

# 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)

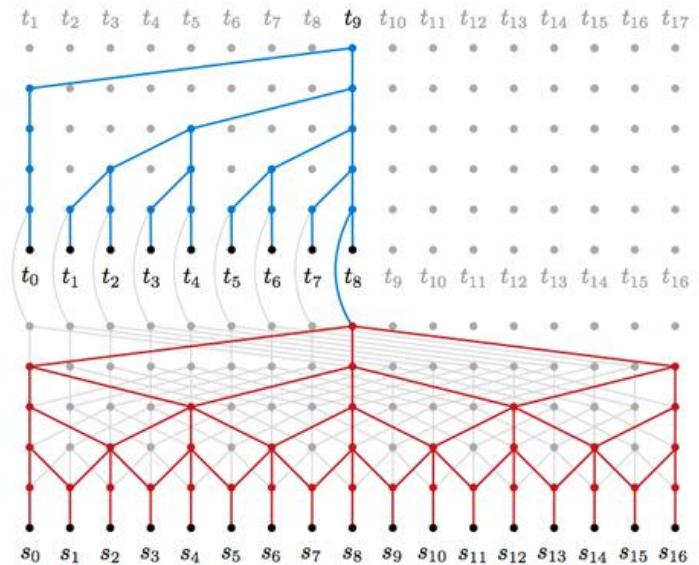
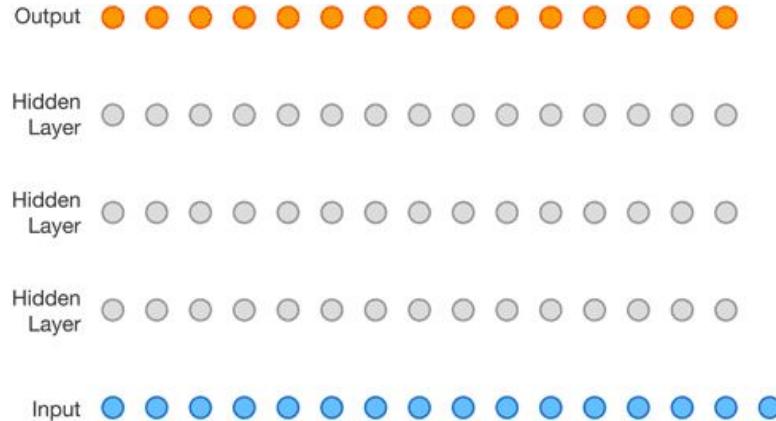
Fit intuition that most dependencies are local

**Path length between positions can be logarithmic**

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

# Auto-Regressive CNNs

## WaveNet and ByteNet



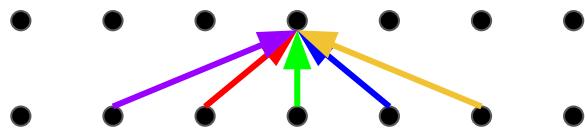
# Attention

Attention between encoder and decoder is crucial in NMT

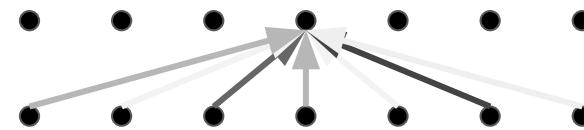
**Why not use (self-)attention for the representations?**

