Shaping the future of AI from the history of Transformer

Why do LLMs work?

→ Use a tool to manually inspect the data.

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Jason!

Q: Why do LLM's work?

→ Manually inspect data

LLM:-

→ Trained on 'next-word' prediction

→ Output prob distribution over every word in the vocab.

→ Loss → How close is the prob of the actual word to the predicted word?

First intuition

Next word prediction ⇒ massively multi-task learning.

AI is advancing so fast that it is hard to keep up

People spend a lot of time and energy catching up with the latest developments

But not enough attention goes to the old things

It is more important to <u>study the change itself</u>

What does it mean to study the change itself?

1. Identify the dominant driving forces behind the change

2. Understand the dominant driving forces

3. Predict the future trajectory

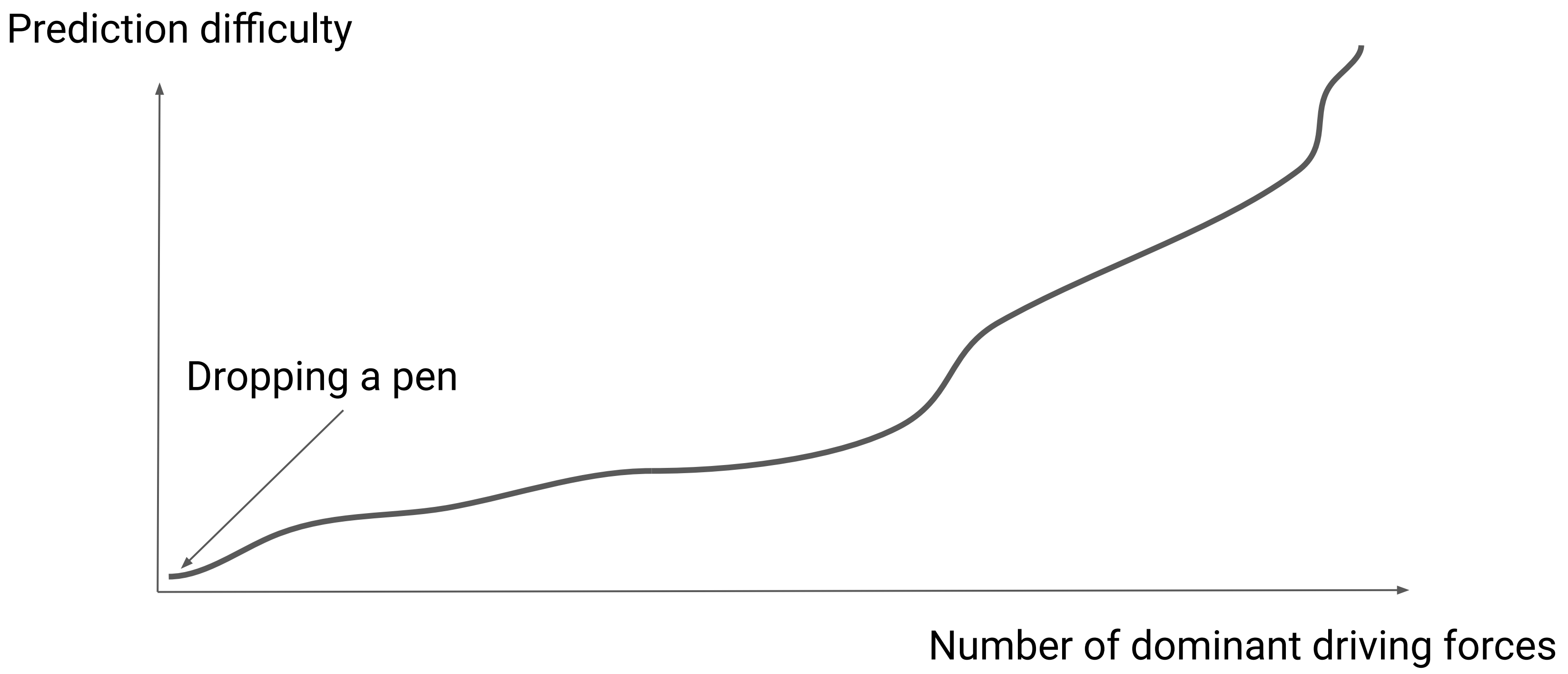
Toy experiment: dropping a pen

1. Identify the dominant driving forces: gravity

2. Understand gravity: Newtonian mechanics provides a good model

3. Predict the future trajectory of the pen $y(t) = \frac{1}{2}gt^2$

Predicting the future trajectory is difficult because there are many driving forces and the complexity of their interactions



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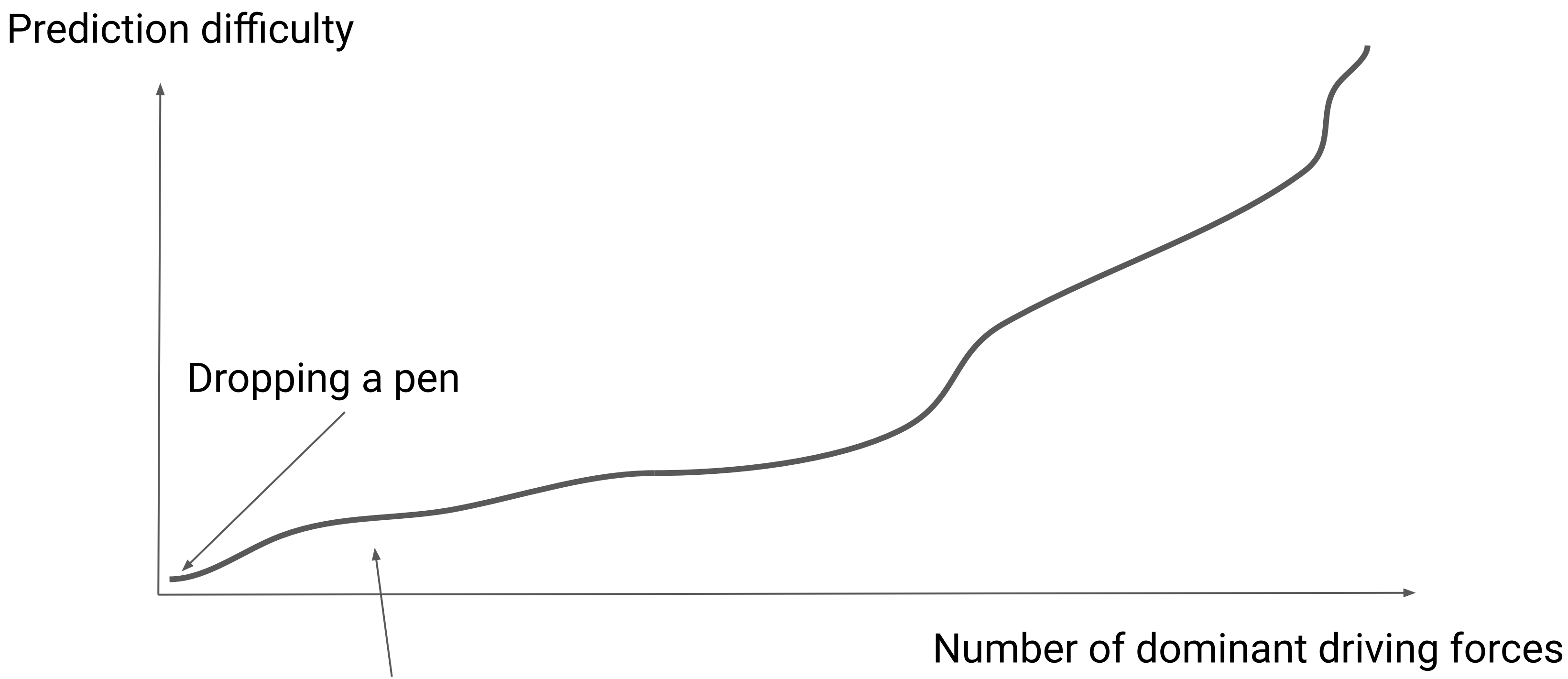
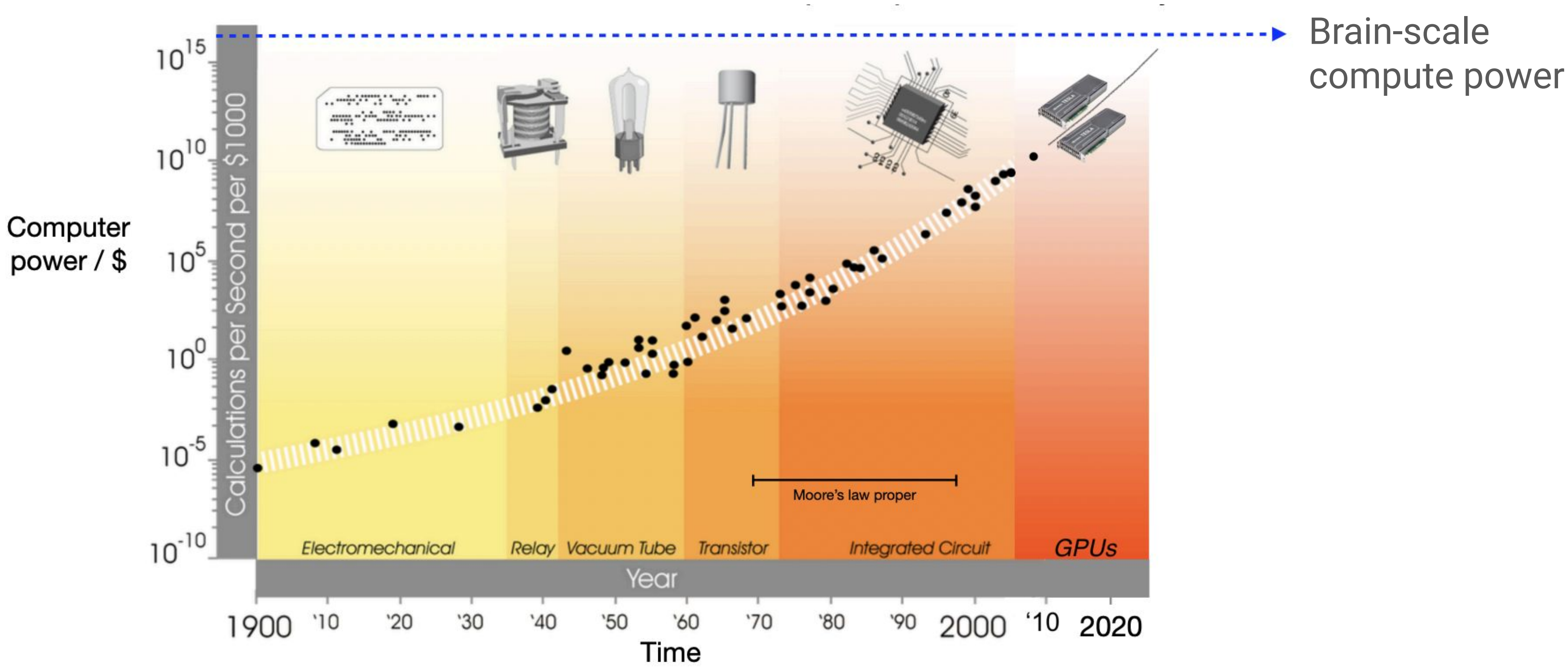


AI research is closer to the left than we feel



Roughly, 10x more compute every 5 years

Figure from Rich Sutton's [WAIC keynote]

The job of AI researchers is to teach machines how to “think”

One (unfortunately common) approach

Teach the machines how *we think* we think

This approach poses structures to the problem, which can become the limitation when scaled up

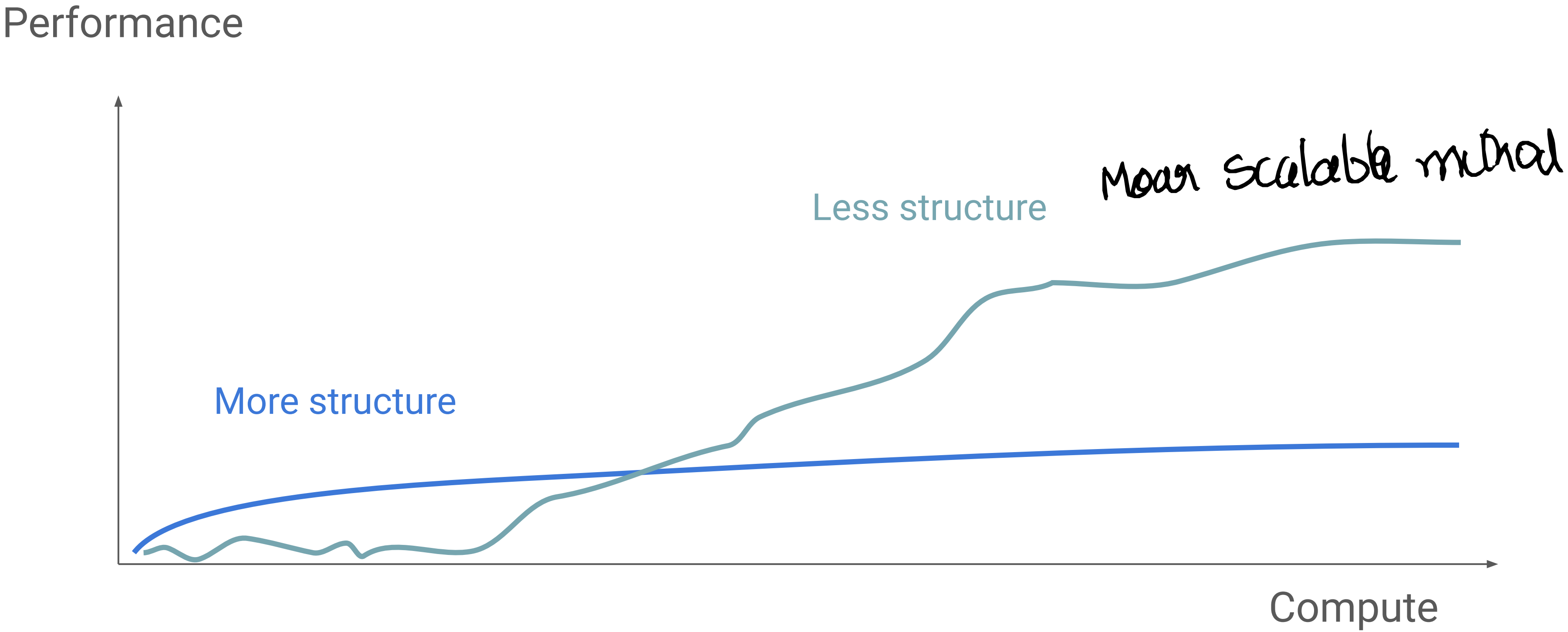
The job of AI researchers is to teach machines how to "think"

Bitter lesson: progress of AI in the past 70 years boils down to

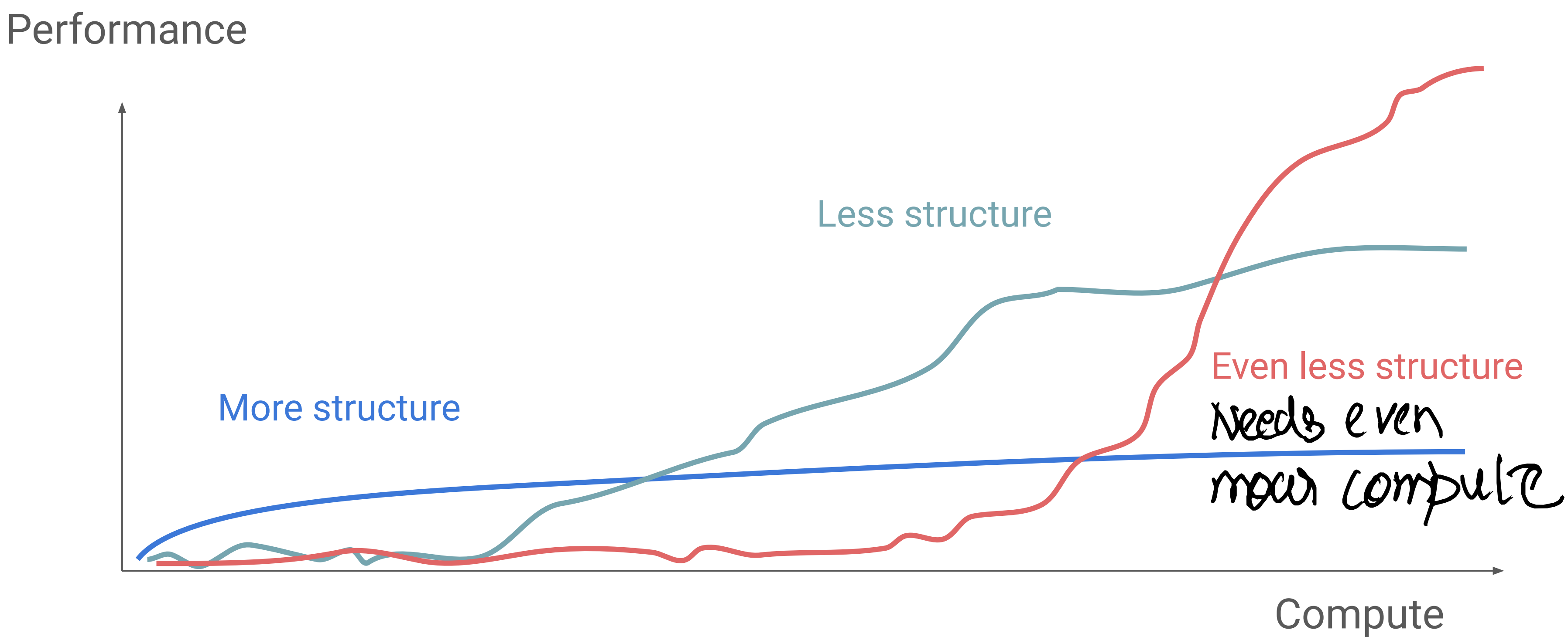
- Develop progressively more general methods with weaker modeling assumptions
- Add more data and computation (i.e. scale up) $$$

Easier to get into AI from a technical perspective.

