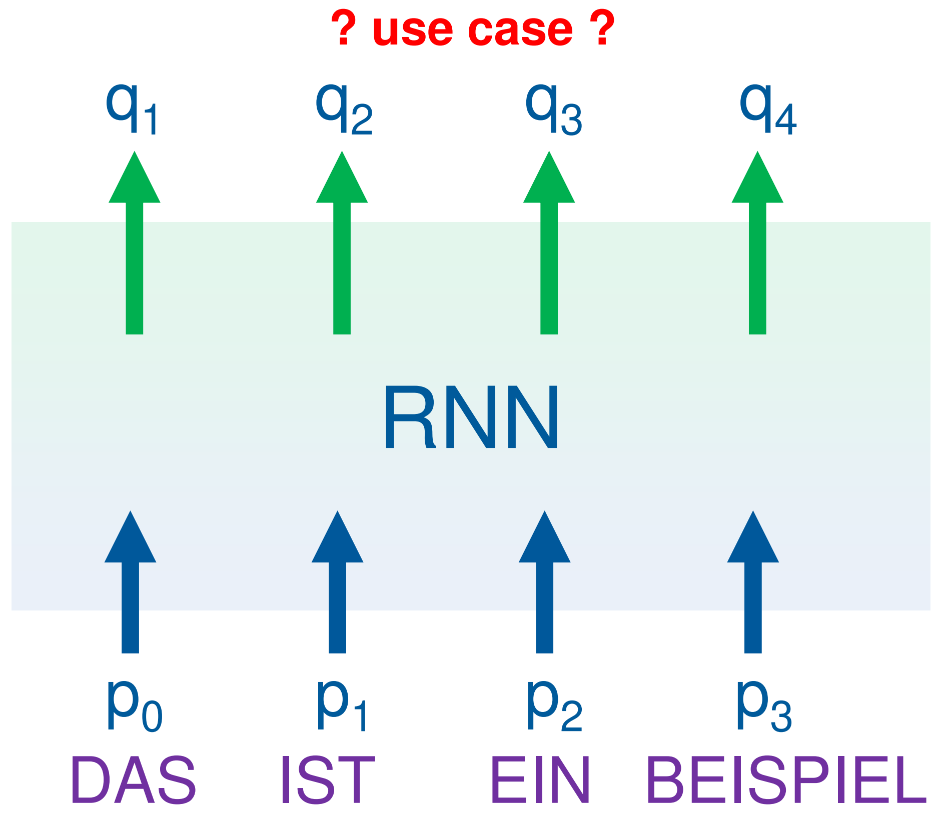
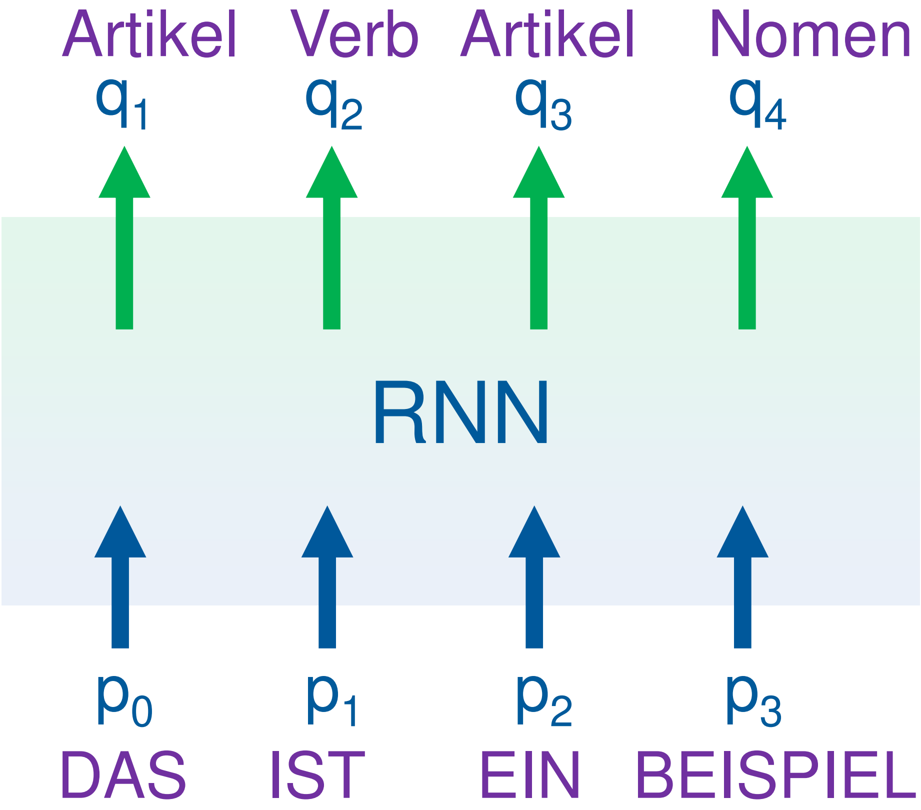
Sequence to Sequence, no delay

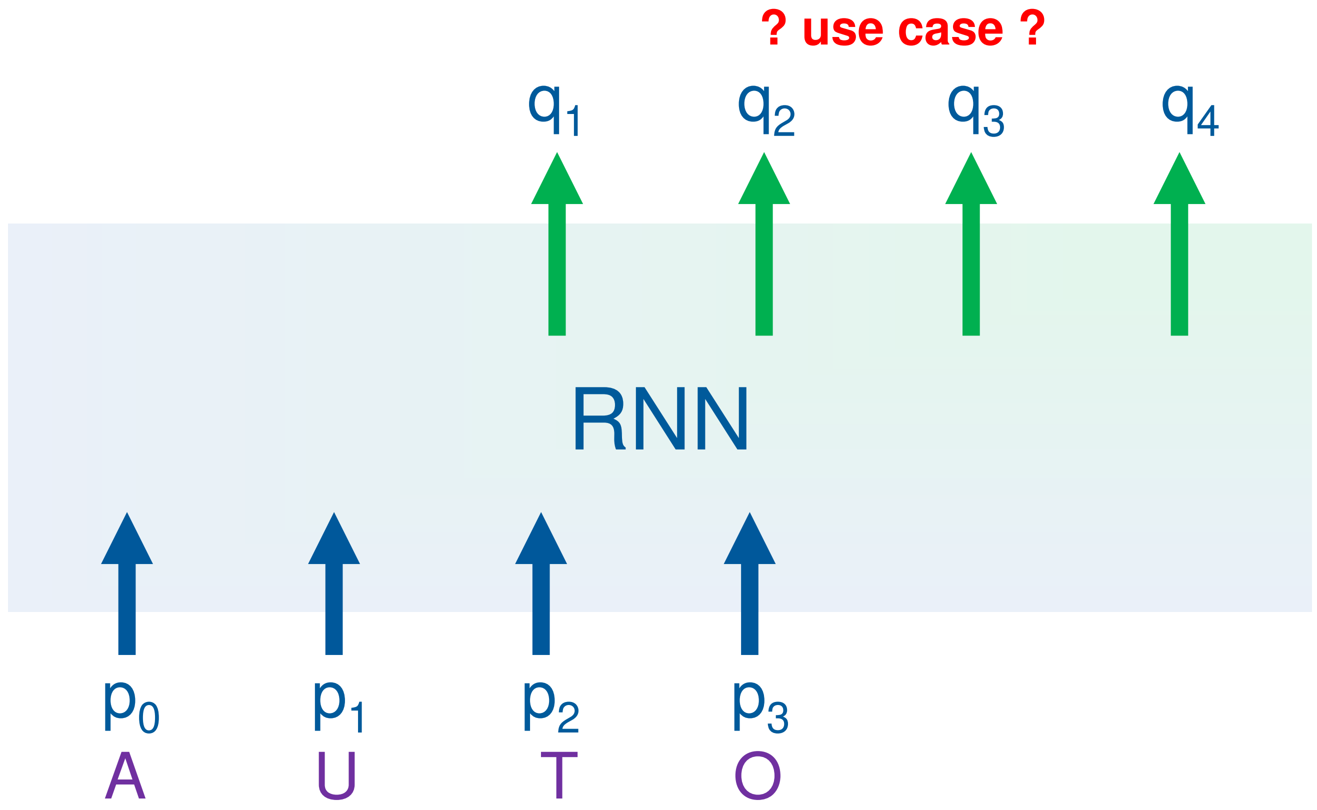


Sequence to Sequence, no delay

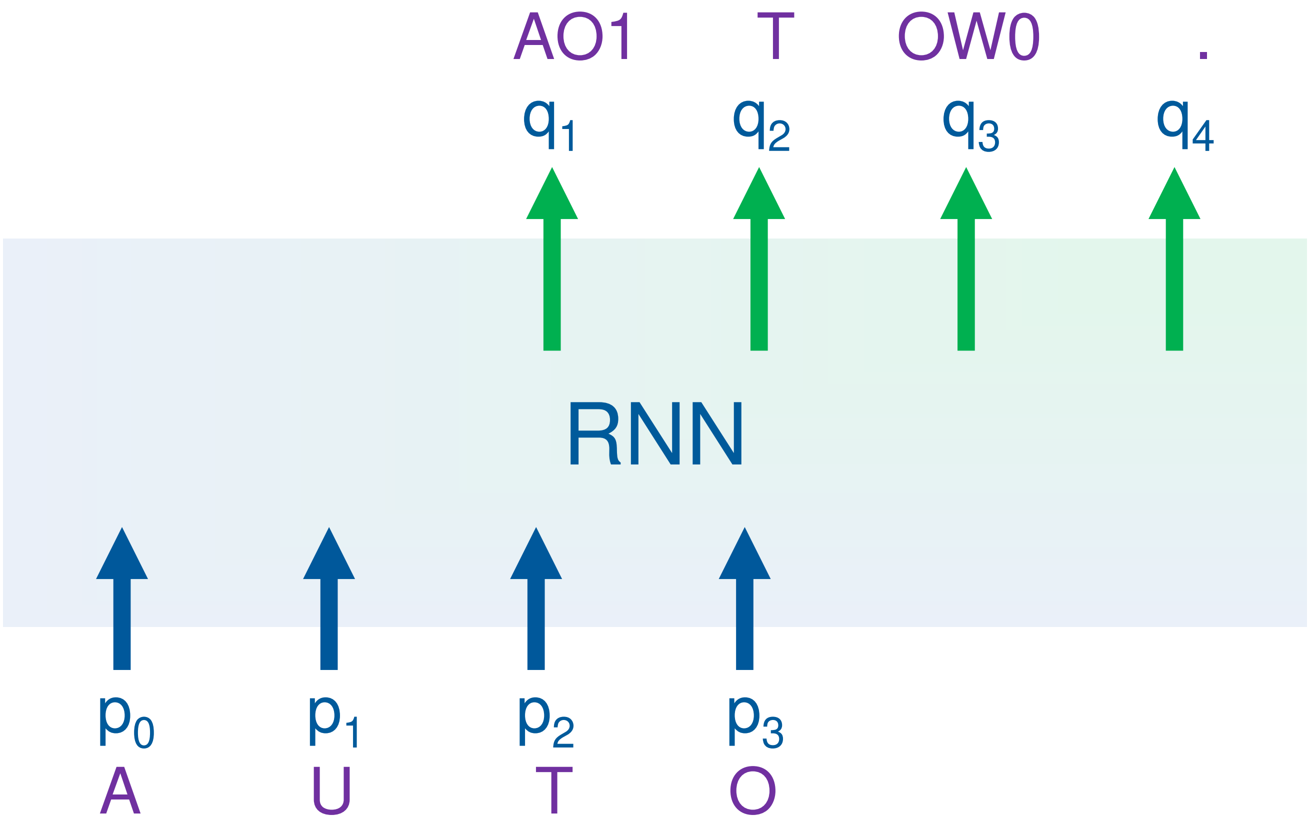


Explore use-cases:
POS, Punctuation,
Formatting, …

Sequence to Sequence, partial delay

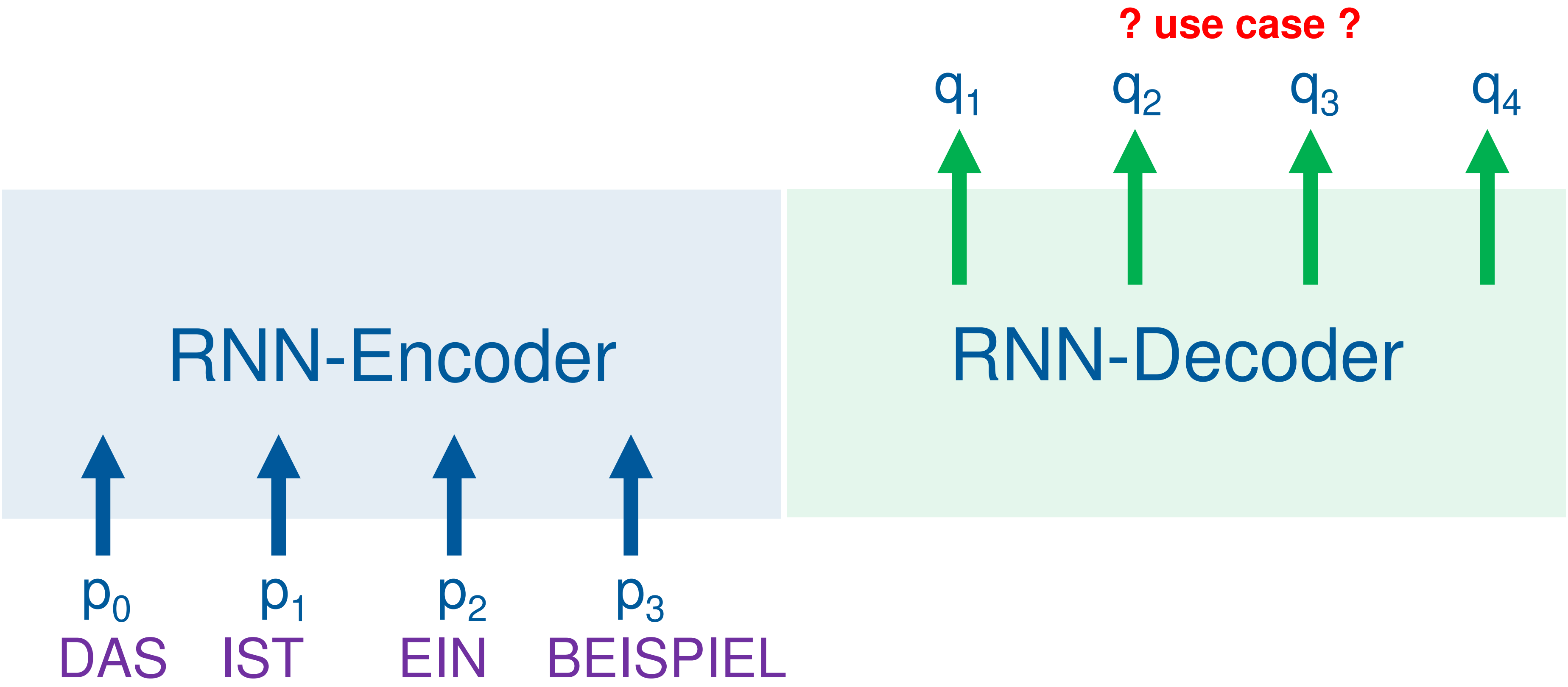


Sequence to Sequence, partial delay

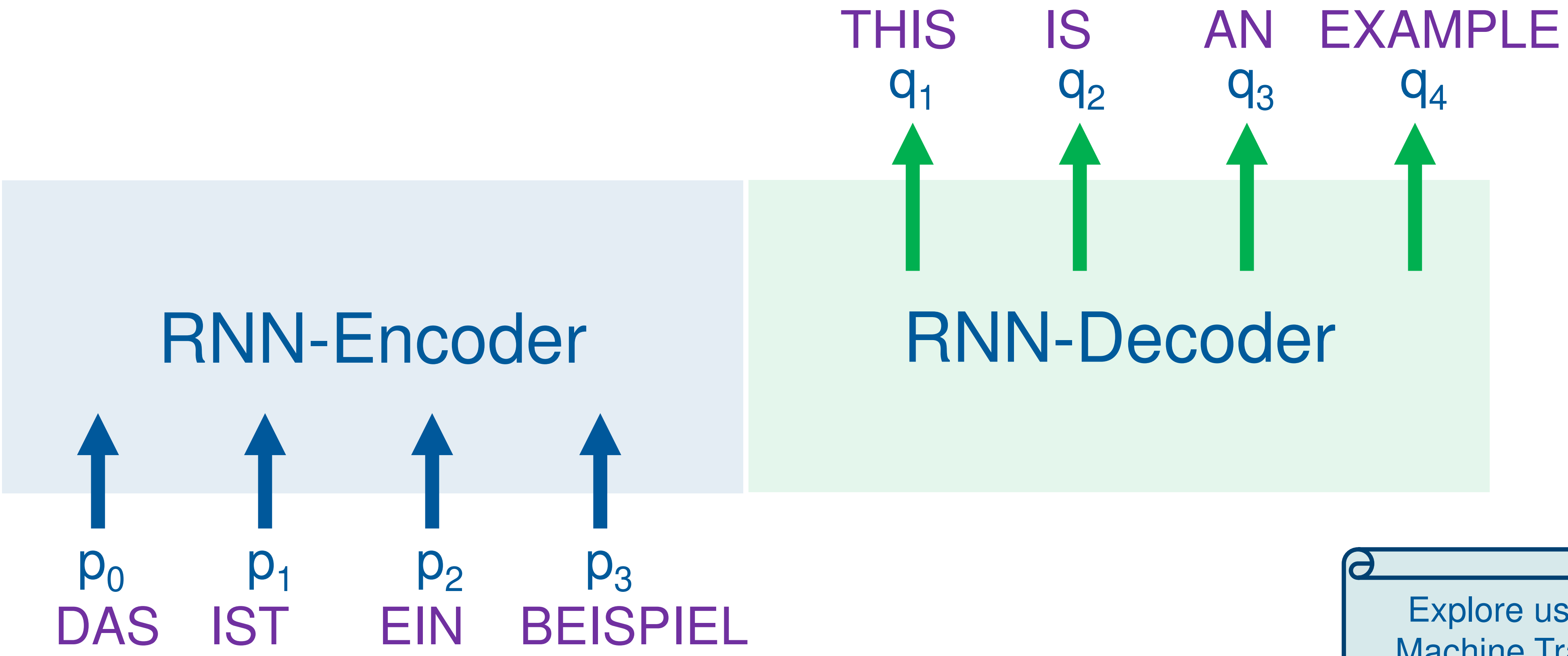


Explore use-cases: POS, G2P, Named Entity Extraction, …

Sequence to Sequence, full delay

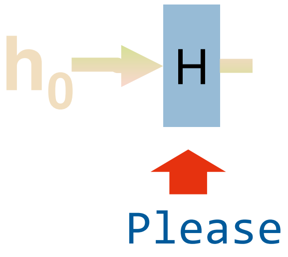


Sequence to Sequence, full delay



Explore use-cases:
Machine Translation,
Question Answering, …

Seq2seq is a family of machine learning approaches used for language processing. Applications include language translation, image captioning, conversational models and text summarization.



Neural Machine Translation

Recurrent Neuronal Network Encoder

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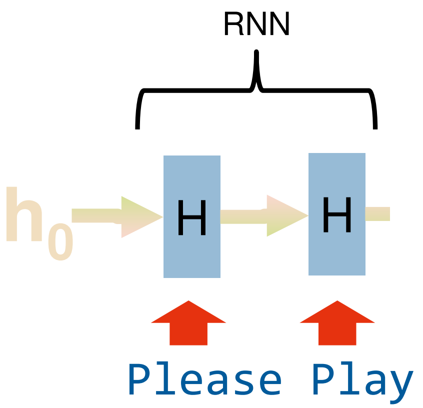

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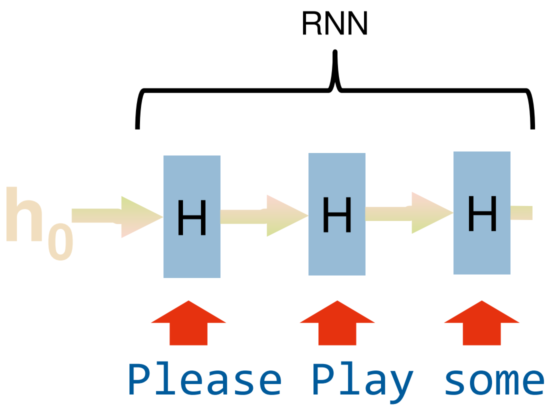

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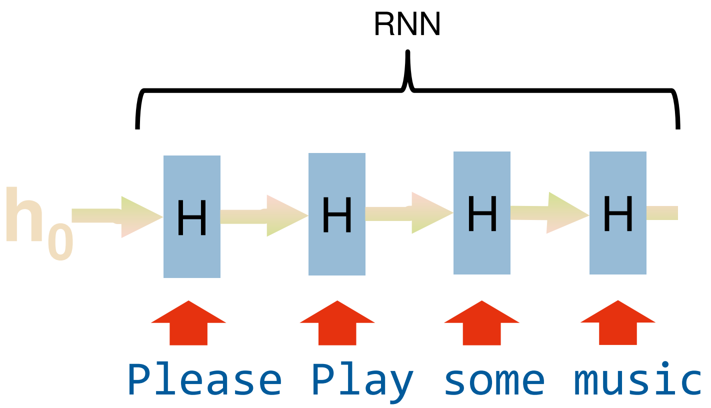

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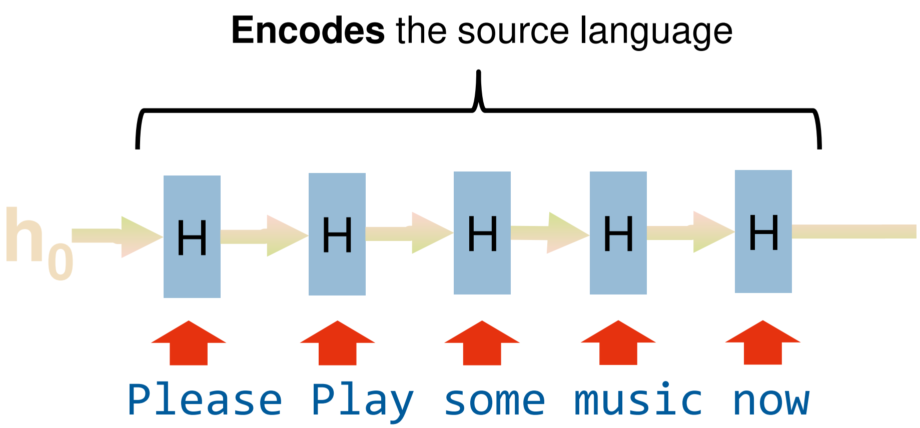

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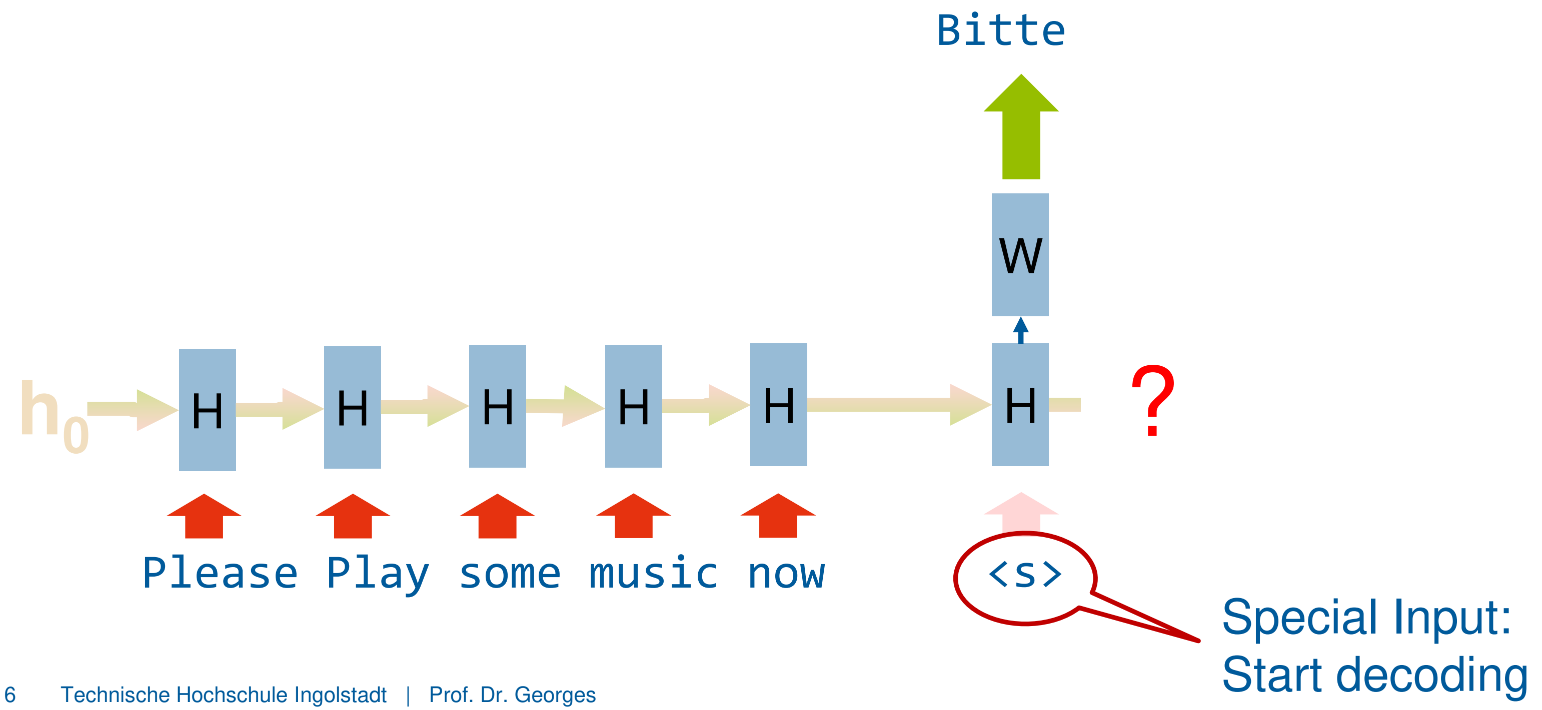

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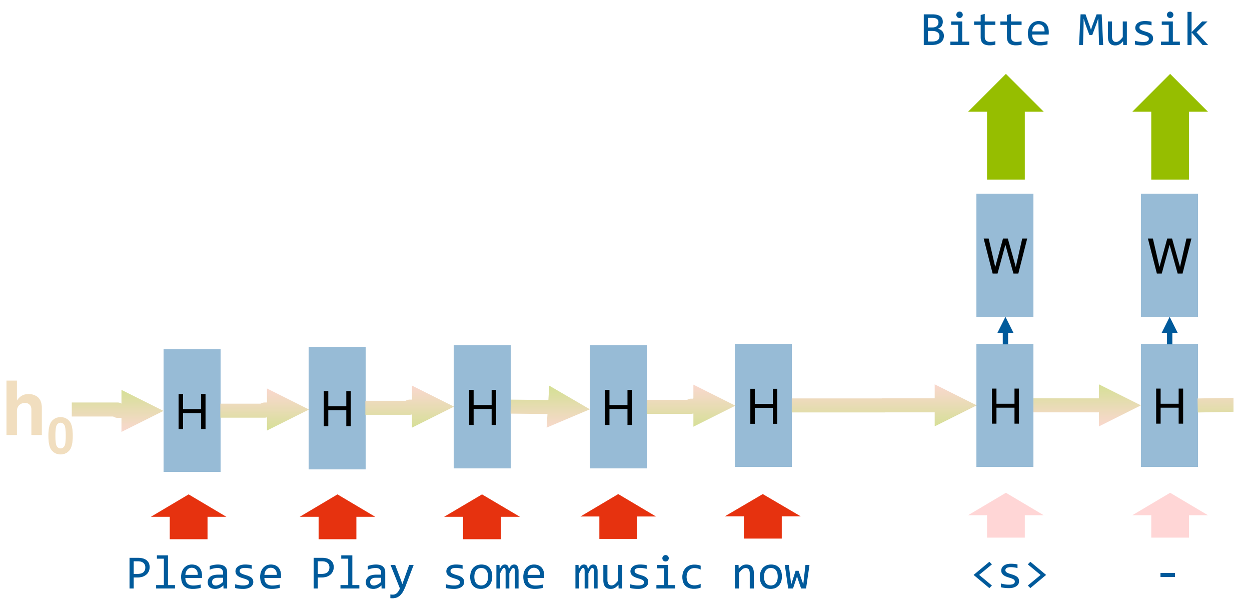

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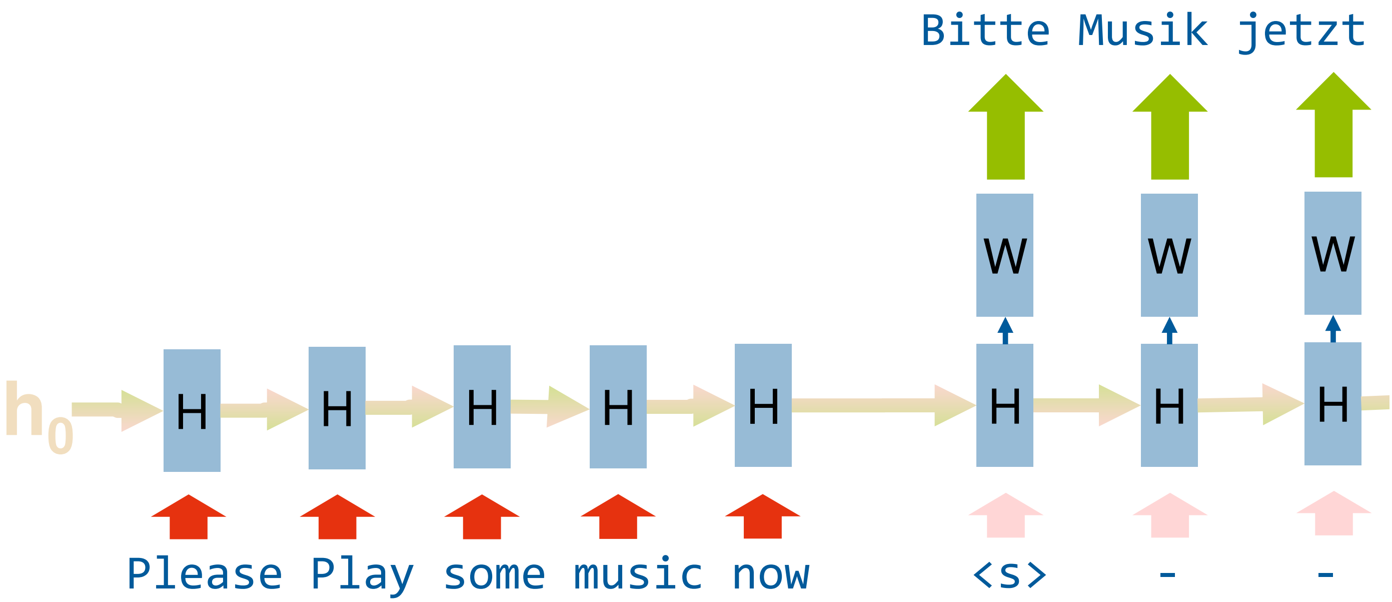

Neural Machine Translation

Encoder-Decoder with Recurrent Neuronal Networks

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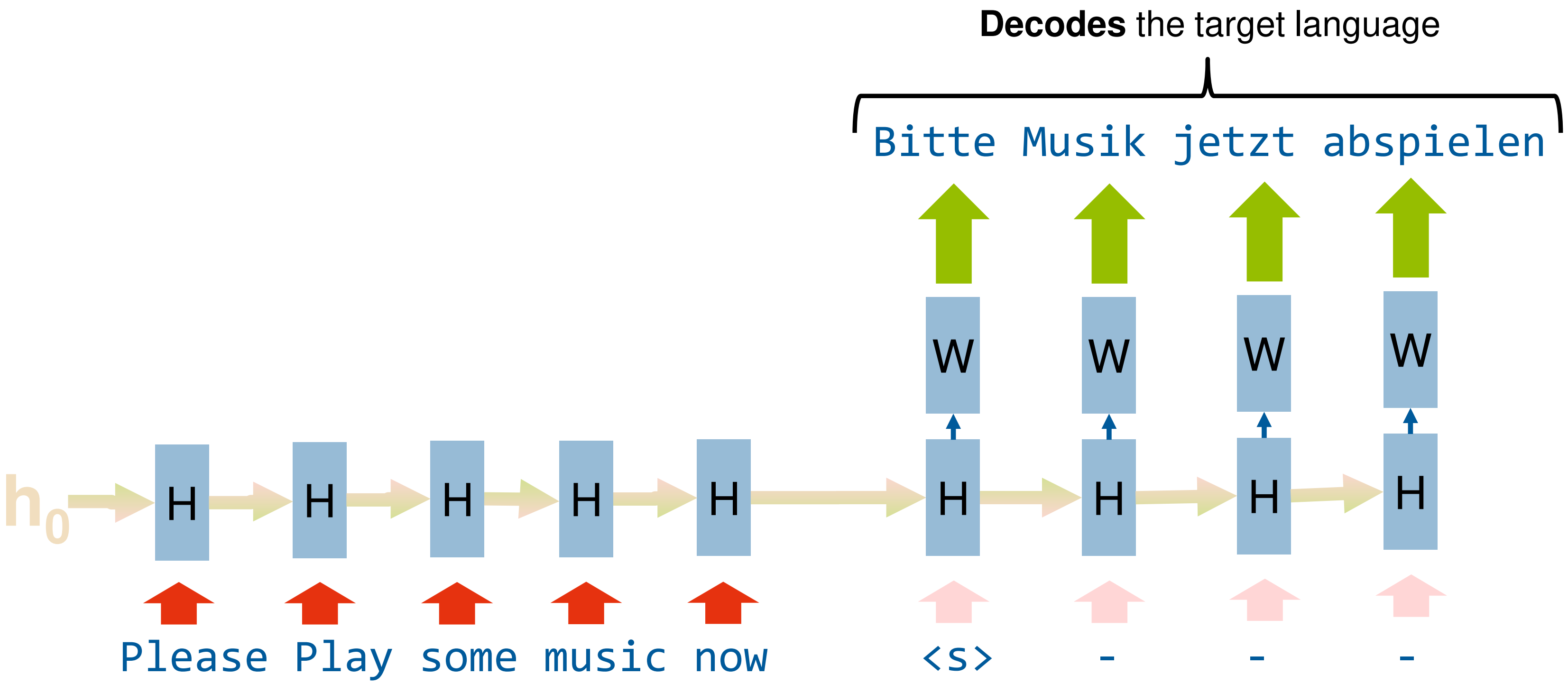

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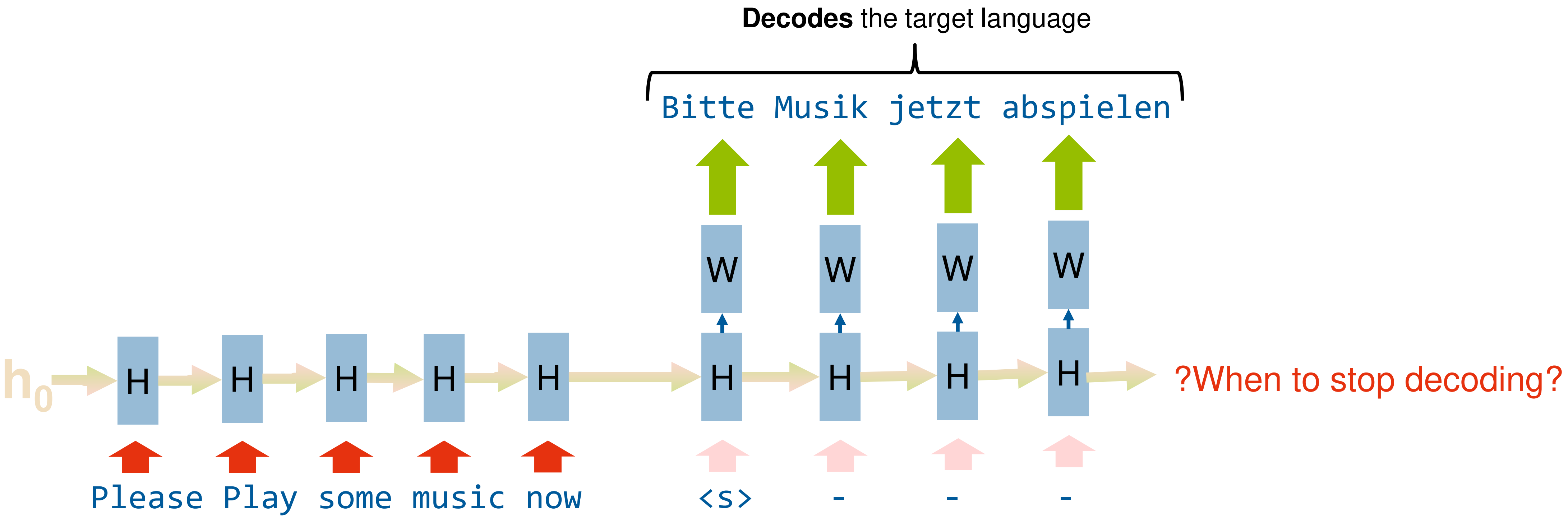

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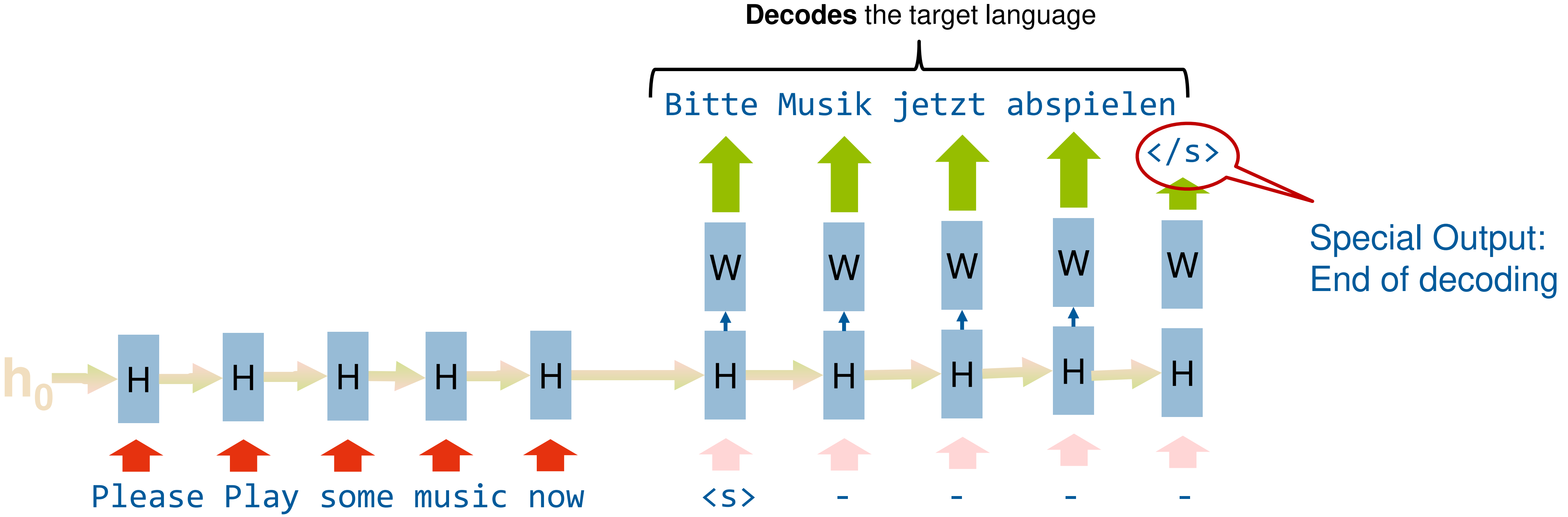
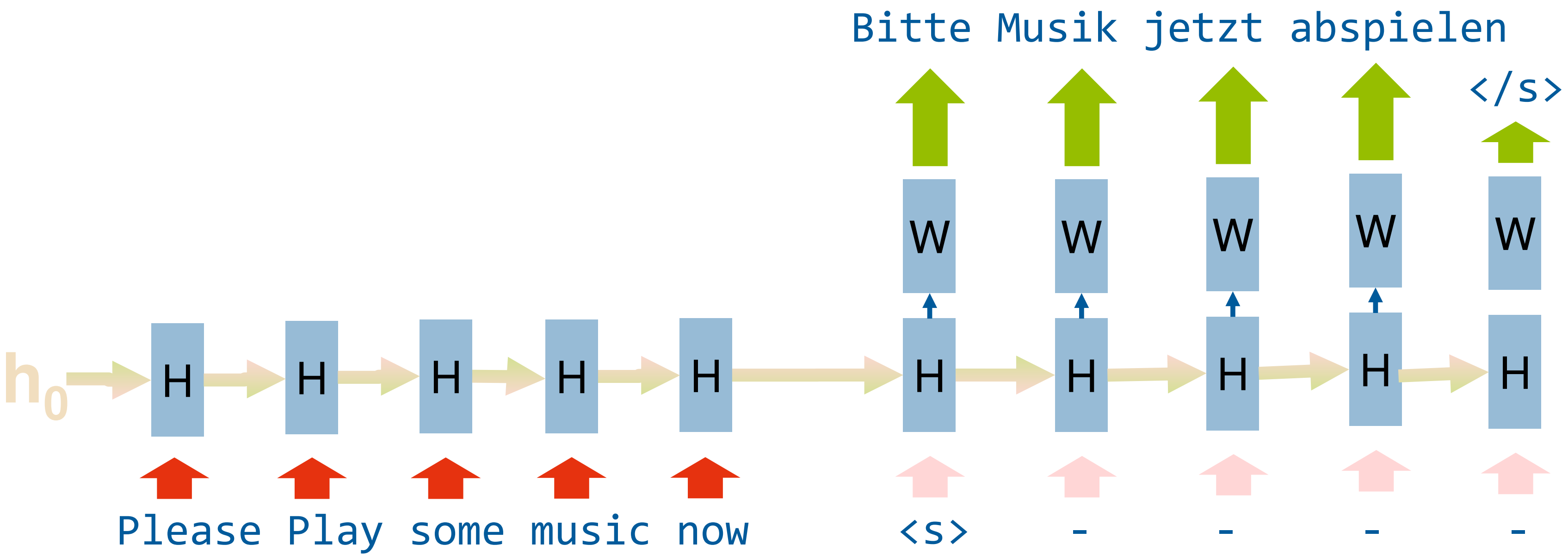


