

UNIVERSITY OF SCIENCE  
ADVANCED PROGRAM IN COMPUTER SCIENCE

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KHOÁ LUẬN TỐT NGHIỆP**

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Tôi xin chân thành cảm ơn ...

Xin cảm ơn!

Tp. Hồ Chí Minh, ngày ... tháng ... năm

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Sinh viên thực hiện

Thai Thien      Van Duy Vinh

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# ABSTRACT

Tóm tắt khóa luận: trình bày tóm tắt vấn đề nghiên cứu, các hướng tiếp cận, cách giải quyết vấn đề và một số kết quả đạt được. Bản tóm tắt dài từ 1 đến 2 trang.

# Chapter 1

## Introduction



# Chapter 2

## Technical Issues

### 2.1 Framework

#### 2.1.1 Torch

Torch <sup>1</sup> is Lua scientific computing framework. Torch support high performing matrix calculation via multi-dimensional array call Tensor. Torch are built with C/C++, CUDA backend. Torch author choose Lua because Lua works well with C/C++ [1]. Thus, Torch is high performing and support GPU. Torch have neural network package (nn) package. Computation graph must be define before forward pass. A simple, single linear layer network can be easily defined with few line of code (see listing 2.1).

```
1 — simple y = Ax + b linear layer
2 l = nn.Linear(2,3)
3 — forward pass
4 x = torch.Tensor(2)
5 y = l:forward(x) — vector dimension of 3
```

Listing 2.1: Simple linear layer in Torch

However, when a model need multiple module, such as multilayer perceptron (MLP), these module must be put into container. Figure A.1 illustrates on function of each nn container . In order to construct two-layer perception (eq 2.1), linear, tanh and softmax module must be packed into sequential module (see listing 2.2).

$$\begin{aligned}h &= \tanh(W_1 * x + b_1) \\ y &= \text{softmax}(W_2 * h + b_2)\end{aligned}\tag{2.1}$$

---

<sup>1</sup><http://torch.ch/>

```

1 model = nn.Sequential()
2 model.add(nn.Linear(2,3))
3 model.add(nn.Tanh())
4 model.add(nn.Linear(3,5))
5 model.add(nn.SoftMax())
6 — forward
7 x = torch.Tensor(2)
8 y = model.forward(x)

```

Listing 2.2: MLP in Torch

Torch provide nnglue package support build more complicate model. For example, define MLP in (eq 2.1) use nnglue (see listing 2.3)

```

1 model = nn.Sequential()
2 model.add(nn.Linear(2,3))
3 model.add(nn.Tanh())
4 model.add(nn.Linear(3,5))
5 model.add(nn.SoftMax())
6 — forward
7 x = torch.Tensor(2)
8 y = model.forward(x)

```

Listing 2.3: MLP using nnglue

Sample code on training a model, see Appendix A.1

## 2.1.2 Theano

Theano<sup>2</sup> is a deep learning library on Python. Its basic function is similar to Torch: matrix calculation, support GPU. Theano is define-and-run schema, which a computer graph must be built before it is executed.

```

1 x = T.dmatrix('x')
2 y = T.dmatrix('y')
3 z = x + y
4 f = function([x, y], z)
5 f([[1, 1], [2, 2]], [[3, 3], [4, 4]])
6 # result [[4, 4], [6, 6]]

```

Listing 2.4: Define function in Theano

---

<sup>2</sup><http://deeplearning.net/software/theano/>

Comparing to Torch7, Theano are slower on most benchmark [1]. Theano does not provide nice template like linear layer. Thus, model must be defined from equation. It give researcher more control over mathematics aspect but cause more trouble for beginner. A sample code for MLP A.2. One more problem is that the 'define-and-run' scheme does not suitable for recursive neural network due to recompile the computation graph each training sample take time.

