Synthetic Data, Similarity-Based Privacy Metrics, and Regulation

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1. Motivation

Synthetic tabular data, or data generated by machine learning generative models, is gaining popularity beyond academia and moving into real-world deployments. Examples include releasing public census data by US (Abowd et al., 2022), UK (UK ONS, 2023), and Israel (Hod & Canetti, 2024), as well as sharing sensitive financial and health data through private synthetic data vendors (UK ICO, 2023; Microsoft, 2024). While these releases satisfy the formal definition of privacy, i.e., Differential Privacy (DP) (Dwork et al., 2006), this is still not the norm in numerous scientific papers (Park et al., 2018; Lu et al., 2019; Zhao et al., 2021; Borisov et al., 2023; Yoon et al., 2023; Kotelnikov et al., 2023; Zhang et al., 2024) and leading synthetic data vendors (Mostly AI, 2020; Syntegra, 2021; Panfilo & Aindo, 2022; Syntho, 2023). Instead, the papers/companies rely entirely on empirical ad-hoc privacy metrics based on the *similarity* between synthetic and real personal datasets.

Main Question. This prompts asking: *"Is using similarity-based privacy metrics enough to consider synthetic data regulatory compliant?"* Due to their fundamental issues and unreliable, inconsistent nature, *we argue that it is not*.

2. Definitions

Synthetic Data. We denote a real personal dataset as $\mathcal{D}$. A generative model, G, is trained on $\mathcal{D}_{train}$ (a subset of $\mathcal{D}$; the remaining data, $\mathcal{D}_{test}$, is set aside for test purposes) to capture a probability representation, and could later be sampled to generate new (synthetic) data $\mathcal{D}_{synth}$ of arbitrary size (see bottom of Fig. 1). Popular generative models include Graphical Models (Zhang et al., 2017; McKenna et al., 2021), GANs (Xie et al., 2018; Jordon et al., 2019; Xu et al., 2019), Diffusion Models (Kotelnikov et al., 2023; Zhang et al., 2024), and Transformers (Borisov et al., 2023).

Similarity-Based Privacy Metrics (SBPMs). The intuition behind SBPMs is that $\mathcal{D}_{synth}$ should be representable and close to $\mathcal{D}_{train}$, but not closer than to $\mathcal{D}_{test}$ (Platzer & Reutterer, 2021; Mobey Forum, 2022). More precisely, the closest pairwise distances for $d_{synth} = d(\mathcal{D}_{train}, \mathcal{D}_{synth})$ and $d_{test} = d(\mathcal{D}_{train}, \mathcal{D}_{test})$ are computed and their distributions compared through a statistical test (see Fig. 1). The passing criterion is a comparison between a simple statistic run on each distribution, e.g., average/5th percentile (p5). In this paper, we focus on the three most widely used SBPMs. ($\mathcal{D}_{synth}$ is deemed private if all three privacy tests pass.)

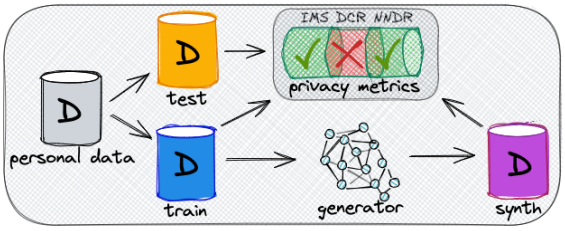

Figure 1. Data flow overview.

Identical Match Share (IMS) calculates the proportion of exact copies (statistic: average; test: $d_{synth} \leq d_{test}$).

Distance to Closest Records (DCR) calculates the distances to the nearest neighbors (statistic: p5; test: $d_{synth} \geq d_{test}$). DCR is meant to protect against scenarios where $\mathcal{D}_{train}$ is just slightly perturbed and passed as $\mathcal{D}_{synth}$.

Nearest Neighbor Distance Ratio (NNDR) follows DCR but divides the distances by the distance to their second neighbor (statistic: p5; test: $d_{synth} \geq d_{test}$). The relative computations are supposed to further protect the outliers.

GDPR. EP and Council (2016a) define *personal data* as "any information relating to an identified or identifiable living individual." Also, EP and Council (2016b) state that effectively anonymized information is not considered personal data and is exempt from data protection regulations.

Sufficient Anonymization. "Effective anonymization reduces identifiability risk to a sufficiently remote level" (ICO UK, 2021). Assessing identifiability involves considering practical factors like cost, time, and technology, focusing on what is reasonably likely to be used rather than any theoretical possibility. We focus on two key technical risks for sufficient anonymization (A29WP, 2014; ICO UK, 2021): i) (*singling out*) isolating any individual, and ii) (*linkability*) combining records/datasets with synthetic data to identify an individual. Lastly, ICO UK (2021) proposes the *motivated intruder* test, suggesting that the risks should be assessed based on whether a competent intruder, with appropriate resources, could achieve identification if motivated enough.

