Natural Language Processing with Deep Learning

Lecture 8 – Text generation 2: Autoregressive encoder-decoder with RNNs and attention

Prof. Dr. Ivan Habernal

November 31, 2023

Natural Language Processing Group
Paderborn University
We focus on Trustworthy Human Language Technologies

PADERBORN UNIVERSITY

www.trusthlt.org

Motivation

Language data – working with sequences (of tokens, characters, etc.)

MLP – fixed input sequence length ❌

RNN – variable length of **input** sequence ✔

What about variable lengths of **output** sequences (compared to input)?

- Text classification ✔
- Sequence labeling ✔
- Sequence generation: translation, summarization 🤔

Overview of NLP tasks

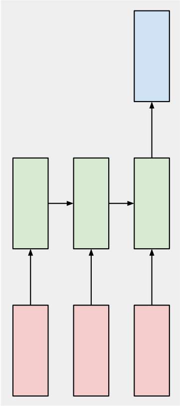
Overview of NLP tasks

Encoder-decoder architectures

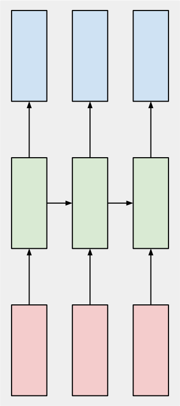
The attention mechanism

- Abstracted attention mechanism
- The attention mechanism: design choices

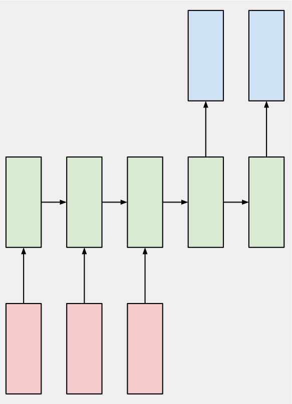
Overview of NLP tasks



(a) Seq. classification

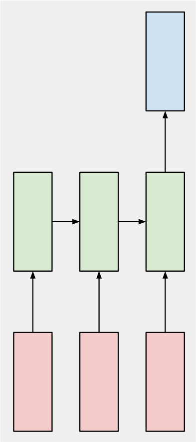


(b) Seq. labeling



(c) Sequence-to-sequence

Sequence classification



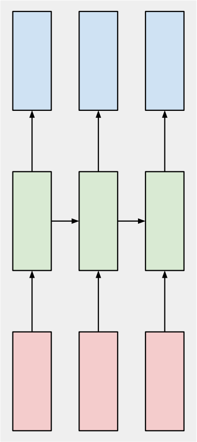
Determine a label for one (or more) text sequences

- News article categorization, sentiment analysis,...

Approach

1. Encode sequence(s) into a sequence representation
2. Pass sequence representation to decoder layer

Sequence labeling



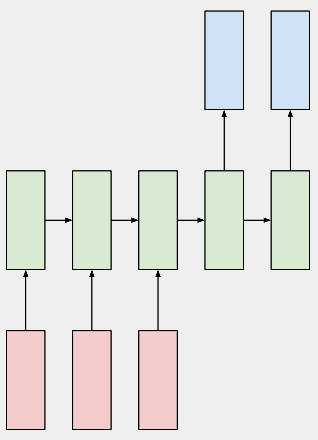
Determine a label for **each element** of a sequence

- Part-of-speech tagging, named entity recognition,...

