

Pseudocode and Diagrams for Differential Privacy Methods

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1 Introduction

This document presents the pseudocode and conceptual diagrams of the differential privacy methods implemented for quantitative and categorical variables. The included algorithms are:

- **Quantitative Data:**

- Duchi et al. Mechanism (`duchi_mechanism`)
- Laplace Mechanism (`laplace_mechanism`)
- Piecewise Mechanism (`piecewise_mechanism`)
- Multidimensional Duchi Mechanism (`multidimensional_duchi_mechanism`)
- Custom Multidimensional Mechanism (`multidimensional_mechanism`)

- **Categorical Data:**

- Direct Encoding (`direct_encoding`)
- Optimized Unary Encoding (OUE) (`optimized_unary_encoding`)
- RAPPOR (`rappor`)

Below, the pseudocode and diagram for each of these methods are presented.

2 Pseudocode and Diagrams for Quantitative Methods

2.1 Duchi et al. Mechanism (`duchi_mechanism`)

Algorithm 1 Duchi et al. Mechanism

Require: Input vector t_i with values in $[-1, 1]$, privacy budget ϵ

Ensure: Privatized vector t_i^*

- 1: **for** each element t_i in the input vector **do**
 - 2: Clone and convert t_i to double precision
 - 3: Compute $\tanh\left(\frac{\epsilon}{2}\right)$
 - 4: Compute probability $p = 0.5 \times (1 + t_i \times \tanh(\epsilon/2))$
 - 5: Generate Bernoulli variable u with probability p
 - 6: Compute scaling factor $w = 1/\tanh(\epsilon/2)$
 - 7: Compute $t_i^* = (2u - 1) \times w$
 - 8: **end for**
 - 9: **return** Vector t_i^*
-

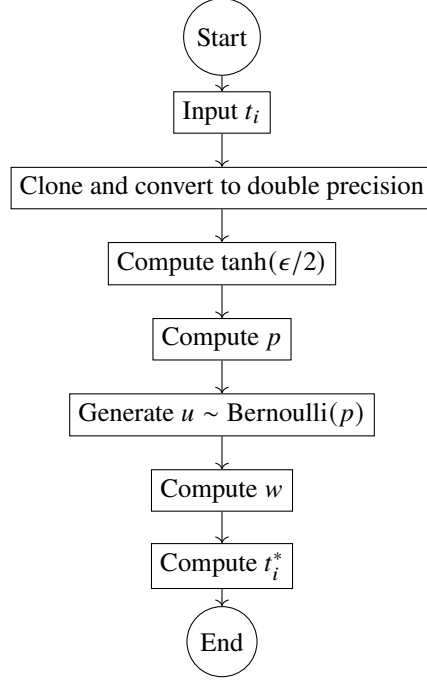


Figure 1: Diagram of the Duchi et al. Mechanism

2.2 Piecewise Mechanism (piecewise_mechanism)

Algorithm 2 Piecewise Mechanism

Require: Input vector t_i with values in $[-1, 1]$, privacy budget ϵ

Ensure: Privatized vector t_i^*

- 1: Compute $e^{\epsilon/2}$ and $C = \frac{e^{\epsilon/2} + 1}{e^{\epsilon/2} - 1}$
 - 2: **for** each element t_i in the input vector **do**
 - 3: Clone and convert t_i to float
 - 4: Compute $l(t_i)$ and $r(t_i)$
 - 5: Generate $x \sim \text{Uniform}(0, 1)$
 - 6: Compute threshold $u = \frac{e^{\epsilon/2}}{e^{\epsilon/2} + 1}$
 - 7: **if** $x < u$ **then**
 - 8: Generate t_i^* uniformly in $[l(t_i), r(t_i)]$
 - 9: **else**
 - 10: Randomly choose between intervals $[-C, l(t_i)]$ and $[r(t_i), C]$
 - 11: Generate t_i^* uniformly in the selected interval
 - 12: **end if**
 - 13: **end for**
 - 14: **return** Vector t_i^*
-