Seq2seq is a family of machine learning approaches used for language processing. Applications include language translation, image captioning, conversational models and text summarization.

$$\hat{s}_t = \underset{s \in \text{Tags}}{\operatorname{argmax}} P(s|\text{words})$$



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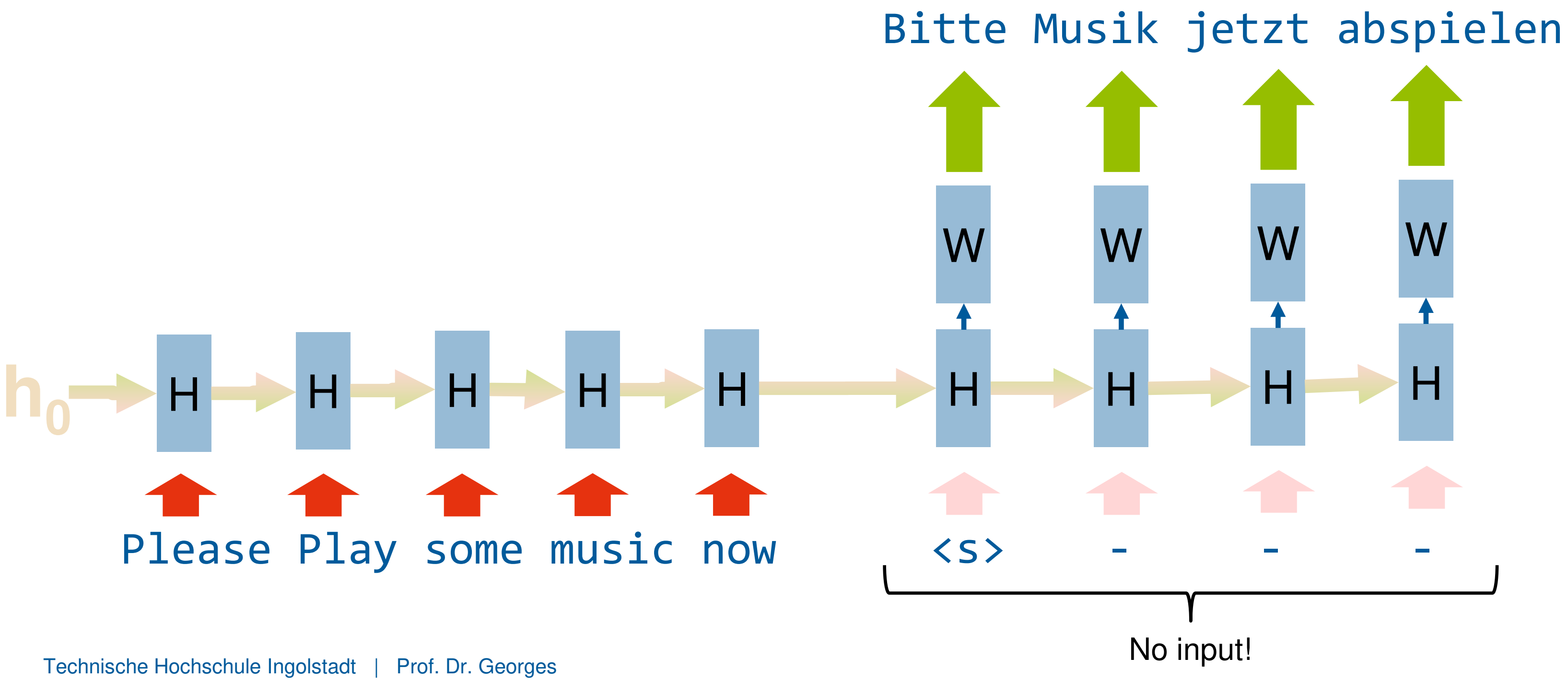

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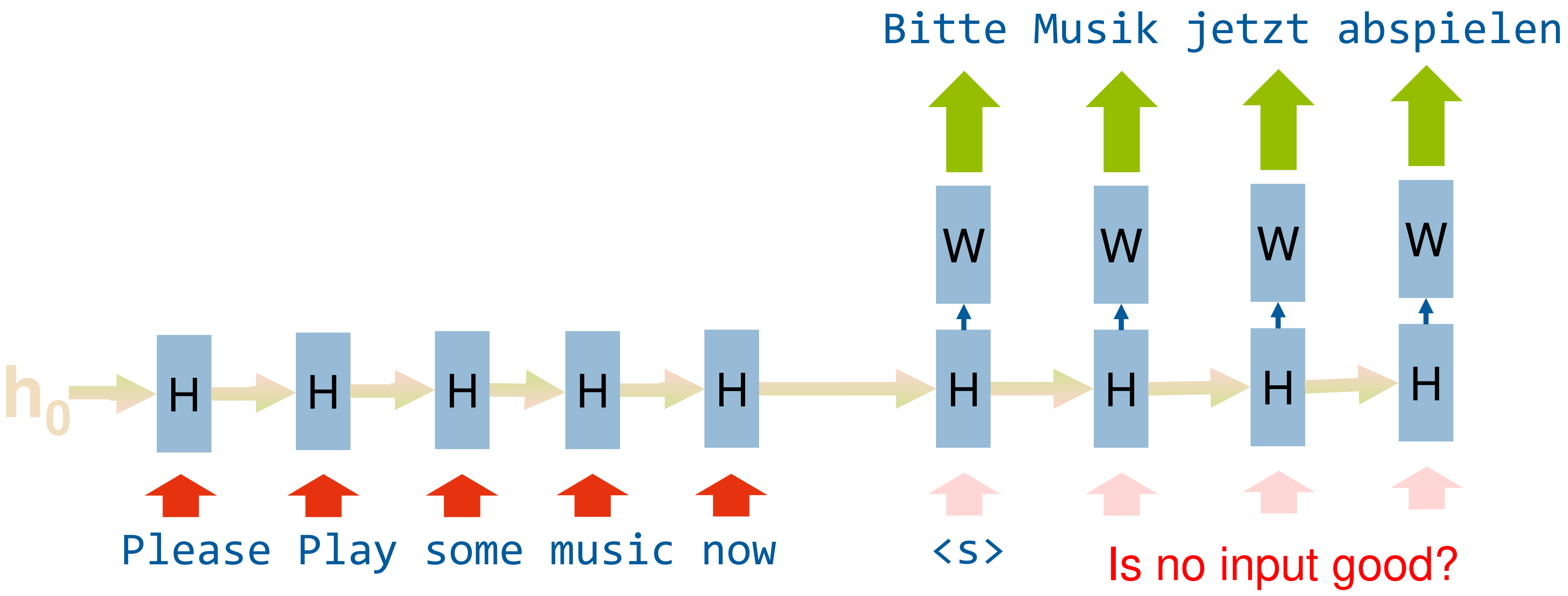

Neural Machine Translation

Encoder-Decoder with Recurrent Neuronal Networks and Autoregression

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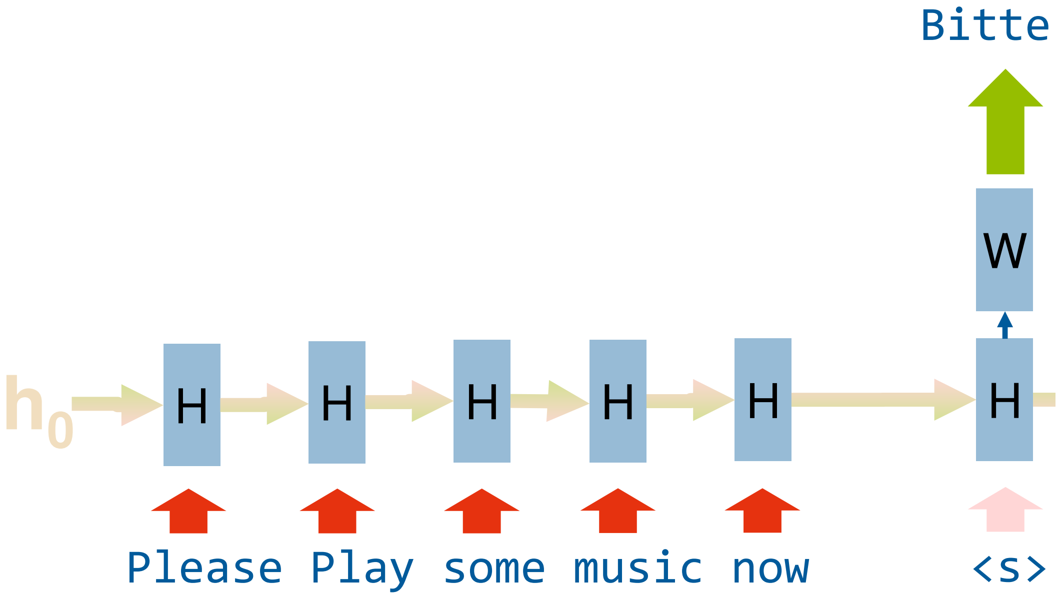

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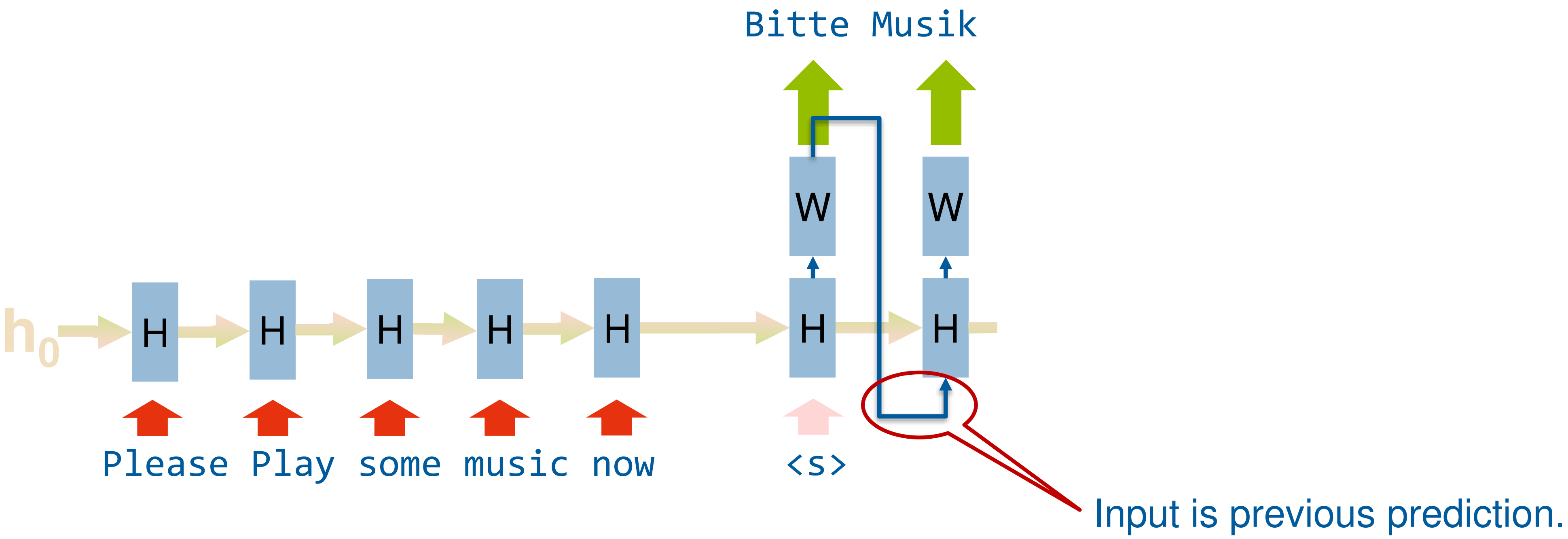

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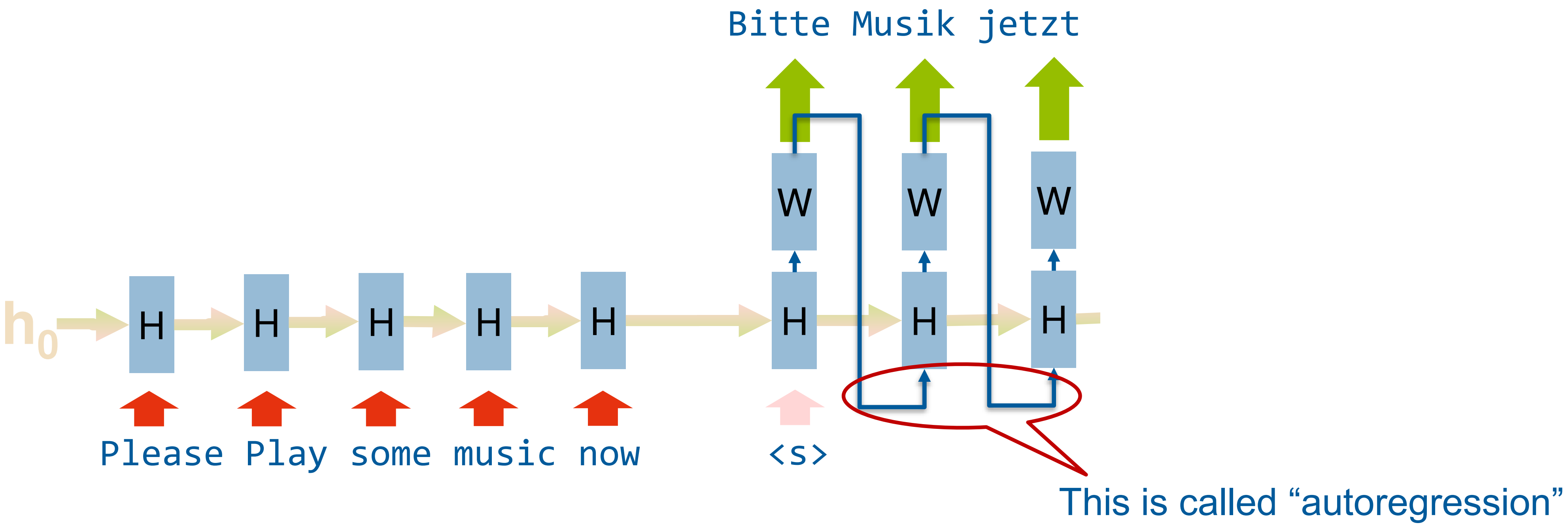

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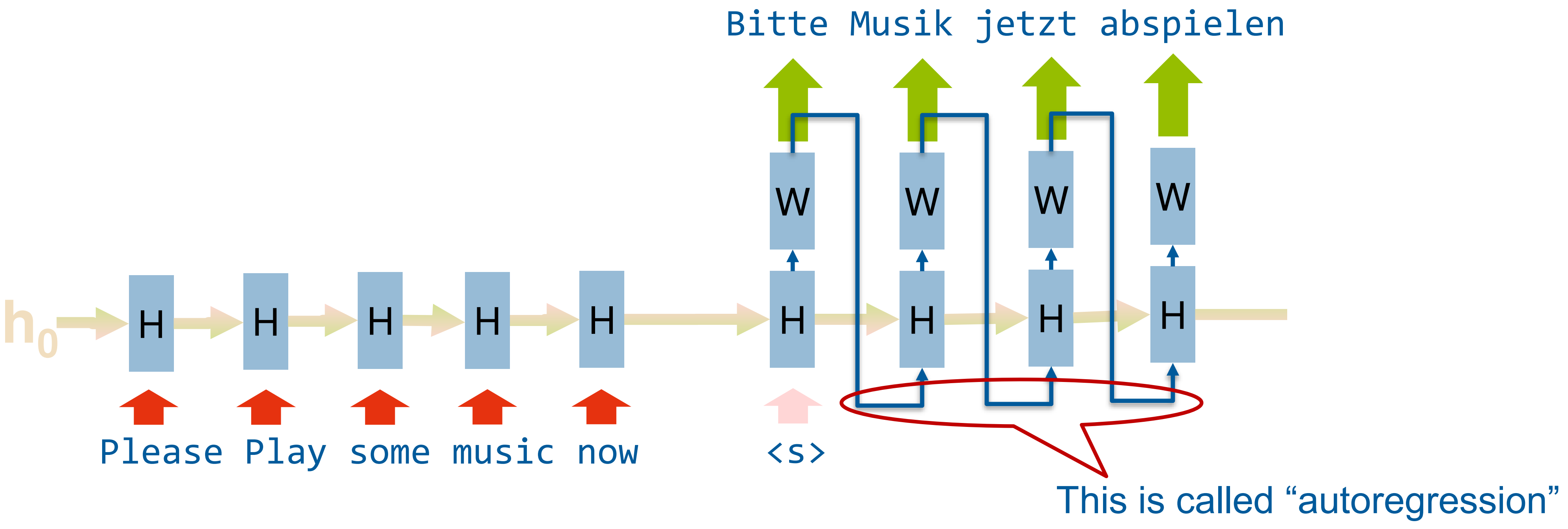

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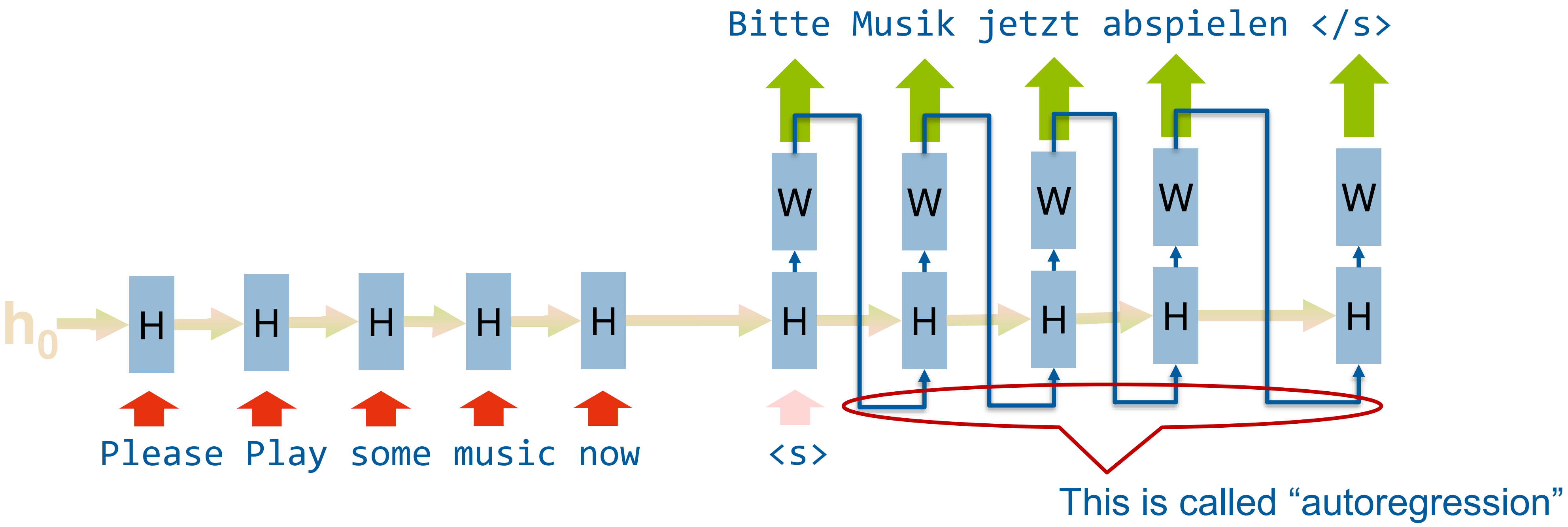

Neural Machine Translation

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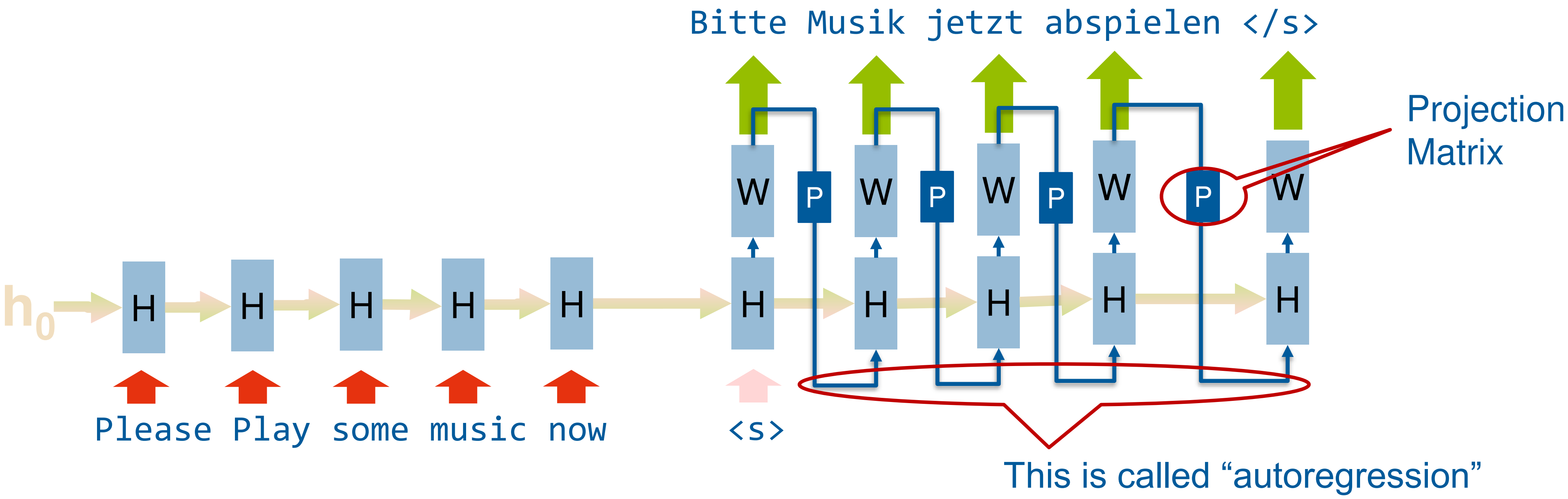

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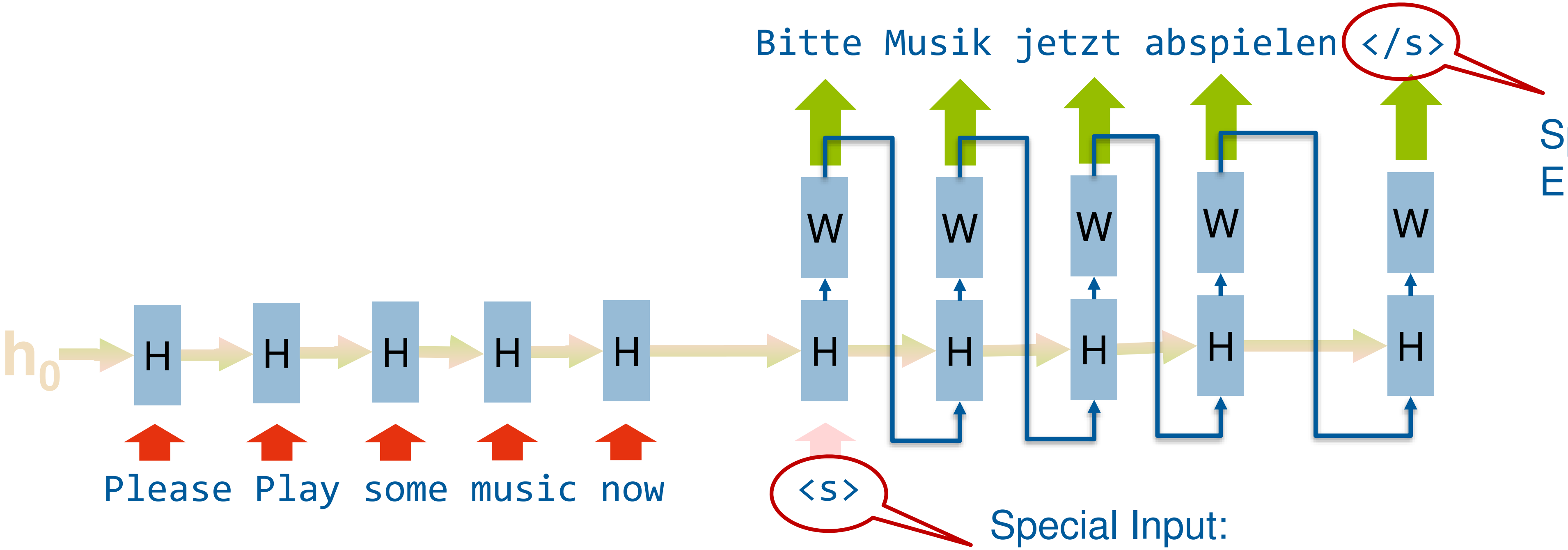
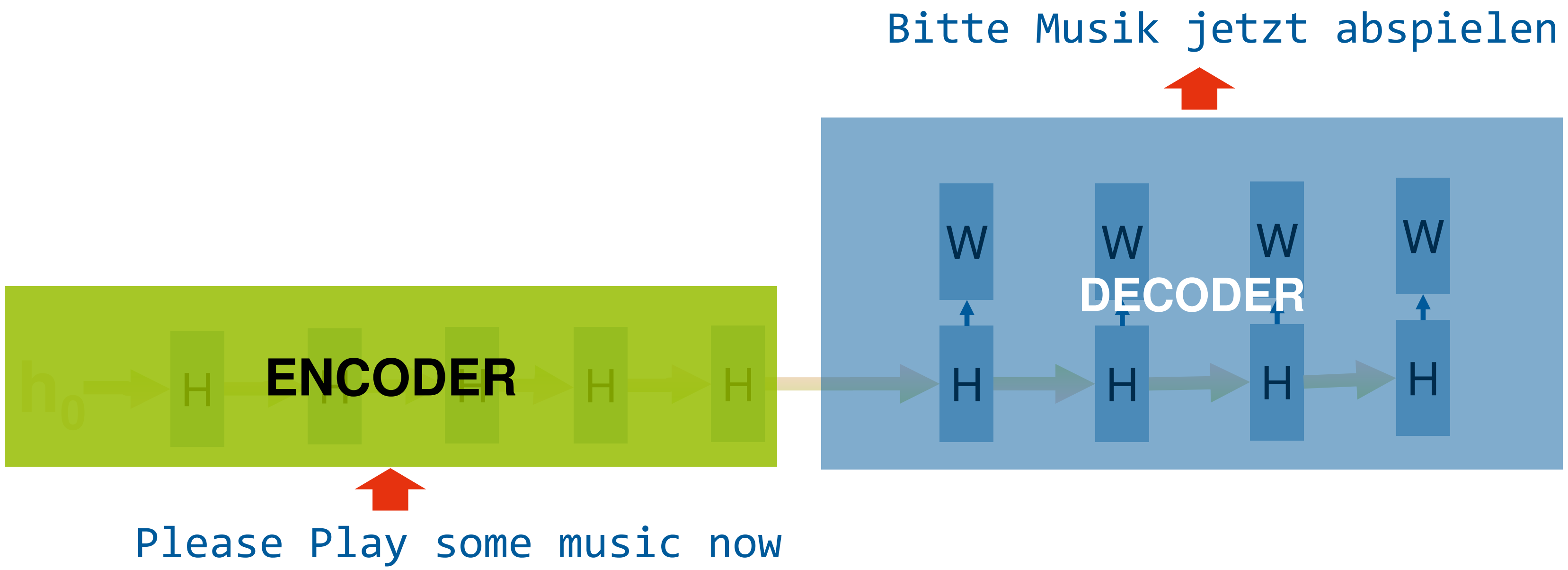


Special Output:
End of decoding

Special Input:
Start decoding

Seq2seq is a family of machine learning approaches used for language processing. Applications include language translation, image captioning, conversational models and text summarization.



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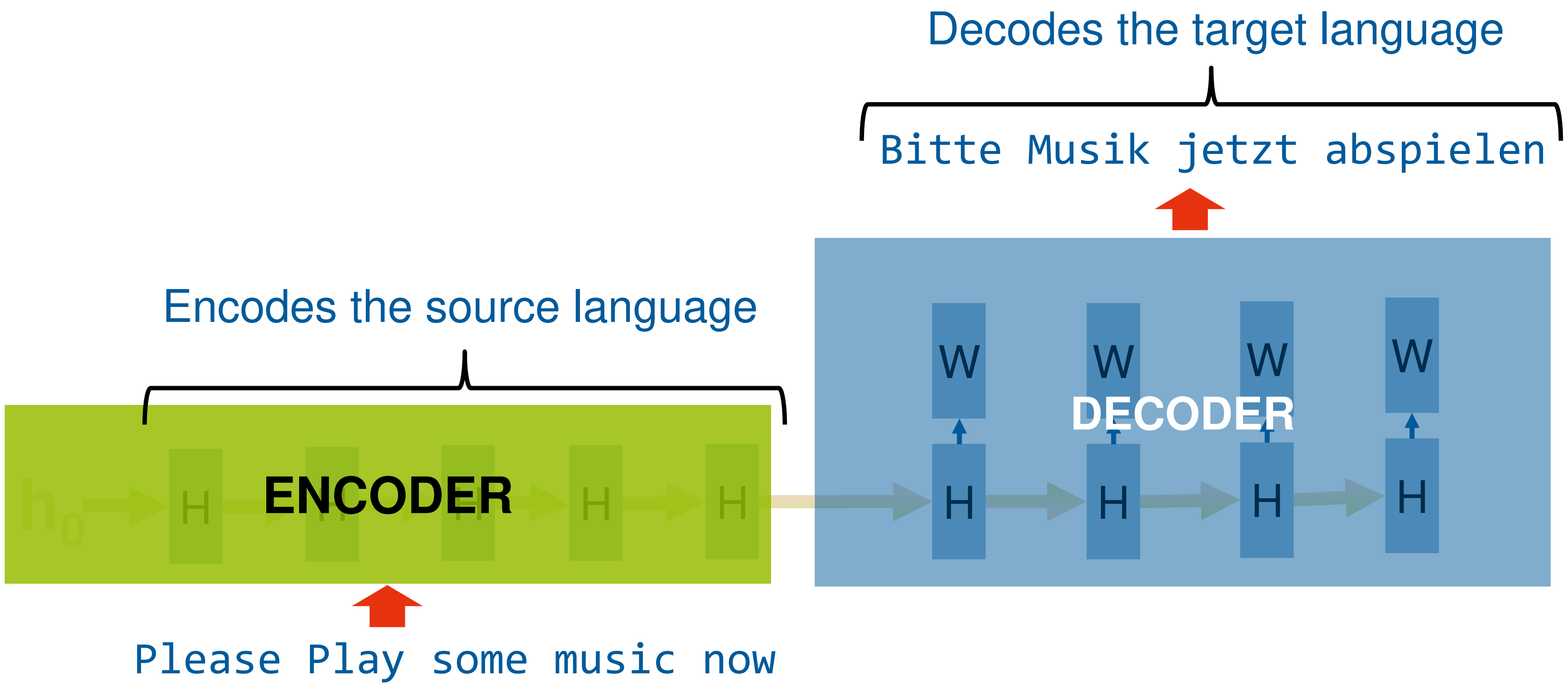

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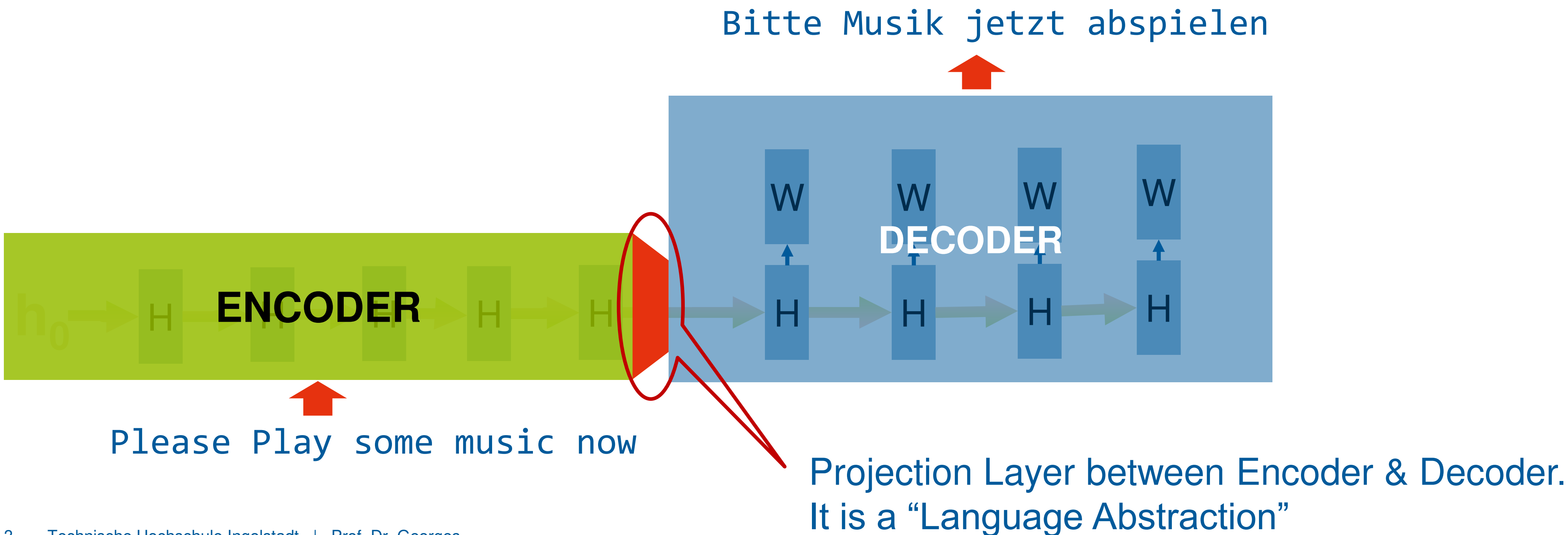

