IAB INSTITUTE FOR EMPLOYMENT RESEARCH
The Research Institute of the Federal Employment Agency

AnigeD

GENERATING SYNTHETIC DATA IS COMPLICATED: KNOW YOUR DATA AND KNOW YOUR GENERATOR

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SECTION 1: INTRODUCTION

OVERVIEW

- Common perception that making synthetic data is easy
- We to show that its complicated
  - You need to know your data
    - Missing values, messy data, etc.
  - You need to know your synthetic data generator (SDG)
    - Compare 3 SDGs: DataSynthesizer, CTGAN, Synthpop
    - How does it deal with missing values?
    - How computationally efficient is it (in terms of duration in time)?
    - How does it meet privacy standards? (but not today)
- Conclusion - Every SDG has advantages/disadvantages (no one, correct solution)
  - Synthpop is good, but has problem with dimensionality
  - DataSynthesizer is not as good, but can set ϵ-DP
  - CTGAN is bad, but maybe the problem is CTGAN, not GANs in general

THE GOOD NEWS – MAKING SYNTHETIC DATA IS EASY

- `Gretel.ai`: The synthetic data platform for developers. Generate artificial datasets with the same characteristics as real data, so you can develop and test AI models without compromising privacy.
- `Mostly.ai`: Synthetic Data. Better than real. Still struggling with real data? Use existing data for synthetic data generation. Synthetic data is more accessible, more flexible, and simply...smarter.
- `Statice.ai`: Generating synthetic data comes down to learning the joint probability distribution in an original, real dataset to generate a new dataset with the same distribution. The more complex the real dataset, the more difficult it is to map dependencies correctly. Deep learning models such as generative adversarial networks (GAN) and variational autoencoders (VAE) are well suited for synthetic data generation.
- `hazy.com`: Synthetic data does not contain any real data points so can be shared freely. Say goodbye to lengthy governance processes associated with real data. Specifically, Hazy data is designed to preserve all the patterns, statistical properties and correlations in the source data, so that it can be used as a drop-in replacement for it.
- DataSynthesizer: The distinguishing feature of DataSynthesizer is its usability — the data owner does not have to specify any parameters to start generating and sharing data safely and effectively.

THE BAD NEWS – MAKING SYNTHETIC DATA IS HARD

- According to the Alan Turing Institute (Jordan et al., 2022)
- Synthetic data is not a replacement for real data. It is a distorted version of the real data.
  - Why are we creating synthetic data?
  - Agreeing on the goal will help us make decisions (synthesizer, measures, etc.)
- How does the synthesizer work? from complete black box to complete user choice
- How different should it be? How do we measure the difference (utility and fidelity)?
  - Utility and fidelity are sometimes called general/broad or specific/narrow measures within the single concept of utility (Snoke et al., 2018; Drechsler and Reiter, 2009).
- Computationally efficiency (i.e. duration in time) is important and often ignored. The algorithm should scale well with the dimension of the data space in a relational way, not exponential way.
- How do we evaluate privacy? (not today)

OUR GOAL IS TO ILLUSTRATE THE CHALLENGES

- Know your data (1 dataset)
  - Social Diagnosis 2011 (SD2011) - Cleaning/pre-processing (most evaluations use clean data)
- Know your generator
  - Evaluate 3 synthetic data generators (SDG): DataSynthesizer, CTGAN, Synthpop
    - How do they actually work? (only briefly described here)
- 4 utility measures
  - Propensity score mean-squared error (pMSE) - Append the original and synthetic datasets. Create an indicator variable for original/synthetic datasets. The probability of being in the synthetic dataset is computed for each record in the combined dataset (n); this is the propensity score (p). Lower scores are better. ($pMSE = \frac{1}{N}\sum_{i=1}^{N}[\hat{p}_i - c]^2$)
  - Ratio of counts/estimates (ROC/ROE) - Calculate the ratio of each value in a given variable for both synthetic/original datasets. Then, calculate the ratio of each value for each dataset, and divide the smaller of these two estimates by the larger one. Higher scores are better. ($ROE = \frac{min(y^1_{orig}, y^1_{synth})}{max(y^1_{orig}, y^1_{synth})}$)
  - Confidence interval overlap from 2 regression models (OLS, GLM)
  - Computationally efficient with respect to duration in time

SECTION 2: KNOW YOUR DATA (SD2011)

REAL DATA

- Social Diagnosis 2011 (SD2011)
- Loads with Synthpop
  - `http://www.diagnoza.com/index-en.html`
  - Not entirely clear how original data is created or cleaned to create data in Synthpop
    - No
- Like real data, has ‘quirks’ or unusual values/variables
  - Includes missings
    - Informative (i.e. for never worked abroad, `wkabdur` is missing)
    - Non-informative
  - Includes ‘errors’
    - `smoke` - Does smoke is NO, but `nociga` - 20/22 cigarettes per day
    - `bmi` = 451, but `height`(cm) = 149 and `weight`(kg) = NA (999)
  - Includes generated variables (Can be problematic for SDGs)
    - `bmi`,`agegr`

DATA (SD2011)

