8.5

Understanding Self-Attention

Part 4: Masked Attention And Positional Encoding

Sebastian Raschka and the Lightning AI Team

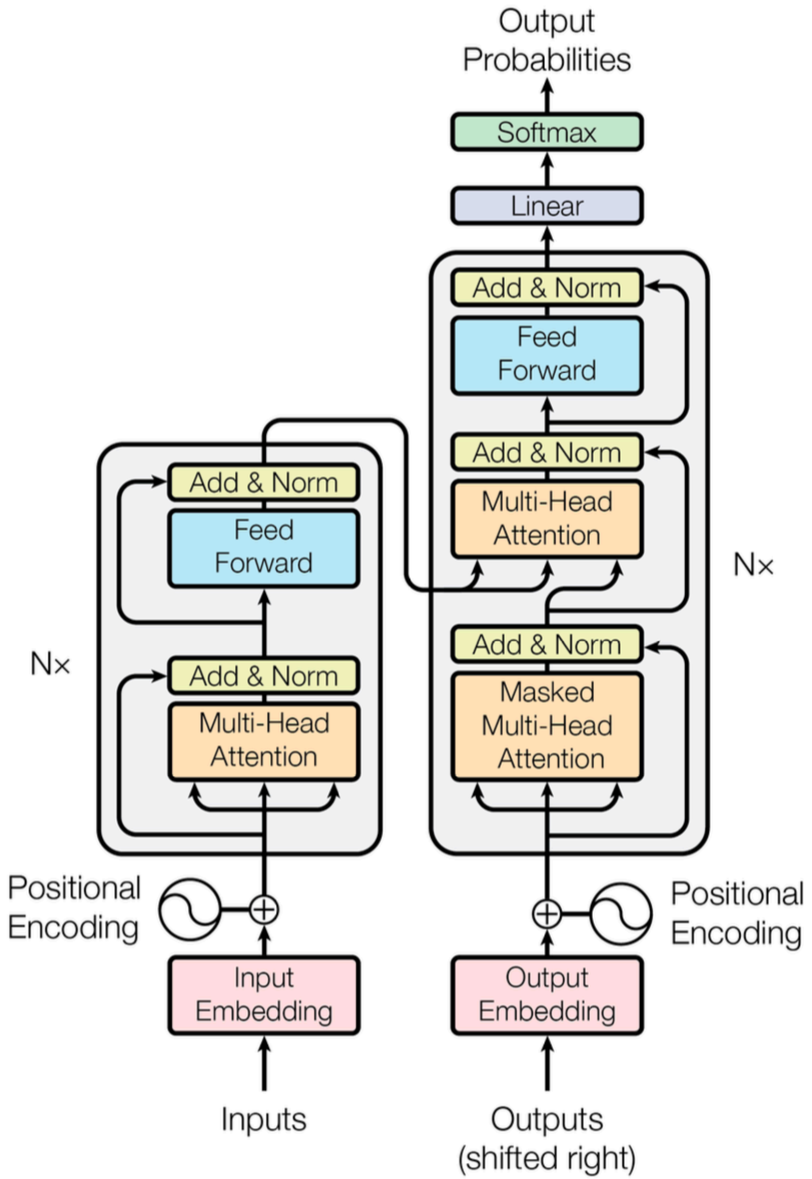
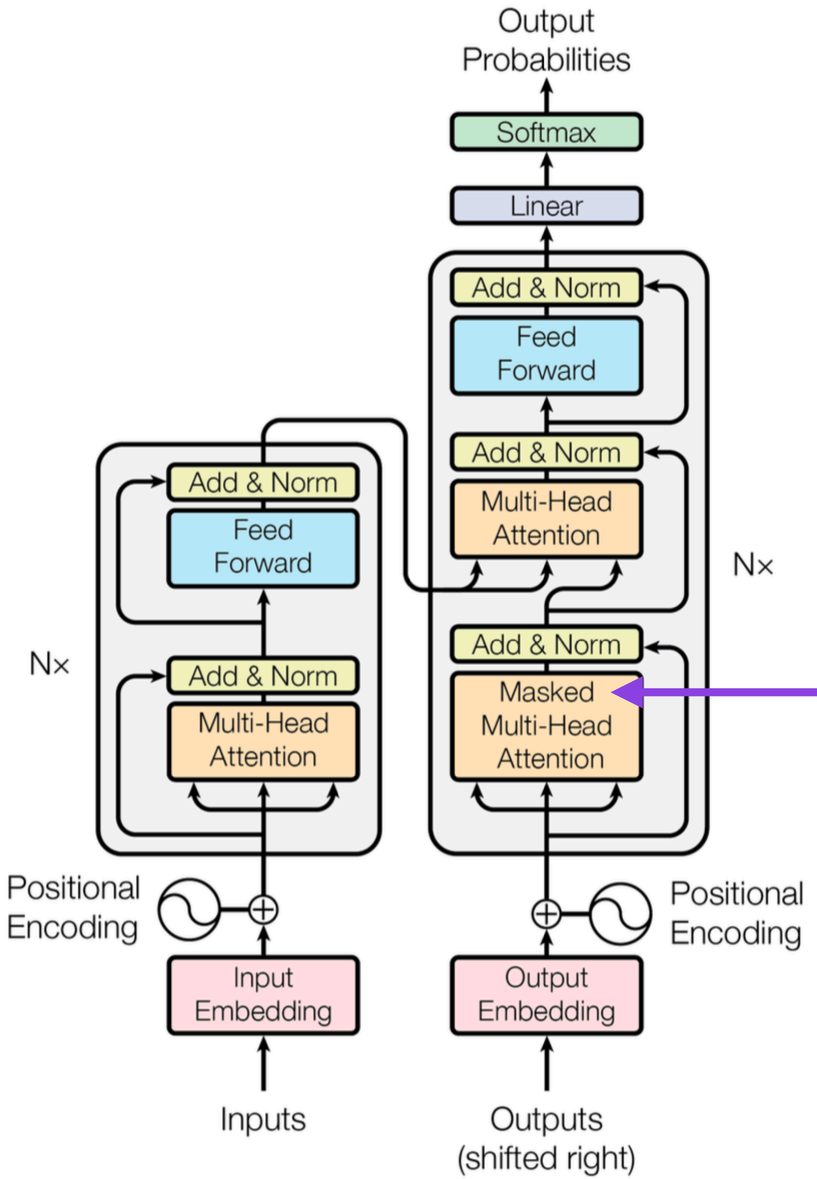