The more structure, the less scalable the method is

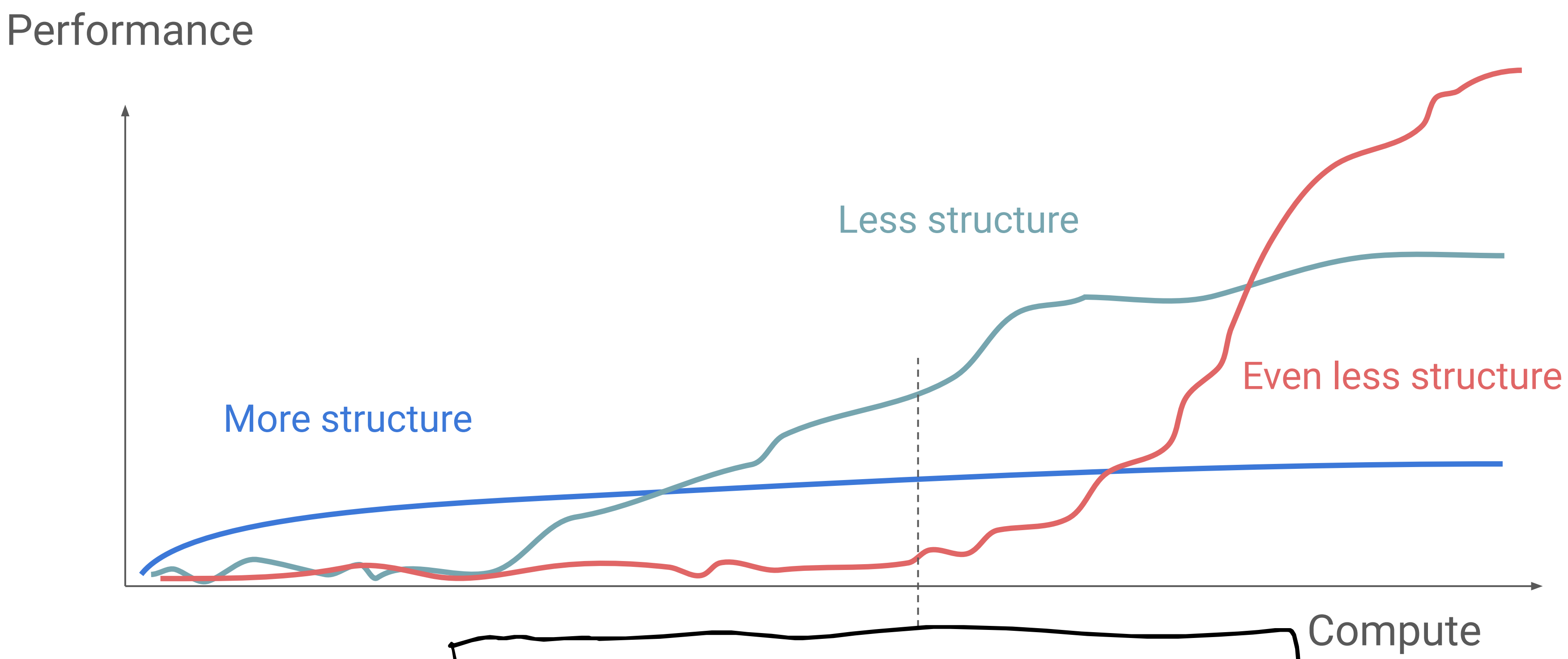


However, we can't just go for the most general method



Inspired by the conversation with Beomjoon Kim

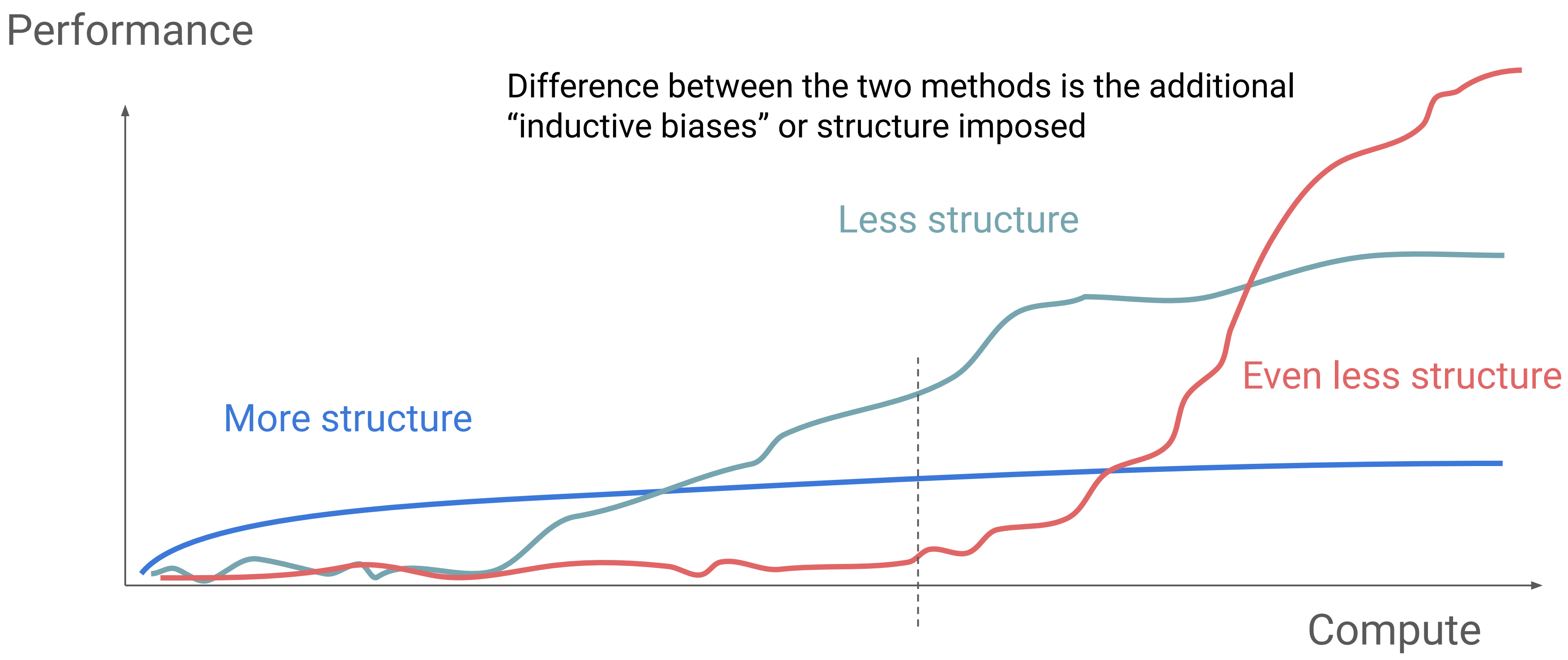
However, we can’t just go for the most general method



If we are here, we should choose “Less structure”. But remember to undo later

Inspired by the conversation with Beomjoon Kim

However, we can't just go for the most general method



If we are here, we should choose "Less structure". But remember to undo later

Inspired by the conversation with Beomjoon Kim

Adding optimal inductive bias for a given level of compute, data, algorithmic development and architecture is critical

These are shortcuts that will hinder further scaling later on. Remove them later.

As a community we do the former well but not the latter

Implications of bitter lesson

What is better in the long term almost always looks worse now

This is somewhat unique to the AI research. If clever modeling techniques and fancy math were the driving force, it would have been completely different story

Summary

We identified the dominant driving force: exponentially cheaper compute and scaling

1

Now we need to understand it better

2

For that we will go to back to early history of Transformer and analyze key structures added by researchers and their motivations.

Then we will see how these structures became less relevant with now that more compute and better algorithm is available

Transformer architectures variants

1. Encoder-decoder → Transformer (MT)
2. Encoder-only → BERT (Not very useful)
3. Decoder-only (least structure) → GPT-3 or other LLM's

Process	Shape
“Unicode characters like emojis may be split.”	[ ]

Process	Shape
Unicode characters like emojis may be split. [7085, 2456, 836, 470, 3975, 284, 530, 11241, 25, 773, 452, 12843, 13]	[length]
⬆ Tokenization	⬆
“Unicode characters like emojis may be split.”	[ ]

Process | **Shape**

2.3	-3.2	8.3	5.4	2.1	3.9	-8.9	3.8	3.9	3.3
4.5	5.9	4.5	7.1	1.0	5.3	5.0	3.1	0.7	5.0
…	…	…	…	…	…	…	…	…	…
3.8	1.2	3.8	9.0	9.3	3.1	4.2	0.8	9.2	5.8

`[d_model, length]`

Embedding

`Unicode characters like emojis may be split.`

`[7085, 2456, 836, 470, 3975, 284, 530, 11241, 25, 773, 452, 12843, 13]`

`[length]`

[Tokenization]

"Unicode characters like emojis may be split."

`[]`

Process | **Shape**

3.2	-2.3	3.8	4.5	1.2	9.3	-9.8	8.3	9.3	3.3
5.4	9.5	5.4	1.7	0.1	3.5	0.5	1.3	7.0	0.5
…	…	…	…	…	…	…	…	…	…
8.3	2.1	8.3	0.9	3.9	1.3	2.4	8.0	2.9	8.5

`[d_model, length]`

↑ Sequence model   Dot product

2.3	-3.2	8.3	5.4	2.1	3.9	-8.9	3.8	3.9	3.3
4.5	5.9	4.5	7.1	1.0	5.3	5.0	3.1	0.7	5.0
…	…	…	…	…	…	…	…	…	…
3.8	1.2	3.8	9.0	9.3	3.1	4.2	0.8	9.2	5.8

`[d_model, length]`

↑ Embedding

`Unicode characters like emojis may be split.`

`[7085, 2456, 836, 470, 3975, 284, 530, 11241, 25, 773, 452, 12843, 13]`

`[length]`

↑ Tokenization

"Unicode characters like emojis may be split."

