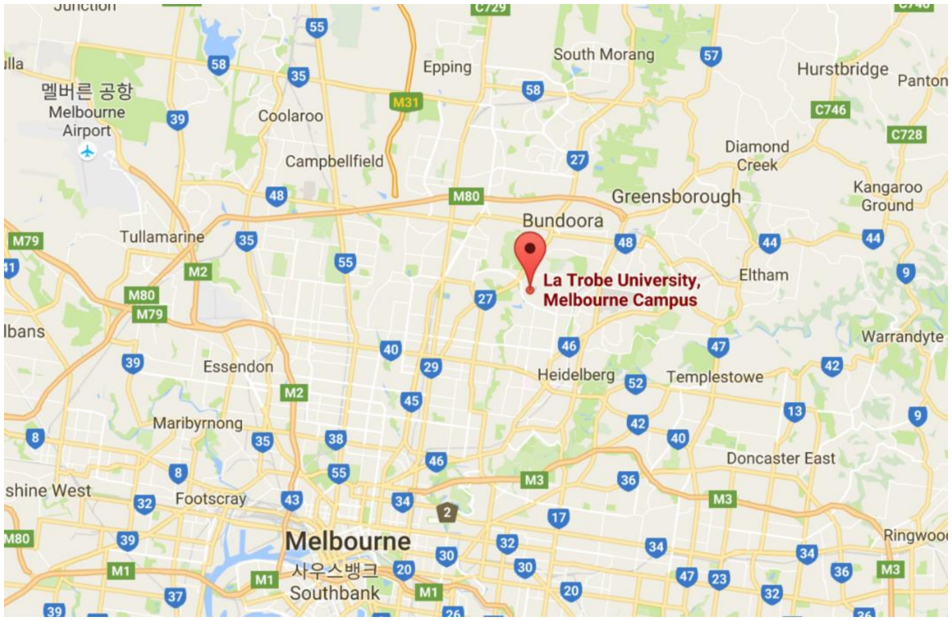
LA TROBE UNIVERSITY

LaTrobe University

주경돈, 김현우, 라형진

CONTENTS



1. Introduction about La Trobe University

2. Deep Learning Project

Introduction about La Trobe University

- **Deep Learning Lab**

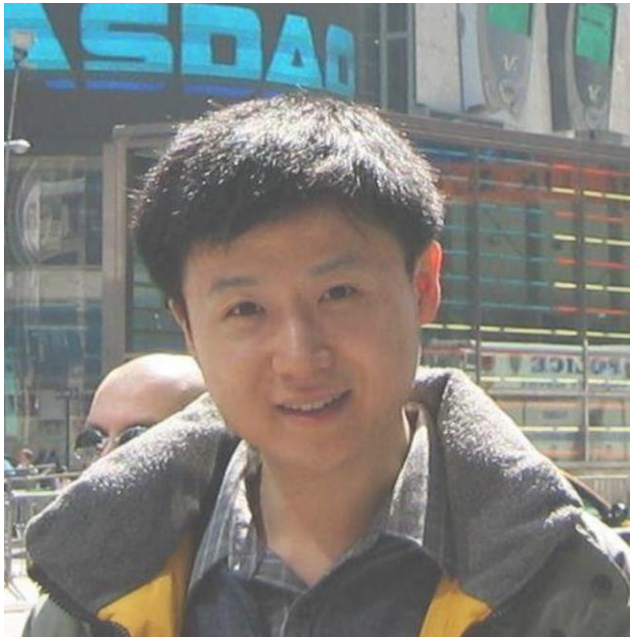
La Trobe University Deep Learning Team focusing on Deep Learning Research by Optimization Parameters and network model

Introduction about La Trobe University

- **Internship under Wenny and Zhen he**

Wenny Rahayu

Head of school,
Engineering &
mathematical sciences



Zhen he

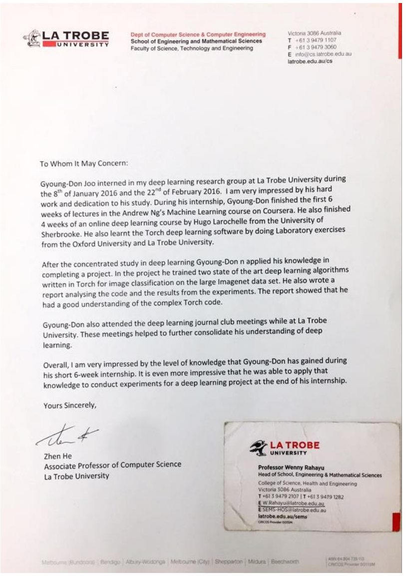
Associate professor

Deep Learning Project

- Project Duration : 2016.01.08~ 2016.02.23

- Project Participants : Prof. Zhen he, Gyoung-Don Joo
  Hyung - Jin Ra, Hyun - woo Kim,

