# Tensor2Tensor Transformers

## New Deep Models for NLP

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# RNNs Everywhere

Very successful for variable-length representations

Sequences (e.g. language), images, …

Gating (LSTM, GRU) for long-range error propagation

At the core of seq2seq (w/ attention)

# But…

Sequentiality prohibits parallelization within instances

Long-range dependencies still tricky, despite gating

**Many modalities are hierarchical-ish (e.g. language)**

**RNNs (w/ sequence-aligned states) are wasteful!**

# CNNs?

Trivial to parallelize (per layer)

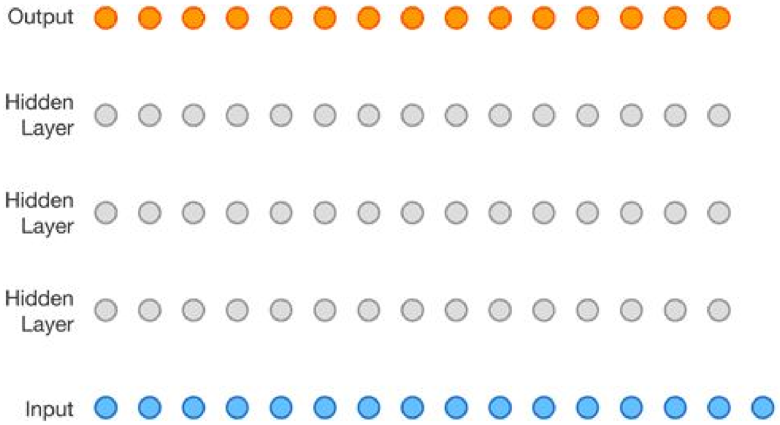
Fit intuition that most dependencies are local

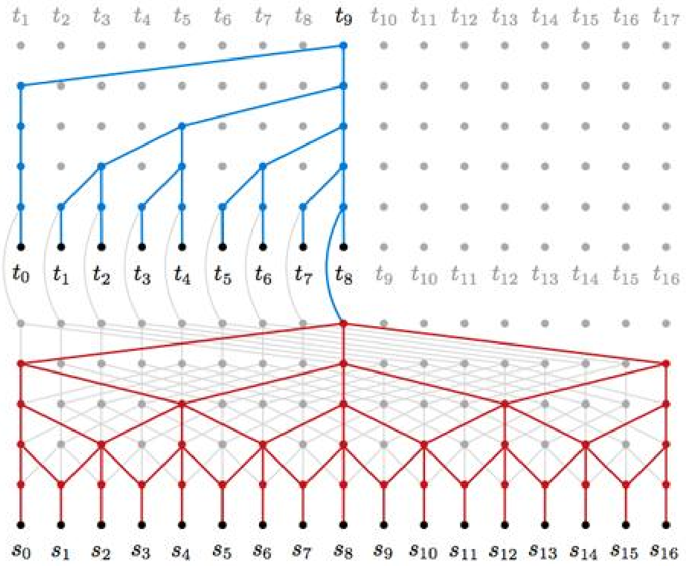
**Path length between positions can be logarithmic**

**when using dilated convolutions, left-padding for text.**

# Auto-Regressive CNNs

## WaveNet and ByteNet



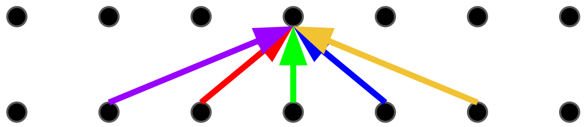
# Attention

Attention between encoder and decoder is crucial in NMT

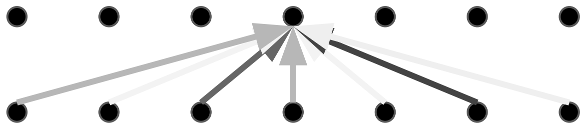
**Why not use (self-)attention for the representations?**

# Self-Attention

Convolution



Self-Attention



# Self-Attention

Constant path length between any two positions

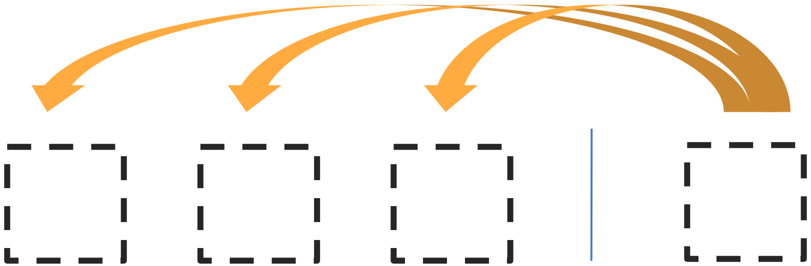
Variable-sized perceptive field

Gating/multiplication enables crisp error propagation

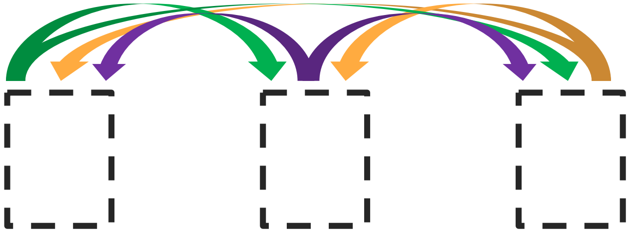
Trivial to parallelize (per layer)

