# Attention is All You Need

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# Attention Is All You Need


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**NIPS** 2017


## Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.0 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature.









Equal contribution

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**NIPS** 2017

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Attention Is All You Need

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9/11/2019

by A Vaswani - 2017 - Cited by 4209 - Related articles

12 Jun 2017 - **Attention Is All You Need**. The dominant sequence transduction models are based on complex recurrent or convolutional neural networks in an encoder-decoder configuration. The best performing models also connect the encoder and decoder through an **attention** mechanism.

Equal contribution

# Outline

- Seq2Seq modelling via RNN Encoder-Decoder
- Attention Mechanism
- Self-Attention
- Transformer

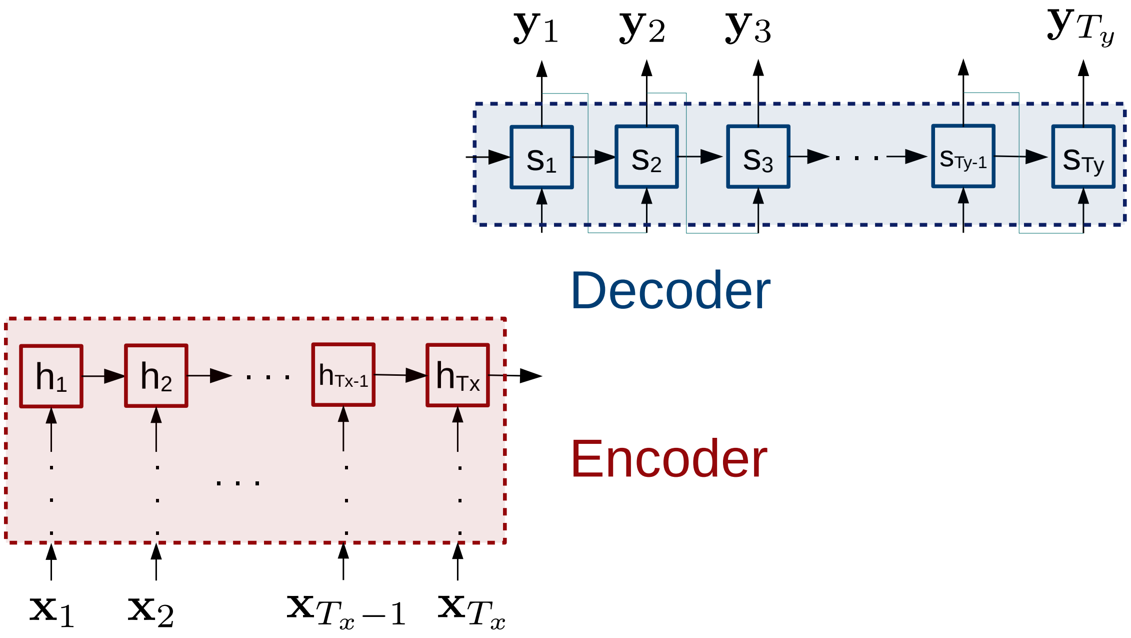
# Sequence-to-Sequence Modelling

- Many-to-Many mapping

$$p(Y_1, Y_2, ..., Y_{T_y} | X_1, X_2, ..., X_{T_x}) = p(Y_1^{T_y} | X_1^{T_x})$$

# Sequence-to-Sequence Modelling

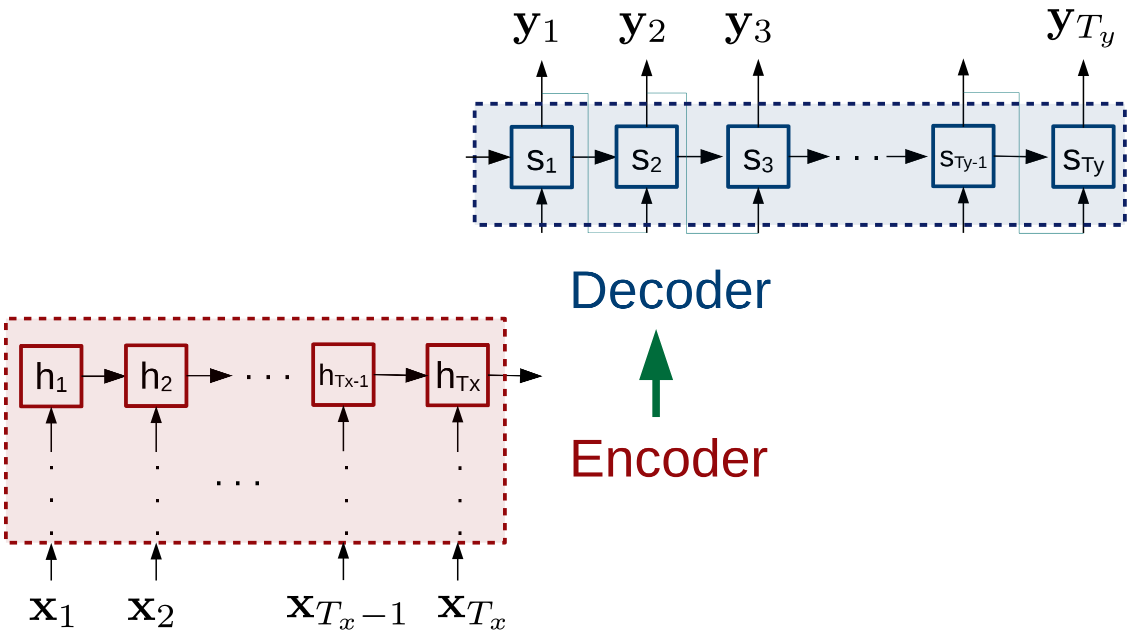
- Many-to-Many mapping




$$p(Y_1, Y_2, ..., Y_{T_y} | X_1, X_2, ..., X_{T_x}) = p(Y_1^{T_y} | X_1^{T_x})$$

# Sequence-to-Sequence Modelling

- Many-to-Many mapping
- Some approximation & conditioning required!




$$p(Y_1, Y_2, ..., Y_{T_y} | X_1, X_2, ..., X_{T_x}) = p(Y_1^{T_y} | X_1^{T_x})$$

# RNN Encoder-Decoder

**Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation**

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**Bart van Merriënboer** **Caglar Gulcehre**
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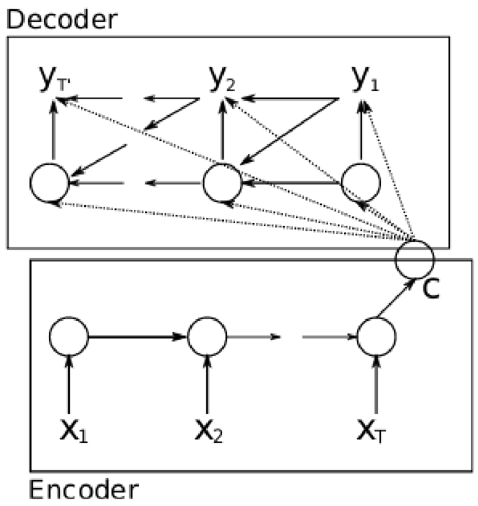



$$p(Y_i|Y_1, \ldots Y_{i-1}, X_1^{T_x}) \approx g(Y_{i-1}, s_i, c)$$

$$s_i = f(y_{i-1}, s_{i-1}, c)$$

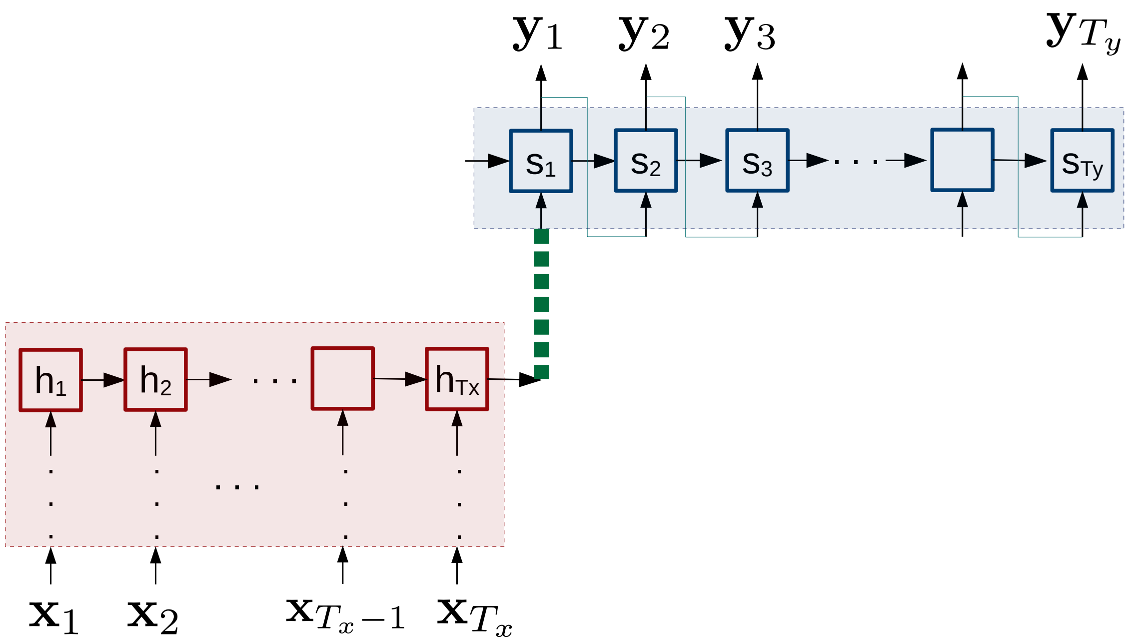
Learning Phrase Representations using RNN Encoder ...
https://arxiv.org › cs ▾
by K Cho - 2014 - Cited by 6907 - Related articles

9/10/2019

3 Jun 2014 - One **RNN** encodes a sequence of symbols into a fixed-length vector **representation**, and the other decodes the **representation** into another sequence of symbols. The **encoder** and **decoder** of the proposed model are jointly trained to maximize the conditional probability of a target sequence given a source sequence.

# RNN Encoder-Decoder

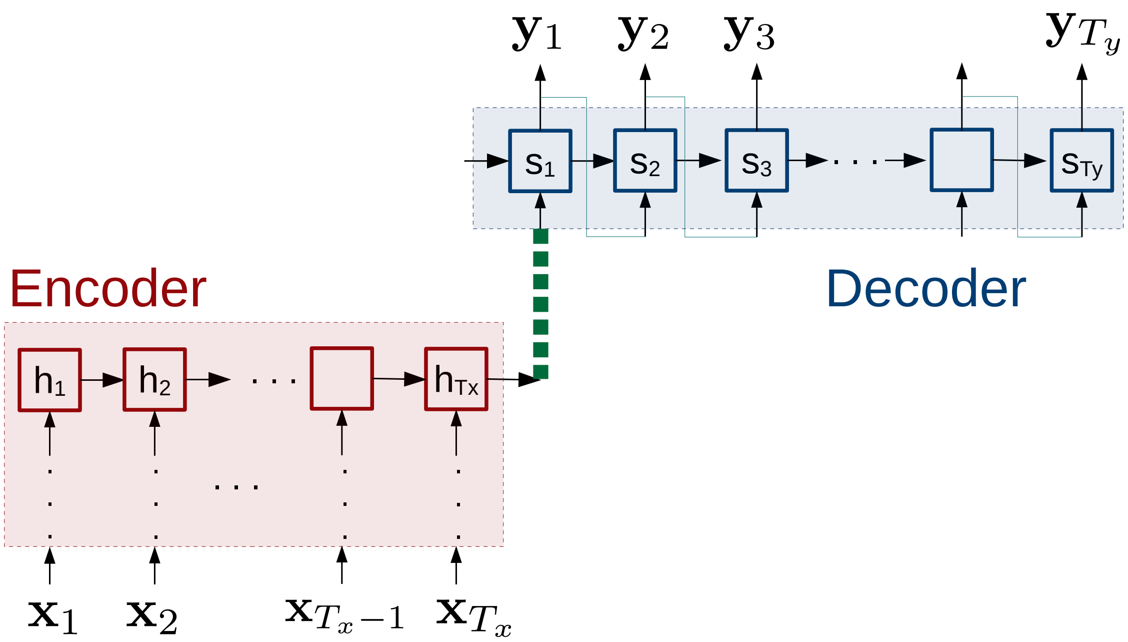
- Break the Many-to-Many into
  - Many-to-**One**
  - **One**-to-Many




$$p(Y_i|Y_1^{i-1}, X_1^{T_x}) \approx g(Y_{i-1}, s_i, \boxed{c})$$

# RNN Encoder-Decoder

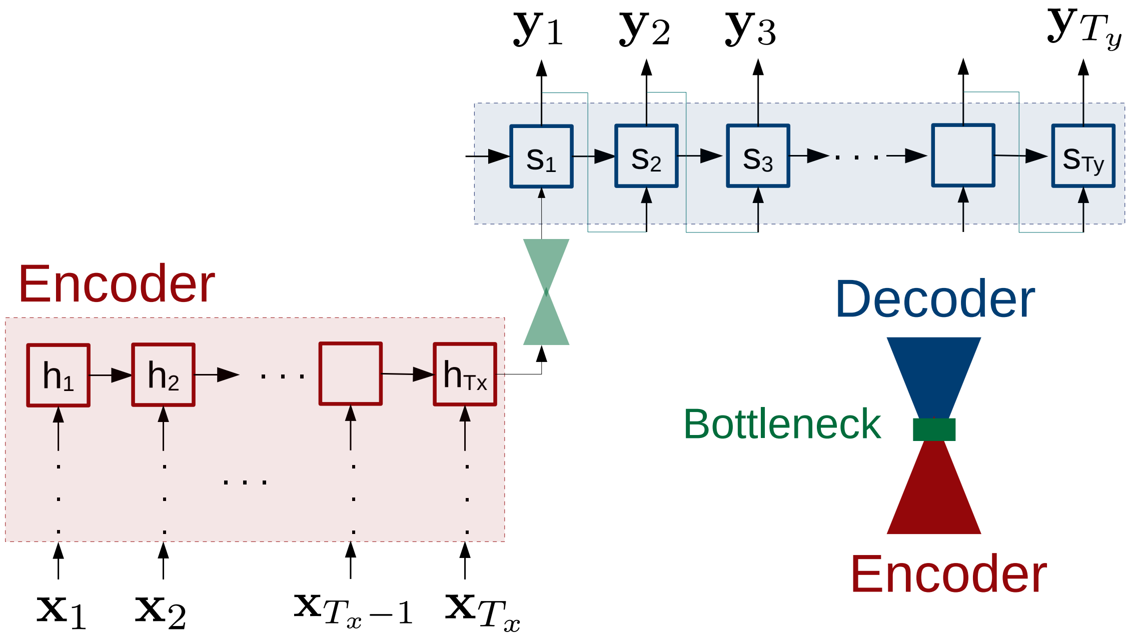
- Break the Many-to-Many into
  - Many-to-**One** $\leftrightarrow$ Encoder
  - **One**-to-Many $\leftrightarrow$ Decoder




$$p(Y_i|Y_1^{i-1}, X_1^{T_x}) \approx g(Y_{i-1}, s_i, \boxed{c})$$

# RNN Encoder-Decoder

- Break the Many-to-Many into
  - Many-to-**One** $\leftrightarrow$ Encoder
  - **One**-to-Many $\leftrightarrow$ Decoder
- **“One” $\rightarrow$ Bottleneck**
  - **C**ontext/thought vector
  - Fixed-length representation
  - Combines all info
    - Local/Global/Dependencies

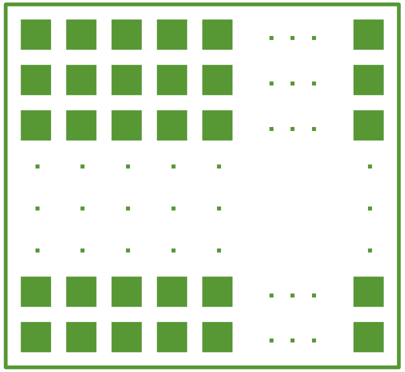



$$p(Y_i|Y_1^{i-1}, X_1^{T_x}) \approx g(Y_{i-1}, s_i, \boxed{c})$$

# RNN Encoder-Decoder Problems (1)

- Sequential computation is hard to parallelise
  - Not what modern HPCs excels at!

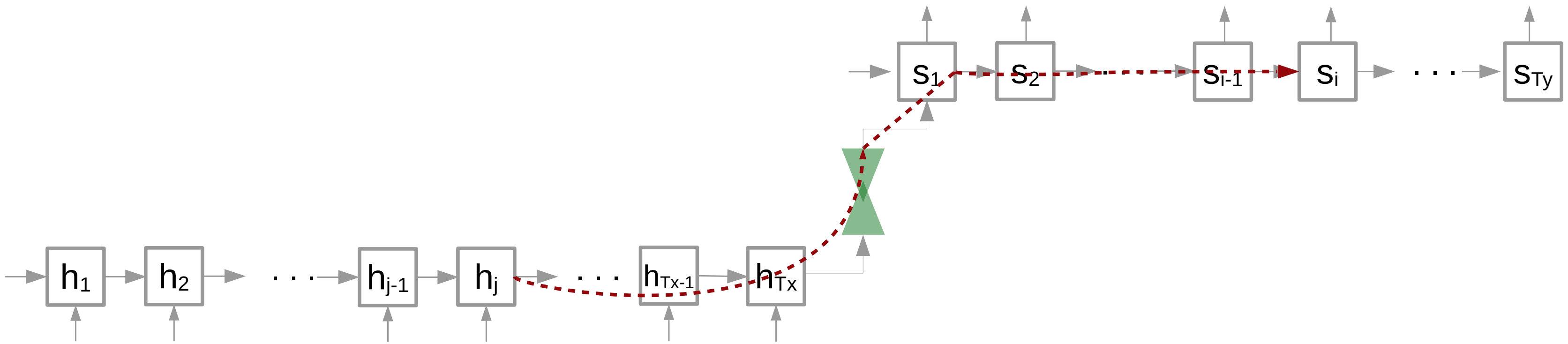
**CPUs → Multiple Cores**



**GPUs → Hundreds to Thousands Cores**

# RNN Encoder-Decoder Problems (2)

- Information flow
  - Combination of all info in a single embedding
  - Info path between En and De states is long
  - Capturing long-term dependencies is tricky



# Possible Solutions/Alternatives

- Attention mechanism
- Transformer
- CNNs for sequence modelling
  - Appendix (A)

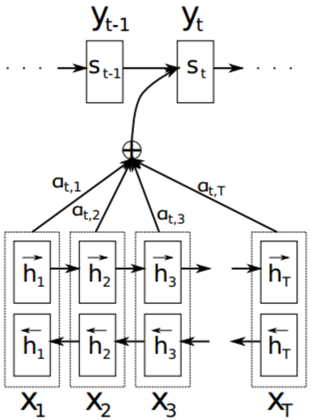
# Attention Mechanism

Published as a conference paper at ICLR 2015

## NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

**Dzmitry Bahdanau**
Jacobs University Bremen, Germany

**KyungHyun Cho** **Yoshua Bengio***
Université de Montréal



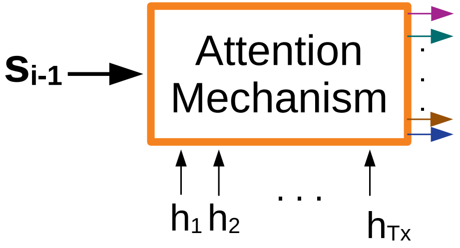

$$p(Y_i|Y_1, ...Y_{i-1}, X_1^{T_x}) \approx g(Y_{i-1}, s_i, c_i)$$

$$s_i = f(y_{i-1}, s_{i-1}, c_i)$$

Neural Machine Translation by Jointly Learning to Align and ...
https://arxiv.org › cs ▾
by D Bahdanau - 2014 - Cited by 9235 - Related articles
**Neural Machine Translation by Jointly Learning to Align and Translate**. ... Unlike the traditional statistical **machine translation**, the **neural machine translation** aims at building a single **neural** network that can be **jointly** tuned to maximize the **translation** performance.

