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A survey on Image Data Augmentation for Deep Learning

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Abstract

Deep convolutional neural networks have performed remarkably well on many Computer Vision tasks. However, these networks are heavily reliant on big data to avoid overfitting. Overfitting refers to the phenomenon when a network learns a function with very high variance such as to perfectly model the training data. Unfortunately, many application domains do not have access to big data, such as medical image analysis. This survey focuses on Data Augmentation, a data-space solution to the problem of limited data. Data Augmentation encompasses a suite of techniques that enhance the size and quality of training datasets such that better Deep Learning models can be built using them. The image augmentation algorithms discussed in this survey include geometric transformations, color space augmentations, kernel filters, mixing images, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning. The application of augmentation methods based on GANs are heavily covered in this survey. In addition to augmentation techniques, this paper will briefly discuss other characteristics of Data Augmentation such as test-time augmentation, resolution impact, final dataset size, and curriculum learning. This survey will present existing methods for Data Augmentation, promising developments, and meta-level decisions for implementing Data Augmentation. Readers will understand how Data Augmentation can improve the performance of their models and expand limited datasets to take advantage of the capabilities of big data.

Keywords: Data Augmentation, Big data, Image data, Deep Learning, GANs

Introduction

Deep Learning models have made incredible progress in discriminative tasks. This has been fueled by the advancement of deep network architectures, powerful computation, and access to big data. Deep neural networks have been successfully applied to Computer Vision tasks such as image classification, object detection, and image segmentation thanks to the development of convolutional neural networks (CNNs). These neural networks utilize parameterized, sparsely connected kernels which preserve the spatial characteristics of images. Convolutional layers sequentially downsample the spatial resolution of images while expanding the depth of their feature maps. This series of convolutional transformations can create much lower-dimensional and more useful representations of images than what could possibly be hand-crafted. The success of CNNs has spiked interest and optimism in applying Deep Learning to Computer Vision tasks.

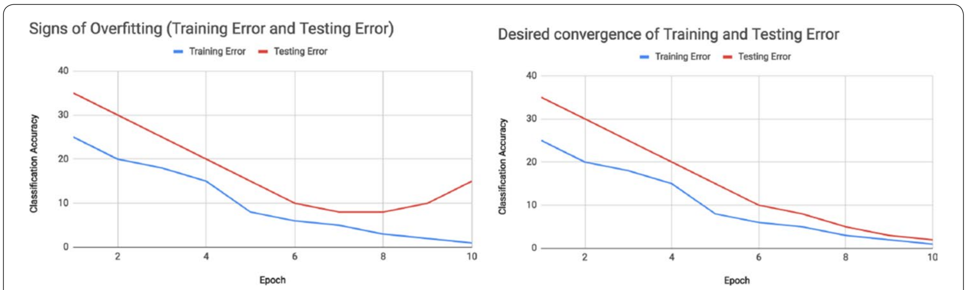

Fig. 1 The plot on the left shows an inflection point where the validation error starts to increase as the training rate continues to decrease. The increased training has caused the model to overfit to the training data and perform poorly on the testing set relative to the training set. In contrast, the plot on the right shows a model with the desired relationship between training and testing error

There are many branches of study that hope to improve current benchmarks by applying deep convolutional networks to Computer Vision tasks. Improving the generalization ability of these models is one of the most difficult challenges. Generalizability refers to the performance difference of a model when evaluated on previously seen data (training data) versus data it has never seen before (testing data). Models with poor generalizability have overfitted the training data. One way to discover overfitting is to plot the training and validation accuracy at each epoch during training. The graph below depicts what overfitting might look like when visualizing these accuracies over training epochs (Fig. 1).

To build useful Deep Learning models, the validation error must continue to decrease with the training error. Data Augmentation is a very powerful method of achieving this. The augmented data will represent a more comprehensive set of possible data points, thus minimizing the distance between the training and validation set, as well as any future testing sets.

Data Augmentation, the focus of this survey, is not the only technique that has been developed to reduce overfitting. The following few paragraphs will introduce other solutions available to avoid overfitting in Deep Learning models. This listing is intended to give readers a broader understanding of the context of Data Augmentation.

Many other strategies for increasing generalization performance focus on the model's architecture itself. This has led to a sequence of progressively more complex architectures from AlexNet [1] to VGG-16 [2], ResNet [3], Inception-V3 [4], and DenseNet [5]. Functional solutions such as dropout regularization, batch normalization, transfer learning, and pretraining have been developed to try to extend Deep Learning for application on smaller datasets. A brief description of these overfitting solutions is provided below. A complete survey of regularization methods in Deep Learning has been compiled by Kukacka et al. [6]. Knowledge of these overfitting solutions will inform readers about other existing tools, thus framing the high-level context of Data Augmentation and Deep Learning.

- Dropout [7] is a regularization technique that zeros out the activation values of randomly chosen neurons during training. This constraint forces the network to learn more robust features rather than relying on the predictive capability of a small subset of neurons in the network. Tompson et al. [8] extended this idea to convolutional