Deep Learning for Natural Language Processing

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Overview

Introduction (very brief)

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- Machine learning that uses deep neural networks
- Deep neural networks $\approx$ multi-layer neural networks

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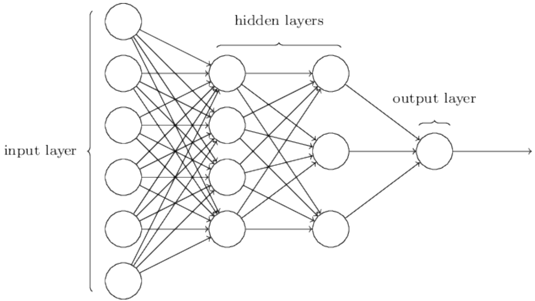

Figure: A feedforward neural network with 2 hidden layers.

(image from: `http://neuralnetworksanddeeplearning.com/`)

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- Recursive neural networks
  - Can operate on trees (e.g., syntax tree)
  - Parameter sharing over parent-children relations
  - Not so popular lately

Recurrent neural networks

Recurrent neural networks [Elman, 1990]

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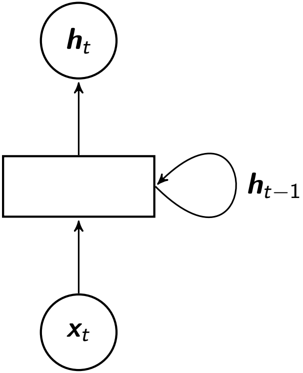

Figure: Architecture of an RNN. To compute the hidden state $\boldsymbol{h}_t$, the previous hidden state $\boldsymbol{h}_{t-1}$ is included as input along with $\boldsymbol{x}_t$.

[Kurniawan, 2017]

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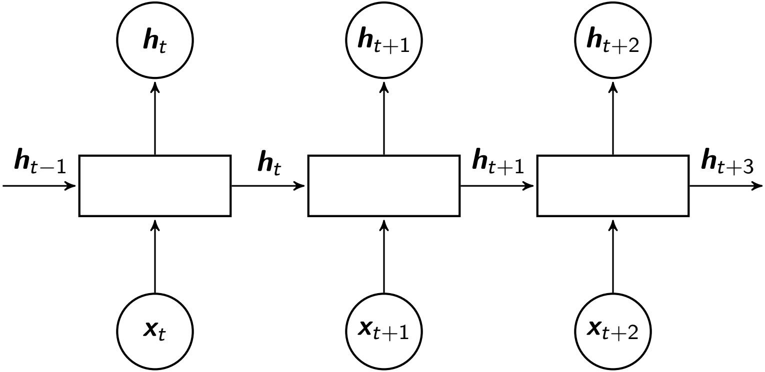

Figure: Architecture of an unfolded RNN for three time steps. This architecture is similar to that of a 3-layer feed-forward neural network.

[Kurniawan, 2017]

Mathematically, if $\boldsymbol{x}_t \in \mathbb{R}^d$ is an input vector at timestep t, then:

$$\boldsymbol{r}_t = \boldsymbol{U}\boldsymbol{x}_t + \boldsymbol{V}\boldsymbol{h}_{t-1} \quad (1)$$

$$\boldsymbol{h}_t = f\left(\boldsymbol{r}_t\right) \quad (2)$$

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Output vector can be computed as:

$$\boldsymbol{s}_t = \boldsymbol{W}\boldsymbol{h}_t \tag{3}$$

$$\boldsymbol{y}_t = g\left(\boldsymbol{s}_t\right) \tag{4}$$

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Note that $\boldsymbol{U}$, $\boldsymbol{V}$ and $\boldsymbol{W}$ are shared over timesteps!