# Self-Attention

## Convolution



## Self-Attention



# Self-Attention

Constant path length between any two positions

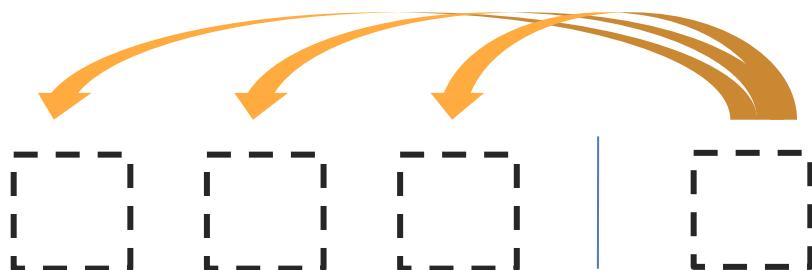
Variable-sized perceptive field

Gating/multiplication enables crisp error propagation

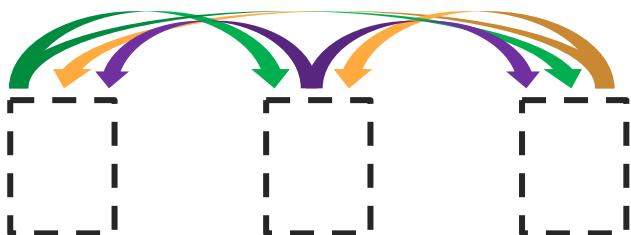
Trivial to parallelize (per layer)

