Data Augmentation Using GANs

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**Abstract**

In this paper we propose the use of Generative Adversarial Networks (GAN) to generate artificial training data for machine learning tasks. The generation of artificial training data can be extremely useful in situations such as imbalanced data sets, performing a role similar to SMOTE or ADASYN. It is also useful when the data contains sensitive information, and it is desirable to avoid using the original data set as much as possible (example: medical data). We test our proposal on benchmark data sets using different network architectures, and show that a Decision Tree (DT) classifier trained using the training data generated by the GAN reached the same, (and surprisingly sometimes better), accuracy and recall than a DT trained on the original data set.

**Keywords:** Generative Adversarial Networks, Data Augmentation, Data Imbalance, Privacy

1. Introduction

When working with machine learning, it is important to have a high-quality data set to train the algorithm. This means that the data should not only be sufficiently large, to cover as many cases as possible, but also be a good representation of the reality. Having a good data set permits the program to have a better model of the underlying characteristics of the data and makes it easier to generalize these traits. In this scenario, the creation of synthetic data can be useful for several reasons like oversampling minority classes and generating new data sets to keep the privacy of the originals.

The first reason for creating synthetic data sets, oversampling the minority class, is relevant when trying to learn from imbalanced data sets. In many instances, it is common for databases to have classes that are underrepresented. For example, when dealing with credit card frauds the ratio between normal and fraudulent transactions can be 10000 to 1. The same can happen when analysing medical information where the number of healthy patients is much higher than affected ones. When this happens, classification algorithms may have difficulties identifying the minority classes since the program would still have a low error even if it classifies all the minority classes wrong. To avoid this problem it is possible to augment the minority data though the creation of new entries by tweaking the original in meaningful ways. This approach not only increases the representation of the minority class, but it may help to avoid over fitting as well.

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The second reason for creating synthetic data sets is to avoid using the original data for privacy reasons. It is possible that a database contains sensitive information, and working on it directly could risk it being misused or breached. For example, medical records could have a lot of personal information about the patients, and even without the names it could be possible to identify them using a combination of other attributes such as date of birth, weight, height, etc. Because of this, it is understandable that many regulations exist on the use of this kind of database, controlling its access. One possible approach to this problem is to not use the original data to train the model, but generate a synthetic data set based on it which sufficiently realistic.

In this research, we studied the use of Generative Adversarial Networks (GAN) to deal with the two previously mentioned issues. In both cases, we obtained public data sets and generated synthetic versions of these data sets using different GAN architectures. The quality of these synthetic data sets as training data was examined in two ways. First, we compared the Accuracy, Precision and Recall obtained by a Decision Tree classifier trained on the original data against one trained on the synthetic data. We were surprised to observe that in some cases, the classifier trained on the synthetic data achieved better results than the one trained in the original data, which suggests that generating synthetic data using GANs can be a good approach to avoid overfitting. Second, we compared the performance of the classifier on imbalanced data sets that were augmented by the GAN, SMOTE (Chawla et al., 2011) and ADASYN (He et al., 2008). In this experiment the GAN improved the results when compared with the original, imbalanced data set, but did not perform better than SMOTE or ADASYN.

2. Background

2.1. Generating Adversarial Networks (GANs)

Generating Adversarial Networks, or GANs for short, were first introduced by Goodfellow et al. (2014). Since then, many researches have been done using the framework and Facebooks AI research director LeCun (2017) recognized it as "the most interesting idea in the last 10 years in machine learning". GANs are a type of generative model, this means that it can produce new content based on its training data.

GANs can have a variety of applications, developing new molecules for oncology (Kadurin et al., 2017), and increasing resolution (Ledig et al., 2017), are some of them. The most common usage for it, however, is for the generation of new images. Below it is possible to see an example of faces generated by a GAN based on a dataset composed by photos of famous people (Karras et al. (2018)).
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A GAN is made of 2 Artificial Neural Networks (ANNs) that compete against each other, the Generator and the Discriminator. The first creates new data instances while the second evaluates them for authenticity.

The discriminator is responsible for evaluating the quality of the data created by the generator. It receives as input data samples from either the original data set, or created by the generator, and tries to predict the source of the sample. The pseudo-code of its training is described in Algorithm 1.

