Feasibility Experiment and Discussion of Cyclegan Generating Data for Retraining Under Unsupervised Scenarios

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Abstract: The main contribution of this paper is a simple unsupervised pipeline that uses the training set that only has rare samples. It tries to answer this question: does it improve the accuracy of the classifier using the cyclegan generating data to expand the training set? In this work, We first selected a portion of the data from the CelebA data set as our raw data set. Using cyclegan to train some specific data transformation models on this dataset. We use these data transformation models to augment our dataset and then test it on a mobienetv2 classifier. The experimental results show that cyclegan used to augment the data set did not achieve good results. Even in some cases, it will be counterproductive. Of course, the results of this experiment are only for the conclusion of this experiment, and may be affected by insufficient experimental data and the effect of the gan model. We also discussed it later in this article.

1. Introduction

Data augmentation is a very important method for dealing with unbalanced data sets or sparse data sets. In particular, the training effect of the neural network model relies heavily on a fully balanced training data set. The usual method of data expansion is to collect and label new data. Of course this is the most useful but also the most time consuming and resource consuming. In addition, it is mainly the synthesis of simulation data and learning methods based on supervised situations. These methods have achieved remarkable results through manual logic participation such as self-consistent regularization, minimization of entropy and traditional regularization schemes. Of course, with the recent rise of the gan model, data expansion with the gan model has become a very popular research direction. Cyclegan is an unpair image generation method proposed by Berkeley in 2017 [1]. We use cyclegan for data generation and then add some artificial adjustments and parameter controls, such as adding identity mapping loss, etc., and other data increase methods, such as inversion, random erasure, etc. to avoid over-fitting. They both have achieved good results in data expansion.

Of course, in the process of using gan to generate data, whether it is due to logical mistrust or natural improvement of algorithm results, the results are adjusted and corrected. Then in terms of universal conditions, what characteristics of gan's generated data itself learned through training? Is there any innovation in it? We are doubtful. In other words, in some cases, if we do not have the conditions to directly observe and supervise the generated data of gan, we are not sure these data have the meaning of new samples. In the extended discussion, gan learned and summarized the old samples through machine learning to extract the features that he considered, and thus generated new samples. These new samples may not be judged in the human cognition with the old samples. But in the eyes of another machine, whether these new samples have a new meaning. This article is to test and discuss such a situation.

2. Related Work

2.1 Generative Adversarial Networks (GANs).

The gan network consists of two networks: a generator G (distributor) and a discriminator (Discriminator) network. Inspired by the two-person zero-sum game, the best result can be achieved by the mutual confrontation between the two networks. In general terms, there are two data fields, X and Y. G is responsible for taking the data in the X domain and desperately imitating it into real data and hiding it in real data, and D is desperately trying to separate the forged data from the real data. After the game between them, the forgery technology of G is getting more and more powerful, and D's identification technology is getting more and more powerful. The process of confrontation reaches a dynamic balance until D can no longer tell whether the data is real or G-generated data.

Cyclegan is essentially two mirror-symmetrical GANs that form a ring network. The two GANs share two generators, each with a discriminator, that is, two discriminators and two generators. The innovation of cyclegan is that it can migrate picture content from the source domain to the target domain without paired training data. Cyclegan, during training, it is only necessary to input the picture of the source domain and the picture of the target domain. The source domain does not need to match the image content of the target domain, and thus cyclegan is often used in data expansion for discussion.

2.2 Unsupervised Learning.

Unsupervised learning is a method of machine learning that automatically classifies or group's incoming data without giving pre-marked training examples [2]. Unsupervised learning is often used as an auxiliary work for supervised learning. Cyclegan is a generated confrontation network for unsupervised learning of mapping between two data distributions. We use the generated data of cyclegan without additional processing and annotation directly to train a simple classifier to observe the usability of this data. Among the various methods of data expansion, due to the cognitive characteristics of machine learning, like inversion, partial distortion and random cropping, we think they are all supervised method of data expansion. Because it does not change the determination of sample tags. Its essence is the generalization of the sample without changing the label certainty. In this paper, we only need data generation requirements for cyclegan, and the authenticity of the tags for generating data is determined by the process of machine learning. Although the experiment itself is not unsupervised learning in the usual sense, the integrated process is an unsupervised process.

