Tabular synthetic data generation: A literature review

Joao Fonseca[1*], Fernando Bacao[1]

[1]NOVA Information Management School, Universidade Nova de Lisboa

*Corresponding Author

Postal Address: NOVA Information Management School, Campus de Campolide, 1070–312 Lisboa, Portugal

Telephone: +351 21 382 8610

The generation of synthetic data can be used for anonymization, regularization, oversampling, semi-supervised learning, self-supervised learning and various other tasks. The wide range of applications of these mechanisms motivated the development of new algorithms specialized in generating data for specific types of data and Machine Learning (ML) tasks. As a result, the analysis of the different types of generative models

1 Introduction

Synthetic data is obtained from a generative process based on properties of real data [1]. The generation of synthetic data is essential for various domains and tasks. For example, synthetic data is used as a form of regularizing neural networks (*i.e.*, data augmentation) **[CITATION]**. One form of anonymizing datasets is via the production of synthetic observations (*i.e.*, synthetic data generation) **[CITATION]**. In settings where only a small portion of training data is labeled, some techniques generate artificial data using both labeled and unlabeled data with a modified loss function to train neural networks (*i.e.*, semi-supervised learning) [2]. In imbalanced learning contexts, synthetic data can be used to balance the target classes' frequencies and reinforce the learning of minority classes (*i.e.*, oversampling) [3]. Some active learning frameworks use data generation to improve the quality of data selection and classifier training [4]. Other techniques employ data generation to produce deep neural networks without labeled data (*i.e.*, self-supervised learning) [5].

The breadth of these techniques span multiple domains, such as facial recognition [6], Land Use/Land Cover mapping **[CITATION]**, medical image processing **[CITATION]**, Natural Language Processing (NLP) [7] or credit card default prediction [8]. According to the domain and data type, the data generation techniques used may vary significantly. Generally speaking, some data generation mechanisms are specific to some domains, data types or tasks. For example, ... Most, if not all, of these techniques are applied on the input or output space.

However, there are various data generation techniques that are invariant to the task or data types used. These techniques can be either applied in the feature space [9] or in tabular datasets. On the one hand, data generation in the feature space uses a generative model to learn a manifold, lower-dimensional abstraction over the input space [10], defined here as the feature space. At this level, any tabular data generation mechanism can be applied and reconstructed into the input space if necessary. On the other hand, synthetic data generation on tabular data can be applied to most problems. Although, the choice of generation mechanism is still dependant on (1) the importance of the relationships found between the different features, (2) the ML task developed and (3) the motivation for the generation of synthetic data. For example, when generating data to address an imbalanced learning problem (*i.e.*, oversampling), the relationships between the different features are not necessarily kept since the goal is to reinforce the learning of the minority class by redefining an ML classifier's decision boundaries. If the goal is to anonymize a dataset, perform some type of descriptive task, or ensure a consistent model interpretability, these relationships need to be kept.

Depending on the context, evaluating the quality of the generated data is a complex task. For example, for image and time series data, perceptually small changes in the original data can lead to large changes in the euclidean distance [1, 11]. The evaluation of generative models typically account primarily for the performance in a specific task, since good performance in one criterion does not imply good performance on another [11]. However, in computationally intensive tasks it is often impracticable to search for the optimal configurations of generative models. To address this limitation, other evaluation methods have been proposed to assist in this evaluation, which can be distinguished into statistical divergence metrics and precision/recall metrics [12]. The relevant performance metrics found in the literature are discussed in Section 5.

1.1 Motivation, Scope and Contributions

This literatrue review focuses on generation mechanisms applied to tabular data and the different ML techniques where tabular synthetic data is used. In addition, we focus on the ML perspective of synthetic data, as opposed to the practical perspective. From a practical sense, synthetic data is used as a proxy of real data. It is assumed to be inaccessible, essential and a secondary asset for tasks like education, software development, or systems demonstrations [13].