The generator learns to map a latent space to the distribution of the data it aims to reproduce, so that when fed with a noise vector from the latent space, it predicts a sample from the estimated distribution. The generator is evaluated by the discriminator, meaning that its goal is to create data samples that are similar to those in the original data set. The pseudo-code for training the generator is described in Algorithm 2.

Algorithm 1 Pseudo-code for training the discriminator

\begin{algorithm}
\textbf{Require:} \text{realData} \quad \triangleright \text{array of samples from the data set} \\
\text{Require:} \text{fakeData} \quad \triangleright \text{array of samples from the generator} \\
\text{Require:} \text{discriminator} \quad \triangleright \text{discriminator network model} \\
\hspace{1em} \text{Set} \text{realDataLabels} \text{as prediction of realData from discriminator;} \\
\hspace{1em} \text{Set} \text{realLoss} \text{as difference between realDataLabels and 1;} \\
\hspace{1em} \text{Update discriminator using realLoss;} \\
\hspace{1em} \text{Set} \text{fakeDataLabels} \text{as prediction of fakeData from discriminator;} \\
\hspace{1em} \text{Set} \text{fakeLoss} \text{as difference between fakeDataLabels and 0;} \\
\hspace{1em} \text{Update discriminator using fakeLoss;} \\
\end{algorithm}

By training both networks at the same time, they will get better by competing against one another, hence the name Generative Adversarial Networks. The discriminator will try to get better at distinguishing fake and real data and the generator is going to output data that is progressively closer to the original. This iteration is described in Figure 2

Figure 1: These people do not exist. Synthetic faces generated by a GAN trained on human pictures (Karras et al., 2018)
Algorithm 2 Pseudo-code for training the discriminator

Require: latentVector  \(\triangleright\) a noise vector sampled from the latent space
Require: generator  \(\triangleright\) generator network model
Require: discriminator  \(\triangleright\) discriminator network model

Generate fakeData as prediction of latentVector from generator;
Set fakeDataLabels as prediction of fakeData from discriminator;
Set fakeLoss as difference between fakeDataLabels and 1;
Update generator using fakeLoss;

Figure 2: How a GAN trains both generator and discriminator network at the same time.

The use of GANs have many advantages, they can create high quality data and be modeled to deal with different problems. On the other hand, their use have some disadvantages and difficulties as well, some of them are: it is hard to generate discrete data (like text), they are hard to train and require large processing power, and like any ANN, its model can be unstable or it can overfit the data.

Regarding the two applications addressed in this work (balancing data and generating synthetic data sets), there is some previous work in the literature using GANs, such as Mariani et al. (2018), Springenberg (2015) and Frid-Adar et al. (2018)). However in all these cases the work was done in images, while we are more interested in standard numerical databases (as most of the initial work in GANs was done on images, although this has began to change recently). Although the techniques used are similar, there are differences in implementation which are worth exploring. For example, the use of convolution does not apply to non-image datasets, since the attributes of a sample vector do not exhibit positional relationships among themselves.

2.2. SMOTE and ADASYN

SMOTE (Chawla et al., 2011) and ADASYN (He et al., 2008) are two approaches to oversampling the minority classes with the goal to balance data sets. In this work, we use their implementation from the imbalanced-learn python library (Lemaitre et al., 2017).

Synthetic Minority Over sampling Technique (SMOTE) create synthetic samples based on the position of the data. First, it randomly selects a point in the minority class, then finds the \(k\) nearest neighbors of the same class. For each of these pairs a new point is
generated in the vector between them, this new point is located in a random percent of the way from the original point.

![Figure 3: Example of SMOTE (from Hu and Li (2013))](image)

ADASYN is similar to SMOTE, and is derived from it. They function on the same way but, after creating the samples, ADASYN adds a random small bias to the points, making them not linearly correlated to their parents. Even though this is a small change it increases the variance in the synthetic data.

3. Proposal and Experimental Design

We evaluate the utility of GANs for generating synthetic numerical data sets in two different domains: To train a classifier using purely synthetic data, and to balance a data set by oversampling the minority class using synthetic data.

For the first domain, we will compare the performance of the classifier on the original data set and the data sets created by variations in our GAN architecture. The idea is that if we can obtain a synthetic data set that is similar enough to the original data set, we can completely avoid training the classifier on the original data set. Yes, training the GAN itself is still necessary. However, many different classifiers for different tasks might need to be
trained by different entities, and using synthetic data will still reduce the need to distribute the original data in this case.