**Can replace sequence-aligned recurrence entirely**

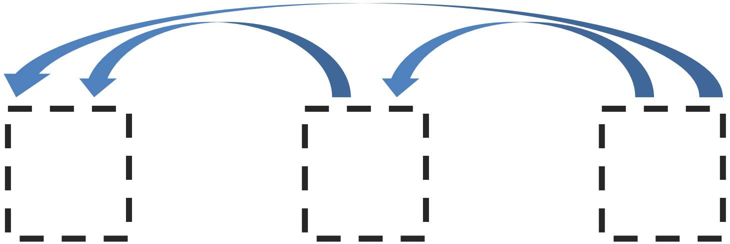
# Three ways of attention



Encoder-Decoder Attention

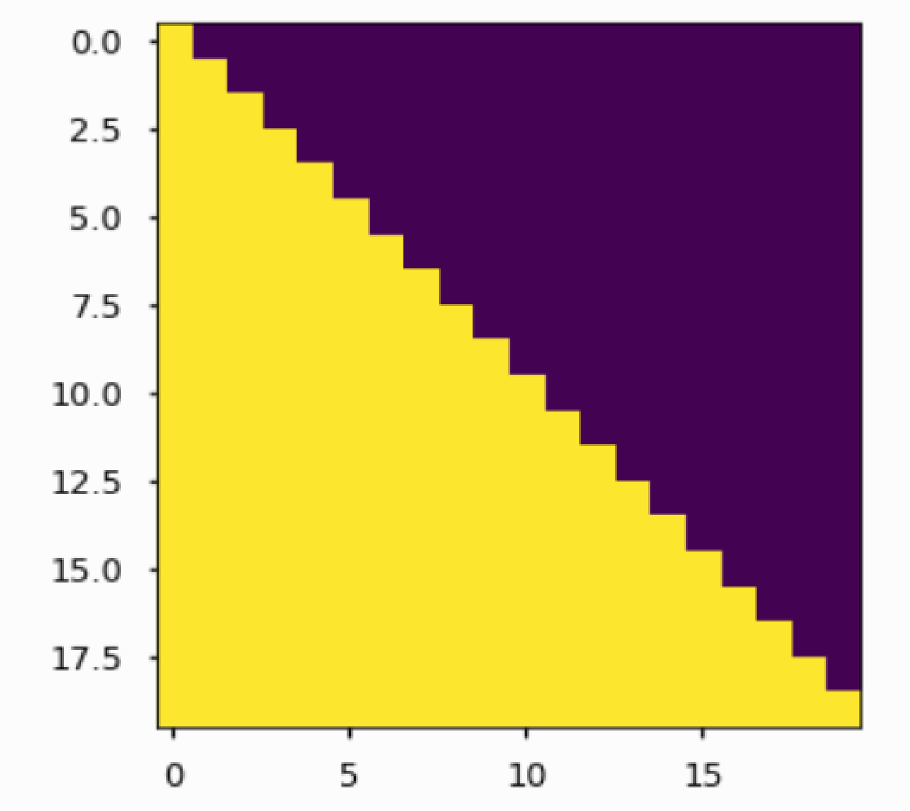


Encoder Self-Attention



MaskedDecoder Self-Attention

# Attention Mask



# The Transformer

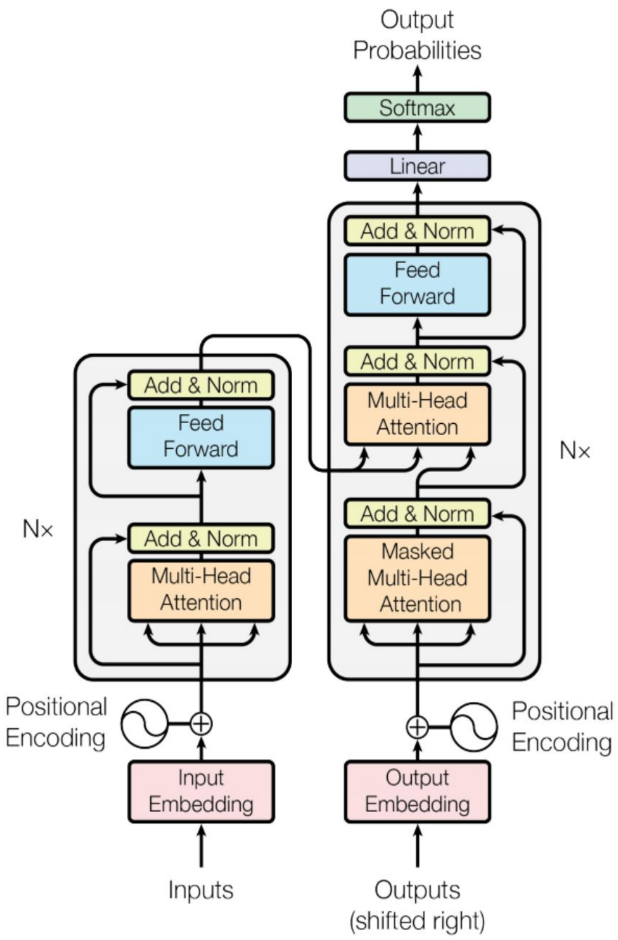
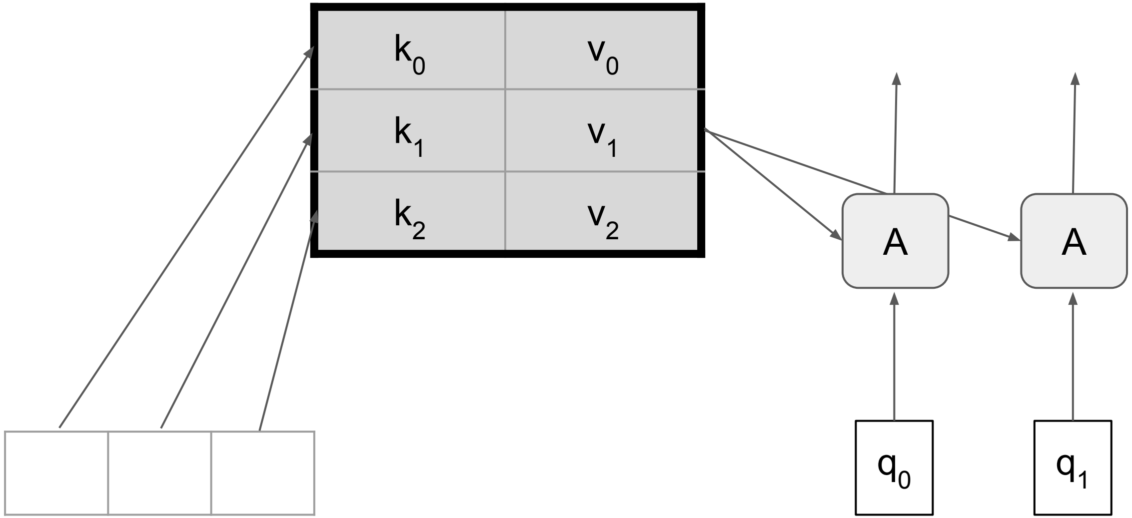