We focus on data generation techniques in the tabular and feature space (*i.e.*, embedded inputs), given its breadth in scope. Related literature reviews are mostly focused on specific algorithmic or domain applications, with little to no emphasis on the core generative process. For this reason, these techniques often appear "sandboxed", even though there is a significant overlap between them. There are some related reviews published since 2019. Assefa et al. [1] provides a general overview of synthetic data generation for time series data anonymization in the finance sector. Hernandez et al. [14] reviews data generation techniques for tabular health records anonymization. Raghunathan [15] reviews synthetic data anonymization techniques that preserve the statistical properties of a dataset. Nalepa et al. [16] reviews data augmentation techniques for brain-tumor segmentation. Bayer et al. [17] distinguishes augmentation techniques for text classification into feature and data space, while providing an extensive overview of augmentation methods within this domain. However, the taxonomy proposed and feature space augmentation methods are not necessarily specific to the domain. Shorten et al. [18], Chen et al. [19], Feng et al. [7] and Liu et al. [20] also review data augmentation techniques for text data. Yi et al. [21] review Generative Adversarial Network architectures for medical imaging. Wang et al. [22] reviews face data augmentation techniques. Shorten et al. [23] and Khosla et al. [24] discuss techniques for image data augmentation. Iwana et al. [25] and Wen et al. [26] also review time series data augmentation techniques. Zhao et al. [27] review data augmentation techniques for graph data. The analysis of related literature

Table 1: Related literature reviews published since 2019.

Reference	Data type	ML problem	Domain	Observations
Assefa et al. [1]	—	Differential privacy	Finance	Analysis of applications, motivation and properties of synthetic data for anonymization.
Hernandez et al. [14]	Tabular	Differential privacy	Healthcare	Focus on GANs.
Raghunathan [15]	Tabular	Differential privacy	Statistics	Focus on general definitions such as differential privacy and statistical disclosure control.
Nalepa et al. [16]	Image	Segmentation	Medicine	Analysis of algorithmic applications on a 2018 brain-tumor segmentation challenge.
Bayer et al. [17]	Text	Classification	—	Distinguish 100 methods into 12 groups.
Shorten et al. [18]	Text	Deep Learning	—	General overview of text data augmentation.
Chen et al. [19]	Text	Few-shot Learning	—	Augmentation techniques for machine learning with limited data
Feng et al. [7]	Text	—	—	Overview of augmentation techniques and applications on NLP tasks.
Liu et al. [20]	Text	—	Various	Analysis of industry use cases of data augmentation in NLP. Emphasis on input level data augmentation.
Yi et al. [21]	Image	—	Medicine	Emphasis on GANs.
Wang et al. [22]	Image	Deep Learning	—	Regularization techniques using facial image data. Emphasis on Deep Learning generative models.
Shorten et al. [23]	Image	Deep Learning	—	Emphasis on data augmentation as a regularization technique.
Khosla et al. [24]	Image	—	—	Broad overview of image data augmentation. Emphasis on traditional approaches.
Iwana et al. [25]	Time series	Classification	—	Defined a taxonomy for time series data augmentation.
Wen et al. [26]	Time series	Various	—	Analysis of data augmentation methods for classification, anomaly detection and forecasting.
Zhao et al. [27]	Graph	Various	—	Graph data augmentation for supervised and self-supervised learning.
Khalifa et al. [28]	Image	—	Various	General overview of image data augmentation and relevant domains of application.

reviews [1] is shown in Table 1.

The different taxonomies established in the literature follow a similar philosophy, but vary in terminology and are often specific to the technique discussed. Regardless, it is possible to establish a broader taxonomy without giving up on specificity. This study provides a joint overview of the different data generation approaches, domains and ML techniques where data generation is being used, as well as a common taxonomy across domains. It extends the analyses found in these articles and uses the compiled knowledge to identify research gaps. We compare the strengths and weaknesses of the models developed within each

[1]Results obtained using Google Scholar, limited to articles published since 2019, using the search query `("synthetic data generation" OR "oversampling" OR "imbalanced learning" OR "data augmentation") AND ("literature review" OR "survey")`. Retrieved on August 11^{th}, 2022. More articles were added later whenever found relevant.