2.3 MobieNetV2 Classification.

MobileNet [3] is mainly used for the mobile computing model. It converts the traditional convolution operation into a two-layer convolution operation. Under the condition of ensuring the accuracy, the calculation time is reduced to 1/9, and the calculation parameter is reduced to the original 1/7. MobileNetV2 is an improvement to MobileNetV1, also a lightweight convolutional neural network [4]. We use the simple and widely used MobileNetV2 classifier to verify the usability of our cyclegan generated data.

3. Network Overview

The main framework of this experiment is to train the gan transformation model from the original data, transform our original data into new generated data through the gan transformation model, and then combine the original data with the newly generated sample data as the training data of the classifier. Our experiments did not make major changes to the gan network structure or the CNN network structure. In addition to the need to change the number of classifications of the last layer of the fully connected layer of the classification network, we focused on the comparison group design for the experiment.

4. Experiment

4.1 Training Cyclegan Conversion Model.

The dataset we use is the CelebA dataset [5]. The CelebFaces property dataset (CelebA) is a large face attribute dataset with more than 200K celebrity images, each with 40 attribute annotations. We selected three characteristics (gender features, whether wearing glasses, and hair color) from CelebA as our research objects. The three feature combinations are eight categories. We record male feature as 1, wearing glasses as 1, and black hair feature as 1, and the others as 0. In order to facilitate the training of the transformation model, we take the golden hair as the opposite side of black hair, that is, the golden hair feature is recorded as 0. For example, the 000 category represents women, no glasses, and golden hair. The 101 category represents men, no glasses, and black hair. We first select 10,000 samples in CelebA for features corresponding to 0 and 1, such as 5000 female and 5000 male images, used to train the cyclegan conversion model. We record the trained feature conversion models as:

Model A: gender conversion. The model has ordinary effect. It can be used to convert 000 types of data into 100 types of data.

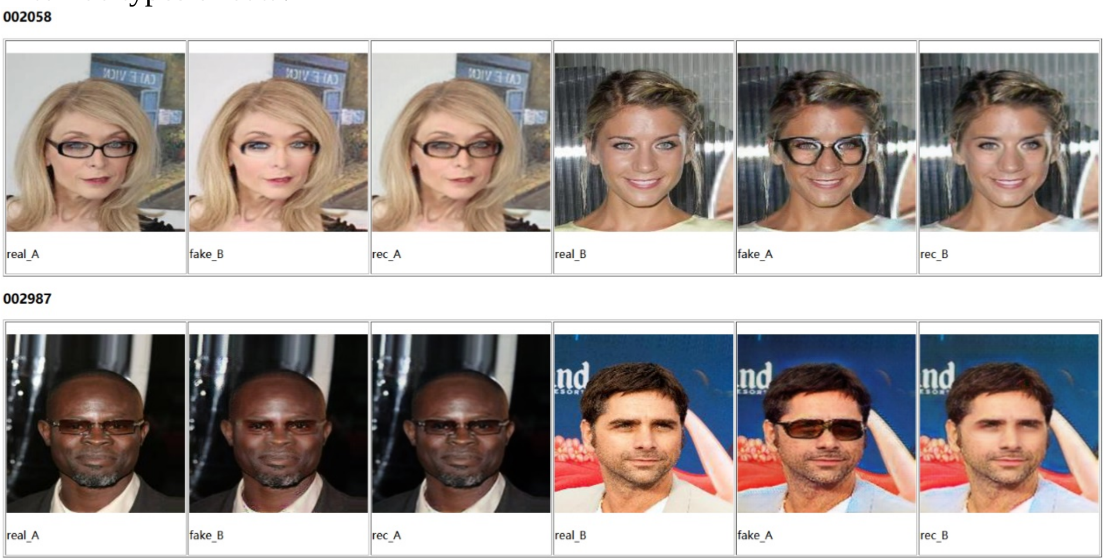

Fig. 1 Partial renderings of the glasses conversion model

Fig. 2 Partial renderings of the color conversion mode

Model B: glasses feature conversion. The effect of this model is that it is better to convert from a picture without glasses to a feature with glasses. The conversion effect of removing the glasses is relatively ordinary. It can be used for mutual conversion of 101 and 111 types of data.

