Connecting Randomized Response, Post-Randomization, Differential Privacy and $t$-Closeness via Deniability and Permutation

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Abstract—We explore some novel connections between the main privacy models in use and we recall a few known ones. We show these models to be more related than commonly understood, around two main principles: deniability and permutation. In particular, randomized response turns out to be very modern in spite of it having been introduced over 50 years ago: it is a local anonymization method and it allows understanding the protection offered by $\epsilon$-differential privacy when $\epsilon$ is increased to improve utility. A similar understanding on the effect of large $\epsilon$ in terms of deniability is obtained from the connection between $\epsilon$-differential privacy and $t$-closeness. Finally, the post-randomization method (PRAM) is shown to be viewable as permutation and to be connected with randomized response and differential privacy. Since the latter is also connected with $t$-closeness, it follows that the permutation principle can explain the guarantees offered by all those models. Thus, calibrating permutation is very relevant in anonymization, and we conclude by sketching two ways of doing it.

Keywords: Differential privacy; randomized response; $t$-closeness; PRAM; permutation paradigm; risk and loss aversion.

I. INTRODUCTION

Privacy models in the literature can be split into four main families, by order of appearance: i) randomized response (1965); ii) $k$-anonymity (1998) and its extensions ($l$-diversity (2006), $t$-closeness (2007), etc.); iii) differential privacy (2006); and iv) the permutation paradigm (2016).

Although the above models were proposed over a 50-year span and were initially believed to be fundamentally different from each other, some connections between pairs of them have been found in the literature. Such connections can be useful to the anonymization practitioner because they give more insight into the risk-utility trade-offs incurred when choosing a certain parameterization for a specific model.

We explore in this paper several connections from a new perspective. Section II connects randomized response and post-randomization (PRAM) in terms of plausible deniability; thus, randomized response is not only an anonymization method avant la lettre, but more interestingly a local version of the PRAM anonymization method. Section III dwell on the known link between randomized response and differential privacy, by taking a new approach based on information theory and deniability; in particular, our analysis allows understanding the effect on privacy of increasing the $\epsilon$ parameter of differential privacy (in an attempt to improve utility). Section IV recalls the connection between differential privacy and $t$-closeness that we demonstrated in a previous paper; the novelty is that our deniability-based analysis permits using $t$-closeness to assess whether a large $\epsilon$ in differential privacy provides enough protection. Section V views PRAM in terms of the permutation paradigm. The lessons learned from the previous sections pave the way to calibrating anonymization in terms of permutation, whatever the privacy model in use; this is dealt with in Section VI. Finally, Section VII contains conclusions and future research issues.

II. RANDOMIZED RESPONSE, PLAUSIBLE DENIABILITY AND PRAM

Randomized response (RR, [6], [15]) is a mechanism that respondents to a survey can use to protect their privacy when asked about the value of sensitive attribute (e.g. did you take drugs last month?). The interesting point is that the data collector can still estimate from the randomized responses the proportion of each of the possible true answers of the respondents.

Let us denote by $X$ the attribute containing the answer to the sensitive question. If $X$ can take $r$ possible values, then the randomized response $Y$ reported by the respondent instead of $X$ follows a $r \times r$ matrix of probabilities

$$\mathbf{P} = \begin{pmatrix} p_{11} & \cdots & p_{1r} \\ \vdots & \ddots & \vdots \\ p_{r1} & \cdots & p_{rr} \end{pmatrix}$$

where $p_{uv} = \Pr(Y = v \mid X = u)$, for $u, v \in \{1, \ldots, r\}$ denotes the probability that the randomized response is $v$ when the respondent’s true attribute value is $u$.

Let $\pi_1, \ldots, \pi_r$ be the proportions of respondents whose true values fall in each of the $r$ categories of $X$ and let $\lambda_v = \sum_{u=1}^{r} p_{uv} \pi_u$ for $v = 1, \ldots, r$, be the probability of
Therefore, using Expression (4) we get that
\[ H(\hat{\pi}) = \log |\tilde{P}|. \]
and also provide an unbiased estimator of the dispersion matrix.

