

VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ

BRNO UNIVERSITY OF TECHNOLOGY

FAKULTA INFORMAČNÍCH TECHNOLOGIÍ
ÚSTAV POČÍTAČOVÉ GRAFIKY A MULTIMÉDIÍ

FACULTY OF INFORMATION TECHNOLOGY
DEPARTMENT OF COMPUTER GRAPHICS AND MULTIMEDIA

IMAGE CAPTIONING WITH RECURRENT NEURAL NETWORKS

SEMESTRÁLNÍ PROJEKT
TERM PROJECT

AUTOR PRÁCE
AUTHOR

Bc. JAKUB KVITA

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POPIS FOTOGRAFIÍ POMOCÍ REKURENTNÍCH NEU- RONOVÝCH SÍTÍ

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Abstrakt

Výtah (abstrakt) práce v českém jazyce.

Abstract

Výtah (abstrakt) práce v anglickém jazyce.

Klíčová slova

Klíčová slova v českém jazyce.

Keywords

Klíčová slova v anglickém jazyce.

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Image Captioning with Recurrent Neural Networks

Prohlášení

Prohlašuji, že jsem tento semestrální projekt vypracoval samostatně pod vedením pana Michala Hradiše.

.....

Jakub Kvita
December 28, 2015

Poděkování

Zde je možné uvést poděkování vedoucímu práce a těm, kteří poskytli odbornou pomoc.

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Tato práce vznikla jako školní dílo na Vysokém učení technickém v Brně, Fakultě informačních technologií. Práce je chráněna autorským zákonem a její užití bez udělení oprávnění autorem je nezákonné, s výjimkou zákonem definovaných případů.

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Chapter 1

Introduction

Klasicky popis toho co se tady bude dit, jak je to dulezite, atd.

Chapter 2

Neural networks

General idea of neural networks was slowly emerging after World War II. Perceptron, as a single neuron unit, was created in 1958 by Frank Rosenblatt¹, but became popular only after creation of backpropagation algorithm in 1975. At that time neural nets have not reached massive popularity, not because they are not working, but due to small computing power of machines back then and lack of datasets. Recently (after 2000) neural nets became popular again, rebranded as ‘Deep Learning’, because researchers realized that it is possible and very useful to stack neural nets on top of each other and create deep architectures, which are more practical than shallow ones. During this reinvention neural nets have been successfully applied in multiple fields like computer vision, speech recognition and natural language processing.

Since then various useful architectures and algorithms are now introduced almost every month. There is vast amount of various architectures and algorithms, in this chapter, I will describe only a couple – those used in this thesis.

2.1 Recurrent neural nets

Feedforward neural nets are extremely powerful models, which can be highly parallelized. Despite that, they can be only applied to problems with inputs and outputs, which have fixed dimensionality (e.g. one-hot encoding vectors). This is a serious drawback, as many of the real-world problems are defined as sequences with lengths that are unknown to us in beforehand. Soon recurrent neural networks were introduced and they proved to be very useful to this kind of task. There is vast amount of recurrent neural networks, many not suitable for sequential tasks like Hopfield network, which are very successful in specific tasks, but nevertheless not useful for us now.

Apart from classification, which can be more precise when using sequences, one of the most important tasks is next value prediction. This core task can be then extended very simply to predict arbitrary number of future values. Prediction problems are all around us, from the weather forecast and stock market prediction to the autocomplete in smartphones or web browsers.

We can understand recurrent neural networks as very deep forward nets with shared weights. It is called RNN unrolling and it is described in figure 1. Layers of this very deep net spread in time, together with the input sequence. This is very innovative idea,

¹The perceptron: A probabilistic model for information storage and organization in the brain. Rosenblatt, F. Psychological Review, Vol 65(6), Nov 1958, 386–408.