Training an RNN

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- Initialize parameters $\boldsymbol{U}$, $\boldsymbol{V}$, and $\boldsymbol{W}$ with small random numbers
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- Perform forward computation to get output vectors $\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots$ and compute the loss L

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$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \frac{\partial L}{\partial \boldsymbol{\theta}} \tag{5}$$

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- This is just *gradient descent*!
- A special backpropagation algorithm is required to compute gradients so RNN actually learns from early timesteps

Backpropagation through time (BPTT)

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At first, training an RNN with simple backpropagation seems straightforward. For example, if $L = \mathcal{L}(\boldsymbol{y}_t)$ denotes the loss of our RNN, the gradient on $\boldsymbol{W}$ seems to be:

$$\frac{\partial L}{\partial \boldsymbol{W}_{ij}} = \sum_k \frac{\partial L}{\partial \left(\boldsymbol{s}_t\right)_k} \frac{\partial \left(\boldsymbol{s}_t\right)_k}{\partial \boldsymbol{W}_{ij}} = \frac{\partial L}{\partial \left(\boldsymbol{s}_t\right)_i} \left(\boldsymbol{h}_t\right)_j \tag{6}$$

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Or, in matrix notation:

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But this is **suboptimal**! Since $\boldsymbol{W}$ is shared across *all* timesteps, not just timestep t, it contributes to $\boldsymbol{s}_t$ for all timestep t. Thus, we need to sum the gradients from all timesteps, *if we want earlier inputs to have contribution to current outputs*.

If T denotes the maximum timestep, what we want is actually:

$$\overline{\boldsymbol{W}} = \sum_{t=1}^{T} \overline{\boldsymbol{s}}_t \boldsymbol{h}_t^\top \tag{8}$$

This is called *backpropagation through time* (BPTT).

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$$\overline{\boldsymbol{U}} = \sum_{t=1}^{T} \overline{\boldsymbol{r}}_t \boldsymbol{x}_t^\top \tag{9}$$

$$\overline{\boldsymbol{V}} = \sum_{t=1}^{T} \overline{\boldsymbol{r}}_t \boldsymbol{h}_{t-1}^\top \tag{10}$$

$$\overline{\boldsymbol{r}}_t = \overline{\boldsymbol{h}}_t * f'(\boldsymbol{r}_t) \tag{11}$$

$$\overline{\boldsymbol{h}}_t = \boldsymbol{W}^\top \overline{\boldsymbol{s}}_t + \begin{cases} 0 & t = T \\ \boldsymbol{V}^\top \overline{\boldsymbol{r}}_{t+1} & \text{otherwise} \end{cases} \tag{12}$$

$$\overline{\boldsymbol{s}}_t = \overline{\boldsymbol{y}}_t * g'(\boldsymbol{s}_t) \tag{13}$$

A more detailed explanation on BPTT and how to implement it in code can be seen on `https://tinyurl.com/bptt-tutorial`.

[Goodfellow et al., 2016]

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Eigenvalues with magnitude greater than one will explode; less than one will vanish. Elements of $\boldsymbol{h}_t$ not associated with the largest eigenvalue will be very small.

[Goodfellow et al., 2016]

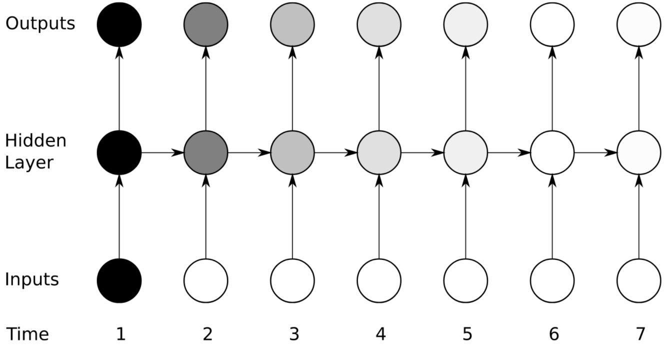

Figure: Vanishing gradient problem for RNN. The darker the shade, the greater the sensitivity of the nodes to the input at timestep one. [Graves, 2012]

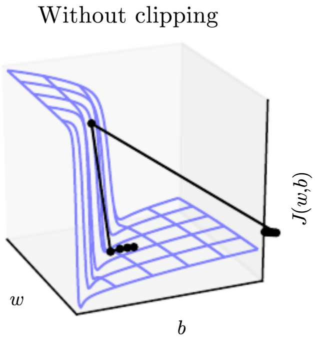

Figure: Illustration of the exploding gradient problem (left) and how gradient clipping might help (right). [Pascanu et al., 2013]

- In practice, gradients usually vanish rapidly for long sequences
- Thus, RNN cannot learn long-term dependency effectively
- To handle exploding gradients, typically gradient clipping is used: if $\|\boldsymbol{g}\| > v$ then

$$\boldsymbol{g} \leftarrow \frac{\boldsymbol{g}}{\|\boldsymbol{g}\|} v \tag{17}$$

- How to handle vanishing gradients?

