

Pseudocode and Diagrams for Differential Privacy Methods

Contents

1	Introduction	2
2	Pseudocode and Diagrams for Quantitative Methods	3
2.1	Duchi et al. Mechanism (duchi)	3
2.2	Laplace Mechanism (laplace)	5
2.3	Piecewise Mechanism (piecewise)	6
2.4	Multidimensional Duchi Mechanism (multidimensional_duchi)	8
2.5	Custom Multidimensional Mechanism (multidimensional)	10
3	Pseudocode and Diagrams for Categorical Methods	12
3.1	Direct Encoding (direct_encoding)	12
3.2	Optimized Unary Encoding (OUE) (optimized_unary_encoding)	13
3.3	RAPPOR (rappor)	15

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`)
- Laplace Mechanism (`laplace`)
- Piecewise Mechanism (`piecewise`)
- Multidimensional Duchi Mechanism (`multidimensional_duchi`)
- Custom Multidimensional Mechanism (`multidimensional`)

- **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)

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:   Clamp  $t_i$  to the range  $[-1, 1]$ 
3:   Compute  $e^\epsilon$ 
4:   Compute  $p = \frac{e^\epsilon}{e^\epsilon + 1}$ 
5:   Compute probability  $q = \frac{1}{e^\epsilon + 1}$ 
6:   Generate uniform random variable  $u$  in  $[0, 1]$ 
7:   if  $u < \frac{1 + t_i}{2}$  then
8:     Set  $t_i^* = 1$  with probability  $p$ ,  $-1$  with probability  $q$ 
9:   else
10:    Set  $t_i^* = -1$  with probability  $p$ ,  $1$  with probability  $q$ 
11:  end if
12: end for
13: return Vector  $t_i^*$ 
