Fakultät für Informatik
Lehrstuhl für Bildverarbeitung und Mustererkennung

Image Classification using the deep learning caffe framework

Neeraj Sujan - 03656452

Praktikum *Maschninelles Lernen für Anwendung des Computersehens* SoSe2015

Submission: 08. May 2015

Image Classification using the Caffe framework.

Neeraj Sujan
Fakultät für Informatik
Technische Universität München
Github: https://github.com/nrj127/week2_assignment
Email: n.p.sujan@tum.de

***Abstract*—The report discusses the popular caffe framework to classify images using deep learning algorithms.The training model is based on the popular imagenet example and the data from the ilsvrc 2012 challenge [1]. The images used for classification were provided by the chair of pattern recognition affiliated to the faculty of computer science, TU München.The paper also discusses the popular back propogation algorithm.**

I. Introduction

Neural Networks: Neural Networks or Artificial Neural Networks,as it is popularly known, are a family of machine learning algorithms, that builds upon the popular single layer perceptron, developed by Rosenblatt. Neural Networks works on the principle of multiple hidden layer with input and output neurons. Each hidden layer contains an activation function, such as a sigmoidal function to make the network as efficient as possible. As in other classification algorithms, the goal of the network remains to minimize the error function.

A. *Caffe Framework*

The Caffe framework [3] from UC Berkeley is designed to let researchers and novice learners create and explore convolutional neural networks and other Deep Neural Networks easily. Caffe provides state-of-the art modeling for advancing and deploying deep learning in research and industry with support for a wide variety of architectures and efficint implementations of prediction and learning.The Caffe framework follows a layered and a hierarchial architecture

1) Back Propogation Algorithm: The following four steps describe the Backpropagation algorithm (taken from Bishop's Book)

1. Apply an input vector x_n to the network and forward propagate through the network using

$$a_j = \sum_i w_{ji} z_i \tag{1}$$

$$z_j = h(a_j) \tag{2}$$

to find the activation of all the hidden and output units.
2. Evaluate the δ_k for all the output units using

$$\delta_k = y_k - t_k \tag{3}$$

3. Backpropagate the $\delta^{'} susing$

$$\delta_j = h^{'}(a_j) \sum_k w_{kj} \delta_k \tag{4}$$

to obtain δ_j for each hidden unit in the network.
4. Use the below equation to evaluate the required derivatives

$$\frac{\partial E_n}{\partial w_{ji}} = \delta_j z_i \tag{5}$$

Modification : If the input neuron is modified such that the activation function is not sigmoidal, then the following changes in the back-propagation algorithm will take place.

In equation (2), $z_j = h(a_j) = f(\sum_i w_{ji} z_i + b)$. Equation (4) will change correspondingly to $\delta_j = f^{'}(\sum_i w_{ji} z_i + b) \sum_k w_{kj} \delta_k$

2) Experiment: The figure (Figure 1) shows the 8 images that were to be classified using the ilsvrc2 2012 training model [1]. The experiment involved the following steps

1. Installing the caffe framework and understanding its architecture.
2. Running caffe installation and installing all the necesarry dependencies.
3. Using the BVLC Reference CaffeNet provided [3] as part of the installation for our training model.
4. Writing code to test the prediction, probability and entropy of the given 8 images.
5. Pre-processing the image to a obtain a better performance.