Figure 1: The Transformer - model architecture.

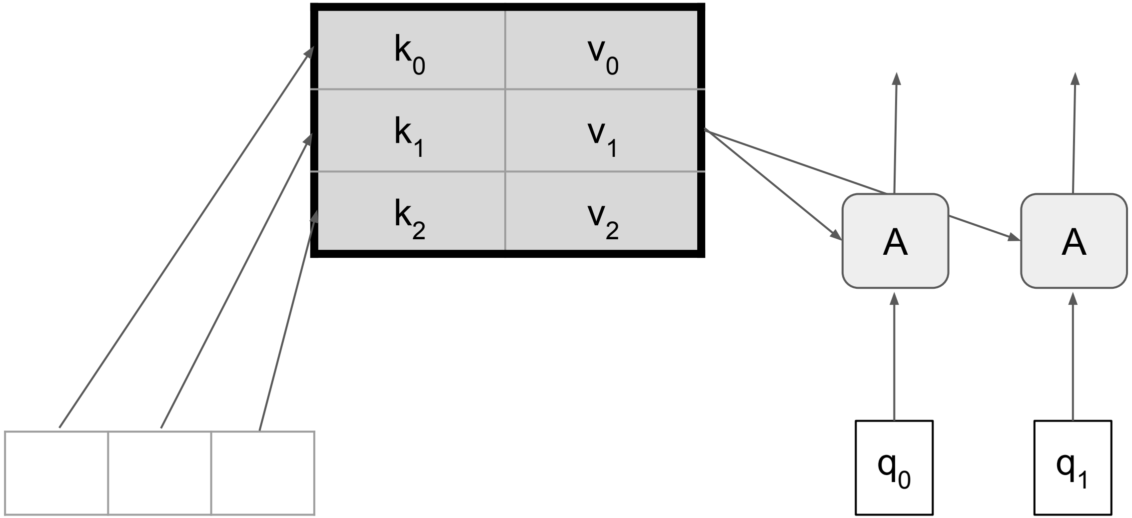
# Dot-Product Attention

$$A(q, K, V) = \sum_i \frac{e^{q \cdot k_i}}{\sum_j e^{q \cdot k_j}} v_i$$



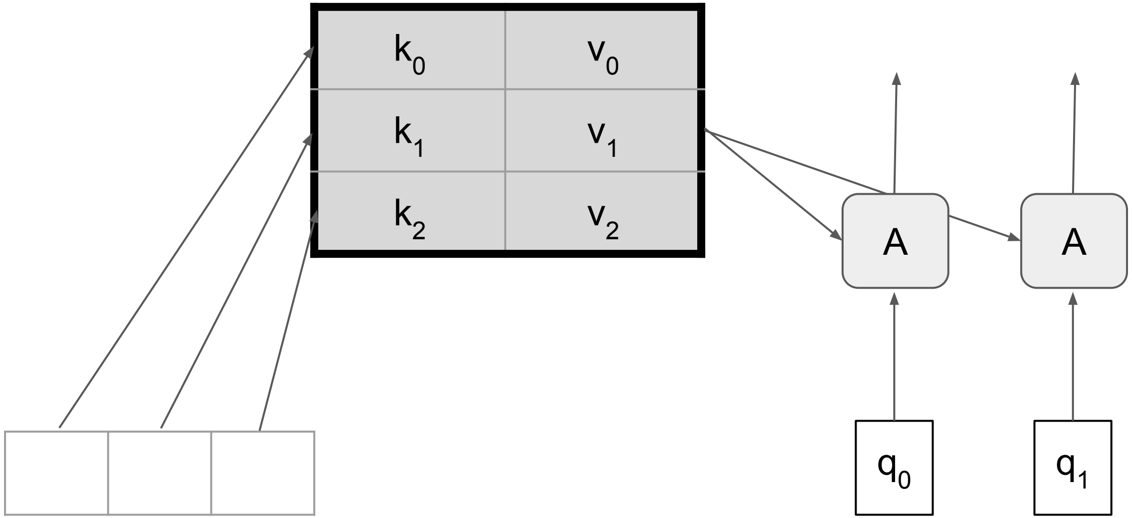
# Dot-Product Attention

$$A(Q, K, V) = softmax(QK^T)V$$



# Scaled Dot-Product Attention:

$$A(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

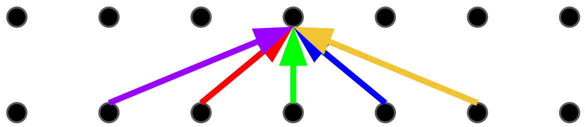


| | Ops | Activations |
|---|---|---|
| Attention (dot-prod) | $n^2 \cdot d$ | $n^2 + n \cdot d$ |
| Attention (additive) | $n^2 \cdot d$ | $n^2 \cdot d$ |
| Recurrent | $n \cdot d^2$ | $n \cdot d$ |
| Convolutional | $n \cdot d^2$ | $n \cdot d$ |

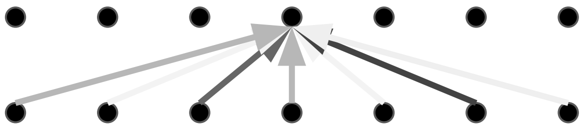
n = sequence length d = depth k = kernel size

# What's missing from Self-Attention?

Convolution



Self-Attention

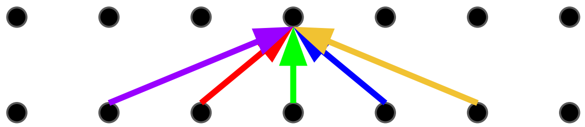


# What’s missing from Self-Attention?

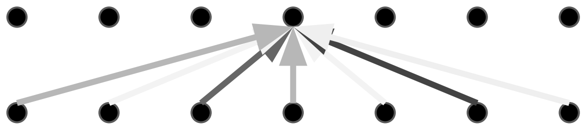
- Convolution: a different linear transformation for each relative position. Allows you to distinguish what information came from where.

- Self-Attention: a weighted average :(

Convolution



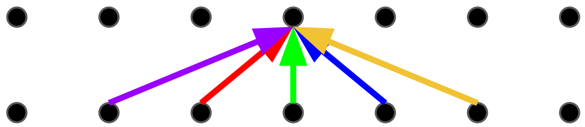
Self-Attention



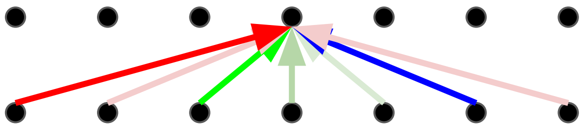
# The Fix: Multi-Head Attention

- Multiple attention layers (heads) in parallel (shown by different colors)
- Each head uses different linear transformations.
- Different heads can learn different relationships.