A. The privacy model of randomized response: plausible deniability

Even if the concept of privacy model (that is, of ex post privacy guarantee) was introduced by \( k \)-anonymity [10] three decades after RR had appeared, RR has an implicit privacy model. The privacy guarantees RR offers to respondents are plausible deniability and secrecy, as we next analyze.

For each possible value \( v \) of the reported attribute \( Y \), by the Bayes’ formula we have
\[
\hat{\pi}_{vu} = \frac{\Pr(X = u | Y = v)}{\Pr(Y = v | X = u) \Pr(X = u)} = \frac{\sum_{u' = 1}^r \Pr(Y = v | X = u') \Pr(X = u')}{\sum_{u' = 1}^r \Pr(Y = v | X = u') \Pr(X = u')} = \frac{\sum_{u' = 1}^r \pi_{u'v} \pi_u}{\sum_{u' = 1}^r \pi_{u'v} \pi_u}.
\]

a) Deniability: Imagine that \( u \) is an embarrassing value of \( X \) (like a value “Yes” for an attribute \( X \) denoting whether drugs were taken last month). As long as \( \Pr(X = u | Y = v) > 0 \), the respondent can deny to have \( X = u \).

Actually, the more similar the probabilities \( \hat{\pi}_{vu} \) corresponding to a given answer \( Y = v \), the higher the deniability. Therefore, given a reported value \( Y = v \), we can measure deniability as a conditional Shannon entropy
\[
H(X | Y = v) = -\sum_{u = 1}^r \hat{\pi}_{vu} \log_2 \hat{\pi}_{vu},
\]
whose maximum value is \( \log_2 r \), corresponding to the case when \( \hat{\pi}_{vu} \) takes the same value \( 1/r \) for all \( u = 1, \ldots, r \).

b) Perfect secrecy: In the special case in which the probabilities within each column of \( P \) are identical (although perhaps different columns contain different probabilities), Expression (5) tells us that \( \hat{\pi}_{vu} = \pi_u \), for \( u, v \in \{1, \ldots, r\} \). Therefore, using Expression (4) we get that \( H(X | Y = v) = H(X) \) for any \( v \), and thus \( H(Y | X) = H(X) \), which implies perfect secrecy in the Shannon sense [11]: the reported answer \( Y \) gives no information at all on the real value of \( X \).

Unfortunately, the price paid for perfect secrecy is high in terms of utility: when the probabilities within two or more columns of \( P \) are identical, matrix \( P \) is singular, and therefore the unbiased estimator of Expression (2) cannot be computed.

Finally, having \( H(Y | X = v) = H(X) \) for some \( v \) yields an uninformative reported value. It is possible to go beyond that and make \( v \) misinformative, by ensuring that \( H(X | Y = v) > H(X) \). However, since \( H(Y | X) \leq H(X) \), if we increase \( H(X | Y = v) \) to make it greater than \( H(X) \) for some \( v \), we are forced to decrease \( H(X | Y = v') \) for other values \( v' \neq v \).

B. Randomized response: a local version of PRAM

The matrix in Expression (1) looks exactly as the transition matrix used in the post-randomization method (PRAM) proposed by [4]. As pointed out in [12], the main difference between RR and PRAM is who performs the randomization: whereas in RR it is the respondent before delivering her response, in PRAM it is the data controller after collecting all responses (hence the name post-randomization). Therefore, RR is a local version of PRAM anonymization, which is not without merit: when RR was invented, the notion of anonymization did not exist, let alone the notion of local anonymization.

III. RANDOMIZED RESPONSE AND DIFFERENTIAL PRIVACY

A randomized query function \( \kappa \) gives \( \epsilon \)-differential privacy [5] if, for all data sets \( D_1, D_2 \) such that one can be obtained from the other by modifying a single record, and all \( S \subseteq \text{Range}(\kappa) \), it holds
\[
\Pr(\kappa(D_1) \in S) \leq \exp(\epsilon) \times \Pr(\kappa(D_2) \in S).
\]

In plain words, the presence or absence of any single record is not noticeable (up to \( \exp(\epsilon) \)) when seeing the outcome of the query. Hence, this outcome can be disclosed without impairing the privacy of any of the potential respondents whose records might be in the data set. A usual mechanism to satisfy Inequality (5) is to add noise to the true outcome of the query, in order to obtain an outcome of \( \kappa \) that is a noise-added version of the true outcome. The smaller \( \epsilon \), the more noise is needed to make queries on \( D_1 \) and \( D_2 \) indistinguishable up to \( \exp(\epsilon) \).

