The Good, The Bad, and The Ugly: Quality Inference in Federated Learning

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Abstract—Collaborative machine learning algorithms are developed both for efficiency reasons and to ensure the privacy protection of sensitive data used for processing. Federated learning is the most popular of these methods, where 1) learning is done locally, and 2) only a subset of the participants contribute in each training round. Despite of no data is shared explicitly, recent studies showed that models trained with FL could potentially still leak some information.

In this paper we focus on the quality property of the datasets and investigate whether the leaked information could be connected to specific participants. Via a differential attack we analyze the information leakage using a few simple metrics, and show that reconstruction of the quality ordering among the training participants’ datasets is possible. Our scoring rules are only using an oracle access to a test dataset and no further background information or computational power. We demonstrate two implications of such a quality ordering leakage: 1) we utilized it to increase the accuracy of the model by weighting the participant’s updates, and 2) using it to detect misbehaving participants.

Index Terms—Federated Learning; Inference Attack; Data Quality

I. INTRODUCTION

Machine Learning (ML) has received much attention over the last decades. For ML tasks, it is well known that more training data will lead to a more accurate model. Unfortunately, in reality, the data is scattered among different entities, hence, data holders could potentially increase their local model’s accuracy by training together a common model with others [32]. Several methods were proposed in the literature to tackle this problem. Probably the least privacy friendly method is centralized learning, where a server pools all participants’ data and trains the desired model. On the other end of the privacy spectrum is multi-party computation [17], a cryptographic technique which guarantees that only the final model is revealed to legitimate collaborators and nothing more. Neither of these extremes are acceptable for real-world use-cases: while first requires participants to directly share their datasets, the latter requires too much computational resource to be a reasonable solution.

Somewhere between these (in terms of privacy protection) is collaborative learning, where first the central node initializes the model and broadcast it to all participants, than the following repeats until convergence: 1) the participants update the model based on their training data and send it back to the server 2) who averages the received updates to improve the global model and broadcasts it to the participants. Federated Learning (FL) [20], [36] is similar, which mitigates the communication bottleneck of collaborative learning by selecting a random subset of participants in each round who calculates and sends their model updates instead of all participants.

These methods provide some privacy protection by design as the actual data never leaves the hardware located within the participants’ premises. Yet, there are considerable amount of literature that from these updates (i.e., gradients) a handful of things can be learned about the underlying training dataset, detailed in the related works.

Several techniques have been developed to conceal the participants updates from the aggregator server, such as adding pairwise noise to them [25], or using MPC [15], which could eliminate the need for a central server in the first place. These techniques protect the participants updates, while the aggregated average enjoys no protection. Without a specific background knowledge it is unlikely that in the collaborative learning scenario an attacker could link the leaked information with a specific participant as the aggregation provides a ’hiding in the crowd’ type of protection.

A. Differential Attack

On the other hand, if the training is FL, where different set of participants contributes in each round, via a differential attack it is possible to tied to specific participants the extracted information. This is especially important, as the aggregated model is broadcasted to all participants, so besides the aggregator server (if exists) this information is available to everyone participating in FL, independently of any secure aggregation protocol.

Example: In Table I we illustrate the differential attack for Membership and Quality Inference attacks. In this example 6 participants train a word predictor model together where in each round 3 randomly selected participant contributes. The membership attack indicates the presence of a specific location and email address in 1st round. Due to safe aggregation, without any background knowledge it is not possible to single out the participants who these data belongs to. The same attack does not indicates the presence of the mail address in the 2nd round, hence, supposedly the mail address belong to F’s dataset. The location does appear in the 2nd and 4th round while it does not in the 3rd and 5th round, but so is both A and

1We assume within a round the participants train for an entire epoch, i.e., use all their data in the rounds they are selected.
Concerning the dataset qualities, within a specific round the selected participants’ updates are hidden, but their aggregated update is public. If a particular round improves the model poorly (or significantly), it could be postulated that some of the participants contributed in that round have low (or high) quality data. By keeping track of such events, the participants could be separated into low/medium/high quality data holders with various confidence. In the example above, the 1st, 2nd, and 4th round the model improved significantly (so either A or E have high quality data as both participated in these rounds), while in the 3rd and 5th round the model did not improve, hence, either C or D have low quality data. Since the last round is neither good nor bad, either both low and high quality data is present or neither of them. Consequently, either A and C or E and D has high and low quality data respectively.

B. Contributions

In this paper we employ rigorous statistical analysis by adopting a stochastic viewpoint of the updates, however, due to the complexity of the task in hand, we turn towards empirical evaluation. We utilize the information leakage from the aggregated update when a safe aggregation mechanism is in place, i.e., where the participant updates (i.e., individual gradients) are hidden. We focus our attention on the honest-but-curious attackers with limited power and resources, i.e., assuming the attacker can only eavesdrop, and it has no background information (besides access to an evaluation oracle) or any computation resource which would enable her to do intricate calculations (concerning the attack). For this reason, we do not consider any existing attacks, as they all require either some computational resources (e.g., training shadow models [35], utilizing GANs [18], etc.) or some background information (e.g., data distribution/subset of the training sample [28], etc.).