For the second domain, we will compare the performance of the classifier on imbalanced data oversampled with GAN, SMOTE and ADASYN, as well as non-oversampled data as a baseline. While SMOTE and ADASYN both produce good results, they tend to not generalize well sparse data and outliers. We wonder if oversampling using GAN can overcome these issues.

For reproducibility purposes, the code of our GAN architecture is available at our github repository.

3.1. GAN architecture and parameter Choice

In both experimental domains, we use the same general GAN architecture to generate the synthetic data. Our GAN architecture has the following parameters:

- *leaky ReLU* as the activation function with a negative slope of 0.2.
- *batch size* = 5
- *learning rate* = 0.0002
- *Use of dropout in the generator with a probability of 0.3.*
- *Binary cross-entropy as the loss function.*
- *Adam as the optimizer algorithm.*
- *No convolution layers.*
- *In the generator, if there are more than one layer, they are ordered in ascending size.*
- *In the discriminator, if there are more than one layer, they are ordered in descending size.*

Leaky ReLU, Adam optimizer and the use of dropout were chosen because they are the standard for this kind of problem (Chintala et al., 2016). There are no convolutional layers because the input is not an image. Binary cross-entropy loss is used because it is the most fit to measure the performance of a model whose output is a probability between 0 and 1.

We tested six different configurations varying the number of layers and the number of nodes in each layer, and all the results are included in the following sections. In this experiment, we intentionally use a simple network and configuration, to focus on the basic proposal of generating synthetic numerical databases.

3.2. Classifier

For both domains of this experiment, we use a Decision Tree classifier as the classifier to test the quality of the synthetic training data generated. We use Decision Tree classifier implementation from the *sklearn* library. This choice was made because Decision Trees are simple to understand and interpret since they can be visualized, they also require little to no data preparation.

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1. https://github.com/fhtanaka/directed_research_CS_2018
3.3. Databases

The experiments on this research were done using the following 3 different data sets:

- **Pima Indians Diabetes Database** (Smith et al. (1988)): This data set consists of 8 independent variables and one target dependent class that represents if the patient has Diabetes or not. It is composed by 768 samples, in which 268 patients present the disease.

- **Breast Cancer Wisconsin (Diagnostic) Data Set** (Dua and Graff (2017)): The features of this data set are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image. The data set has a target class to determine if the cancer is benign or malignant. There are 357 benign and 212 malignant samples.

- **Credit Card Fraud Detection** (Dal Pozzolo et al. (2017)): This data set contains transactions made by credit cards in September 2013 by European cardholders. It presents transactions that occurred in two days, where there are 492 frauds out of 284,807 transactions. The data set is highly imbalanced, the positive class (frauds) account for only 0.172% of all transactions.

The goal class on the **Breast Cancer Wisconsin (Diagnostic) Data Set** was represented by a char, "B" = benign and "M" = malignant but this label was changed to 0 and 1 respectively to be consistent with the other examples. With the exception of this case, all attributes are fully numeric, which was the reason for this choice of data sets. Working with fully numeric examples allows the GAN to generate discrete results. They are also faster to compute and train when compared to image data sets. Each of these data sets was divided in two subsets, one for training the GAN (the first 70% of the original data) and other for testing it (the remaining 30%). A summary of the data sets is in table 1.

| Database Name                          | Number of features | Size    | Label Distribution       |
|----------------------------------------|--------------------|---------|--------------------------|
| Pima Indians Diabetes Database         | 9                  | 768     | No diabetes: 500, Diabetes: 268 |
| Breast Cancer Wisconsin (Diagnostic) Data Set | 32                 | 569     | Benign: 357, Malignant: 212 |
| Credit Card Fraud Detection            | 31                 | 284807  | Non-frauds: 284315, Frauds: 492 |

Table 1: Databases used in this research

Notice that, before using these databases, their attribute values were all scaled to be in the interval [0,1] by the min-max method. This was done because it makes the range for all attributes to be the same, preventing one of them to dominate the others because of its scale. This reduces the range of values that the generator has to produce as well.