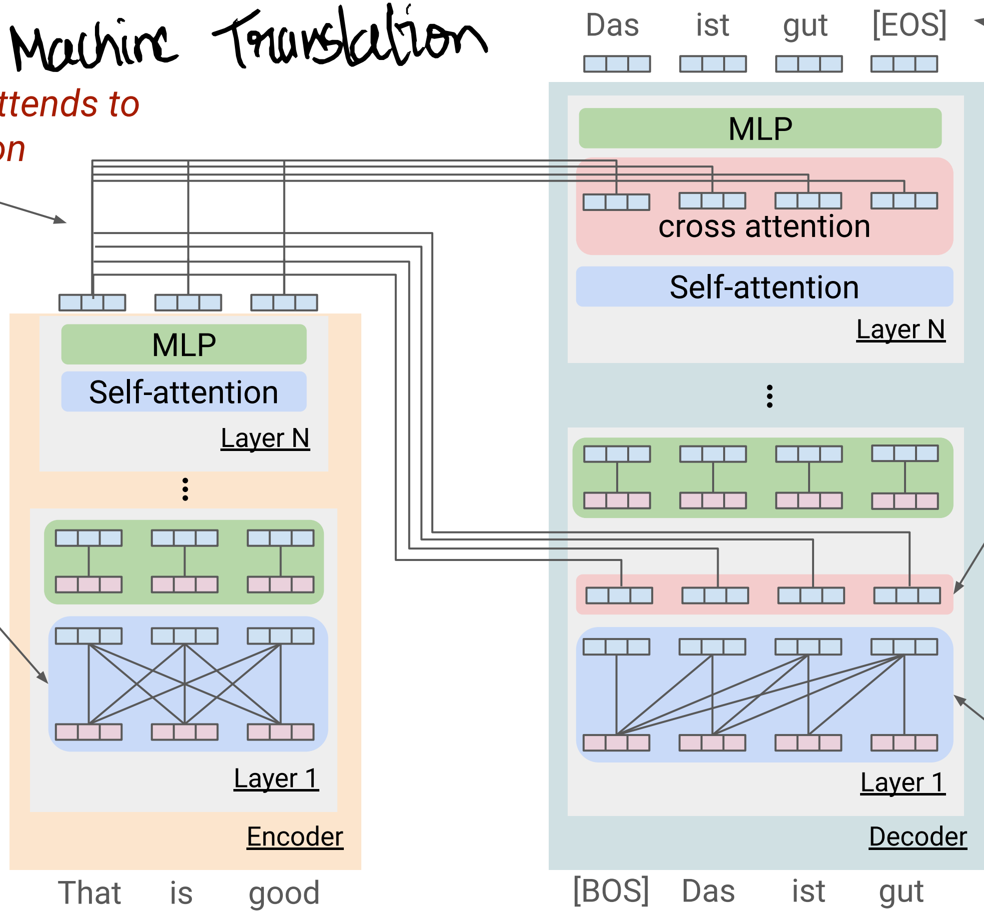
`[]`

Encoder-decoder

Machine Translation

Cross attention only attends to the final layer activation

Output is a sequence



Bidirectional self-attention

Cross-attention connects encoder and decoder

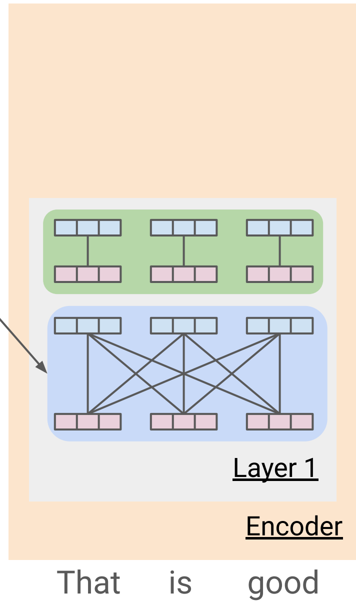
Causal self-attention

Particular type of seq model

|

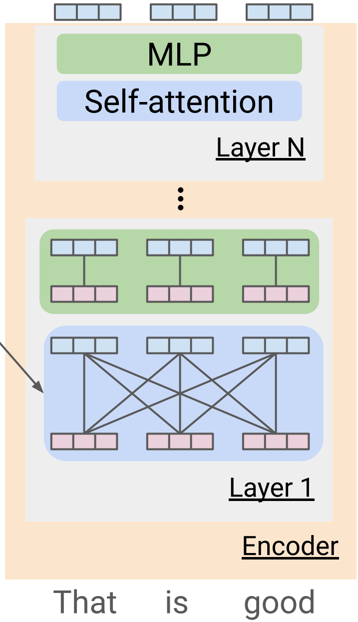
Encoder-decoder

Bidirectional self-attention



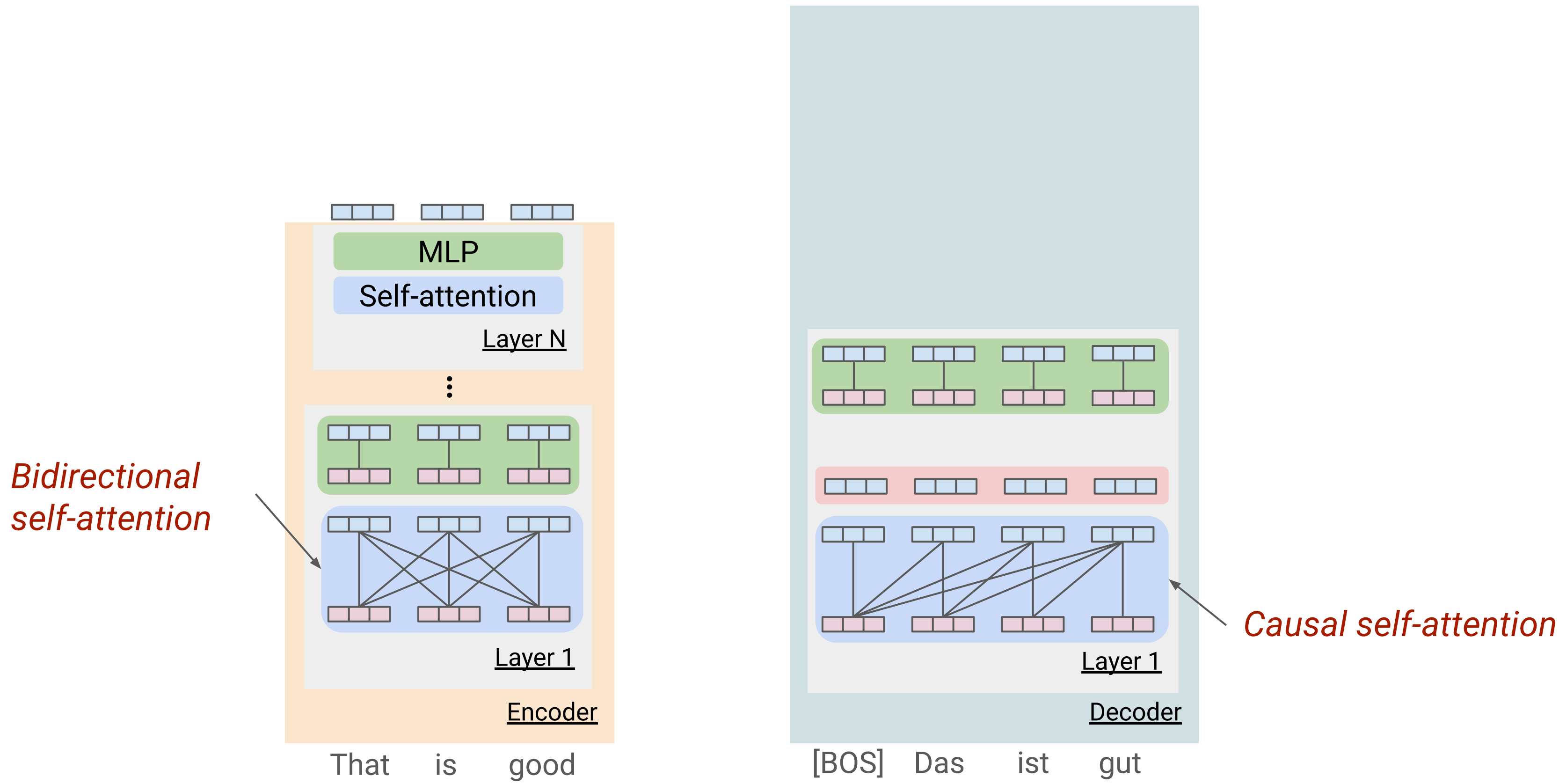
Encode to dense vec
& take dot product
MLP is per token
Repeat N-times