Our novel attack aims to recover the quality of the aggregated updates; consequently, the quality of the contributing participants’ datasets. To obtain this quality information, we take advantage of the inferred information across multiple rounds’ aggregated updates and the subset of participants associated with the corresponding aggregates. Of course, such a quality measure is relative to the particular task and to the other participants’ datasets, so we aim to retrieve a relative quality ordering of the participants (compared to each other for the particular use-case).

The quality inference (i.e., relative quality ordering reconstruction) attack works by evaluating the aggregated updates in each round (based on a test dataset which is available for all participants and easily obtainable for the server) and assign scores to the contributors based on three simple rules called The Good, The Bad, and The Ugly. These accumulated scores (after many rounds) form a quality-wise ordering of the participants. Although the inferred ordering is only partially correct according to our experiments, it is successfully separates the participants in less fine-grained quality bins such as low, medium and high quality participants.

We run experiments on two architecture and two datasets (we assume the participants have IID dataset, which also simplifies the simulation and the measurement of the dataset qualities). We conclude that the quality inference accuracy depends on the complexity of the FL task itself as well as on the complexity of the model, which is being trained: with more complexity comes higher quality inference. In the most simple case (MNIST - MLP), our inferred quality ordering is barely better than a random guess, while in the most complex case (CIFAR - CNN), it is more than two times (≈ 2.2) better than a random guess.

We consider two application of quality inference: misbehaving detection and training efficiency boosting. Concerning misbehaving we investigated two attacks: gradient inverting and freeriding. While the first actively pulls back the learning, the second is neutral to the learning process. This is reflected in their detection rates as well: the detection rate is at least twice as good as a random guess for both gradient inverting participant after few rounds and for freerider after many rounds. Concerning the training efficiency boosting we found that weighting the participant’s contributions based on the inferred quality scores improves more the accuracy of the simple cases (> 1.1%) than of the complex ones (< 0.25%).

C. Organization

In section II we introduce the used variables through the paper and the model the data quality leakage in FL. In section III we describe how we simulate different datasets quality and detail our three quality scoring rules. In section IV besides elaborating on the experiments’ settings, we present our quality inference metric and the base attack performance. In section V we consider further increasing the quality inference accuracy by parameter fine tuning. In section VI we dive into the details of some possible applications of the inferred dataset qualities. In section VII we discuss some possible mechanism to mitigate quality inference leakage. In section VIII we mention a handful of related works, while in section IX we conclude the paper and mention some possible future works.

II. THEORETICAL MODEL

In this section we introduce the theoretical model of quality inference and highlight its complexity.
We note with \( n \) a participant in FL while \( N \) denotes the number of all participants. Similarly, \( i \) denotes a round in FL, while \( I \) denotes the number of all rounds. \( S_i \) contains the randomly selected participants for round \( i \). \( b = |S_i| \) capture the number of selected participants. \( D_n \) is the \( n \)th participant dataset, which consist of \( (x, y) \in D_n \) data-label pairs. A summary of the variables in this paper are listed in Table III.

### Table III

| Variable | Description |
|----------|-------------|
| \( n \in [1, 2, \ldots, N] \) | Participants |
| \( i \in [1, 2, \ldots, I] \) | Training rounds |
| \( b \) | Num. of selected participants |
| \( (x, y) \in D_n \) | Participants \( n \)'s dataset |
| \( q(n) \) | \( n \)th inferred quality-wise position |
| \( q \) | Quality Inference's accuracy |
| \( \alpha \) | Num. of cheating participants |
| \( r \) | Num. of (last) observed positions |
| \( c \) | Cheater detection rate |
| \( \kappa \) | Weight updating rate |

The notation used in the paper.

We assume participant \( n \) is associated with a single scalar quantity, measuring the quality of its dataset, named \( u_n \). Essentially, the quality of the aggregated gradients (noted as \( v_i \) for the \( i \)th round) form a linear equation system \( Au = v \), where \( u = [u_1, \ldots, u_N] \), \( v = [v_1, \ldots, v_I] \), and \( a_{n,i} \in A_{N \times I} \) indicates whether participant \( n \) is selected for round \( i \). Depending on the dimensions of \( A \), the system can be under- or over-determined. In case \( I < N \) (i.e., no solution exists) the problem and the solution is shown in Equation (1), while if \( I > N \) (i.e., many solutions exist) the problem and the solution is shown in Equation (2) [33].

\[
\begin{align*}
\min_u \|v - Au\|^2_2 \quad \Rightarrow \quad & u = (A^TA)^{-1}A^Tv \quad (1) \\
\min_u \|u\|^2_2 \quad \text{s.t.} \quad & Au = v \quad \Rightarrow \quad u = A^T(AA^T)^{-1}v \quad (2)
\end{align*}
\]

The above equations do not take into account the randomness explicitly. Since the training is stochastic, we consider the quality of the \( n \)th participant’s update (i.e., gradient) as a random variable \( \theta_n \) sampled from a distribution with parameter \( u_n \). Moreover, we can represent \( \theta_n = u_n + e_n \) where \( e_n \) correspond to a random variable sampled from a distribution with zero mean. We can further assume expected characteristic of the noise (i.e, error), namely that \( e_n \) and \( e_n' \) are IID for \( n \neq n' \). As a result, we can express \( v_i = \sum_n a_{n,i}u_n + E \) sampled from the convolution of the PDF of \( e \).