Long short-term memory

Long short-term memory [Hochreiter and Schmidhuber, 1997]

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- LSTM is a variant of RNN that is better equipped to handle the vanishing gradient problem
- Central to LSTM is the *cell state/memory cell*, which is a connection that runs through all timesteps
- LSTM can read from/write to the cell state freely, regulated by several *gates*
- We'll see more in the next few slides

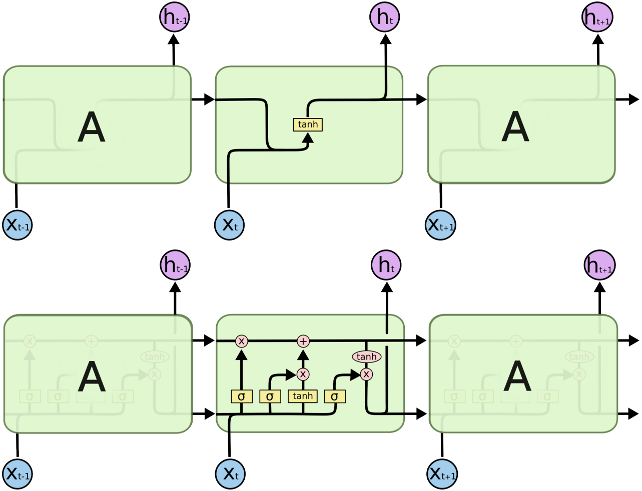
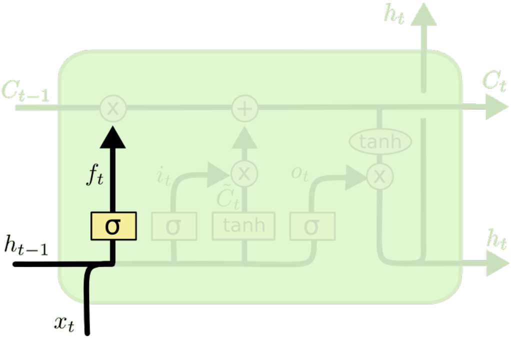


Figure: An unfolded RNN (top) and LSTM (bottom).

(image from: `https://colah.github.io/posts/2015-08-Understanding-LSTMs/`)

Forget gate



$$\boldsymbol{f}_t = \sigma\left(\boldsymbol{U}_f \boldsymbol{x}_t + \boldsymbol{V}_f \boldsymbol{h}_{t-1}\right) \tag{18}$$

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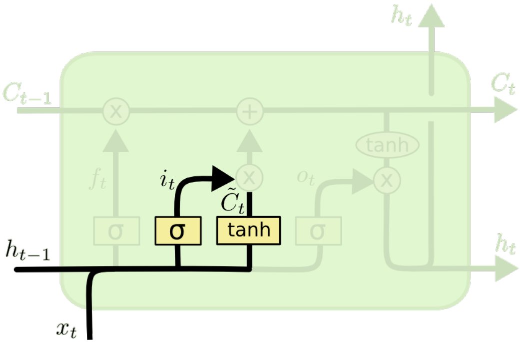
Input gate

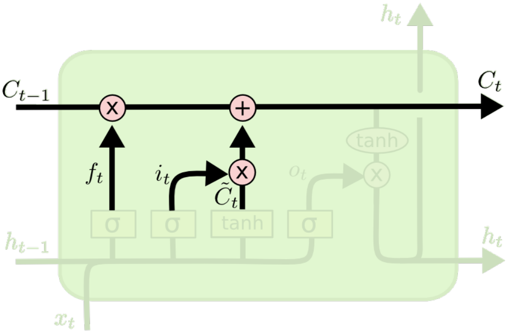


$$\boldsymbol{i}_t = \sigma\left(\boldsymbol{U}_i \boldsymbol{x}_t + \boldsymbol{V}_i \boldsymbol{h}_{t-1}\right) \tag{19}$$

$$\tilde{\boldsymbol{C}}_t = \tanh\left(\boldsymbol{U}_C \boldsymbol{x}_t + \boldsymbol{V}_C \boldsymbol{h}_{t-1}\right) \tag{20}$$