Approach

1. Encode (contextualize) sequence elements
2. Pass representation of each element to (same) decoder layer

Sequence to sequence



Generate a sequence of tokens given a sequence of tokens

- Machine translation, summarization, text generation,…

Approach

1. Use encoder network to encode input sequence
2. Use decoder network to generate output sequence

Encoder-decoder architectures

The problem of variable output sequence length

We have a sequence of n **input** vectors $\boldsymbol{x}_{1:n} = \boldsymbol{x}_1, \dots, \boldsymbol{x}_n$

Each input vector has the same dimension d_{in} : $\boldsymbol{x}_i \in \mathbb{R}^{d_{in}}$

We also have a **sequence** of d_{out}-dimensional vector $\boldsymbol{y}_{1:\hat{n}} \in \mathbb{R}^{\hat{n} \times d_{out}}$ **outputs**

RNNs produce a sequence of outputs

$$\boldsymbol{y}_{1:n} = \mathrm{RNN}(\boldsymbol{x}_{1:n})$$

- **What are we missing?**
  - The input and output sequence are rarely of same length

Generating a variable length sequence

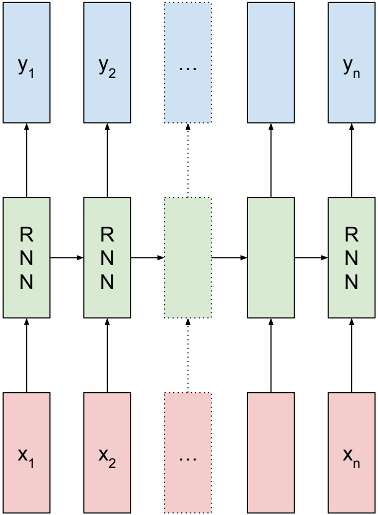
Translate to German: *I like attending deep learning lectures*

Output: *Ich besuche gerne Deep-Learning-Vorlesungen*

Current approach:

1. Tokenize input sequence
2. Obtain a word embedding (e.g. word2vec) for each token
3. Use a RNN (e.g. LSTM) to encode sequence of tokens
4. Generate token sequence in target language
    - Multi-class classification over target vocabulary

Generating a variable length sequence

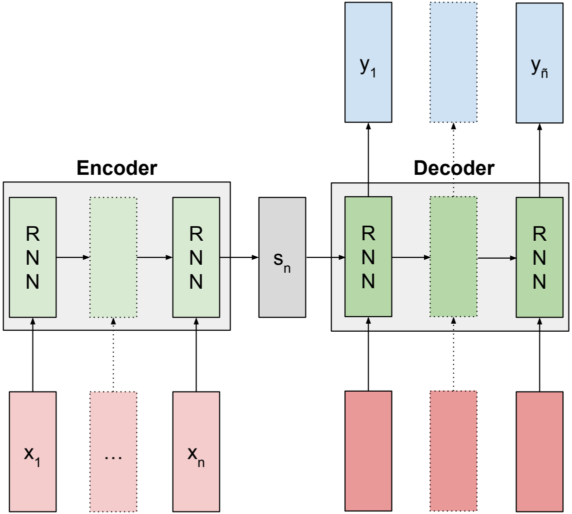


How to solve the issue of varying input/output lengths?

1. We **don't have to** stop generating after the last input
2. We can only consider outputs up to a special **"end token"**

Neither ideal

Sequence-to-sequence models



Two networks

- **Encoder** (reader) RNN
- **Decoder** (writer) RNN

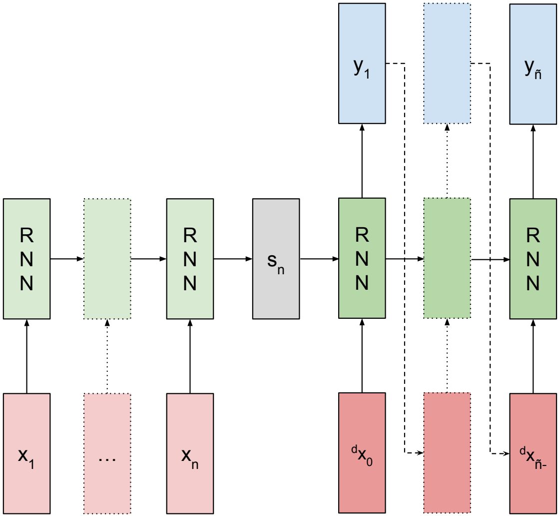
Note:

