A Critical Review on the Use (and Misuse) of Differential Privacy in Machine Learning

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Abstract

We review the use of differential privacy (DP) for privacy protection in machine learning (ML). We show that, driven by the aim of preserving the accuracy of the learned models, DP-based ML implementations are so loose that they do not offer the \textit{ex ante} privacy guarantees of DP. Instead, what they deliver is basically noise addition similar to the traditional (and often criticized) statistical disclosure control approach. Due to the lack of formal privacy guarantees, the actual level of privacy offered must be experimentally assessed \textit{ex post}, which is done very seldom. In this respect, we present empirical results showing that standard anti-overfitting techniques in ML can achieve a better utility/privacy/efficiency trade-off than DP.

Keywords: differential privacy, machine learning, federated learning, data utility.

1 Introduction

As long ago as the 1970s, official statisticians \cite{Dalenius1977} began to worry about potential disclosure of private information on people or companies linked to the publication of statistical outputs. This ushered in the statistical disclosure control (SDC) discipline \cite{Hundepool2012}, whose goal is to provide methods for data anonymization. Also related to SDC is randomized response (RR, \cite{Warner1965}), which was designed in the 1960s as a mechanism to eliminate evasive answer bias in surveys and turned out to be very useful for anonymization. The usual approach to anonymization in official statistics is \textit{utility-first}: anonymization parameters are iteratively tried until a parameter choice is found that preserves sufficient analytical utility while reducing below a certain threshold the risk of disclosing confidential information on specific respondents. Both utility and privacy are evaluated \textit{ex post} by respectively measuring the information loss and the probability of re-identification of the anonymized outputs.

In the late 1990s, in the wake of the explosion of the web and the consequent surge of data collection and exchange beyond official statistics, privacy protection became a mainstream topic in the computer science community, which introduced a different angle, namely \textit{privacy-first} data protection. In this approach, a \textit{privacy model} specifying an \textit{ex ante} privacy condition is enforced using one or several SDC methods, such as noise addition, generalization or microaggregation \cite{Domingo-Ferrer2016}. The parameters of the SDC methods thus depend on the privacy model parameters, and too strict a choice of the latter may result in poor utility. Privacy models have the advantage of setting the privacy level by design, without having to empirically evaluate it. The first privacy model was \textit{k}-anonymity \cite{Samarati1998}, which was followed by a number of extensions, such as \textit{l}-diversity \cite{Machanavajjhala2007}, \textit{t}-closeness \cite{Li2010} and others. All privacy models in the \textit{k}-anonymity family were designed to anonymize microdata sets, that is, data sets formed by records that correspond to individual respondents.

\textit{Differential privacy} \cite{Dwork2006} is a privacy model that arose later, in 2006, in the cryptographic community. Unlike \textit{k}-anonymity, DP was designed to anonymize the outputs of interactive queries to a database. Given \(\epsilon \geq 0\), a randomized query function \(\kappa\) (that returns the exact answer to a query function \(f\) plus some noise) satisfies \(\epsilon\)-DP if, for all data sets \(D_1\) and \(D_2\) that differ in one record and all \(S \in \text{Range}(\kappa)\), it holds that

\[
\Pr(\kappa(D_1) \in S) \leq \exp(\epsilon) \times \Pr(\kappa(D_2) \in S).
\]

In plain words, the presence or absence of any single record in the database must not be noticeable from the query answers, up to a factor exponential in \(\epsilon\). If each record corresponds to a different individual respondent, this means that the individual’s information stays confidential. The smaller \(\epsilon\), also known as the \textit{privacy budget},
the higher the protection. The amount of noise that $\kappa$ must incorporate to satisfy DP is inversely proportional to $\epsilon$ and directly proportional to the global sensitivity $\Delta(f)$, that is, to how much the output of the query function $f$ can change due to the addition, deletion or change of a single record in the database. Mild noise may suffice when $f$ is a rather insensitive function such as the median or the mean, but much larger noise may be needed for more sensitive query functions such as maxima or minima.

DP has several advantages w.r.t. privacy models in the $k$-anonymity family and the utility-first approach:

- DP provides a strong privacy guarantee that is largely independent of the attacker’s background knowledge. In contrast, in $k$-anonymity an assumption on the attacker’s knowledge is implicit in the choice of quasi-identifier attributes. However, as noted in [Kifer and Machanavajjhala(2011)] and [Clifton and Tassa(2013)], DP is not entirely free of assumptions either.

- DP has very nice composability properties. Sequential composition states that, if the outputs of queries $\kappa_i$, for $i = 1, \ldots, m$, on non-independent data sets are individually protected under $\epsilon_i$-DP, then the output obtained by composing all individual query outputs is protected under $\sum_{i=1}^m \epsilon_i$. This formalizes the intuition that, the more outputs are accumulated on overlapping data, the weaker is the extant protection. Parallel composition states that, in the specific case that $m$ query outputs were computed on $m$ disjoint and independent data sets and protected under $\epsilon$-DP, then the composition of those outputs is still protected under $\epsilon$-DP.

To understand the practical protection offered by a certain privacy budget $\epsilon$, let us use the connection between DP and the aforementioned randomized response. Consider RR for a binary attribute, so that the reported randomized answer is equal to the true answer with probability $p = 0.5$ and different with probability $1 - p$. It is shown in [Wang et al.(2014)] and [Wang et al.(2016)] that, if $p = \exp(\epsilon)/(1 + \exp(\epsilon))$, then binary RR satisfies $\epsilon$-DP. For example, DP with $\epsilon = 8$ is satisfied by RR with $p = 0.9996646$, that is, by RR reporting the true answer with probability practically 1 (which basically amounts to no disclosure protection being offered). In this sense, the inventor of DP recommends setting $\epsilon \leq 1$ [Dwork(2011)], so that the practical protection obtained comes reasonably close to the theoretical privacy guarantee. Actually, one of the DP co-inventors is reported to have stated that using values of $\epsilon$ as high as 14 is pointless in terms of privacy [Greenberg(2017)]. This contrasts with other parameterized privacy models, for which any value of the privacy parameter is privacy-meaningful. For instance, with $k$-anonymity, the re-identification risk is upper-bounded by $1/k$ for any positive integer $k$.

The downside of DP in interactive settings is that it limits the number of queries that can be usefully answered. If $m$ queries are to be answered on the same subject’s data, sequential composition requires the overall budget $\epsilon$ to be split for the $m$ queries. In case of equal splitting, each query has budget $\epsilon/m$, which entails an $m$-fold noise increase, with the subsequent utility decrease. Moreover, since noise is calibrated to the output sensitivity of a particular query, queries that have higher sensitivity cannot be answered. See [Clifton and Tassa(2013)] for additional criticisms to DP.

Nonetheless, due to its convenient properties and strong privacy guarantee, DP was rapidly adopted by the research community, up to the point that many researchers now consider DP the gold standard in privacy protection [Edmond(2020)]. Not surprisingly, many works have endeavored to apply DP outside the interactive setting it was designed for. Unfortunately, they often neglect the assumptions, limitations and prerequisites of DP.

Such is the case when using DP to anonymize microdata sets. The record corresponding to a respondent can be viewed as the output of an identity query, that is, a query whose function $f$ merely extracts the value of a certain record from the microdata set. The global sensitivity $\Delta(f)$ of such a single-record query is typically enormous, because the attribute values in the record can change within their entire domains. Hence, a correspondingly enormous amount of noise is required for each identity query to enforce DP with a reasonably safe $\epsilon$. As a result, a DP microdata set is obtained whose records differ very significantly from the corresponding original records [Soria-Comas et al.(2014)]. In summary, if DP is properly applied, the utility of microdata releases is seriously decreased. Practical applications of DP for microdata have tried to circumvent this problem through sloppy implementations or unreasonably high privacy budgets $\epsilon$ [Domingo-Ferrer et al.(2021)].