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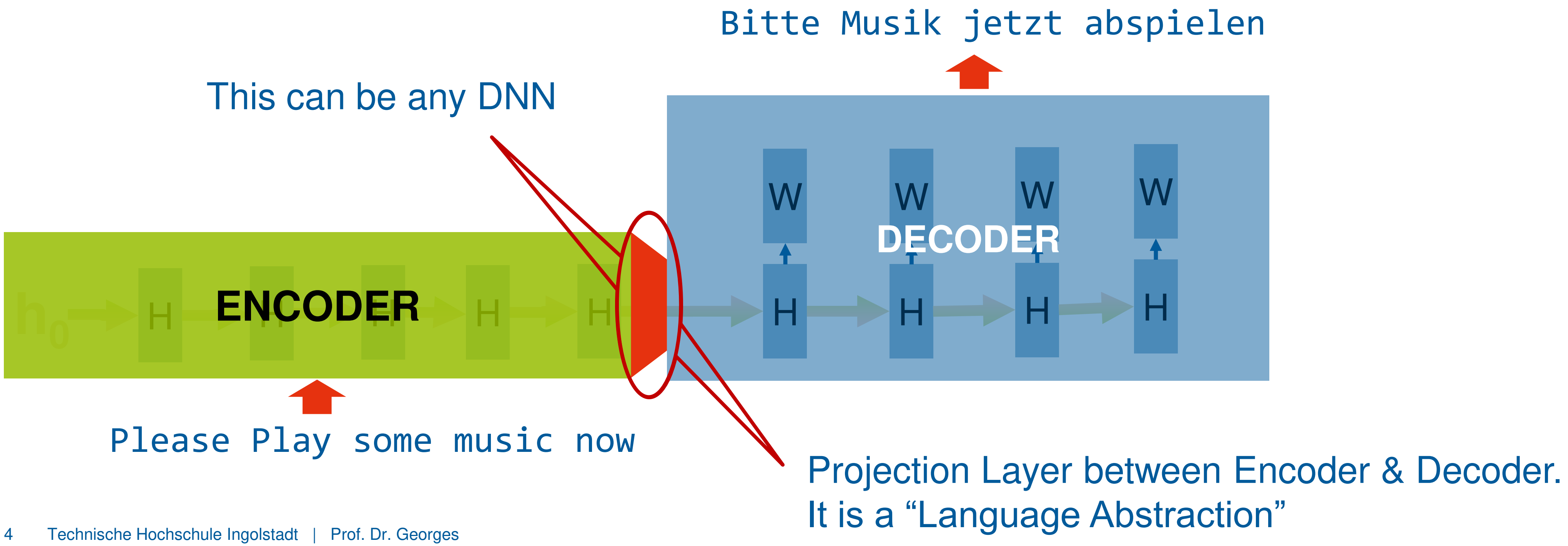
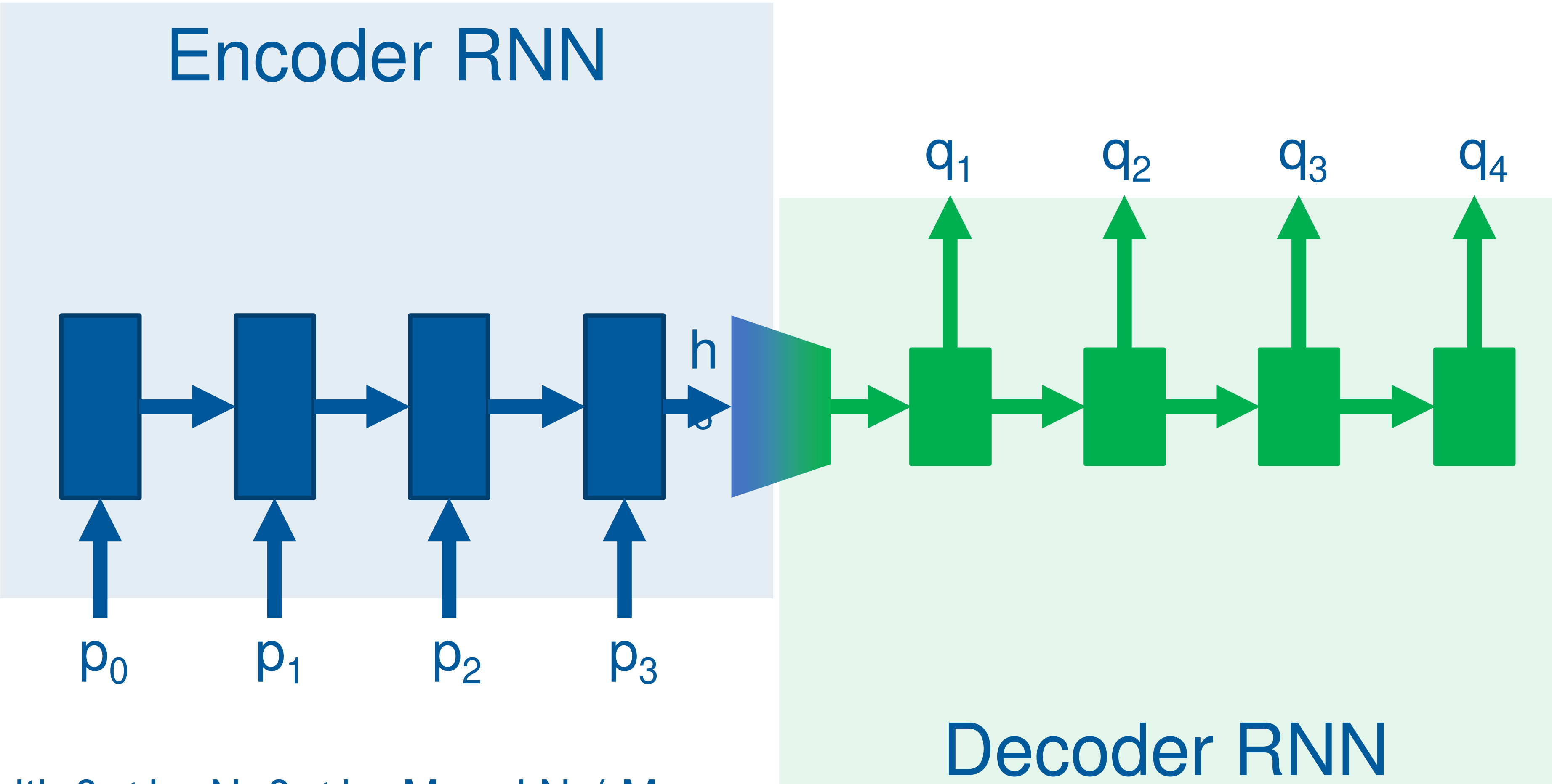
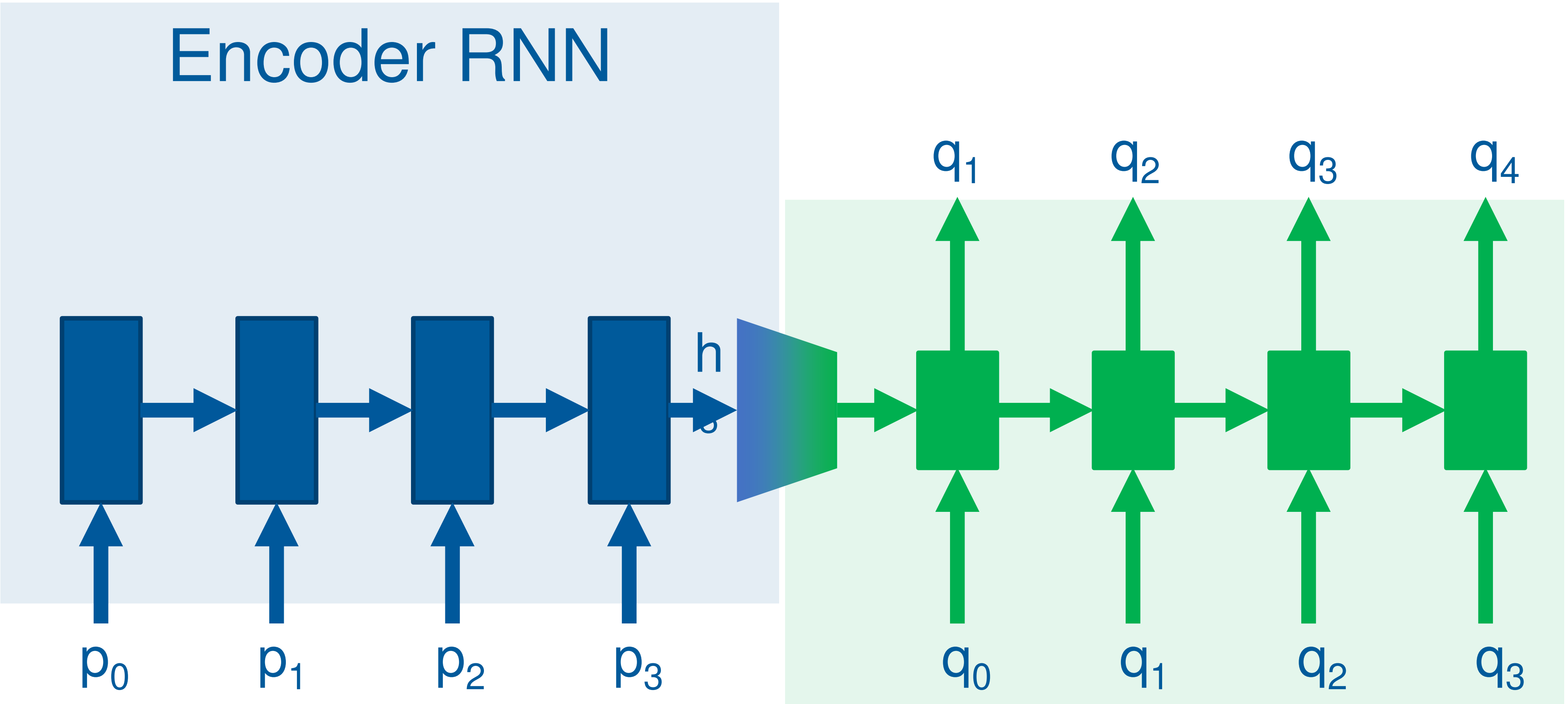




p_i , q_j with $0 \leq i < N$, $0 \leq j < M$ and $N \neq M$
Variable length of input and output sequence

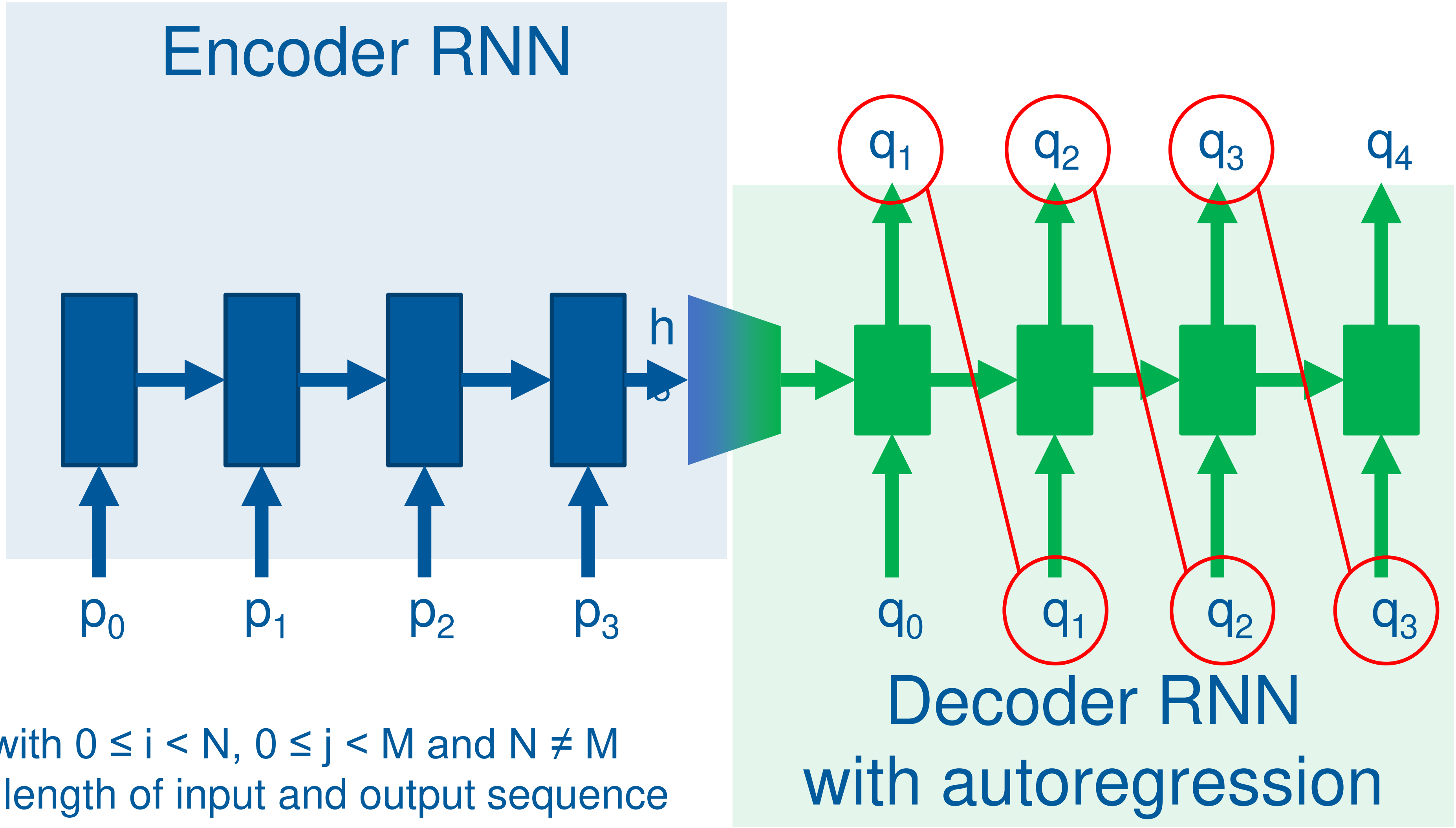
Sequence to Sequence, full delay with autoregressive decoder



Decoder RNN
with autoregression

p_i , q_j with $0 \leq i < N$, $0 \leq j < M$ and $N \neq M$
Variable length of input and output sequence

Sequence to Sequence, full delay with autoregressive decoder



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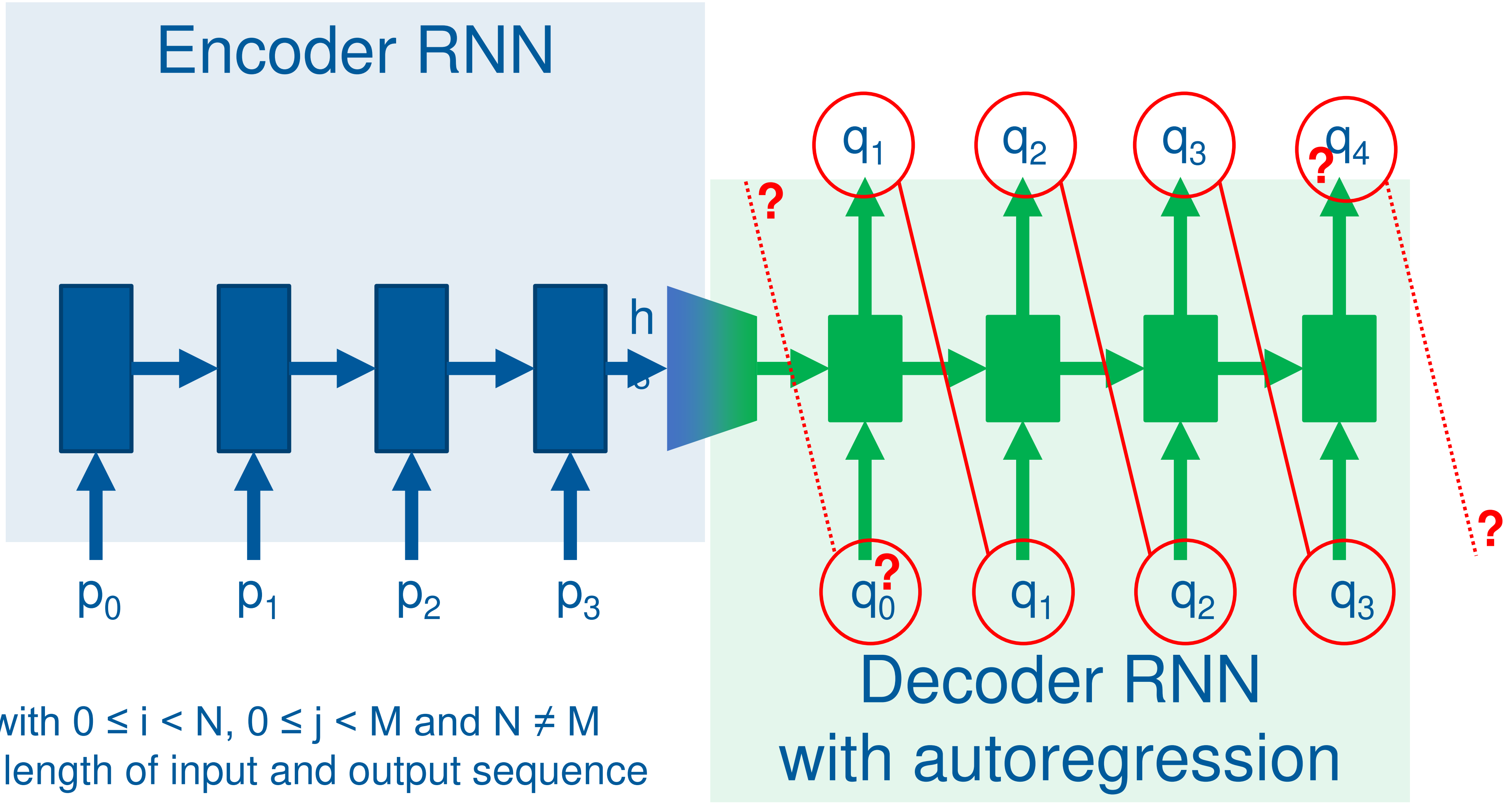
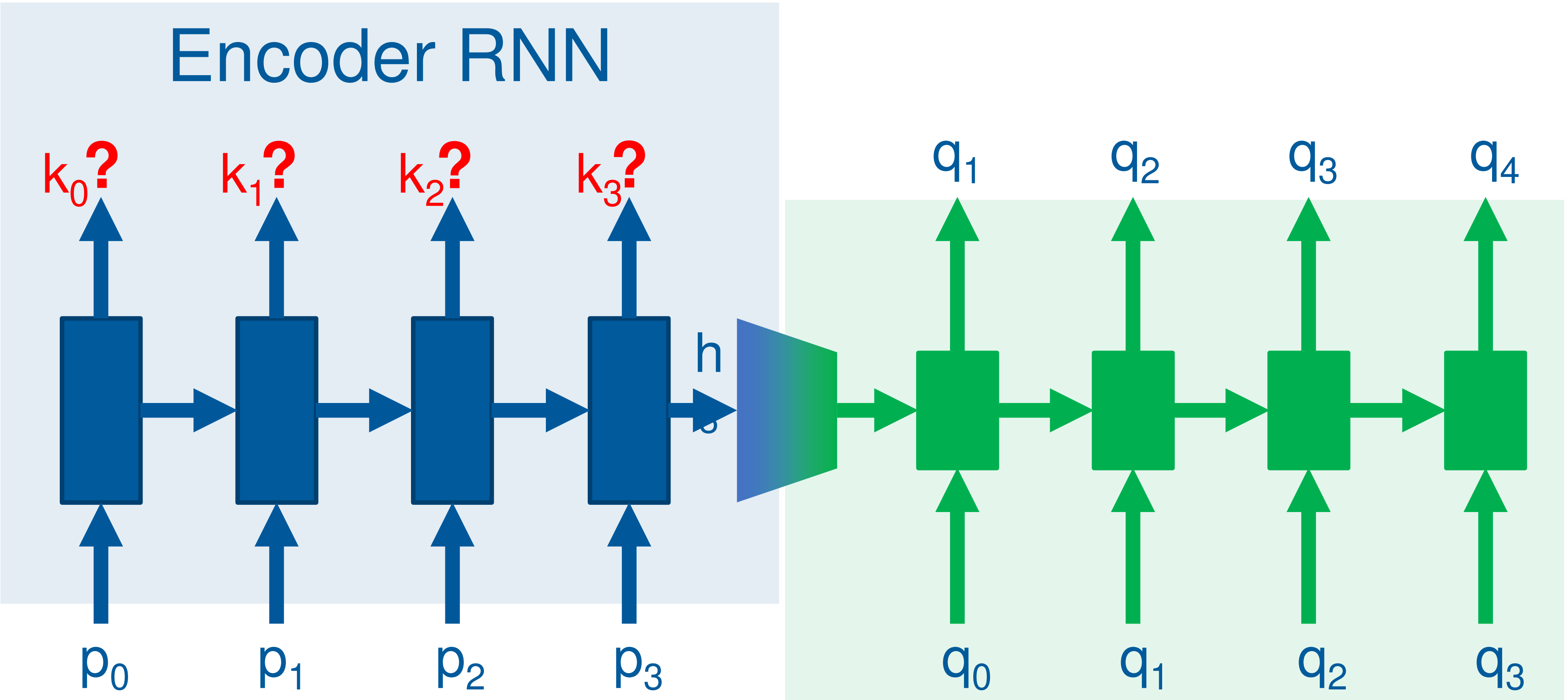


p_i , q_j with $0 \leq i < N$, $0 \leq j < M$ and $N \neq M$

Variable length of input and output sequence

Sequence to Sequence, full delay with autoregressive decoder

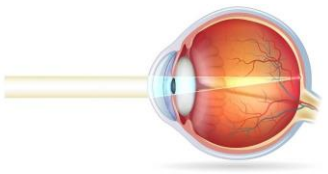


Decoder RNN
with autoregression

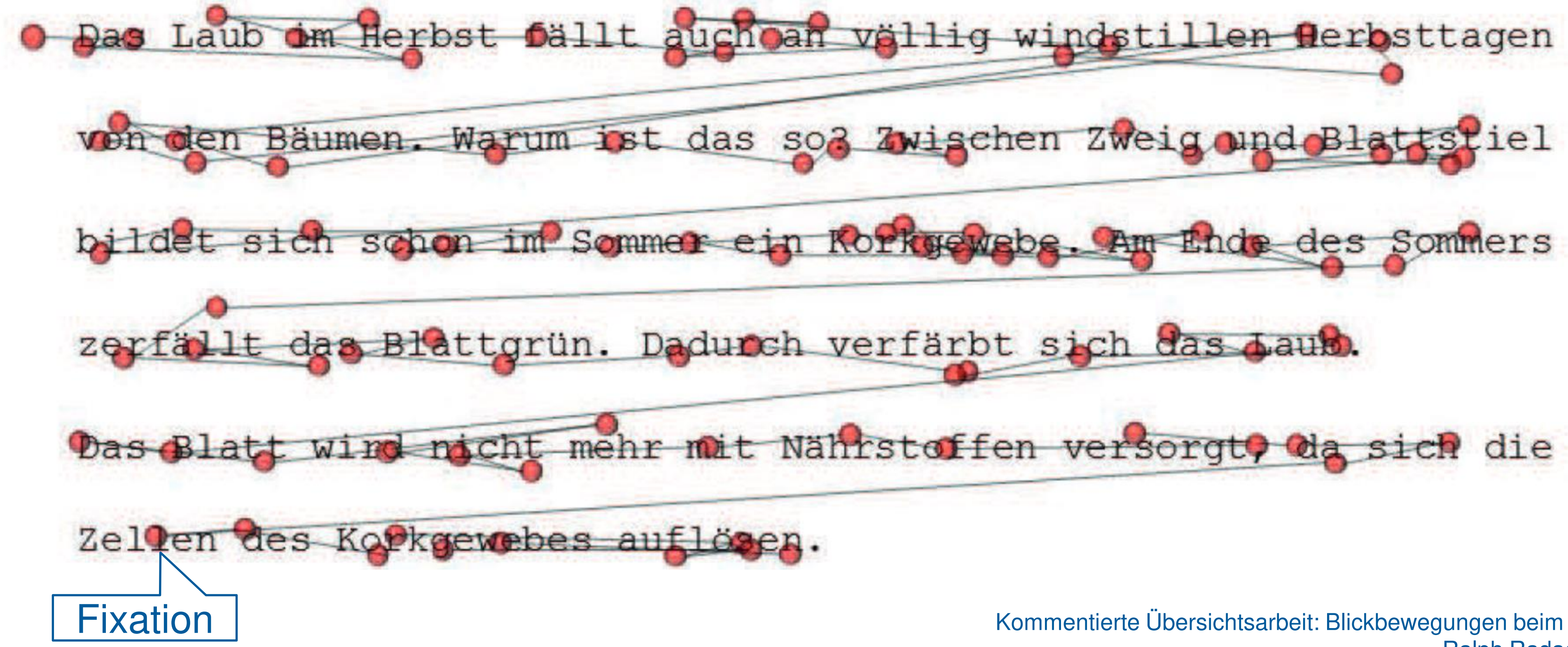
p_i , q_j with $0 \leq i < N$, $0 \leq j < M$ and $N \neq M$
Variable length of input and output sequence

Fixation und Sakkaden

Lecture



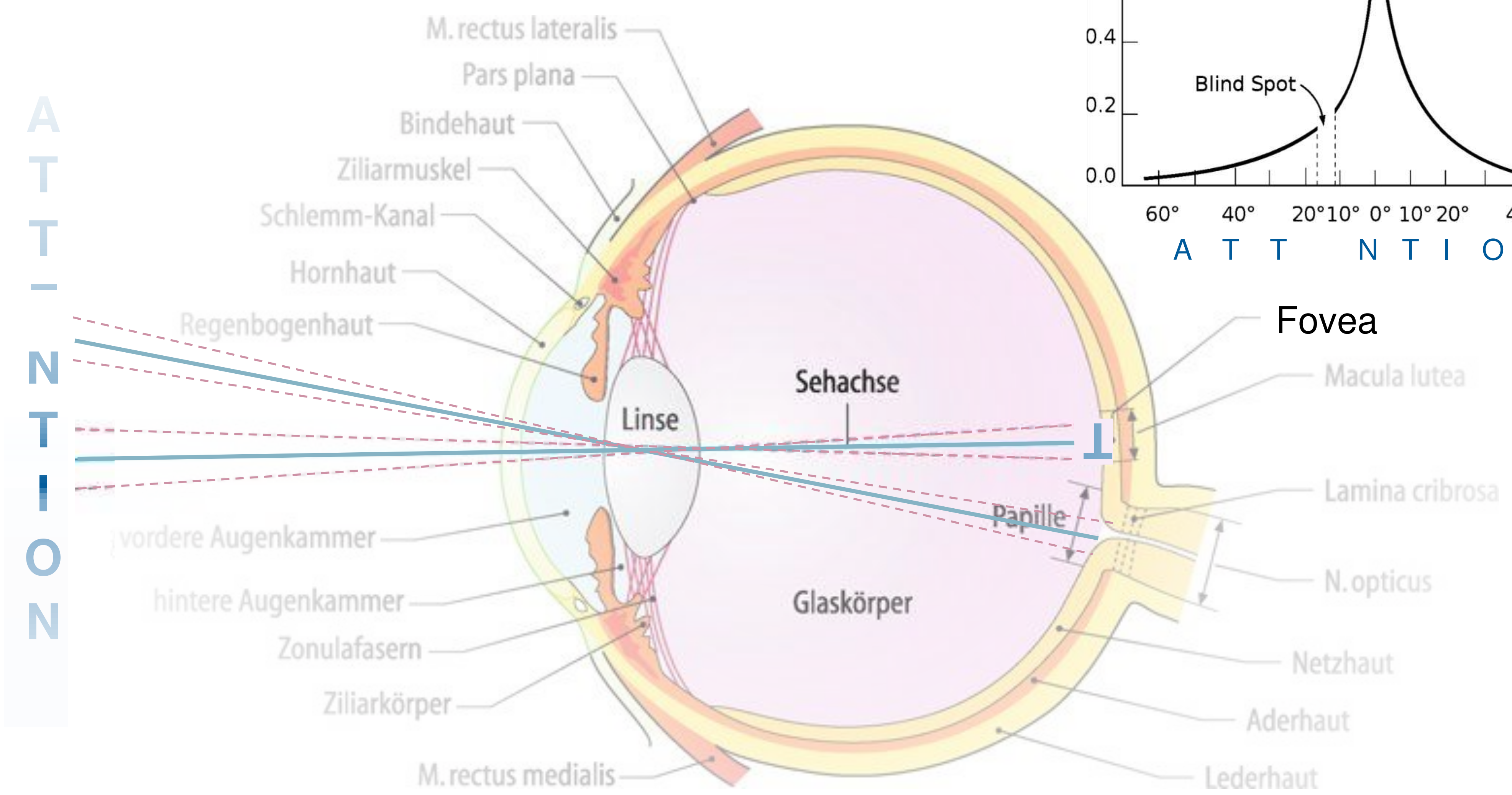
Typisches Blickbewegungsmuster eines Schülers der vierten Klasse beim Lesen einer relativ schwierigen Textseite.

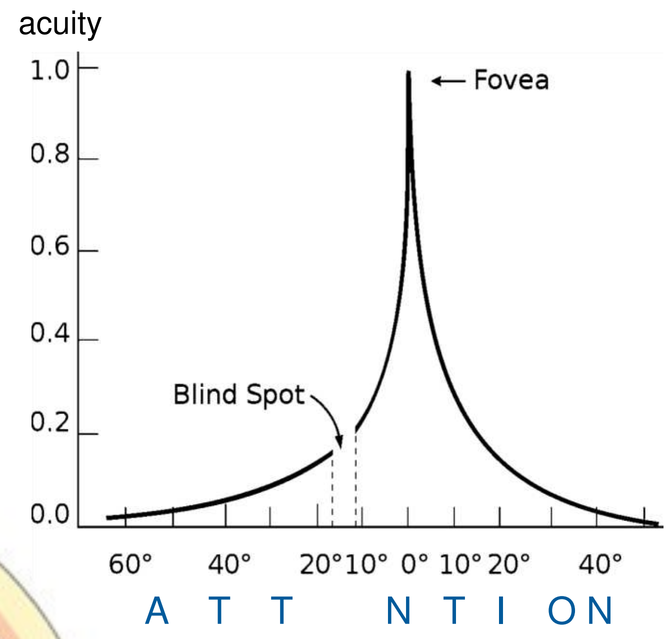


Kommentierte Übersichtsarbeit: Blickbewegungen beim Lesen, Leseentwicklung und Legasthenie
Ralph Radach, Thomas Günther und Lynn Huestegge

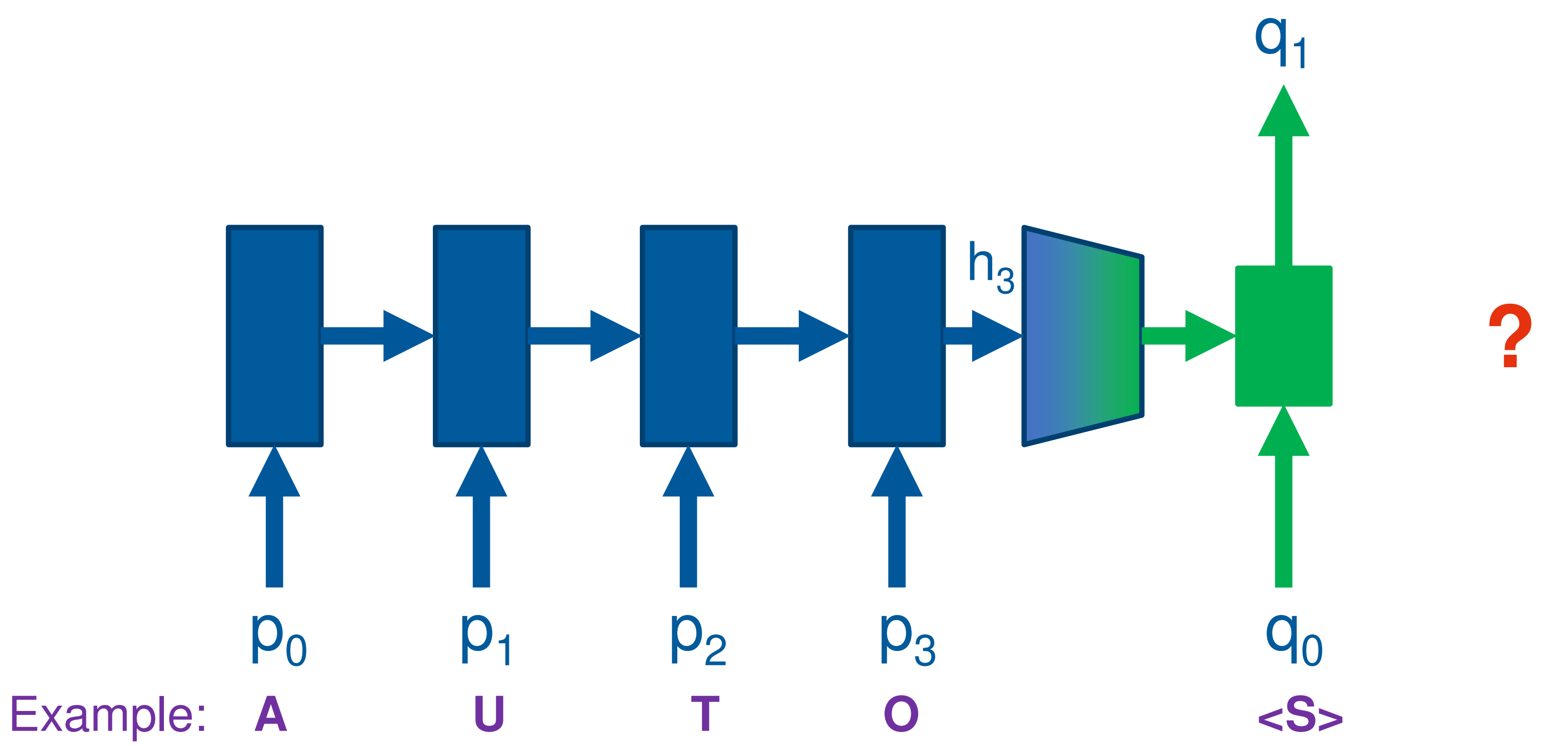
http://www.augen-attersee.at/auge.html
https://www.allgemeinepsychologie.uni-wuppertal.de/fileadmin/psychologie/allgemeinepsychologie/Artikel/Artikel_Radach/Radach_G%C3%BCnther_Huestegge_Leseentwicklung_Lernen_Lernst%C3%B6rungen_2012.pdf

Attention, please!





Recurrent Neural Network with Attention Layer



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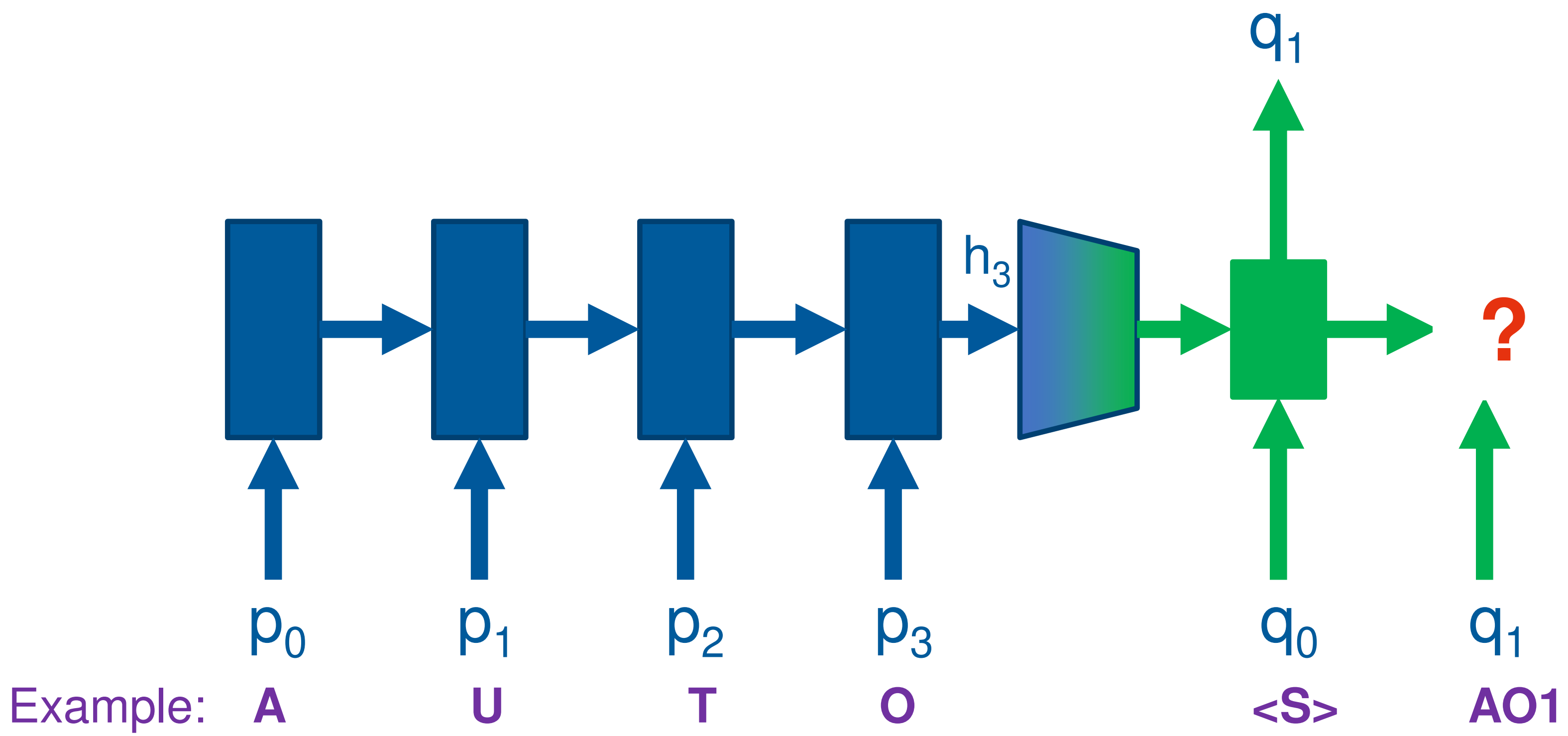
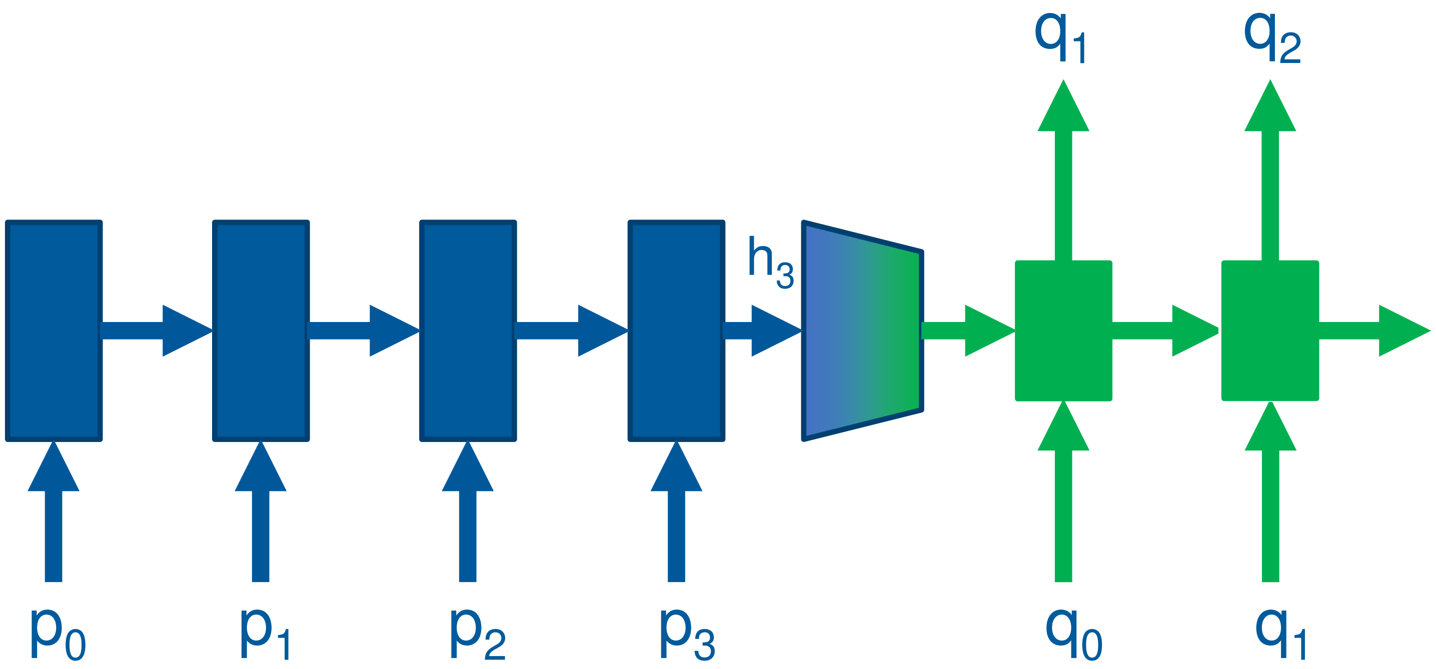
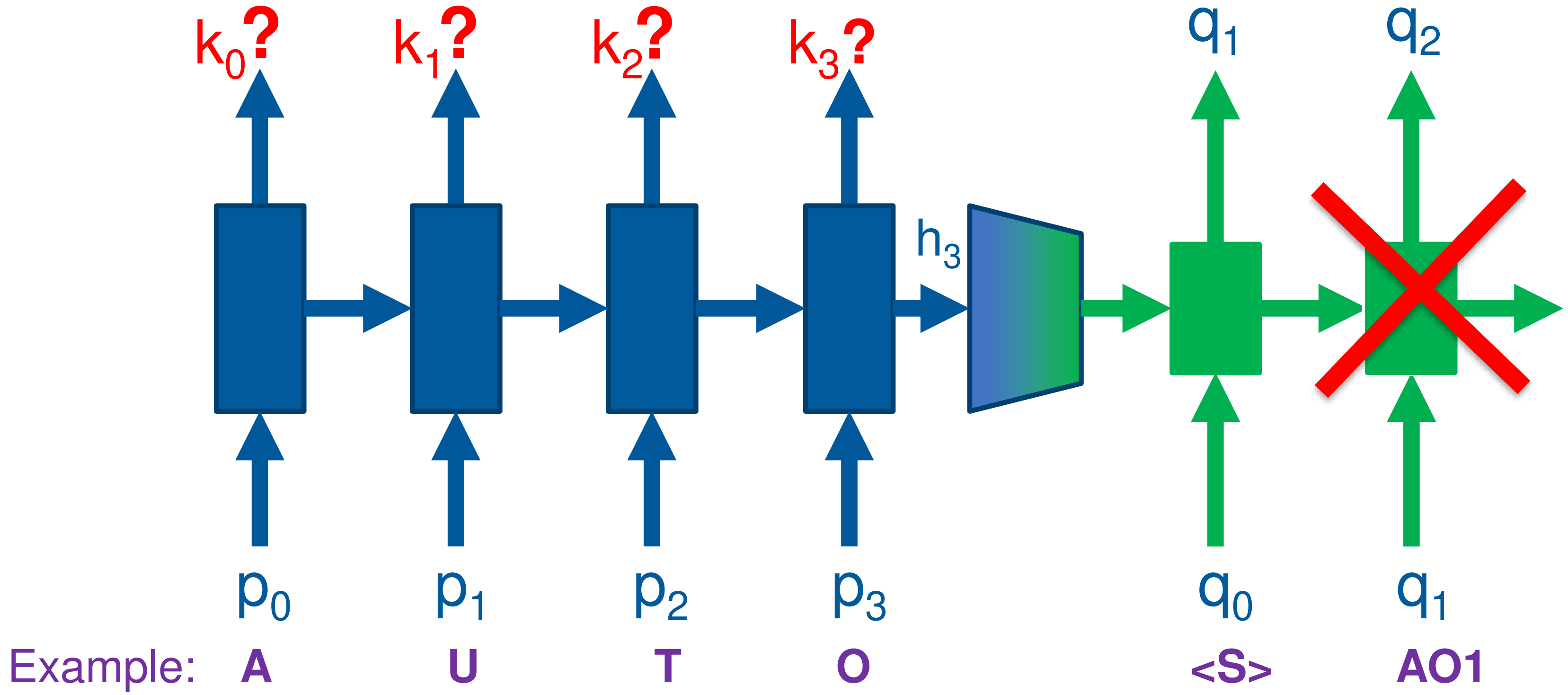