9/11/2019

# Attention Mechanism




$$p(Y_i|Y_1^{i-1}, X_1^{T_x}) \approx g(Y_{i-1}, s_i, c_i)$$

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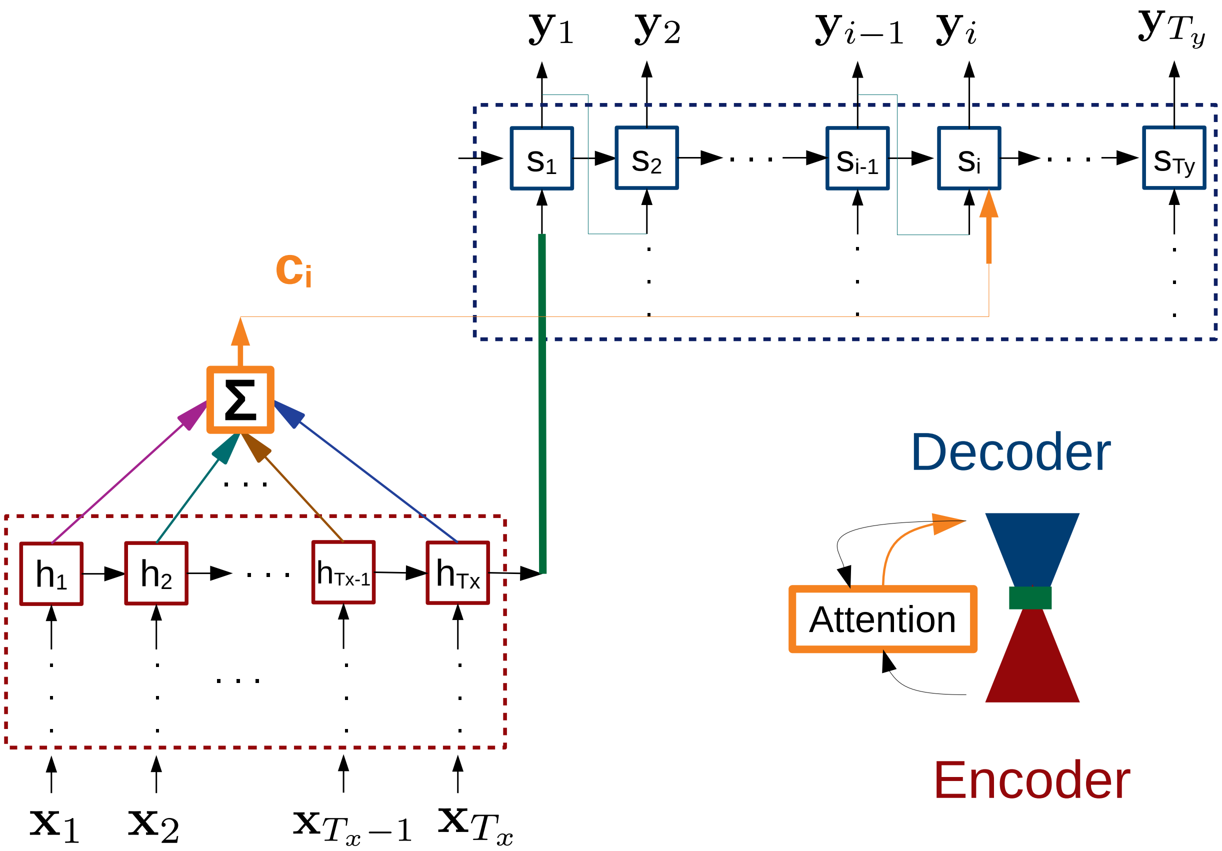
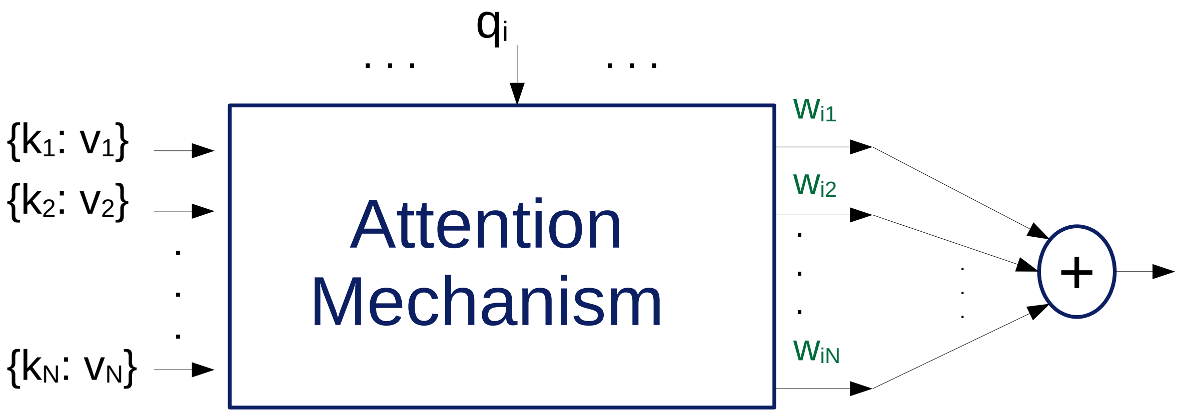


# Attention Mechanism

- Attention is a focus mechanism on task-important parts of input
- **Input** $\leftarrow$ A set of {key:value} pairs, and queries
- **Output** $\rightarrow$ A weighted mean of values

# Attention Mechanism

- Attention is a focus mechanism on task-important parts of input




{key: value}

# Attention Mechanism

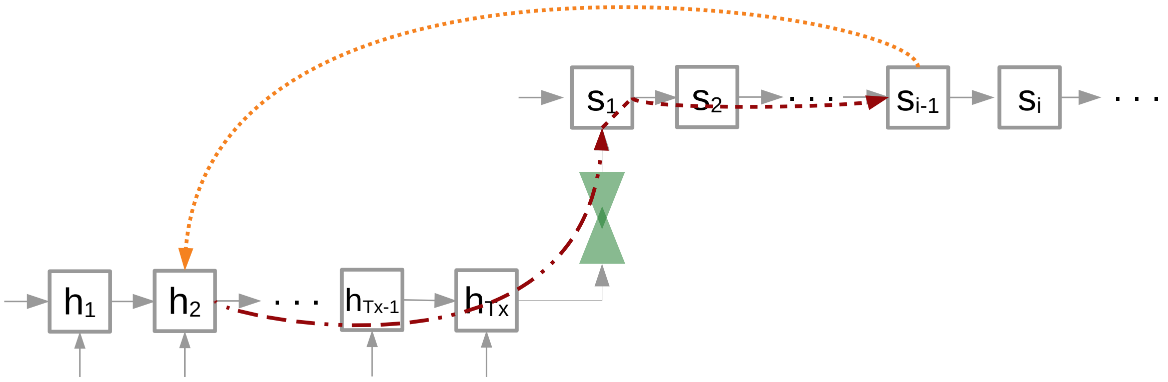
- Attention is a focus mechanism on task-important parts of input
- **Input** $\leftarrow$ A set of key-value pairs, and queries
- **Output** $\rightarrow$ A weighted mean of values
- Weights $\rightarrow$ prop. to similarity of query & keys

# Attention Mechanism

- **Query** (Q)
  - Determines where focus should be steered
- **Keys** (K) and **Values** (V) pairs, {k:v}
  - Some prototypes
- In RNN En-De models
  - **Q** → Decoder states ($\mathbf{s_{i-1}}$)
  - **K** and **V** → Encoder states ($\mathbf{h_{1:Tx}}$) → Identical HERE!

# Attention Advantages

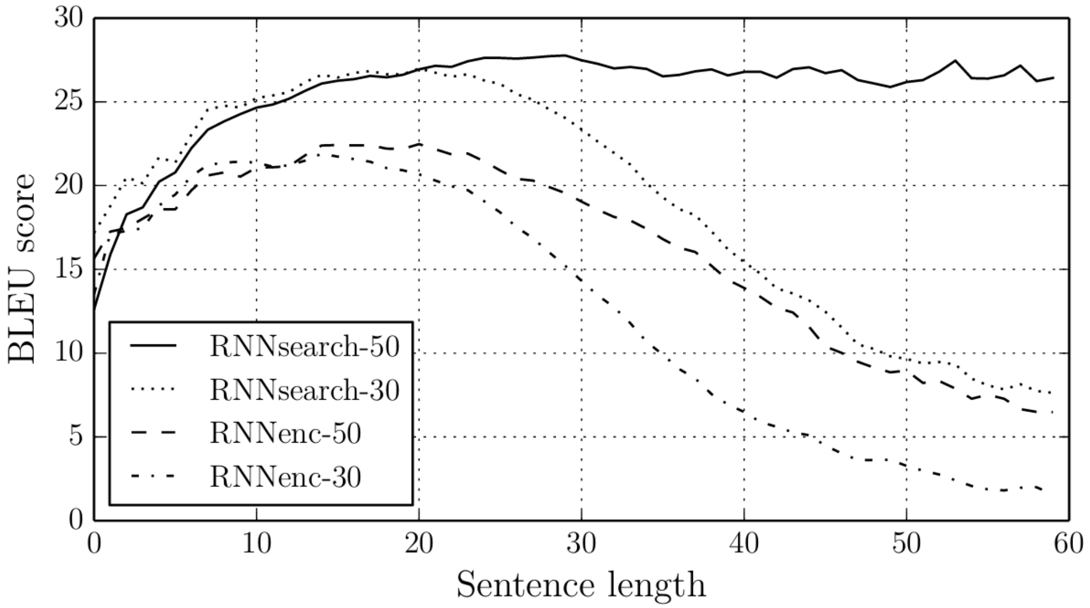
- Solves the info bottleneck issue of RNN En-De
- Shorten info path between $\mathbf{h}_{1:Tx}$ and each $\mathbf{s}_i$
  - Long-range dependencies better captured/modelled

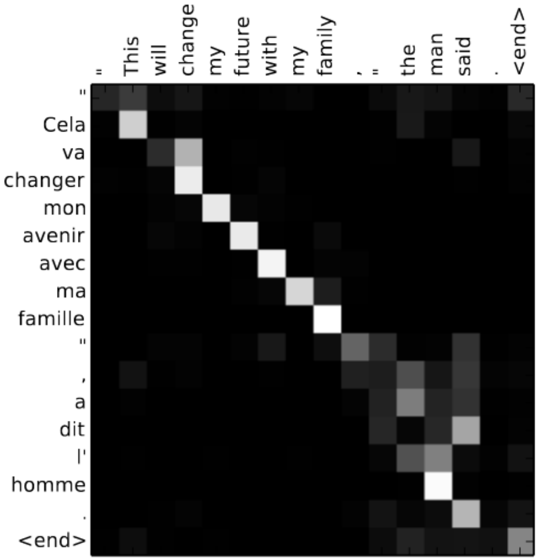


# Attention Advantages

- Solves the info bottleneck issue of RNN En-De
- Shorten info path between $\mathbf{h}_{1:Tx}$ and each $\mathbf{s}_i$
- Helps with gradient vanishing
- Jointly learns alignment & classification
  - Visualisation and understanding

# Attention Advantages in NMT




**Dealing with long-range dependencies**

**Visualisation of alignment**

# Attention Model

- Score ($e_{ij}$)
- Alignment ($\alpha_{ij}$)
- Context ($c_{ij}$)
  - aka *glimpse* ($g_i$)

- RNN Decoder

$$\begin{aligned}\alpha_{ij} &= \text{Attention}(\mathbf{s}_{i-1}, \mathbf{h}_j) \\ &= \text{softmax}(e_{ij})\end{aligned}$$

$$\mathbf{c}_i = \alpha_i^T \ \mathbf{h}_j = \sum_j \alpha_{ij} \ \mathbf{h}_j$$

$$\mathbf{y}_i \sim \text{Label-Distribution}(\mathbf{y}_{i-1}, \mathbf{s}_i, \mathbf{c}_i)$$

# Alignment model → Compute Score

- Dot-product
  - Basic

$$e_{ij} = \mathbf{s}_i^T \mathbf{h}_j$$

  - Linear projection

$$e_{ij} = \mathbf{s}_i^T \, W \, \mathbf{h}_j$$

# Alignment model → Compute Score

- Dot-product
  - Basic

$$e_{ij} = \mathbf{s}_i^T \mathbf{h}_j$$

  - Linear projection

$$e_{ij} = \mathbf{s}_i^T \; W \; \mathbf{h}_j$$

- Additive
  - Content

$$e_{ij} = v^T \; \tanh(W\mathbf{s}_{i-1} + V\mathbf{h}_j + \mathbf{b})$$

  - Location

$$e_{ij} = v^T \; \tanh(W\mathbf{s}_{i-1} + V\mathbf{h}_j + U \; f_{ij} + \mathbf{b})$$

$\alpha_{i-1}$

# Sharpening the Focus / Attention

- **Use *inverse temperature*, *β*,**
  - $\beta > 1$ => *sharpening* the pdf
  - $\beta < 1$ => *smoothing* the pdf

$$a_{ij} = \frac{\exp(\beta e_{ij})}{\sum_{j'} \exp(\beta e_{ij'})}$$

- **Top-k**
  - Keep top k values of $\boldsymbol{e}_i$ → Set the rest to zero → Normalise
- Caveat: requires computing all $e_{ij}$ s
  - Computational complexity → $O(T_x T_y)$
  - **Solution**: Windowed attention

# Sharpening the Focus / Attention

- **Windowed Attention**
  - Window length: $2w \rightarrow 2w \ll L$
  - Window centre: $p_i \rightarrow$ median of $\alpha_{i-1}$
    - $\alpha_{i-1}$ shortlists the encoder states ($h_j$)
  - Compute attention only on $\tilde{h} = (h_{p_i - w}, ..., h_{p_i + w - 1})$
- Caveats:
  - Not useful for short utterances, too sharp
    - **Solution** → *Smoothing* → Replace *exp* with *sigmoid* in *softmax*
  - Window length and location are suboptimal
    - **Solution** → *Fully-trainable Windowed Attention*

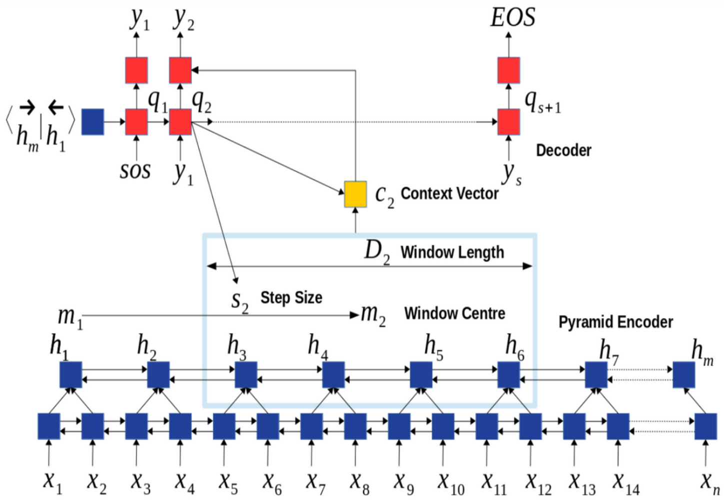
# (Fully-Trainable) Windowed Attention

**WINDOWED ATTENTION MECHANISMS FOR SPEECH RECOGNITION**

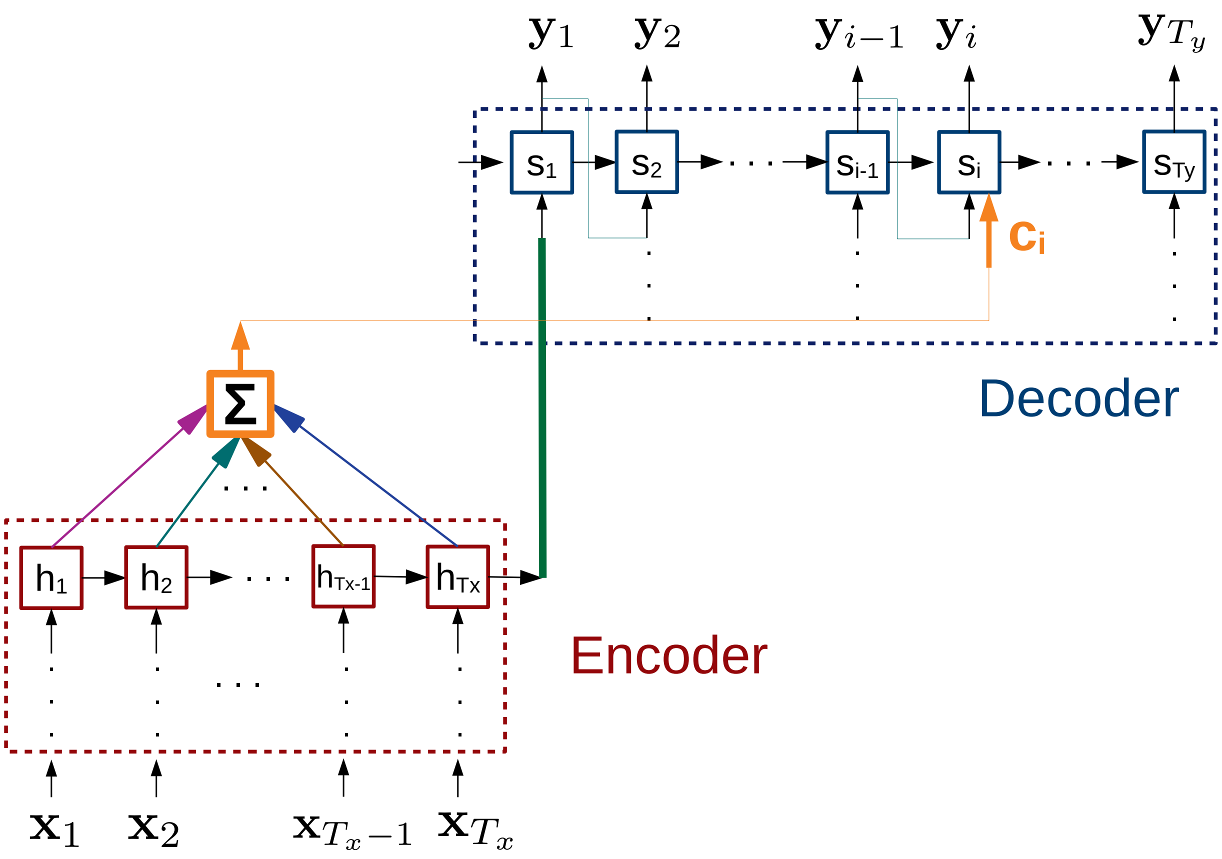
*Shucong Zhang, Erfan Loweimi, Peter Bell, Steve Renals*