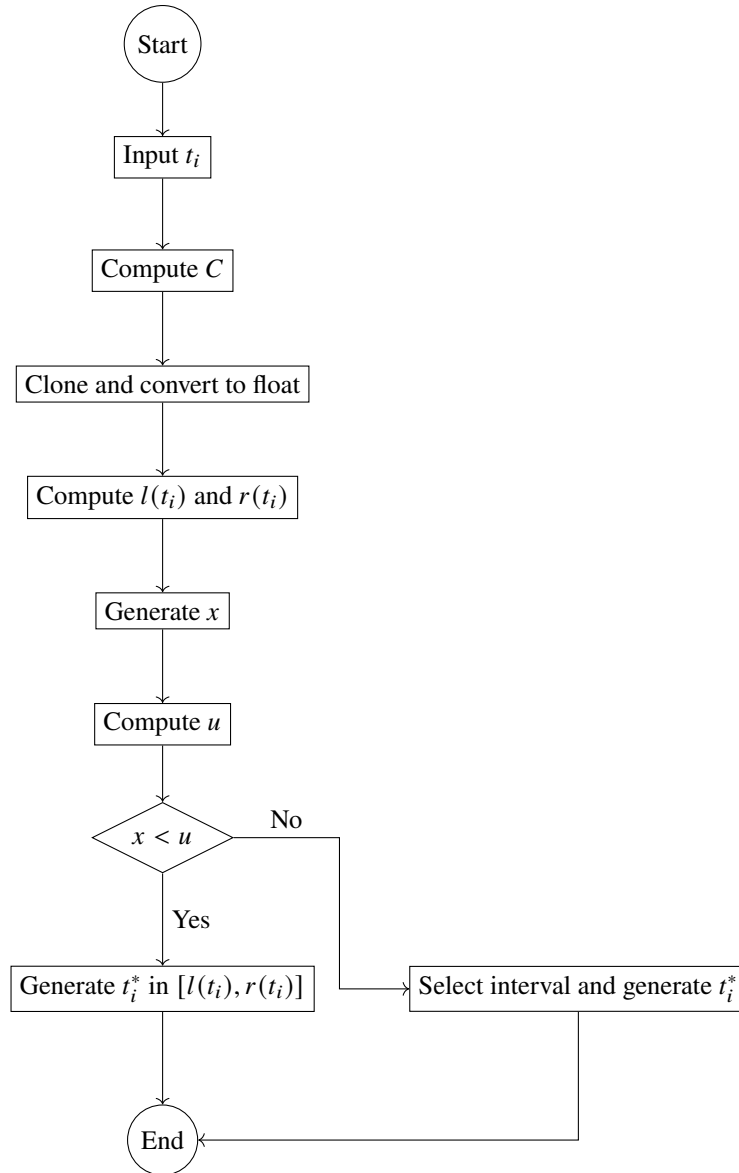


Figure 2: Diagram of the Piecewise Mechanism

2.3 Laplace Mechanism (laplace_mechanism)

Algorithm 3 Laplace Mechanism

Require: Input vector t_i , privacy budget ϵ , sensitivity s

Ensure: Privatized vector t_i^*

- 1: **for** each element t_i in the input vector **do**
 - 2: Clone and convert t_i to float
 - 3: Compute scale $b = s/\epsilon$
 - 4: Generate Laplace noise $n \sim \text{Laplace}(0, b)$
 - 5: Compute $t_i^* = t_i + n$
 - 6: **end for**
 - 7: **return** Vector t_i^*
-

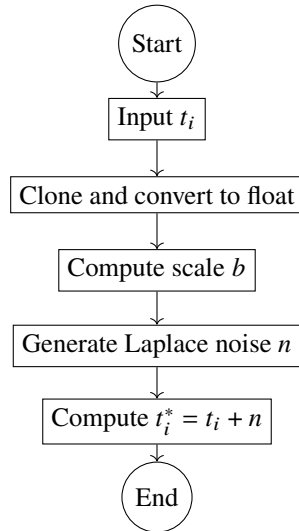


Figure 3: Diagram of the Laplace Mechanism

2.4 Multidimensional Duchi Mechanism (multidimensional_duchi_mechanism)

Algorithm 4 Multidimensional Duchi Mechanism

Require: Input vector t_i of dimension d , privacy budget ϵ , number of samples N

