds the best k by applying the K-Means algorithm multiple times and estimating the best k .

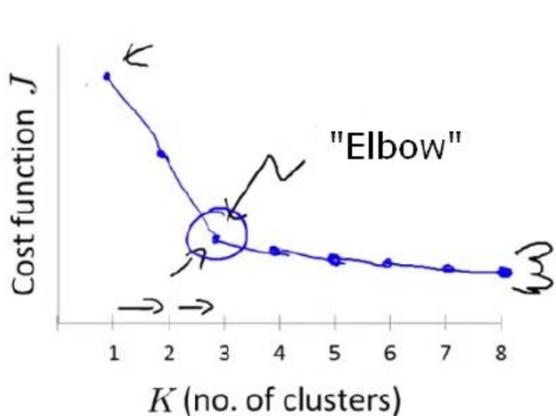


Figure 2.5: Illustration of determining k using the "elbow" method [Kodinariya and Makwana, 2013]

In this situation, a Silhouette plot can be used to determine the k . This method uses the Silhouette coefficient for each cluster [SAPUTRA et al., 2020]. Because this metric measures

the separation and cohesion of the cluster, it can be used to choose an optimal amount of clusters [SAPUTRA et al., 2020]. By visualizing the silhouette scores, the K with the highest coefficient has the best-separated clusters.

Another method is the Gap statistic method [Yuan and Yang, 2019]. It compares the total within-cluster variation for different values of k with their expected values under a null reference distribution of the data [Tibshirani et al., 2001]. A practical appliance of this method uses a line plot for comparing the k -value and gap value [Yuan and Yang, 2019]. Based on the line's visual change, someone can select the best k (the "elbow").

In summary, no fixed method exists to choose a good k for K-Means. The elbow method is standard in the existing literature and is very popular due to its simplicity. However, one disadvantage is that it can be challenging to determine the "elbow" point, as it is not always present [Kodinariya and Makwana, 2013]. In that case, the silhouette or gap statistic method is a good alternative, where the silhouette score is the simpler method.

AFFINITY PROPAGATION

Although the algorithm is parameterless, important properties could potentially impact the clustering [Wang et al., 2007].

Choosing preference(p): Indicates the preference for selecting a data point as cluster center [Wang et al., 2007]. It highly influences the number of clusters; a high one would lead to more clusters and a small one to less [Moiane and Machado, 2018]. Depending on the data, a good choice is to set the p to the median of all data similarities [Wang et al., 2007]. But, the effectiveness of this could be highly influenced based on the dataset. Analyzing the silhouette coefficient [Moiane and Machado, 2018] to validate if the preference is correctly set is possible.

Choosing damping factor($lam \in [0, 1]$): The damping factor improves the stability (convergence) of the algorithm [Wang et al., 2007]. By default, this value is 0.5 and can be increased to 1 to reduce the impact of numerical oscillations. This value can be found manually by re-running the algorithm to find the optimal value. However, the approach takes a lot of time, especially for bigger datasets [Wang et al., 2007].

To conclude on this, damping is important if big datasets are considered. On the other hand, the preference could influence the results a lot. In general, it should be sufficient to take the median.

OPTICS

With the introduction of OPTICS, we no longer need to worry about the $radius(\epsilon)$ value. Therefore, only $minPts$ remains an important parameter to consider.

The $minPts$ is the minimum amount of points that have to be within the $radius(\epsilon)$ to mark it a cluster. This hyperparameter is analyzed in a paper by Sander et al. The work describes calculating this parameter by applying two times the feature amount [Sander et al., 1998]. So, using this approach, a dataset with two features will have an $minPts$ of four [Schubert et al., 2017].

DBSCAN is a little more complicated due to the variety of datasets and noise-altering mechanisms we experiment with. This complexity is why we use **OPTICS** to determine the best value for $radius(\epsilon)$ and choose $minPts$ based on the number of features times two.

2.2.3. EVALUATION METHODS

Clustering comparison measures are important in cluster analysis for external validation by comparing clustering solutions to a "ground truth" clustering [Vinh et al.]. These external validity indices are a common way to assess the quality of unsupervised machine learning methods like clustering [Warrens and van der Hoef, 2022]. A method that could be used for this is the Rand Index [Rand, 1971]. It is a commonly applied method for comparing two cluster algorithms [Wagner and Wagner]. An improvement of this method is adjusted for chance by considering the similarity of pairwise cluster comparisons [Vinh et al.]. Both the Rand Index (RI) and Adjusted Rand Index (ARI) [Hubert and Arabie, 1985] report a value between 0 and 1. Where 0 is for no-similarity and 1 for identical clusters. Alternatives for RI are the Fowlkes-Mallows Index and Mirkin Metric. However, these two methods have their disadvantages. They are, respectively, sensitive to a few clusters and cluster sizes [Wagner and Wagner]. The ARI metric suffers from cluster size imbalance as well, so it only provides not a lot of information on smaller clusters [Warrens and van der Hoef, 2022]. Instead, they recommend using the cluster index metric proposed by Fränti et al. [Fränti et al., 2014].

Another popular group of methods is the information theoretic-based measures [Vinh et al.]. This metric measures the information between centroids; the higher the value, the better [Vinh et al.]. **Mutual Information (MI)** is a metric that calculates the probability of an element belonging to cluster C or C'. But, it is not easy to interpret as it does not have a maximum value [Wagner and Wagner]. To this end, **Normalized Mutual Information (NMI)** can be used to report a value between 0 and 1 using the geometric mean [Strehl and Ghosh, 2002]. The metric also exists in an adjusted version as **Adjusted Mutual Information (AMI)**. This metric works in the same way as for the **Adjusted Rank Index (ARI)** and is mainly needed if the number of data items is small in comparison to the number of clusters [Vinh et al.].

Besides the external validity measurements for clustering, it is also possible to use internal validation methods. These metrics focus entirely on the intrinsic dataset properties instead of relying on an external baseline cluster algorithm [Craenendonck and Blockeel]. They are assessing two essential concepts of clustering: compactness and separation [Hassani and Seidl, 2017]. Both studies consider three different metrics and measure both concepts at the same time [Hassani and Seidl, 2017]:

1. **Calinski-Harabasz Index (CHI)** [Caliński and Harabasz, 1974] is used to measure the cluster variance (well-separated clusters) and low variance within the clusters (tightly coupled data). A high score indicates better clustering.
2. **Silhouette Index** [Rousseeuw, 1987] This metric is similar in measuring cohesion within and separating clusters. However, this metric uses the pairwise distance Hassani and Seidl [2017]. A score of -1 indicates incorrect clustering and +1 for dense clusters Rousseeuw [1987].
3. **Davies-Bouldin** [Davies and Bouldin, 1979] uses the average distance between centroids. A lower score indicates good clustering.

K-Means scores relatively high for CHI [Craenendonck and Blockeel; Hassani and Seidl, 2017] and SI [Craenendonck and Blockeel]. The same applies to DBSCAN, which scores relatively high on SI and DB due to noise sensitivity [Craenendonck and Blockeel].

EXISTING LITERATURE

Comparable studies with differential privacy use external validation [Sun et al., 2022; Xia et al., 2020]. Their experiment setup uses a so-called non-private cluster algorithm as external validation. This cluster algorithm is trained without the perturbed data and compared with the same clustering algorithm trained with perturbed data. Thus, the non-private variant provides the ground truth as an external validation.

They compare the mutual information between a baseline cluster algorithm using AMI [Huang et al., 2021] or NMI [Sun et al., 2022; Xia et al., 2020]. Another study for evaluating DP with AP uses both ARI and AMI. In addition to mutual information and rand index scores, it is also not uncommon to calculate the error between the two cluster algorithm's centroids [Huang et al., 2021; Xia et al., 2020]. These two studies used Relative Error (RE) for this.

RESEARCH DIRECTION

This chapter outlines the evaluation methods used and provides a definition and brief explanation for each method.

In the literature, both internal and external evaluation methods are commonly used. While some studies choose one over the other, this thesis will perform both validations. This approach is crucial to measure how well the data shape is preserved (internal validation) and how the algorithm performs in real-world scenarios (external validation).

Since certain cluster algorithms may score higher or lower on specific metrics, it is essential to choose two metrics for each type of validation. Based on existing studies and the literature, we have selected metrics adjusted to compensate for the data distribution characteristics. Hence, we will focus on these metrics' "adjusted" variants:

1. Internal validation:

- (a) **Calinski Harabasz Index:** The definition of CHI is defined in several steps [Liu et al., 2010]: The first definition is the between cluster sum of squares.

$$B = \sum_{i=1}^k n_i \cdot (C_k - C)^2 \quad (2.7)$$

- i. n_k is the number of data points in cluster k .
- ii. C_k is the centroid of cluster k .
- iii. C is the dataset centroid

The second part of the definition is defined as follows:

$$W_k = \sum_{i=1}^n n_i \cdot (x_i - C_k)^2 \quad (2.8)$$

W_k is the within-cluster sum of squares and x_i is the i th data point. Finally, the CHI is calculated by combining the between and within-cluster calculations:

$$CH = \frac{B}{\sum_{k=1}^K} \cdot \frac{N - k}{k - 1} \quad (2.9)$$

- i. K is the number of clusters.
 - ii. N is the number of data points.
- (b) **Silhouette coefficient:** This metric is defined as follows [Liu et al., 2010; Rousseeuw, 1987]:

$$s(i) = \frac{b(i) - a(i)}{\max(b(i) - a(i))} \quad (2.10)$$

- i. $s(i)$ is the silhouette coefficient for a single datapoint i .
- ii. $a(i)$ is the mean distance of i and all the other points in the same cluster.
- iii. $b(i)$ is the mean distance of i and all the other points in the next nearest cluster.

Finally, the final silhouette score is the mean of all datapoint coefficients $s(i)$.

2. External validation:

- (a) **Adjusted Rand Index:** The ARI is defined in two steps, one to calculate the actual Rand Index and the other to adjust it for chance. The Rand Index formula is defined as follows [Hubert and Arabie, 1985]²:

$$RI = \frac{a + b}{C_2^N} \quad (2.11)$$

- i. C the ground truth elements (So the actual correct predictions/ classes).
- ii. a is the number of pairs of elements part of the ground truth C and part of the predicted class.
- iii. b is the number of pairs of elements in different sets of C and different sets of the predicted class.
- iv. C_2^N is the total number of pairs of elements in the dataset.

To compensate for the amount of clusters, the adjusted formula is defined as follows [Sinnott et al., 2016]:

$$ARI = \frac{RI - \text{Expected}(RI)}{\max(RI) - \text{Expected}(RI)} \quad (2.12)$$

- (b) **Adjusted Mutual Information:** As was the case for the ARI, the AMI is also defined in two steps. The first step is to calculate the actual MI, and the second is to adjust it for chance. The MI is defined as follows [Vinh et al.]:

$$H = - \sum_{i=1}^U p(i) \cdot \log p(i) \quad (2.13)$$

H is the uncertainty for one variable given another variable. So it can be used to measure the (dis)similarity between two variables.

- i. U is a label to calculate the uncertainty for.
- ii. $p(i)$ is the probability of a random point i falling into class/labe U .

This same calculation is executed for the second label V and divided by each other.

$$MI = \frac{MI - \text{Expected}(MI)}{\text{mean}(H(U), H(V)) - \text{Expected}(MI)} \quad (2.14)$$

²Explanation is part of Sklearn: <https://scikit-learn.org/stable/modules/clustering.html>

2.3. LITERATURE REVIEW

In the search for related literature, we focused mainly on (L)DP mechanisms that can be used for general purposes (e.g. not only mean estimation), which is the most comparable to our mechanism. The related literature is divided into three parts:

1. Differential privacy and clustering: We explain how differential privacy is used for clustering.
2. Differential privacy methods: We explain the different methods for differential privacy.
3. Cluster methods with (L)DP: We explain the different methods for clustering with (L)DP.

Afterward, we provide a summary for both in a table. This table includes components such as the type (LDP or DP) and whether a public code is available.

2.3.1. DIFFERENTIAL PRIVACY AND CLUSTERING

There are different ways how to combine differential privacy with clustering [Baraheem and Yao, 2022]:

1. Input perturbation: This method adds noise to the input data, so the cluster algorithms are trained on perturbed data.
2. Gradient perturbation: The term gradient is used in machine learning algorithms that solve an optimization problem like deep learning [Hassan et al., 2019]. Perturbing the gradients ensures the optimization algorithm is private [Ji et al., 2014].
3. Output/label perturbation: This method adds noise to the output of the clustering algorithm. The noise is added to the cluster labels, so the results are perturbed.
4. Objective perturbation: This method slightly differs from output/label perturbation but also adds noise to the output. The difference is it is added to the output of a loss function instead of the labels (for example, logistic regression) [Baraheem and Yao, 2022].

Many approaches targeting local differential privacy mechanisms must adapt the clustering algorithm (for example, k-Cluster) [Sun et al., 2019], which we explain later in this chapter. For this reason, we concentrate on input perturbation in this study, as it allows the dataset to be used multiple times to train various clustering algorithms.

1. First, each local dataset is perturbed using our method (locally).
2. All data is collected and used to train a clustering algorithm (on the server).
3. A cluster model is privately trained because we train the algorithm on private data.
4. Because we use input perturbation, a third party like a "data analyst" can also directly access the data privately.

The following section focuses on the differential privacy algorithms that are of interest to this type of input perturbation.

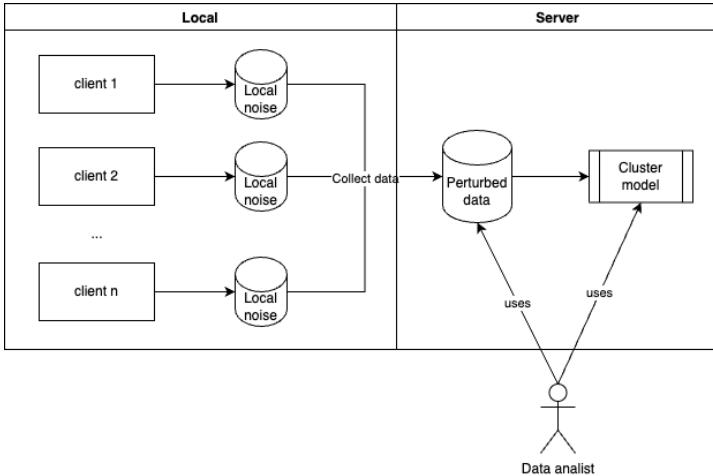


Figure 2.6: Example on how our approach of private training works for clustering and DP

2.3.2. DIFFERENTIAL PRIVACY METHODS

As discussed earlier, the Laplace method was the first to establish DP [Dwork, 2006]. The first paper we discuss is provided by Soria-Comas et al. and considers the distribution of the dataset for generating noise [Soria-Comas and Domingo-Ferrer, 2013]. Their work claims the Laplace mechanism is not optimal for a univariate function and aims at improving it by extending the Laplace mechanism. The proposed method performs slightly better than Laplace on multivariate/multiple queries.

Quan et al. also proposed a new method to extend Dwork et al.'s Laplace algorithm [Geng et al., 2015]. They introduced the Staircase mechanism for 1-dimensional noise, which was later extended to support multidimensional data [Geng et al., 2015]. The mechanism aims to improve utility by adding the same level of privacy while adding less noise. It represents a staircase-shaped Probability Density Function (PDF), hence the name Staircase Mechanism (SM). This mechanism accepts three configurable parameters comparable to those of the Laplace mechanism. The authors' work can handle multidimensional numerical data and preserve the (ϵ) -differential privacy. In the previous two paragraphs, we have mainly focused on the interesting literature regarding differential privacy.

Next, the succeeding paragraphs will mainly center on related literature concerning local differential privacy.

Nguyen et al. introduced a new LDP mechanism for working with numerical data [Nguyễn et al., 2016]. Their primary focus is estimating means and frequencies on data and applying machine learning techniques such as Support Vector Machines (SVM) and linear regression using Empirical Risk Minimization. Initially, the authors analyze Duchi et al.'s method [Duchi et al., 2013] and highlight several shortcomings. To address these issues, they introduce Harmony as a mechanism for LDP perturbation. This mechanism can perturb categorical and numerical data, providing high accuracy for classification and regression tasks. To compare Harmony to other methods, they create the Hybrid Mechanism (HM), a combination of two existing methods for categorical and numerical data. For this purpose, they extend other work [Bassily and Smith, 2015] for perturbing multidimensional categorical attributes and use Duchi et al.'s method for numerical data [Duchi et al., 2013]. This combination of mechanisms allows them to compare their Harmony mechanism to the hybrid mechanism and measure the utility/accuracy differences.

Duchi et al. improved their method by formalizing the trade-off between statistical utility and (local) privacy, analyzing multiple estimation problems [Duchi et al., 2017]. Examples include mean, median, and density estimation. To achieve this, they use minimax, a technique for finding the worst-case probability distribution. Additionally, they focus on existing work and propose several optimization strategies.

Duchi et al.'s method was extended a couple of years later by adding support for bounded and multidimensional data [Wang et al., 2019]. The authors introduce the **Piecewise Mechanism (PM)** to handle numeric and categorical data and the Hybrid Mechanism (HM), which combines **PM** and Duchi et al.'s method for 1-dimensional data. Their method's effectiveness is demonstrated using **Support Vector Machine (SVM)**, linear regression, and mean estimation. **PM** and HM are compared to Laplace and Duchi et al.'s solutions. Optimized Unary Encoding (OUE) [Wang et al.] is also used for comparison, but for categorical data only, as the other methods do not support this.

2.3.3. CLUSTER METHODS WITH (L)DP

This chapter examines the various studies conducted on clustering in combination with differential privacy. Initially, we looked at the most fundamental papers in this field. Subsequently, the focus shifted toward researching well-known papers published since 2020.

The first work we highlight was proposed by Nissim et al. and aimed at improving differential privacy methods, such as Laplace, which uses sensitivity to compensate the noise for a function [Nissim et al., 2007]. In addition to compensating the function, they also consider the dataset itself. The algorithm is called "smooth sensitivity" and is used for instance-specific noise. To apply it, the authors introduce a method/framework to calculate it effectively. They use K-means, among other cluster algorithms, to demonstrate the method's effectiveness. Their method requires the calculation of cluster distances using Wasserstein distance instead of Euclidean distance.

Another study focuses on interactive and non-interactive approaches for differential privacy in K-Means [Su et al., 2015]. The study builds upon the work done for DPLlloyd, an interactive privacy extension of K-Means described by Blum et al. [Blum et al., 2005]. The DPLlloyd mechanism partitions an n -dimensional dataset into a grid and releases the count for each grid by adding Laplacian noise to each count. Another part of their research focuses on determining the width of the data cells. The grid estimation method used in their research is called the extended uniform grid approach (EUG), and the complete K-Means method is called EUGkM. The experiment evaluates it against the DPLlloyd mechanism, which performs better in an interactive setting. Therefore, they combine their algorithm for combining both aspects into a hybrid approach (EUGkM + DPLlloyd approach) and show a better final performance.

The study of Nissim et al. researches finding the smallest possible radius in the Euclidean space R^d for a set of n points [Nissim and Stemmer, 2018]. They propose a new solution that uses locality-sensitive hashing (LSH) for differential privacy to find 1-cluster in the d -dimensional Euclidean space. This method works for differential privacy (LSH-GoodCenter), but they also extend this to the local model (LDP-GoodCenter). The algorithm to find this radius is used to count the points enclosed by the radius, and Laplace noise is added to the count to preserve differential privacy. The mechanism is combined and applied to work with the K-Means algorithm (LDP-K-Mean). This mechanism was extended in a paper proposed by Kaplan et al. and introduced a similar LDP method [Kaplan

and Stemmer, 2018]. They aim to reduce the number of interactions needed between the server and users to one, instead of the $O(k \log n)$ required for Nissam et al.'s solution [Nissim and Stemmer, 2018]. To increase the success probability, they use the same idea but extend it to have multiple centers instead of a single large one. They call it the LSH-Procedure, and the algorithm Private-Centers is applied to generate centers to use with K-Means. Then, they apply the same method to the LDP method initially proposed by Nissam et al. (LDP-GoodCenter). The most recent work by Stemmer et al. focuses on improving the work done by Kaplan et al. [Kaplan and Stemmer, 2018; Stemmer, 2021]. Because the original mechanism has a higher additive error, the noise added introduces a lot of error. To solve this, the authors aim to reduce this error by improving the original GoodCenter algorithm [Nissim and Stemmer, 2018]. Their extended method is called WeightedCenters and also adds weights to candidate centers. In the final iteration, the weights are used to create the K-Means or K-Median clusters.

Sun et al. proposed a mechanism for distributed clustering using local differential privacy (LDP) to preserve distance-based information. They claim to have the first non-interactive LDP algorithm for clustering [Su et al., 2015]. This means they can perturb the data locally at once and send it to the server to cluster with both K-Means and DBSCAN without interaction between data points. They encode the client-side data into an anonymous hamming space using Bit Vector (BV) and modify the encoding to preserve Euclidean distance. Their mechanism only shares distance information, so they could not use K-Means directly. To overcome this, they modified the algorithm and called it K-Cluster. Finally, the method is evaluated using Normalized Mutual Information (NMI) and Average Estimated Error (AEE).

Xia et al. noticed the shortcoming of Sun et al.'s work which is the need to share privacy-sensitive distance information [Xia et al., 2020]. Therefore, they create an interactive method for distributed K-means clustering using LDP. The method converts features to binary strings and uses the Random Response mechanism (RR) to perturb each feature into a feature vector. The privacy cost depends on the length of the bits of each feature transformation, meaning that a longer length yields more information at the expense of the privacy budget. In each iteration, the serverside calculates and sends K-means centroids to each user, who recalculates distances until the centroids become stable. The approach has the disadvantage of a high correlation between user data and the clusters. To solve this problem, the algorithm is improved by having the client side send the user data and a set of random zero strings. The server side then performs similar calculations to determine the actual cluster. Huang et al. propose a private distributed K-means clustering algorithm for interval data that addresses a shortcoming in Xia et al.'s work by using Condensed Local Differential Privacy (CLDP) for small-scale values and LDP for large-scale values [Huang et al., 2021]. They preserve distance using a Square Wave (SW) mechanism and apply a classical K-Means algorithm on the server side to the perturbed data.

which shortcoming?

A very recent mechanism that also builds around K-Means to preserve LDP is called the LDPK mechanism [Yuan et al., 2021]. As K-Means works only with numerical data, they use K-prototypes for supporting mixed data types. The LDPK mechanism perturbs the user data first locally and interactively exchanges information with the server to complete the clustering process. The mechanism they use for perturbation is the Harmony algorithm, proposed earlier by [Nguyen et al., 2016]. The S-Hist method is used to support categorical data, which was also introduced by Nguyen et al. The server could still infer the correct information because of the correlation between the cluster centroids and the actual data.

Therefore, the author replaces S-Hist with OUE [Wang et al.] to improve accuracy. To improve their mechanism further, the authors disturb the user's cluster information with an extra extension to the LDPK method, called ELDPK. For this purpose, they perturb the clusters with the GRR (Generalized Random Response) algorithm. They show that the clustering quality increases if the data points increase.

Most existing work focuses on (L)DP in combination with K-Means. Finally, two interesting studies focus on differential privacy for AP or DBSCAN. A study conducted by Cai et al. focuses on AP [Cai et al., 2020]. Their method involves adding Laplace noise to the responsibility matrix. For each sample data, a neighborhood is specified using a radius around the data point. This area is called the neighborhood density, and each sample point's preference value is adjusted according to its density value. Higher density yields a higher chance of belonging to a cluster center and being ranked based on size. The perturbed responsibility matrix and densities are combined and used to run AP. They evaluated their method using the ARI, Fowlkes-Mallows Index (FMI), and AMI.

Another study focuses on differential privacy for DBSCAN [Bozdemir et al.]. The proposed solution involves clustering data between two or more parties using two servers. Secure two-party computation (S2PC) is used to achieve this. Using S2PC, both servers receive a random-looking secret share. To recover the original data, both servers must combine their shares using S2PC, which combines the data without the servers having access to the full value. The proposed protocol is privacy-preserving DBSCAN (ppDBSCAN). The calculations in this study are based on squared Euclidean distance (SED) and are evaluated using different methods. To evaluate the performance of ppDBSCAN, the study compares its Adjusted Rand Index (ARI) to that of K-means.

year	Name	Data type	Dataset	Code implementations	Preserving	Type	Interactive	Methods
2022 [Sun et al., 2022]	PrivBV: Distance-aware encoding for distributed...	-	Synthetic dataset	-	(ϵ, δ) -LDP	K-Means	Non interactive	-
2021 [Huang et al., 2021]	Private distributed K-means clustering on inter...	-	-	-	LDP	K-Means	Interactive	-
2021 [Stemmer, 2021]	Locally Private k-Means Clustering	numerical	-	-	LDP	K-Means	Interactive	-
2021 [Yuan et al., 2021]	Privacy-preserving mechanism for mixed data clu...	n-dimensional numeric & categorical	Adult dataset, US Census dataset	-	LDP	K-Prototypes	Interactive	LDPK and ELDPK
2021 [Bozdemir et al.]	Privacy-preserving Density-based Clustering	-	Deer dataset, Lsun dataset, S1	-	DP	DBSCAN	-	ppDBSCAN
2020 [Cai et al., 2020]	DP-AP: Differential Privacy-Preserving Affinity...	-	Iris dataset, Seeds dataset	-	DP	AffinityPropagation	-	DP-AP
2020 [Xia et al., 2020]	Distributed K-Means clustering guaranteeing loc...	n-dimensional numerical data	3D Road Network, CarGPS	-	LDP	K-Means	Interactive	LDPKmeans
2019 [Sun et al., 2019]	Distributed Clustering in the Anonymized Space...	n-dimensional numerical data	Aggregation dataset, Digit dataset, Pathbased d...	-	LDP	DBSCAN, K-Means	Non interactive	Distance Aware Bit Vector (DPBV)
2018 [Nissim and Stemmer, 2018]	Clustering algorithms for the centralized and l...	n-dimensional numerical data	-	-	(ϵ, δ) -LDP	K-Means	Interactive	LDP-GOODCenter
2018 [Nissim and Stemmer, 2018]	Differentially private K-means with constant mu...	-	-	-	-	K-Means	Interactive	LSH-Procedure & Private-Centers
2015 [Su et al., 2015]	Differentially Private k-Means Clustering	2 - 10-dimensional numerical data	Adult dataset, Gowalla dataset, Image dataset, ... ³	DP	K-Means	Both	EUGkM and hybrid EUGkM + DPLloyd	
2007 [Nissim et al., 2007]	Smooth sensitivity and sampling in private data...	n-dimensional numeric	-	-	(ϵ, δ) -LDP	K-Means	Non interactive	Smooth sensitivity

Table 2.1: Summary table of the literature review for (L)DP clustering algorithms.

year	Name	Data type	Dataset	Code implementations	Preserving	Interactive	Methods
2019 [Wang et al., 2019]	Collecting and Analyzing Multidimensional Data ...	n-dimensional (PM), but HM is 1-dimensional and...	BR, MR	https://github.com/forestneo/sunPytools/blob/main/	LDP	-	- Piecewise Mechanism (PM)
2017 [Duchi et al., 2017]	Minimax optimal procedures for locally private ...	1-dimensional numerical data	-	https://github.com/forestneo/sunPytools/blob/main/	LDP	-	- Hybrid Mechanism (HM)
2016 [Nguyén et al., 2016]	Collecting and analyzing data from smart device...	numerical, binary and categorical data. Domain ...	BR	-	ϵ -LDP	-	Harmony
2015 [Geng et al., 2015]	The staircase mechanism in differential privacy	n-dimensional numerical data	-	https://github.com/IBM/differential-privacy-lib...	DP	Differential privacy method	Staircase mechanism (SM)
2013 [Geng and Viswanath, 2013]	Optimal data-independent noise for differential...	n-dimensional	-	-	ϵ -DP	Non interactive	-

Table 2.2: Summary table of the literature review for (L)DP algorithms.

number	name	samples	features	target	Source	Realworld data?
1	Adult	48,842	14 numerical/categorical/boolean	income (>50k, <= 50k)	UCI	Yes
2	Seeds	210	7 numerical	type	UCI	Yes
3	Iris	150	4 numerical	class (type of iris)	UCI	Yes
4	CarGPS	17,785,500	3 geographical data	-	-	Yes
5	3D Road Network	434,874	3 geographical data	-	-	Yes
6	Pathbased	300	2 numerical	ground truth clusters	PapersWithCode	No
7	Aggregation	788	2 numerical	-	-	Unknown
8	Digit	1797	8x8 numerical	number	Scikit-learn	Yes
9	Lsun	400	2 numerical	ground truth clusters	-	No
10	S1	1500	2 numerical	ground truth clusters	-	No
11	Deer	20,033	2 numerical	-	-	Yes
13	Gowalla	6,442,890	5 (geographical data, ids and time)	-	https://snap.stanford.edu/data/loc-gowalla.html	Yes

Table 2.3: The different datasets used in the related literature.

