Exercises on Natural Language Processing with Recurrent Neural Networks

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Submit as a group of 2–3 members (unless specified otherwise in the lectures) a report (max. 10 pages, PDF format) for exercises 1 and 2. You may optionally submit also exercise 6 for extra bonus (your report may then be up to 15 pages). Include in your report all the required information, especially experimental results. Do not include code in the report, but include a link to a Colab notebook with your code. Make sure to divide fairly the work of your group to its members and describe in your report the contribution of each member. The contribution of each member will also be checked during the oral examination of your submission. For delayed submissions, one point will be subtracted per day of delay.

1. Repeat exercise 9 of Part 3 (text classification with MLPs), now using a bi-directional stacked RNN (with GRU or LSTM cells) with self-attention, all implemented (by you) in Keras/TensorFlow or PyTorch. You can use a self-attention MLP (slides 18–20) or a single dense layer to obtain attention scores. Tune the hyper-parameters (e.g., number of stacked RNNs, number of hidden layers in the self-attention MLP, dropout probability) on the development subset of your dataset. Monitor the performance of the RNN on the development subset during training to decide how many epochs to use. You may optionally add an extra RNN layer to produce word embeddings from characters (slide 21), concatenating each resulting character-based word embedding with the corresponding pre-trained word embedding (e.g., obtained with Word2Vec). Include experimental results of a baseline majority classifier, as well as experimental results of your best probabilistic classifier from exercise 15 of Part 2 and your MLP classifier from exercise 9 of Part 3, now treated as baselines. Include in your report:

- Curves showing the loss on training and development data as a function of epochs.
- Precision, recall, F1, precision-recall AUC scores for each class and classifier, separately for the training, development, and test subsets, as in exercise 9 of Part 3.
- Macro-averaged precision, recall, F1, precision-recall AUC scores (averaging the corresponding scores of the previous bullet over the classes), for each classifier, separately for the training, development, and test subsets, as in exercise 9 of Part 3.
- A short description of the methods and datasets you used, including statistics about the datasets (e.g., average document length, number of training/dev/test documents, vocabulary size) and a description of the preprocessing steps that you performed.

You may optionally wish to try ensembles (e.g., majority voting of the best checkpoints, temporal averaging of the weights of the best checkpoints).

2. Repeat exercise 10 of Part 3 (text classification with MLPs), now using a bi-directional stacked RNN (with GRU or LSTM cells) implemented (by you) in Keras/TensorFlow or PyTorch. Tune the hyper-parameters (e.g., number of stacked RNNs, dropout probability) on the development subset. Monitor the performance of the RNN on the development subset during training to decide how many epochs to use. You may optionally add an extra RNN layer to produce word embeddings from characters (slide 21), concatenating each resulting character-based word embedding with the corresponding pre-trained word embedding (e.g., obtained with Word2Vec). Include experimental results of a baseline that tags each word with the most frequent tag it had in the training data; for words that were not encountered in the training data, the baseline should return the most frequent tag (over all words) of the training data. Also include experimental results of your best method of exercise 10 of Part 3, now treated as an additional baseline. Include in your report:

- Curves showing the loss on training and development data as a function of epochs.
- Precision, recall, F1, precision-recall AUC scores for each class (tag) and classifier, separately for the training, development, and test subsets, as in exercise 10 of Part 3.
- Macro-averaged precision, recall, F1, precision-recall AUC scores for each classifier, separately for the training, development, and test subsets, as in exercise 10 of Part 3.
- A short description of the methods and datasets you used, including statistics about the datasets (e.g., average document length, number of training/dev/test documents, vocabulary size) and a description of the preprocessing steps that you performed.

You may optionally wish to try ensembles (e.g., majority voting of the best checkpoints, temporal averaging of the weights of the best checkpoints).

3. Write down the equations for a modified version of the "RNN with deep self-attention" (slide 20), where the uni-directional RNN with GRU cells is replaced by a stacked bi-directional RNN with GRU cells. Use the notation $\text{GRU}(h_{t-1}, \tau_t)$ to denote the new state of a GRU cell with previous state h_{t-1} and input τ_t.

