On the Utility Recovery Incapability of Neural Net-based Differential Private Tabular Training Data Synthesizer under Privacy Deregulation

Yucong Liu∗, Chi-Hua Wang † and Guang Cheng ‡

Abstract

Devising procedures for auditing generative model privacy-utility tradeoff is an important yet unresolved problem in practice. Existing works concentrates on investigating the privacy constraint side effect in terms of utility degradation of the train on synthetic, test on real paradigm of synthetic data training. We push such understanding on privacy-utility tradeoff to next level by observing the privacy deregulation side effect on synthetic training data utility. Surprisingly, we discover the Utility Recovery Incapability of DP-CTGAN and PATE-CTGAN under privacy deregulation, raising concerns on their practical applications. The main message is “Privacy Deregulation does NOT always imply Utility Recovery”.

1 Introduction

Differential private synthetic training data receives rising attentions from both academics and industry [1, 2, 3]. Such attention is due to the capability of differential private synthetic training data to train machine learning models in a way that aligns modern privacy regulations (e.g. GDPR [4] or CCPA). The capability differential private synthetic training data to support trustworthy machine learning lifecycle is fruitful and hence invites both scientists and practitioners to investigate the pros and cons of adopting differential private synthetic training data [1, 5]. In particular, what are the costs and benefits for machine learning model training if we replace real training dataset with differential private synthetic training data?

Indeed, the benefits is a machine learning training process with individual-level privacy protection, and the costs is performance degradation [6]. Such observation depreciates the practical usage of differential private synthetic training data, motivating us to investigate a more involved study of the privacy-utility tradeoff [7, 8] behind synthetic data training. In

∗Master Student, Department of Statistics, University of Chicago, IL, 60637. Email: yucongliu@uchicago.edu
†Postdoctoral Scholar, Department of Statistics, UCLA, CA, 90095. Email: chihuawang@ucla.edu
‡Professor, Department of Statistics, UCLA, CA, 90095. Email: guangcheng@ucla.edu
particular, our investigation focus on the setting of synthesizing differential private tabular training dataset for machine learning classifier training. Given intrinsic individual-level privacy protection by replacing real training data with differential private synthetic training data, this paper is guided by the following question: **which family of differential private tabular training data synthesizer have the best utility recovery capability?**

At the moment, synthetic data generation research community do not reach an consensus on the mechanism of ensuring differential privacy on synthetic training dataset \[5, 12, 13\]. In this study, we visit three major family of training data synthetizer with governable differential privacy mechanism: **DP-GAN** \[14\], **PATE-GAN** \[15\] and **PrivBayes** \[11\]. These three governable differential privacy mechanism have their counter part on tabular data synthesizers, which are **DP-CTGAN** \[9\], **PATE-CTGAN** \[10\] and **DataSynthesizer** \[16\]. Consequently, our aim is to investigate the privacy-utility tradeoff behind these three differential private tabular training data synthesizer.

In this work, we take the **privacy deregulation** perspective to delineate the privacy-utility tradeoff behind differential private tabular training data synthesizer. Privacy deregulation perspective means that we observe the change of machine learning model utility of synthetic training dataset by changing the privacy budget we required in the differential private training datasets. And we hypothesize that an trustworthy training data synthesizer should show utility recovery after loosing privacy protection requirement. However, Figure 1 suggests an upsetting implication that

**the current art of neural net-based differential private tabular training data synthesizer is Utility Recovery Incapable.**

Specifically, we observed that classifier trained on differential private synthetic dataset by **DP-CTGAN** suffers permanent utility utility damage across different level of privacy budget. On the other hand, **PATE-CTGAN**-generated differential private training dataset shows certain phrase transition before and after privacy budget \( \varepsilon = 3 \). Such an upsetting observation raises concerns about the usage differential private synthetic training data in wide range tabular data-based machine learning system. Fortunately, bayesian network-based differential private tabular training data synthesizer, **PrivBayes** \[11\] is observed to be immune from such Utility Recovery Incapability phenomenon.
Contribution: Utility Recovery Incapability Universality Disclosure. In this work, we disclose the Utility Recovery Incapability of neural net-based differential private tabular training data synthesizers. The utility recovery incapability phenomenon raises concerns on whether general utility requirement on differential privacy is a reliable standard to audit the quality of synthetic dataset. Such concern calls for further investigation the specific utility of differential private training data, especially for downstream task-oriented metric.

Paper Organization. We structure this work as follows. Section 2 provides a comprehensive reviews on related research topics across notion of utility and differential privacy (section 2.1), differential private tabular data synthesizer (section 2.2) and privacy-utility trade-off (section 2.3). Section 3 gives experiment details on how to implement differential privacy and privacy deregulation (section 3.1), implementation details of synthesizer (section 3.2) and the train on synthetic test on real paradigm (section 3.3). Section 4 gives empirical evidence to support our claim that the Utility Recovery Incapability phenomenon is universal across different machine learning models (section 4.1), different utility metrics (section 4.2) and different source real dataset (section 4.3). Section 5 gives conclusion and discussion on future direction.

