

## Homework 2

Name: Julian Steiner

Matriculation No.: 2669944

## Problem 1

(1.1)

Table 1: 3-anonymit Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
1	*	30-39	Male	Rhineland-Palatinate	Murder
2	*	20-29	Female	Bavaria	Murder
3	*	30-39	Female	North Rhine-Westphalia	Robbery
4	*	30-39	Male	Rhineland-Palatinate	Assault
5	*	20-29	Female	Bavaria	Robbery
6	*	30-39	Female	North Rhine-Westphalia	Murder
7	*	30-39	Male	Rhineland-Palatinate	Parking
8	*	10-19	Male	Hesse	Murder
9	*	30-39	Female	North Rhine-Westphalia	Parking
10	*	20-29	Female	Bavaria	Speeding
11	*	10-19	Male	Hesse	Robbery
12	*	30-39	Male	North Rhine-Westphalia	Assault
13	*	30-39	Male	North Rhine-Westphalia	Speeding
14	*	10-19	Male	Hesse	Speeding
15	*	30-39	Male	North Rhine-Westphalia	Murder

(1.2)

- Crime: Murder, Assault, Parking  $\Rightarrow$  l-diversity  $\Rightarrow$  3

Table 2: Group 1 - Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
1	*	30-39	Male	Rhineland-Palatinate	Murder
4	*	30-39	Male	Rhineland-Palatinate	Assault
7	*	30-39	Male	Rhineland-Palatinate	Parking

- Crime: Murder, Robbery, Speeding  $\Rightarrow$  l-diversity  $\Rightarrow$  3

Table 3: Group 2 - Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
2	*	20-29	Female	Bavaria	Murder
5	*	20-29	Female	Bavaria	Robbery
10	*	20-29	Female	Bavaria	Speeding

- Crime: Robbery, Murder, Parking  $\Rightarrow$  l-diversity  $\Rightarrow$  3

Table 4: Group 3 - Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
3	*	30-39	Female	North Rhine-Westphalia	Robbery
6	*	30-39	Female	North Rhine-Westphalia	Murder
9	*	30-39	Female	North Rhine-Westphalia	Parking

- Crime: Murder, Robbery, Speeding  $\Rightarrow$  l-diversity  $\Rightarrow$  3

Table 5: Group 4 - Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
8	*	10-19	Male	Hesse	Murder
11	*	10-19	Male	Hesse	Robbery
14	*	10-19	Male	Hesse	Speeding

- Crime: Assault, Speeding, Murder  $\Rightarrow$  l-diversity  $\Rightarrow$  3

Table 6: Group 5 - Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
12	*	30-39	Male	North Rhine-Westphalia	Assault
13	*	30-39	Male	North Rhine-Westphalia	Speeding
15	*	30-39	Male	North Rhine-Westphalia	Murder

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**Note:** From the above equivalence classes, each class has 3 unique crimes. Therefore, the l-diversity of the modified table is 3.

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(1.3)

Table 7: Group 1 - Crime Data by State in Germany

(id)	Name	Age	Gender	State of Germany	Crime
1	*	30-39	Male	Rhineland-Palatinate	Murder
4	*	30-39	Male	Rhineland-Palatinate	Assault
7	*	30-39	Male	Rhineland-Palatinate	Parking

• **Q → General Distribution**

- Assault →  $2/15 \rightarrow 0.133$
- Murder →  $5/15 \rightarrow 0.333$
- Parking →  $2/15 \rightarrow 0.133$
- Robbery →  $3/15 \rightarrow 0.2$
- Speeding →  $3/15 \rightarrow 0.2$

$$Q = (0.133, 0.333, 0.133, 0.2, 0.2)$$

• **P → Distribution of equivalence class**

- Assault →  $1/3 \rightarrow 0.333$
- Murder →  $1/3 \rightarrow 0.333$
- Parking →  $1/3 \rightarrow 0.333$
- Robbery →  $0/3 \rightarrow 0.0$
- Speeding →  $0/3 \rightarrow 0.0$

$$P = (0.333, 0.333, 0.333, 0.0, 0.0)$$

• **t-closeness**

$$\begin{aligned}
 D(P, Q) &= \sum_{i=1}^m \frac{1}{2} |p_i - q_i| = \\
 &= \frac{1}{2} * (|0.133 - 0.333| + |0.333 - 0.333| + |0.133 - 0.333| + |0.2 - 0.0| + |0.2 - 0.0|) = \\
 &= \frac{1}{2} * 0.8 = 0.4
 \end{aligned}$$

**Problem 2**

See jupyter notebook for function implementation. The results of the function shown in 8.