4. Results and Analysis

In the results below, the synthetic databases generated by the 6 variations of the GAN architecture are described using the names shown in table 2.
Table 2: Names used for the synthetic and original data sets in the results

| Data set name | Architecture of the GAN |
|---------------|-------------------------|
| original data | The first 70% of the original database |
| 256/512/1024  | Generated by a GAN with 3 hidden layers with size 256, 512 and 1024 |
| 256/512       | Generated by a GAN with 2 hidden layers with size 256 and 512 |
| 256           | Generated by a GAN with 1 hidden layer with size 256 |
| 128/256/512   | Generated by a GAN with 3 hidden layers with size 128, 256 and 512 |
| 128/256       | Generated by a GAN with 2 hidden layers with size 128 and 256 |
| 128           | Generated by a GAN with 1 hidden layer with size 128 |

4.1. Experiment 1: Training the classifier using fully synthetic data

To evaluate the creation of synthetic data the experiments were done using the following steps:

1. Trained the GAN using the full training subset of the original database for 1500 epochs.
2. Used the newly trained GAN to generate a new synthetic data set with the exact size of the original.
3. Since the GANs generated the classification label as a continuous value between 0 and 1, this value has to be turned to a discrete by rounding it to the nearest integer.
4. The new data set is used to train a classification tree.
5. The tree is tested using the test subset of the original data set.

It is important to note that the GAN was trained using the label classes as well. This means that the data generated can have any of the classes and the GAN itself defines how each data point should be classified.

The tests were done using the diabetes and cancer databases. Both are not very unbalanced and have less than 1000 entries. Figure 4 shows the distribution of some attributes of the new synthetic cancer data set compared with the original.
Tables 3 and 4 show an early result where a single classification test is done using synthetic data generated after 1500 epochs of training. Tables 5 and 6 are a more in-depth analysis of the results. We generate 20 different synthetic data sets, and perform the previous classification experiment on each of them. The values between parenthesis are the standard deviations of the results.

Tables 7 and 8 show the mean Euclidean distance between the points in the synthetic database and the closest point to it in the original. This is used to evaluate the similarity between the two data sets. Again, the average results of 20 data sets is displayed.

| Database       | Label Proportion | Test Accuracy |
|----------------|------------------|---------------|
| original data  | 56.53/43.47      | 0.888         |
| 256/512/1024   | 52.26/47.74      | 0.818         |
| 256/512        | 56.28/43.72      | 0.941         |
| 256            | 56.78/43.22      | 0.906         |
| 128/256/512    | 54.02/45.98      | 0.953         |
| 128/256        | 58.04/41.96      | 0.935         |
| 128            | 54.27/45.73      | 0.912         |

Table 3: Label proportion and accuracy of the tests in the Cancer database
| Database                  | Label Proportion | Test Accuracy |
|--------------------------|------------------|---------------|
| original data            | 64.8/35.2        | 0.748         |
| 256/512/1024             | 71.69/28.31      | 0.7           |
| 256/512                  | 67.23/32.77      | 0.548         |
| 256                      | 67.6/32.4        | 0.748         |
| 128/256/512              | 60.15/39.85      | 0.661         |
| 128/256                  | 65.18/34.82      | 0.739         |
| 128                      | 68.9/31.1        | 0.697         |

Table 4: Label proportion and accuracy of the tests in the Diabetes database

| Database                  | Accuracy   | Precision  | Recall    |
|--------------------------|------------|------------|-----------|
| Original data            | 0.888      | 0.679      | 0.974     |
| 256/512/1024             | 0.91 (0.042) | 0.786 (0.127) | 0.888 (0.054) |
| 256/512                  | **0.935** (0.03) | **0.853** (0.107) | **0.896** (0.086) |
| 256                      | 0.907 (0.053) | 0.772 (0.126) | 0.904 (0.071) |
| 128/256/512              | 0.869 (0.066) | 0.702 (0.144) | 0.821 (0.148) |
| 128/256                  | 0.896 (0.048) | 0.74 (0.122) | 0.908 (0.086) |
| 128                      | 0.906 (0.054) | 0.775 (0.131) | 0.894 (0.055) |

Table 5: Mean and standard deviation (n=20) of the classification results in the cancer database.