2 Relate Work

2.1 Notion of general utility, specific utility and differential privacy

Notion of General and Specific Utility. Devising procedures for auditing generative model privacy-utility tradeoff requires more sophisticated thoughts on the notion of utility. In this work, we emphasizes the difference between general utility (whether synthetic data distribution is comparable to the original dataset) and specific utility (the similarity of downstream task results from the synthetic data and the original data) [17]. Also see table 1-1 in [18] for different type of synthetic data and their utility. In this work, we focus on evaluating specific utility of differential private tabular training data synthesizer.

Differential Privacy. Differential Privacy started with a long line work of algorithmic privacy [19, 20, 21], then [22] gives the definition of differential privacy. Early work focused on mechanisms of adding noise, like Laplace Mechanism [22] and Gaussian Mechanism [23]. These works gave good insight and theoretical support.

2.2 Differential Private Tabular Training Data Synthesizer

Neural Network-based Tabular Data Synthesizer. Here we review basic and 2 privacy mechanisms to empower neural network-based tabular data synthesizer. (1) Methods of neural network-based tabular data synthesizer (without differential privacy) include CGAN for tabular data [24], DePart [25], Table-GAN [26], TGAN [27] and CTAB-GAN [28]. (2) On the other hand, those with differential privacy mechanism enable include DP-SGD [29], DPGAN [14] and extension [30], DP-CGAN [31], GS-WGAN [32], differentially private autoencoder-based generative model (DP-AuGM) and differentially private variational autoencoder-based generative
model (DP-VaeGM) [33], DP-MERF [34], PEARL [35] DP-SYN [36]. (3) Under PATE framework [37], works include PATE-GAN [15], PATE-CTGAN [10] and G-PATE (Privacy-preserving data Generative model based on the PATE framework) [38].

**Bayesian Network-based Tabular Training Data Synthesizer.** The most representative work of Bayesian Network-based tabular data synthesis methodology is the PrivBayes [11]. The PrivBayes utilizes Bayesian network to synthesize (high-dimensional) tabular data with differential privacy guarantee. Read [39] for detailed probabilistic synthetic data generation framework based on Bayesian Networks. Bayesian methods serve as a fundamental design to synthesize tabular dataset especially, such as Naive Bayes method for synthesizing healthcare record datasets [40] and for generating histogram (PrivTree [41]). Works to improve PrivBayes with more sophisticated graphical model design includes Private-PGM([42]), APPGM([43]) and even random markov field-based method PrivMRF ([44]). We implement Bayesian network-based synthesizer via the DataSynthesizer [16].

2.3 Works address Privacy-Utility Tradeoff.

**Empirical evaluation framework for privacy-utility trade-off.** Here we review existing works on evaluating synthetic datasets privacy-utility trade-off with empirical studies. [45] compares DP-SGD and PATE with testing accuracy of ML models trained on synthetic dataset. [10] adopts AUCROC and F1-score as utility metric to evaluate synthetic ranking agreement over five classification models at different privacy regulation level ($\varepsilon = [0.01, 0.1, 0.5, 1.0, 3.0, 6.0, 9.0]$). In additions, PATE-CTGAN [10] and DP-GAN [14] compared Wasserstein distance for different privacy regulation level $\varepsilon = 9.6, 14, 29$. Our work investigates the privacy-utility tradeoff through privacy deregulation perspective, by changing $\varepsilon$ gradually from 0.1 to 4.0, to see how fast the utility recover for each family of tabular training datasets synthesizer.

**Auditing framework for privacy-utility trade-off.** Privacy-Utility trade-off of synthetic datasets is hard to predict [12]. [7] evaluates the general utility (fidelity, diversity, generalization) but not into specific utility of generative models. [8] also evaluate differentially private synthetic tabular data, on both general utility (individual attribute distribution, pairwise correlation) and specific utility (accuracy of ML classification). Further, [46] provides visualization and [47, 48] gives formal framework to study the privacy-utility tradeoff. We remarks that [45] also observed different patterns of privacy-utility tradeoff about DP-SGD and PATE from general utility perspective, while our work reveals the Utility Recovery Incapability from the specific utility perspective.