- Encoder and decoder have **separate** params

The encoder-decoder architecture specifics

1. How to **initialize** decoder hidden **state**?
    - $h_0^{dec} = h_n^{enc}$: simply copy the last encoder state
    - $h_0^{dec} = \text{NN}_\theta(h_n^{enc})$: transform the last encoder state
2. When do we **stop generating** with the decoder?
    - We use a **special token** (<EOS>, \n) to indicate the end-of-sequence
    - When the **maximum generation length** is exceeded
3. What are the **inputs** of the decoder?
    - The **previous output** of the decoder
        - Teacher forcing (with probability p): use the **correct output**
    - What is the **initial input** x_0^{dec}?
        - A beginning-of-sequence **special token** (<BOS>)

The encoder-decoder architecture



Decoder inputs

- x_0^{dec} = <BOS>
- $x_i^{dec} = y_i^{dec}$ **if** no teacher forcing
- $x_i^{dec} = \hat{y}_i$ **if** we use teacher forcing

Summary

- Sequence generation tasks difficult to solve with a single RNN
- Encoder-decoder architecture: use two separate RNN networks
  - The encoder reads the input text and compresses it into a fixed size vector
  - The decoder uses the input text representation and generates output text
- Encoder-decoder specifics:
  - Special tokens: <BOS>, <EOS>
  - Helping the network: teacher forcing

The attention mechanism

Overview of NLP tasks

Encoder-decoder architectures

The attention mechanism

- Abstracted attention mechanism
- The attention mechanism: design choices

Motivation

… we apply our multilayer bidirectional LSTM network to a machine translation problem.

What **types of instances** would it perform bad on? **Why**?

The problem of **long dependencies**

- The hidden state of a RNN network is **finite**
- The more tokens the RNN reads, the less it remembers **individual** tokens

The long dependency problem

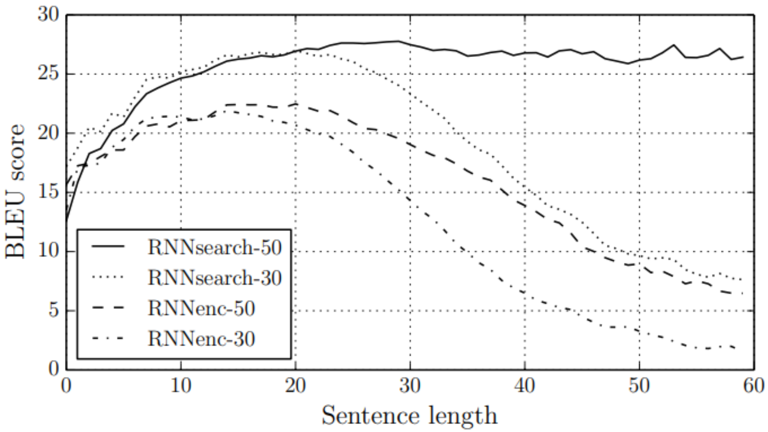


Figure from Bahdanau, Cho, and Bengio, 2015

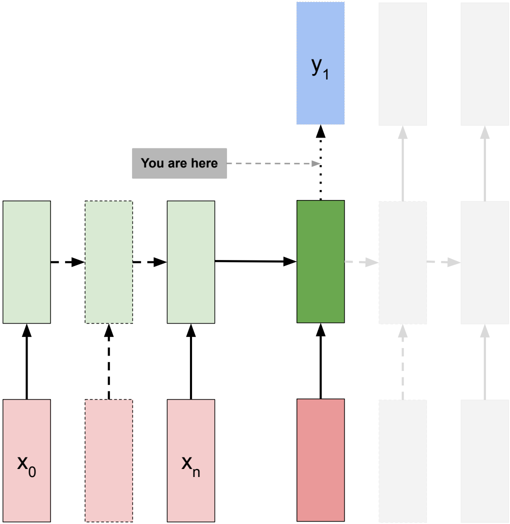
D. Bahdanau, K. Cho, and Y. Bengio (2015). **"Neural Machine Translation by Jointly Learning to Align and Translate".** In: *3rd International Conference on Learning Representations (ICLR)*. ed. by Y. Bengio and Y. LeCun. San Diego, CA, USA

The attention mechanism: intuition

Idea: our recurrent state does not have perfect memory of previous content. However, it should know which content **was relevant**.

