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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: BACKGROUND

OVERVIEW

- Background:
  - Synthetic data are increasingly used to share data while preserving privacy.
  - Numerous synthetic data generators (SDGs) using variety of methods
  - CART-based SDGs: high statistical utility with high privacy risk (Little et al., 2025; Fossing, 2024; Dankar and Ibrahim, 2021)
- Research question:
  - If that is true, how would we know?
  - Do common privacy measures capture disclosure risk in synthetic data generated by CART models?
- Evaluate 3x privacy measures:
  - Identity disclosure risk
  - Attribute disclosure risk
  - Bayesian estimation of disclosure risk
- 2x Data:
  - Simulated dataset (Reiter et al., 2014 design: 1,000 obs., 4 binary vars., unique case).
  - Public survey data: Social Diagnosis 2011 (SD2011).
- Contributions:
  1. We show that CART-based models may produce synthetic data that sacrifices privacy protection for statistical utility.
  2. Commonly used disclosure risk measures may not capture disclosure risk.
  3. We propose some solutions for measuring disclosure risk (Bayesian).
  4. More generally, users interested in measuring privacy risk should be aware of the challenges we describe here.

SECTION 2: GENERATE SIMULATED DATA (ORIGINAL AND SYNTHETIC)

ORIGINAL DATA SET: SIMULATED DATA

- 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 ($var1 = 1, var2 = 1, var3 = 1, var4 = 1$).
- The value of the simulated data is that we know there is a unique record because we created it.

SYNTHETIC DATA SET

- Generate 1 synthetic data set from a CART-based SDG using the Synthpop package in R
  - We use the default settings and hyperparameter values and set a seed=1237.
- As a sensitivity test, we create 10 synthetic data sets from the original simulated data.

COMPARE SIMULATED AND SYNTHETIC DATA

Figure 1: Frequency

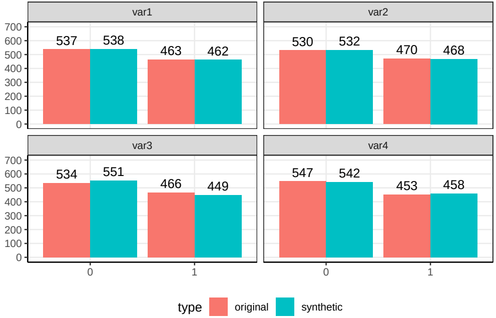
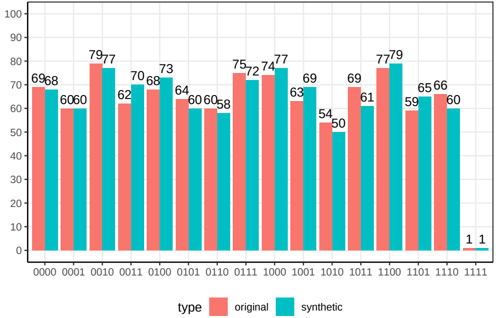
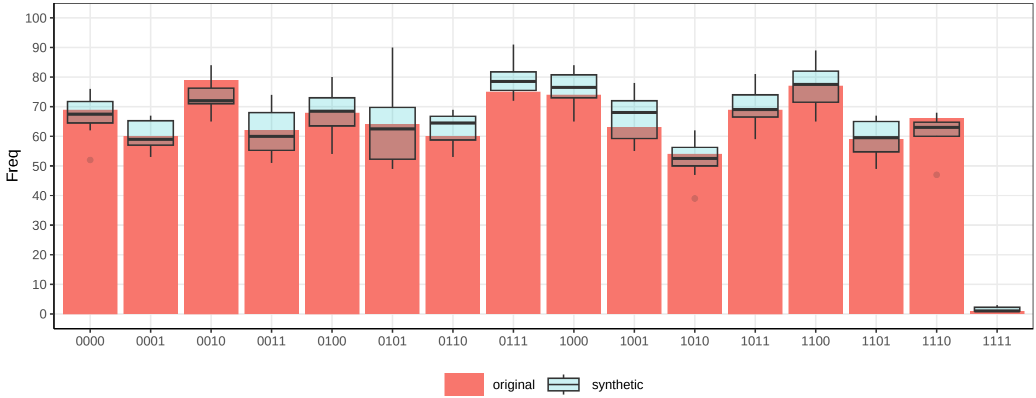


Figure 2: Histogram



COMPARE HISTOGRAM X 10 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?