Ensure: Privatized vector t_i^*

- 1: Clone and clamp t_i to the range $[-1, 1]$
 - 2: Generate random vector $v \in \{-1, 1\}^d$ based on t_i
 - 3: Generate sets T_+ and T_- via random sampling
 - 4: Compute probability $p = \frac{e^\epsilon}{e^\epsilon + 1}$
 - 5: Generate Bernoulli variable u with probability p
 - 6: **if** $u = 1$ and $T_+ \neq \emptyset$ **then**
 - 7: Randomly select t_i^* from T_+
 - 8: **else if** $T_- \neq \emptyset$ **then**
 - 9: Randomly select t_i^* from T_-
 - 10: **else**
 - 11: Assign $t_i^* = B$ or $-B$ according to u
 - 12: **end if**
 - 13: **return** Vector t_i^*
-

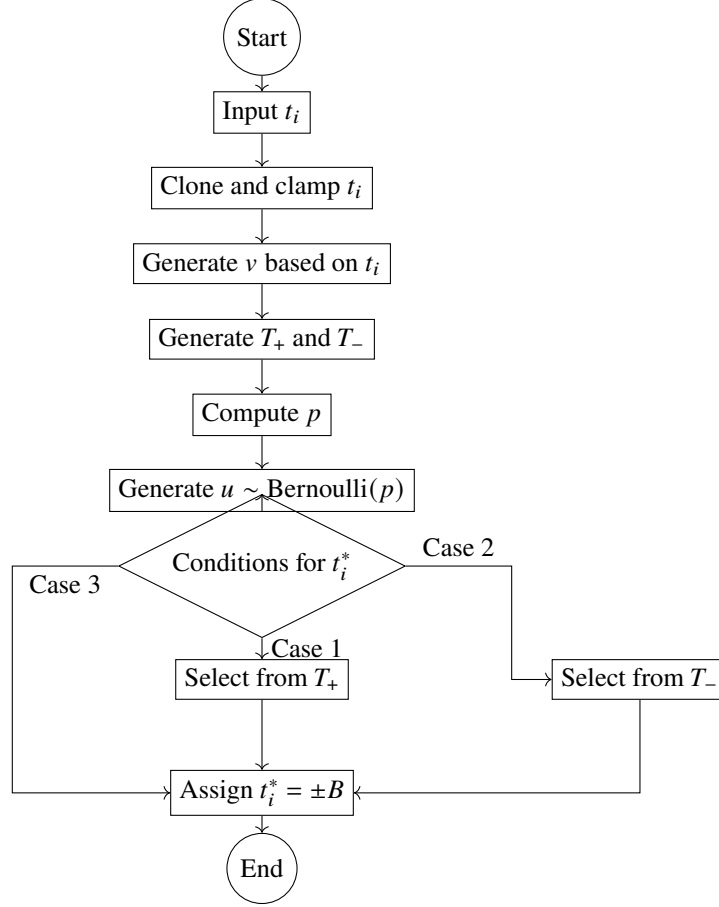


Figure 4: Diagram of the Multidimensional Duchi Mechanism

2.5 Custom Multidimensional Mechanism (multidimensional_mechanism)

Algorithm 5 Custom Multidimensional Mechanism

Require: Input vector t_i of dimension n , privacy budget ϵ , unidimensional mechanism M , constant C

Ensure: Privatized vector t_i^*

- 1: Clone and clamp t_i to the range $[-1, 1]$
 - 2: **for** each index i in n **do**
 - 3: Apply mechanism M to t_i with budget ϵ
 - 4: Scale t_i^* by multiplying with C
 - 5: **end for**
 - 6: Clamp t_i^* to the range $[-C, C]$
 - 7: **return** Vector t_i^*
-

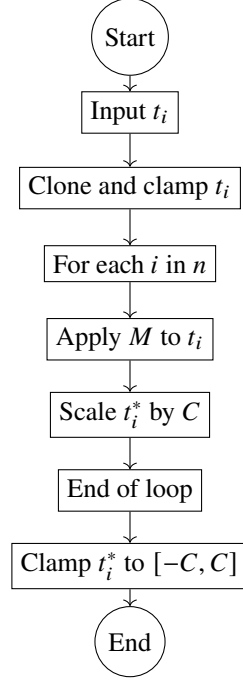


Figure 5: Diagram of the Custom Multidimensional Mechanism

3 Pseudocode and Diagrams for Categorical Methods

3.1 Direct Encoding (direct_encoding)

Algorithm 6 Direct Encoding

Require: Categorical data X , privacy budget ϵ

Ensure: Privatized data X^*

- 1: Encode categories with numerical values
 - 2: Obtain the number of categories k
 - 3: Compute $p = \frac{e^\epsilon}{e^\epsilon + k - 1}$
 - 4: Compute $q = \frac{1}{e^\epsilon + k - 1}$
 - 5: **for** each element x_i in X **do**
 - 6: Assign probabilities: p to the original category, q to the others
 - 7: Generate category x_i^* based on the assigned probabilities
 - 8: **end for**
 - 9: **return** Privatized data X^*
-