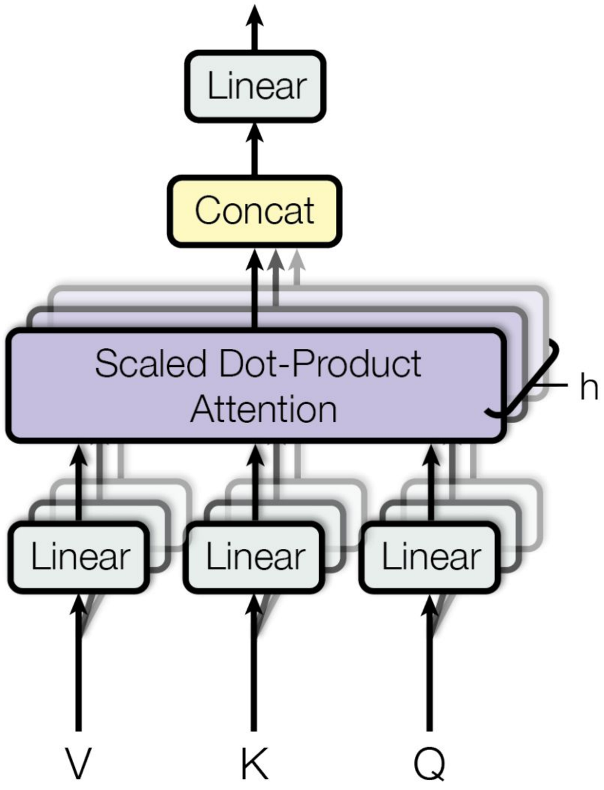
## Convolution



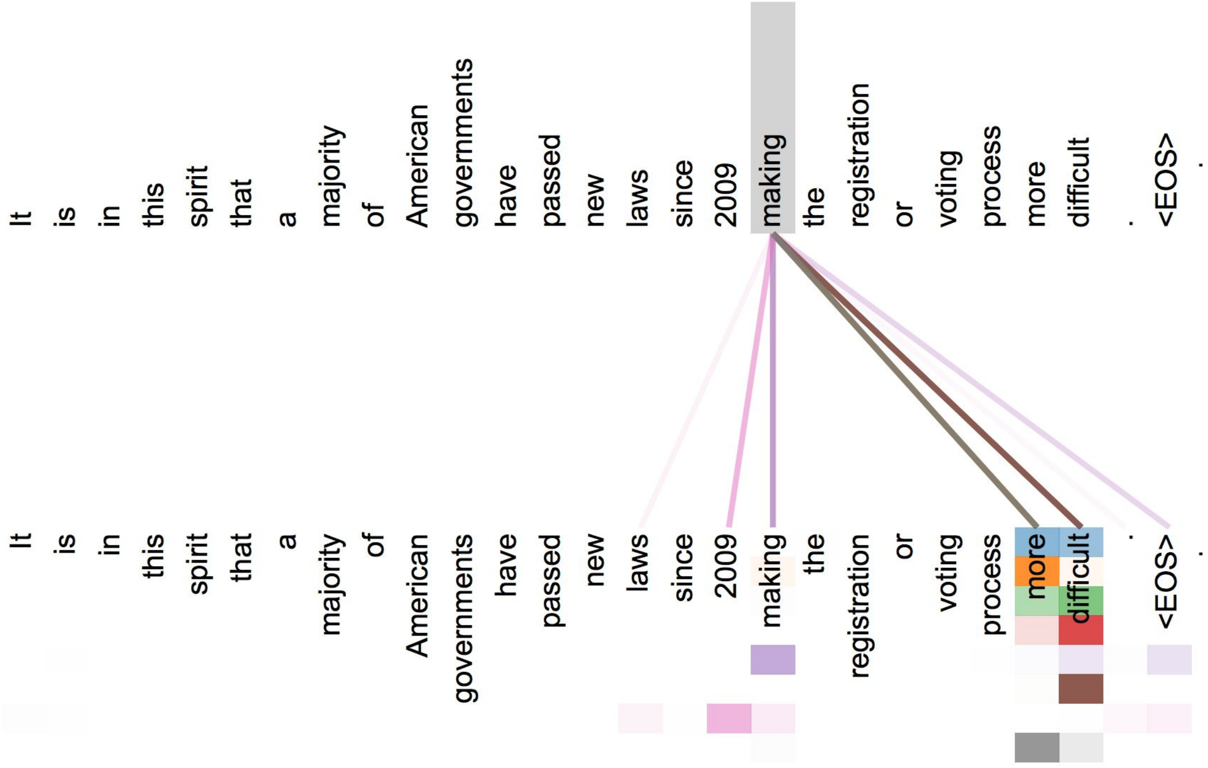
## Multi-Head Attention



# The Fix: Multi-Head Attention



# The Fix: Multi-Head Attention



| | Ops | Activations |
|---|---|---|
| Multi-Head Attention<br>with linear transformations.<br>For each of the h heads,<br>$d_q = d_k = d_v = d/h$ | $n^2 \cdot d + n \cdot d^2$ | $n^2 \cdot h + n \cdot d$ |