In [13], [14], a connection between RR and differential privacy is established: RR is \( \epsilon \)-differentially private if
\[
eq \max_{v = 1, \ldots, r} \frac{\max_{u = 1, \ldots, r} \pi_{uv} \pi_u}{\min_{u = 1, \ldots, r} \pi_{uv}} \geq \exp(\epsilon).
\]
The rationale is that the values in each column \( v \in \{1, \ldots, r\} \) of matrix \( P \) correspond to the probabilities of the reported value being \( Y = v \), given that the real value is \( X = u \) for \( u \in \{1, \ldots, r\} \). Differential privacy requires that the maximum ratio between the probabilities in a column be bounded by \( e^\epsilon \), so that the influence of the real value \( X \) on the reported value \( Y \) is limited. Thus, the reported value can be released with limited disclosure of the real value.

A. Connection with entropy

The smaller the value of \( \epsilon \) in Inequality (6), the more similar the probabilities \( \pi_{uv} \) (\( u = 1, \ldots, r \)) in the columns of \( P \), for columns \( v = 1 \) to \( r \). In turn, the more similar these probabilities, the more \( \hat{\pi}_{uv} \) approaches \( \pi_u \), as it can be seen from Expression (5).

In the extreme case, when \( \epsilon = 0 \), Inequality (6) forces the probabilities within each column to be identical to each other (although not necessarily equal to probabilities in other columns). As shown in Section II-A, this implies \( H(Y | X) = H(X) \). Therefore, if randomized response...
achieves the strictest differential privacy ($\epsilon = 0$), it also achieves perfect secrecy in the Shannon sense.

Yet, one might argue that conditional entropy $H(X|Y)$ captures more information than Inequality (6), because it takes all probabilities into account, whereas Inequality (6) (and hence the above connection of RR with differential privacy) only takes into account the maximum and the minimum probabilities in each column.

### B. Explaining large $\epsilon$ in terms of deniability

One of the shortcomings of the differential privacy model is that its ex ante privacy guarantee is only intuitive when $\epsilon$ is very small. Specifically, when one takes not-so-small $\epsilon$ values in Expression (5) to preserve more utility, the privacy guarantee is hard to explain: is $\epsilon$ is not that small, one cannot guarantee any more that the presence or absence of any single record/respondent is really unnoticeable.

The connection with randomized response and hence deniability given by Inequality (6) is useful to gain an intuition on what large $\epsilon$ implies. We illustrate this in the following example.

#### Example 1: If one takes $\epsilon = 2$, this means that in some columns of $P$ the ratio between the largest probability and the smallest probability may be as large as $e^2 = 7.389$. In particular, if say, $r = 2$, one might have a column $v$ with one probability $p_{1v} = 0.7389$ and the other probability $p_{2v} = 0.1$. In this situation, if the prior probabilities of the two values of $X$ are similar, Expression (5) tells us that, after reporting $Y = v$, the most likely value of $X$ is 1 and there is only a narrow margin for denying it. This clearly shows that $\epsilon = 2$ does not seem to provide enough privacy.

### IV. Differential Privacy and $t$-Closeness

Given two random distributions $F_1$ and $F_2$ taking values in a discrete set $\{x_1, x_2, \cdots, x_t\}$, consider the following distance between them:

$$d(F_1, F_2) = \max_{i=1,2,\cdots,t} \ \left\{ \frac{\Pr_{F_1}(x_i)}{\Pr_{F_2}(x_i)}, \frac{\Pr_{F_2}(x_i)}{\Pr_{F_1}(x_i)} \right\}. \quad (7)$$

In Expression (7), we take the quotients of probabilities to be zero if both $\Pr_{F_1}(x_i)$ and $\Pr_{F_2}(x_i)$ are zero, and to be infinity if only the denominator is zero.