**Can replace sequence-aligned recurrence entirely**

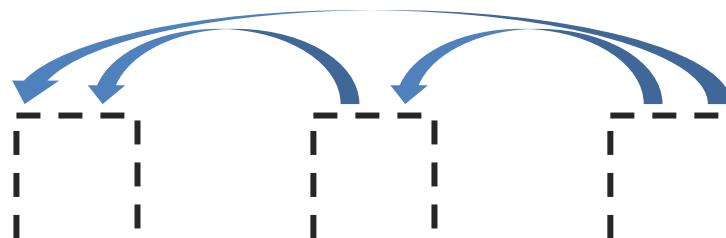
# Three ways of attention



Encoder-Decoder Attention



Encoder Self-Attention



Masked Decoder Self-Attention

# The Transformer

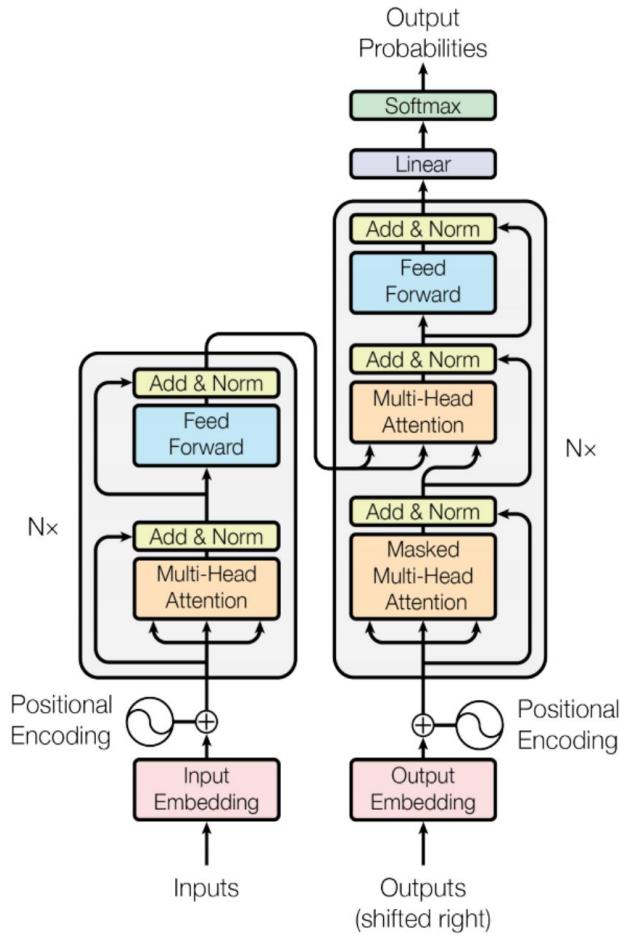
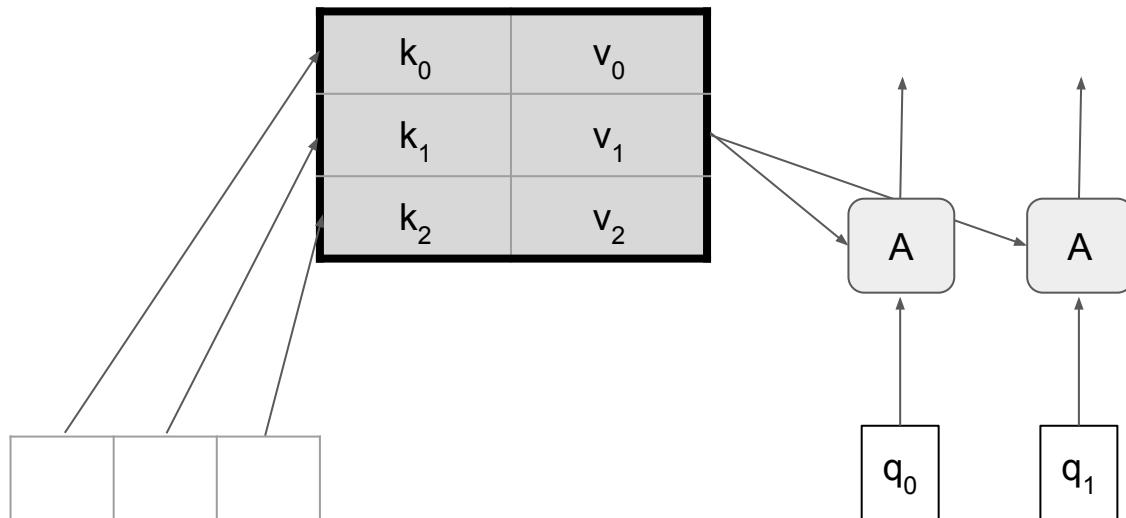