Model C: hair color conversion. This model is doing very well.

4.2 Experimental Group Design.

We filter our raw dataset from CelebA according to the characterization. We then divide the raw data set into training set A and training set B and verification set according to a 1:1:1 allocation. Make sure the training set and validation set are not duplicated. As shown in Table 1.

Now we have two smaller training sets, trainA trainB and a validation set Val. Then we use the feature transformation model obtained by cyclegan training to expand our training set. The expansion process is:

000 and 001 converts 402 sheets to each other using the model C (so this is converted using a relatively good model).

Table. 1 Experimental Data

RAW DATA label (male:1 glasses:1 blackhair:1)								
Picture category	000	001	010	011	100	101	110	111
Quantity	1200	1200	1200	470	1200	1200	1200	1200
TrainA								
Picture category	000	001	010	011	100	101	110	111
Quantity	402	402	402	157	402	402	402	402
TrainB								
Picture category	000	001	010	011	100	101	110	111
Quantity	402	402	402	157	402	402	402	402
Val								
Picture category	000	001	010	011	100	101	110	111
Quantity	402	402	402	157	402	402	402	402
	Val011: Rare data set				**Val000: Regular data set**			
Quantity	155				396			

010 and 110 convert 402 sheets to each other using the model A.

101 and 111 use the model B to convert 402 sheets to each other to 804 sheets.

100 is converted from 101 using the model C (select a better converter)

After the expansion, we get the new training sets as shown in Table 2.

In addition to the val validation set, we add the validation set val011 and val000 to output the experimental results separately, and observe the improvement of the classification accuracy of a certain class.

Therefore, we have a total of five training groups as controls, namely: trainA, trainAA, trainAB, trainA+cycA+rm315, trainA+cycA+rm804, with output of three verification results. They are the classification accuracy rate for the validation set val and the two separate classes 011 and 000.

4.3 Experimental Result.

The result of the verification sets is as shown in Table 3. The training process can be seen in Fig 3.

The training data added by group 2 relative to group 1 is only the same duplicate data. Compared with the additional real data added by group 3, the change of accuracy rate is within a normal fluctuation range. We believe that it does not have a substantial breakthrough in the progress of the classifier.

Comparing Group 4 and Group 5, the change of best_total accuracy rate is also within 0.6%. We believe that the classifier does not obtain additional feature recognition from the generated data.

The additional features brought about by the real data of Group 3 significantly improve the accuracy of the classifier by more than 2%.

Table. 2 New Training Sets

TrainA+cycA+rm315 (additional 011 data is converted from 010 using the model C)								
Picture category	000	001	010	011	100	101	110	111
Quantity	804	804	804	315	804	804	804	804
TrainA+cycA+rm804 (rm804 means that 011 class is complemented using the gan generation method, and the three models are used to evenly convert from other data sets.)								
Picture category	000	001	010	011	100	101	110	111
Quantity	804	804	804	804	804	804	804	804
TrainAB (This data set is a combination of the trainA training set and the trainB training set, and therefore is real data and best training set.)								
Picture category	000	001	010	011	100	101	110	111
Quantity	804	804	804	315	804	804	804	804
TrainAA (This training set is only to copy the trainA training set (each sample is repeated) as a control group that controls the quantity variable.)								
Picture category	000	001	010	011	100	101	110	111
Quantity	804	804	804	315	804	804	804	804

Group 4 is added with an additional 000 class data and others relative to Group 1. From the foregoing, the increase of 000 data is converted from the better-performing C-conversion model (the amount of data has doubled), and its classification effect has never shown an advantage to group 1 (77.27%) in this category. We can see that the data directly increased by gan does not work.