In [5], it is proven that, if an anonymized static data set satisfies $\exp(\epsilon/2)$-closeness (an extension of $k$-anonymity) when the distance between the distribution of the sensitive attributes over entire data set and the distribution of the sensitive attribute within a cluster of records is measured using Expression (7), then the data set satisfies differential privacy in the sense stated in the following proposition.

#### Proposition 1: Let $k_1(D)$ be the function that returns the view on subject $I$’s sensitive attributes given a data set $D$. If $D$ satisfies $\exp(\epsilon/2)$-closeness when using the distribution distance of Expression (7), then $k_1(D)$ satisfies $\epsilon$-differential privacy. In other words, if we restrict the domain of $k_1$ to $\exp(\epsilon/2)$-close data sets, then we have $\epsilon$-differential privacy for $k_1$.

Proposition [1] is helpful to explain differential privacy in terms of an intruder’s knowledge gain on the sensitive attribute values of a target respondent if the intruder can determine the target respondent’s cluster. This is shown in the next example.

#### Example 2: If one uses $\epsilon$-differential privacy with $\epsilon = 2$, by Proposition 1, the probability weight attached to a certain value of a sensitive attribute $X$ can grow by a factor of $e \approx 2.718$ if the target individual’s cluster is learned by the intruder. If the probability attached to a sensitive value in the cluster-level distribution is deemed too high, then one needs to reduce $\epsilon$.

To decide whether a probability has grown too much, one can resort to the connection with deniability highlighted in Section II-A as follows:

- Consider that the reported value $v$ is now the cluster identifier.
- Consider that the probabilities $\hat{p}_{uv} = \Pr(X = u|Y = v)$, for $u = 1, \ldots, r$ are the probabilities assigned by the cluster-level distribution to the values of the sensitive attribute within the cluster (we assume without loss of generality that the cluster contains $r$ different values).

With the above considerations, the problem of determining the real value $X$ given the reported value $Y$ becomes the problem of finding the target respondent’s sensitive value $X$ given the target respondent’s cluster $Y$. Thus, we can use the following deniability argument to assess whether the cluster-level distribution has become too inhomogeneous:

#### Example 3: Assume the sensitive attribute can take $r = 5$ different values and that its data set-level empirical distribution is uniform, so that the relative frequency of each value is 1/5. Take $\epsilon = 2$ as in Example 2. A cluster-level distribution where one value has relative frequency $1/5 \times \exp(1) = 0.5436$ and the remaining four values have relative frequencies 0.1141 satisfies $\exp(1)$-closeness; therefore, according to Proposition 1, it satisfies 2-differential privacy. However, whereas an intruder cannot guess the sensitive attribute value for a target respondent upon seeing the data set-level distribution, the guess is much easier if the intruder knows the target respondent’s cluster, because one of the values concentrates more than 50% of the relative frequency. Thus, $\epsilon = 2$ does not seem to offer enough protection.

### V. PRAM and the Permutation Paradigm

In [2], a permutation paradigm of anonymization was introduced. The authors first presented the following algorithm, that considers in turn each attribute $X$ in an original data set $X$ and the corresponding attribute $Y$ in the anonymized data set $Y$, and outputs an attribute $Z$ that is called the reverse-mapped version of $X$:

**Require:** Original attribute $X = \{x_1, x_2, \cdots, x_n\}$
**Require:** Anonymized attribute $Y = \{y_1, y_2, \cdots, y_n\}$

For $i = 1$ to $n$ do
- Compute $j = \text{Rank}(y_i)$
- Set $z_i = x_{(j)}$ (where $x_{(j)}$ is the value of $X$ of rank $j$)
end for

**return** $Z = \{z_1, z_2, \cdots, z_n\}$
From the algorithm description, $Z$ is a permutation of $X$, and the rank order of $Z$ is the same as the rank order of $Y$. Since the above algorithm makes no assumption on the anonymization procedure being used, it follows that any microdata anonymization technique is *functionally equivalent* to performing the following two steps one after the other:

1) **Permutation.** Each attribute $X$ of the original dataset is permuted into the corresponding $Z$. Thus, the data set $X$ is transformed into a data set $Z$.