3 Approach and Evaluation Framework

In this section, we give full details on our evaluation framework to disclose the Utility Recovery Incapability phenomenon of neural net-based differential private tabular data training. At section 3.1, we formulate the concept of differential privacy and the procedure of privacy deregulation. At section 3.2, we gives essential implementation details on synthesizing differential private tabular training datasets. Section 3.3 establishes the synthetic training and real data testing procedure of our results.
Table 1: Datasets

| Name                        | Instances | Classes |
|-----------------------------|-----------|---------|
| Banknote Authentication     | 1372      | 2       |
| Iris                        | 150       | 3       |
| Social Network Ads          | 400       | 2       |
| Titanic                     | 1309      | 2       |

3.1 Differential Privacy and Privacy Deregulation Synthetic Training

Three differential private mechanisms to synthesize training dataset. We adopt DP-CTGAN, PATE-CTGAN and PrivBayes to synthesize differential private tabular training data with same privacy budget $\varepsilon$ on several source real datasets. We review the differential privacy mechanism behind these three synthesizers family here. DP-CTGAN [9] incorporates differential privacy within the CTGAN model. It tracks the privacy loss with the privacy accountant framework [49]. The utility degradation of DP-CTGAN-based training dataset is due to the difficulties of GAN convergence and privacy loss estimation. PATE-CTGAN [10] partition source real dataset into $k$ subdatasets to initialize $k$ conditional generators and then to train $k$ differentially private teacher discriminators. PrivBayes [11] adopt Exponential Mechanism to construct differentially private Bayesian network.

Privacy deregulation. By privacy deregulation synthetic training, we mean keeping training procedure fixed and changing the training dataset with different privacy budgets. For each differential private tabular training dataset synthesizer, we generate dataset under privacy budgets $\varepsilon \in \{0.1, 0.2, 0.3, 0.4, \cdots, 4.0\}$.

3.2 Differential Private Tabular Training Data Synthesis.

Source Real Datasets. Our experiments are based on four commonly used machine learning datasets from UCI machine learning repository\(^1\) and Kaggle\(^2\) (see Table 1). (i) Banknote. The Banknote Authentication dataset involves predicting whether a given banknote is authentic given a number of measures taken from a photograph. (ii) Iris. The Iris Dataset contains four features of 50 samples of three species of Iris. (iii) Social Network Ads. The Social Network Ads is a categorical dataset to determine whether a user purchased a particular product. (iv) Titanic. The Titanic dataset tells whether a passenger survived the sinking of the Titanic.

We clean the original dataset by deleting identity-related columns like names. Then, we randomly splits the dataset into training data and test data for 10 times, such that the size of the former is 80% of the original data. For each dataset, we apply a pre-processing procedure with label-encoding and standardization by sklearn.\(^3\)

\(^1\)http://archive.ics.uci.edu/ml
\(^2\)https://www.kaggle.com/
\(^3\)https://scikit-learn.org/stable/modules/classes.html#module-sklearn.preprocessing
Implementation detail of Tabular Training Data Synthesis. DP-CTGAN [9] and PATE-CTGAN [10] are implemented with open-source library of SmartNoise\(^4\). Data-synthesizer (DS) [16] is a data generator that takes the structure of the Bayesian network in PrivBayes [11]. So, we implement this with correlated attribute mode in DS.\(^5\) For each \(\varepsilon\), we employ these three methods on the original training dataset respectively and generate 3 synthetic datasets with same size.

Implementation detail of Privacy derregulation. For each \(\varepsilon\), we generate a synthetic training dataset. So, for each synthetic methods, there are 40 synthetic data with different \(\varepsilon\) (except for PATE-CTGAN, which fails to generate with \(\varepsilon = 0.1, 0.2\) on Banknote and Titanic).

3.3 Synthetic Data Training and Real Data Testing for Machine Learning Classifier

Model class of Classifier. We approach the classification tasks by applying six different machine learning algorithms, namely Naïve Bayes, Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Decision Tree, Random Forests and Logistic Regression. All classifiers are implemented with sklearn package\(^6\), and we use standard parameters.

Synthetic Data Training procedure We train each of our 6 classifiers with original training data and synthetic training data respectively. We test these classifiers on the original test data for 6 metrics.

Real Data Testing metric We use 6 different metrics in our experiments, including Accuracy, Precision, Recall, F1 Score, Area Under the Receiver Operating Characteristic Curve (AUROC) and Average Precision. All metrics are implemented with sklearn package. We calculate the mean, maximum and minimum of each metric for totally 10 data splits. Because Iris dataset has multi-class, we don’t calculate Average Precision for this dataset.

4 Evaluation Results

In this section, we provide empirical evidences to support our claim that

the Utility Recovery Incapability phenomenon is universal.

Our evaluation across three major dimension in synthetic data training: Model (Classifier), Metric (Utility) and Data (Source Dataset). Section 4.1 gives the result across different classifier with Accuracy metric on Banknote source dataset. Section 4.2 gives the result across different utility metric with KNN model on Banknote source dataset. Section 4.3 gives the result across different source dataset with Random Forest model with Accuracy metric. See Appendix A, B, C for our extensive investigation results to support the universality of Utility Recovery Incapability phenomenon.