| Recurrent | $n \cdot d^2$ | $n \cdot d$ |
| Convolutional | $n \cdot d^2$ | $n \cdot d$ |

$n$ = sequence length $d$ = depth $k$ = kernel size

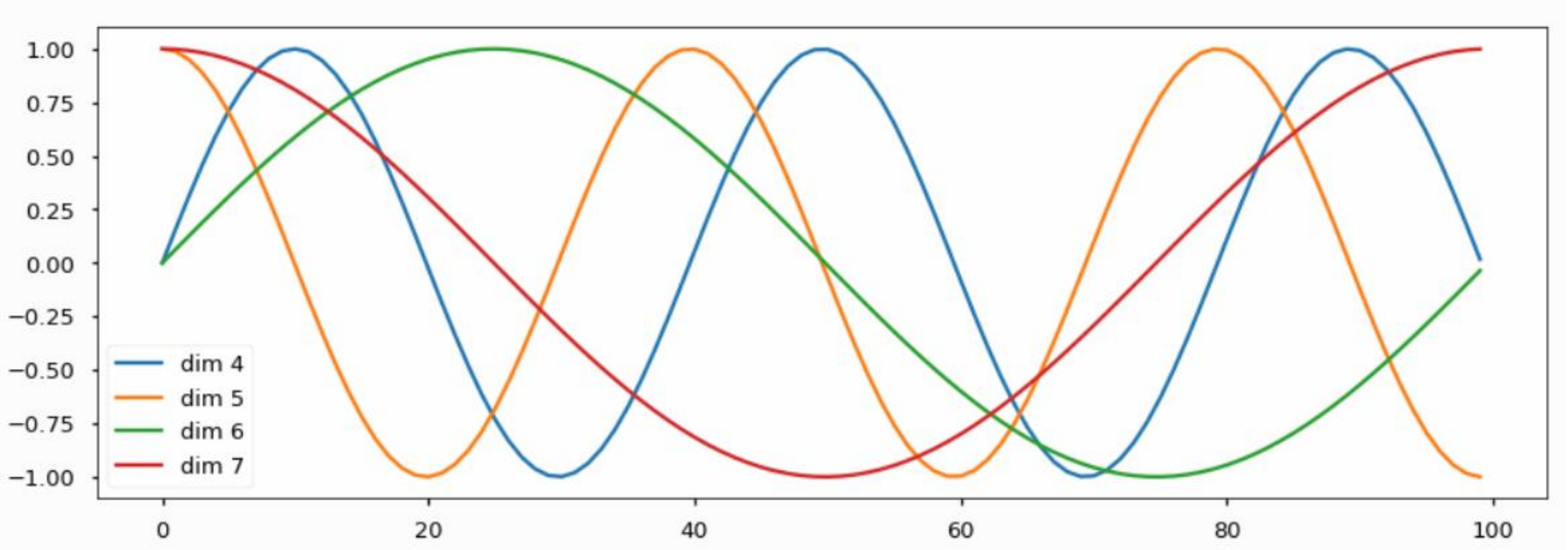
# Positional Encoding

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

For any fixed offset k,

$PE_{(pos+k)}$ can be represented as a linear function of $PE_{pos}$.