In this case, due to the GaussMarkov theorem [16], the solution in Equation (1) is the best linear unbiased estimator (BLUE), with error \( \|v - Au\|^2_2 = v^T(I - A(A^TA)^{-1}A^Tv) \) (where \( I \) is the identity matrix) which expected value is \( b(I - N) \). Note, that with more iteration, more information is leaking, making the error less-and-less. However this is not captured via the Gauss-Markov theorem as that considers every round as new constraint. On the other hand, in our case there is only \( \binom{I}{2} \) different constrains (with noise) which is the number of possible rounds with different participants.

All-in-all, this problem is within estimation theory [24], from which we already know that estimating a single random variable with added noise is already hard, not even mentioning the fact that in our setting, we have multiple, forming an equation system. Moreover, these random variables are varying round-wise, which we were ignoring so far. Nevertheless, in each iteration, a different contribution level is expected, as the early iterations improve the model’s accuracy greater than later one’s. Consequently, to estimate the dataset qualities we must know the expected learning curve which depends on exactly that. For this reason, we do not wish to pursue this theoretical direction; instead, focus on the empirical direction to break this circle.

### III. Quality Scoring Rules

In this section we describe how we simulate different datasets quality and detail our three quality scoring rules.

#### A. Quality Simulation

Data quality could mean several things; [3] defined 8 dimension of it (accuracy, completeness, redundancy, accessibility, consistency, usefulness, and trust), several having its own subcategories. Even restricting ourselves to images (used for the experiments), it spans over multiple dimensions. Image quality is relative for two reasons: it can only be considered in terms of the proposed use, and in relation to other examples. Visual perception is a complex process; hence, we do not manipulate the images themselves to simulate different qualities. Rather, since we focus on supervised machine learning, we modify the label \( y \) corresponding to a specific image \( x \).

For our experiments, we assume the aggregator does have a test dataset (e.g., a publicly available dataset) or at least a query access to an evaluator oracle. Consequently, we split the dataset randomly into \( N + 1 \) parts, representing the \( N \) datasets of the participants and the test set used to determine the quality of the aggregated updates. The splitting is done in a way that the resulted datasets are IID, otherwise the splitting would introduce some quality difference between the participants. Since the participant’s datasets are from the same underlying distribution, they quality is assumed to be identical [3].

To have a clear quality-wise ordering between the datasets, we perturbed the labels of the participants differently: the \( N \)th participant’s dataset is not perturbed, while the 1st participant’s dataset is fully perturbed (i.e., all labels are randomized). Each label for the rest of the participant’s datasets are randomized with a linearly decreasing probability from 1 to 0. Mathematically this is described in Equation (3).

\[
\Pr(y_k \text{ is randomized } | (x_k, y_k) \in D_n) = \frac{N - n}{N - 1} \quad (3)
\]

1Label perturbation [29], [30] could also be used to achieve differential privacy [10], hence, in this case data quality could be interpreted as the noise size or the privacy parameter.
2There can be slight variations due to the random splitting, however, we run our experiments 10-fold, which mitigates this issue sufficiently.
Assigning the qualities linearly following the participant IDs does not introduce any bias in our experiments since both the initial datasets splitting and the round-wise participant selection are random.

B. Scoring Rules

Based on the round-wise improvements, we created three fairly simple heuristic scoring rules to reward or punish the participants. We name them The Good, The Bad, and The Ugly, as the first one rewards the more useful contribution, the second punishes the less useful ones, while the last punishes when the contribution is just plain useless:

- **The Good**: all the participants who contribute in a round which improve the model more than the previous round receive +1 score.
- **The Bad**: all the participants who contribute in a round which improve the model less than the following round receive −1 score.
- **The Ugly**: all the participants who contribute in a round which do not improve the model (i.e., decrease the accuracy) will receive −1 score.

It is expected that consecutive rounds’ improvements are decreasing: first the model improves rapidly, while in later rounds it increases with a much lower pace. The first two scoring rules (The Good and The Bad) captures the deviation from this pattern: we can postulate that 1) high dataset quality increase the improvement more than in the previous round, and 2) low dataset quality decrease the improvement, which would be compensated in the following round. Our last scoring rules (The Ugly) assumes that if a particular round do not improve the model, there is a higher chance that some of the contributors’ dataset qualities are low.

Independently from the contributors dataset qualities, 1) the round-wise improvements could deviate from this pattern due to the stochastic nature of the learning, and 2) the improvement could be negative after sufficient training rounds as the model starts to overfit. We assume both of this affects all participants evenly, so the relation between the scores are not significantly affected by this ‘noise’.

IV. MEASURING THE QUALITY INFERENCE

In this section besides elaborating on the experiments’ settings (i.e., which datasets and model structures are used with what parameters) we present our quality inference metric and the base attack performance.

