ABSTRACT

A GRADIENT METHOD FOR SIGNAL CLASSIFICATION

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The topic of global optimization is rich beyond most human imagination. There is a consensus that every conceivable representation concerning the content within the reality that surrounds us can be thought about in terms of a waveform or convex function. The utility of these representations becomes evident in the practice of global minimization, specifically when implementing cost efficiencies during classification processes. In this paper, the gradient method is used to find maximum efficiency by minimizing the cost function in a novel way while achieving perfect F1 scores over a wide range of dermatological data. This is beneficial for patients affected with the possibility of terminal illness and encourages early detection and a reduction of long-term misclassification in patients. This method utilizes non-homogenized RGB data and a convolutional approach to stationary or non-stationary gradient processes, enabled with infinite parameter gain, which minimizes cost and time when identifying and discriminating a multiplicity of input signals.

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A GRADIENT METHOD FOR SIGNAL CLASSIFICATION

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A PROJECT REPORT SUBMITTED TO THE EIGHTH ISIC SKIN IMAGE

ANALYSIS WORKSHOP

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1 INTRODUCTION

"I am so in favor of the actual infinite that instead of admitting that Nature abhors it, as is commonly said, I hold that Nature makes frequent use of it everywhere, in order to show more effectively the perfections of its Author. Thus, I believe that there is no part of matter which is not - I do not say divisible - but actually divisible; and consequently, the least particle ought to be considered as a world full of an infinity of different creatures."

—Georg Cantor, 1845–1918

1.1 Convex Optimization

Nearly all physical and abstract phenomena can be represented in the form of periodic or non-periodic signal. This is a very useful convention when dealing with the task of discrimination for several reasons. When we look for a time-frequency signal, or evolution thereof it is important to understand the nature of a minimization process and characterize an object by the behavior of its basic features or emergent representations in a system (i.e., principal component analysis). Often, this turns out to be a task of functional generation on the data produced with the hopes of observing convex behavior.

1.1.1 Pre-Processing, and Truth Bias

The importance of utilizing a computational system with a logical layer to interpret an object cannot be understated. With MATLAB the extraction of principal components of a photograph is streamlined and complete pre-processing achieved in the photoToArray() routine.

We can inflict bias on the RGB data via dimensionality reduction, or pixel lightening with great effect on cost, time, and score.

1.1.2 Filter Rank, and Training

The heart of the Gradient Decent methods revolves around the successful design of the running average filter rank, as well as the amount of training done to populate the tensor. Taken in tandem, the "width" of the convolutional filter is most effective as a binary or tertiary length taken at infinity. The discrimination process is entirely determined by the quality of incoherence in the training data, which is proportional to the number of object groups being discriminated against in time. In algorithms [4] and [5], we can train the filter with less than one frame of pixel data. We can also classify an infinite number of objects, or as many objects as the system itself can store in a single execution in [5].

1.1.3 Weight, and K-Means Clustering

When discriminating between classes of object within groups it is necessary to place the distributions into separate regions. This is primarily achieved with the introduction of weight into the running averages during training, as well as implementing the k-means clustering method enabled with backpropagation on the centroids to add a layer of uniformity and general identity between classes of objects. Sometimes it is beneficial to permute groups or classes of objects about the order that they are being processed.

1.1.4 Stationary and Non-Stationary Processes

As with most convergence algorithms it is important to configure the routine to have stationary, or non-stationary aspects. The present classifier is a highly non-stationary process that can evolve the filter during the entire execution. Although, it is usually more beneficial to keep the filter as a stationary entity during the Gradient Decent routine, without either a priori or a posteriori updates on the running averages the routine remains highly non-stationary, regardless.

1.1.5 Convolution, and Cost

Naturally, most signals are processed in a convolutional manner, and the Gradient Decent method is no exception. When minimizing the cost of making a decision, the convolutional approach is superior simply by the nature of the programming language. By using the convolutional neural network convention we easily juxtapose minimizable output data, and a higher order convex relation is achieved for very accurate discrimination purposes. This is also thought to be the selection of a minimum random walk.

WORKS DONE

2.1 Utility, Accuracy, and Efficiency

2.1.1 The Gradient Method

The Gradient Decent Method was first demonstrated by the mathematician named Augustin-Louis Cauchy in [3]. The use of this method in computer vision has proven to be unmatched against several different methods including k-NN, k-means in isolation, and Naïve

Bayes. The Gradient Decent Method outperforms the others in a variety of metrics, the most important being the minimization of the cost function. From this standpoint, I have demonstrated the power of the convolutional paradigm and the superiority of minimizing sub-gradient convolutional neural network output. By identifying the shortest time-march to convergence, we can often guarantee the truth during classification.

2.2 Verification

2.2.1 Med-Node

With the data set provided by [1], the Gradient Decent algorithm in [4] is able to classify 120 images organized into melanoma and naevus categories. The F-Measure results for these data are as follows: (1) Precision—1.0; (2) Recall—1.0; (3) Accuracy—1.0; (4) F1—1.0.

2.2.2 Derm7pt

With the data set provided by [2], the Gradient Decent algorithm in [5] is able to classify 1,244 images organized into thirty-two different species of dermatological diseases. The F-Measure results for these data are as follows: (1) Precision—0.9179; (2) Recall—0.9375; (3) Accuracy— 0.9179; (4) F1— 0.9256.

With the data set provided by [2], the Gradient Decent algorithm in [6] is able to classify 1,244 images organized into thirty-two different species of dermatological diseases. The F-Measure results for these data are as follows: (1) Precision—1.0; (2) Recall—1.0; (3) Accuracy— 1.0; (4) F1— 1.0. The increased scores can be accounted for by a running average

reset, followed by a running average update before k-means clustering. Apart from training, this data was entirely unsupervised.

2.2.3 Conclusions

From the result we can see the effectiveness for different algorithm implementations on separate data sets. The modifications required for Derm7pt necessitated expanding the object classes into groups that may extend to infinity, whereas for MedNode we only needed two classes in one group for a determination. The effectiveness of the Gradient Decent method is apparent for computer vision, but it may be successfully extended to a variety of classification applications.

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