2.3.4. EVALUATION

It is important to compare our kD-Laplace method with other studies for this research. Studies that are similar to ours mainly utilize LDP for clustering and add noise to cluster centroids [Huang et al., 2021; Xia et al., 2020; Yuan et al., 2021]. Or, require modifications of the K-Means algorithm [Sun et al., 2019].

As explained earlier, we aim to create a general-purpose LDP mechanism that can be used with multiple cluster algorithms 2.3.1. Based on the literature study, two LDP mechanisms fall into this category: Harmony and Piecewise [Nguyễn et al., 2016; Wang et al., 2019]. Published open-source code is available for Piecewise but, unfortunately, not for Harmony. Therefore, we will only focus on the Piecewise mechanism as means of comparison material. The following sections focus on investigating the Piecewise mechanism.

DUCHI ET AL.'S MECHANISM

The Piecewise mechanism is based on Duchi et al.'s mechanism for one-dimensional data. Therefore, we start by explaining this mechanism first. Duchi et al.'s mechanism is a relatively simple method based on the Bernoulli distribution [Duchi et al., 2017]. This distribution yields either a 0 (negative) or a 1 (false) based on specified probabilities ⁴. The mechanism works on a domain tuple [-1, 1] and returns -1 or 1. Hence, the PDF of this function is as follows ⁵:

$$P(n) = \begin{cases} 1-p & \text{if } n = 0 \\ p & \text{if } n = 1 \end{cases} \quad (2.15)$$

The probabilities are calculated based on the input value and can then be used to estimate a mean value. Compared to Laplace, Duchi et al. solution performs better in variance for epsilons smaller than 2 [Wang et al., 2019]. However, it performs worse when the epsilon value is higher because the algorithm does not consider the privacy budget for values that are 0. The multidimensional variant looks like the one-dimensional version but samples each data point's noise independently.

PIECEWISE MECHANISM

The authors aim to create a method that combines the advantages of the Laplace mechanism and Duchi et al.'s methods [Wang et al., 2019]. The goal is to reduce the variance for a broader range of privacy budgets. Like the mechanism above, the Piecewise mechanism only accepts data from -1 to 1. We first explain the one-dimensional variant and then the multidimensional variant.

The mechanism for one-dimensional has an output of $c \in [-C, C]$. Which is defined based on the privacy budget:

$$C = \frac{\exp(\epsilon/2) + 1}{\exp(\epsilon/2) - 1} \quad (2.16)$$

The noise is sampled from this distribution by conditionally executing one of two algorithms (see for reference Wang et al.'s paper) [Wang et al., 2019]. Due to the symmetric nature of their mechanism's PDF, the authors can handle the value of 0. Imagine it as a histogram with the distribution centered around 0. The histogram consists of three "parts" on the left, right, and center (0). This approach allows for determining the probability of 0 based on a certain likelihood, unlike Duchi et al.'s solution.

⁴<https://mathworld.wolfram.com/BernoulliDistribution.html>

⁵<https://mathworld.wolfram.com/BernoulliDistribution.html>

The authors generate a randomly sampled set of values k for the multidimensional approach. Next, for each value from k , the value is sampled using the one-dimensional Piecewise mechanism. A critical factor in the overall calculation is the scale factor C_d , which, in addition to C (referring to Equation 2.16), also considers the number of dimensions d . Finally, the authors also provide an extension to support categorical data.

3

nD-LAPLACE

In this chapter, we delve deeper into geo-indistinguishability and the various mechanisms that work with it. We also explain the theory behind the nD-Laplace mechanism and how we modify it and apply it for clustering. This explanation is build-up out of several sections, each dedicated 2, 3, and n-dimensional data:

1. 2D-Laplace
2. 3D-Laplace
3. nD-Laplace

For each mechanism, we explain the equation for GI, the mechanism, and the data truncation.

3.1. 2D-LAPLACE

The idea of GI was introduced to solve the issue of privacy and location data [Andrés et al., 2012]. To recall what was explained earlier (Equation 2.4). It offers an alternative approach for achieving (local) differential privacy for geographical data (latitude/longitude). The mechanism achieves this by locally adding noise to the location before sending it to a location-based system (LBS). This section starts with an introduction to mathematics, and for each of the different subsections, we visualize and explain open challenges and theoretic for applying them for clustering.

3.1.1. PLANAR AND POLAR LAPLACE

In section 2.1.1, an explanation of the concept of GI has been given. As indicated, the method works on 2-dimensional data, and when visualized, this can be done with a so-called plane [Andrés et al., 2012]. From there, the term "Planar" Laplace originated and was used thoughtfully by Andres et al.

The idea of Planar Laplace is to generate an area around $x_0 \in X$ according to the multivariate Laplace distribution. The mechanism of planar Laplace is a modification of the Laplace algorithm to support distance [Andrés et al., 2012]. This distance method $dist(x, x')$ is a method to calculate the Euclidean distance between two points x and x' . Recalling the

definition of Laplace, this method $|x - x'|$ is replaced by the distance metric. Hence, the definition of the PDF) by Andrés et al. is:

$$\frac{\epsilon^2}{2 * \pi} e(-\epsilon d(x_0, x)) \quad (3.1)$$

Which is the likelihood a generated point $z \in Z$ is close to x_0 . The method works for Cartesian coordinates but was modified to support polar coordinates by including θ . So each point is reflected as (r, θ) . A point $z \in Z$ where $z = (r, \theta)$ is randomly generated using two separate methods for calculating r and θ . This idea is visualized in the following figure:

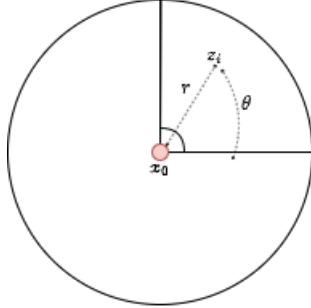


Figure 3.1: Representation of the generated $z = r\theta$ and original point x_0 .

Calculating r : This variable is defined as $dist(x_0, z)$ and can be randomly drawn by inverting the Cumulative Distribution Function (CDF) for the Laplace distribution:

$$C_\epsilon^{-1}(p) = -\frac{1}{\epsilon}(W_{-1}(\frac{p-1}{e}) + 1) \quad (3.2)$$

For this equation, W_{-1} is a Lambert W function with a -1 branch. The Lambert w function (also called the product logarithm) is defined as $W(x)e^{W(x)} = x$ [Lehtonen, 2016]. The purpose of the Lambert w function is to invert the CDF of the Laplace distribution to generate random noise for one of the coordinates (r) using the random value of p .

Calculating θ : The other variable (θ) is defined as a random number $[0, 2\pi]$. To visualize the data, it is necessary to convert the polar coordinates for $z = (r, \theta)$ back to planar coordinates $z = (x, y)$. This conversion is described as step 4 of the planar Laplace algorithm [Andrés et al., 2012] and visualized using figure 3.2.

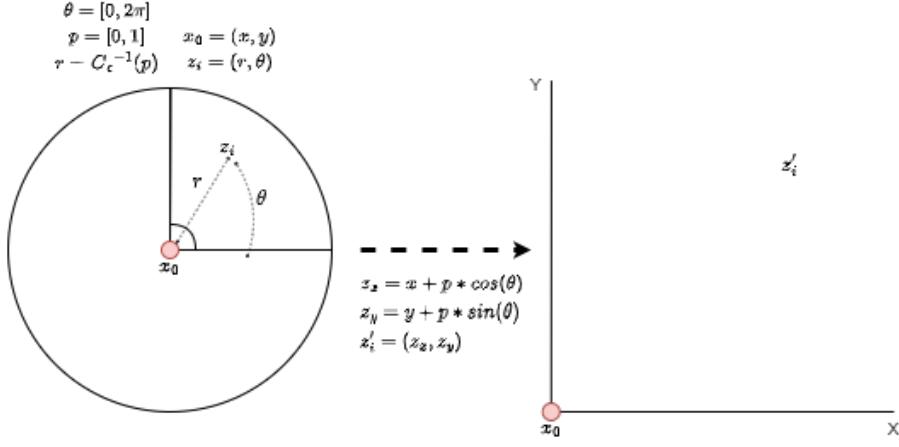


Figure 3.2: Representation of converting the perturbed point $z = (r, \theta)$ to a point z_x, z_y

3.1.2. TRUNCATION

After adding the noise to the data, it cannot be ensured the data is within the original domain (figure 3.3). If this is not the case, the data is easily distinguished by an unwanted adversary [Andrés et al., 2012; Min et al., 2022]. The truncation is an essential part of the mechanism to ensure the data is contained within the domain of the original data X . A vi-

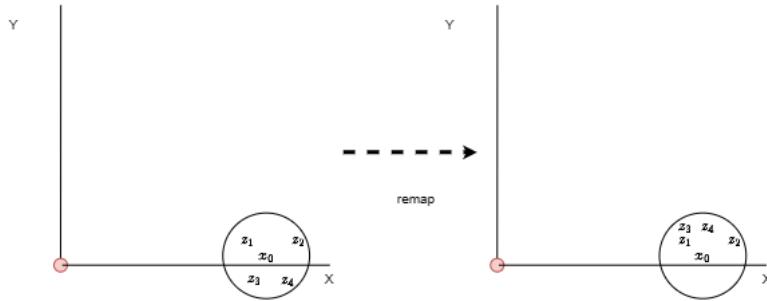


Figure 3.3: Representation of truncation of data points for 2-dimensional Laplace mechanism.

able solution is to create a grid around the diameter of the set of points $X = R^2$ that belong to the user [Andrés et al., 2012]. This grid is defined as $G = \{g_1, g_2, \dots, g_n\}$ where g_i is a grid point. So, a point generated outside the given domain is remapped to the closest in $X \subset G$.

This idea was later improved by Chatzikokolakis et al., introducing an optimized way of remapping [Chatzikokolakis et al., 2017]. The algorithm uses the Bayesian rule to minimize the loss of utility while remapping the data. Instead of remapping to the closest point, it remaps to a location where the loss is minimal. To decrease the performance impact of this algorithm, it is possible only to consider a specific region around the perturbed point z . The disadvantage of this method is the need for a prior set of data points to calculate the optimal remapping.

3.1.3. OPTIMIZING FOR CLUSTERING

The decision of the parameters for the algorithm is straightforward as it depends on the ϵ . This constant is calculated by defining the radius r , and the desired level of privacy l and ϵ is calculated using l/r . The l is a predefined constant $l \in R^+$ but usually will be below 10.

For geographical data, the r can be configured using meters as a unit of measure. So, for example, $r = 200$ corresponds to a radius of 200m around point x_0 . Without a unit, it is a challenge to define a reasonable radius.

In that regard, the radius can also be a flexible value defined based on the crowdedness of a region [Chatzikokolakis et al., 2015]. Suppose a user's location is within a crowded area. In that case, the radius can be smaller than if the user is located in a rural area (because the user's location is indistinguishable due to the overlap of other users' locations). Instead of providing GI, the authors introduce a more flexible privacy definition d_x -privacy. The r is calculated based on the mass of other regional locations r , which they call *privacy mass*. So, the total mass of a set A is defined as $M(A) = \sum_{x \in A} m(x) = a + q(x)b$. Where $m(x)$ is the mass of a location x and is of value $[0, 1]$. For this formula, a is the number of points assigned to each location. The authors define $q(x)$ as the "quality" of a point, which is essentially the number of other users that are also interested in the same point (e.g. a mall).

The a is defined as a Euclidean ball $B_r = x' | d_{euc}(x, x') \leq r$, which returns all locations within the radius r . To retrieve a value within $[0, 1]$, the authors use the following formula:

$$a = \frac{1}{|B_r|} \quad (3.3)$$

If the locations are only considered for space and not quality, $q(x)$ is defined as 0 [Chatzikokolakis et al., 2015].

Although the method is an interesting approach to increasing utility while not reducing privacy, it is hard to adopt for clustering. For applying it for LDP, it is required to supply each user with prior knowledge of the dataset. This approach would require interaction between data points, hence an interactive setup of the mechanism instead of a non-interactive one.

Nonetheless, the idea of using crowded locations is an exciting approach that is researched further in section 3.3.2

3.1.4. FINAL MECHANISM

Finally, we provide as means of a summary the final algorithm for the Laplace mechanism for 2D space

Algorithm 1 Full algorithm for perturbing training data for 2D-clustering using planar/2D-Laplace [Andrés et al., 2012]

```

Input:  $x \in X$                                      ▷ 2D array of points
Input:  $l \in R^+$ 
Input:  $r \in R^+$                                 ▷ sensitivity
Output:  $z \in Z$                                  ▷ 2D array of perturbed points
 $\epsilon = \frac{l}{r}$                                ▷ Calculating privacy budget [Andrés et al., 2012]
 $x_{min} \leftarrow min(X)$ 
 $x_{max} \leftarrow max(X)$ 
 $Z \leftarrow []$ 
for  $point_i \in X$  do
     $\theta \leftarrow [0, \pi/2]$                          ▷ Random noise for  $\theta$ 
     $p \leftarrow [0, 1]$ 
     $z_i \leftarrow C_\epsilon^{-1}(p)$                   ▷ formula 3.2
     $x_{perturbed} \leftarrow point_{i_x} + (z_{i_x} * \cos(\theta))$  ▷ add noise to x-coordinate
     $y_{perturbed} \leftarrow point_{i_y} + (z_{i_y} * \sin(\theta))$  ▷ add noise to y-coordinate
    append  $x_{perturbed}, y_{perturbed}$  to  $Z$ 
end for
return  $Z$ 

```

3.2. 3D-LAPLACE

The previous sub-section described the use of 2-dimensional noise on geographical data. This approach has recently been extended to support 3-dimensional data, which benefits indoor navigation [Min et al., 2022]. The method is similar to the 2D approach but includes the azimuth angle ψ besides the polar angle θ and radial distance r .

3.2.1. GEO-INDISTINGUISHABILITY

To establish the same privacy guarantees for 3-dimensional data as for 2-dimensional data, the original equation 2.4 is extended [Min et al., 2022].

$$K(x_1)(z) \leq e^{\epsilon * d_3(x_1, x_2)} K(x_2)(z) \quad (3.4)$$

Where x_1 and x_2 are two real data points in the same dataset X .

3.2.2. SPHERICAL LAPLACE

The implementation of Min et al. projects the dimensions onto a sphere instead of a circle [Min et al., 2022]. This sphere is a unit sphere calculated with a radius of 1. The polar angle θ and azimuth angle ψ are randomly calculated based on this sphere.

Calculating θ and ψ : The tuple $U = (\theta, \psi)$ is randomly drawn from the unit sphere using the following equations [Min et al., 2022]:

$$\theta = \frac{1}{\pi} \quad (3.5)$$

$$\psi = \frac{1}{2\pi} \quad (3.6)$$

Calculating r : The radial distance r is calculated using the following equation:

$$r = \frac{1}{2} \epsilon^3 * r^2 * e^{-\epsilon * r} \quad (3.7)$$

The gamma scale is the same as for 2D-Laplace but with a shape of 3 instead of 2. The noise is added to the original location x to obtain the perturbed location $z = x + U * r$. A clear example of the generated noise by this method is shown in figure 3.4. Finally, the spherical coordinates are converted to the Cartesian coordinate system to obtain the perturbed location z :

$$\begin{aligned} z_x &= r * \sin(\theta) * \sin(\psi) \\ z_y &= r * \sin(\theta) * \cos(\psi) \\ z_z &= r * \cos(\theta) \end{aligned}$$

The complete overview is visualized in figure 3.5.

Kernel density plot of a point x_0 (centre) with 50 random generated points according to the formula for 3D-Laplace in a projected sphere with epsilon 3

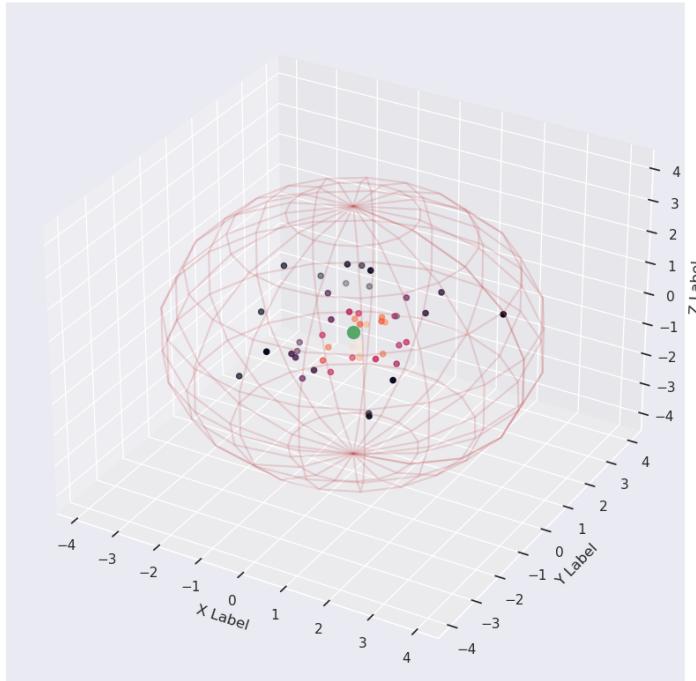


Figure 3.4: 50 random noise samples generated around point x_0 (green dot) using the 3D-Laplace noise method [Min et al., 2022] plotted on a sphere.

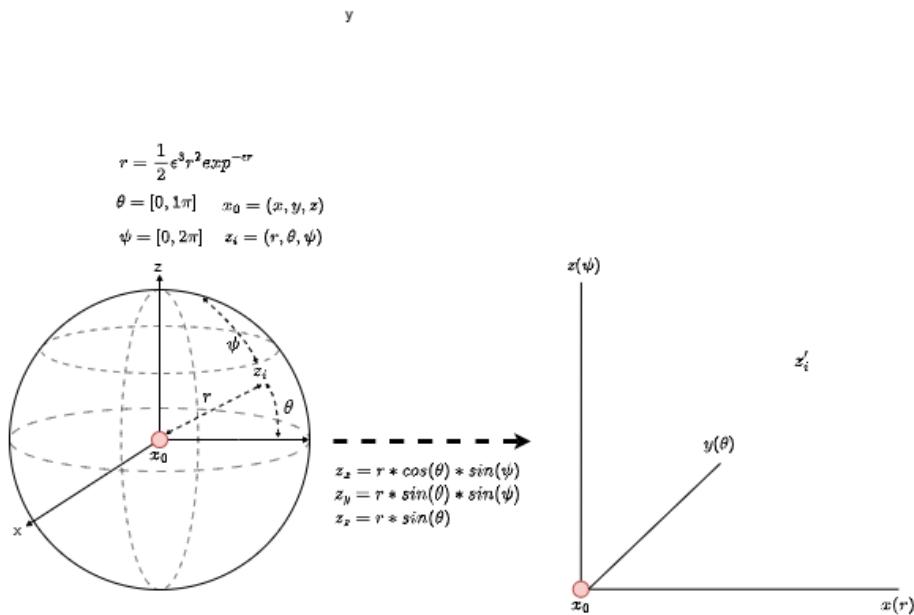


Figure 3.5: 3D-Laplace noise distribution according to the method proposed by Min et al. [Min et al., 2022]

3.2.3. TRUNCATION

As with the 2D-Laplace method, the 3D-Laplace method also needs a truncation method. This truncation method is also based on the same method as the 2D-Laplace method. Instead of a plane grid, a cuboid grid is used for 3-dimensional space. This cuboid remaps the noise to the closest grid cell $g \in G$ or existing point in X . We plotted example data points on a 3-dimensional grid in figure 3.6 to demonstrate this:

Example of generating noise for a dataset and remapping it to $X \subset G$ when outside the domain

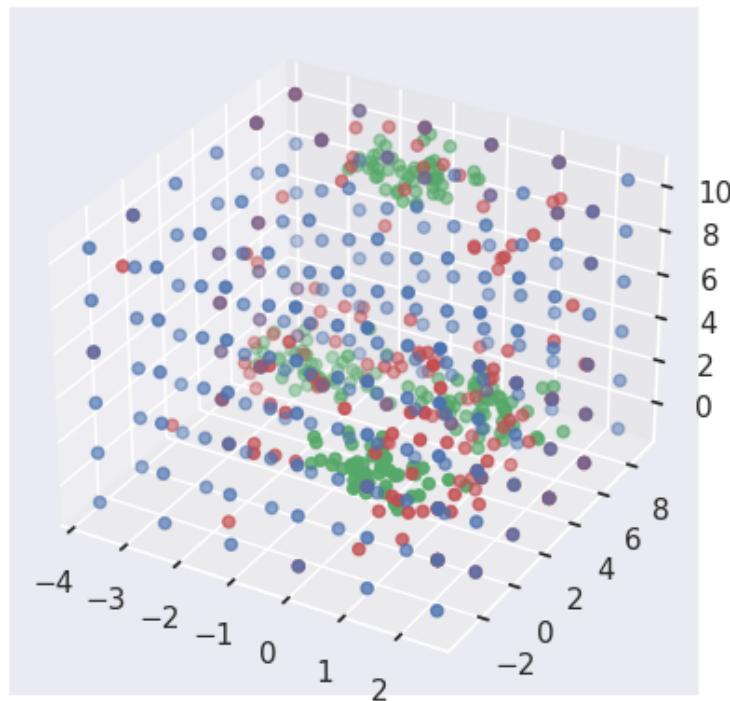


Figure 3.6: Applying 3-dimensional noise with $\epsilon = 1$ (red dots) to a dataset X (green dots). Demonstrating remapping to the closest grid point (blue) or X .

3.2.4. FINAL MECHANISM

Finally, we provide as means of a summary the final algorithm for the Laplace mechanism for 3D space

Algorithm 2 Full algorithm for perturbing training data for 3D-clustering using planar/2D-Laplace [Andrés et al., 2012]

Input: $x \in X$ ▷ 3D array of points
Input: $l \in R^+$
Input: $r \in R^+$
Output: $z \in Z$ ▷ 3D array of perturbed points

$\epsilon \leftarrow \frac{l}{r}$ ▷ Calculating privacy budget [Andrés et al., 2012]
 $Z \leftarrow []$

for $point_i \in X$ **do**

- $\theta \leftarrow 1, \pi 2$ ▷ Random noise according to equation 3.7
- $p \leftarrow \frac{1}{2\pi}$ ▷ Random noise according to equation 3.8
- $r \leftarrow \frac{1}{2}\epsilon^3 * r^2 * e^{-\epsilon * r}$ ▷ Draw r based on equation 3.7
- $z_x \leftarrow r * \sin(\theta) * \sin(p)$
- $z_y \leftarrow r * \sin(\theta) * \cos(p)$
- $z_z \leftarrow r * \cos(\theta)$
- $Z ::= Add(z)$ ▷ Adds z to the list Z.

end for

return Z

3.3. ND-LAPLACE

As mentioned in the previous chapter, the paper introduced by Min et al. can handle 3-dimensional data. A small recap: a point (r, θ, ψ) gives us the spherical coordinates of a given 3-dimensional sphere. An important property is that these coordinates can be generated separately [Andrés et al., 2012; Min et al., 2022]. The r gives us the radius or distance from (θ, ψ) to the center of the sphere¹. So, instead of having just these two coordinates, we can extend this to n-dimensions by considering an n-hypersphere [Fernandes et al., 2019; Min et al., 2022]. To this end, in addition to points θ and ψ , we consider $\theta \in S^n$, where S is a unit hypersphere.

The first step to generate the noise is first to select the r . This method is almost identical to the one for 3-dimensional (3.7). But, instead of applying a scale of 3, the scale will be n for the number of dimensions in the data [Fernandes et al., 2019]:

$$\gamma(n, 1/\epsilon) \quad (3.8)$$

For the other dimensions, we consider a vector $U = (\theta_1, \theta_2, \theta_n)$ which is uniformly selected based on a unit n -hypersphere S^n [Fernandes et al., 2019]. We consider the work that was proposed by Marsaglia et al. for a 4d-sphere that can be used for selecting points from an n-hypersphere [Marsaglia, 1972]. This method resolves around selecting points from a hypersphere by using a uniform distribution for the domain $[0, 1]$. For this purpose, an approach to draw data points from a Gaussian distribution is adopted².

3.3.1. CARTESIAN COORDINATES

As with the 2/3D-Laplace, the spherical coordinates need to be converted to Cartesian to be able to cluster. It is comparable to the way it was done in the previous chapters; however, as there are an n -amount of angles, the equation is repeated and slightly different:

$$x_1 = r * \cos(\theta_1) \quad (3.9)$$

$$x_2 = r * \sin(\theta_1) * \cos(\theta_2) \quad (3.10)$$

$$x_n = r * \sin(\theta_1) \dots \sin(\theta_{n-2}) * \cos(\theta_{n-1}) \quad (3.11)$$

$$x_n = r * \sin(\theta_{n-1}) * \sin(\theta_{n-2}) * \sin(\theta_{n-1}) \quad (3.12)$$

The combination of sections 1 and 2 of this chapter provides a good overview of the solution using a similar image as the 2D and 3D variants (figure 3.7).

¹<https://mathworld.wolfram.com/SphericalCoordinates.html>

²<https://mathworld.wolfram.com/SpherePointPicking.html>

$$r = \gamma(4, 1/\epsilon)$$

$$U = \frac{1}{1\sqrt{2\pi}} \exp^{-\frac{1}{2}(\frac{x-0}{1})^2}$$

$$\theta_n \in U$$

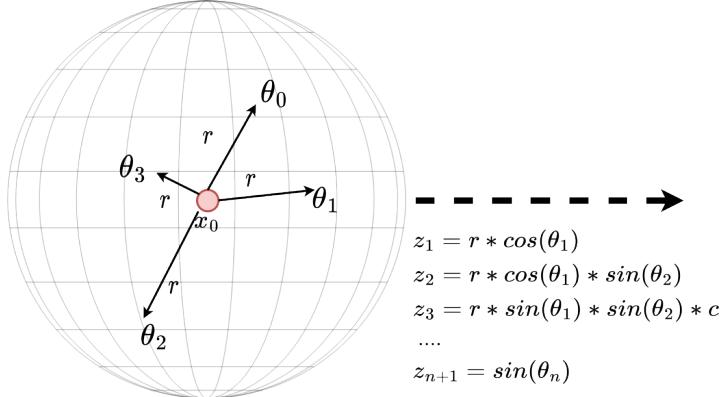


Figure 3.7: Overview of the nD-Laplace mechanism

3.3.2. PRIVACY VERSUS UTILITY

If we continue adding dimensions, we notice the noise is shrinking proportionally. We must first examine the formula for a hypersphere's volume to understand this behavior.

$$S_n = \frac{2\pi^{n/2}}{\gamma(\frac{1}{2}n)} \quad (3.13)$$

γ is the Gamma distribution determined based on the number of dimensions n ³. As the amount of dimensions increases, the most volume is located on the hypersphere surface. When we convert the points to Cartesian coordinates, some will be located at the center (e.g., 0.5), while others will be close to the surface (e.g., 0.0). However, as the number of dimensions increases, most will be close to the surface (e.g., 0.99). The decreasing amount of volume is illustrated using this figure:

³<https://mathworld.wolfram.com/Hypersphere.html>

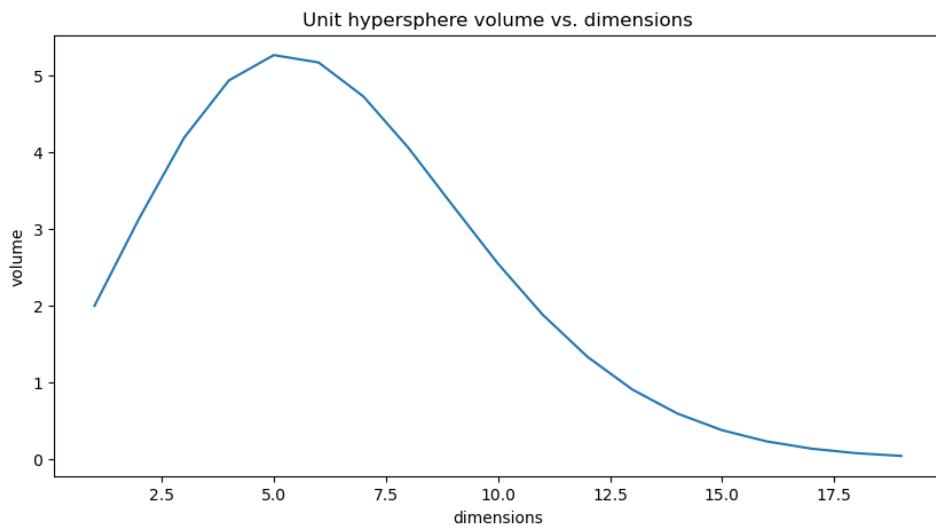


Figure 3.8: Illustration of the decreasing volume while increasing the number of dimensions

The noise decreases as the dimensions increase, increasing utility. Hence, observing the behavior of privacy relative to utility is intriguing. This behavior will be further emphasized in a later stage of this research.