A. Datasets & Models & Experiment Setup

For our experiments, we used the MNIST [6] and the CIFAR [22] datasets. MNIST contains 70,000 hand-written digits in a form of 28x28 gray-scale pictures, while CIFAR consist of 60,000 32x32 colour images of airplanes, automobiles, birds, cats, deer, dogs, frogs, horse, ships, and trucks. For training we use multi-layer preceptor (MLP) and convolutional neural network (CNN) architecture. For MLP, we used a three-layered structure with hidden layer size 64, while for CNN, we used two convolutional layer with 10 and 20 kernels of size 5x5 followed by two fully connected hidden layer of sizes 120 and 84. For the optimizer we used SGD with learning rate 0.01 and drop out rate 0.5. In the rest of the paper, we will refer to these four use-case as MM for MNIST-MLP, CM for CIFAR-MLP, MC for MNIST-CNN, and CC for CIFAR-CNN. We run every experiment 10-fold. The implementation could be found at [31]. The exact parameters used for our experiments are presented in Table III.

| N  | b  | i      | α  | r         |
|----|----|--------|----|-----------|
| 5  | 2  | {10, 20, 30, 40, 50} | 1  | (1,2)     |
| 25 | 5  | {10, 20, 30, 40, 50} | 1.2 | (2,4)     |
| 100| 10 | {50, 100, 150, 200, 250} | 2   | (5,10)    |

TABLE III

The used parameters for the experiments.

The round-wise accumulated quality scores (averaged over all use-cases, i.e., over MM, CM, MC, and CC) using all 3 rules for the 3 experiment (detailed in Table III) are presented in Figure 1, where each participant’s dataset quality is degraded proportionally to their ID (i.e., noise is added according to Equation 3: 1’s dataset has the lowest, while N’s has the highest quality.)

![Figure 1](image)

Fig. 1. The average scores across the 4 use-cases (i.e., MM, CM, MC, and CC) for each participant when $N = 5, b = 2, i = \{10, 20, 30, 40, 50\}$ (top left), $N = 25, b = 5, i = \{10, 20, 30, 40, 50\}$ (top right) and $N = 100, b = 10, i = \{50, 100, 150, 200, 250\}$ (bottom).

It is visible, that after a few rounds there is no significant difference between participants’ quality scores with low and high dataset quality (i.e., highest light-blue curve) for all participants. On the other hand, the difference keeps growing as the number of rounds grow, mostly by decreasing the scores of the low ID participants (who correspond to low dataset quality) more than the other participants. Note, that even the $N$th participant (corresponding to the highest dataset quality) quality score is decreasing with more rounds. This is an expected characteristic of the scoring rules for two reasons: 1) as the model overfits, all participants’ quality scores will decrease due to the The Ugly scoring rule, and 2) there is only one rule increasing the score (The Good) while two decreasing it (The Bad and The Ugly).
It is visible that the three heuristic scoring rules combined fairly well recovers the original dataset quality order of the participants. As the number of participants grows, the difference of the dataset qualities between the nth and the n+1th participant shrinks. Consequently, it is harder and harder to correctly order them: it is unrealistic to recover the exact quality ordering for more than a handful of participants. On the other hand, our quality inference method for more than a handful of participants the exact quality ordering is suitable to give a high-level view (e.g., high/medium/high) of the participants dataset qualities in relation to each other.

In turn, the difference of the dataset quality of two participants with very different IDs are significant, so our heuristic scoring rule is capable of differentiating the two: if we define 3 dataset quality classes (e.g., low, high and medium), we can perfectly classify the lowest and highest dataset quality participants. For instance, in case of \( N = 25 \) (\( N = 100 \)) participants the 8 (26) lowest dataset quality participants’ score is always below -30 (-100), while the 11 (23) highest dataset quality participant’s score is always above -20 (-80), so the best and worst quarter of participants can be separated from each other.

In Figure 2 we show the scores with \( N = 100 \) participants for the four experiments (i.e., MM, CM, MC, CC) separately. One can see that for simple models such as MLP, the quality scores are less punctual than for more complex algorithms such as CNN. It is also visible that the complexity of the task (i.e., MNIST or CIFAR) only plays a minor role.

\[ d_S = \frac{1}{N^2} \sum_{n=1}^{N} ||(n, q(n))||_1 \quad \hat{q} = 1 - \frac{d_S}{N^2} \quad (4) \]

Since \( d_S \) depends on the number of participants, we have to normalize it to have an uniform quality metric \( \hat{q} \) and divide it with its maximum value which is \( \frac{N^2}{2} \) (corresponding to \( 1, 2, \ldots, N \rightarrow [N, \ldots, 2, 1] \)). Finally, we invert this value, so it is within \([0,1]\) where 1 represents perfect inference, as shown on the right side of Equation (4).

The \( \hat{q} \) values averaged over the 4 use-case corresponding to 5 and 25 participant (i.e., as in Figure 1) are \{1, 1, 1, 1\} and \{0.77, 0.89, 0.87, 0.85\} for \( i = \{10, 20, 30, 40, 50\} \) respectively. The \( \hat{q} \) values for 100 participants case-wise (i.e. as in Figure 2) are presented in Figure 3.