Figure 1: The Transformer - model architecture.



Masked?

Figure 1: The Transformer - model architecture.

Masked Multi-Head Attention

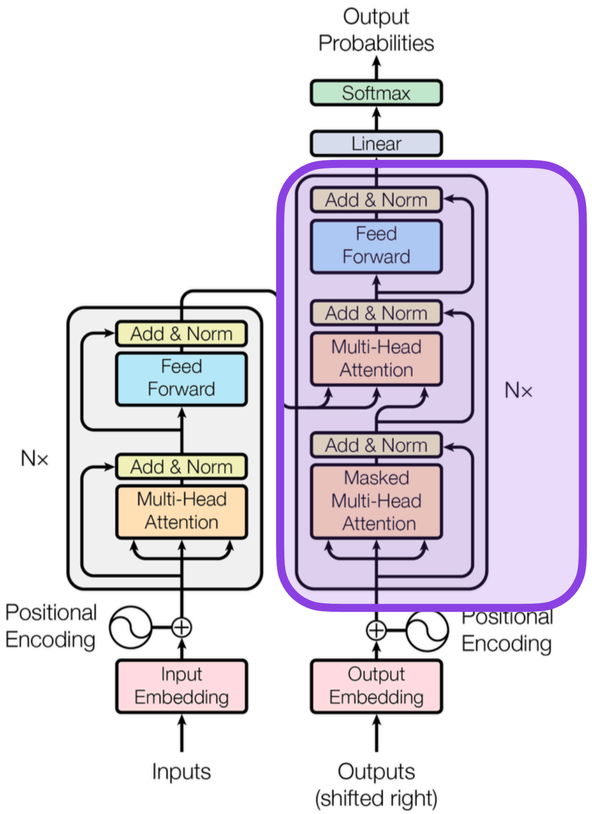
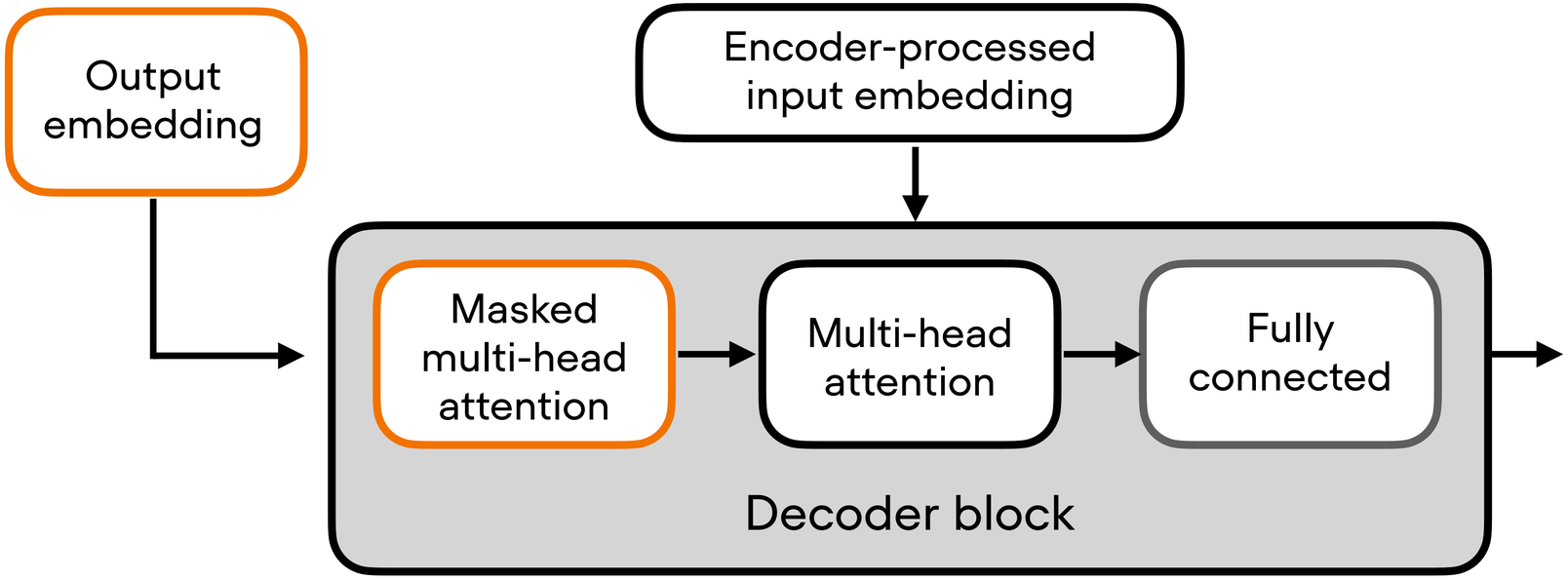