DP has been also used by big companies in the context of microdata collection (rather than release), by locally anonymizing data under DP at the source respondent’s device. For this to be possible with reasonable utility, Apple has used $\epsilon$ values ranging between 6 and 43 [Greenberg(2017)], and Google use $\epsilon$ up to 9 in the RAPPOR technology [Erlingsson et al.(2014)]. Moreover, to escape the use of sequential composition in continuous data collection on the same subject, which would exponentially reduce the utility of the data, Apple considered the data on an individual gathered in different days to be independent [Greenberg(2017)], and Google considered sequential composition just on values that have not changed from the previous collection [Cyphers(2017)]. Both approaches are severely flawed, since it is obvious that different pieces of data on the same individual cannot be viewed as independent [Domingo-Ferrer et al.(2021)].

More recently, DP has been extensively applied to enhance privacy in machine learning (ML). The rationale is that ML requires huge amounts of training data that are most often personal data and thus need to be protected. Protecting the individuals’ data used to train ML models or protecting the learned models prior to releasing them bear many similarities with protecting continuous data collection or protecting data releases,
respectively. Therefore, the challenges are similar, basically the difficulty of reconciling the strong privacy of DP with enough data utility (model accuracy in the ML context). However, recent advances in the application of DP to ML promise DP-protected ML models with minimum accuracy loss and with reasonably safe DP parameters (and thus with “enough” privacy) [Abadi et al.(2016)]. This seems counterintuitive, given the strong constraints imposed by DP and the privacy implications of releasing an ML model trained on personal data.

Contributions and plan of this survey

In this survey we critically review the use of DP in ML. Specifically, we focus on the following assertion by the DP inventor [Dwork et al.(2019)] about the state of the art of DP-based ML:

When meaningfully implemented, DP supports deep data-driven insights with minimal worst-case privacy loss. When not meaningfully implemented, DP delivers privacy mostly in name.

We will show that DP-based ML implementations are mainly on the non-meaningful side. Not only because of the use of unreasonably unsafe privacy parameters, but also due to the use of relaxations that should not be counted as DP. These flaws are motivated by the attempt to salvage utility, i.e. model accuracy, which is of utmost importance in ML and is often incompatible with strict DP. In fact, in many implementations reported in the ML literature, the use of DP amounts to little more than adding noise without precise ex ante privacy guarantees. For this reason, the actual level of privacy achieved must be evaluated empirically, as typically done in the utility-first approach common in official statistics.

Therefore, in addition to surveying the empirical figures reported by works on DP-protected ML, we also report our own original empirical results on the practical utility/privacy/efficiency achieved by common implementations of DP in ML. These show that, as expected, privacy risks in ML models come from fitting too much of the (private) training data (i.e., overfitting). Further, it can be seen that DP not only fails to mitigate overfitting better than standard methods employed in ML for that purpose, but it adds very significant computation overhead.

Compared to previous related surveys such as [Gong et al.(2020), Yin et al.(2021)], which systematically and theoretically review the current literature, we offer a critical analysis, both theoretical and empirical, of (the flaws in) the application of DP to ML. Compared to more practical surveys, such as [Jayaraman and Evans(2019)], we provide a more up-to-date compilation of works on DP-protected ML (including non-centralized ML applications of DP such as federated learning), and we also contribute original experimental work reporting practical accuracy, privacy and computational cost.

The remainder of the paper is organized as follows. Section 2 reviews state-of-the-art strategies used to fit DP for ML. Sections 3 and 4 review works applying DP to ML, both in centralized and decentralized settings. Section 5 reports our empirical work. Finally, conclusions are gathered in Section 6.

2 Fitting (or bending) DP for ML

As introduced above, protecting the individuals’ data used to train ML models via DP faces similar difficulties as protecting continuous data collection: since successive model training epochs are computed on the same (or at least, not completely disjoint) data, sequential composition applies. For this reason, the effective $\epsilon$ grows with the number of epochs, which, worse yet, is not known in advance. This means that a great amount of noise needs to be added at each epoch to keep the effective $\epsilon$ small, but this comes at the expense of the model’s accuracy. Moreover, due to the distortion caused by the added noise, the convergence of the model becomes slower, and thus more training epochs are required and, in turn, more noise per epoch must be added to meet a certain target $\epsilon$. A vicious cycle ensues from which it is difficult to escape.

The amount of noise added (and hence the utility loss) is also directly proportional to the query sensitivity. Thus, a way to avoid increasing $\epsilon$ is to try to reduce the sensitivity of queries, even if this may sound a bit contrived. In ML, two sensitivity-reduction strategies are favored:

- **Output truncation.** It is a standard practice to truncate gradients in order to decrease their sensitivity [Abadi et al.(2016)], although this may slow down or bias the learning process.
- **Prior subsampling.** The query output (e.g. the gradient or model update) is computed on a random sample of the private data set rather than on its entirety. The fact that records with extreme values may not be part of the sample reduces the “expected” query sensitivity. However, subsampling may slow down the learning process or bias it. Additionally, Dwork indicates in [Dwork(2011)] that subsampling is insufficient to protect privacy: if an extreme individual happens to be part of the subsample, she or he may be spotted.

Due to the impossibility of obtaining usable models with safe/small-enough $\epsilon$, strict DP has been rarely applied in ML [Triastcyn and Faltings(2019), Jayaraman and Evans(2019)]. Instead, relaxations of the DP definition are used across the board. By far, the most common relaxation is $(\epsilon, \delta)$-DP [Dwork et al.(2006)].
which is satisfied by a randomized query function $\kappa$ if, for all data sets $D_1$ and $D_2$ that differ in one record and all $S \in \text{Range}(\kappa)$, it holds that

$$Pr(\kappa(D_1) \in S) \leq \exp(\epsilon) \times Pr(\kappa(D_2) \in S) + \delta.$$  \hspace{1cm} (2)

$\delta > 0$ is usually called the failure probability, that is, the probability that strict $\epsilon$-DP is not satisfied. However, a close look at Expression (2) shows that it is possible to satisfy it always while violating Expression (1). In fact, $(\epsilon, \delta)$-DP amounts to $\epsilon'$-DP, for some $\epsilon' > \epsilon$ that depends on $\epsilon$ and $\delta$ (note that $\epsilon'$ must satisfy $\exp(\epsilon') \times Pr(\kappa(D_2) \in S) = \exp(\epsilon) \times Pr(\kappa(D_2) \in S) + \delta$). In [Dwork and Roth(2014)] it is mentioned that one should take $\delta \ll 1/n$, where $n$ is the number of records in the database; otherwise, satisfying $(\epsilon, \delta)$-DP might be compatible with leaking a certain number of records. A usual mechanism to satisfy $(\epsilon, \delta)$-DP is Gaussian noise addition [Dwork and Roth(2014)].

Other relaxations of DP are concentrated DP [Dwork and Rothblum (2016)], zero-concentrated DP [Bun and Steinke(2016)] and Rényi DP [Mironov(2017)]. These variants look at the privacy loss as a random variable and bound the tails of its distribution. In so doing, they consider the average rather than the worst-case privacy loss. The result is a refinement of $(\epsilon, \delta)$-DP which turns $\delta$ into a real failure probability. These variants are not broadly used because, among other reasons, their parameters are hard to interpret. In [Triastcyn and Falkings(2019)] a table is given that expresses these three variants in terms of $(\epsilon, \delta)$-DP. For a more intuitive discussion, see also [Canonne(2021)].

The common purpose of $(\epsilon, \delta)$-DP and the other aforementioned variants is to relax $\epsilon$-DP and thereby require less noise addition, which in turn should allow more utility preservation. Yet, the price paid is the possibility of more privacy leakage, as demonstrated in [Jayaraman and Evans(2019)].