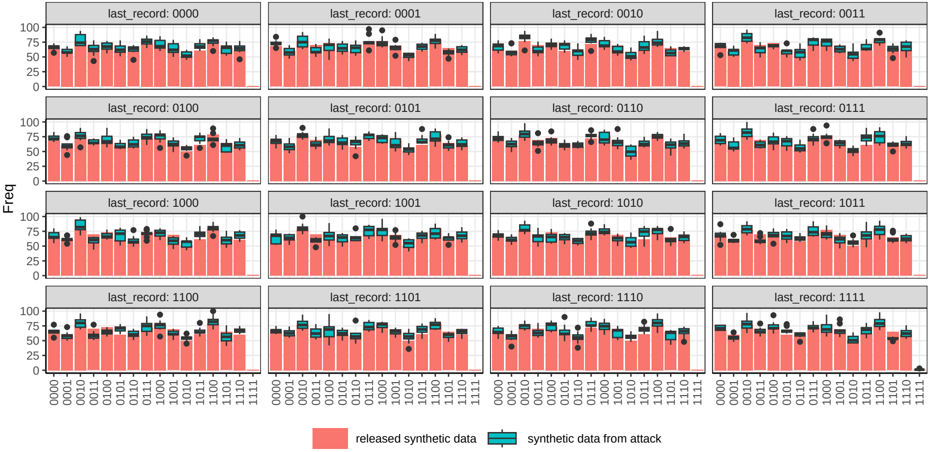
SECTION 3: THE ATTACK

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

HISTOGRAM OF 16 WORLDS X 10 SYNTHETIC DATASETS

Figure 4



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 DISCLOSURE RISK

THREE DISCLOSURE RISK MEASURES

- 2x Common disclosure risk measures reflect the current state of the art (Raab et al., 2025)
  - Identity risk (*repU*): the ability to identify individuals in the data from a set of known characteristics or ‘keys’ (q).
    - $q = var1(0, 1), var2(0, 1), var3(0, 1)$
    - Disclosure risk is how often uniqueness in the synthetic data translates into uniqueness in the original data
    - This should be 0 because these three attributes yield $2^3 = 8$ possible combinations, none of which are unique in the dataset
  - Attribute risk (*DiSCO*): the ability to find out from the keys (q) something, not previously known or ‘target’ (t)
    - $t = var4(0, 1)$
    - Disclosure risk is the proportion of records in the synthetic data with the same level of t for a given set of q
    - This should be > 0 because when $q = 111$, there is a unique record if $t = 1$.
- 1x Alternative disclosure risk measure
  - Bayesian approach (Reiter et al., 2014):
    - If posterior probability is close to the prior (e.g., uniform distribution), little or no new information is revealed.
    - If posterior probability is substantially larger, the intruder has learned something about the last or unique record.
    - In our data this should be > 0, i.e. positive

RESULTS DISCLOSURE RISK MEASURES

Table 1: x 1 synthetic data set (seed = 1237)

Data	Unique	Identity Risk (*repU*)	Attribute Risk (*DiSCO*)	Bayesian Estimate of Risk
Original	1	0.00	0.00	1.00
Synthetic	1	0.00	0.00	1.00

- $DiSCO > 0$ only when t is constant within the set of records sharing the same q
- If there is at least one unique record in the synthetic data, then there is no attribute disclosure risk because there are 2 values of t within q (0,1).
- At the same time, if a synthetic data set is released without the unique record, then there is an attribute disclosure risk because there is only 1 value of t within q (1).