# Positional Encoding



# Why Self-Attention?

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. $n$ is the sequence length, $d$ is the representation dimension, $k$ is the kernel size of convolutions and $r$ the size of the neighborhood in restricted self-attention.

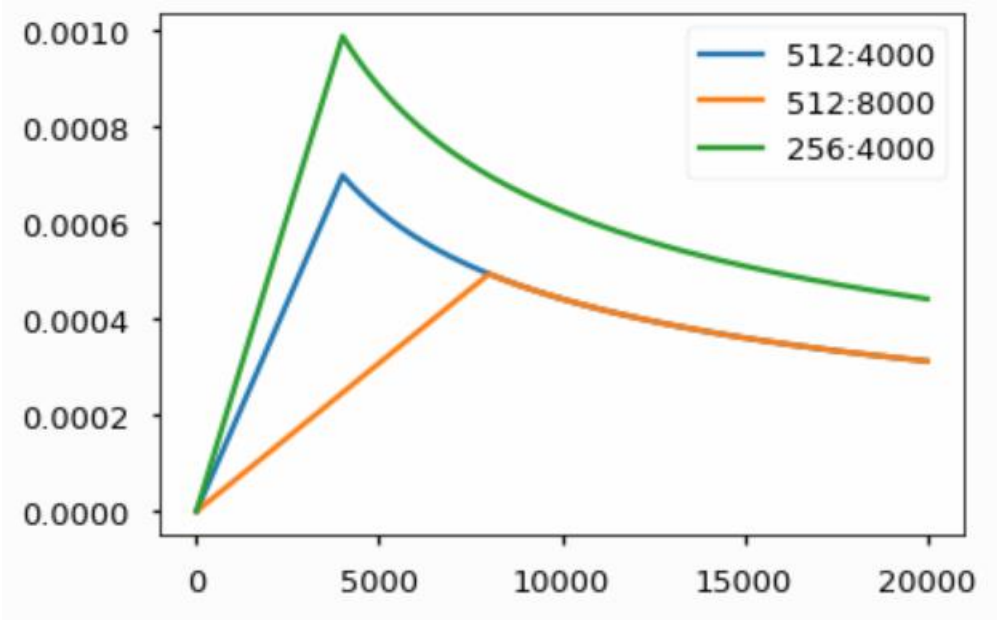
| Layer Type | Complexity per Layer | Sequential Operations | Maximum Path Length |
|---|---|---|---|
| Self-Attention | $O(n^2 \cdot d)$ | $O(1)$ | $O(1)$ |
| Recurrent | $O(n \cdot d^2)$ | $O(n)$ | $O(n)$ |
| Convolutional | $O(k \cdot n \cdot d^2)$ | $O(1)$ | $O(log_k(n))$ |
| Self-Attention (restricted) | $O(r \cdot n \cdot d)$ | $O(1)$ | $O(n/r)$ |

# Training and Decoding - usual tricks

- ADAM optimizer with learning rate proportional to ($step^{-0.5}$)
- Dropout during training at every layer just before adding residual
- Label smoothing
- Auto-regressive decoding with beam search and length penalties
- Checkpoint-averaging

# Optimizer

$$lrate = d_{\text{model}}^{-0.5} \cdot \min(step\_num^{-0.5}, step\_num \cdot warmup\_steps^{-1.5})$$



# Machine Translation Results: WMT-14

| Model | BLEU | | Training Cost (FLOPs) | |
|---|---|---|---|---|
| | EN-DE | EN-FR | EN-DE | EN-FR |
| ByteNet [17] | 23.75 | | | |
| Deep-Att + PosUnk [37] | | 39.2 | | $1.0 \cdot 10^{20}$ |
| GNMT + RL [36] | 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 [31] | 26.03 | 40.56 | $2.0 \cdot 10^{19}$ | $1.2 \cdot 10^{20}$ |
| Deep-Att + PosUnk Ensemble [37] | | 40.4 | | $8.0 \cdot 10^{20}$ |
| GNMT + RL Ensemble [36] | 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** | **41.0** | $2.3 \cdot 10^{19}$ | |

# Ablations

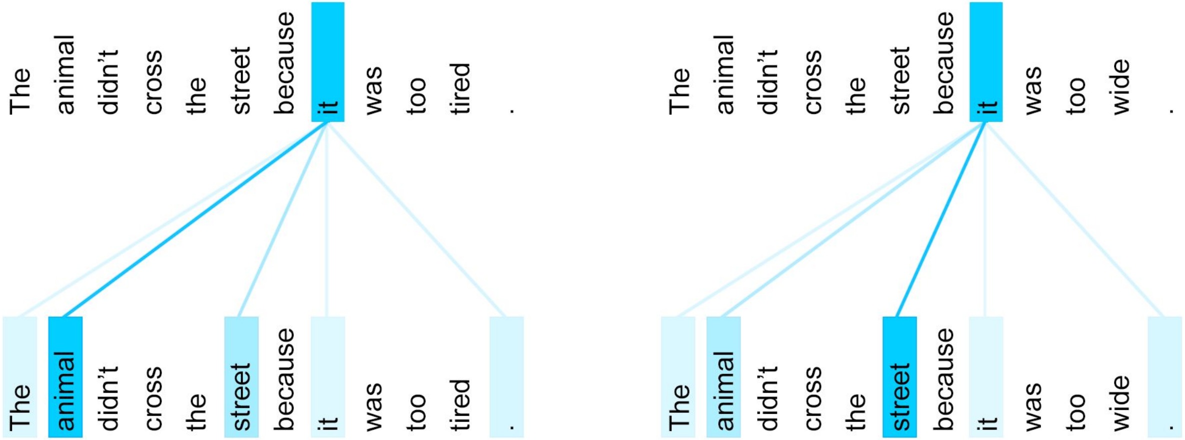
| | $N$ | $d_{\text{model}}$ | $d_{\text{ff}}$ | $h$ | $d_k$ | $d_v$ | $P_{drop}$ | $\epsilon_{ls}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| base | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65 |
| (A) | | | | 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 |