Current Solution:



Example: **A** **U** **T** **O** **<S>** **AO1**

Current Solution:



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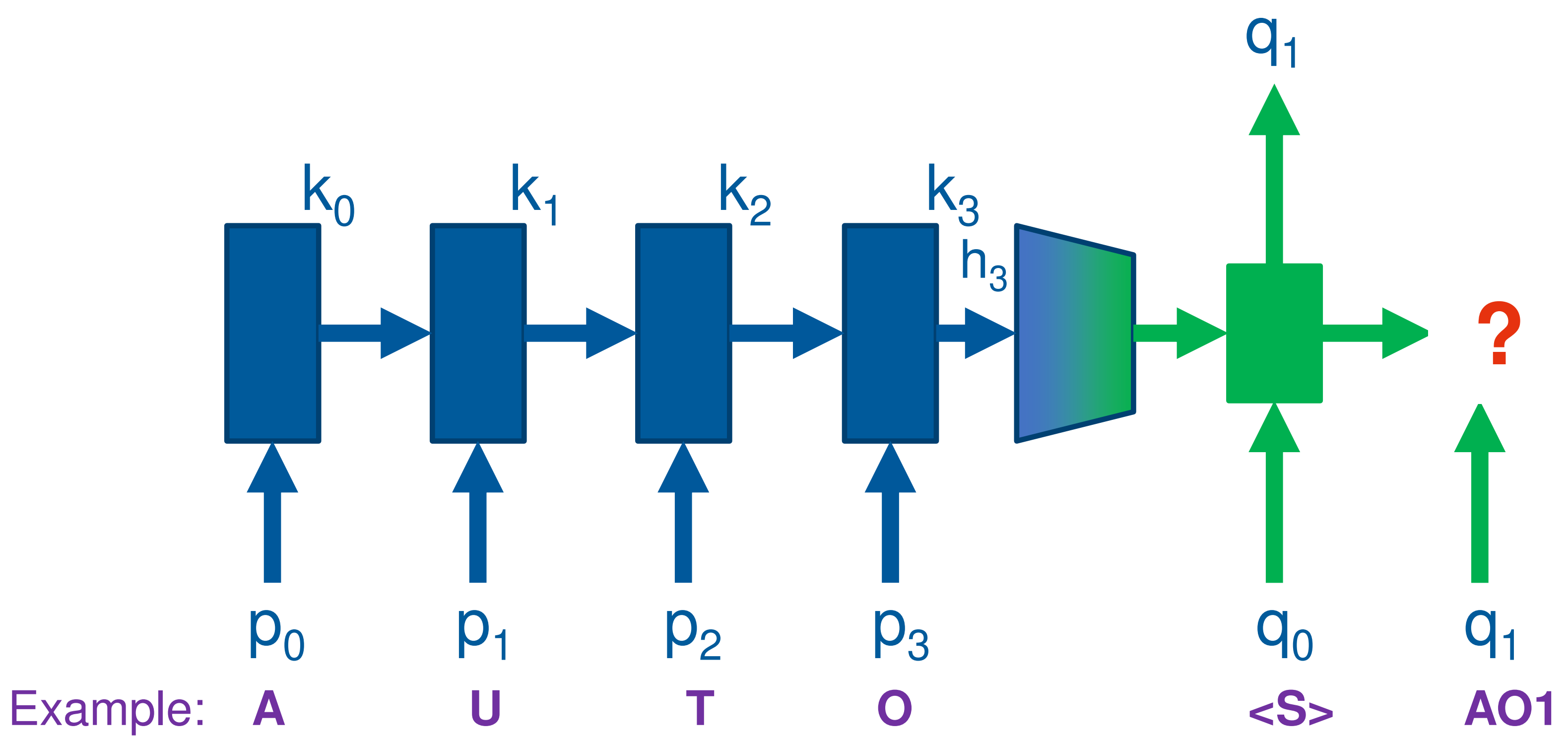

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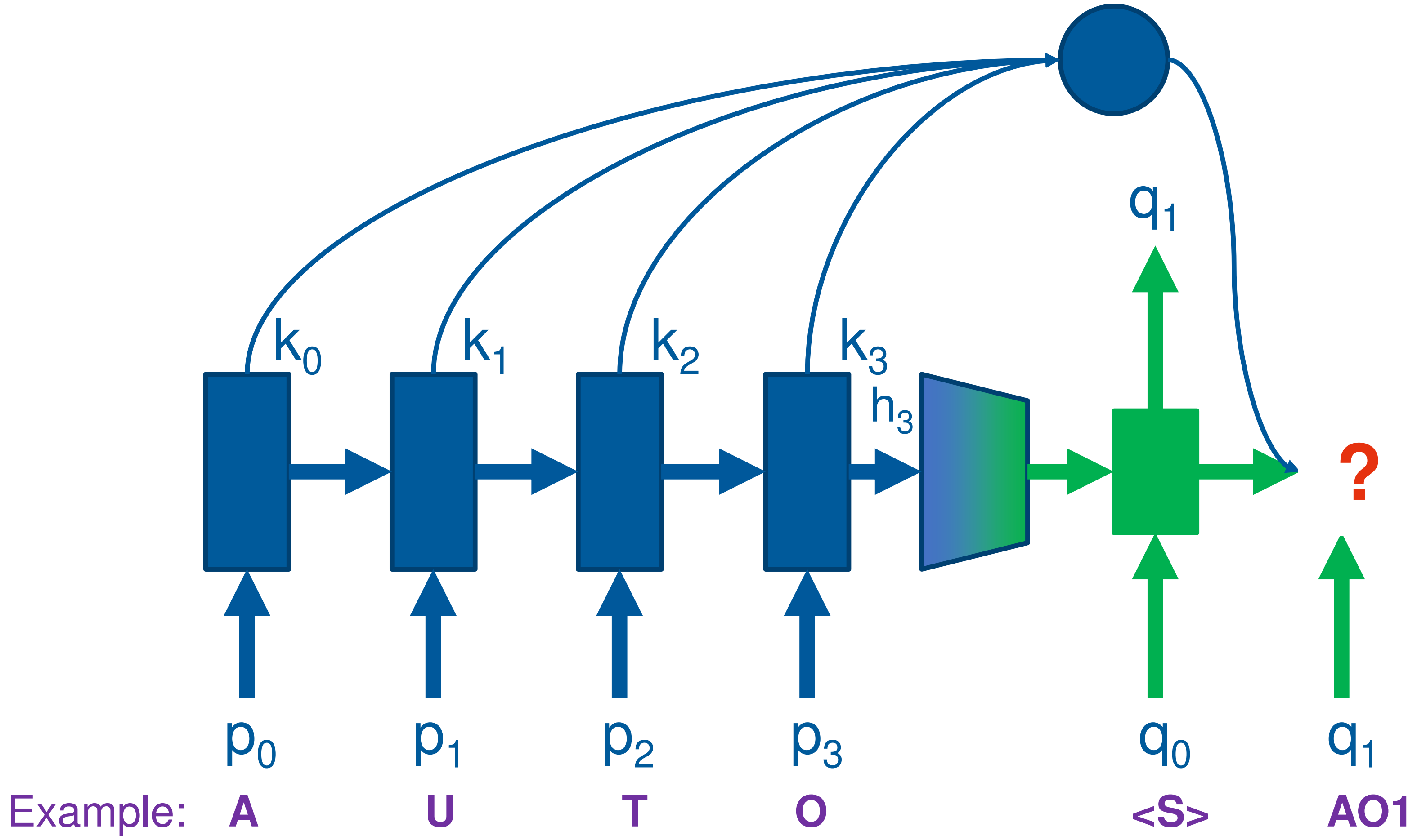

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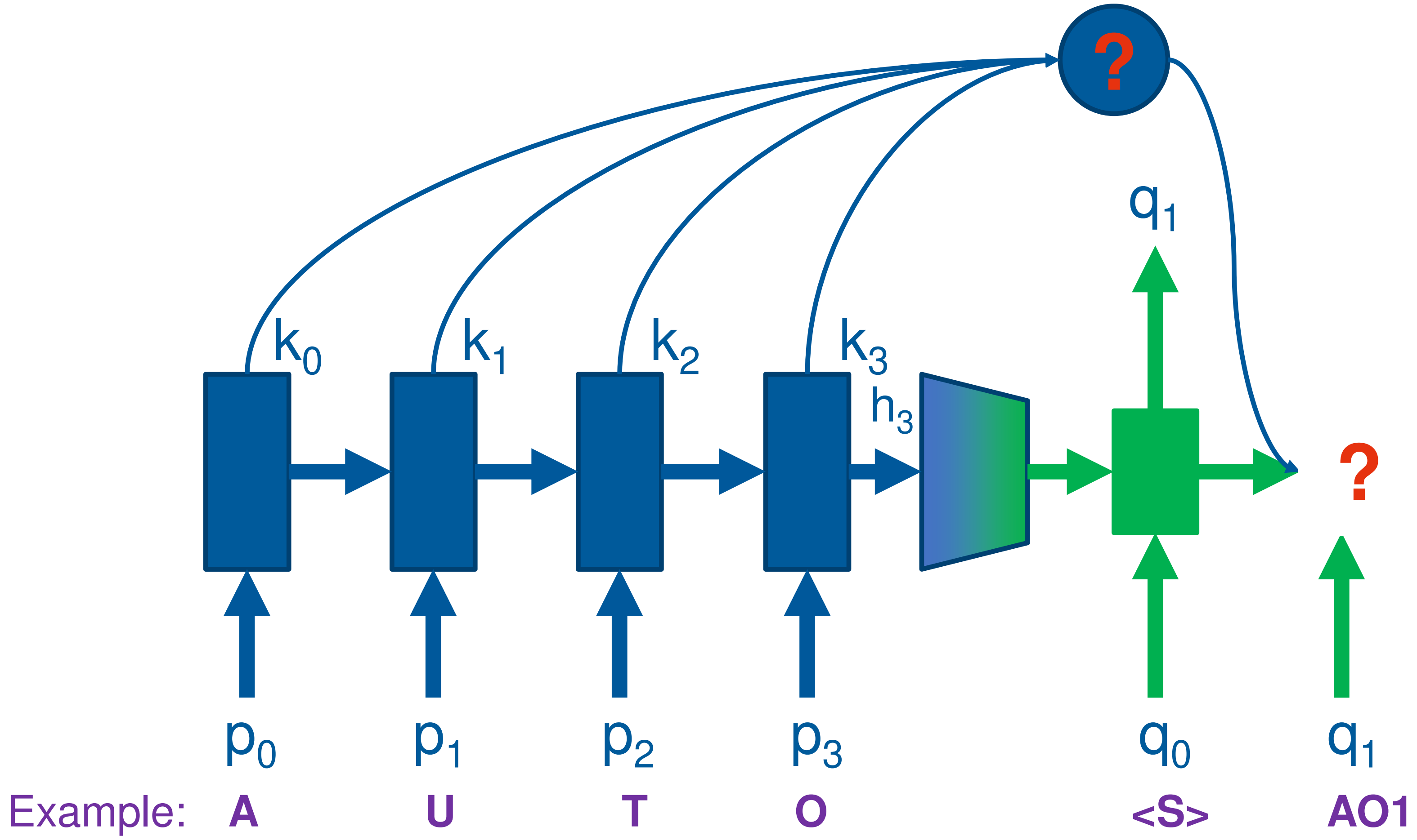

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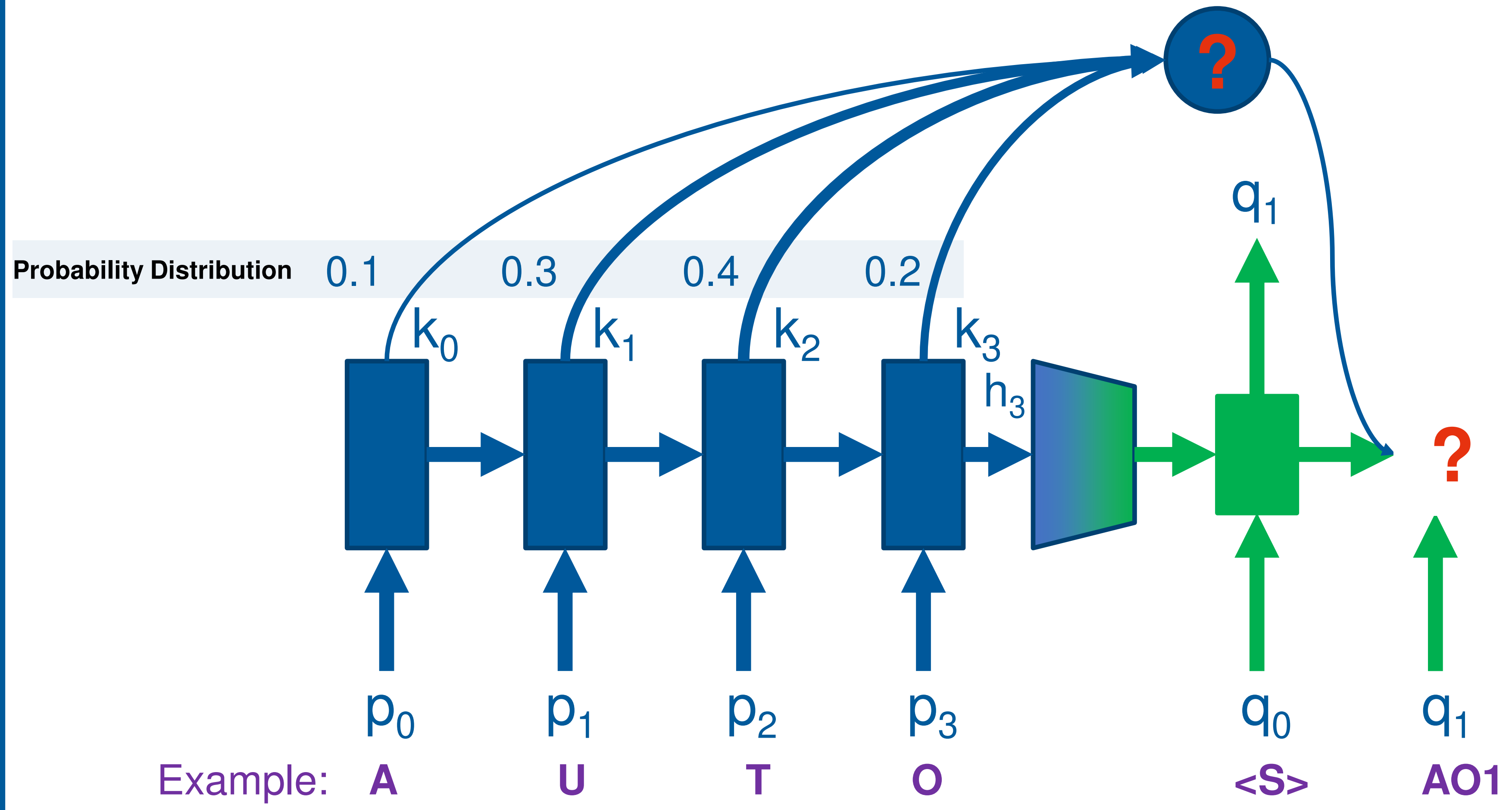

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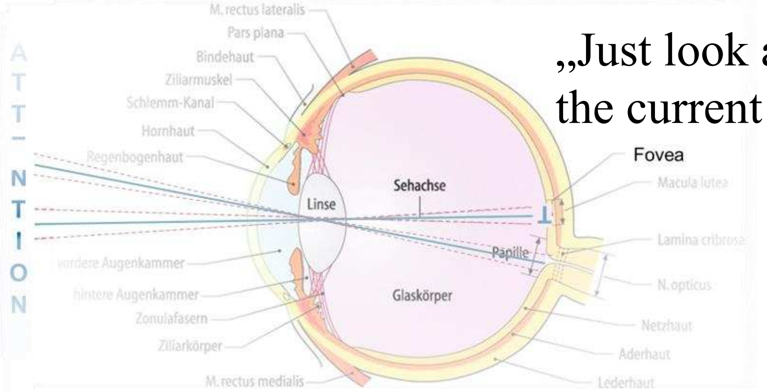
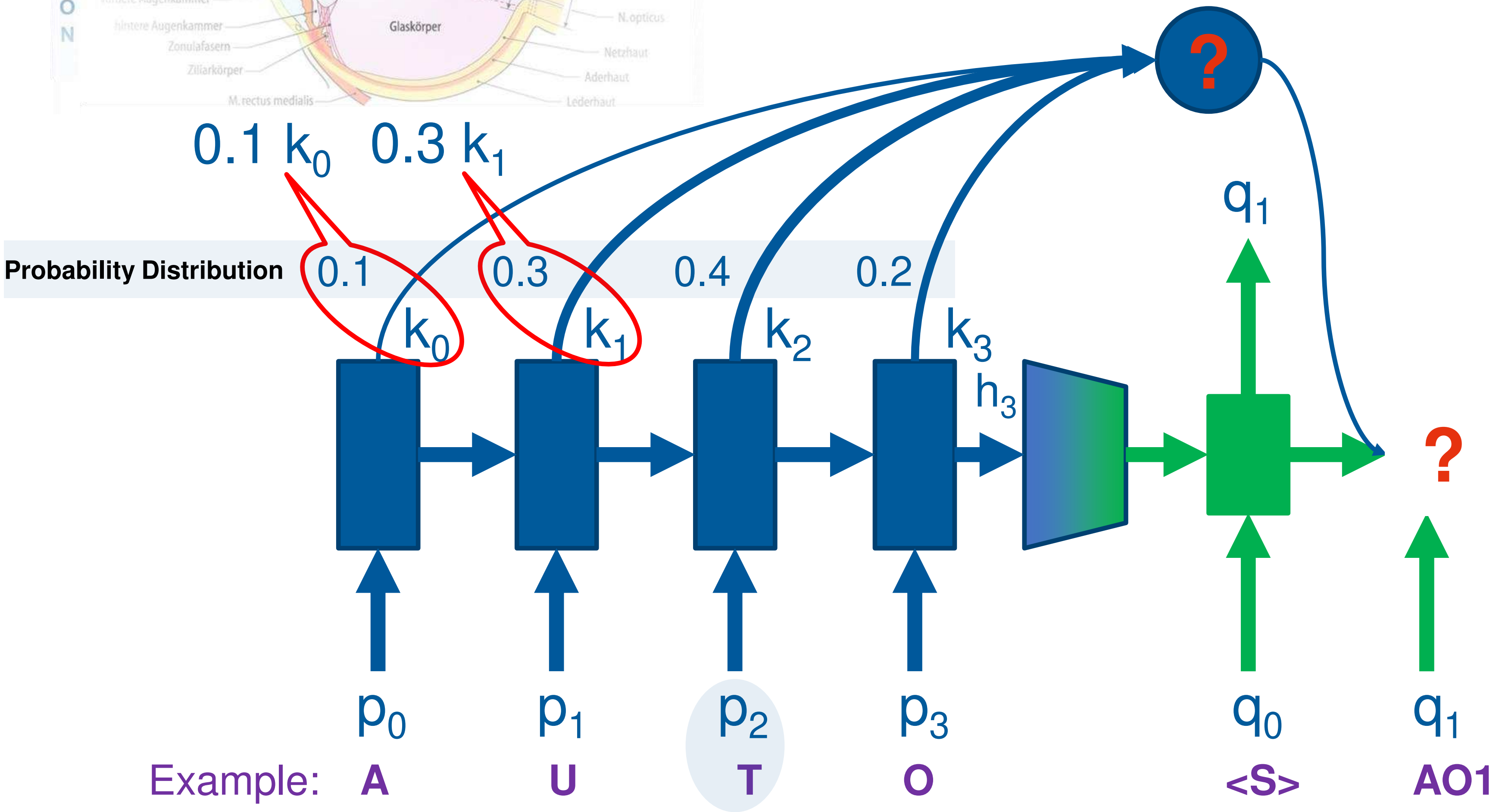
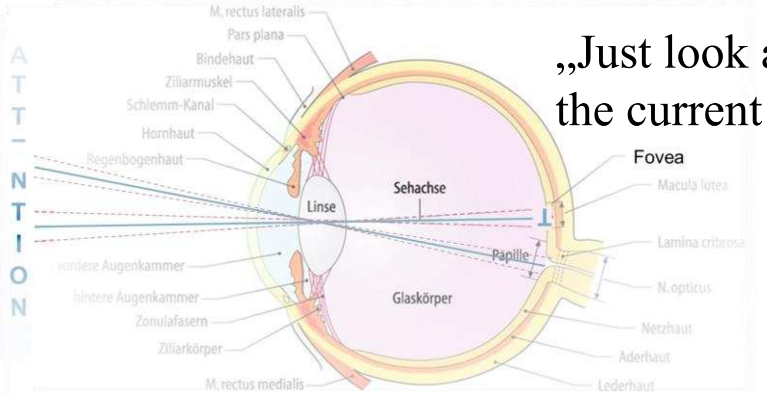


„Just look at the input which is relevant for the current output, control your attention"



Recurrent Neural Network with Attention Layer



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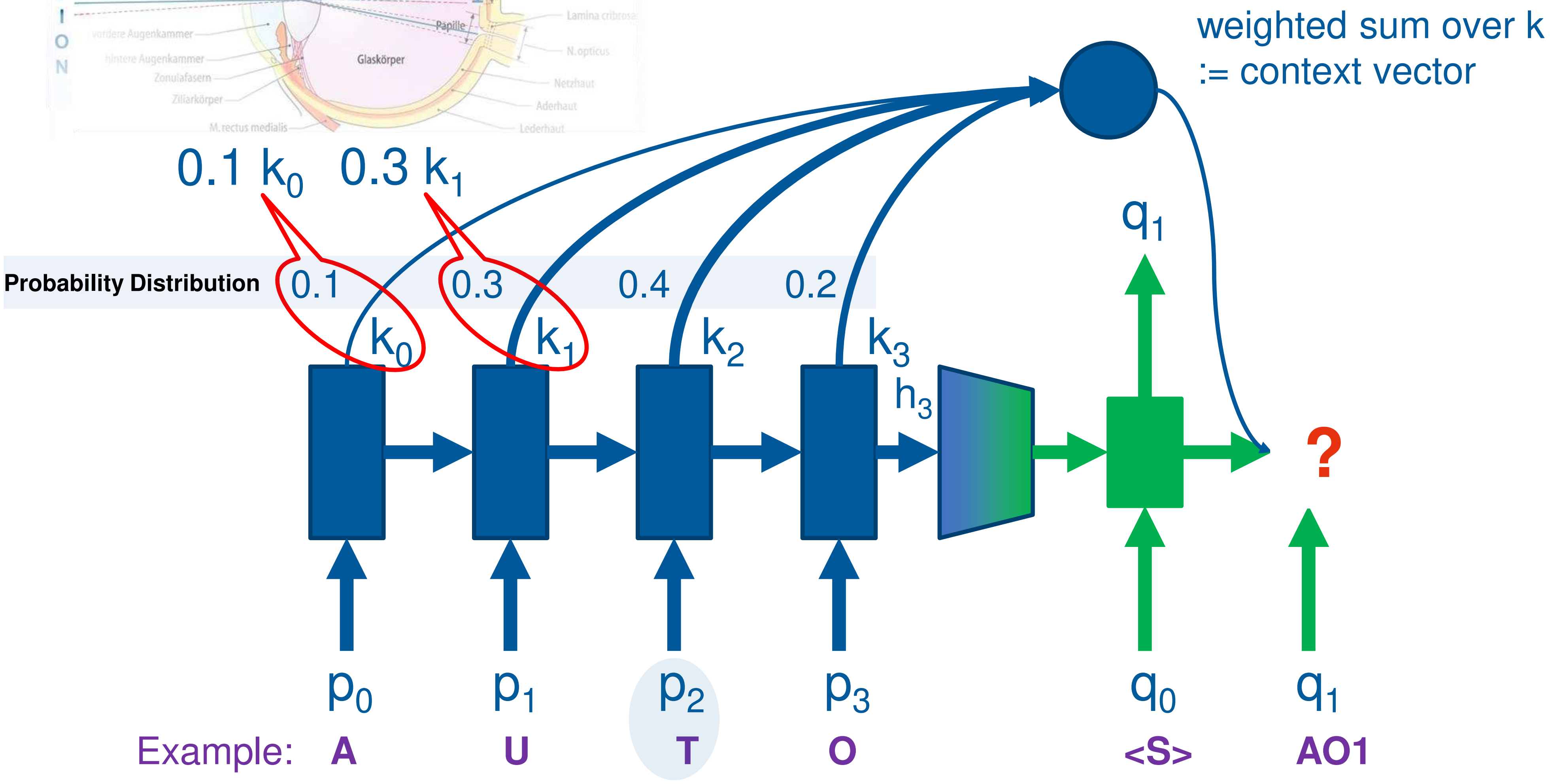
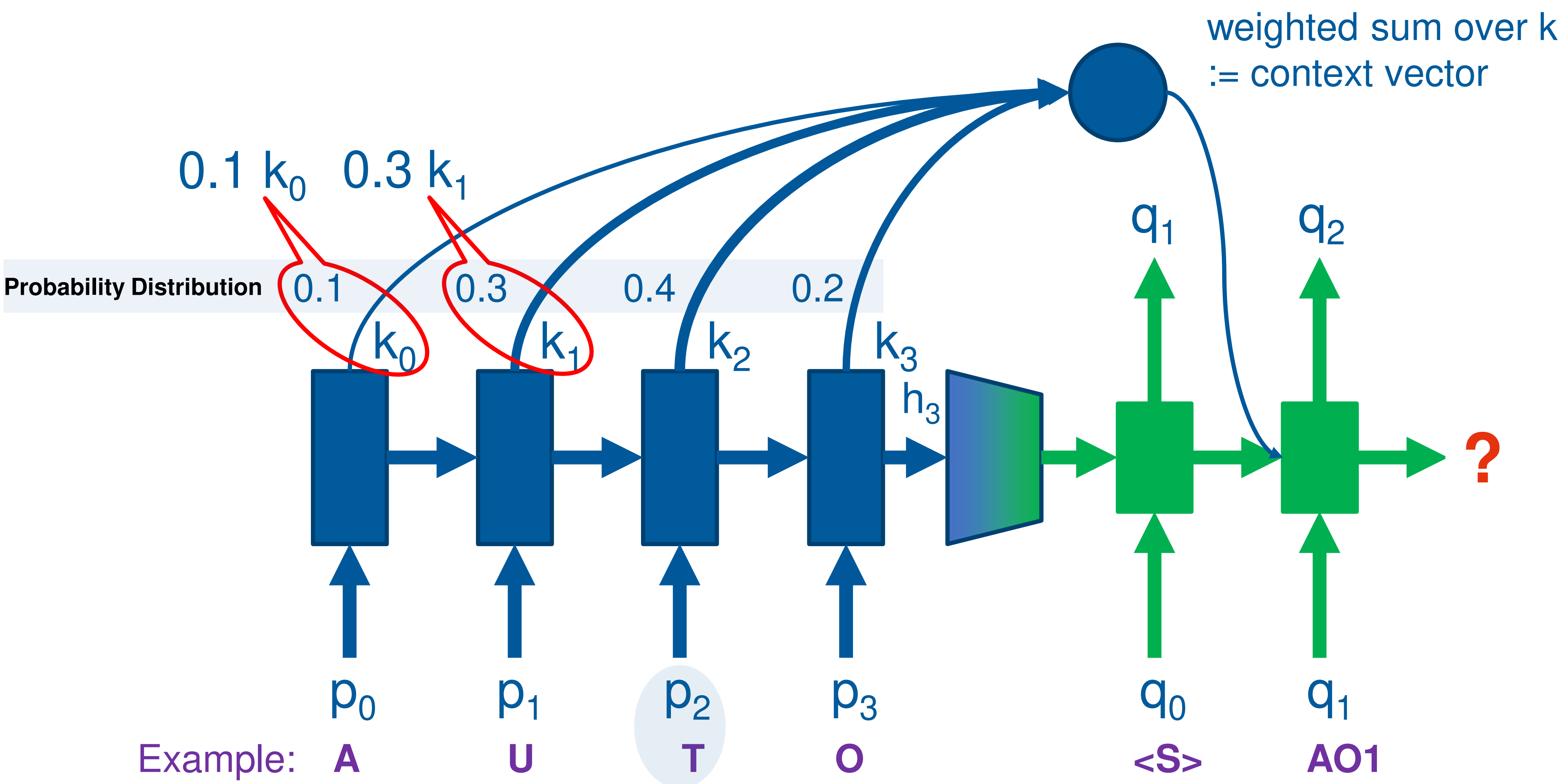
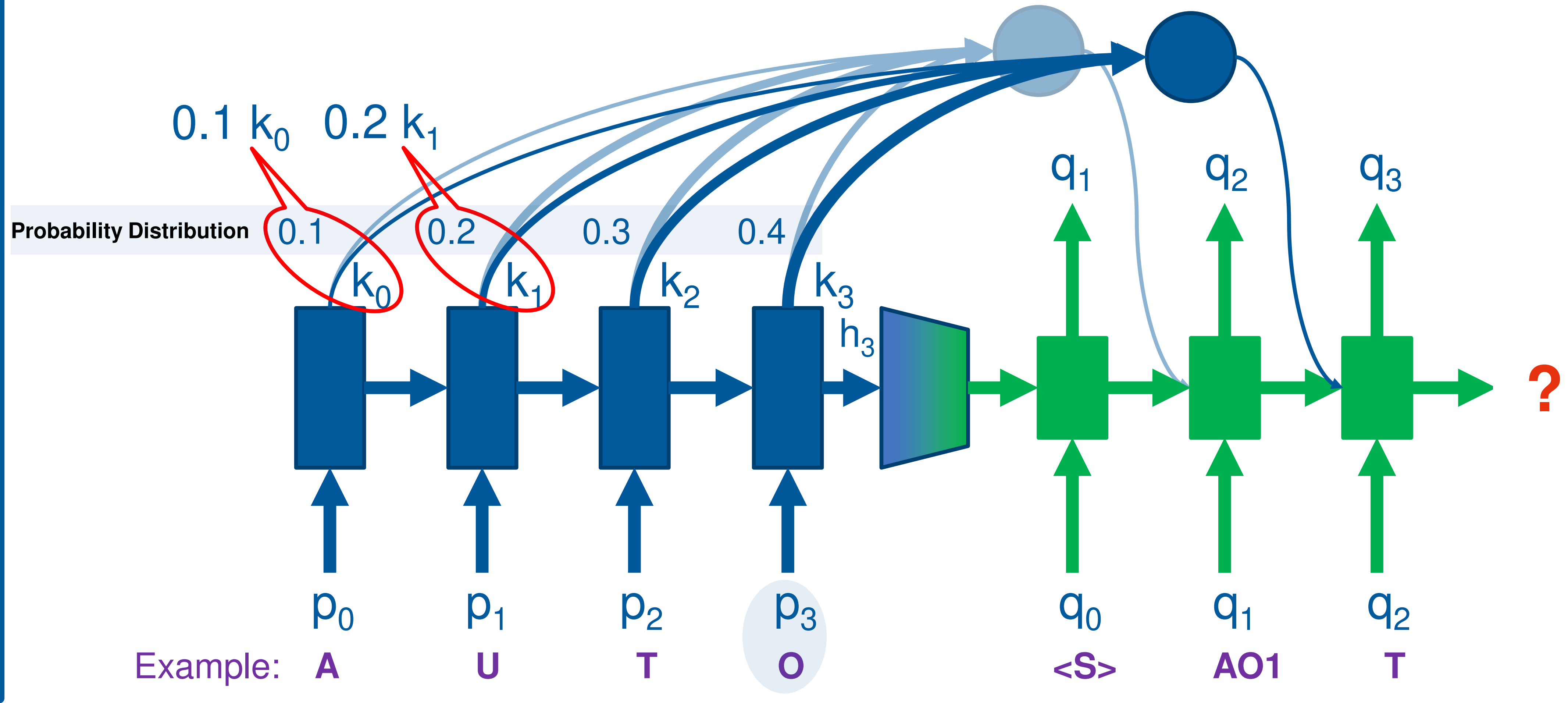


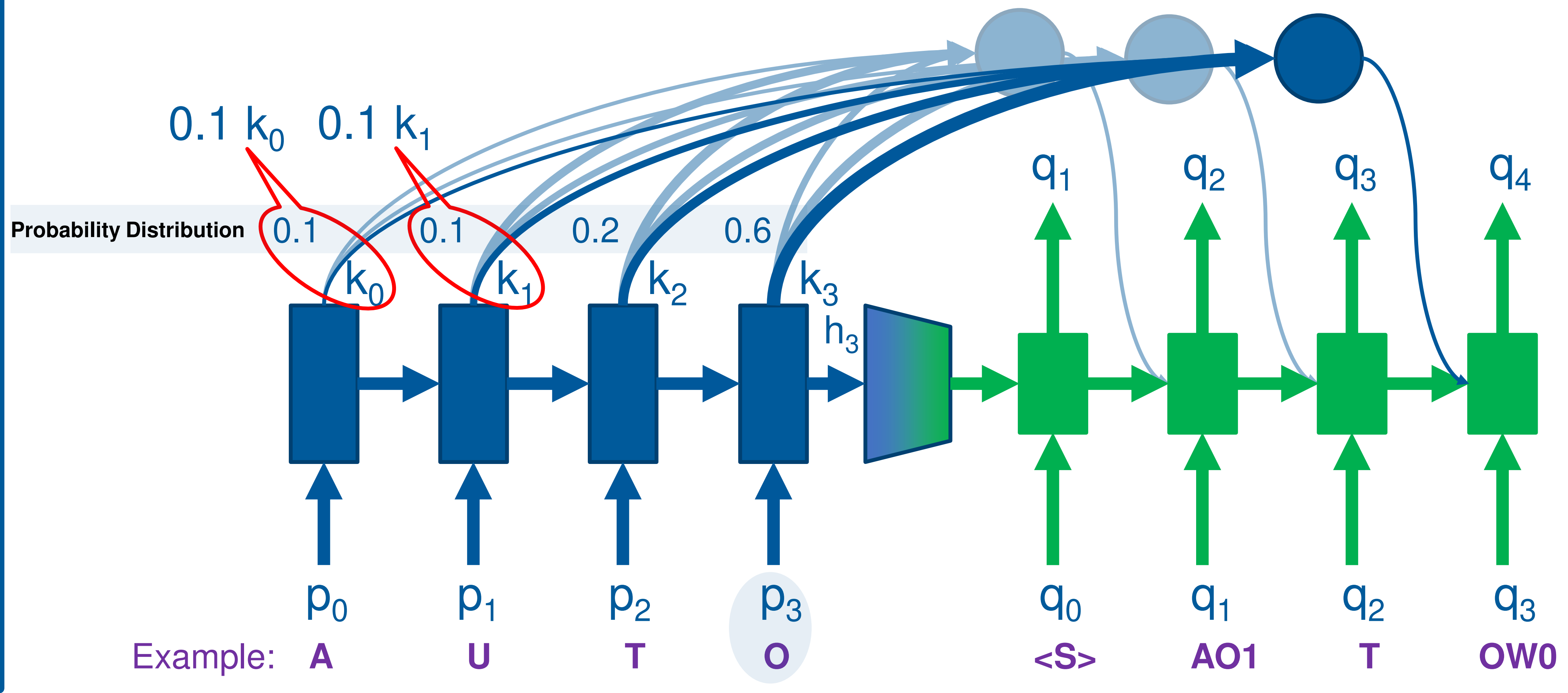
Recurrent Neural Network with Attention Layer



Recurrent Neural Network with Attention Layer

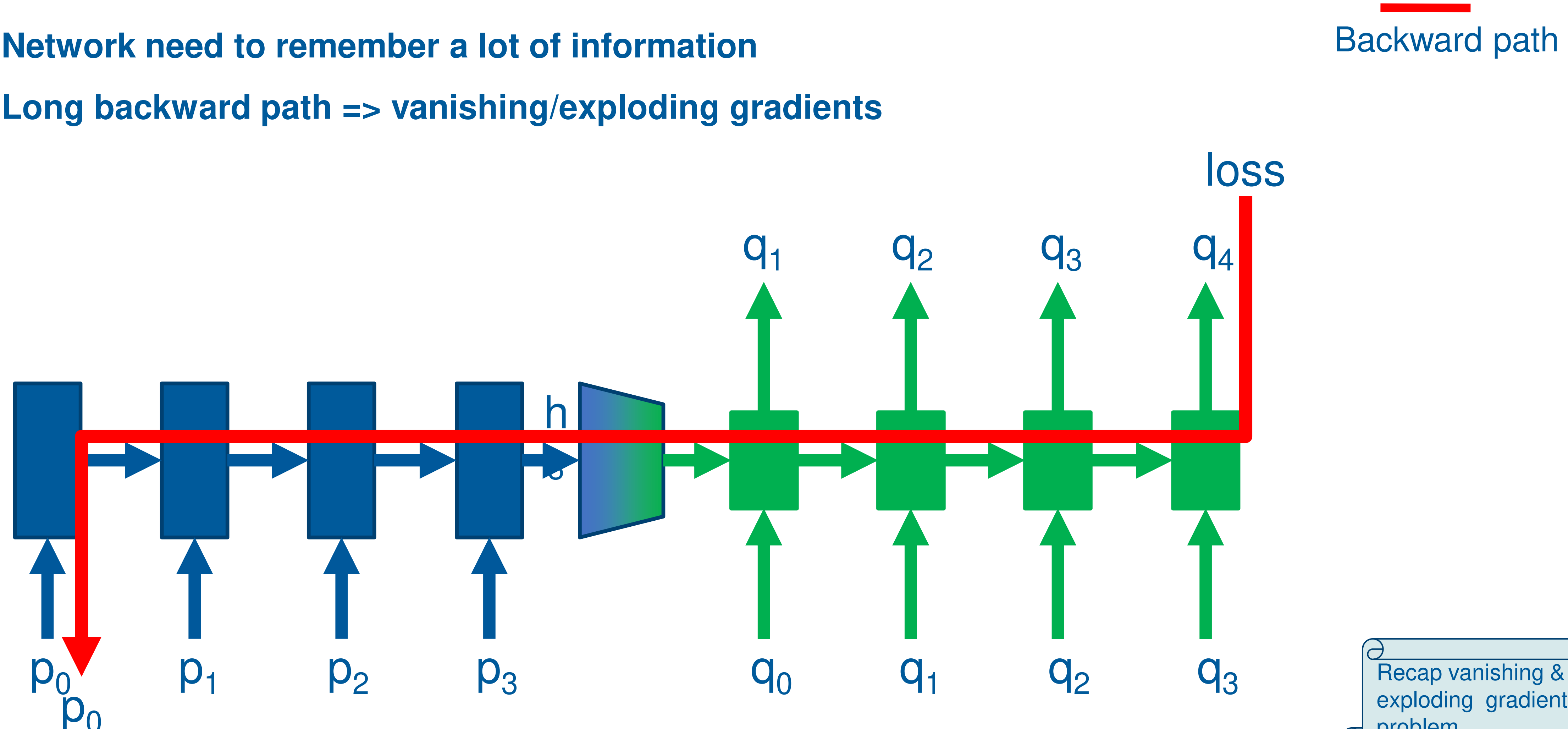


Recurrent Neural Network with Attention Layer



Sequence to Sequence, full delay

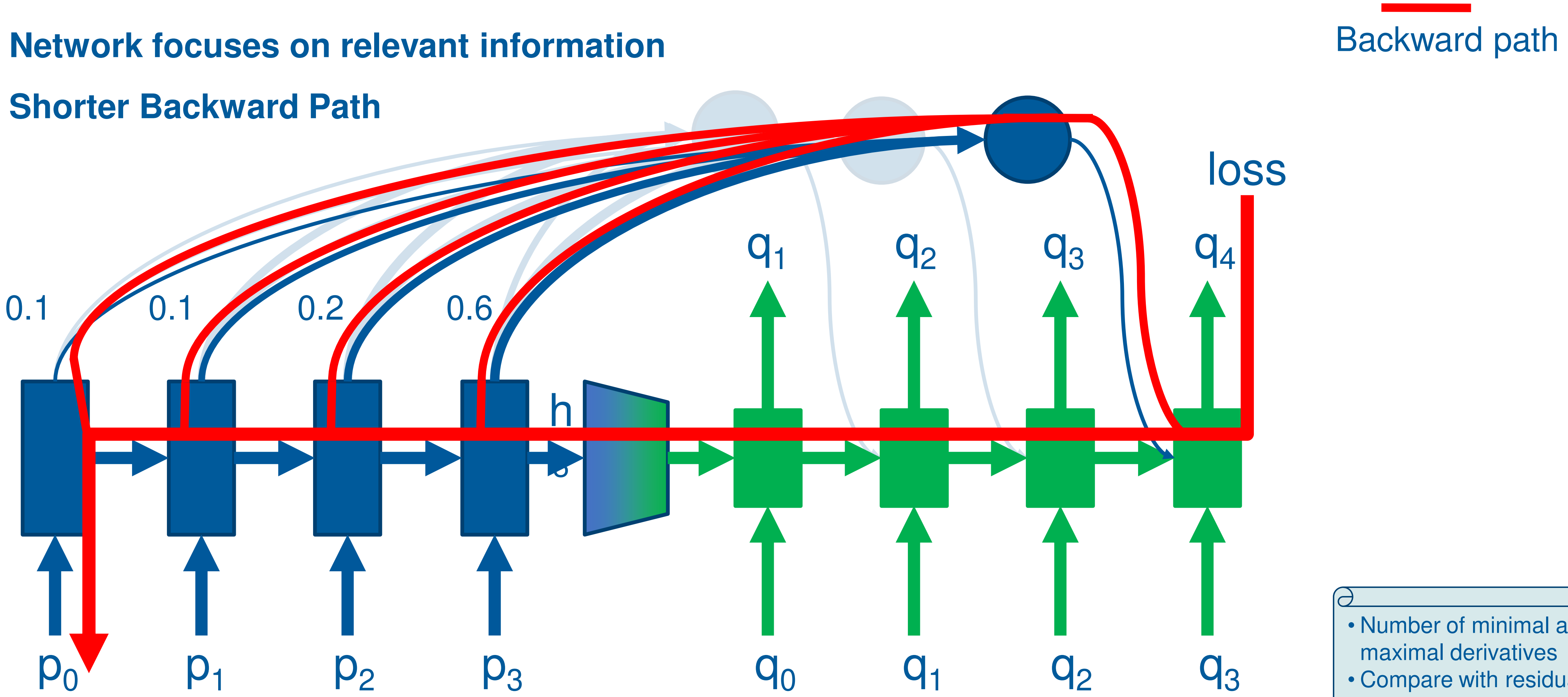
- **Network need to remember a lot of information**
- **Long backward path => vanishing/exploding gradients**



