

# BUYER BEWARE: UNDERSTANDING THE TRADE-OFF BETWEEN UTILITY AND RISK IN CART BASED MODELS USING SIMULATION DATA

Berlin,  
7-8. Oktober, 2024

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## SECTION 1: INTRODUCTION

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## BACKGROUND

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- This is work in progress.
- We think this idea is interesting.
- We think others should know about it.
- But we are still developing it.
- Comments and critiques would be helpful.

## WHAT DO WE KNOW?

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- It is well established that there is a trade-off between utility and privacy using a synthetic data generator (SDG)
- Utility and privacy in CART based SDGs seems to be high (Little et al., 2022; Danker and Ibrahim, 2021)
- Therefore, CART models seem to be less sensitive to this trade-off than other SDGs (i.e. higher utility, lower risk)

## WHAT DO WE NOT KNOW?

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- How does CART seem to be able to minimize the R-U trade off?
  - Relative to other SDGs with certain types of data (i.e. low dimensional data).

## WHAT DO WE DO HERE?

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- Using simulation data (Reiter et al., 2014), we show that synthetic data from CART models are disclosive
- **The problem:** Disclosive in ways that are not observable with common privacy metrics
- **The solution:** It is possible to increase protection (by reducing utility)
- **The question:** Why would we reduce utility if we did not know there was a problem?

## SECTION 2: GENERATE THE ORIGINAL AND SYNTHETIC DATA

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# GENERATE ORIGINAL DATA USING A SIMULATION

Borrowing from Reiter et al. (2014), we set the first 999 observations to be a random sample from a multinomial distribution for all combinations of  $var1(0, 1)$ ,  $var2(0, 1)$ ,  $var3(0, 1)$ ,  $var4(0, 1)$  except ( $var1 = 1, var2 = 1, var3 = 1, var4 = 1$ ), which we set to be the 1000<sup>th</sup> observation.