Encoder-decoder



Bidirectional self-attention

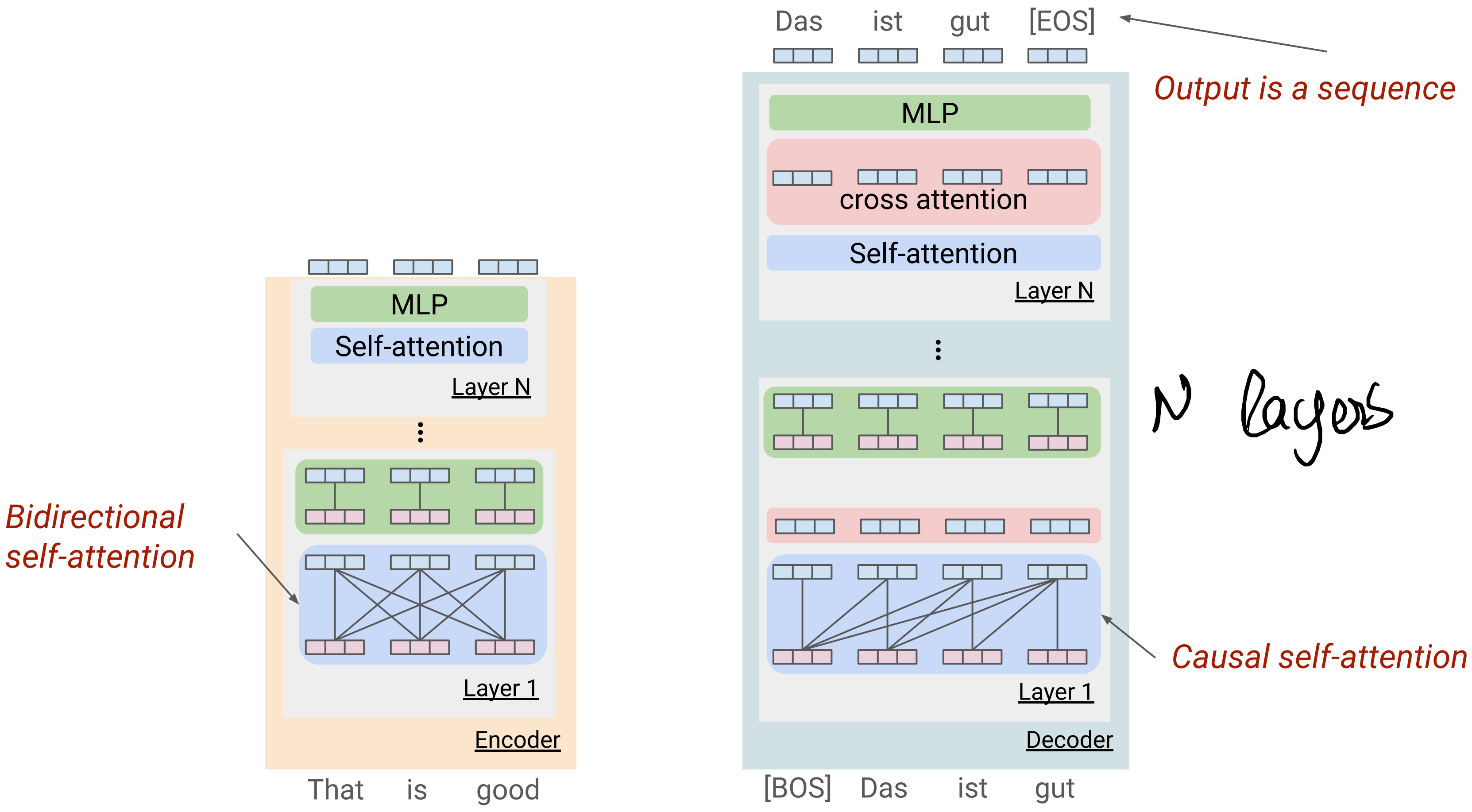
Encoder-decoder



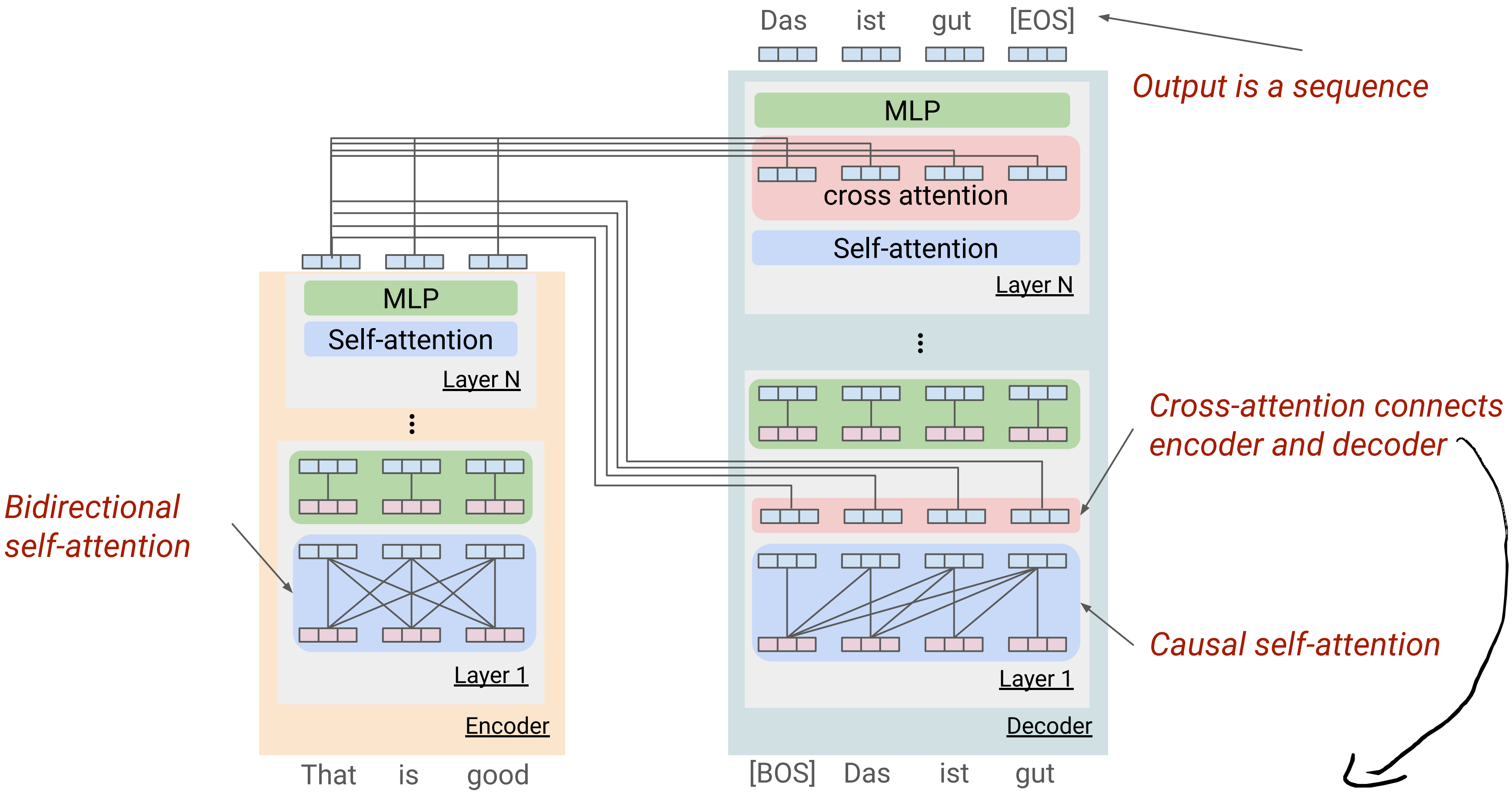
Decoder

Causal SA → Tokens at t
can only attend upto t-1

Encoder-decoder



Encoder-decoder

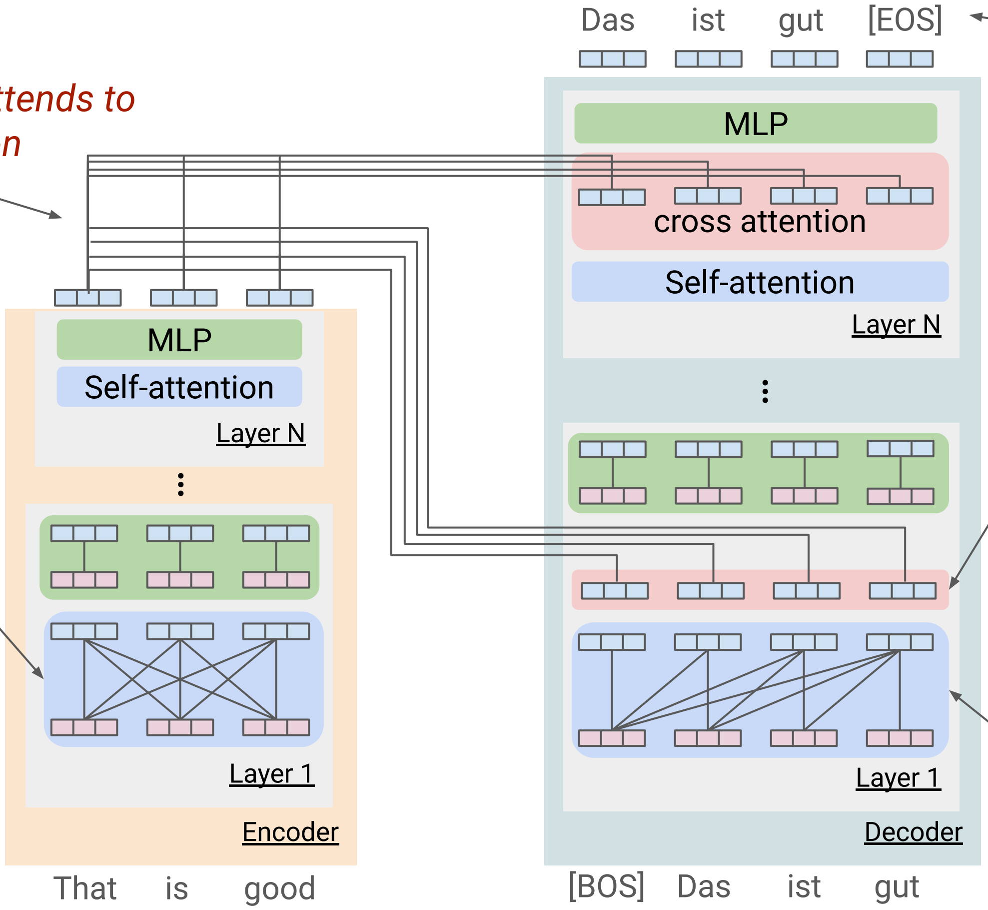


Each seq in O/P should attend to some part of the encoder

Encoder-decoder

Cross attention only attends to the final layer activation

Bidirectional self-attention

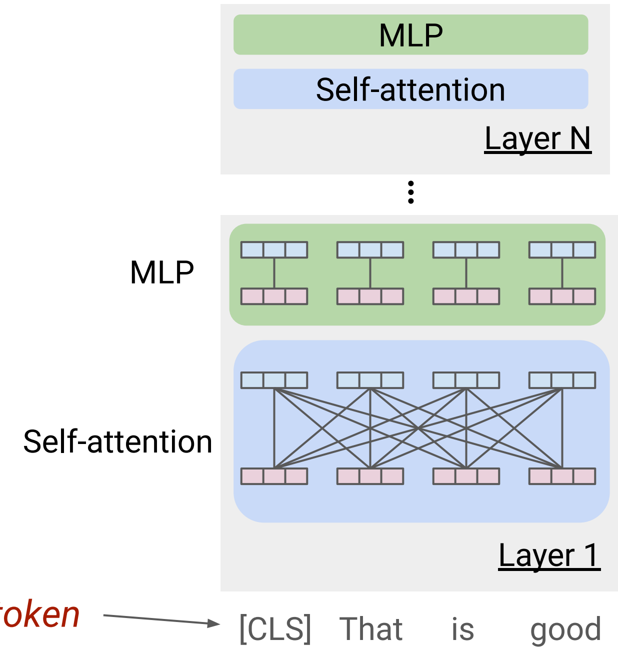


Output is a sequence

Cross-attention connects encoder and decoder

Causal self-attention

Encoder-only



Prepend a special token

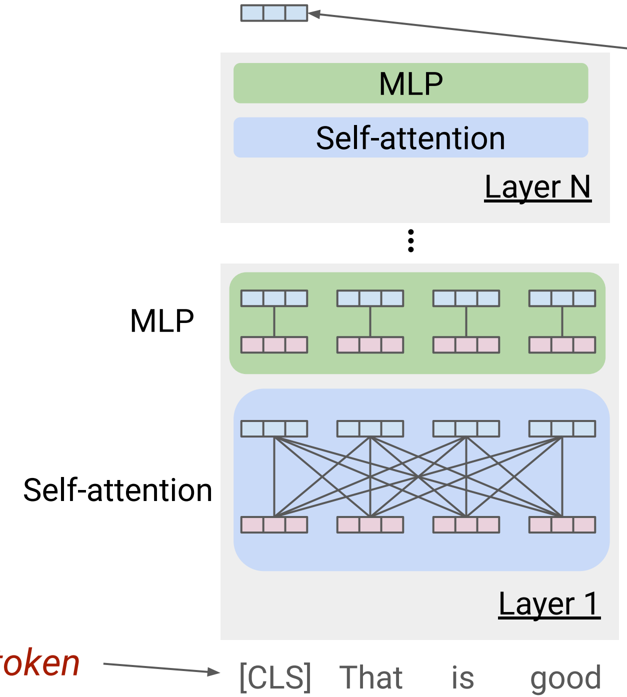
Input is a sequence

Input in similar structure

O/P is a single vector

Encoder-only

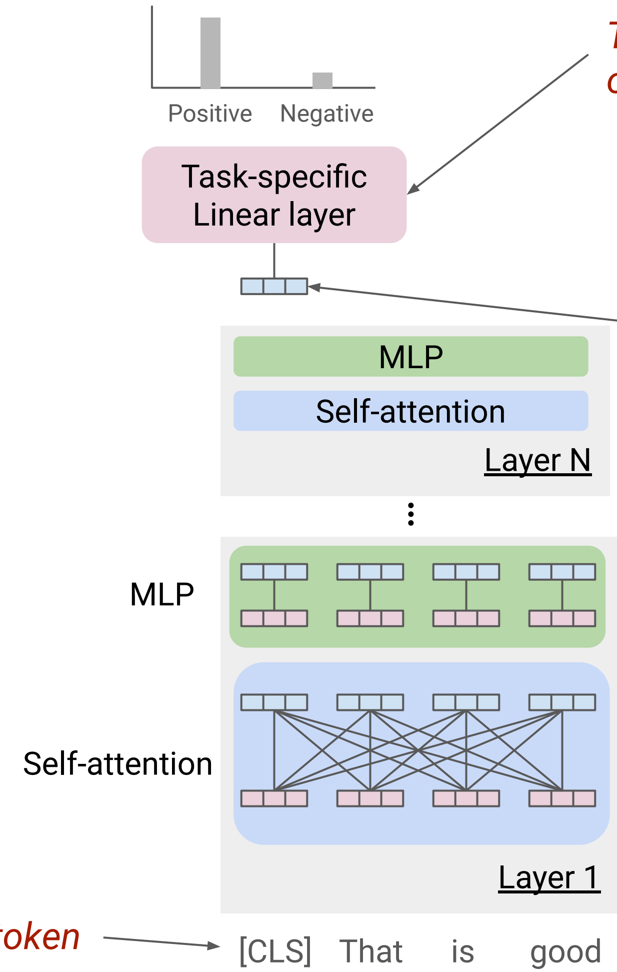
Output is a single vector that <u>encodes</u> the input sequence



Prepend a special token

Input is a sequence

Encoder-only



Task-specific layer is necessary to map output vector to classification label space

Output is a single vector that encodes the input sequence

Input is a sequence

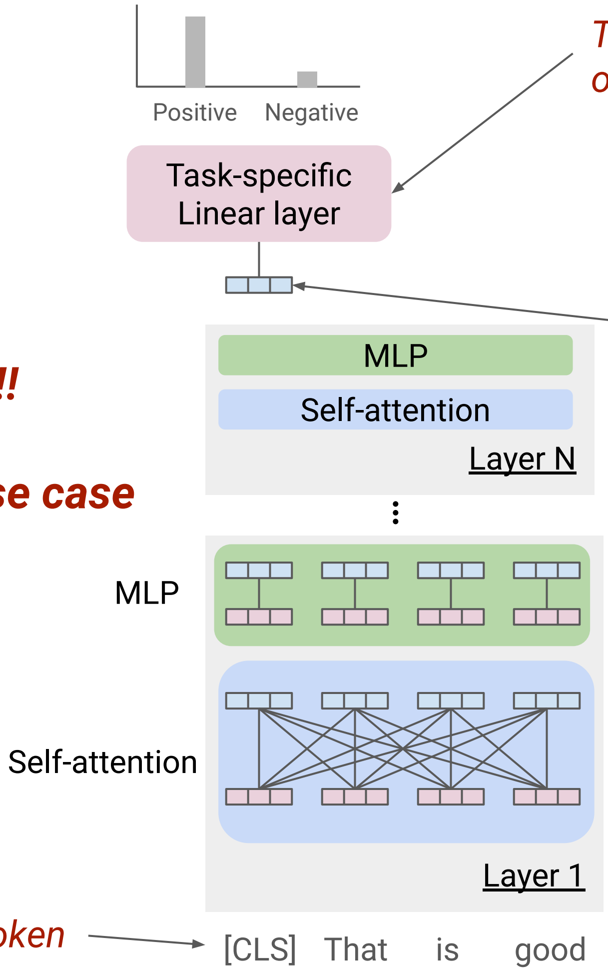
Prepend a special token

BERT was SOTA on GLUE Benchmark

Give up on generation i.e decoder.

Not very useful

Encoder-only



Task-specific layer is necessary to map output vector to classification label space

Output is a single vector that encodes the input sequence

Can't generate a sequence!!

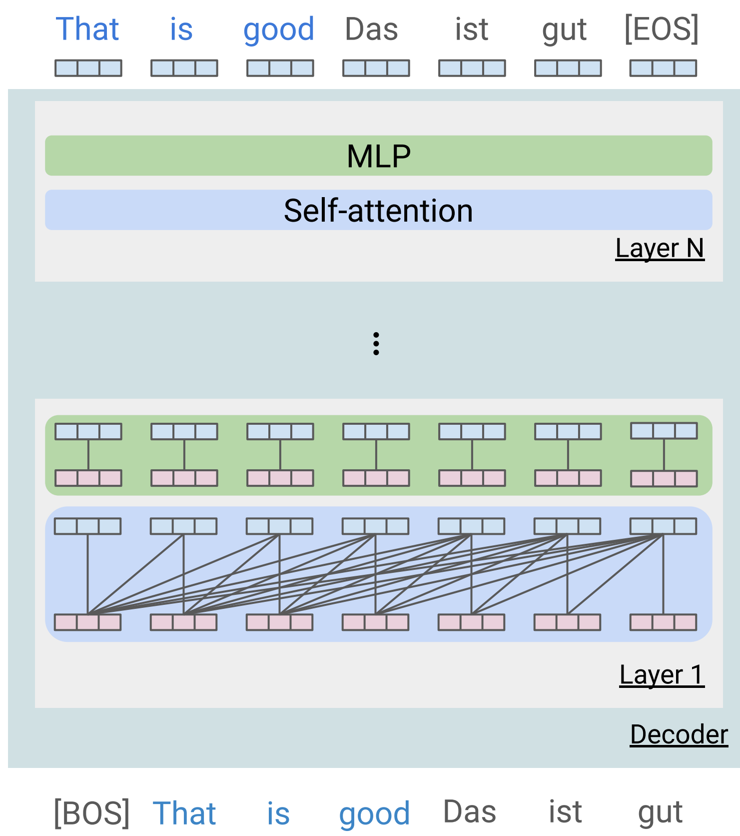
Deal breaker for general use case

Prepend a special token

Input is a sequence

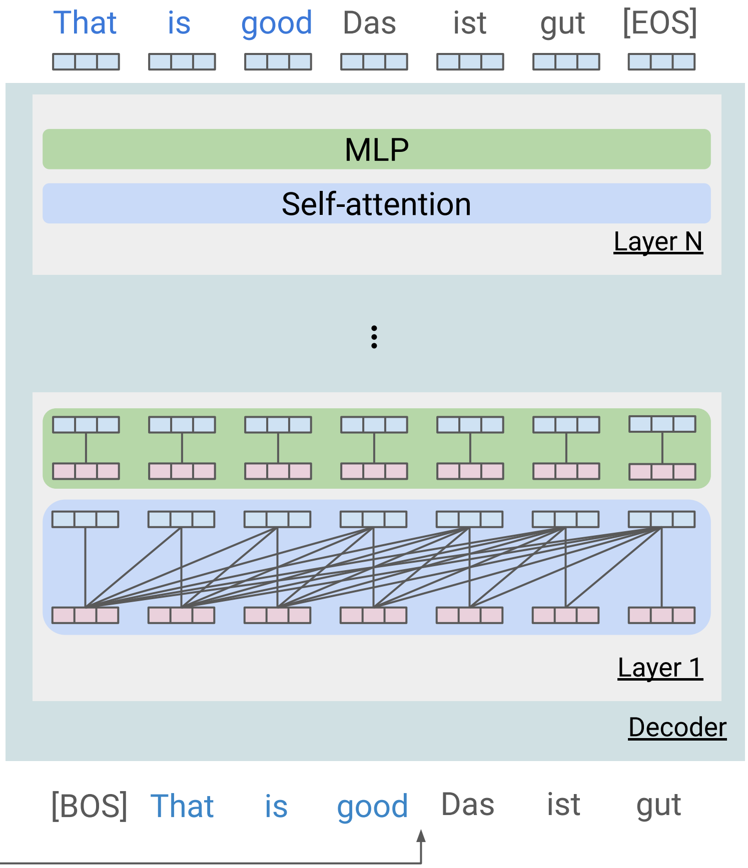
self att is handling both causal att & self att. between I/P & target sequences.

Decoder-only



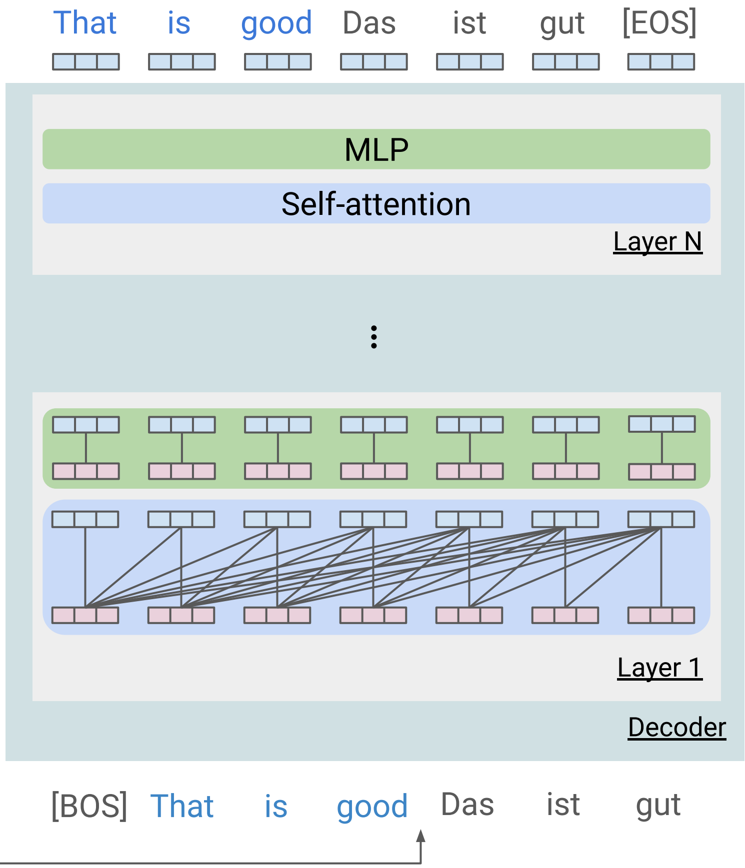
Can also be used for supervised learning!
→ Concatenate input with target. Then, the next token prediction essentially becomes supervised learning i.e seq in, seq out

