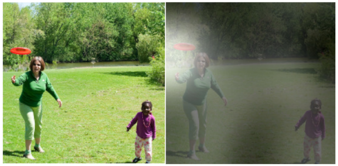
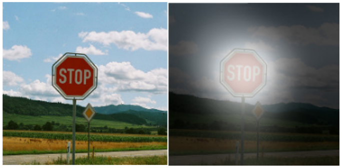
# Deep Learning

# Attention and Transformers


A woman is throwing a frisbee in a park.


A stop sign is on a road with a mountain in the background.

## Learning goals

- Attention
- Transformers
- RNN vs CNN

# Attention

## ATTENTION

- In a classical decoder-encoder RNN all information about the input sequence must be incorporated into the final hidden state, which is then passed as an input to the decoder network.
- With a long input sequence this fixed-sized context vector is unlikely to capture all relevant information about the past.
- Each hidden state contains mostly information from recent inputs.
- Key idea: Allow the decoder to access all the hidden states of the encoder (instead of just the final one) so that it can dynamically decide which ones are relevant at each time-step of the decoding process.
- This means the decoder can choose to "focus" on different hidden states (of the encoder) at different time-steps of the decoding process similar to how the human eye can focus on different regions of the visual field.
- This is known as an **attention mechanism**.

## ATTENTION

- The attention mechanism is implemented by an additional component in the decoder.
- For example, this can be a simple single-hidden layer feed-forward neural network which is trained along with the RNN.
- At any given time-step $i$ of the decoding process, the network computes the relevance of encoder state $\boldsymbol{z}^{[j]}$ as:

$$rel(\boldsymbol{z}^{[j]})^{[i]} = \boldsymbol{v}_a^\top \tanh(\boldsymbol{W}_a[\boldsymbol{g}^{[i-1]}; \boldsymbol{z}^{[j]}])$$

  where $\boldsymbol{v}_a$ and $\boldsymbol{W}_a$ are the parameters of the feed-forward network, $\boldsymbol{g}^{[i-1]}$ is the decoder state from the previous time-step and ';' indicates concatenation.
- The relevance scores (for all the encoder hidden states) are then normalized which gives the *attention weights* $(\alpha^{[j]})^{[i]}$:

$$(\alpha^{[j]})^{[i]} = \frac{\exp(rel(\boldsymbol{z}^{[j]})^{[i]})}{\sum_{j'} \exp(rel(\boldsymbol{z}^{[j']})^{[i]})}$$

## ATTENTION

- The attention mechanism allows the decoder network to focus on different parts of the input sequence by adding connections from all hidden states of the encoder to each hidden state of the decoder.

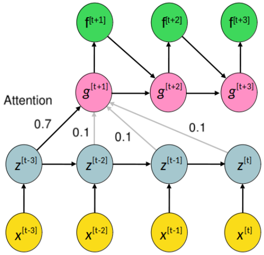


**Figure:** Attention at $i = t + 1$

## ATTENTION

- At each time step *i*, a set of weights $(\alpha^{[j]})^{[i]}$ is computed which determine how to combine the hidden states of the encoder into a context vector $c^{[i]} = \sum_{j=1}^{n_x} (\alpha^{[j]})^{[i]} \boldsymbol{z}^{[j]}$, which holds the necessary information to predict the correct output.

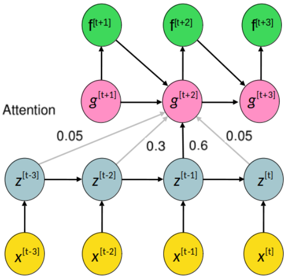
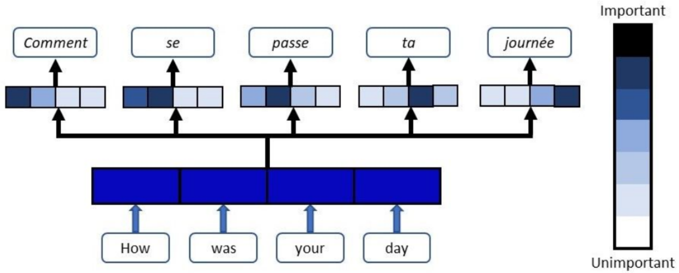