For a long time, even relaxed DP remained unachievable in many practical ML settings. Some attempts led to unreasonably high $\epsilon$ values [Shokri and Shmatikov(2015)], which were shown to be ineffective against attacks [Hitaj et al.(2017)]. A major breakthrough in the reduction of the required $\epsilon$ was done in [Abadi et al.(2016)] with the introduction of the moments accountant method for bounding the cumulative privacy loss across the successive epochs. This method is currently the standard for keeping track of the privacy loss during training due to its practical implementation in the TensorFlow-Privacy library. In comparison with sequential composition, the moments accountant method considers that only a fraction of the individual's training data is employed at each epoch, which allows tighter privacy bounds. With this method, single-digit $\epsilon$ values (barely below 10) can be reached, which are viewed as very good in ML, that is, preserving some meaningful utility.

3 Applying DP to centralized ML

In centralized ML the learning process is entirely managed by a single entity. This manager may apply privacy protection to the input of the learning process (by acting on the training data or on the objective function), to the intermediate results of the learning process (by protecting successive model updates), or to the output of learning (by protecting the learned model prior to releasing it).

When applying DP to centralised ML, an important distinction is whether the objective function is convex or not. In the convex case, DP can be applied by adding noise to the objective function. The amount of noise needed to satisfy DP requires computing the sensitivity of the ML algorithm [Chaudhuri et al.(2011)].

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The non-convex case basically amounts to deep learning with neural networks, which is the most popular approach to ML nowadays. Due to the hidden layers of neural networks, there may be multiple local minima. As noted in [Jayaraman and Evans(2019)], the sensitivity analysis methods of [Chaudhuri et al.(2011)] cannot be used in this case. As a consequence, adding DP perturbation to the objective function is not an option in deep learning. The most popular strategy to achieve DP in deep learning is to add noise to the gradients. The problem is that in deep learning gradients are unbounded, which entails unbounded sensitivity and unbounded noise addition to attain DP. We explained in Section 2 that the usual fix is to manually clip the gradients at each epoch [Abadi et al.(2016)], which bounds sensitivity and also bounds the noise that needs to be added.

As discussed earlier, the standard approach to DP-based ML consists in enforcing $(\epsilon, \delta)$-DP by clipping updates to a fixed threshold $\mathcal{C}$ and then adding Gaussian noise with variance $C^2\sigma^2$. The $\sigma$ parameter is calibrated to bound the privacy loss in each epoch, and the privacy loss ($\epsilon$) is accumulated via the moments accountant method [Abadi et al.(2016)]. As introduced in Section 2, the $\epsilon$ parameter is set to be smaller than $1/n$, where $n$ is the number of records in the database.

In Table 1 we survey the performance of several highly cited works following this approach. Note that the variation in the accuracy obtained for the same data set is caused by the different learning models, number of epochs and train/test sets employed by the various works. Thanks to the use of the moments accountant method, $\epsilon$ values are single-digit, although they often reach 8 or above. However, contrary to the widespread opinion in the ML community, $\epsilon \in [1,10]$ cannot truly be regarded as safe. For the DP condition (1) to really express small influence of any single record on the DP output, the value of $\epsilon$ must be small, “say, 0.01, 0.1,
or in some cases, \( \ln 2 \) or \( \ln 3 \). In Section [1], we showed that \( \epsilon = 8 \) in strict DP amounts to no confidentiality at all in the binary randomized response equivalence. On top of that, all works use values of \( \delta \) which are very close or even larger than \( 1/n \). This implies that strict DP is not satisfied with a high probability. For such weak privacy parameters, the theoretical guarantees of DP are so diminished that, as stated by the DP inventor [Dwork et al.2019], one can hardly call the outputs DP-protected at all.

This lack of protection is formally demonstrated in [Yeom et al.2018], where the authors define the theoretical upper bound on possible leakage in ML for DP guarantees against membership inference attacks (MIAs). In such attacks, an adversary aims to formally determine the presence or absence of a record in the data set, which is exactly what DP aims to obfuscate. Thus, MIAs are the natural way to evaluate the practical guarantees offered by DP in ML [Jayaraman and Evans2019]. In [Yeom et al.2018] the authors define the adversary’s advantage as the difference between the adversary’s true and false positive rates in MIAs, and prove that, if the model satisfies \( \epsilon \)-DP, then the adversary’s advantage is upper-bounded by \( \epsilon^2 - 1 \). For values of \( \epsilon > 1 \), the adversary advantage may be well above 1, which means that the theoretical guarantee does not provide real protection. As our experiments will show, avoiding ML model overfitting turns out to be more effective against MIAs.

If the theoretical guarantees of DP do not hold, an empirical confidentiality assessment should be carried out (e.g. by mounting inference attacks). In this respect, [Jayaraman and Evans2019] shows that differential privacy relaxations with weak privacy parameters have a practical leakage commensurate with the amount of noise they add for a given \( \epsilon \), rather than with the \( \epsilon \) value itself. This also means that, in practice, protecting ML via DP relaxations boils down to plain noise addition, a 40-year old technique criticized for its poor privacy/utility trade-off [Paass1988, Tendick1991].

Unfortunately, most works using DP relaxations in ML fail to offer empirical privacy assessments, because any formulation and parameterization connected to DP is often viewed as private enough.

On the other hand, thanks to very relaxed (and unsafe) implementations of DP, the works surveyed in Table 4 often achieve moderate accuracy losses. Yet, for the most difficult tasks, losses are 20% or higher, which is doubtfully acceptable if one wants ML to stay useful.

### 4 Applying DP in decentralized ML

Decentralized machine learning (DML) allows training an ML model by a community of peers holding private local data sets. The most popular architecture of DML is federated learning (FL) [Konečný et al.2016], in which a single server (called model manager) orchestrates the learning process. The model manager sends an initial model to all peers (called clients), who compute model updates on their own private data and return the updates to the model manager. The manager aggregates the updates and re-distributes the new model. Communication iterations carry on until the model converges. Other DML forms exist, such as fully decentralized machine learning (FDML) [Tang et al.2018], in which all peers may be managers of their own models and clients for other’s models.

DML (and FL specifically) favors privacy because the clients do not need to upload their own private data to the manager. However, the updates returned by the clients to the manager may still leak their private data [Blanco-Justicia et al.2021]. Moreover, as it happens in centralized ML, the learned model may also leak private data on the participating clients. To prevent such leakages, DP has been employed–again– as the gold standard to protect clients’ data. According to how DP is enforced in FL, three types of approaches and subsequent privacy guarantees can be distinguished.

In the first approach the noise addition required for DP is performed locally by each client, either by applying perturbations to the updates resulting from training the local model, or by using DP stochastic gradient descent (DP-SGD) during training [Abadi et al.2016]. This approach, known as local differential privacy (LDP) [Naseri et al.2022], protects the clients’ single data points (records) by making their contribution to the learned model unnoticeable. Some works using this approach are [Pihur et al.2018] and [Truex et al.2020]—big companies such as Google, Apple and Microsoft also employ this method to systematically collect data of their users [Ding et al.2018, Erlingsson et al.2014, Thakurta et al.2017]. Nevertheless, since quite often all the data points of a client refer to the client herself (e.g. fitness or health measurements over time), the data may be highly correlated; hence, LDP may not offer client-level privacy, but just instance-level pri-