Number	Variable	Description	Type	Observations	Unique.Values	Missings	Negative.values	Generated	Quirks
1	sex	Sex	factor	5000	2	0	0		
2	age	Age of person, 2011	numeric	5000	79	0	0		
3	agegr	Age group, 2011	factor	5000	7	4	0	Yes	Yes
				...					
7	eduspec	Discipline of completed qualification	factor	5000	28	20	0		Yes
				...					
10	income	Personal monthly net income	numeric	5000	407	683	603		
11	marital	Marital status	factor	5000	7	9	0		
12	mmarr	Month of marriage	numeric	5000	13	1350	0		
13	ymarr	Year of marriage	numeric	5000	75	1320	0		
14	msepdiv	Month of separation/divorce	numeric	5000	13	4300	0		
15	ysepdiv	Year of separation/divorce	numeric	5000	51	4275	0		
				...					
22	nofriend	Number of friends	numeric	5000	44	0	41		
23	smoke	Smoking cigarettes	factor	5000	3	10	0		
24	nociga	Number of cigarettes smoked per day	numeric	5000	30	0	3737		Yes
				...					
27	workab	Working abroad in 2007-2011	factor	5000	3	438	0		
28	wkabdur	Total time spent on working abroad	numeric	5000	33	0	4875		Yes
				...					
33	height	Height of person	numeric	5000	65	35	0		
34	weight	Weight of person	numeric	5000	91	53	0		
35	bmi	Body mass index (weight - kg/(height - cm^2)*10000)	numeric	5000	1396	59	0	Yes	Yes

SECTION 3a): KNOW YOUR GENERATOR (DATASYNTHESIZER)

“DataSynthesizer, a Python package, implements a version of the PrivBayes (Zhang et al., 2017) algorithm. DataSynthesizer learns a differentially private Bayesian Network which captures the correlation structure between attributes and then draws samples.” (Little et al., 2021)

Variable type: The Bayesian network only works with discrete variables. One way to discretize continuous variables is by binning them.

DATASYNTHESIZER

- Hyperparameters
  - ϵ Differential Privacy (DP): we turn it off (default 0.1)
  - k-degree Bayesian network (parents): 1 (independent), 2, 3, or 4 (default is 'greedy')
  - In Fig. 1, $k = 2$, but not known in reality

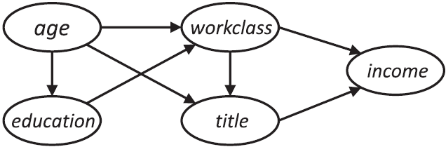
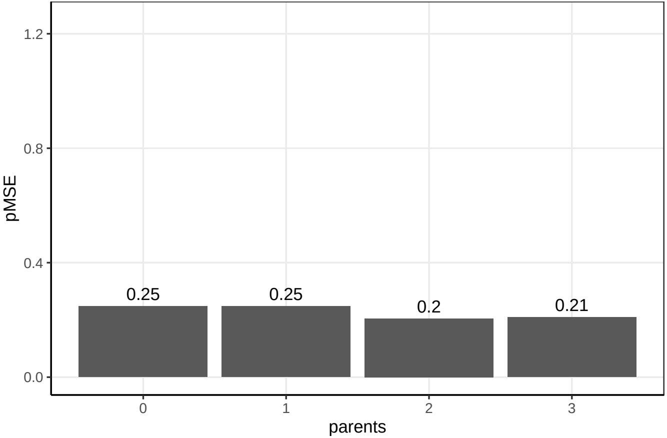


Fig. 1. A Bayesian network $\mathcal{N}_1$ over five attributes.