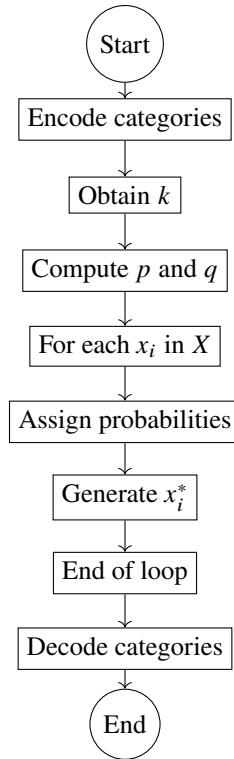


Figure 6: Diagram of Direct Encoding

3.2 Optimized Unary Encoding (OUE) (optimized_unary_encoding)

Algorithm 7 Optimized Unary Encoding (OUE)

Require: Categorical data X , privacy budget ϵ

Ensure: Privatized data X^*

```
1: Encode categories with numerical values
2: Obtain the number of categories  $d$ 
3: Create original binary matrix (One-Hot Encoding)
4: Set  $p = 0.5$  and  $q = \frac{1}{e^\epsilon + 1}$ 
5: for each binary vector  $u_i$  do
6:   for each bit  $u_{ij}$  in  $u_i$  do
7:     if  $u_{ij} = 1$  then
8:       Perturb  $u_{ij}$  with probability  $p$ 
9:     else
10:      Perturb  $u_{ij}$  with probability  $q$ 
11:    end if
12:  end for
13:  Reconstruct  $x_i^*$  from the perturbed vector
14: end for
15: return Privatized data  $X^*$ 
```