- Attention allows the network to **view previous states**

The attention mechanism: visual context



The attention mechanism: formalization

A standard encoder-decoder network produces a **sequence of states** $s_i^{\text{enc/dec}}$

At a (decoder) time-step t, we want to obtain a **fixed size** update (with respect to sequence length N) representing **relevant information** from the past

We **have**: s_t^{dec}, $S^{\text{enc}} = \{s_i^{\text{enc}}\}_{i=1}^{n}$, we **want**:
$a \approx \text{relevant}(S^{\text{enc}} | s_t^{\text{dec}})$

The attention mechanism: formalization

1. Compute the **energy** (similarity, relevance) function between two dense vectors (the **current** decoder state and **one** encoder state)

$$\alpha_i = \mathsf{attn}(s_i^{\mathsf{enc}}, s_t^{\mathsf{dec}}) \approx \underbrace{s_i^{\mathsf{enc}} \cdot s_t^{\mathsf{dec}}}_{\text{dot product}}$$

The attention mechanism: formalization

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin (2017). **“Attention Is All You Need”.** In: *Advances in Neural Information Processing Systems 30*. Long Beach, CA, USA: Curran Associates, Inc., pp. 5998–6008

2. We **scale** the output of the dot product to preserve scale of variance (Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser, and Polosukhin, 2017) (otherwise values get too large – issue for next step)

$$\hat{\alpha}_i = \frac{s_i^{\text{enc}} \cdot s_t^{\text{dec}}}{\sqrt{d_{\text{dec}}}}$$

d_{dec} is the dimensionality of the decoder state

The attention mechanism: formalization

3. We **normalize** the energy to a probability distribution over (encoder) states

$$\alpha_i = \text{softmax}(\hat{\alpha}_i) = \frac{\exp(\hat{\alpha}_i)}{\sum_j^N \exp(\hat{\alpha}_j)}$$

Why would the scale of $\hat{\alpha}_i$ be an issue? (softmax)

The attention mechanism: formalization

We now have **importance** α_i of each (encoder) element.
How to produce the *summary* a?

4. We can **sum** over the elements with α_i as the elements' weight!

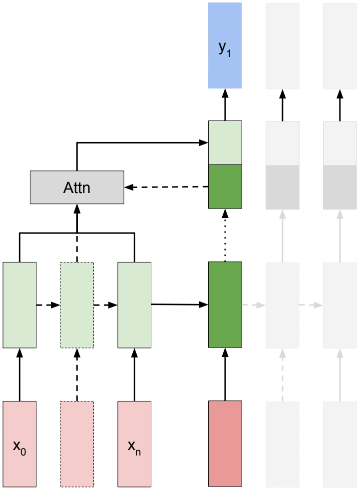
$$a = \sum_{i}^{n} \alpha_i s_i^{\text{enc}}$$

- $\alpha_i \approx$ **importance** of state s_i^{enc}
- $s_i^{\text{enc}} \approx$ information we are **recalling**

This is the initial formulation of **dot-product encoder-decoder** attention.

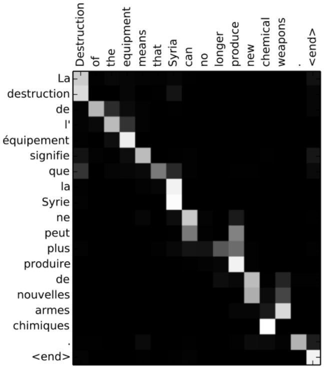
- Attention is a weighted sum over a set of elements.