Table 2: x 10 synthetic data sets

Data	Unique	Identity Risk (*repU*)	Attribute Risk (*DiSCO*)	Bayesian Estimate of Risk
Original	1	0.00	0.00	1.00
Synthetic 1	1	0.00	0.00	1.00
Synthetic 2	0	0.00	6.60	0.02
Synthetic 3	1	0.00	0.00	1.00
Synthetic 4	3	0.00	0.00	1.00
Synthetic 5	2	0.00	0.00	1.00
Synthetic 6	1	0.00	0.00	1.00
Synthetic 7	3	0.00	0.00	1.00
Synthetic 8	0	0.00	6.60	0.03
Synthetic 9	1	0.00	0.00	1.00
Synthetic 10	1	0.00	0.00	1.00
Average	-	0.00	1.32	-

- $DiSCO = 6.6$. This is the equivalent 66/1000 ((65/1000 = var1=1,var2=2,var3=1)+(1/1000 = var1=1,var2=2,var3=1,var4=1))

SUMMARY

- According to common privacy measures, CART generates synthetic data with low risk
- However (and this is the point): We know there is a problem (because we created it)
- Only Bayesian approach captures disclosure risk and uncertainty about risk
  - Risk is 1 whenever at least one record equal to $(1, 1, 1, 1)$ appears in the synthetic data.
  - Risk $>$ 0 when (1,1,1,1) does not reappear in the synthetic data.

SECTION 5: IS THIS SCENARIO REALISTIC?

REAL WORLD DATA (SD2011)

- Following the authors of Synthpop (Raab, 2024; Raab et al., 2024), we rely on data from Social Diagnosis 2011 (SD2011).
- In their paper, they generate 5 synthetic data sets to illustrate their method for measuring attribute disclosure by identifying values in the target variable `depress` from keys: `sex` `age` `region` `placesize`.
- To illustrate why it is a problem to measure attribute disclosure as the set of records with constant t within q, we set t as constant for all observations in all 5 synthetic data sets. 0 was chosen because it is the most frequent value in the variable `depress` (22% of all records). By definition, this reduces attribute disclosure risk.
- In their example, attribute risk is about 9%. However, when we modify `depress` so that it is constant (0), the risk *increased* to around 15%.
- Therefore, even though we know risk declined (because we reduced it), *DiSCO* increases.

RESULTS

Table 3: Risk measures for `depress` from keys: `sex`, `age`, `region`, `placesize` (SD2011)

	Identity risk (*repU*)		Attribute risk (*DiSCO*)	
Data	Raab et al., 2024	Modified	Raab et al., 2024	Modified
Original data	48.38	48.38	53.30	53.30
Synthetic 1	14.82	14.82	8.96	14.74
Synthetic 2	14.20	14.20	9.90	14.82
Synthetic 3	15.16	15.16	10.46	14.94
Synthetic 4	14.12	14.12	9.68	14.50
Synthetic 5	14.30	14.30	8.88	14.66
Average	14.52	14.52	9.58	14.73

Note: Modified indicates that values of `depress`=0 for all records in the synthetic data

SUMMARY

- When we create synthetic data to reduce attribute disclosure risk, *DiSCO* measure increases
- The package authors are aware of the problem
  - that the *DiSCO* measure of attribute disclosure risk can indicate a high level of risk for a target variable where a high proportion of records have one level (Raab et al., 2024).
  - The package includes a flag to allow the user to identify values within a variable that explain most of the disclosures (`check_1way`).
- We agree, but our example illustrates that the disclosure measure increases, when it should decrease.
- The key point is that we show that *DiSCO* mismeasures risk using real world data

SECTION 6: CONCLUSION

SUMMARY

- CART-based synthetic data generators reproduce original data with high utility, but offer little protection for disclosive records under default settings.
- Common privacy metrics may fail to detect or even misstate disclosure risk.
- Bayesian approach can be a good solution, but only in low-dimensional data
- Key takeaway: users must understand both how SDGs generate data and how privacy measures operate. There is no one-size-fits-all solution.

THANK YOU

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Reproducible code: `https://github.com/jonlatner/KEM_GAN/tree/main/latner/projects/simulation`