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

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SECTION 1: INTRODUCTION

BACKGROUND

- We had a question and we developed a way to test it.
- We think this idea is interesting.
- We think others should know about it.
- But, this is work in progress.
- And, we are still developing it.
- Comments and critiques would be helpful.

WHAT DO WE KNOW?

- It is well established that there is a trade-off between utility and privacy when generating synthetic data using a synthetic data generator or SDG (Duncan et al., 2004)
- Classification and Regression Trees (CART) models are one type of SDG (Reiter, 2005)
  - 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?

- The question: How do CART based SDGs 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).

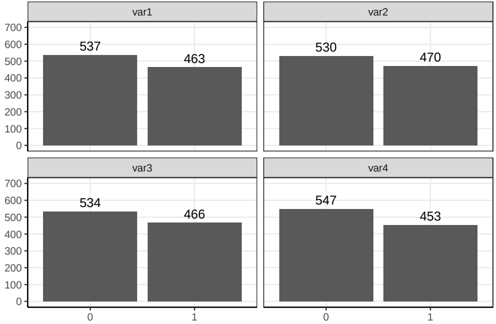
WHAT DO WE DO HERE?

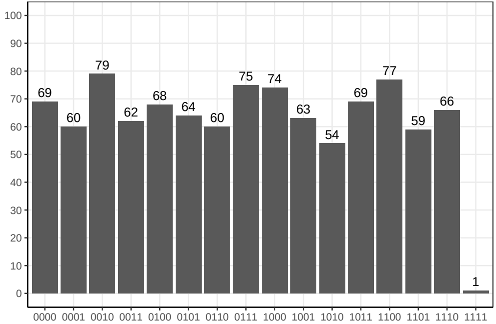
- Using simulation data (Reiter et al., 2014), we show that synthetic data from CART models can be disclosive
- **The problem:** Disclosive in ways that are not observable with common privacy metrics
- **The solution:** It is possible to increase protection (by reducing utility)
- **The question:** Why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

SECTION 2: GENERATE THE ORIGINAL AND SYNTHETIC DATA

GENERATE ORIGINAL DATA USING A SIMULATION

- Borrowing from Reiter et al. (2014), we create a data set with $n = 1000$ and 4 dichotomous, categorical variables.
- 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 the last one
- The last (1000^{th}) observation is ($var1 = 1, var2 = 1, var3 = 1, var4 = 1$).





GENERATE SYNTHETIC DATA WITH CART (SYNTHPOP)

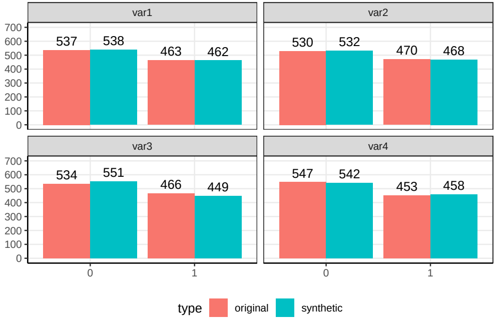


Figure 1: Frequency

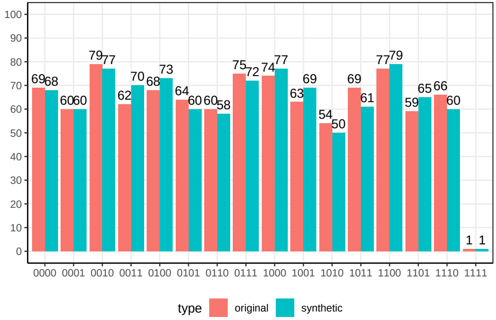
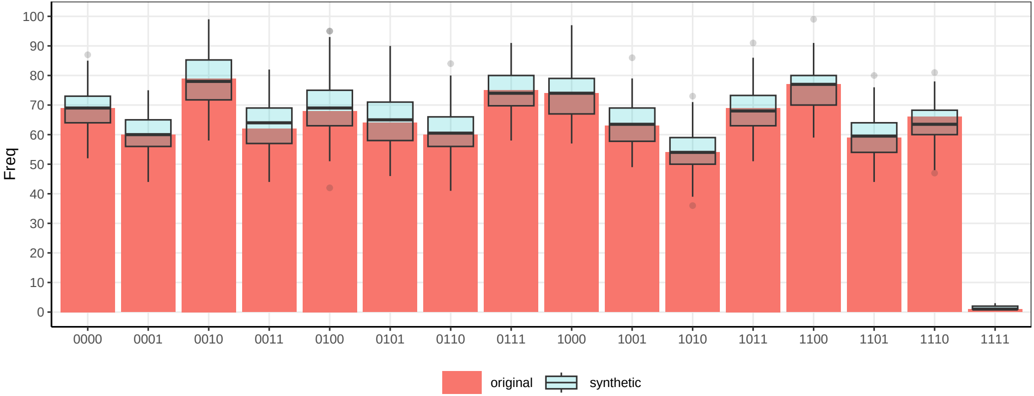