3.3.3. TRUNCATION

In section 3.1.3, we introduced a method to optimize the 2D Laplace mechanism based on crowdedness (point density). This method is extended with the help of a more recent paper provided by Chatzikokolakis et al. [Chatzikokolakis et al., 2017]. We use this work to extend and optimize the grid-remapping method for 2D/3D Laplace (Sections 3.1.2 and 3.1.3) and introduce optimal grid-remapping to improve the utility further. We want to emphasize that this section focuses on improving utility with remapping. Any remap method preserves geo-indistinguishability Chatzikokolakis et al. [2017], so the required privacy is still preserved.

Recalling both mechanisms, the 2D version operates on a plane and approximates on a grid G , while the 3D version works in a 3D space using a cuboid grid. Given a set of input points $X \subset R^2$, we can truncate points that are outside the domain by remapping them to points within G ($Z = X \cap G$) [Andrés et al., 2012]. Here, X represents other data points reported locally by the same user. To extend this approach to n-dimensional data, we need an efficient way to search points in an n-dimensional hypersphere. To do this, we adopt the idea proposed by Chatzikokolakis et al. of using a kd-tree to search the grid efficiently [Chatzikokolakis et al., 2017]. In their research, they describe the utilization of a kd-tree for searching nearby points for a given point. For this reason, we also use a kd-tree for the following tasks:

1. Finding nearby points for $z \in G$ (section: [Grid with kd-tree remapping](#)).
2. Finding nearby points for $x \in X$ and $z \in Z$ (section [Optimal remapping](#)).

For visualization purposes, this section will primarily focus on 2D data. However, it is essential to emphasize that the same algorithm will also be applied to 3D and nD data. The underlying principles and steps of the algorithm remain the same.

We first introduce kd-trees on the next page and then explain how we apply them for the two tasks.

KD-TREES

A kd-tree algorithm can search a grid for nearby points [Bentley, 1975]. It can do so by recursively splitting the grid into a binary tree to search for grid coordinates [Washington, 2]. In addition, it preserves spatial information of the data so it can be utilized to find nearby points using Euclidean distance (nearest neighbor search). The following example provides an idea of how this works (Figure 3.9):

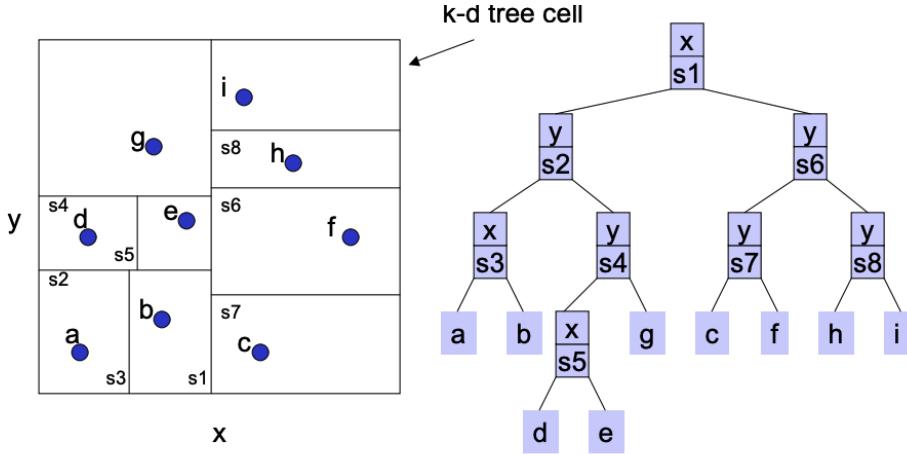


Figure 3.9: Representation of constructing a kd-tree with 2 dimensions [Washington, 2].

Take, for example, the 2D Laplace algorithm that utilizes a plane (left side). The data points can be divided based on their x and y coordinates. Each coordinate becomes a node in the binary tree, and the grid is divided based on these splits. The binary tree allows us to search the grid efficiently. An example of this is provided in the following image (Figure 3.10):

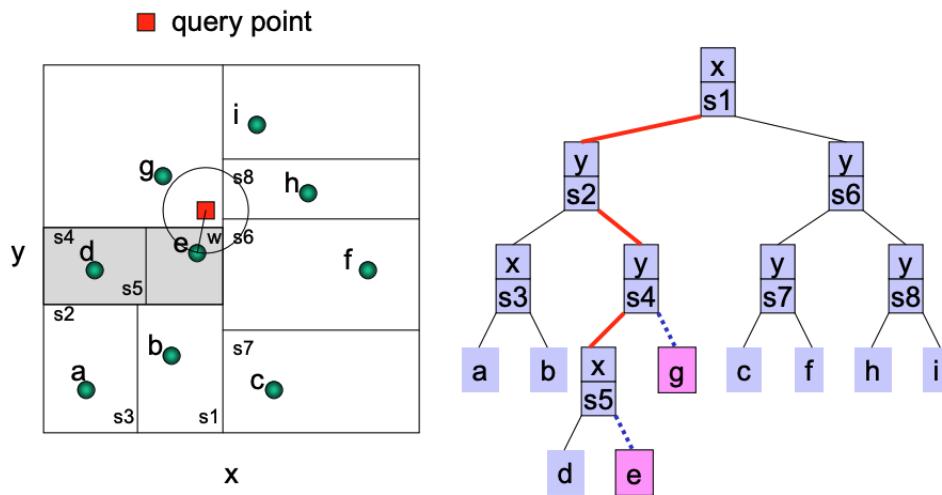


Figure 3.10: Representation of searching a kd-tree with 2 dimensions [Washington, 2].

In the example, we are searching for all points that fall within the radius of a random query point. Thanks to the grid being divided into a binary tree, a portion can be efficiently

searched, evaluated, and referenced. The most significant advantage is that this greatly reduces the complexity of searching. Constructing the kd-tree costs $O(kn)$, where k is the number of dimensions and n is the dataset size. Searching for the nearest neighbor is a little less efficient, with a time complexity of $O(\log n)$ [Washington, 2] (See Figure 5 for an overview of the Big-O notation). A reference to the Big O notation can be found in the appendix .

[add reference](#)

GRID WITH KD-TREE REMAPPING

As explained in the previous paragraph, a kd-tree can be used to perform a nearest neighbor search. This search method is highly relevant to our research as it proves to be beneficial for the optimizations we are striving for. To this end, we adopt this approach for remapping the perturbed data points $z \in Z$ to a grid G .

We have illustrated the three steps required for this below:

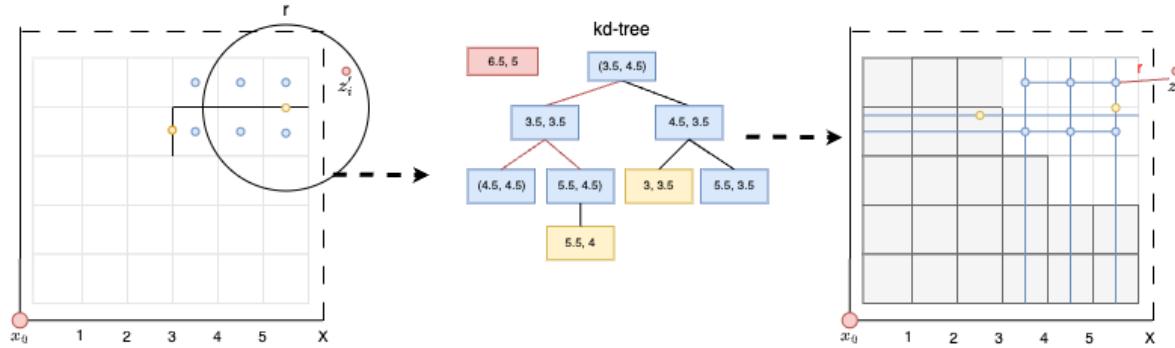


Figure 3.11: Representation of a kd-tree with 2 dimensions to remap based on a grid.

The above illustration presents the grid-remapping algorithm. Firstly, a grid is generated, where each (blue) point represents the center of a grid cell. Together, these centroids form the grid dataset, denoted as G . The yellow points and x_i are part of the original collection, denoted as X . Here, r represents the radius used to generate a private version of the data point x_i , named z_i , based on 2D-Laplace (in this case). In the illustration, you can observe that z_i falls outside the original domain of X , so it needs to be remapped. We accomplish this by utilizing the nearest-neighbor search from the kd-tree algorithm, allowing us to search in $X \cup G$. Using this algorithm, we can effectively remap point $z \in Z$ to either X or G based on the closest Euclidean distance (Algorithm 4 and Algorithm 3).

The utility of this method depends on the number of grid cells in G since a smaller distance will result in more frequent mapping to the surface of the grid. When ϵ is very low (and thus farther away), the data points are more likely to map to the grid surface (3.4, 3.6). Increasing the number of grid cells can improve the utility, but this comes at the cost of significantly increased space complexity for k dimensions. This is because a grid of $n * m$ dimensions has a $O(n^2)$ complexity. Therefore, we also explore the optimal remapping algorithm proposed by Chatzikokolakis et al. [Chatzikokolakis et al., 2017].

Algorithm 3 Algorithm for finding points outside the domain of X .

Input: $x \in X$ ▷ original dataset
Input: $z \in Z$ ▷ perturbed dataset

$X_{domain} \leftarrow \text{KDTREE::QUERY}(Z)$ ▷ find the closest points.
 $X_{features} \leftarrow \text{LIST::GETFEATURES}(X)$ ▷ retrieve dataset dimensions

$X_{outside-domain} \leftarrow []$

for $feature \in X_{features}$ **do** ▷ iterate over all features and check if any points are outside the domain.

if $feature \leq X::\text{MIN}(Z)$ **then**
 ROW::APPEND($X_{outside-domain}$)
 end if
 if $feature \geq X::\text{MAX}(Z)$ **then**
 ROW::APPEND($X_{outside-domain}$)
 end if
end for

return $X_{outside-domain}$ ▷ The index of points outside the domain of X .

Algorithm 4 Algorithm for generating and remapping to a grid.

Input: $x \in X$ ▷ original dataset
Input: $z \in Z$ ▷ perturbed dataset
Input: $grid$ ▷ grid structure ($n * m$)

$d_X = Z::\text{DIST}(X)$ ▷ euclidean distances between X and Z .
 $d_{grid} = Z::\text{DIST}(grid)$
 $Z_{out-domain} \leftarrow X::\text{FINDPOINTSOUTSIDEDOMAIN}(Z)$ ▷ Algorithm 3
 $grid_tree \leftarrow \text{KDTREE::BUILDTREE}(grid)$ ▷ create kd-tree
 $grid_mask \leftarrow \text{KDTREE::QUERY}(Z)$ ▷ find indices of $z \in Z$ that are closeby grid cells.
 $Z_{grid-mask} \leftarrow Z_{out-domain} \cup d_{grid} < d_X$ ▷ All points $z \in Z$ that are closeby grid cells and are outside domain.
 $Z' \leftarrow Z[grid[grid_mask][Z_{grid-mask}]]$ ▷ combine masks to set appropriate indexes to $g \in grid$.
return Z'

OPTIMAL REMAPPING

As discussed, the remapping will be performance intensive to provide good utility, so we adopt the optimal remapping [Chatzikokolakis et al., 2017]. Consider the grid proposed in 3.11. After remapping point z_i , it is mapped to the center for the grid cell. Based on the cell width, the distance to the original point x_i and z_i could be really large. We aim to remap the center of the grid cell (now z_i) to a point closer to x_i (if applicable).

This remapping is visualized by zooming into the last step of the grid-remapping (Figure 3.11).

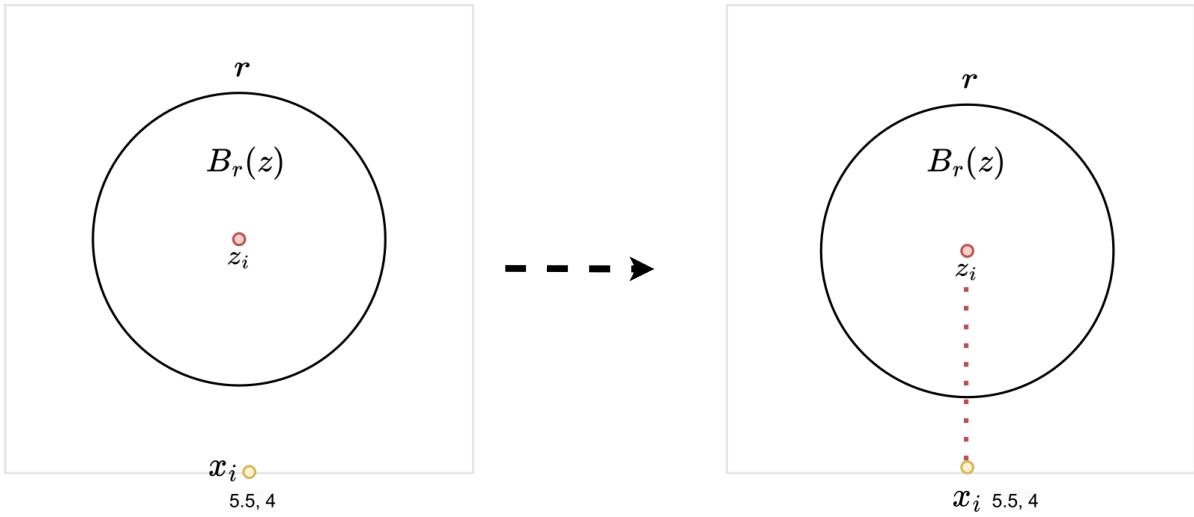


Figure 3.12: Representation of optimal remapping [Chatzikokolakis et al., 2017], where z_i is remapped to x_i using $\sigma(x)$ instead of the center of the grid cell.

In Figure 3.12, we can observe that z_i is remapped to the center of the grid cell as a consequence of the grid-remapping. For the reasons mentioned earlier, this is not optimal, and we can further optimize it by utilizing the other data points. The remapping algorithm works on the idea of crowded places 3.1.3, with the intuition that a crowded place leverages indistinguishability by crowdedness [Chatzikokolakis et al., 2017]. For the remainder of this thesis, we will use the term "density" instead of "crowdedness" because it better aligns with the clustering of data.

The first step is to calculate $B_r(z)$, which refers to all the data points within the original radius r around the data point z_i . The next step in the algorithm is to collect the data points around x_i to calculate how closely it can be remapped to z_i while preserving distinguishability. This variable is the collection (convex hull) of all original data points $x \in X$ close to x_i , determined based on the radius r around x_i . Finally, we combine both sets to obtain $Q_r = B_r \cap X$. Now that we have the sets of points around x_i and z_i , we can calculate the density for each point $q \in Q_r$ [Chatzikokolakis et al., 2017]:

$$\forall x \in Q_r \quad \sigma(x) = \frac{w(x)e^{-\epsilon d(x,z)}}{\sum_{q \in Q_r} w(q)e^{-\epsilon d(q,z)}} \quad (3.14)$$

Where $w(q)$ is the weight of a point q in Q_r and can be seen as points visited earlier by the user or other users (e.g., point of interest). We will revisit this topic in the next paragraph when discussing the practical implementation of the nd-Laplace algorithm. The same applies to $w(x)$ but for an individual point $q \in Q_r$ instead of the summation. The outcome of

the formula is a collection of values that indicate the degree of density, which we call $\sigma \in S$. With this data, we can calculate a new z' closer to x_i to minimize the expected loss of utility [Chatzikokolakis et al., 2017].

The collection S can be seen as the coefficient for each point $x \in X$, which can be used as a scale to apply for each point X [Chatzikokolakis et al., 2017]:

$$\bar{\sigma} = \sum_{\sigma \in S} \sigma(x) * x \quad (3.15)$$

Then next, the probabilities are calculated:

$$W = \forall \sigma \in S = \frac{\sigma(x)}{\bar{\sigma}} \quad (3.16)$$

Finally, the z' is calculated by calculating the average with the probabilities as weight:

$$z' = \frac{\sum_{weight \in W} x * weight}{\sum_{weight \in W} weight} \quad (3.17)$$

PRACTICAL IMPLEMENTATION

It is challenging to interpret $w(q) \in Q_r$ beforehand based on other users, as we do not have this information (there is a way, but we explain this at the end of this section). To this end, we will interpret $w(x)$ as the number of points within the radius r around a point $x \in Q_r$. Afterward, it is possible to divide the outcome of this value by the sum of these points (as done in Algorithm 3.14). We, therefore, remain with the same algorithm as proposed by Chatzikokolakis et al. but interpret the weight differently.

It is, however, still possible to interpret $w(q)$ as the weight based on other users' data points. This requires us to implement the mechanism interactively. In this approach, all clients perturb their data and send it to the server. The server clusters the private data, calculates weight based on cluster information (e.g., crowdedness/density), and shares it with the clients. The clients then use the optimal remap and share their private information with the server again. Although this system requires only a single round-trip between server and clients, it reveals cluster information, so we prefer the non-interactive setup.

Algorithm 5 Algorithm to implement the optimal remapping of $z \in Z$ to be in the domain of $x \in X$

Input: $x \in X$ ▷ n-dimensional array of original points
Input: $z \in Z$ ▷ n-dimensional array of grid-remapped perturbed points
Input: ϵ ▷ privacy budget
Output: $z' \in Z$ ▷ n-dimensional array of optimal-remapped perturbed points

$Z' = \text{FindRemappedPoints}(Z)$
 $tree \leftarrow \text{KDTree}(X)$ ▷ construct a KDTree from the original data.
for $z' \in Z'$ **do**
 $r = \text{FINDRADIUS}((z'))$ ▷ Get original radius r .
 $X_r \leftarrow \text{KDTREE::QUERY}(x)$ ▷ find $q \in X$ around x with radius r .
 $B_r \leftarrow \text{KDTREE::QUERY}(z')$
 $\sigma(x) = []$
 $Q_r = X_r \cap B_r$
 for $q \in Q_r$ **do**
 $q \leftarrow \text{KDTREE::QUERY}(q)$
 $w_x = \text{LENGTH}(X_r, B_r)$ ▷ weight is simply adding density of X_r and B_r .
 $w_q = \text{LENGTH}(Q_r)$ ▷ w_q is the density of each point q within Q_r .
 $\sigma(w_x) \leftarrow \text{REMAP}(w_x, \epsilon)$ ▷ Use equation 3.14 to remap w_x .
 $\sigma(x) \leftarrow \text{APPEND}(\sigma(x), \frac{\sigma(w_x)}{w_q})$ ▷ add to the list $\sigma(x)$.
 end for
 $z' \leftarrow \text{AVERAGE}(\sigma(x), P)$ ▷ Calculate z' using the equations: 3.15, 3.16 and 3.17.
end for

3.3.4. PUTTING IT TOGETHER: KD-LAPLACE

Now that we have defined everything, we can write the algorithm in a step-by-step manner:

Algorithm 6 Full algorithm for perturbing training data for nD-clustering using kd-Laplace

Input: $x \in X$ ▷ n-dimensional array of original points
Input: ϵ ▷ privacy budget
Output: $z \in Z$ ▷ n-dimensional array of optimal-remapped perturbed points
 $sphere = \text{GENERATEUNITS SPHERE}(x)$ ▷ construct a sphere around x .
for $row \in X$ **do**
 $d \leftarrow \text{LENGTH}(row)$ ▷ amount of dimensions
 $r \leftarrow \text{GENERATERADIUS}(d)$ ▷ generate radius r using Equation 3.8.
 $sphere \leftarrow \text{GENERATETHETA}(d)$ ▷ perturb the sphere Figure 3.7.
 $noise \leftarrow \text{CARTESIAN}(row, \epsilon)$ ▷ use Equation 3.12 to perturb row and convert
 to cartesian.
 $z = x + noise$
 $\text{APPEND}(Z, z)$
end for
return Z

It is important to note that with the introduction of this algorithm, it is no longer a non-interactive method, as the data points now interact with each other. Therefore, we expect the introduction of optimal grid remapping with kd-tree will bring more utility [Wang et al., 2020; Xiong et al., 2020b]. The introduction of the kd-tree is also why we present our method as *kd-Laplace*, where k is the number of dimensions.

3.3.5. MECHANISM FLOWCHART

All formulas and theories are established for 2D, 3D, and kD-Laplace, so the mechanism design applies to all three variants:

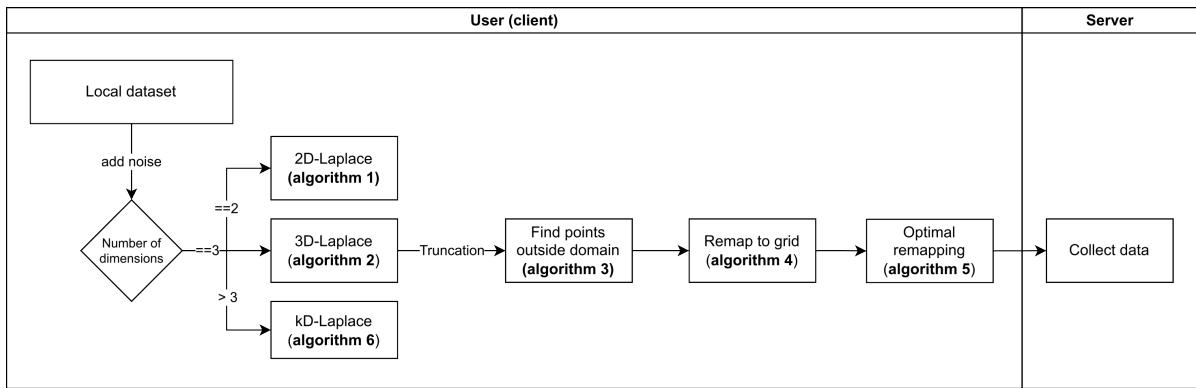


Figure 3.13: Non-interactive mechanism design for kD-Laplace.

For easy navigation, we provide a list of all algorithms:

1. 2D-Laplace: 1
2. 3D-Laplace: 2
3. kD-Laplace: 6
4. Find points outside domain: 3
5. Grid remapping: 4
6. Optimal remapping: 5

PRACTICAL EXAMPLE

The shape of the dataset is necessary for the usefulness of clustering. With our algorithm, there are four different shapes/variants of the dataset. For example, this has been visualized using a 3D dataset based on the heart dataset (5.1.3). Our mechanism aims to provide privacy and preserve the dataset's shape to benefit the utility of clustering. Grid remapping and optimal remapping are used to achieve this goal.

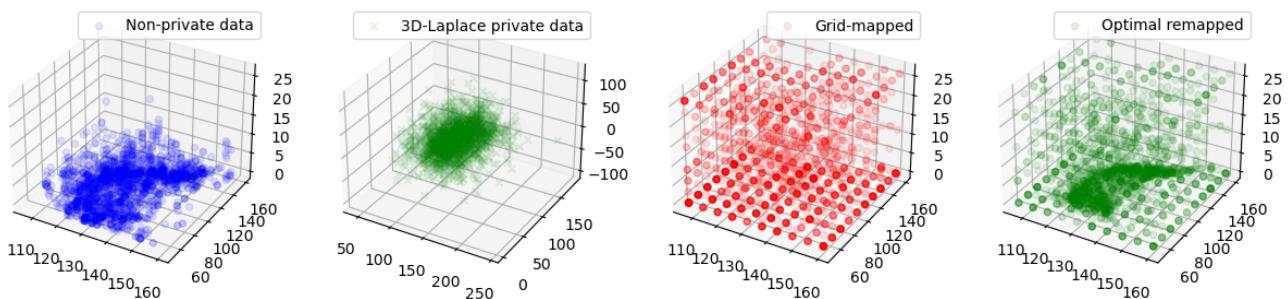


Figure 3.14: Example of optimal remapping for the 3D-dataset: Cardiotocography. The example shows the different steps of the mechanism in sequence for a dataset perturbed with a privacy budget of 0.1.

1. Dataset: the blue dots represent the original dataset without any modifications.
2. Adding noise: the green crosses represent the dataset after adding noise; for this particular example, this is 3D-Laplace (Algorithm 2): As can be observed, the data is generated from the center, causing many data points to fall outside the original domain of the dataset.
3. Grid-remapping: the red dots represent the dataset after grid-remapping (Algorithm 4) After performing the grid remapping algorithm, all points within the domain are plotted. However, the original shape of the data is mostly lost. This makes it challenging to cluster the data as was possible with the original data.
4. Optimal-remapping: the green dots represent the dataset after optimal-remapping (Algorithm 5). After completing the previous step, the data points are again remapped based on the (original) density. This results in restoring the original shape of the data and, consequently, the clusters.

4

ATTACKS ON PRIVACY

This chapter is devoted to investigating and evaluating attacks on machine learning models. Differential privacy protects the centrally stored dataset from leaking sensitive information. Therefore, assessing the mechanism's privacy is best measurable using common attacks [Jayaraman and Evans]. In this context, we evaluate attacks that explicitly uncover training data from a privately trained model. We consider two types of attacks:

1. **Membership inference attack:** An adversary attempts to infer whether a data point was used for training.
2. **Reconstruction attack:** An adversary attempts to reconstruct the training data using the model.

The knowledge of the attacker (adversarial knowledge) is an important factor to consider. This knowledge can be divided into white-box and black-box approaches [Hu et al., 2022].

1. **White-box:** The attacker has all the needed data. Including target model parameters, the training dataset and even the architecture [Hu et al., 2022].
2. **Black-box:** The attacker has limited information, like training data distribution and the trained model [Hu et al., 2022].

We will discuss both types of attacks and types in the next two sections.

4.1. MEMBERSHIP INFERENCE ATTACKS

An attack model that plays a significant role in machine learning is **Membership Inference Attack (MIA)**. With this attack, an adversary attempts to infer the training data $x \in X$ (member) from a given data point $z \in Z$ (non-member). The attack happens exclusively on supervised learning models, which predict labels or probabilities. Most attacks on models trained on a centralized dataset occur during the inference phase, where the trained model is used to make predictions. [Rigaki and Garcia, 2021]. This is also why we are primarily interested in this phase, as we are not using a distributed learning model.

The most well-known member inference attack is training shadow models [Rigaki and Garcia, 2021]. In this attack, an attacker trains multiple models. These models do not necessarily have to be the same as the original model, and the focus is mainly on the data

input/output. It is a black-box attack, but the attacker often needs knowledge of the data distribution to create a good shadow dataset [Rigaki and Garcia, 2021].

One of the earlier works that used this attack was Shokri et al. [Shokri et al., 2017]. An attacker trains multiple models (shadow model) to overfit the original modal. This idea is based on the model giving higher scores to the data on which it was trained (overfitting). Using this approach, attackers can retrieve the model's training data (member data) by injecting many fake data (non-membership data).

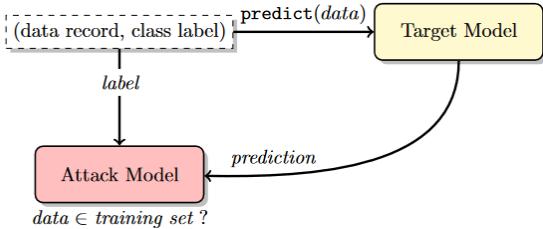


Figure 4.1: Black-box MIA attack on a machine learning model [Shokri et al., 2017]

Another approach to a black-box attack was introduced by Peng et al. and only considers that the attacker has access to the already trained model. They first rescale the probabilities using temperature scaling to compensate for overconfident models [Peng et al.]. So instead of having a probability between two classes with, for example, 99% against 1%, it will be more evenly distributed based on the training data. They then cluster the probabilities into two clusters using K-Means and label the higher confidence scores as members.

The above attacks do rely on the model to also provide the confidence or probabilities of the predictions. This information is often unavailable, so Choquette-Choo et al. introduced a label-only attack. While the existing models exploit MIA's probability output, they rely solely on labels [Choquette-Choo et al., 2021]. They use the "HopSkipJump" attack, a so-called decision-based attack [Chen et al., 2020]. Choquette-Choo et al. consider a more semi-black-box approach, for which the attacker still requires access to a subset of the original training data and the trained model. Another paper using "HopSkipJump" requires only the trained model and achieves higher accuracy using an approach with random data [Li and Zhang, 2021].

Access to only the output of the model is a typical characteristic of black-box attacks. If the attacker also knows architecture, for example, it is referred to as a white-box attack. Another take on this is prediction and confidence-based MIA, both proposed by [Yeom et al., 2018]. They assume that an attacker knows the standard error and has access to the perturbation dataset. The algorithm can then extract the truth label by minimizing the loss.

4.2. RECONSTRUCTION ATTACK

The concept of reconstruction attacks predates differential privacy, as this principle also gave rise to the idea of necessary database privatization [Dinur and Nissim, 2003]. An adversary could reconstruct training data from a given (classifier) model using a reconstruction attack. Their research evaluates the perturbation that needs to be added to a database to protect it versus a reconstruction attack.

A general reconstruction attack for our use-case is the attribute inference attack [Dwork et al., 2017] or model inference [Rigaki and Garcia, 2021]. Both terms are essentially the same, and we have chosen to name attribute inference attack, as it is the most common one in most literature [Jegorova et al., 2022]. Attribute inference focuses on a reconstruction attack with the adversary's goal of retrieving the secret from each user [Dwork et al., 2017]. For example, an attacker may attempt to reconstruct information about someone's heart disease using the individual's properties.

