Deep Learning for Natural Language Processing

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

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June 06, 2023

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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 🤔

Encoder-decoder architectures

The problem of variable output sequence length

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

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

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

RNNs produce a sequence of outputs

$$\mathbf{y}_{1:n} = \text{RNN}(\mathbf{x}_{1:n})$$

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

Generating a variable length sequence

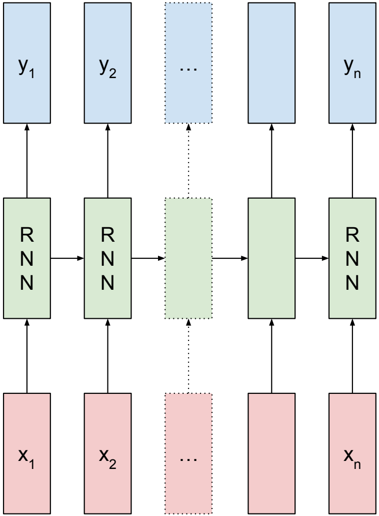
Translate to German: *I like attending deep learning lectures*

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

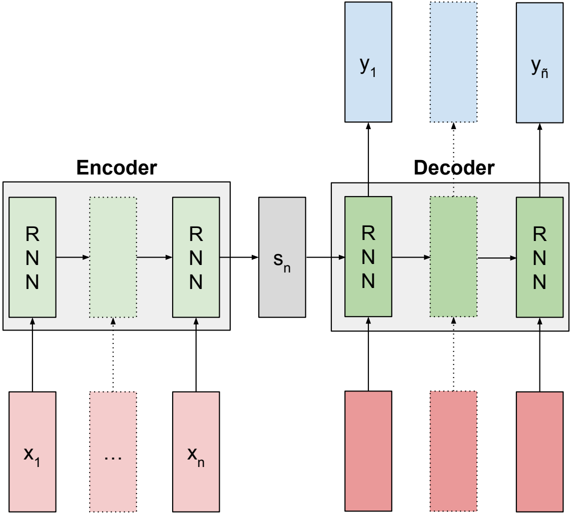


How to solve the issue of varying input/output lengths?

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

Both of these approaches are not ideal

Sequence-to-sequence models



Idea: separate the solution into two networks

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

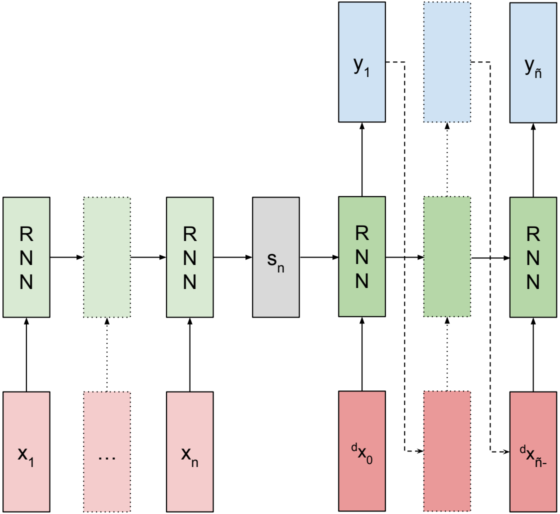
Note:

- Encoder and decoder have **separate** parameters
- Initial state of decoder = **last state** of encoder

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 (**Why?**)
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

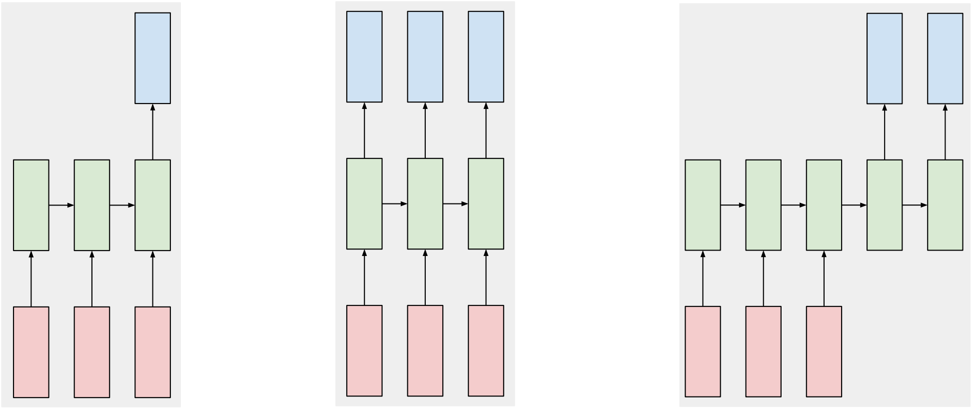
- $x_0^{dec} = \text{<BOS>}$
- $x_i^{dec} = y_i^{dec}$ **if** no teacher forcing
- $x_i^{dec} = \hat{y}_i$ **if** we use teacher forcing