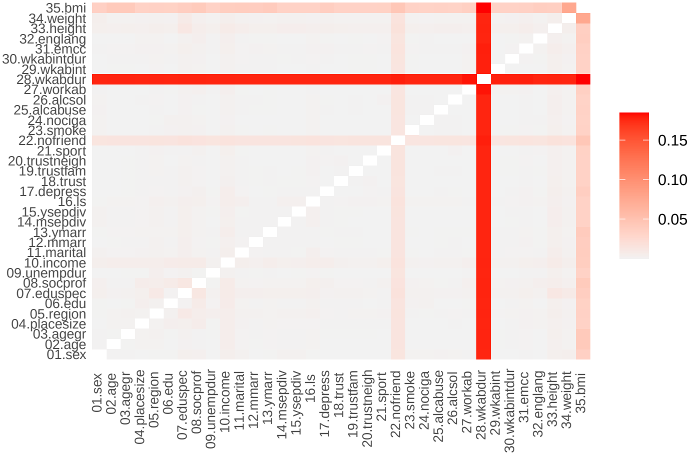
SD2011 - PMSE BY NUMBER OF PARENTS

Figure 1: Model fit does not improve after $k = 2$



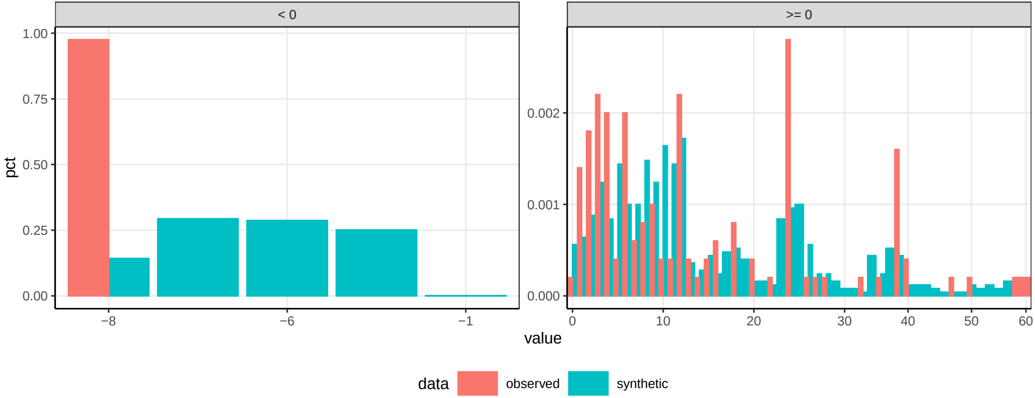
TWO-WAY PMSE FOR PAIRS OF VARIABLES

Figure 2: SD2011(a) – Raw data



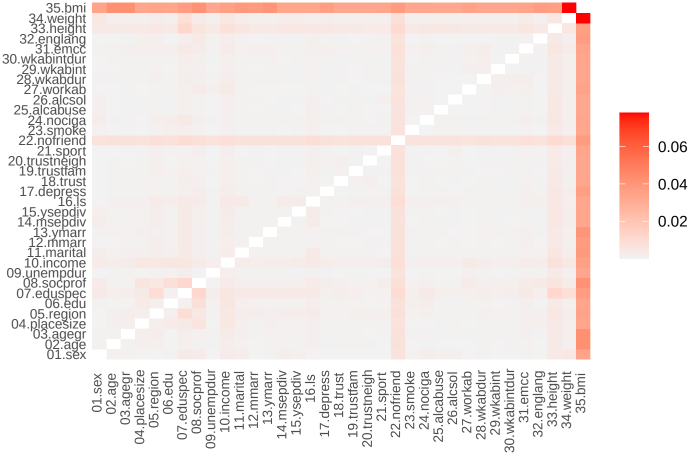
VARIABLE: WKABDUR (WORK ABROAD DURATION)

Figure 3: Captures values $<$ 0 as continuous, not missing/categorical



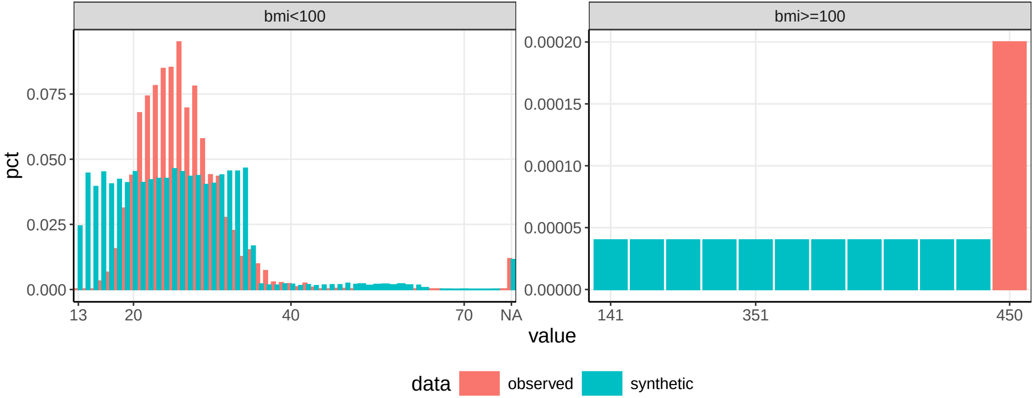
TWO-WAY PMSE FOR PAIRS OF VARIABLES

Figure 4: SD2011(b) – missing are numerical values <0 and “ ” categorical values



VARIABLE: BMI

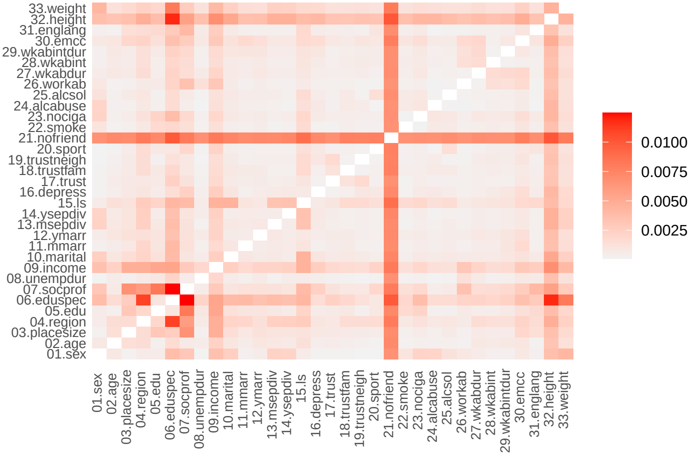
Figure 5: BMI $<$ 20 is underweight/malnourished



errors: `bmi` = 451, but `height` (cm) = 149 and `weight` (kg) = NA (999)

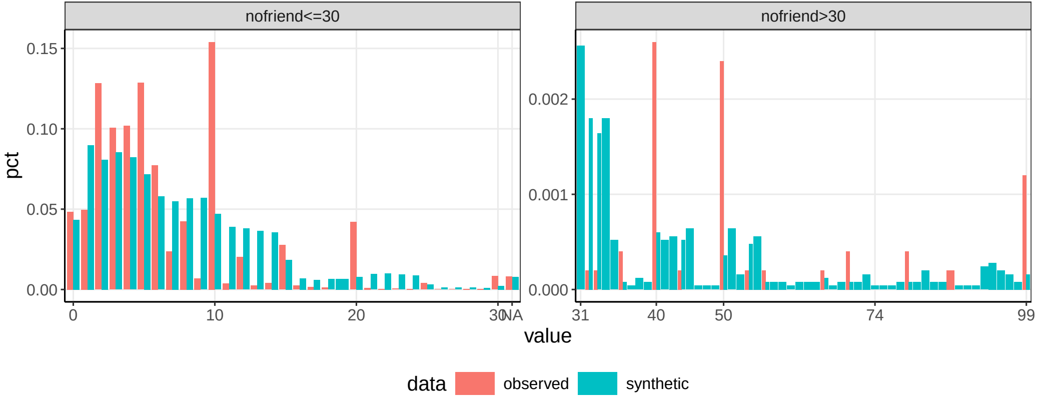
TWO-WAY PMSE FOR PAIRS OF VARIABLES

Figure 6: SD2011(c) – drop generated variables (bmi and agegr)