\(^{4}\)https://github.com/opendp/smartnoise-sdk

\(^{5}\)https://github.com/DataResponsibly/DataSynthesizer

\(^{6}\)https://scikit-learn.org/stable/index.html
Figure 2: Utility Recovery Incapability across different Machine Learning Models (Section 4.1). Testing accuracy result on Banknote dataset. DP-CTGAN shows utility recovery incapability. PATE-CTGAN shows utility recovery incapability under strict privacy requirement ($\epsilon < 3$) and recover utility under loose privacy requirement ($\epsilon > 3$). DataSynthesizer shows stable utility recovery. Thus, we recommend Bayesian Network-based synthesizer.

4.1 Utility Recovery Incapability phenomenon across different Machine Learning Models

Figure 2 shows that Accuracy on Banknote dataset has similar trend across 6 different classifiers.

First, accuracy of DP-CTGAN is always around 50% no matter which classifier is used. This implies that the classifier with DP-CTGAN synthesized data is just a random guess. Moreover, when $\epsilon$ increases, Accuracy stays. Thus, DP-CTGAN is incapable for utility recovery.

Second, the test accuracy with PATE-CTGAN starts to recover when $\epsilon > 3$ for all classifier. And the interval range between maximum and minimum tends to shrink, which implies the test accuracy with PATE-CTGAN becomes stable when $\epsilon$ increases. We can interpret this as robustness under synthesizing. However, when $\epsilon < 3$, PATE-CTGAN also fails on the classification and has similar performance as DP-CTGAN. There is no phenomenon of recovery for small $\epsilon$.

Finally, DataSynthesizer show best performance out of these three synthesizing methods. It has best accuracy, smallest extremum range and also a utility recovery phenomenon. This Bayesian Network method also achieves a acceptable performance when $\epsilon$ is small. For more results, see Appendix A.

4.2 Utility Recovery Incapability phenomenon across different classification utility metrics

Figure 3 shows different metrics results on Banknote dataset with KNN classifier. The trends on different metrics are also close.

First, DP-CTGAN stays at a low mean value for all metrics at almost all $\epsilon$. DP-CTGAN also has a very large range for Precision, Recall and F1 Score. These results imply the prediction with DP-CTGAN is not reliable.

Second, PATE-CTGAN has consistent performance for each metrics. Only when $\epsilon > 3$, metrics with PATE-CTGAN rises fast. It still works badly with small $\epsilon$.

Finally, DataSynthesizer keeps to be the best one and rises steadily with increasing $\epsilon$. It also has the smallest value range for each $\epsilon$. For some classifier, DataSynthesizer has different
Figure 3: Utility Recovery Incapability phenomenon across different Classification Utility Metrics (Section 4.2): Results of KNN classifier on Banknote dataset. DP-CTGAN shows different recovery patterns under different utility metrics. PATE-CTGAN shows utility recovery incapability under strict privacy requirement ($\epsilon < 3$) and recover utility under loose privacy requirement ($\epsilon > 3$). DataSynthesizer shows stable utility recovery. Thus, we recommend Bayesian Network-based synthesizer.

Figure 4: Utility Recovery Incapability phenomenon across different Source Real Dataset (Section 4.3): Testing accuracy results of Random Forest classifier. DP-CTGAN shows utility recovery incapability over 4 source dataset. PATE-CTGAN shows utility recovery only on Banknote and Iris source dataset under loose privacy requirement. DataSynthesizer shows stable utility recovery over 4 source datasets. Thus, we recommend Bayesian Network-based synthesizer.

performance on Recall. To be detailed, some Recall curve doesn’t rise but still maintains at a high value level. For more results, see Appendix B.

4.3 Utility Recovery Incapability phenomenon across different source real dataset

Figure 4 shows Accuracy with Random Forest on different datasets. Different from previous evaluation, results among different datasets has different trend, especially for PATE-CTGAN. DP-CTGAN and DataSynthesizer are roughly consistent. DP-CTGAN fails and DataSynthesizer shows good utility recovery phenomenon for all datasets.

Differently, PATE-CTGAN works well on Banknote and Iris but fails on Social Network Ads and Titanic. Moreover, the accuracy with PATE-CTGAN starts to rise at different $\epsilon$, about 3 on Banknote and about 1.5 on Iris. When trained with PATE-CTGAN, accuracy on Banknote also has much smaller value range than accuracy on Iris. Therefore, the performance of PATE-CTGAN is strongly affected by the dataset. For more results, see Appendix C.
5 Conclusion

In this work, we provide a practical evaluation of differential private tabular data synthesizer for synthetic training of machine learning classifier. Our evaluation covers data, models, and metrics to support the claim that the utility recovery incapability phenomenon is universal.