Decoder-only



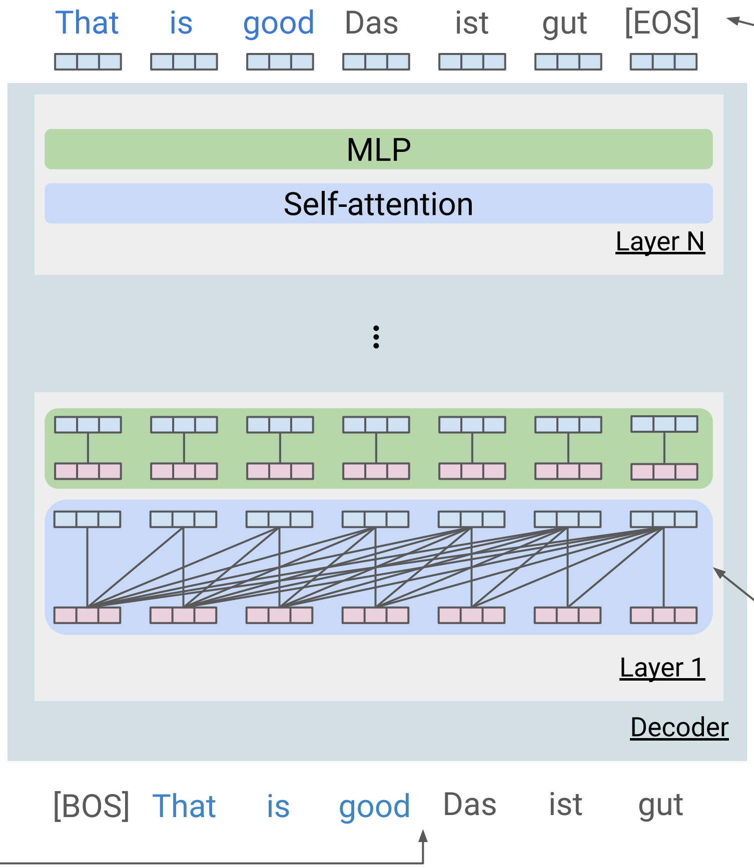
Input and target are concatenated

Decoder-only



Input and target are concatenated

Decoder-only



Output is a sequence

Causal self-attention

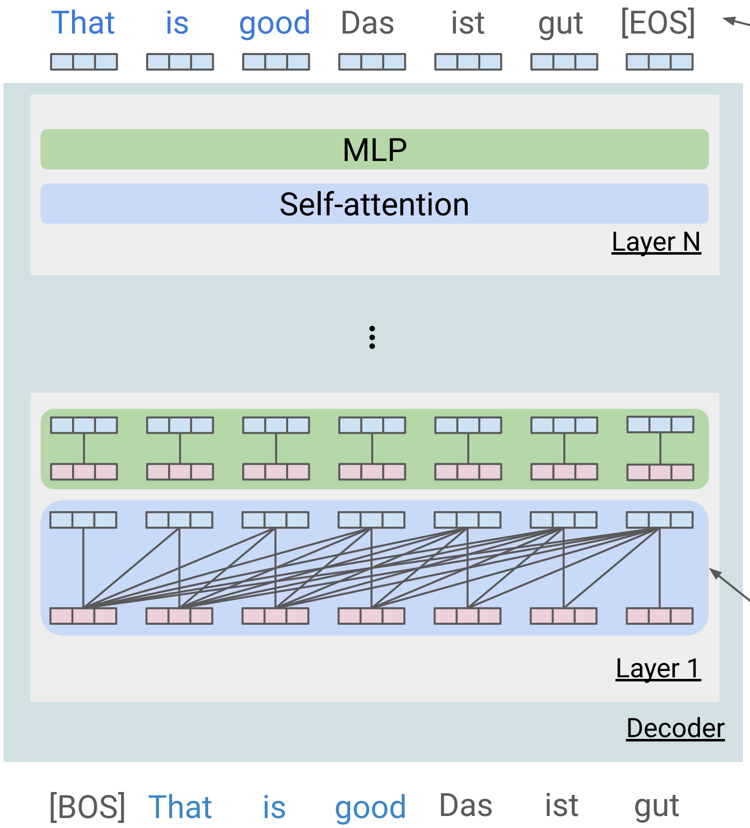
Input and target are concatenated

Decoder-only

Key design features

Self attention also serves the role of cross-attention

Same set of parameters apply to both input and target sequences



Output is a sequence

Causal self-attention

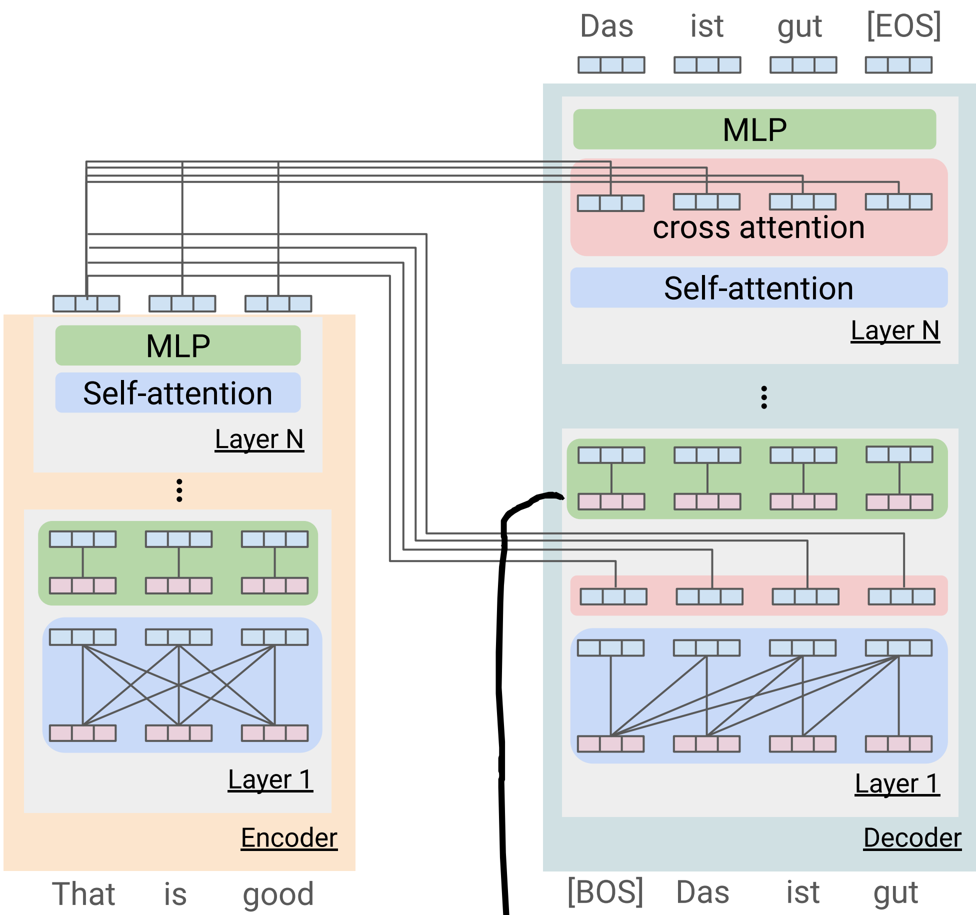
Input and target are concatenated

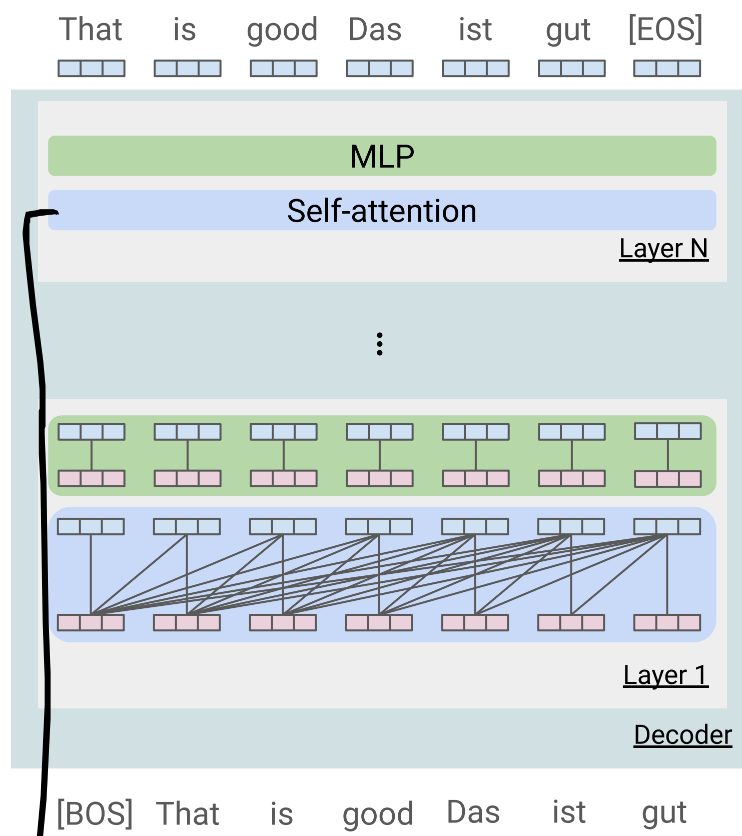
How different are encoder-decoder and decoder-only architectures?

Let’s try to transform encoder-decoder into decoder-only

Summary of the differences

	Encoder-decoder	Decoder-only
Additional cross attention		
Parameter sharing		
Target-to-input attention pattern		
Input attention		



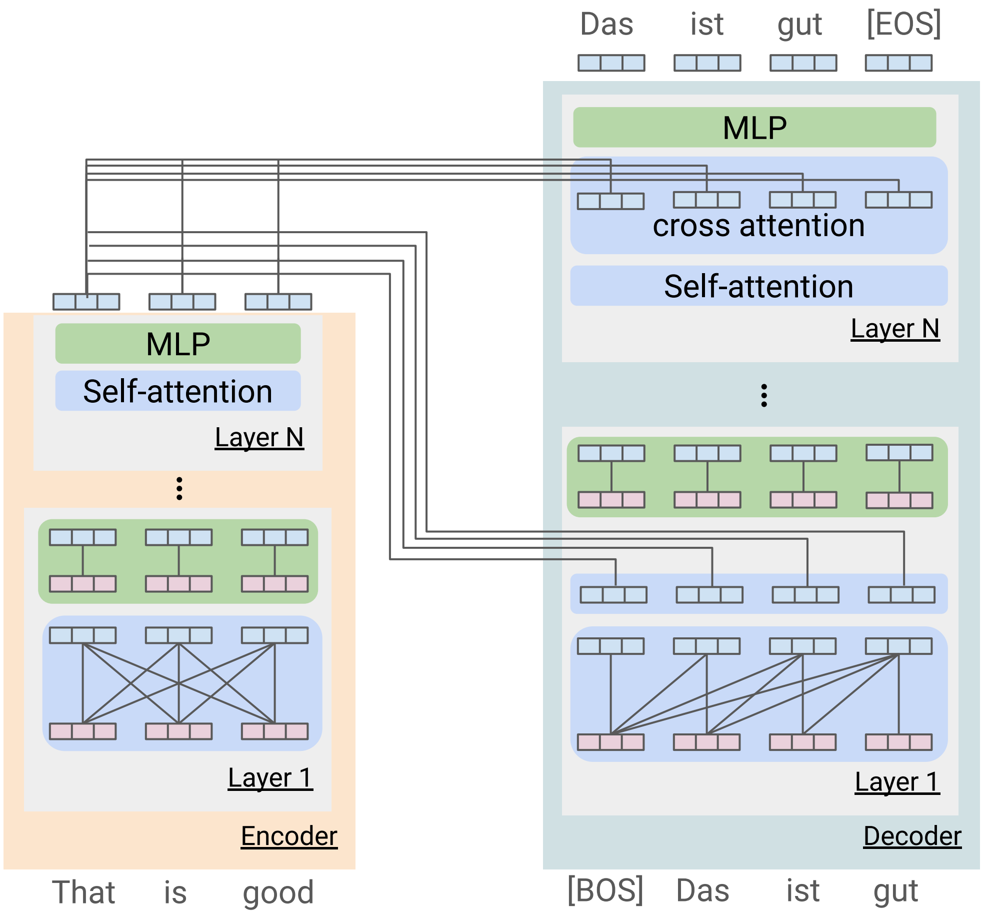


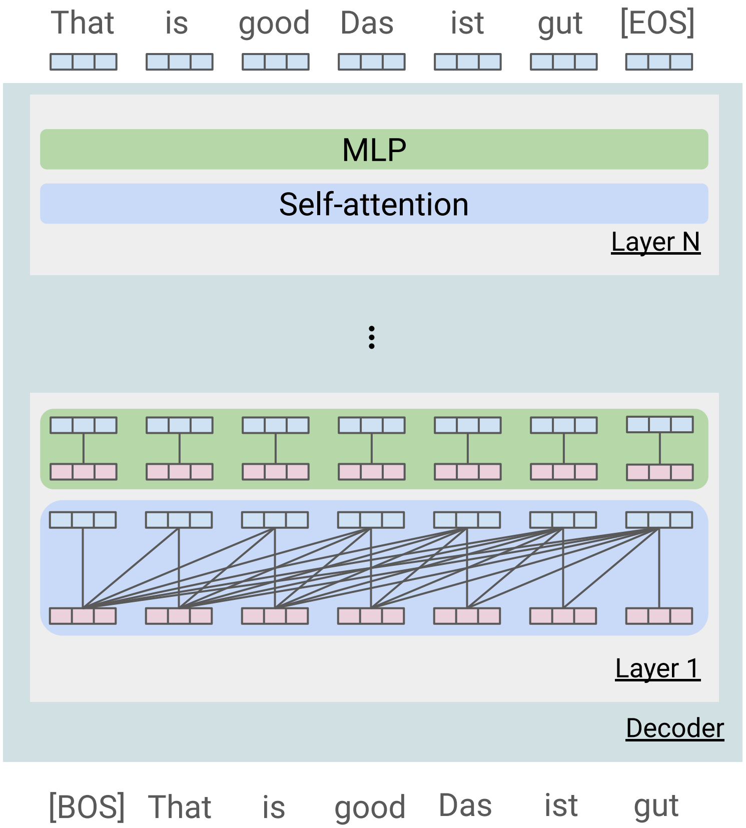
This is extra
i.e seperate cross
attention

Share params
since same
matrices

self & cross have same no. of params.
Hence, share them.

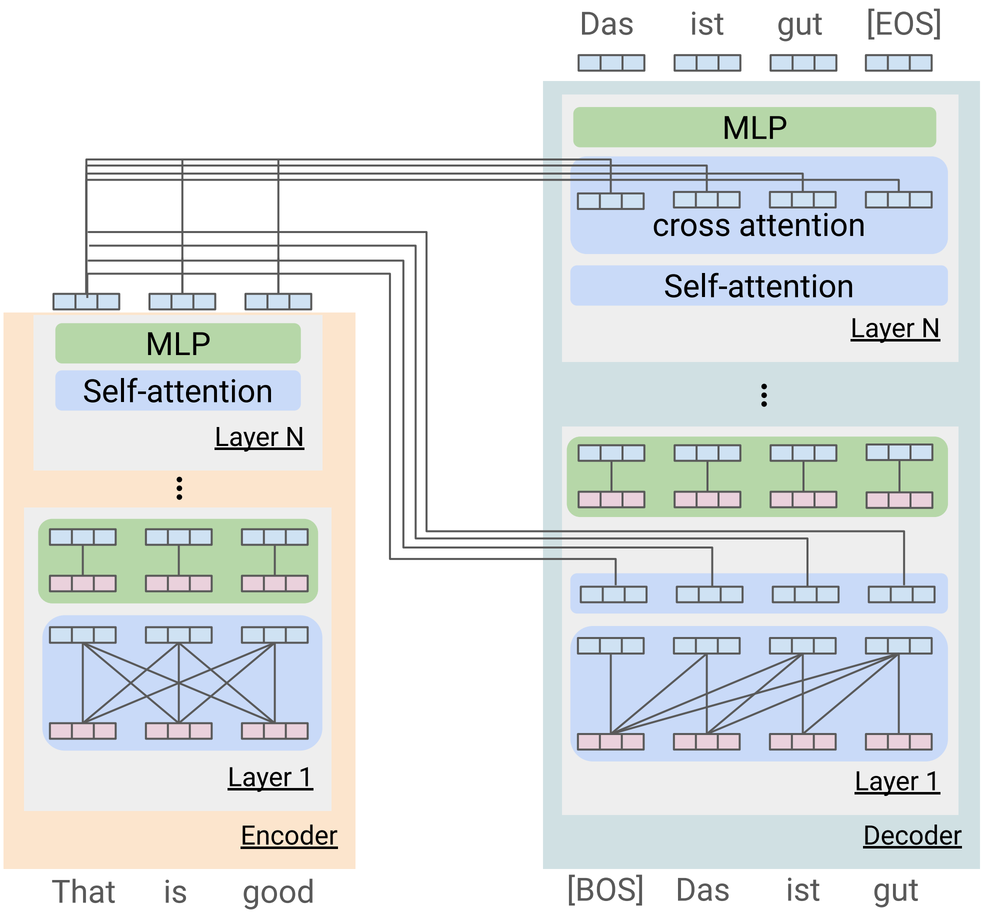
1. Share cross and self-attention parameters

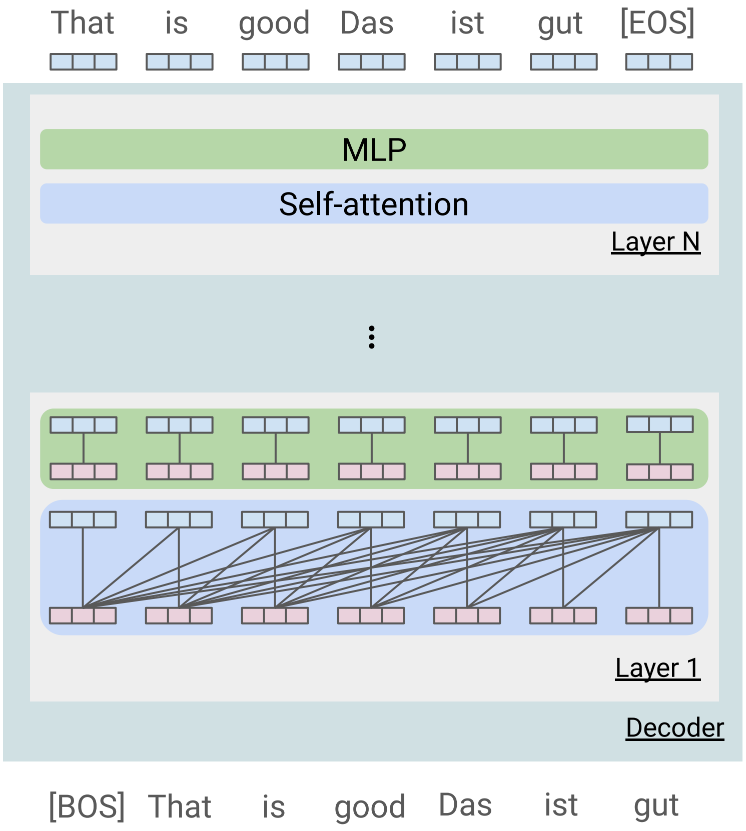




Summary of the differences

	Encoder-decoder	**Decoder-only**
Additional cross attention	Separate cross attention	Self-attention serving both roles
Parameter sharing		
Target-to-input attention pattern		
Input attention		