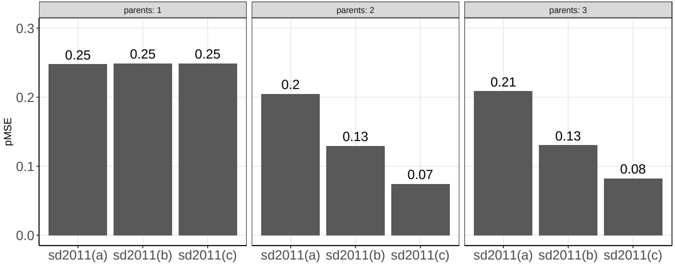
VARIABLE: NOFRIEND

Figure 7: Doesn’t capture rounding/discontinuity



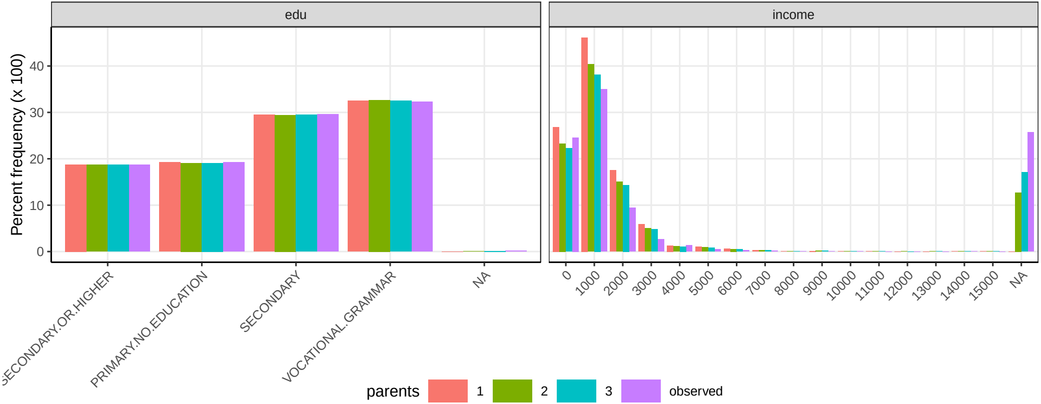
SD2011 - PMSE

Figure 8: We use SD2011(c) - cleaned missing values, dropped generated variables, and $k = 2$



PERCENT FREQUENCY FOR SELECTED VARIABLES BY PARENTS

Figure 9: No missings if parents $<$ 2, better for categorical than numeric variables



SUMMARY

- General lessons
  - You have to ‘know’ your data (missings, negative values, etc.)
  - No need to replicate generated variables
- DataSynthesizer lessons for SD2011
  - Will only capture missing values if parents (k) $>=$ 2 (is this a bug? am i doing it wrong?)
  - Better at capturing distribution of categorical variables than continuous variables
- Its the only SDG that incorporates ϵ DP as a setable hyperparameter

SECTION 3b): KNOW YOUR GENERATOR (CTGAN)

GANs (Goodfellow et al., 2014), simultaneously train two NN models: a generative model which captures the data distribution, and a discriminative model that aims to determine whether a sample is from the model distribution or the data distribution.

The generative model starts off with noise as inputs and relies on feedback from the discriminative model to generate a data sample. This goes back and forth until the discriminator cannot distinguish between the actual data and the generated data.

Unlike DataSynthesizer, GANs were created to deal with continuous variables.

EXPERIMENT WITH ‘PRIMARY’ HYPERPARAMETERS

- epochs = Number of times the GAN gets to see the full dataset (default is 300).
- batch size = Number of samples to process in each step (default is 500)

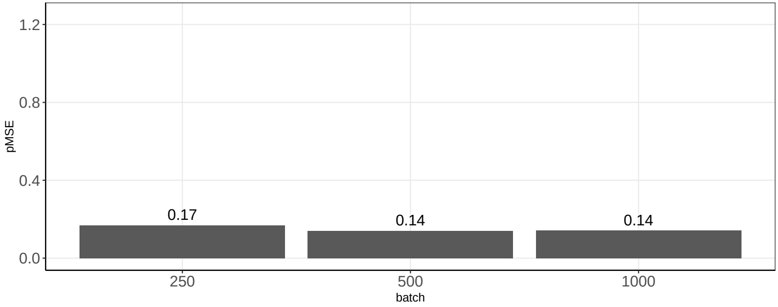
Table 1: Batch size and epochs = actual steps

N	Batch size	Steps per Epoch	Epochs	Actual Steps
5.000	500	10	100	1,000
5.000	500	10	300	3,000
5.000	500	10	600	6,000
5.000	500	10	900	9,000
5.000	100	50	60	3,000
5.000	250	20	150	3,000
5.000	500	10	300	3,000
5.000	1.000	5	600	3,000

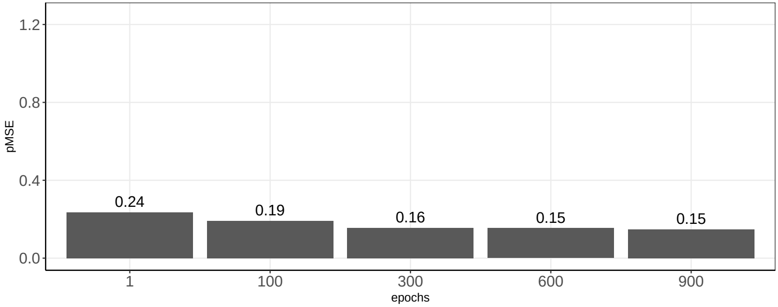
EXPERIMENT WITH ‘ADVANCED’ HYPERPARAMETERS

