# Natural Language Processing with Deep Learning

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


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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 ✔

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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

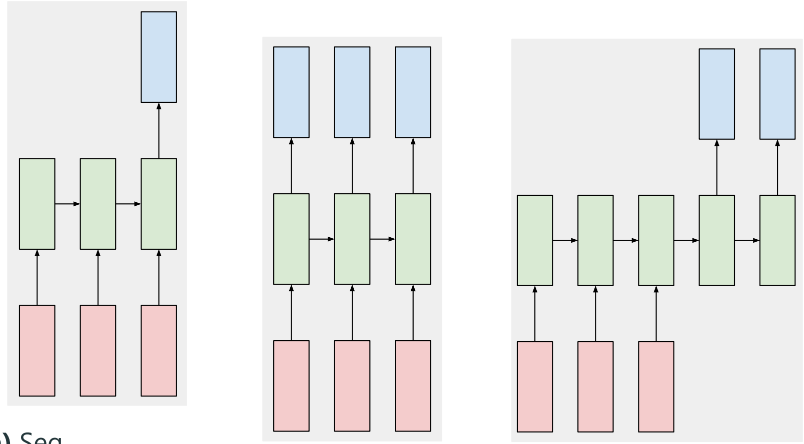

Overview of NLP tasks

Encoder-decoder architectures

The attention mechanism

- Abstracted attention mechanism
- The attention mechanism: design choices

# Overview of NLP tasks

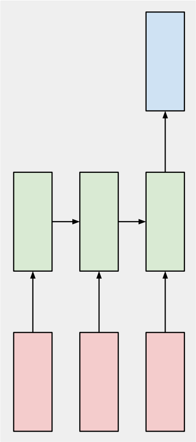


**(a)** Seq. classification

**(b)** Seq. labeling

**(c)** Sequence-to-sequence

# Sequence classification



Determine a label for one (or more) text sequences

- News article categorization, sentiment analysis,...

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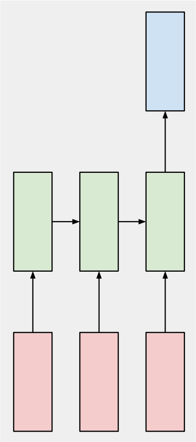

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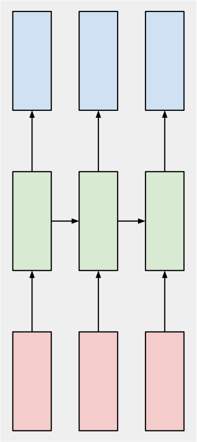
**Approach**

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,...

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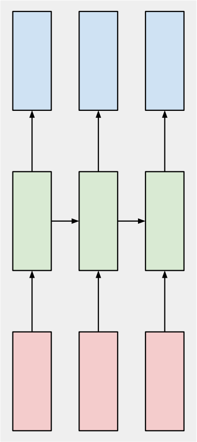

Determine a label for **each element** of a sequence

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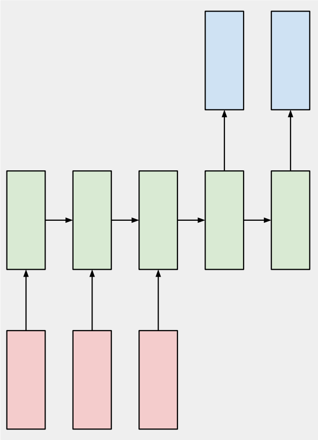
**Approach**

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

Overview of NLP tasks
Encoder-decoder architectures
The attention mechanism
    Abstracted attention mechanism
    The attention mechanism: design choices

# The problem of variable output sequence length

We have a sequence of $n$ **input** vectors $\boldsymbol{x_{1:n}} = \boldsymbol{x_1}, \ldots, \boldsymbol{x_n}$

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

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  - The input and output sequence are rarely of same length

# Generating a variable length sequence

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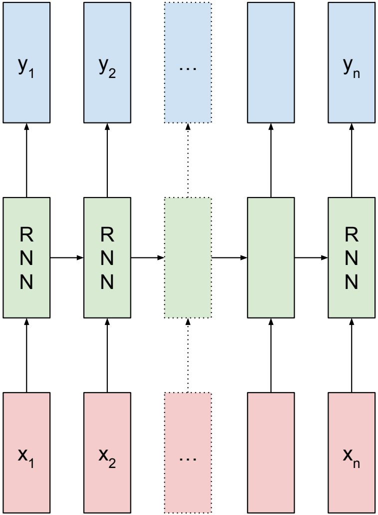