A practical implementation of the attack was provided by Fredrikson et al. as a way to infer sensitive features [Fredrikson et al., 2015]. To accomplish this, they used a decision tree attack, a white-box approach, as they also accessed the count of instances for each decision tree branch. They also considered a black-box approach with access only to the target model (ML-as-a-service in this example). The attack targets gradient descent, which is used to optimize the input data of an attack to mimic the original data. It has only been shown to work on a neural network for face identification images (named MIFace) [Fredrikson et al., 2015], but it could be extended to another machine learning classifier if it uses gradient descent (e.g. Support Vector Machines) [Nicolae et al., 2019]. A more general approach was undertaken by Yeom et al., building upon the same research discussed in the previous section (Member inference). In their work, Yeom et al. proposed a membership inference attack, which can also be utilized for attribute inference in a white-box setting. The attribute inference attack follows a similar methodology, wherein the target model is queried to assess the loss of synthetic data based on adversarial knowledge. Repeating the process, the attack identifies and selects the value with the highest prior probability, incorporating membership information [Jayaraman and Evans, 2022; Yeom et al., 2018]. Evaluating the effectiveness of such attacks is challenging, as it relies on the correlation between attributes, irrespective of whether the data belongs to the training or test dataset [Zhao et al., 2021]. Therefore, Yeom et al. focus on the similarity between membership/attribute-inference and combine them to evaluate the attribute inference attack [Yeom et al., 2018].

Differential privacy aims to introduce sufficient noise to mitigate the risk of various attacks [Dwork et al., 2017; Jayaraman and Evans]. Assessing the privacy leakage of our model can be effectively accomplished by employing attribute/membership inference techniques. Within this thesis, our focus is mainly on MIA. We aim to establish a quantifiable measure for our mechanism, and combining both attribute and membership attacks is not beneficial since they essentially capture the same information. Therefore, it is sufficient to concentrate on membership inference attacks.

4.3. ATTACK EVALUATION

In this section, we evaluate the membership inference attack and evaluate it as it is the most appropriate for this study (See previous chapter). We assess whether differential privacy provides protection against the attack and discuss how this can be measured.

4.3.1. MEMBER INFERENCE ATTACKS

Most current research for MIA is evaluated for neural networks [Rigaki and Garcia, 2021]. A tiny percentage evaluates this attack for supervised learning, with the majority using classification with decision trees. Most studies have used a black-box approach [Rigaki and Garcia, 2021] for these attacks. This approach is not surprising, as these attacks have a high success rate and pose a greater risk of exploitation.

Introducing differential privacy reduces the impact of a member inference attack [Hu et al., 2022; Rigaki and Garcia, 2021]. This is because the input to the model is perturbed. While it is still possible to retrieve the training data, the leaked privacy is significantly reduced. A simple but effective way to measure the privacy leakage is by calculating the accuracy of correctly predicting membership by the adversary [Choquette-Choo et al., 2021].

Yeom et al. created a metric specifically for membership inference attacks which can be measured using an "adversarial advantage." This metric describes the percentage of privacy compromised during a member inference attack [Yeom et al., 2018]. This metric is calculated by subtracting the False Positive Rate (FPR) from the True Positive Rate (TPR). The TPR represents the number of correctly predicted member data (training data), and the FPR represents the number of correctly predicted non-member data. Although these metrics are commonly applied in the literature for MIA, they do not provide enough information [Carlini et al., 2022]. Both metrics do not consider the imbalance between the TPR and FPR. The metric should emphasize the TPR, as this is the percentage of correctly predicted member data. Therefore, they propose to use a ROC curve to show the effectiveness of a membership inference attack [Carlini et al., 2022].

In conclusion, the attacks that use MIA are all (mis)using supervised machine learning. However, in this study, we use cluster algorithms. Therefore, a semi-supervised approach can be used, as illustrated in this figure:

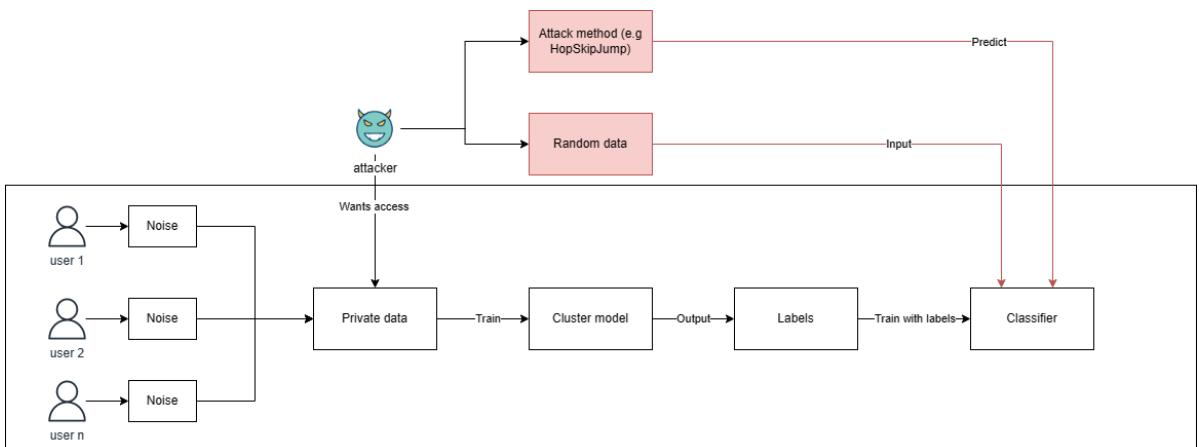


Figure 4.2: Semi-supervised black-box approach to execute a member inference attack.

5

METHODOLOGY

We conducted experiments to gain insights into the proposed methods for researching the appliance of (ND)-Laplace for cluster algorithms. The experiment results are used to evaluate our method against other literature. In this chapter, we explain:

1. Research design: The background and research questions are explained. Furthermore, we explain the datasets and privacy mechanisms used in the experiments.
2. Data collection: The methods used to collect the data necessary to answer the research questions. These are methods for running experiments to collect data about utility and privacy.
3. Data analysis: We explain how we analyze the data collected in the previous step.

5.1. RESEARCH DESIGN

This section explains the research background, questions, datasets, and environmental setup.

5.1.1. RESEARCH BACKGROUND

Clustering data is a crucial part of machine learning, aiming to discover patterns in the data that may not be immediately visible to the human eye. To achieve this, the data is trained on large datasets. However, storing such data is unsafe, as unauthorized access could lead to breaches.

Local Differential Privacy (LDP) has been introduced to safeguard user privacy while preserving data patterns. Adding local noise means flat data is never stored on a central server. Nevertheless, the limited available data in the local view distorts the patterns excessively in each noise addition.

Current literature has attempted to address these challenges, but the solutions fall short. They either require modifications to the clustering algorithm or lack practical applicability due to the use of synthetic data.

To address these limitations, we propose a new LDP method called kd-Laplace, utilizing the concept of GI. Our method enables secure training of cluster algorithms based on input-perturbation. We will test three variants of the kd-Laplace mechanism to assess their

utility and privacy characteristics. Also, we will compare the kd-Laplace mechanism to Piecewise, which is another LDP mechanism (See Section 2.3).

The research combines real-world and synthetic data to demonstrate practical applicability. Extensive external and internal validation experiments will be conducted to establish the method's practical relevance and effectiveness.

5.1.2. RESEARCH QUESTIONS

The main question of the research is as follows:

"How can the kD-Laplace algorithm be applied in training privacy-preserving clustering algorithms on distributed k-dimensional data?"

The main question is divided into three smaller sub-questions:

1. RQ1: How can 2D-Laplace be used to protect the privacy of 2-dimensional data employed for training clustering algorithms?

This research question investigates the utility and privacy differences among the three kd-Laplace variants and compares the mechanism with the Piecewise Mechanism. We focus on the implementation of kd-Laplace on n-dimensional data.

2. RQ2: How can 3D-Laplace be extended to protect the privacy of n-dimensional data employed for training clustering algorithms?

The setup for this research question is the same as for research question 1, but instead of 2D data, we focus on 3D and n-dimensional data.

3. RQ3: What is the impact of different privacy budgets, dataset properties, and other clustering algorithms on the research conducted for research question 2?

In this research question, we compare the behavior of our mechanism with what we have observed in the literature for similar mechanisms. To do this, we have formulated several hypotheses.

(a) *Adding optimal remapping improves utility without sacrificing privacy:* Since the noise is updated based on the density of the data points, the clusters stay preserved (5). As a result, the utility increases while the data points remain indistinguishable. Therefore, we have extended our mechanism with optimal remapping and named it kd-Laplace/grid/optimal. This variant is included in the next three sections and further research using the next two hypotheses.

(b) *The privacy leakage (adversary advantage) increases for a higher number of dimensions:* The hypothesis arose from our observation while investigating/implementing kd-laplace/grid/optimal (3.3.2). Adding more dimensions ($5 >$) decreases the added noise gradually. The study is conducted for the kd-Laplace/grid/optimal mechanism to analyze its behavior.

(c) *The shape of the data negatively impacts the kd-Laplace mechanism in terms of privacy and utility:* Because the mechanism heavily relies on Euclidean distance, the shape (distance between the data points) can ultimately harm utility and privacy. We have already observed this difference when comparing the heart and seed datasets in research questions 1 and 2. But, to rule out the potential impact of the number of data points (the heart dataset has 2126 samples

and the seed-dataset 210), we generate three synthetic datasets, each with 1000 samples (See section 5.1.3).

5.1.3. DATASETS

For this research, we selected datasets based on the related papers (2.3). The datasets are sourced from the UCI Machine Learning Repository [noa, c].

1. **Seeds dataset**¹: This dataset was used in several related works and contains 210 samples with 7 (numerical) attributes. The dataset contains information about seeds, like kernel width and density. We conducted experiments with 2, 3, and 7 dimensions and decided to use the following features (based on the correlation between the features):
 - (a) 2-dimensional data: area and perimeter.
 - (b) 3-dimensional data: the kernel's area, perimeter, and length.
 - (c) 7-dimensional data: All numerical features.
2. **Heart dataset**²: This dataset is selected because of the mixed data and amount of instances. It has 23 attributes, ten numerical attributes, and 2126 samples. The dataset contains information about measurements of fetal heart rate (FHR) and uterine contraction (UC). We conducted experiments with 2, 3, and 10 dimensions and decided to use the following features (based on the correlation between the features):
 - (a) 2-dimensional data: FHR baseline and histogram-min.
 - (b) 3-dimensional data: FHR baseline, histogram-min, and accelerations.
 - (c) 10-dimensional data: All numerical features.

The following datasets are for a component investigated in research question 3. Further detail is provided in Section: 3.

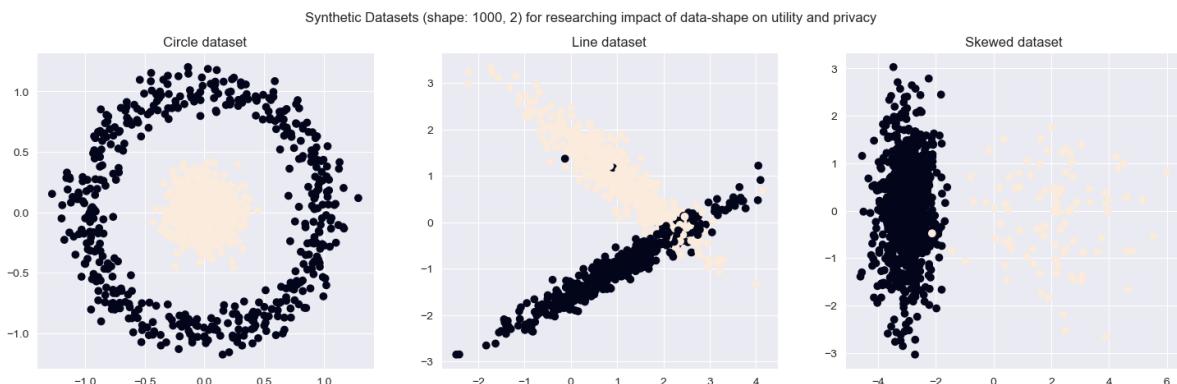


Figure 5.1: Synthetic datasets with 1000 samples and 2-dimensions

1. **circle dataset:** Dataset with a circle shape.
2. **line dataset:** Dataset is a line (shape is much like the seeds dataset).

¹<http://archive.ics.uci.edu/ml/datasets/seeds>

²<https://archive.ics.uci.edu/ml/datasets/cardiotocography>

3. **skewed dataset:** Dataset samples are skewed/concentrated to one side (shape is much like the heart dataset).

5.1.4. PRIVACY MECHANISMS

We will evaluate two different privacy frameworks called kd-Laplace (our method) and piecewise (2.16). For the first one, we test three configurations/variants:

1. kd-Laplace: Plain mechanism without any additions for truncation.
2. kd-Laplace/grid: Mechanism with truncation using grid-remapping (See Equation: 4).
3. kd-Laplace/grid/optimal: Mechanism with truncation using grid-remapping in combination with optimal-remapping (See Equation: 5).

The kd-Laplace variants differ on the implementation level for 2, 3, and n-dimensional data (See figure 3.13). Piecewise, however, will be the same for any data dimension.

We evaluate all privacy mechanisms by comparing them in utility and privacy. To reduce the measurement bias of results, we executed them ten times for multiple privacy budgets and reported the average for each [Huang et al., 2021].

1. The experiments run ten times, and we report the mean.
2. All experiments run for multiple epsilons: 0.1, 0.5, 1, 2, 3, 5, 7, 9.

Firstly, we primarily focus on evaluating the utility in terms of clustering. Then, we shift our focus to comparing the privacy mechanisms themselves. Lastly, we compare the four mechanisms in terms of privacy.

5.1.5. ENVIRONMENTAL SETUP

For running the experiments, we use 16GB RAM and an i7-10750H 2.6Ghz processor. The experiments are run using a Docker container which runs a pre-configured distribution of Linux Alpine. It includes a pre-installed Anaconda environment for Python ^{3,4}. We run the container using the dev-container feature for visual-studio code ⁵. This allows us to create a reproducible experiment environment.

LIBRARIES & CODE VERSIONS

We use Python version 3.9.13 with Jupyter Notebook for creating a reproducible experimental environment. The packages for Python are:

- Scikit-learn: 1.0.*
- Yellow-brick: 1.5
- Numpy: 1.24.*
- Pandas: 2.0.*

³<https://github.com/devcontainers/images/tree/main/src/anaconda>

⁴tag: mcr.microsoft.com/devcontainers/anaconda:0-3

⁵<https://code.visualstudio.com/docs/devcontainers/containers>

- Seaborn: 0.11.*
- Mathplotlib: 3.5.*

5.2. DATA COLLECTION

This section explains what methods/ algorithms we use to collect the data necessary to answer the research questions.

5.2.1. CLUSTERING METHODS

For the three different algorithms: K-Means, AP, and OPTICS, we analyzed the most important decisions regarding parameter selection (See section 3.1.3). This section gives a short list and explanation of the parameters we used throughout the experiments. In addition to this, we also provide the corresponding algorithms as implemented by the Scikit-learn package.

K-MEANS

$$\sum_{i=0}^n \min_{\mu_j \in C} (\|x_i - \mu_j\|^2) \quad (5.1)$$

Parameter	Description	Value	Dataset
K-value	Calculated based on an "elbow" plot.	4 (see Figure 1)	Seeds dataset
K-value	" "	TODO	Heart dataset
K-value	" "	5 (see Figure 2)	circle dataset
K-value	" "	4 (see Figure 3)	line dataset
K-value	" "	4 (see Figure 4)	skewed dataset

Table 5.1: K-Means hyperparameters for dataset 1 - 3

AFFINITY PROPAGATION

As specified in section 2.2.2, the clustering algorithm has two types of similarity. The following formula calculates the responsibility:

$$r(i, k) \leftarrow s(i, k) - \max[a(i, k') + s(i, k') \forall k' \neq k] \quad (5.2)$$

Then the availability is given using this formula:

$$a(i, k) \leftarrow \min[0, r(k, k) + \sum_{i' \text{ s.t. } i' \notin \{i, k\}} r(i', k)] \quad (5.3)$$

And iteratively calculated while considering the damping factor.

Parameter	Description	Value	Dataset
Preference	We decided to use the median similarity as described in section 2.2.2	Median	Seeds dataset
Preference	""	Median	Heart dataset
Damping factor	Default value as specified in section 2.2.2	0.5	Seeds dataset
Damping factor	""	0.5	Heart dataset

Table 5.2: Affinity Propagation hyperparameters for the datasets

OPTICS

As previously explained in section 2.2.2, we use OPTICS to automatically implement DBSCAN to determine the epsilon/radius.

Parameter	Description	Value	Dataset
Minimum points	Decided using the formula $minPts = n * 2$, where n is the number of features (2.2.2)	4	Seeds dataset (2-dimensions)
Minimum points	""	6	Seeds dataset (3-dimensions)
Minimum points	""	14	Seeds dataset (7-dimensions)
Minimum points	Decided using the formula $minPts = n * 2$, where n is the number of features (2.2.2)	4	Heart dataset (2-dimensions)
Minimum points	""	6	Heart dataset (3-dimensions)
Minimum points	""	20	Heart dataset (10-dimensions)

Table 5.3: DBSCAN hyperparameters for datasets 1 - 3

5.2.2. UTILITY AND PRIVACY EVALUATION

UTILITY

To measure cluster utility, both internal and external validation methods are used:

1. **External validation:** The external validation is measured by comparing the labels of non-private trained cluster algorithms with those trained using a privacy mechanism. The outcome is between 0 and 1, where 1 indicates the highest similarity (thus the best result). AMI (Adjusted Mutual Information) and ARI (Adjusted Rand Index) are used to assess the external validity of the cluster algorithms (See Section 2.2.3).
2. **Internal validation:** The internal validation measures the intrinsic properties of the clustering algorithms. The outcome is a value between -1 and 1 for the SC evaluation. Where -1 indicates incorrect clustering and 1 dense clustering. Another metric we use is the CH metric, where a higher value suggests good clustering (See Section 2.2.3).

Because the cluster algorithms rely on Euclidean distance, we need to apply some data standardization. For this purpose, we use standard scaling provided by the Scikit-learn package⁶.

PRIVACY

Privacy is hard to quantify, but we can measure the privacy loss/gain by calculating the Euclidean distance between the non-perturbed and perturbed data. In addition, we evaluate privacy by simulating a membership inference attack and calculating the adversary advantage.

1. **Privacy distance:** The first measurement we evaluate is the distance between the dataset's non-private and private variants. This metric gives us a sense of how much extra distance (and privacy) the privacy mechanisms offer compared to the non-private variant. To this end, the average Euclidean distance is measured and reported per epsilon. A higher distance indicates more privacy.
2. **Adversarial advantage:** We used the Membership Inference Attack (MIA) that Shokri et al. proposed with the implementation that was provided by Adversarial Robustness Toolkit (ART) [Nicolae et al., 2019]. An earlier study also explored this attack to evaluate differential privacy. Similar to this attack, we train a classifier with perturbed data and evaluate it using non-perturbed data (test-data / shadow-data) [Zhao et al., 2020]. We consider a semi-supervised setup (figure 4.2), where we train a classifier with the perturbed data and evaluate it using non-perturbed data (test-data / shadow-data). For the classifier, we use a RandomForestClassifier [Rigaki and Garcia, 2021]. Finally, we evaluate the adversary advantage (percentage) using $TPR - FPR$ [Yeom et al., 2018]. Figure: 5.2 provides a visual setup of the experiment.

Although the adversary advantage is a proven method for measuring MI attacks, we also include the TPR as an essential measurement. This metric is most interesting to us because this displays the percentage of the actual leaked labels (see Section 4.3).

⁶<https://scikit-learn.org/stable/modules/preprocessing.html>

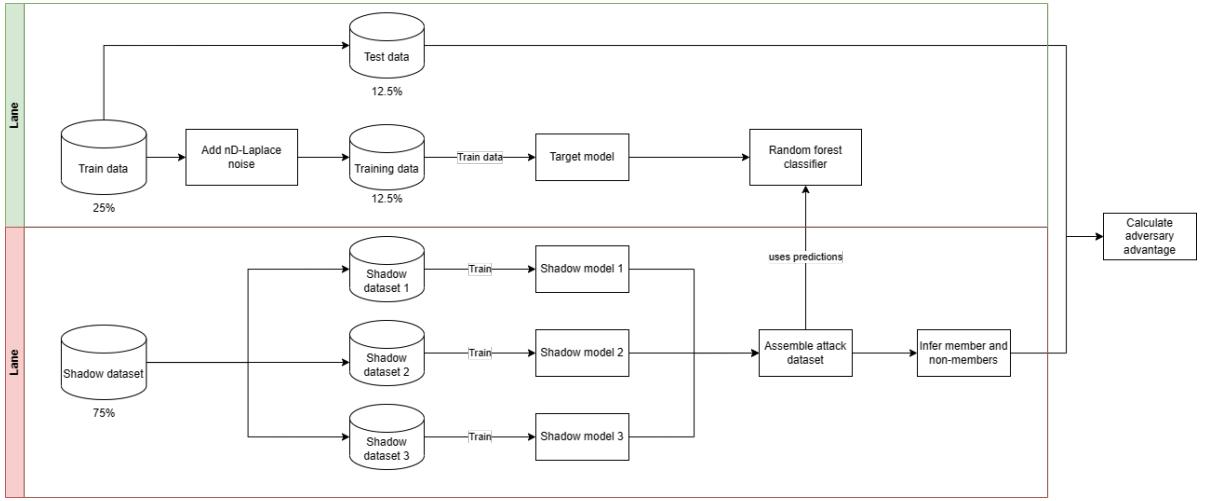


Figure 5.2: Member inference attack using shadow models. The green swim lane illustrates the normal setup, and the red swim lane projects the adversary steps.

Unlike the other utility metrics, the lower the adversary score and TPR, the better.

5.3. DATA ANALYSIS

For the data analysis, we utilize visualization libraries in Python, primarily Matplotlib, in combination with Seaborn.

- Line/bar plot: These plots visualize comparisons between the different privacy mechanisms. The different epsilon values are displayed on the x-axis, and the utility/privacy metric is displayed on the y-axis.
- Heatmap plot: These plots visualize the interaction between dimensions and epsilons. This way, we can display two categorical values (dimension/epsilon) and one continuous value.

6

RESULTS

This chapter aims to present the results to the reader. As indicated in the methodology, we tested four mechanisms (three variants of kd-Laplace and Piecewise) for their utility and privacy. The results are presented in the following order:

1. Cluster utility: We use external validation (AMI/ARI) to compare the results between the three different cluster algorithms when trained privately with kd-laplace (3.13) and piecewise.
2. Mechanism utility: We compare the three variants of kd-Laplace and Piecewise using external validation. For the comparison, we use K-Means as a clustering algorithm.
3. Privacy: We compare the three variants of kd-Laplace and Piecewise by evaluating the membership inference attack (MIA).
4. Dimensionality: We evaluate the number of dimensions' influence on privacy.
5. Shape: We are investigating the shape of the data to measure its impact on the utility and privacy of the kd-Laplace mechanism. For the comparison, we use K-Means as a clustering algorithm.

All results are reported for each dataset (See methodology: 5.1.3) separately.

6.1. CLUSTER UTILITY

The results below display the difference between the three cluster algorithms for Piecewise and kd-Laplace/grid/optimal for 2/3/n-dimensional data. The first figure shows the seeds dataset, and the second shows the heart dataset.

Displaying the different cluster algorithms and their corresponding hyperparameters is done using the legend. The x-axis shows the privacy budget, and the y-axis shows the adjusted mutual information (AMI) and the adjusted rand index (ARI). We conducted this research for the following cluster algorithms.

1. **K-Means:** Displayed as a blue line.
2. **Affinity Propagation:** Displayed as a red line. The AP experiments are omitted for the larger datasets (>1000 data points with $3 >$ dimensions). This algorithm required too much computational power for our experimental setup.
3. **OPTICS:** Displayed as a green line.

Please refer to the plots in the appendix for internal validation and the other variants (Laplace / Laplace-truncated): [.3](#).

6.1.1. 2-DIMENSIONAL DATA

Figure 6.1: External validation piecewise & kd-Laplace/grid/optimal for the 2-dimensional data seeds-dataset

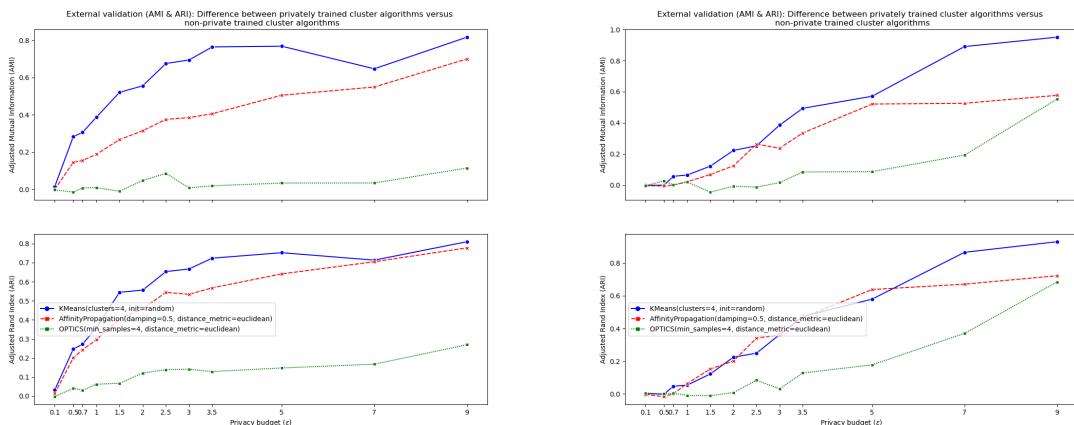
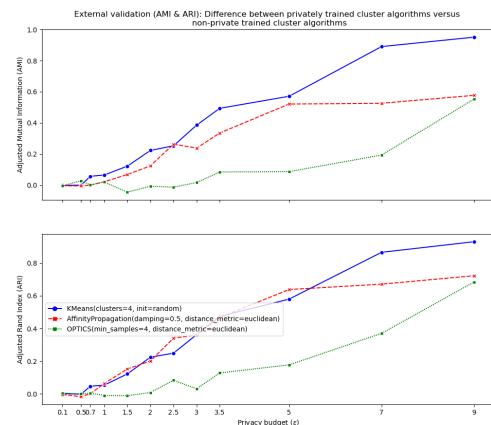


Figure 6.2: External validation (ARI/ AMI) for the 2-dimensional data seeds-dataset for kd-Laplace with dimensional data seeds-dataset for piecewise mechanism



The above plots show the AMI and ARI scores for the seeds-dataset with kd-laplace/grid/optimal (left-side) and piecewise (right-side). Piecewise shows a higher AMI / ARI for epsilons 7 and 9. In contrast, the kd-Laplace mechanism scores higher for all the other epsilons (0.1 onward 7). K-Means achieves the best score for kd-Laplace with a slight margin compared to AP. However, for the Piecewise mechanism, K-Means performs better. For both the mechanisms, OPTICS underperforms heavily but still scores the same as AP for Piecewise.

Figure 6.4: External validation piecewise & kd-Laplace/grid/optimal mechanisms for the 2-dimensional data heart-dataset

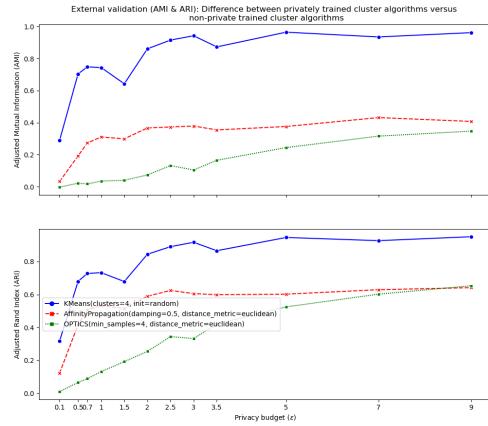


Figure 6.5: External validation (AMI/ ARI) for the 2-dimensional data heart-dataset for kd-Laplace with optimal truncation

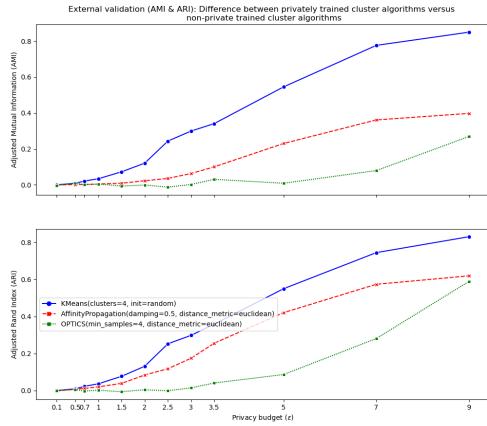


Figure 6.6: External validation (AMI/ ARI) for the 2-dimensional data heart-dataset for piecewise mechanism

The kd-Laplace mechanism performs better (0.8 - 1.0 from epsilon 1.0 to 9) for all epsilons for K-Means. AP and OPTICS show the same trend, reaching their peaks around epsilon 7 and 9. Both underperform by delivering maximum results for these epsilons below 0.3-0.4 AMI/ARI.

