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FAKULTA INFORMAČNÍCH TECHNOLOGIÍ
ÚSTAV POČÍTAČOVÉ GRAFIKY A MULTIMÉDIÍ

FACULTY OF INFORMATION TECHNOLOGY
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IMAGE CAPTIONING WITH RECURRENT NEURAL NETWORKS

SEMESTRÁLNÍ PROJEKT
TERM PROJECT

AUTOR PRÁCE Bc. JAKUB KVITA
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POPIS FOTOGRAFIÍ POMOCÍ REKURENTNÍCH NEURONOVÝCH SÍTÍ

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Abstrakt
Výtah (abstrakt) práce v českém jazyce.

Abstract
Výtah (abstrakt) práce v anglickém jazyce.

Klíčová slova
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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 29, 2015

Poděkování

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

Contents

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 Rosenblatt[1], 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,

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

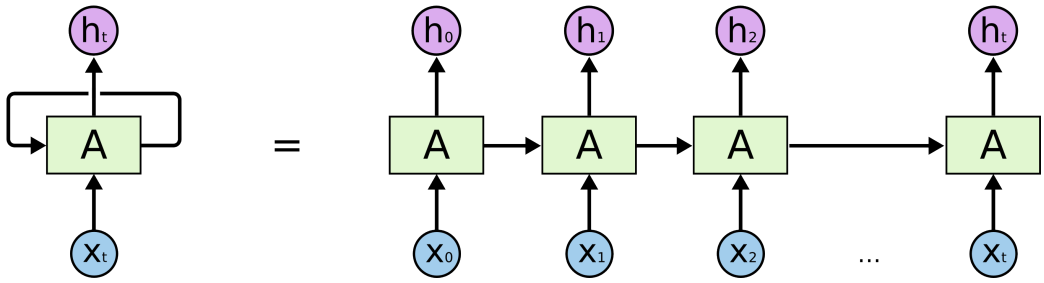

Figure 1: Unrolling of the recurrent neural net. (C. Olah 2015 [13])

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.

Mam to tady rozebrat vice?

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 [7] 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 keep 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.

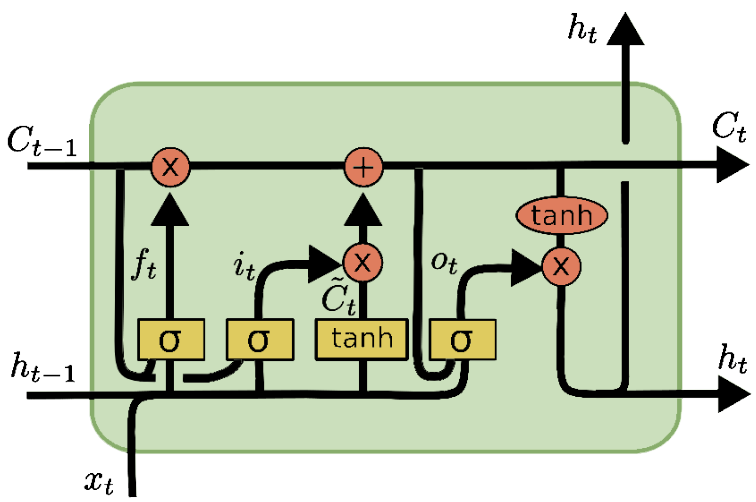

Figure 2: Variation of the LSTM unit. (C. Olah 2015 [13])

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 unit output h_{t-1} to compute next state c_t and output h_t. Variables i_t, f_t, o_t denotes value of input, forget and output gates which are used to control the information flow.

$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) && (1)\\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) && (2)\\
z_t &= \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) && (3)\\
c_t &= f_t \odot c_{t-1} + i_t \odot z_t && (4)\\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) && (5)\\
h_t &= o_t \odot \tanh(c_t) && (6)
\end{aligned}
$$

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

LSTM based on these equations is using total of 11 weight matrices and 4 bias vectors for computations and sigmoid function σ defined in the equation (7) and the operation $\odot$ denotes the element-wise vector product. 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. Some of the versions are omitting 'peephole connections', which allows gates to look at stored value C_{t-1}, C_t or include only some of them.

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 backpropagated error is fed back to each of the gates.