Compared with group 4, group 5 supplements the smaller number of 011 types of data to the same number of other classes through the conversion model, which is 804 sheets. The original training set 011 type data is only 157, which is not distinguished by the classifier. It can be understood. It is still not distinguished by the classifier, it can be seen that the increased 011 data has no effect.

Table. 3 Experimental Result

Group Number	Training set	Best_total accuracy (%)	011 accuracy (%)	000 accuracy (%)
1	TrainA	79.74	0	77.27
2	TrainAA	79.91	0	81.82
3	TrainAB	82.54	0	83.33
4	TrainA+cycA+rm315	79.40	0	69.44
5	TrainA+cycA+rm804	80.08	0	75.76

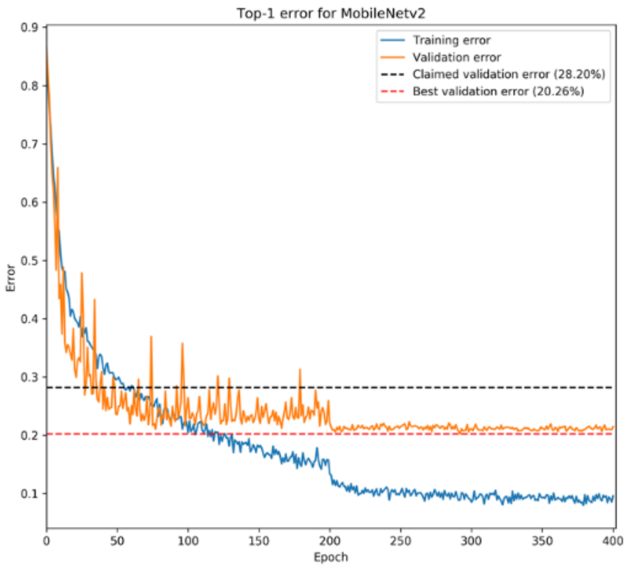

Fig. 3 The top error of TrainA training set

5. Discussion and Conclusion

The basis for selecting these three features in the experiment. Hair color change is the easiest thing to do with a style migration network because it doesn't involve deformation. Glasses have some difficulty because they involve local deformation. Gender transformation involves the transformation of the overall style. They represent three types

The experiment did not set a comparison of classification effects for individual features. The style migration effect of cyclegan for different features is very different. Even if cyclegan's data for a particular style of migration can achieve good results, but it is not universal, then finding this particular feature is also inefficient.

Overall, based on the current experimental results, the cyclegan model does not seem to achieve good results when the generated data is directly used for retraining without manual intervention. Of course, this experiment is limited by the selection feature and dataset size. The conclusion of this experiment also has its limitations.

Views on gan model for data generation retraining in unsupervised scenarios. The gan model itself can increase the abundance or density of the data set, but it does not increase the breadth of the data set. Abundance can make the training model more stable, and the breadth can improve the adaptability of

The model. In short, the data generated by gan can improve the utilization of existing data, but from the perspective of information theory, it will not produce more effective information, the most important one, does not improve the universality of the model.

From another point of view, for the defect dataset, the trained gan model itself has its drawbacks. To get a better gan model, a more complete dataset is needed. If the dataset is complete, there is no need to use gan for expansion. That is contradictory.

Thirdly, from the genetic point of view, increasing the universality of the model is achieved by adding noise and data filtering, but the discriminator itself is based on real data, it is impossible to generate additional judgment criteria (because we give it the “truth”), even if it is generated in its discriminating environment. It will be corrected in the "real" direction. That is, the possibility of evolution occurring in an independent environment will only be adapted to its independent environment (given the actual data set). To achieve universal evolution, it is necessary to introduce external changes (ie additional information). That is why we call it statistical intelligence.

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