2) **Residual noise addition.** Noise is added to each value of $Z$ to obtain the anonymized data set $Y$. (The noise is residual, because the ranks of $Z$ and $Y$ must stay the same).

Let us now look at how PRAM fits in the permutation paradigm. PRAM does not permute in the sense of swapping attribute values between records in the data set. Rather, it permutes in the *domain* of attributes: that is, a data set anonymized with PRAM may contain attribute values not present in the original data set. Hence, in terms of the permutation paradigm, PRAM should be viewed as permutation plus some noise. However, if $Y$ is a PRAM-ed data set, it can be reverse-mapped to a permuted data set $Z$ as explained above.

**VI. Calibrating Anonymization**

In Section II we connected PRAM and randomized response, in Section III we connected randomized response and differential privacy, in Section IV we connected differential privacy and $t$-closeness and in Section V we connected PRAM and the permutation paradigm. Therefore, the privacy notions captured by all those privacy models are less different than it seems. In particular, all of them can be expressed in terms of any of the following basic privacy ideas: deniability and permutation.

As illustrated in the examples above, deniability is useful to understand the privacy implications of relaxing the privacy parameters of $\epsilon$-differential privacy or $t$-closeness in quest of utility.

Permutation may also be useful to understand the level of privacy achieved and calibrate the anonymization parameters suitably. In [8], we showed how to use the permutation distance to find anonymization parameters that make any linkage claimed by an intruder between the anonymized data set and an external identified data set plausibly deniable by the data controller. In general, the stronger the anonymization, the more similar the permutation distances to those of random permutation, and the more linkage deniability. In the extreme case, a very strong anonymization can be viewed as a random permutation yielding random-looking data; any linkage between random-looking data and original data is intrinsically deniable.

We next explore two tools to calibrate permutation to attain suitable protection against disclosure and acceptable information loss. Due to the connections between permutation and the main privacy models shown in this paper, calibrating permutation can have broad applicability.

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**A. (d, v, f)-permuted privacy**

A privacy model called $(d, v, f)$-permuted privacy inspired in the above permutation paradigm was proposed in [2]. Given a vector $d = (d_1, ..., d_m)$ of non-negative integers, a vector $v = (v_1, ..., v_m)$ of non-negative real numbers, an original data set $X$ and an anonymized data set $Y$ both with $m$ attributes, and a record-level mapping $f : X \rightarrow Y$, we say $Y$ satisfies $(d, v, f)$-permuted privacy with respect to original record $x = (x_1, ..., x_m)$ in $X$ if $y_{i,j}^d$ being the value of the $j$-attribute $Y^j$ in the anonymized data set closest to $x^j$ for $j = 1, ..., m$.

1) The anonymized record $f(x) = (y_1, ..., y_m)$ satisfies $|\text{Rank}(y_j) - \text{Rank}(y_{i,j}^d)| \geq d_j (j = 1, 2, ..., m)$ ($d_j$ is called the *permutation distance* for the $j$-th attribute);

2) If $S^j(d_j)$ is the set of values of the sorted $Y^j$ whose rank differs no more than $d_j$ from the rank of $y_{1,j}^d$, then the diversity of $S^j(d_j)$ is greater than $v^j$ according to a given diversity criterion.

If anonymization is just a permutation, then $y_{1,j}^d = x^j$. For each original record $x$, the data protector can take as $f(x)$ the anonymized record derived from $x$. Diversity criteria for $S^j(d_j)$ may be the variance, one of the $l$-diversity criteria, or the $l$-closeness criterion. If $(d, v, f)$-permuted privacy holds w.r.t. all records in $X$, then we say it holds for the dataset $X$.