- Project Objective : Test image recognition ratio according to change of optimization parameter and network model



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To Whom It May Concern:

Gyoung-Don Joo interned in my deep learning research group at La Trobe University during the 8th of January 2016 and the 22nd of February 2016. I am very impressed by his hard work and dedication to his study. During his internship, Gyoung-Don finished the first 6 weeks of lectures in the Andrew Ng's Machine Learning course on Coursera. He also finished 4 weeks of an online deep learning course by Hugo Larochelle from the University of Sherbrooke. He also learnt the Torch deep learning software by doing Laboratory exercises from the Oxford University and La Trobe University.

After the concentrated study in deep learning Gyoung-Don n applied his knowledge in completing a project. In the project he trained two state of the art deep learning algorithms written in Torch for image classification on the large Imagenet data set. He also wrote a report analysing the code and the results from the experiments. The report showed that he had a good understanding of the complex Torch code.

Gyoung-Don also attended the deep learning journal club meetings while at La Trobe University. These meetings helped to further consolidate his understanding of deep learning.

Overall, I am very impressed by the level of knowledge that Gyoung-Don has gained during his short 6-week internship. It is even more impressive that he was able to apply that knowledge to conduct experiments for a deep learning project at the end of his internship.

Yours Sincerely,

Zhen He
Associate Professor of Computer Science
La Trobe University

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- Project Process

- Week 1 : Meeting for project introduction with prof. Zhen he. Understand about machine learning and studied about principle of perceptron, cost function, gradient descent.

- Week 2 : Studied Lua (script language), and finished oxford machine learning practical using Torch Library. Understand about feed forward neural network and back propagation based on CNN.

- Week 3 : Finished Labs made by prof. Zhen he and studied about deep learning models.

- Project Process

- Week 4 : Conduct image recognition using models. Analysis performance some models (VGG, Alexnet) by regulating epoch size.

- Week 5 : Suggest new model based on CNN and tested for verification. Test training accuracy by regulating the hyper-parameters like learning rate, Weight decay, momentum.

- Week 6 : Plan to draw up document and program manual about research. wrote Document about new implemented code. compare learning rate between Googlenet and new model.

- **Demonstration**

```lua
local function paramsForEpoch(epoch)
    if opt.LR ~= 0.0 then -- if manually specified
        return { }
    end
    local regimes = {
        -- start, end,    LR,   WD,
        {  1,     18,   1e-2,   5e-4, },
        { 19,     29,   5e-3,   5e-4  },
        { 30,     43,   1e-3,   0 },
        { 44,     52,   5e-4,   0 },
        { 53,    1e8,   1e-4,   0 },
    }

    for _, row in ipairs(regimes) do
        if epoch >= row[1] and epoch <= row[2] then
            return { learningRate=row[3], weightDecay=row[4] }, epoch == row[1]
        end
    end
end
```

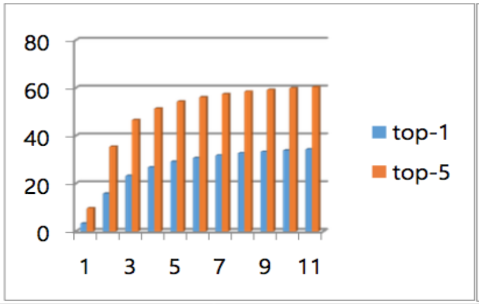
Regulating Hyper-parameter according to Epoch size

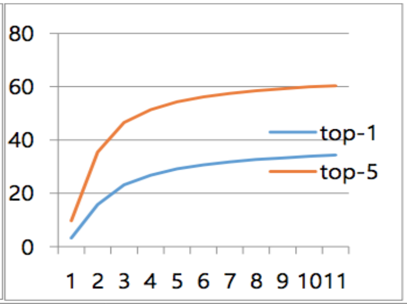
- **Demonstration**

```lua

    local top5 = 0
    do
        local _,prediction_sorted = outputs:float():sort(2, true)
        for i=1,opt.batchSize do
            for j=1, 5 do
                if prediction_sorted[i][j] == labelsCPU[i] then
                    top5_epoch = top5_epoch + 1;
                    top5 = top5+1
                end
            end
        end
        top5 = top5 * 100 / opt.batchSize;
        end
   -- Calculate top-1 error, and print information
   print(('Epoch: [%d][%d/%d]\tTime %.3f Err %.4f Top1-%%: %.2f Top5-%%: %.2f LR %.0e DataLoadingTime %.3f Momentum %.2f WeightDecay : %.0e'):format(
          epoch, batchNumber, opt.epochSize, timer:time().real, err, top1,top5,
          optimState.learningRate, dataLoadingTime, optimState.momentum, optimState.weightDecay))

    dataTimer:reset()
end