Figure 1: The Transformer - model architecture.



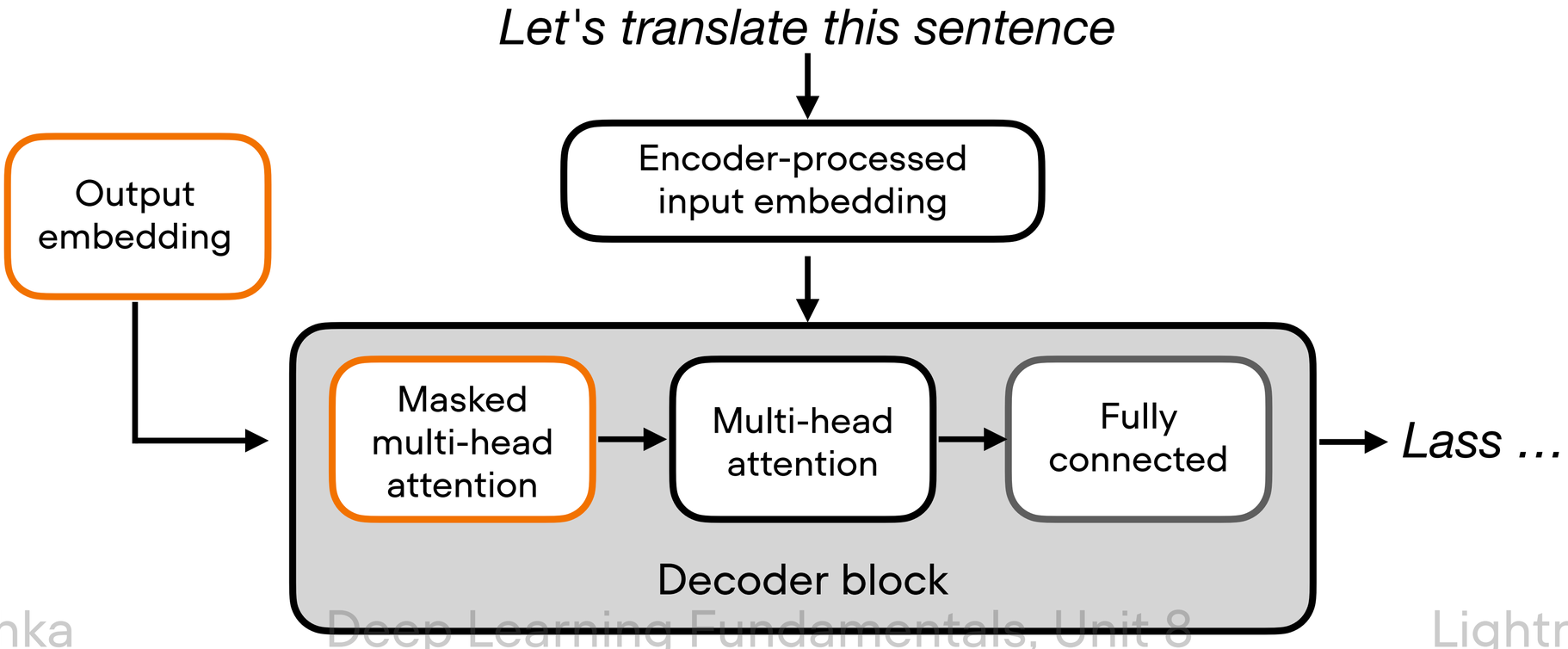
(A concise sketch of the decoder block)