2.1.2 GRU – Gated Recurrent Unit

Gated Recurrent Unit is slightly more dramatic variation on the LSTM theme from 2014 paper [2]. It combines hidden state of the unit h_t with the saved value C_t, merges input and forget gates into one update gate and removes peephole connections. These changes are simplifying standard LSTM models, but not at the expense of performance, and cause rapid growth in popularity. Diagram of the GRU unit is on the figure 3.

$$
\begin{aligned}
r_t &= \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) && (8)\\
z_t &= \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) && (9)\\
\widetilde{h}_t &= \tanh(W_{xh}x_t + W_{hh}(h_{t-1} \odot r_t) + b_h) && (10)\\
h_t &= (1-z_t) \odot \widetilde{h}_t + z_t \odot h_{t-1} && (11)
\end{aligned}
$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \qquad (12)$$

Equations (8)→(11) describe a version of GRU unit used in this work, with sigmoid function σ defined in equation (12). The operation $\odot$ again denotes the element-wise

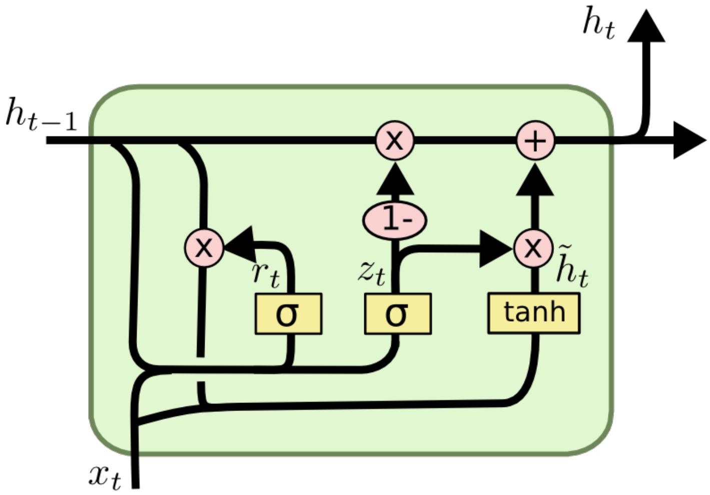

Figure 3: Variation of a GRU unit. (C. Olah 2015 [13])

vector product. While it is using only 4 weight matrices, 3 biases and just 1 state variable, researchers studied whether this can achieve at least same performance as previous LSTM unit.

Last year, study by Chung [3] was done, where different types of recurrent units were compared on the polyphonic music datasets. In this task LSTM and GRU were significantly better than all the other architectures, with GRU slightly in the lead. Generally researchers agree that most of the LSTM variations, including GRU, are roughly on the same level of performance. In [6] GRU is an average variation, slightly better than vanilla LSTM, with much simpler architecture.

In paper [9], which emphasized variety of tasks and the data, GRU outperformed LSTM unit on all tasks with the exception of language modeling. There are multiple approaches to model languages and in this work I will explore different type than the one mentioned in Jozefowicz's [9] paper. More will be explained in following chapters. Interestingly they also found that LSTM nearly matched the GRU's performance, when its forget gate bias was initialized to 1 and not to naive initialization around 0. It is also worth mentioning that Jozefowicz in his paper discovered several architectures similar to GRU, but with slightly better general performance. They were found by evolutionary algorithm working on candidate architectures represented by the computational graph.

2.1.3 Text sequences – Word level embeddings and character level

Mozna trochu upravit nazev. language modeling - 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 subsekce na vrstvy, staci popsat jak to funguje vsechno dohromady, jednotlive vrstvy ve vetach v jednom odstavci. Obrazek. V diplomce rozpracovat vic.

Chapter 3

Experiments

Kapitola jen na semestralni projekt. V diplomce ji odstranim.

Jak se to implementuje, jake knihovny se pouzivaji - Caffe, Theano, TensorFlow, Torch. Popsat ze Torch bude v tehle kapitole.

Budu popisovat veci co jsem zkousel implementovat v Torchi.

3.1 Torch

Torch se zrecykluje do diplomky.

Udelat tady tabulku o ruznych balicich co torch ma

Jak funguji rekurentni site v Torchi.

Nacitani modelu z Caffe, ukladani v Torchi...

[1]

3.1.1 nn, nngraph

Linky na knihovny v poznamkach pod carou.

3.1.2 rnn

3.1.3 Other packages

loadcaffe, optim,...

3.2 Predicting next character in sequence

Jak jsem to udelal, co to dela, ukazky.

Reference na Karpathyho char-rnn

[10]

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

[17] [15]

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

[18]

Clanek z Coco z Montrealu/Toronta

4.1.3 From Captions to Visual Concepts and Back

[5]

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

[4]

Clanek z Coco z berkeley

4.2 Datasets

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

4.2.1 MS COCO

[12]

4.2.2 Flickr 30k,8k

[19] [8]

4.2.3 CIDEr datasets

[16]

4.3 Evaluation metrics

BLEU, cIDER, jak se pouzivaji, co delaji…

4.3.1 BLEU

[14]

4.3.2 CIDEr

[16]

4.3.3 METEOR

[11]

Chapter 5

Model

Do semestralniho projektu nebo az na diplomku?

Design modelu, co chci pouzit, jake metody chci zkusit.

Polozit si principialni otazku a zjistit jestli to nejak pomuze, jak to funguje.

5.1 Architecture

Architektura modelu, jake matematicke modely jsem pouzil, bez implementacnich detailu.

5.2 Training details

Popis pomoci jakeho algoritmu jsme trenovali, s jakyma parametrama, minibatches, datasety.

Chapter 6

Conclusion

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

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