Recap vanishing & exploding gradients problem

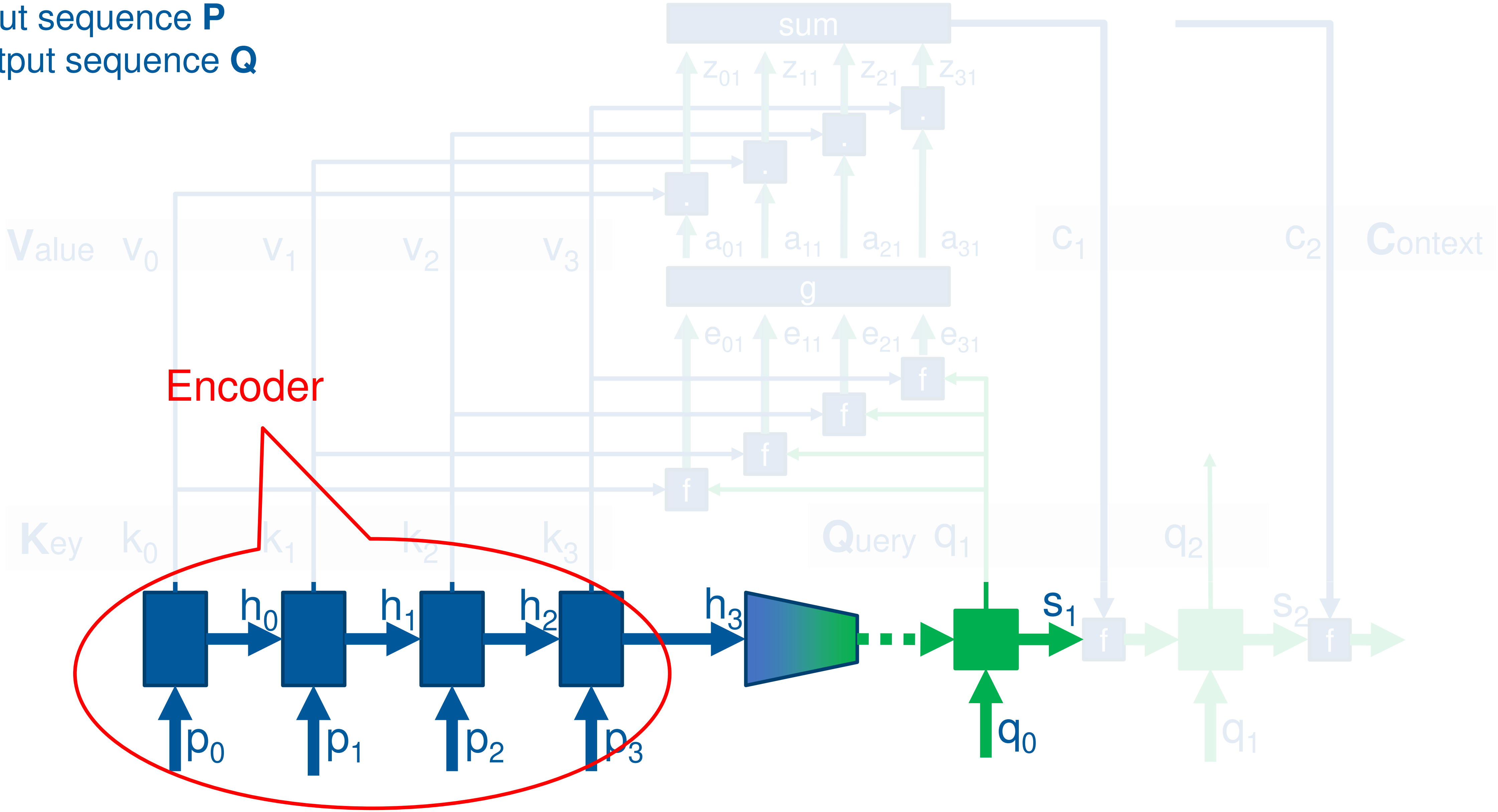
Sequence to Sequence, full delay with Attention

- **Network focuses on relevant information**
- **Shorter Backward Path**



- Number of minimal and maximal derivatives
- Compare with residual connections?

Encoder: RNN
Decoder: Autoregressive RNN
Input sequence **P**
Output sequence **Q**



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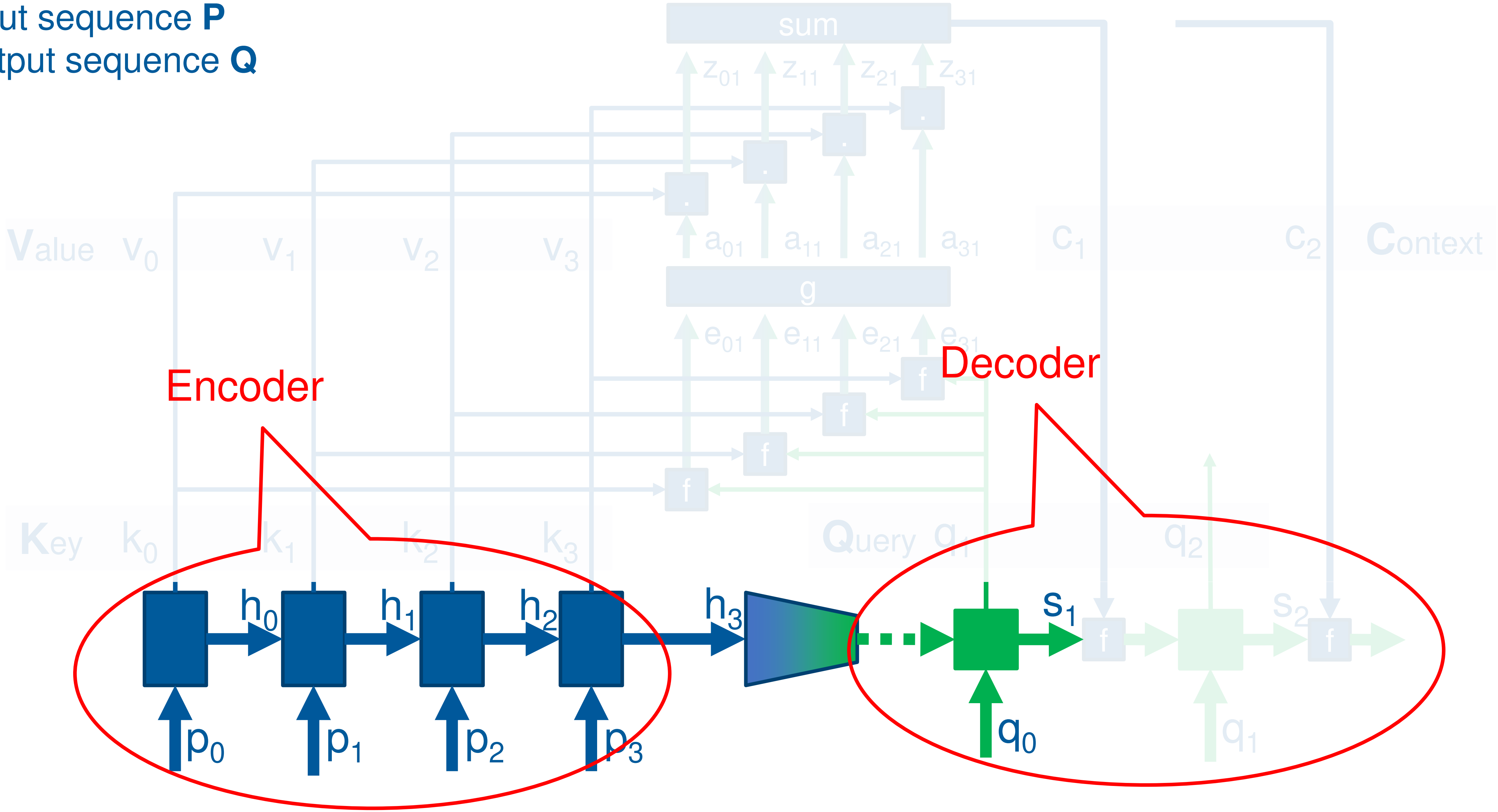

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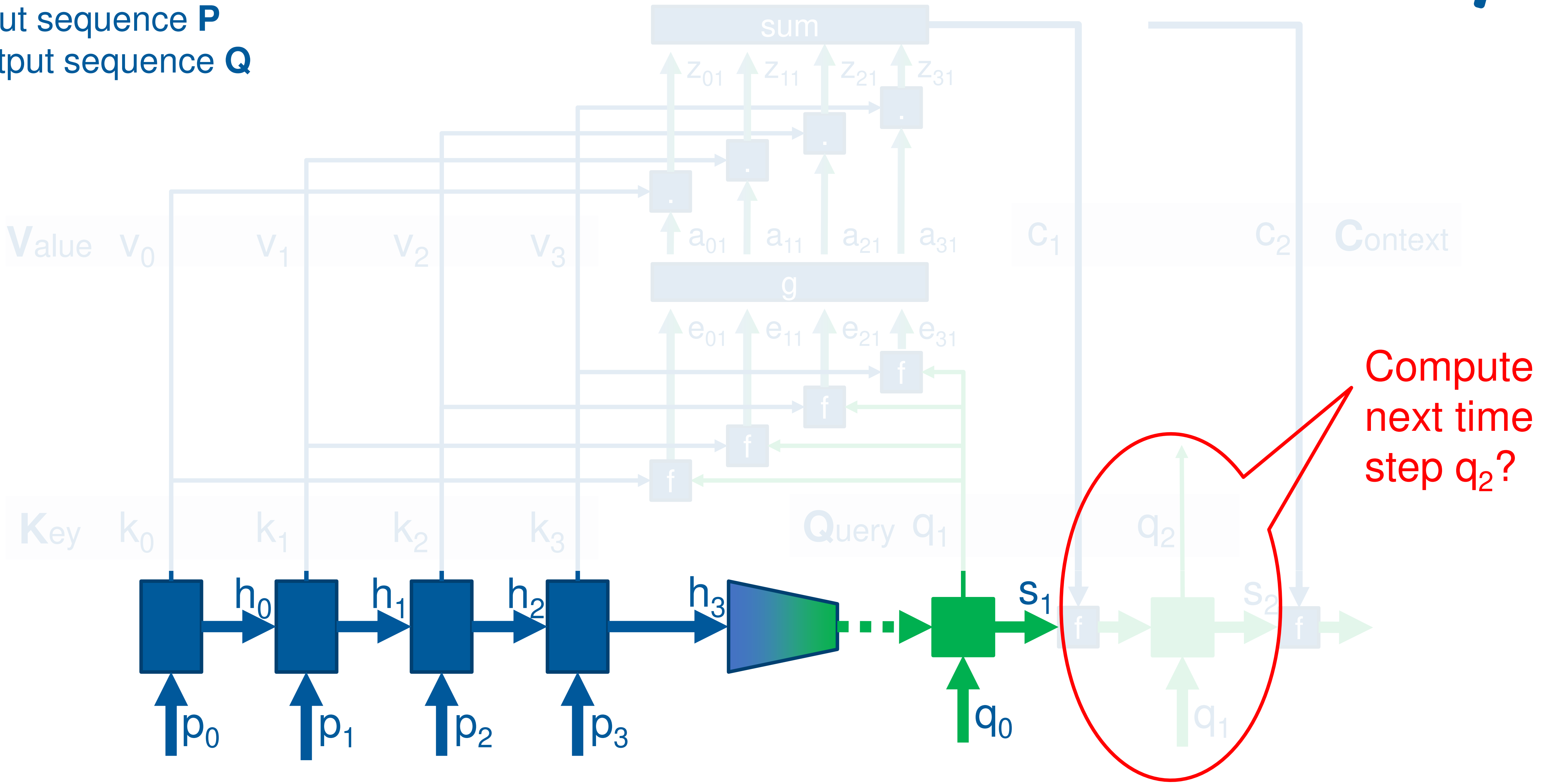
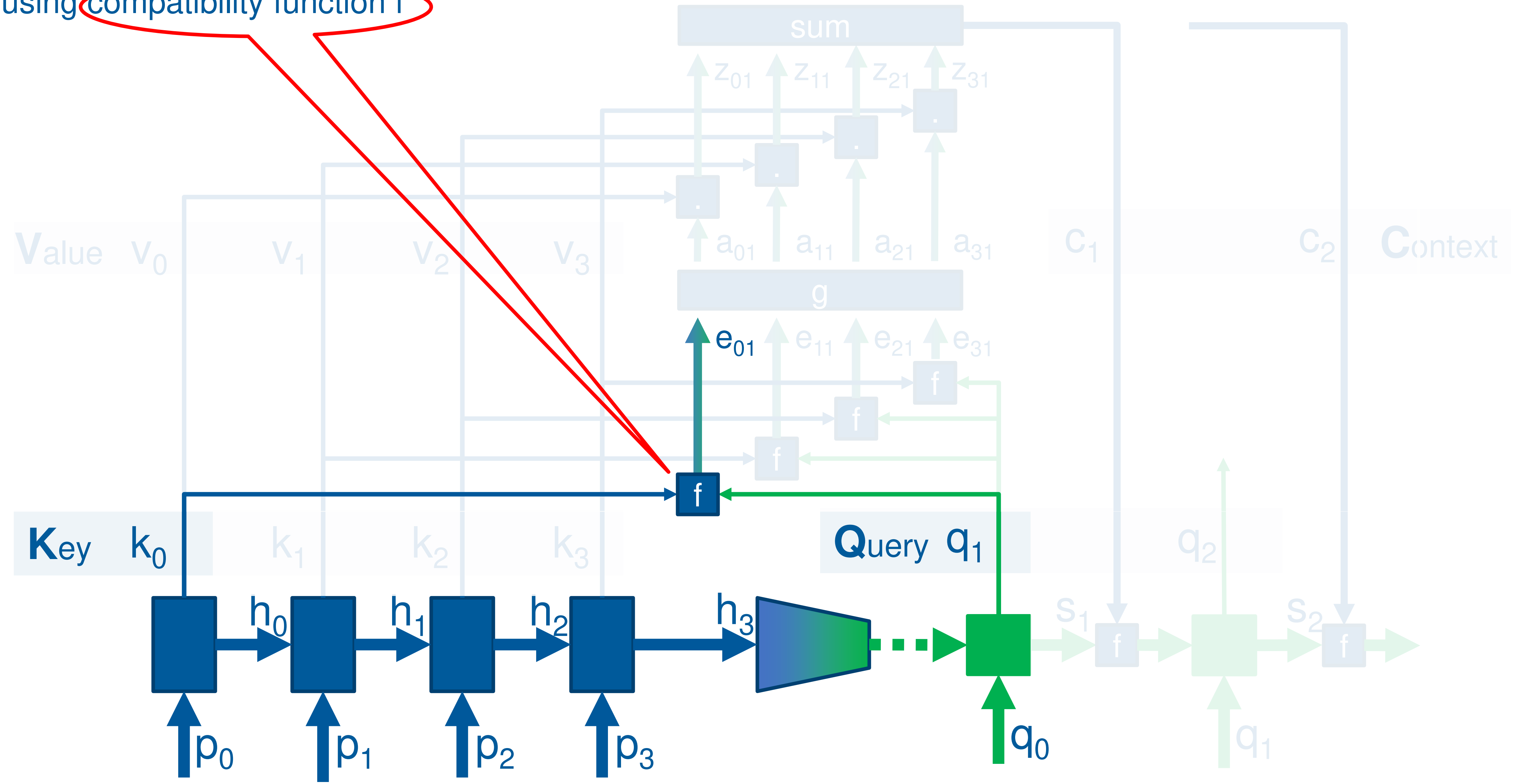
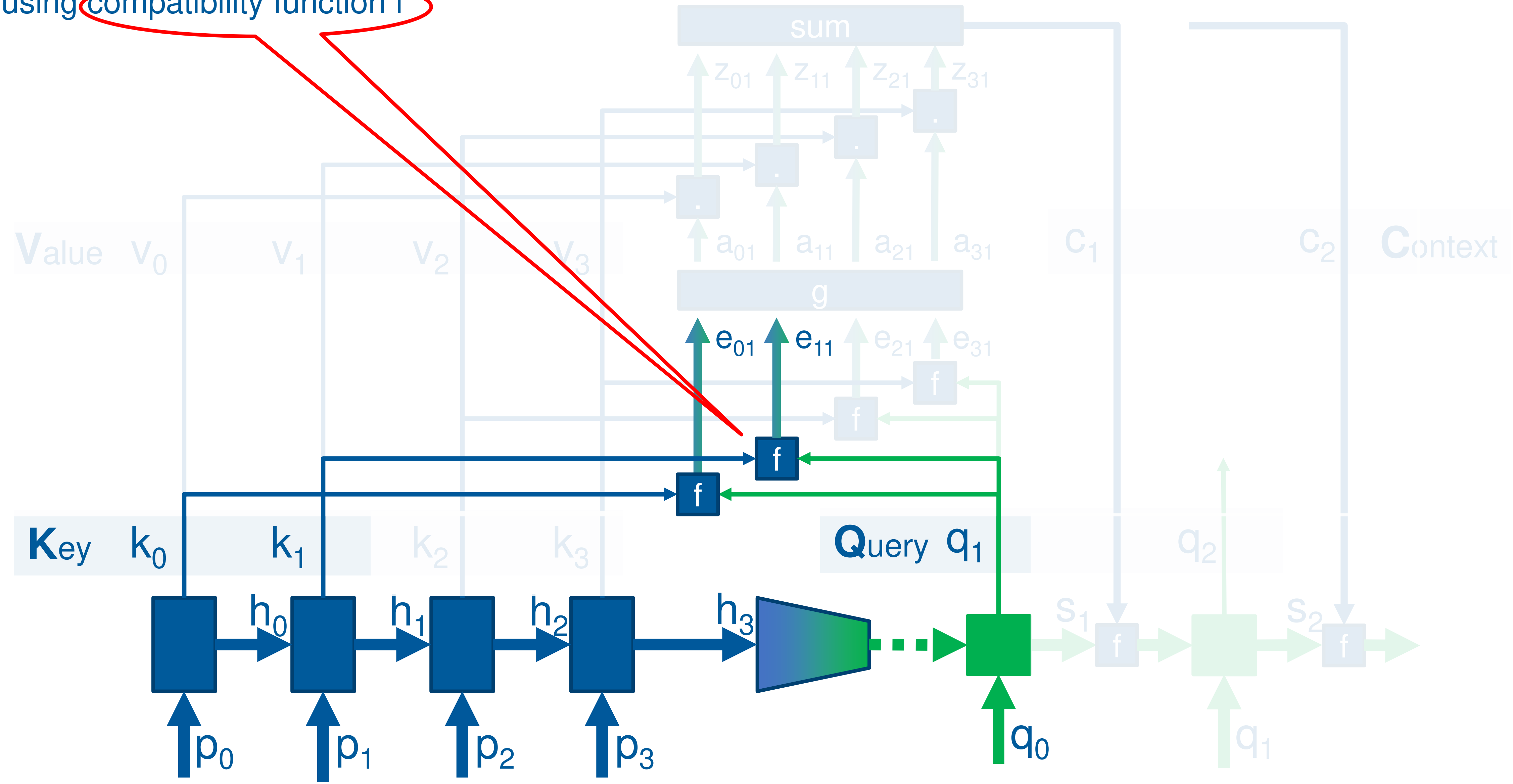
Input sequence **P**
Output sequence **Q**



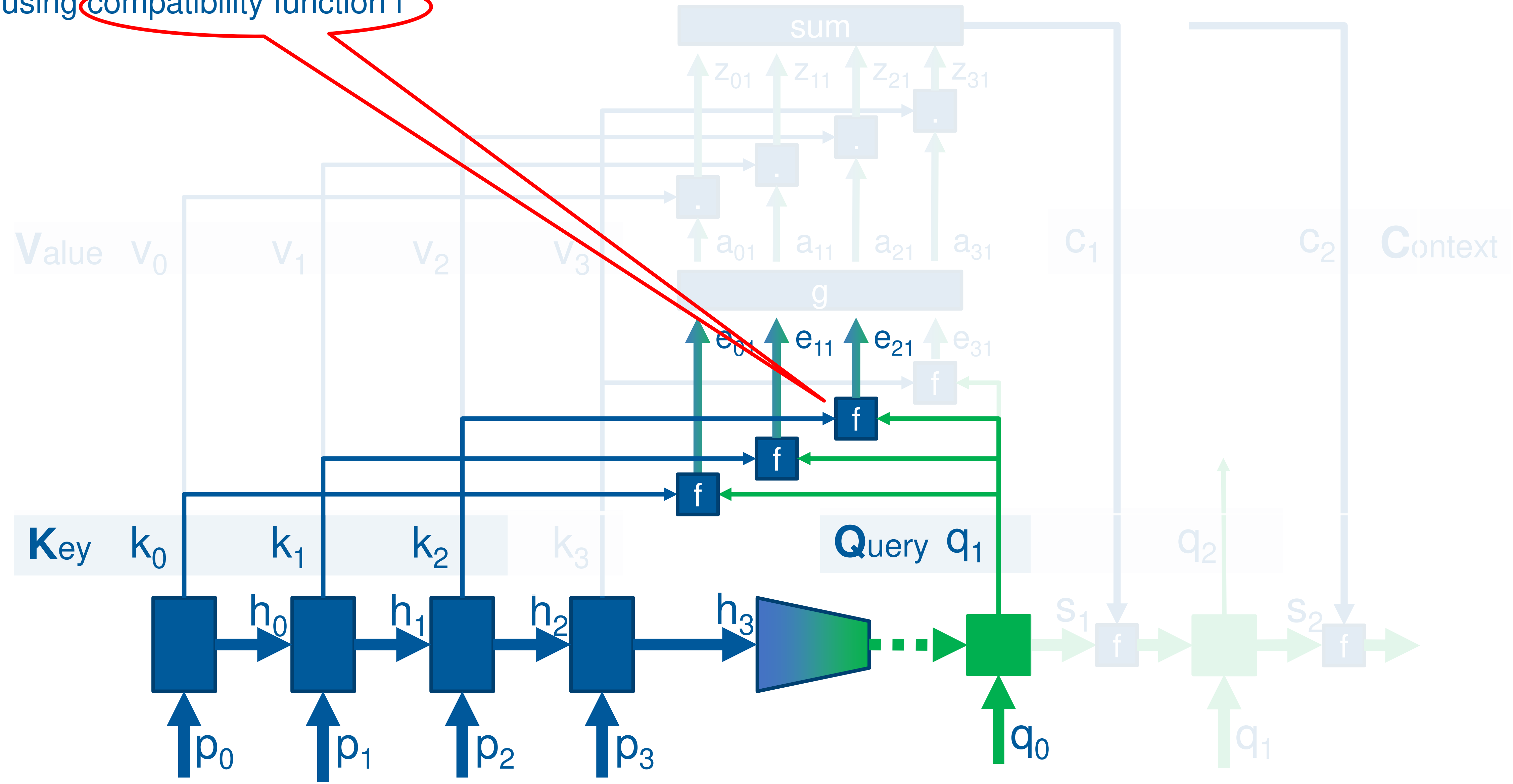
Compute the energy e of p_0 and q_0 using compatibility function f



Compute the energy e of p_0 and q_0 using compatibility function f

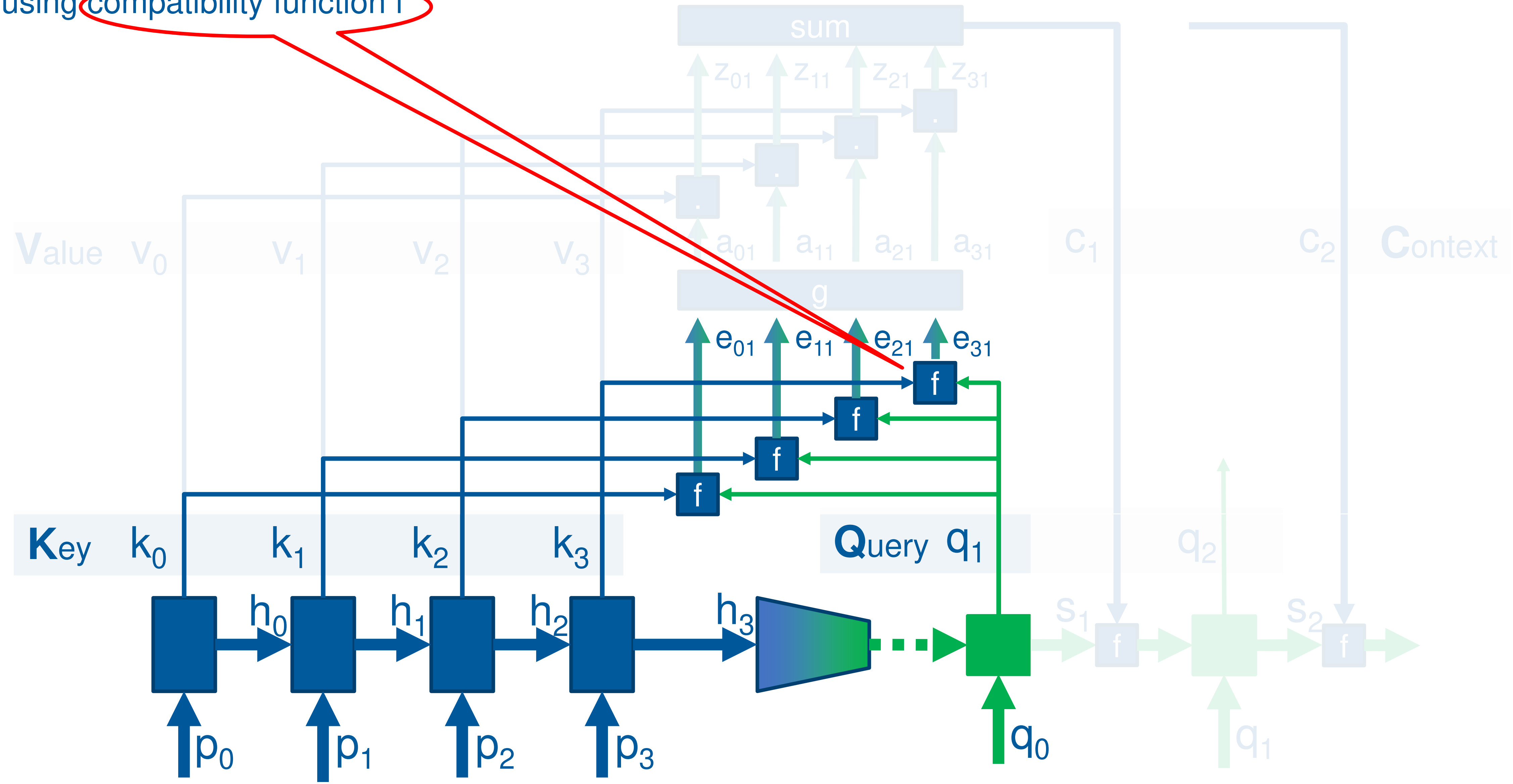


Compute the energy e of p_0 and q_0 using compatibility function f



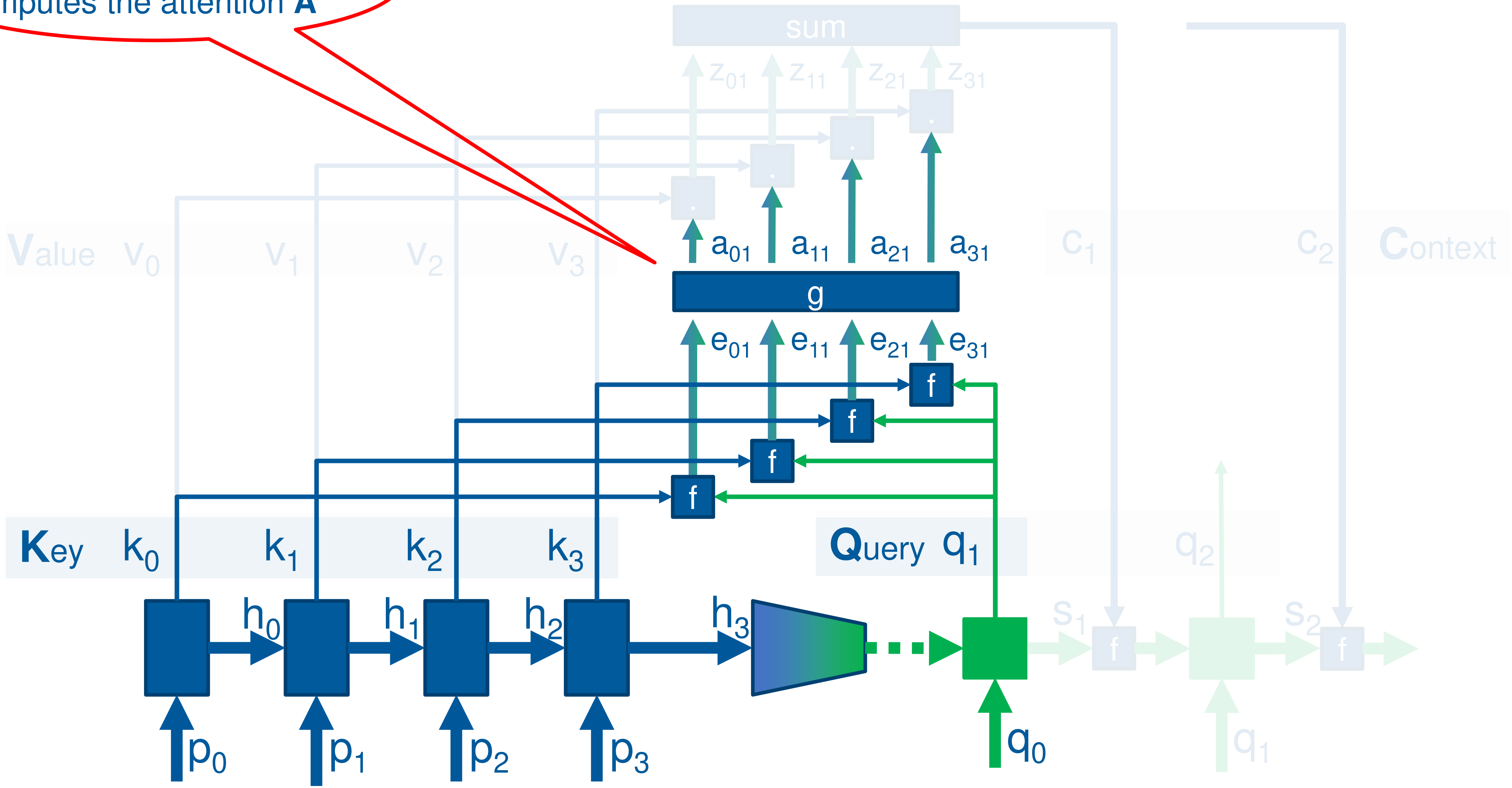
$\mathbf{E} := f(\mathbf{K},\mathbf{Q}) = \mathbf{QK}^T$

Compute the energy e of p_0 and q_0 using compatibility function f

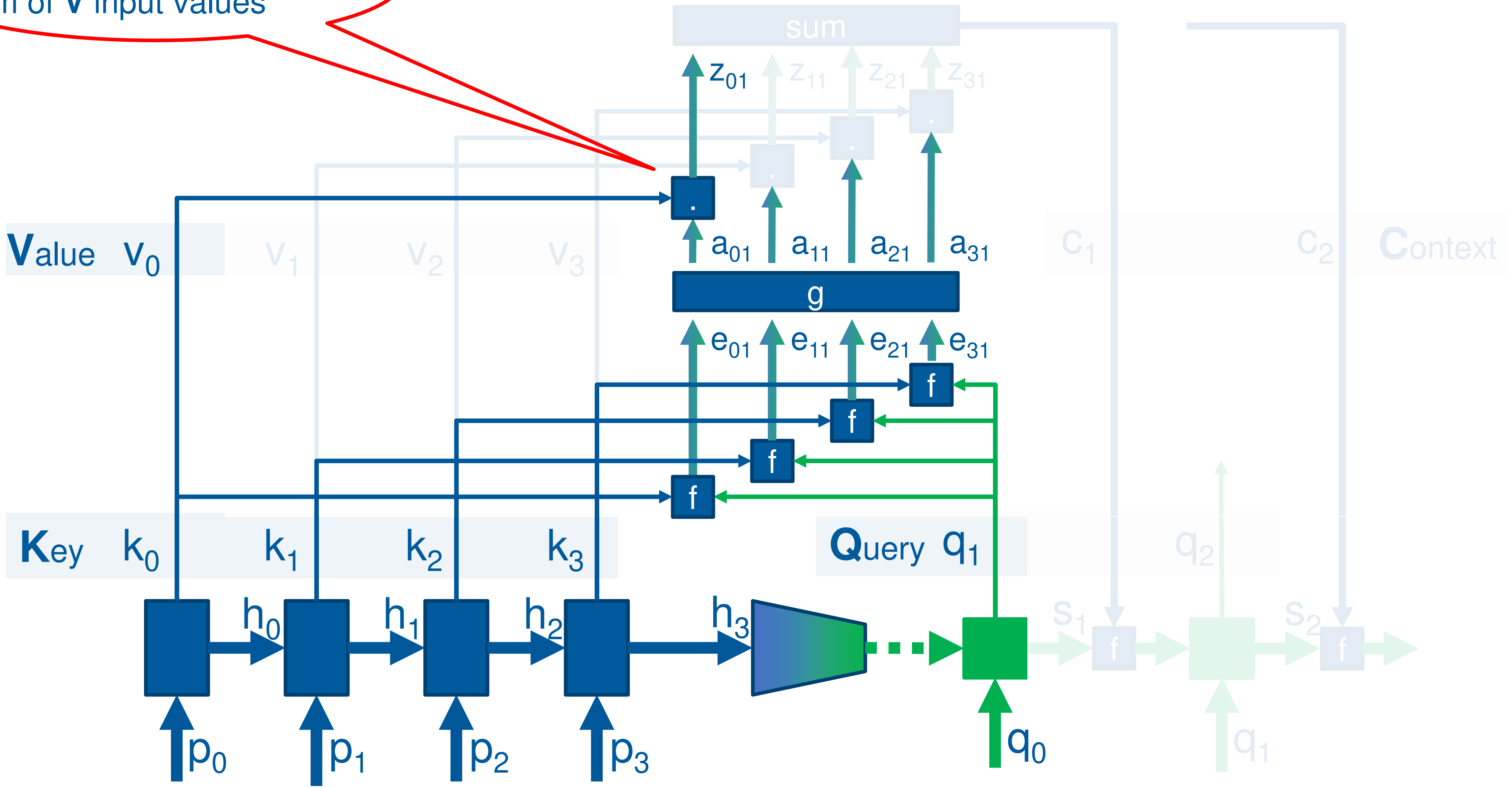


$$\mathbf{E} := f(\mathbf{K},\mathbf{Q}) = \mathbf{Q}\mathbf{K}^T$$
$$\mathbf{A} := G(\mathbf{E}) = \mathrm{softmax}(\mathbf{E})$$