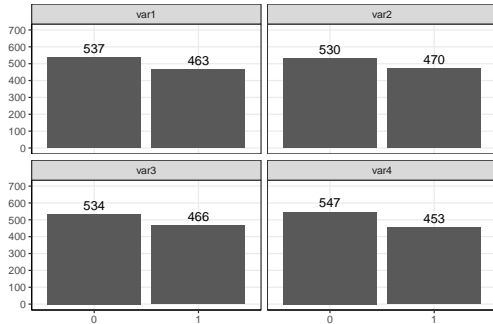


Figure 1: Frequency

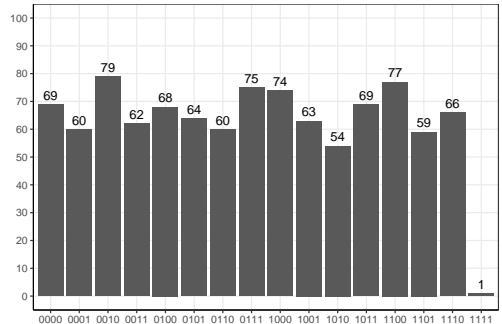


Figure 2: Histogram



# GENERATE SYNTHETIC DATA WITH CART (SYNTHPOP)

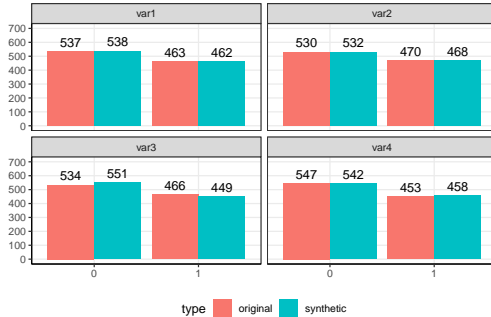


Figure 3: Frequency

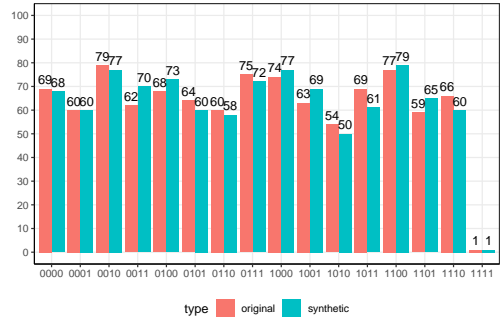
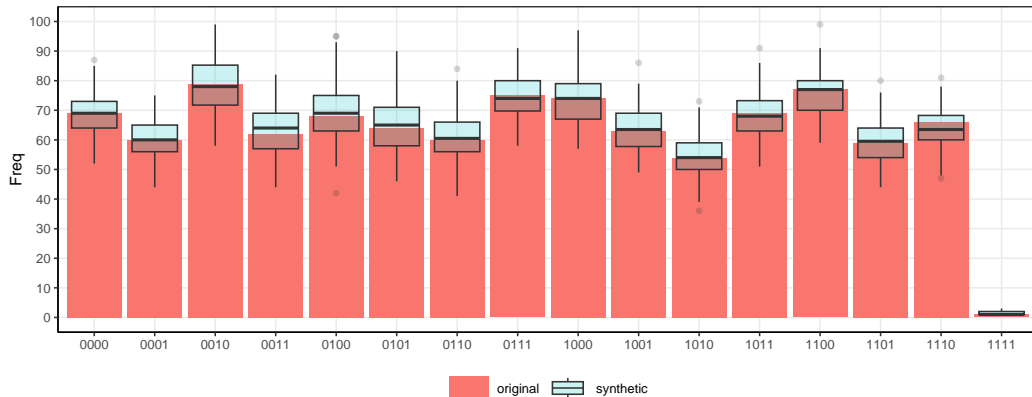


Figure 4: Histogram

## COMPARE HISTOGRAM X 100 SYNTHETIC DATASETS

Figure 5: Multiple synthetic data sets does not reduce privacy risk



# SUMMARY

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- The problem (in our data): Synthetic data from CART models are disclosive
- The reason:
  - A record can only be in the synthetic data if it is also in the original data.
  - Or the opposite: if a record is not in the original data, then it can never be in the synthetic data.
- Next section: Can an attacker identify the disclosure?

## SECTION 3: SET UP THE ATTACK

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## SETTING UP THE ATTACK

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- Its a game between two entities.
  - The statistical agency has the data and wants to release it in a privacy preserving way.
  - The attacker wants to identify someone in the data (either membership or attribute inference).
- The question: What can the attacker learn from a released synthetic data set about an individual they do not have knowledge of?

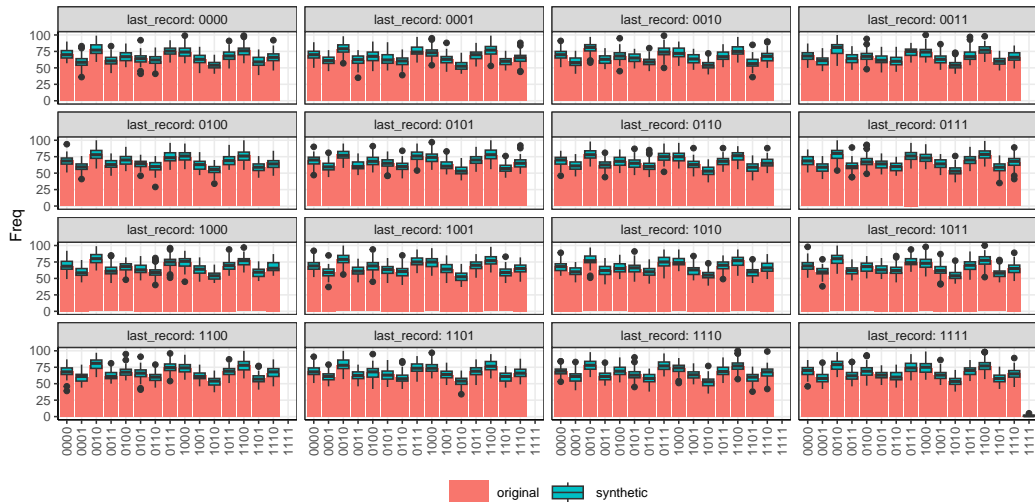
## DESCRIBING THE ATTACK

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- We assume a 'strong' attacker who has the following knowledge similar to the attack model in differential privacy (DP).
  - Knows the SDG model type (i.e. sequential CART).
  - Knowledge of all observations in the data except the last one.
  - The 16 possible combinations that the last one could be.
- The attacker sees the synthetic data
- The attacker runs the same synthetic data model (SDG) for all of the 16 different possibilities.
- Then they update their beliefs about what the last record could be

# ILLUSTRATING THE ATTACK WITH CART (DEFAULT PARAMETERS)

Figure 6: Histogram of 16 worlds x 100 synthetic datasets



## SUMMARY

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- In our attack with our assumptions, the attacker can easily identify the last record
- Next section: Can we measure this disclosure?