Das
ist
gut
[EOS]
MLP
cross attention
Self-attention
Layer N
MLP
Self-attention
Layer N
Layer 1
Encoder
Layer 1
Decoder
That
is
good
[BOS]
Das
ist
gut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ist
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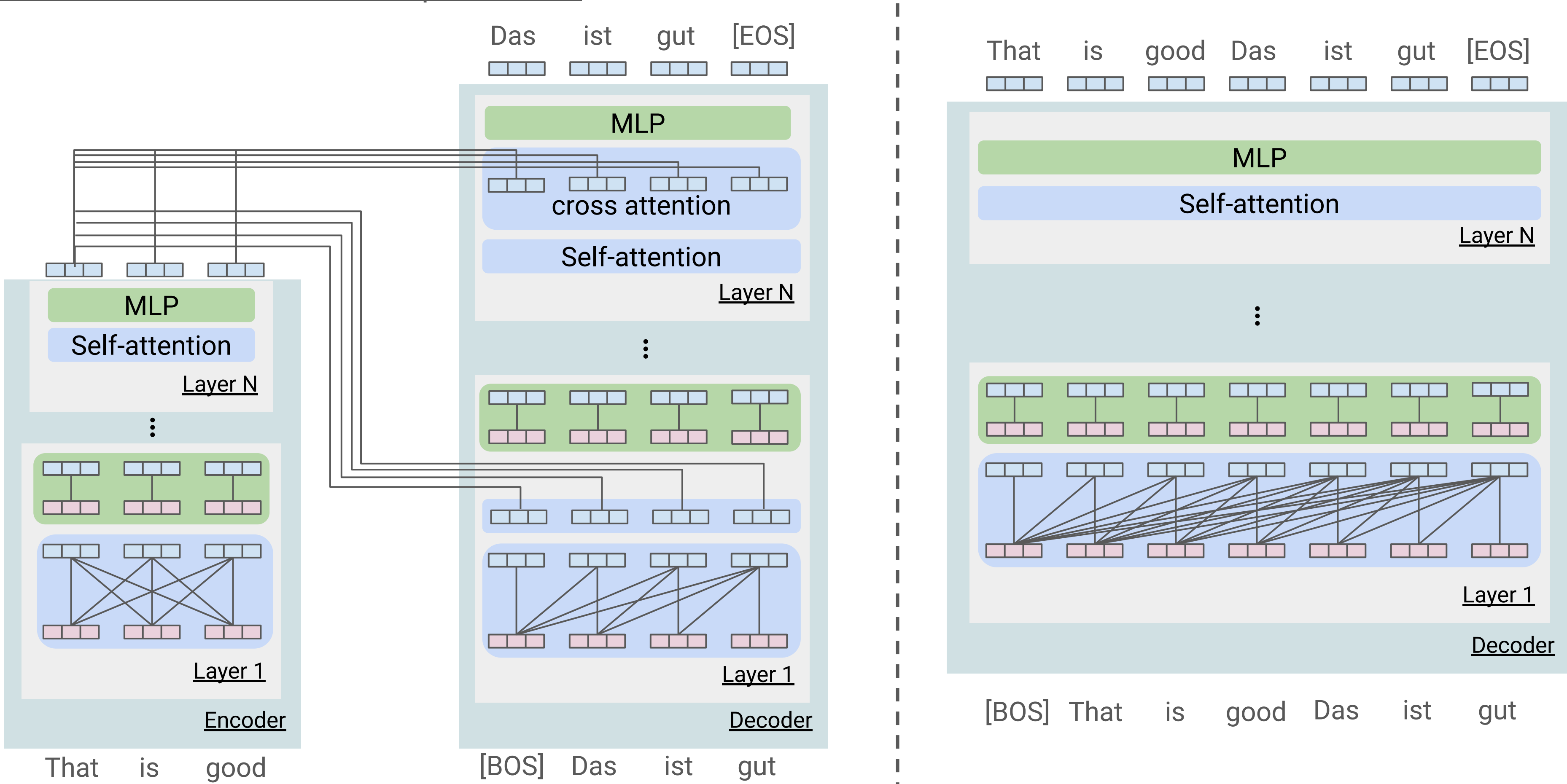
Layer N
Layer 1
Decoder
[BOS]
That
is
good
Das
ist
gut

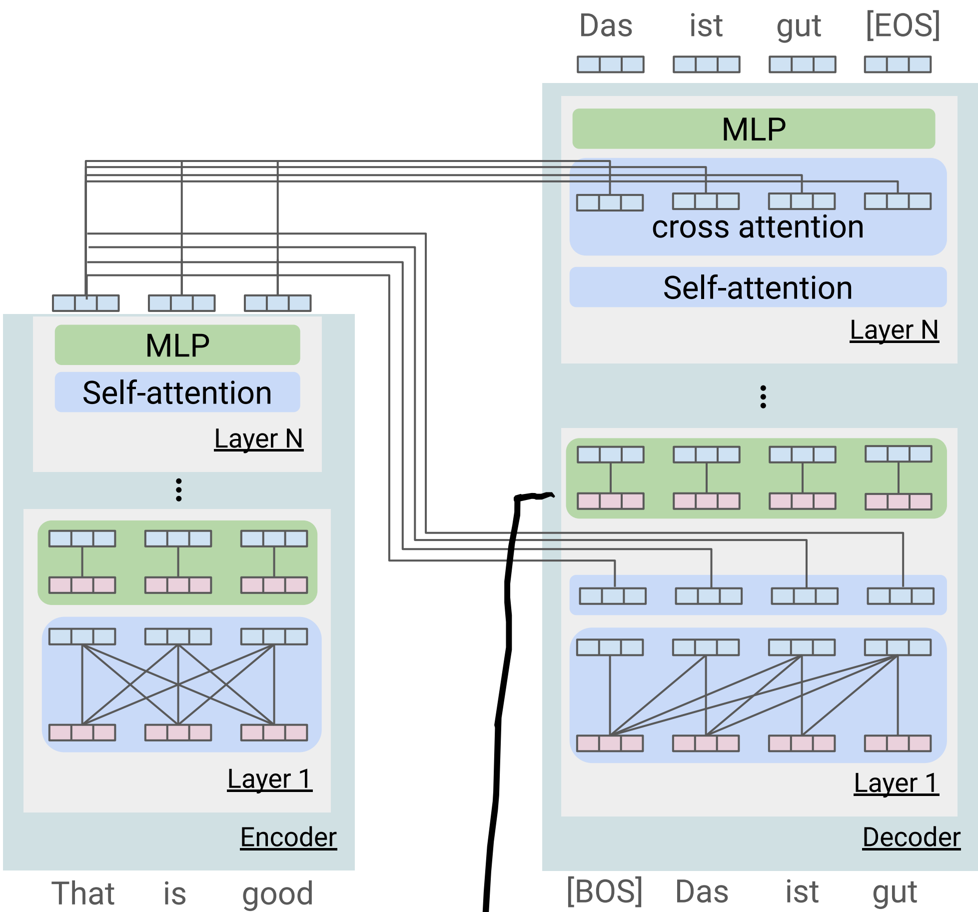
2. Share encoder and decoder parameters



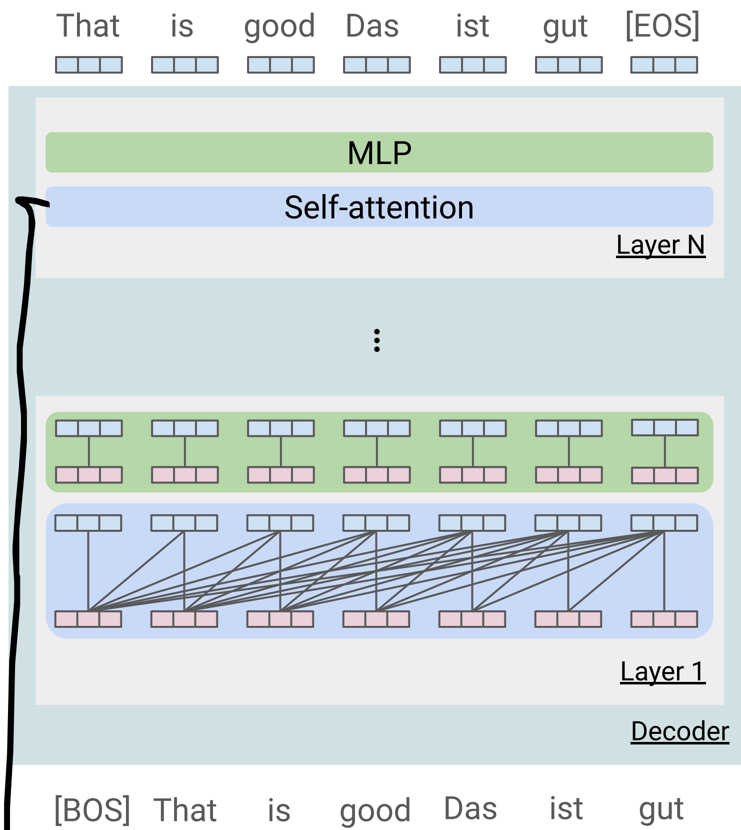
Between I/P & O/P, enc-dec uses different parameters.
Dec-only combines & uses same set of params

Summary of the differences

	Encoder-decoder	**Decoder-only**
Additional cross attention	Separate cross attention	Self-attention serving both roles
Parameter sharing	Separate parameters for input and target	Shared parameters
Target-to-input attention pattern		
Input attention		

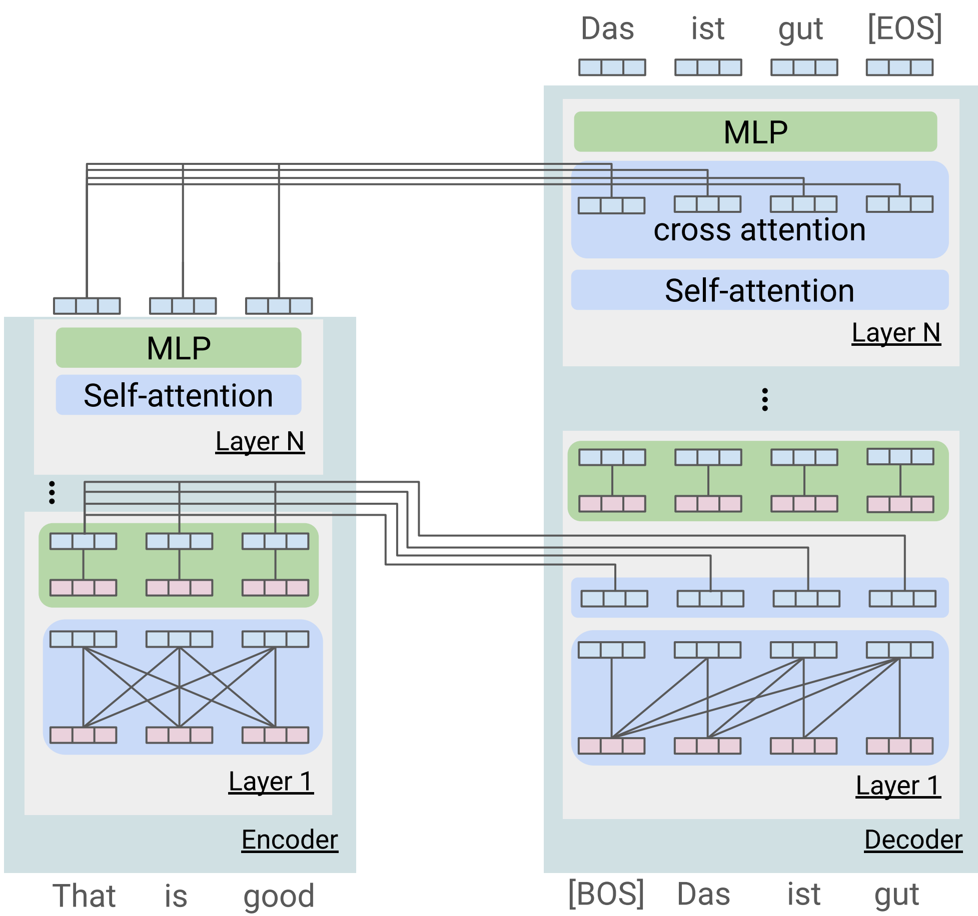


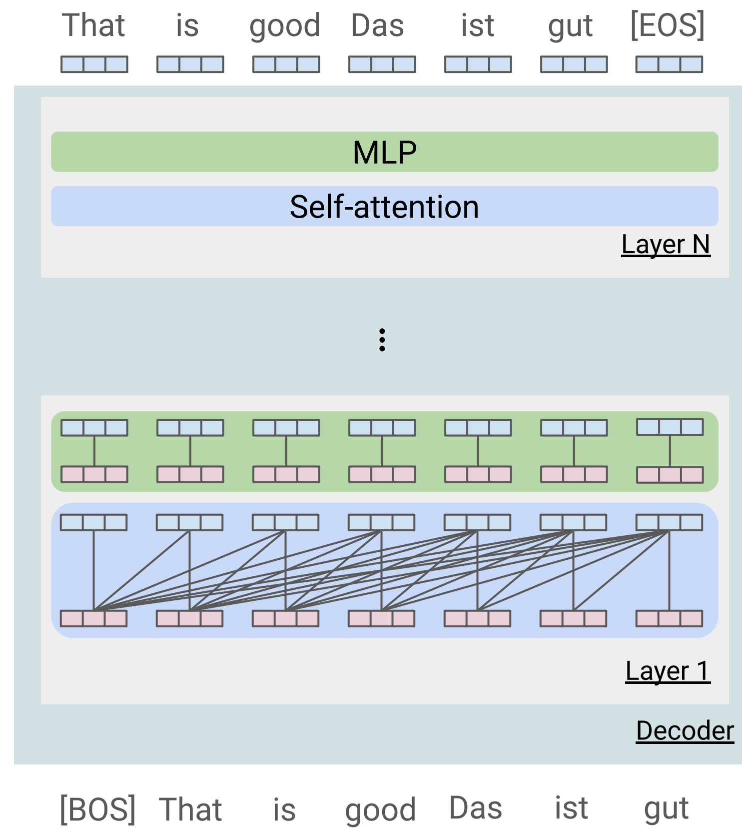
Helps connect
I/P to O/P



Does everthing.

