Randori: Local Differential Privacy for All

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Abstract. Polls are a common way of collecting data, including product reviews and feedback forms. However, few data collectors give upfront privacy guarantees. Additionally, when privacy guarantees are given upfront, they are often vague claims about ‘anonymity’. Instead, we propose giving quantifiable privacy guarantees through the statistical notion of differential privacy. Nevertheless, privacy does not come for free. At the heart of differential privacy lies an inherent trade-off between accuracy and privacy that needs to be balanced. Thus, it is vital to properly adjust the accuracy-privacy trade-off before setting out to collect data.

Motivated by the lack of tools to gather poll data under differential privacy, we set out to engineer our own tool. Specifically, to make local differential privacy accessible for all, in this systems paper we present Randori, a set of novel open source tools for differentially private poll data collection. Randori is intended to help data analysts keep their focus on what data their poll is collecting, as opposed to how they should collect it. Our tools also allow the data analysts to analytically predict the accuracy of their poll. Furthermore, we show that differential privacy alone is not enough to achieve end-to-end privacy in a server-client setting. Consequently, we also investigate and mitigate implicit data leaks in Randori.

Keywords: accuracy bounds · data collection · data privacy · differential privacy · polls · randomized response · side-channels · tools

1 Introduction

Polls are a widely used way of collecting data. For example, one might be asked to fill out a review after purchasing an item online. Now, these polls can consist of an arbitrary number of intertwined questions. For example, after purchasing an item online, one might be asked “How do you feel about your purchase?” with answer alternatives ‘Happy’, ‘Neutral’ and ‘Unhappy’. Now, the merchant can also choose to add a follow-up question asking “What’s the reason you feel unhappy?” to all respondents that answer that they were unhappy with their purchase. That is, polls can become complex depending on the number of questions and follow-up questions.

Having established that polls are indeed an interesting way to gather data, we ask ourselves how we could gather such data while also providing our respondents with useful privacy guarantees. A popular topic within the area of
privacy-preserving data collection is **differential privacy**. Differential privacy is a rigorous statistical notion of privacy where privacy loss is quantified. To achieve privacy data is perturbed, usually through injecting data with controlled noise. As such, at the core of differential privacy lies an inherent trade-off between accuracy and privacy.

While differential privacy is widely accepted as a strong notion of privacy, it is mainly used in prototypes created by academics. So far, differential privacy in real, deployed systems, is only observed at tech giants such as Apple [21,22], Google [6] and Microsoft [2]. The US Census Bureau [8] also point out that there are several issues such as setting the privacy parameter ($\varepsilon$) and the lack of tools to verify the correctness of the implementation of differential privacy. We want to provide a tool that tackles the privacy parameter from an accuracy perspective, and that at the same time guarantees differential privacy. As such, we want to offer differential privacy for all interested in collecting poll data.

In order to successfully apply differential privacy to data collection, an analyst must not only correctly implement the noise injection, but also balance the accuracy-privacy trade-off for their particular data. What’s more, allowing arbitrarily intertwined data through follow-up questions creates additional challenges. From the example before, having answered the follow-up question leaks that the respondent felt unhappy about their purchase. Put differently, the poll structure has the ability to create unintentional, implicit information flows. As such, the data collection process can also contain side-channels that leak information, all of which are not captured by differential privacy itself.

Consequently, we identify three main problems with collecting poll data under differential privacy:

- Implementation needs to be correct
- Gathered data may be too inaccurate
- Side-channels may arise during collection

To make differential privacy accessible for all, we present a novel set of open source tools called **RANDORI**. RANDORI helps a data analyst first design a poll, tune the accuracy-privacy trade-off, and later collect data from respondents under differential privacy. What’s more, we have investigated and addressed side-channels that can arise when a respondent receives and answers a poll. These side-channels include, but are not limited to, implicit leaks from follow-up questions. As such, not only are we interested in accurate differentially private data collection, but we also protect privacy end-to-end throughout the entire collection process. By presenting RANDORI our contributions are:

+ Tools for designing polls, and collecting data under differential privacy
+ A tool for predicting and tuning accuracy for a given poll
+ A data collection process that is end-to-end private

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1 Source code available at (anonymous account):

https://www.dropbox.com/sh/kb0tvttt17eszdvb/AACC5RLsLjQ1xUh14__aHK1ea
2 Differential Privacy

Differential privacy is a statistical notion of privacy that represents a property of an algorithm, as opposed to being a property of data. As such, differential privacy is fundamentally different from privacy models such as k-anonymity [20], l-diversity [14] and t-closeness [12], where privacy guarantees are derived from what values are present in the data.

In this paper we focus specifically on local differential privacy [10], which is relevant whenever the mechanism is applied locally at the data source rather than centrally. In the rest of the paper, when we talk about differential privacy, we mean specifically local differential privacy.

Definition 1 ($\varepsilon$-Differential Privacy) A randomized algorithm $M$, with an input domain $A$ and an output domain $B$, is $\varepsilon$-differentially private if for all possible inputs $a$ and $a'$, and all possible output values $b$,

$$Pr[M(a) = b] \leq e^\varepsilon \times Pr[M(a') = b].$$

The core mechanism used in this paper to achieve differential privacy is a variant of the classic randomized response algorithm [24]. Using a binary input domain (‘yes’ or ‘no’), the randomized response algorithm can be described as follows: flip a coin $t$. If $t$ lands heads up then respond with the true answer (the input). Otherwise flip a second coin $r$ and return ‘yes’ if heads, and ‘no’ if tails.