| Reference (cite) | Data set | Size | Original acc | DP parameters | DP accuracy | Relative accuracy loss |
|------------------|----------|------|--------------|---------------|-------------|-----------------------|
| [Abadi et al.2016] | CIFAR10 | 50,000 | 86% | \( \epsilon = (2, 4, 8), \delta = 10^{-5} \) | \( 87.0, 73.3\% \) | \( 22.1, 16.6, 15.1\% \) |
| [Abadi et al.2016] | MNIST | 60,000 | 98.3% | \( \epsilon = (0.5, 2, 8), \delta = 10^{-5} \) | \( 90.0, 95.9\% \) | \( 8.4, 3.3, 1.3\% \) |
| [Papernot et al.2017] | MNIST | 60,000 | 99.18% | \( \epsilon = (2, 0.4, 8), \delta = 10^{-5} \) | \( 98.6, 98.1\% \) | \( 1.9, 1.1\% \) |
| [Papernot et al.2017] | SVHN | 60,000 | 92.8% | \( \epsilon = (5, 0.4, 19), \delta = 10^{-5} \) | \( 92.7, 90.7\% \) | \( 10.9, 2.3\% \) |
| [Hynes et al.2018] | CIFAR10 | 50,000 | 92.4% | \( \epsilon = 4, \delta = 10^{-5} \) | \( 90.6\% \) | \( 1.72\% \) |
| [Rahman et al.2018] | CIFAR10 | 50,000 | 73.7% | \( \epsilon = (1, 2, 4, 8), \delta = 10^{-5} \) | \( 25.4, 45.6, 60.7, 68.1\% \) | \( 65.5, 38.9, 17.6, 7.6\% \) |
| [Rahman et al.2018] | MNIST | 60,000 | 97% | \( \epsilon = (1, 2, 4, 8), \delta = 10^{-5} \) | \( 75.7, 87.9, 96.6, 93.2\% \) | \( 21.9, 10.3, 6.6, 3.9\% \) |
| [Papernot et al.2021] | MNIST | 60,000 | 99% | \( \epsilon = 2, \delta = 10^{-5} \) | \( 98.1\% \) | \( 0.9\% \) |
| [Papernot et al.2021] | CIFAR10 | 50,000 | 76.6% | \( \epsilon = 7, \delta = 10^{-5} \) | \( 66.2\% \) | \( 13.6\% \) |
| [Huang et al.2019] | Adult | 48,842 | 82% | \( \epsilon = (0.1, 0.5, 1, 0.1, 2, 1), \delta = 10^{-3} \) | \( 55.5, 75.7, 76.7\% \) | \( 32.9, 8.5, 7.3, 6.0\% \) |
In scenarios with clients holding correlated data points, this approach can barely be called DP at all: making the presence or absence of a certain data point (instance) unnoticeable does not offer any privacy to the client if that data point is highly correlated to the rest of data points in the client’s data set.

The second approach is more in line with the DP guarantee, and its goal is to hide the presence of any single client in the training process \cite{Geyer2018}. This method is known as central differential privacy (CDP) \cite{Naseri2022} and provides client-level privacy guarantees. With CDP, the FL aggregation function is perturbed by the model manager to bound the influence of any single client’s data on the model parameters. This means that clients need to entrust the manager with their exact model updates, and rely on the manager to correctly perform the perturbation. Assuming trust in the model manager goes against the purpose of privacy protection, even though it is still better than sharing entire data sets in clear form. Some works using this approach are \cite{Geyer2018} and \cite{McMahan2018}.

A third approach is described in \cite{Zhu2020}. Each client trains her local model and never reveals it to the manager. When asked to make a prediction on an instance, every client computes a label with her respective local model; then the client adds noise to her label; finally, clients engage in secure multiparty computation to determine the safe aggregation of the votes. This approach allows instance-level Rényi DP thanks to the noise added to local labels, and also client-level Rényi DP thanks to the voting.

As in centralized ML, DP relaxations are used systematically in FL, with \((\epsilon, \delta)\)-DP being the most usual choice. The \( \sigma \) parameter is calibrated to bound the privacy loss in each communication round (which requires setting the number of rounds beforehand), and the privacy loss \( \epsilon \) is accumulated via the moments accountant method \cite{Abadi2016}. The \( \delta \) parameter is set according to the number of clients participating in the learning process, so that \( \delta \) stays well below \( 1/|\text{clients}| \).

In Table 2 we survey the empirical results reported by works employing DP in FL. Deep learning models are the most usual in FL. Hence, we focus on deep learning methods offering \((\epsilon, \delta)\)-DP and client-level privacy, which, as argued above, is the most interesting and challenging type of privacy. To simulate a FL scenario, these works split the records in the evaluation data set across a number of simulated clients. The records held by a client are assumed to describe such client and, therefore, are considered non-independent data. According to how records are distributed across clients, we can differentiate between independent and identically distributed (i.i.d.) data and non-i.i.d. data, with the latter being the most realistic in FL settings \cite{Zhu2021}. Since results are highly dependent on the number of clients, we report figures on the same data set for various numbers of clients, when available.

By examining the DP parameters and accuracy values listed in Table 2 we can extract the following conclusions:

- The values of the privacy parameter \( \epsilon \) are on the unsafe side, like in Table 1 on centralized ML. Therefore, the arguments presented in Section 5 for DP-protected centralized ML also apply to DP-FL.

- The number of participating clients has a major impact on the model accuracy for a given privacy level. In general, if the number of clients stays below 1,000, the impact on the model accuracy is significant, up to the point that the model hardly converges \cite{Geyer2018}. Even though DP-FL almost matches the accuracy of non-private FL when the number of clients is around 10,000, this configuration is only realistic for scenarios involving mobile services deployed by big companies such as Google \cite{Hard2018} or Apple \cite{Ramaswamy2019}. However, FL is employed in many occasions in much smaller configurations, for example in medical applications \cite{Brisimi2018}: unfortunately, resorting to DP-FL to address the privacy requirements of such configurations can lead to unacceptable accuracy loss.

- The fact that in FL the data might be non-i.i.d. among clients is particularly challenging for privacy, because the different distributions of the local data of the various clients may render some clients easily distinguishable. Consequently, it takes more effort (noise) to hide their contribution to the model, as shown in \cite{Triastcyn2019}.

In summary, DP-FL only seems to offer competitive accuracy (but still weak privacy guarantees), when the number of clients is exceedingly high and data are i.i.d. among clients. On the one side, these assumptions are
often unrealistic. On the other side, if there is a great number of clients and their private data are similarly distributed, clients already enjoy some natural privacy protection because they are “hidden in the crowd”, in which case resorting to non-private FL might be safe enough and certainly simpler.

5 Empirical results

As argued in the previous sections, the theoretical privacy guarantees of DP should not be taken for granted in the current implementations of DP-based privacy-preserving ML. In line with what is done in the SDC literature, privacy and utility should be evaluated ex post by empirically measuring the resistance against membership inference attacks and the accuracy of the models. In this section we report the results of such an empirical evaluation on three data sets commonly employed in the data privacy and ML literature (Adult, MNIST, and CIFAR10) in four different ML settings: i) a multi-layer perceptron for Adult, ii) a shallow convolutional model for MNIST, iii) a deep convolutional model for CIFAR10, and iv) a second deep model using transfer learning for CIFAR10.

The experiments were run on an AMD Ryzen 7 5800X with 16 GB of RAM and an NVIDIA GeForce RTX 3070 GPU with 8 GB of VRAM, using Windows 10, Python 3.8.10, and CUDA 11.2. We used TensorFlow 2.5.0 to build the deep learning models and the TensorFlow-Privacy 0.6.2 implementations of the moments accountant DP training algorithm and the membership inference attacks.

Next, we describe the model architectures used in each of the experimental settings. The model architecture for the Adult data set consisted of two fully connected layers of 40 units each, with ReLU as activation function, and an output layer with two neurons. For the MNIST data set, we used a model consisting of a convolution layer with 12 channels, kernel size 3, and ReLU activation, followed by a max pooling layer and the output layer, with 10 neurons. For the CIFAR10 data set, the model architecture included 2 sets of convolution and max pooling layers, with 20 and 50 channels respectively, kernel size 5, and ReLU activation, followed by a fully connected layer of 50 neurons with ReLU activation and the output layer with 10 neurons. For the CIFAR10 data set with transfer learning (CIFAR10-TL), the architecture was composed of the bottom layers of DenseNet-201, trained on the ImageNet data set, with frozen weights, followed by a fully connected layer of 256 neurons with ReLU activation, and the output layer with 10 neurons. All settings used the categorical cross-entropy loss function and the Adam optimizer, with learning rate $1.5 \times 10^{-4}$, batch size of 100, and 50 training epochs.