One promising future work direction is to devise utility recovery monitoring process for differential private tabular data synthesizer. Such monitoring process is indispensable for synthetic data practitioner, and we believe more studies on this regard would empower machine learning research toward trustworthy usage of synthetic data methodology in near future.
References

[1] James Jordan, Lukasz Szpruch, Florimond Houssiau, Mirko Bottarelli, Giovanni Cherubin, Carsten Maple, Samuel N Cohen, and Adrian Weller. Synthetic data—what, why and how? arXiv preprint arXiv:2205.03257, 2022.

[2] Ryan McKenna, Gerome Miklau, and Daniel Sheldon. Winning the nist contest: A scalable and general approach to differentially private synthetic data. Journal of Privacy and Confidentiality, 11(3), Dec. 2021.

[3] Rachel Cummings and Deven Desai. The role of differential privacy in gdpr compliance. In FAT’18: Proceedings of the Conference on Fairness, Accountability, and Transparency, 2018.

[4] 2018 reform of eu data protection rules.

[5] Giorgio Visani, Giacomo Graffi, Mattia Alfero, Enrico Bagli, Davide Capuzzo, and Federico Chesani. Enabling synthetic data adoption in regulated domains. arXiv preprint arXiv:2204.06297, 2022.

[6] Markus Hittmeir, Andreas Ekelhart, and Rudolf Mayer. On the utility of synthetic data: An empirical evaluation on machine learning tasks. In Proceedings of the 14th International Conference on Availability, Reliability and Security, pages 1–6, 2019.

[7] Ahmed Alaa, Boris Van Breugel, Evgeny S Saveliev, and Mihaela van der Schaar. How faithful is your synthetic data? sample-level metrics for evaluating and auditing generative models. In International Conference on Machine Learning, pages 290–306. PMLR, 2022.

[8] Yuchao Tao, Ryan McKenna, Michael Hay, Ashwin Machanavajjhala, and Gerome Miklau. Benchmarking differentially private synthetic data generation algorithms. arXiv preprint arXiv:2112.09238, 2021.

[9] Mei Ling Fang, Devendra Singh Dhami, and Kristian Kersting. Dp-ctgan: Differentially private medical data generation using ctdense. In International Conference on Artificial Intelligence in Medicine, pages 178–188. Springer, 2022.

[10] Lucas Rosenblatt, Xiaoyan Liu, Samira Pouyanfar, Eduardo de Leon, Anuj Desai, and Joshua Allen. Differentially private synthetic data: Applied evaluations and enhancements, 2020.

[11] Jun Zhang, Graham Cormode, Cecilia M. Procopiuc, Divesh Srivastava, and Xiaokui Xiao. Privbayes: Private data release via bayesian networks. ACM Trans. Database Syst., 42(4), oct 2017.

[12] Theresa Stadler, Bristena Oprisanu, and Carmela Troncoso. Synthetic data–anonymisation groundhog day. In 31st USENIX Security Symposium (USENIX Security 22), pages 1451–1468, 2022.
[13] John M Abowd and Lars Vilhuber. How protective are synthetic data? In International Conference on Privacy in Statistical Databases, pages 239–246. Springer, 2008.

[14] Liyang Xie, Kaixiang Lin, Shu Wang, Fei Wang, and Jiayu Zhou. Differentially private generative adversarial network. arXiv preprint arXiv:1802.06739, 2018.

[15] Jinsung Yoon, James Jordon, and Mihaela van der Schaar. PATE-GAN: Generating synthetic data with differential privacy guarantees. In International Conference on Learning Representations, 2019.

[16] Haoyue Ping, Julia Stoyanovich, and Bill Howe. Datasythesizer: Privacy-preserving synthetic datasets. In Proceedings of the 29th International Conference on Scientific and Statistical Database Management, pages 1–5, 2017.

[17] Joshua Snoke, Gillian M Raab, Beata Nowok, Chris Dibben, and Aleksandra Slavkovic. General and specific utility measures for synthetic data. Journal of the Royal Statistical Society: Series A (Statistics in Society), 181(3):663–688, 2018.

[18] Khaled El Emam, Lucy Mosquera, and Richard Hoptroff. Practical synthetic data generation: balancing privacy and the broad availability of data. O’Reilly Media, 2020.

[19] Irit Dinur and Kobbi Nissim. Revealing information while preserving privacy. In Proceedings of the twenty-second ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems, pages 202–210, 2003.

[20] Cynthia Dwork and Kobbi Nissim. Privacy-preserving datamining on vertically partitioned databases. In Annual International Cryptology Conference, pages 528–544. Springer, 2004.

[21] Avrim Blum, Cynthia Dwork, Frank McSherry, and Kobbi Nissim. Practical privacy: the sulq framework. In Proceedings of the twenty-fourth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems, pages 128–138, 2005.