English → German Translation

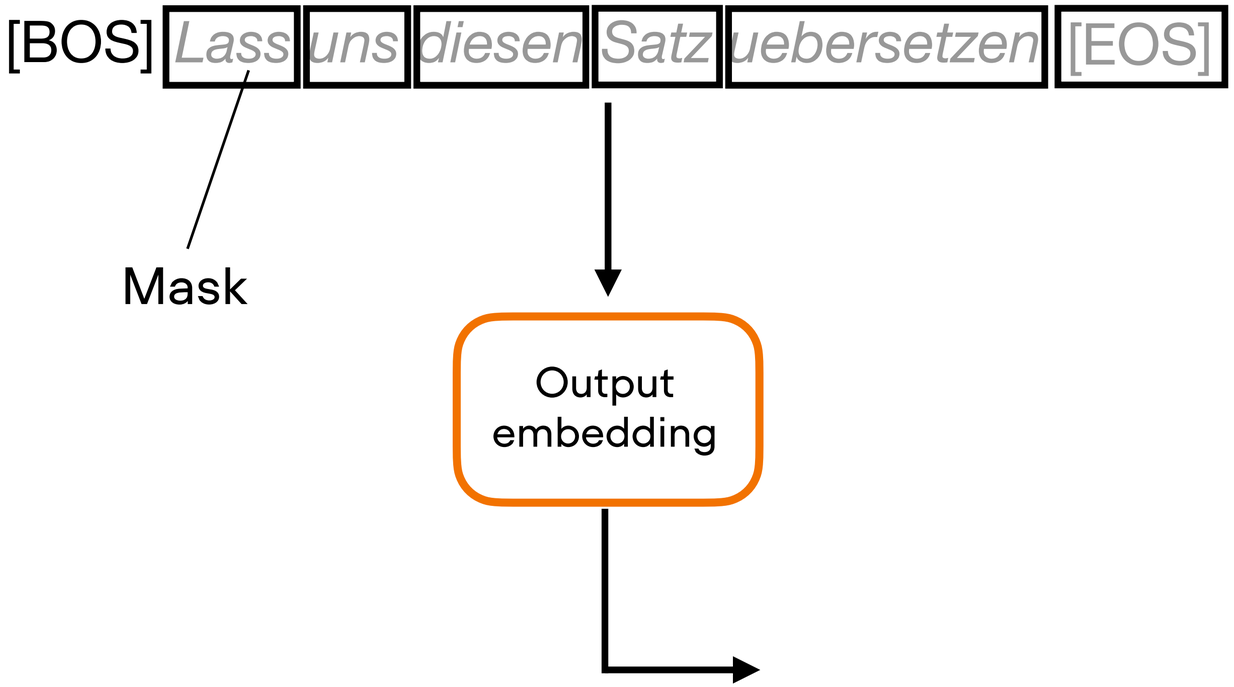
Input: *Let's translate this sentence*

Target: *Lass uns diesen Satz uebersetzen*

Task is to translate the input into German



Masked attention masks out tokens the model hasn't seen before (here visualized on the input instead of embedding)