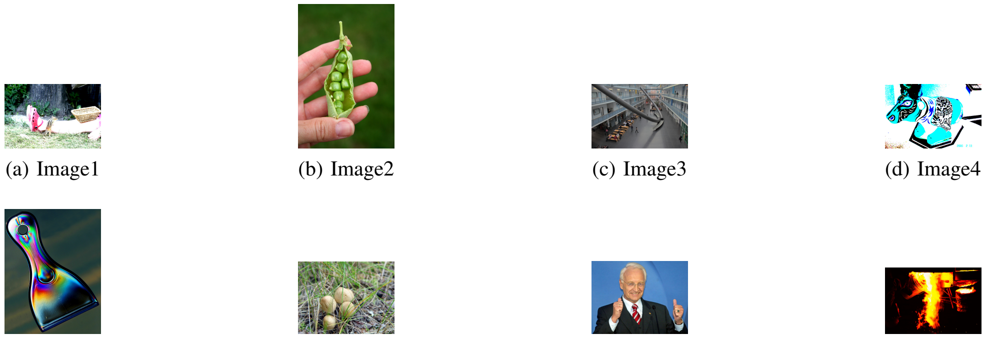
Probability of class [2] : In a multi-output classification problem, the probability if a class plays a very import role. The probability of a class indicates the likelihood of occurrence of a particular class. Given a particular unknown input, the corresponding output vector O, then the estimated probabilty that it belongs to each class is given as follows.

$$P_{cO}(c \mid O) = \frac{p(c \mid O)}{\Sigma_{c'} p(c^l \mid O)}$$

Entropy : Entropy is defined as the measure of impurity. For a binary class, it is represented as follows

$$Entropy = -p(a) * log(p(a)) - p(b) * log(p(b))$$

.



(a) Image1 (b) Image2 (c) Image3 (d) Image4

(e) Image5 (f) Image6 (g) Image7 (h) Image8

Fig. 1. Images provided

TABLE I

TABLE SHOWING LABEL, PROBABILITY AND ENTROPY OF THE CLASS

Image	Class	Probability of the class	Entropy
1	8(hen)	0.155564	4.50067
2	315(mantis,mantid)	0.234804	3.29147
3	421(bannister,banister,balustrade,balusters,handrail)	0.100069	4.36765
4	639(maillot,tank suit)	0.0476254	4.9167
5	673(mouse, computer mouse)	0.259835	3.07259
6	947 (mushroom)	0.376555	1.64067
7	834 (suit, suit of clothes)	0.642554	1.10757
8	980 (volcano)	0.172035	3.90447

B. *Results*

As shown in the above table, the model was able to classify the 6th image correctly as a mushroom, whereas for all other images it gave a very good guess deciphering part of the image. For instance, in image 4, the model was able to predict the suit, whereas in the Alexnet model, the prediction was a tie. The image in example 2 looks like a grasshopper, hence the model predicted it to be a mantis (Gottesanbeterin in German),whereas the image actually is a plant found in tropical countries but due to the colour and shape of the plant, it was predicted to be a mantis. The model also managed to decipher the hand-rail in the 3rd image which was a very complex images with many features like a slide, people, rails etc. The 8th image was a picture of a factory with some kind of heavy machinery, whereas the model predicted it to be a volcanic eruption, due to the fire shown in the image. The model performed sub-optimally for the 1st,4th and the 5th image and it classified them to be a hen, tank suit and a computer mouse respectively.

Cropping: On cropping the image there was a slight improvement in predicting image 1 and image 7. In image one it the network predicted a brambling which is not quite accurate but it was able to capture some interesting properties of the animal, like the shape of the animal which resembles very closely to a brambling. In the 7th image, it gave a more accurate prediction by detecting the type of the tie which was a considerable improvement with the default parameters. In the 4th image, the network predicted a zebra which is quite close is in shape and structure of the given image. For all other images, the performance of the netork degraded, specially in the 6th image, the network was not abel to predict a mushroom, instead it predicted an earth star, which does not resemble the image.

II. CONCLUSION

The model performed quite well for simple images like the mushrrom shown in Image 6, an animal like creature as shown in image 1 and the tie shown in image 7. For all other images, the model was not able to deliver an accurate prediction. As a result the model performed sub-optimally for complex images with many features.

REFERENCES

[1] http://www.image-net.org/challenges/LSVRC/2012/

[2] J. Denker and Yann leCunn, *Transforming Neural-Net Output Levels to Probability Distributions*. AT & T Bell Laboratories, Holmdel,NJ 0773

[3] http://caffe.berkeleyvision.org