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

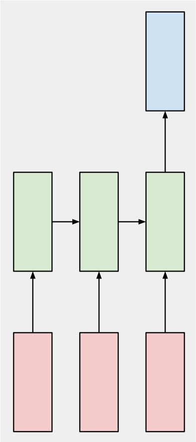
Overview of NLP tasks

Overview of NLP tasks



(a) Seq. classification (b) Seq. labeling (c) Sequence-to-sequence

Sequence classification



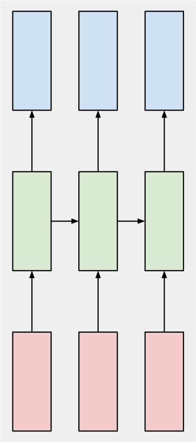
Determine a label for one (or more) text sequences

- News article categorization, sentiment analysis,...

Approach

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

Sequence labeling



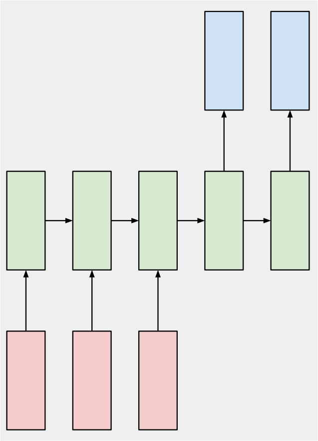
Determine a label for **each element** of a sequence

- 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

The attention mechanism

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

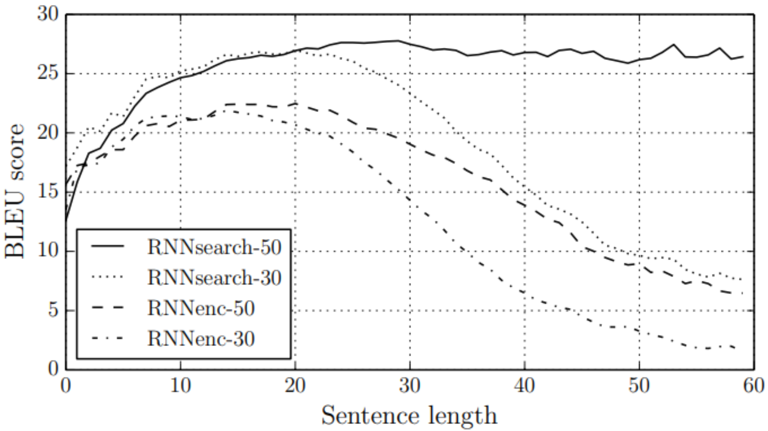


Figure from Bahdanau et al., 2014

The attention mechanism: intuition

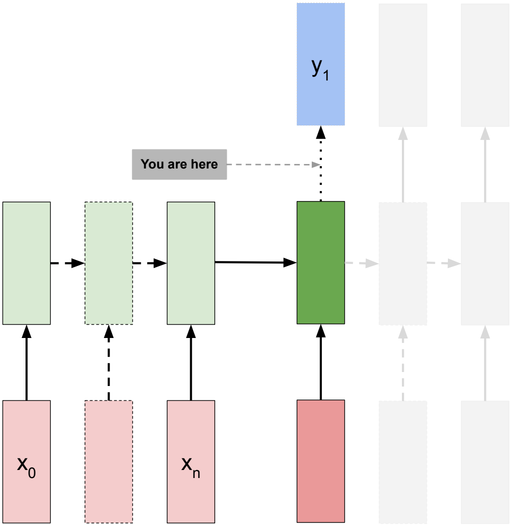
"When I'm translating a sentence, I pay special attention to the word I'm presently translating. When I'm transcribing an audio recording, I listen carefully to the segment I'm actively writing down. And if you ask me to describe the room I'm sitting in, I'll glance around at the objects I'm describing as I do so."

– By Christopher Olah

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**: $a \approx \text{relevant}(S^{\text{enc}} | s_t^{\text{dec}})$

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

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

The attention mechanism: formalization

2. We **scale** the output of the dot product to preserve scale of variance (Vaswani et al., 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 (Why decoder?)

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

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

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!