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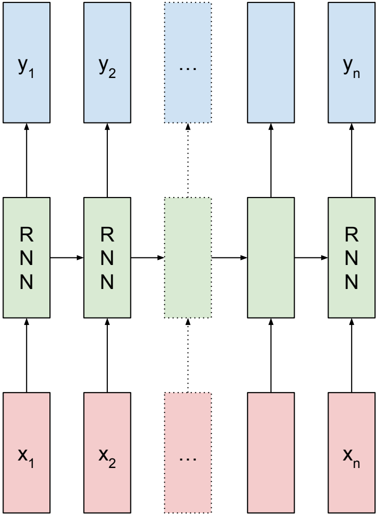


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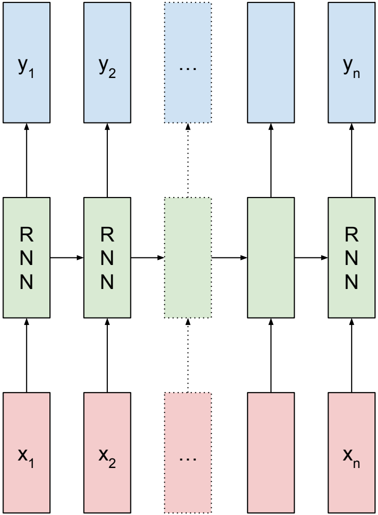


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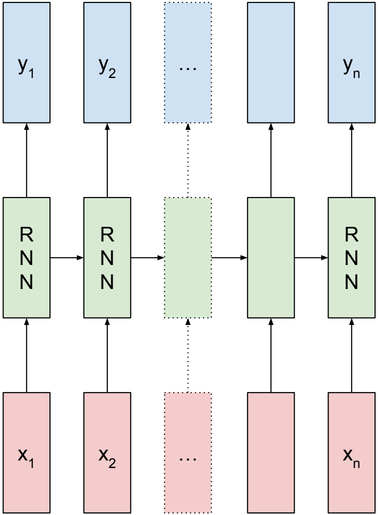


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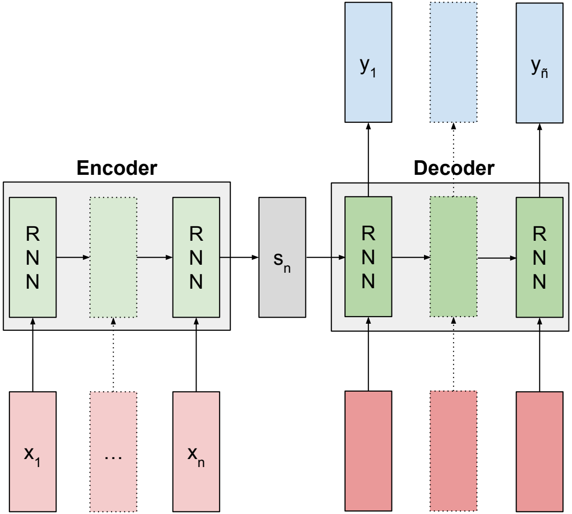

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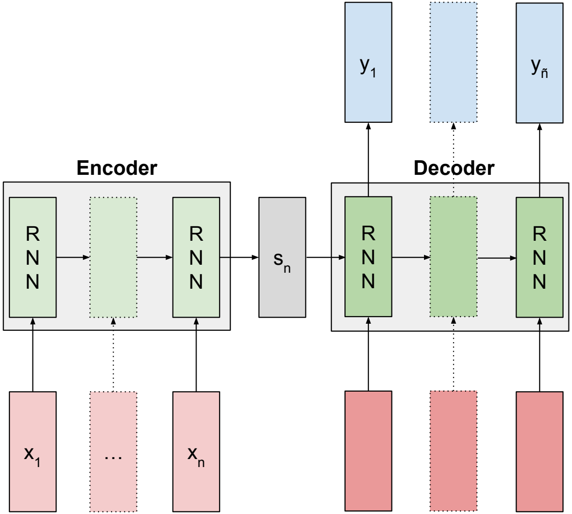