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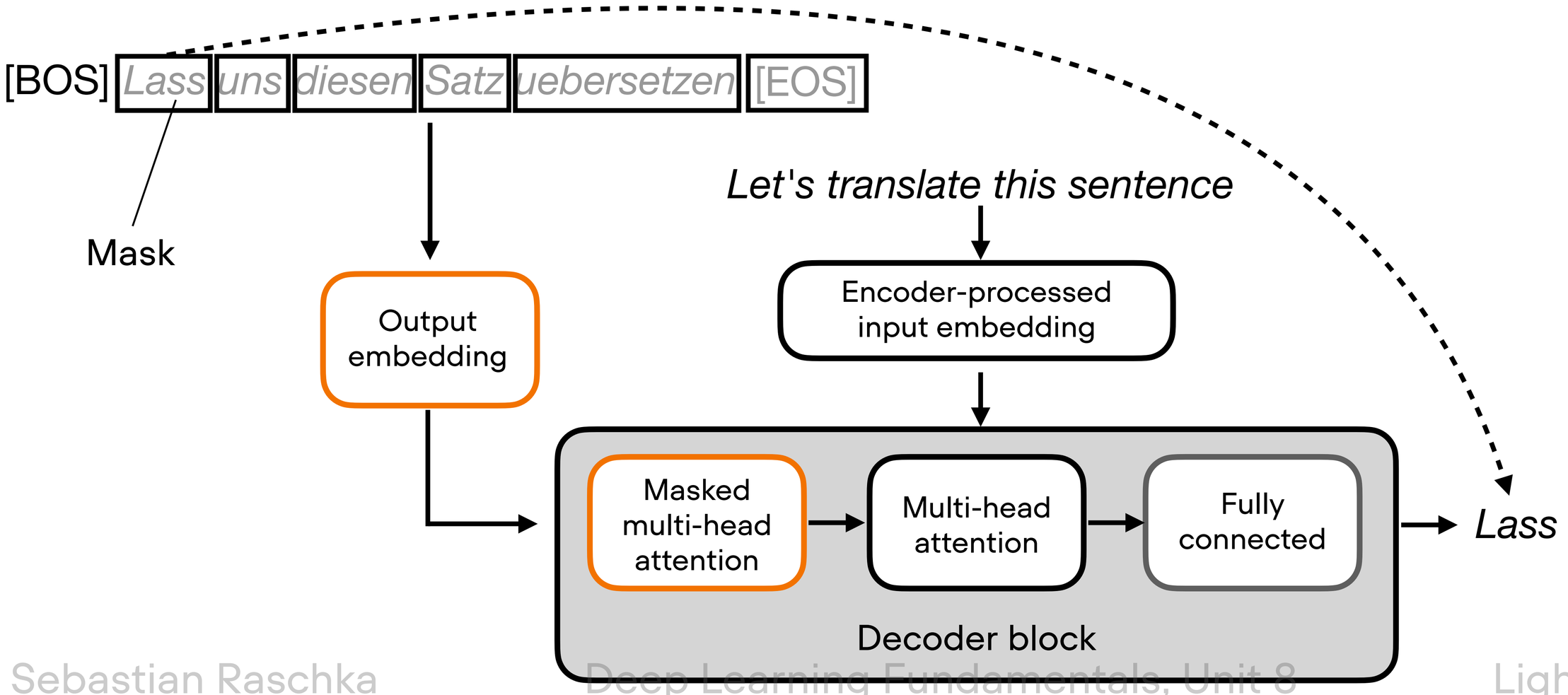