Centre for Speech Technology Research, University of Edinburgh, Edinburgh, UK

ICASSP 2019

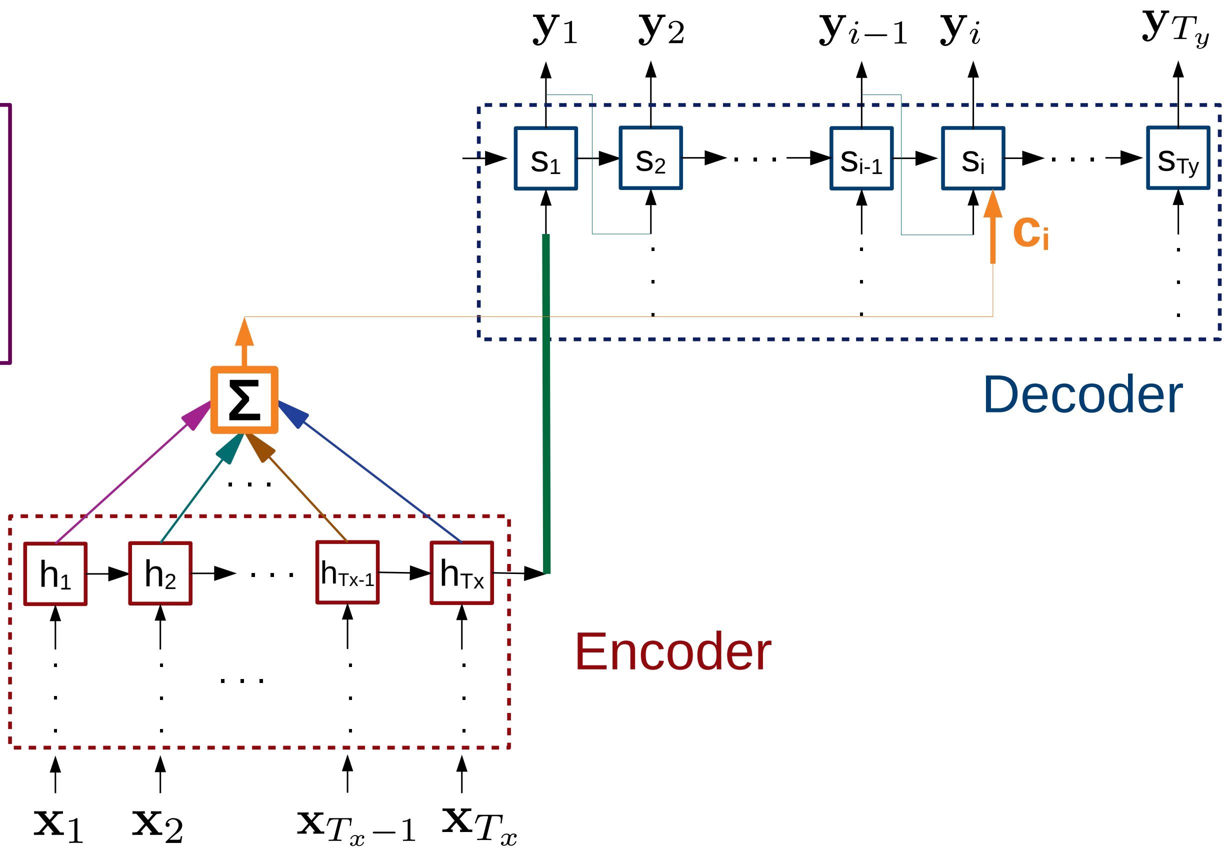


# (Fully-Trainable) Windowed Attention



# (Fully-Trainable) Windowed Attention

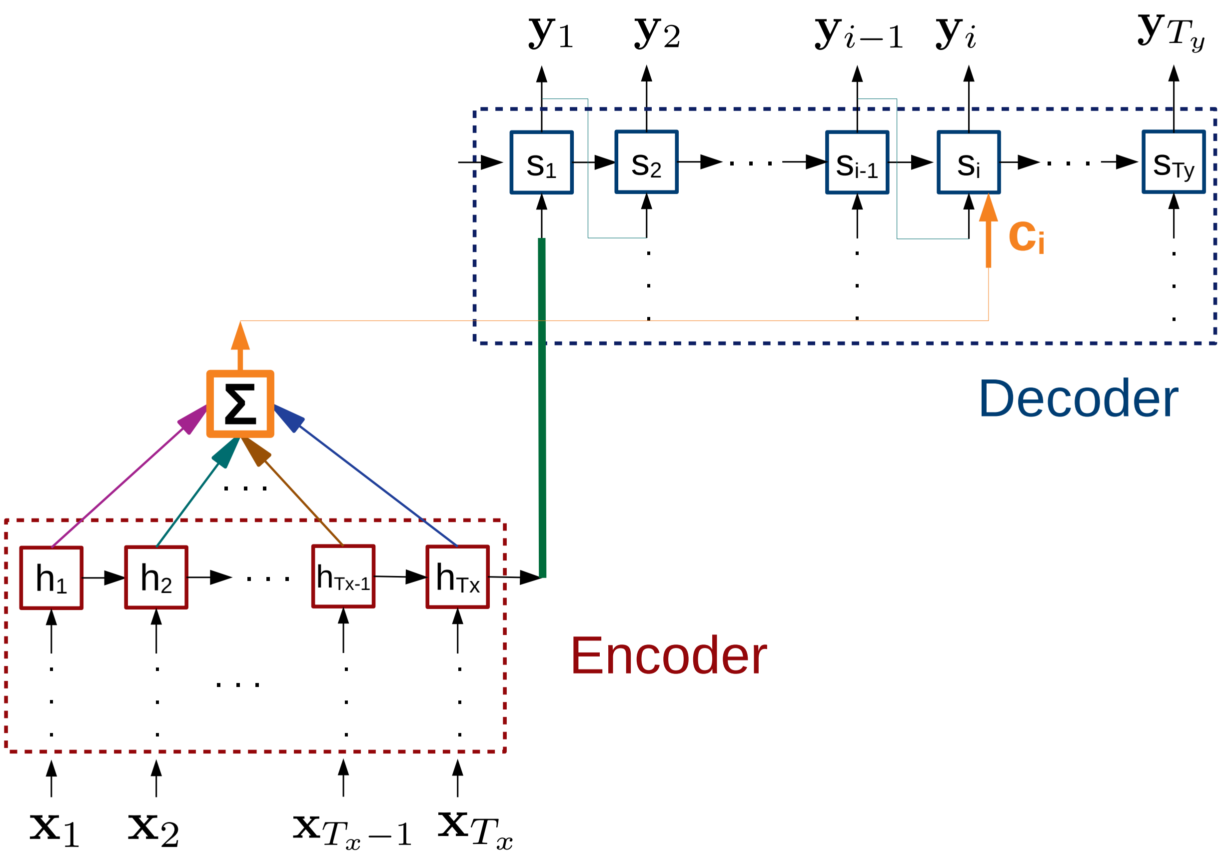
What if **X** sequence is very long & $\mathbf{y}_i$ is only correlated with a small part of **X** ...



# (Fully-Trainable) Windowed Attention

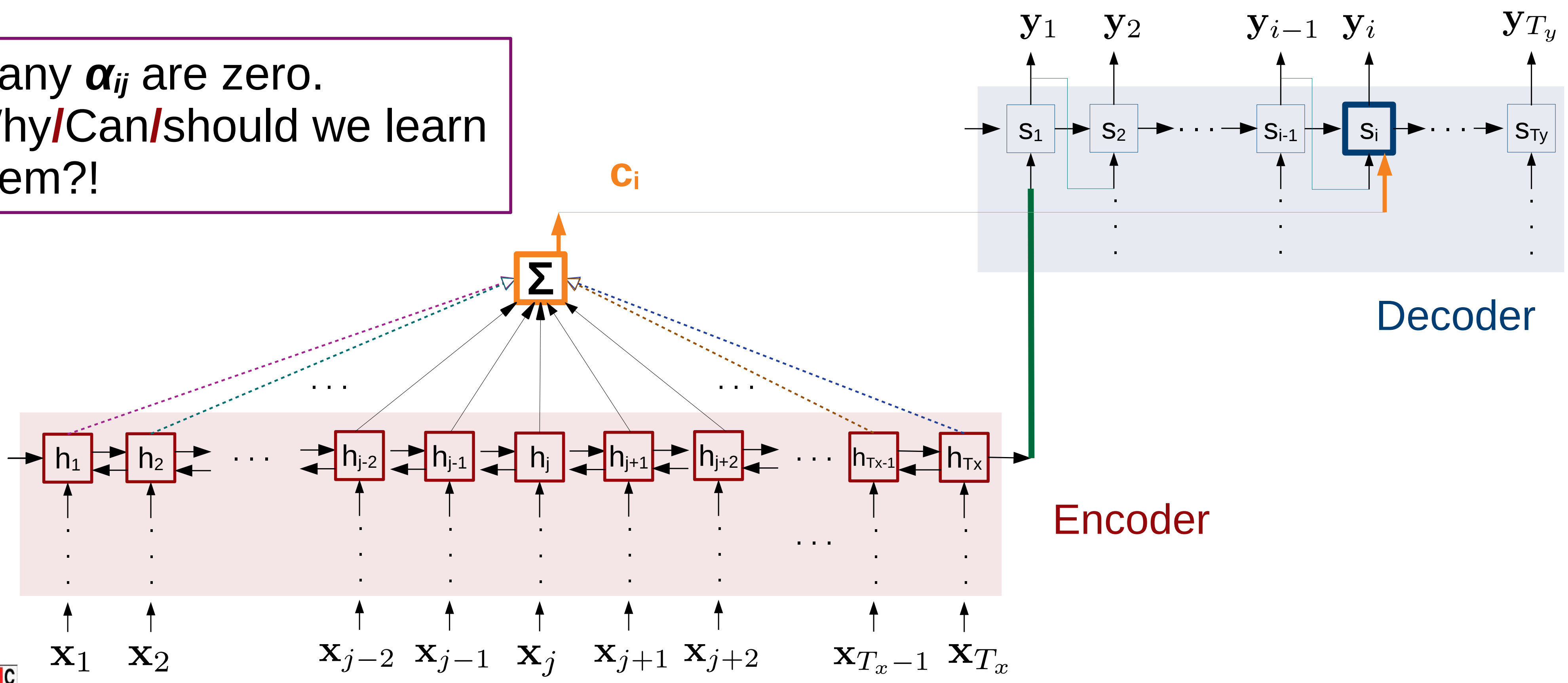
What if **X** sequence is very long & $\mathbf{y}_i$ is only correlated with a small part of **X** ...

$c_i$ contains noisy info from irrelevant $h_j \rightarrow$ Suboptimal attention



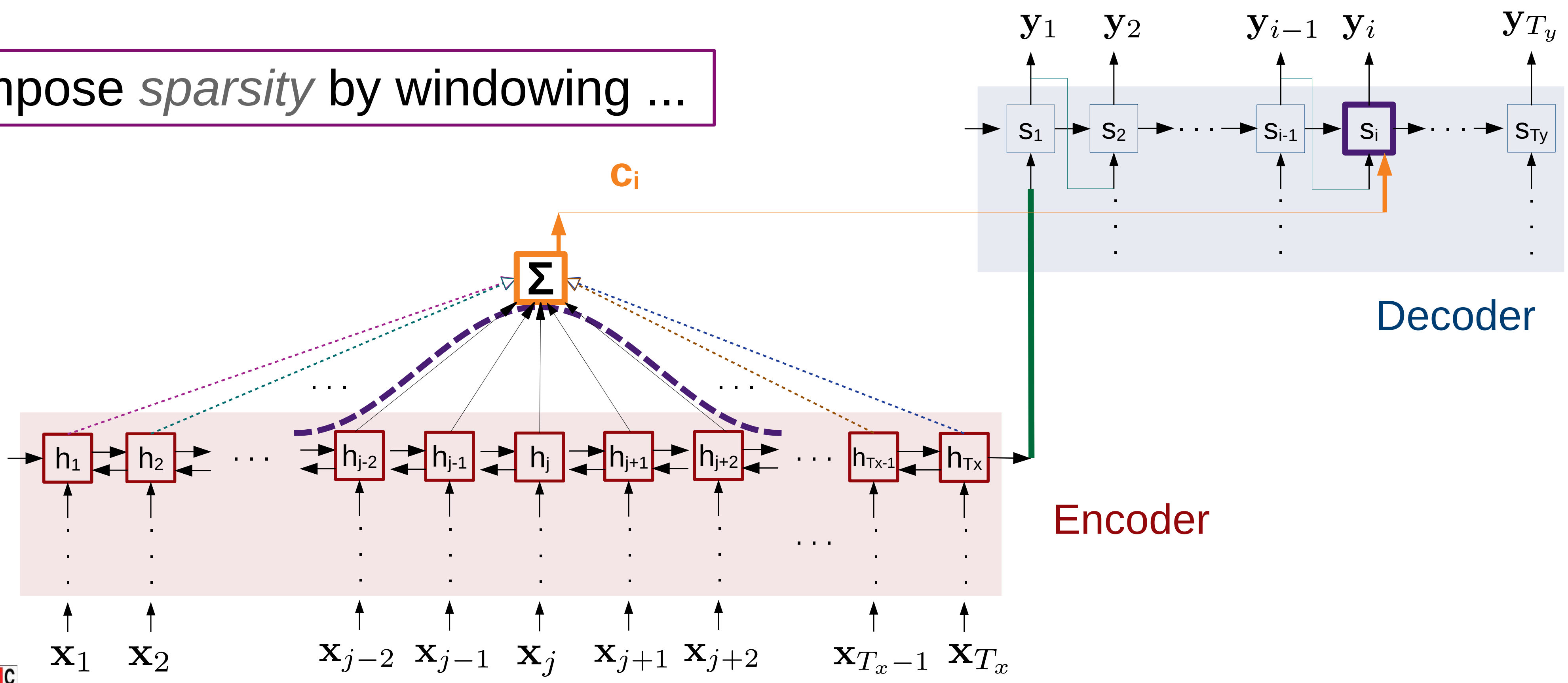
# (Fully-Trainable) Windowed Attention

Many $\alpha_{ij}$ are zero.
Why/Can/should we learn them?!



# (Fully-Trainable) Windowed Attention

Impose *sparsity* by windowing ...



# (**Fully-Trainable**) Windowed Attention

$$L_i = L_{max}\ \sigma(MLP(\mathbf{s}_i))$$

$$sh_i = SH_{max}\ \sigma(MLP(\mathbf{s}_i))$$

$$m_i = m_{i-1} + sh_i$$

$$l_{ij} = \begin{cases} \exp(-\frac{(j-m_i)^2}{2(D_{iL}/2)^2}, j \in (m_i - D_{iL}, m_i) \\ \exp(-\frac{(j-m_i)^2}{2(D_{iR}/2)^2}, j \in (m_i, m_i - D_{iR}) \end{cases}$$

$$\alpha_{ij} = \frac{\exp(e_{ij})\ l_{ij}}{\sum_{m_i-D_{iL}}^{m_i+D_{iR}} \exp(e_{ik})\ l_{ik}}$$

*Fully-trainable* → BOTH window length and window shift are learned.