of these fields. Finally, we identify possible future research directions to address some of the limitations found. The contributions of this paper are summarized below:

- Bridge different ML concepts using synthetic data generation in its core (Algorithmic applications + Review of the State-of-the-art).
- Propose a synthetic data generation/data augmentation taxonomy to resolve the ambiguity in the literature (Data augmentation taxonomy).
- Characterize all relevant data generation methods using the proposed taxonomy.
- Discuss the ML techniques in which synthetic data generation/data augmentation is used, beyond regularization and consolidate the current data generation mechanisms across the different techniques (Algorithmic Applications).
- Bring to light the key challenges of synthetic data generation and put forward possible research directions in the future.

1.2 Paper Organization

This paper is organized as follows: Section 2 defines and formalizes the different concepts, goals, trade-offs and motivations related to synthetic data generation. Section 3 establishes the taxonomy used to categorize all the methods described in the paper. Section **??** reviews synthetic data generation mechanisms in the feature space. Section **??** reviews synthetic data generation mechanisms in the input space. Section 4 describes the applications of synthetic data in ML methods. Section 5 reviews performance evaluation methods of synthetic data generation mechanisms. Section 6 summarizes the main findings and discusses limitations and possible research directions in the state-of-the-art. Section 7 presents the main conclusions drawn from this study.

2 Background

In this section we define basics concepts, common goals, trade-offs and motivations regarding the generation of synthetic data in ML. We define synthetic data generation as the production of observations using a generative model (regardless of its nature) that resemble naturally occurring observations within a certain domain. It requires access to either a training dataset, a generative process, or a data stream. However, additional requirements might be imposed depending on the ML task being developed. For example, to generate artificial data for regularization purposes in supervised learning (*i.e.*, data augmentation) the training dataset must be annotated **[CITATION]**. The generation of synthetic data for anonymization purposes assumes synthetic datasets to be different from the original data, while following the same statistical properties **[CITATION]**. Domain knowledge may also be necessary to encode specific relationships among features into the generative process.

2.1 Use Cases

The breach of sensitive information is an important barrier to the sharing of datasets, especially when it concerns personal information [29]. A common solution for this problem is the generation of synthetic data without identifiable information. Generally speaking, ML tasks that require data with sensitive information are not compromised when using synthetic data. The experiment conducted by Patki et al. [30] using relational datasets showed that in 11 out 15 comparisons ($\approx 73\%$), practitioners performing predictive modelling tasks using fully synthetic datasets performed the same or better than those using the original dataset. This topic is discussed in Section 4.1.

A common problem in the training of deep neural networks are their capacity to generalize [31] (*i.e.*, reduce the difference in classification performance between known and unseen observations). Data augmentation is a common method to address this problem. The generation of synthetic observations increases the range of the possible input space used in the training phase, which reduces the performance difference between known and unseen observations. Although other regularization methods exist, data augmentation is a useful method since it does not affect the choice in the architecture of the ML classifier and does not exclude the usage of other regularization methods. In domains such as computer vision and NLP, data augmentation is also used to improve the robustness of models against adversarial attacks [32, 33]. These topics are discussed into higher detail in Section 4.2.

In supervised learning, synthetic data generation is often motivated by the need to balance target class distributions (*i.e.*, oversampling). Since most ML classifiers are designed to perform best with balanced datasets, defining an appropriate decision boundary to distinguish rare classes becomes difficult [34]. Although there are other approaches to address imbalanced learning, oversampling techniques are generally easier to implement since they do not involve modifications to the classifier. This topic is discussed into higher detail in Section 4.4.

In supervised learning projects where labeled data is not readily available, but can be labeled, an Active Learning (AL) method may be used to improve the labelling process. AL aims to reduce the cost of producing training datasets by finding the most informative observations to label and feed into the classifier [35]. In this case, the generation of synthetic data is particularly useful to reduce the amount of labelled data required for a successful ML project and its costs. A similar motivation applies to the case of few-shot learning: small datasets may be expanded with synthetic data [36]. These topics are discussed in Sections 4.5 and 4.6.