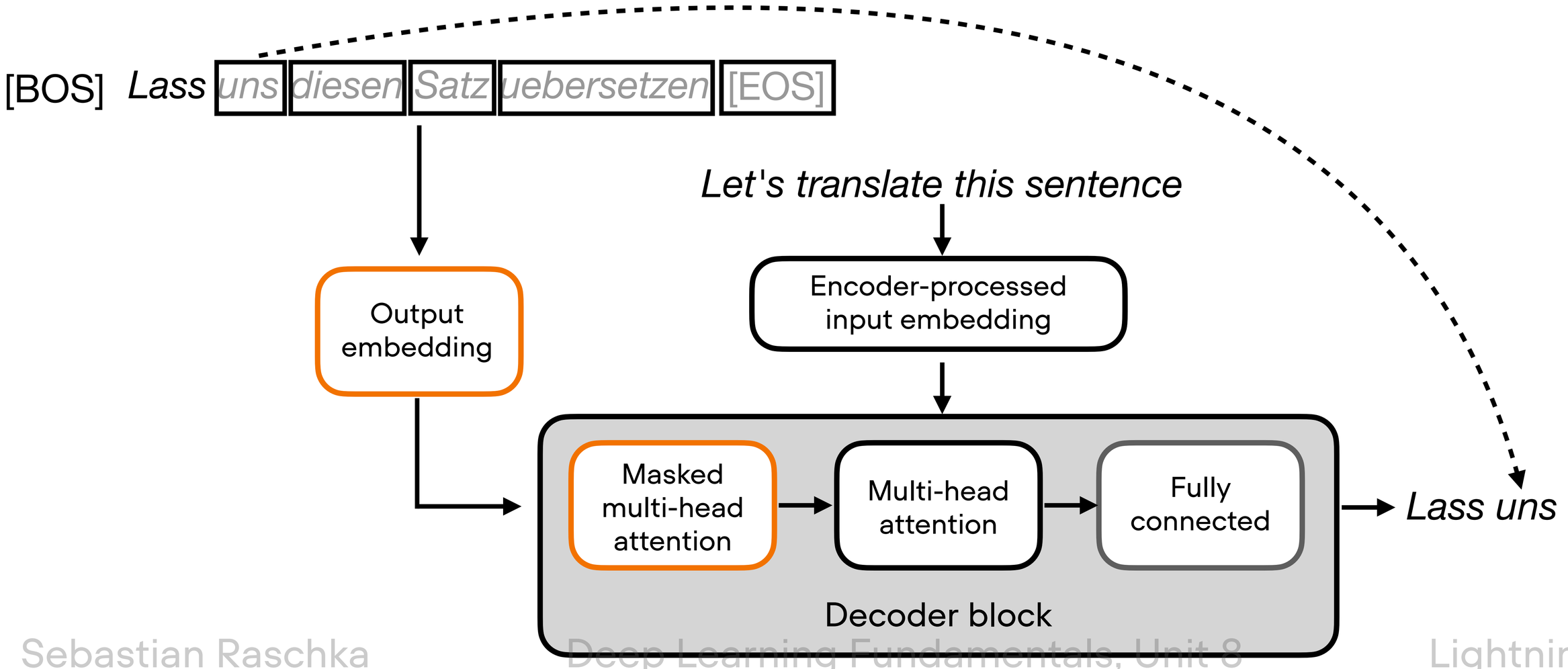
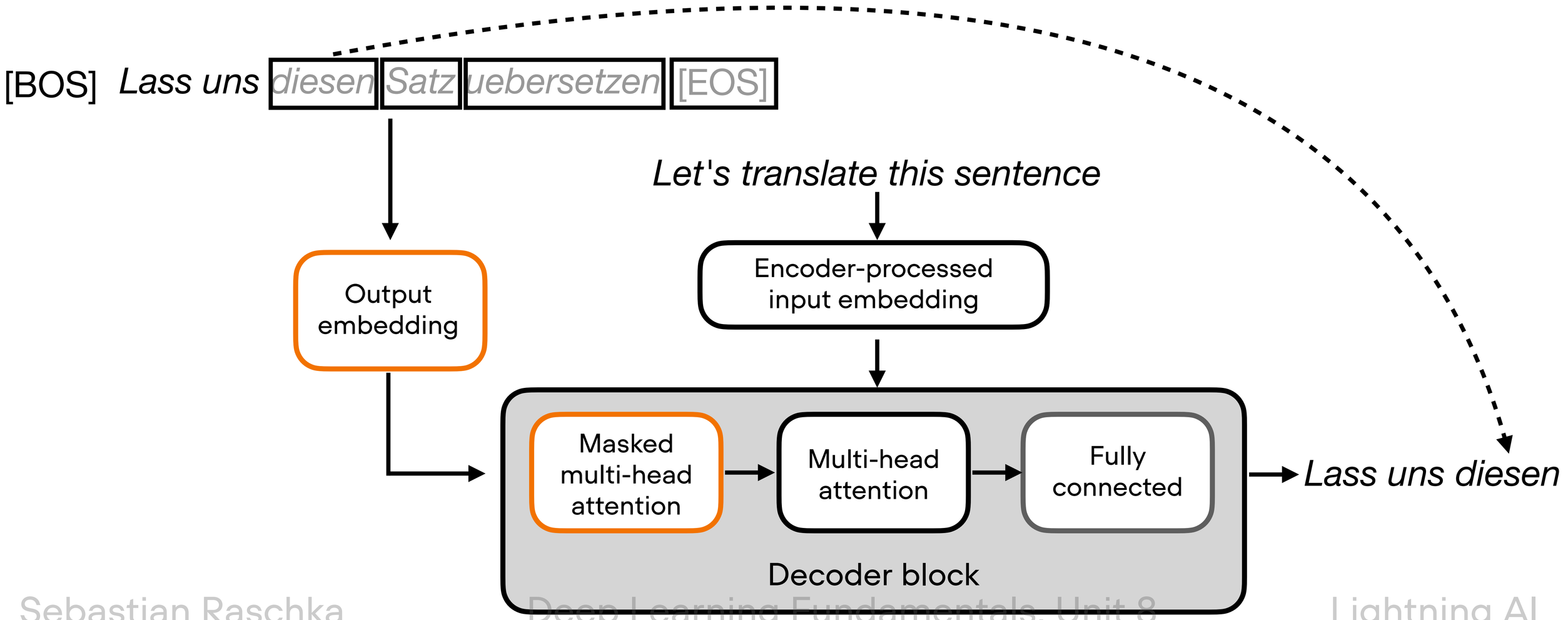