Two networks

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

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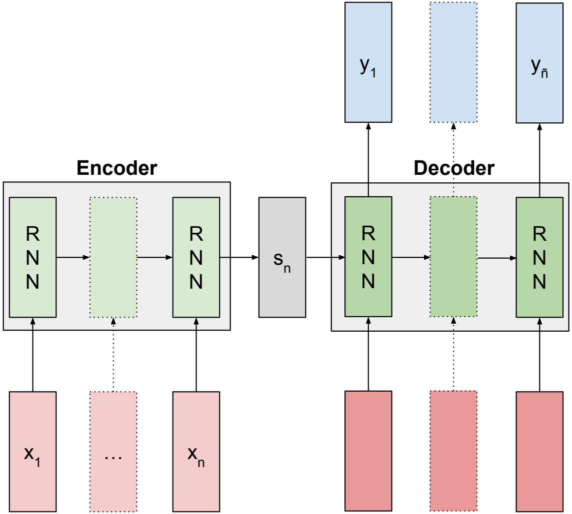


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Note:

- Encoder and decoder have **separate** params

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     - A beginning-of-sequence **special token** (<BOS>)

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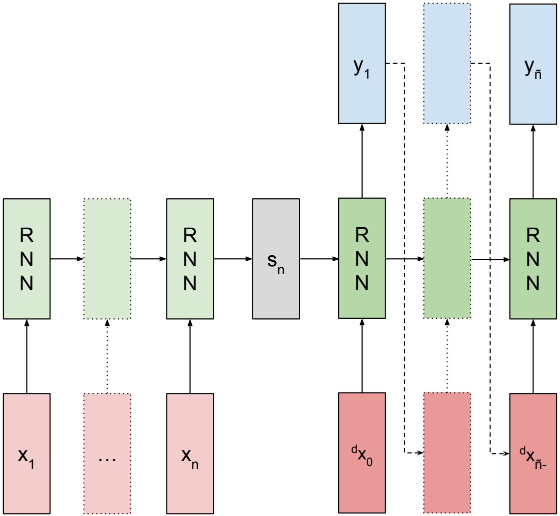

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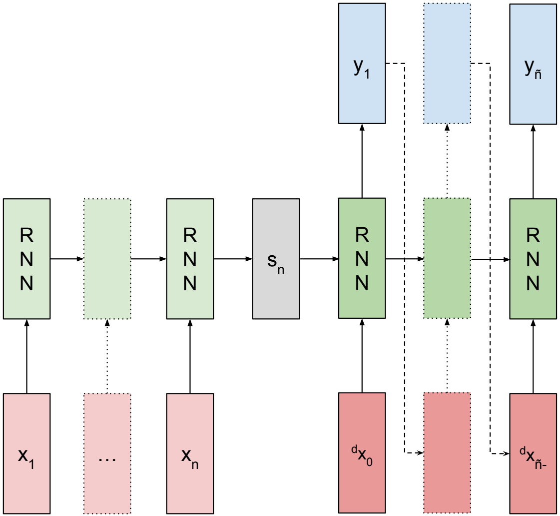


Decoder inputs

- $x_0^{dec}$ = <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

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

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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