Basically, this algorithm will either deliver the true answer, or randomly choose one of the viable answers. By delivering an answer in this way, we say that the respondent enjoys plausible deniability. That is, a respondent may always claim that their response was different from their true answer, without anyone being able to disprove their claim.

In this algorithm the bias of the coin $t$ determines the privacy-accuracy trade-off, whereas the coin $r$ can always be unbiased (i.e. it has a uniform distribution). The variant of this mechanism used in this paper is a simple generalization: it (i) allows for a non binary input domain, and (ii) permits the bias of the coin $t$ to be dependent on the value of the input.

Definition 2 (Randomized Response) Let $A$ be the data domain, and $T = \{t_a\}_{a \in A}$ be an indexed set of values in $[0, 1]$. Given these, we define the randomized response mechanism $M_T$, a randomized function from $A$ to $A$, as follows:

$$Pr[M_T(a) = b] = \begin{cases} t_a + r_a & \text{when } a = b, \\ r_a & \text{otherwise} \end{cases}$$

where $r_a = (1 - t_a)/|A|$.

A given randomized response mechanism $M_T$ can be viewed as a transition matrix. For example, suppose we have $A = \{a_1, a_2, a_3\}$ and $T = \{t_1, t_2, t_3\}$, then
$M_T$ can be represented as the transition matrix:

$$M_T = \begin{pmatrix} a_1 & a_2 & a_3 \\ a_1 & t_1 + r_1 & r_1 \\ a_2 & r_2 & t_2 + r_2 \\ a_3 & r_3 & t_3 + r_3 \end{pmatrix}$$

Note that each row sums to one (by definition of the $r_i$). The definition of differential privacy essentially compares any two values drawn from the same column of the matrix, so $\varepsilon$ is determined by the worst case among these:

**Theorem 1 (Differential Privacy of RR)** Randomized response mechanism $M_T$ is $\varepsilon$-differentially private, where $\varepsilon$ is given by maximizing the value of $(t_a + r_a)/r_b$ over $a, b \in A$ where $a \neq b$.

At this point it is appropriate to mention why we allow the ‘truth’ probability $t_a$ to be different for each input: we want this additional degree of control because we will support mechanisms built from making follow-up questions, as in “Do you smoke?” then if the answer is yes, follow with “More than 10 per day?” Since the follow-up question will effectively increase the precision of the ‘yes’ answer, we may choose to lower the initial precision of the ‘yes’ answer by lowering the value of $t_{\text{yes}}$. We say that we allow for non-uniform diagonals in our transition matrix. Later, in Section 6, we elaborate on the challenges non-uniformity creates when predicting accuracy.

Now, we also want to be able to reason about the accuracy of our algorithm. Deriving from the concept of a misclassification rate [10], we define our metric for error in Definition 3. That is, if a response $a$ gets mapped by the randomized response mechanism to a value other than itself, it is considered misclassified.

**Definition 3 (Error Metric)** Let $M_T$ represent randomized response, then given for any answer $a \in A$ the error is the probability of outputting any other output in $A$:

$$X_a = \Pr[M_T(a) \neq a]$$

A general analytical error bound [3], for any algorithm, is given by the Chernoff bound in Theorem 2. We say that an algorithm is ($\alpha, \beta$)-useful [25].

**Theorem 2 (Analytical Accuracy)** Let $X$ be a random variable representing the error of the output of a differentially private algorithm, and $\alpha, \beta$ two error bounds, then with probability $1-\beta$, the error $X$ is bounded by at most error $\alpha$:

$$\Pr[X \leq \alpha] \geq 1 - \beta$$

Next, we express $\beta$ in terms of $\alpha$ and include the population size $n$ in the equation by using additive Chernoff bounds:

$$\Pr[X \leq \alpha] \geq 1 - 2e^{-2\alpha^2n}$$
3 Methodology and Assumptions

In order to show that it is possible to build a tool for differentially private data collection that is end-to-end private in a server-client setting, we construct a proof of concept called Randori. Our intended goal is to build a prototype that works, not necessarily build one that is optimal from an accuracy, usability or performance aspect. Hence, our main focus is to make sure Randori’s data collection is indeed differentially private, and that the process itself is protected against information leakage. To limit our possible implementations, we have constructed a list of functional requirements for Randori in Section 3.1.

Recalling our example with a customer scoring a product they purchased online, Randori must protect all of the customers’ true answers. Note that differential privacy guarantees that any two outputs are (\(\epsilon\)-) indistinguishable, but since we capture and process the data in an interactive setting, we also need to make sure there are no implicit leaks. That is, we will also examine what data could potentially leak from the server-client setting. In order to make a thorough investigation, we introduce a threat model in Section 3.2.

3.1 Functionality Requirements

Our goal is to make a system that is I) differentially private by design, II) able to predict error and III) protected against side-channels. We break these goals down into requirements as follows:

1. Randomized response should be implemented automatically. Specifically, implementation details should be hidden from the data analyst.
2. \(\epsilon\) should be calculated automatically:
   (a) For the data analyst
   (b) For the respondent, since they do not trust the data analyst
3. The data analyst should be able to predict the error of a poll
4. The data analyst should be able to tweak the predicted error by changing the probability \((t)\) of randomly choosing each answer
5. Statistical noise should be filtered away automatically
6. Several data analysts should be able to cooperate, eliminating the need for every analyst to be a privacy expert themselves

Essentially, we want to remove most of the tedious details of implementing a differentially private algorithm, and let the data analysts focus on what data to collect, instead of how to collect it. With Item 1 and Item 5, we hide the implementation of randomized response under the hood of Randori.