Answer: At the first layer of the GRU RNN, we have (for $t = 1, \ldots, k$):

$$\vec{h}_t^{(1)} = \text{GRU}\left(\vec{h}_{t-1}^{(1)}, x_t\right)$$

$$\overleftarrow{h}_t^{(1)} = \text{GRU}\left(\overleftarrow{h}_{t+1}^{(1)}, x_t\right)$$

$$h_t^{(1)} = [\vec{h}_t^{(1)}; \overleftarrow{h}_t^{(1)}]$$

where $\vec{h}_0^{(1)}$ is the initial state of the left-to-right GRU RNN of the first layer, $\overleftarrow{h}_{k+1}^{(1)}$ is the initial state of the right-to-left GRU RNN of the first layer, `;' denotes concatenation, and $x_1, \ldots, x_k$ are the word embeddings of the input word sequence.

Similarly, at the m-th layer of the GRU RNN:

$$\vec{h}_t^{(m)} = \text{GRU}\left(\vec{h}_{t-1}^{(m)}, h_t^{(m-1)}\right)$$

$$\overleftarrow{h}_t^{(m)} = \text{GRU}\left(\overleftarrow{h}_{t+1}^{(m)}, h_t^{(m-1)}\right)$$

$$h_t^{(m)} = [\vec{h}_t^{(m)}; \overleftarrow{h}_t^{(m)}]$$

The other equations remain as on slide 20.

4. (a) Modify the equations of the neural network of the previous exercise to support *multi-label classification*, i.e., cases where the same text (e.g., tweet) may belong in multiple classes (labels). As a twist, use a separate *label-specific self-attention-head* for each class, which will produce a different distribution of attention scores $a_{c,1}, \ldots, a_{c,k}$ (where k is again the length of the input text, counted in words) and a different $h_{sum,c}$ for each class c. Feed the $h_{sum,c}$ of each class c to a separate (different per class) dense layer with a sigmoid to produce the probability that the input text should be assigned class c.

Answer: Let C be the set of possible classes (labels). We modify the self-attention MLP of slide 20, so that $a_t^{(l)} \in \mathbb{R}^{|C|}$, i.e., $a_t^{(l)}$ is now a vector (not a scalar) containing $|C|$ attention scores $a_{1,t}, \ldots, a_{|C|,t}$ for word position t, one for each possible class. To achieve this, we

modify the dimensions of $W^{(l)}$ and $b^{(l)}$ of layer l of the self-attention MLP, to be $|C| \times d$ and $|C|$, respectively, where d is the dimensionality of the previous layer $a_t^{(l-1)}$.

The softmax of slide 20 is now applied *label-wise*, on the attention scores of a particular class, i.e., for each possible class c:

$$a_{c,t} = \text{softmax}(a_{c,t}^{(l)}; a_{c,1}^{(l)}, \ldots, a_{c,k}^{(l)})$$

We form a separate weighted sum $h_{sum,c}$ for each possible class c:

$$h_{sum,c} = \sum_{t=1}^{k} a_{c,t} h_t^{(M)}$$

where M is the number of stacked GRU RNNs of the previous exercise, and we feed each $h_{sum,c}$ to a separate dense layer (a transposed vector really, why?) $W_{p,c}$ with bias term $b_{p,c}$ per class c, to compute the probability of the corresponding class:

$$P(c|x_1, \ldots, x_k) = \sigma(W_{p,c} h_{sum,c} + b_{p,c})$$

The other equations of the neural network remain as in the previous exercise.

(b) Couldn't we use a single (shared) self-attention-head (and a single h_{sum}) for all the classes? What would change in that case in the equations above? What is the advantage of using a separate *label-specific* self-attention-head for each class?