The two other techniques reliant on synthetic data generation is Semi-supervised and Self-supervised learning. The former leverages both labeled and unlabeled data in the training phase, simultaneously. Most of the methods in the literature apply perturbations on the training data as part of the training procedure [37]. Self-supervised learning is a technique used to train neural networks in the absence of labeled data. Both techniques use synthetic data generation as an internal procedure for most of these methods. These techniques are discussed in Sections 4.7 and 4.8.

2.2 Problem Formulation

The original dataset, $\mathcal{D} = \mathcal{D}_L \cup \mathcal{D}_U$, is a collection of real observations and is distinguished according to whether a target feature exists, $\mathcal{D}_L = ((x_i, y_i))_{i=1}^{l}$, or not, $\mathcal{D}_U = (x_i)_{i=1}^{u}$. All three datasets, $\mathcal{D}$,

$\mathcal{D}_L$ and $\mathcal{D}_U$ consist of ordered collections with lengths $l+u$, l and u, respectively. Synthetic data generation is performed using a generator, $f_{gen}(x;\tau) = \tilde{x}$, where τ defines the generation policy (*i.e.*, its hyperparameters), $x \in \mathcal{D}$ is an observation and $\tilde{x} \in \mathcal{D}^s$ is a synthetic observation. Analogous to $\mathcal{D}$, the synthetic dataset, $\mathcal{D}^s$, is also distinguished according to whether there is an assignment of a target feature, $\mathcal{D}^s_L = ((\tilde{x}_j, \tilde{y}_j))_{j=1}^{l'}$, or not, $\mathcal{D}^s_U = (\tilde{x}_j)_{j=1}^{u'}$.

Depending on the ML task, it may be relevant to establish metrics to measure the quality of $\mathcal{D}^s$. In this case, a metric $f_{qual}(\mathcal{D}^s, \mathcal{D})$ is used to determine the level of similarity/dissimilarity between $\mathcal{D}$ and $\mathcal{D}^s$. In addition, a performance metric to estimate the performance of a model on the objective task, f_{per}, may be used to determine the appropriateness of a model with parameters θ, *i.e.*, f_θ. The generator's goal is to generate $\mathcal{D}^s$ with arbitrary length, given $\mathcal{D} \sim \mathbb{P}$ and $\mathcal{D}^s \sim \mathbb{P}^s$, such that $\mathbb{P}^s \approx \mathbb{P}$, $x_i \neq x_j \forall x_i \in \mathcal{D} \wedge x_j \in \mathcal{D}^s$. $f_{gen}(x;\tau)$ attempts to generate a $\mathcal{D}^s$ that maximizes either f_{per}, f_{qual}, or a combination of both.

3 Data Generation Taxonomy

The taxonomy proposed in this paper is a compilation of different definitions found in the literature, along with other traits that vary among domains and generation techniques. Within image data studies, Shorten et al. [23] and Khalifa et al. [28] divide data augmentation techniques into "basic" or "classical" approaches and deep learning approaches. In both cases, the former refers to domain-specific generation techniques, while the latter may be applied to any type of data. Iwana et al. [25] proposes a time-series data augmentation taxonomy divided in four families: (1) Decomposition, (2) Pattern mixing, (3) Generative models and (4) Decomposition. With exception to generative models, the majority of the methods presented in the remaining families are well established and domain specific. Hernandez et al. [14] defines a taxonomy for synthetic tabular data generation approaches divided in three types of approaches: (1) Classical, (2) Deep learning and (3) Others. Most taxonomies found followed similar definitions with variations in terminology or distinction criteria. In addition, all taxonomies with categories defined as "basic", "traditional" or "classical" use these to characterize domain-specific transformations.