```

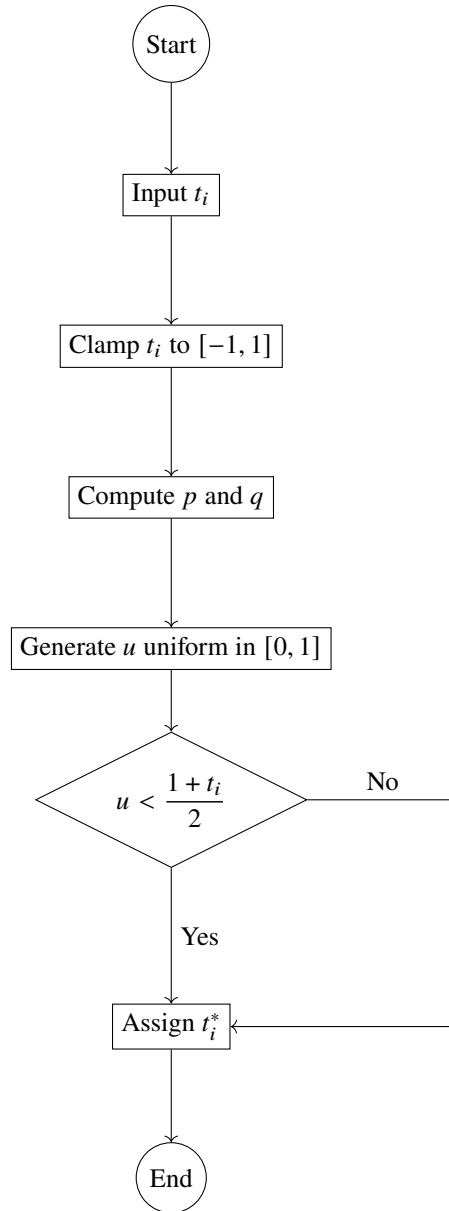


Figure 1: Diagram of the Duchi et al. Mechanism

2.2 Laplace Mechanism (laplace)

Algorithm 2 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: Generate Laplace noise b with mean 0 and scale $\frac{s}{\epsilon}$
 - 3: Calculate $t_i^* = t_i + b$
 - 4: **end for**
 - 5: **return** Vector t_i^*
-

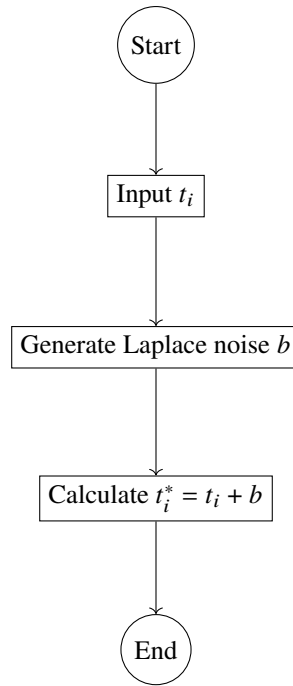


Figure 2: Diagram of the Laplace Mechanism

2.3 Piecewise Mechanism (piecewise)

Algorithm 3 Piecewise Mechanism

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

Ensure: Privatized vector t_i^*

- 1: Compute $C = \frac{e^{\epsilon/2} + 1}{e^{\epsilon/2} - 1}$
 - 2: **for** each element t_i in the input vector **do**
 - 3: Compute $l(t_i)$ and $r(t_i)$
 - 4: Generate u uniform in $[0, 1]$
 - 5: **if** $u \leq \frac{e^{\epsilon/2}}{e^{\epsilon/2} + 1}$ **then**
 - 6: Generate t_i^* uniformly in $[l(t_i), r(t_i)]$
 - 7: **else**
 - 8: Randomly select $[-C, l(t_i)]$ or $[r(t_i), C]$
 - 9: Generate t_i^* uniformly in the selected interval
 - 10: **end if**
 - 11: **end for**
 - 12: **return** Vector t_i^*
-

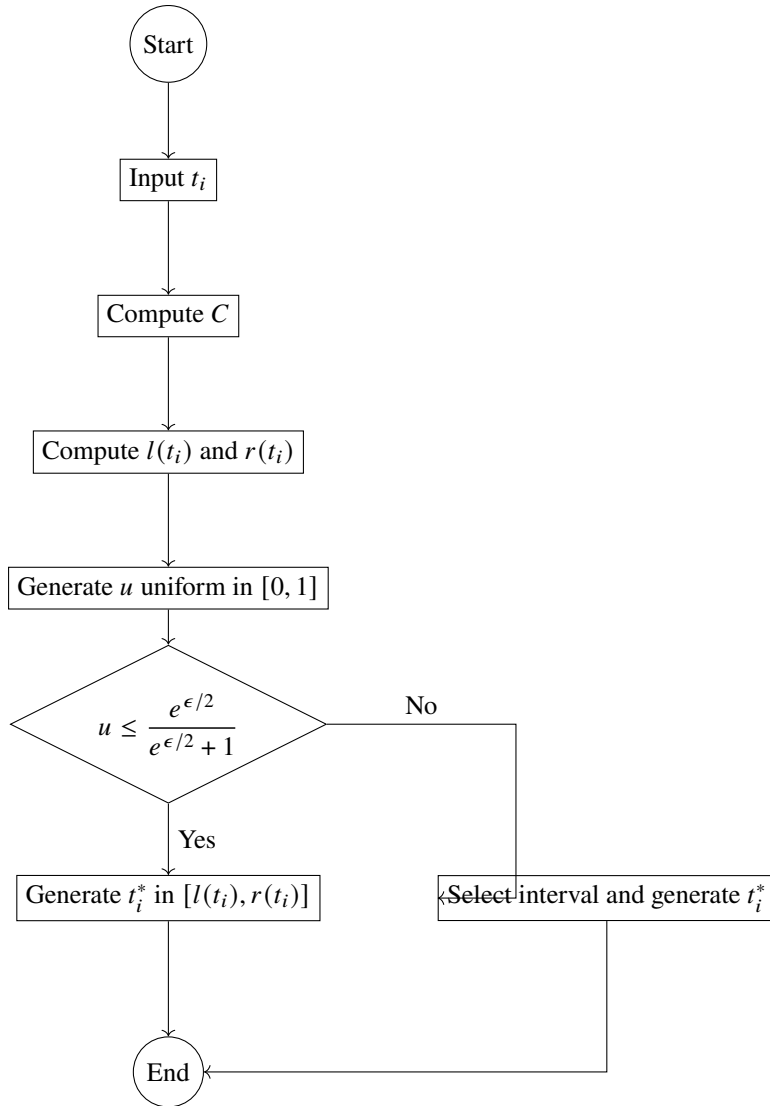


Figure 3: Diagram of the Piecewise Mechanism

2.4 Multidimensional Duchi Mechanism (multidimensional_duchi)

Algorithm 4 Multidimensional Duchi Mechanism

Require: Input matrix T of dimension $n \times d$, privacy budget ϵ

Ensure: Privatized matrix T^*