To evaluate privacy, we used the standard black-box membership inference attack implementation in TensorFlow-Privacy, which is based on the works by Shokri et al. [Shokri et al.(2017)] and Salem et al. [Salem et al.(2018)]. We ran all implemented attack specifications, using slices including data from all classes, data from each single class, correctly classified data points, and incorrectly classified data points. As proposed in Yeom et al. [Yeom et al.(2016)], the attack performance (i.e., the inverse of privacy protection) was reported as the maximum attacker advantage (i.e., the difference between the adversary’s true and false positive rates in MIAs) obtained throughout all attack specifications and slices. Note, however, that attack-based privacy figures are limited to showing a lower bound on the information leakage since they measure the effectiveness of a particular attack. This contrasts with DP guarantees, which provide an upper bound on the possible leakage [Jayaraman and Evans(2019)]. As discussed in Section 3, the upper bound for the adversary’s advantage is $e^\epsilon - 1$, which means that for $\epsilon > 1$ the adversary’s advantage may be well above 1.

For the sake of reproducibility, the code of our experiments is available at https://github.com/ablancoj/dp-mia

**Baseline results** Table 3 reports baseline results for the four experimental settings with no protection. We see that, for the three settings other than Adult, the attacker’s advantage was around or over 0.5. Also, we see that in these three cases there was a big gap between the training and validation losses. Such results are in line with previous studies [Yeom et al.(2018)], which directly connect the generalization gap (i.e., the difference between training and testing losses or accuracies) to the vulnerability against both membership and attribute inference attacks.

**Results using anti-overfitting** To test the relationship between the (excessive) fitting of ML models to the (private) training data and their vulnerability against membership attacks, we next tested the performance of models when trained using anti-overfitting methods, namely dropout and $L_2$-regularization. Dropout layers in neural network architectures randomly suppress connections between neurons at each training epoch according

| Data set   | Training loss | Testing loss | Training accuracy | Testing accuracy | Training time (s) | Attacker’s advantage |
|------------|---------------|--------------|--------------------|------------------|-------------------|----------------------|
| Adult      | 0.2797        | 0.3685       | 0.8696             | 0.8444           | 46                | 0.131                |
| MNIST      | 0.0066        | 0.0782       | 0.9986             | 0.9968           | 60                | 0.577                |
| CIFAR10    | 0.0050        | 1.4429       | 0.9836             | 0.6743           | 88                | 0.642                |
| CIFAR10-TL | 0.0015        | 0.8154       | 1.00               | 0.8517           | 43                | 0.467                |
In fact, since anti-overfitting changes were specifically tailored to enable the model to generalize better, they more harmful for the learning process than the meaningful changes introduced by anti-overfitting techniques. The smallest distortion added by DP was enough to counter practical membership attacks, such a distortion was lower than those obtained with a reasonable amount of anti-overfitting. This suggests that, even though the (test) accuracy was also highly impacted: even for the weakest values of $\epsilon$, getting the desired $\epsilon$ value computed by the moments accountant method after the training process was finished. As we discuss below, getting the desired $\epsilon$ is not trivial and, for extreme values, it may not even be possible.

At a first glance, it is clear that DP significantly reduced the attacker’s advantage compared to the baseline results for all $\epsilon$ values. The reduction was in line with the results obtained with anti-overfitting techniques. However, the (test) accuracy was also highly impacted: even for the weakest values of $\epsilon$, test accuracies were lower than those obtained with a reasonable amount of anti-overfitting. This suggests that, even though the smallest distortion added by DP was enough to counter practical membership attacks, such a distortion was more harmful for the learning process than the meaningful changes introduced by anti-overfitting techniques. In fact, since anti-overfitting changes were specifically tailored to enable the model to generalize better, they

| Table 4: Results for the four experimental settings with different anti-overfitting techniques |
|-----------------------------------------------|
| Data set | Dropout | $L_2$ regularization | Training accuracy | Test accuracy | Training time (s) | Attacker’s advantage |
|-----------------|-------|------------------|-----------------|-------------|-----------------|---------------------|
| Adult           | 0.25  | $\times$         | 0.8621          | 0.8477      | 53              | 0.132               |
|                 | 0.50  | $\times$         | 0.8552          | 0.8492      | 51              | 0.116               |
|                 | 0.75  | $\times$         | 0.8353          | 0.8453      | 51              | 0.085               |
|                 | 0.25  | $\checkmark$    | 0.8246          | 0.8235      | 59              | 0.063               |
|                 | 0.50  | $\checkmark$    | 0.8225          | 0.8255      | 59              | 0.071               |
|                 | 0.75  | $\checkmark$    | 0.7897          | 0.8137      | 60              | 0.069               |
| MNIST           | 0.25  | $\times$         | 0.9885          | 0.9847      | 61              | 0.454               |
|                 | 0.50  | $\times$         | 0.9768          | 0.9837      | 46              | 0.188               |
|                 | 0.75  | $\times$         | 0.9503          | 0.9805      | 36              | 0.214               |
| CIFAR10         | 0.25  | $\checkmark$    | 0.9650          | 0.9725      | 48              | 0.196               |
|                 | 0.50  | $\checkmark$    | 0.9552          | 0.9758      | 52              | 0.189               |
|                 | 0.75  | $\checkmark$    | 0.9314          | 0.9714      | 67              | 0.183               |
| CIFAR10-TL      | 0.25  | $\times$         | 0.8762          | 0.7336      | 92              | 0.596               |
|                 | 0.50  | $\times$         | 0.7080          | 0.7368      | 94              | 0.227               |
|                 | 0.75  | $\times$         | 0.4840          | 0.4786      | 92              | 0.132               |
|                 | 0.25  | $\checkmark$    | 0.8069          | 0.7178      | 97              | 0.099               |
|                 | 0.50  | $\checkmark$    | 0.6048          | 0.6730      | 101             | 0.136               |
|                 | 0.75  | $\checkmark$    | 0.4560          | 0.4756      | 101             | 0.111               |
|                 | 0.25  | $\times$         | 0.8770          | 0.8611      | 51              | 0.275               |
|                 | 0.50  | $\times$         | 0.7729          | 0.8414      | 50              | 0.120               |
|                 | 0.75  | $\times$         | 0.6038          | 0.7785      | 49              | 0.135               |
|                 | 0.25  | $\checkmark$    | 0.8177          | 0.8427      | 59              | 0.132               |
|                 | 0.50  | $\checkmark$    | 0.7542          | 0.8206      | 58              | 0.159               |
|                 | 0.75  | $\checkmark$    | 0.6300          | 0.7882      | 59              | 0.125               |
Table 5: Results for the four experimental settings using differential privacy