**Figure:** Attention at $i = t + 2$

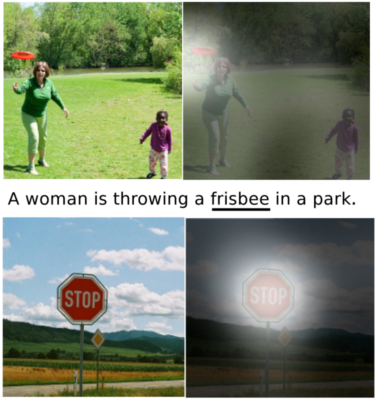
## ATTENTION



Credit: Gabriel Loye

**Figure:** An illustration of a machine translation task using an encoder-decoder model with an attention mechanism. The attention weights at each time-step of the decoding/translation process indicate which parts of the input sequence are most relevant. (There are 4 attention weights because there are 4 encoder states.)

## ATTENTION



A woman is throwing a frisbee in a park.

A stop sign is on a road with a mountain in the background.

**Figure:** Attention for image captioning: the attention mechanism tells the network roughly which pixels to pay attention to when writing the text (Kelvin Xu al. 2015)

## TRANSFORMERS

- Advanced RNNs have similar limitations as vanilla RNN network.
  - Lack of parallelization, RNNs process the input data sequentially, as the output of a step depends on the output of the previous step.
  - Difficulties in learning long term dependency, Although GRU or LSTM perform superior compared to vanilla RNN, even they struggle to remember the context from a word which stands much earlier in long sequences.
- These challenges are successfully tackled by transformer networks.

## TRANSFORMERS

- Transformers are solely based on attention (no RNN or CNN).
- In fact, the paper which coined the term *transformer* is called *Attention is all you need*.
- They are the state-of-the-art networks in natural language processing (NLP) tasks since 2017.
- Transformer architectures like BERT (Bidirectional Encoder Representations from Transformers, 2018) and GPT-3 (Generative Pre-trained Transformer-3, 2020) are pre-trained in a large text and can be fine-tuned (quickly adapt) to specific language tasks.

## CNNs or RNNs?

## CNNS OR RNNS?

- Historically, RNNs were the default models used in sequence processing tasks.
- However, some families of CNNs (especially those based on Fully Convolutional Networks (FCNs)) *can* be used to process variable-length sequences such as text or time-series data.
- If a CNN doesn't contain any fully-connected layers, the total number of weights in the network is independent of the spatial dimensions of the input because of weight-sharing in the convolutional layers.
- Recent research [Bai et al. , 2018] indicates that such convolutional architectures (which the authors term Temporal Convolutional Networks (TCNs)) can outperform RNNs on a wide range of tasks.
- A major advantage of TCNs is that the entire input sequence can be fed to the network at once (as opposed to sequentially).