Still, the value of \(\epsilon\) is something we cannot abstract away from the system completely. That is, we cannot set \(\epsilon\) to a ‘good’ value since ‘good’ is subjective and highly domain dependent. In the same way, error tolerance is also distinctly domain dependent. For example, \(\pm 10\sigma\) might be an acceptable error range when constructing scales for people, but not for scales used in medicine manufacturing. Hence, instead of trying to abstract away \(\epsilon\), we let the data analyst tune the privacy/accuracy trade-off themselves. The privacy/accuracy tuning is achieved through a combination of Item 2, Item 3 and Item 4.
Furthermore, we argue that Item 6 is important to make RANDORI more accessible in our case. Namely, by allowing multiple users, not every data analyst needs to be a privacy expert. That is, any data analyst can design the poll and collect the data without breaking differential privacy. Still, at least one user should be a privacy expert in the sense that someone needs to approve of the privacy/accuracy balance achieved.

3.2 Threat Model and System Privacy Guarantees

Adversary Model and Assumptions. We assume that adversaries can be either passive or active. The active adversary can send out polls using RANDORI. Consequently, we assume that the adversary can pose as a data analyst. The passive adversary can observe and read the contents of all network traffic between data analyst and respondent. That is, we consider both the case where the communication takes place in plain text, and the case where the adversary is strong enough to break any encryption used during communication. That is, we assume an adversary that can read message contents even when the communication is done over HTTPS. Still, we assume that the internal state of the code the respondent is running and the respondent’s hardware cannot be monitored by the adversary. That is, the respondent is entering their true answers into a trusted computing base.

We also assume that the respondent does not close their client before our code has finished executing. Later, we elaborate on ways to handle non-termination and the challenges of implementing these defenses in our discussion (Section 6).

We do not consider cases where the respondent is an adversary that tries to attack the accuracy of the poll by skewing their answers. That is, we will only consider attacks on privacy, and not attacks on accuracy.

Trust. The sensitive data in this setting is the respondents’ true answers to polls. That is, responses produced by randomized response are not considered sensitive as the respondent enjoys plausible deniability. Hence, sensitive data only resides in the respondent’s application.

Moreover, we consider the code running on the respondent’s device to be completely trusted by the respondent. That is, the code the respondent is running is allowed to hold and take decisions based on sensitive data.

As for the data analysts, we do not consider any of their data to be sensitive. Consequently, the poll questions are considered public data. Hence, the ϵ for any poll is also public data. We will also assume that the value of each respondent’s privacy budget is public. That is, whether or not a respondent has participated in a poll also becomes public. We do not attempt to hide the identity of the respondents, but settle for plausible deniability.

Furthermore, the data analysts are considered untrusted by the respondent. That is, the respondent only wants to share their poll answers under differential privacy, and do not wish to share any other data than what is publicly known with the data analysts.

System Guarantees. We guarantee that the respondent will enjoy differential privacy, meaning we assure plausible deniability. If the data analyst turns out
to be an adversary, the respondent still has plausible deniability, which we will not consider a privacy breach. We will guarantee that no matter the parameters fed to Randori, differential privacy still holds. For example, the probability of answering truthfully is guarded by a truth threshold value, since answering 100% truthfully provides no privacy. However, we do not guarantee that the value of the truth threshold nor the value of the respondent’s privacy budget are set to useful values: we merely enforce them.

As for randomness, we strive to make a best effort given the programming language used. Hence, our implementation of differential privacy uses Javascript’s Crypto library to ensure cryptographically strong random values [17], which is the strongest implementation of randomness available in JavaScript.

Furthermore, we guarantee that Randori protects against a number of side-channels that would break end-to-end privacy. To the best of our knowledge, these are all side-channels under our given threat model.

System Limitations. In Randori, the respondents do not have a persistent application. Hence, we cannot store the privacy budget between sessions. Instead, we assume a maximum budget per poll.

In its current state, Randori does not contain a trusted third party to send the Respondent UI to the respondents. Still, adding a third party only requires a minor change where the respondent visits the trusted third party to receive the Respondent UI, but polls can still be served by the untrusted data analyst.

We do not consider the identity of the respondents to be secret, and thus we do not protect against leaking information through participation alone.

Also, we do not guarantee security through encryption, since we assume an adversary strong enough to break encryption. Still, we expect the users to encrypt the communication and take adequate measures to store the collected data securely, but we leave this outside of our system scope.

4 Randori

Randori is a set of tools with two focal points as far as functionality goes. These focal points are: poll design and data collection. In this section we will both describe the functionality of Randori, the tools it consists of, as well as how differential privacy is achieved. Lastly, we describe the steps taken to assure end-to-end privacy, as this property is not captured by differential privacy itself.

4.1 Tools and Vision

Randori is a set of tools (Figure 1) that enable data analysts to first design, and then perform data collections under differential privacy.

We allow for multiple data analysts (Requirement item 6) by first focusing the scope of each tool, and secondly by choosing a portable data format that can easily be imported and exported by each tool.

Poll Design: Poll Editor The Poll Editor is where the data analyst creates and edits the poll structure and content. To be able to hide details under the hood it consists of two modes: edit and explore.
In the edit mode (screenshot in Appendix Figure 3) the data analyst can focus solely on the poll content: order of questions, number of answers and what answers trigger follow-up questions. That is, in the edit mode it is as if the data analysts is editing any poll, not a special poll that is to be gathered under differential privacy. Polls are imported/exported on our JSON format (Appendix Listing 1).