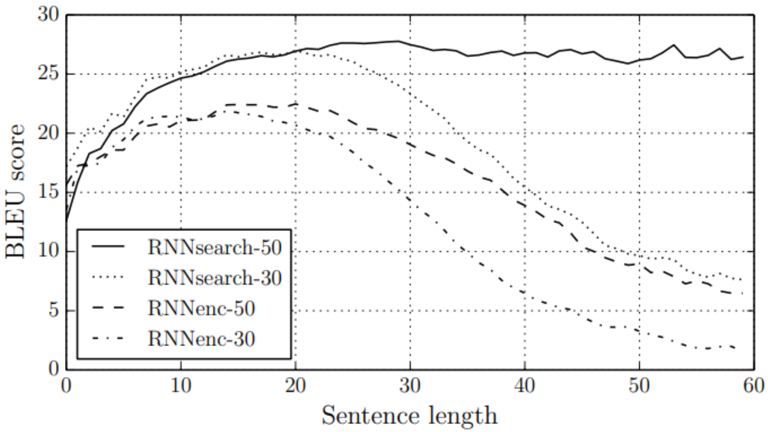


Figure from Bahdanau, Cho, and Bengio, 2015

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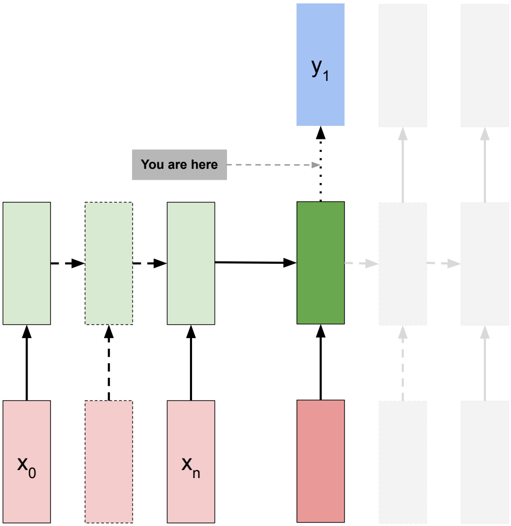
# The attention mechanism: intuition

**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



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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**: $s_t^{\text{dec}}$, $S^{\text{enc}} = \{s_i^{\text{enc}}\}_{i=1}^{n}$, 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)

$$\alpha_i = \mathsf{attn}(s_i^{\mathsf{enc}}, s_t^{\mathsf{dec}})$$

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

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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)

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

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$d_{\text{dec}}$ is the dimensionality of the decoder state

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

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

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

4. We can **sum** over the elements with $\alpha_i$ as the elements' weight!

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

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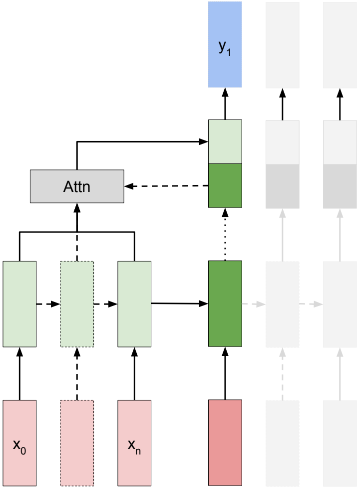
This is the initial formulation of **dot-product encoder-decoder** attention.

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

# The attention mechanism: visual context



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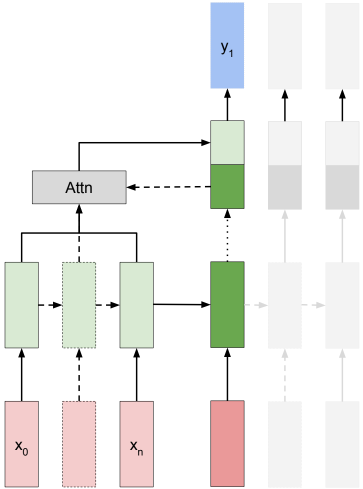


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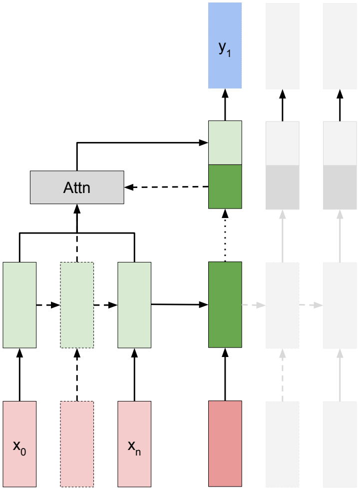


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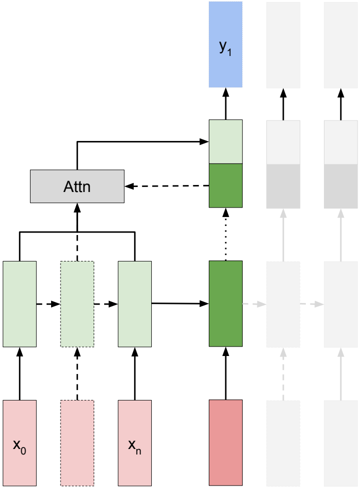


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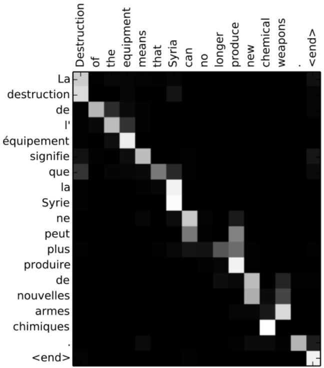
3. Predict the next token $y_t$