*Windowed Attention Mechanism for Speech Recognition*, Zhang et al, ICASSP 2019

# (Fully-Trainable) Windowed Attention

$$L_i = L_{max}\ \sigma(MLP(\mathbf{s}_i))$$

$$sh_i = SH_{max}\ \sigma(MLP(\mathbf{s}_i))$$

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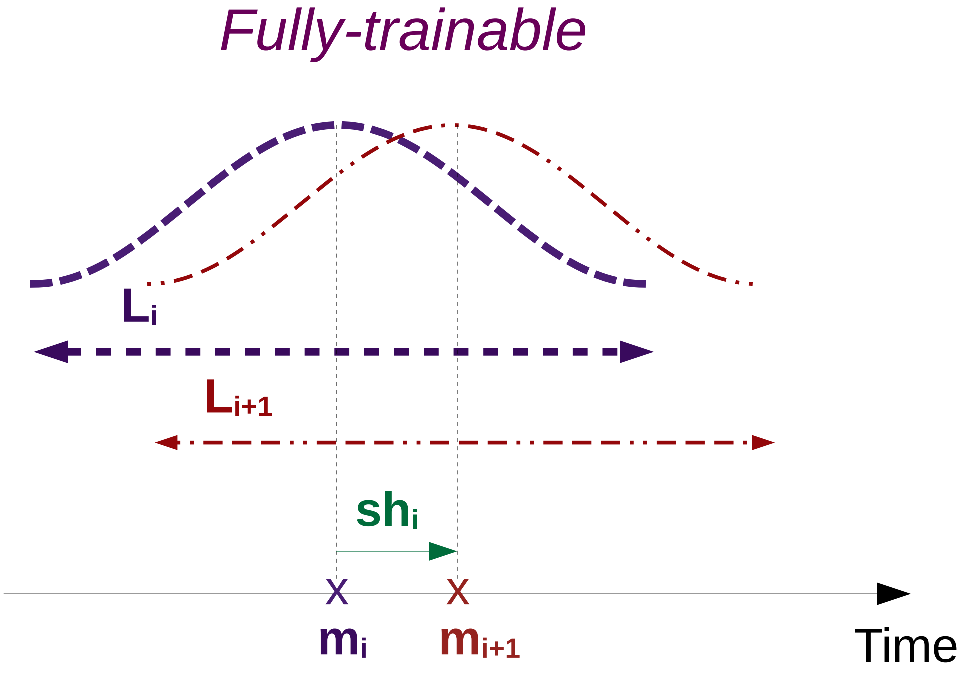
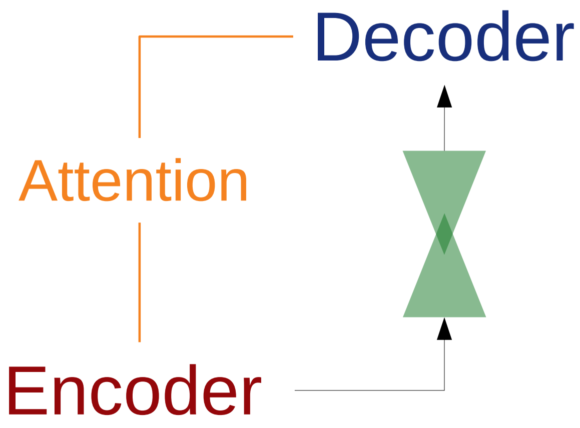
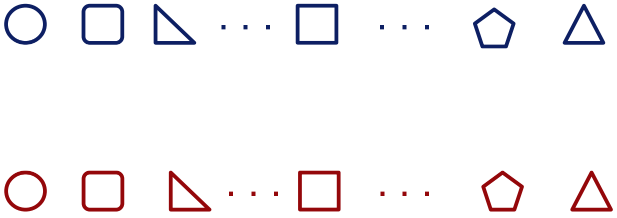



*Windowed Attention Mechanism for Speech Recognition*, Zhang et al, ICASSP 2019

# Self-Attention

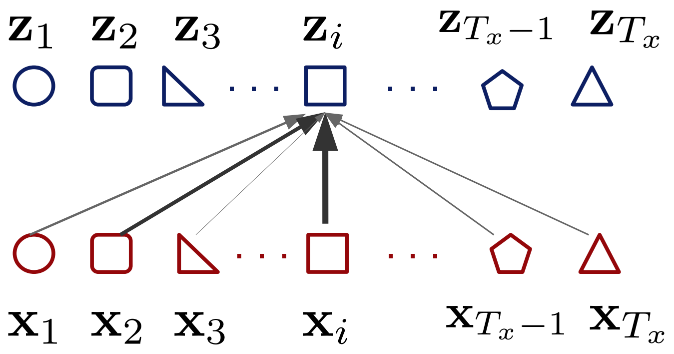
- An attention within a layer (representation)
  - Encoder ↔ Classic attention ↔ Decoder



# Self-Attention

- An attention within a layer (representation)
- Each weight is prop. to similarity of two vertices

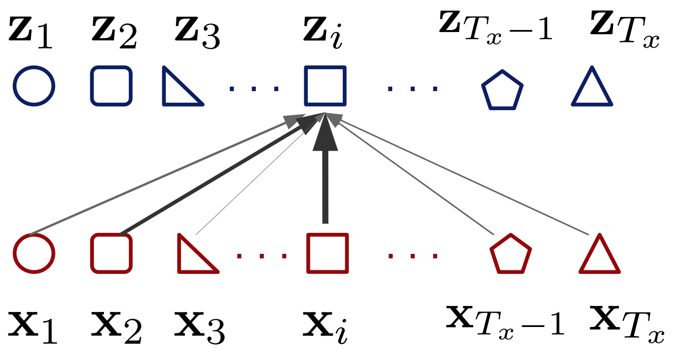


# Self-Attention

- An attention within a layer (representation)
- Each weight is prop. to similarity of two vertices

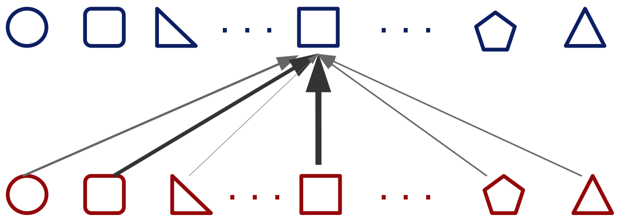
$$\mathbf{z}_i = \sum_j w_{ij}\mathbf{x}_j$$

$$\begin{cases} w_{ij} = \text{similarity}(\mathbf{x}_i, \mathbf{x}_j) \\ w_{ij} \geq 0, \ \ \sum_j w_{ij} = 1 \end{cases}$$



# Self-Attention Advantages

- ✔ Constant path length between positions, O(1)
  - Direct interaction, no locality bias
- ✔ Long-range dependencies are captured well
- ✔ Multiplicative interaction → some kind of gating
- ✔ Permutation invariant
- ✔ Trivial to parallelise



# Convolution vs Self-Attention

- CNN
  - Linear Time Invariant
  - Suboptimal filter replication
  - Seq. modelling requires depth

- Self-Attention
  - Linear(?) Time Variant
  - One filter per node
  - Direct interaction for all

# Self-Attention Disadvantageous

- Globally, sequentiality is lost
  - has no notion of temporal order!
  - Permutation invariant!
- Locally, temporal resolution is lost
  - Owing to attention-weighted averaging

# Self-Attention Disadvantageous

- Globally, sequentiality is lost
  - has no notion of temporal order!
  - Permutation invariant!
- Locally, temporal resolution is lost
  - Owing to attention-weighted averaging
- **Solution**: Positional Encoding

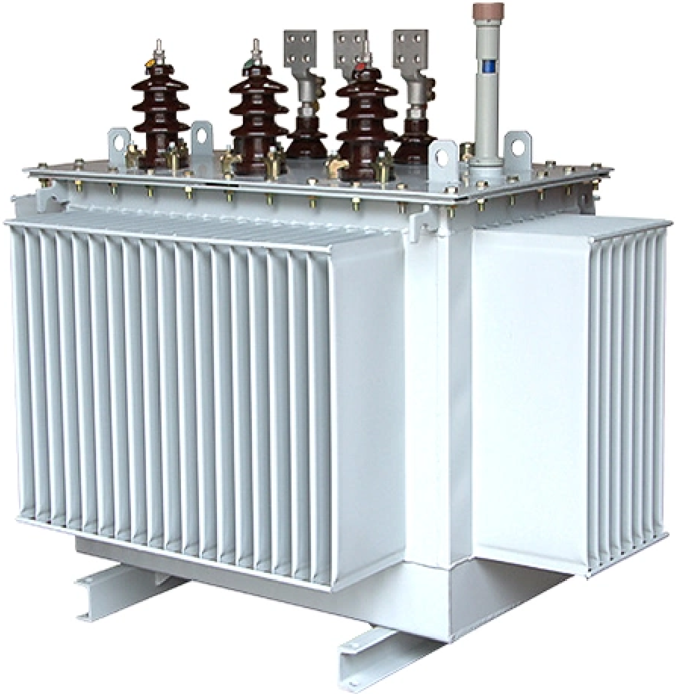
# Computational Complexity

- Self-attention → $O(n^2d)$
  - Quadratic in sequence length (n)
  - Linear in representation dimension (d)
- RNN → $O(nd^2)$
  - Linear in seq. length; Quadratic in repr. dim

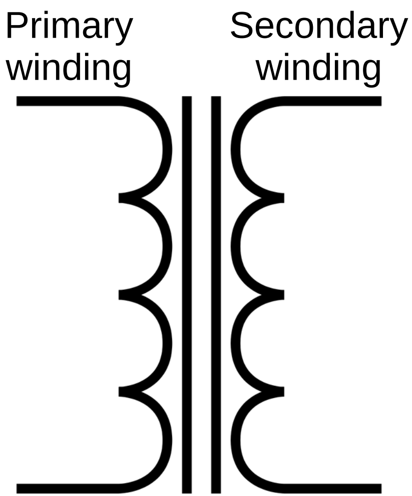
# Computational Complexity

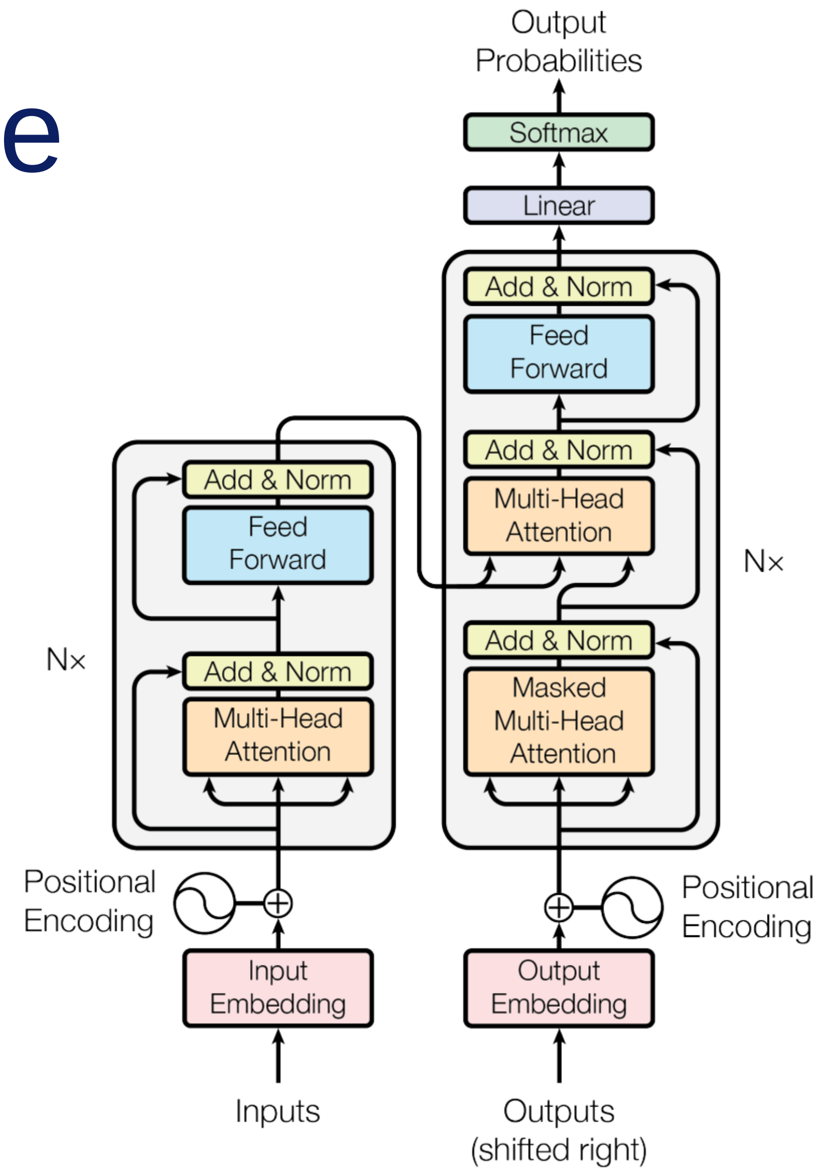
- Self-attention → $O(n^2d)$
  - Quadratic in sequence length (n)
  - Linear in representation dimension (d)
- RNN → $O(nd^2)$
  - Linear in seq. length; Quadratic in repr. dim
- If $n < d$ → Self-attention is more economic, e.g. NMT
- If $n > d$ → Self-attention is parallelisable, e.g. ASR

# Transformers

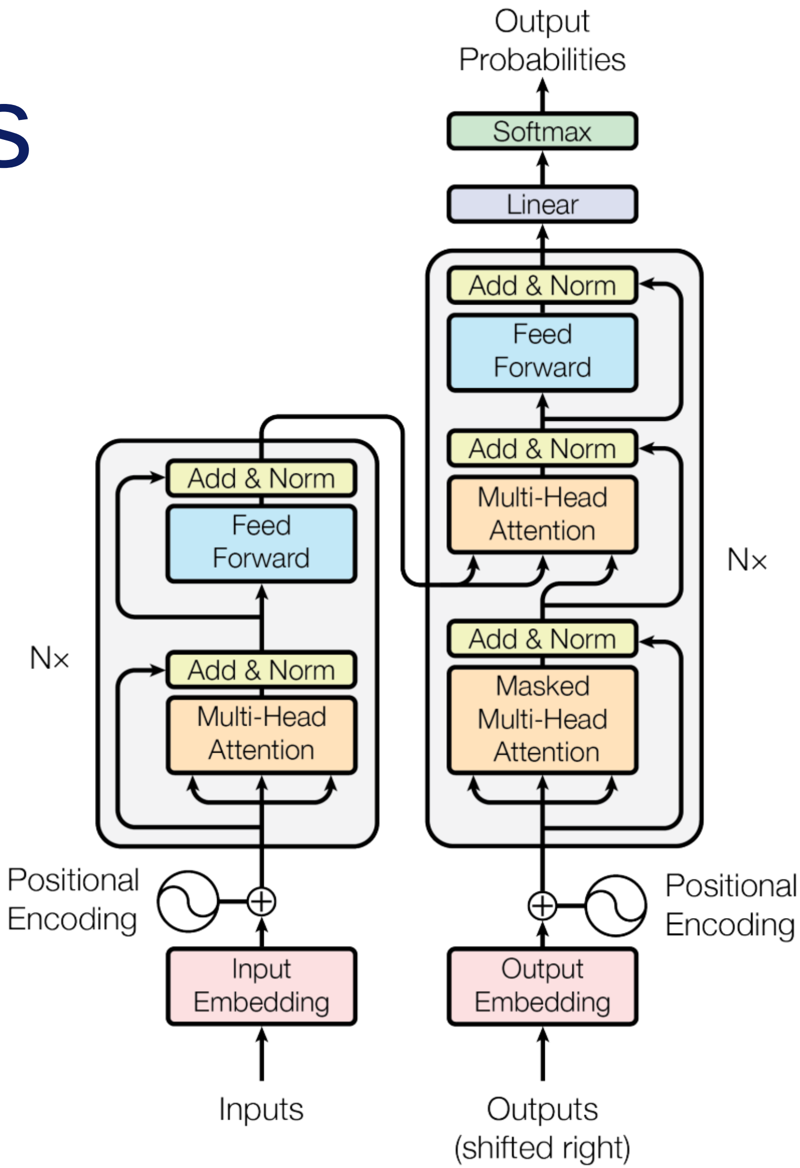



# Architecture

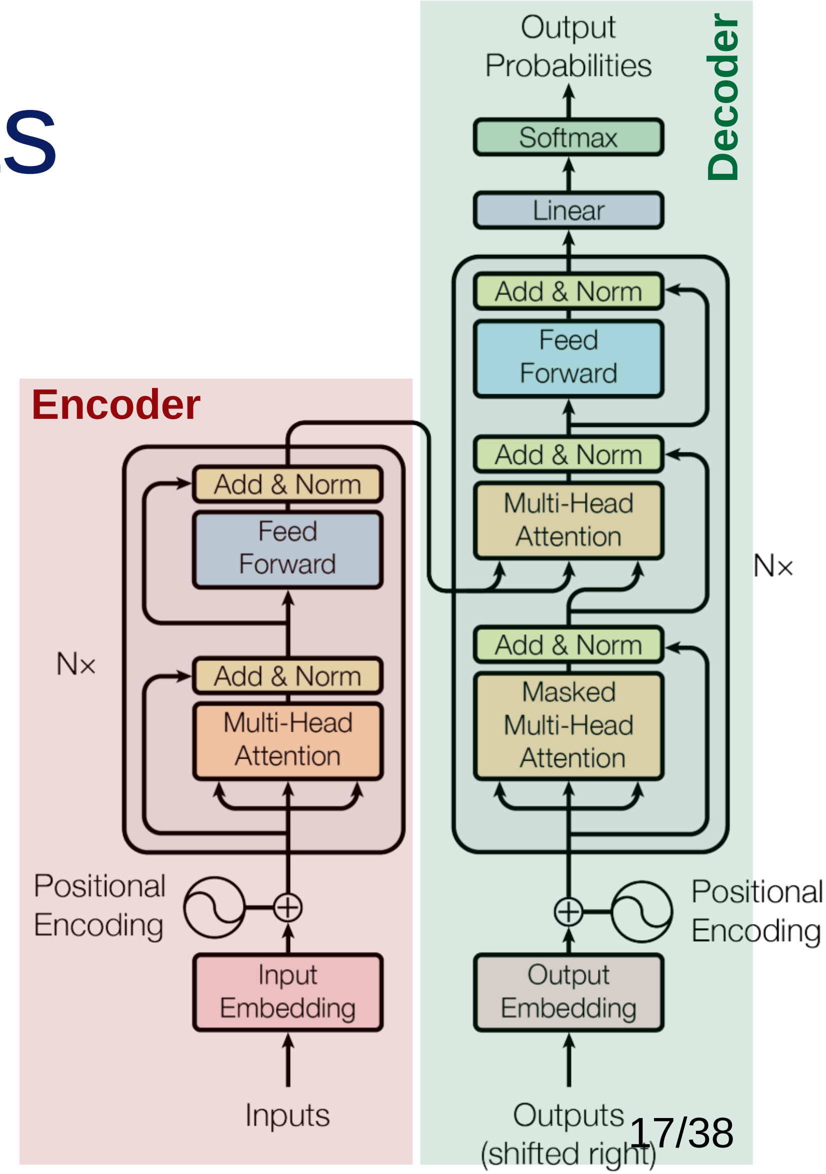



# Ingredients



# Ingredients

- **Encoder**-**Decoder** structure
- Positional Embedding
- Multi-Head self-Attention
- Feed Forward NN (FFNN)
- Add & Norm