Within the taxonomies considered, none of them consider how a generation mechanism employs $\mathcal{D}$ into the generation process or, if applicable, the training phase. However, it is important to understand whether a generation mechanism randomly selects x and a set of close neighbors, thus considering local information only, or considers the overall dataset or data distribution for the selection of x and/or generation of $\tilde{x}$. Our proposed taxonomy is depicted in Figure 1. It characterizes data generation mechanisms using four properties:

1. Architecture. Defines the broader type of data augmentation. It is based on domain specificity, architecture type or data transformations using a heuristic or random perturbation process. Generation techniques that apply a form of random perturbation, interpolation or geometric transformation to the data with some degree of randomness are considered randomized approaches. Typical, domain-specific data generation techniques are considered traditional architectures. These techniques apply transformations to a data point using *a priori* domain knowledge. Generative models based on neural network architectures are defined as network-based. These architectures attempt to either generate observations in the feature space and/or by producing observations that are difficult to distinguish from the original dataset.

2. Application level. Refers to the phase of the ML pipeline where the generative process is included.

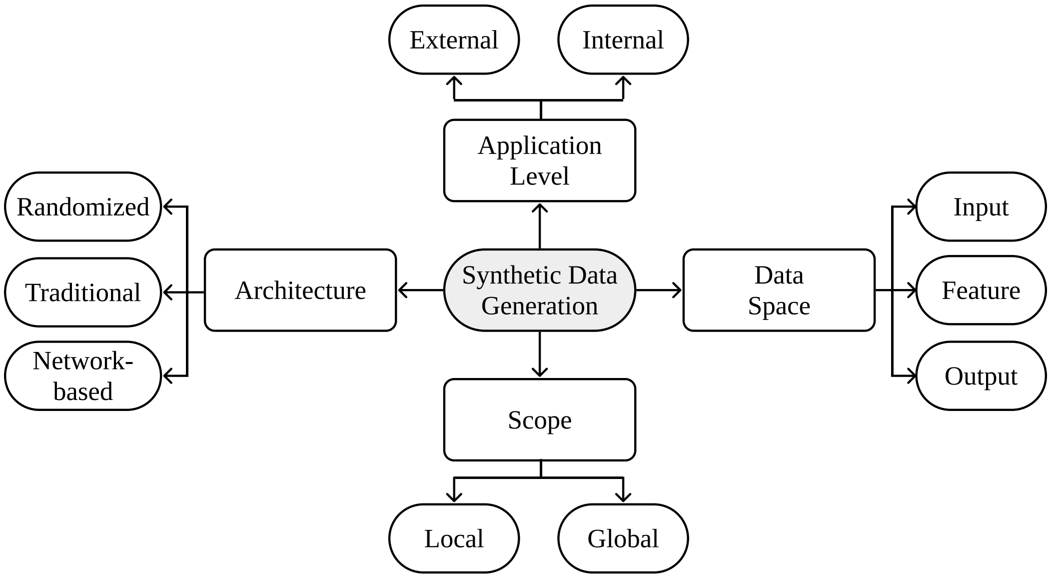

Figure 1: General taxonomy of data generation mechanisms proposed in this paper.

Generative models are considered internal if they are used alongside the primary ML task, whereas models used prior to the development of the primary ML task are considered external.

3. Scope. Considers the usage of the original dataset's properties. Generative models that consider the density of the data space, statistical properties of $\mathcal{D}$, or attempt to replicate specific relationships found in $\mathcal{D}$ are considered to have a global scope, whereas generative models that consider a single observation and/or a set of close neighbors are considered to have a local scope. On the one hand, generative models with a local scope do not account for $\mathbb{P}^s$ but allow for a larger diversity of candidate x^s and higher variance within $\mathcal{D}^s$. On the other hand, generative models with a global scope have a higher capacity to model $\mathbb{P}^s$ but produce candidate x^s with lower diversity and lower variance within $\mathcal{D}^s$.

4. Data space. Refers to the type data representation used to apply the generative model. Generation mechanisms can be applied using the raw dataset (*i.e.*, on the input space), an embedded representation of the data (*i.e.*, on the feature space) or based on the target feature (*i.e.*, on the output space).

Throughout the analysis of the different types of generation mechanisms, all relevant methods were characterized using this taxonomy and listed in Table 2.