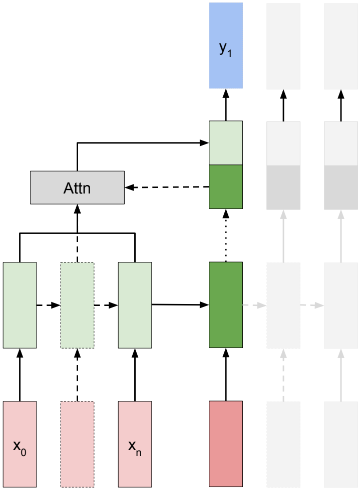
$$a = \sum_{i}^{n} \alpha_i s_i^{\text{enc}}$$

- $\alpha_i \approx$ **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.

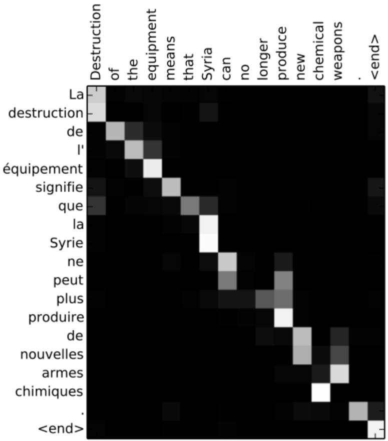
- Attention is a weighted (convex) sum over a set of elements.

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

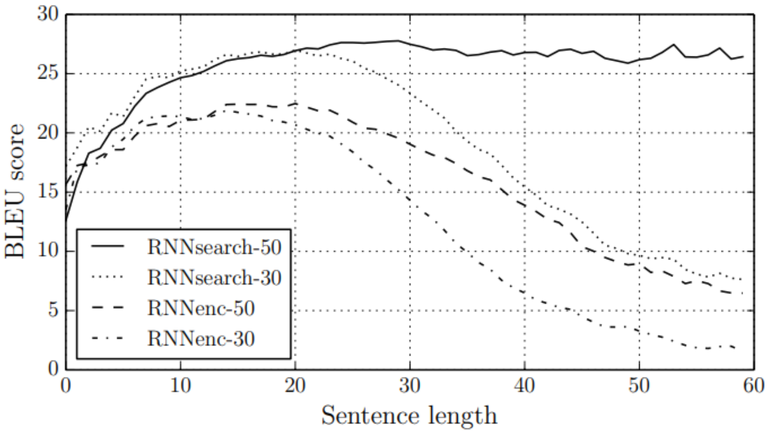
The attention mechanism: visalizing attention



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

Figure from Bahdanau et al., 2014.

The attention mechanism: effect of attention



RNNsearch architectures use attention. Figure from Bahdanau et al., 2014.

The attention mechanism

Abstracted attention mechanism

The attention mechanism: abstraction

Components of the attention mechanism

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).

$$a = \sum_i^n \alpha_i v_i \tag{1}$$

$$\hat{\alpha}_i = \frac{q^T \cdot k_i}{\sqrt{d_{\text{dec}}}} \tag{2}$$

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 ([·|·] = concatenate)

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

- **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

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

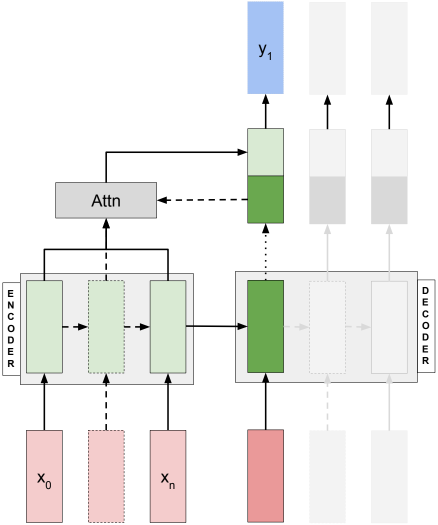
      - **No requirements** on dimensions of states
      - Additional parameters $W \in \mathbb{R}^{d_q \times d_k}$

The attention mechanism: parametrization

2. <u>Parametrizations of inputs & outputs</u>
   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



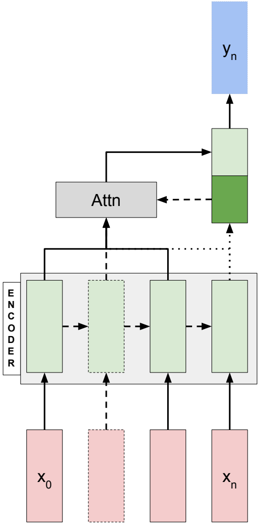
3. <u>Direction of attention</u>

   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. <u>Direction of attention</u>

   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

Encoder-decoder architectures

Overview of NLP tasks

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

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