Figure 1: The Transformer - model architecture.

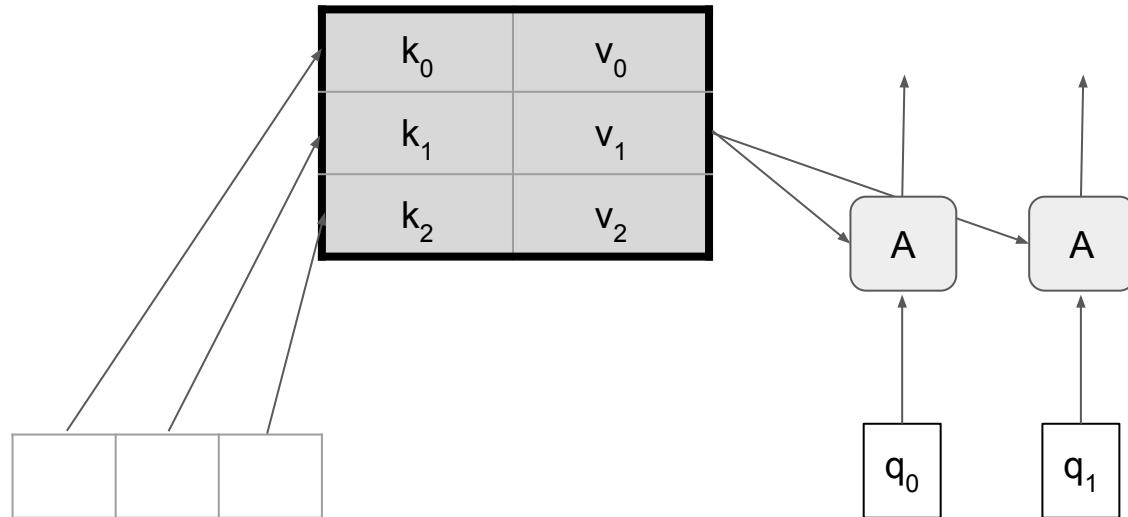
# Dot-Product Attention

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



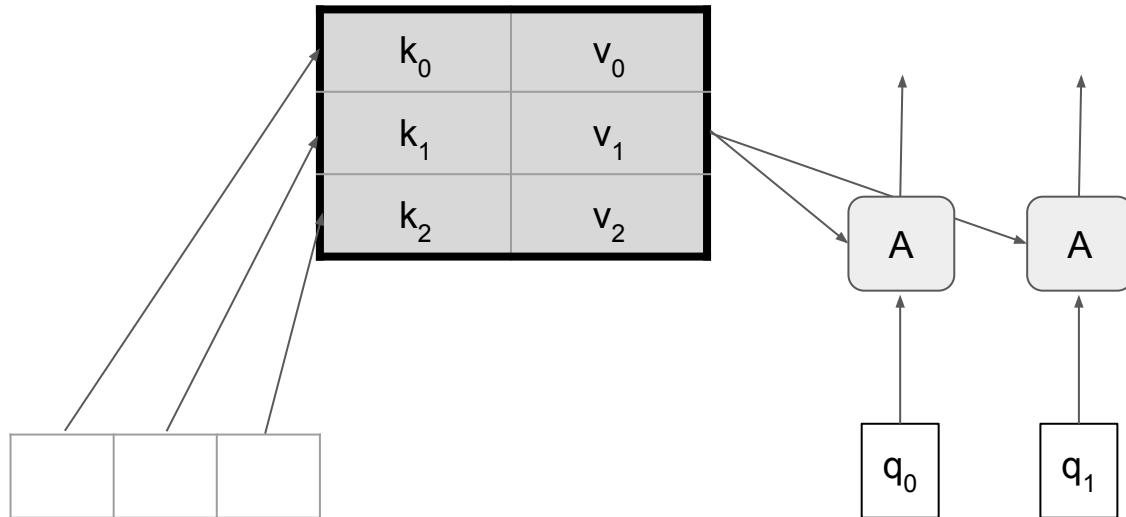
# Dot-Product Attention

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



# Scaled Dot-Product Attention:

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



	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	$n \cdot d^2$	$n \cdot d$

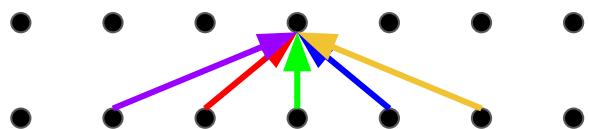
$n$  = sequence length

$d$  = depth

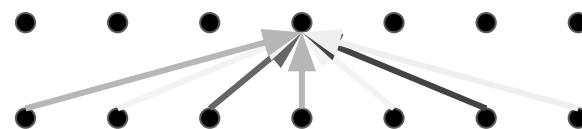
$k$  = kernel size

# What's missing from Self-Attention?

Convolution



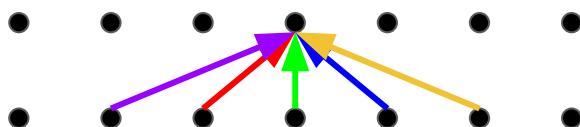
Self-Attention



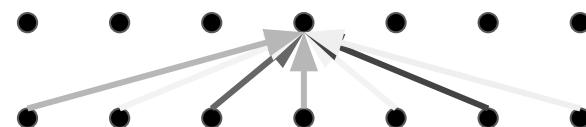
# What's missing from Self-Attention?