# Constituency Parser

Table 4: The Transformer generalizes well to English constituency parsing (Results are on Section 23 of WSJ)

| Parser | Training | WSJ 23 F1 |
|---|---|---|
| Vinyals & Kaiser el al. (2014) [37] | WSJ only, discriminative | 88.3 |
| Petrov et al. (2006) [29] | WSJ only, discriminative | 90.4 |
| Zhu et al. (2013) [40] | WSJ only, discriminative | 90.4 |
| Dyer et al. (2016) [8] | WSJ only, discriminative | 91.7 |
| Transformer (4 layers) | WSJ only, discriminative | 91.3 |
| Zhu et al. (2013) [40] | semi-supervised | 91.3 |
| Huang & Harper (2009) [14] | semi-supervised | 91.3 |
| McClosky et al. (2006) [26] | semi-supervised | 92.1 |
| Vinyals & Kaiser el al. (2014) [37] | semi-supervised | 92.1 |
| Transformer (4 layers) | semi-supervised | 92.7 |
| Luong et al. (2015) [23] | multi-task | 93.0 |
| Dyer et al. (2016) [8] | generative | 93.3 |

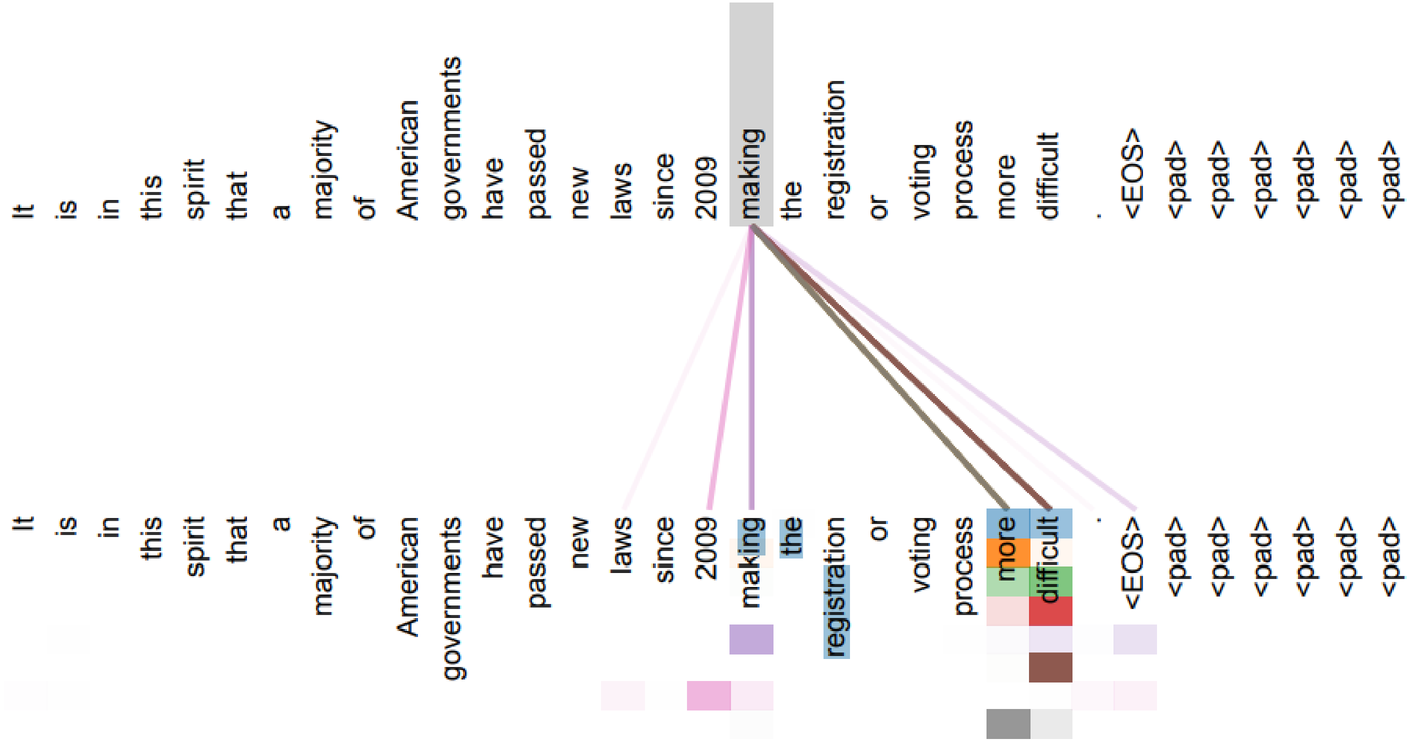
# Coreference resolution (Winograd schemas)