```

Modify code for printing top 5 accuracy

- **Demonstration**





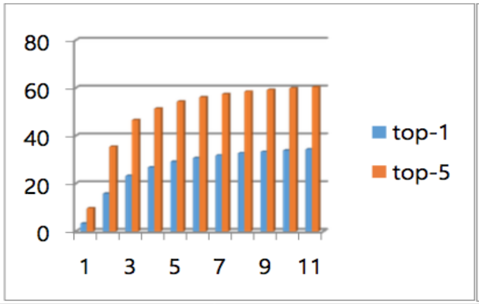
Epoch	Top-1 accuracy	Top-5 accuracy
1	3.24	9.63
2	15.76	35.43
3	23.18	46.58
4	26.8	51.4
5	29.14	54.3
6	30.65	56.14
7	31.72	57.43
8	32.7	58.47
9	33.26	59.25
10	33.86	59.95
11	34.31	60.35

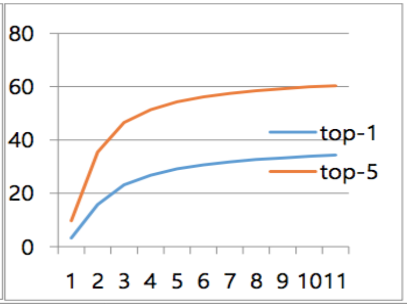
Top1 and Top5 accuracy
(Hyper parameter is fixed by epoch size)

- **Demonstration**

```
local regimes = {
  -- start, end,    LR,   WD,
  {  1,      2,   1e-2,   5e-4, },
  { 3,       4,   5e-3,   5e-4  },
  { 5,       6,   1e-3,   0 },
  { 7,       8,   5e-4,   0 },
  { 9,     1e8,   1e-4,   0 },
}
```

Regulate Hyper parameter according to epoch size





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Top1 and Top5 accuracy according to epoch size

Reading deep learning papers

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

Karen Simonyan[*] & Andrew Zisserman[+]
Visual Geometry Group, Department of Engineering Science, University of Oxford
{karen,az}@robots.ox.ac.uk

ABSTRACT

In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results. We have made our two best-performing ConvNet models publicly available to facilitate further research on the use of deep visual representations in computer vision.

1 INTRODUCTION

Convolutional networks (ConvNets) have recently enjoyed a great success in large-scale image and video recognition (Krizhevsky et al., 2012; Zeiler & Fergus, 2013; Sermanet et al., 2014; Simonyan & Zisserman, 2014) which has become possible due to the large public image repositories, such as ImageNet (Deng et al., 2009), and high-performance computing systems, such as GPUs or large-scale distributed clusters (Dean et al., 2012). In particular, an important role in the advance of deep visual recognition architectures has been played by the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2014), which has served as a testbed for a few generations of large-scale image classification systems, from high-dimensional shallow feature encodings (Perronnin et al., 2010) (the winner of ILSVRC-2011) to deep ConvNets (Krizhevsky et al., 2012) (the winner of ILSVRC-2012).

With ConvNets becoming more of a commodity in the computer vision field, a number of attempts have been made to improve the original architecture of Krizhevsky et al. (2012) in a bid to achieve better accuracy. For instance, the best-performing submissions to the ILSVRC-2013 (Zeiler & Fergus, 2013; Sermanet et al., 2014) utilised smaller receptive window size and smaller stride of the first convolutional layer. Another line of improvements dealt with training and testing the networks densely over the whole image and over multiple scales (Sermanet et al., 2014; Howard, 2014). In this paper, we address another important aspect of ConvNet architecture design – its depth. To this end, we fix other parameters of the architecture, and steadily increase the depth of the network by adding more convolutional layers, which is feasible due to the use of very small (3×3) convolution filters in all layers.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