Figure 2: Histogram

COMPARE HISTOGRAM X 100 SYNTHETIC DATASETS

Figure 3: Multiple synthetic data sets does not reduce privacy risk



SUMMARY

- 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 (in this simulated 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: THE ATTACK

SETTING UP THE ATTACK

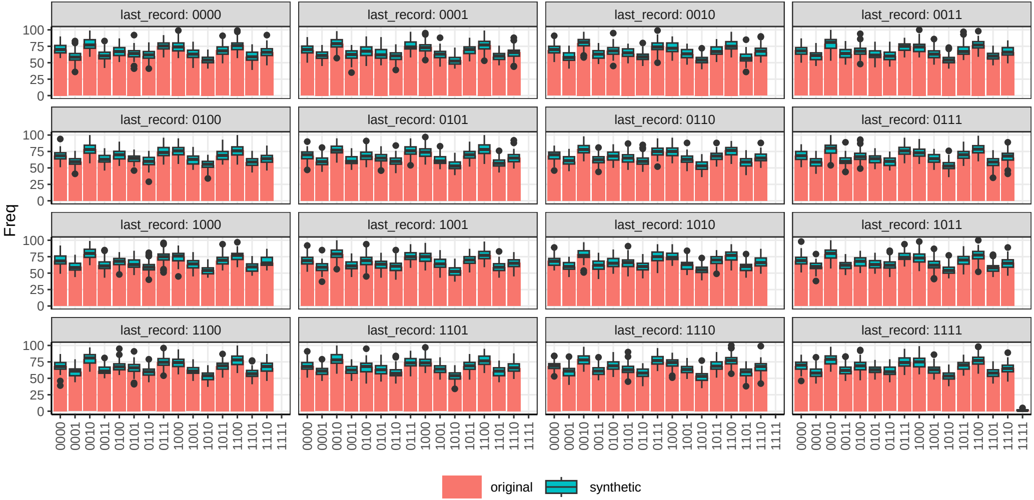
- Its a game between two entities.
  - The statistical agency has the data and wants to release it in a privacy preserving way.
  - The attacker wants to identify someone in the data (either membership or attribute inference).
- The question: What can the attacker learn from a released synthetic data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

DESCRIBING THE ATTACK

- We assume a ‘strong’ attacker similar to the attack model in differential privacy (DP).
- An attacker has the following knowledge
  - 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 4: Histogram of 16 worlds x 100 synthetic datasets



SUMMARY

- In our attack with our assumptions, the attacker can easily identify the last record
- The reason (to repeat):
  - A record can only be in the synthetic data if it is also in the original data (in this simulated 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 we measure this disclosure?

SECTION 4: MEASURING PRIVACY

PRIVACY MEASURES

- 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)

```
> print(t1, plot = FALSE, to.print = "ident")
Disclosure risk for 1000 records in the original data

Identity disclosure measures
from keys: var1 var2 var3
For original  ( UiO )  0 %
For synthetic ( repU ) 0 %.
> print(t1, plot = FALSE, to.print = "attrib")

Table of attribute disclosure measures for var1 var2 var3
Original measure is  Dorig and synthetic measure is DiSCO
Variables Ordered by synthetic disclosure measure

       attrib.orig attrib.syn check1 Npairs check2
1 var4           0          0             0
```

```
> replicated.uniques (sds, df_ods)
    var1 var2 var3 var4
973    1    1    1    1
Uniques and replicated uniques for  1  synthesised data set(s)
 from keys:  var1 var2 var3 var4

Uniques in  original data:
 1 from  1000 records ( 0.1 %)
Uniques in synthetic data:
 1 from  1000 records ( 0.1% )

Replicated uniques:
 1
as a % of uniques in synthetic  100%
as a % of original records (repU) 0.1%
```

