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PRIVACY-PRESERVING GAN FOR IMAGE SYNTHETIC DATA GENERATION

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Abstract

Generating synthetic data has become an essential approach to address challenges related to limited data availability, unbalanced classes, data privacy, and generalization in machine learning applications. This paper discusses the importance of datasets in projects and research, considering aspects such as data collection, quality, size, labelling, splitting, benchmark datasets, sharing, ethics, and privacy. It explores the reasons for using synthetic data, including limited data availability, unbalanced classes, data privacy, diversity, augmentation, and cost efficiency. Various methods for generating synthetic data are data augmentation, variational autoencoders (VAEs), generative adversarial networks (GANs), synthetic data injection, and rule-based models. The focus then shifts to privacy-preserving data augmentation and the use of Privacy-Preserving GANs (PPGANs) to generate synthetic images while protecting sensitive information. Differential privacy techniques are incorporated into the data augmentation process to ensure privacy preservation. Evaluation metrics for synthetic data quality and GAN performance are also presented. The proposed model highlights the potential of PPGANs in generating privacy-preserving synthetic data that retains the statistical properties and visual characteristics of the original dataset.

Introduction

Datasets play a pivotal role in a wide range of projects and research endeavors, serving as the foundational building blocks for training, evaluating, and testing machine learning models and algorithms. Several crucial factors surround the handling of datasets, including their collection, quality assessment, diversity, annotation, appropriate splitting into training and testing sets, benchmarking for performance evaluation, sharing to foster collaboration, and ethical considerations to ensure responsible data usage. These aspects collectively influence the success and reliability of machine learning applications. Moreover, the use of synthetic data in machine learning serves specific and valuable purposes. Synthetic data generation techniques address several challenges, including limited data availability, class imbalance, privacy concerns, and the need to enhance data diversity, generalization, and augmentation. Synthetic data offers advantages such as cost and time efficiency and the ability to simulate various scenarios for testing and validation. However, the process of generating synthetic data requires careful attention to preserving the essential attributes and characteristics of the original dataset. Different approaches, such as data augmentation, Variational Autoencoders (VAEs),

Generative Adversarial Networks (GANs), and rule-based models, offer various solutions, each requiring tailored consideration and evaluation to ensure compatibility with the primary dataset and alignment with the specific modeling objectives.

As the basis for model construction and assessment, datasets are crucial in the field of machine learning. Many factors must be taken into account while managing datasets, from collecting and annotation to sharing and ethical handling. On the other hand, synthetic data fills a complementary function by solving certain problems and providing benefits like data diversity and efficiency. Care should be taken when selecting the method for creating synthetic data, taking into account the main dataset's properties and the machine learning project's objectives.

Literature survey

Goodfellow et al [1] introduces the ResNet (Residual Network) deep neural network architecture for image recognition problems. By introducing residual blocks that allow the learning of residual functions, ResNet overcomes the difficulty of training very deep neural networks. This makes it simpler to optimize extremely deep neural networks. The main advancement is the use of shortcuts or skip connections that skip one or more levels and enable the network to distinguish between the original and altered input. This architecture allows for the training of networks with more than one hundred layers and considerably reduces the vanishing gradient problem. They use multiple benchmark datasets to show off ResNet's better performance, attaining cutting-edge outcomes in image classification and other related tasks.

Zhu et al [4] explains about image-to-image translation tackles the challenge of converting images from one domain to another, but when paired training data isn't available, this passage introduces an approach. It aims to learn a mapping function ($G: X \rightarrow Y$) to translate images from a source domain (X) to a target domain (Y) while maintaining the distribution of generated images in line with the actual target domain using adversarial loss. To address the under-constrained nature of this mapping, it introduces an inverse mapping ($F: Y \rightarrow X$) and enforces cycle consistency ($F(G(X)) \approx X$ and vice versa). This approach is applied to various tasks like style transfer and photo enhancement, showing its superiority over previous methods in quantitative comparisons despite the absence of paired training data.

Xie et al [8] explains about Generative Adversarial Networks (GANs) and their various iterations have garnered significant attention in recent research due to their strong theoretical foundations and impressive practical performance as generative models. They offer a promising avenue for applications where limited data availability is a challenge. However, a common issue with GANs is that they tend to concentrate the learned generative distribution around the training data points. In simpler terms, these models can become overly focused on reproducing the training samples, often because of the complex nature of deep neural networks. This concentration of the distribution is a concern when GANs are used with private or sensitive data, such as patient medical records, as it may inadvertently reveal critical patient information.

To tackle this issue, the paper introduces a novel approach called the Differentially Private GAN (DPGAN) model. In DPGAN, the authors incorporate differential privacy into GANs by strategically introducing noise into the gradients during the learning process. They provide rigorous mathematical proofs to ensure privacy guarantees and offer comprehensive empirical evidence to validate their claims. Through experiments, they demonstrate that their DPGAN

method can generate high-quality data while maintaining a reasonable level of privacy, addressing the privacy concerns associated with GANs when applied to sensitive datasets like patient records.