- dimensionality - The number of layers in the generator/discriminator networks
  - discriminator_dim (tuple or list of ints): Size of the output samples for each one of the Discriminator Layers. A fully connected layer will be created for each one of the values provided. Defaults to (256, 256).
  - generator_dim (tuple or list of ints): Size of the output samples for each one of the Residuals. A Residual Layer will be created for each one of the values provided. Defaults to (256, 256).
- embedding_dim (int): Size of the random sample passed to the Generator. Defaults to 128.
  - The embedding dimension essentially influences how much the information in the original data set is compressed
- Other hyperparameters exist that we do not experiment with (i.e. learning rate, weight decay, etc.)

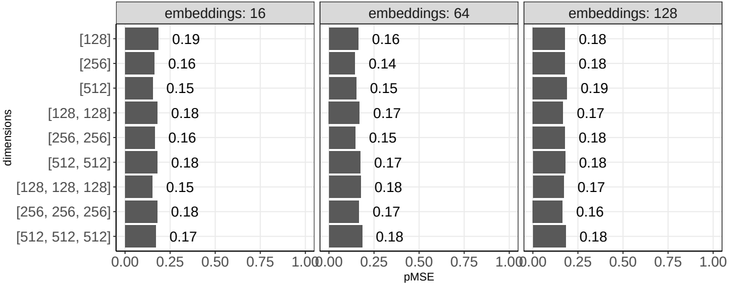
CTGAN: EFFECT OF BATCH SIZE (CONSTANT STEPS)



CTGAN: EFFECT OF EPOCHS (CONSTANT BATCH SIZE)

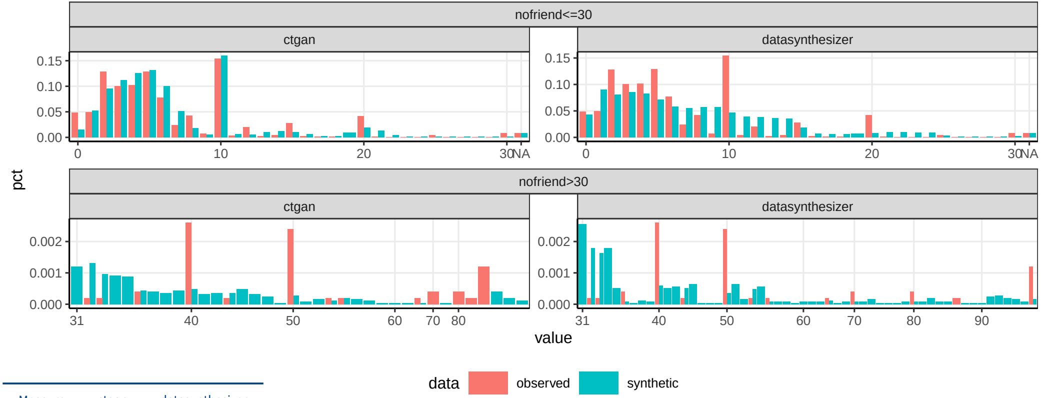


CTGAN: EFFECT OF DIMENSIONS



VARIABLE: NOFRIEND

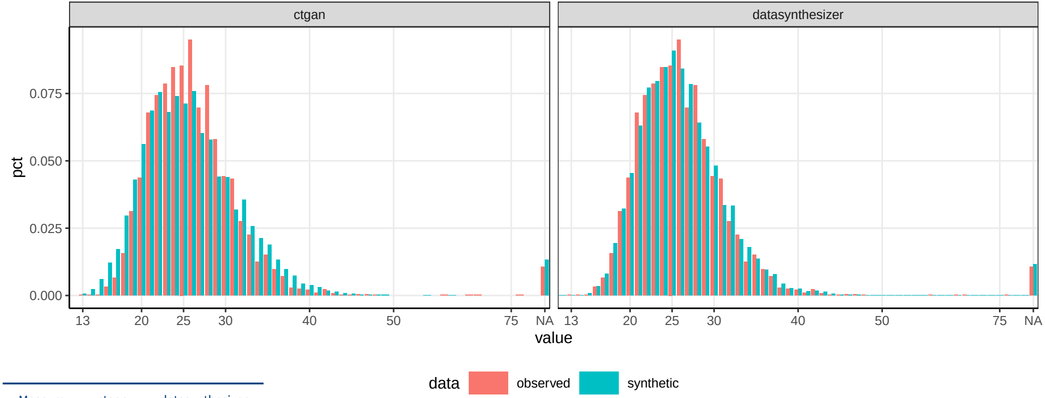
Figure 10: CTGAN is better than DataSynthesizer below 30, but both are bad above 30