(image from: `https://colah.github.io/posts/2015-08-Understanding-LSTMs/`)

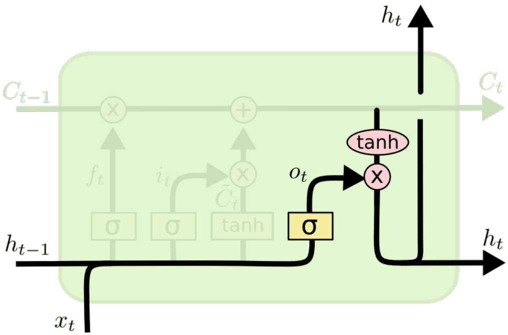
Cell state



$$\boldsymbol{C}_t = \boldsymbol{f}_t * \boldsymbol{C}_{t-1} + \boldsymbol{i}_t * \tilde{\boldsymbol{C}}_t \tag{21}$$

(image from: `https://colah.github.io/posts/2015-08-Understanding-LSTMs/`)

Output gate



$$o_t = \sigma\left(U_o x_t + V_o h_{t-1}\right) \tag{22}$$

$$h_t = o_t * \tanh(C_t) \tag{23}$$

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Why LSTM?

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- Address the vanishing gradient problem in RNN
  - The cell state acts as an "expressway", allowing gradients to flow easily
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- Address the vanishing gradient problem in RNN
  - The cell state acts as an "expressway", allowing gradients to flow easily
  - Reading/writing information to the cell state is regulated by the gates
- Very widely used and successful for many NLP tasks
  - POS tagging, NER, parsing, language modeling, machine translation, etc.
  - Vanilla RNN are almost never used in practice nowadays

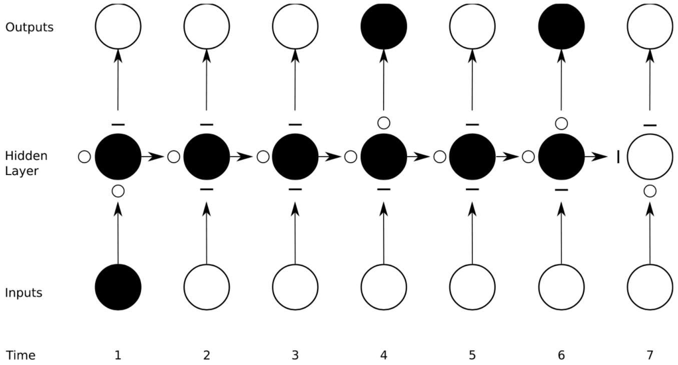

Figure: Preservation of gradient information by LSTM. For simplicity, gates are either open ('O') or closed ('–'). [Graves, 2012]

Example cases

Case 1: Character-level language modeling

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- N-gram language models approximate this probability by considering only the previous $n-1$ word as history, and represent the probability as multinomial distribution
- For example, with $n = 2$:

$$\Pr\left(w_{t+1} | w_t\right) = \frac{\text{count}\left(w_t, w_{t+1}\right) + \alpha}{\text{count}\left(w_t\right) + \alpha V} \tag{25}$$

where α is a smoothing parameter and V is the vocabulary size

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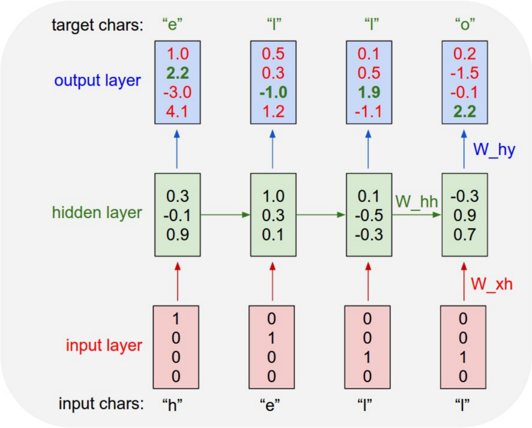
- **Issue 2**: Smoothing parameter can prevent zero probabilities, but then all of them will have equal probability
- RNN-based language models can mitigate these issues!
- We'll see specifically character-level RNN-based language models, which operate on characters instead of words



An example RNN with 4-dimensional input and output layers, and a hidden layer of 3 units (neurons). This diagram shows the activations in the forward pass when the RNN is fed the characters "hell" as input. The output layer contains confidences the RNN assigns for the next character (vocabulary is "h,e,l,o"); We want the green numbers to be high and red numbers to be low.