COMPARING PRIVACY MEASURES (SEED = 1240, I.E. ‘LAST RECORD’ = 3)

```
> print(t1, plot = FALSE, to.print = "ident")
Disclosure risk for 1000 records in the original data

Identity disclosure measures
from keys: var1 var2 var3
For original  ( UiO )  0 %
For synthetic ( repU ) 0 %.
> print(t1, plot = FALSE, to.print = "attrib")

Table of attribute disclosure measures for var1 var2 var3
Original measure is  Dorig and synthetic measure is DiSCO
Variables Ordered by synthetic disclosure measure

       attrib.orig attrib.syn check1 Npairs check2
1 var4           0          0             0
```

```
> replicated.uniques (sds, df_ods)
Uniques and replicated uniques for  1  synthesised data set(s)
 from keys:  var1 var2 var3 var4

Uniques in  original data:
 1 from  1000 records ( 0.1 %)
Uniques in synthetic data:
 0 from  1000 records ( 0% )

Replicated uniques:
 0
as a % of uniques in synthetic  NaN%
as a % of original records (repU) 0%
```

SUMMARY

- 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

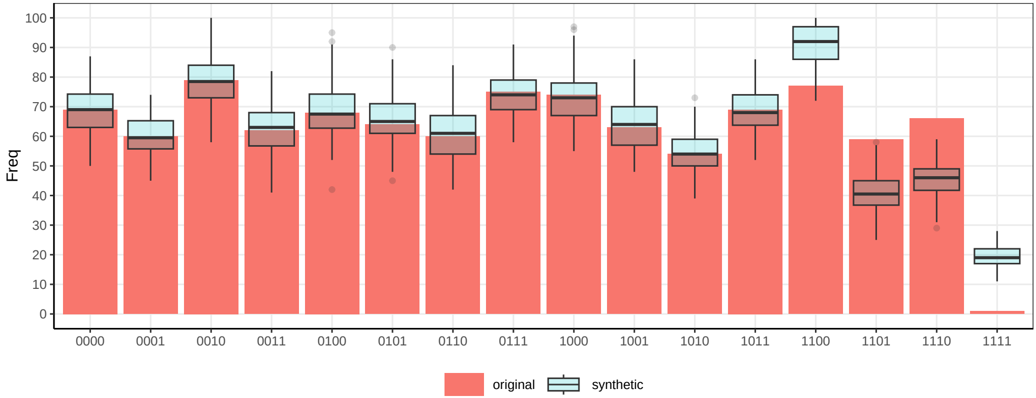
SECTION 5: SOLUTION

THE GOOD NEWS: SOLUTIONS

- 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

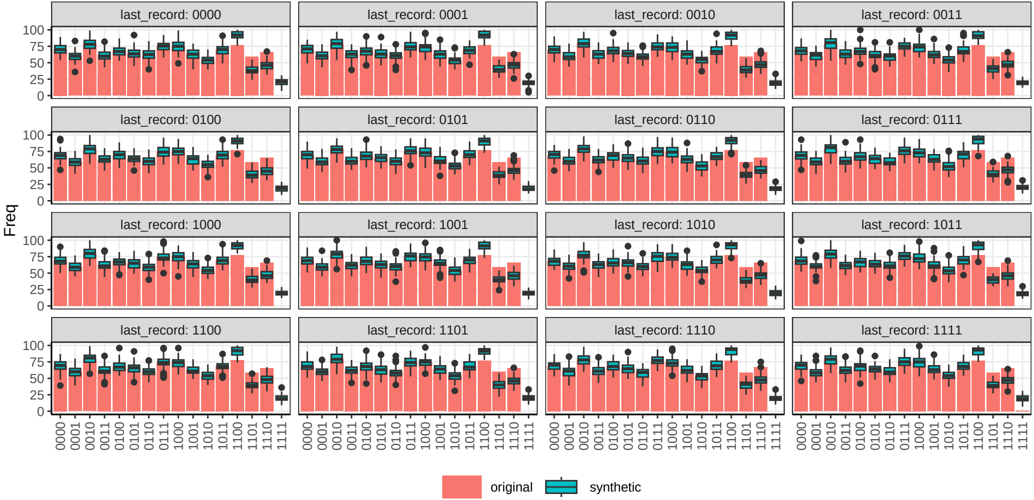
GENERATE SYNTHETIC DATA WITH CART (MODIFIED PARAMETERS)

Figure 5: Compare histogram x 100 synthetic datasets



ILLUSTRATING THE ATTACK WITH CART (MODIFIED PARAMETERS)

Figure 6: Histogram of 16 worlds x 100 synthetic datasets



THE BAD NEWS

- 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

SUMMARY

- 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?

- No, this is not a problem.
  - A ‘strong’ attacker is unrealistic.
    - Knows the SDG model type (i.e. sequential CART).
    - Knowledge of al 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

- 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