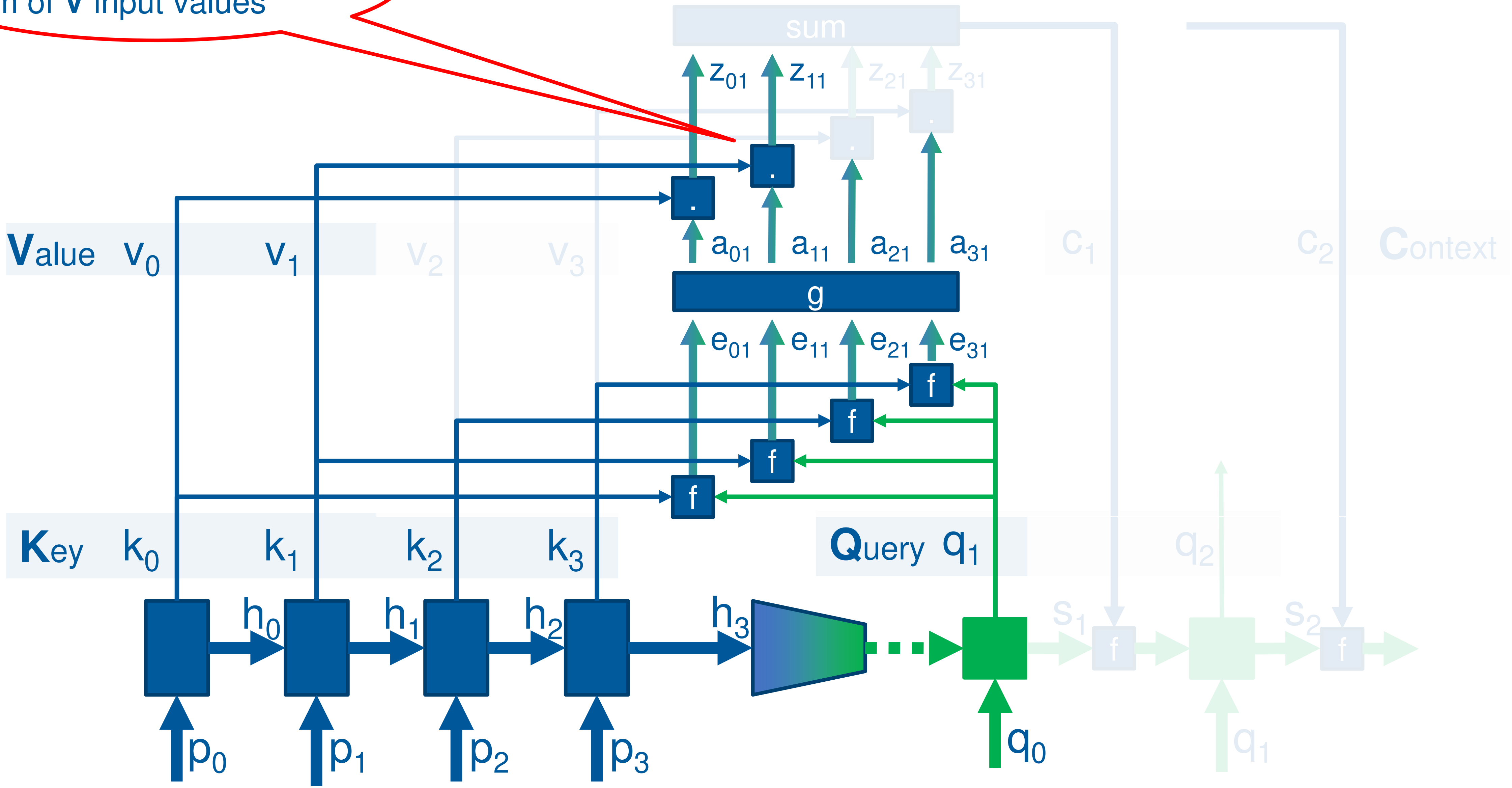
Distribution function g: **E** -> **A** computes the attention **A**



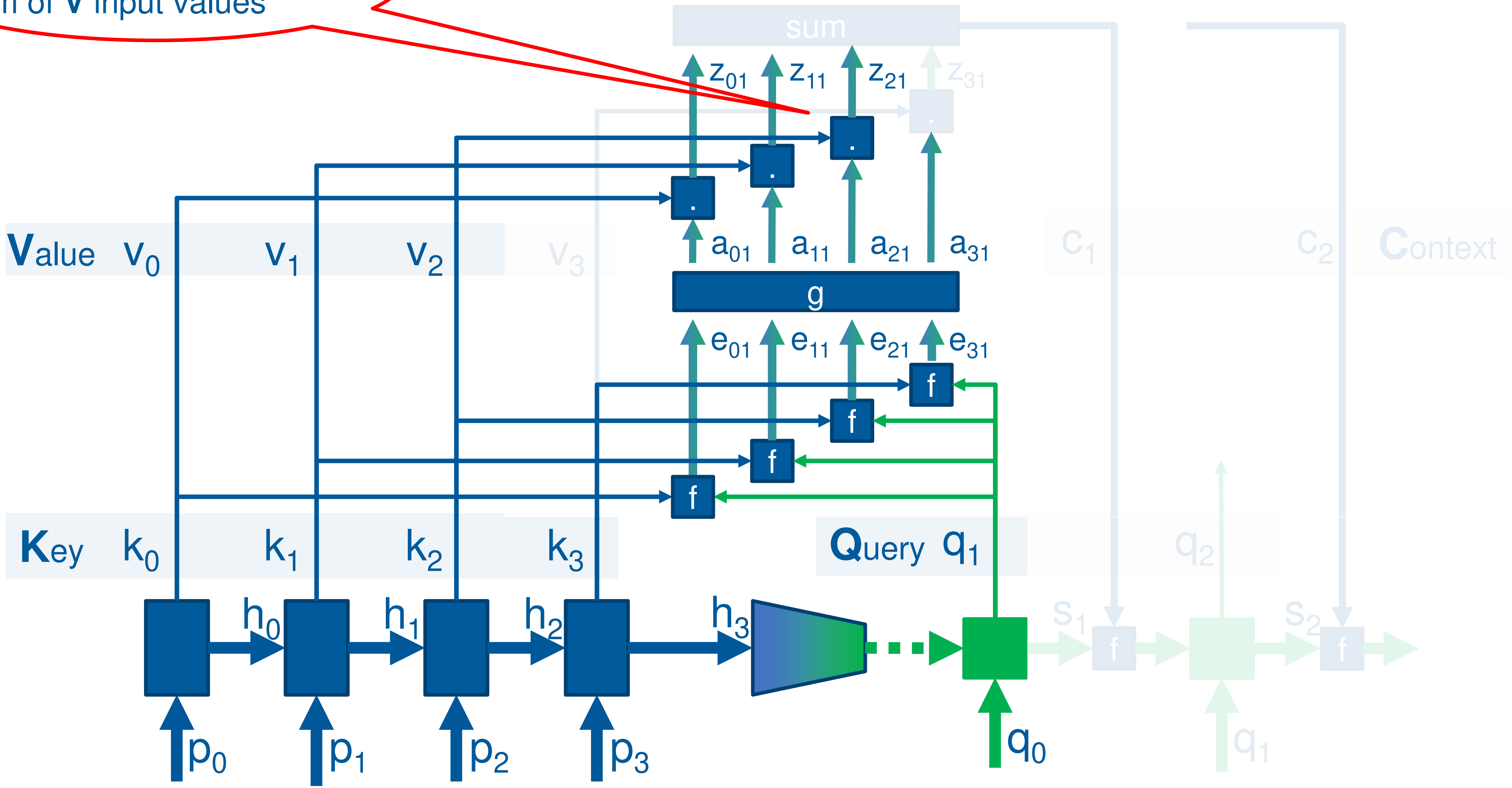
Compute the **A** weighted sum of **V** input values

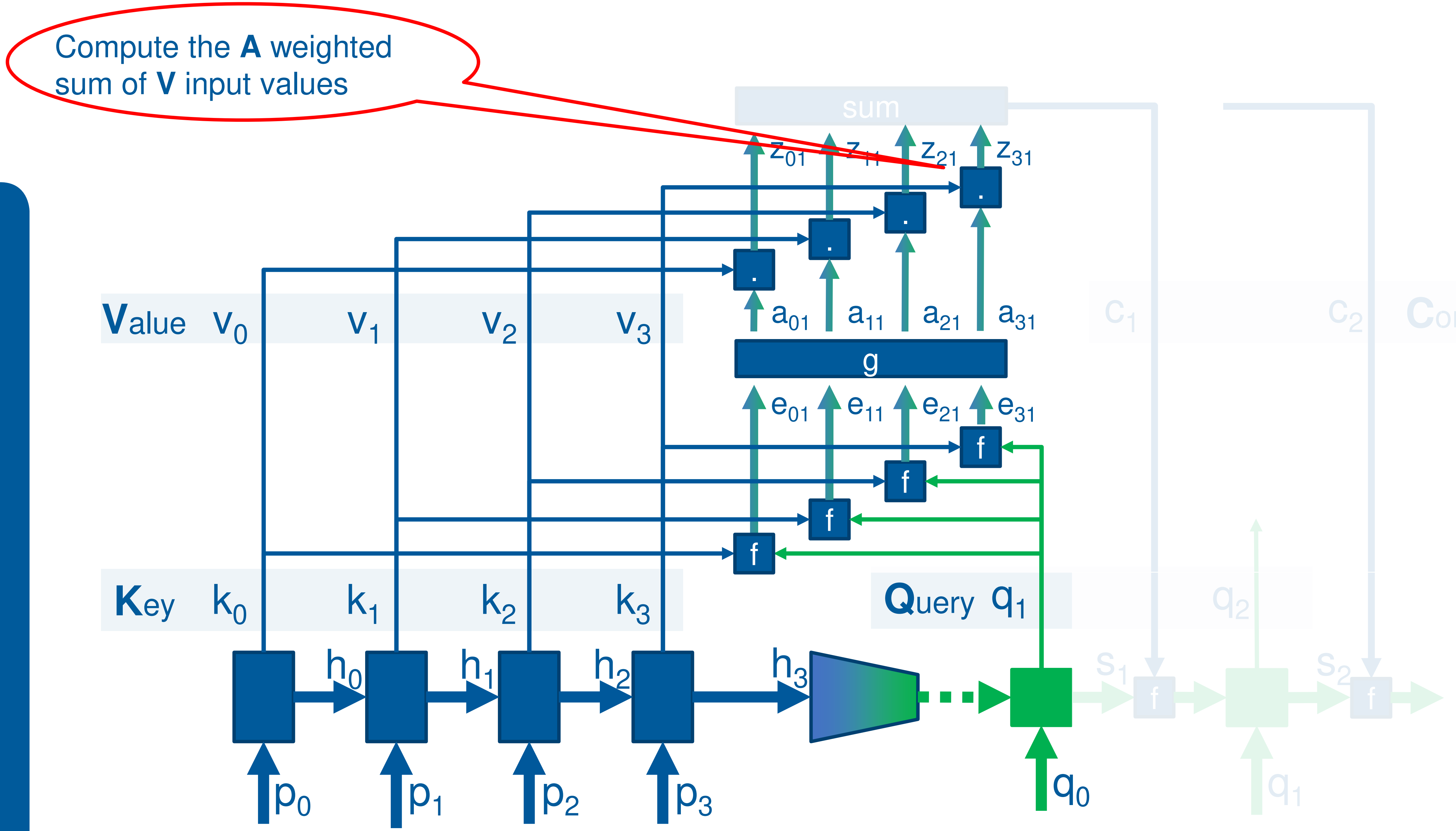


Compute the **A** weighted sum of **V** input values



Compute the **A** weighted sum of **V** input values





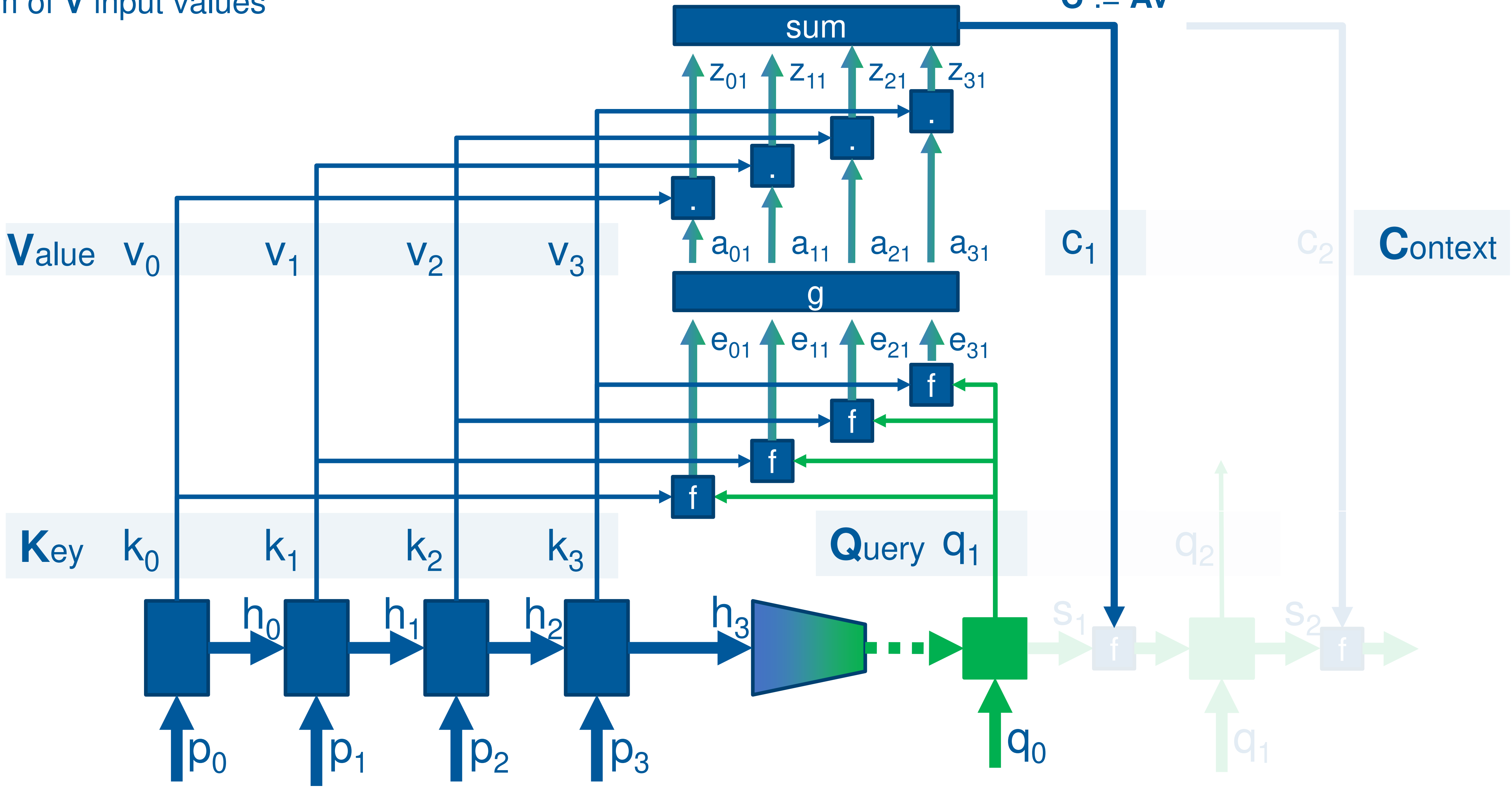
Compute the **A** weighted sum of **V** input values
sum
z_{01} z_{11} z_{21} z_{31}
a_{01} a_{11} a_{21} a_{31}
g
e_{01} e_{11} e_{21} e_{31}
f
Value v_0 v_1 v_2 v_3
Key k_0 k_1 k_2 k_3
Query q_1
h_0 h_1 h_2 h_3
p_0 p_1 p_2 p_3
q_0
c_1 c_2 **C**ontext
q_2
s_1 s_2
q_1

Compute the **A** weighted sum of **V** input values

$\mathbf{E} := f(\mathbf{K},\mathbf{Q}) = \mathbf{QK}^T$

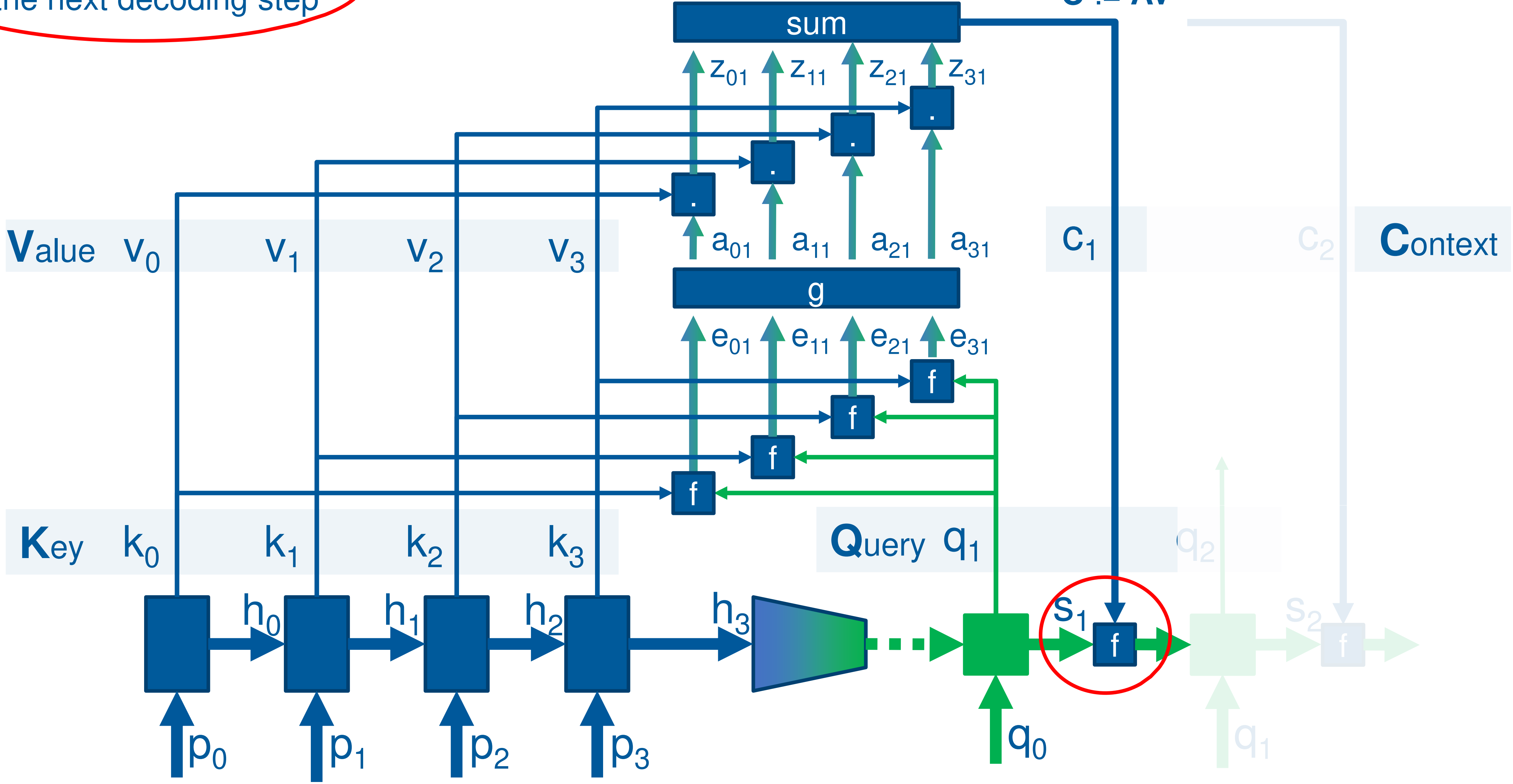
$\mathbf{A} := G(\mathbf{E}) = \mathrm{softmax}(\mathbf{E})$

$\mathbf{C} := \mathbf{AV}$

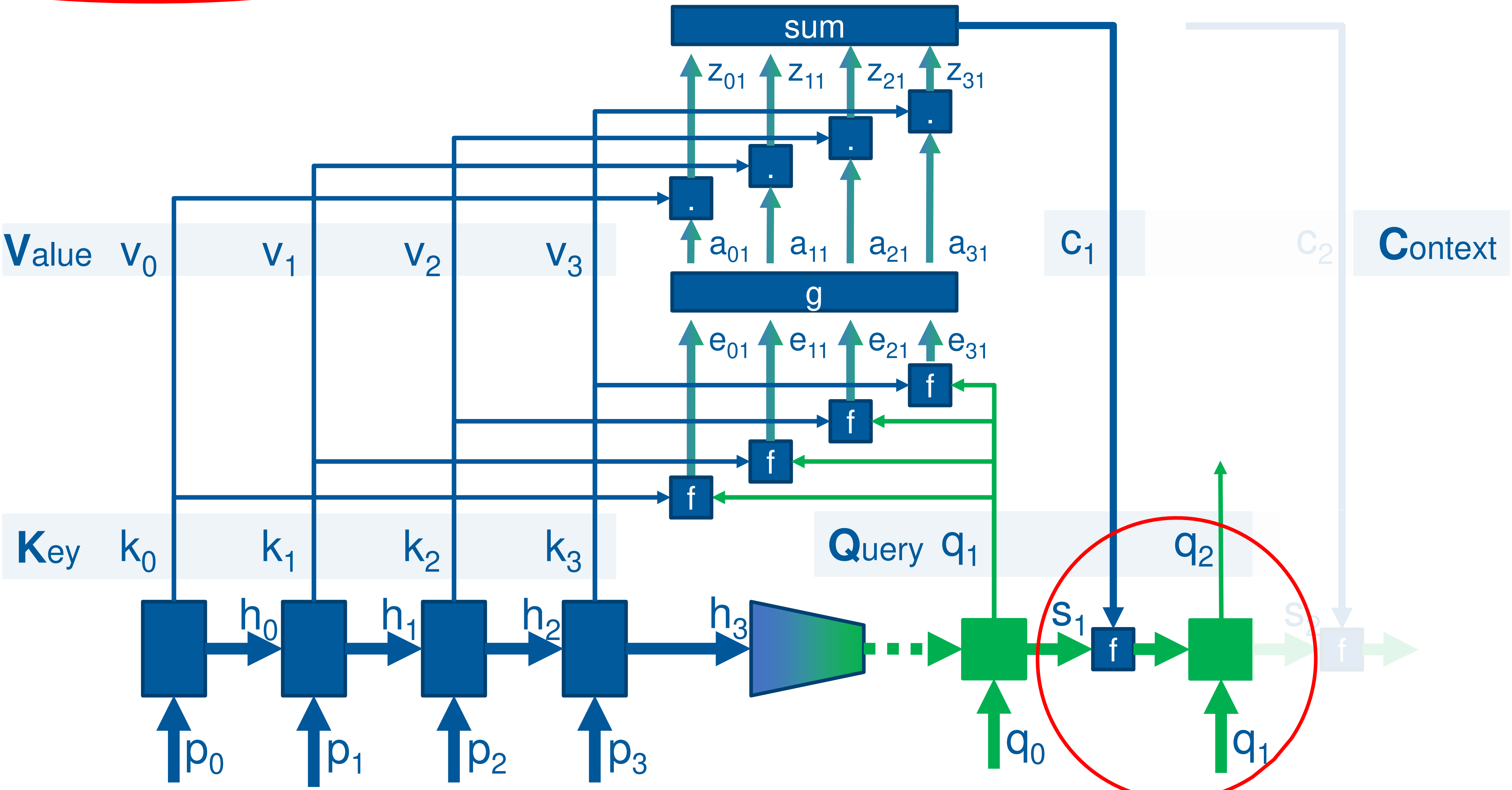


Introduce context vector c_0 to the next decoding step

$E := f(K,Q) = QK^T$
$A := G(E) = \text{softmax}(E)$
$C := AV$

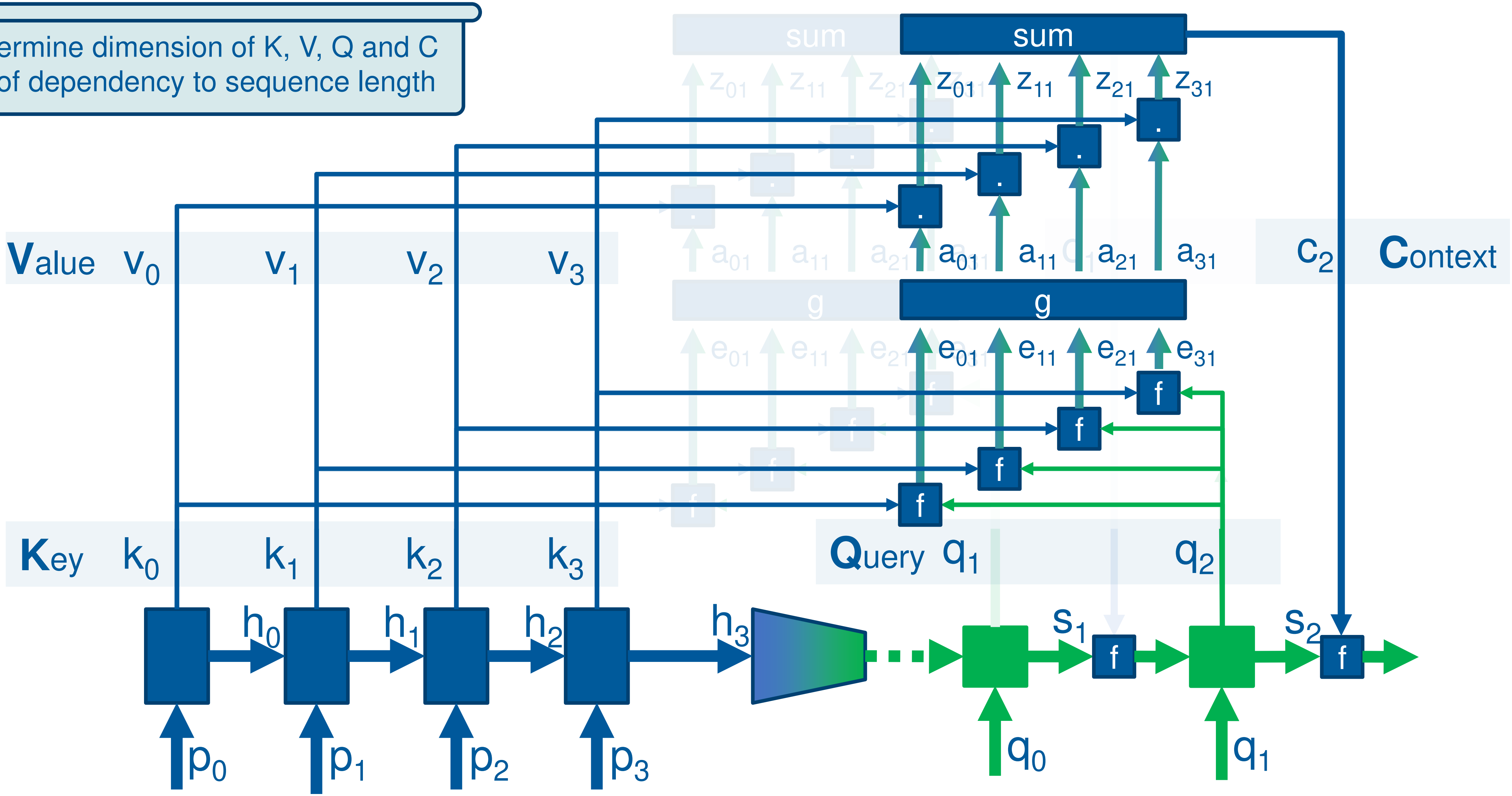


Compute next decoder step



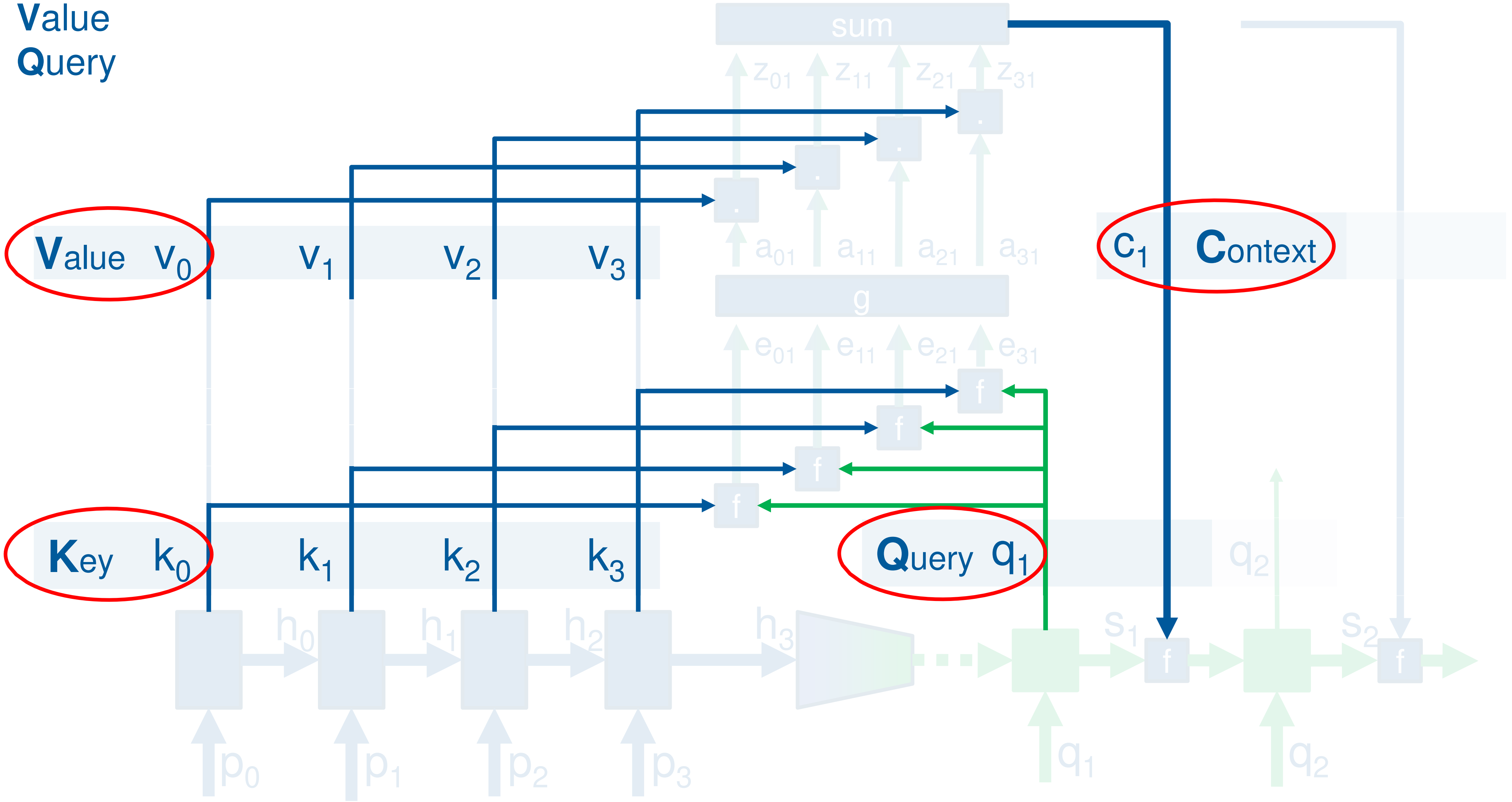
Repeat the attention process

- Determine dimension of K, V, Q and C
- Proof dependency to sequence length



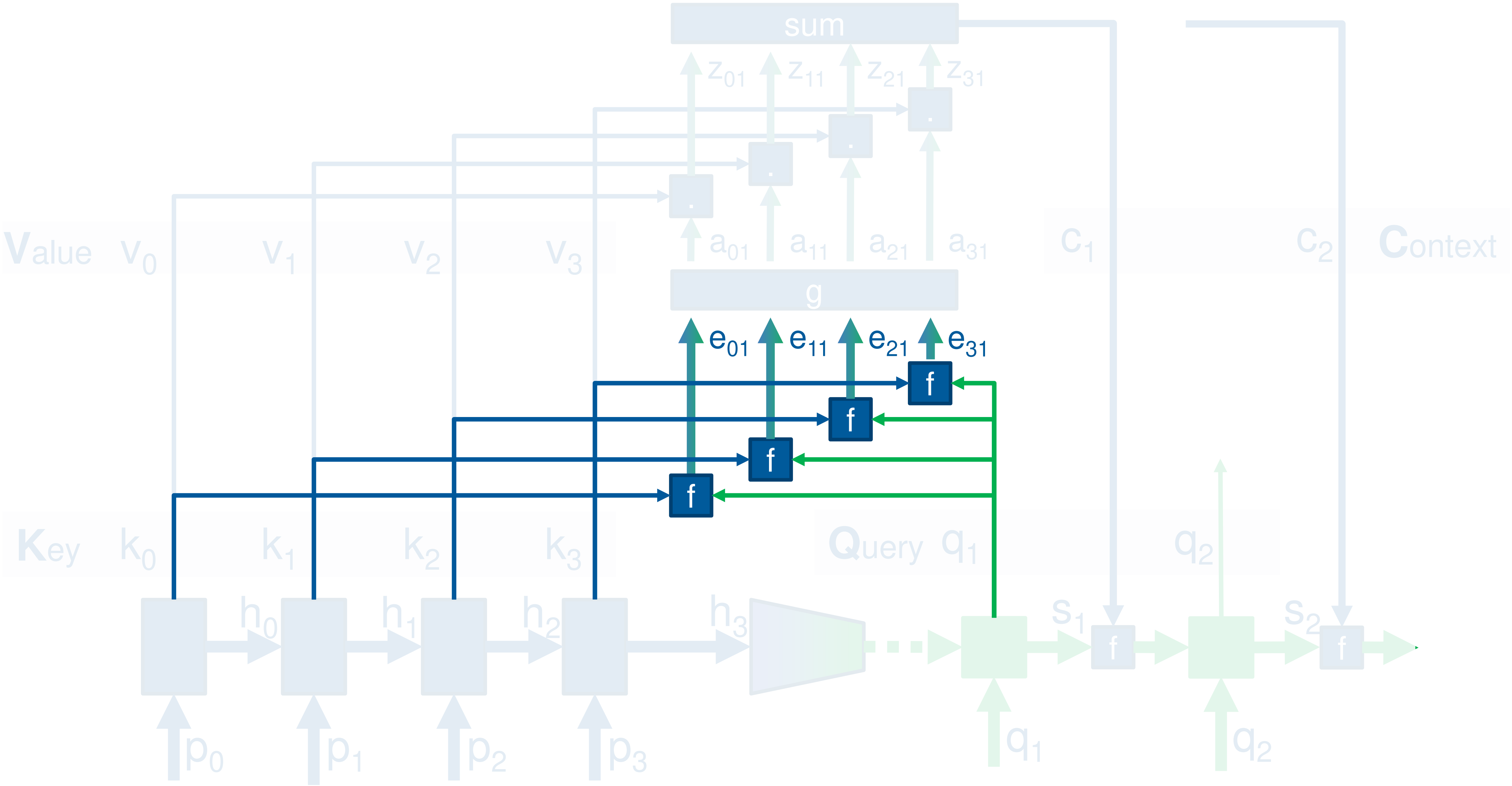
Input:
- Key
- Value
- Query

Output:
- Context



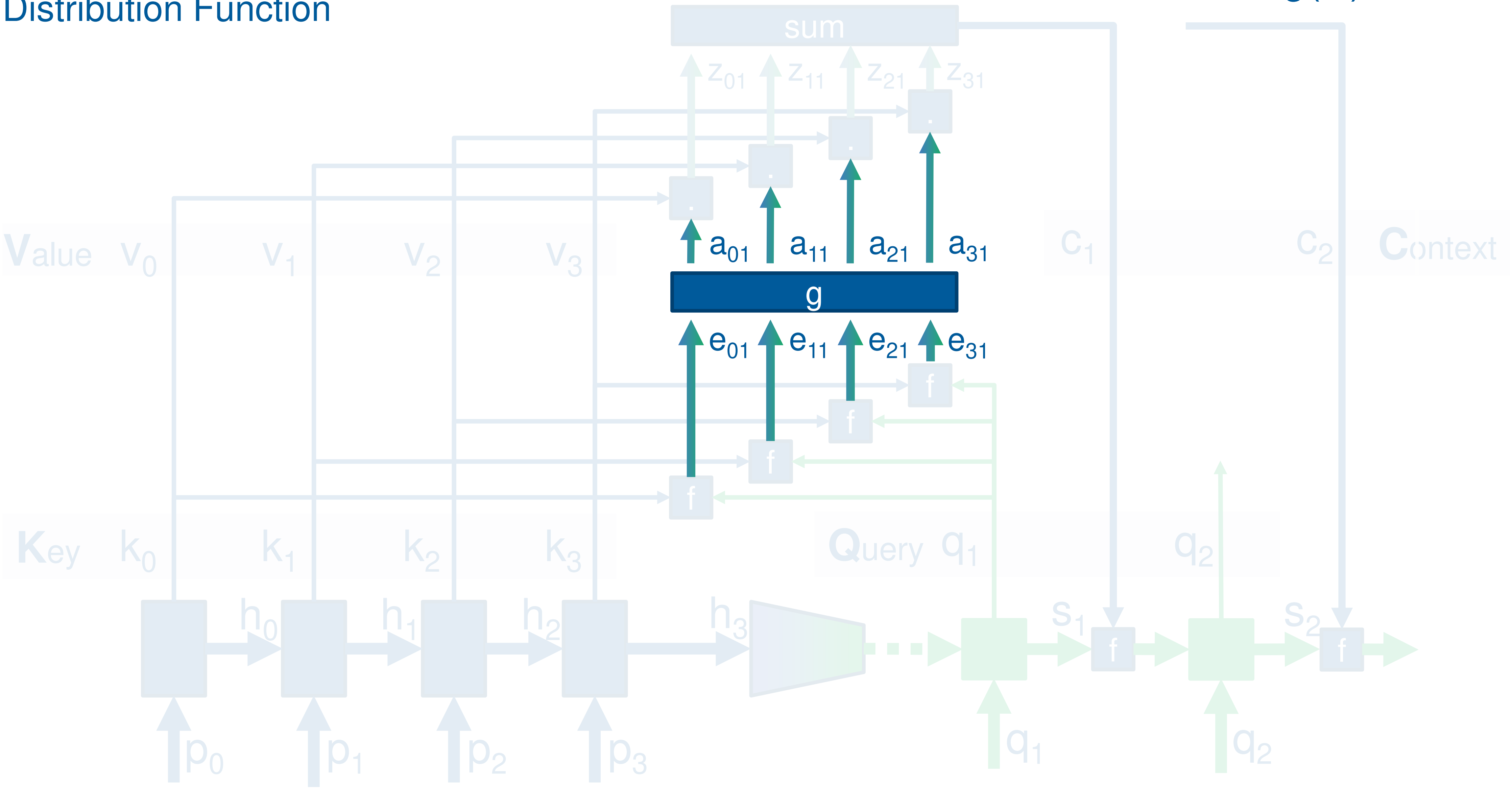
(1) Compatibility Function

$\mathbf{E} := f(\mathbf{K},\mathbf{Q})$



(1) Compatibility Function
(2) Distribution Function

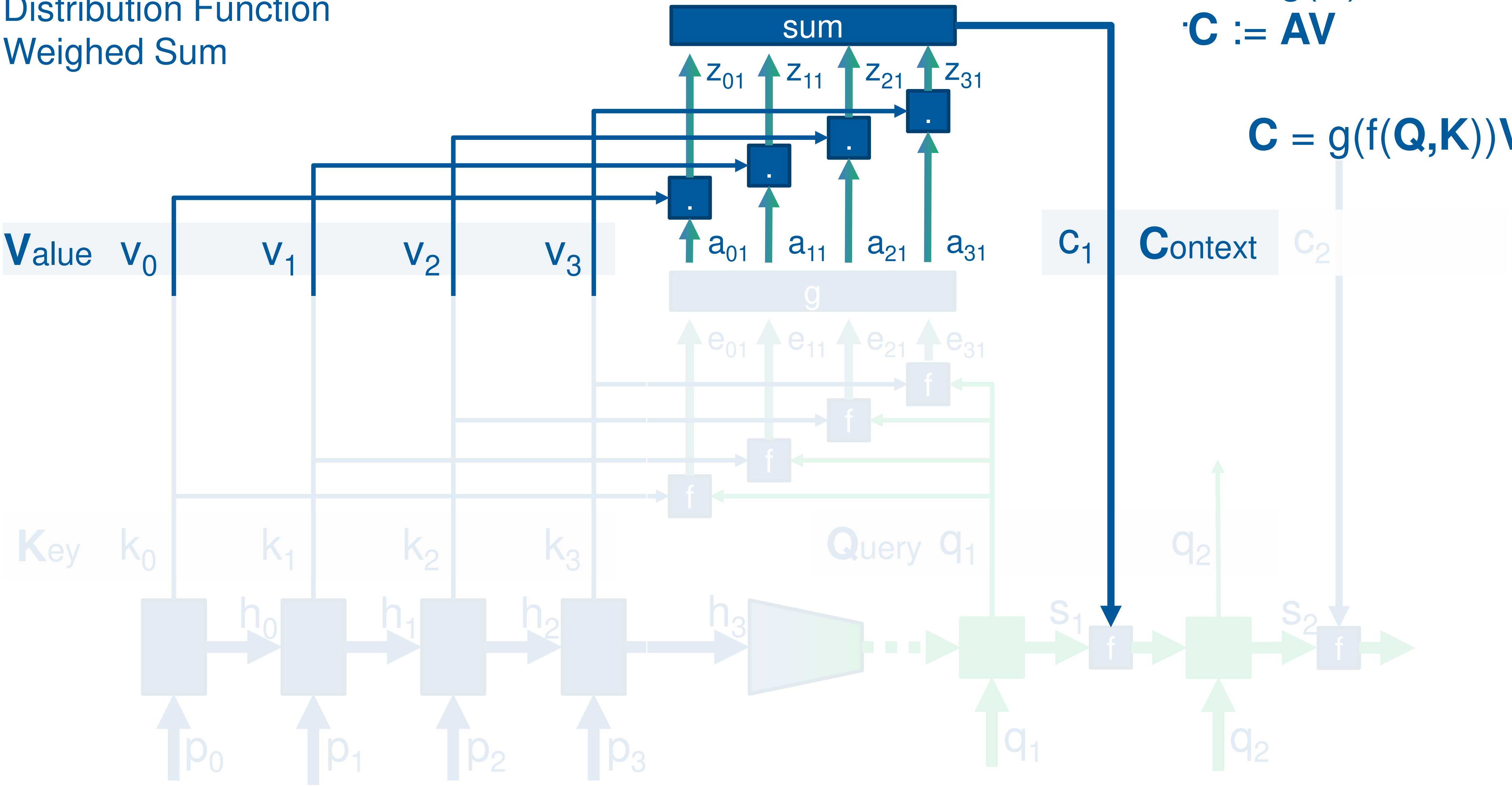
$\mathbf{E} := f(\mathbf{K},\mathbf{Q})$
$\mathbf{A} := g(\mathbf{E})$



(1) Compatibility Function
(2) Distribution Function
(3) Weighed Sum

$\mathbf{E} := f(\mathbf{K},\mathbf{Q})$
$\mathbf{A} := g(\mathbf{E})$
$\mathbf{C} := \mathbf{AV}$

$\mathbf{C} = g(f(\mathbf{Q},\mathbf{K}))\mathbf{V}$



Attention Layer

(1) Compatibility Function	$\mathbf{E}$	$= f(\mathbf{K},\mathbf{Q})$
(2) Distribution Function	$\mathbf{A}$	$= g(\mathbf{E})$
(3) Weighed Sum	$\mathbf{C}$	$= \mathbf{AV}$

$$\mathbf{C} = g(f(\mathbf{K},\mathbf{Q}))\mathbf{V}$$

Dot-Product Attention

(1) Compatibility Function	$\mathbf{E}$	$= f(\mathbf{K},\mathbf{Q}) := \mathbf{Q}\mathbf{K}^T$
(2) Distribution Function	$\mathbf{A}$	$= g(\mathbf{E}) := \mathrm{softmax}(\mathbf{E})$
(3) Weighed Sum	$\mathbf{C}$	$= \mathbf{A}\mathbf{V}$

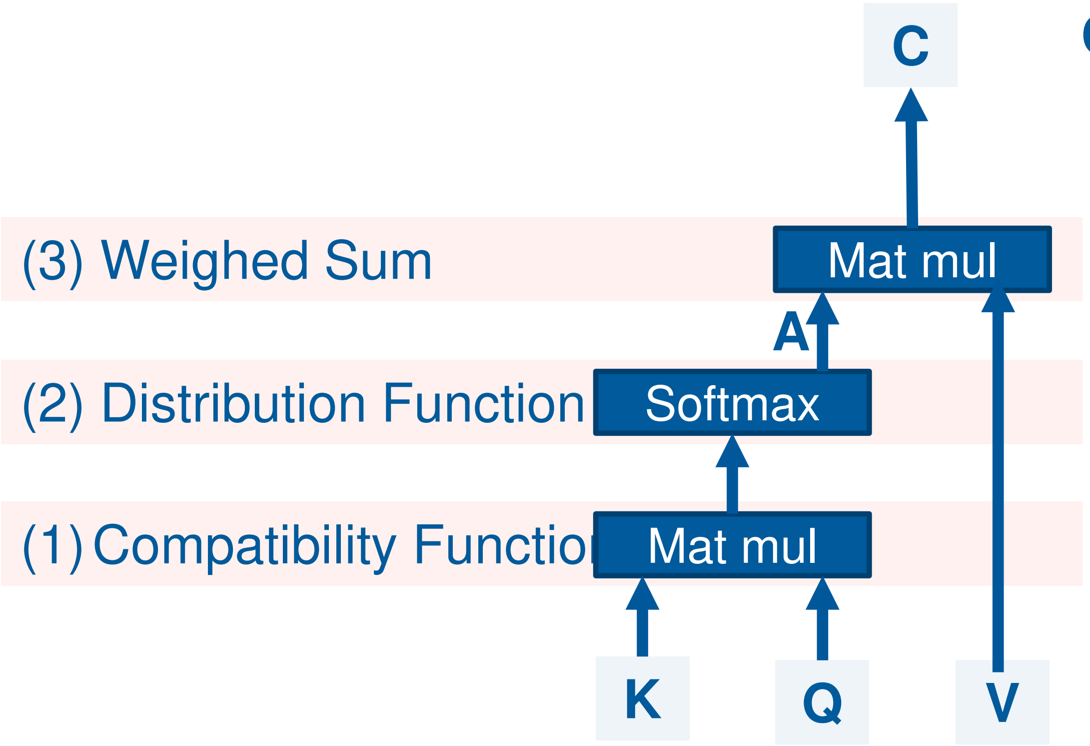
$$\mathbf{C} = \mathrm{softmax}(\mathbf{Q}\mathbf{K}^T)\mathbf{V}$$

Note: There are no weights to train!