```
1: for each row  $t_i$  in  $T$  do
2:   Generate random vector  $v_i \in \{-1, 1\}^d$ 
3:   Calculate  $s_i = \frac{e^\epsilon}{e^\epsilon + 1}$ 
4:   Generate Bernoulli random variable  $u_i$  with probability  $s_i$ 
5:   if  $u_i = 1$  then
6:     Assign  $t_i^* = v_i$ 
7:   else
8:     Assign  $t_i^* = -v_i$ 
9:   end if
10: end for
11: return Matrix  $T^*$ 
```

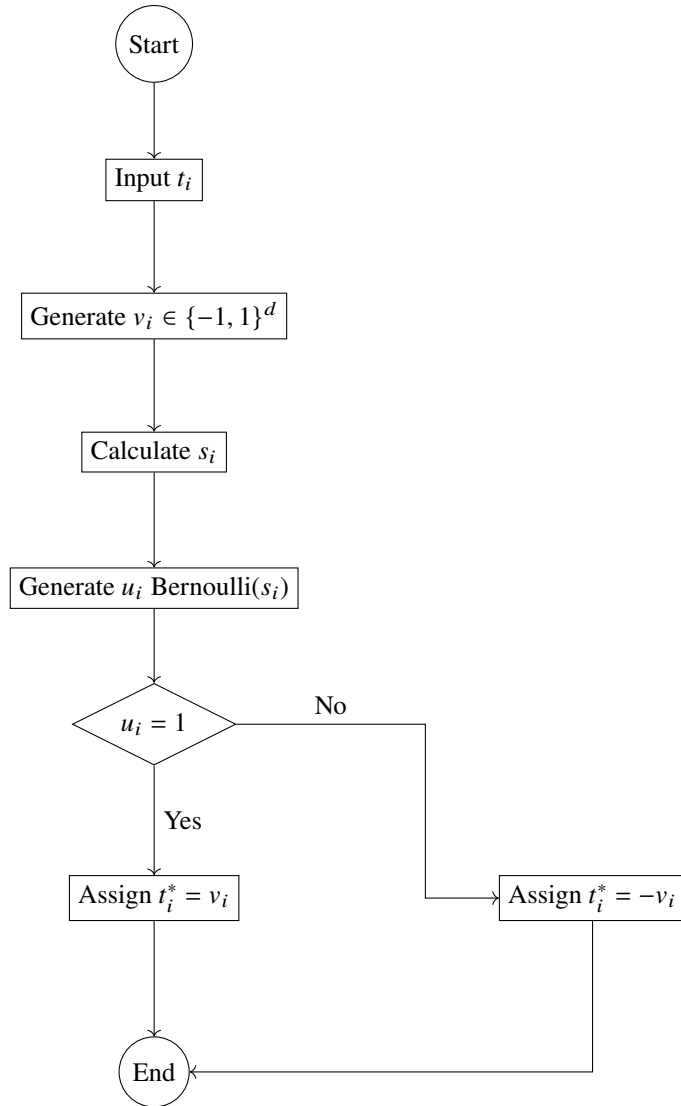


Figure 4: Diagram of the Multidimensional Duchi Mechanism

2.5 Custom Multidimensional Mechanism (multidimensional)

Algorithm 5 Custom Multidimensional Mechanism

Require: Input matrix T of dimension $n \times d$, privacy budget ϵ , unidimensional mechanism M , constant C

Ensure: Privatized matrix T^*

- 1: Calculate $k = \max \left(1, \min \left(d, \left\lfloor \frac{\epsilon}{2.5} \right\rfloor \right) \right)$
 - 2: **for** each row t_i in T **do**
 - 3: Select k random indices without replacement from $[1, d]$
 - 4: **for** each selected index j **do**
 - 5: Apply mechanism M to element t_{ij} with budget $\frac{\epsilon}{k}$