| Data set | Target $\epsilon$ | $\sigma$ | Computed $\epsilon$ | Training accuracy | Test accuracy | Training time (s) | Attacker’s advantage |
|----------|-------------------|---------|---------------------|------------------|---------------|-------------------|---------------------|
| Adult    | 0.1               | 0.1120  | 0.7498              | 0.7535           | 774           | 0.083             |
|          | 0.5               | 0.5000  | 0.8076              | 0.8016           | 794           | 0.076             |
|          | 1                 | 0.9999  | 0.8186              | 0.8090           | 741           | 0.082             |
|          | 2                 | 2.0000  | 0.8225              | 0.8190           | 781           | 0.077             |
|          | 4                 | 3.9969  | 0.8201              | 0.8132           | 790           | 0.062             |
|          | 8                 | 7.9999  | 0.8228              | 0.8201           | 850           | 0.099             |
|          | 16                | 15.922  | 0.8250              | 0.8201           | 778           | 0.061             |
|          | 100               | 97.440  | 0.8294              | 0.8234           | 754           | 0.074             |
|          | 1,000             | 484.87  | 0.8318              | 0.8283           | 854           | 0.079             |
|          | 0.1               | 0.1120  | 0.8388              | 0.8514           | 2,555         | 0.201             |
|          | 0.5               | 0.4999  | 0.8912              | 0.9009           | 2,308         | 0.17              |
|          | 1                 | 0.9999  | 0.8990              | 0.9086           | 2,460         | 0.153             |
|          | 2                 | 1.9851  | 0.9052              | 0.9110           | 2,457         | 0.165             |
|          | 4                 | 3.9161  | 0.9114              | 0.9172           | 2,450         | 0.19              |
|          | 8                 | 7.9737  | 0.9154              | 0.9208           | 2,312         | 0.179             |
|          | 16                | 15.953  | 0.9154              | 0.9208           | 2,312         | 0.179             |
|          | 100               | 97.604  | 0.9172              | 0.9217           | 2,311         | 0.191             |
|          | 1,000             | 482.07  | 0.9294              | 0.9337           | 2,312         | 0.188             |
| MNIST    | 0.1               | 0.1120  | 0.2624              | 0.2662           | 3,796         | 0.12              |
|          | 0.5               | 0.4999  | 0.3166              | 0.3160           | 3,832         | 0.12              |
|          | 1                 | 0.9999  | 0.3777              | 0.3830           | 3,830         | 0.10              |
|          | 2                 | 2.0000  | 0.4110              | 0.4068           | 3,821         | 0.13              |
|          | 4                 | 3.9718  | 0.4177              | 0.4181           | 3,791         | 0.15              |
|          | 8                 | 7.9556  | 0.4399              | 0.4397           | 3,819         | 0.09              |
|          | 16                | 15.936  | 0.4502              | 0.4435           | 3,918         | 0.12              |
|          | 100               | 97.520  | 0.4895              | 0.4857           | 4,093         | 0.12              |
|          | 1,000             | 483.49  | 0.5109              | 0.4988           | 4,095         | 0.11              |
| CIFAR10  | 0.1               | 0.1120  | 0.6535              | 0.6535           | 1,605         | 0.112             |
|          | 0.5               | 0.4999  | 0.7723              | 0.7577           | 1,620         | 0.124             |
|          | 1                 | 0.9999  | 0.7979              | 0.7911           | 1,627         | 0.16              |
|          | 2                 | 2.0000  | 0.8149              | 0.8030           | 1,618         | 0.123             |
|          | 4                 | 3.9718  | 0.8247              | 0.8086           | 1,615         | 0.14              |
|          | 8                 | 7.9556  | 0.8327              | 0.8169           | 1,728         | 0.128             |
|          | 16                | 15.936  | 0.8385              | 0.8180           | 1,652         | 0.143             |
|          | 100               | 97.520  | 0.8433              | 0.8280           | 1,612         | 0.136             |
|          | 1,000             | 483.49  | 0.8615              | 0.8377           | 1,614         | 0.128             |

also produced the same effect as DP-ML, namely to make the model more agnostic about the (private) training data. On the other hand, the accuracy losses for safe values of $\epsilon$ (1 or less) were unacceptable, which seems to indicate that “true” DP is unsuitable to achieve privacy protection while preserving usable accuracy in ML. To make things worse, note that the training times for DP are much higher than those of the baseline and the anti-overfitting scenarios.

In fact, a suboptimal privacy/utility trade-off is not the only issue faced when using DP-SGD. The choice of hyperparameters to train a model under DP is a challenging task, as we discuss in the what follows. The compute_noise function in TensorFlow-Privacy allows computing the noise multiplier $\sigma$ required to achieve a certain target $\epsilon$, given a fixed $\delta$, the size of the training data set, the batch size, and the expected number of training epochs. This noise multiplier is then used to compute the noise added to each of the model gradients at each training epoch. Then, the get_privacy_spent function returns the effective $\epsilon$ value computed by the moments accountant after the training is done. However, as introduced in Section 2, if a model is trained until convergence (as is usually the case), the computation of the noise multiplier is unreliable —if the model is finally trained for more epochs than expected, the final effective $\epsilon$ will be greater than intended, which means that more noise should have been added at each training epoch to achieve the target $\epsilon$. But, in turn, adding more noise might require more training epochs for the model to converge. On the other hand, if the model converges before the number of epochs specified when computing $\sigma$, the effective $\epsilon$ will be smaller than intended, which means too much noise was added during training, with the subsequent potential (and unnecessary) loss of model accuracy.

The above-described pitfalls of hyperparameter choice are exemplified in Table 6. In this experiment we trained a model to classify CIFAR10 until convergence, that is, until the training loss did not significantly change for 3 consecutive epochs. The target privacy budget $\epsilon$ was set to 0.1. We initially computed the required noise multiplier $\sigma$ by using compute_noise and specifying 10 training epochs. The model turned out to converge in 72 epochs, with a computed effective $\epsilon = 0.2704$. Next, we re-computed $\sigma$ by specifying 72 training epochs and we trained again until convergence. However, since the amount of noise added per epoch had changed, so did the epochs needed to attain convergence: just 12 epochs were needed this time. This required repeating the process until an effective $\epsilon = 0.0999$ was obtained, which was deemed close enough to the target $\epsilon = 0.1$. This trial and error process is similar to the utility-first approach traditionally followed by official statisticians since the 1970s, well before privacy models and DP were introduced: choose noise parameters, protect the data.
Table 6: Iterative process to obtain the desired \( \epsilon \) value of 0.1

| Target training epochs | \( \sigma \) | Epochs to converge | \( \epsilon \) | Test accuracy |
|------------------------|-------------|---------------------|--------------|--------------|
| 10                      | 5.92        | 72                  | 0.2704       | 0.25         |
| 72                      | 15.75       | 12                  | 0.0878       | 0.1          |
| 12                      | 6.478       | 85                  | 0.2681       | 0.26         |
| 85                      | 17.10       | 40                  | 0.0966       | 0.15         |
| 40                      | 11.75       | 48                  | 0.1179       | 0.18         |
| 48                      | 12.87       | 28                  | 0.0999       | 0.12         |

using an SDC method with those parameters, and check if the protected data are accurate and private enough according to some requirements.

Furthermore, DP-SGD does not scale well for complex models, as it causes their accuracy to cap at approximately 1 over the number of classes (i.e., random guessing). This can be sometimes solved by leveraging transfer learning. In that case, the bottom layers (or feature extractor) are already trained using some public data set, and only the top layers (the classifier) are trained using DP-SGD.

Finally, the DP-SGD algorithm requires gradients to be clipped before any noise is added to them on a per-training-instance basis, which eliminates the performance gains of using GPUs to process the training data in batches. Whereas the microbatches variable in TensorFlow-Privacy can be adjusted to treat the training instances in bigger batches, which reduces the training time, it does so at the cost of a greater accuracy loss compared to the baseline results. Giving up batches explains why the training times of DP-SGD reported in Table 5 are 15 to 40 times longer than those of the baseline and anti-overfitting experiments reported in Tables 3 and 4.

Even if the experiments reported in this section are for centralized ML, the conclusions reached can be expected to be valid for FL as well. Note that guaranteeing privacy in FL can be even more challenging, because membership attacks may be easier if the clients’ local data are non-i.i.d.