| Database                  | Accuracy   | Precision  | Recall    |
|--------------------------|------------|------------|-----------|
| Original data            | **0.748**  | **0.784**  | 0.367     |
| 256/512/1024             | 0.682 (0.064) | 0.545 (0.093) | 0.534 (0.206) |
| 256/512                  | **0.706** (0.05) | **0.582** (0.078) | **0.584** (0.097) |
| 256                      | 0.601 (0.097) | 0.438 (0.118) | 0.438 (0.213) |
| 128/256/512              | 0.685 (0.058) | 0.568 (0.109) | 0.544 (0.158) |
| 128/256                  | 0.639 (0.094) | 0.507 (0.106) | 0.579 (0.185) |
| 128                      | 0.653 (0.086) | 0.51 (0.117) | 0.462 (0.219) |

Table 6: Mean and standard deviation (n=20) of the classification results in the diabetes database.
Table 7: Mean and standard deviation of the euclidean distance between the points in the synthetic and original cancer database.

| Database       | Distance  |
|----------------|-----------|
| 256/512/1024   | 0.345 (0.156) |
| 256/512        | 0.314 (0.121) |
| 256            | 0.328 (0.135) |
| 128/256/512    | 0.371 (0.190) |
| 128/256        | 0.331 (0.128) |
| 128            | 0.342 (0.143) |

Table 8: Mean and standard deviation of the euclidean distance between the points in the synthetic and original diabetes database.

| Database       | Distance  |
|----------------|-----------|
| 256/512/1024   | 0.158 (0.071) |
| 256/512        | 0.17 (0.071) |
| 256            | 0.208 (0.106) |
| 128/256/512    | 0.172 (0.069) |
| 128/256        | 0.187 (0.080) |
| 128            | 0.189 (0.088) |

4.2. Analysis of the results for the fully synthetic data set

The early results in both the cancer and the diabetes data sets showed that GANs can produce synthetic data with a similar class and attribute distribution as the original data, without an explicit instruction to do so. This is the result of training the GAN with the complete training set, without separation of the classes. This indicates that for practical use it is not necessary to separate the data in classes before training, reducing the burden for the data provider, and the need of domain knowledge for the data user.

Considering the mean accuracy, precision and recall results, the 256/512 layer architecture had the best overall outcomes in both data sets, with statistically significant difference \((p < 0.05)\) for the accuracy measure. It is hard to explain precisely why this architecture was better, but we recommend it’s use until further experiments provide more information. The following considerations will use this architecture as the baseline.

When we compare the accuracy obtained by training the classifier with the synthetic data with the accuracy obtained by training the classifier with the original data, the accuracy of the synthetic data is the close to the original data in the diabetes dataset, and better than the original data in the cancer data set. This is a good indicator that using synthetic GAN data as training data for classifiers is a promising technique.

However, when classifying medial data, we are more interested in the Recall than the Accuracy, since false negatives can be disastrous when deciding if a patient needs a treatment or has a certain diagnostic. In this aspect, the synthetic data from GAN obtained great
results in the diabetes data set, while the results in the cancer data set were slightly lower than the recall on the original data set.

We also want to know if synthetic GAN data can be used to improve the privacy of handling medical data sets in training models. Since the experiments were done in a dataset where all attributes are scaled to the 0,1 interval, the euclidean distance between the data points in the original and synthetic data set are a good estimation of similarity between the data sets. Tables 7 and 8 show this distance. The large distance observed in for each model, specially for the cancer database, indicates that it is unlikely that an ill-intentioned user with access to the synthetic data set would be able to use it to pinpoint exact information about any one user in the original data set.

As a summary, the classifier trained with synthetic data from the GAN was able to reproduce the results obtained from training on the original data fairly well. On the other hand, depending on the characteristics of the problems, this approach could result in an increase of false negatives or false positives. More effort should be spent to try to understand exactly when these differences take place, and what attributes of the problem make the GANs have better or worse precision and recall.

4.3. Experiment 2: Oversampling the Minority Class with Synthetic Data

To evaluate the effects of balancing a data set by oversampling the minority class using synthetic data produced from a GAN, our experiment uses the following steps:

1. Separated the training set based on the target class (For example, the credit card database was separated in non-frauds and frauds).
2. Trained the GAN using only the minority class data. The label was included as an attribute in the training.
3. Used the GAN to add new entries to the training data set until it becomes balanced.
4. Used the newly balanced training data set to train the classifier.
5. The classifier was tested on two databases: the original test set and a balanced version of it obtained by undersampling the majority class.