Time step 2


[BOS]
Lass
uns
diesen
Satz
uebersetzen
[EOS]
Let's translate this sentence
Output embedding
Encoder-processed input embedding
Masked multi-head attention
Multi-head attention
Fully connected
Decoder block
Lass uns

Time step 3


[BOS]
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Lass uns diesen

Positional encodings?

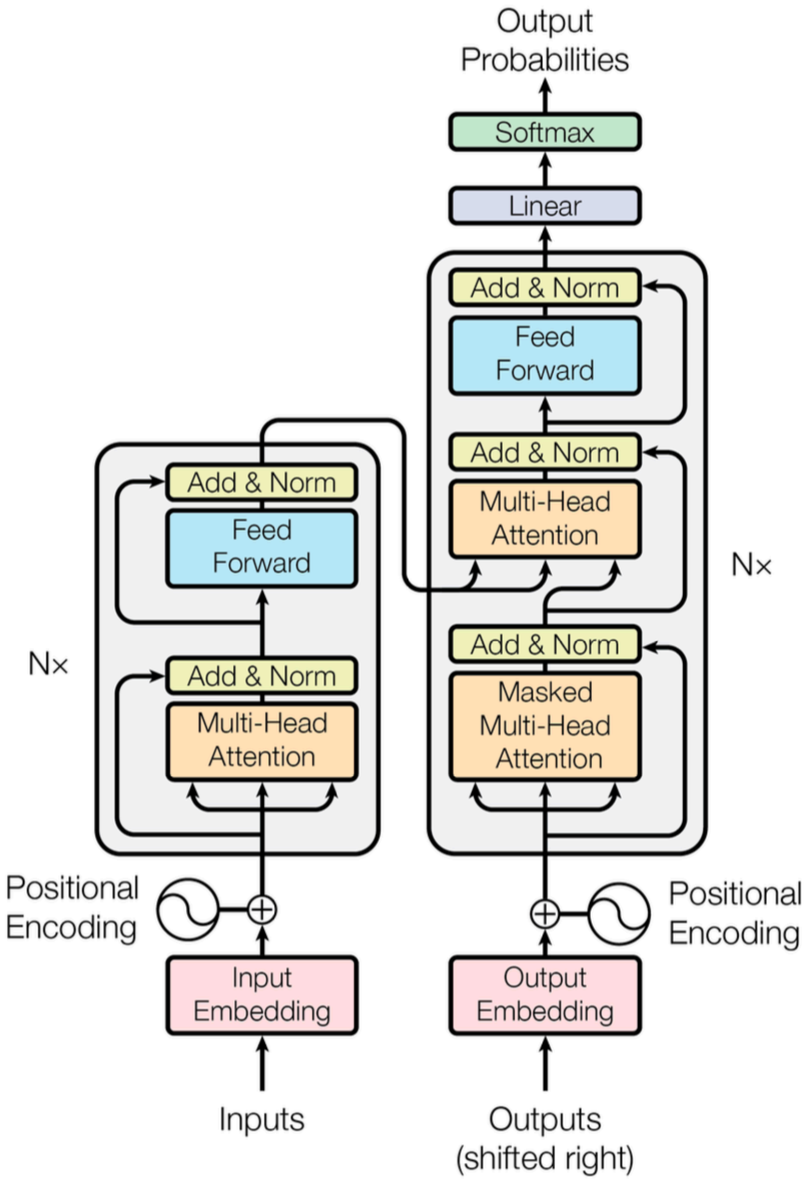

Figure 1: The Transformer - model architecture.

