Comparison study to augment dataset using ConditionalGAN and InfoGAN

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Abstract

Supervised Learning is expensive as a classifier always needs labeled data. In domains where datasets are small, methods like scaling, shifting and rotating of images have been used to augment the dataset to learn meaningful features. Later with semi-supervised learning, unlabeled datasets have been leveraged to augment the dataset improving the accuracy of the classifier. In this study, we will use multiple deep generative models to compare the classifier's performance using a novel dataset augmentation algorithm by conducting experiments on various datasets.

1 Introduction

Since the inception of Generative adverserial networks (1), it has been used in various domains to generate realistic images. In last couple of years, several variations of GANs have been published which improved the quality of generated images than the original vanilla GAN. Two of such variations are ConditionalGAN (2) and InfoGAN (3). In this work, we will use these two variations to augment the dataset and then, compare the accuracy of the classifier.

2 Model Structure

2.1 Conditional GAN

In a standard GAN, there is no way to control the types of images that are generated other than trying to figure out the complex relationship between the latent space input to the generator and the generated images. In ConditionalGAN, we pass on the label to the generator which generates the images conditioned on the label.

2.2 InfoGAN

In the ConditionalGAN, a noise vector and the given class are given as input to the generator. In contrast to the ConditionalGAN, InfoGAN does not require to be provided with another additional class information externally, it will require an additional algorithm (Information maximization) to capture the class label from the noise vector itself. In InfoGAN, the output of the generator will be feed to the discriminator for classifying real and fake samples and also to another neural network which will be able to construct the class from the generated image from generator using Information Maximization.

2.3 Classifier

The classifier, we will use, will be follow a standard Lenet5 (4) architecture where we will have a bunch of convolution, max-pool and fully connected layers to classify the given images.

3 Dataset

- MNIST
- CIFAR10

4 Experiments

1. First divide the dataset with 80-20% train-test split.
2. Train the classifier and test with the test set to record the classifier accuracy.
3. Train the ConditionalGAN and InfoGAN with the train set and store the generated image.
4. Augment the train set with the generated image.
5. Train the classifier with the augmented train set.
6. Test the classifier with test set and compare the accuracy of the classifier with the earlier one.
7. Repeat the process for with 60, 40, 20 % train set and compare the accuracies of the classifier.

5 Responsibilities

Both the team member will contribute equally to the project and report. Kalpak will be responsible for writing data preprocessing, classifier model design, training, reporting the accuracies and plotting pipelines while Shantanu will mostly be responsible with GAN design and training.

6 Frameworks and tools

- Python
- Pytorch
- Scikit-learn
- Matplotlib

7 Tentative schedule

Week	Tentative milestones
1	Data preprocessing pipelines
2	Design and train the classifier with all the train set
3-4	Design and train CondtionalGAN with all the various train set
5-6	Design and train InfoGAN with all the various train set
7	Test the classifier with generated image from GAN, plot the accuracies, prepare the report

References

[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in neural information processing systems*, pp. 2672–2680, 2014.

[2] M. Mirza and S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, 2014.

[3] X. Chen, Y. Duan, R. Houthooft, J. Schulman, I. Sutskever, and P. Abbeel, "Infogan: Interpretable representation learning by information maximizing generative adversarial nets," in *Advances in neural information processing systems*, pp. 2172–2180, 2016.

[4] Y. LeCun *et al.*, "Lenet-5, convolutional neural networks," *URL: http://yann. lecun. com/exdb/lenet*, vol. 20, no. 5, p. 14, 2015.