Table 2: Summary of synthetic data generation mechanisms discussed in this work.

Algorithm	ML problem	Domain	Architecture	Level	Data Space	Scope
SynSys [38]	Reg.	Healthcare	**[Statistical]**	External	Input	Global
CTGAN [39]		—	Net.	External	Feature	Global
SenseGen [40]	Anon. + Reg.	Sensor	Net. + **[Stat.]**	External	Input	Global
SDV [30]	Anon.	—	**[Copula]**	External	Input	Global
MST [41]	DP					
QUAIL [42]	DP					
SuperQUAIL [43]	DP					

Continued on next page

Table 2: Summary of synthetic data generation mechanisms discussed in this work.

Algorithm	ML problem	Domain	Architecture	Level	Data Space	Scope
MWEM [44]	DP					
MWEM-PGM [45]	DP					
PrivBayes [46]	DP					
DPGAN [47]	DP					
DPCTGAN [42]	DP					
DP-CTGAN [48]	DP	Healthcare				
PATE-GAN [49]	DP					
PATECTGAN [42]	DP					
FEM [50]	DP					
RAP [51]	DP					
Kamino [52]	DP					
RON-GAUSS [53]	DP					
SMOTE [54]	Ovs					
SMOTENC [54]	Ovs					
SMOTEN [54]	Ovs					
Borderline-SMOTE [55]	Ovs					
G-SMOTE [56]	Ovs					
ADASYN [57]	Ovs					
KernelADASYN [58]	Ovs					
Safe-level SMOTE [59]	Ovs					
LR-SMOTE [60]	Ovs					
K-means SMOTE [61]	Ovs					
CGAN [62]	Ovs					
K-means CTGAN [63]	Ovs					
G-SMOTER [64]	Ovs + Reg					
SMOTER [65]	Ovs + Reg					

4 Algorithmic applications

In this section we discuss the data generation mechanisms for the different contexts where they are applied. We emphasize the constraints in each problem that condition the way generation mechanisms are used.

CTGAN [39]

4.1 Dataset Anonymization

Synthetic data generation is a technique used to produce synthetic, anonymized versions of datasets [29]. It is considered a good approach to share sensitive data without compromising significantly a given data mining task [66, 67]. Traditional data anonymization techniques, as well as federated learning are two other viable solutions for privacy-preserving data publishing tasks, but contain drawbacks [14]. On the one hand, traditional data anonymization requires domain knowledge, is labor intensive and remains susceptible to disclosure [68]. On the other hand, federated learning is a technically complex task that consists on training ML classifiers on edge devices and aggregating temporarily updated parameters on a centralized server, instead of aggregating the training data [69]. Although it prevents sharing sensitive data, its applicability is dependent on the task. Dataset anonymization via synthetic data generation attempts to balance disclosure risk and data utility in the final synthetic dataset. The goal is to ensure observations are not identifiable and the relevant data mining tasks are not compromised [70, 71].

The generation of synthetic datasets allow a more flexible approach to the successful implementation of ML tasks. To do this, it is important to guarantee that sensitive information in $\mathcal{D}$ is not leaked into $\mathcal{D}^s$. Differential privacy (DP), a formalization of privacy, offers strict theoretical privacy guarantees [42]. A differentially private generation mechanism produces a synthetic dataset, regulated by the privacy parameter ϵ, with statistically indistinguishable results when using either $\mathcal{D}$ or neighboring datasets $\mathcal{D}' = \mathcal{D} \backslash \{x\}$, for any $x \in \mathcal{D}$. A synthetic data generation model (f_{gen}) guarantees (ϵ, δ)-differential privacy if $\forall S \subseteq Range(f_{gen})$ all $\mathcal{D}, \mathcal{D}'$ differing on a single entry [44]:

$$Pr[f_{gen}(\mathcal{D}) \in S] \leq e^{\epsilon} \cdot Pr[f_{gen}(\mathcal{D}') \in S] + \delta \tag{1}$$

In this case, ϵ is a non-negative number defined as the privacy budget. A lower ϵ guarantees a higher level of privacy, but reduces the quality of the produced synthetic data. The generation of DP synthetic data is especially appealing since DP is not affected by post-processing; any ML pipeline may be applied using $\mathcal{D}^s$ without a loss of differential privacy.