(image from: `https://karpathy.github.io/2015/05/21/rnn-effectiveness/`)

Generating text

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- Training: the correct next character is given as target output, and the model is trained to minimize negative log likelihood loss
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- Start token `<INIT>` and end token `<EOS>` are added to training sentences
- Generating: Feed `<INIT>` as input for the first timestep, select the most probable output as the next character, and feed that as the next input
- Generation stops when the model generates `<EOS>`
- We'll see the generation result of a model trained on Linux source code

Looks like a valid C code:

```c
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
  return segtable;
}
```

(image from: `https://karpathy.github.io/2015/05/21/rnn-effectiveness/`)

Copyright notice and include headers:

```
/*
 *  Copyright (c) 2006-2010, Intel Mobile Communications.  All rights reserved.
 *
 *   This program is free software; you can redistribute it and/or modify it
 * under the terms of the GNU General Public License version 2 as published by
 * the Free Software Foundation.
 *
 *        This program is distributed in the hope that it will be useful,
 * but WITHOUT ANY WARRANTY; without even the implied warranty of
 *   MERCHANTABILITY or FITNESS FOR A PARTICULAR PURPOSE.  See the
 *
 *  GNU General Public License for more details.
 *
 *   You should have received a copy of the GNU General Public License
 *    along with this program; if not, write to the Free Software Foundation,
 *  Inc., 675 Mass Ave, Cambridge, MA 02139, USA.
 */

#include <linux/kexec.h>
#include <linux/errno.h>
#include <linux/io.h>
#include <linux/platform_device.h>
#include <linux/multi.h>
#include <linux/ckevent.h>

#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system_info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>
```

(image from: `https://karpathy.github.io/2015/05/21/rnn-effectiveness/`)

- The model can produce output that looks like a valid C code
- The output has nice indentations, matching brackets, comments, and even copyright notice and include headers
- But the model does not seem to “understand” the code: unused variables, undeclared variables, etc.

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- Usually formulated as a sequence labeling problem, i.e. each word will be labeled as either (B)eginning, (I)nside, or (O)utside
- For example:

```
B-PER   O       O     B-LOC  I-LOC
Mark    lives   in    New    York
```

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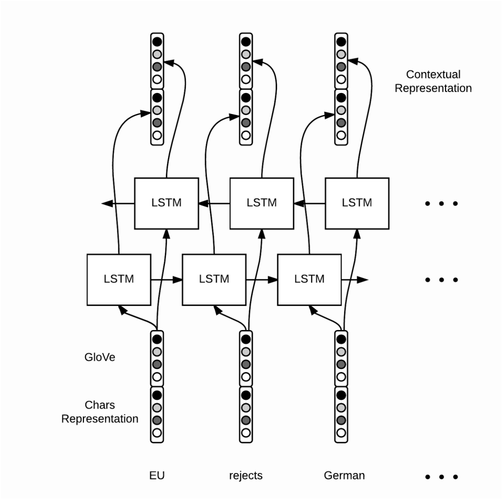
- For example:

`B-PER`	`O`	`O`	`B-LOC`	`I-LOC`
`Mark`	`lives`	`in`	`New`	`York`

- A very common neural architecture for this task is based on [Lample et al., 2016]

Architecture



The output layer is a feedforward layer, followed by either a softmax or CRF layer.

(image from: `https://guillaumegenthial.github.io/sequence-tagging-with-tensorflow.html`)

Word representation from characters

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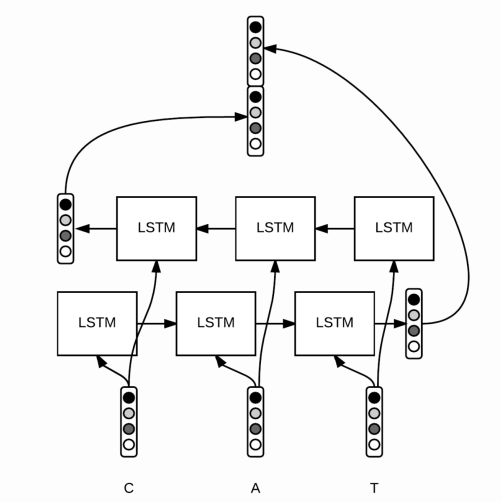