### 2.1.3 Pytorch

PyTorch uses same backend as Torch. However, PyTorch specially designed for Python. Pytorch have pre-define module (Linear layer, Convolution layer) like Torch. However, Pytorch does not require to pack model into container. In Pytorch a network are defined in forward-pass thanks to Dynamic Neural Networks feature. Therefore, user can use Python control flow to define a network. For example, one can use for loop to run recurrent neural network (see listing 2.5) .The features allows us to implement Recursive Neural Network for NLP, which the network change for every sample, much more easier.

```
1 import torch
2 import torch.nn as nn
3 rnn = nn.RNNCell(10, 20)
4 seq_len = 10
5 input_dim = 100
6 hidden_dim = 150
7 input = Variable(torch.randn(seq_len, 1, input_dim))
8 hx = Variable(torch.zeros(1, hidden_dim))
9 output = []
10 for i in range(6):
11     hx = rnn(input[i], hx)
12     output.append(hx)
```

Listing 2.5: RNN

We also implement treelstm from original Torch7 <sup>3</sup> sentiment classification task in PyTorch and publish on Github <sup>4</sup>.

We choose PyTorch because:

---

<sup>3</sup><https://github.com/stanfordnlp/treelstm>

<sup>4</sup><https://github.com/ttpro1995/TreeLSTMSentiment>

- Dynamic Neural Networks feature works well on data sequence with different length
- Intuitive framework
- Easy to install and run on CUDA

# Chapter 3

## Experiment

### 3.1 Dataset

#### 3.1.1 Stanford Sentiment Treebank

In this thesis, we use Stanford Sentiment Treebank (SST) dataset [2]. Stanford Sentiment Treebank contains 11,855 sentences. Each data sentence consist of fined-grain sentiment labeled phrases in constituency parse tree structure (see **Figure 3.1**). There are total 215,154 phrases in whole dataset. The dataset was splitted into train/dev/test contain 8544/1101/2210 sentences each for training and evaluation models. After remove neutral sentiment sentences, there are 6920/872/1821 sentences remained in train/dev/test set.

SST dataset are publicly available online <sup>1</sup>.

---

<sup>1</sup><https://nlp.stanford.edu/sentiment/index.html>

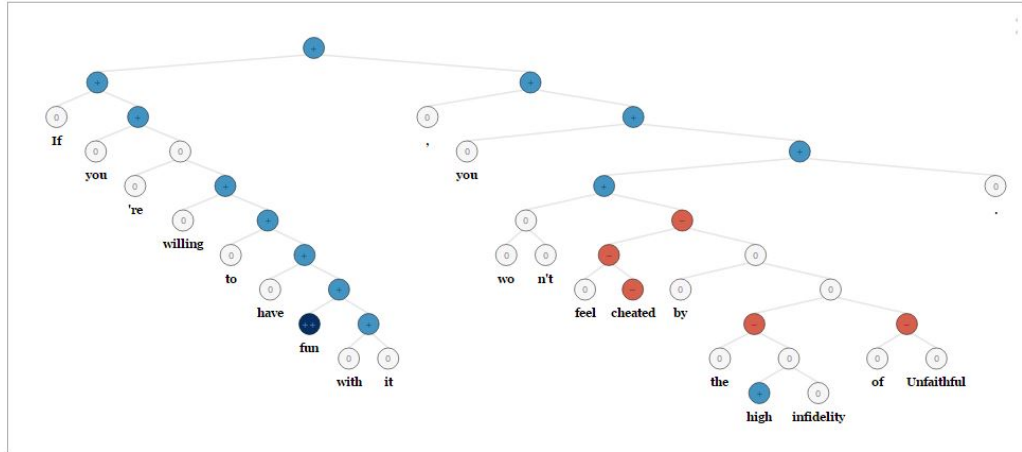


Figure 3.1: A parsed sentence in SST <sup>a</sup>

<sup>a</sup>Render by Pytreebank <https://github.com/JonathanRaiman/pytreebank>

## Preprocess

We use preprocess source code from [2] implementation <sup>2</sup> to preprocess SST.