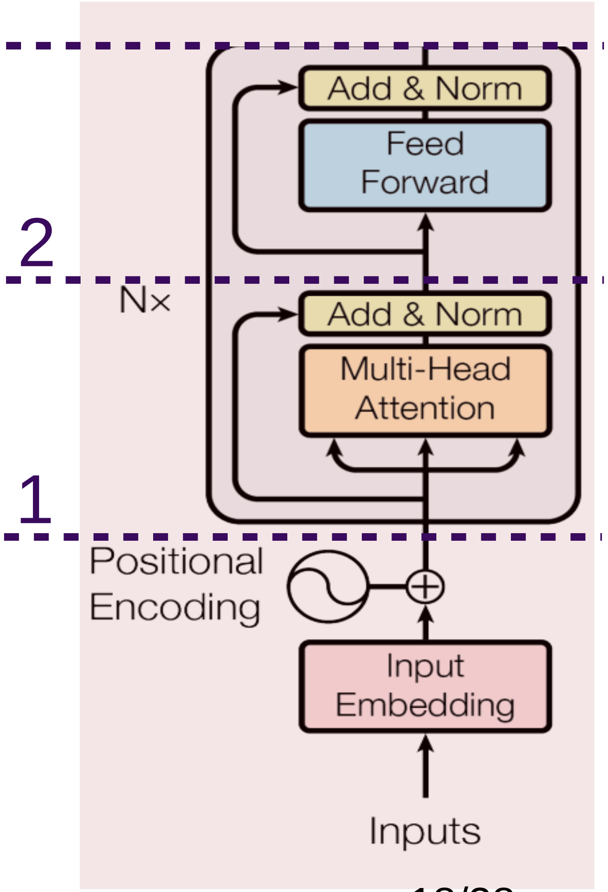



E. Loweimi

# Encoder

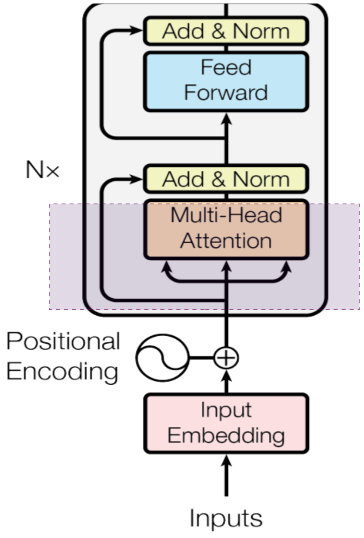
- **6** Layers, each one has ...
  - Sublayer 1: Multi-head Self-attention
  - Sublayer 2: (Point-wise) FFNN

- Add & Norm after each sublayer
  - Sublayer = Norm(x+sublayer(x))



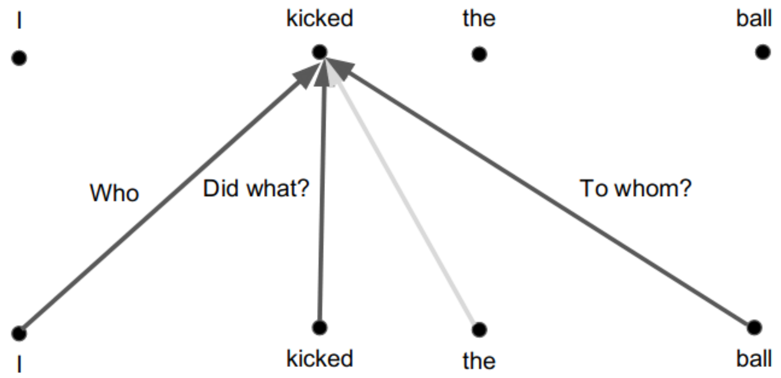
# Multi-head Self-attention – Intuition

- Process multiple types/streams of info or subtasks *independently*



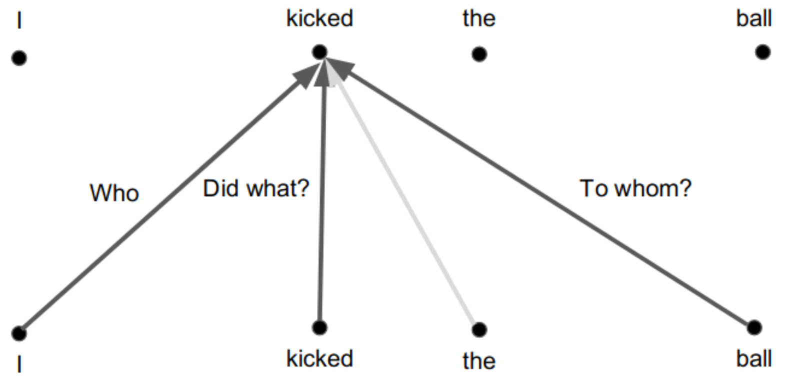
# Multi-head Self-attention – Intuition

- Process multiple types/streams of info or subtasks *independently*, e.g.
  - Who?
  - Did what?
  - To whom?



# Multi-head Self-attention – Intuition

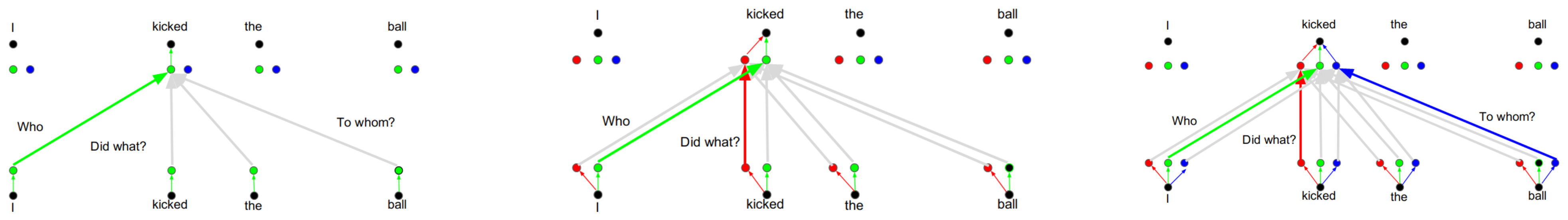
- Process multiple types/streams of info or subtasks *independently*, e.g.
  - Who?
  - Did what?
  - To whom?




Each subtask and/or piece of info requires a different solution and attention.

# Multi-head Self-attention – Intuition

- Process multiple types of info

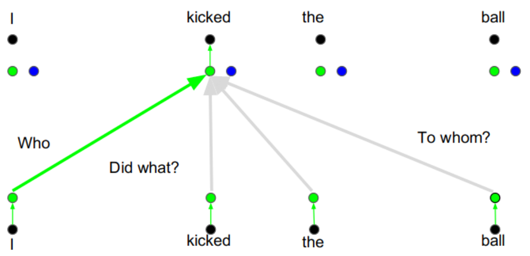



**Head 1**: Who?    **Head 2**: Did what?    **Head 3**: To whom?

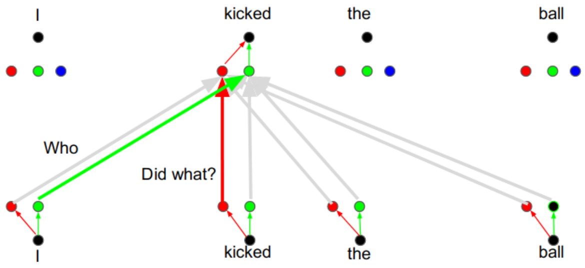
# Multi-head Self-attention – Intuition

- Process multiple types of info

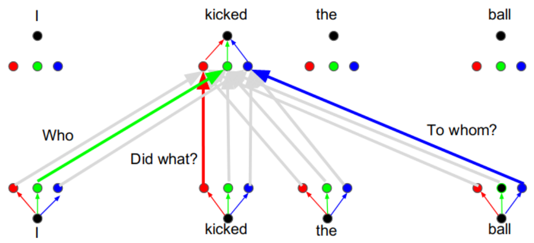
Parallelisable




**Head 1**: Who?

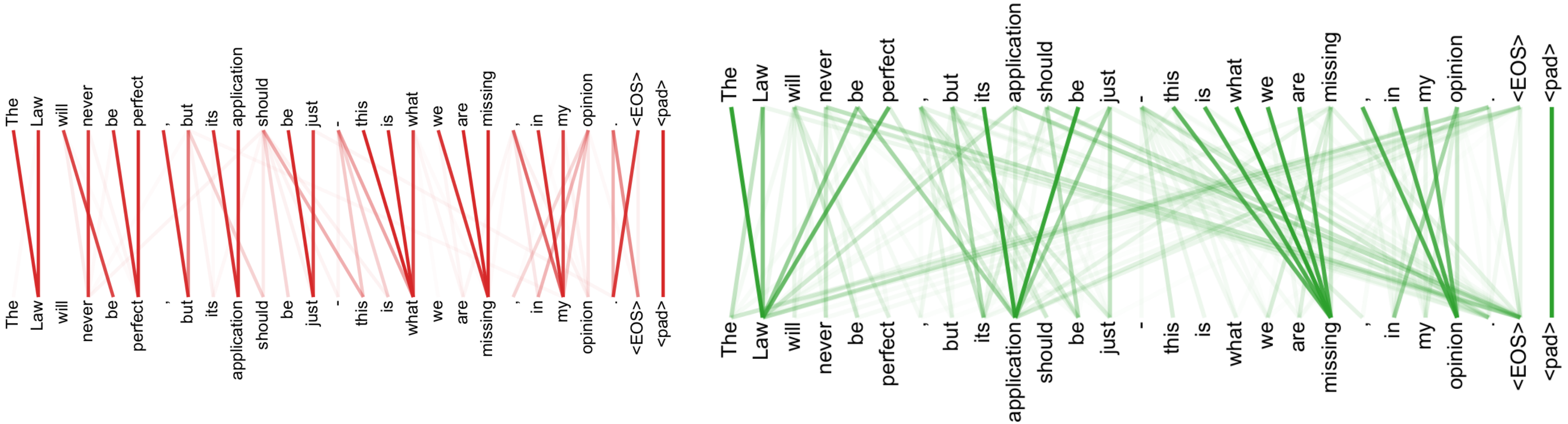



**Head 2**: Did what?




**Head 3**: To whom?

# Multi-head Self-attention – Intuition




– Two heads form encoder self-attention at layer 5 (out of 6).

– Heads learn to perform different tasks.

# Multi-head self-Attention

$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

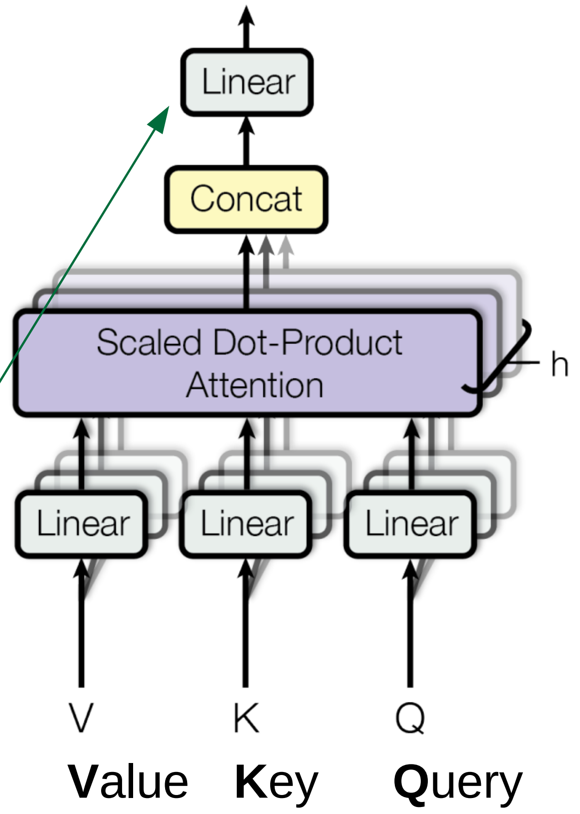
$W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$

$W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$

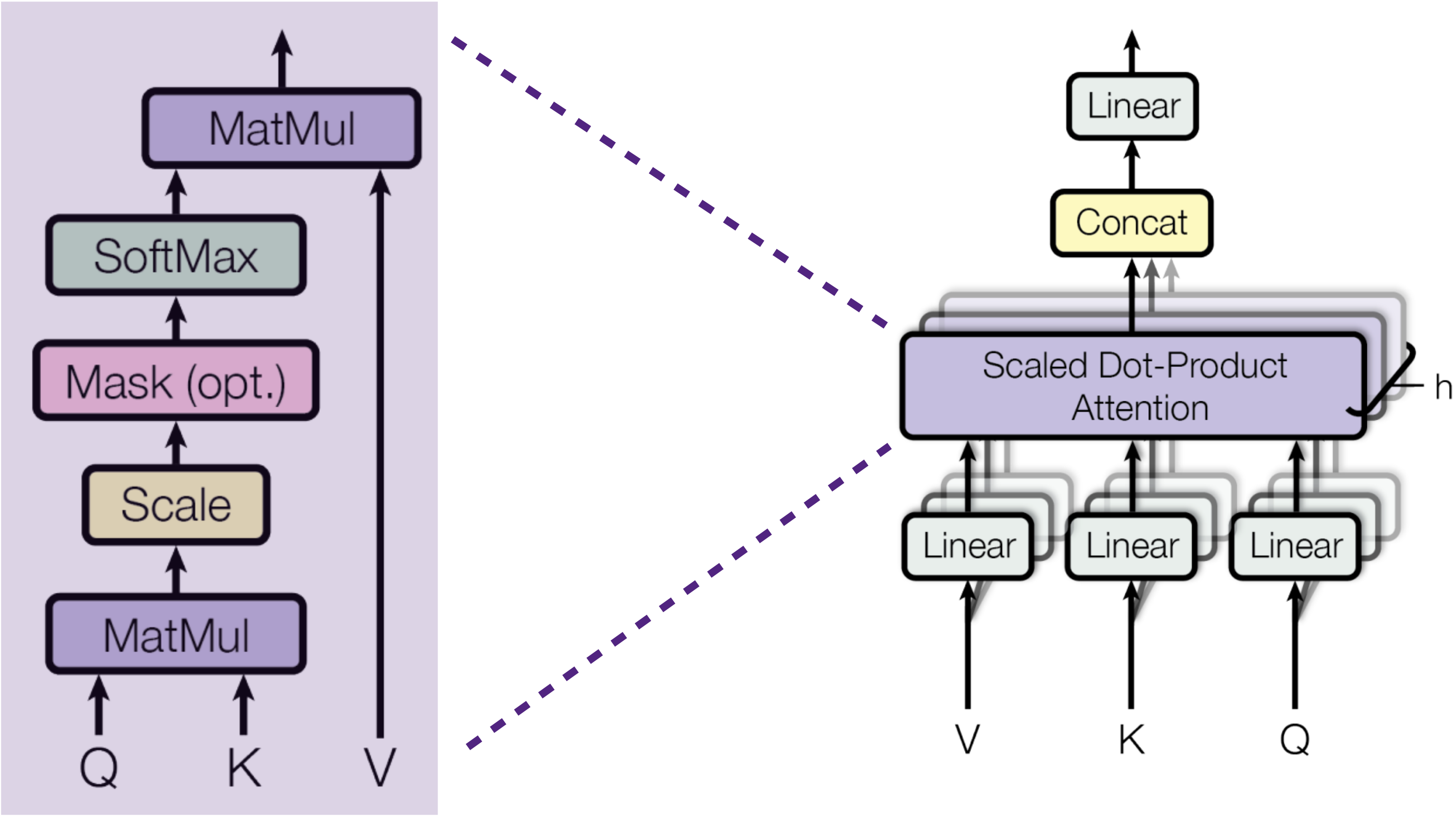
$W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$

$W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$

Linearly combines heads' outputs.



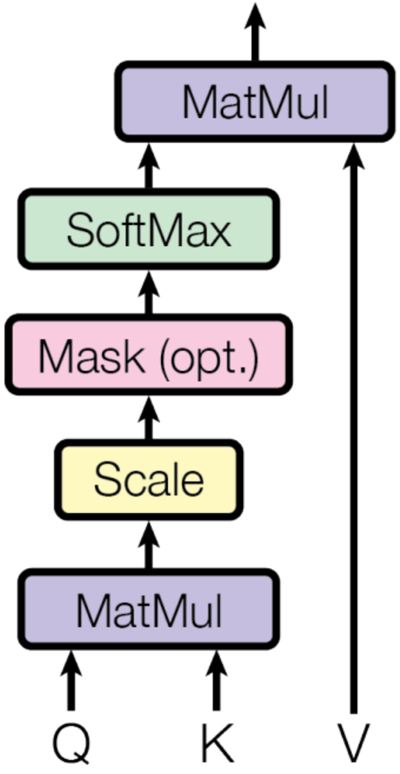
# Single-head self-Attention



# Single-head self-Attention

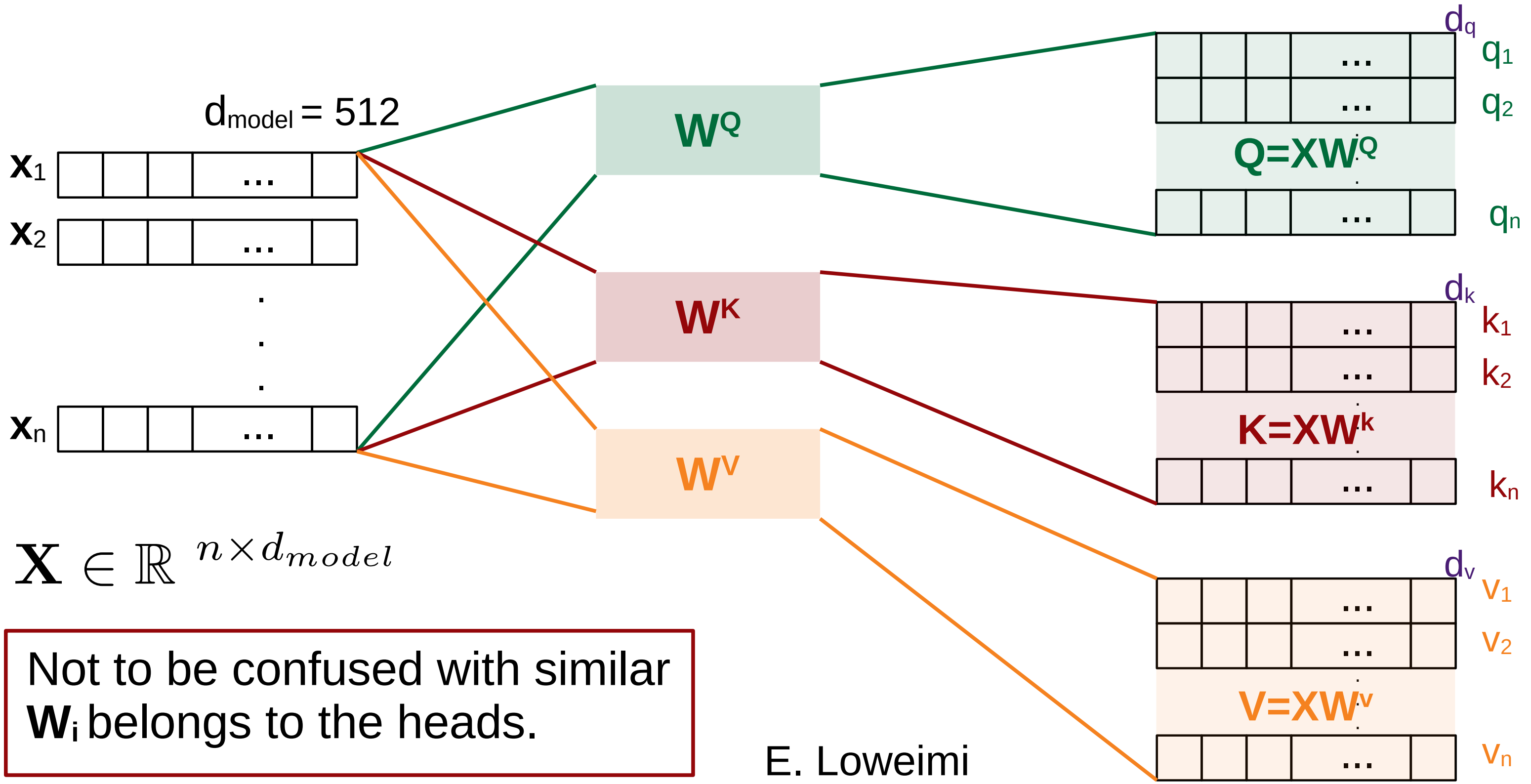
- Given: **Q**uery, **K**ey and **V**alue ({k:v})
- Output: attention-weighted mean of Values
- Weights prop. to similarity of **K** & **Q**
- Similarity: scaled-dot product
  - Scaled → to control magnitude@high dim

$$\text{Attention} = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V$$



# Generate Q, K, V via Linear transformation

- Embedding → Linear transformation




$$\mathbf{X} \in \mathbb{R}^{n \times d_{model}}$$

Note $d_q = d_k$

Not to be confused with similar $\mathbf{W}_i$ belongs to the heads.