Then, the fact that data is to be gathered under differential privacy is visible in the explore mode (screenshot in Appendix Figure 10). Arguably, without adequate accuracy, collected data becomes useless to the data analyst. To mitigate the problem of high error, we let the data analysts explore the accuracy-privacy trade-off through two sets of parameters: (i) True/Random answers and Weight, and (ii) Alpha, Beta and Population.

The parameters from set (i) influence the value of $\varepsilon$, where the slider is a coarse-grained adjustment affecting all answers ($t_1, ..., t_n$ from transition matrix), and weight is a fine-grained adjustment available per answer (affecting a specific $t_a$). However, the analysts never directly sets any of the values in the transition matrix. Instead, $t_a$ is calculated from the product of the truth/random ratio, every parent’s weight and the answer’s own weight.

All parameters from set (ii) are part of the Chernoff bound and are calculated using Section 4.1. The parameters population, alpha and beta are shown on a per answer basis. The data analyst is required to set values for two of the parameters per answer, and the POLL EDITOR calculates the third parameter. For example, if the analyst requires a certain accuracy ($\alpha$), they can set $\alpha$ and explore what values of population and $\beta$ gives them their desired accuracy. Hence, the POLL EDITOR implements Requirements item 3 and item 4.

Based on Vadhan [23] we construct the following equation system to display the relationship between $\alpha$, $\beta$, $n$ and $\varepsilon$.

\[
\begin{align*}
\alpha &= \frac{1+e^\varepsilon}{e^\varepsilon-1} \\
\beta &= 2e^{-2\lambda^2n} \\
\varepsilon &= \log\left(\frac{n}{1-\frac{1}{\alpha}}\right) \\
n &= \frac{(1+e^\varepsilon)^2\log(2/\beta)}{2\alpha^2(e^\varepsilon-1)^2}
\end{align*}
\]

where $\lambda = \sqrt{\frac{\log \frac{2}{\varepsilon}}{2n}}$

**Data Collection: Server** The SERVER holds the currently active poll on our JSON format. The RESPONDENT UI then accesses the poll from e.g. `localhost:`
Next, data analysts can access poll results through e.g. localhost:5000/results. The server post-processes responses from the respondents by filtering away statistical noise using Bayes’ theorem. The results are shown to the data analysts in form of a JSON file. Hence, we fulfill Requirement item 5.

**Data Collection: Respondent UI** The Respondent UI (screenshot in Appendix Figure 11) is a JavaScript client running on the respondents’ device. As the Respondent UI is trusted by the respondent, it can branch on sensitive data to present the respondent with questions based on their previous answers. Hence, to the respondent, a Randori poll looks just like any other poll, but randomized response runs in the background. Hence, the Respondent UI also takes care of Requirement item 1. Also, since the respondents do not trust entities outside of the Respondent UI, the Respondent UI re-calculates $\epsilon$.

### 4.2 Differential Privacy

Differential privacy is achieved in Randori through randomized response. Since we are in the local setting, ensuring differential privacy is entirely done by the Respondent UI. In particular, we ensure differential privacy through the two following practices:

- Use of a strong random number generator client-side (Section 4.2)
- Data representation that prevents information leakage from follow-up questions (Section 4.2)

**Implementation of Randomized Response** The strongest implementation of randomness in JavaScript is a cryptographically random number generator. Hence, we will use JavaScript’s crypto library in our implementation. We show our implementation mainly as pseudo-code in Listing 1.6 in the Appendix.

Then, we calculate the corresponding value of $\epsilon$ (Listing 1.7). Here, we find the biggest possible ratio, when changing any answer, between the probabilities in the transition matrix. That is, we find the biggest possible ratio per column.

Before we let the respondent answer the poll, we check that they have enough budget left for the full poll. We have also introduced a truth threshold (here set to a dummy value of 0.99), as even polls with 100% of truthful answers would otherwise be considered valid polls. The corresponding validity checks are shown in Listing 1.8.

**Mitigating Structural Information Leakage** Next, we address implicit information leaks. In particular, we investigate how we can allow for follow-up questions without letting them leak information about their parent questions. Recalling our example from the introduction with the question “How do you feel about your purchase?”, only respondents that answer ‘Unhappy’ get a follow-up question. Accordingly, any answer to the follow-up question leaks that the first answer was ‘Unhappy’. We want to ensure that Randori can handle follow-up questions without leaking answers to other questions.
**Implementation:** Poll structure Version 1 (Figure 2)

**Problem:** By allowing first ‘Happy’, ‘Neutral’ and ‘Unhappy’ to be sent, then any reply reveals that the respondent answered that they were unhappy with their purchase. We need to make sure that the number of replies sent is indistinguishable no matter the actual answers.

![Figure 2: Version 1](image)

**Implementation:** Poll structure Version 2 (Figure 3)

**Reasoning:** We introduce an answer that is always valid for respondent’s that did not trigger the follow-up question, namely ‘N/A’.

**Problem:** The number of replies is indistinguishable, but we spend budget on ‘N/A’ which in this case implies not ‘Unhappy’. Note that we cannot determine if ‘N/A’ means ‘Happy’ or ‘Neutral’ in this case, so we are not able to achieve any additional accuracy even though we spent privacy budget on ‘N/A’. As such, while we do not break differential privacy, we end up wasting our budget by having to add ‘N/A’ for every follow-up question.

