
dedication (optional)

Summary

Write your summary here...

Preface

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Table of Contents

Summary	i
Preface	ii
Table of Contents	iii
List of Tables	v
List of Figures	vii
Abbreviations	viii
1 Introduction	1
1.1 Equations	1
1.2 Figures	1
1.3 References	2
1.4 Tables	2
2 Literature Review	5
3 Basic Theory	7
4 Experiment	9
5 Analysis	11
6 Conclusion	13
Bibliography	15
Appendix	17

List of Tables

1.1 Table 1. 3

List of Figures

1.1	Pikachu.	2
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Abbreviations

Symbol = definition

Chapter 1

Introduction

1.1 Equations

To write an equation

```
\begin{eqnarray}\label{eq1}  
F = m \times a  
\end{eqnarray}
```

This will produceasdasd asdf asdf asdf

$$F = m \times a \tag{1.1}$$

To refer to the equation

```
\eqref{eq1}
```

This will produce (1.1).

1.2 Figures

To create a figure

```
\begin{figure}[h!]  
  \centering  
  \includegraphics[width=0.5\textwidth]{fig/pikachu}  
  \caption{Pikachu.}  
  \label{fig1}  
\end{figure}
```

To refer to the figure

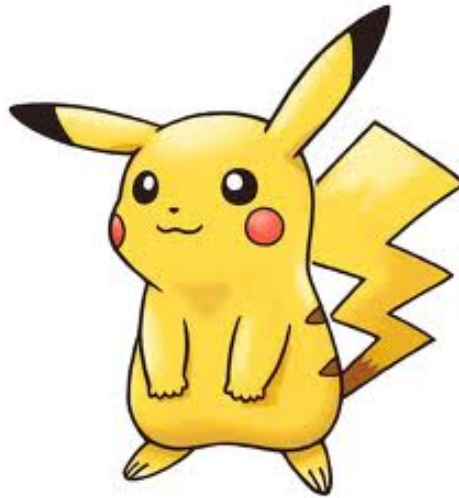


Figure 1.1: Pikachu.

```
\textbf{Fig. \ref{fig1}}
```

This will produce **Fig. 1.1**

1.3 References

To cite references

```
\cite{1,2,3}
```

or

```
\citep{1,2,3}
```

This will produce: Sarma and Chen (2008); Brouwer and Jansen (2004); Muskat (1937)
or (Sarma and Chen, 2008; Brouwer and Jansen, 2004; Muskat, 1937), respectively.

1.4 Tables

To creat a table

```
\begin{table}[!h]
\begin{center}
\begin{tabular}{| 1 | 1 | 1 | 1 |}
\hline
\textbf{No.} & \textbf{Data 1} & \textbf{Data 2} & \textbf{Data 3} \\
\hline
\end{tabular}
\end{center}
\end{table}
```

```
1 & a1 & b1 \\ \hline
2 & a2 & b2 \\ \hline
\end{tabular}
\end{center}
\caption{Table 1.}
\label{Tab1}
\end{table}
```

This will produce

No.	Data 1	Data 2
1	a1	b1
2	a2	b2

Table 1.1: Table 1.

To refer to the table

```
\textbf{Table. \ref{Tab1}}
```

This will produce **Table. 1.1.**

Chapter 2

Literature Review

Chapter 3

Basic Theory

In a world where massive amounts of sensitive personal data are being collected, attacks on the individual's privacy are becoming more and more of a threat. One type of attack is the identification of an individual's personal information from massive data sets, such as people's movie ratings from the Netflix data set Narayanan and Shmatikov (2008), and the medical records of a former governor of Massachusetts Barth-Jones (2012). These types of privacy breaches may lead to the unwanted discovery of a person's embarrassing information, and could also lead to the theft of an individual's private data or identity.

Many different approaches have been tried by data custodians to privatize the data they hold, such as removing any columns containing Personally Identifiable Information (PII), anonymizing the data by providing k-anonymity protection Sweeney (2002), or perform group based anonymization through l-diversity Machanavajjhala et al. (2007). All of these methods mentioned have been proved to be susceptible in some way or form to attacks Ganta et al. (2008). Motivated by these shortcomings, a researcher at Microsoft came up with a data theoretical framework called differential privacy, which operates off a solid mathematical foundation and have strong theoretical guarantees on the privacy and utility of the released data.

The term "differential privacy" was defined by Dwork as a description of a promise, made by a data holder to a data subject: "You will not be affected, adversely or otherwise, by allowing your data to be used in any study or analysis, no matter what other studies, data sets, or information sources, are available." Dwork and Roth (2013) In an ideal situation, databases which implement differential privacy mechanisms can make confidential data widely available for accurate data analysis, without resorting to data usage agreements, data protection plans, or restricted views. Nevertheless, the Fundamental Law of Information Recovery states that overly accurate answers to too many questions will destroy privacy in a spectacular way Dwork and Roth (2013), meaning that data utility will eventually be consumed.

The classic example for explaining a security breach is the case of Mr White: Suppose you have access to a database that allows you to compute the income of all residents in a specified area. If you knew that Mr White was going to move, simply querying the

database before and after his relocation would allow you to deduce his income.

Formally, differential privacy is defined as follows: A randomized function K gives ϵ -differential privacy if for all data sets D and D' differing on at most one row, and all $S \subseteq \text{Range}(K)$,

$$Pr[K(D) \in S] \leq \exp(\epsilon) \times Pr[K(D') \in S]$$

What this means is that the risk to an individual's privacy should not be substantially increase as a result of participating in a statistical database, as the risk is bounded by the parameter ϵ . Therefore an attacker should not be able to learn anything about any participant that they would not have learned if the participant had opted out of participating.

This is guaranteed by applying noise to the result of an query to the dataset, by using the function $K()$. There are many different mechanisms for applying this noise, but the two most common are the Laplace mechanism and the Exponential mechanism.

The Laplace mechanism involves adding random noise which follows the Laplace statistical distribution. The most common question that needs to be answered before doing research with differentially private data, is how we should define our Laplace random variable, i.e how much noise needs to be added. The Laplace distribution centered around zero has only one parameter, its scale, and this is proportional to its standard deviation. The scale is naturally dependent on the privacy parameter ϵ , and also on the risk of the most different individual having their private information leaked from the data. This risk is called the sensitivity of the query, and is defined mathematically as:

$$\Delta f = \max_{D, D'} \|f(D) - f(D')\|_1$$

Chapter 4

Experiment

Chapter 5

Analysis

Chapter 6

Conclusion

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Appendix

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