## SECTION 4: MEASURING PRIVACY

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# PRIVACY MEASURES

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- Synthpop (Raab et al., 2024)
  - Identity disclosure: the ability to identify individuals in the data from a set of known characteristics (i.e. 'keys').
  - Attribute disclosure: the ability to find out from the keys something, not previously known
  - Replicated uniques

## COMPARING PRIVACY MEASURES (SEED = 1237, I.E. 'LAST RECORD' = 1)

```
1 > print(t1, plot = FALSE, to.print = "ident")
2 Disclosure risk for 1000 records in the original data
3
4 Identity disclosure measures
5 from keys: var1 var2 var3
6 For original ( Ui0 ) 0 %
7 For synthetic ( repU ) 0 %.
8 > print(t1, plot = FALSE, to.print = "attrib")
9
10 Table of attribute disclosure measures for var1 var2 var3
11 Original measure is Dorig and synthetic measure is DiSCO
12 Variables Ordered by synthetic disclosure measure
13
14      attrib.orig attrib.syn check1 Npairs check2
15 1 var4          0          0          0
```

```
1 > replicated.uniques (sds, df_ods)
2      var1 var2 var3 var4
3 973      1      1      1
4 Uniques and replicated uniques for 1 synthesised data set(s)
5 from keys: var1 var2 var3 var4
6
7 Uniques in original data:
8 1 from 1000 records ( 0.1 %)
9 Uniques in synthetic data:
10 1 from 1000 records ( 0.1% )
11
12 Replicated uniques:
13 1
14 as a % of uniques in synthetic 100%
15 as a % of original records (repU) 0.1%
```

## COMPARING PRIVACY MEASURES (SEED = 1240, I.E. 'LAST RECORD' = 3)

```
1 > print(t1, plot = FALSE, to.print = "ident")
2 Disclosure risk for 1000 records in the original data
3
4 Identity disclosure measures
5 from keys: var1 var2 var3
6 For original ( Ui0 ) 0 %
7 For synthetic ( repU ) 0 %.
8 > print(t1, plot = FALSE, to.print = "attrib")
9
10 Table of attribute disclosure measures for var1 var2 var3
11 Original measure is Dorig and synthetic measure is DiSCO
12 Variables Ordered by synthetic disclosure measure
13
14      attrib.orig attrib.syn check1 Npairs check2
15 1 var4          0          0          0
```

```
1 > replicated.uniques (sds, df_ods)
2 Uniques and replicated uniques for 1 synthesised data set(s)
3 from keys: var1 var2 var3 var4
4
5 Uniques in original data:
6 1 from 1000 records ( 0.1 %)
7 Uniques in synthetic data:
8 0 from 1000 records ( 0% )
9
10 Replicated uniques:
11 0
12 as a % of uniques in synthetic NaN%
13 as a % of original records (repU) 0%
```

## SUMMARY

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- Using common privacy measures, CART generates synthetic data with low risk
- 1 measure indicates there may be a problem, but all the other measures indicate there is no problem.
- However (and this is the point):
  - We know there is a problem (because we created it)
  - We know that common measures do not capture the problem

## SECTION 5: SOLUTION

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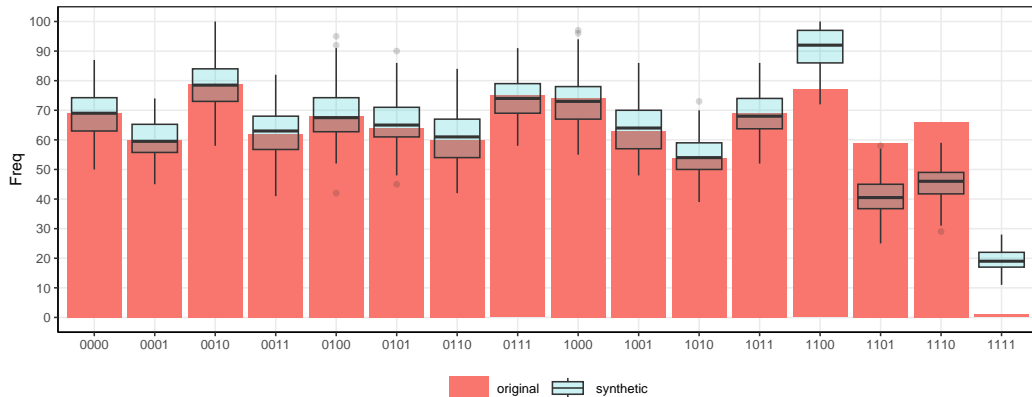
# THE GOOD NEWS: SOLUTIONS