3. Decoder layer 1 attends to encoder layer 1



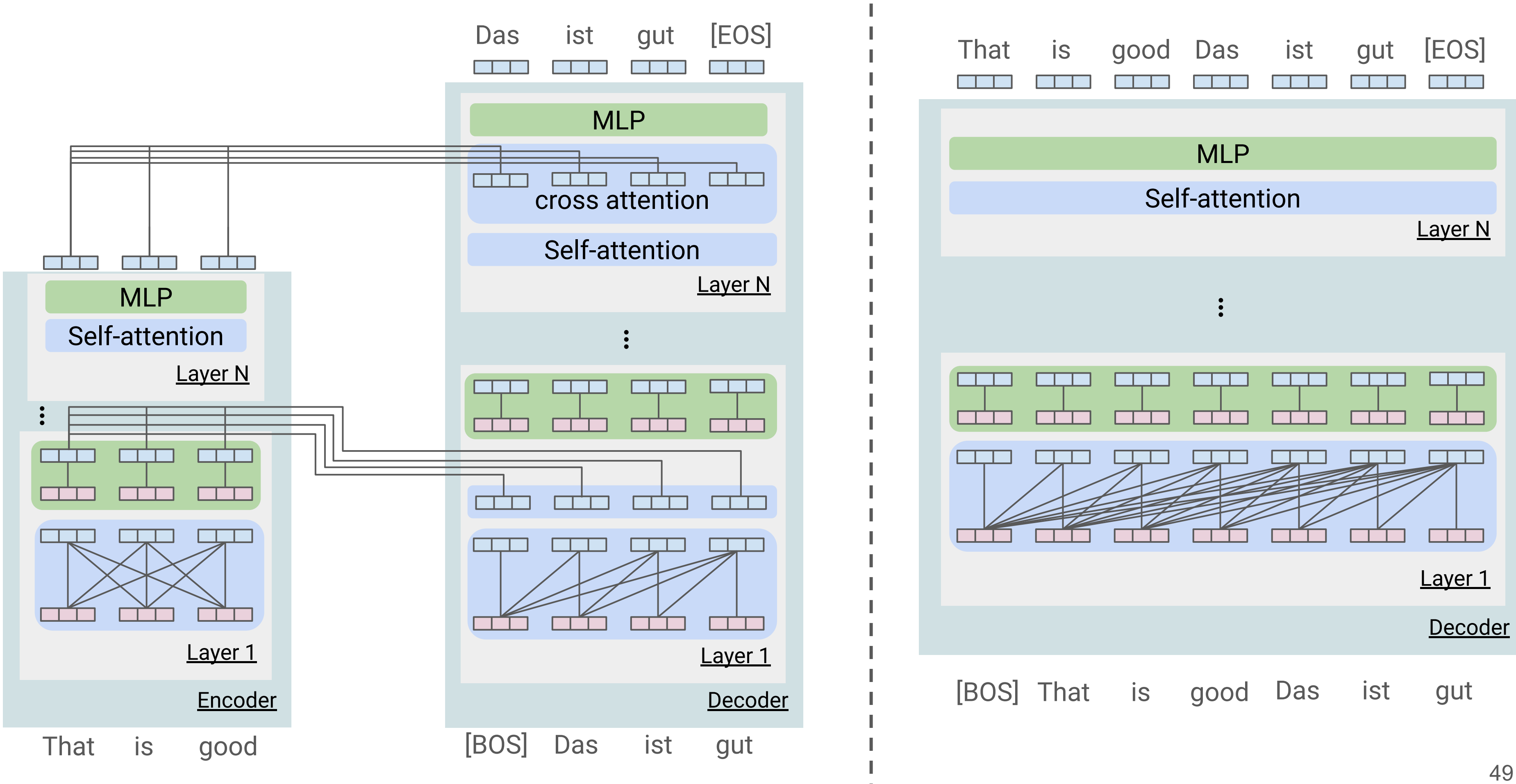


Attend within layer

Summary of the differences

	Encoder-decoder	**Decoder-only**
Additional cross attention	Separate cross attention	Self-attention serving both roles
Parameter sharing	Separate parameters for input and target	Shared parameters
Target-to-input attention pattern	Only attends to the last layer of encoder's output	Within-layer (i.e. layer `l` attends to layer `l`)
Input attention		

* input attention can be bidirectional

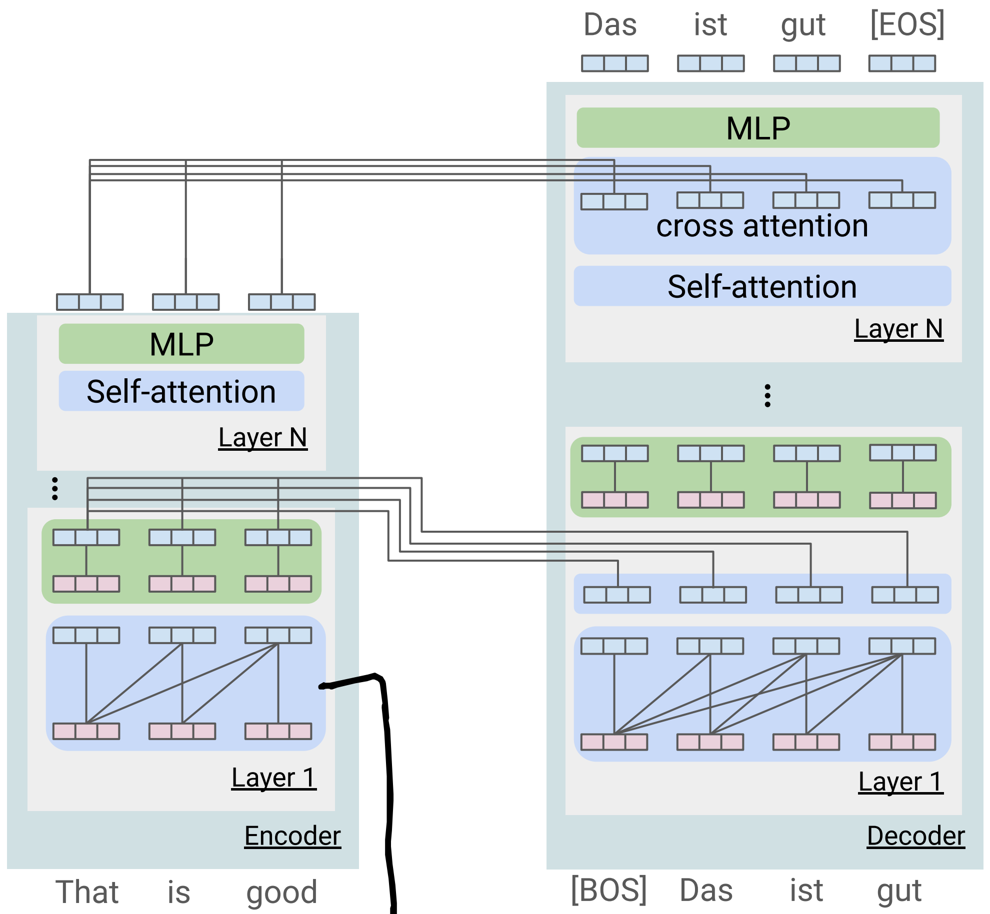


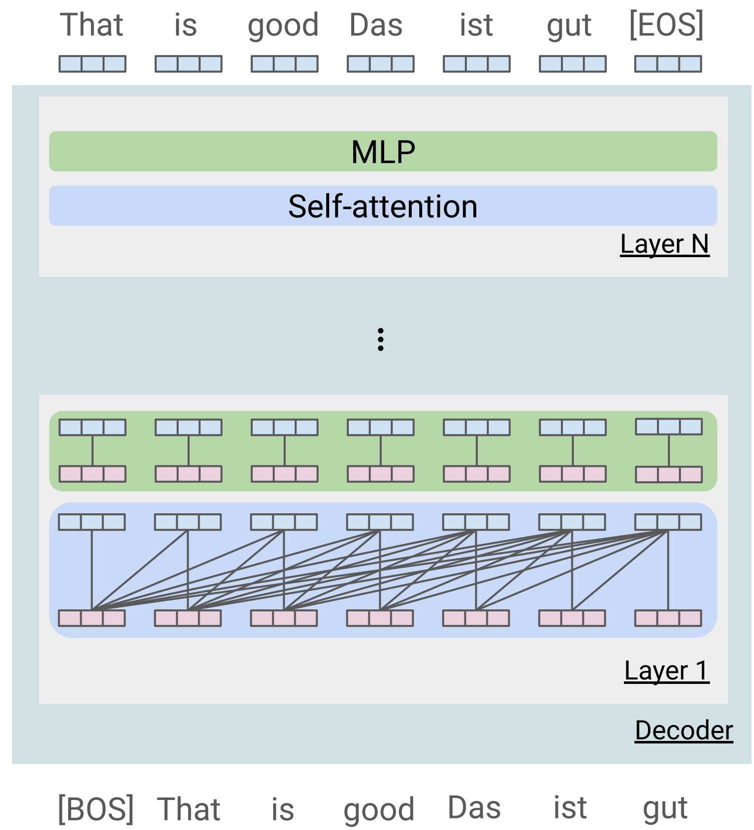
This has I/P att & O/P att.

This essentially means that we need to make the len of att matching.

Here, in dec-only, we get rid of I/P attention

4. Make encoder self-attention causal





Got rid of some of the arrows here.

Summary of the differences

	Encoder-decoder	**Decoder-only**
Additional cross attention	Separate cross attention	Self-attention serving both roles
Parameter sharing	Separate parameters for input and target	Shared parameters
Target-to-input attention pattern	Only attends to the last layer of encoder's output	Within-layer (i.e. layer `l` attends to layer `l`)
Input attention	Bidirectional	Unidirectional*

* input attention can be bidirectional

This makes them almost identical.

Additional structures in encoder-decoder compared to decoder-only

1. Input and target sequences are sufficiently different that using separate parameters can be effective

2. The target element can attend to the fully encoded representation of the input

3. When encoding the input sequence, all-to-all interaction among the sequence elements is preferred

Additional structures in encoder-decoder compared to decoder-only

1. Input and target sequences are sufficiently different that using separate parameters can be effective

2. The target element can attend to the fully encoded representation of the input

3. When encoding the input sequence, all-to-all interaction among the sequence elements is preferred

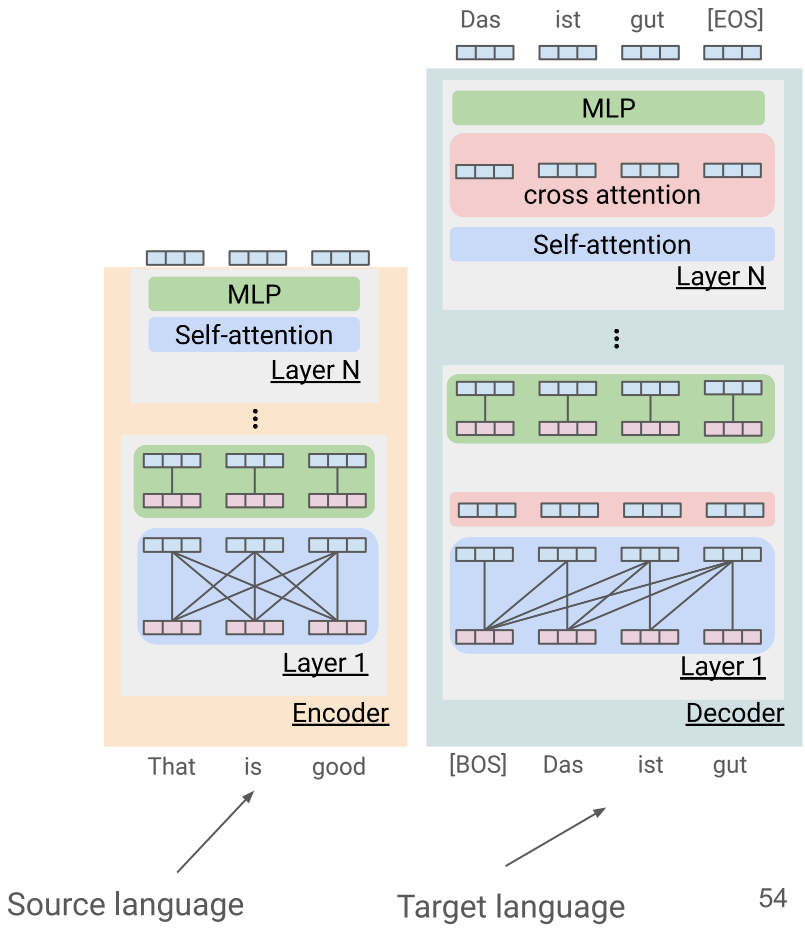
→ Useful assumption for Machine Translation.

Example 1: machine translation

When Transformer was introduced in 2017, translation was a popular and difficult task

Input and target are in different languages

If the only goal is to learn translation, separate parameters make sense



Example 1: machine translation

When Transformer was introduced in 2017, translation was a popular and difficult task

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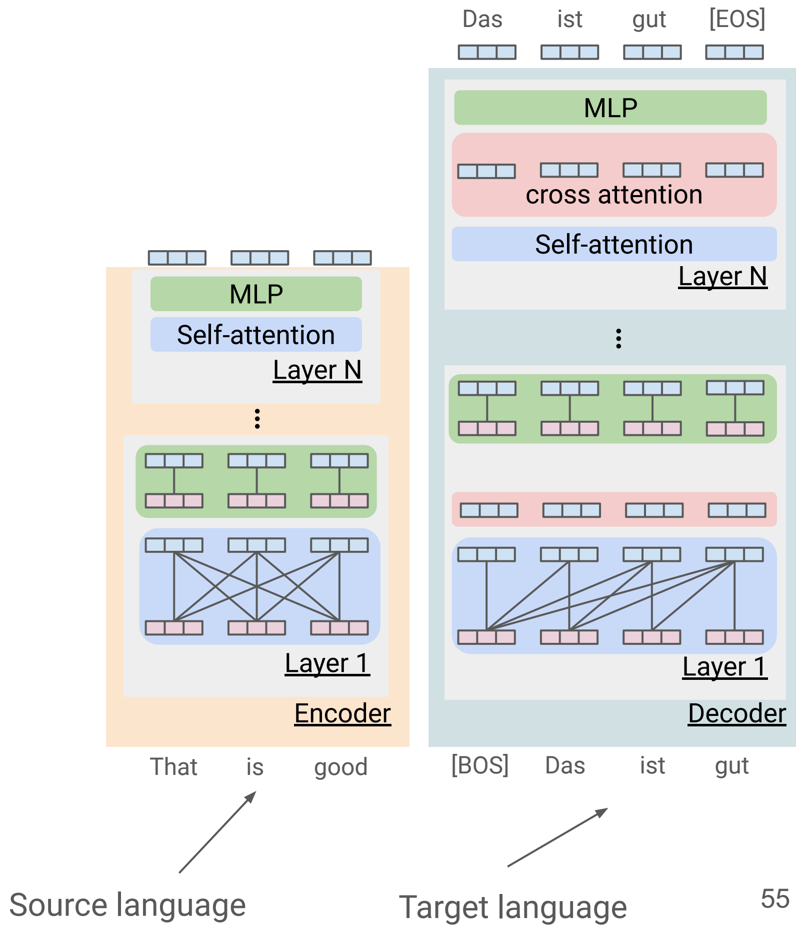
If the only goal is to learn translation, separate parameters make sense

Modern language models learn the world knowledge

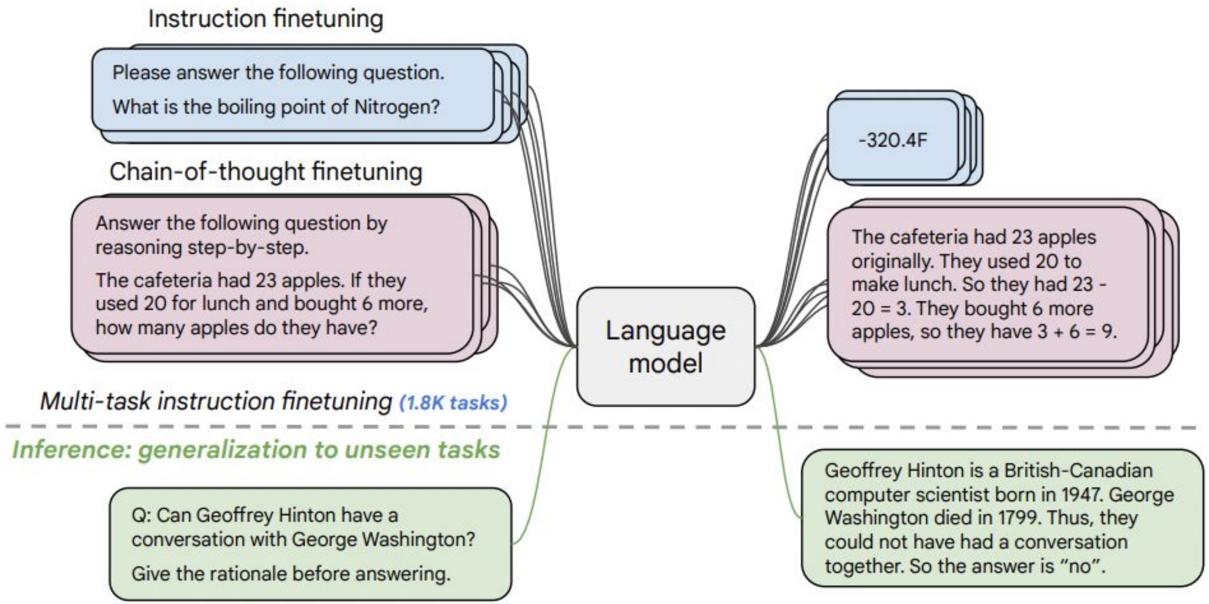
Separate parameters for knowledge just expressed in different languages? 🤔

Probably not!

For larger models, this assumption is unnatural.