VGG Netwrok

Reading deep learning papers

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
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Ilya Sutskever
University of Toronto
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Geoffrey E. Hinton
University of Toronto
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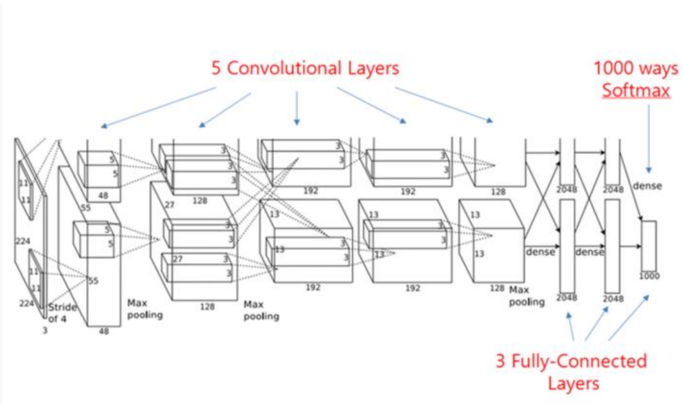
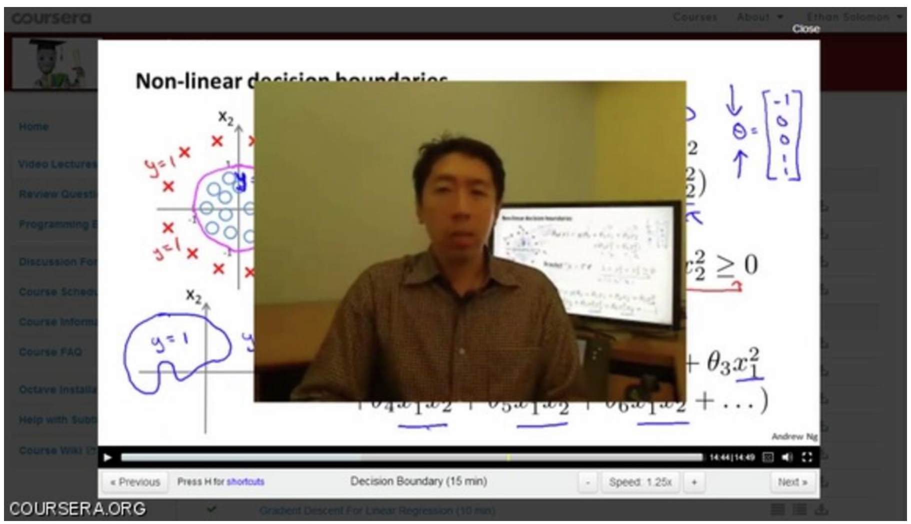
Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

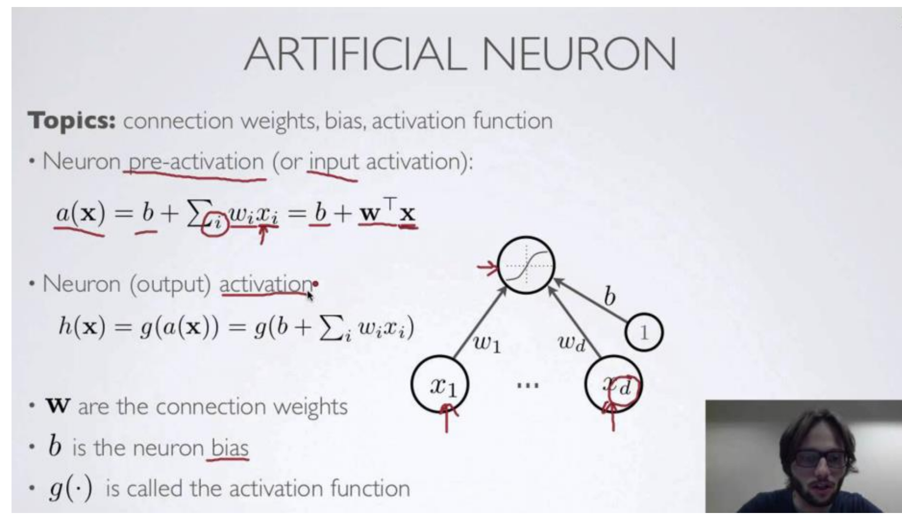


Alexnet

Online course of deep learning

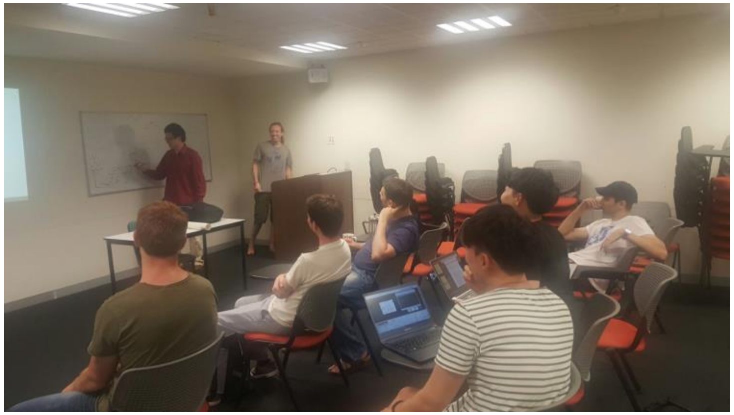


Andrew Ng, Machine learning course
(Cousera) 6 weeks course



Hugo Larochelle, deep learning course
(Sherbrooke) 4 weeks course

Campus life in La trobe



Deep learning journal meeting

In library

Campus life in La trobe

Campus bridge

Going to meeting

Recommendation from professor

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Thank you