Measure	ctgan	datasynthesizer
ROE	0.28	0.17

VARIABLE: BMI

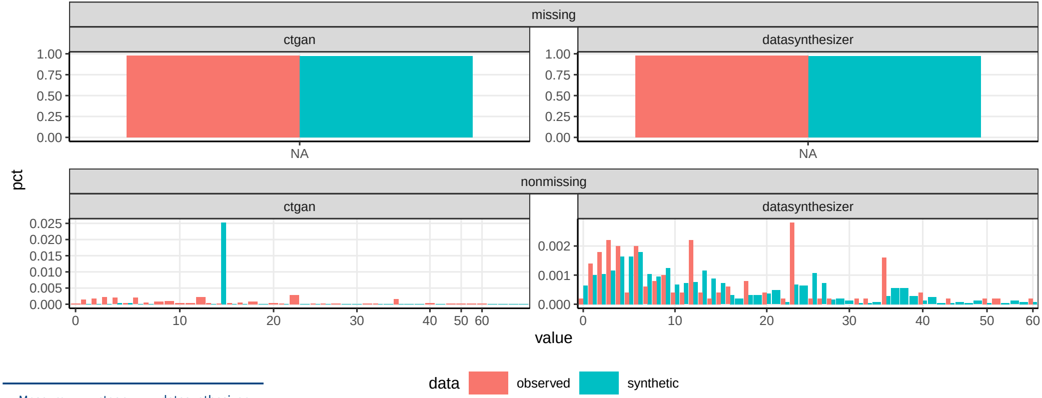
Figure 11: CTGAN/DataSynthesizer estimate the median, but CTGAN is skewed a bit more to the right



Measure	ctgan	datasynthesizer
ROE	0.54	0.52

VARIABLE: WKABDUR (WORK ABROAD DURATION)

Figure 12: CTGAN does not correctly estimate the distribution, DataSynthesizer gets the median (10)



Measure	ctgan	datasynthesizer
ROE	0.06	0.29

SUMMARY

- CTGAN is not a good SDG for this particular dataset, but . . .
- Role of hyperparameters
  - Did not improve model fit in this data
  - We could still alter other hyperparameters
  - We know hyperparamters help in other data (unpublished - under review)
- Distinguish between the package and the synthesizer
  - CTGAN is not the only GAN
  - Can we make a better GAN? Yes, we can . . .

SECTION 3c): KNOW YOUR GENERATOR (SYNTHPOP)

“Synthpop, R package, uses methods based on classification and regression trees (CART, developed by Breiman et al. (1984)), which can handle mixed data types and is non-parametric. Synthpop synthesises the data sequentially, one variable at a time; the first is sampled, then the following are predicted using CART (in the default mode) with the previous variables used as predictors. ” (Little et al., 2021)

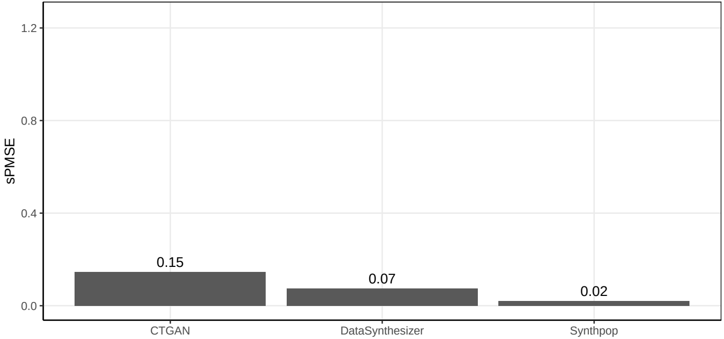
Variable order

“This means that the order of variables is important (and can be set by the user)...As suggested by Raab et al. (2017), variables with many categories may be moved to the end of the sequence, therefore the ordering was set by the least to maximum number of categories, with age first.” (Little et al., 2021)

In our opinion: Problems and recommendations about variable order are not so clear in Raab et al., 2017.