 - 6: Multiply result by $\frac{d}{k}$ and assign to t_{ij}^*
 - 7: **end for**
 - 8: **end for**
 - 9: **return** Matrix T^*
-

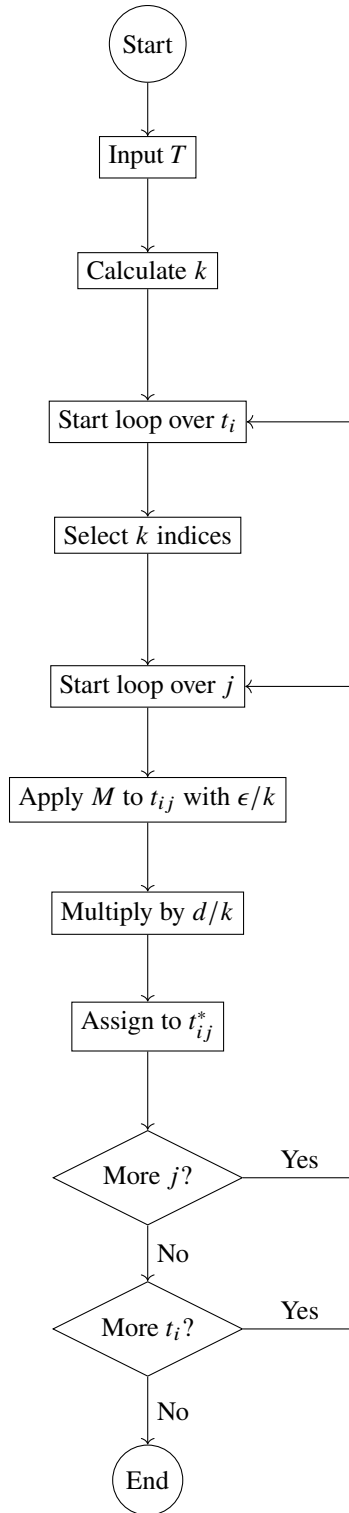


Figure 5: Diagram of the Custom Multidimensional Mechanism

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: Obtain the number of categories k
 - 2: Calculate $p = \frac{e^\epsilon}{e^\epsilon + k - 1}$
 - 3: Calculate $q = \frac{1}{e^\epsilon + k - 1}$
 - 4: **for** each element x_i in X **do**
 - 5: For each category c_j :
 - 6: Assign probability p if $x_i = c_j$, q otherwise
 - 7: Generate category x_i^* based on the assigned probabilities
 - 8: **end for**
 - 9: **return** Privatized data X^*
-

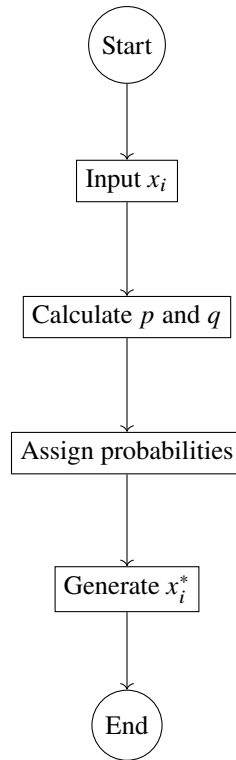


Figure 6: Diagram of Direct Encoding

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: Obtain the number of categories  $d$ 
2: Represent each data point  $x_i$  as a unary vector  $u_i$ 
3: Set  $p = 0.5$ 
4: Calculate  $q = \frac{1}{e^\epsilon + 1}$ 
5: for each unary 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  $X^*$ 
```