[22] Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. Calibrating noise to sensitivity in private data analysis. In Theory of cryptography conference, pages 265–284. Springer, 2006.

[23] Cynthia Dwork, Aaron Roth, et al. The algorithmic foundations of differential privacy. Foundations and Trends® in Theoretical Computer Science, 9(3–4):211–407, 2014.

[24] Lei Xu, Maria Skoularidou, Alfredo Cuesta-Infante, and Kalyan Veeramachaneni. Modeling tabular data using conditional gan. Advances in Neural Information Processing Systems, 32, 2019.

[25] Sofiane Mahiou, Kai Xu, and Georgi Ganev. dpart: Differentially private autoregressive tabular, a general framework for synthetic data generation. arXiv preprint arXiv:2207.05810, 2022.
[26] Noseong Park, Mahmoud Mohammadi, Kshitij Gorde, Sushil Jajodia, Hongkyu Park, and Youngmin Kim. Data synthesis based on generative adversarial networks. *Proc. VLDB Endow.*, 11(10):1071–1083, jun 2018.

[27] Lei Xu and Kalyan Veeramachaneni. Synthesizing tabular data using generative adversarial networks. *arXiv preprint arXiv:1811.11264*, 2018.

[28] Zilong Zhao, Aditya Kunar, Robert Birke, and Lydia Y Chen. Ctab-gan: Effective table data synthesizing. In *Asian Conference on Machine Learning*, pages 97–112. PMLR, 2021.

[29] Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*, pages 308–318, 2016.

[30] Lorenzo Frigerio, Anderson Santana de Oliveira, Laurent Gomez, and Patrick Duverger. Differentially private generative adversarial networks for time series, continuous, and discrete open data. In *IFIP International Conference on ICT Systems Security and Privacy Protection*, pages 151–164. Springer, 2019.

[31] Reihaneh Torkzadehmahani, Peter Kairouz, and Benedict Paten. Dp-cgan: Differentially private synthetic data and label generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, June 2019.

[32] Dingfan Chen, Tribhuvanesh Orekondy, and Mario Fritz. Gs-wgan: A gradient-sanitized approach for learning differentially private generators. In *Neural Information Processing Systems (NeurIPS)*, 2020.

[33] Qingrong Chen, Chong Xiang, Minhui Xue, Bo Li, Nikita Borisov, Dali Kaarfar, and Haojin Zhu. Differentially private data generative models. *arXiv preprint arXiv:1812.02274*, 2018.

[34] Frederik Harder, Kamil Adamczewski, and Mijung Park. Dp-merf: Differentially private mean embeddings with random features for practical privacy-preserving data generation. In *International conference on artificial intelligence and statistics*, pages 1819–1827. PMLR, 2021.

[35] Seng Pei Liew, Tsubasa Takahashi, and Michihiko Ueno. PEARL: Data synthesis via private embeddings and adversarial reconstruction learning. In *International Conference on Learning Representations*, 2022.

[36] Nazmiye Ceren Abay, Yan Zhou, Murat Kantarcioglu, Bhavani Thuraisingham, and Latanya Sweeney. Privacy preserving synthetic data release using deep learning. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 510–526. Springer, 2018.
[37] Nicolas Papernot, Martín Abadi, Úlfar Erlingsson, Ian Goodfellow, and Kunal Talwar. Semi-supervised knowledge transfer for deep learning from private training data. In *International Conference on Learning Representations*, 2017.

[38] Yunhui Long, Boxin Wang, Zhuolin Yang, Bhavya Kailkhura, Aston Zhang, Carl Gunter, and Bo Li. G-pate: Scalable differentially private data generator via private aggregation of teacher discriminators. *Advances in Neural Information Processing Systems*, 34:2965–2977, 2021.

[39] Grigoriy Gogoshin, Sergio Branciamore, and Andrei S Rodin. Synthetic data generation with probabilistic bayesian networks. *Mathematical biosciences and engineering: MBE*, 18(6):8603, 2021.

[40] Laura Aviñó, Matteo Ruffini, and Ricard Gavaldà. Generating synthetic but plausible healthcare record datasets. *arXiv preprint arXiv:1807.01514*, 2018.

[41] Jun Zhang, Xiaokui Xiao, and Xing Xie. Privtree: A differentially private algorithm for hierarchical decompositions. In *Proceedings of the 2016 International Conference on Management of Data*, pages 155–170, 2016.

[42] Ryan McKenna, Daniel Sheldon, and Gerome Miklau. Graphical-model based estimation and inference for differential privacy. In *International Conference on Machine Learning*, pages 4435–4444. PMLR, 2019.

[43] Ryan McKenna, Siddhant Pradhan, Daniel R Sheldon, and Gerome Miklau. Relaxed marginal consistency for differentially private query answering. *Advances in Neural Information Processing Systems*, 34:20696–20707, 2021.