Despite the formalization and the ability to quantify differential privacy, there are popular synthetic data-based anonymization approaches that perform this task without DP guarantees. Specifically, the Synthetic Data Vault (SDV) [30] is a method for database anonymization that uses Gaussian Copula models for generating data. However, this method allows the usage of other generation mechanisms. A posterior extension of SDV was proposed to generate data using a CTGAN [39] and to handle sequential tabular data using a conditional probabilistic auto-regressive neural network [72].

Anonymizing data using synthetic data generation in the financial sector [1].

A benchmark of various differentially private synthetic data generation mechanisms [73].

Guidelines for effective synthetic data generation [29]

4.2 Regularization in Supervised Learning

The performance of Machine Learning models is highly dependent on the quality of the training dataset used [74, 75]. The presence of imbalanced and/or small datasets, target labels incorrectly assigned, outliers and high dimensional input spaces reduce the prospects of a successful machine learning (ML) model implementation [75, 76, 77]. In the case of deep learning, for example, these models are often limited by a natural inclination to overfitting, label noise memorization and catastrophic forgetting [78]. Regularization methods are the typical approach to address these problems, but producing robust ML solutions is still a challenge [31].

It is frequently assumed that the training data is sampled from a fixed data source, it is balanced and does not contain label noise. Under these conditions, the resulting ML classifier is expected to achieve good generalization performance [79]. Although, in practical applications, this is rarely the case. When the training data is not representative of the true population, or the model is over-parametrized, it becomes particularly prone to overfitting [80]. Regularization methods attempt to address these limitations. They can be divided into three categories [81]:

1. Output level modifications. Transforms the labels in the training data.

2. Algorithmic level modifications. Modifies the classifier's architecture, loss function or other components in the training procedure.

3. Input level modifications. Modifies the training dataset by expanding it with synthetic data.

The last approach, input level modifications, is known as data augmentation. Data augmentation is used to increase the size and data variability of data in a training dataset, by producing synthetic observations [82, 83]. Since it is applied at the data level, it can be used for various types of problems and classifiers [84].

Problems such as fraud detection and healthcare are frequently tackled via synthetic data generation [85].

"Su et al. [78] show that 70.97% of images can be misclassified by changing just one pixel" Shorten et al. [23]

"Moreover, the current research about so called adversarial attacks on CNNs showed that deep neural networks can be easily fooled into misclassification of images just by partial rotations and image translation [1], adding the noise to images [5] and even changing one, skillfully selected pixel in the image [6]." Mikołajczyk et al. [86]

Data augmentation can also be used to improve a model's robustness against adversarial attacks.

4.3 Time Series

Synsys [38] approaches time-series using both Hidden Markov and regression models. They show the method's effectiveness in the Healthcare domain with limited ground truth data by comparing it to models trained using only real data. A related model, Sensegen [40], uses an adversarial training approach to train an LSTM that predicts the parameters of Gaussian Mixture Models (GMM) at each time stamp, using real data as an input. Finally, the GMM estimations are used to sample synthetic data.

Generative adversarial networks in time series

4.4 Oversampling

KernelADASYN [58]

The original author of SMOTE recently published the paper "Efficient Augmentation for Imbalanced Deep Learning" [87]

4.5 Active Learning

4.6 Few-shot Learning

Analysis of six feature space data augmentation techniques for few-shot learning [36]

FlipDA [88]

Data generation can be used to address Few-shot learning in three ways [89]: (1) transforming samples from the dataset, (2) transforming samples from a weakly labeled or unlabeled dataset, or (3) transforming samples from similar datasets.

4.7 Semi-supervised Learning

Synthetic data generation for semi-supervised learning given limited labeled data regarding the COVID-19 pandemic [90].