Example 2: instruction finetuning with academic datasets



[Scaling Instruction-Finetuned Language Models](#)
Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus et al. (2022)

Example 2: instruction finetuning with academic datasets

Params	Model	Norm. avg.
80M	T5-Small	-9.2
	Flan-T5-Small	-3.1 (**+6.1**)
250M	T5-Base	-5.1
	Flan-T5-Base	6.5 (**+11.6**)
780M	T5-Large	-5.0
	Flan-T5-Large	13.8 (**+18.8**)
3B	T5-XL	-4.1
	Flan-T5-XL	19.1 (**+23.2**)
11B	T5-XXL	-2.9
	Flan-T5-XXL	23.7 (**+26.6**)
8B	PaLM	6.4
	Flan-PaLM	21.9 (**+15.5**)
62B	PaLM	28.4
	Flan-PaLM	38.8 (**+10.4**)
540B	PaLM	49.1
	Flan-PaLM	58.4 (**+9.3**)
62B	cont-PaLM	38.1
	Flan-cont-PaLM	46.7 (**+8.6**)
540B	U-PaLM	50.2
	Flan-U-PaLM	59.1 (**+8.9**)

Encoder-decoder

Decoder-only

Encoder-decoder models had much bigger gain!

Example 2: instruction finetuning with academic datasets

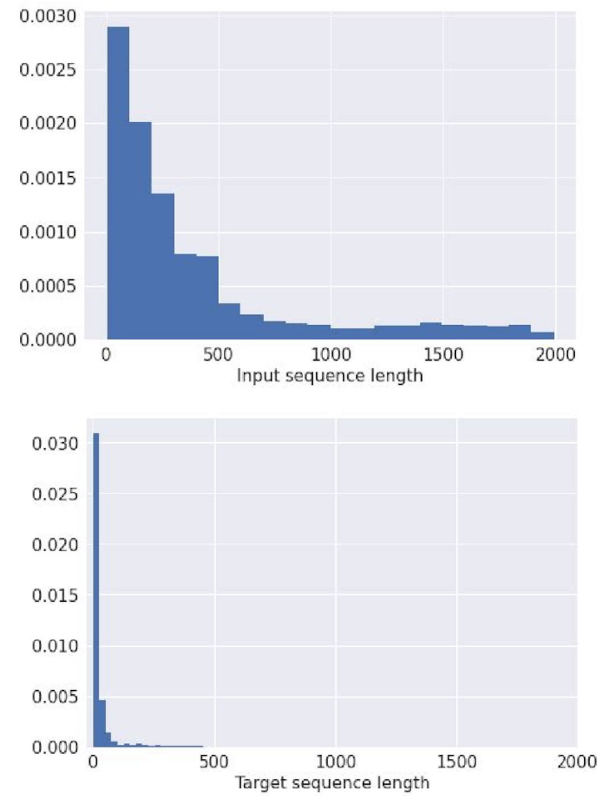
Academic datasets have distinctive length distribution: long input and short target

This is due to inherent difficulty of grading long text

Hypothesis
Having separate parameters for longer text in input and shorter text in target was an effective *structure*

No longer a good structure as more interesting language model use cases have longer generation

Longer targets now are interesting. Not being able to grade in not bad anymore.



Length distribution of finetuning datasets

→ Length of I/P but small length of input

→ Diff type of seq in I/P & O/P.

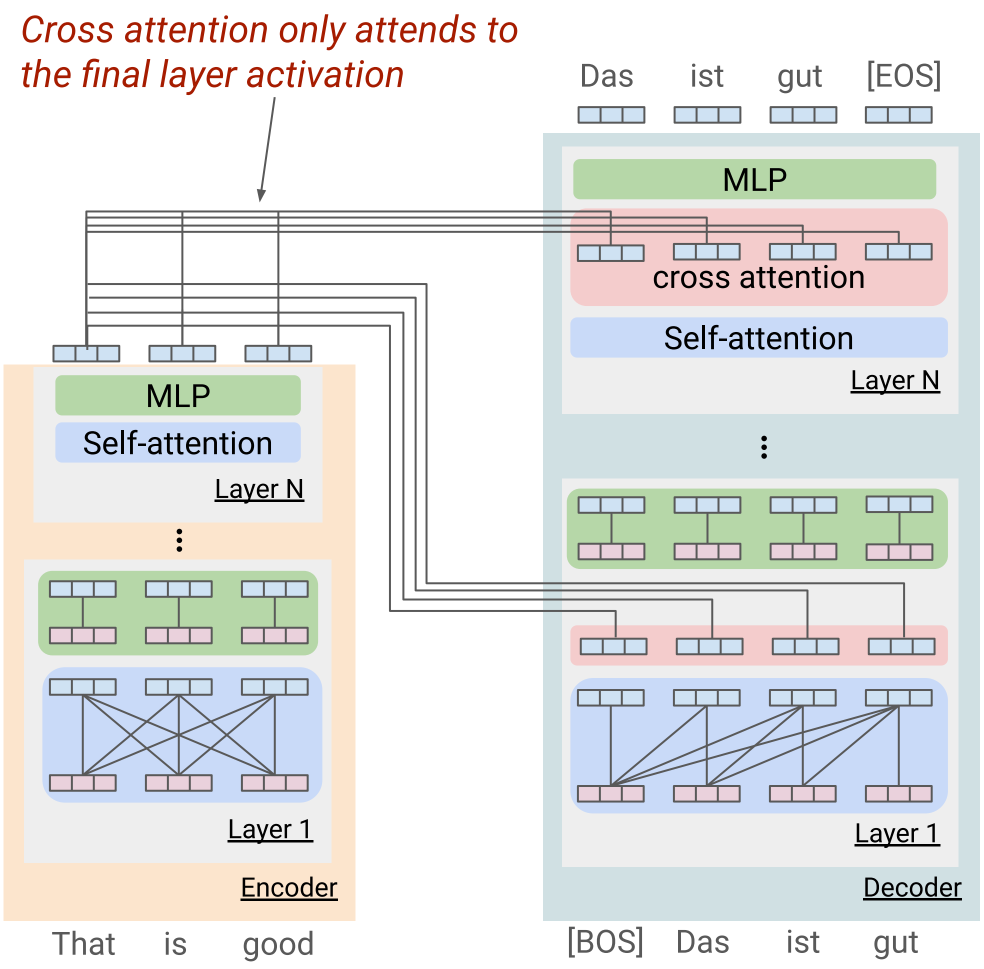
→ This structure shines in enc-dec architecture

Additional structures in encoder-decoder compared to decoder-only

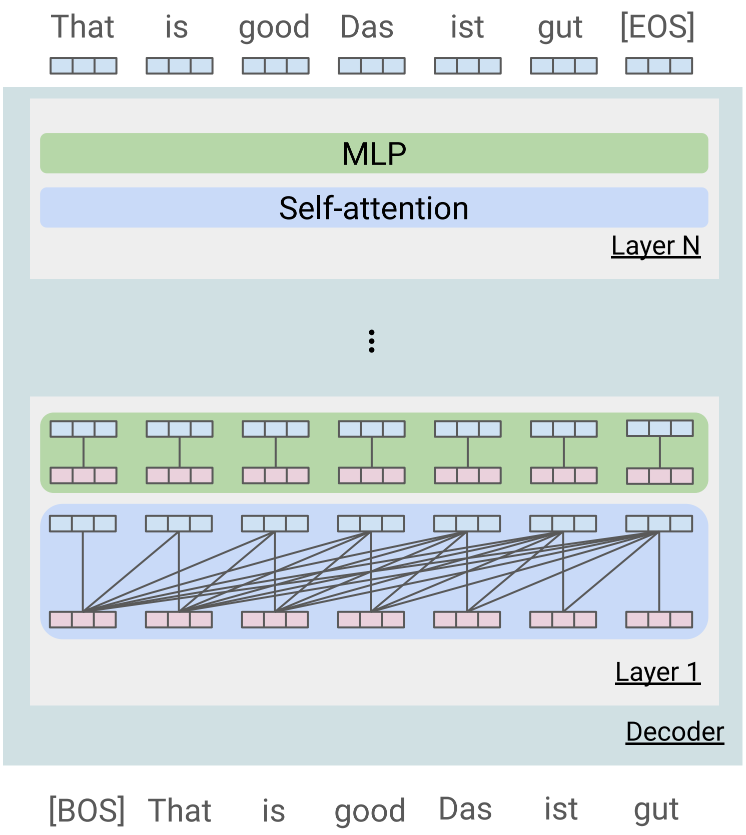
1. Input and target sequences are sufficiently different that using separate parameters can be effective

2. The target element can attend to the fully encoded representation of the input

3. When encoding the input sequence, all-to-all interaction among the sequence elements is preferred



Cross attention only attends to the final layer activation
Das
ist
gut
[EOS]
MLP
cross attention
Self-attention
Layer N
MLP
Self-attention
Layer N
Layer 1
Encoder
That
is
good
Layer 1
Decoder
[BOS]
Das
ist
gut



That
is
good
Das
ist
gut
[EOS]
MLP
Self-attention
Layer N
Layer 1
Decoder
[BOS]
That
is
good
Das
ist
gut

→ In CV, lower layers contain edges, higher contain faces. Called hierachical learning

In deep neural networks, the bottom and top layers encode information at a different level of granularity

For example, in computer vision, the bottom layers learn to encode edges and the top layers learn higher level features (e.g. cat face)

Can decoder only attending to the final layer of encoder be an *information bottleneck* if encoder is sufficiently deep? 🤔

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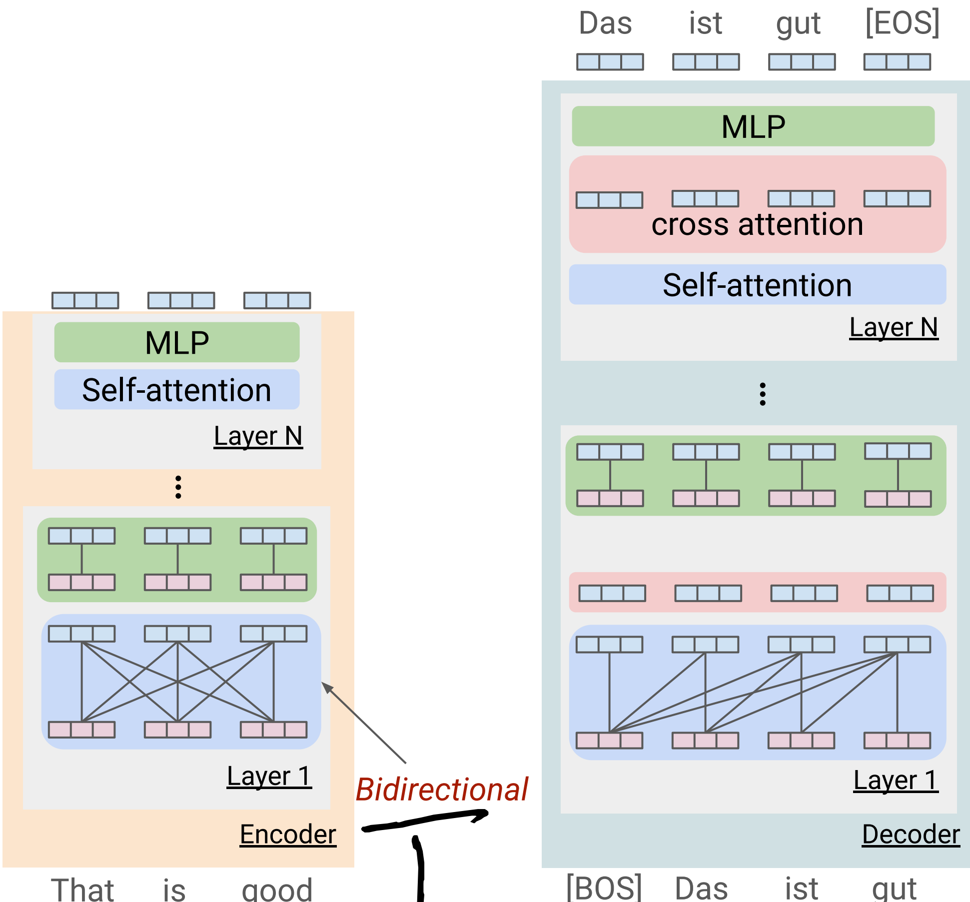
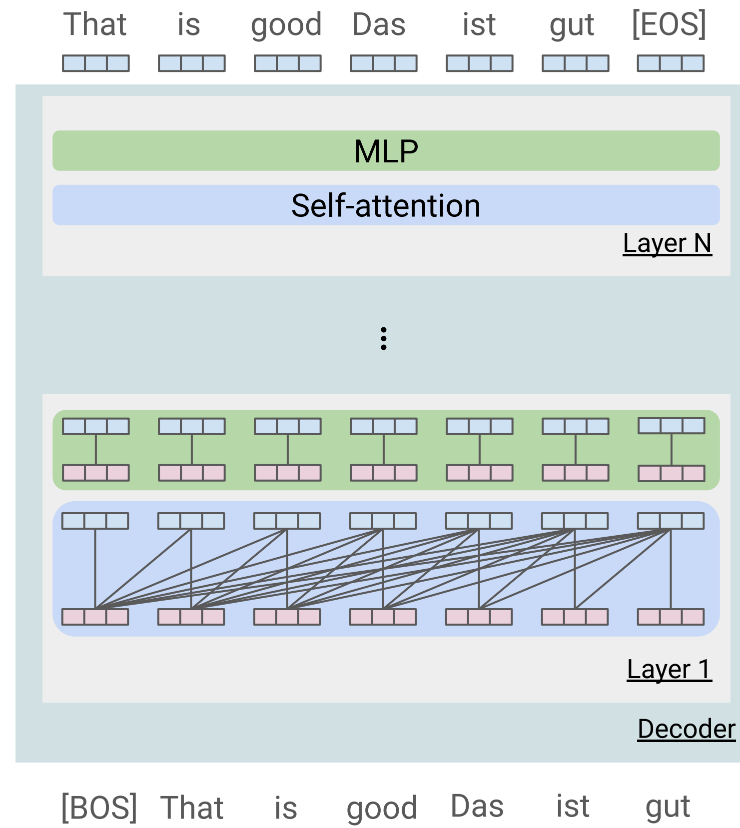




Is this necessary?

Based on Flan-2. No diff btw bi & uni directional

(Highly anecdotal) At sufficient scale, bidirectionality doesn’t seem to matter much

Bidirectionality brings in engineering challenges for multi-turn chat application

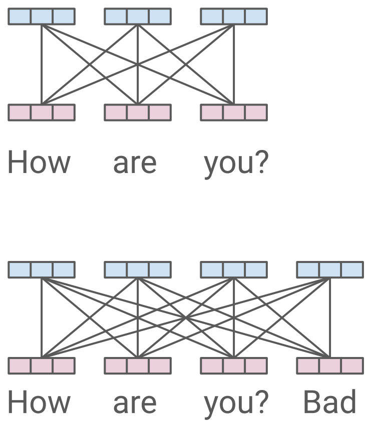
At every turn, the new input has to be encoded again; for unidirectional attention, only the newly added message needs to be encoded.

Input attention pattern for multi-turn conversation

Bidirectional

USER
How are you?

ASSISTANT
Bad

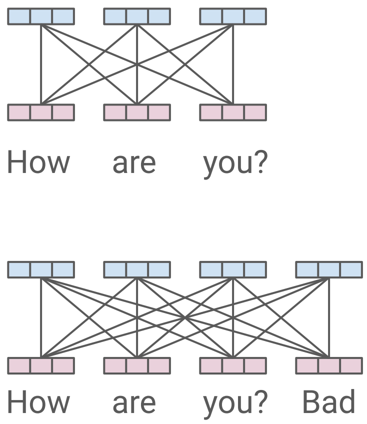


USER
Why?

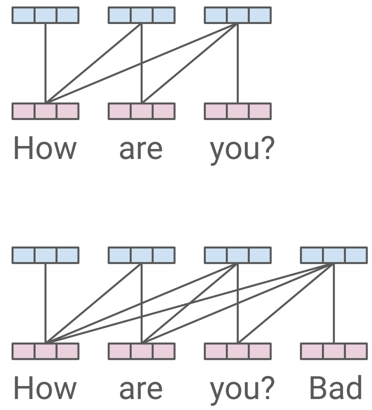
Encode I/P with bad before output

Input attention pattern for multi-turn conversation

Bidirectional



Unidirectional



USER
How are you?

ASSISTANT
Bad

USER
Why?

Do better
when gen 'Why?'
don't need to redo
How?
It can be cached !!

Conclusion

Identify the dominant driving force as exponentially cheaper compute and associated scaling

Analyzed additional structure of encoder-decoder from the perspective of scaling

Hopefully this perspective and analysis can be useful for understanding what is happening today and predict the future trajectory