[44] Kuntai Cai, Xiaoyu Lei, Jianxin Wei, and Xiaokui Xiao. Data synthesis via differentially private markov random fields. *Proceedings of the VLDB Endowment*, 14(11):2190–2202, 2021.

[45] Georgi Ganev. Dp-sgd vs pate: Which has less disparate impact on gans? *arXiv preprint arXiv:2111.13617*, 2021.

[46] Priyanka Nanayakkara, Johes Bater, Xi He, Jessica Hullman, and Jennie Rogers. Visualizing privacy-utility trade-offs in differentially private data releases. *arXiv preprint arXiv:2201.05964*, 2022.

[47] Milan Lopuhaä-Zwakenberg and Jasper Goseling. The privacy-utility tradeoff of robust local differential privacy. *arXiv preprint arXiv:2101.09139*, 2021.

[48] Hao Zhong and Kaifeng Bu. Privacy-utility trade-off. *arXiv preprint arXiv:2204.12057*, 2022.

[49] Martin Abadi, Andy Chu, Ian Goodfellow, H Brendan McMahan, Ilya Mironov, Kunal Talwar, and Li Zhang. Deep learning with differential privacy. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*, pages 308–318, 2016.
[50] Oscar Giles, Kasra Hosseini, Grigoris Mingas, Oliver Strickson, Louise Bowler, Camila Rangel Smith, Harrison Wilde, Jen Ning Lim, Bilal Mateen, Kasun Amarasinghe, et al. Faking feature importance: A cautionary tale on the use of differentially-private synthetic data. *arXiv preprint arXiv:2203.01363*, 2022.
A More Results for Utility Recovery Incapability phenomenon across different Machine Learning Models

Banknote Authentication Instead of Accuracy 2 shown before, we here present results for other four metrics. Precision 5, F1 Score 7, AUROC 8 and Average Precision 9 show similar phenomenon as shown in Accuracy 2. Both DataSynthesizer and PATE-CTGAN have the trend of utility recovery. And DataSynthesizer has the best performance especially when $\varepsilon$ is small. As mentioned before, Recall 6 has slightly different result for DataSynthesizer but it still maintains at a good level.

Iris Iris is a three-classes dataset. So, there is no average precision on Iris. We only test other five metrics on this Iris dataset, shown in figure 10, 11, 12, 13 and 14. For other metrics except for Accuracy, we calculate unweighted mean for each label as the metric. Results on Iris is slightly different from previous result. Both DataSynthesizer and PATE-CTGAN shows the phenomenon of utility recovery and PATE-CTGAN exceed DataSynthesizer when $\varepsilon$ increases. Same as results on Banknote dataset, only PATE-CTGAN has the recovery on Recall. There are also difference between each classifier. DataSynthesizer works better with
Naïve Bayes and SVM on Accuracy, Precision, Recall and F1 Score. PATE-CTGAN seems to fail with Naïve Bayes. This implies Bayesian Network based methods may work better with Bayesian methods.

Social Network Ads On this dataset, results are quite different from results on previous datasets. PATE-CTGAN fails on this dataset, as well as DP-CTGAN. Both of them only have accuracy around 0.5, no utility recovery for all metrics and a very large range between minimum and maximum. To the opposite, DataSynthesizer achieve best performance, which is very close to result on original training data. It works better with Naïve Bayes, SVM and Logistic Regression, compared with other classifier. When \( \epsilon \) increases, performance recover except for Recall. However, this method has Recall more than 0.6 for most \( \epsilon \) with Naïve Bayes, SVM and Logistic Regression. DataSynthesizer also has a small range between minimum and maximum. As a result, it is accurate and robust on Social Network Ads. See Figures below for Accuracy 15, Precision 16, Recall 17, F1 Score 18, AUROC 19 and Average Precision 20.

Titanic Results on Titanic is very similar with results on Social Network Ads. Only DataSynthesizer has good performance. Interestingly, when \( \varepsilon = 1.0 \), the performance of DataSynthesizer is already very close to the performance of real training data.
for Accuracy 21, Precision 22, Recall 23, F1 Score 24, AUROC 25 and Average Precision 26 on Titanic dataset.
Figure 13: Iris F1 Score

Figure 14: Iris AUROC

Figure 15: Social Network Accuracy

Figure 16: Social Network Precision

Figure 17: Social Network Recall

18
Figure 18: Social Network F1 Score

Figure 19: Social Network AUROC

Figure 20: Social Network Average Precision

Figure 21: Titanic Accuracy

Figure 22: Titanic Precision
Figure 23: Titanic Recall

Figure 24: Titanic F1 Score

Figure 25: Titanic AUROC

Figure 26: Titanic Average Precision
More Results for Utility Recovery Incapability phenomenon across different classification utility metrics

**Naïve Bayes** Figures show the performance of Naïve Bayes on Banknote 27, Iris 28, Social Network Ads 29 and Titanic 30. DataSynthesizer gets very close to the results on original training data, which are much better than other two GAN-based methods.