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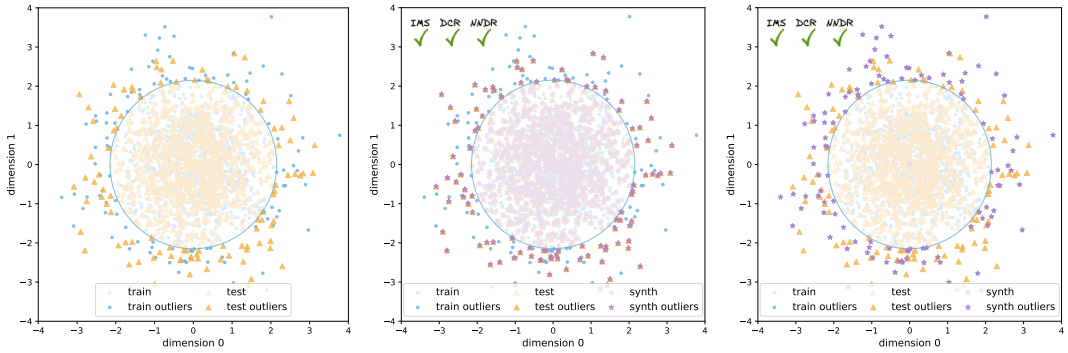
Preliminary work. Under review by the International Conference on Machine Learning (ICML). Do not distribute.



(a) $\mathcal{D}_{train}$ and $\mathcal{D}_{test}$ (b) $\mathcal{D}_{synth}$ leaking all $\mathcal{D}_{test}$ (c) $\mathcal{D}_{synth}$ leaking $\mathcal{D}_{train}$ outliers

Figure 2. 2d Gauss data counter-examples.

For more detailed discussion, refer to: synthetic data (Jordon et al., 2022; De Cristofaro, 2024), SBPMs (Boudewijn et al., 2023; Desfontaines, 2024), and regulation (López & Elbi, 2022a;b; Gal & Lynskey, 2023; Ganev, 2023).

3. Fundamental Issues of SBPMs

We identify several fundamental issues with using SBPMs to reason about privacy through empirical pass/fail tests.

No Theoretical Guarantees. SBPMs lack a defined threat model or strategic adversary, ignoring key security (Anderson, 2020) and regulatory principles like the motivated intruder test. They rely on arbitrarily chosen average-case statistics and held-out datasets, falling into the "Generalization Implies Privacy" fallacy (Del Grosso et al., 2023), where generalization is average-case issue but privacy is a worst-case. Thus, even if a model passes all tests and generalizes, it can still memorize data (Song et al., 2017). Consequently, SBPMs offer no theoretical guarantees and are vulnerable to adversarial attacks.

Privacy as Binary/Data Property. SBPMs treat privacy leakage as binary, assuming one synthetic dataset is as safe as many. However, the "Fundamental Law of Information Reconstruction" (Dwork & Roth, 2014) warns that too many accurate answers can severely compromise privacy. Additionally, SBPMs see privacy as a data property, not of the generating process, requiring tests on each dataset, which can lead to inconsistent results and increase privacy leakage. This can also increase singling out and linkability risks.

Non-Contrastive Process. SBPMs do not compare computations with or without an individual. Without noise or randomness, plausible deniability is ruled out, making the system vulnerable to attacks like differencing attacks.

Incorrect Interpretation. The tests can be misinterpreted, as failing to reject the null hypothesis ("privacy is preserved") does not confirm that privacy is indeed preserved.

Practical Issues. Most SBPMs implementations require discretizing the data, leading to imprecise calculations and overstated privacy protections. Also, the typical need for a 50/50% train-test split can hurt the synthetic data quality.

4. SBPMs Counter-Examples

We present three counter-examples showing the unreliability and inconsistency of SBPMs. We use *2d Gauss* which consists of 2,000 points (split evenly between $\mathcal{D}_{train}$ and $\mathcal{D}_{test}$) drawn from a standard normal 2d distribution with no correlation (see Fig. 2(a)). Approximately 10% of the records, those outside the blue circle, are considered outliers.

Leaking All Test Data. Assume $\mathcal{D}_{synth}$ is an exact replica of $\mathcal{D}_{test}$ (Fig. 2(b)). All privacy tests pass as $d_{synth} = d_{test}$. Naturally, publishing half of the personal records cannot be considered regulatory compliant as it would fail the two technical risks, singling out and linkability.

Leaking Train Data Outliers. Next, assume that $\mathcal{D}_{synth}$ contains all $\mathcal{D}_{train}$ outliers (with small perturbations) and numerous copies of the value (0, 0) (Fig. 2(c)). Again, all tests pass: there are no exact matches, and the (0, 0) values skew the distances enough to trick both DCR and NNDR. Publishing $\mathcal{D}_{synth}$ will leave the outlier individuals unconvinced that their privacy is preserved (UK ONS, 2018; UK ICO, 2022) and would again fail the two technical risks.

SBPMs Inconsistency. We assume access to an oracle with knowledge of the generative process of $\mathcal{D}$. Using the oracle, we sample 1,000 new $\mathcal{D}_{synth}$s. Since no generative model was trained, this preserves $\mathcal{D}_{train}$'s privacy. However, on only 274 occasions do all privacy tests pass, showing that the SBPMs fail to accurately capture the generating process.

The individual metric pass rates are 1 for IMS, 0.48 for DCR, and 0.38 for NNDR, revealing significant inconsistency. Despite sampling from a fixed distribution, DCR and NNDR behave randomly. Even if G captures the underlying process without overfitting or memorization, the pass/fail outcome is sample-dependent, noisy, and unreliable.

5. Conclusion

In this paper, we argue that SBPMs cannot ensure compliance of synthetic data. SBPMs do not protect against singling out and linkability and, among other fundamental issues, completely ignore the motivated intruder test.

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