The attention mechanism: visual context



1. Given the current decoder state s_t^{dec} and encoder states $S^{\text{enc}} = \{s_i^{\text{enc}}\}_{i=1}^{n}$ compute the output of the attention mechanism $a_t = \sum_i^n \alpha_i s_i^{\text{enc}}$
2. **Concatenate** the output of attention and the current decoder state $\hat{s}_t^{\text{dec}} = [s_t^{\text{dec}} | a_t]$
3. Predict the next token y_t

The attention mechanism: visualizing attention

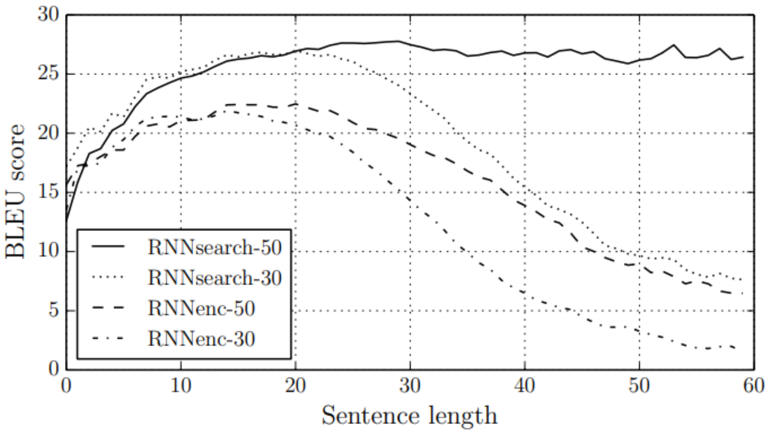


D. Bahdanau, K. Cho, and Y. Bengio (2015). **"Neural Machine Translation by Jointly Learning to Align and Translate".** In: *3rd International Conference on Learning Representations (ICLR)*. ed. by Y. Bengio and Y. LeCun. San Diego, CA, USA

White = attention (btw enc. and dec. state) is high. Black = attention is low.

Figure from Bahdanau, Cho, and Bengio, 2015.

The attention mechanism: effect of attention



RNNsearch architectures use attention. Figure from Bahdanau, Cho, and Bengio, 2015.

D. Bahdanau, K. Cho, and Y. Bengio (2015). **"Neural Machine Translation by Jointly Learning to Align and Translate".** In: *3rd International Conference on Learning Representations (ICLR)*. ed. by Y. Bengio and Y. LeCun. San Diego, CA, USA

The attention mechanism

Abstracted attention mechanism

The attention mechanism: abstraction (Components)

1. The **query** $q = f_q(s_t^{\text{dec}}); \quad q \in \mathbb{R}^{d_q}$
   - The query is the state representation based on which we **seek information**
2. The **keys** $K = f_k(\{s_i^{\text{enc}}\}_{i=1}^{n}); \quad K \in \mathbb{R}^{n \times d_k}$
   - The keys are the representations we **compare** the query to
3. The **values** $V = f_v(\{s_i^{\text{enc}}\}_{i=1}^{n}); \quad V \in \mathbb{R}^{n \times d_v}$
   - The values are the representations we **sum over** given the attention scores

Where f_q, f_k, f_v are arbitrary functions (neural network layers).

$$a = \sum_i^n \alpha_i v_i \qquad (1) \qquad\qquad \hat{\alpha}_i = \frac{q^T \cdot k_i}{\sqrt{d_{\text{dec}}}} \qquad (2)$$

The attention mechanism

The attention mechanism: design choices

The attention mechanism: choices

Key choices when using the attention mechanism:

1. The **energy** (similarity, relevance) function
   - Defines how we **compute energy** between two state representations
2. Parametrization
   - Determines how (and if) we **apply transformations** to attention components
3. Direction
   - Determines which components we **attend over**