![Figure 3: Version 2](image)

**Implementation:** Poll structure Version 3 (Figure 4)

**Reasoning:** In this case, we represent the tree logically in the same way as version 2, but we only send one response. That is, the dotted nodes represent answers that the respondent can choose, but that are never sent. Basically, we allow for the respondent to traverse the tree and choose an answer to
each triggered question, but in reality the client will only send one response to each subtree (a question and all its follow-ups) of the poll. Since the client is a trusted component, branching on secrets is ok, so we can do this without leaking information. In this example, the respondents that choose ‘Happy’ or ‘Neutral’, are never asked why they were unhappy (which they were not), but the server never learns this due to the use of a single response.

![Diagram of the poll structure](image)

Fig. 4: **Version 3:** Follow-up with less answers than previous implementation to preserve privacy budget

### 4.3 End-to-End Privacy

Simply implementing randomized response to deliver responses is not enough to protect respondents’ privacy, since the data collection process is may leak additional information. For example, information leakage through side-channels such as differences in timing, is not captured by randomized response. Consequently, to achieve end-to-end privacy, we need to make sure RANDORI protects against side-channels. Next, we iterate through our implementation of the RESPONDENT UI to show the side-channels we have encountered.

| Listing (1.1) Version 1                  | Listing (1.2) Version 2                  |
|-----------------------------------------|-----------------------------------------|
| 1 var answers = {};                     | 1 var answers = {};                     |
| 2 fetch('/poll');                       | 2 var timeout = 9000; //Example          |
| 3 ...                                   | 3 fetch('/poll');                       |
| 4 // Respondent answers poll            | 4 setTimeout(submit, timeout);          |
| 5 ...                                   | 5 ...                                   |
| 6 let reply = rr(answers);              | 6 // Respondent answers poll            |
| 7 fetch('/submit', {                   | 7 ...                                   |
| 8 method: ‘POST’,                       | 8 function submit(){                   |
| 9 body: JSON.stringify(reply)          | 9 let reply = rr(answers);              |
| 10 });                                  | 10 fetch('/submit', {                |
|                                         | 11 method: ‘POST’,                      |
|                                         | 12 body: JSON.stringify(reply)         |
|                                         | 13 });                                 |
|                                         | 14 }                                   |
Listing (1.3) Version 3

```javascript
function submit (){
  for (answer in answers) {
    if (answers[answer] == null) {
      answers[answer] = random();
    }
  }

  let reply = rr(answers);
  fetch ('/submit', { method: 'POST', body: JSON.stringify(reply) });
}
```

Listing (1.4) Version 4

```javascript
... 

var shadow = {};
var random = {};
fetch ('/poll');
for (question in poll) {
  random[question] = random();
}
setTimeout(submit, timeout);

function submit () {
  for (answer in random) {
    if (shadow[answer] == null) {
      answers[answer] = random[answer];
    } else {
      answers[answer] = shadow[answer];
    }
  }

  //RR
}
```

▷ **Implementation**: Version 1 ([Listing 1.1](#))

✓ **Problem**: Answering time depends on answers to poll. That is, when the response is sent depends on the real answers. Hence, the answering time represents a timing channel.

▷ **Implementation**: Version 2 ([Listing 1.2](#))

✓ **Reasoning**: By using Javascript’s `setTimeout(time, function)` we are able to call `submit()` in constant time. Essentially, `setTimeout` sleeps for a given time and then executes the function. Furthermore, even though the respondent can press a submit button, that button does not trigger a POST. Consequently, even if a respondent finishes the poll before timeout occurs, the client still waits for the timeout.

✓ **Problem**: If timeout happens before the respondents answers the full poll, the collector learns which questions were not answered. Hence, we need to populate all unanswered questions.

▷ **Implementation**: Version 3 ([Listing 1.3](#), full version [Listing 1.9](#))

✓ **Problem**: The amount of unanswered questions will create a difference in timing. That is, the more unanswered questions, the more times line 3-4 will be executed. Hence, filling in unanswered questions creates a new timing channel.

▷ **Implementation**: Version 4 ([Listing 1.4](#), full version [Listing 1.10](#))

✓ **Reasoning**: By pre-populating each question with a random answer, we create a loop that executes in constant time (only depends on the amount of questions, which is not secret).
5 Privacy Evaluation

In this section, we will first convince the reader that our implementation is in fact differentially private (Section 5.1). Next, we will evaluate end-to-end privacy by investigating the two attack surfaces available to the adversary: the communication and the content of the response sent (Section 5.2).

5.1 Differential Privacy

As we use randomized response which is already a well established differentially private algorithm, we will only check that our implementation is sane. First, we check the validity of \( t_1, ..., t_n \) and \( r_1, ..., r_n \) on line 5 and 4 respectively (Listing 1.8). Next, we give formal privacy guarantees. From Listing 1.7, it is clear that we find the biggest ratio for any outputs in the same column of the transition matrix. That is, we calculate the biggest possible difference between two data sets as by the definition of differential privacy (Definition 1). Consequently, our implementation is \( \varepsilon \)-differentially private, with an \( \varepsilon \) depending on the amount of answers, and \( t_1, ..., t_n \).

Through line 6 (Listing 1.8), we enforce the respondents’ budget threshold. Since the server is untrusted by the respondent, the client calculates the value of \( \varepsilon \) from the poll structure (line 3 Listing 1.8). The client will not allow the respondent to answer any question if the respondent cannot afford the full poll (line 7 Listing 1.8). Since we assume the value of a respondent’s budget is public information, we do not leak any additional information by not answering due to insufficient budget.