### 3.1.2 Amazon Movies Review

We get Amazon Movies and TV reviews (4,607,047 reviews) and Amazon Book reviews (22,507,155 reviews) [he2016ups]. Listing ?? is sample of one book review.

```

1  {
2    "reviewerID": "AH2L9G3DQHHAJ",
3    "asin": "00000000116",
4    "reviewerName": "chris",
5    "helpful": [5, 5],
6    "reviewText": "Interesting Grisham tale of a lawyer that takes
7    millions of dollars from his firm after faking his own death. Grisham
8    usually is able to hook his readers early and ,in this case, doesn't
9    play his hand to soon. The usually reliable Frank Mueller makes this
10   story even an even better bet on Audiobook.",
    "overall": 4.0,
    "summary": "Show me the money!",
    "unixReviewTime": 1019865600,
    "reviewTime": "04 27, 2002"

```

<sup>2</sup><https://github.com/stanfordnlp/treelstm>

Table 3.1: My caption

	Constituency Tree-LSTM	LSTM
Glove 42B		
Glove 840B		
Glove (Amazon)	88.45	
Glove (Amazon Sorted)	88.85	
Paragram-Phrase XXL		
SSWEu		

11

}

Listing 3.1: Amazon reviews sample

### Preprocess

**Step 1:** We extract reviewText and overall from review dataset. We assume that overall values are sentiment score for reviews. Reviews with overall 5 is very positive and 0 is very negative. We keep asin, reviewText, overall and omit other data points.

**Step 2:** We group dataset by product (reviews with same asin). Then for each product, we sort by overall.

**Step 3:** We dump all reviewText into plain text file. We preprocess Stanford Tokenizer [3].

We also make a version of unsorted dataset. We preprocess as we do to our sorted dataset. However, in **Step 2:**, instead sort review, we shuffle all reviews.

### Train Glove on Amazon Review dataset

We train our word representation from Amazon dataset using Glove [pennington2014glove] on 15 iteration with windows size of 20.

## 3.2 Evaluation

# Danh mục công trình của tác giả

1. Tạp chí ABC
2. Tạp chí XYZ



# TABLE OF CONTENTS

## English

- [1] Collobert, Ronan, Kavukcuoglu, Koray, and Farabet, Clément. “Torch7: A matlab-like environment for machine learning”. In: *BigLearn, NIPS Workshop*. EPFL-CONF-192376. 2011.
- [2] Socher, Richard et al. “Recursive deep models for semantic compositionality over a sentiment treebank”. In: *Proceedings of the conference on empirical methods in natural language processing (EMNLP)*. Vol. 1631. 2013, p. 1642.
- [3] Tokenizer, Stanford. “Part-of-Speech Tagger, and Named Entity Recognizer. Downloaded from: <http://nlp.stanford.edu/software/> ()