**Figure 27: Banknote with Naïve Bayes**

**Figure 28: Iris with Naïve Bayes**

**Figure 29: Social Network with Naïve Bayes**

**SVM** SVM has similar results with Naïve Bayes. DataSynthesizer is the best one. PATE-CTGAN can only get close to DataSynthesizer with large $\varepsilon$ on Banknote 31 and Iris 32 and become as bad as DP-CTGAN on Social Network 33 and Titanic 34.

**KNN** Despite of results on Banknote 3, here are results on KNN classifier on Iris 35, Social Network 36 and Titanic 37. PATE-CTGAN exceeds DataSynthesizer with large $\varepsilon$ on Iris 35. Different with previous classifier, DataSynthesizer show a slight recovery trend on Recall. Results on Social Network 36 and Titanic 37 are similar with previous results.
DataSynthesizer is still the best one with Decision Tree on Banknote 38, Social Network 40 and Titanic 41. PATE-CTGAN also has good performance on Iris 39 with large $\varepsilon$.

Random Forest DataSynthesizer has the utility recovery phenomenon on Recall metric with this Random Forest method, see figures for Banknote 42, Iris 43, Social Network 44 and Titanic 45. PATE-CTGAN defeats DataSynthesizer on Iris with $\varepsilon > 2$.

Logistic Regression Different result with logistic regression is that DataSynthesizer doesn’t have the recovery trend on Recall. But it has better Recall score than Original training data on Social Network 48 and Titanic 49. Results on Banknote 46 and Iris 47 are similar with other methods.
Figure 42: Banknote with Random Forest

Figure 43: Iris with Random Forest

Figure 44: Social Network with Random Forest

Figure 45: Titanic with Random Forest

Figure 46: Banknote with Logistics Regression
Figure 47: Iris with Logistics Regression

Figure 48: Social Network with Logistics Regression

Figure 49: Titanic with Logistics Regression
C More Results for Utility Recovery Incapability phenomenon across different source real dataset

Since there is no Average Precision on Iris dataset, we don’t take account for Average Precision in this section.

**Accuracy** For Accuracy, DataSynthesizer has better performance with Naïve Bayes 50, SVM 51, and Logistic Regression 54 for all four datasets. PATE-CTGAN has good performance on Iris with KNN 52, Decision Tree 53. Results with Random Forest 4 has been shown before. DP-CTGAN always does badly on this work.

![Figure 50: Accuracy with Naïve Bayes](image)

![Figure 51: Accuracy with SVM](image)

![Figure 52: Accuracy with KNN](image)

**Precision** DataSynthesizer is still roughly consistent on four datasets, while PATE-CTGAN doesn’t work well on Social Network and Titanic. See figures below for Naïve Bayes 55, SVM 56, KNN 57, Decision tree 58, Random Forest 59 and Logistic Regression 60.

**Recall** The Utility recovery phenomenon is not obvious on Recall metric. See figures below for Naïve Bayes 61, SVM 62, KNN 63, Decision tree 64, Random Forest 65 and Logistic Regression 66.
Figure 53: Accuracy with Decision tree

Figure 54: Accuracy with Logistic Regression

**F1 Score** Results for F1 Score are similar, see here for Naïve Bayes 67, SVM 68, KNN 69, Decision tree 70, Random Forest 71 and Logistic Regression 72.

**AUROC** As mentioned before, PATE-CTGAN can only work well on Banknote and Iris. It is heavily influenced by the dataset. See figures for Naïve Bayes 73, SVM 74, KNN 75, Decision tree 76, Random Forest 77 and Logistic Regression 78.
Figure 55: Precision with Naïve Bayes

Figure 56: Precision with SVM

Figure 57: Precision with KNN

Figure 58: Precision with Decision tree

Figure 59: Precision with Random Forest
Figure 60: Precision with Logistic Regression

Figure 61: Recall with Naïve Bayes

Figure 62: Recall with SVM

Figure 63: Recall with KNN

Figure 64: Recall with Decision tree
Figure 65: Recall with Random Forest

Figure 66: Recall with Logistic Regression

Figure 67: F1 Score with Naïve Bayes

Figure 68: F1 Score with SVM

Figure 69: F1 Score with KNN
Figure 70: F1 Score with Decision tree

Figure 71: F1 Score with Random Forest

Figure 72: F1 Score with Logistic Regression

Figure 73: AUROC with Naïve Bayes

Figure 74: AUROC with SVM
Figure 75: AUROC with KNN

Figure 76: AUROC with Decision tree

Figure 77: AUROC with Random Forest

Figure 78: AUROC with Logistic Regression