From Section 4.2 it is clear that the implicit flow introduced by follow-up questions is mitigated through flattening each question tree. To clarify, since questions with any amount of follow-up questions and questions with no follow-up question both return exactly one response, they are indistinguishable to the attacker.

| Property                | Implementation                  |
|-------------------------|---------------------------------|
| Validity of poll        | Checked on trusted device       |
| Calculation of \( \varepsilon \) | By Theorem 1 on trusted device |
| Enforcement of budget   | Before poll                     |
| Follow-up question triggered or untriggered | Indistinguishable |

Table 1: Evaluated properties

5.2 Side-Channels

Based on our threat model (Section 3.2), the passive adversary can observe and read any network traffic between a data analyst (or an adversary) and a respondent. Since we already explore the implementation of differential privacy, we now assume that all responses sent have plausible deniability. Hence, the adversary cannot learn anything about the true answer from observing a response.

In order to learn the true answers, the adversary hopes to observe differences in communication or responses and be able to reverse engineer the true
answers. Since we are trying to prove the absence of side-channels, our goal is to exhaustively show all possible cases where true answers could cause differences in communication and poll answers, and refute the possibility of them arising in RANDORI. Thus, our objective is to make sure different answers are indistinguishable to the adversary.

There are two attack surfaces available to the adversary: the communication itself and the message content. We have identified three cases (Figure 7), which we walk through next.

(a) The adversary can learn true answers to questions if a respondent requests (or does not request) follow-up questions

(b) From observing when a poll is received and when the responses are sent, the adversary learns the answering time

(c) Illustration of a poll response with unanswered questions

Fig. 7: The three identified cases

Case A

- **Attack surface:** communication.
- **Adversary goal:** learn which follow-up questions the respondent triggers, to deduce answer to previous question.
- **Example attack:** irrelevant and different follow-up questions to each answer. That is, the adversary would be able to observe which questions the respondent requests from the server (Figure 7a).

There are only two types of communication between the Respondent UI and the Server in our implementation: 1) poll request and 2) response post. We need to make sure that the number of GET and POST messages are not related to the respondent’s true answers.

**Mitigation:** Always send the full poll. Our implementation does not allow the respondent’s client to send any data when requesting a poll (Listing 1.10 line 5) thus requesting anything but the whole poll is impossible. Also, the Respondent UI only replies with one POST containing all responses at once. Hence, the scenarios next listed are indistinguishable by design:

- Respondent requests all questions
- Respondent requests some questions
- Respondent requests no questions
Case B

- **Attack surface:** communication.
- **Adversary goal:** learn one specific answer.
- **Example attack:** many follow-ups for one specific answer. That is, the adversary will be able to observe differences in how long time it takes for the respondent to finish the poll (Figure 7b). Here, longer answering time means the follow-up was triggered.

There could be different reasons for differences in answering time, and while it may not be possible for the attacker to say with 100% certainty that the answering time is because of the adversary’s follow-ups being triggered, the adversary will be able to shift the probability of this being true. Thus, the adversary would be able to gain an advantage.

Consequently, we want to make any reason for differences in timing indistinguishable to an attacker, such that differences in timing do not leak any additional information.

**Mitigation:** timeout assures constant answering time, since `submit()` is triggered by the timeout (Listing 1.10 line 9). Furthermore, the same amount of instructions are executed (Listing 1.10 line 16-17 vs line 19-20) whether the question has been answered or a random pre-populated answer is used. What’s more, the for-loop is over `var random`, which is of constant size as it contains all question in the poll. Lastly, since the adversary cannot examine the respondent’s hardware, they cannot distinguish between the paths in the if-else. Next, we list the differences in timing our implementation takes into account and mitigates:

- Respondent triggers no follow-ups
- Respondent triggers some follow-ups
- Respondent triggers all follow-ups
- Respondent answers fast, not related to follow-up
- Respondent answers slowly, not related to follow-ups

Case C

- **Attack surface:** message content.
- **Adversary goal:** learn one specific answer.
- **Example attack:** many follow-ups for one specific answer which cause the respondent to timeout before answering the last question (Listing 1.5). No answer to the last question means the follow-ups were triggered. Note that this specific attack is introduced by our need to use a timeout.

Since the request for the poll contains no data entered by the respondent, the only place for possible information leakage is through the response post. As each response to a question benefits from plausible deniability due to randomized response, the actual response leak no information. However, unanswered questions would indeed leak if the respondent answered the question or not. Accordingly, the adversary could learn something by observing how many and which questions are unanswered/answered in the response message.
Mitigation: Since our implementation ensures that each question will have exactly one answer (Listing 1.10 line 14-27), the adversary cannot learn anything new from observing which questions are answered/unanswered. Next, we iterate through all different scenarios where the amount of answered questions could differ:

- Respondent answers no questions
- Respondent answers some questions
- Respondent answers all questions

6 Discussion, Limitations and Future Work

We believe one of the key issues for data analysts to start using differential privacy is understanding the accuracy loss differential privacy causes. In our setting, there is a potential for dependence between answers due to the fact that we allow follow-up questions which makes reasoning about accuracy more complicated. For example, recalling the question “How do you feel about your purchase?”, answering anything to the follow-up question implies that you were unhappy with your purchase. Hence, each follow-up answer adds accuracy to their parent answer. Then, since we allow the data analysts to create polls with arbitrary amount of follow-ups, each answer can have complex dependencies. As such, it is no longer clear that uniform randomized response is optimal (i.e. gives each answer equal accuracy), since accuracy is skewed by the fact that the relationships between answers is inherently known by design.