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

Convolution



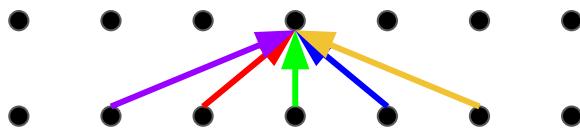
Self-Attention



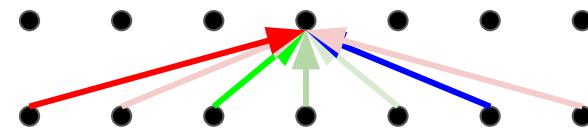
# The Fix: Multi-Head Attention

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

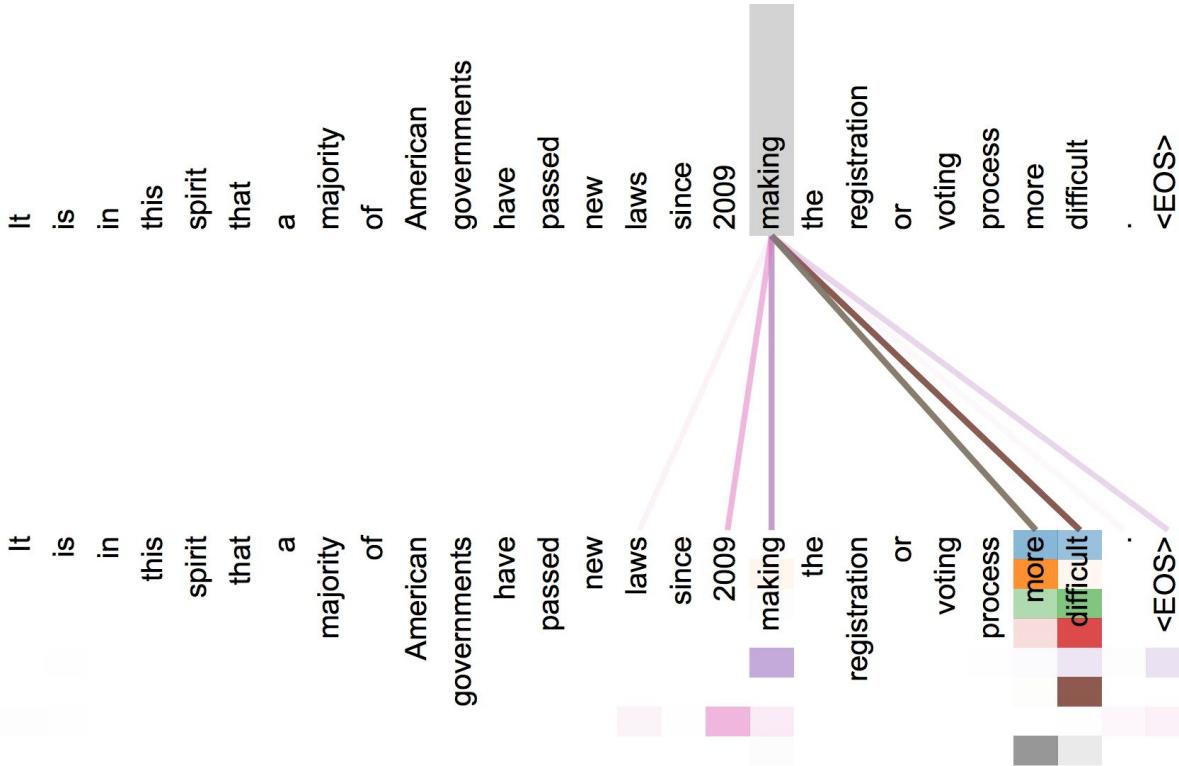
Convolution



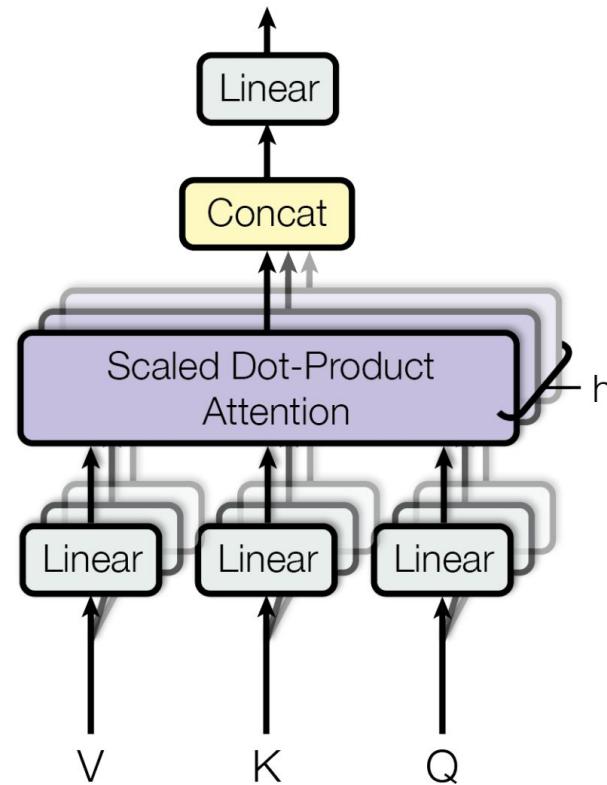
Multi-Head Attention



# The Fix: Multi-Head Attention



# The Fix: Multi-Head Attention



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

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

# Training and Decoding - usual tricks

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

# 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	<b>41.29</b>	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	<b><math>3.3 \cdot 10^{18}</math></b>	
Transformer (big)	<b>28.4</b>	<b>41.0</b>	$2.3 \cdot 10^{19}$	

# Ablations

	$N$	$d_{\text{model}}$	$d_{\text{ff}}$	$h$	$d_k$	$d_v$	$P_{\text{drop}}$	$\epsilon_{ls}$	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)										5.29	24.9	
										5.00	25.5	
										4.91	25.8	
										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	5.75	24.5	28
									1024	4.66	26.0	168
									1024	5.12	25.4	53
									4096	4.75	26.2	90
									0.0	5.77	24.6	
									0.2	4.95	25.5	
