A Benchmark on Deep-Learning Convolutional Neural Network for the Representation of Natural Scenes with Large Seasonal Variations

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Abstract

This document demonstrates the format requirements for papers submitted to the British Machine Vision Conference. The format is designed for easy on-screen reading, and to print well at one or two pages per sheet. Additional features include: pop-up annotations for citations [? ?]; a margin ruler for reviewing; and a greatly simplified way of entering multiple authors and institutions.

All authors are encouraged to read this document, even if you have written many papers before. As well as a description of the format, the document contains many instructions relating to formatting problems and errors that are common even in the work of authors who *have* written many papers before.

1 Introduction

Check `bmvc_guidelines.pdf` for the original text.

2 Related Works

- Deep nets for plant recognition [5],

- Deep nets for place recognition [7],

- Change detection across seasons, [3], not based on deep nets

- the framework of cedric and shane for the lake dataset and image alignements : "Survey Registration For Long-Term Natural Environment Monitoring"

- Oxford article on regression, [4]

- AlexNet paper with great details on parameter choice, [2]

- OxfordNet, [6]

- Average faces over American Yearbooks, [1]

3   Methodology

3.1   Classification

Labels chosen to divide the dataset in 1-meter intervals around the lake, along with heading separated in 10 degrees increments. Goal : obtain classes of images representing the same area with the same angle, to facilitate classification.

At training : class selection and reindexing. All classes must have at least 50% of the highest class image count. This way, all classes are represented enough times for the network to learn their features. This represents around 1k images per class, for around 300 classes.

Fine tuning was made on number of images (more is better), size of minibatches (more is faster, less is more precise) and learning rate (decrease more times, but less each time). Other parameters remained as is.

The aim was not necessarily to obtain a great classification, but to create good features for each class, independently of seasonal changes. We want good convolutional layers.

Implementation made on Caffe, which is a good framework for classification tasks. No changes on the network structure, but trained from scratch. Unlike regression, Caffe was adapted to the task.

3.2   Regression

Labels: - We need the label to include the information on the position and angle of the view - 4 dimensions labels (coordinates of the robot + coordinates of the point we are looking at on the shore) - Normalization issues: The solution was to recenter and rescale the labels in [0,1]. - Datasets creations: Same as for the classification we built our datasets with images from the most highly represented classes. By taking a given number of images from each highly represented class we make sure that no class is overly represented so that we do not induce bias.

Loss: - Euclidean loss, made possible because our labels were homogeneous

Network structure: - CaffeNet (a replication of the model described in the AlexNet publication) that performs well for classification tasks (on the ImageNet dataset). - Accuracy layer is irrelevant on a regression problem so we removed it (the loss is our accuracy indicator) - We changed the loss layer to the euclidean loss layer

Implementation: - Framework Caffe: easy to use for the usual cases, python wrapper - Not directly adapted for our problem: float labels, multilabel regression - Can work with some tricks - We would not recommend Caffe for similar problems

4 Dataset and Experimental Setup

Dataset: - Environmental images from 2013 to 2015 - Seasonal changes - Lighting changes - Video frames from camera XXXXX

Classification:

Regression: - Gaussian initialization of weights had to be tuned so that the convolution layers pass information to the fully connected layers (variances and biases) - Learning rate adaptation depending of the nature of the layer (fc or conv). - Weight decay - Tests after loading the weights from the classification - Influence of the dropout layer

5 Results

5.1 Classification

5.2 Regression

6 Conclusions

References

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