Why positional encodings?

Self-attention and fully-connected layers
are permutation invariant

```
import torch

input_values = torch.tensor([[1.,  5., -2.],  # 1st example
                             [-1., .3, 1.4]]) # 2nd example

torch.manual_seed(123)
layer = torch.nn.Linear(3, 1)

with torch.no_grad():
    print(layer(input_values))
```

```
tensor([[0.6514],
        [0.0574]])
```

```python
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input_values = torch.tensor([[1.,  5., -2.],  # 1st example
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with torch.no_grad():
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```

```
tensor([[0.6514],
        [0.0574]])
```

```python
shuffle = [2, 0, 1]
input_values = input_values[:, shuffle]
layer.weight = torch.nn.Parameter(layer.weight[:, shuffle])
```

```
import torch

input_values = torch.tensor([[1.,  5., -2.],  # 1st example
                             [-1., .3, 1.4]]) # 2nd example

torch.manual_seed(123)
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tensor([[0.6514],
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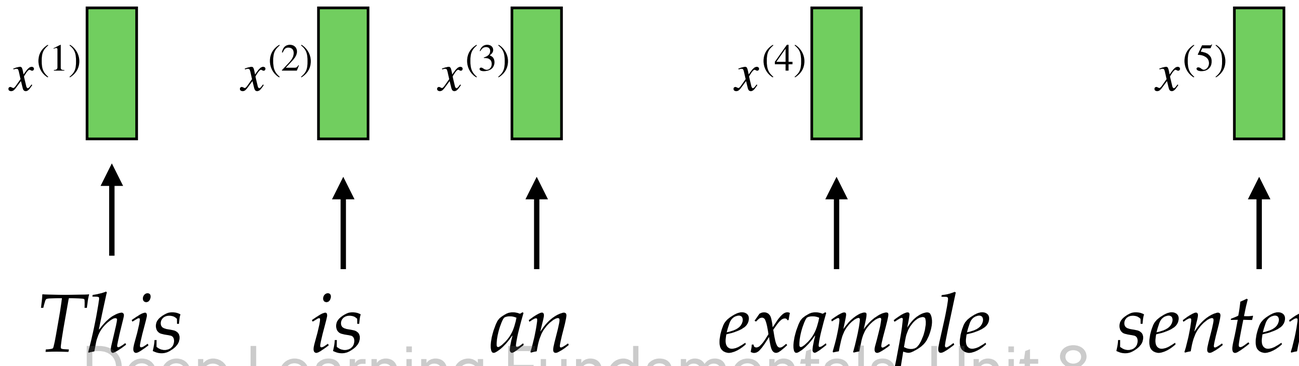
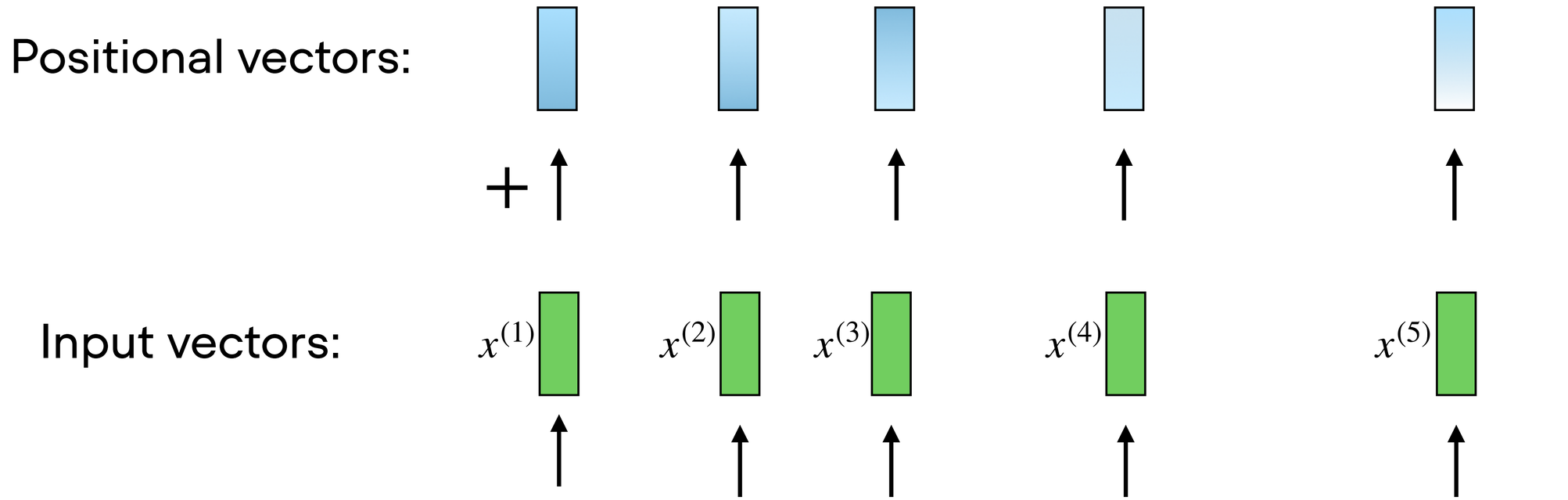
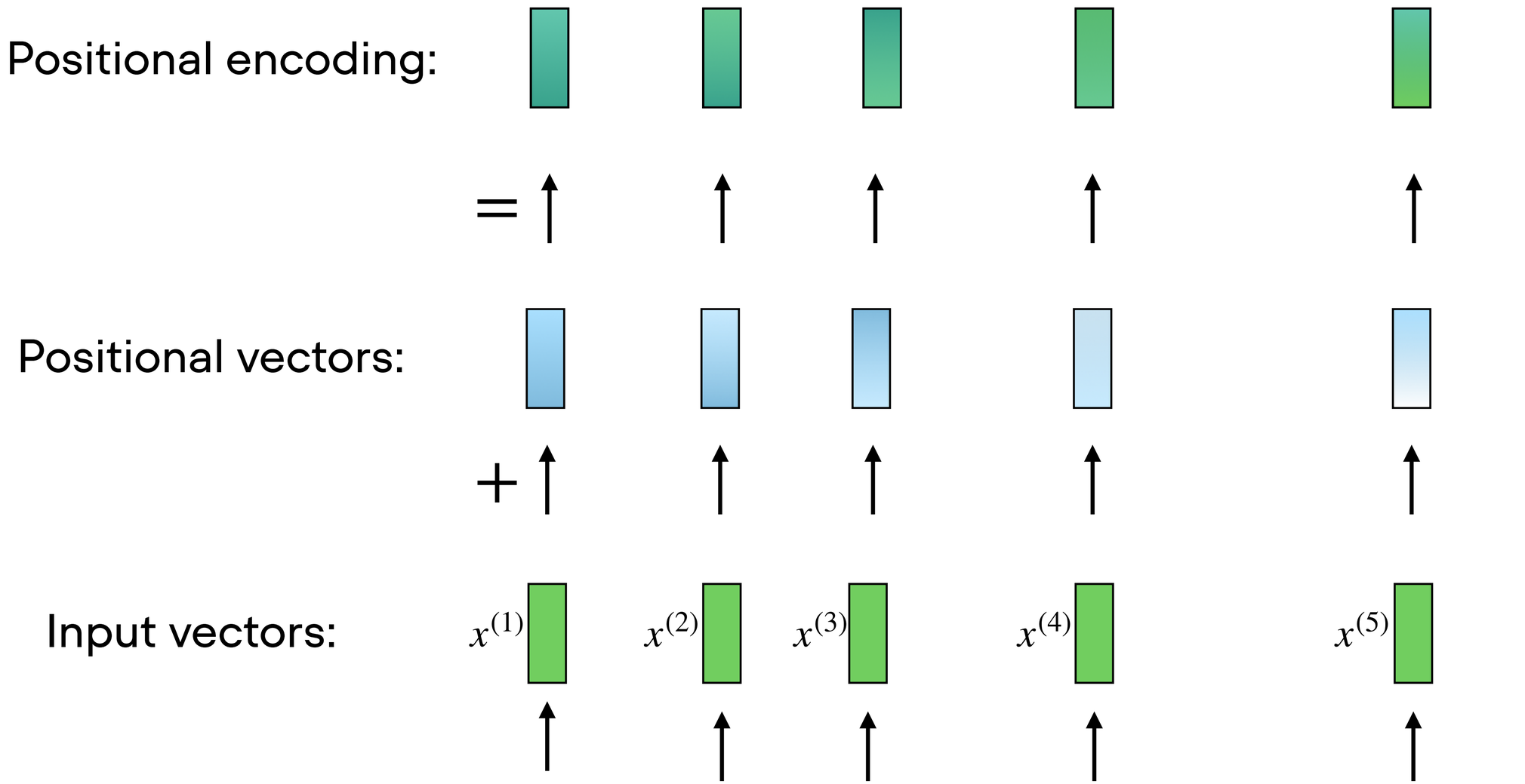
Input vectors:




Positional vectors:
Input vectors:
$x^{(1)}$
$x^{(2)}$
$x^{(3)}$
$x^{(4)}$
$x^{(5)}$
This
is
an
example
sentence


Positional encoding:
=
Positional vectors:
+
Input vectors:
$x^{(1)}$
$x^{(2)}$
$x^{(3)}$
$x^{(4)}$
$x^{(5)}$
This
is
an
example
sentence

Next: Large language models