## CNNS OR RNNS?

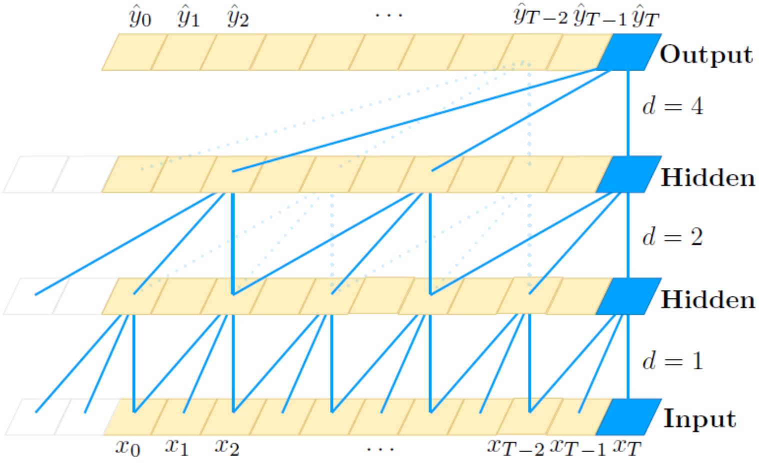
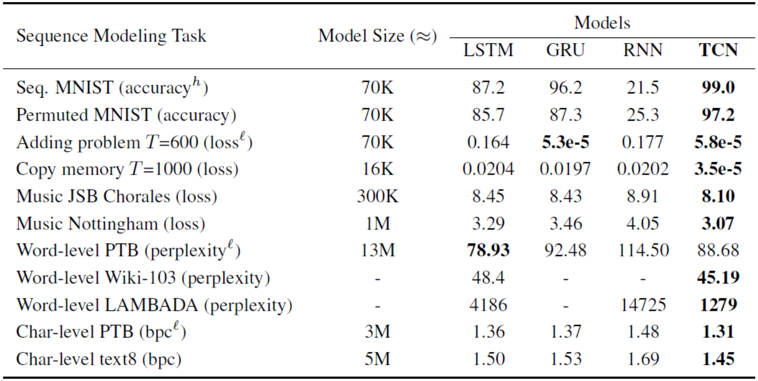

$\hat{y}_0$ $\hat{y}_1$ $\hat{y}_2$ $\cdots$ $\hat{y}_{T-2}$ $\hat{y}_{T-1}$ $\hat{y}_T$
Output
$d = 4$
Hidden
$d = 2$
Hidden
$d = 1$
Input
$x_0$ $x_1$ $x_2$ $\cdots$ $x_{T-2}$ $x_{T-1}$ $x_T$

**Figure:** A TCN (we have already seen this in the CNN lecture!) is simply a variant of the one-dimensional FCN which uses a special type of dilated convolutions called **causal dilated** convolutions.

# CNNS OR RNNS?



| Sequence Modeling Task | Model Size ($\approx$) | Models | | | |
|---|---|---|---|---|---|
| | | LSTM | GRU | RNN | **TCN** |
| Seq. MNIST (accuracy$^h$) | 70K | 87.2 | 96.2 | 21.5 | **99.0** |
| Permuted MNIST (accuracy) | 70K | 85.7 | 87.3 | 25.3 | **97.2** |
| Adding problem $T$=600 (loss$^\ell$) | 70K | 0.164 | **5.3e-5** | 0.177 | **5.8e-5** |
| Copy memory $T$=1000 (loss) | 16K | 0.0204 | 0.0197 | 0.0202 | **3.5e-5** |
| Music JSB Chorales (loss) | 300K | 8.45 | 8.43 | 8.91 | **8.10** |
| Music Nottingham (loss) | 1M | 3.29 | 3.46 | 4.05 | **3.07** |
| Word-level PTB (perplexity$^\ell$) | 13M | **78.93** | 92.48 | 114.50 | 88.68 |
| Word-level Wiki-103 (perplexity) | - | 48.4 | - | - | **45.19** |
| Word-level LAMBADA (perplexity) | - | 4186 | - | 14725 | **1279** |
| Char-level PTB (bpc$^\ell$) | 3M | 1.36 | 1.37 | 1.48 | **1.31** |
| Char-level text8 (bpc) | 5M | 1.50 | 1.53 | 1.69 | **1.45** |

**Figure:** Evaluation of TCNs and recurrent architectures on a wide range of sequence modelling tasks. $^h$ means higher is better and $^\ell$ means lower is better. Note: To make the comparisons fair, all models have roughly the same size (for a given task) and the authors used grid search to find good hyperparameters for the recurrent architectures.

## SUMMARY

- RNNs are specifically designed to process sequences of varying lengths.
- For that recurrent connections are introduced into the network structure.
- The gradient is calculated by backpropagation through time.
- An LSTM replaces the simple hidden neuron by a complex system consisting of cell state, and forget, input, and output gates.
- An RNN can be used as a language model, which can be improved by word-embeddings.
- Different advanced types of RNNs exist, like Encoder-Decoder architectures and bidirectional RNNs.[1]

1. A bidirectional RNN processes the input sequence in both directions (front-to-back and back-to-front).

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