Consequently, we allow for non-uniform diagonals in our transition matrix. While this gives the data analyst more freedom to properly weight their accuracy among answers, it also makes understanding the error more difficult. Hence, we show a Chernoff bound per answer, but this also means that the parameters \((\alpha, \beta, n)\) also needs to be tweaked per answer. So while we let the data analyst explore the estimated error, we also believe that analytical error bounds may be too blunt for complex polls. Thus, extending RANDORI to include empirical error evaluation remains an open and interesting challenge. In fact, we are currently working on a simulation environment that allows for this kind of empirical evaluation.

As for trust, we acknowledge that the respondent’s receive their client code from the untrusted server. Since the source code of the client is released open source, we assume that the respondent would trust a third party to verify the client code. However, we do not perform any third party checks before letting the respondent answer the poll at this time. A possible and simple extension would be to let a third party serve the client code, and the data analyst would just send the poll.

Regarding the respondent not having a persistent application: this raises two problems. First of all, we do not have a way to save budgets between sessions. We have noted this in our system limitations, but in a real setting this of course becomes a problem, especially when dealing with multiple polls. Our intention is for RANDORI’s RESPONDENT UI to be part of an already existing system, for example a web page where the respondent already has an account, which is
why we left persistent budgets out of scope. Still, it is important to remember that the respondent’s budget needs to be held and updated by a system that the respondent trusts.

Secondly, since the respondent does not have a persistent application, the timeout fails if the respondent closes their client before timeout happens. When the timeout fails, the analyst will not get any response, and as such the analyst’s answer may become less accurate than expected (since the prediction is based on $n$ answers, not $n-1$). With a persistent application, the timeout could be paused and resumed if the respondent closes the application. Hence, the data analysts could possibly lose less answers, given that the respondents opened their application again. While this new behavior would change our setting, it would only allow adversaries to learn when the respondent used the application, and not anything about the respondent’s true answers. Consequently, allowing the timeout to be kept alive across sections could be beneficial to the data analyst in terms of accuracy, but does not change the respondent’s privacy guarantees. However, implementing a persistent timeout process that the respondent could not (accidentally nor maliciously) kill would allow us to loosen our assumptions by no longer requiring “the respondent does not close the poll before timeout occurs”.

We also acknowledge that the timeout the client uses to avoid timing side-channels introduces a new problem area: if it is too long, we risk that the participant closes the client too early, and if it is too short, the participant might not have time to answer all questions. We do not provide a definitive answer as to what is the best value for this timeout. The problem is mainly that deciding on an optimal value for a timeout is case dependent, and thus very difficult to give a general answer to.

Lastly, one entirely unexplored area of RANDORI is usability. So far, we present RANDORI as a way of making differential privacy more accessible to data collectors, as opposed to the optimal way. We have also chosen to focus on making differential privacy usable for the data analysts. Hence, interesting next steps for future work include user studies 1) where real data analysts collect data using RANDORI, and 2) where we collect data from real respondents. In particular, it would be interesting to let the respondents control their own privacy budget. That is, which values of $\varepsilon$ they are comfortable with before they start answering the polls. As of now, the client only calculates the $\varepsilon$, but does not enforce a ‘useful’ (customized) value of $\varepsilon$ in relation to the respondent.

7 Related Work

The real world example that is most similar to RANDORI based on what data is collected is the US Census Bureau’s deployment of differential privacy [7]. Even though we collect similarly structured data, a big difference is that the Census Bureau’s implementation has been tailored to specific data and therefore deploys release mechanisms under centralized differential privacy.
Several other applications have achieved end-to-end privacy by using local
differential privacy, for example applications by Google [6], Apple [21,22,1] and
Microsoft [2]. A key difference between RANDORI and these application is how
we choose to gather data. Hence, interacting with respondents and gathering
inherently dependent data makes RANDORI novel in comparison.

Next up, work that focuses on making differential privacy accessible. First,
the Haskell library DPella [13] is similar to RANDORI when it comes to our
use of Chernoff bounds for exploring accuracy. Still, DPella is intended to be
used by programmers, and assumes that the data is already stored in a database.
DPella is also not limited to randomized response as opposed to RANDORI.

Secondly \( \epsilon\)kTeLO shares a similar objective with RANDORI as far as providing
accurate, differentially private algorithms to users. Noted, \( \epsilon\)kTeLO is much more
general than RANDORI, and allows users to define new algorithms. What’s more,
\( \epsilon\)kTeLO also concerns the performance of algorithms, which is something we have
left completely out of scope in this paper.

Next, Pythia [11] has a similar objective as far as providing a tool for non-
experts to be able to use differential privacy. Pythia is a meta-algorithm that
privately finds the most accurate differentially private algorithm to be used for
certain input data. Where Pythia aims to find the most accurate algorithm,
with RANDORI we aim to help the analyst construct the poll that can give them
the most accurate results.

Along the same line of reasoning, the entire Harvard privacy tools project [9]
shares a common goal with RANDORI as far as making privacy accessible. The
project’s currently released software focusing on differential privacy are OpenDP
and \( \Psi \). OpenDP is a combination of open tools and end-to-end differentially
private systems. As such, RANDORI could have very well been a part of OpenDP
as RANDORI is both open source and an end-to-end differentially private system.
\( \Psi \) on the other hand is a system for sharing collected data under differential
privacy. In essence, RANDORI and \( \Psi \) only share accessibility as a goal, as RAN-
DORI is focused on private data collection whereas \( \Psi \) is intended for centralized
data sharing.