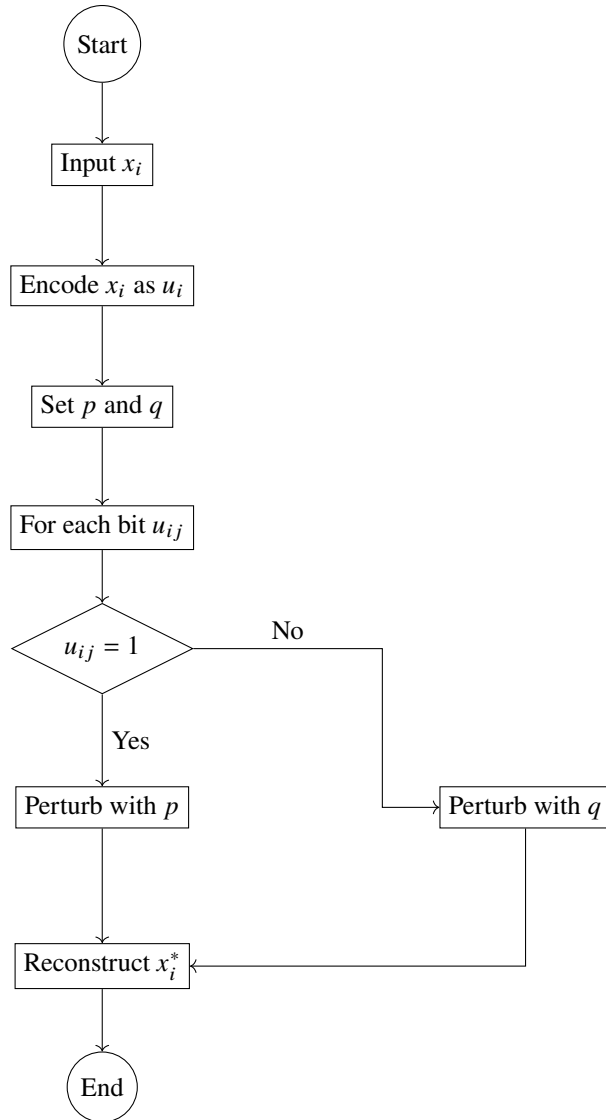


Figure 7: Simplified Diagram of Optimized Unary Encoding (OUE)

3.3 RAPPOR (rappor)

Algorithm 8 RAPPOR

Require: Categorical data X , privacy budget ϵ

Ensure: Privatized data X^*

```
1: Obtain the number of categories  $d$ 
2: Represent each data point  $x_i$  as a unary vector  $u_i$ 
3: Calculate  $f = \frac{1}{e^\epsilon + 1}$ 
4: for each unary vector  $u_i$  do
5:   for each bit  $u_{ij}$  in  $u_i$  do
6:     if  $u_{ij} = 1$  then
7:       Perturb  $u_{ij}$  with probability  $1 - f$ 
8:     else
9:       Perturb  $u_{ij}$  with probability  $f$ 
10:    end if
11:  end for
12:  Reconstruct  $x_i^*$  from the perturbed vector
13: end for
14: return Privatized data  $X^*$ 
```

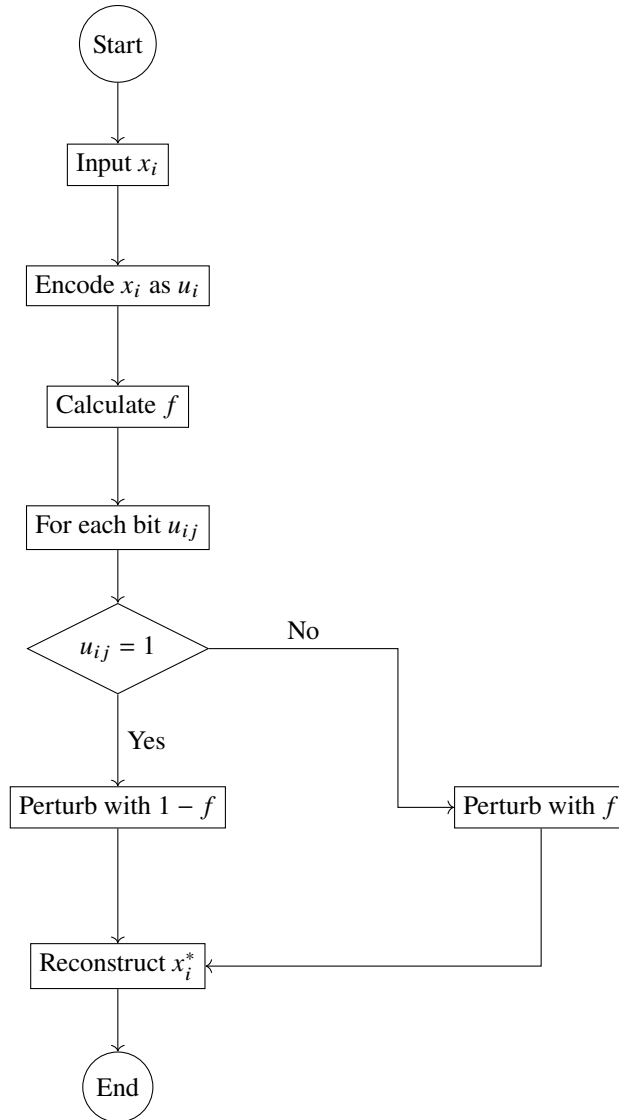


Figure 8: Simplified Diagram of RAPPOR