6.1.2. 3-DIMENSIONAL DATA

Figure 6.7: External validation piecewise & kd-Laplace/grid/optimal for the 3-dimensional data seeds-dataset

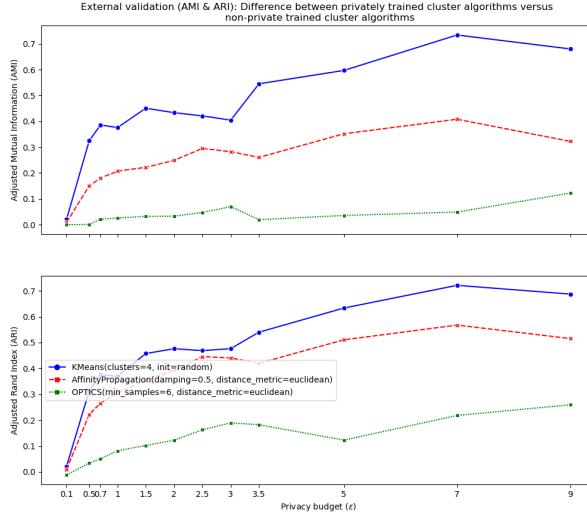


Figure 6.8: External validation (ARI/ AMI) for the 3-dimensional data seeds-dataset for kd-Laplace

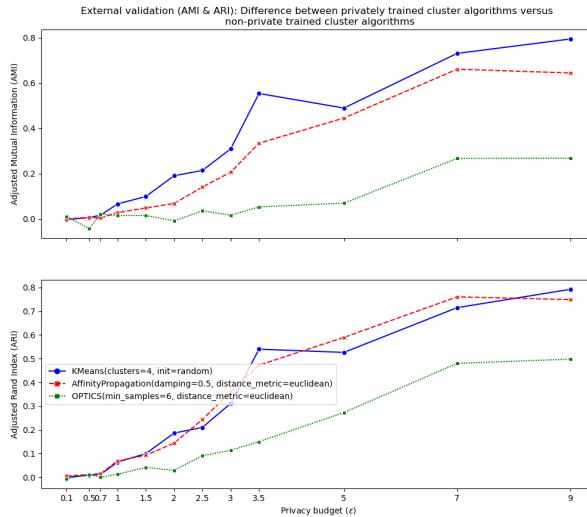


Figure 6.9: External validation (ARI/ AMI) for the 3-dimensional data seeds-dataset for piecewise mechanism

Piecewise performs better for epsilon 9 but worse for the lower epsilons (0.1 - 5). K-Means scores 0.7 - 0.8 AMI/ARI, followed by AP, which is 0.6. The kd-Laplace mechanism, on the other hand, shows more difference (K-Means 0.65 - 0.7 and AP 0.3 - 0.2). OPTICS scores are again low but show a slight upwards trend when the epsilon increases.

Figure 6.10: External validation piecewise & kd-Laplace/grid/optimal mechanisms for the 3-dimensional data heart-dataset

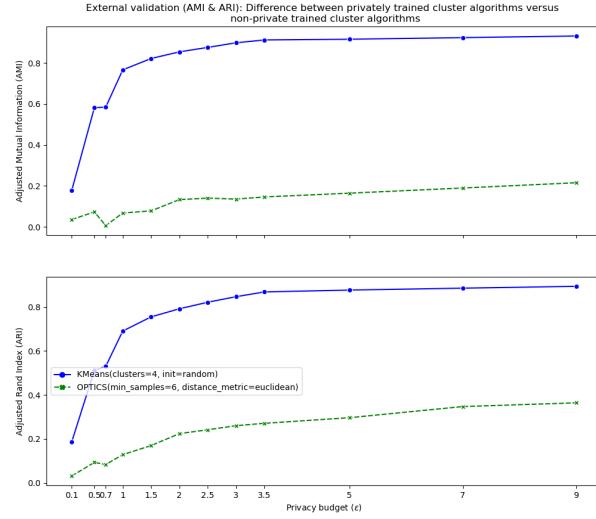


Figure 6.11: External validation (ARI/ AMI) for the 3-dimensional data heart-dataset for kd-Laplace with optimal truncation

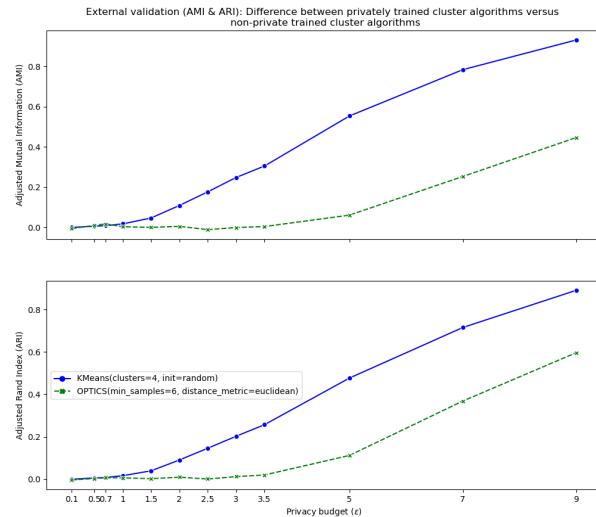


Figure 6.12: External validation (ARI/ AMI) for the 3-dimensional data heart-dataset for piecewise mechanism

Piecewise for K-Means performs well (0.78 and 0.93 ARI) for epsilon 7 and 9, respectively. However, from epsilon 1 onwards kd-Laplace scores 0.77 to 0.93 ARI for K-Means. On the other hand, OPTICS scores low for kd-Laplace. It shows an upward trend for Piecewise as the algorithm scores 0.45 ARI and 0.6 AMI for epsilon 9. While kd-Laplace scores 0.22 ARI and 0.36 AMI for epsilon 9. OPTICS scores below 0.4 ARI/AMI for both mechanisms if the epsilon is < 9 .

6.1.3. N-DIMENSIONAL DATA

Figure 6.13: External validation piecewise & kd-Laplace/grid/optimal mechanisms for the n-dimensional data seeds-dataset

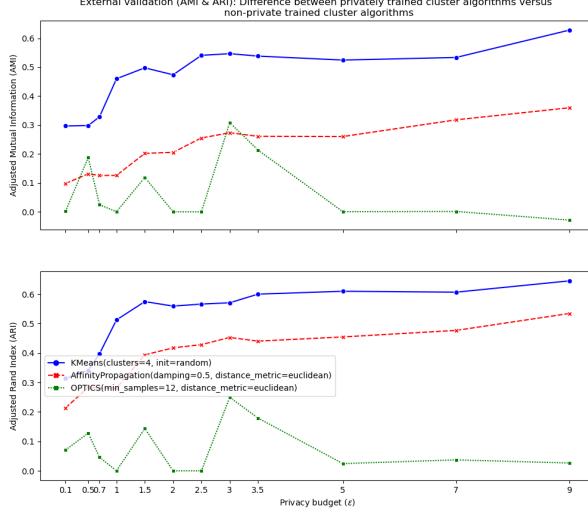


Figure 6.14: External validation (ARI/ AMI) for the n-dimensional data seeds-dataset for kd-Laplace with optimal truncation

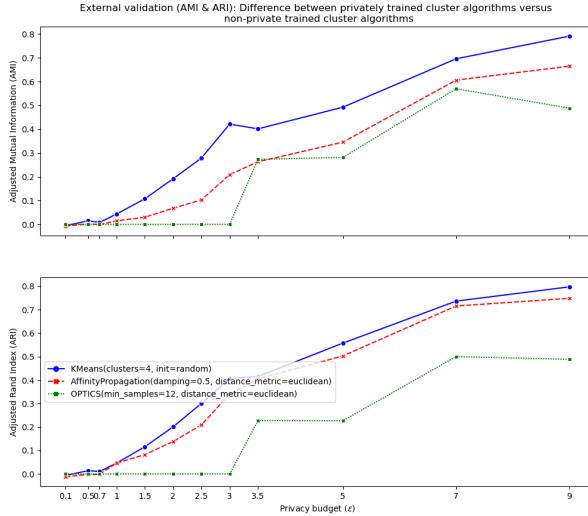


Figure 6.15: External validation (ARI/ AMI) for the n-dimensional data seeds-dataset for piecewise mechanism

The above plots show the ARI and AMI scores for the heart dataset with kd-laplace/grid/optimal (left-side) and piecewise (right-side). Piecewise performs well (0.89 and 0.87 ARI) for epsilon 9 and 7 for K-Means, respectively. In comparison, kd-Laplace scores worse for the same epsilon values (0.56 and 0.51 ARI); on the other hand, kd-Laplace scores better for all the other epsilons. After K-Means, the best scoring cluster algorithm is OPTICS for Piece-

wise, with a score of 0.62 ARI for 9 epsilon. However, the other epsilons **AP** scores better. For kd-Laplace, **AP** is second after K-Means, and OPTICS scores much worse for AMI. But, for ARI, the scores for OPTICS and **AP** lay close together for epsilon 9.

Figure 6.16: External validation piecewise & kd-Laplace/grid/optimal mechanisms for the n-dimensional data heart-dataset

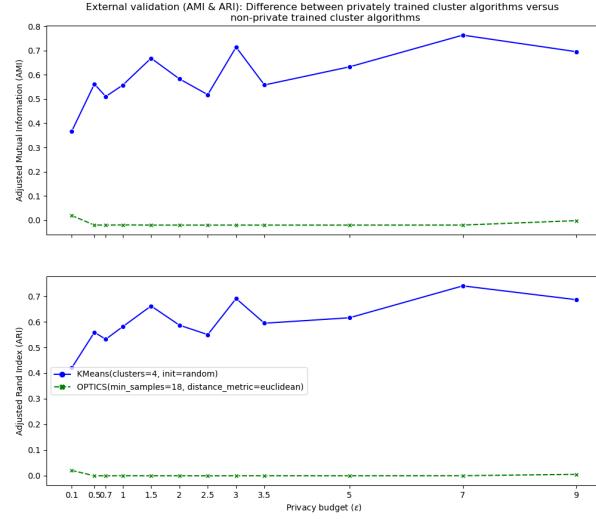


Figure 6.17: External validation (ARI/ AMI) for the n-dimensional data heart-dataset for kd-Laplace with optimal truncation

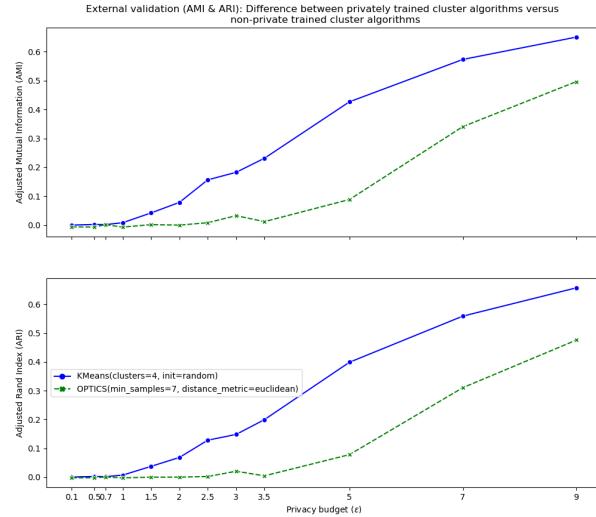


Figure 6.18: External validation (ARI/ AMI) for the n-dimensional data heart-dataset for piecewise mechanism

Piecewise shows similar trends for K-Means and OPTICS. But, K-Means scores better (0.65 ARI) for epsilon 9, while OPTICS peaks at 0.5 ARI. However, Piecewise scores (<0.2 ARI) for epsilon 0.1 til 3.5. In contrast, kd-Laplace scores more evenly (0.6 - 0.7 ARI) between epsilon 3.5 and 9. Conversely, OPTICS scores lower (< 0.2 ARI) for all epsilon values.

6.2. MECHANISM UTILITY

In the sections below, the different types of Laplace mechanisms and piecewise are compared using a barplot. Since ARI and AMI provide the same information, we show only the Adjusted Mutual Information (AMI) to avoid redundant information. For the same reason, only the K-Means algorithm was used to calculate the AMI. The x-axis displays the privacy budget, and the y-axis shows the corresponding AMI. The privacy mechanisms are displayed as follows:

1. **Piecewise:** Displayed as a yellow bar or line.
2. **kd-Laplace:** Displayed as a red bar or line.
3. **kd-Laplace/grid:** Displayed as a blue bar or line.
4. **kd-Laplace/grid/optimal:** Displayed as a green bar or line.

Please refer to the plots in the appendix for internal validation: [.3](#).

6.2.1. 2-DIMENSIONAL DATA

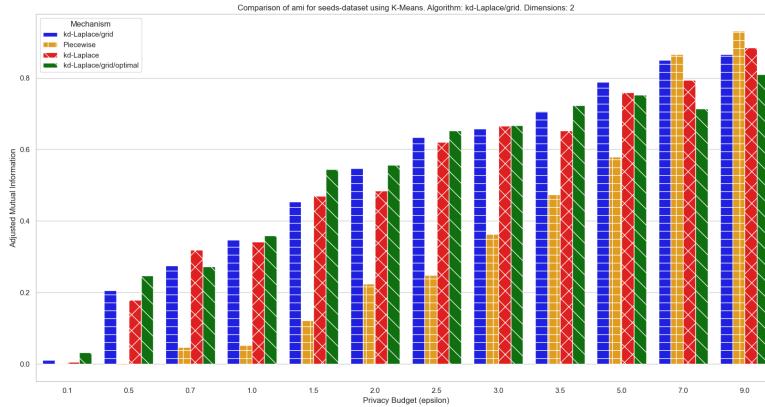


Figure 6.19: Adjusted Mutual Information comparison for the seeds-dataset

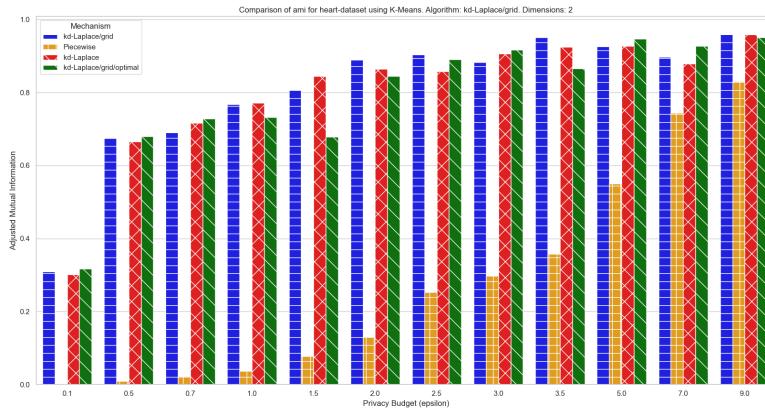


Figure 6.20: Adjusted Mutual Information comparison for the heart-dataset

The two plots compare external validation (AMI) between the two privacy frameworks, Piecewise, and kd-Laplace, with three variants. A clear trend in AMI can be observed in the top plot, with the lowest epsilon (0.1) yielding the lowest score for the mechanisms. Piecewise consistently scores lower for all epsilons, except for epsilons 7 and 9. Additionally, we notice minimal differences among the variants of kd-Laplace, but kd-Laplace/grid/optimal performs slightly better for epsilon 0.1 while scoring worse for 7 and 9.

6.2.2. 3-DIMENSIONAL DATA

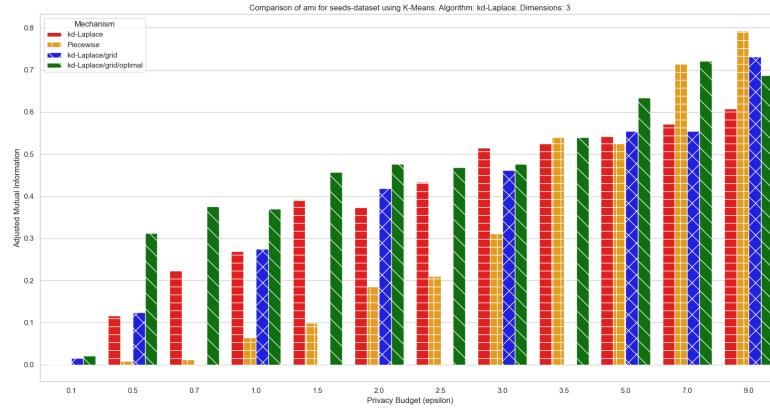


Figure 6.21: Adjusted Mutual Information comparison for the 3-dimensional seeds-dataset

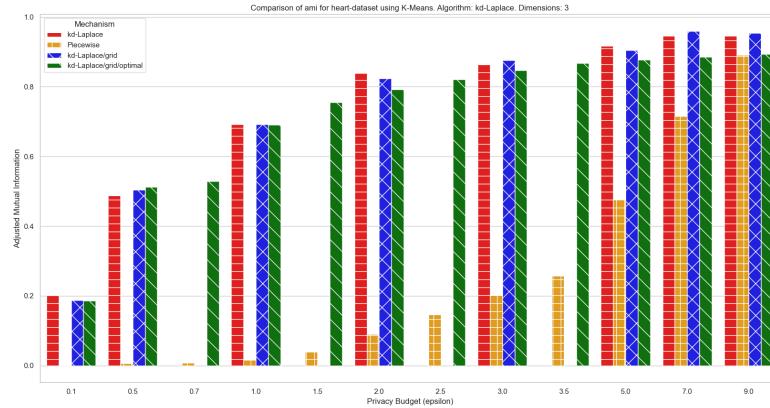


Figure 6.22: Adjusted Mutual Information comparison for the 3-dimensional heart-dataset

Between the seeds and heart datasets, the kd-Laplace mechanism with variants scored better overall than the piecewise mechanism. The Piecewise mechanism scores low (< 0.5 ARI) for the epsilons 0.1 to 3.5 in the seeds dataset. In contrast, kd-Laplace with variants reach this score for around epsilon 3.0. For epsilon 7 and 9, the Piecewise mechanism catches up with kd-Laplace and scores around equal (0.7 & 0.8 ARI). Kd-Laplace/grid/optimal scores are a little better for epsilon 5 and 7, but the difference between the variants is minimal overall.

The kd-Laplace mechanism with variants score > 0.6 AMI for epsilon 1 and higher. As with the seeds dataset, the Piecewise mechanism scores low (< 0.5 ARI) for the epsilons 0.1 to 7.0. For epsilon 9, the Piecewise mechanism scores around 0.8 AMI, which equals kd-Laplace. Between the different kd-Laplace variants, the difference is small. But, kd-Laplace/grid/optimal scores are slightly worse for all epsilons.

6.2.3. N-DIMENSIONAL DATA

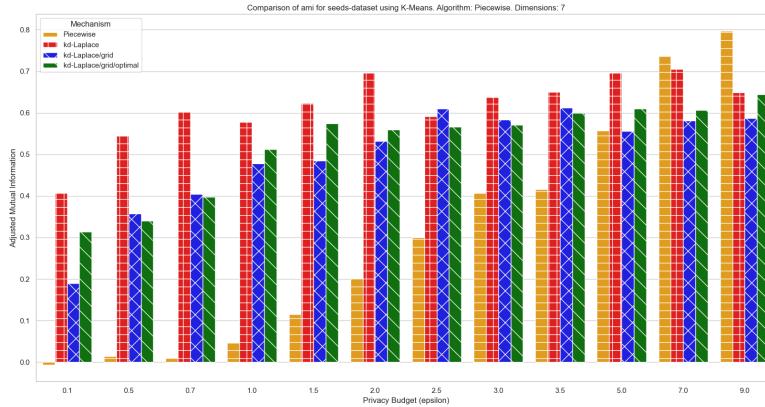


Figure 6.23: Adjusted Mutual Information comparison for all numerical features for the seeds-dataset

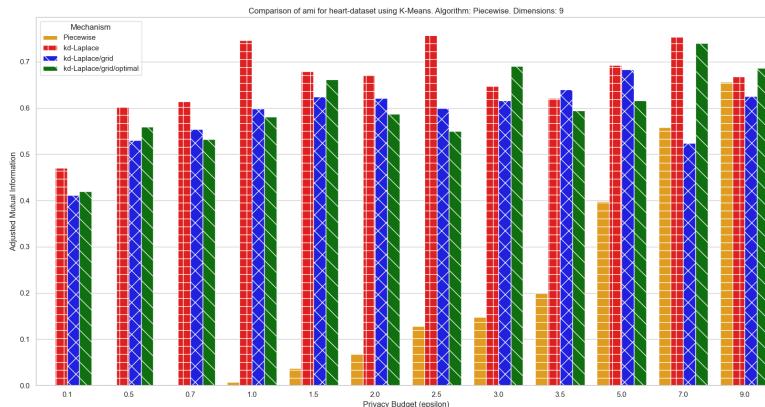


Figure 6.24: Adjusted Mutual Information comparison for all numerical features for the heart-dataset

The above plot represents the Adjusted Mutual Information (AMI) for n-dimensional data. The seeds dataset (top) shows a clear peak for kd-Laplace without any optimization. Piecewise consistently scores lower than the kd-Laplace variants for most epsilon values, except for epsilon 7 and 9 where Piecewise performs better (AMI > 0.7). The latter performs slightly better among kd-Laplace/grid and kd-Laplace/grid/optimal variants.

For the heart dataset (bottom graph), the scores are relatively similar across all kd-Laplace variants. Piecewise scores below 0.5 AMI until epsilon 7 and performs at an equivalent level as the kd-Laplace variants for epsilon 9. The kd-Laplace variants score significantly better, as they already surpass 0.5 AMI from epsilon 0.5. Among the kd-Laplace variants, kd-Laplace without optimization stands slightly higher (AMI > 0.7).

6.3. PRIVACY

The images below display bar plots for the membership advantage and TPR of membership inference attacks as described in the methodology. We use the same color scheme in the previous section to display the different mechanisms. In addition, a red line was drawn to indicate the baseline TPR (the non-private dataset's TPR).

6.3.1. 2-DIMENSIONAL DATA

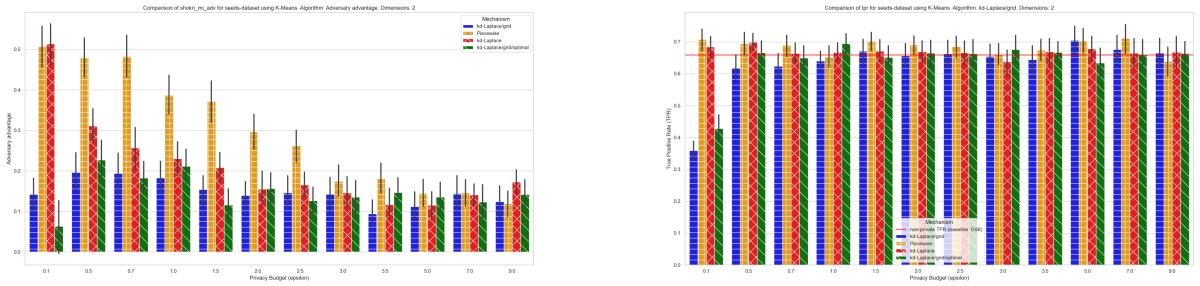


Figure 6.25: Barplot for adversary advantage (left) and TPR (right) per privacy mechanism for seeds-dataset.

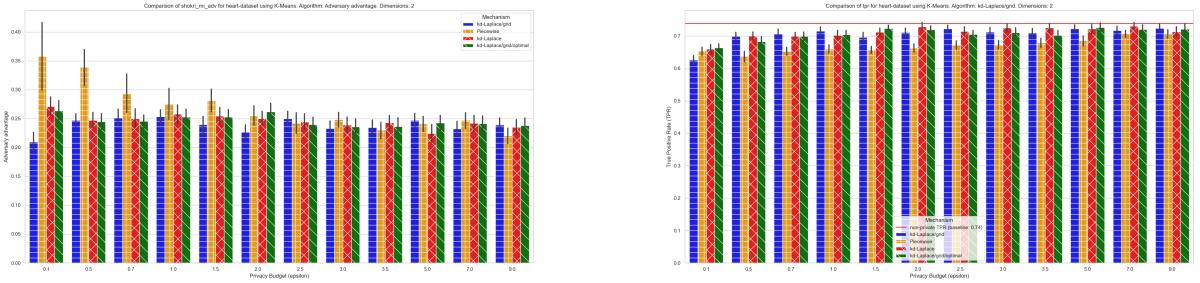


Figure 6.26: Barplot for adversary advantage (left) and TPR (right) per privacy mechanism for heart-dataset.

The above bar plot shows the adversary advantage based on the membership inference attack. The first graph displays the attack on the seeds dataset, where a clear peak of 0.5 adversary advantage is visible for both Piecewise and kd-Laplace at epsilon 0.1. The other variants of kd-Laplace score similarly, and all fall below 0.2. Piecewise reaches below 0.2 at epsilon 3, while kd-Laplace reaches it at epsilon 2.

For the heart dataset, the difference is slightly smaller, but Piecewise spikes to 0.36 and 0.34 adversary advantage at epsilon 0.1 and 0.5, respectively. Furthermore, kd-Laplace and Piecewise hover around 0.25 adversary advantage for the remaining epsilons.

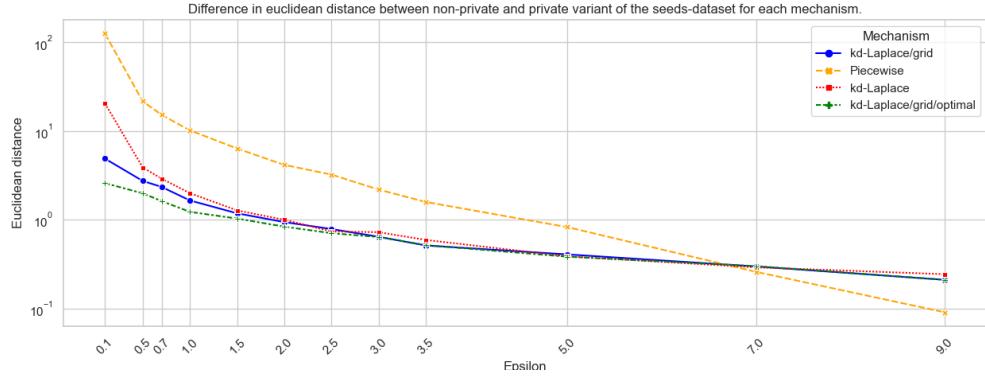


Figure 6.27: Privacy distance for each mechanism for seeds-dataset.

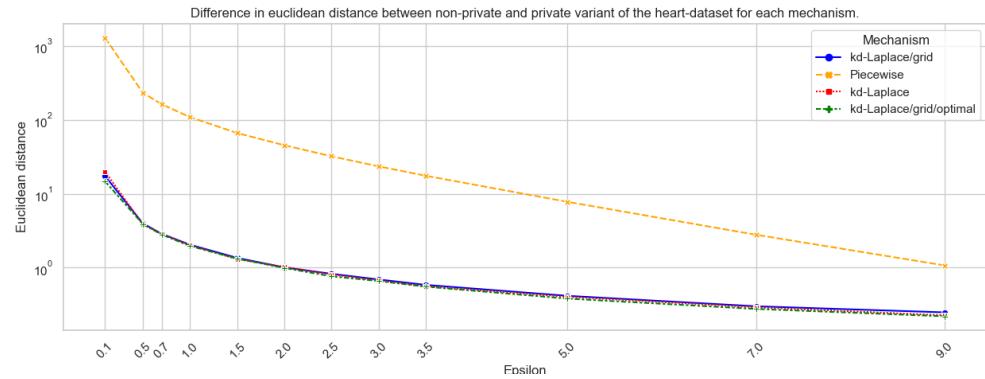


Figure 6.28: Privacy distance for each mechanism for heart-dataset.

The above graph represents the average Euclidean distance added by each privacy mechanism compared to the two datasets. We use a logarithmic scale for the Euclidean distance to better visualize the results. For both datasets, the Piecewise mechanism adds the most privacy. When considering the kd-Laplace variants on the seeds dataset, kd-Laplace without optimizations adds the most distance, followed by kd-Laplace/grid and kd-Laplace/grid/optimal. For the heart dataset, all variants of kd-Laplace are nearly equal.

6.3.2. 3-DIMENSIONAL DATA

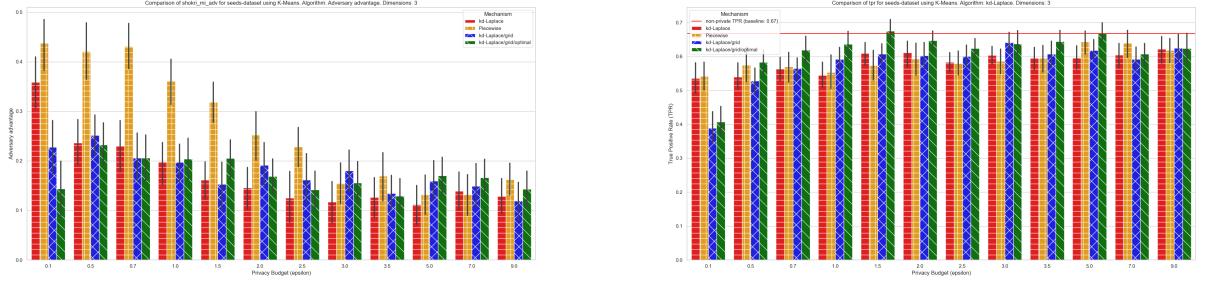


Figure 6.29: Barplot for adversary advantage (left) and TPR (right) per privacy mechanism for seeds-dataset.