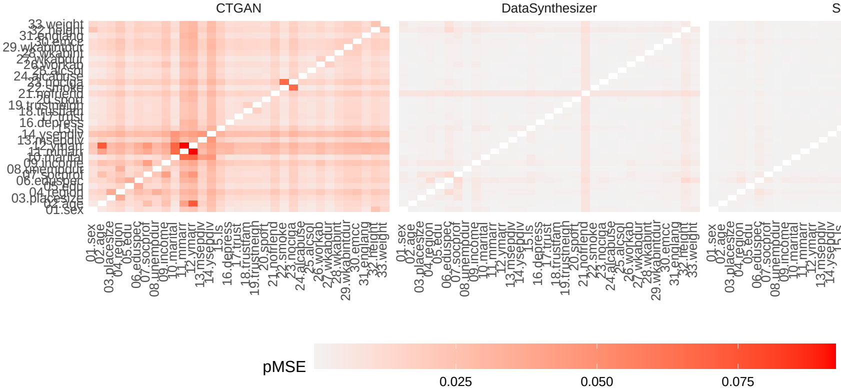
SD2011 - PMSE

Figure 13



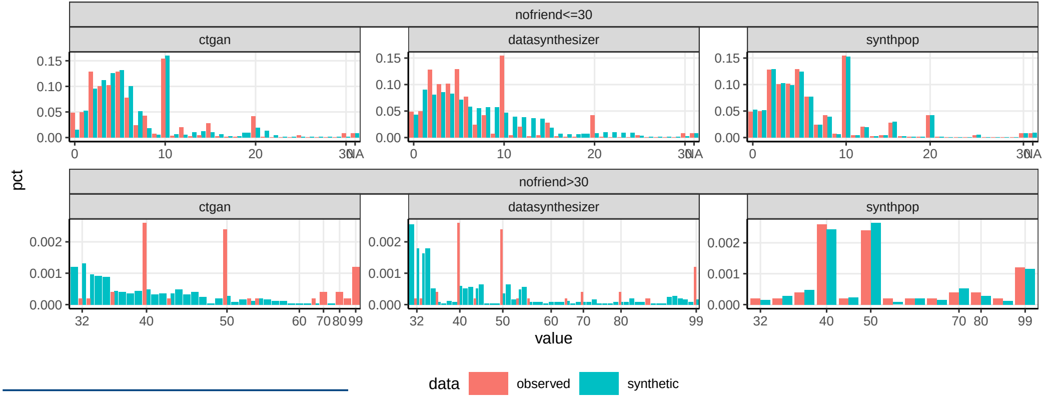
TWO-WAY PMSE FOR PAIRS OF VARIABLES

Figure 14



VARIABLE: NOFRIEND

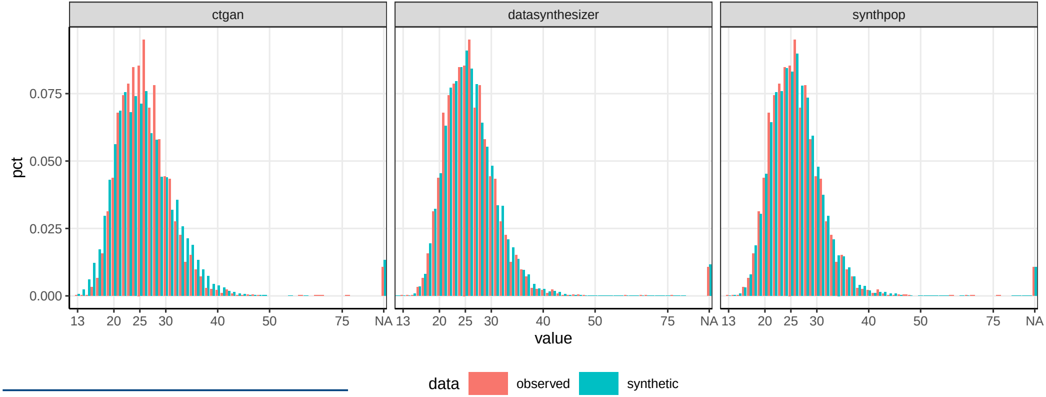
Figure 15: Synthpop captures the distribution



Measure	ctgan	datasynthesizer	synthpop
ROE	0.28	0.17	0.40

VARIABLE: BMI

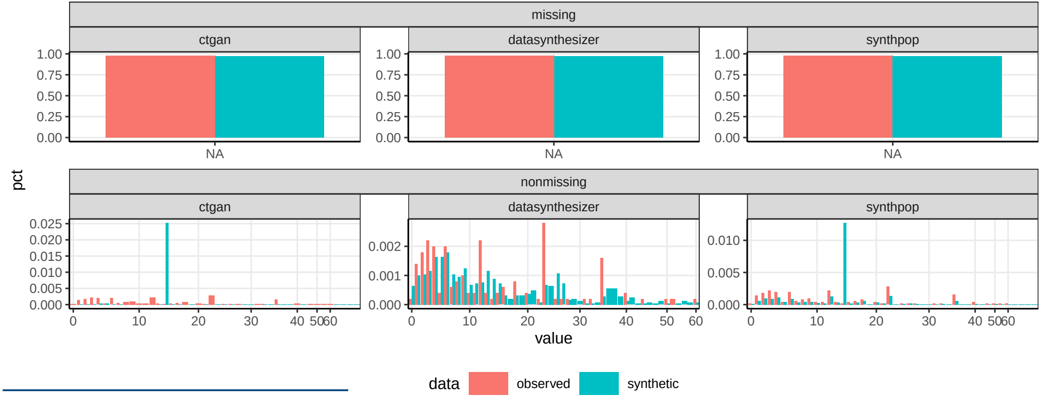
Figure 16: DataSynthesizer is similar to Synthpop



Measure	ctgan	datasynthesizer	synthpop
ROE	0.54	0.52	0.48

VARIABLE: WKABDUR (WORK ABROAD DURATION)

Figure 17: Like CTGAN, Synthpop is higher than median (10), but is better with the distribution than CTGAN/DataSynthesizer



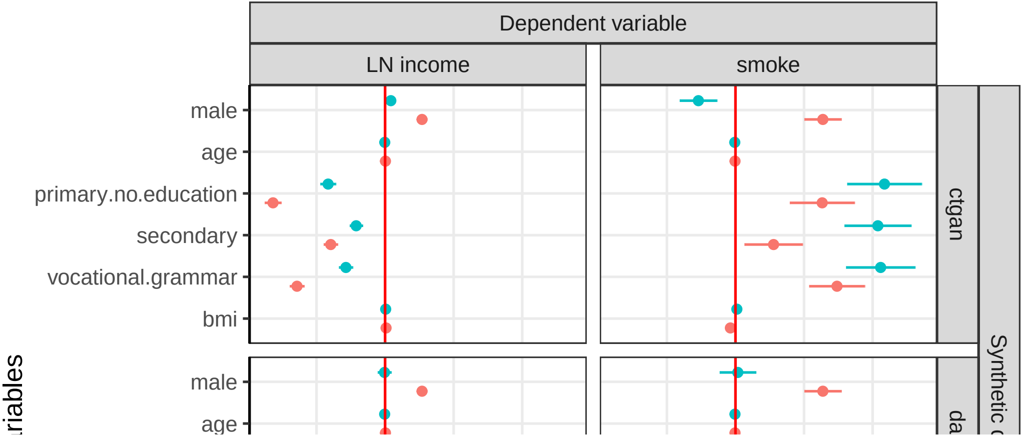
Measure	ctgan	datasynthesizer	synthpop
ROE	0.06	0.29	0.38