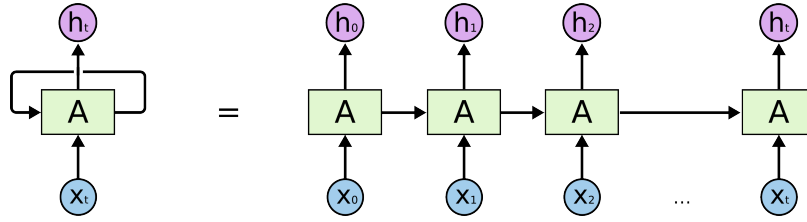


Figure 1: Unrolling of the recurrent neural net. (C. Olah 2015)

which enabled training RNN with backpropagation through time. It also shows that, as very deep networks, they have vanishing or exploding gradient problem, which means that the network is not able to learn long-term dependencies, even though in theory it should. This is a serious issue, which is caused by iterating many times over the weights and the activation function with derivatives > 1 (exploding gradient) or < 1 (vanishing gradient). Gradient then dies out and learning stops for distant dependencies. Among others this problem has been solved by the LSTM unit described in part 2.1.1, which is most popular now and following research resulting in GRU described in part 2.1.2.

2.1.1 LSTM – Long Short-Term Memory

Long Short-Term Memory nets are special kind of recurrent network, capable of learning long-term dependencies. This architecture was introduced by Hochreiter & Schmidhuber (1997) in [6] after prior research of vanishing gradient problem. Later architecture was refined and popularized by other researchers and nowadays LSTM is most used and popular RNN architecture used.

The LSTM unit designed that it can remember a value for an arbitrary length of time. It contains gates that determine when the input is significant enough to remember, when it should continue to remember or forget the value, and when it should output the value. To understand the flow of data, see the diagram of a simplified LSTM unit is on the figure 2.

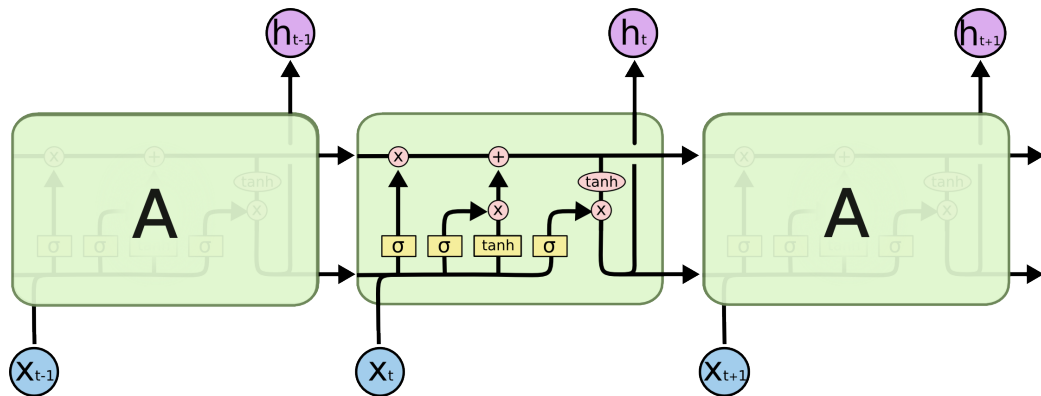


Figure 2: An unrolled LSTM unit. (C. Olah 2015)

All these gates can be described by series of equations (1)→(6). In each time slice the unit is using current input x_t , last stored value c_{t-1} and hidden state of the unit h_{t-1} to compute next state c_t , h_t and output o_t . Equations described in this work are not the only way how to create an LSTM unit, but they will be used later while implementing the proposed model.

$$i_t = \sigma(W_x^i x_t + W_h^i h_{t-1} + W_c^i c_{t-1} + b^i) \quad (1)$$

$$f_t = \sigma(W_x^f x_t + W_h^f h_{t-1} + W_c^f c_{t-1} + b^f) \quad (2)$$

$$z_t = \tanh(W_x^c x_t + W_h^c h_{t-1} + b^c) \quad (3)$$

$$c_t = f_t c_{t-1} + i_t z_t \quad (4)$$

$$o_t = \sigma(W_x^o x_t + W_h^o h_{t-1} + W_c^o c_t + b^o) \quad (5)$$

$$h_t = o_t \tanh(c_t) \quad (6)$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (7)$$

LSTM based on the equations (1)→(6) is using total of 11 weight matrices and 4 bias vectors for computations and σ is sigmoid function defined in the equation (7).