# Multi-head self-Attention

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where } \text{head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

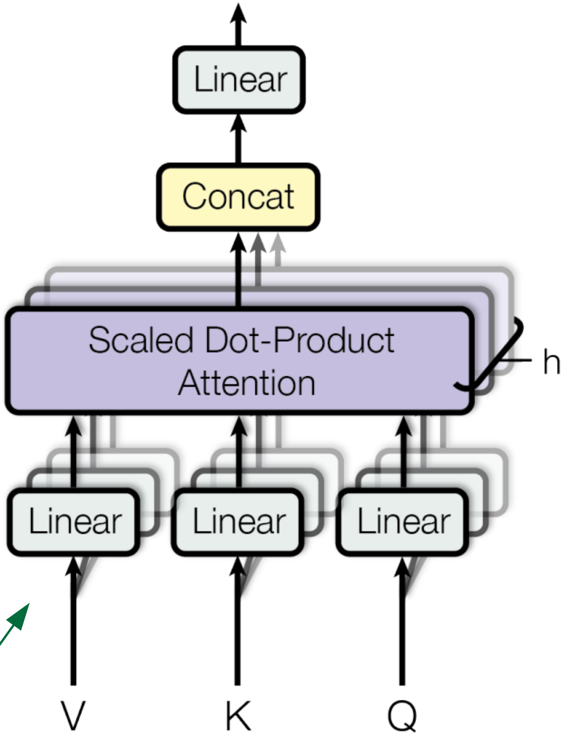
$W_i^Q \in \mathbb{R}^{d_\text{model} \times d_k}$

$W_i^K \in \mathbb{R}^{d_\text{model} \times d_k}$

$W_i^V \in \mathbb{R}^{d_\text{model} \times d_v}$

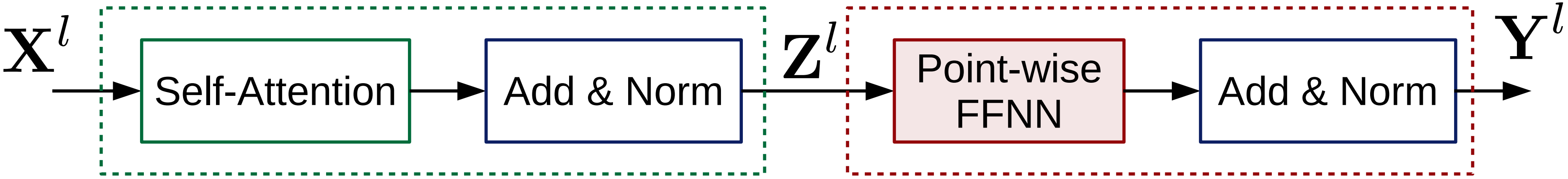
– $d_q = d_k = d_v = d_\text{model} / h$
– $d_\text{model} = 512, \quad h = 8$

Linear projection to space where dot product is a better proxy for similarity.

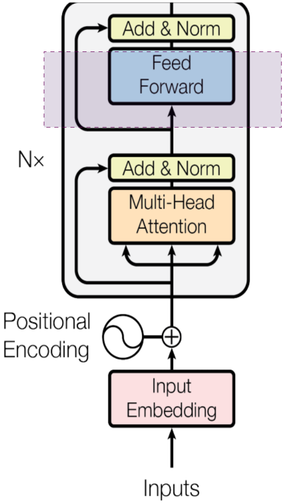



**Value** **Key** **Query**

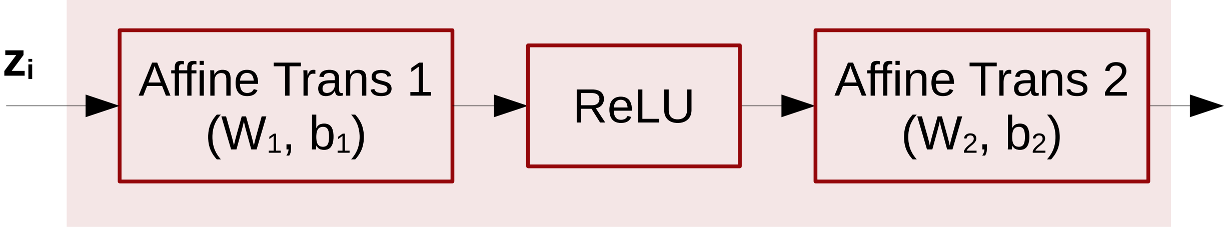
# Point-wise FFNN



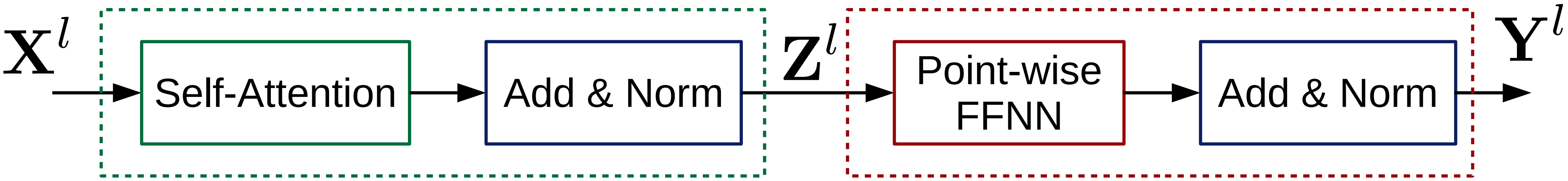

$$\mathbf{y}_i^l = FFNN(\mathbf{z}_i^l) = ReLU(\mathbf{z}_i^l W_1^l + b_1^l) W_2^l + b_2^l$$



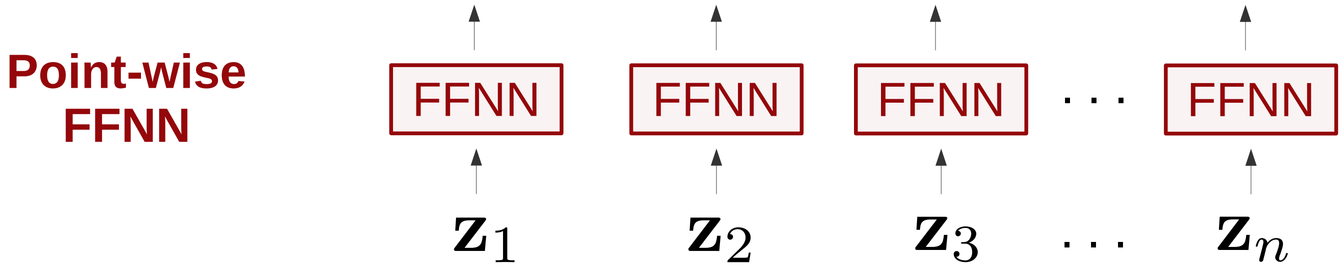

Point-wise FFNN



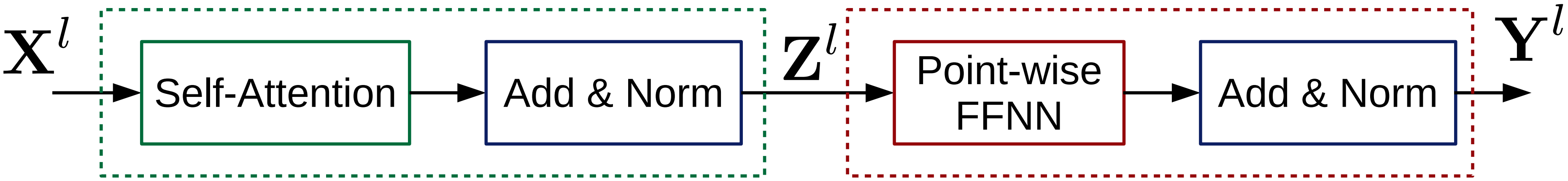
# Point-wise FFNN




$$\mathbf{y}_i^l = FFNN(\mathbf{z}_i^l) = ReLU(\mathbf{z}_i^l W_1^l + b_1^l)W_2^l + b_2^l$$



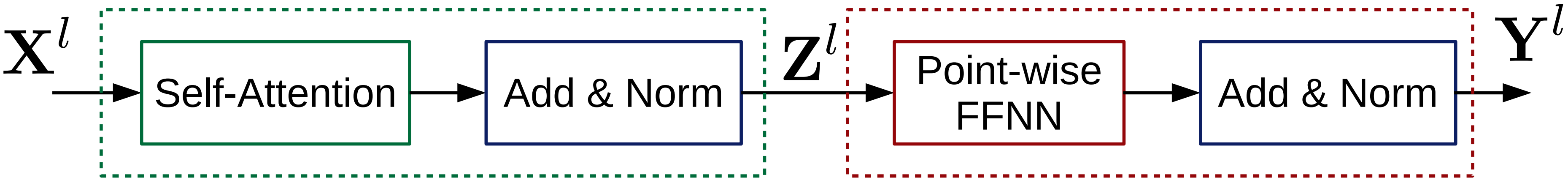
# Point-wise FFNN




$$\mathbf{y}_i^l = FFNN(\mathbf{z}_i^l) = ReLU(\mathbf{z}_i^l W_1^l + b_1^l)W_2^l + b_2^l$$

- **Point-wise**: applied to each position ($\mathbf{z}_i$) independently & identically.
- Each layer has its own FFNN, shared inside layer.
- Dimensions: $W_1^l \in \mathbb{R}^{d_{model} \times d_{ff}}$ and $W_2^l \in \mathbb{R}^{d_{ff} \times d_{model}}$ ($d_{ff} = 2048$)

# Point-wise FFNN




$$\mathbf{y}_i^l = FFNN(\mathbf{z}_i^l) = ReLU(\mathbf{z}_i^l W_1^l + b_1^l)W_2^l + b_2^l$$

The representation dimension does not change across layers and sublayers.

$\mathbf{X} \in \mathbb{R}^{n \times d_{model}}$

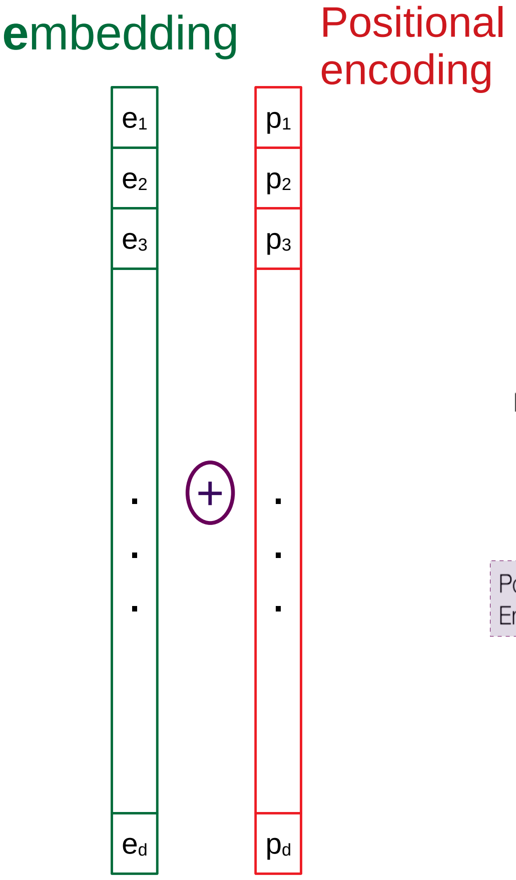
$\mathbf{Z} \in \mathbb{R}^{n \times d_{model}}$

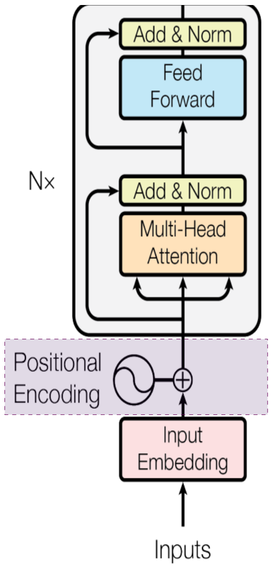
$\mathbf{Y} \in \mathbb{R}^{n \times d_{model}}$

# Positional Coding

- **Problem:**
  - Self-attention is agnostic to temporal or positional order

- **Solution**: Positional encoding
  - Add it to embeddings
    - Element-wise or concatenate



# Positional Coding

- **Problem:**
  - Self-attention has no notion of temporal order
- **Solution**:
  - Positional encoding
- Sinusoidal positional encoding
  - Limited/stable range → [-1,1]
  - Deals with any (unseen) length

$$PE_{(pos,2d)} = \sin(\frac{pos}{10^{\frac{8d}{D}}})$$

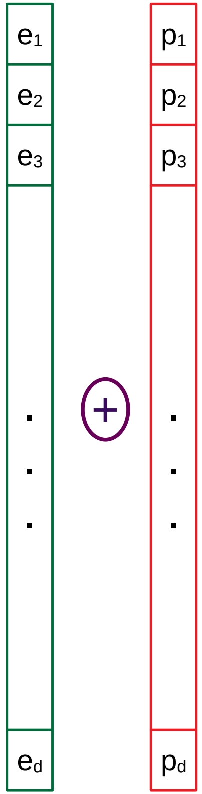
$$PE_{(pos,2d+1)} = \cos(\frac{pos}{10^{\frac{8d}{D}}})$$

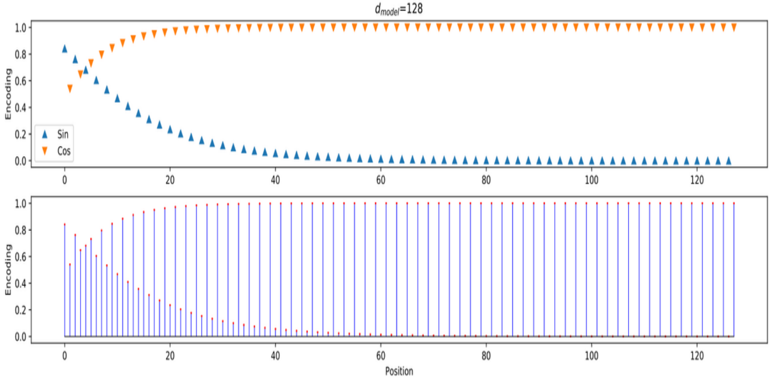
$$0 \leq pos < n$$

$$d = 0, 1, ..., D/2$$

# Positional Coding

embedding




$$PE_{(pos,2d)} = \sin\left(\frac{pos}{10^{\frac{8d}{D}}}\right)$$

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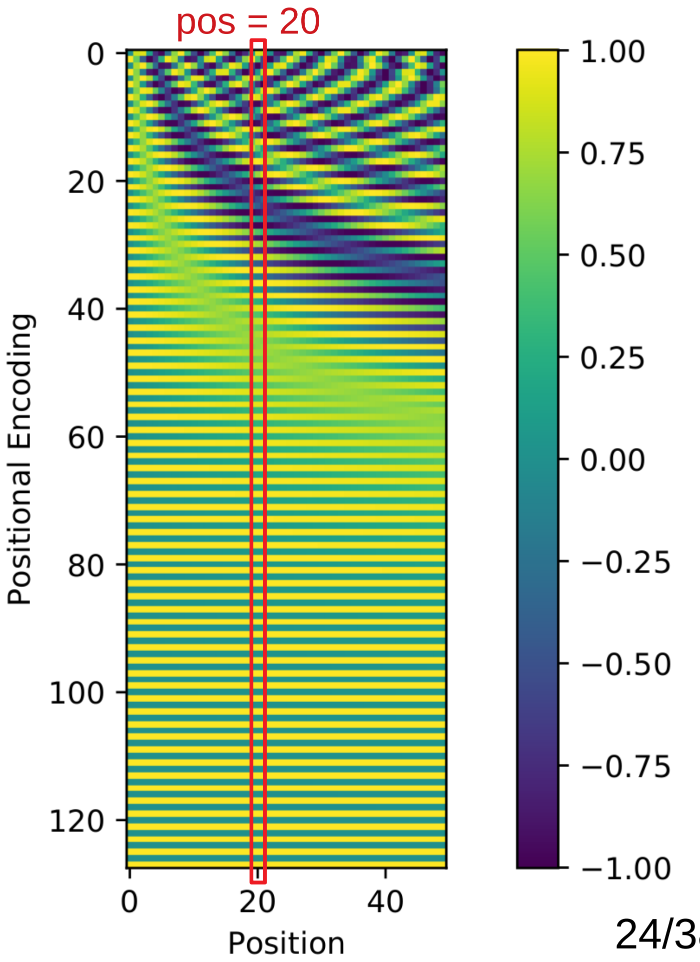
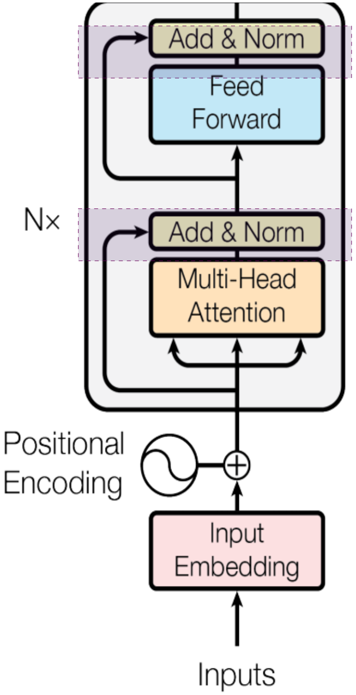