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- Reduce utility by preventing overfitting
  - minbucket = 75 (default = 5): increase the minimum number of observations in any terminal node
  - cp = 0.05 (default =  $1e^{-8}$ ): decrease the size of the tree
  - Other options also exist

# GENERATE SYNTHETIC DATA WITH CART (MODIFIED PARAMETERS)

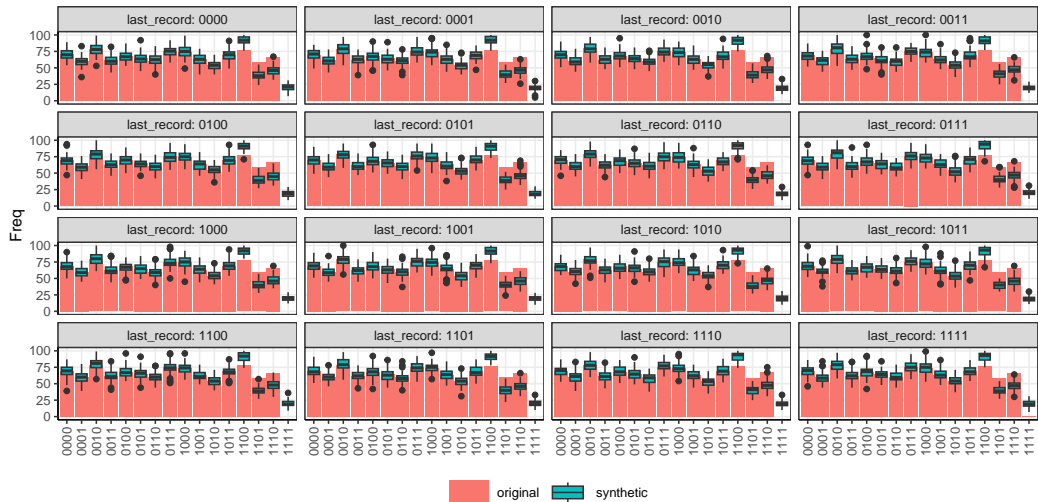
Figure 7: Compare histogram x 100 synthetic datasets





# ILLUSTRATING THE ATTACK WITH CART (MODIFIED PARAMETERS)

Figure 8: Histogram of 16 worlds x 100 synthetic datasets



## THE BAD NEWS

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- We don't know how to identify the privacy risk
- We have to know a problem exists before we would do something about it

## SECTION 6: CONCLUSION

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# SUMMARY

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- It has long been understood that there is a trade-off between utility and risk
- Previous research indicated that CART models were less sensitive to this trade-off than other SDGs
- Using a simulated data set, we show that CART are sensitive to this trade-off
- The good news: It is possible to reduce risk in CART with parameters
- The bad news:
  - Common privacy metrics do not capture risk in our simulated data
  - We must sacrifice utility
- Question: If you did not know there was a problem, why would you sacrifice utility?

# IS THE SCENARIO REALISTIC? IS THIS A PROBLEM?

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- No, this is not a problem.
  - A ‘strong’ attacker is unrealistic.
    - Knows the SDG model type (i.e. sequential CART).
    - Knowledge of all observations in the data except the last one.
    - The 16 possible combinations that the last one could be.
- Yes, this is a problem
  - Unique records
    - are always the records we need to protect most
    - It is well known that SDGs struggle to protect unique records while also providing utility
    - In this data, eliminating unique records does not solve the problem
  - The simulation
    - We show that a disclosure happened in this data
    - We show that these risk measures did not capture this disclosure

# CONCLUSION

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- We are not saying:
  - All synthetic data are disclosive
  - CART-based SDGs are disclosive
- We are saying:
  - Do not assume that all risk measures will identify all problems
  - This simulation offers a type of ‘bound’ on understanding disclosure risks

# THANK YOU

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Reproducible code: [https://github.com/jonlatner/KEM\\_GAN/tree/main/latner/projects/simulation](https://github.com/jonlatner/KEM_GAN/tree/main/latner/projects/simulation)