Compatibility Function in Attention

Name	Equation	Reference
similarity	$f(\boldsymbol{q}, \boldsymbol{K}) = sim(\boldsymbol{q}, \boldsymbol{K})$	Graves et al., 2014
multiplicative or *dot*	$f(\boldsymbol{q}, \boldsymbol{K}) = \boldsymbol{q}^\intercal \boldsymbol{K}$	Luong et al., 2015
scaled multiplicative	$f(\boldsymbol{q}, \boldsymbol{K}) = \frac{\boldsymbol{q}^\intercal \boldsymbol{K}}{\sqrt{d_k}}$	Vaswani et al., 2017
general or *bilinear*	$f(\boldsymbol{q}, \boldsymbol{K}) = \boldsymbol{q}^\intercal \boldsymbol{W} \boldsymbol{K}$	Luong et al., 2015
biased general	$f(\boldsymbol{q}, \boldsymbol{K}) = \boldsymbol{K}^\intercal (\boldsymbol{W} \boldsymbol{q} + \boldsymbol{b})$	Sordoni et al., 2016
activated general	$f(\boldsymbol{q}, \boldsymbol{K}) = act(\boldsymbol{q}^\intercal \boldsymbol{W} \boldsymbol{K} + \boldsymbol{b})$	Ma et al., 2017
concat	$f(\boldsymbol{q}, \boldsymbol{K}) = \boldsymbol{w_{imp}}^\intercal act\big(\boldsymbol{W}[\boldsymbol{K}; \boldsymbol{q}] + \boldsymbol{b}\big)$	Luong et al., 2015
additive	$f(\boldsymbol{q}, \boldsymbol{K}) = \boldsymbol{w_{imp}}^\intercal act(\boldsymbol{W_1} \boldsymbol{K} + \boldsymbol{W_2} \boldsymbol{q} + \boldsymbol{b})$	Bahdanau et al., 2015
deep	$f(\boldsymbol{q}, \boldsymbol{K}) = \boldsymbol{w_{imp}}^\intercal \boldsymbol{E}^{(L-1)} + \boldsymbol{b}^L$ $\boldsymbol{E}^{(l)} = act(\boldsymbol{W_l} \boldsymbol{E}^{(l-1)} + \boldsymbol{b}^l)$ $\boldsymbol{E}^{(1)} = act(\boldsymbol{W_1} \boldsymbol{K} + \boldsymbol{W_0} \boldsymbol{q} + \boldsymbol{b}^1)$	Pavlopoulos et al., 2017
location-based	$f(\boldsymbol{q}, \boldsymbol{K}) = f(\boldsymbol{q})$	Luong et al., 2015

Dot-Product Attention

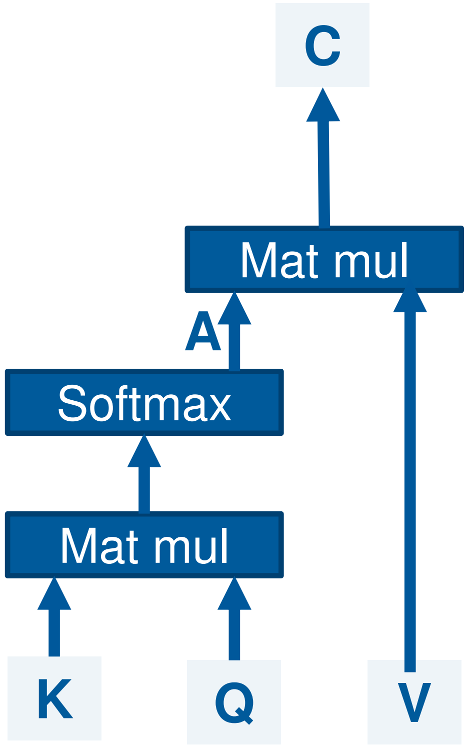


$\mathbf{C} = \text{softmax}(\mathbf{Q}\mathbf{K}^T)\mathbf{V}$:= **Dot-Product Attention**

```python
def forward(self, K, V, Q):
    E = self.compatibility_function(K, Q)
    A = self.distribution_function(E)
    C = self.weighted_sum(V,A)
    return C, A
```

Compute number of parameters

Dot-Product Attention: Are there issues?

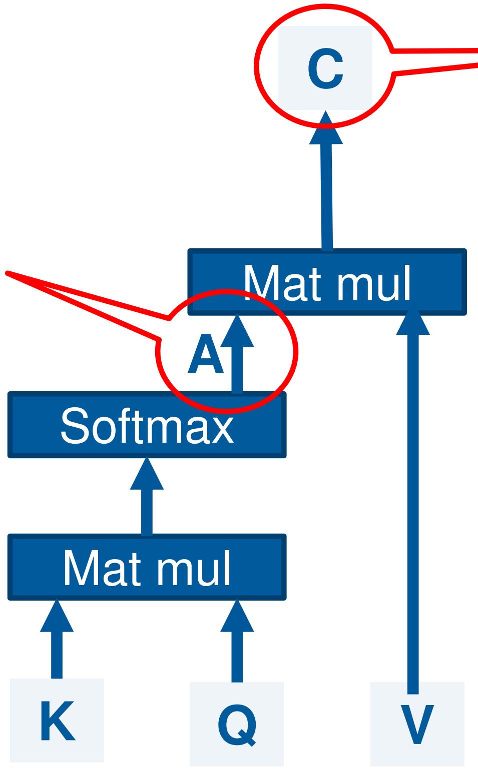


Intent Classification: P(<intent> | <word sequence>)

WIE WIRD MORGEN DAS **WETTER** IN MÜNCHEN ? => WEATHERFORECAST
WIE WIRD MORGEN DAS WETTER IN **MÜNCHEN** ? => LOCATION
WIE WIRD **MORGEN** DAS WETTER IN MÜNCHEN ? => DATE
WIE WIRD MORGEN DAS WETTER IN MÜNCHEN **?** => QUESTION
WIE **WIRD** MORGEN **DAS** WETTER **IN** MÜNCHEN ? => NOISE

Dot-Product Attention: Are there issues?

This is just 1 scalar
for each value-vector
in the input sequence!



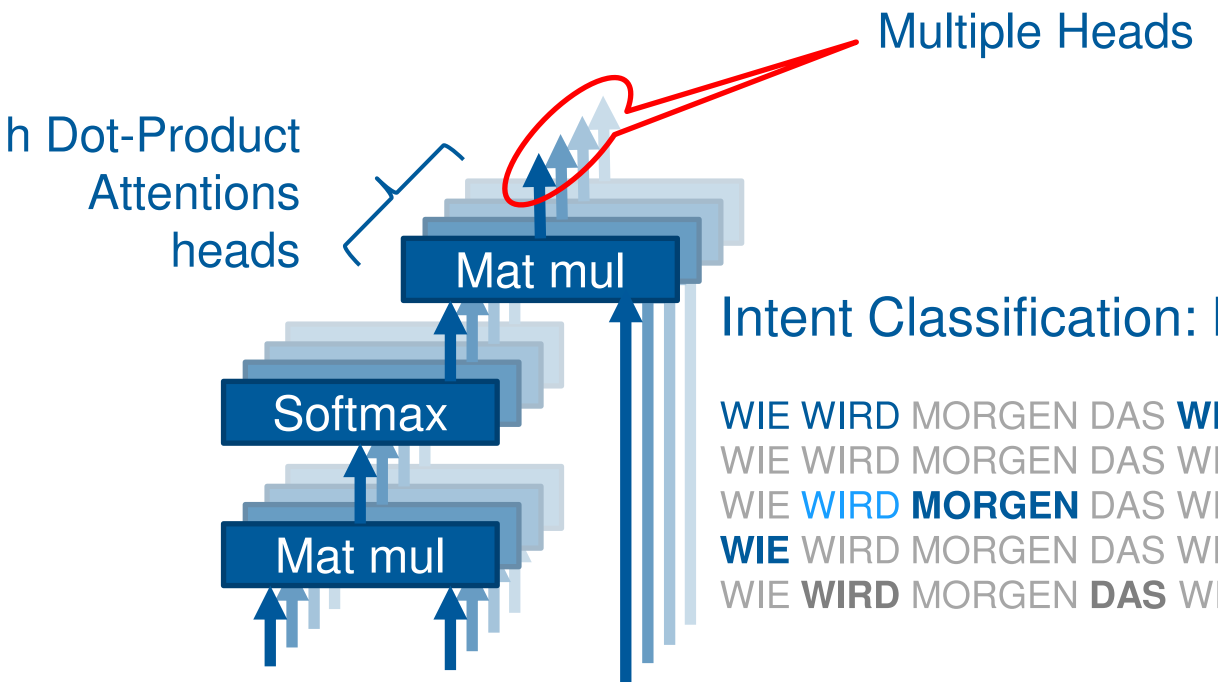
The context vector can only focus on one aspect of the input sequence, but language is not unique!

Intent Classification: P(<intent> | <word sequence>)

WIE WIRD MORGEN DAS **WETTER** IN MÜNCHEN ? => WEATHERFORECAST
WIE WIRD MORGEN DAS WETTER IN **MÜNCHEN** ? => LOCATION
WIE WIRD **MORGEN** DAS WETTER IN MÜNCHEN ? => DATE
WIE WIRD MORGEN DAS WETTER IN MÜNCHEN **?** => QUESTION
WIE **WIRD** MORGEN **DAS** WETTER **IN** MÜNCHEN ? => NOISE

Solution?

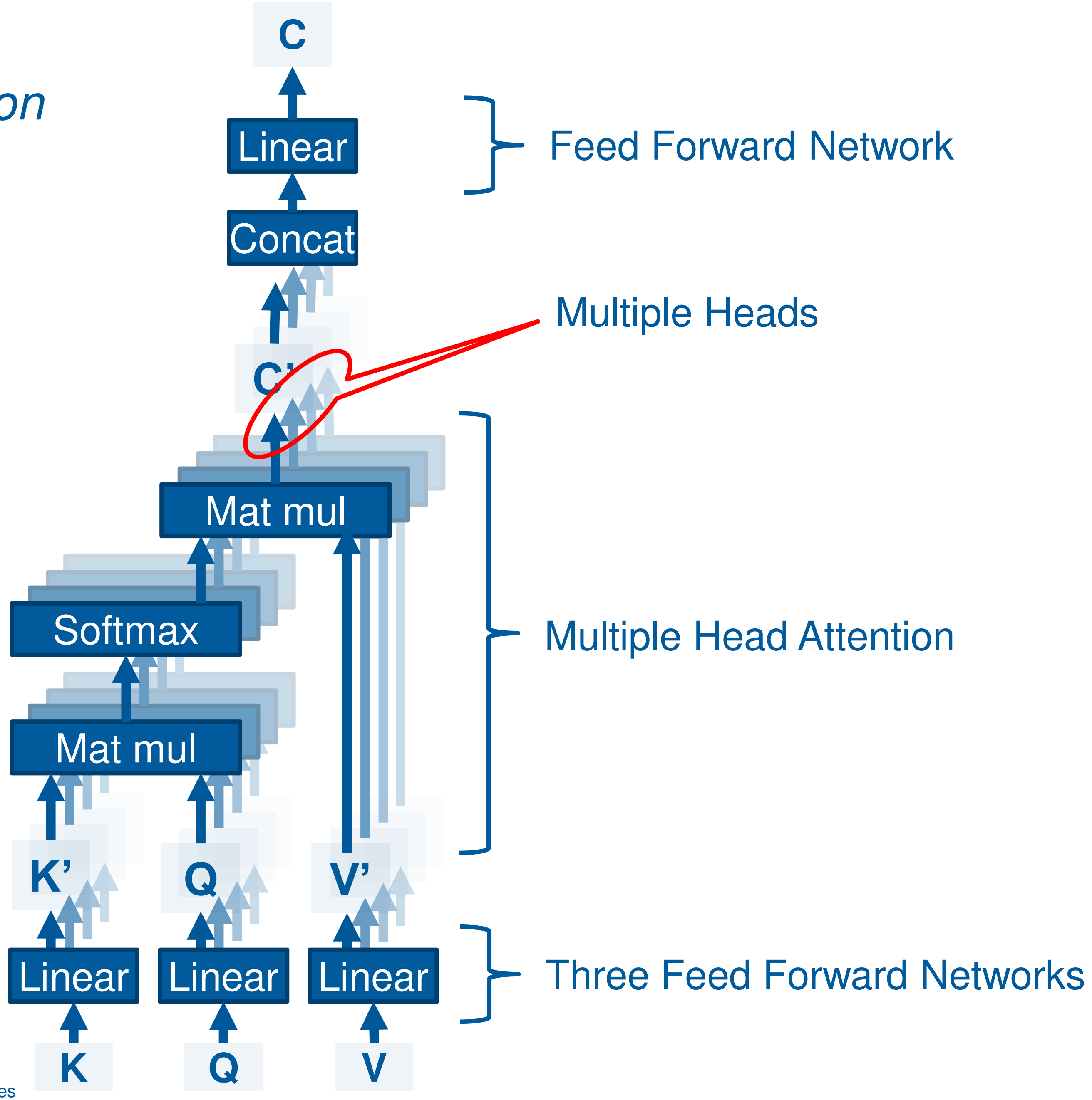
Dot-Product Attention: Are there issues?



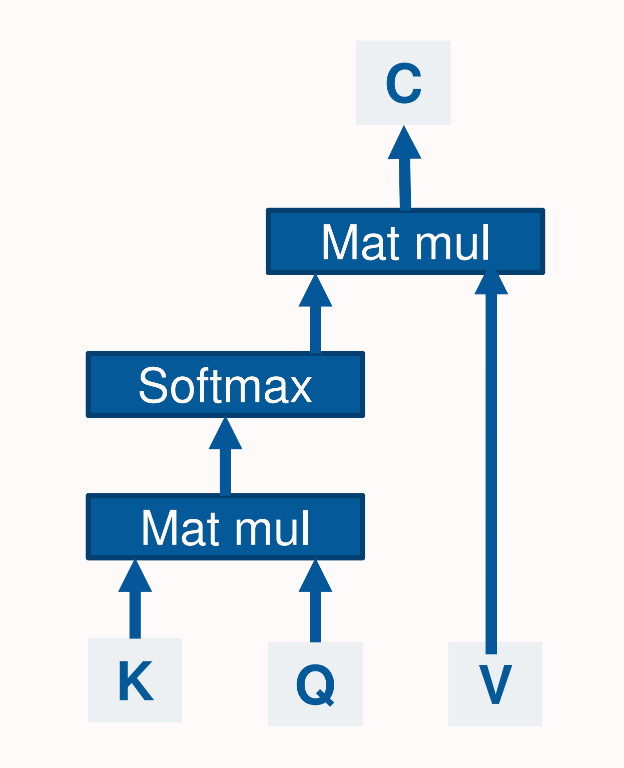
Intent Classification: P(<intent> | <word sequence>)

WIE WIRD MORGEN DAS **WETTER** IN MÜNCHEN ? => WEATHERFORECAST
WIE WIRD MORGEN DAS WETTER IN **MÜNCHEN** ? => LOCATION
WIE WIRD **MORGEN** DAS WETTER IN MÜNCHEN ? => DATE
WIE WIRD MORGEN DAS WETTER IN MÜNCHEN **?** => QUESTION
WIE **WIRD** MORGEN **DAS** WETTER **IN** MÜNCHEN ? => NOISE

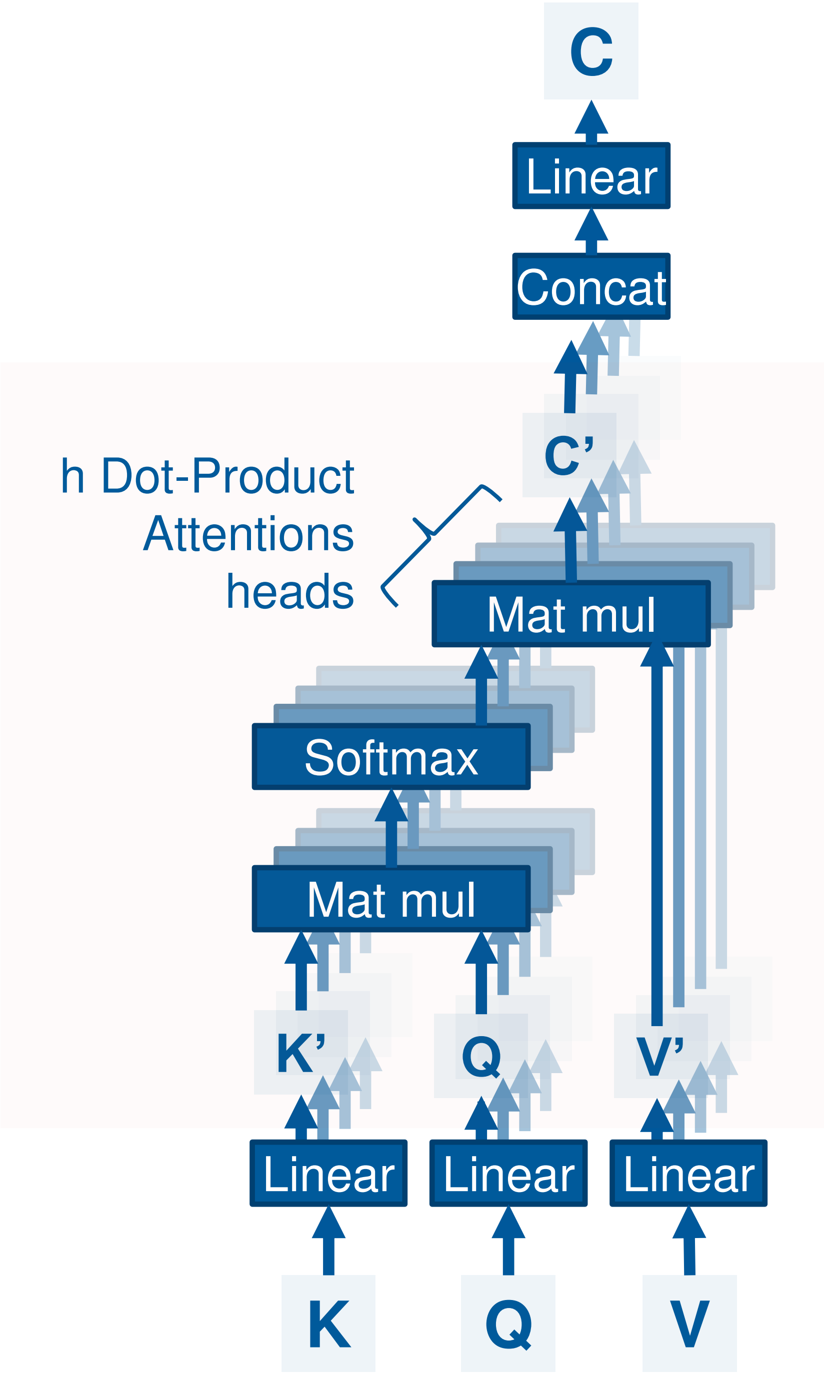
Multi-Head Attention



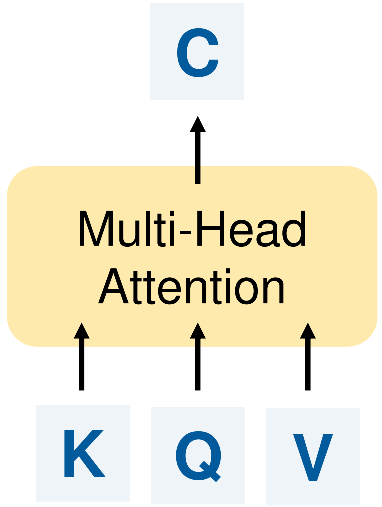
Multi-Head Dot-Product Attention



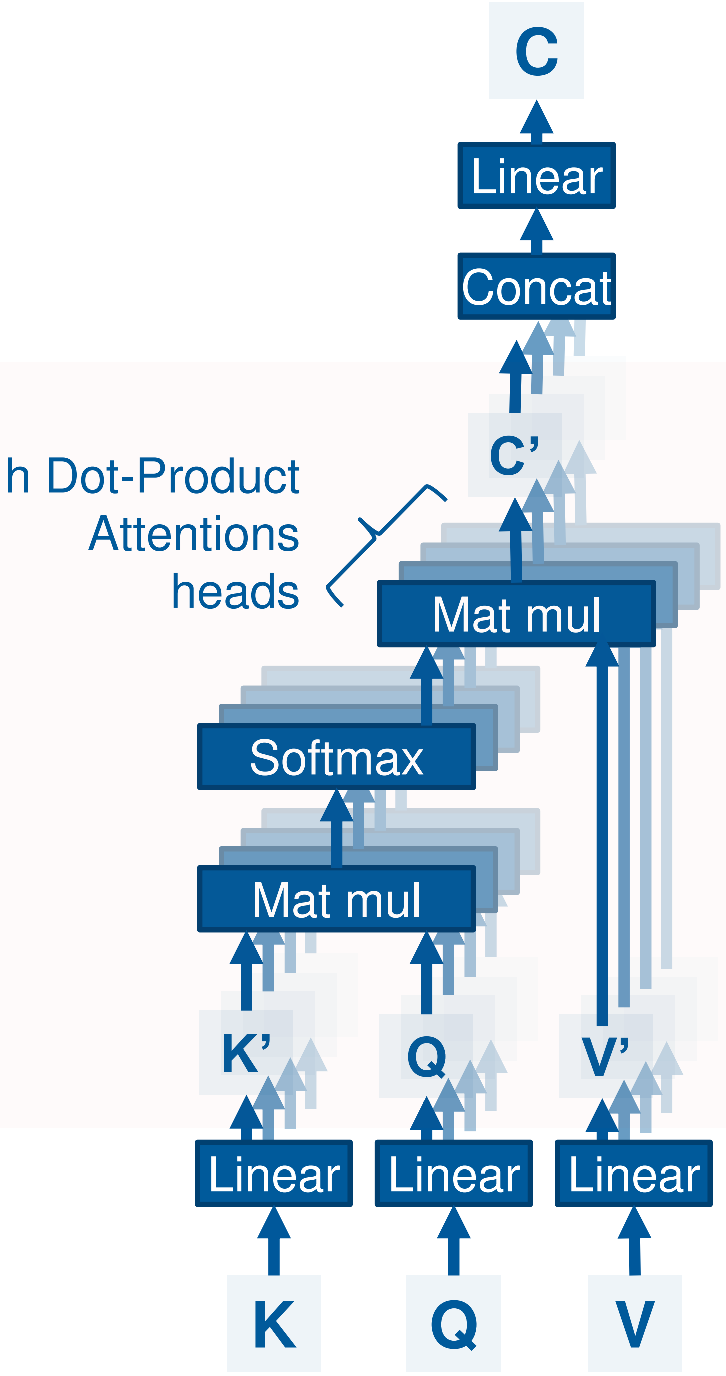
Let the model decided to attend on various aspects!



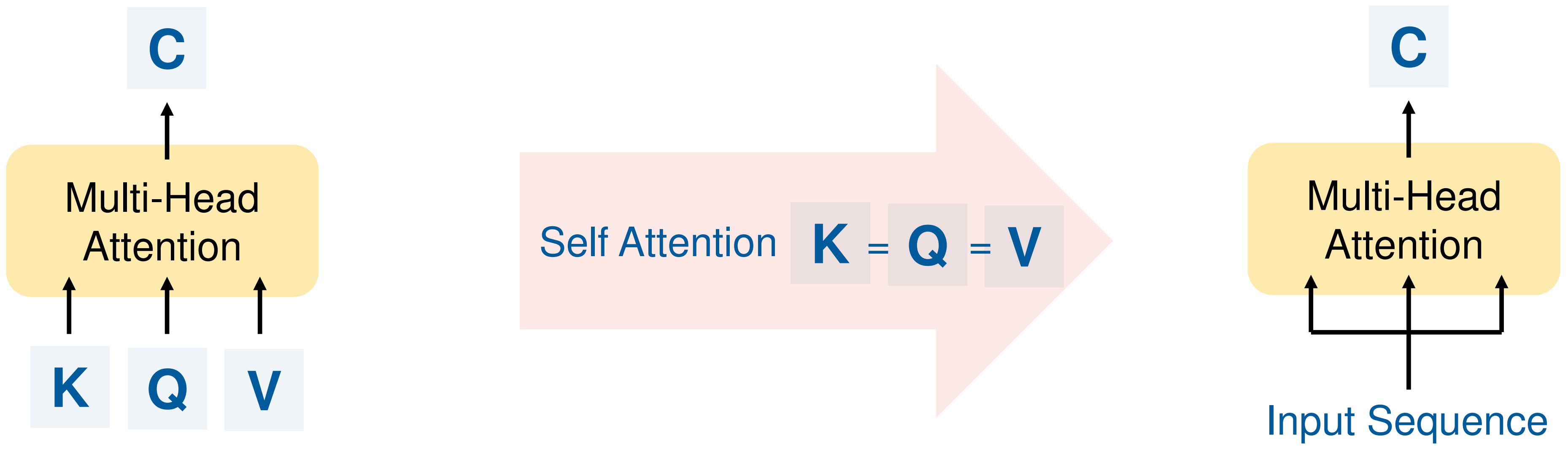
Multi-Head Dot-Product Attention



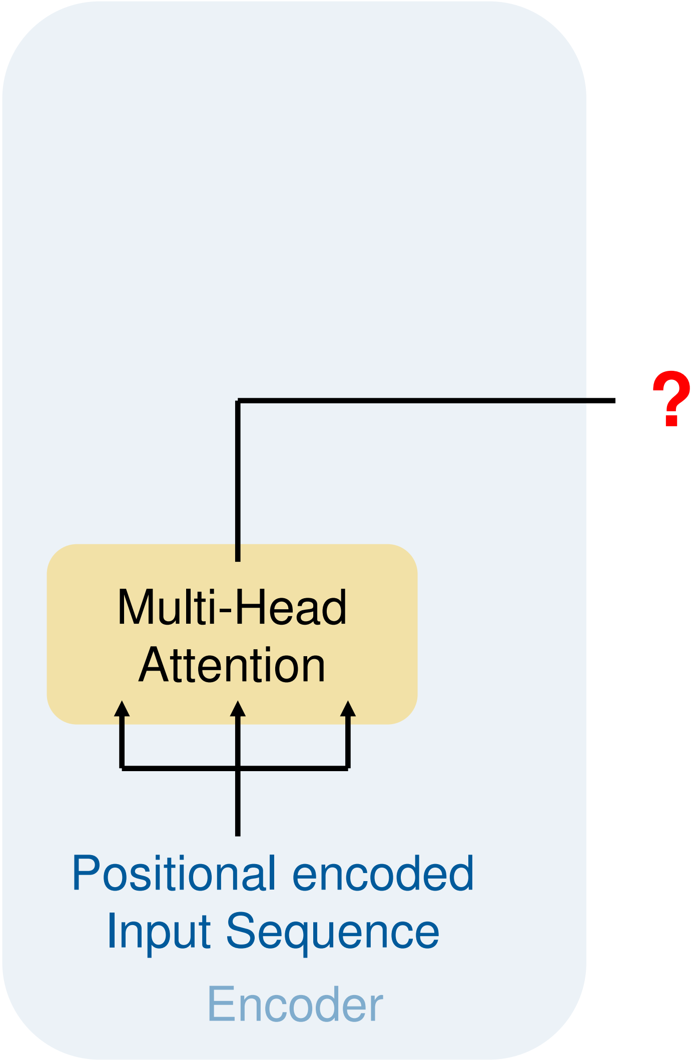
Let the model decided to attend on various aspects!



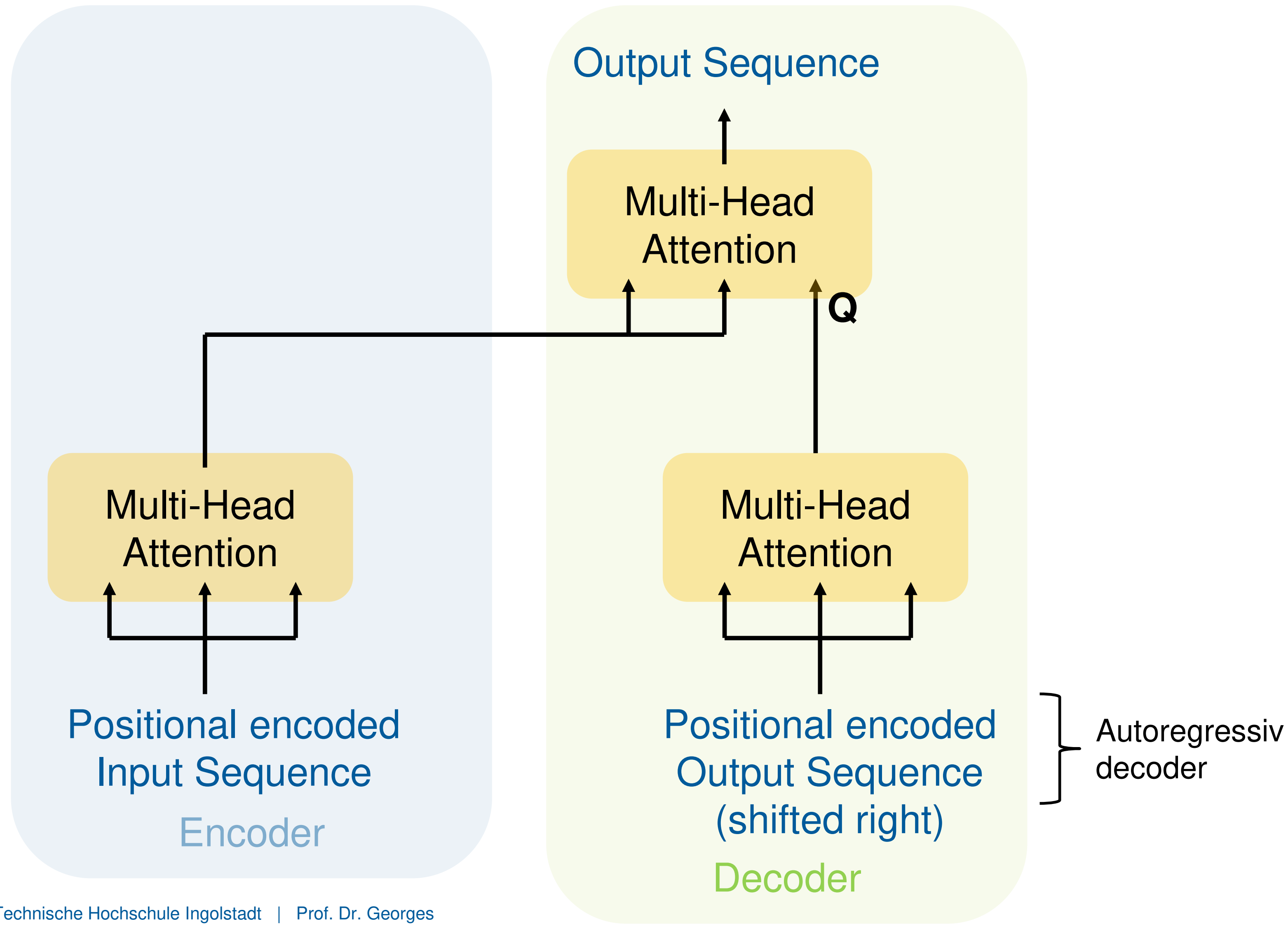
Multi-Head Self (Dot-Product) Attention



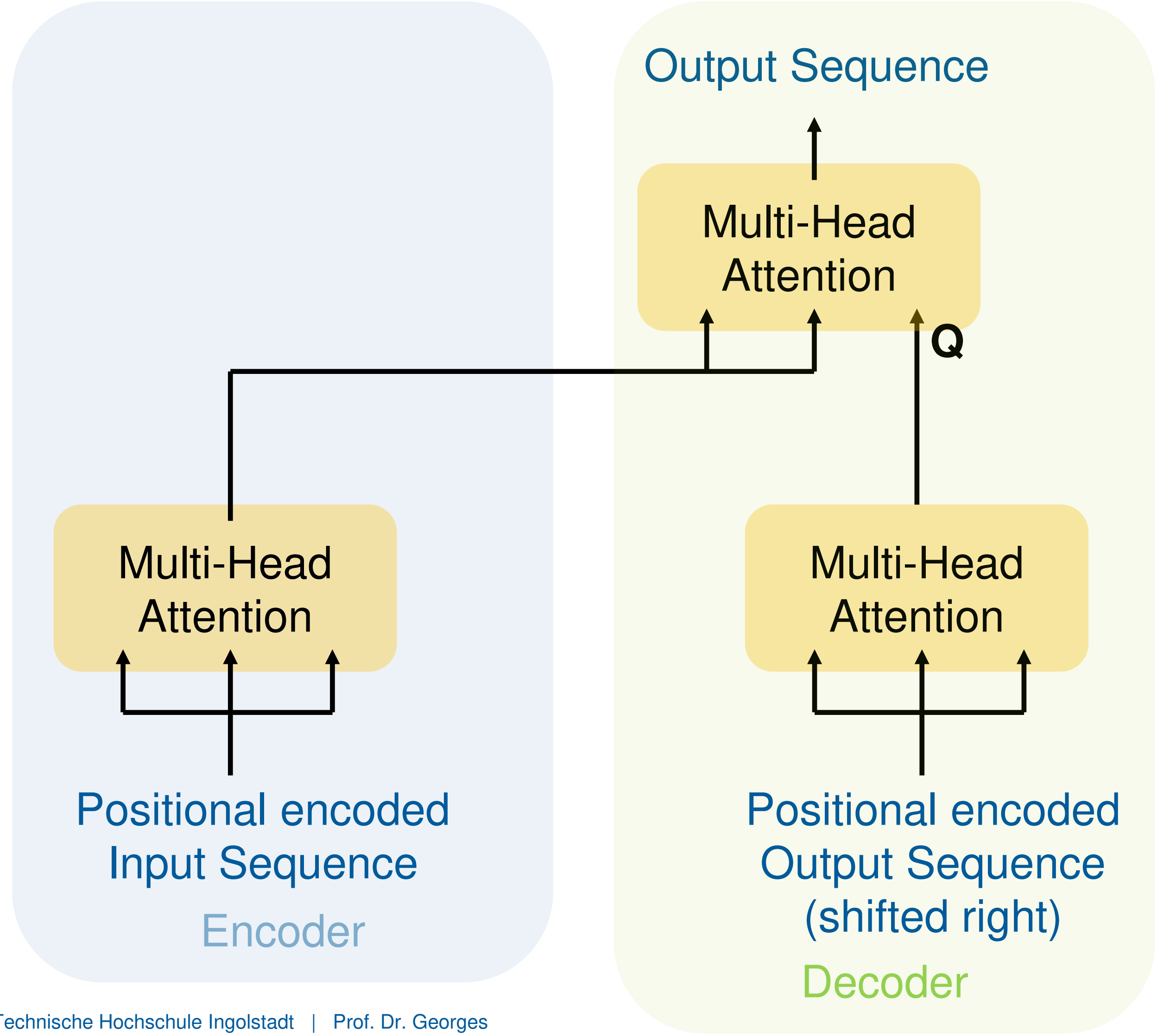
Transformer (simplified)