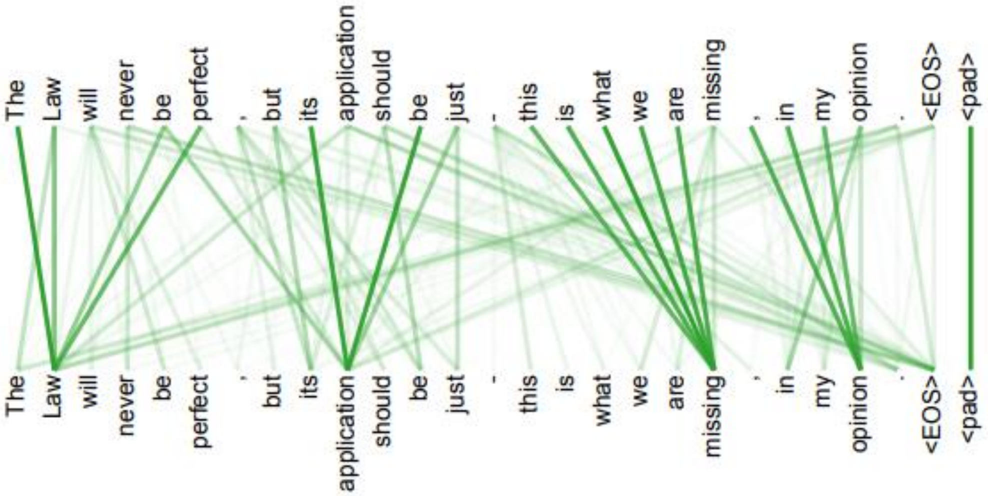
# Coreference resolution (Winograd schemas)

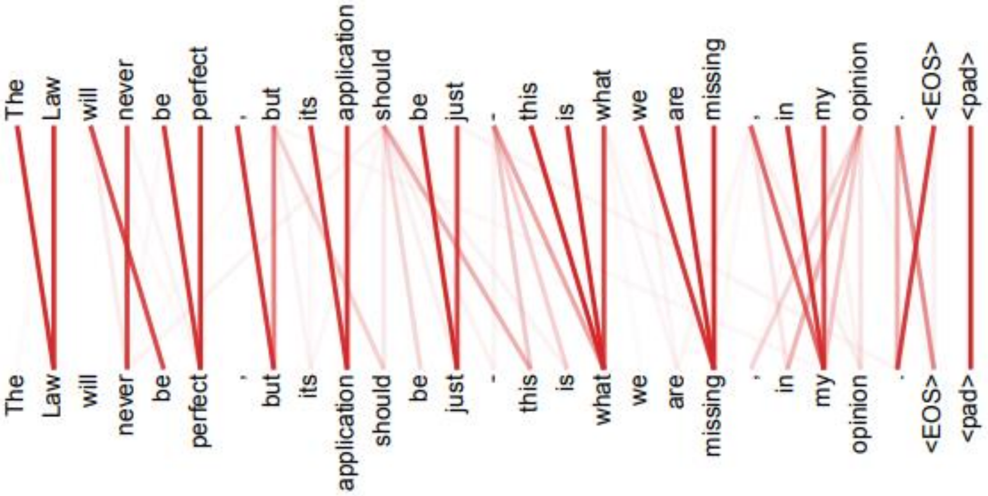
| Sentence | Google Translate | Transformer |
|---|---|---|
| The cow ate the hay because it was **delicious**. | La vache mangeait le foin parce **qu'elle** était délicieuse. | La vache a mangé le foin parce **qu'il** était délicieux. |
| The cow ate the hay because it was **hungry**. | La vache mangeait le foin parce **qu'elle** avait faim. | La vache mangeait le foin parce **qu'elle** avait faim. |
| The women stopped drinking the wines because they were **carcinogenic**. | Les femmes ont cessé de boire les vins parce **qu'ils** étaient cancérogènes. | Les femmes ont cessé de boire les vins parce **qu'ils** étaient cancérigènes. |
| The women stopped drinking the wines because they were **pregnant**. | Les femmes ont cessé de boire les vins parce **qu'ils** étaient enceintes. | Les femmes ont cessé de boire les vins parce **qu'elles** étaient enceintes. |
| The city councilmen refused the female demonstrators a permit because they **advocated** violence. | Les conseillers municipaux ont refusé aux femmes manifestantes un permis parce **qu'ils** préconisaient la violence. | Le conseil municipal a refusé aux manifestantes un permis parce **qu'elles** prônaient la violence. |
| The city councilmen refused the female demonstrators a permit because they **feared** violence. | Les conseillers municipaux ont refusé aux femmes manifestantes un permis parce **qu'ils** craignaient la violence | Le conseil municipal a refusé aux manifestantes un permis parce **qu'elles** craignaient la violence.* |

# Attention Visualization



# Attention Vis



# Tensor2Tensor Library

https://github.com/tensorflow/tensor2tensor

Transformer (Attention is All You Need)
MultiModel (One Model to Learn Them All)
SliceNet
NeuralGPU
ByteNet, Xception, LSTM, ...

# Tensor2Tensor Baselines

Finally a good single-gpu few-days translation model!

```
pip install tensor2tensor && t2t-trainer \
  --generate_data \
  --data_dir=~/t2t_data \
  --problems=wmt_ende_tokens_32k \
  --model=transformer \
  --hparams_set=transformer_base_single_gpu \
  --output_dir=~/t2t_train/base \
  --decode_interactive
```

# Join Tensor2Tensor
# add datasets and models

https://github.com/tensorflow/tensor2tensor

```
pip install tensor2tensor && t2t-trainer \
  --generate_data \
  --data_dir=~/t2t_data \
  --problems=wmt_ende_tokens_32k \
  --model=transformer \
  --hparams_set=transformer_base_single_gpu \
  --output_dir=~/t2t_train/base \
  --decode_interactive
```

Thank you for your attention