The attention mechanism: energy

1. The **energy** (similarity, relevance) function
    - Dot product attention

$$\hat{\alpha}_i = \frac{q^T \cdot k_i}{\sqrt{d_k}}$$

- Requires $\dim(q) = \dim(k)$
- Introduces **no additional parameters**

The attention mechanism: energy

1. The **energy** (similarity, relevance) function
   - Bahdanau (**tanh**) attention ($[\cdot|\cdot]$ = concatenate)

$$\hat{\alpha}_i = W_2 \text{tanh}(W_1 [q | k_i])$$

- **No requirements** on dimensions of inputs (states)
- Additional parameters $W_1 \in \mathbb{R}^{(d_q + d_k) \times h}$, $W_2 \in \mathbb{R}^h$
- h is the dimension of the **attention hidden layer**

The attention mechanism: energy

1. The **energy** (similarity, relevance) function
    - **Bilinear** attention

$$\alpha_i = q^T W k_i$$

- **No requirements** on dimensions of states
- Additional parameters $W \in \mathbb{R}^{d_q \times d_k}$

The attention mechanism: parametrization

2. Parametrizations of inputs & outputs

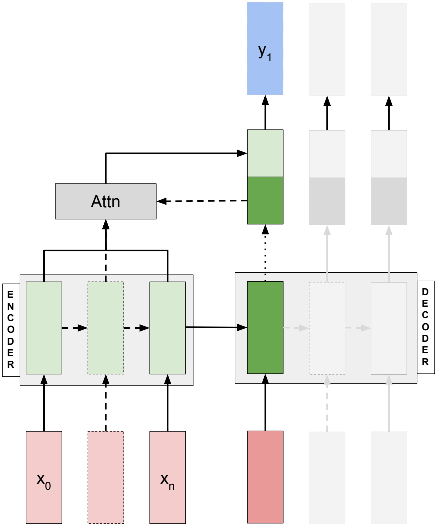
   Remember: f_q, f_k, f_v are arbitrary functions (neural network layers).

   What are the most common ways to parametrize these functions?

   - Linear transformations: $f_{\{q,k,v\}} \in \mathbb{R}^{d_{\{q,k,v\}\_in} \times d_{\{q,k,v\}}}$

   Intuition: hidden states contain information which is not relevant for **computing energy** (query, keys) or **retrieving information** (values) – linear transformations can filter (map to null space) unnecessary information.

The attention mechanism: direction



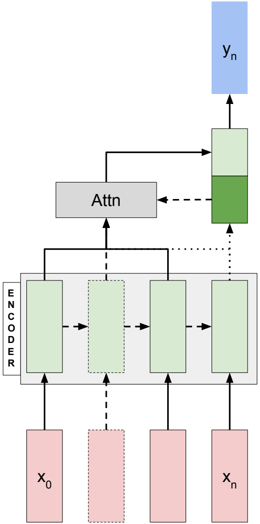
3. <u>Direction of attention</u>

   We have so far only shown encoder-decoder **cross attention**

   Flavors of attention

   - **Cross-attention**: between encoder and decoder (or any **query** and **a sequence** of hidden states)

The attention mechanism: direction



3. Direction of attention

   We have so far only shown encoder-decoder **cross attention**

   Flavors of attention

   - **Self-attention**: between a sequence of hidden states and a query originating from the **same sequence** of hidden states

Recap

Overview of NLP tasks

Encoder-decoder architectures

The attention mechanism

- Abstracted attention mechanism
- The attention mechanism: design choices

Take aways

- Encoder-decoder architecture – used for generating variable (wrt. input) length sequences
- Three classes of sequence problems: classification, labeling & seq2seq
- RNNs are bad at long dependencies
- Attention mechanism allows networks to *look at* previous states
- Abstraction of attention mechanism: (1) query, (2) keys, (3) values
- Design choices of attention: (1) energy function, (2) parametrization, (3) direction

License and credits

Credits

Ivan Habernal, Martin Tutek