# The attention mechanism: visualizing attention

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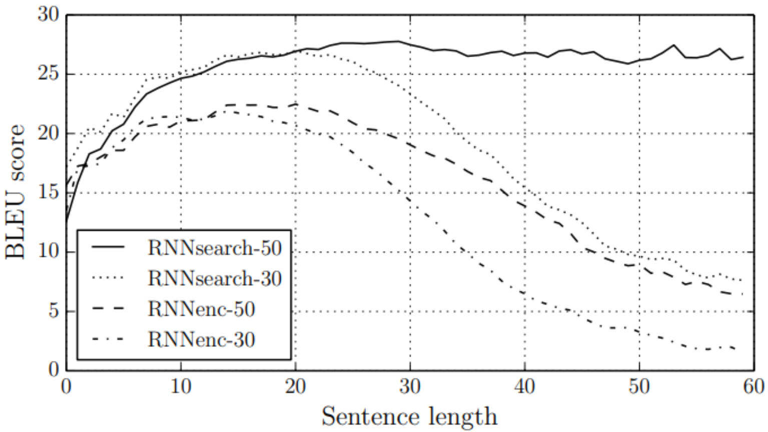
White = attention (btw enc. and dec. state) is high. Black = attention is low.

Figure from Bahdanau, Cho, and Bengio, 2015.

# The attention mechanism: effect of attention

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

# The attention mechanism

## Abstracted attention mechanism

# The attention mechanism: abstraction (Components)

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   - 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

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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

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- 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)

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

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- **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

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   - **Bilinear** attention

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# The attention mechanism: parametrization

2. Parametrizations of inputs & outputs
   Remember: $f_q, f_k, f_v$ are arbitrary functions (neural network layers).

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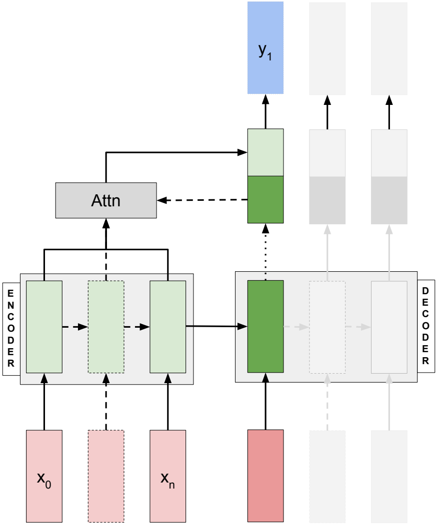
   **Intuition**: hidden states contain information which is not relevant for **computing energy** (query, keys) or **retrieving information** (values) – linear transformations can filter (map to null space) unnecessary information.

# The attention mechanism: direction

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

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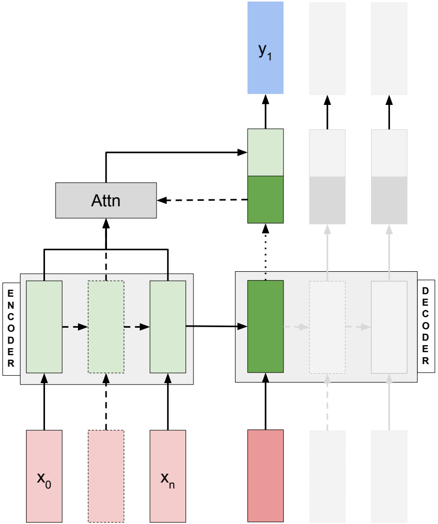
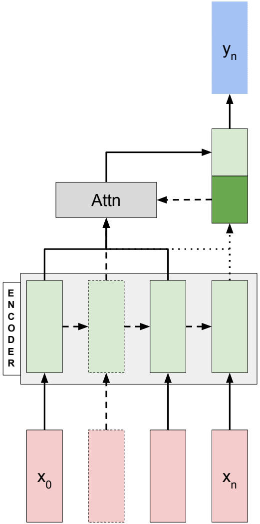



3. <u>Direction of attention</u>
   We have so far only shown encoder-decoder **cross attention**
   Flavors of attention
   - **Cross-attention**: between encoder and decoder (or any **query** and **a sequence** of hidden states)

# The attention mechanism: direction

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   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