![Fig. 2. The case-wise quality scores of each participant when \( N = 100 \) and \( b = 10 \) for \( i = \{50, 100, 150, 200, 250\} \).](image)

**B. Quantifying the Quality Inference**

To quantify the inferred quality ordering of the participants, we need to convert the relation between the quality scores into a single value. For this purpose, we use the Spearman’s distance \( d_S \) [8], which measures the sum of the absolute differences of all participants’ inferred (i.e., \( q(n) \)) and correct position (i.e., \( n \) due to Equation (3)) in the quality ordering. Note, that Spearman’s distance handles equally any misalignment irrespective of the position. It is calculated according to the left side of Equation (4).

It is visible that for complex architecture (i.e., CNN) the quality inference accuracy almost linearly grows in respect to the rounds, while for simpler architecture (i.e., MLP) it is rather decreasing. Note, that since the expected value of \( \hat{q} \) for a random ordering is roughly \( \frac{N^2}{2} \), the baseline is \( \hat{q} = 0.3 \), which we highlight on all figures with a square on the scale.

**V. Fine-tuning the Scoring Rules**

In this section we consider further increasing the quality inference accuracy \( \hat{q} \) by parameter fine tuning. We vary the thresholds which determines when to trigger which rule, we measure the accuracy for different combinations of the rules, consider ignoring the first few rounds, and use the actual improvement difference as a score.

**A. Threshold Optimization**

Since the learning is stochastic, it is expected that participants with low (high) dataset quality by chance receive positive (negative) scores in some rounds. To mitigate these effects, we considered to use a threshold: for The Ugly, we score only if the improvement is below some negative value (instead of 0).

In contrast, for The Good and The Bad we score only if the improvement difference is above or below such a threshold respectively.

In Figure 4 we show \( \hat{q} \) for all the use-cases with 100 participants after 250 rounds for each scoring rule separately and accumulated. As the performance is similar for all the considered threshold across all use-cases, we present the average value as a line on a shorter scale on the right. The Good performs the best with threshold \( t = 0.05 \), The Bad with \( t = 0.15 \) and The Ugly with \( t = 0.15 \). The bottom right
reflects the accuracy when all the scoring rules are combined, which performs the best when \( t = 0.15 \).

### B. Rule Combinations

Not surprisingly, the combination of all the scoring rules outperforms all the single rules. This holds for all possible combination as we show in Table IV below.

| \( t \) | Good | Bad | Ugly | G&B | G&U | B&U | All |
|---|---|---|---|---|---|---|---|
| 0.00 | 0.438 | 0.546 | 0.533 | 0.536 | 0.548 | 0.547 | 0.560 |
| 0.15 | 0.490 | 0.587 | 0.541 | 0.620 | 0.588 | 0.600 | 0.632 |

**TABLE IV**

*The average \( \hat{q} \) scores for the 4 use-cases with different combinations of the 3 scoring rule when \( N = 100, b = 10, \ i = 250 \) and \( t = \{0.00, 0.15\} \).*

### C. Improvement Value as Scores

Scoring the participants contribution with \( \pm 1 \) ignores the actual accuracy changes: for example in case of The Ugly, it does not matter how negative a round’s improvement is, the corresponding participants receive \( -1 \) uniformly. Taking such information into account might improve the quality inference in our scoring rules, so we consider alternative rule variants when the improvement values are used instead of \( \pm 1 \).

We compared \( \hat{q} \) using the actual improvement differences (referred to as Value) within the 3 rules instead of essentially counting by \( \pm 1 \) how many times the rules have been applied (referred to as Count). Hence, we considered adding to the participants scores the actual negative improvement in case of The Ugly and the improvement differences in case of The Good and The Bad with the previous and following round respectively. As seen on Figure 5 (which show the average \( \hat{q} \) over all use-cases corresponding to 100 participants after 250 rounds), these results are inconsistent: \( \hat{q} \) improves slightly for The Ugly, inconclusive in case of The Bad and counterproductive in case of The Good.

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5 We set the thresholds separately for each scoring rule; however, the final accuracy was not better than when we set it uniformly to \( t = 0.15 \), so we only present this latter.

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6 Several things are visible: concerning Value, skipping the first 2 rounds improves \( \hat{q} \) considerably (61% \( \rightarrow \) 63%), while later round skipping only corresponds to minor improvements. Concerning Count, skipping is actually counter-productive, as the scores are essentially normalized to \( \pm 1 \), so skipping rounds only results in information loss. It is also visible that parameter fine-tuning does not really effects Value, while for Count it is non-negligible (56% \( \rightarrow \) 63%). Finally, we can conclude that neither is superior to the other, as the same accuracy could be reached via Count with parameter tuning and Value with iteration skipping.

### D. Round Skipping

The above result is surprising, since by considering the actual values instead of counting the events we do consider more information in our scoring rules. We anticipate, this is due to the learning curve: in the first few rounds the improvement is so vast, the scores for the participants selected in those rounds barely change afterwards as in the succeeding rounds the improvements (i.e., scores) are insignificant in magnitude compared to them.