(image from: `https://guillaumegenthial.github.io/sequence-tagging-with-tensorflow.html`)

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- Handles out-of-vocabulary (OOV) problem
- Captures morphology to some extent

Results

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Model	$\mathbf{F_1}$
Collobert et al. (2011)*	89.59
Lin and Wu (2009)	83.78
Lin and Wu (2009)*	90.90
Huang et al. (2015)*	90.10
Passos et al. (2014)	90.05
Passos et al. (2014)*	90.90
Luo et al. (2015)* + gaz	89.9
Luo et al. (2015)* + gaz + linking	**91.2**
Chiu and Nichols (2015)	90.69
Chiu and Nichols (2015)*	90.77
LSTM-CRF (no char)	90.20
LSTM-CRF	**90.94**
S-LSTM (no char)	87.96
S-LSTM	90.33

Table 1: English NER results (CoNLL-2003 test set). * indicates models trained with the use of external labeled data

[Lample et al., 2016]

Results

Model	$\mathbf{F_1}$
Florian et al. (2003)*	72.41
Ando and Zhang (2005a)	75.27
Qi et al. (2009)	75.72
Gillick et al. (2015)	72.08
Gillick et al. (2015)*	76.22
LSTM-CRF – no char	75.06
LSTM-CRF	**78.76**
S-LSTM – no char	65.87
S-LSTM	75.66

Table 2: German NER results (CoNLL-2003 test set). * indicates models trained with the use of external labeled data

[Lample et al., 2016]

Using characters for OOV

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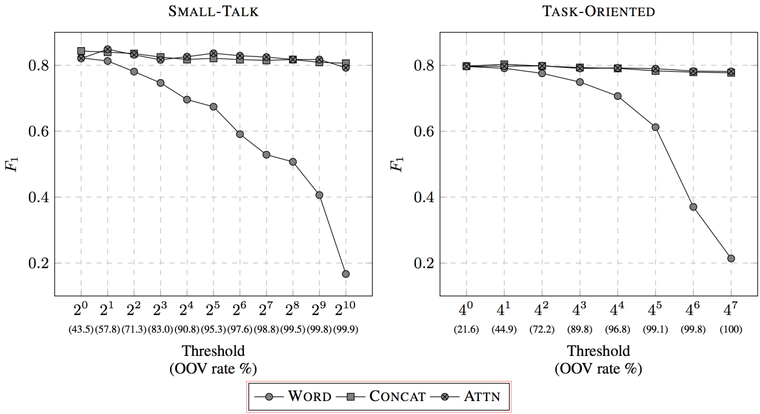

Figure 2: F_1 scores on the test set of each dataset with varying threshold. Words occurring fewer than this threshold in the training set are converted into the special token for OOV words. OOV rate increases as threshold does (from left to right). WORD, CONCAT, and ATTN refers to the word embedding-only, concatenation, and attention model respectively.

[Kurniawan and Louvan, 2018]

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  where $c = \text{RNN}_{\text{enc}}(\{x_1, \ldots, x_N\})$ and N may not equal M
- This model is usually called **sequence-to-sequence** or **encoder-decoder**
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- This model is usually called **sequence-to-sequence** or **encoder-decoder**
- Output layer is a softmax layer
- Training: the correct sentence pairs are given, and the model is trained to minimize negative log likelihood loss
- Decoding: decoder selects the most likely word at each timestep and feeds it back as input for the next timestep

[Sutskever et al., 2014]