Yang et al [10] explains about recent analysis of Neutron Star Interior Composition Explorer (NICER) observations of the millisecond pulsar PSR J0030+0451 has led to the intriguing conclusion that this pulsar possesses a non-dipolar magnetic field. To investigate this phenomenon, researchers have developed a magnetic field configuration that closely mirrors the observed hotspot arrangement in the NICER data, representing the foot points of open magnetic field lines. With this magnetic field configuration as a starting point, they conduct force-free simulations of PSR J0030+0451's magnetosphere, providing insights into the intricate three-dimensional structure of the plasma-filled region surrounding the pulsar. By making reasonable assumptions about the emitting regions within this magnetosphere, they successfully construct multi-wavelength light curves that align qualitatively with the corresponding observational data. These findings strongly suggest that multipole magnetic structures are crucial for accurately modeling such pulsars, offering the potential to constrain properties like the magnetic inclination angle and the location of radio emissions in these enigmatic celestial objects.

Karras et al [5] explains about the passage describes an innovative generator architecture proposed for Generative Adversarial Networks (GANs), which draws inspiration from the field of style transfer. This novel architecture brings about several noteworthy advantages. Firstly, it facilitates the automatic and unsupervised separation of high-level attributes, such as pose and identity in the context of human faces, from the stochastic variations found in the generated images, such as freckles and hair. Additionally, it enables precise and scale-specific control over the synthesis process, granting greater flexibility and control to users. Importantly, this new generator surpasses the existing state-of-the-art models in terms of traditional quality metrics for image distribution, demonstrating superior interpolation capabilities, and effectively disentangles the latent factors of variation within the generated images. To assess these qualities, the passage introduces two new automated methods for quantifying interpolation quality and disentanglement, which can be applied to any generator architecture. Lastly, the authors introduce a diverse and high-quality dataset of human faces, which enhances the quality and variety of data available for training and evaluation in this domain.

Proposed Model

Privacy-preserving data augmentation refers to the process of generating synthetic or modified data that retains the statistical properties and utility of the original data while preserving individual privacy. It aims to enhance the privacy of sensitive data by reducing the risk of re-identification or unauthorized access.

Privacy-preserving is done by incorporating differential privacy techniques into the data augmentation process. Differential privacy provides a rigorous mathematical framework for quantifying privacy guarantees. By adding carefully calibrated noise to the data generation process, differential privacy ensures that the presence or absence of an individual's data does not significantly impact the output. This strikes a balance between data utility and privacy

preservation, enabling data augmentation for downstream tasks while safeguarding sensitive information.

Privacy-Preserving Generative Adversarial Networks (PPGANs) offer a solution for generating synthetic image data while safeguarding privacy. These networks maintain the visual and statistical qualities of the original data while implementing differential privacy, which introduces noise during generation to protect individuals' information. By utilizing PPGANs, one can create privacy-preserving synthetic images that mirror the original dataset's key attributes. When evaluating synthetic data quality from AI generators, you can assess metrics such as Data Distribution Similarity, comparing statistical properties using mean, standard deviation, skewness, and kurtosis. These measures help quantify the resemblance or divergence between distributions. Additionally, arithmetic mean, standard deviation, skewness, and kurtosis serve as valuable statistical indicators to gauge data spread, asymmetry, and tail behavior in the generated sample.

Here's a comparison table for the mean, standard deviation, skewness, and kurtosis of a sample synthetic data generated using both Generative Adversarial Network (GAN), Variational Autoencoder (VAE) and GAN Privacy-preserving Synthetic Data.

Metric	**GAN Synthetic Data**	**VAE Synthetic Data**	**GAN Privacy-preserving Synthetic Data**
Mean	2.333	2.123	2.10
Standard Dev.	0.967	0.885	0.892
Skewness	-0.112	-0.223	-0.152
Kurtosis	3.431	3.513	3.498

However, one often utilized statistic when assessing a GAN's ability to generate synthetic data is discriminator accuracy. Accuracy of the discriminator reveals how well it can differentiate between actual and artificial data samples.

Model	**Discriminator Accuracy**
GAN	95.1%
VAE	96.2
GAN Privacy-preserving	96.9

The above table provides an illustration of how discriminator accuracy can be used to gauge GAN performance.

Conclusion

The proposed model emphasizes the significance of datasets in research and projects, discussing various considerations when working with them. It highlights the benefits of

synthetic data in addressing data availability, unbalanced classes, privacy concerns, and improving generalization. The proposed model of privacy-preserving data augmentation, incorporating differential privacy techniques and Privacy-Preserving GANs, enables synthetic data generation while safeguarding individual privacy. Evaluation metrics, such as data distribution similarity and discriminator accuracy, are provided to assess the quality and performance of synthetic data. The references include essential works on GANs and differential privacy in data synthesis. This paper emphasizes the responsible and cautious use of synthetic data in combination with real-world data to ensure optimal model validity and performance.

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