5. We train the following neural machine translation model.

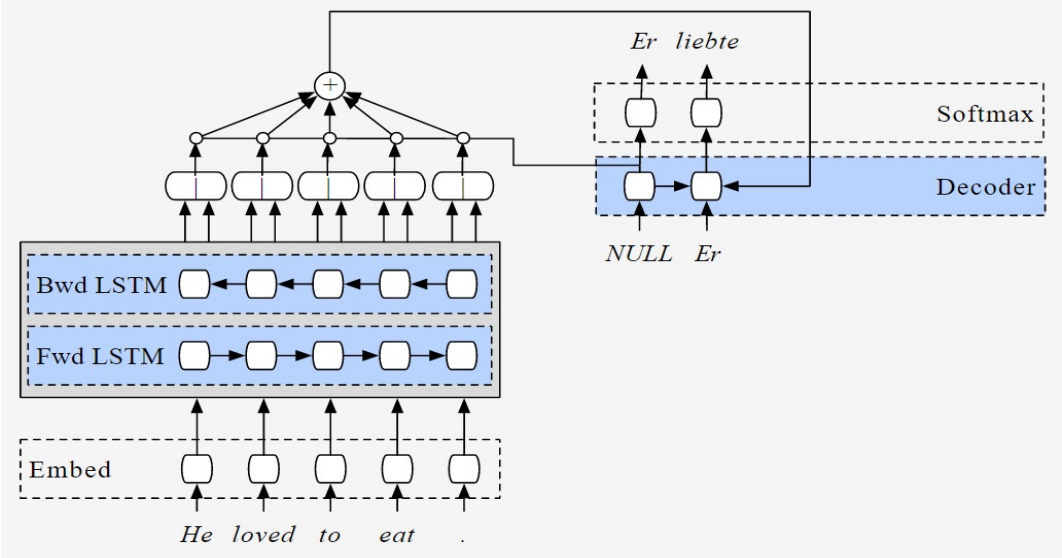


Image from Stephen Merity's http://smerity.com/articles/2016/google_nmt_arch.html

Let V, V' be the vocabularies of the source language (English) and target language (German), respectively. Each training instance is a pair consisting of (i) a sequence of one-hot vectors:

$$x_1, x_2, x_3, \ldots, x_n \in \{0,1\}^{|V|}$$

corresponding to an English sentence (each vector shows the position of the corresponding word in V) and (ii) a sequence of one-hot vectors:

$$y_1, y_2, y_3, \ldots, y_m \in \{0,1\}^{|V'|}$$

corresponding to a German sentence that is the correct (gold) translation of the English one (each vector shows the position of the corresponding word in V').

Let $E \in \mathbb{R}^{d^{(e)} \times |V|}$ and $E' \in \mathbb{R}^{d^{(e)} \times |V'|}$ contain the word embeddings of the source and target language, respectively. (Word embeddings in both languages have $d^{(e)}$ dimensions.)

The following formulae describe how the model works and how the loss (L) is computed, given a training instance. **Fill in the blanks** (for the solution, they have been filled in in red). The notation $[\ldots;\ldots]$ denotes concatenation and f, g denote activation functions.

Encoder: ($i \in \{1, 2, 3, \ldots, \mathrm{n}\}$)

$e_i = E\, x_i \in \mathbb{R}^{d^{(e)}}$ (The embedding of the English word at position *i*.)

$\vec{h}_i = \mathrm{LSTM}(\vec{h}_{i-1}, e_i) \in \mathbb{R}^{d^{(h)}}$ $\quad \vec{h}_0 \in \mathbb{R}^{d^{(h)}}$

$\overleftarrow{h}_i = \mathrm{LSTM}(\overleftarrow{h}_{i+1}, e_i) \in \mathbb{R}^{d^{(h)}}$ $\quad \overleftarrow{h}_{n+1} \in \mathbb{R}^{d^{(h)}}$

$h_i = [\vec{h}_i; \overleftarrow{h}_i] \in \mathbb{R}^{2 \cdot d^{(h)}}$

Decoder: ($i \in \{1, 2, 3, \ldots, \mathrm{n}\}$, $j \in \{1, 2, 3, \ldots, m\}$)

$t_j = E' y_j \in \mathbb{R}^{d^{(e)}}$ (The embedding of the correct German word at position *j*.)