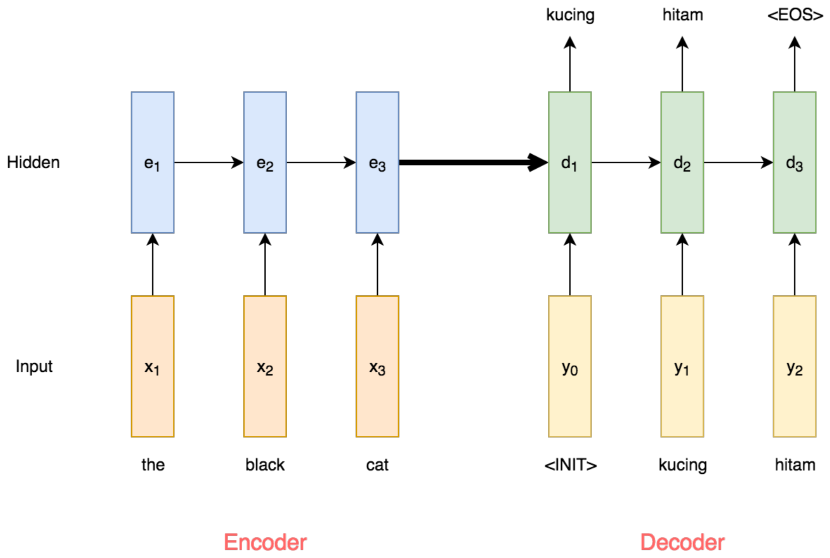
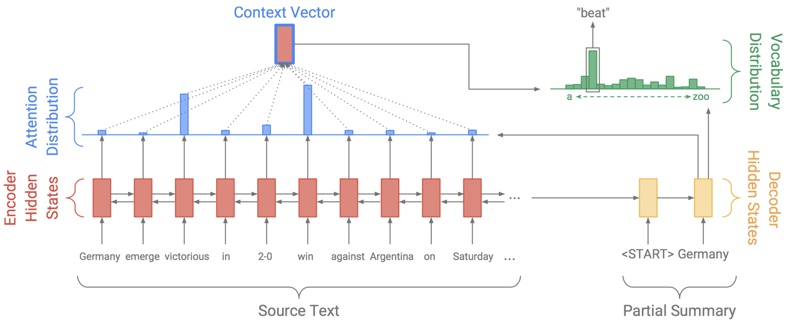


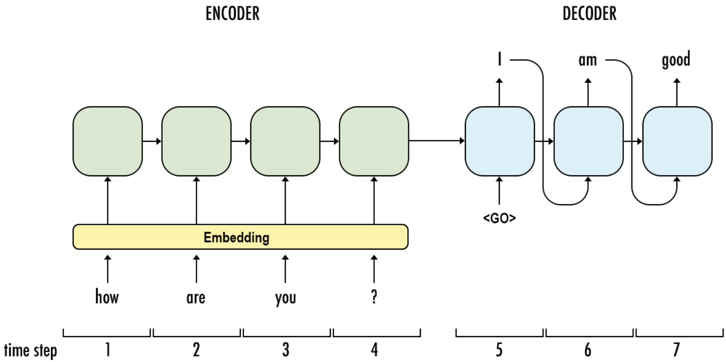
Figure: Illustration of an encoder-decoder network.

Encoder-decoder model can be used for many other tasks! For example, text summarization:



[See et al., 2017]

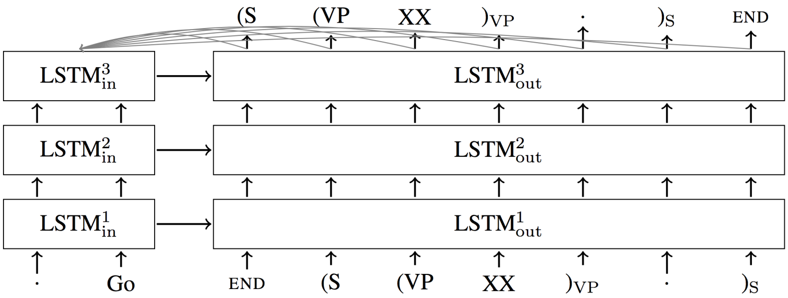
Dialog generation for open-domain dialog systems:



(image from:

https://towardsdatascience.com/sequence-to-sequence-model-introduction-and-concepts-44d9b41cd42d)

Even syntactic parsing:



[Vinyals et al., 2015]

Summary and Notes

Summary and Notes

- Deep learning is useful for NLP
- RNN is by far the most successful neural network architecture for NLP
- Watch out for vanishing/exploding gradient problem; use LSTM and gradient clipping!
- Don't worry too much about gradients; libraries like PyTorch, Keras, Tensorflow, etc. will compute them automatically
- Exciting stuff that aren't covered: attention, transfer learning, cross-lingual learning, etc.
- Start doing NLP **now**! Kata.ai is hiring!

Q & A

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