# Appendix A

## APPENDICES 1

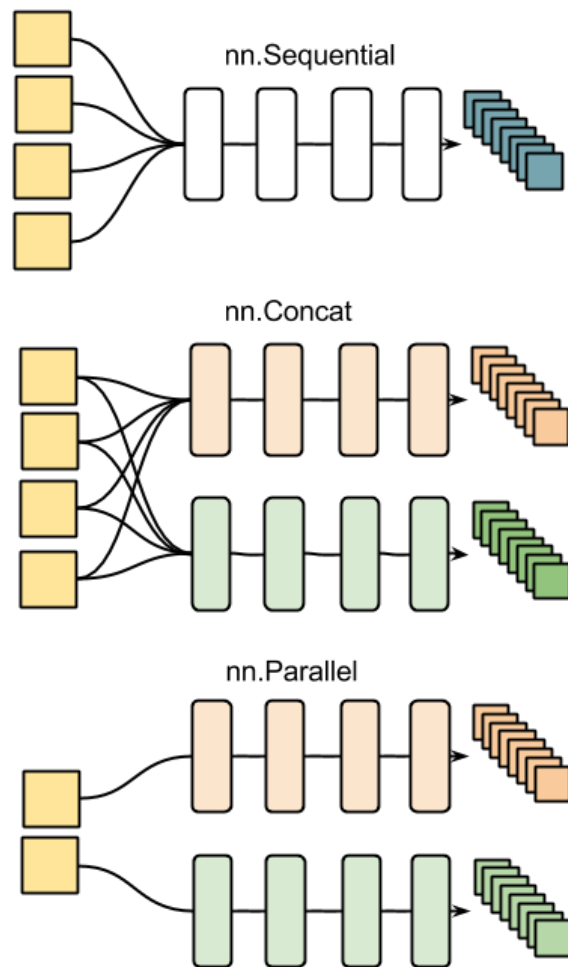


Figure A.1: Torch nn container <sup>a</sup>

<sup>a</sup><https://github.com/soumith/cvpr2015/blob/master/Deep%20Learning%20with%20Torch.ipynb>

```

1 require 'nn'
2 require 'optim'
3
4 model = nn.Sequential()
5 model:add(nn.Linear(1,1))
6
7 criterion = nn.MSECriterion()
8
9 x = torch.Tensor{{1,2,3,4,5,6,7,8,9,10}}
10 x = x:t()
11 y = torch.Tensor{{3,5,7,9,11,13,15,17,19,21}}
12 y = y:t()
13
14 params, gradParams = model:getParameters()
15
16 function feval(params)
17 gradParams:zero()
18 local outputs = model:forward(x)
19 local loss = criterion:forward(outputs,y)
20 local dloss_doutput = criterion:backward(outputs,y)
21 model:backward(x, dloss_doutput)
22 return loss, gradParams
23 end
24
25 local optimState = {
26 learningRate = 0.01
27 }
28
29 for epoch = 1, 100 do
30 optim.sgd(feval,params, optimState)
31 end
32
33 test = torch.Tensor{{1,3,5,7,9,11,100}}
34 test = test:t()
35
36 print (model:forward(test))

```

Listing A.1: MLP using nngraph

```

1 import numpy as np
2 import theano
3 import theano.tensor as T
4 import theano.tensor.nnet as nnet

```

```

5
6 class MLP:
7     def __init__(self):
8         x = T.dvector()
9         y = T.dscalar()
10        t1 = np.array(np.random.rand(3, 3), dtype=theano.config.floatX)
11        theta1 = theano.shared(t1) # 3x3 weight matrix
12        t2 = np.array(np.random.rand(4, 1), dtype=theano.config.floatX)
13        hid1 = MLP.sigmoid_layer(x, theta1) # hidden layer
14        theta2 = theano.shared(t2) # 4x1 weight matrix
15        output_layer = T.sum(MLP.sigmoid_layer(hid1, theta2))
16        fc = (output_layer - y)**2
17        self.cost = theano.function(inputs=[x,y], outputs = fc, updates=[
18            (theta1, Xor.grad_desc(fc, theta1)),
19            (theta2, Xor.grad_desc(fc, theta2))
20        ])
21        self.run_forward = theano.function(inputs=[x], outputs=output_layer)
22
23    @staticmethod
24    def sigmoid_layer(x, w):
25        b = np.array([1], dtype=theano.config.floatX)
26        new_x = T.concatenate([x,b])
27        m = T.dot(w.T, new_x)
28        h = nnet.sigmoid(m)
29        return h
30
31
32    @staticmethod
33    def grad_desc(cost, theta):
34        alpha = 0.1
35        return theta - (alpha* T.grad(cost, wrt=theta))
36
37    def forward(self, x):
38        output = self.run_forward(x)
39        return output
40
41
42    def train(self, train_x, train_y, n_epoch):
43        cur_cost = 0
44        for epoch in range(n_epoch):
45            for i in range(len(train_x)):
46                cur_cost = self.cost(train_x[i], train_y[i])

```

```
47 if epoch % 1000 == 0:  
48     print(cur_cost)  
49     print ('train complete')
```

Listing A.2: Theano MLP

# Appendix B

## APPENDICES 2

Đây là phụ lục 2.