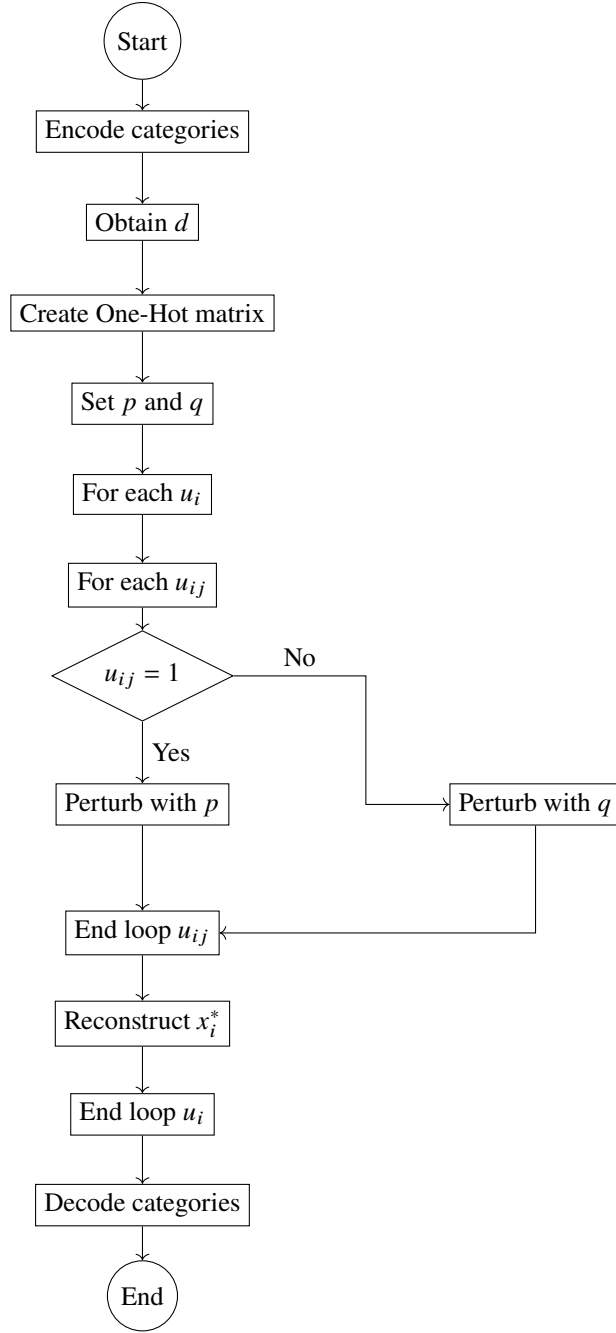


Figure 7: Diagram of Optimized Unary Encoding (OUE)

3.3 RAPPOR (rappor)

Algorithm 8 RAPPOR

Require: Categorical data X , privacy budget ϵ

Ensure: Privatized data X^*

- 1: Encode categories with numerical values
 - 2: Obtain the number of categories d
 - 3: Create original binary matrix (One-Hot Encoding)
 - 4: Compute $f = \frac{1}{e^\epsilon + 1}$
 - 5: **for** each binary vector u_i **do**
 - 6: **for** each bit u_{ij} in u_i **do**
 - 7: **if** $u_{ij} = 1$ **then**
 - 8: Perturb u_{ij} with probability $1 - f$
 - 9: **else**
 - 10: Perturb u_{ij} with probability f
 - 11: **end if**
 - 12: **end for**
 - 13: Reconstruct x_i^* from the perturbed vector
 - 14: **end for**
 - 15: **return** Privatized data X^*
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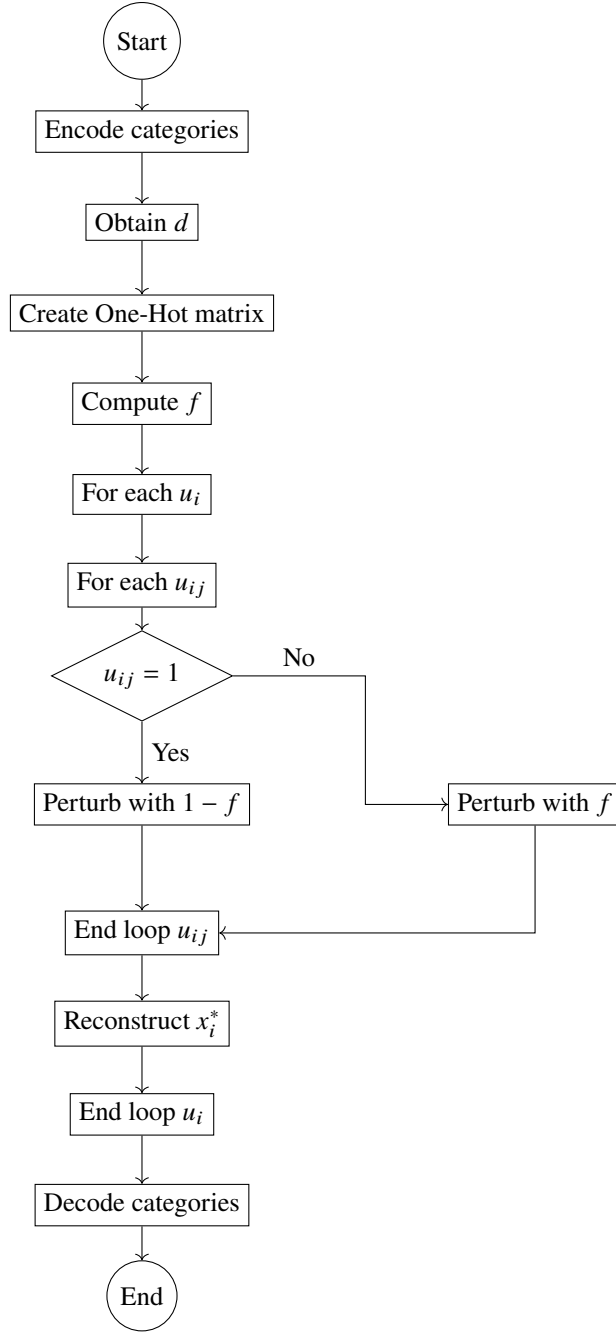


Figure 8: Diagram of RAPPOR