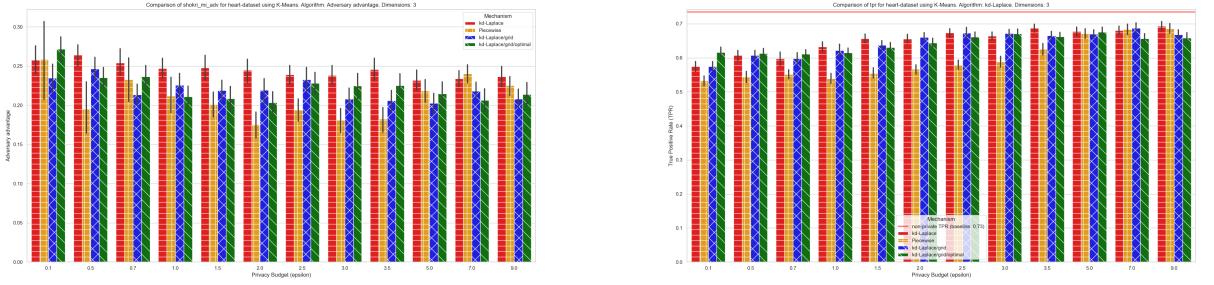


Figure 6.30: Barplot for adversary advantage (left) and TPR (right) per privacy mechanism for heart-dataset.

The graphs above show the adversary advantage (left) and TPR (right) for the seeds dataset (top) and heart dataset (bottom). The first dataset we analyze is the seeds dataset. We can observe a clear pattern for the Piecewise mechanism based on the adversary advantage plot for the seeds dataset. It scores between 0.4 and 0.5 for epsilon values ranging from 0.1 to 0.7 and drops below 0.2 for epsilon values higher than 3. The kd-Laplace mechanism, particularly the variant without optimizations (red), has a high adversary advantage (0.35) for epsilon 0.1. After that, all kd-Laplace variants perform similarly. When we compare them to the TPR, we still see that Piecewise and the regular kd-Laplace variant have higher scores for epsilon 0.1 (0.5+). After that, the mechanisms perform similarly, but we notice that kd-Laplace/grid/optimal consistently outperforms the others. Additionally, the latter is above the baseline value for epsilon 1.5.

Now, let's turn our attention to the heart dataset. Here, we can see that the adversary advantage shows less variation than the seeds dataset. For all epsilon values, kd-Laplace without optimizations stands out. The mechanisms perform similarly, but the Piecewise mechanism performs better for epsilon values between 1.5 and 5.0. For the TPR, all mechanisms are below the baseline value. They score the same, but the Piecewise mechanism is approximately 0.05 TPR lower than the kd-Laplace variants for epsilon values 0.1 to 3.5.

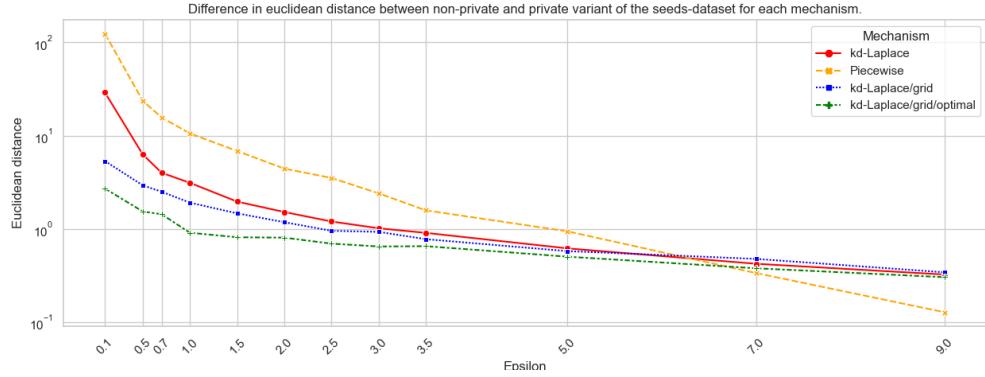


Figure 6.31: Privacy distance for each mechanism for 3D seeds-dataset.

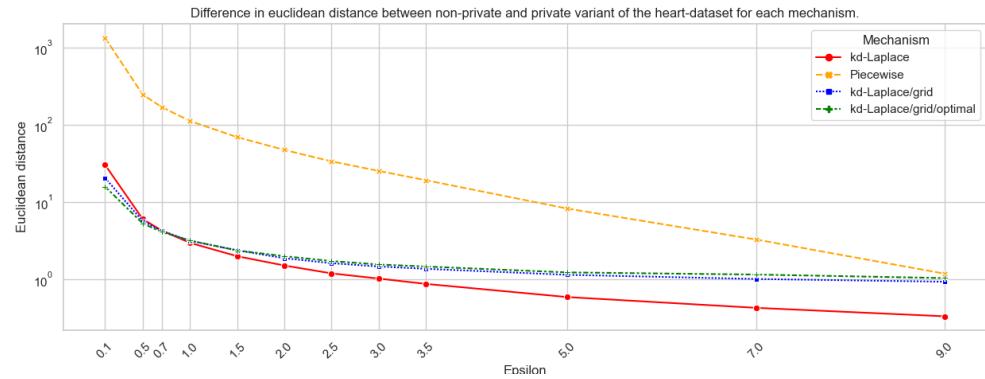


Figure 6.32: Privacy distance for each mechanism for 3D heart-dataset.

At epsilon values 7 and 9, the Piecewise mechanism adds the least distance. Among the various kd-Laplace variants, the variant without optimizations adds the most distance. This trend continues until epsilon 5, after which the variants become equal.

Similarly, a noticeable difference is observed between the Piecewise mechanism and kd-Laplace for the heart dataset. At epsilon 9, the Piecewise mechanism has the same score as kd-Laplace. Among the kd-Laplace variants, the variant without optimizations adds the least distance, but it is slightly higher than the other variants for epsilon 0.1.

6.3.3. N-DIMENSIONAL DATA

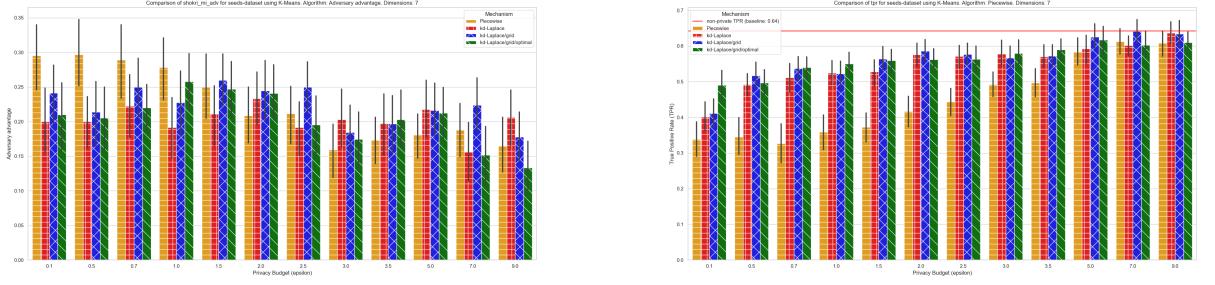


Figure 6.33: Barplot for adversary advantage (left) and TPR (right) per privacy mechanism for seeds-dataset.

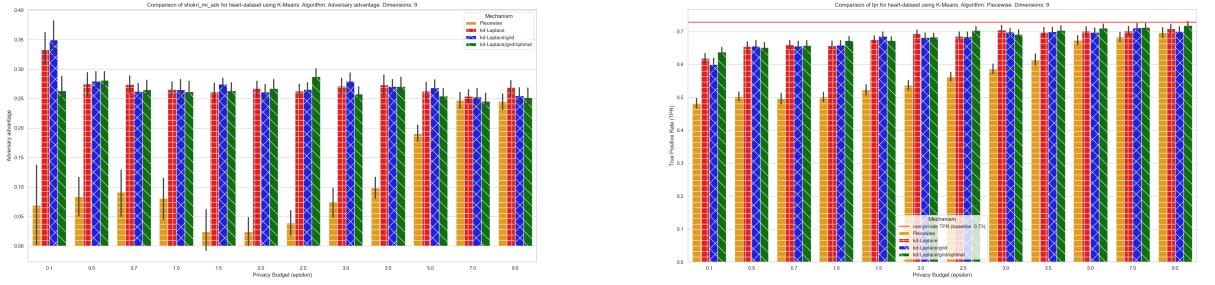


Figure 6.34: Barplot for adversary advantage (left) and TPR (right) per privacy mechanism for heart-dataset.

The seeds dataset shows that Piecewise has a higher adversary advantage for epsilons ranging from 0.1 to 1. However, the TPR for Piecewise is consistently lower than that of kd-Laplace. There is no clear distinction among the kd-Laplace variants. However, for epsilon values 7 and 9, kd-Laplace/grid/optimal does not exceed the baseline for TPR, while the other variants do.

For the heart dataset, the Piecewise mechanism scores below 0.10 for adversary advantage for epsilons 0.1 to 3. In contrast, the kd-Laplace variants yield values above 0.25 for the same epsilon values. The Piecewise mechanism also scores lower for epsilon values 3.5 and 5, but they have nearly equal scores for epsilon values 7 and 9. Among the variants of kd-Laplace, kd-Laplace, and kd-Laplace/grid perform slightly worse for epsilon 0.1, but for the other epsilons, they function similarly. The TPR follows a similar trend to the adversary advantage, except for epsilon 0.1, where the kd-Laplace variants have equal scores.

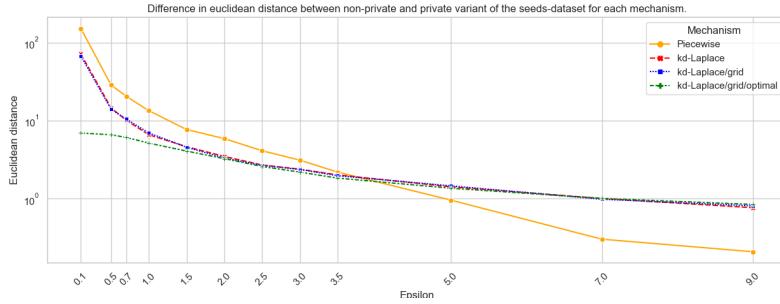


Figure 6.35: Privacy distance for each mechanism for nD seeds-dataset.

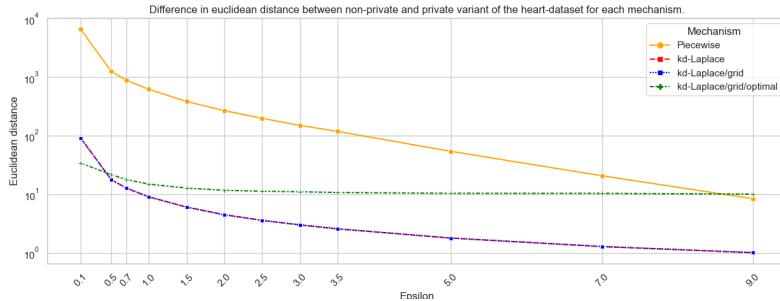


Figure 6.36: Privacy distance for each mechanism for nD heart-dataset.

The Piecewise mechanism for epsilon 0.1 to 3.5 for the seeds dataset adds the most Euclidean distance. After that, the Piecewise mechanism decreases significantly and scores lower than the kd-Laplace variants. For kd-Laplace/grid/optimal, the privacy distance starts lowest up to epsilon 1.5. After that, the variants of the kd-Laplace score are almost the same.

For the heart dataset, the Piecewise mechanism also adds the most Euclidean distance, only now for all epsilons. The kd-Laplace/grid/optimal mechanism starts as the lowest again but is then the highest of all variants, and scores for epsilon 9 are almost equal to the Piecewise mechanism. The other two variants of kd-Laplace (grid / no optimization) score the same.

6.4. DIMENSIONALITY

The chart below provides two heat maps for the seeds dataset (top) and the heart dataset (bottom). The y-axis column represents the privacy budget (ϵ), and the x-axis represents the dimensions. In each cell of the matrix, the TPR (True Positive Rate) is indicated, so the darker the cell, the higher the TPR. A higher value implies that, on average, more information is leaked.

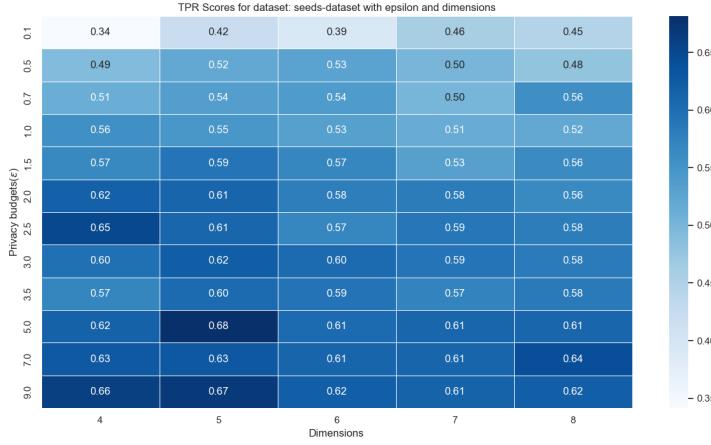


Figure 6.37: Heatmap for TPR and dimensionality for the seeds-dataset for kd-Laplace/grid/optimal

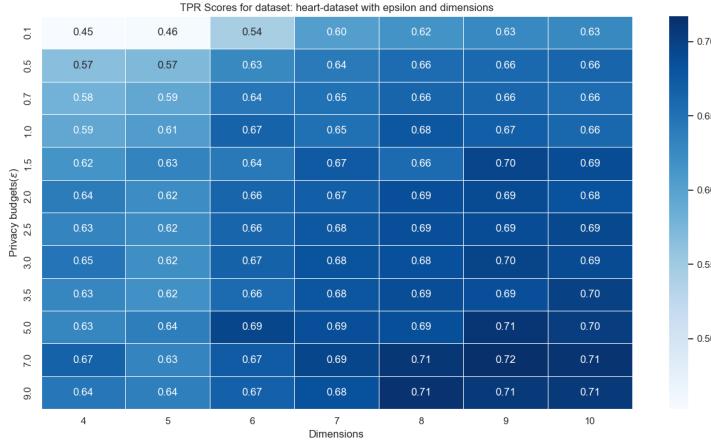


Figure 6.38: Heatmap for TPR and dimensionality for the heart-dataset for kd-Laplace/grid/optimal

Generally, a higher ϵ value corresponds to a higher TPR for the seeds dataset. Dimensions 4 and 5 have the highest scores ($0.60 >$) starting from $\epsilon = 0.5$. The bottom row achieves the highest scores, and for dimensions 4, 5, and 6, TPR values less than 0.40 are reported for $\epsilon = 0.1$. No clear trend is visible for the remaining ϵ values based on increasing dimensions.

The heart dataset's lowest scores (< 0.50) are also observed for $\epsilon = 0.1$ and dimensions 4 and 5. From $\epsilon = 0.2$ onwards, the values increase (> 0.50 TPR) for dimensions 4 and 5. The heatmap becomes darker for dimensions higher than 5, indicating TPR values higher than 0.60. From $\epsilon = 0.6$ and 8 dimensions, the scores exceed 0.70 TPR.

6.5. SHAPE

This chapter examines three datasets with a specific shape: circle, line, and left-skewed. The adversary advantages (privacy) and AMI (utility) are compared between the mechanisms for all three datasets. We compare kd-Laplace/grid/optimal (green) and Piecewise (yellow).

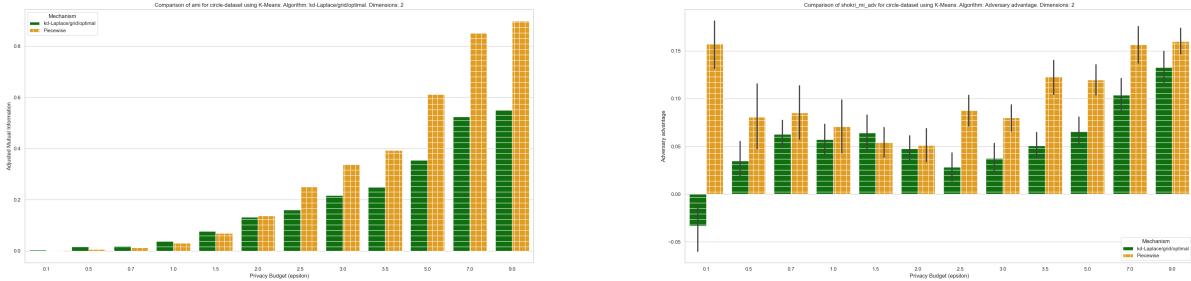


Figure 6.39: The AMI (left) and adversary advantage (right) for the circle-dataset

There's a noticeable difference between the Piecewise and kd-Laplace/grid/optimal mechanisms in the circle dataset. For the AMI, Piecewise scores are significantly higher at epsilon 7 to 9. In comparison, kd-Laplace/grid/optimal scores are lower than 0.2 for most other epsilons. Regarding the adversary advantage, kd-Laplace/grid-optimal scores are lower than Piecewise, except for epsilon 1 and 1.5.

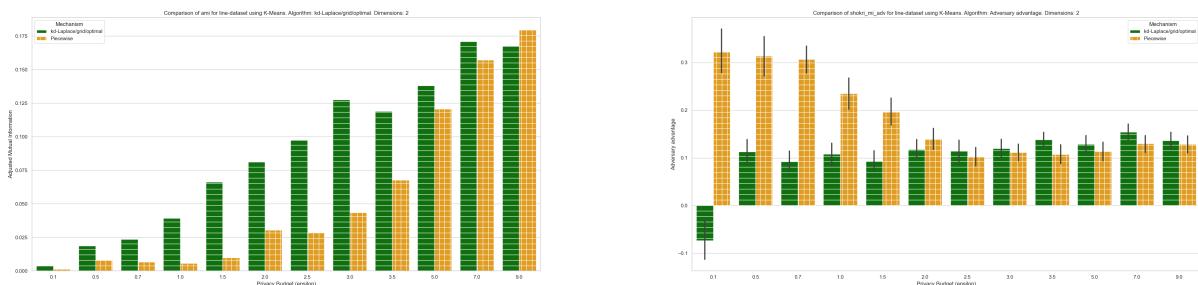


Figure 6.40: The AMI (left) and adversary advantage (right) for the line dataset

In the line dataset, Piecewise outperforms kd-Laplace/grid/optimal for epsilon values above 5 for the AMI metric. For epsilons between 0.1 and 5, kd-Laplace/grid/optimal scores are higher. Regarding adversary advantage, Piecewise performs worse for epsilons between 0.1 and 1.5, while kd-Laplace/grid/optimal scores worse for epsilons 2 to 7.

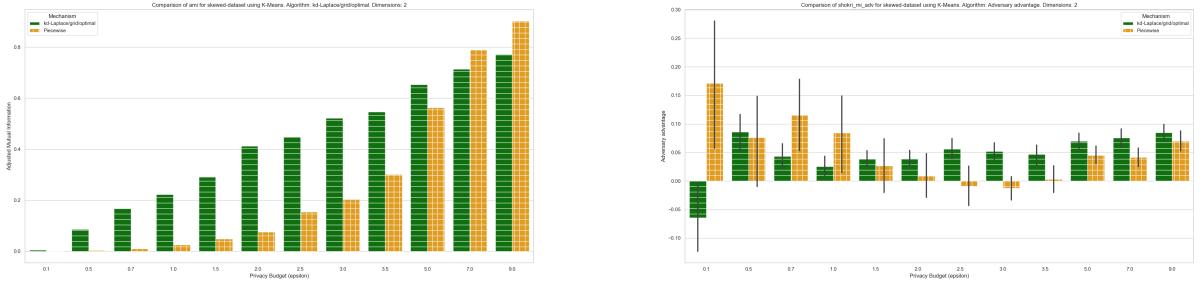


Figure 6.41: The AMI (left) and adversary advantage (right) for the skewed dataset

Kd-Laplace/grid/optimal is better than Piecewise for skewed datasets, across all epsilon values, with AMI scores ranging from 0.6 to 0.8. For adversary advantage, Kd-Laplace/grid/optimal outperforms Piecewise between 0.1 and 1.0 epsilon values. The adversary advantage stays low for both mechanisms (below 0.1).

7

DISCUSSION

In progress

8

CONCLUSION

In progress

BIBLIOGRAPHY

EUR-Lex - 32018R1725 - EN - EUR-Lex. <https://eur-lex.europa.eu/eli/reg/2018/1725/oj>, a. 1

Global big data industry market size 2011-2027. <https://www.statista.com/statistics/254266/global-big-data-market-forecast/>, b. 1

UCI Machine Learning Repository: Cardiotocography Data Set. <https://archive.ics.uci.edu/ml/datasets/cardiotocography>, c. 53

Mohiuddin Ahmed, Raihan Seraj, and Syed Mohammed Shamsul Islam. The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics*, 9(8):1295, 2020. ISSN 2079-9292. 11

Muhammad Aitsam. Differential Privacy Made Easy, December 2021. 6

Miguel E. Andrés, Nicolás Emilio Bordenabe, Konstantinos Chatzikokolakis, and Catuscia Palamidessi. Geo-indistinguishability: Differential privacy for location-based systems. *CoRR*, abs/1212.1984, 2012. 2, 8, 25, 26, 27, 29, 33, 34, 37

Mihai Ankerst, Markus M Breunig, Hans-Peter Kriegel, and Jörg Sander. OPTICS: Ordering Points To Identify the Clustering Structure. 10

Samah Baraheem and Zhongmei Yao. A Survey on Differential Privacy with Machine Learning and Future Outlook, November 2022. 16

Raef Bassily and Adam Smith. Local, Private, Efficient Protocols for Succinct Histograms. In *Proceedings of the Forty-Seventh Annual ACM Symposium on Theory of Computing*, pages 127–135, June 2015. doi: 10.1145/2746539.2746632. 17

Jon Louis Bentley. Multidimensional binary search trees used for associative searching. *Communications of the ACM*, 18(9):509–517, September 1975. ISSN 0001-0782. doi: 10.1145/361002.361007. 38

Avrim Blum, Cynthia Dwork, Frank McSherry, and Kobbi Nissim. *Practical Privacy: The SulQ Framework*. June 2005. doi: 10.1145/1065167.1065184. 18

Beyza Bozdemir, Sébastien Canard, Orhan Ermis, Helen Möllering, Melek Önen, and Thomas Schneider. Privacy-preserving Density-based Clustering. 20, 21

Hanbo Cai, Jinyan Wang, Xiaohong Liu, and Xianxian Li. DP-AP: Differential Privacy-Preserving Affinity Propagation Clustering. In *2020 IEEE 14th International Conference on Big Data Science and Engineering (BigDataSE)*, pages 73–79, Guangzhou, China, December 2020. IEEE. ISBN 978-1-66540-396-2. doi: 10.1109/BigDataSE50710.2020.00018. 20, 21

Tadeusz Caliński and Jerzy Harabasz. A dendrite method for cluster analysis. *Communications in Statistics-theory and Methods*, 3(1):1–27, 1974. ISSN 0090-3272. [13](#), [ix](#)

Nicholas Carlini, Steve Chien, Milad Nasr, Shuang Song, Andreas Terzis, and Florian Tramer. Membership Inference Attacks From First Principles, April 2022. [50](#)

Konstantinos Chatzikokolakis, Catuscia Palamidessi, and Marco Stronati. Constructing elastic distinguishability metrics for location privacy. *Proceedings on Privacy Enhancing Technologies*, 2015(2):156–170, June 2015. ISSN 2299-0984. doi: 10.1515/popets-2015-0023. [8](#), [28](#)

Konstantinos Chatzikokolakis, Ehab Elsalamouny, and Catuscia Palamidessi. Efficient utility improvement for location privacy. *Proceedings on Privacy Enhancing Technologies*, 2017(4):308–328, 2017. [27](#), [37](#), [39](#), [41](#), [42](#)

Jianbo Chen, Michael I. Jordan, and Martin J. Wainwright. HopSkipJumpAttack: A Query-Efficient Decision-Based Attack, April 2020. [48](#)

Christopher A. Choquette-Choo, Florian Tramer, Nicholas Carlini, and Nicolas Papernot. Label-Only Membership Inference Attacks, December 2021. [48](#), [50](#)

Toon Van Craenendonck and Hendrik Blockeel. Using Internal Validity Measures to Compare Clustering Algorithms. [13](#), [14](#)

David L Davies and Donald W Bouldin. A cluster separation measure. *IEEE transactions on pattern analysis and machine intelligence*, (2):224–227, 1979. ISSN 0162-8828. [13](#)

Irit Dinur and Kobbi Nissim. Revealing information while preserving privacy. In *Proceedings of the Twenty-Second ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems*, pages 202–210, San Diego California, June 2003. ACM. ISBN 978-1-58113-670-8. doi: 10.1145/773153.773173. [49](#)

Freedom of Information Act (FOIA) Division. The Privacy Act. <https://www.hhs.gov/foia/privacy/index.html>, April 2007. [1](#)

Salim Dridi. *Unsupervised Learning - A Systematic Literature Review*. December 2021. doi: 10.13140/RG.2.2.16963.12323. [1](#)

John Duchi, Martin Wainwright, and Michael Jordan. Minimax Optimal Procedures for Locally Private Estimation, November 2017. [18](#), [21](#), [23](#)

John C. Duchi, Michael I. Jordan, and Martin J. Wainwright. Privacy Aware Learning, October 2013. [17](#)

Cynthia Dwork. Differential privacy. In *Automata, Languages and Programming: 33rd International Colloquium, ICALP 2006, Venice, Italy, July 10-14, 2006, Proceedings, Part II* 33, pages 1–12. Springer, 2006. ISBN 3-540-35907-9. [1](#), [6](#), [9](#), [17](#)

Cynthia Dwork, Adam Smith, Thomas Steinke, and Jonathan Ullman. Exposed! A Survey of Attacks on Private Data. *Annual Review of Statistics and Its Application*, 4(1):61–84, March 2017. ISSN 2326-8298, 2326-831X. doi: 10.1146/annurev-statistics-060116-054123. [49](#)

Úlfar Erlingsson, Vasyl Pihur, and Aleksandra Korolova. RAPPOR: Randomized Aggregatable Privacy-Preserving Ordinal Response. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security*, pages 1054–1067, Scottsdale Arizona USA, November 2014. ACM. ISBN 978-1-4503-2957-6. doi: 10.1145/2660267.2660348. 9

Martin Ester, Hans-Peter Kriegel, and Xiaowei Xu. A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. 10

Adil Fahad, Najlaa Alshatri, Zahir Tari, Abdullah Alamri, Ibrahim Khalil, Albert Y. Zomaya, Sebti Foufou, and Abdelaziz Bouras. A Survey of Clustering Algorithms for Big Data: Taxonomy and Empirical Analysis. *IEEE Transactions on Emerging Topics in Computing*, 2(3):267–279, September 2014. ISSN 2168-6750. doi: 10.1109/TETC.2014.2330519. 10

Natasha Fernandes, Mark Dras, and Annabelle McIver. Generalised Differential Privacy for Text Document Processing, February 2019. 2, 34

Pasi Fränti, Mohammad Rezaei, and Qinpei Zhao. Centroid index: Cluster level similarity measure. *Pattern Recognition*, 47(9):3034–3045, September 2014. ISSN 00313203. doi: 10.1016/j.patcog.2014.03.017. 13

Matt Fredrikson, Somesh Jha, and Thomas Ristenpart. Model Inversion Attacks that Exploit Confidence Information and Basic Countermeasures. In *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security*, pages 1322–1333, Denver Colorado USA, October 2015. ACM. ISBN 978-1-4503-3832-5. doi: 10.1145/2810103.2813677. 49

Brendan J. Frey and Delbert Dueck. Clustering by Passing Messages Between Data Points. *Science*, 315(5814):972–976, February 2007. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.1136800. 10

Arik Friedman and Assaf Schuster. Data mining with differential privacy. In *Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 493–502, Washington DC USA, July 2010. ACM. ISBN 978-1-4503-0055-1. doi: 10.1145/1835804.1835868. 6

Quan Geng and Pramod Viswanath. The Optimal Mechanism in Differential Privacy, October 2013. 21

Quan Geng, Peter Kairouz, Sewoong Oh, and Pramod Viswanath. The staircase mechanism in differential privacy. *IEEE Journal of Selected Topics in Signal Processing*, 9(7):1176–1184, October 2015. ISSN 1932-4553, 1941-0484. doi: 10.1109/JSTSP.2015.2425831. 17, 21

Muneeb Ul Hassan, Mubashir Husain Rehmani, and Jinjun Chen. Differential Privacy Techniques for Cyber Physical Systems: A Survey, September 2019. 16