$z_j = \mathrm{LSTM}(z_{j-1}, [t_{j-1}; c_j]) \in \mathbb{R}^{d^{(z)}}$ $\quad z_0 \in \mathbb{R}^{d^{(z)}}, t_0 \in \mathbb{R}^{d^{(e)}}$

(We assume we are in training mode and that we use teacher forcing, hence we use the correct previous German word as the previous word, which has embedding t_{j-1}.)

$\tilde{a}_{i,j} = v^T \cdot f(W^{(a)} h_i + U^{(a)} z_{j-1} + b^{(a)}) \in \mathbb{R}$

$W^{(a)} \in \mathbb{R}^{d^{(z)} \times 2 \cdot d^{(h)}}$
$U^{(a)} \in \mathbb{R}^{d^{(z)} \times d^{(z)}}$
$b^{(a)} \in \mathbb{R}^{d^{(z)}}$, $v \in \mathbb{R}^{d^{(z)}}$

$$a_{i,j} = \frac{\exp(\tilde{a}_{i,j})}{\sum_{i'=1}^{n} \exp(\tilde{a}_{i',j})}$$

$c_j = W^{(c)} \cdot g(\sum_i a_{i,j} h_i) \in \mathbb{R}^{d^{(e)}}$ $\quad W^{(c)} \in \mathbb{R}^{d^{(e)} \times 2 \cdot d^{(h)}}$

$\tilde{o}_j = W^{(o)} z_j + b^{(o)} \in \mathbb{R}^{|V'|}$

$W^{(o)} \in \mathbb{R}^{|V'| \times d^{(z)}}$
$b^{(o)} \in \mathbb{R}^{|V'|}$

$$o_{j,k} = \frac{\exp(\tilde{o}_{j,k})}{\sum_{k=1}^{|V'|} \exp(\tilde{o}_{j,k})}$$

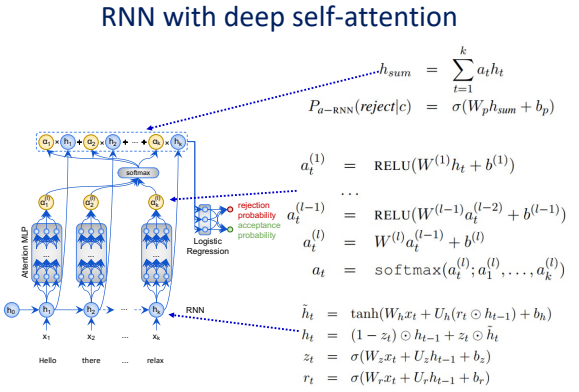
(How probable the model believes it is for the *k*-th word of the German vocabulary to be the correct word for the *j*-th position of the translation.)

$r_j = \text{argmax}_l\ y_{j,l}$ (According to the 1-hot y_j, the correct word for the j-the position of the translation is the r_j-th word of the German vocabulary.)

$L = -\sum_{j=1}^{m} \log o_{j,r_j}$ (By minimizing L, we maximize the likelihood of the correct German word, at every position of the German translation.)

6. [**optional**] Repeat exercise 3 of Part 1 (n-gram language models and context-aware spelling correction) now using an RNN language model, instead of an n-gram language model. Compare the WER and CER scores you obtain using the RNN language model to those you had obtained with the bigram and trigram language models of Part 1 (and the optional MLP language model of exercise 12 of Part 3, if you implemented it).

7. (**a**) In the neural network of slide 20, the hidden states $h_1, h_2, \ldots, h_k$ of the RNN (with GRU cells) are vectors of 128 dimensions each. The hidden layers (1), …, $(l-1)$ of the Attention MLP have 64 neurons each, and the outputs of the hidden layers are $a_t^{(1)}, \ldots, a_t^{(l-1)}$. The output layer of the Attention MLP has a single neuron with output $a_t^{(l)}$.