Other differentially private systems include Airavat [19] and Gupt [16].
Airavat is a distributed system catered for non-privacy experts. Since Airavat
is a complete system, the authors also focuses on several other issues, such as
performance and access control. In a similar manner, Gupt is a system intended
for enforcing centralized differential privacy on large volumes of data, to be used
by non-experts. Our work is only similar through the shared goal of making
differential privacy more accessible.

Lastly, we note that there exist several programming languages that make dif-
ferential privacy accessible to programmers. Among these are PINQ [15], FUZZ [18]
and the framework PRETPOST [10], all intended to be used by experienced pro-
grammers. In comparison, our work is more general from an accessibility per-
spective, by focusing on aiding non-experts that are not necessarily programmers
to use differential privacy.
8 Conclusion

We implement Randori, a set of tools for poll design and data collection under differential privacy. A novel part of Randori is that we include the data collection process when reasoning about privacy, and hence we also protect against implicit information leakage. What’s more, we make Randori available for all by releasing it as open source software, in order to motivate uninitiated parties to collect data under differential privacy.

To convince the reader that Randori is indeed both differentially private and end-to-end private, we show that our implementation adheres to differential privacy through investigating the code line by line. Then, we evaluate and address how we protect polls from implicit information flows. Next, we evaluate end-to-end privacy by systematically walking through each attack surface and eliminate potential attacks. Consequently, through Randori, we have made three contributions that map to our originally identified problems. Namely, we provide:

+ tools for designing polls and collecting data under differential privacy
+ a tool for predicting and tuning accuracy of a given poll
+ an end-to-end private implementation of randomized response in a server-client setting

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Appendix

Pseudo Code

Listing 1.6: Randomized response as pseudo-code

```javascript
var transitions = pollToMatrix();
function rr(answers){
  for(answer in answers){
    // Find output space
    let outputs = {};
    // Use transitions to get
    // probability per output
    let ranges = {};
    // Use cryptographic random [1, gcd]
    let random = getRandomInt(1, gcd);
    outputs[answer] = ranges[random];
  }
}
```

Listing 1.7: Calculation of $\varepsilon$ as pseudo-code

```javascript
var epsilon = undefined;
// For each question subtree
let potential_epsilon = undefined;
// For each answer
let max = undefined;
let min = undefined;
// Loop through all other answers
// Get max probability ratio
let check=Math.max(max.div(min), min.div(max));
// Bigger?
if(potential_epsilon===undefined || potential_epsilon<=check){
  potential_epsilon = check;
}
epsilon+=potential_epsilon;
```

Listing 1.8: Enforcement of budget thershold

```javascript
var budget = 100; // ln(budget)
var truth_threshold = 0.99;
var cost = calculateEpsilon();
var ok_truth = withinThreshold();
if(cost > budget){
  //Disable UI
} else if(!ok_truth){
  //Disable UI
} else {
  budget-=cost;
  // Show poll
}
```
Listing 1.9: Version 3

```javascript
var answers = {};
var timeout = 9000; // Example
fetch('/poll');
setTimeout(submit, timeout);

// Respondent answers poll

function submit(){
  for(answer in answers){
    if(answers[answer]==null){
      answers[answer]=random();
    }
  }
  let responses = rr(answers);
  fetch('/submit', {
    method: 'POST',
    body: JSON.stringify(responses)
  });
}
```

Listing 1.10: Version 4

```javascript
var answers = {};
var shadow = {};
var random = {};
var timeout = 9000; // Example
fetch('/poll'),
for(question in poll){
  random[question]=random();
}
setTimeout(submit, timeout);

// Respondent answers poll

function submit(){
  for(answer in random){
    if(shadow[answer]==null){
      answers[answer]=
    random[answer];
    } else {
      answers[answer]=
    shadow[answer];
    }
  }
  let responses = rr(answers);
  fetch('/submit', {
    method: 'POST',
    body: JSON.stringify(responses)
  });
}
Graphical Interfaces

Fig. 8: The edit mode of the Poll Editor
Listing 1.11: JSON format of the example question

```json
{
  "children": [
    {
      "qid": "F1",
      "question": "What’s the reason you feel unhappy?",
      "answers": ["Didn’t meet my expectations", "Product was damaged", "Other"],
      "probability": ["1/3", "1/3", "1/3"]
    }
  ],
  "roots": [
    {
      "qid": "Q1",
      "truth": "1/2",
      "question": "How do you feel about your purchase?",
      "answers": ["Happy", "Neutral", "Unhappy"],
      "probability": ["1/3", "1/3", "1/3"]
    }
  ],
  "paths": ["Q1", "Unhappy", "F1"],
  "order": ["Q1"]
}
```

Fig. 9: The JSON produced by the example question

Chernoff bound:

Pr(error <= alpha) >= beta,
where error = Pr[¬ answer|random]

Fig. 10: The explore mode of the Poll Editor
How do you feel about your purchase?

- Happy
- Neutral
- Unhappy

Cost is: 2.0794415416798357 (ln(7.999999999999999))

Fig. 11: The respondent’s view of the poll, here explicitly showing ε and chosen answers. Note that fractions are used in calculations internally, but here we are showing cost as floating point numbers.