Hence, we consider not scoring the participants during the early rounds to mitigate this effect. We show the corresponding \( \hat{q} \) for both Count and Value when all 3 rules are applied with and without threshold optimization in Table V.

| Ignore \( t \) | 0 | 2 | 4 | 6 | 8 | 10 |
|---|---|---|---|---|---|---|
| Count \( t = 0.15 \) | 0.560 | 0.556 | 0.531 | 0.544 | 0.536 | 0.529 |
| Value \( t = 0 \) | 0.510 | 0.630 | 0.630 | 0.632 | 0.628 | 0.628 |
| Value \( t = 0 \) | 0.509 | 0.625 | 0.631 | 0.638 | 0.640 | 0.634 |

**TABLE V**

*\( \hat{q} \) for Count and Value with \( t = \{0.00, 0.15\} \) with various amount of first rounds skipping for \( N = 100, b = 10 \) and \( i = 250 \).*

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7 \( t = 0.15 \) performs the best in case of Value as well.
and 0.82 for CC via parameter tuning. Hence, fine-tuning helps when the task is simple (i.e., MNIST) while it barely improves in case of complex data/task (i.e., CIFAR).

Without fine-tuning on average \( \hat{q} \) performs +25% better than the baseline 33%. Fine-tuning increase this further with +7%. This extra 7% comes with a cost though: fine-tuning the parameters is possible via shadow models [35], which does require access to computational resources and datasets (instead of only an evaluation oracle). Due to these reasons in the rest of the paper we use the base Count method.

VI. APPLICATION OF QI

In this section, we dive into the details of some possible applications of the inferred dataset qualities. Although we foresee many, we detail only two: misbehavior detection and training efficiency boosting.

A. Catching Attackers & Freeriders

The leaking information about the participant’s dataset quality could be used to isolate potential misbehaving. We consider two kinds of deviation.

- **Inverting:** The participant’s goal is to worsen the quality of the aggregated model actively. One was to achieve this is to submit the additive inverse of the calculated correct gradient.
- **Freeride:** The participant’s goal is to benefit from the aggregated model passively. One was to achieve this is not to calculate the correct gradients but instead submit zero gradient.

We assume the rest of the participant’s datasets are of equal quality; hence, we expect that the cheating participants should be at the bottom of the inferred quality order. We note the catching probability of the cheaters with \( c(r) \), which depends on the number of the last observed positions \( r \) rather than on the number of cheaters \( \alpha \). \( c(r) \) measures the fraction of the cheaters who are isolated in the last \( r \) places of the inferred quality ordering, i.e., the accuracy is shown on Equation (5) where \( \alpha_j \) is the \( j \)th attacker and \( n_r \) it the participants with the \( r \)th lowest quality score.

\[
c(r) = \frac{\#\{a_j | q(a_j) \leq q(n_r)\}^\alpha_{j=1}}{\sum_j^\alpha \binom{\alpha}{j} \binom{N-\alpha}{r-j} \cdot \frac{j}{\alpha} \approx \frac{r}{N}} \tag{5}
\]

The baseline (i.e., the value of \( c \) with random ordering) is also shown above, which is independent of the number of cheaters. For instance, \( c(10) = 0.8 \) means that 0.8 fraction of the cheaters were in the last ten places (e.g., 4 in case of 5 cheaters). Obviously \( c(0) = 0 \) and \( c(N) = 1 \). The average \( c \) values of the four use-cases based on the 10-fold experiments with the settings defined in Table III are shown in Figure 6. The first corresponds to \( N = 5 \) with \( \alpha = 1 \), the second and third to \( N = 25 \) with \( \alpha = 1 \) and 2 respectively, while the fourth and fifty corresponds to \( N = 100 \) with \( \alpha = 2 \) and 4 respectively.
Although the baseline of $c$ (which is highlighted with a square on the scale with the corresponding color for both $r$) does not depend on $\alpha$, it is negatively effected by it: it gets harder-and-harder to detect the cheaters when there are more-and-more of them (i.e., see the difference between the 2nd and 3rd, and the 4th and 5th figure). It is visible that in case of inverting after few rounds $c$ already outperformed the baseline. On the other hand, in case of freeride, $c$ is not better than a random guess after few rounds.

Not surprisingly, the detection gets more accurate when the quality scores are based on more rounds. According to our experiments, in case of inverting (which is obviously easier to detect than freeride) $c$ gets 3-4 times higher than the baseline. Even for freeride the detection rate is still twice as much.

These figures also showed the average and highest inferred positions of the cheaters: as expected, the position decreases with more rounds and increases with more cheaters. Note, that the highest positions reached by a cheater were never in the top 20% of the participants, even for freeride.

B. Boosting the Training

Based on the data quality, it is expected that both the training speed and the obtained accuracy could be improved when putting more emphasis on high-quality data. Hence, we consider weighting the participant’s updates based on their quality scores.