Training of the LSTM based network can be performed effectively by standard methods like stochastic gradient descend in the form of backpropagation through time. Major problem with vanishing gradients during training described earlier is not an issue as back-propagated error is fed back to each of the gates until they learn to deal with it.

2.1.2 GRU – Gated Recurrent Unit

Zminit jako updatovanou verzi

[2] [5]

2.1.3 Text sequences – Word level embeddings and character level

Mozna trochu upravit nazev. (Character level and word level embeddings)

Popis toho jak se pracuje s textem v rnn, ze to je taky sekvence. Character level, word level, embeddings. Popis rozdilu toho jak funguji preklady a generovani dalsiho prvku sekvence.

2.2 Convolutional neural nets

Kratky uvod do toho, kde se pouzivaji, jak se vyvinuly, jednoduchy popis toho jak funguji. Obrazek?

Asi neni potreba davat subsekcce na vrstvy, staci popsati jak to funguje vsechno dohromady, jednotlivé vrstvy ve vetach v jednom odstavci. Obrazek. V diplomce rozpracovat vic.

Chapter 3

Experiments

Kapitola jen na semestrální projekt. V diplomce ji odstraním.

Jak se to implementuje, jaké knihovny se používají - Caffe, Theano, TensorFlow, Torch. Popsat ze Torch bude v této kapitole.

Budu popisovat věci co jsem zkoušel implementovat v Torch.

3.1 Torch

Torch se zrecykluje do diplomky.

Udělat tedy tabulku o různých balících co torch má

Jak fungují rekurentní sítě v Torch.

Nacítání modelu z Caffe, ukládání v Torch...

[1]

3.1.1 nn, nngraph

Linky na knihovny v poznámkách pod čarou.

3.1.2 rnn

3.1.3 Other packages

loadcaffe, optim,...

3.2 Predicting next character in sequence

Jak jsem to udělal, co to dělá, ukázky.

Reference na Karpatyho char-rnn

[8]

Chapter 4

Image caption generation

Znovu uvod k tomu jak je to dulezite a tentokrat jak na tom lidi pracuji, co je potreba a jak se to hodnoti.

4.1 Related Work

Dat tomu nejake lepsi jmeno, clanky o popisovani obrazku ktere jsem cetl, pouzil.

4.1.1 Show and Tell

[14] [12]

Clanek z Coco od Googlu.

Zminit i strojovy preklad (Sequence to Sequence Learning with Neural Networks), architektura encoder, decoder

4.1.2 Show, Attend and Tell

[15]

Clanek z Coco z Montrealu/Toronta

4.1.3 From Captions to Visual Concepts and Back

[4]

Clanek z Coco od Microsoftu, mrknout se i na pokracovani v druhem clanku

4.1.4 Long-term Recurrent Convolutional Networks for Visual Recognition and Description

[3]

Clanek z Coco z berkeley

4.2 Datasets

COCO, Flickr, popis jake jsou. Asi zrusit sekce, udelat jen tabulku a mensi popis.

4.2.1 MS COCO

[10]

4.2.2 Flickr 30k,8k

[16] [7]

4.2.3 CIDEr datasets

[13]

4.3 Evaluation metrics

BLEU, cIDER, jak se používají, co dělají...

4.3.1 BLEU

[11]

4.3.2 CIDEr

[13]

4.3.3 METEOR

[9]

Chapter 5

Model

Do semestrálního projektu nebo až na diplomku?

Design modelu, co chci použít, jaké metody chci zkusit.

Položit si principiální otázku a zjistit, jestli to nějak pomůže, jak to funguje.

5.1 Architecture

Architektura modelu, jaké matematické modely jsem použil, bez implementačních detailů.

5.2 Training details

Popis pomocí jakého algoritmu jsme trénovali, s jakými parametry, minibatches, datasety.

Chapter 6

Conclusion

Udelat jeden zaver pro semestralni projekt, pak ho prepsat pro diplomku.

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