Extensive literature review on semi-supervised learning [37]

4.8 Self-supervised Learning

5 Evaluating the Quality of Synthetic Data

The log-likelihood (and equivalently the Kullback-Leibler Divergence) is a de-facto standard to train and evaluate generative models [11]. Other common metrics include Parzen window estimates, which Theis et al. [11] show that these metrics behave independently and should generally be avoided. Therefore, it is necessary to evaluate generative models with respect to the application these models are being developed for.

The evaluation of generative models should quantify three key aspects of synthetic data [12]:

1. Fidelity

2. Diversity

3. Generalization

The 3-dimensional metric proposed by Alaa et al. [12] quantifies these aspects via the combination of three metrics (α-Precision, β-Recall and Authenticity) for various application domains.

5.1 Statistical Divergence Metrics

5.2 Precision/Recall Metrics

6 Discussion

6.1 Main Findings

The combination of data generation strategies is an approach commonly found in different problems, such as self-supervised learning [5]. It can be more frequently found in text data applications [17] and image data **[CITATION]**.

6.1.1 RQ1: bla bla bla

6.1.2 RQ2: bla bla bla

6.1.3 RQ3: bla bla bla

6.2 Limitations

Research across the different applications appears to be sandboxed even though all techniques integrate synthetic data in its core.

Given the breadth and complexity of input-level and feature-level data generation mechanisms, it is increasingly important to find a method to efficiently determine the most appropriate data generation policies. However, the complexity of this task is determined by various factors: different data types, ML problems, model architectures, computational resources, performance metrics and contextual constraints. Auto-augmentation and meta learning aim to address this challenge and are still subject to active research.

The evaluation of anonymization techniques lack standardized, objective and reliable performance metrics and benchmark datasets to allow an easier comparison across classifiers to evaluate key aspects of data anonymization (resemblance, utility, privacy and performance). These datasets should contain mixed data types (*i.e.*, a combination of categorical, ordinal, continuous and discrete features) and the metrics should evaluate the performance of different data mining tasks along with the anonymization reliability. This problem appears to be universal across domains. For example, Hernandez et al. [14] observed the lack of a universal method or metric to report the performance synthetic data generation algorithms for tabular health records. Therefore, in order to facilitate the usage of these techniques in industry domains, these benchmarks must also be realistic. Rosenblatt et al. [42] attempts to address this problem by proposing a standardized evaluation methodology using standard datasets and real-world industry applications.

Computational cost and inconsistent quality of synthetic data generated with GANs (*e.g.*, mode collapse).

Unlike with data privacy solutions, data augmentation techniques generally do not consider the similarity/dissimilarity of synthetic data. The study of quality metrics for supervised learning may reduce computational overhead and experimentation time. No studies related to the relationship of quality metrics and performance in the primary ML task were found **[CONFIRM!!!]**.

There is not a clear understanding of what types of data augmentation methods are more appropriate according to different model architectures, ML tasks or domains and the reason why they work better or worse depending on the task. In addition, it is still unclear *why* data augmentation works. Research on this topic lacks depth and fails to address the theoretical underpinnings [7].

"Dao et al. (2019) note that "data augmentation is typically performed in an ad-hoc manner with little understanding of the underlying theoretical principles", and claim the typical explanation of DA as regularization to be insufficient." [7]

There is a lack of research on oversampling solutions to generate synthetic data with mixed data types and datasets with exclusively non metric features.

There is a lack of methods adapted to use categorical features for tabular data.

There is a paucity of research on the usage of probabilistic-based generation mechanisms in oversampling.

There is no clear understanding of the most appropriate data augmentation techniques used to train self-supervised models and how their behavior and performance varies according to the data generation method used.

oversampling does not seem to be a relevant source of bias in behavioral research and does not appear to have an appreciably different effect on results for directly versus indirectly oversampled variables [91]

6.3 Research directions

Quantifying the quality of the generated data:

1. Realistic
2. Similarity
3. Usefulness (determine purpose and relevant performance metric)
4. Understand the relationship between the 3 factors

7 Conclusions

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