J. Pavlopoulos, P. Malakasiotis and I. Androutsopoulos, "Deeper Attention to Abusive User Content Moderation", EMNLP 2017, http://nlp.cs.aueb.gr/pubs/emnlp2017.pdf. 20

What are the dimensions (shapes) of $W^{(1)}, W^{(2)}, \ldots, W^{(l)}$? Briefly explain your answers.

Matrix $W^{(1)}$ has shape 64×128, to convert each vector $h_1, h_2, \ldots, h_k$ (the RNN states, which have dimensions 128×1 each) to vectors of dimensions 64×1, i.e., to vectors with as many elements as the neurons of layer (1) of the MLP. Each resulting 64×1 vector is the output $a_t^{(1)}$ (for $t = 1, \ldots, k$) of layer (1) of the MLP, when the MLP is applied to the corresponding state h_t of the RNN.

Matrices $W^{(2)}, \ldots, W^{(l-1)}$ have dimensions 64×64, to convert the 64×1 vectors that $W^{(1)}$ produces to vectors again of dimensions 64×1, i.e., to vectors with as many elements as the neurons of layers (2), …, $(l-1)$ of the MLP. Each resulting 64×1 vector is the output $a_t^{(2)}, \ldots, a_t^{(l-1)}$ of layer (2), …, $(l-1)$, respectively, of the MLP.

Matrix $W^{(l)}$ has shape 1×64 (it will be a transposed vector), to convert each vector 64×1 generated by $W^{(l-1)}$ to a single real number, i.e., it will produce the real numbers $a_1^{(l)}, \ldots, a_\kappa^{(l)}$ of slide 20.

What are the dimensions (shapes) of $b^{(1)}, b^{(2)}, \ldots, b^{(l)}$? Briefly explain your answers.

$b^{(1)}$ is a vector 64×1, to be added it to the 64×1 vector generated by the multiplication $W^{(1)} h_t$ (for $t = 1, \ldots, k$) and obtain $a_t^{(1)}$, which is also 64×1. (An activation function, here ReLU, does not change the shape of a vector it is applied to, it is simply applied to each element of the vector.)

Similarly $b^{(2)}, \ldots, b^{(l-1)}$ are vectors of shape 64×1, to add each one to the 64×1 vector generated by the multiplication $W^{(2)} a_t^{(1)}, \ldots, W^{(l-1)} a_t^{(l-2)}$, respectively (for $t = 1, \ldots, k$) and obtain the vectors $a_t^{(2)}, \ldots, a_t^{(l-1)}$, respectively, which are also 64×1 each.

$b^{(l)}$ is real number (degenerate vector 1×1), to be added to the real number produced by the multiplication $W^{(l)} a_t^{(l-1)}$ (for $t = 1, \ldots, k$) and obtain the real numbers $a_1^{(l)}, \ldots, a_k^{(l)}$.

(b) We wish to use the network of the previous slide to classify tweets (that refer to a particular product) in classes c_1 (positive opinion), c_2 (negative opinion), c_3 (no opinion), c_4 (conflict, i.e., positive and negative opinion together). Each tweet is to be classified in <u>exactly one class</u>. We replace the formula $P_{a-RNN}(\text{reject}|c) = \sigma(W_p h_{sum} + b_p)$ of the slide above with the following formula, which you need to complete. The new formula produces (on its left-hand-side) a vector $p \in \mathbb{R}^4$ containing the probabilities (one per class) that the network assigns to the input tweet. **Complete the right-hand-side of the formula and specify the dimensions (shapes) of every matrix and vector involved**. **Briefly explain your answers**.

New formula:

$p =$_____ $\in \mathbb{R}^4$

Dimensions of matrices and vectors of the right-hand-side and **brief explanation**:

The new formula will be the following.

$$p = \text{softmax}(W_p h_{sum} + b_p)$$

Matrix W_p has shape 4×128, to convert the vector h_{sum} (which has shape 128×1, since it is the sum of states of the RNN) to a vector of four real number, which the softmax then converts to a probability distribution.

b_p is a 4×1 vector, to be added to the 4×1 vector produced by the multiplication $W_p h_{sum}$.