We adopt a multiplicative weight update approach \cite{Algorithm 1}, which multiplies the weights (which are initially uniformly 1) with a fixed rate $\kappa$ when any of the scoring mechanism applies. This method is shown in Algorithm 1 where $S_i$ notes selected participants for the $i$th round (declared in line 4), and $imp$ captures the round-wise improvements (declared in line 8 using the accuracy $Acc$ difference of the current and previous model). The weights ($w_1, \ldots, w_N$) are updated in the $i$th round with $\kappa < 1$ each time on of the three scoring mechanism applies (line 10, 11, and 13 for The Good, The Bad, and The Ugly respectively). For our experiments we set $\kappa = \{1.00, 0.95, 0.90\}$ where the first corresponds to the baseline without participant weighting.

Concerning the size of $\kappa$, we observe that low dataset quality participants’ weights are more sensitive than others: a decrease in $\kappa$ results in more weight drop for them. As this is exactly the same effect what we already captured in Figure 1 for quality scores in relation with the round number, we do not visualize our results here. Besides these expected characteristics, we did not find any universal findings in relation with the size of $\kappa$: neither higher nor lower rates does consistently outperform the other, and the achieved accuracy varies greatly primary on the used architecture and secondly on the dataset.

One thing which is conclusive though is that using weights based on our scoring rules improves the original accuracy in most of the studied cases. We present our results (averaged over 10 executions) corresponding to the accuracy improvement when $\kappa = \{0.95, 0.90\}$ in Table VI for the four use-cases and for the 3 experiment from Table III with $\{50, 50, 250\}$ respectively.

These results are surprising and counter-intuitive: one would expect more gain from the weighting when the quality scoring captures the dataset qualities better (i.e., in case of more complex model such as CNN). On the other hand, precisely the opposite can be seen. While the quality inference performs consistently better on the most complex case (i.e., in CIFAR/CNN), the weighting barely or not improves the accuracy (i.e., < 0.25%), while the highest improvement (i.e., > 1.1%) by weighting is achieved in the most straightforward task (i.e., MNIST/MLP), where the quality inference is barely better than the baseline random ordering.

VII. Mitigation Strategies

In this section, we discuss some possible mechanism to mitigate against the quality inference. Note, that this leakage is not intended, so this is a bug, rather than a feature in FL. The simplest and most straight forward way to mitigate this risk is to enforce all participant to contribute in each round. However, this is not feasible for thousands of participants.

The leakage of the data’s quality inevitably present in the aggregated updates. How often this information is available to the participants plays a significant role in the success of the QI attack, as Figure 1, 2, and 3 already demonstrated. Hence, on way to mitigate this leakage is to decrease the access to these updates. It can be done in many ways, for instance 1) limiting the number of rounds by allowing the participants to train multiple epochs within one round, or 2) instead of

\begin{algorithm}[H]
1: $S_{b \times r}; imp = [imp_1, \ldots, imp_I]; W = [W_1, \ldots, W_N]$
2: $W = [1, \ldots, 1]$
3: for $i \in [1, \ldots, I]$ do
4: Select $b$ contributors ($S_i$)
5: for $c \in S_i$ do
6: Update model ($Model_{i-1} \rightarrow Model_i(c)$)
7: Aggregate ($Model_{i} = Avg([W_c \cdot Model_i(c)]_{c \in S_i})$)
8: $imp_i = Acc(Model_{i}) - Acc(Model_{i-1})$
9: if $imp_i > imp_{i-1}$ then
10: for $c \in S_i, do$ $W_c = W_c \cdot \kappa^{-1}$
11: for $c \in S_{i-1} do$ $W_c = W_c \cdot \kappa$
12: if $imp_i < 0$ then
13: for $c \in S_i, do$ $W_c = W_c \cdot \kappa$

\caption{On-the-fly participant weighting}
\end{algorithm}

\begin{table}[H]
\centering
\begin{tabular}{|c|c|c|c|c|}
\hline
\textbf{N} & \textbf{\{50, 50, 250\}} & \textbf{\{50, 50, 250\}} & \textbf{\{50, 50, 250\}} & \textbf{\{50, 50, 250\}} \\
\hline
\textbf{MNIST/MLP} & 1.70 & 2.56 & 3.80 & 4.62 & 2.93 & 1.15 \\
\textbf{CIFAR/MLP} & 0.19 & 0.36 & 0.99 & 1.24 & 1.32 & 1.02 \\
\textbf{MNIST/CNN} & 0.05 & 0.02 & 0.04 & -0.02 & 0.00 & 0.02 \\
\textbf{CIFAR/CNN} & 0.13 & 0.24 & -0.49 & -0.32 & -0.63 & -0.49 \\
\hline
\end{tabular}
\caption{The accuracy improvements due to the multiplicative weighting with $\kappa = \{0.95, 0.90\}$ on the four experiments when $N = 5, b = 2, i = 50, N = 25, b = 5, i = 50$ and $N = 100, b = 10, i = 250$.}
\end{table}
broadcasting the updated model, the server send it only to the participants who are going to contribute in the next round.