(D)									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	<b>4.33</b>	<b>26.4</b>	213

# Coreference resolution (Winograd schemas)

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

The diagram illustrates coreference resolution for the word 'it' in the sentence. A blue rectangular box highlights 'it'. Three light blue arrows point from 'animal', 'street', and 'tired' to the highlighted 'it', indicating they are all referring to the same entity.

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

The diagram illustrates coreference resolution for the word 'it' in the sentence. A blue rectangular box highlights 'it'. Three light blue arrows point from 'animal', 'street', and 'wide' to the highlighted 'it', indicating they are all referring to the same entity.

# Coreference resolution (Winograd schemas)

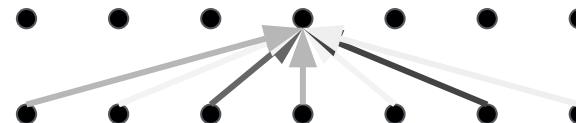
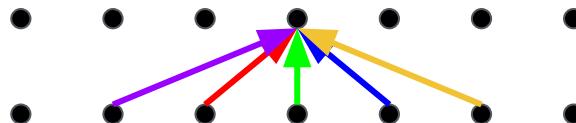
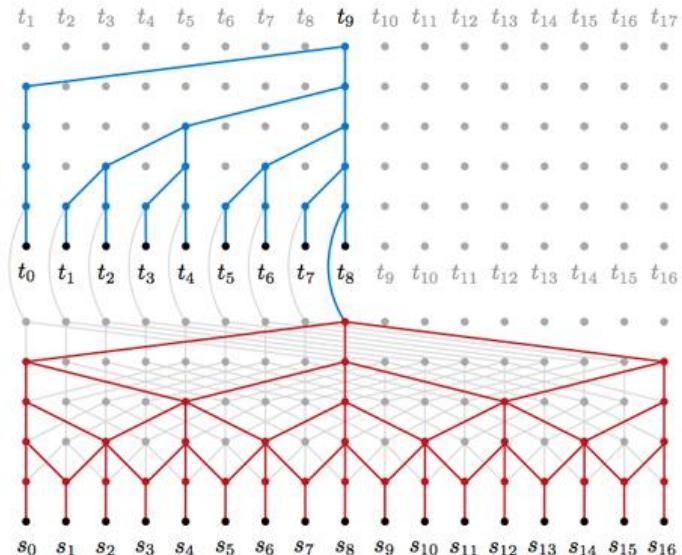
Sentence	Google Translate	Transformer
The cow ate the hay because it was <b>delicious</b> .	<b>La vache mangeait le foin parce qu'elle était délicieuse.</b>	<b>La vache a mangé le foin parce qu'il était délicieux.</b>
The cow ate the hay because it was <b>hungry</b> .	<b>La vache mangeait le foin parce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