Tables 9 and 10 show the mean results from 5 repetitions, with the standard deviation in parenthesis. The smaller number of repetitions is due to the large quantity of data in the data sets. As the SMOTE and ADASYM implementation in the imblearn library (Lemaitre et al., 2017) always produced the same output, the standard deviation for these two cases is zero.
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| Database   | Accuracy  | Precision | Recall  |
|------------|-----------|-----------|---------|
| Original   | 0.999     | 0.896     | 0.556   |
| SMOTE      | 0.958     | 0.026     | 0.861   |
| ADASYN     | 0.958     | 0.026     | 0.861   |
| 128        | 0.798 (0.372) | 0.051 (0.029) | 0.806 (0.042) |
| 256        | 0.986 (0.005) | 0.077 (0.031) | 0.789 (0.018) |
| 128/256    | 0.974 (0.01) | 0.045 (0.02)  | 0.82 (0.028)  |
| 256/512    | 0.964 (0.017) | 0.033 (0.013) | 0.808 (0.069) |

Table 9: Classification results from testing on the imbalanced test set

| Database   | Accuracy  | Precision | Recall  |
|------------|-----------|-----------|---------|
| Original   | 0.782     | 1.0       | 0.565   |
| SMOTE      | 0.912     | 0.959     | 0.861   |
| ADASYN     | 0.921     | 0.979     | 0.861   |
| 128        | 0.807 (0.165) | 0.89 (0.202) | 0.806 (0.042) |
| 256        | 0.894 (0.01) | 0.998 (0.005) | 0.789 (0.018) |
| 128/256    | 0.902 (0.012) | 0.981 (0.015) | 0.82 (0.028)  |
| 256/512    | 0.888 (0.032) | 0.962 (0.018) | 0.808 (0.069) |

Table 10: Classification results from testing on the balanced test set

#### 4.4. Analysis of the "oversampling on the minority class" experiment

First we that the GAN with only one layer of 128 nodes displayed particularly bad results when compared to the other GAN variations. Clearly there was a catastrophic divergence in the training of this GAN and we should strive to be able to identify and correct these cases.

For all the methods, oversampling the minority class improved the recall score and worsened the precision score. This is to be expected, because the original data set is so imbalanced that the tree trained on it predicts almost all samples as in the negative (non-fraud) class. Also, we observe that for all methods, the balanced test set shows better results than the imbalanced test set. Again, this makes sense because the classifier has an easier time to identify positive labels. That said, more importance should be given to the imbalanced test set results, as we cannot expect that the test data in actual applications will be balanced.
With that in mind, when dealing with the unbalanced test set, the GAN had better accuracy and precision and worse recall when compared to ADASYN and SMOTE. The importance of each of these results may vary depending on the problem domain but, in the case of fraud evaluation on credit cards, it is much more important to identify frauds. As such, a good recall is desired. In this aspect ADASYN and SMOTE should be preferred to our GAN framework for data synthesis.

Even so, using GAN for data augmentation improved the results when compared to just using the original data set. With a little more work on the GAN architecture and parameters, it is not unreasonable to expect comparable results to the other two algorithms.

5. Conclusions and Future Work

In this work we proposed the use of a GAN to generate synthetic data for a numeric dataset, with the objective to train a classifier without using the original data set, and to oversample the minority class in an imbalanced classification scenario. In both scenarios the data sets generated by GAN were suitable for the tasks proposed.

Training the classifier using only GAN synthetic data in the balanced scenario showed better accuracy and precision than training on the original data set. On the imbalanced scenario, the GAN synthetic data performed better than the original data, but did not perform better than SMOTE or ADASYN. One benefit of using GANs is that the user does not have to define any rules or constraints in general.

As an initial inquiry, this research limits itself to one GAN architecture and 6 variations of network depth and width. We also used only three data sets that are widely used as classification benchmarks. Our future work will analyze many different network architectures as well as data sets with different characteristics. We are specifically interested in investigating the use of an autoencoder to initialize the GAN network, as suggested in BAGAN by citeBAGAN, and in investigating the influence of the number of classes and attributes in the data set and the final results. Other aspects that can influence the results are the quality and distribution of samples in the data set, and the influence of mislabeled data and missing data.

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