6 Conclusions

The ML research community have embraced DP as the gold standard for privacy protection. Yet, none of the related works in the literature employs the original formulation of DP, but relaxations of it, such as \((\epsilon, \delta)\)-DP and others. On top of that, the privacy parameters used are quite far from what is considered theoretically “safe” (i.e., \( \epsilon \leq 1 \) and negligible \( \delta \) w.r.t. the population size). For such loose implementations, the privacy guarantees of DP do not hold, and what is done can only be viewed as old plain noise addition, which at best provides \( \epsilon \) post protection depending on the amount of noise added for a given \( \epsilon \), rather than on the \( \epsilon \) value itself. This renders it rather pointless to claim use of the DP privacy model and comes close to the (often criticized) utility-first paradigm used in SDC for decades. Thus, the use of the “differential privacy” label by a lot of works whose implementations offer an actual privacy very far from truly sound DP can only be regarded as deceptive. To aggravate the matter, most of those works systematically omit empirical privacy analyses, because they consider any relaxation and parameterization of DP to be privacy-preserving enough.

In spite of all the aforementioned DP “twisting and bending”, the practical accuracy/privacy trade-off of DP-ML is worse than that of standard methods used in ML to mitigate overfitting. Our experiments indicate that the latter provide comparable practical protection, better accuracy and significantly lower learning cost than DP-based ML. On the other hand, even with DP relaxations and adjusted privacy accounting methods, using theoretically sound privacy parameters (\( \epsilon \leq 1 \)) is still infeasible, due to the unacceptably high accuracy loss they entail. This makes “true” DP unsuitable for protecting ML models with usable accuracy.

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References

[Abadi et al.(2016)] M. Abadi, A. Chu, I. Goodfellow, H. B. McMahan, I. Mironov, K. Talwar, and L. Zhang. 2016. Deep learning with differential privacy. In Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security. 308–318.
[Blanco-Justicia et al.(2021)] A. Blanco-Justicia, J. Domingo-Ferrer, S. Martínez, D. Sánchez, A. Flanagan, and K. E. Tan. 2021. Achieving Security and Privacy in Federated Learning Systems: Survey, Research Challenges and Future Directions. *Engineering Applications of Artificial Intelligence* 106 (2021), 104468.

[Brismi et al.(2018)] T. S. Brismi, R. Chen, T. Mela, A. Oshevisky, I. C. Paschalidis, and W. Shi. 2018. Federated learning of predictive models from federated electronic health records. *International Journal of Medical Informatics* 112 (2018).

[Bun and Steinke(2016)] M. Bun and T. Steinke. 2016. Concentrated differential privacy: Simplifications, extensions, and lower bounds. In *Theory of Cryptography Conference*. Springer, 635–658.

[Canonne(2021)] C. Canonne. 2021. What is $\delta$, and what difference does it make? [https://differentialprivacy.org/flavoursofdelta/](https://differentialprivacy.org/flavoursofdelta/)

[Chaudhuri et al.(2011)] K. Chaudhuri, C. Monteleoni, and A. D. Sarwate. 2011. Differentially private empirical risk minimization. *Journal of Machine Learning Research* 12, 3 (2011).

[Clifton and Tassa(2013)] G. Clifton and T. Tassa. 2013. On syntactic anonymity and differential privacy. *Transactions on Data Privacy* 6, 2 (2013), 161–183.

[Cyphers(2017)] B. Cyphers. 2017. Differential privacy, part 3: extraordinary claims require extraordinary scrutiny. [https://www.accessnow.org/differential-privacy-part-3-extraordinary-claims-require-extraordinary-scrutiny/](https://www.accessnow.org/differential-privacy-part-3-extraordinary-claims-require-extraordinary-scrutiny/)

[Dalenius(1977)] T. Dalenius. 1977. Towards a methodology for statistical disclosure control. *Statistik Tidskrift* 15, 429–444 (1977), 2–1.

[Ding et al.(2018)] B. Ding, J. Kulkarni, and S. Yekhanin. 2018. Collecting telemetry data privately. In *Advances in Neural Information Processing System*. 3571—-3580.

[Domingo-Ferrer et al.(2021)] J. Domingo-Ferrer, D. Sánchez, and A. Blanco-Justicia. 2021. The limits of differential privacy (and its misuse in data release and machine learning). *Commun. ACM* 64, 7 (2021), 33–35.

[Domingo-Ferrer et al.(2016)] J. Domingo-Ferrer, D. Sánchez, and J. Soria-Comas. 2016. *Database Anonymization: Privacy Models, Data Utility, and Microaggregation-based Inter-model Connections*. Morgan & Claypool.

[Dwork(2006)] C. Dwork. 2006. Differential privacy. In *Proceedings of the 33rd Intl. Colloquium on Automata, Languages and Programming-ICALP 2006*. 1–12.

[Dwork(2011)] C. Dwork. 2011. A firm foundation for private data analysis. *Commun. ACM* 54, 1 (2011), 86–95.

[Dwork et al.(2006)] C. Dwork, K. Kenthapadi, F. McSherry, I. Mironov, and M. Naor. 2006. Our data, ourselves: Privacy via distributed noise generation. In *Annual International Conference on the Theory and Applications of Cryptographic Techniques*. Springer, 486–503.

[Dwork et al.(2019)] C. Dwork, N. Kohli, and D. Mulligan. 2019. Differential Privacy in Practice: Expose your Epsilons! *Journal of Privacy and Confidentiality* 9, 2 (2019).

[Dwork and Roth(2014)] C. Dwork and A. Roth. 2014. The algorithmic foundations of differential privacy. *Found. Trends Theor. Comput. Sci.* 9, 3-4 (2014), 211–407.

[Dwork and Rothblum(2016)] C. Dwork and G. N. Rothblum. 2016. Concentrated differential privacy. arXiv preprint arXiv:1603.01887.

[Edmond(2020)] C. Edmond. 2020. How statistical noise is protecting your data privacy. [https://news.microsoft.com/on-the-issues/2020/08/27/statistical-noise-data-differential-privacy/](https://news.microsoft.com/on-the-issues/2020/08/27/statistical-noise-data-differential-privacy/)

[Erlingsson et al.(2014)] Ú. Erlingsson, V. Pihur, and A. Korolova. 2014. RAPPOR: Randomized aggregatable privacy-preserving ordinal response. In *Proceedings of the 2014 ACM SIGSAC conference on computer and communications security*. 1054—-1067.

[Geyer et al.(2018)] R. C. Geyer, T. Klein, and M. Nabi. 2018. Differentially private federated learning: A client level perspective. arXiv preprint arXiv:1712.07557. In *NIPS 2017 Workshop: Machine Learning on the Phone and other Consumer Devices*.

[Gong et al.(2020)] M. Gong, Y. Xie, K. Pan, K. Feng, and A. K. Qin. 2020. A survey on differentially private machine learning. *IEEE Computational Intelligence Magazine* 15, 2 (2020), 49–64.
[Greenberg(2017)] A. Greenberg. 2017. How one of Apple’s key privacy safeguards falls short. Wired (7 sep 2017).

[Hard et al.(2018)] A. Hard, K. Rao, R. Mathews, S. Ramaswamy, F. Beaufays, S. Augenstein, H. Eichner, C. Kiddon, and D. Ramage. 2018. Federated learning for mobile keyboard prediction. arXiv preprint arXiv:1811.03604.

[Hitaj et al.(2017)] B. Hitaj, G. Ateniese, and F. Pérez-Cruz. 2017. Deep models under the GAN: information leakage from collaborative deep learning. In ACM SIGSAC Conference on Computer and Communications Security. ACM, 603–618.

[Huang et al.(2019)] Z. Huang, R. Hu, Y. Guo, E. Chan-Tin, and Y. Gong. 2019. DP-ADMM: ADMM-based distributed learning with differential privacy. IEEE Transactions on Information Forensics and Security 15 (2019), 1002–1012.

[Hundepool et al.(2012)] A. Hundepool, J. Domingo-Ferrer, L. Francconi, S. Giessing, E. Schulte Nordholt, K. Spicer, and P.-P. De Wolf. 2012. Statistical disclosure control. John Wiley & Sons.