Marwan Hassani and Thomas Seidl. Using internal evaluation measures to validate the quality of diverse stream clustering algorithms. *Vietnam Journal of Computer Science*, 4(3):171–183, August 2017. ISSN 2196-8896. doi: 10.1007/s40595-016-0086-9. 13, 14

Hongsheng Hu, Zoran Salcic, Lichao Sun, Gillian Dobbie, Philip S. Yu, and Xuyun Zhang. Membership Inference Attacks on Machine Learning: A Survey, February 2022. [47](#), [50](#)

D. Huang, X. Yao, S. An, and S. Ren. Private distributed K-means clustering on interval data. In *2021 IEEE International Performance, Computing, and Communications Conference (IPCCC)*, pages 1–9, Los Alamitos, CA, USA, October 2021. IEEE Computer Society. doi: [10.1109/IPCCC51483.2021.9679364](#). [2](#), [14](#), [19](#), [21](#), [23](#), [54](#)

Lawrence Hubert and Phipps Arabie. Comparing partitions. *Journal of classification*, 2: 193–218, 1985. ISSN 0176-4268. [13](#), [15](#), [ix](#)

Bargav Jayaraman and David Evans. Evaluating Differentially Private Machine Learning in Practice. [47](#), [49](#)

Bargav Jayaraman and David Evans. Are Attribute Inference Attacks Just Imputation? In *Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security*, pages 1569–1582, Los Angeles CA USA, November 2022. ACM. ISBN 978-1-4503-9450-5. doi: [10.1145/3548606.3560663](#). [49](#)

Marija Jegorova, Chaitanya Kaul, Charlie Mayor, Alison Q. O’Neil, Alexander Weir, Roderick Murray-Smith, and Sotirios A. Tsaftaris. Survey: Leakage and Privacy at Inference Time, September 2022. [49](#)

Zhanglong Ji, Zachary C. Lipton, and Charles Elkan. Differential Privacy and Machine Learning: A Survey and Review, December 2014. [16](#)

Matthew Joseph, Jieming Mao, Seth Neel, and Aaron Roth. The Role of Interactivity in Local Differential Privacy. In *2019 IEEE 60th Annual Symposium on Foundations of Computer Science (FOCS)*, pages 94–105, Baltimore, MD, USA, November 2019. IEEE. ISBN 978-1-72814-952-3. doi: [10.1109/FOCS.2019.00015](#). [7](#)

Haim Kaplan and Uri Stemmer. Differentially Private k-Means with Constant Multiplicative Error, July 2018. [18](#), [19](#)

Shiva Prasad Kasiviswanathan, Homin K. Lee, Kobbi Nissim, Sofya Raskhodnikova, and Adam Smith. What Can We Learn Privately?, February 2010. [1](#)

Hannah Keller, Helen Möllering, Thomas Schneider, and Hossein Yalame. Balancing Quality and Efficiency in Private Clustering with Affinity Propagation:. In *Proceedings of the 18th International Conference on Security and Cryptography*, pages 173–184, Online Streaming, — Select a Country —, 2021. SCITEPRESS - Science and Technology Publications. ISBN 978-989-758-524-1. doi: [10.5220/0010547801730184](#). [10](#)

Trupti M Kodinariya and Prashant R Makwana. Review on determining number of Cluster in K-Means Clustering. *International Journal*, 1(6):90–95, 2013. [11](#), [12](#)

Jussi Lehtonen. The Lambert W function in ecological and evolutionary models. *Methods in Ecology and Evolution*, 7(9):1110–1118, 2016. ISSN 2041-210X. doi: [10.1111/2041-210X.12568](#). [26](#)

Zheng Li and Yang Zhang. Membership Leakage in Label-Only Exposures, September 2021.
[48](#)

Bo Liu, Ming Ding, Sina Shaham, Wenny Rahayu, Farhad Farokhi, and Zihuai Lin. When Machine Learning Meets Privacy: A Survey and Outlook. *ACM Computing Surveys*, 54(2): 1–36, March 2022. ISSN 0360-0300, 1557-7341. doi: 10.1145/3436755. [1](#)

Jinfei Liu, Joshua Huang, Jun Luo, and Li Xiong. Privacy preserving distributed DBSCAN clustering. *Transactions on Data Privacy*, 6, March 2012. doi: 10.1145/2320765.2320819. [10](#)

Yanchi Liu, Zhongmou Li, Hui Xiong, Xuedong Gao, and Junjie Wu. Understanding of internal clustering validation measures. In *2010 IEEE International Conference on Data Mining*, pages 911–916. IEEE, 2010. ISBN 1-4244-9131-2. [14](#), [15](#)

S. Lloyd. Least squares quantization in PCM. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982. doi: 10.1109/TIT.1982.1056489. [10](#)

George Marsaglia. Choosing a point from the surface of a sphere. *The Annals of Mathematical Statistics*, 43(2):645–646, 1972. ISSN 0003-4851. [34](#)

Xianrui Meng, Dimitrios Papadopoulos, Alina Oprea, and Nikos Triandopoulos. Private Hierarchical Clustering and Efficient Approximation. In *Proceedings of the 2021 on Cloud Computing Security Workshop*, pages 3–20, November 2021. doi: 10.1145/3474123.3486760. [10](#)

Minghui Min, Liang Xiao, Jiahao Ding, Hongliang Zhang, Shiying Li, Miao Pan, and Zhu Han. 3D Geo-Indistinguishability for Indoor Location-Based Services. *IEEE Transactions on Wireless Communications*, 21(7):4682–4694, 2022. doi: 10.1109/TWC.2021.3132464. [2](#), [27](#), [30](#), [31](#), [34](#)

André Fenias Moiane and Álvaro Muriel Lima Machado. EVALUATION OF THE CLUSTERING PERFORMANCE OF AFFINITY PROPAGATION ALGORITHM CONSIDERING THE INFLUENCE OF PREFERENCE PARAMETER AND DAMPING FACTOR. *Boletim de Ciências Geodésicas*, 24(4):426–441, December 2018. ISSN 1982-2170, 1413-4853. doi: 10.1590/s1982-21702018000400027. [12](#)

Thôñg T. Nguyêñ, Xiaokui Xiao, Yin Yang, Siu Cheung Hui, Hyejin Shin, and Junbum Shin. Collecting and Analyzing Data from Smart Device Users with Local Differential Privacy, June 2016. [17](#), [19](#), [21](#), [23](#)

Maria-Irina Nicolae, Mathieu Sinn, Minh Ngoc Tran, Beat Buesser, Ambrish Rawat, Martin Wistuba, Valentina Zantedeschi, Nathalie Baracaldo, Bryant Chen, Heiko Ludwig, Ian M. Molloy, and Ben Edwards. Adversarial Robustness Toolbox v1.0.0, November 2019. [49](#), [58](#)

Kobbi Nissim and Uri Stemmer. Clustering Algorithms for the Centralized and Local Models. In *Proceedings of Algorithmic Learning Theory*, pages 619–653. PMLR, April 2018. [18](#), [19](#), [21](#)

Kobbi Nissim, Sofya Raskhodnikova, and Adam Smith. Smooth sensitivity and sampling in private data analysis. In *Proceedings of the Thirty-Ninth Annual ACM Symposium on Theory of Computing*, pages 75–84, San Diego California USA, June 2007. ACM. ISBN 978-1-59593-631-8. doi: 10.1145/1250790.1250803. [9](#), [18](#), [21](#)

Yuefeng Peng, Bo Zhao, and Hui Liu. Unsupervised Membership Inference Attacks Against Machine Learning Models. [48](#)

William M Rand. Objective criteria for the evaluation of clustering methods. *Journal of the American Statistical association*, 66(336):846–850, 1971. ISSN 0162-1459. [13](#)

Maria Rigaki and Sebastian Garcia. A Survey of Privacy Attacks in Machine Learning, April 2021. [47](#), [48](#), [49](#), [50](#), [58](#)

Peter J Rousseeuw. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, 20:53–65, 1987. ISSN 0377-0427. [13](#), [15](#)

Jörg Sander, Martin Ester, Hans-Peter Kriegel, and Xiaowei Xu. Density-Based Clustering in Spatial Databases: The Algorithm GDBSCAN and Its Applications. *Data Mining and Knowledge Discovery*, 2(2):169–194, June 1998. ISSN 1573-756X. doi: 10.1023/A:1009745219419. [12](#)

Danny Matthew SAPUTRA, Daniel SAPUTRA, and Liniyanti D OSWARI. Effect of distance metrics in determining k-value in k-means clustering using elbow and silhouette method. In *Sriwijaya International Conference on Information Technology and Its Applications (SICONIAN 2019)*, pages 341–346. Atlantis Press, 2020. ISBN 94-6252-963-9. [11](#), [12](#)

Erich Schubert, Jörg Sander, Martin Ester, Hans Peter Kriegel, and Xiaowei Xu. DBSCAN Revisited, Revisited: Why and How You Should (Still) Use DBSCAN. *ACM Transactions on Database Systems*, 42(3):1–21, September 2017. ISSN 0362-5915, 1557-4644. doi: 10.1145/3068335. [10](#), [12](#)

Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership Inference Attacks against Machine Learning Models, March 2017. [48](#)

R. O. Sinnott, H. Duan, and Y. Sun. Chapter 15 - A Case Study in Big Data Analytics: Exploring Twitter Sentiment Analysis and the Weather. In Rajkumar Buyya, Rodrigo N. Calheiros, and Amir Vahid Dastjerdi, editors, *Big Data*, pages 357–388. Morgan Kaufmann, January 2016. ISBN 978-0-12-805394-2. doi: 10.1016/B978-0-12-805394-2.00015-5. [15](#)

Jordi Soria-Comas and Josep Domingo-Ferrer. Optimal data-independent noise for differential privacy. *Information Sciences*, 250:200–214, November 2013. ISSN 0020-0255. doi: 10.1016/j.ins.2013.07.004. [17](#)

Uri Stemmer. Locally private k-means clustering. *The Journal of Machine Learning Research*, 22(1):7964–7993, 2021. ISSN 1532-4435. [19](#), [21](#)

Alexander Strehl and Joydeep Ghosh. Cluster ensembles—a knowledge reuse framework for combining multiple partitions. *Journal of machine learning research*, 3(Dec):583–617, 2002. [13](#)

Dong Su, Jianneng Cao, Ninghui Li, Elisa Bertino, and Hongxia Jin. Differentially Private $k\$$ -Means Clustering, April 2015. [18](#), [19](#), [21](#)

Lin Sun, Jun Zhao, and Xiaojun Ye. Distributed Clustering in the Anonymized Space with Local Differential Privacy, June 2019. [2](#), [16](#), [21](#), [23](#)

Lin Sun, Guolou Ping, and Xiaojun Ye. PrivBV: Distance-aware encoding for distributed data with local differential privacy. *Tsinghua Science and Technology*, 27(2):412–421, April 2022. ISSN 1007-0214. doi: 10.26599/TST.2021.9010027. [14](#), [21](#)

Latanya Sweeney. K-ANONYMITY: A MODEL FOR PROTECTING PRIVACY. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 10(05):557–570, October 2002. ISSN 0218-4885, 1793-6411. doi: 10.1142/S0218488502001648. [1](#)

Robert Tibshirani, Guenther Walther, and Trevor Hastie. Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 63(2):411–423, 2001. ISSN 1369-7412. [12](#)

Nguyen Xuan Vinh, Julien Epps, and James Bailey. Information Theoretic Measures for Clusterings Comparison: Variants, Properties, Normalization and Correction for Chance. [13](#), [15](#)

Silke Wagner and Dorothea Wagner. Comparing Clusterings - An Overview. [13](#)

Kaijun Wang, Junying Zhang, Dan Li, Xinna Zhang, and Tao Guo. Adaptive Affinity Propagation Clustering. 2007. [12](#)

Ning Wang, Xiaokui Xiao, Yin Yang, Jun Zhao, Siu Cheung Hui, Hyejin Shin, Junbum Shin, and Ge Yu. Collecting and Analyzing Multidimensional Data with Local Differential Privacy, June 2019. [18](#), [21](#), [23](#)

Teng Wang, Xuefeng Zhang, Jingyu Feng, and Xinyu Yang. A Comprehensive Survey on Local Differential Privacy toward Data Statistics and Analysis. *Sensors*, 20(24), 2020. ISSN 1424-8220. doi: 10.3390/s20247030. [8](#), [44](#)

Tianhao Wang, Jeremiah Blocki, Ninghui Li, and Somesh Jha. Locally Differentially Private Protocols for Frequency Estimation. [18](#), [20](#)

Stanley L Warner. Randomized response: A survey technique for eliminating evasive answer bias. *Journal of the American Statistical Association*, 60(309):63–69, 1965. ISSN 0162-1459. [9](#)

Matthijs J. Warrens and Hanneke van der Hoef. Understanding the Adjusted Rand Index and Other Partition Comparison Indices Based on Counting Object Pairs. *Journal of Classification*, 39(3):487–509, November 2022. ISSN 1432-1343. doi: 10.1007/s00357-022-09413-z. [13](#)

Washington. K-D Trees, February 2. [38](#), [39](#)

Chang Xia, Jingyu Hua, Wei Tong, and Sheng Zhong. Distributed K-Means clustering guaranteeing local differential privacy. *Computers & Security*, 90:101699, 2020. ISSN 0167-4048. [2](#), [14](#), [19](#), [21](#), [23](#)

Xingxing Xiong, Shubo Liu, Dan Li, Zhaojun Cai, and Xiaoguang Niu. A Comprehensive Survey on Local Differential Privacy. *Security and Communication Networks*, 2020:8829523, October 2020a. ISSN 1939-0114. doi: 10.1155/2020/8829523. [7](#), [9](#)

Xingxing Xiong, Shubo Liu, Dan Li, Zhaojun Cai, and Xiaoguang Niu. A Comprehensive Survey on Local Differential Privacy. *Security and Communication Networks*, 2020:8829523, October 2020b. ISSN 1939-0114. doi: 10.1155/2020/8829523. [8](#), [44](#)

Dongkuan Xu and Yingjie Tian. A Comprehensive Survey of Clustering Algorithms. *Annals of Data Science*, 2(2):165–193, June 2015. ISSN 2198-5812. doi: 10.1007/s40745-015-0040-1. [10](#)

Mengmeng Yang, Lingjuan Lyu, Jun Zhao, Tianqing Zhu, and Kwok-Yan Lam. Local Differential Privacy and Its Applications: A Comprehensive Survey, August 2020. [1](#)

Samuel Yeom, Irene Giacomelli, Matt Fredrikson, and Somesh Jha. Privacy Risk in Machine Learning: Analyzing the Connection to Overfitting. In *2018 IEEE 31st Computer Security Foundations Symposium (CSF)*, pages 268–282, Oxford, July 2018. IEEE. ISBN 978-1-5386-6680-7. doi: 10.1109/CSF.2018.00027. [48](#), [49](#), [50](#), [58](#)

Chunhui Yuan and Haitao Yang. Research on K-value selection method of K-means clustering algorithm. *J*, 2(2):226–235, 2019. ISSN 2571-8800. [12](#)

Liujiye Yuan, Shaobo Zhang, Gengming Zhu, and Karim Alinani. Privacy-preserving mechanism for mixed data clustering with local differential privacy. *Concurrency and Computation: Practice and Experience*, July 2021. ISSN 1532-0626, 1532-0634. doi: 10.1002/cpe.6503. [19](#), [21](#), [23](#)

Tian Zhang, Raghu Ramakrishnan, and Miron Livny. BIRCH: An efficient data clustering method for very large databases. *ACM SIGMOD Record*, 25(2):103–114, June 1996. ISSN 0163-5808. doi: 10.1145/235968.233324. [10](#), [11](#)

Benjamin Zi Hao Zhao, Mohamed Ali Kaafar, and Nicolas Kourtellis. Not one but many Tradeoffs: Privacy Vs. Utility in Differentially Private Machine Learning. In *Proceedings of the 2020 ACM SIGSAC Conference on Cloud Computing Security Workshop*, pages 15–26, November 2020. doi: 10.1145/3411495.3421352. [58](#)

Benjamin Zi Hao Zhao, Aviral Agrawal, Catisha Coburn, Hassan Jameel Asghar, Raghav Bhaskar, Mohamed Ali Kaafar, Darren Webb, and Peter Dickinson. On the (In)Feasibility of Attribute Inference Attacks on Machine Learning Models, March 2021. [49](#)

GLOSSARY

Adjusted Mutual Information Comparable with **Adjusted Rand Index** this algorithm is modified to account to chance. This means it accounts for a higher MI for a higher amount of clusters between two cluster algorithms. Therefore, the calculations are strongly influenced by that of **Adjusted Rand Index** [?]. . viii, 12

Adjusted Rand Index The Rand Index is improved and adjusted for chance [Hubert and Arabie, 1985]. This algorithm takes also into consideration the number of clusters and can be used to also compare different cluster algorithms [?]. . viii, 12

Average Estimation Error This is the difference between an estimated value and the real value.. viii

Bit Vector List or array to store several bits.. viii

Calinski-Harabasz Index This is a way to measure the similarity of clusters [Caliński and Harabasz, 1974]. It tells how well the clusters are separated from each other and how well the points are grouped.. viii, 12

Mutual Information This metric can be used to explain the amount of information about a random variable if compared to another random variable. Therefore, it can also be used to compare two cluster similarities.. viii, 12

Normalized Mutual Information The normalized version is a scaled version of **Mutual Information** to always be a value between 0 (no correlation) and 1 (perfect correlation). This version of **Mutual Information** is not adjusted and therefore highly influenced by cluster amount [?]. So it suffers the same issue as with **Mutual Information**.. viii, 12

Rand Index Compares the similarity between two clusters by comparing all pairs. It can therefore be used to measure the performance between two clustering algorithms [Hubert and Arabie, 1985]. . viii

ACRONYMS

AEE Average Estimated Error. viii, *Glossary*: Average Estimation Error

AMI Adjusted Mutual Information. viii, 12, 13, 17, *Glossary*: Adjusted Mutual Information

AP Affinity Propagation. viii, 10, 13, 17, 50, 56–58, 61

ARI Adjusted Rank Index. viii, 12, 13, 17, *Glossary*: Adjusted Rand Index

BIRCH Balanced Iterative Reducing and Clustering using Hierarchies. viii

BV Bit Vector. viii

CHI Calinski-Harabasz Index. viii, 12, *Glossary*: Calinski-Harabasz Index

DBSCAN Density-based spatial clustering of applications with noise. viii, 10, 17, 51

DP Differential Privacy. viii, 4, 6, 8, 13, 14

DPC Density Peaks Clustering. viii

GI Geo-indistinguishability. viii, 6, 7, 22, 24

LDP Local Differential Privacy. viii, 5, 8, 25

MI Mutual Information. viii, 12, *Glossary: Mutual Information*

NMI Normalized Mutual Information. viii, 12, 13, *Glossary: Normalized Mutual Information*

HYPERPARAMETERS

.1. K-MEANS

For selecting the appropriate amount of clusters, we used an "elbow" plot in combination with the silhouette score.

1. Seeds dataset: 4 clusters (see figure: 1)
2. Heart dataset: TODO
3. Circle dataset: 5 clusters (see figure: 2)
4. Line dataset: 4 clusters (see figure: 3)
5. Skewed dataset: 4 clusters (see figure: 4)

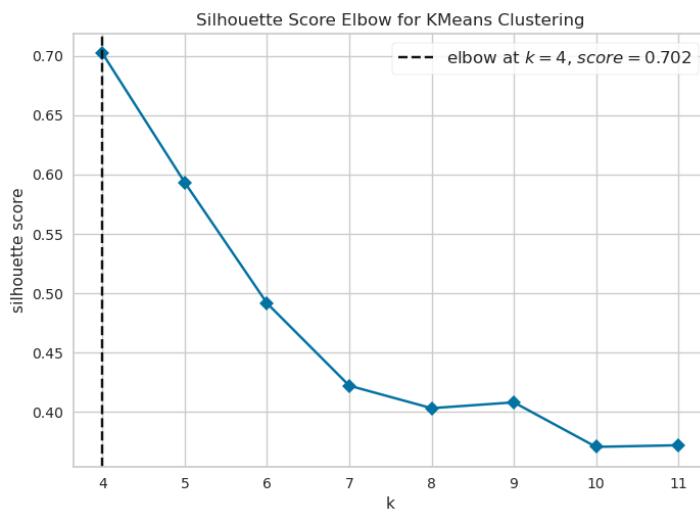


Figure 1: Selecting the k for K-Means for seeds dataset using the "elbow plot" using section 2.2.2

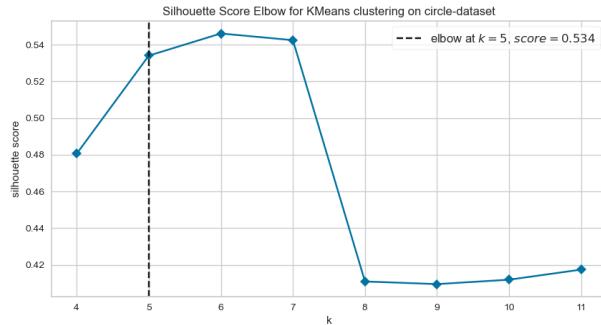


Figure 2: Selecting the k for K-Means for the circle dataset using the "elbow plot" using section 2.2.2

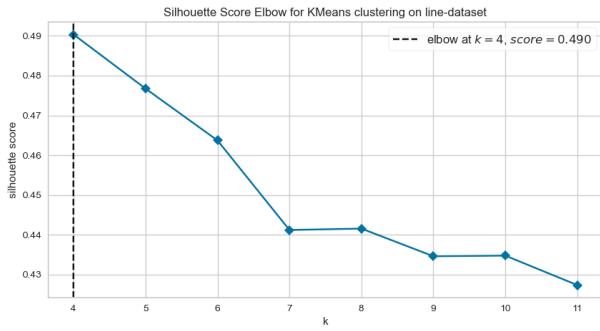


Figure 3: Selecting the k for K-Means for the line dataset using the "elbow plot" using section 2.2.2

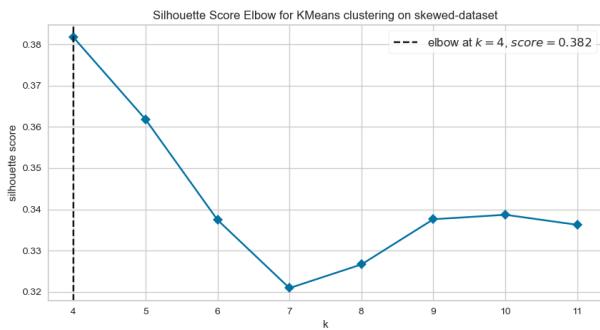


Figure 4: Selecting the k for K-Means for the skewed dataset using the "elbow plot" using section 2.2.2

THEORY

.2. BIG O NOTATION

The big O notation is a common way to describe the complexity of an algorithm. It is used to describe the worst-case scenario of an algorithm. For example, if an algorithm has a complexity of $O(n)$, it means that the algorithm will take at most n steps to complete (source for figure: https://en.wikipedia.org/wiki/Big_O_notation):

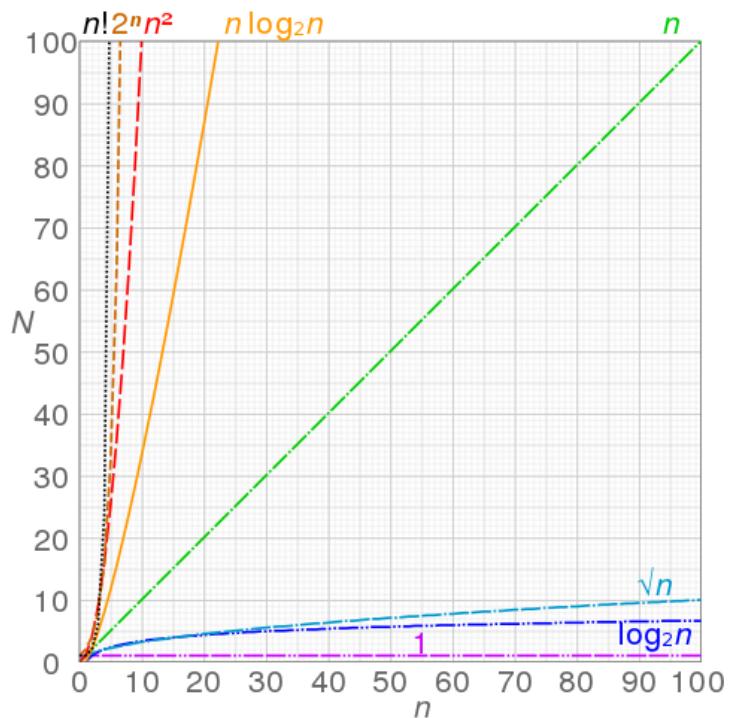


Figure 5: Graphical representation of the big O notation

RESULTS

.3. CLUSTER UTILITY

.3.1. 2-DIMENSIONAL DATA

Figure 6: Internal validation for all mechanisms the 2-dimensional data heart-dataset

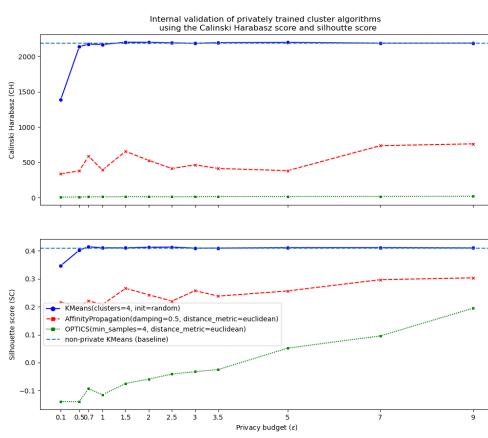


Figure 7: Internal validation (CH/ SC) for the 2-dimensional data heart-dataset for laplace.

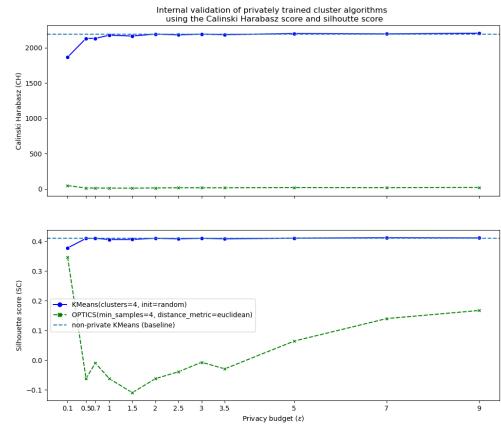


Figure 8: Internal validation (CH/ SC) for the 2-dimensional data heart-dataset for laplace with truncation.

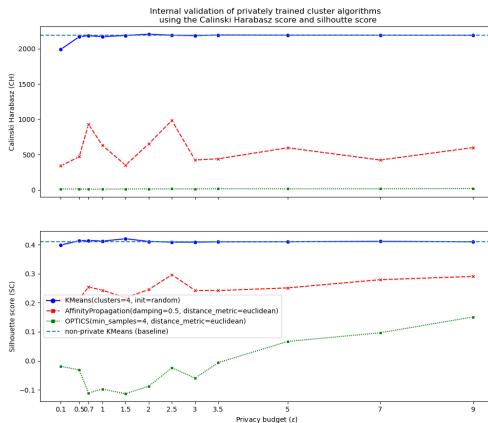


Figure 9: Internal validation (CH/ SC) for the 2-dimensional data heart-dataset for laplace with optimal truncation

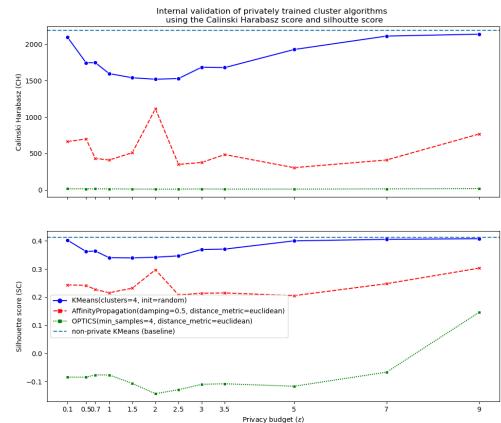


Figure 10: Internal validation (CH/ SC) for the 2-dimensional data heart-dataset for piecewise mechanism

Figure 11: Internal validation for all mechanisms the 2-dimensional data seeds-dataset

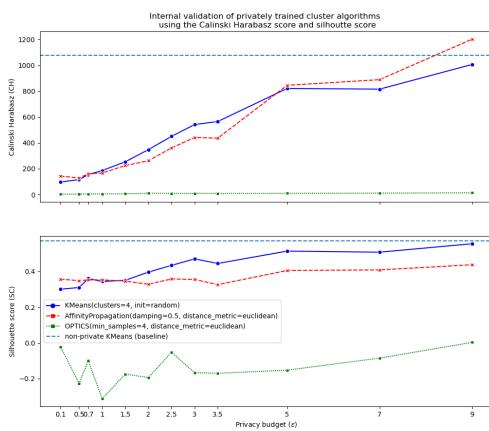


Figure 12: Internal validation (CH/ SC) for the 2-dimensional data seeds-dataset for laplace.