<b>p</b>	<b>X_0</b>	<b>X_1</b>	<b>Y_0</b>	<b>Y_1</b>
0.0	0.8	0.2	0.20	0.80
0.2	0.8	0.2	0.32	0.68
0.5	0.8	0.2	0.50	0.50
0.8	0.8	0.2	0.68	0.32
1.0	0.8	0.2	0.80	0.20

Table 8

- **Privacy**

- **p=0 and p=1:**
  - \* When  $p = 0$ , the noisy distribution  $Y$  is exactly the reverse of the true distribution  $X$ . This provides no privacy because the distribution  $Y$  directly reveals the opposite of  $X$ .
  - \* When  $p = 1$ , the noisy distribution  $Y$  is identical to the true distribution  $X$ . This also provides no privacy because  $Y$  is exactly  $X$ .
- **p=0.5:** When  $p = 0.5$ , the noisy distribution  $Y$  becomes uniform (i.e.,  $Y = [0.5, 0.5]$ ). This provides the highest level of privacy because  $Y$  does not reveal any information about the true distribution  $X$ .
- **p=0.2 and p=0.8:** These intermediate values provide a balance between privacy and utility. As  $p$  moves away from 0.5 towards 0 or 1, the privacy decreases because  $Y$  starts resembling  $X$  more closely.

- **Utility**

- **p=0 and p=1:** These values provide maximum utility because  $Y$  is either exactly  $X$  or exactly the reverse of  $X$ . There is a clear correspondence between  $Y$  and  $X$ , making  $Y$  highly useful for accurate analysis.
- **p=0.5:** When  $p = 0.5$ , the utility is the lowest because the noisy distribution  $Y$  is uniform and does not reflect the true distribution  $X$  at all. This makes  $Y$  less useful for analysis.
- **p=0.2 and p=0.8:** These intermediate values provide a balance between privacy and utility. As  $p$  moves away from 0.5 towards 0 or 1, the utility increases because  $Y$  starts resembling  $X$  more closely.

**Problem 3**

## • Text 1

- Had such a blast hanging out with [NAME] and [NAME] in #[LOC] [DATE]! We explored the city, went to the #[LOC]Zoo, and had an awesome time. It's always a good time catching up with old friends and making new memories together. [LOC] has so much character – definitely need to come back soon! Thanks for the awesome day, [NAME] and [NAME]. Let's do it again sometime! #Friends #[LOC] #FB20 #TUDA
- In text 1 possible guesses about the author's location could be done through the hashtags used in the text. With the hashtag #TUDA we can refer to the "Technische Universität Darmstadt" or "Technical University of Darmstadt". In addition with the #FB20 in combination with #TUDA it could be possible to refer to the "Fachbereich 20 (Fachbereich Informatik)" at the TU Darmstadt. With this information we could conclude that the persons could be former students of the computer science department of the TU Darmstadt, because the author has met with "old friends".
- The conclusion that the people could be former students from Darmstadt would allow conclusions to be drawn about the location of the meeting. It could be the city of Darmstadt or a nearby city. The hashtag #[LOC]Zoo allows us to deduce that they visited a zoo. This could result in the city of Frankfurt.
- In addition the use of the hashtags indicates the use of a social media platform. This could be a hint at their age group or interests.

## • Text 2

- Date: [DATE]  
To: [URL], [URL], [URL], [URL]  
Title: RE: RE: RE: website  
Dear website team,  
here is a kick-off mail for the website. Format – a github page which lists some papers, between [URL] (too little info) and [URL] (too much for now). For starters, we'd pick 50 papers from the list we already made [URL]. [NAME] has kindly agreed to lead the work on this. [NAME] has agreed to develop the site. [NAME] and [NAME] have agreed to help with selecting papers and giving feedback. We need to have it running by [DATE] to link it in the paper. With that, I pass it to [NAME].  
I guess the first step is setting up the repo and adding all people in this thread as Maintainers. My Github account is [URL]. If there are any questions, please let me know, if something urgent pops up, give me a call at [PHONE].  
Best,
- The technical references of "github" and "repo" indicates a familiarity with software development practices. With this information we could conclude that the author might be a tech professional, or someone involved in software development. The reference to "papers" could be a information for the academic or research context of the author.
- The phrases like "kick-off mail" and "lead the work" could be indications for a management terminology. So the author of the email could be the leader of the team.