# Side note: no compression, no state

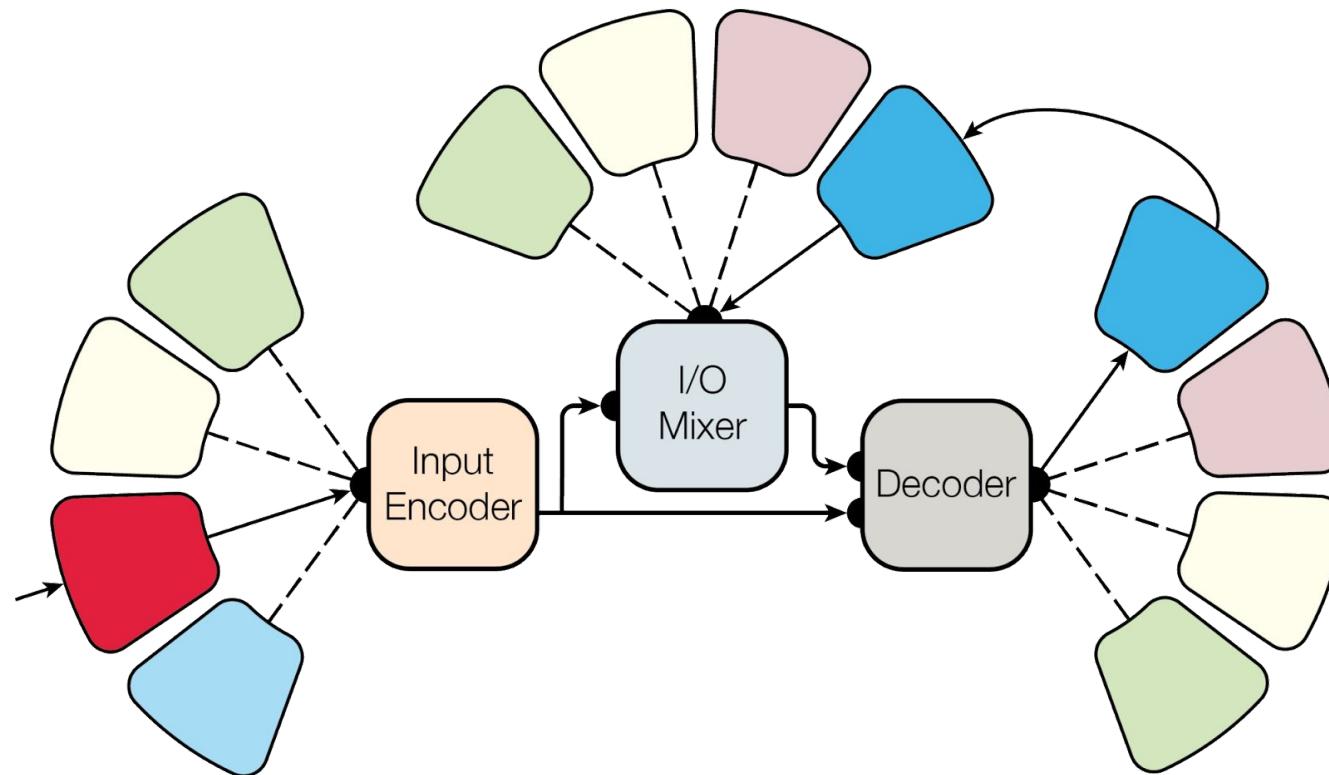
## What does sentence X mean?

Here it means what it says.