# Add and Norm

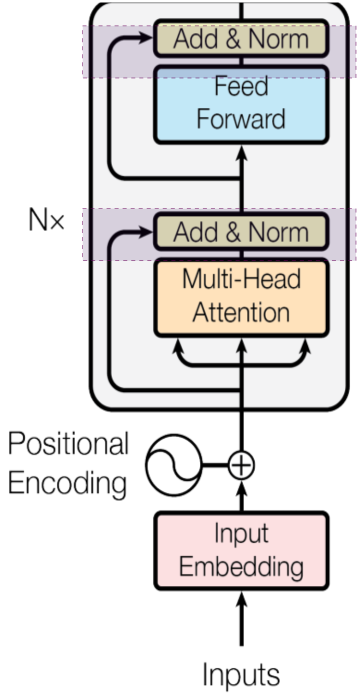
- Applied after each sublayer
  - Add → residual connection
  - Norm → Layer Normalisation
  - Sublayer = Norm(x + DropOut {sublayer(x)})

- **Note**: here (similar to working w/ RNNs) batch size is small → unreliable stats for Batch Norm



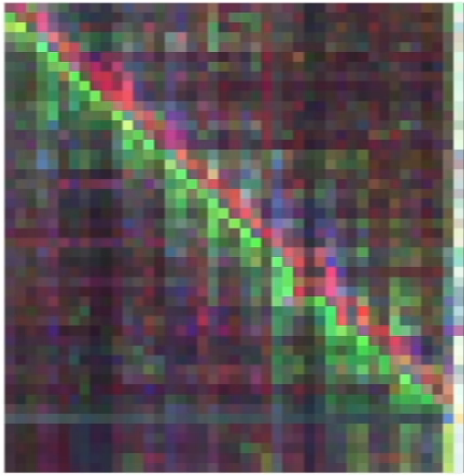
# Add and Norm

- Applied after each sublayer
  - Add → residual connection
  - Norm → Layer Normalisation
  - Sublayer = Norm(x + DropOut {sublayer(x)})
- Residual connection
  - Stabilises the training
  - Injects positional info into the model

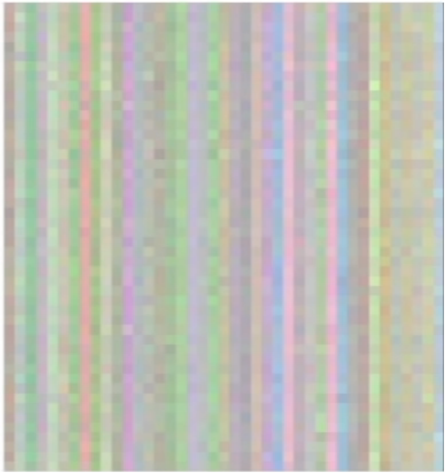


# Residual Connection Role

- Residual connection injects positional info into model
  - *Diagonal alignment* in Attention Encoder-Decoder



**With** residual connections

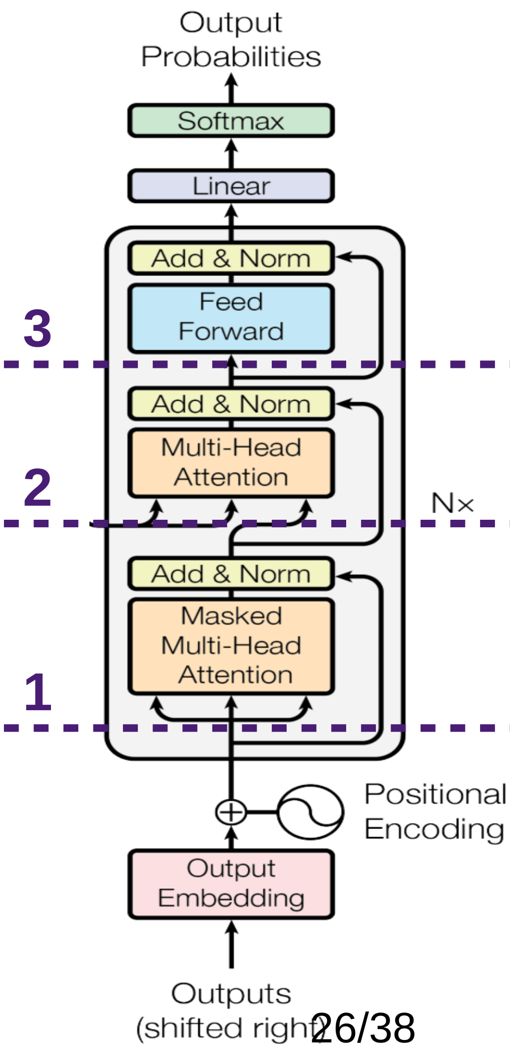


**Without** residual connections

# Decoder

- 6 layers, each one has ...
  - Sublayer 1: Masked MHSL*
  - Sublayer 2: Attention Encoder-Decoder
  - Sublayer 3: Point-wise FFNN

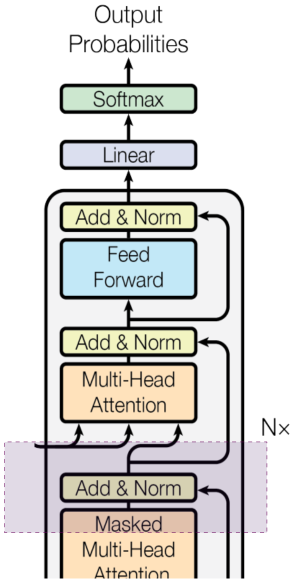
- Each sublayer has Add & Norm




MHSA*: Multi-head Self-attention

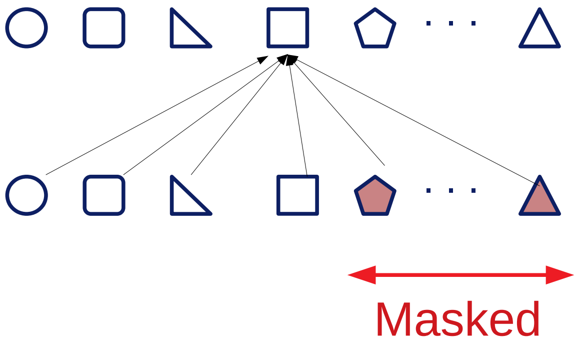
# Masked Multi-head Self-Attention

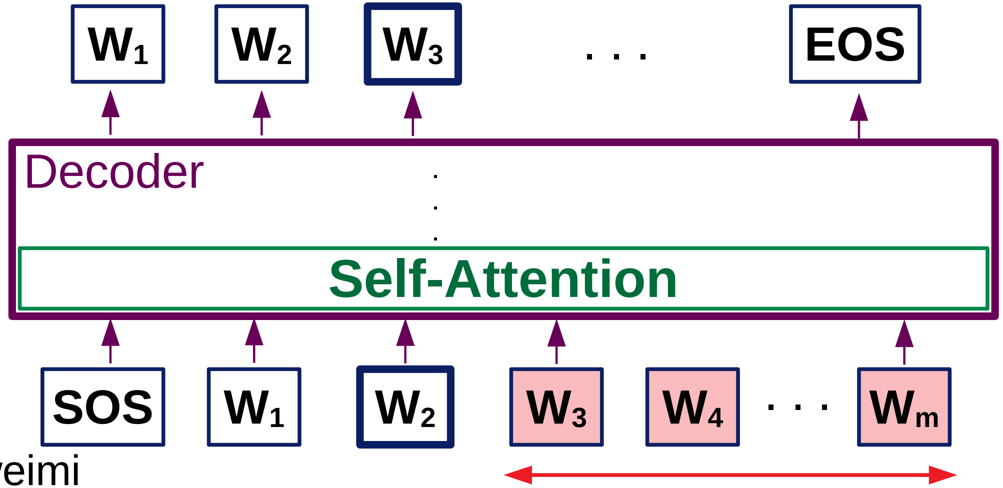
- Decoder generates one word at a time, left-to-right
- Masks preserve causality and autoregressive property of decoder, e.g. at $t=3$, $w_i$ for $i>3$ should be masked



# Masked Multi-head Self-Attention

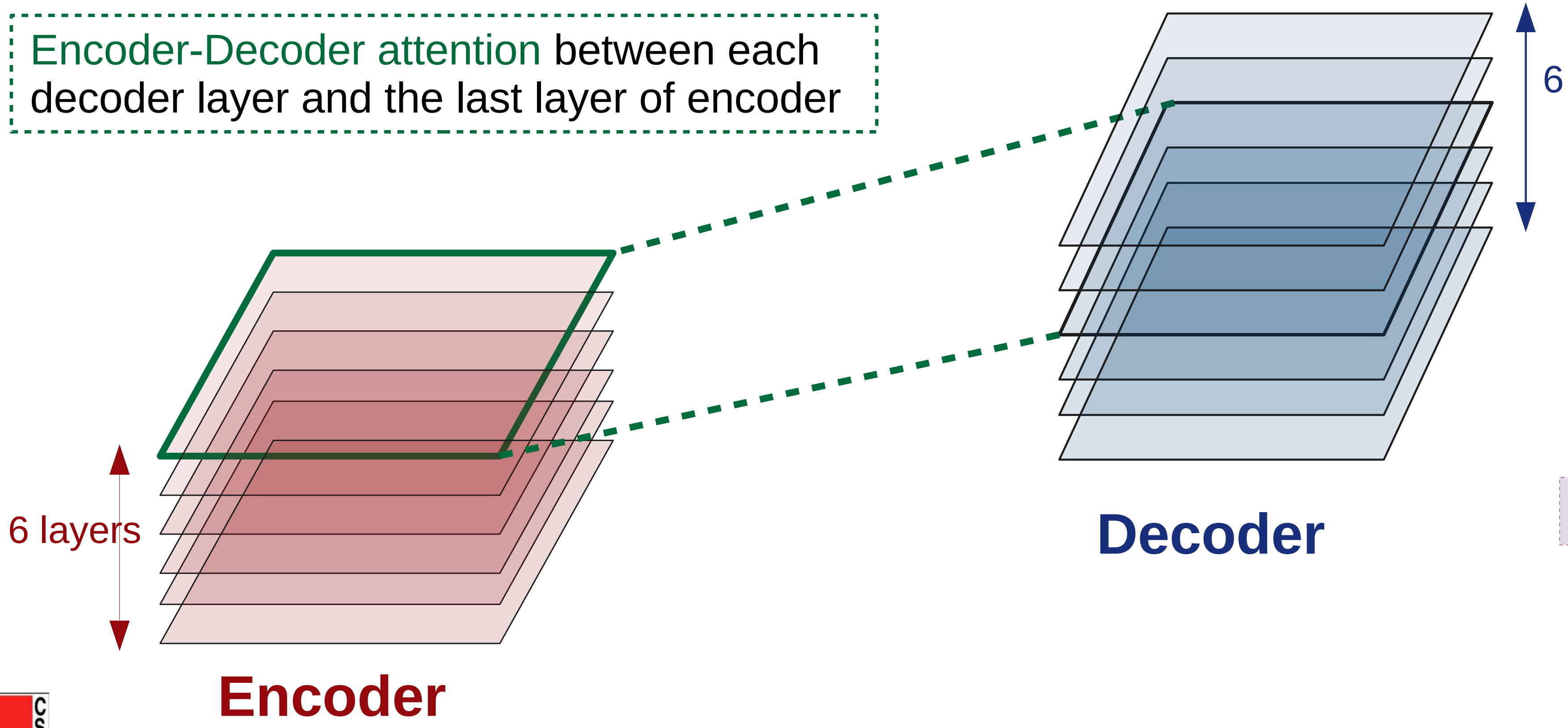
- Decoder generates one word at a time, left-to-right
- Masks preserve causality and autoregressive property of decoder, e.g. at $t=3$, $w_i$ for $i>2$ should be masked

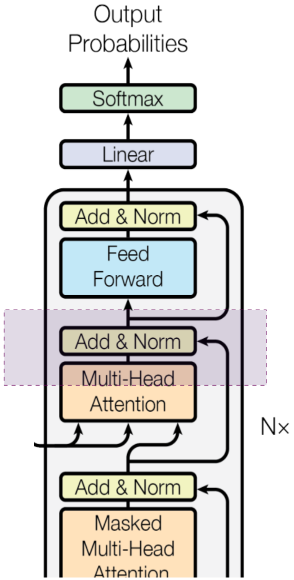


# Attention Encoder-Decoder

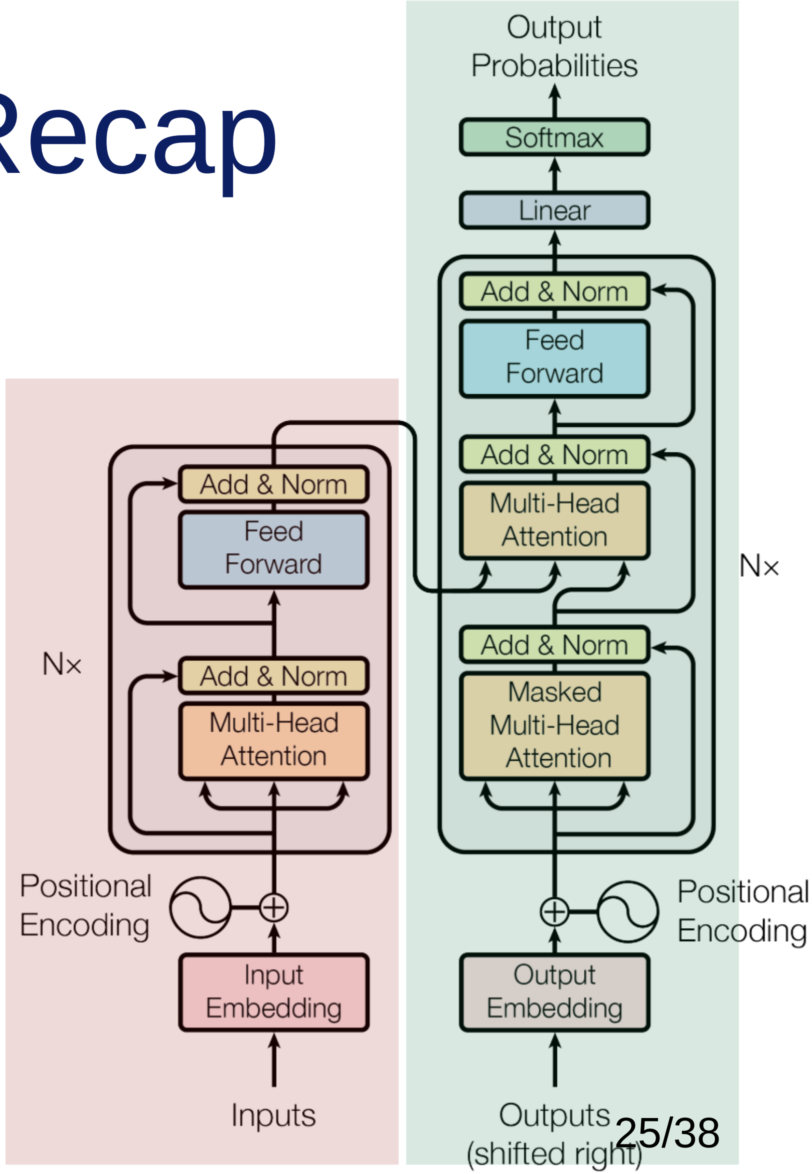
Encoder-Decoder attention between each decoder layer and the last layer of encoder



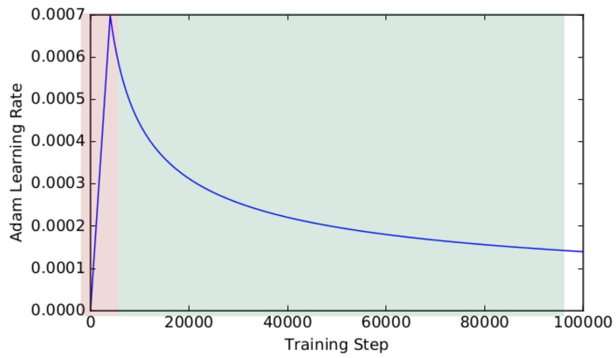
# Ingredients – Recap

- **Encoder**-**Decoder** structure
- Positional Embedding
- Multi-Head self-Attention
- Feed Forward NN (FFNN)
- Add & Norm



# Training Setup

- TensorFlow → Tensor2Tensor library → github
- Optimisation
  - Adam w/ learning rate warmup and exponential decay
- Regularisation
  - Dropout → rate: 0.1
  - Label smoothing → $\varepsilon_{ls} = 0.1$
    - Relax confidence on labels (C: #classes)