COMPUTATIONAL EFFICIENCY - DURATION IN SECONDS

version	description	ctgan	datasynthesizer	synthpop (csv)	synthpop (package)
v00	Raw (SD2011)	331.01	245.37	2132.12	5474.39
v01	Without eduspec or wkabdur	290.30	264.43	10.99	8.45
v02	Without wkabdur	337.07	351.76	13.96	11.02
v03	Without eduspec	306.46	351.24	11.39	8.92
v04	Last variables: eduspec-wkabdur	374.57	344.02	14.23	287.85
v05	Last variables: wkabdur-eduspec	419.60	339.92	14.60	3657.55
v06	as.numeric(wkabdur) and last variable: eduspec	356.02	347.36	14.12	11.05
v07_1_20	+ 1 factor variable (20 values)	339.05	264.96	42.23	
v07_1_25	+ 1 factor variable (25 values)	400.28	326.84	137.47	
v07_1_30	+ 1 factor variable (30 values)	339.73	269.72	363.18	
v07_2_20	+ 2 factor variable (20 values)	369.74	339.45	74.96	
v07_2_25	+ 2 factor variable (25 values)	364.56	361.81	631.43	
v07_2_30	+ 2 factor variable (30 values)	373.25	346.15	1222.54	
v07_3_20	+ 3 factor variable (20 values)	393.99	369.58	122.77	
v07_3_25	+ 3 factor variable (25 values)	401.03	383.40	881.53	
v07_3_30	+ 3 factor variable (30 values)	394.44	424.64	3654.59	

CONFIDENCE INTERVAL OVERLAP (CIO)

Figure 18: Synthpop still misses role of education in smoking



SUMMARY

- Advantages
  - Synthpop is an excellent SDG for this particular data set
  - Much better than CTGAN/DataSynthesizer
- Disadvantages
  - Questions about privacy (not addressed here)
  - Issues with high dimensional data

SECTION 4: CONCLUSION

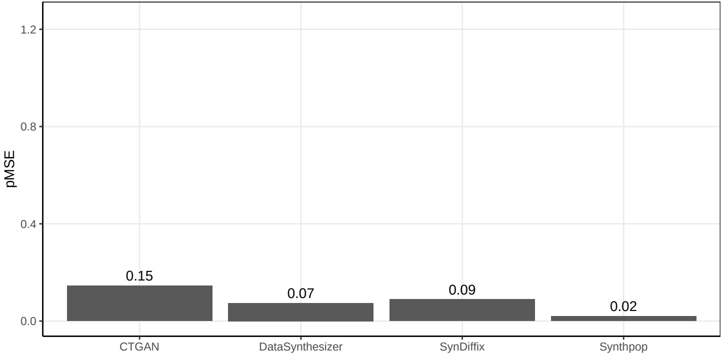
RESULTS: ITS COMPLICATED

- Know the data
  - Cleaning/preprocessing are important (errors, missing values, generated variables)
  - Data variables/values are not always clear or easy to learn (This takes time)
- Know your synthesizer. Its hard - don’t hope it will be just one click
  - Each of the three synthetic data generators (SDGs) has their own set of advantages/disadvantages
    - Synthpop is good, but has problem with dimensionality
    - DataSynthesizer is not as good, but can set ϵ-DP
    - CTGAN is bad, but maybe the problem is CTGAN, not GANs in general
  - We have focused on utility, privacy is its own separate, complicated issue
    - Is privacy a function of the generator or the data?
- Possible disconnect between knowledge of the data and knowledge of the generator
  - Private companies may not know the data, but may know the generator(s) - which is best and for what
  - Statistical agencies may know the data, but may not know the generator(s)

THANK YOU

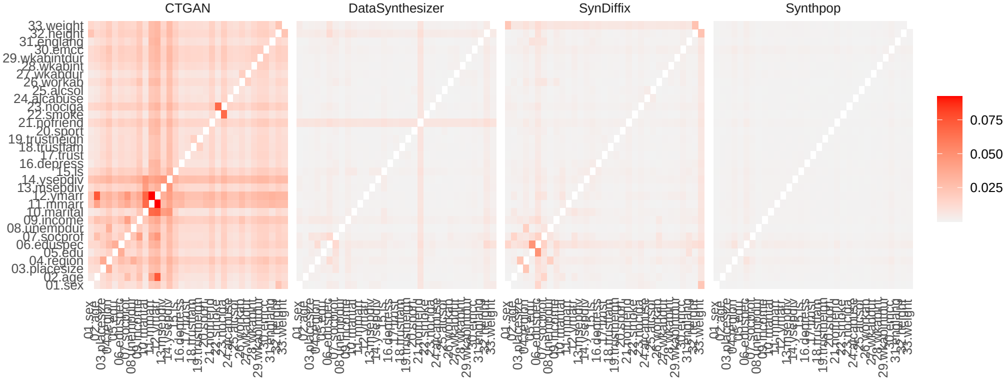
SYNDIFFIX: PMSE

Figure 19



SYNDIFFIX: TWO-WAY PMSE FOR PAIRS OF VARIABLES

Figure 20


CTGAN
DataSynthesizer
SynDiffix
Synthpop
01.sex
02.age
03.placesize
04.region
05.edu
06.eduspec
07.socprof
08.unempdur
09.income
10.marital
11.mmarr
12.ymarr
13.msepdiv
14.ysepdiv
15.ls
16.depress
17.trust
18.trustfam
19.trustneigh
20.sport
21.nofriend
22.smoke
23.nociga
24.alcabuse
25.alcsol
26.workab
27.wkabdur
28.wkabint
29.wkabintdur
30.emcc
31.englang
32.height
33.weight