[Hynes et al.(2018)] N. Hynes, R. Cheng, and D. Song. 2018. Efficient Deep Learning on Multi-Source Private Data. arXiv preprint arXiv:1807.06689.

[Jayaraman and Evans(2019)] B. Jayaraman and D. Evans. 2019. Evaluating Differentially Private Machine Learning in Practice. In Proceedings of the 28th USENIX Security Symposium. 1895–1912.

[Kifer and Machanavajjhala(2011)] Daniel Kifer and Ashwin Machanavajjhala. 2011. No free lunch in data privacy. In Proceedings of the 2011 ACM SIGMOD International Conference on Management of Data. 193–204.

[Konečný et al.(2016)] J. Konečný, H. B. McMahan, D. Ramage, and P. Richtárik. 2016. Federated Optimization: Distributed Machine Learning for On-Device Intelligence. arXiv preprint arXiv:610.02527.

[Li et al.(2010)] N. Li, T. Li, and S. Venkitasubramaniam. 2010. Closeness: a new privacy measure for data publishing. IEEE Transactions on Knowledge and Data Engineering 22, 7 (2010), 943–956.

[Machanavajjhala et al.(2007)] A. Machanavajjhala, J. Gehrke, D. Kifer, and M. Venkitasubramaniam. 2007. l-Diversity: privacy beyond k-anonymity. ACM Transactions on Knowledge Discovery from Data 1, 1 (2007), 3.

[McMahan et al.(2018)] H. B. McMahan, D. Ramage, K. Talwar, and L. Zhang. 2018. Learning differentially private recurrent language models. In Proceedings of the Sixth International Conference on Learning Representations (ICLR 2018).

[Mironov(2017)] I. Mironov. 2017. Rényi differential privacy. In 2017 IEEE 30th Computer Security Foundations Symposium (CSF). IEEE, 263–275.

[Naseri et al.(2022)] M. Naseri, J. Hayes, and E. DeCristofaro. 2022. Local and Central Differential Privacy for Robustness and Privacy in Federated Learning. arXiv preprint arXiv:2009.03561. In 29th Network and Distributed System Security Symposium (NDSS 2022).

[Paass(1988)] G. Paass. 1988. Disclosure risk and disclosure avoidance for microdata. Journal of Business & Economic Statistics 6 (1988), 487–500.

[Papernot et al.(2017)] N. Papernot, M. Abadi, Ú. Erlingsson, I. Goodfellow, and K. Talwar. 2017. Semi-supervised knowledge transfer for deep learning from private training data. In 5th International Conference on Learning Representations – ICLR 2017.

[Papernot et al.(2021)] N. Papernot, A. Thakurta, S. Song, S. Chien, and Ú. Erlingsson. 2021. Tempered Sigmoid Activations for Deep Learning with Differential Privacy. In Thirty-Fifth AAAI Conference on Artificial Intelligence, AAAI 2021. AAAI Press, 9312–9321.

[Pihur et al.(2018)] V. Pihur, A. Korolova, F. Liu, S. Sankuratripati, M. Yung, D. Huang, and R. Zeng. 2018. Differentially-Private ‘Draw and Discard’ Machine Learning. In Privacy in Machine Learning and Artificial Intelligence Workshop (ICML).

[Rahman et al.(2018)] A. Rahman, T. Rahman, R. Laganière, N. Mohammed, and Y. Wang. 2018. Membership Inference Attack against Differentially Private Deep Learning Model. Transactions on Data Privacy 11 (2018), 61–79.

[Ramaswamy et al.(2019)] S. Ramaswamy, R. Mathews, K. Rao, and F. Beaufays. 2019. Learning for Emoji Prediction in a Mobile Keyboard. arXiv preprint arXiv:1906.04329.
[Salem et al.(2018)] A. Salem, Y. Zhang, M. Humbert, P. Berrang, M. Fritz, and M. Backes. 2018. ML-leaks: Model and data independent membership inference attacks and defenses on machine learning models. arXiv preprint arXiv:1806.01216 (2018).

[Samarati and Sweeney(1998)] P. Samarati and L. Sweeney. 1998. Protecting privacy when disclosing information: k-anonymity and its enforcement through generalization and suppression. Technical Report. SRI International.

[Shokri and Shmatiko(2015)] R. Shokri and V. Shmatiko. 2015. Privacy-preserving deep learning. In Proceedings of the 22nd ACM SIGSAC conference on computer and communications security. 1310–1321.

[Shokri et al.(2017)] R. Shokri, M. Stronati, C. Song, and V. Shmatikov. 2017. Membership inference attacks against machine learning models. In 2017 IEEE Symposium on Security and Privacy (SP). IEEE, 3–18.

[Soria-Comas et al.(2014)] J. Soria-Comas, J. Domingo-Ferrer, D. Sánchez, and S. Martínez. 2014. Enhancing data utility in differential privacy via microaggregation-based k-anonymity. VLDB Journal 23, 5 (2014), 771–794.

[Tang et al.(2018)] H. Tang, X. Lian, M. Yan, C. Zhang, and J. Liu. 2018. D^2: Decentralized training over decentralized data. In International Conference on Machine Learning. PMLR, 4848–4856.

[Tendick(1991)] P. Tendick. 1991. Optimal noise addition for preserving confidentiality in multivariate data. Journal of Statistical Planning and Inference 27 (1991), 341–353.

[Thakurta et al.(2017)] A. G. Thakurta, A. H. Vyrros, U. S. Vaishampayan, G. Kapoor, J. Freudiger, V. V. Prakash, A. Legendre, and S. Duplinsky. 2017. Emoji frequency detection and deep link frequency. US Patent 9,705,908.

[Triastcyn and Faltings(2019)] A. Triastcyn and B. Faltings. 2019. Federated Learning with Bayesian Differential Privacy. In Proceedings of the 2019 IEEE International Conference on Big Data. 2587–2596.

[Truex et al.(2020)] S. Truex, L. Liu, K.-H. Chow, M. E. Gursoy, and W. Wei. 2020. LDP-Fed: Federated Learning with Local Differential Privacy. In Proceedings of the 3rd International Workshop on Edge Systems, Analytics and Networking. 61–66.

[Wang et al.(2014)] Y. Wang, X. Wu, and D. Hu. 2014. Using Randomized Response for Differential Privacy Preserving Data Collection. Technical Report DPL-2014-003. University of Arkansas.

[Wang et al.(2016)] Y. Wang, X. Wu, and D. Hu. 2016. Using randomized response for differential privacy preserving data collection. In Proceedings of the EDBT/ICDT 2016 Joint Conference. Bordeaux, France.

[Warner(1965)] S. L. Warner. 1965. Randomized response: A survey technique for eliminating evasive answer bias. J. Amer. Statist. Assoc. 60, 309 (1965), 63–69.

[Yeom et al.(2018)] S. Yeom, I. Giacomelli, M. Fredrikson, and S. Jha. 2018. Privacy risk in machine learning: Analyzing the connection to overfitting. In 2018 IEEE 31st Computer Security Foundations Symposium (CSF). IEEE, 268–282.

[Yin et al.(2021)] X. Yin, Y. Zhu, and J. Hu. 2021. A Comprehensive Survey of Privacy-preserving Federated Learning: A Taxonomy, Review, and Future Directions. ACM Computing Surveys (CSUR) 54, 6 (2021), 1–36.

[Zhu et al.(2021)] H. Zhu, J. Xu, S. Liu, and Y. Jin. 2021. Federated learning on non-IID data: A survey. Neurocomputing 465 (2021), 371–390.

[Zhu et al.(2020)] Y. Zhu, X. Yu, Y.-H. Tsai, F. Pittaluga, M. Faraki, M. Chandraker, and Y.-X. Wang. 2020. Voting-based Approaches For Differentially Private Federated Learning. arXiv preprint arXiv:2010.04851.