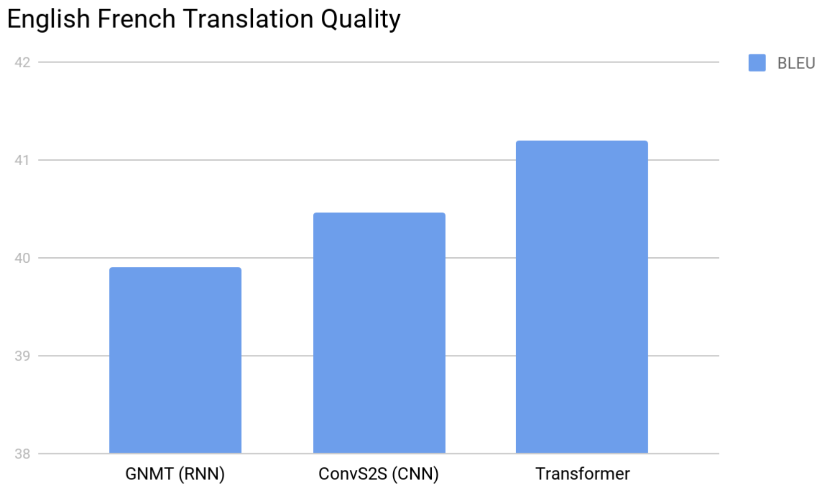

$$y_c \leftarrow y_c(1-\epsilon_{ls}) + \epsilon_{lk}/C$$

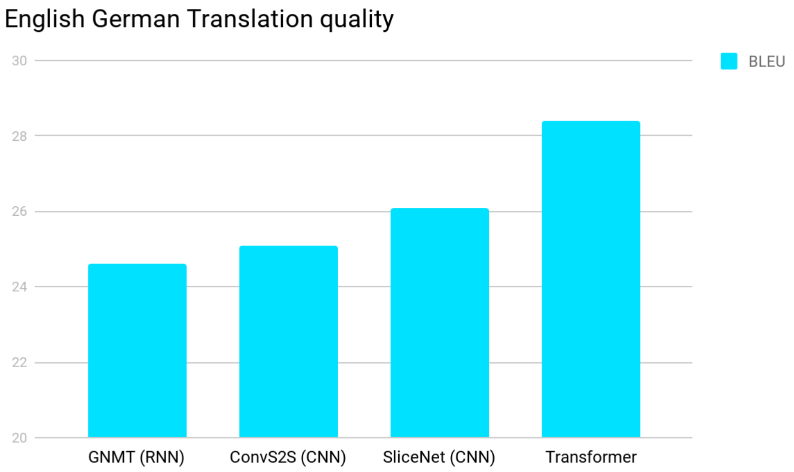
# State-of-the-art on WMT 2014

| Model | BLEU | | Training Cost (FLOPs) | |
|---|---|---|---|---|
| | EN-DE | EN-FR | EN-DE | EN-FR |
| ByteNet [18] | 23.75 | | | |
| Deep-Att + PosUnk [39] | | 39.2 | | $1.0 \cdot 10^{20}$ |
| GNMT + RL [38] | 24.6 | 39.92 | $2.3 \cdot 10^{19}$ | $1.4 \cdot 10^{20}$ |
| ConvS2S [9] | 25.16 | 40.46 | $9.6 \cdot 10^{18}$ | $1.5 \cdot 10^{20}$ |
| MoE [32] | 26.03 | 40.56 | $2.0 \cdot 10^{19}$ | $1.2 \cdot 10^{20}$ |
| Deep-Att + PosUnk Ensemble [39] | | 40.4 | | $8.0 \cdot 10^{20}$ |
| GNMT + RL Ensemble [38] | 26.30 | 41.16 | $1.8 \cdot 10^{20}$ | $1.1 \cdot 10^{21}$ |
| ConvS2S Ensemble [9] | 26.36 | **41.29** | $7.7 \cdot 10^{19}$ | $1.2 \cdot 10^{21}$ |
| Transformer (base model) | 27.3 | 38.1 | $\mathbf{3.3 \cdot 10^{18}}$ | |
| Transformer (big) | **28.4** | **41.8** | $2.3 \cdot 10^{19}$ | |

– BLEU score: * EN-DE: 28.4 * EN-FR: 41.8
– Data amount: * 4.5M pairs * 36M pairs

# NMT → WMT 2014

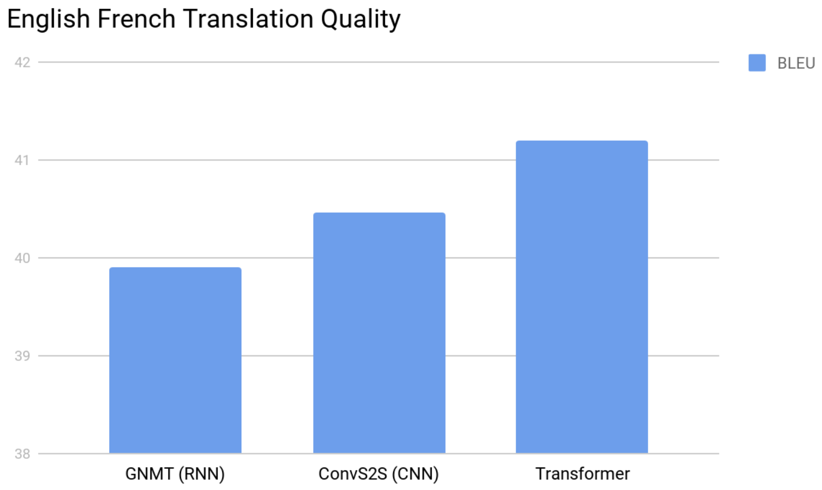


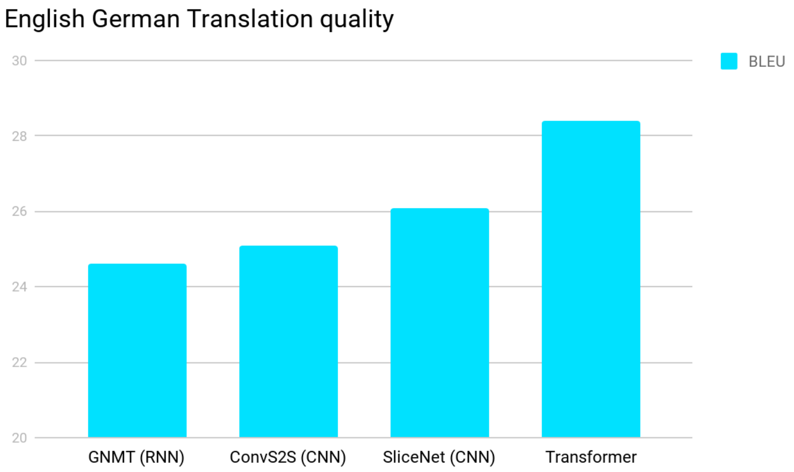




– Measure: BLEU scores (higher is better)

– Task/Data: Standard WMT newstest2014

# WMT 2014




*In WMT 2016 summary report, ”RNN” appeared 44 times.*
*In WMT 2018 report “RNN” appeared 9 and “Transformer” 63 times.*
*https://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture07-fancy-rnn.pdf*

# Transformer Hyperparameters

- Data: devset EN-DE
  - testnews2013

| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Transformer Hyperparameters

- Base vs big models
  - $d_{model} \rightarrow$ 512 vs 1024
  - $d_{ff} \rightarrow$ 2048 vs 4096
  - $h \rightarrow$ 8 vs 16
  - $P_{drop} \rightarrow$ 0.1 vs 0.3
  - #param $\rightarrow$ 65 vs 213 M
  - Bigger model is better

| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Transformer Hyperparameters

- **(A) → #heads (*h*)**
  - *h*=1 → BLEU 0.9 worse
  - *h*=16 → BLEU 0.4 worse
  - *h* should not be too large

| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Transformer Hyperparameters

- **(B) → key size ($d_k$)**
  - Reducing key size hurts
  - More sophisticated compatibility function may be beneficial

| | $N$ | $d_{model}$ | $d_{ff}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Transformer Hyperparameters

- **(C) → Model size**
  - Larger $N$ helps
  - Larger $d_{model}$ helps
  - Larger $d_{ff}$ helps
  - Larger model is better

| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Transformer Hyperparameters

- **(D)** → **Regularisation**
  - Dropout helps
  - Label smoothing helps
  - Rate should be adjusted
    - 0.1 better than 0 or 0.2

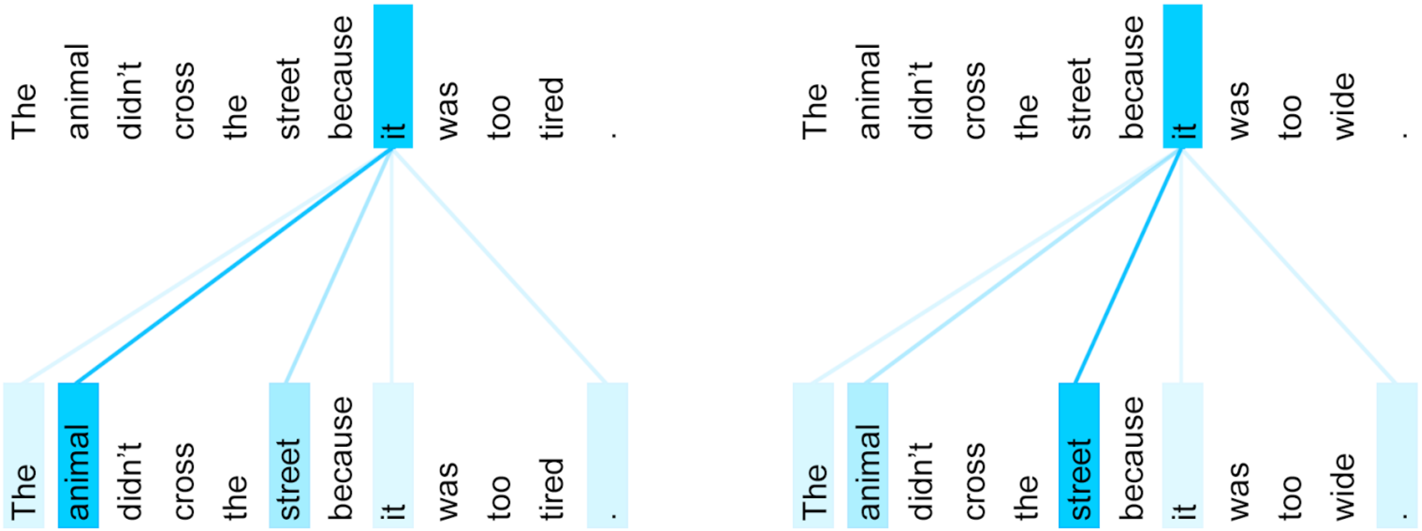
| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | | positional embedding instead of sinusoids | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Transformer Hyperparameters

- **(E) → Positional Coding**
  - Learning embedding slightly worsen results
  - Sinusoidal encoding is good enough

| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 1 | 512 | 512 | | | | 5.29 | 24.9 | |
| | | | | 4 | 128 | 128 | | | | 5.00 | 25.5 | |
| | | | | 16 | 32 | 32 | | | | 4.91 | 25.8 | |
| | | | | 32 | 16 | 16 | | | | 5.01 | 25.4 | |
| (B) | | | | | 16 | | | | | 5.16 | 25.1 | 58 |
| | | | | | 32 | | | | | 5.01 | 25.4 | 60 |
| (C) | 2 | | | | | | | | | 6.11 | 23.7 | 36 |
| | 4 | | | | | | | | | 5.19 | 25.3 | 50 |
| | 8 | | | | | | | | | 4.88 | 25.5 | 80 |
| | | 256 | | | 32 | 32 | | | | 5.75 | 24.5 | 28 |
| | | 1024 | | | 128 | 128 | | | | 4.66 | 26.0 | 168 |
| | | | 1024 | | | | | | | 5.12 | 25.4 | 53 |
| | | | 4096 | | | | | | | 4.75 | 26.2 | 90 |
| (D) | | | | | | | 0.0 | | | 5.77 | 24.6 | |
| | | | | | | | 0.2 | | | 4.95 | 25.5 | |
| | | | | | | | | 0.0 | | 4.67 | 25.3 | |
| | | | | | | | | 0.2 | | 5.47 | 25.7 | |
| (E) | positional embedding instead of sinusoids | | | | | | | | | 4.92 | 25.7 | |
| big | 6 | 1024 | 4096 | 16 | | | 0.3 | | 300K | **4.33** | **26.4** | 213 |

# Coreference Resolution (Winograd Schemas)

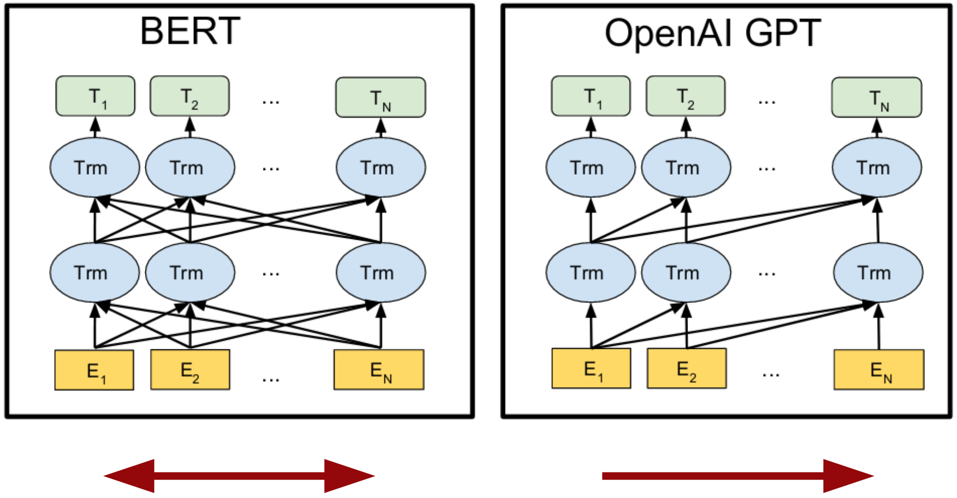



– Encoder self-attention visualisation at layer 5 (out of 6) ...

* The ***animal*** didn't cross the **street** because ***it*** was too **tired**.
* The **animal** didn't cross the **street** because ***it*** was too **wide**.

# Ongoing Work ...

- BERT and OpenAI GPT
- Self-supervision and classification
- Multitask learning
- And many more ...



# That's it!

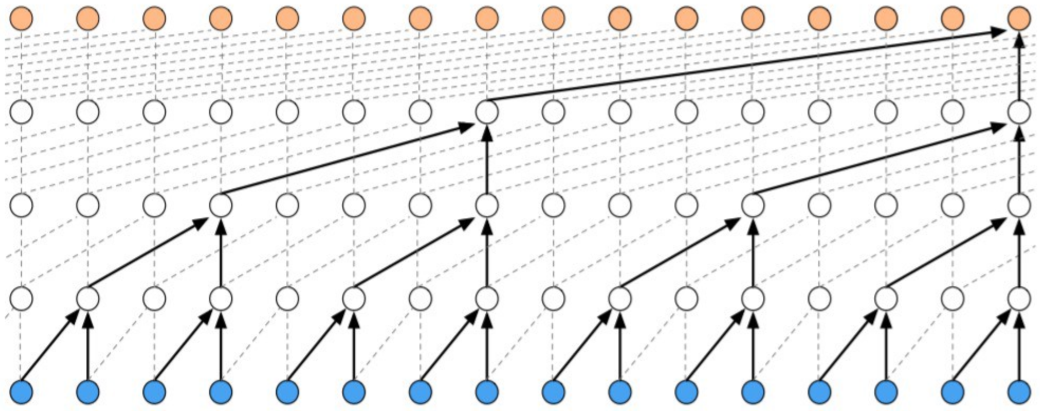
- Thanks for your ATTENTION!
  - That's all I needed ;-)
- Q/A

- Appendix

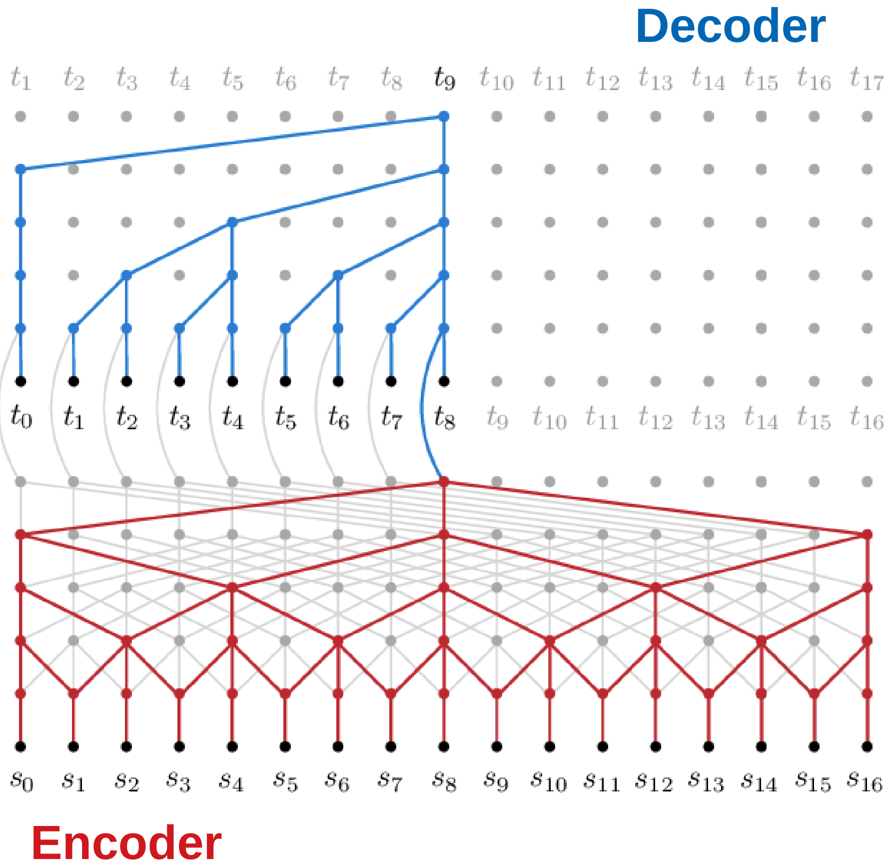
  (A) CNN Encoder-Decoder

# (A) CNN Encoder-Decoder

- Exp: ByteNet and ConvS2S



wavenet



# (A) CNN Encoder-Decoder

- CNN advantages
  - Sparsity of connections → weight sharing
  - Exploiting local dependencies → kernel size
  - Translational invariance → pooling
  - Easy to parallelise within layer

# (A) CNN Encoder-Decoder

- Modelling long-range dependencies requires
  - Many layers → makes training harder
  - Large kernel → computational cost, overfitting

- Path length between positions (in a sequence)
  - Linear ↔ no dilation
  - Log ↔ with dilation