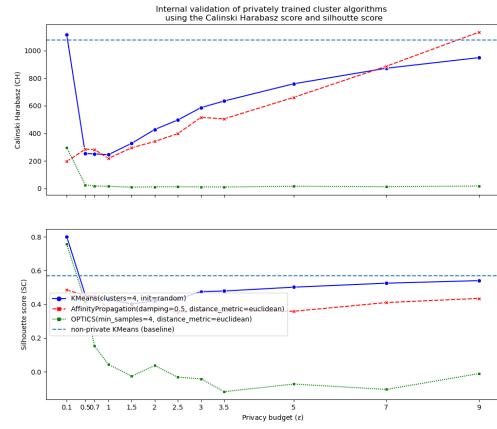


Figure 13: Internal validation (CH/ SC) for the 2-dimensional data seeds-dataset for laplace with truncation.

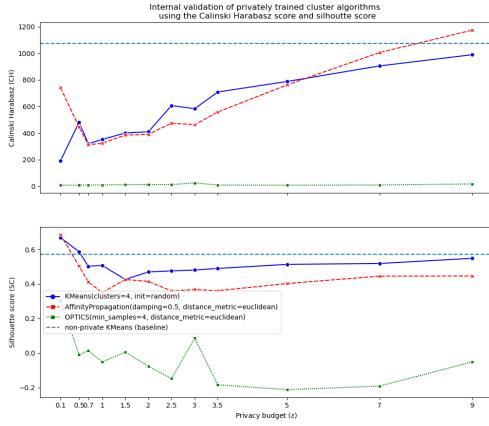


Figure 14: Internal validation (CH/ SC) for the 2-dimensional data seeds-dataset for laplace with op-timal truncation

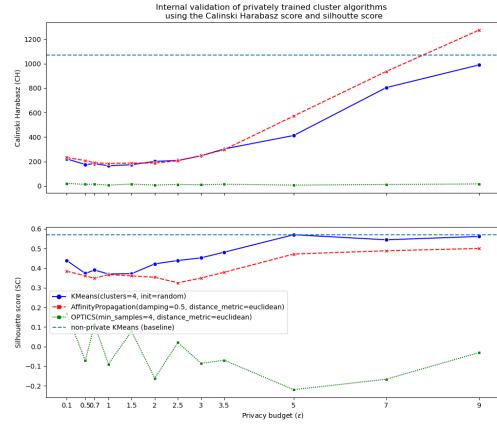


Figure 15: Internal validation (CH/ SC) for the 2-dimensional data seeds-dataset for piecewise mechanism

3.2. 3-DIMENSIONAL DATA

Figure 16: Internal validation for all mechanisms the 3-dimensional data seeds-dataset

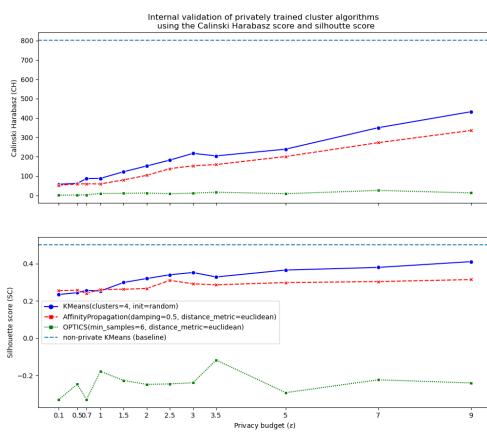


Figure 17: Internal validation (CH/ SC) for the 3-dimensional data seeds-dataset for laplace.

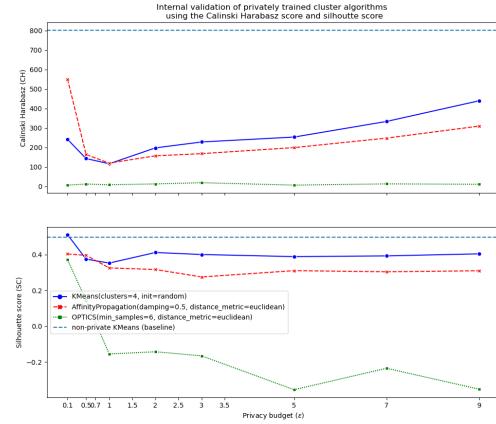


Figure 18: Internal validation (CH/ SC) for the 3-dimensional data seeds-dataset for laplace with truncation.

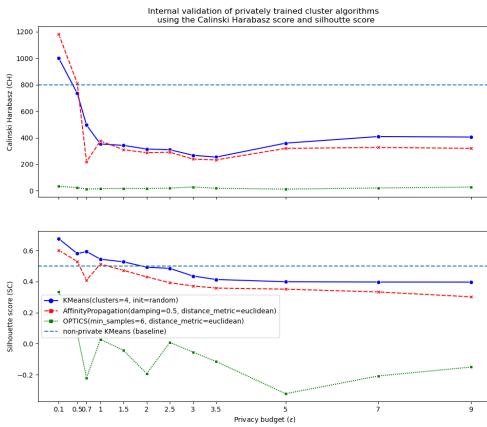


Figure 19: Internal validation (CH/ SC) for the 3-dimensional data seeds-dataset for laplace with op-truncation

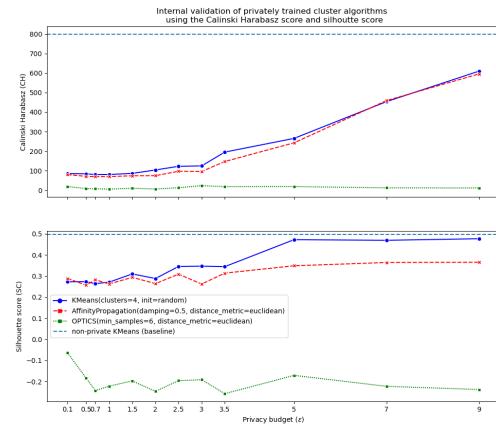


Figure 20: Internal validation (CH/ SC) for the 3-dimensional data seeds-dataset for piecewise mechanism

Figure 21: Internal validation for all mechanisms the 3-dimensional data heart-dataset

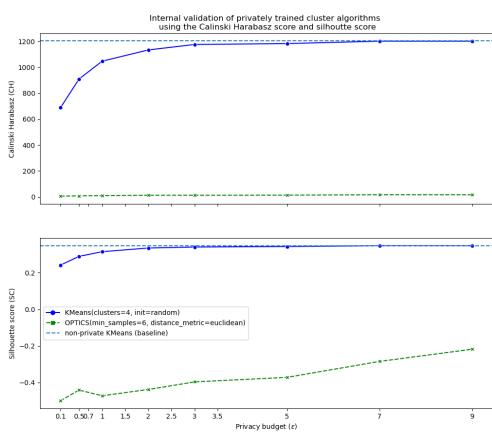


Figure 22: Internal validation (CH/ SC) for the 3-dimensional data heart-dataset for laplace.

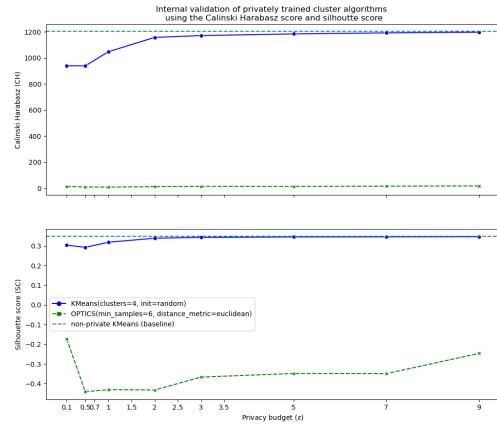


Figure 23: Internal validation (CH/ SC) for the 3-dimensional data heart-dataset for laplace with truncation.

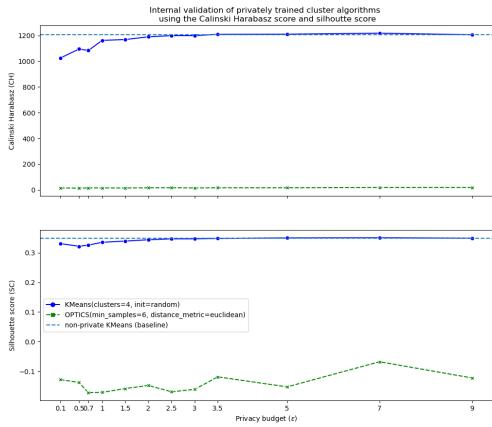


Figure 24: Internal validation (CH/ SC) for the 3-dimensional data heart-dataset for laplace with op-timal truncation

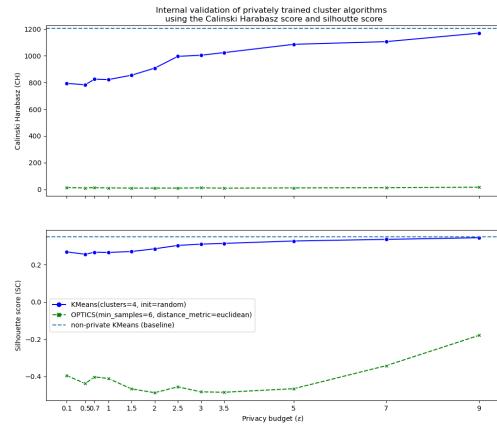


Figure 25: Internal validation (CH/ SC) for the 3-dimensional data heart-dataset for piecewise mechanism

3.3. N-DIMENSIONAL DATA

Figure 26: Internal validation for all mechanisms the n-dimensional data seeds-dataset

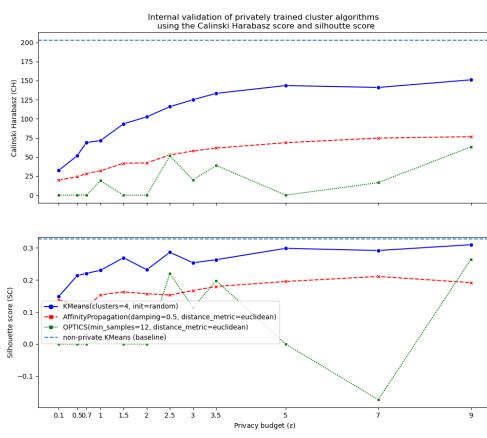


Figure 27: Internal validation (CH/ SC) for the n-dimensional data seeds-dataset for laplace.

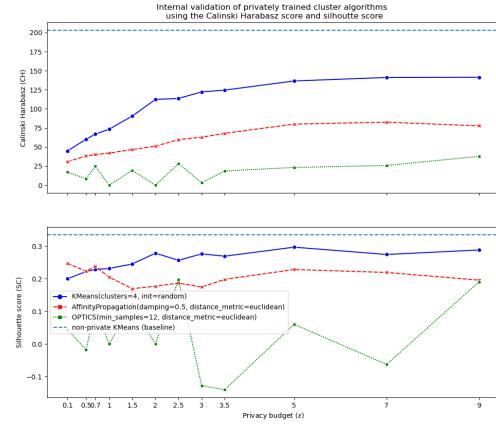


Figure 28: Internal validation (CH/ SC) for the n-dimensional data seeds-dataset for laplace with truncation.

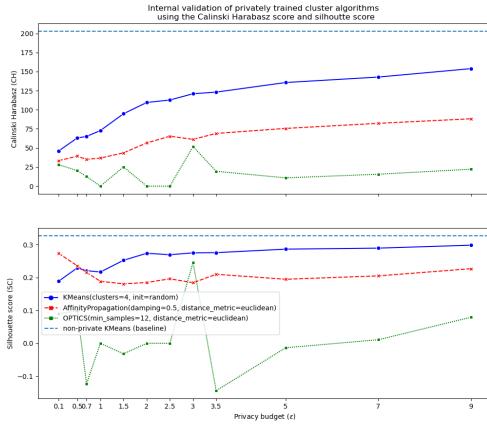


Figure 29: Internal validation (CH/ SC) for the n-dimensional data seeds-dataset for laplace with op-timal truncation

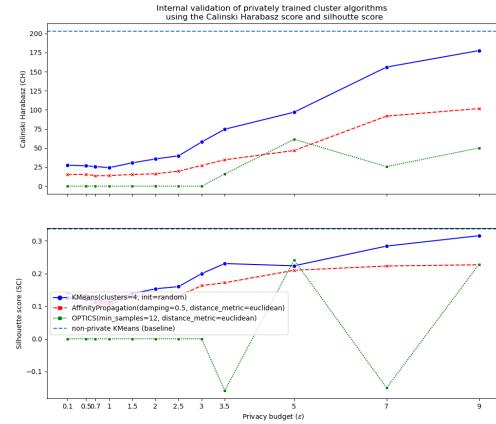


Figure 30: Internal validation (CH/ SC) for the n-dimensional data seeds-dataset for piecewise mechanism

Figure 31: Internal validation for all mechanisms the n-dimensional data heart-dataset

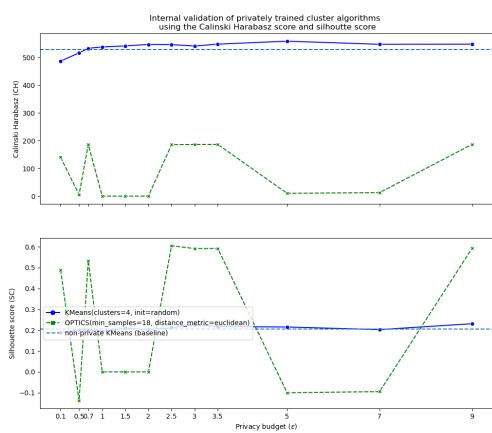


Figure 32: Internal validation (CH/ SC) for the n-dimensional data heart-dataset for laplace.

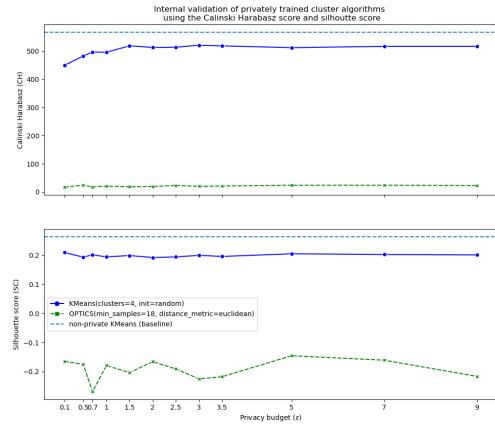


Figure 33: Internal validation (CH/ SC) for the n-dimensional data heart-dataset for laplace with truncation.

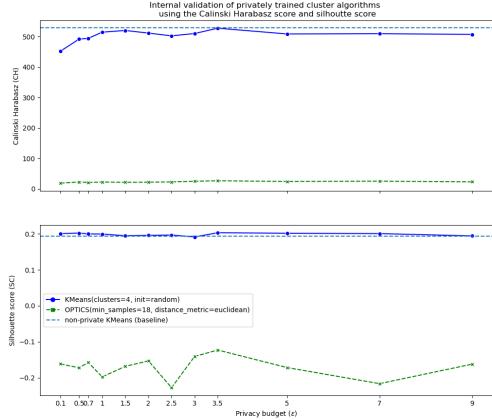


Figure 34: Internal validation (CH/ SC) for the n-dimensional data heart-dataset for op-timal truncation

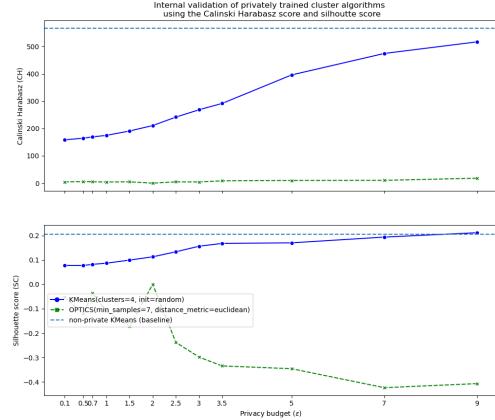


Figure 35: Internal validation (CH/ SC) for the n-dimensional data heart-dataset for piecewise mechanism

4. MECHANISM UTILITY

4.1. 2-DIMENSIONAL DATA

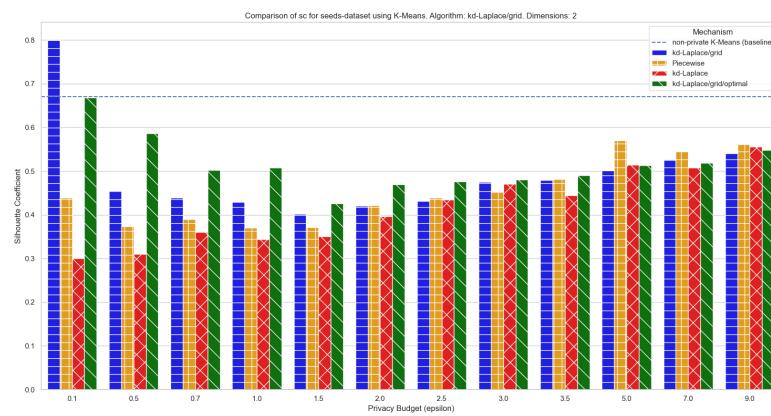


Figure 36: Silhouette score comparison for the 2D seeds-dataset

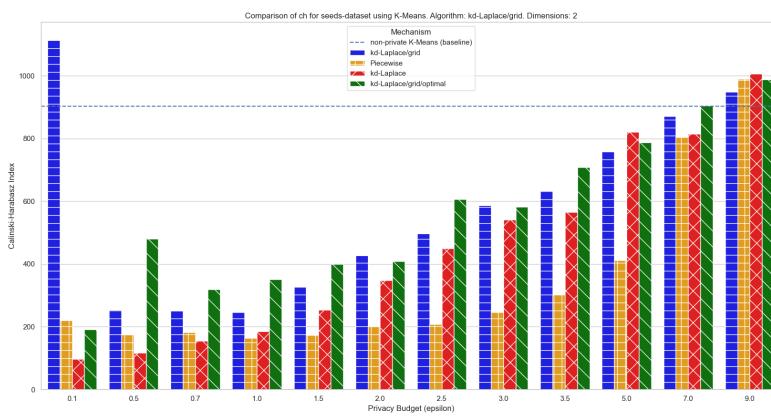


Figure 37: Calinski Harabasz score comparison for the 2D seeds-dataset

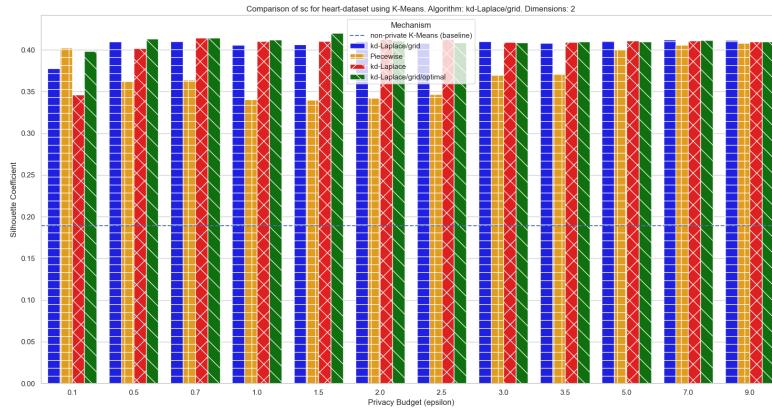


Figure 38: Silhouette score comparison for the 2D heart-dataset

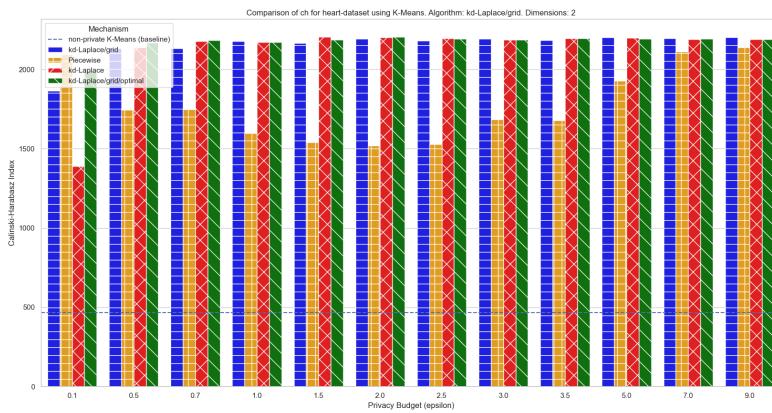


Figure 39: Calinski Harabasz score comparison for the 2D heart-dataset

.4.2. 3-DIMENSIONAL DATA

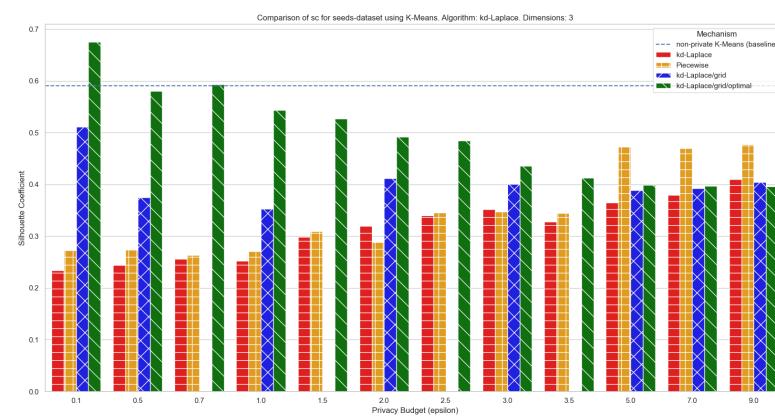


Figure 40: Silhouette score comparison for the 3D seeds-dataset

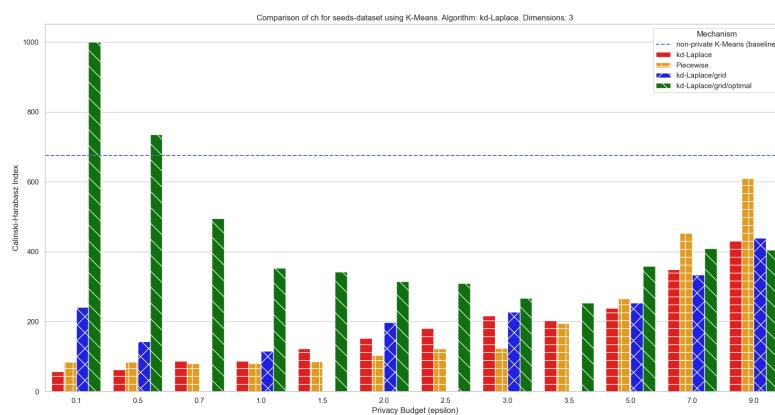


Figure 41: Calinski Harabasz score comparison for the 3D seeds-dataset

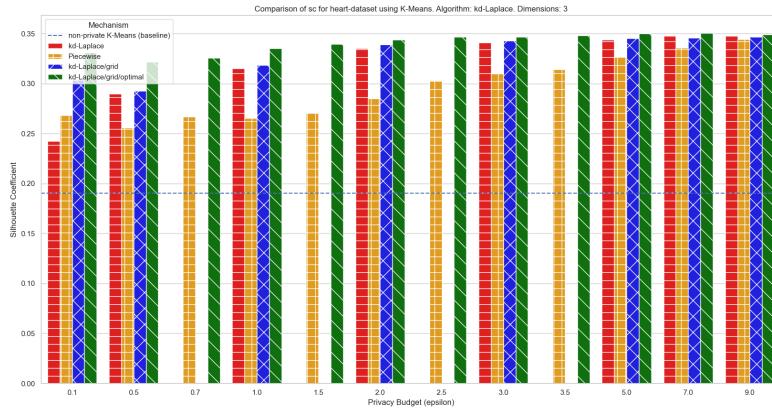


Figure 42: Silhouette score comparison for the 3D heart-dataset

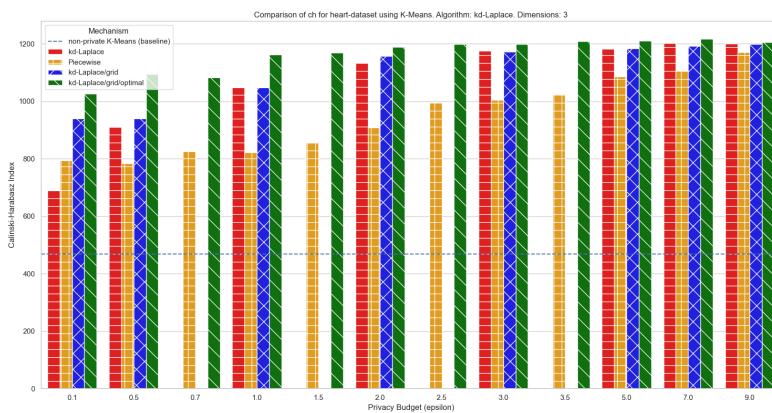


Figure 43: Calinski Harabasz score comparison for the 3D heart-dataset

.4.3. N-DIMENSIONAL DATA

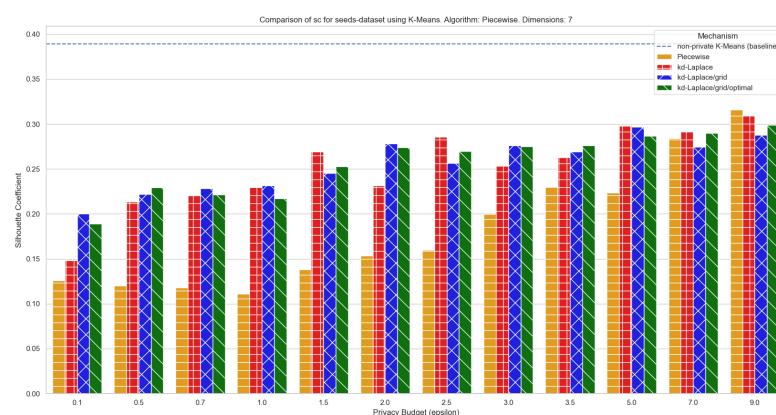


Figure 44: Silhouette score comparison for the nd seeds-dataset

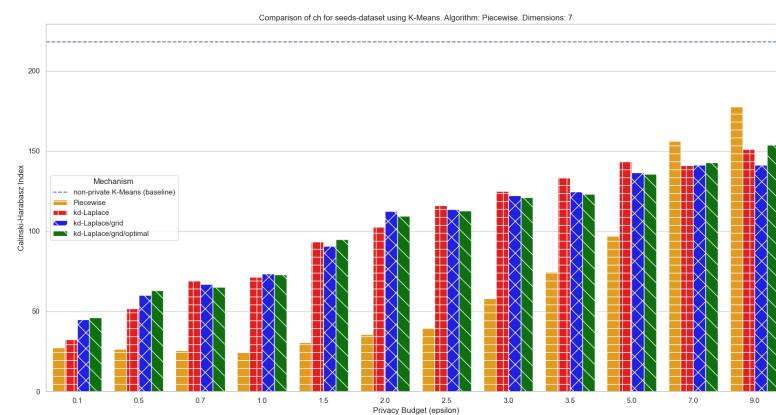


Figure 45: Calinski Harabasz score comparison for the nd seeds-dataset

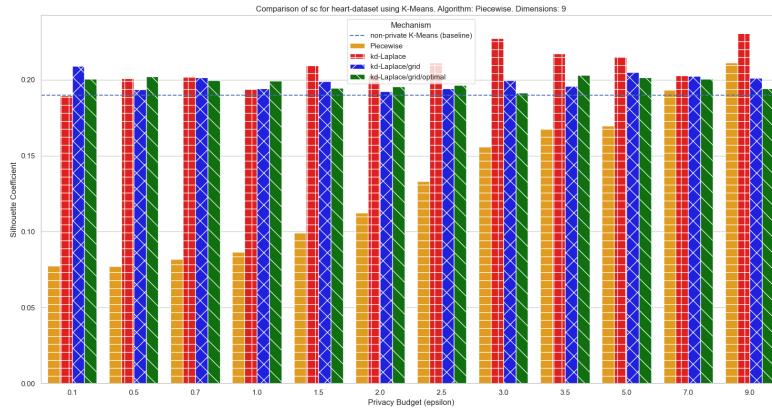


Figure 46: Silhouette score comparison for the nd heart-dataset

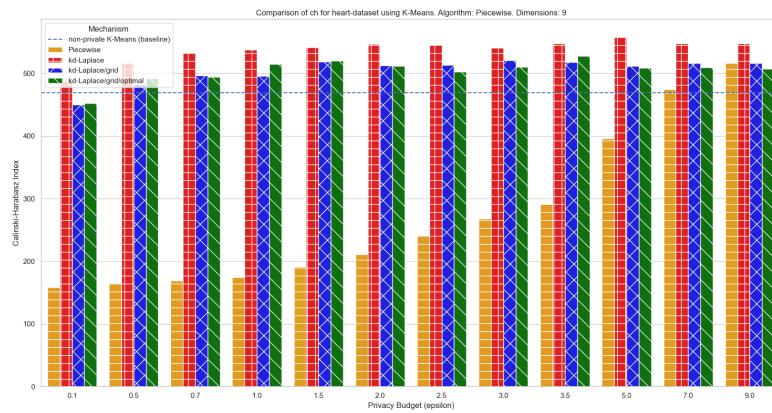


Figure 47: Calinski Harabasz score comparison for the nd heart-dataset