- no recurrent state to represent semantics
- but all Harry Potter books are ~1M words
- 10 years \* 20M tokens \* 4B/token= 800MB
- we could fit it all on GPU, even 10x...
- do we need compression? do we want it?



# MultiModel

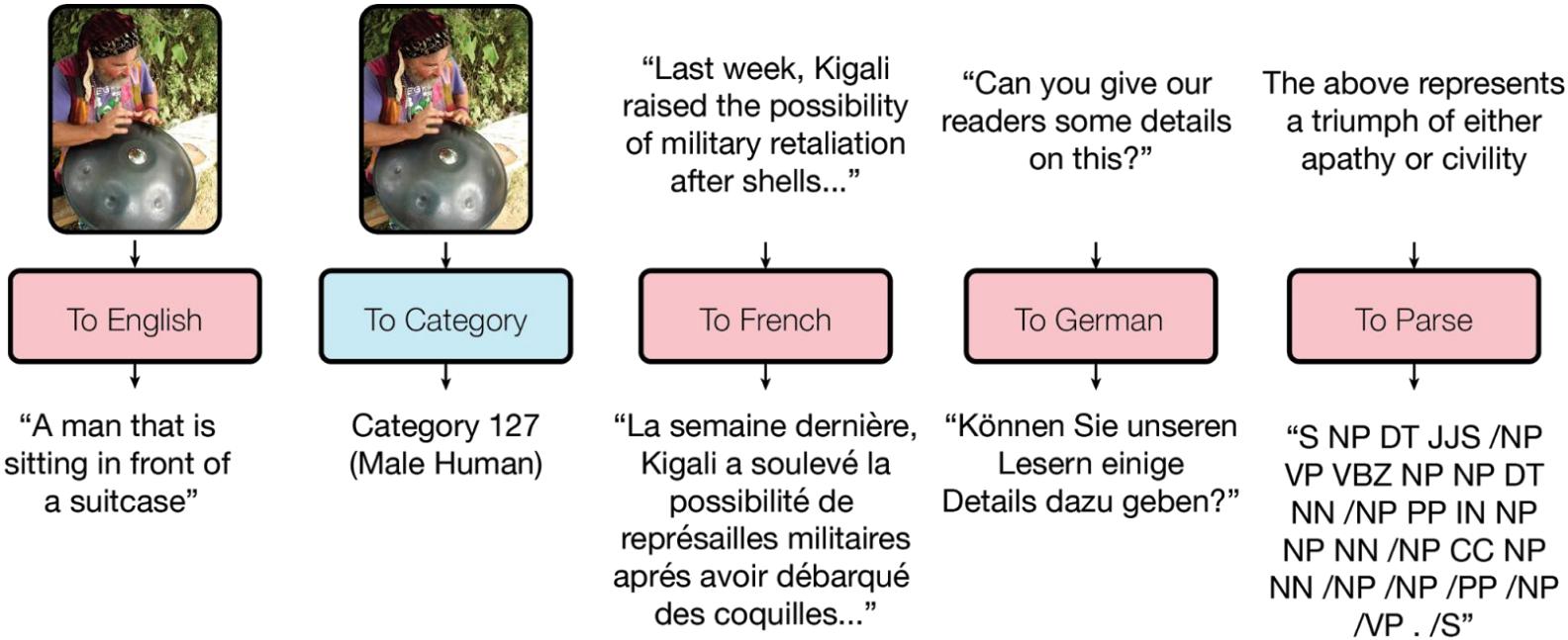


# MultiModel

- Trained on 8 tasks (4 WMT, ImageNet, COCO, WSJ, PTB)
- Images still like convolutions (pure attention doesn't work)
- Modalities: down-stride and up-stride images, embed text
- Architecture: convolutional encoder, transformer decoder
  - Convolution FF improves attention on many large tasks
- Capacity: use Mixture-of-Experts as feed-forward layers

How comes ImageNet improves PTB results?

# MultiModel



# 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