If an anonymization method $M$ with parameter $\text{parms}$ is used to obtain the anonymized version $Y$ of an original data set $X$, the data protector can compute what values of $d$ and $v$ the $(d, v, f)$-permuted privacy model holds with. If the variabilities in $v$ are not deemed sufficient or if the permutation distances in $d$ are not enough to provide deniable linkages, then the anonymization parameters $\text{parms}$ should be stronger or the method $M$ should be changed.

**B. Aggregation measures based on power means**

Also drawing inspiration on the permutation paradigm, an aggregation measure based on power means was proposed in [9] to aggregate the absolute permutation distances $p_1, ..., p_n$ resulting from anonymizing the values of an attribute in the $n$ records of a data set:

$$J((p_1, ..., p_n), \alpha) = \begin{cases} \frac{1}{n} \sum_{i=1}^{n} p_i^{\alpha} & \text{for } \alpha \neq 0; \\ \Pi_{i=1}^{n} p_i^{\alpha} & \text{for } \alpha = 0, \end{cases}$$

where $\alpha < 1$ turns the above measure into a disclosure risk measure and $\alpha > 1$ into an information loss measure. Indeed, the more $\alpha$ approaches $-\infty$, the greater is the weight of smaller permutation distances in Expression (8), since disclosure occurs when permutation distances for some values are too small; we have a disclosure risk measure when $\alpha$ is small. On the other hand, the more $\alpha$ approaches $+\infty$, the greater is the weight of larger permutation distances in Expression (8); since large permutation distances are the ones that most deteriorate utility, we have an information loss measure when $\alpha$ is large. Thus, for $\alpha < 1$, the greater the value
of $J((p_1, \ldots, p_n), \alpha)$, the more disclosure risk, whereas, for $\alpha > 1$, the greater the value of $J((p_1, \ldots, p_n), \alpha)$, the more information loss.

From the above discussion, when $\alpha < 1$, we have that $\alpha$ behaves as a risk aversion parameter: the smaller the $\alpha$ value chosen by the data controller, the more intolerable is disclosure considered. Analogously, when $\alpha > 1$, we have that $\alpha$ behaves as an information loss aversion parameter: the larger the $\alpha$ chosen by the data controller, the more intolerable is information loss.

Thus, if the controller is able to parameterize her risk aversion by choosing $\alpha_1 < 1$ and her information loss aversion by choosing $\alpha_2 > 1$, she can use $J((p_1, \ldots, p_n), \alpha_1)$ and $J((p_1, \ldots, p_n), \alpha_2)$ to calibrate the anonymization method $M$ and its parameters $\text{parms}$. Admittedly, choosing the right $\alpha_1$ and $\alpha_2$ and assessing whether $J((p_1, \ldots, p_n), \alpha_1)$ and $J((p_1, \ldots, p_n), \alpha_2)$ are acceptable may not be intuitive in most cases.

Anyway, these power-means measures may be used to compare the disclosure protection and the information loss achieved by two different anonymization methods $M$ and $M'$ (or by the same method $M$ with different parameters $\text{parms}$ and $\text{parms}'$).

VII. CONCLUSIONS AND FURTHER RESEARCH

We have highlighted several connections between privacy models, which gives a deeper insight into their nature. They turn out to be more related than anticipated, around the principles of deniability and permutation. In particular, randomized response turns out to be very modern in spite of it having been introduced more than 50 years ago: it is a local anonymization method and it allows understanding the protection offered by $\epsilon$-differential privacy when $\epsilon$ is increased to improve utility. A similar understanding of the effects of a larger $\epsilon$ can be gained by looking at the connection between $\epsilon$-differential privacy and $t$-closeness under the light of deniability. Finally, since PRAM can be viewed as permutation and is connected with randomized response and differential privacy, and the latter is connected to $t$-closeness, the permutation principle can be used to explain the guarantees offered by all those models. Hence, calibrating permutation is a matter of high interest in anonymization, and we have sketched two ways of approaching this issue.

Future research will involve giving more detailed guidelines for calibrating privacy models and anonymization methods in view of optimizing the trade-off between disclosure risk and information loss. Also, the knowledge gained on the common underlying principles of those models and methods should be helpful to tackle the grand challenge of applying and/or adapting them to big data.

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