Object tracking with deep neural networks

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ABSTRACT OF THE
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Abbreviations

CNN Convolutional Neural Network

DNN Deep Neural Network

MLP MultiLayer Perceptron

NN Neural Network

ReLU Rectified Linear Unit

1 Introduction

Object tracking is a large and actively researched sub-area of computer vision. The main task for a tracker is to find and follow the desired subject in a sequence of images. Object tracking is closely related to other image analysis tasks so the implementations also share elements.

The field of image classification took a leap forward in 2012, when Krizhevsky et. al. presented record performance in the ImageNet-classification challenge using a convolutional network. Previous work had dismissed the network type as unfit for the task. [1] Since then, research has shifted to using convolutional networks as they have several clear advantages over other network types when used on picture analysis.

Comment by author: go into benefits and/or give a source for the claim

With the adoption of convolutional networks, much of the research revolves around deep neural networks. They consist of visible input and output layers with several so-called hidden layers in between them. The training of deep neural networks requires a large amount of training data and their development has been made easier by an increase in the size of applicape datasets.

This thesis will present the architectures and principles currently used in deep neural networks tailored to object tracking tasks. The practices behind training and evaluating such networks are also introduced.

2 Deep Learning

This chapter introduces the basic concepts and is based on the book Deep Learning by Goodfellow et. al. [2]

2.1 Deep neural networks

A Deep Neural Network (DNN) is commonly defined as a Neural Network (NN), that has a **visible** input and output layer with several **hidden layers** between them. The distinction between visible and hidden layers is important because training of the network only evaluates the output layer's performance. During training, a **learning algorithm** optimizes the individual hidden layers to best approximate the desired output of the whole network.

The input layer takes in the data to be processed, which typically means a vector of color values in the case of object tracking. These are then processed by the hidden layers and finally the output layer produces the target's position in the frame. These models usually come in the form of a **feedforward neural network** or **MultiLayer Perceptron (MLP)**. The name comes from the fact that information flows from the input through computations to the output with no **feedback** connections.

In NNs, each layer consist of several **units** with a weight and activation function. A bias-term can also be defined for each unit. The weights of a layer are commonly represented by a matrix by which the input-vector is multiplied. Units in a layer also have a common activation function. A unit's activation function is fed by the sum of its weighted inputs in addition to the possible bias, and the result is output to the next layer alongside the layers other units' outputs. A commonly used unit type is the **Rectified Linear Unit (ReLU)**, which is defined by the activation function $g(z) = \max\{0, z\}$. It provides a nonlinear transformation while being comparable to linear models in terms of generalizing well and being easy to optimize.

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Before training, the weights of a MLP are initialized to small random values and biases to zero or small positive values. Then an algorithm called **stochastic gradient descent** is commonly applied alongside a training dataset. The basic procedure is to calculate the error of the netwok's output values compared to the desired ones using a **loss function**. The function's gradient can then be calculated for example by **back-porpagation**, which feeds the errors back through the network to assign a contribution value to each unit. These values are then used to calculate the gradient of the loss function relative to the weights. Each weight is adjusted slightly to the opposite sign to minimize the loss function.

2.2 Convolutional networks

A Convolutional Neural Network (CNN) is simply a NN that uses convolution instead of general matrix multiplication in at least one of its layers. The main benefits of convolution in NNs are that it's dramatically more efficient in terms of memory requirements, it reduces the amount of computation needed and it makes it possible to work with variable input sizes.

A typical convolutional layer consists of three stages: a convolution stage, detector stage and pooling stage. These can be implemented by individual layers. First, a **kernel** is applied to the input data in positions separated by a stepsize. This means that a linear activation function is fed by the matrix product of the input location and the kernel's weight matrix. In the detector stage, the results are then run through a non-linear activation, for example a ReLU. Finally, a **pooling function** is used to combine the results of multiple nearby outputs as the final output.

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Convolutional layers enable indirect connections to all or most of the input data deeper in the network even when individual layers' connections are very sparse.

3 Object tracking

Object tracking in video sequences has been researched for decades and the approaches have included tracking based on subspaces [3] and different kinds of filtering [4]. Recently, the advancement in NN's capabilities in object classification has resulted in much research on NNs in object tracking tasks. [5]

3.1 Deep neural networks in tracking

Overview of task from DNN-point of view, strengths and weaknesses compared to more traditional solutions.

3.2 Data sets and evaluation

Overview of the data sets used for training and analysis. Methods used for comparing performance.

4 Challenges

Subsections dealing with the present challenges in object tracking and examples for dealing with them.

5 Conclusions

Summarize the current state of object tracking with DNNs with possibly some insight to future developments.

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