Another technique is adaptive selection of the participants for each round (instead of random), however this sword has two edges: adaptive selection can be used to mitigate the information leakage as well as increase it. Yet another approach is to hide the participant’s IDs, so no-one knows which participant collaborated in which round beside the participants themselves. This can be achieved with various techniques such as mix nets \(^5\) and MPC \(^15\).

Finally, the the aggregation itself could be done in a differentially private manner as well, where a carefully calculated noise is added to each round. Moreover client-level DP \(^13\) would by default hide the dataset quality of the participants, although that require large volume of noise. On the other hand, using the shuffle mode \(^2\), \(^4\) could solve this problem.

VIII. RELATED WORKS

In this section we enlist the related works, including but not limited to well known privacy attacks against machine learning and data quality.

Concerning freeriding, \(^11\) deals with this problem in peer-to-peer systems, and introduce the penalty mechanism, which could be build on top of our scoring rules. A more recent work \(^23\) presents a freerider detection mechanisms for collaborative learning which works only if no secure aggregation is in place.

A. Privacy Attacks

There are several indirect threats concerning ML models. According to a recent survey \(^27\), these could be categorized into model inversion or attribute inference (e.g., \(^12\)), membership inference and reconstruction attacks (e.g., \(^35\), \(^40\)), (hyper)parameter inference (e.g. \(^37\), \(^38\)), and property inference (e.g., \(^26\)). Our quality inference could be considered as an instance of the last.

Another property inference attack is quantity composition attack \(^39\), which aim is to infer the proportion of training labels among the participants in FL. The authors showed that an attacker participating in the training (with minimal power) could extract valuable information from training data without requiring access to the individual updates. Consequently, the attack is successful even with secure aggregation protocols or under the protection of DP. Our setting is similar, as we require even less knowledge and computational resource from the attacker while allowing secure aggregation to be in place.

B. Privacy Defenses

As we simulate different dataset qualities with the amount of added noise, essentially, what we want to prevent the leakage of the added noise size. Consequently, this problem also relates to the private privacy parameter selection, as label perturbation \(^29\), \(^30\) (which is used to mimic different dataset quality levels) is one of the 5 known techniques \(^27\) to achieve differential privacy (DP) \(^10\), \(^7\). In previous works the authors set the privacy parameter for DP using economic incentives \(^9\), \(^32\) or offer the selection as a service \(^21\). We are not aware of any research (both within and outside DP literature) which does consider to define the privacy parameter itself also privately.

C. Data Quality

In this work we naively assumed the data quality is in a direct relation with the added noise present in the data. This served our purpose right, however, there is a computer science discipline about data quality. For a comprehensive survey we refer the reader to the book \(^3\).

A complementary work is Data Shapley \(^14\), which determines the value of datasets used for FL. Originally the Shapley value \(^24\) was designed to allocate goods to players proportionally to their contributions. The Shapley value is the only fair payment rule, i.e., it satisfies the four properties: efficiency (all the gain is distributed among the players), symmetry (players with same contributions receive the same payment), linearity (additivity of the Shapley value between games) and null player (players contributing nothing receive no payment). The main drawback of this payment distribution is that it is computationally not feasible as it requires exponentially more computations than the number of participants. Moreover, besides this computational burden, to calculate the Shapley values, one must have access to all datasets. Although the first problem could be solved by approximating the Shapley value via sampling \(^14\), accessing the datasets remains an issue. Consequently, our scoring mechanism could be interpreted as an approximation of a solution concept.

IX. Conclusion

Federated learning is the most popular collaborative learning framework, wherein each round only a subset of participants update a common model. In this paper, we devised three quality scoring rules which could successfully recover the relative ordering of the participant’s dataset qualities using the size of the improvement of each training round. Our method does neither require any computation power (such as shadow models) nor any background information besides a small dataset (or access to an evaluator oracle) in order to be able to evaluate the improvement of the model accuracy after each round.

Our results are twofold: first, we conclude that the quality inference accuracy does depend on the complexity of the model, which is being trained: with more complexity comes higher quality inference accuracy (i.e., for a simple case it is barely better than a random guess, while for more complex ones it is more than twice of that). Second, paradoxically to the first, weighting the participants based on the inferred quality scores have a minor effect in the complex case while it improves the final accuracy of the simple case consistently with more than one percent.

Such a quality inference within federated learning could have several applications. Besides the already mentioned weighting, it could be used to identify freeriders and cheaters of the supposedly commonly trained model. In this paper
we also showed that catching such cheaters based on the scoring rules is twice as effective as random guessing.

**Future Work**

The paper barely scratched the surface of a potentially fruitful direction, namely the quality inference using aggregated updates. Besides the already mentioned two directions (misbehavior detection and participant weighting) there are several other, such as **approximating the Shapley value using the introduced scoring rules**. The privacy implications of the this information leakage is also of interest: could such a **quality information be considered private?**

The scoring rules themselves could also be a subject of further research as they can be improved, replaced, weighted, etc. Finally, the **theoretical analysis of** the quality inference is an orthogonal direction to this empirical study: **attempting to reconstruct the dataset quality order** is similar to the problem studied in [9], which aims to reconstruct the entire dataset based on query outputs.

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