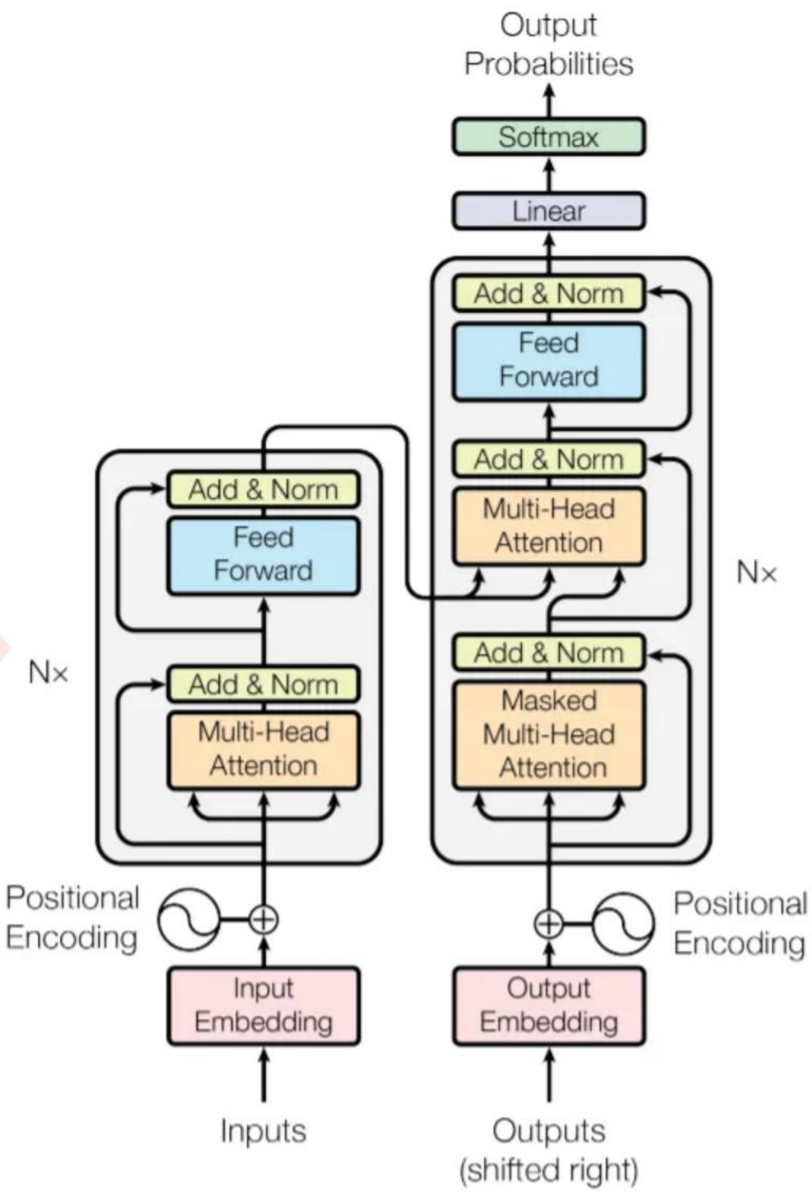


Transformer (simplified)



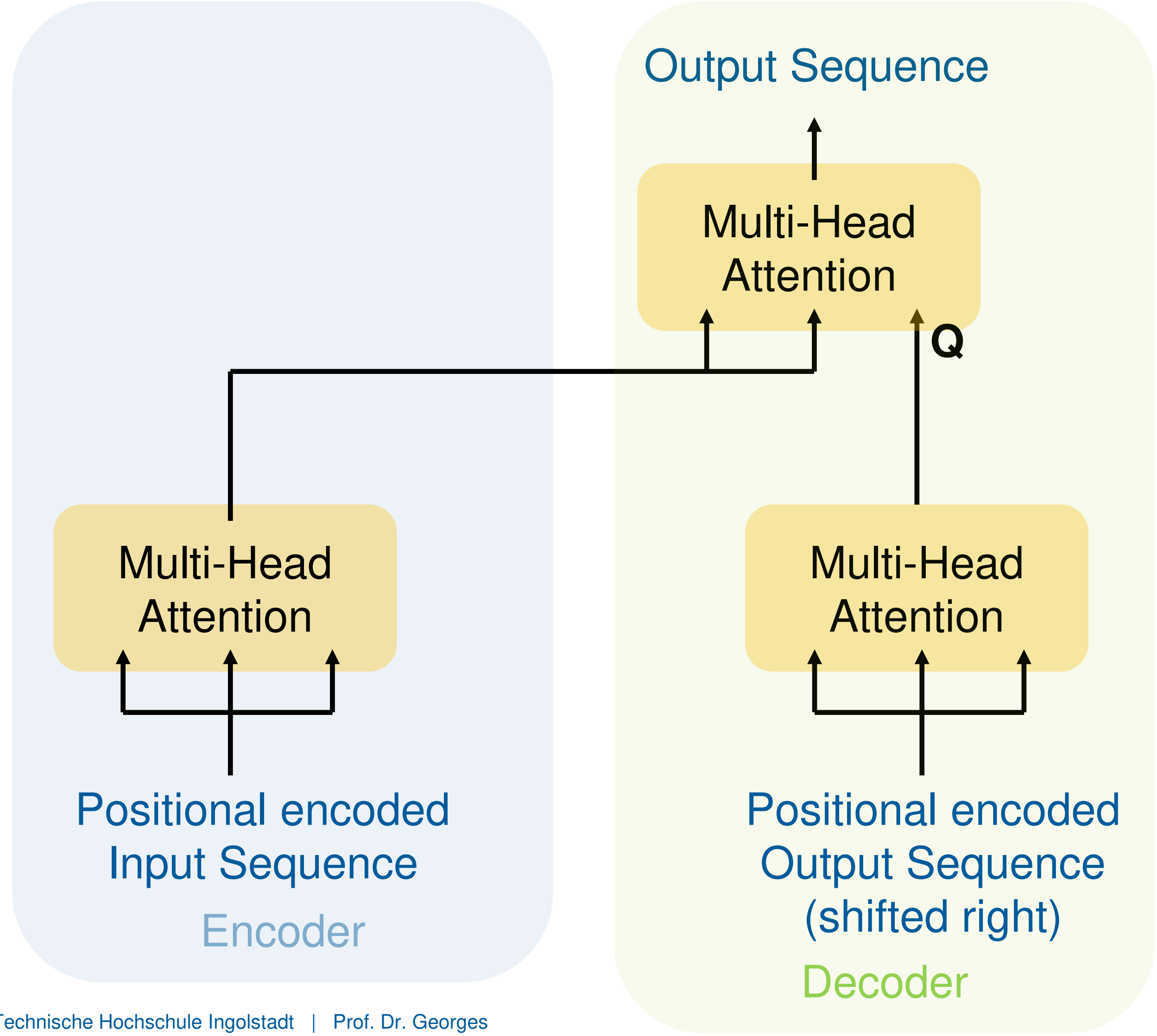
Transformer

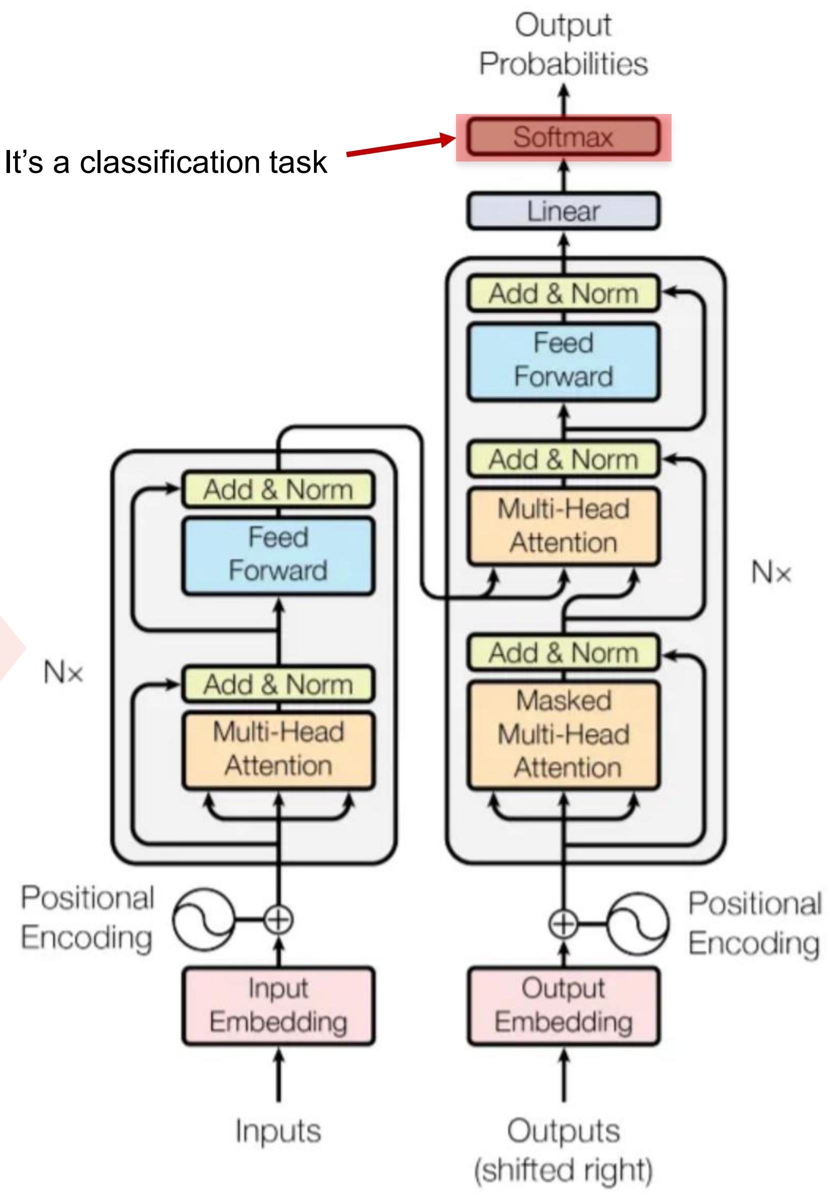




https://glassboxmedicine.com/2019/08/15/the-transformer-attention-is-all-you-need/

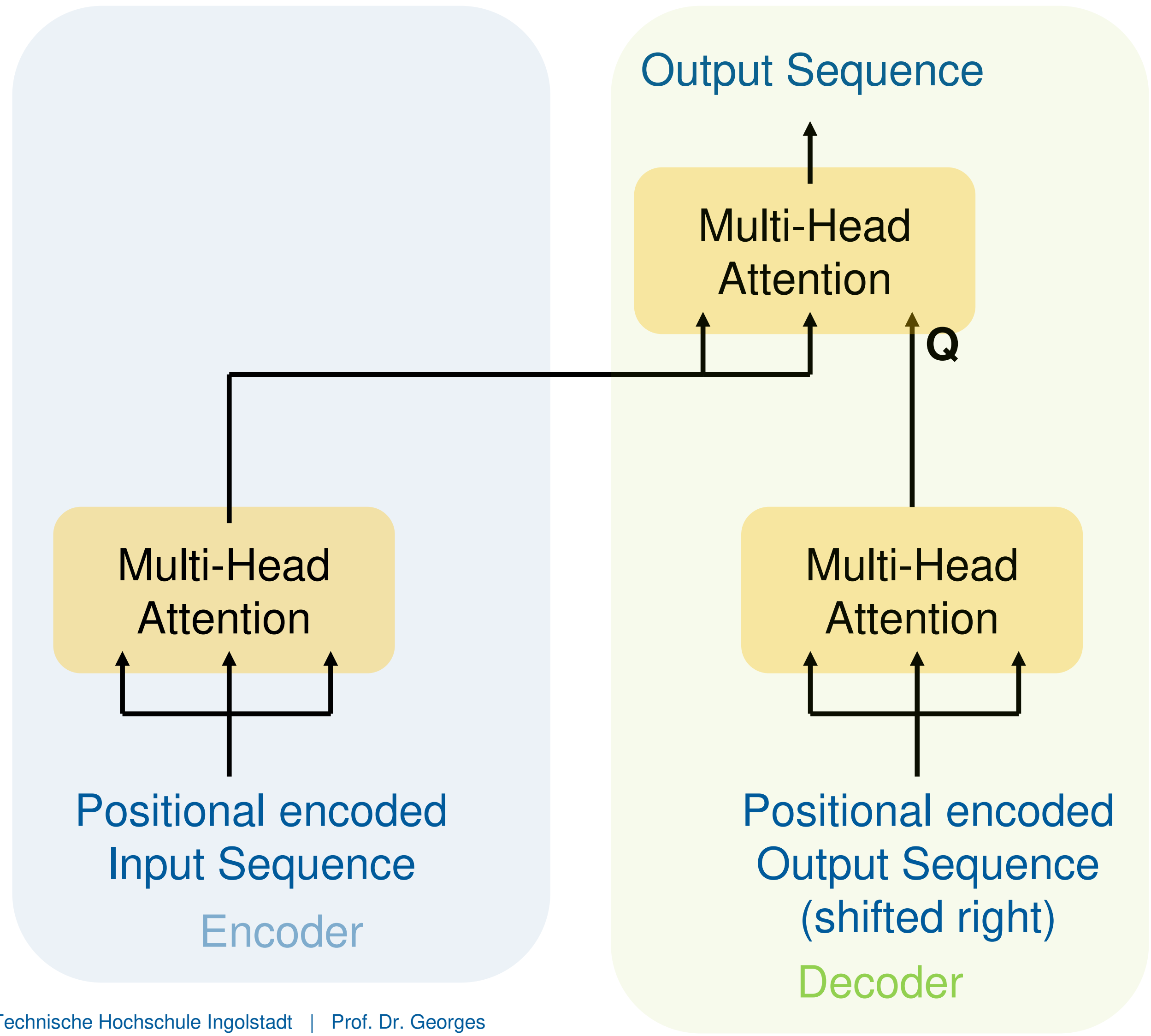
Transformer

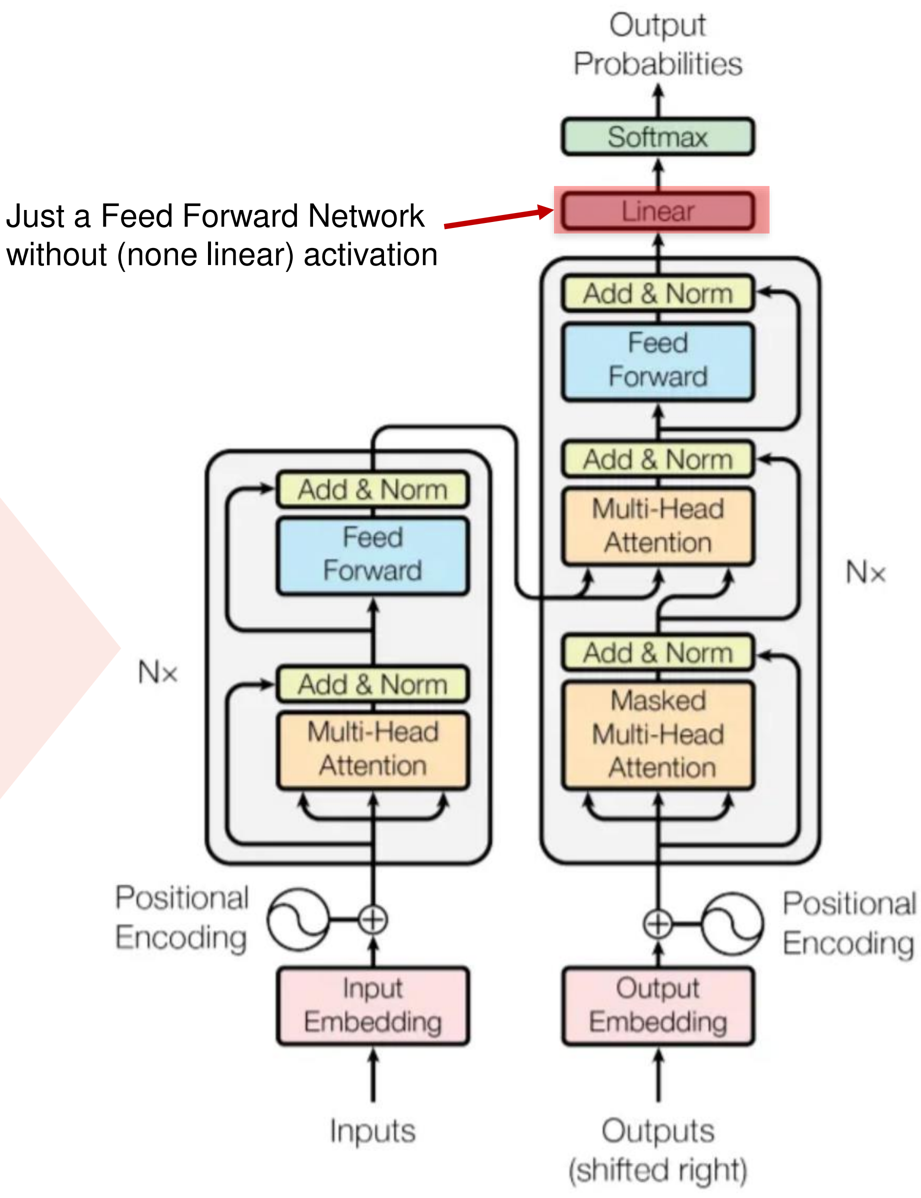




https://glassboxmedicine.com/2019/08/15/the-transformer-attention-is-all-you-need/

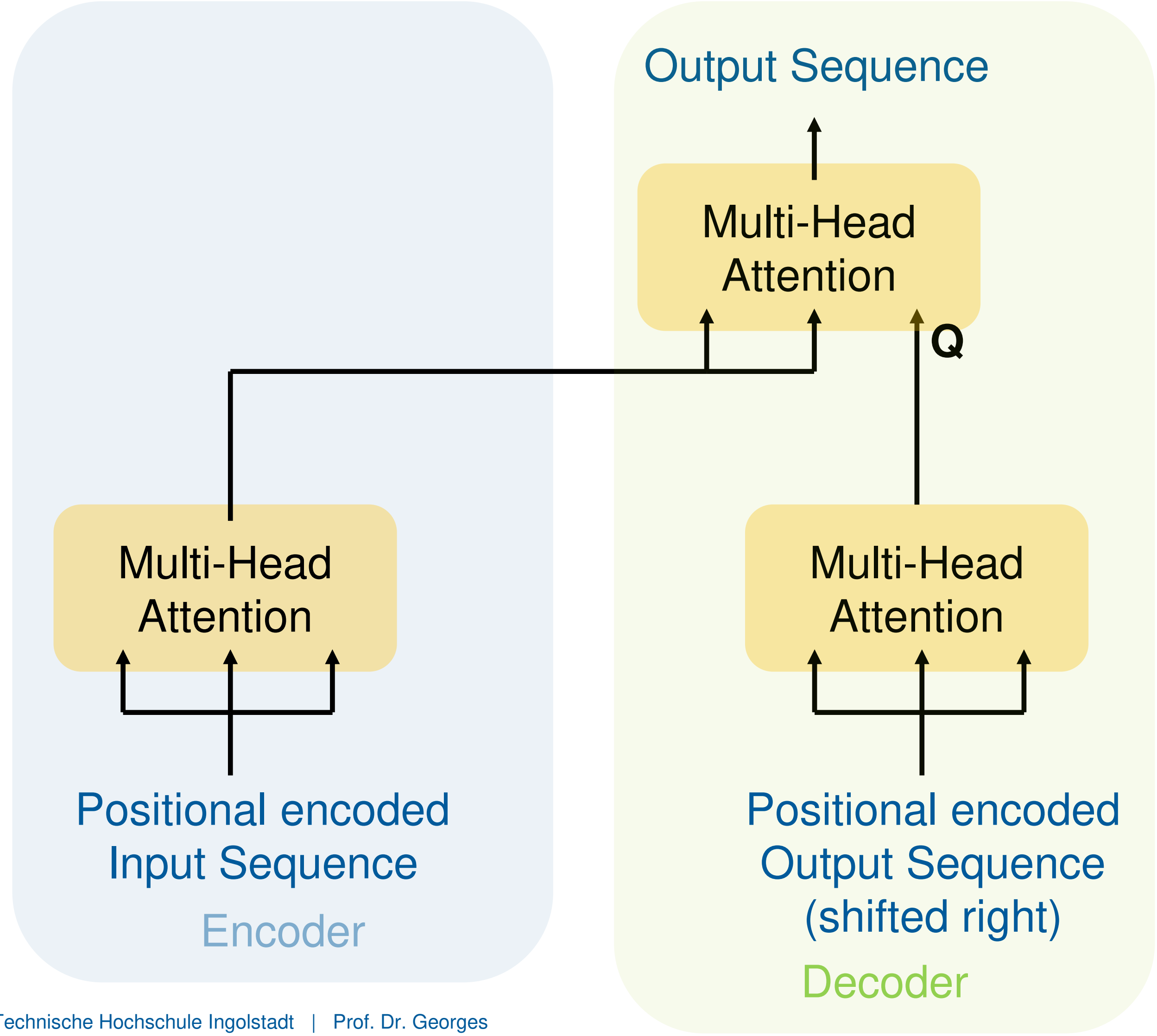
Transformer

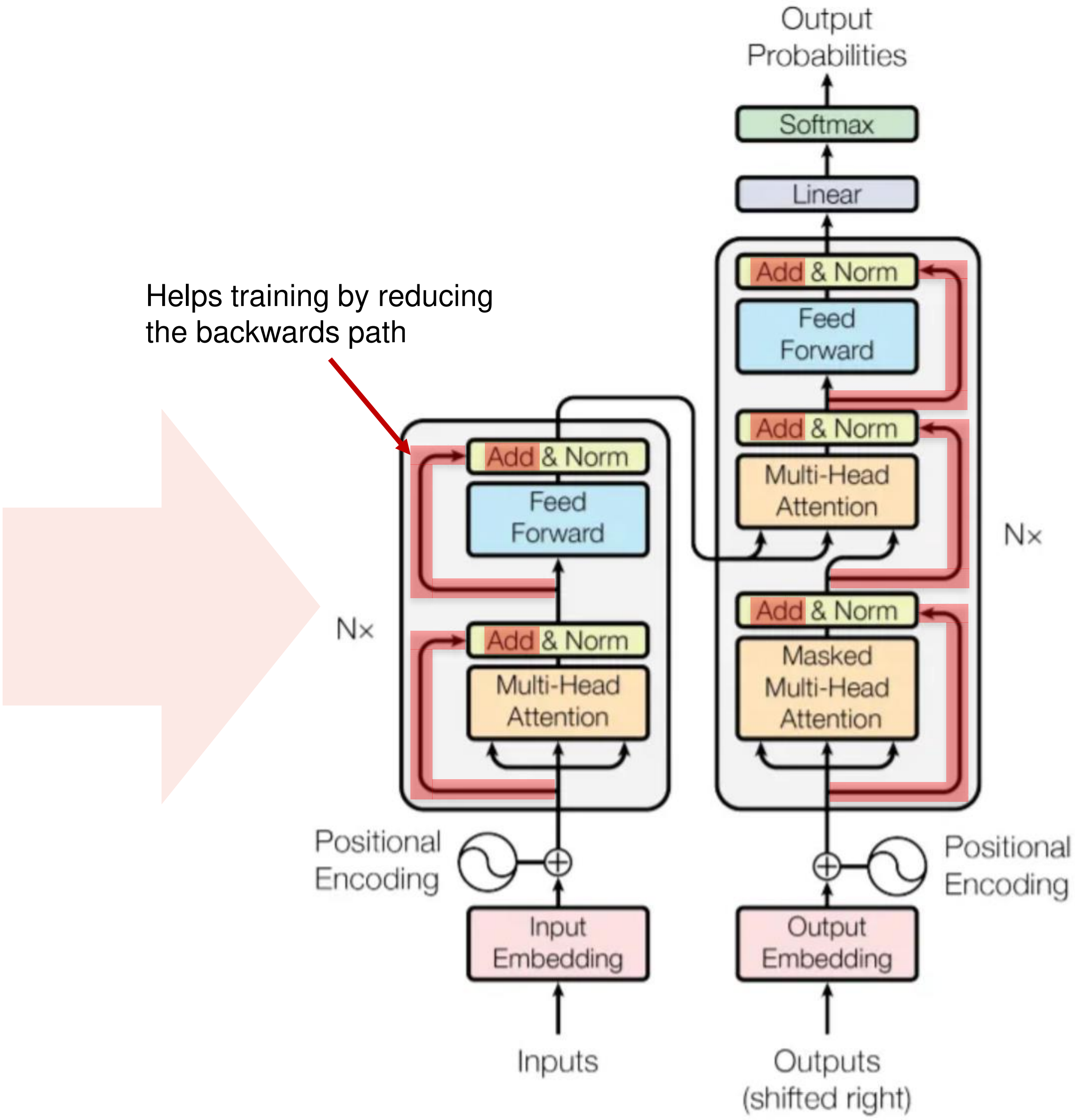




https://glassboxmedicine.com/2019/08/15/the-transformer-attention-is-all-you-need/

Transformer





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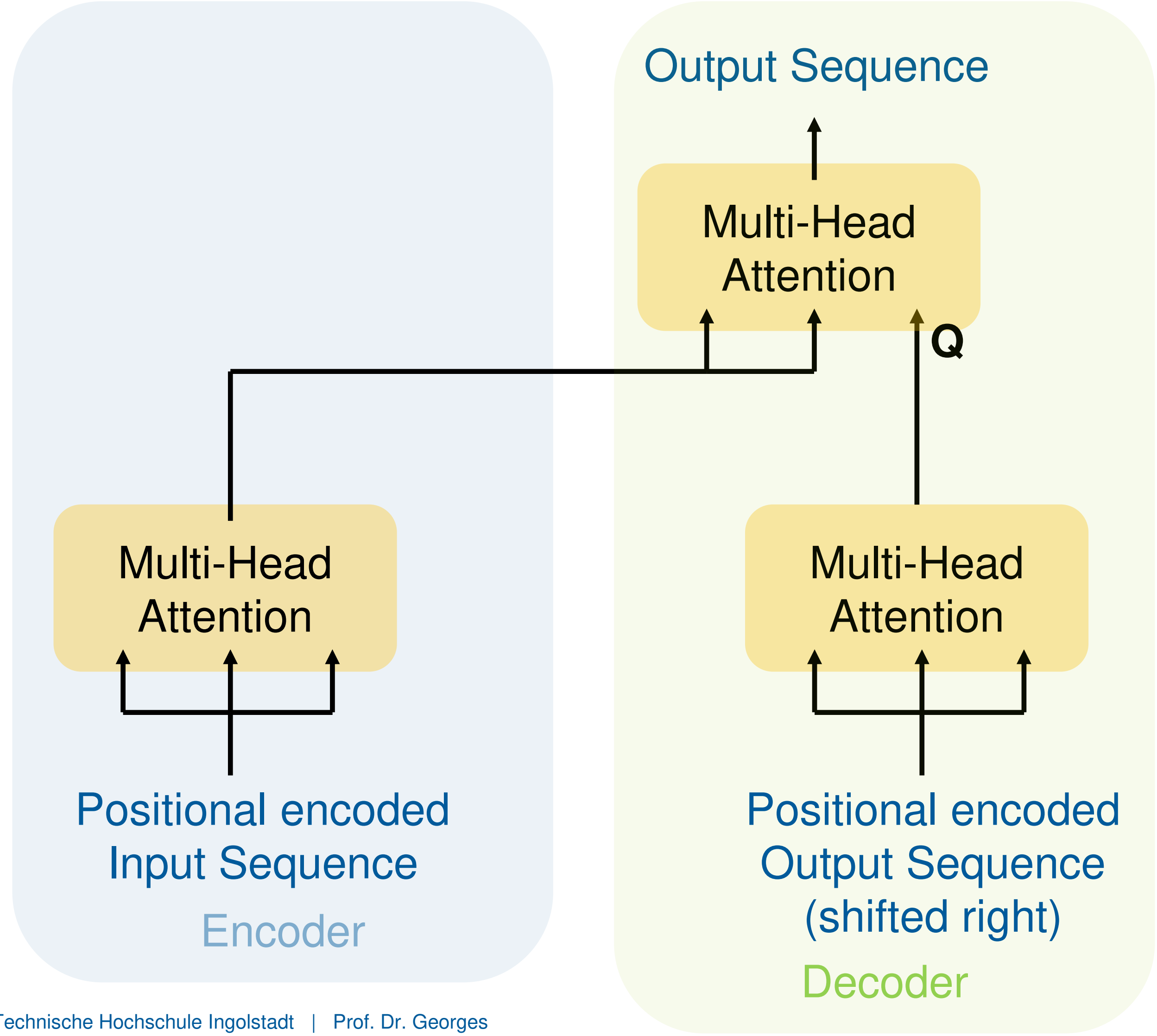
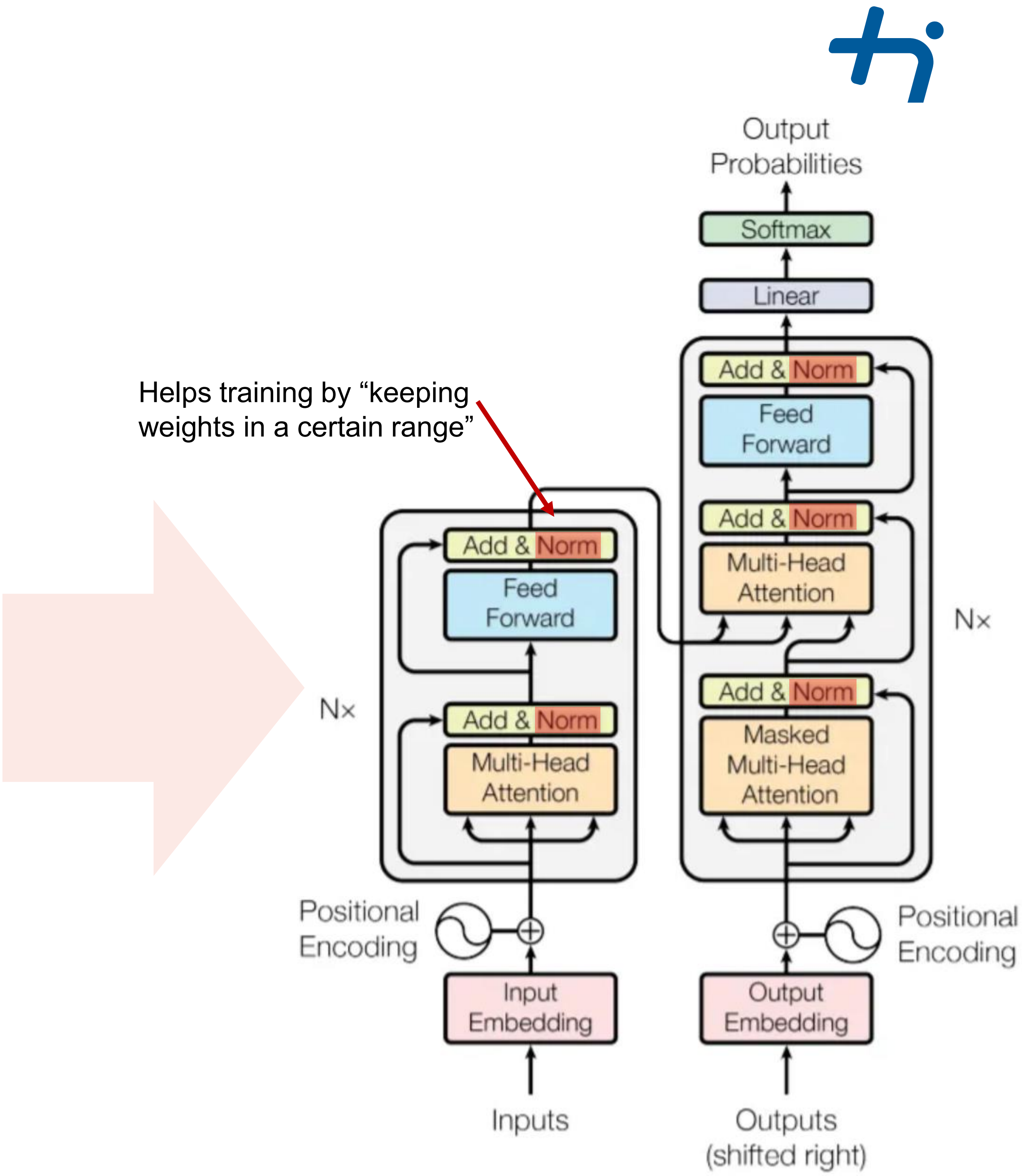
Transformer





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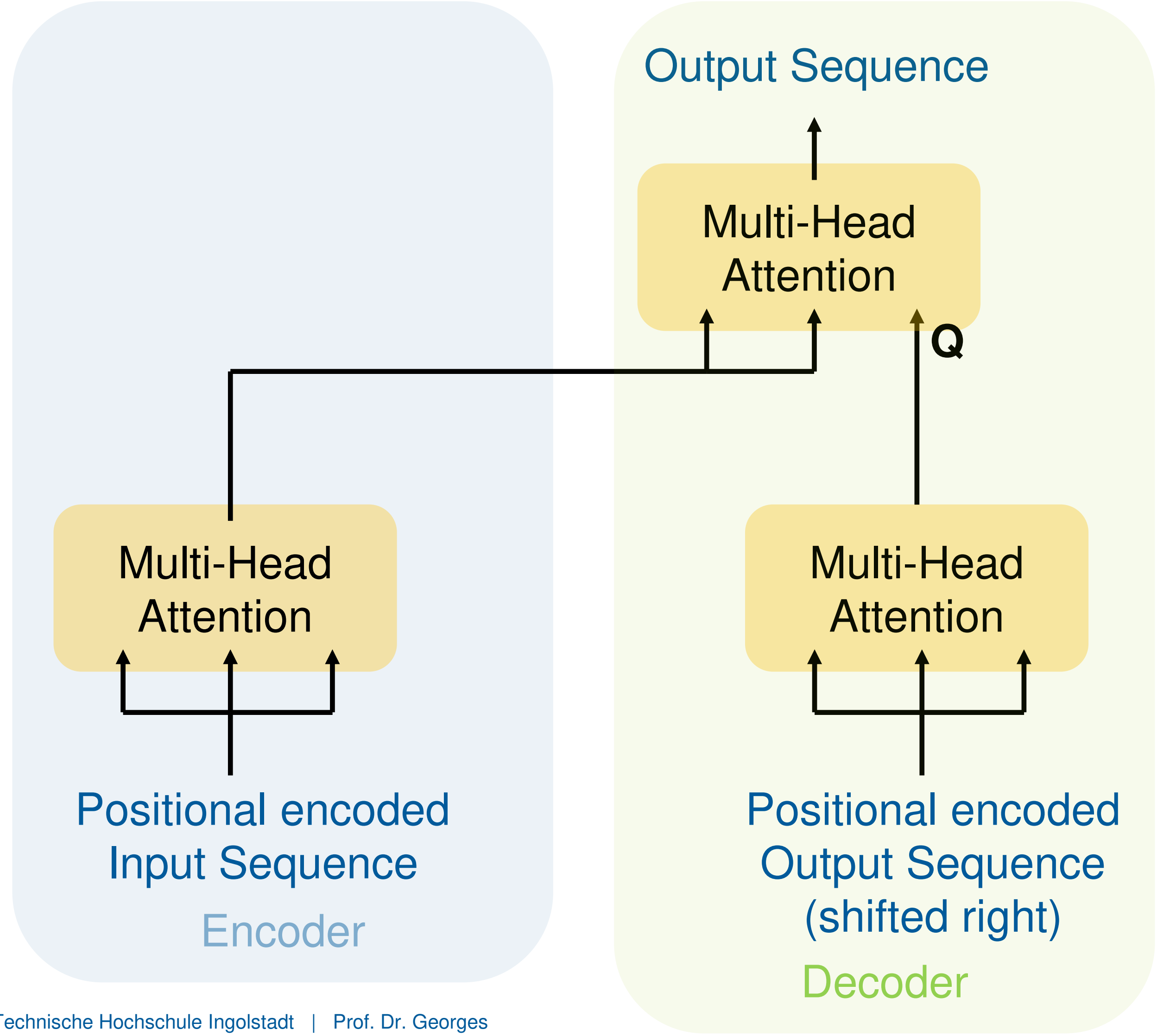
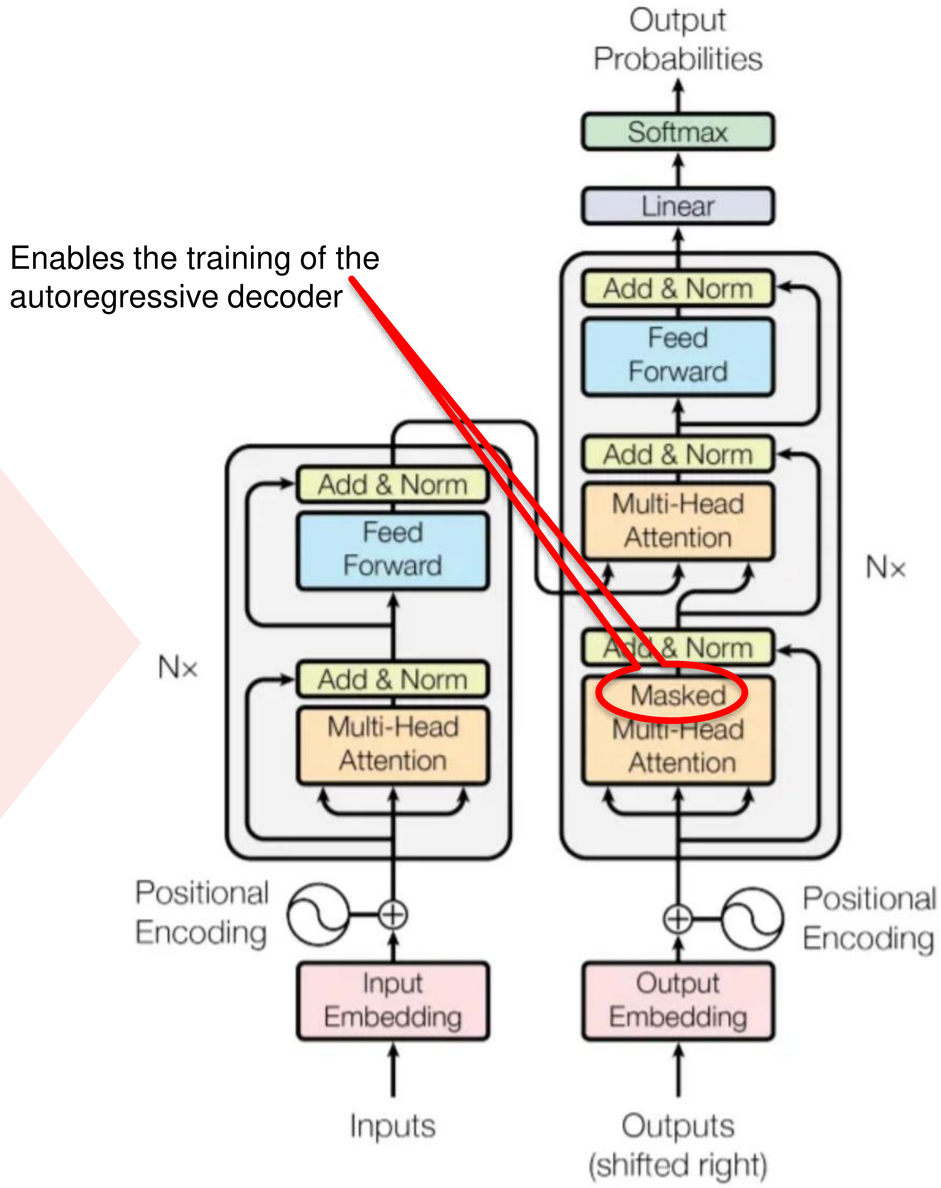
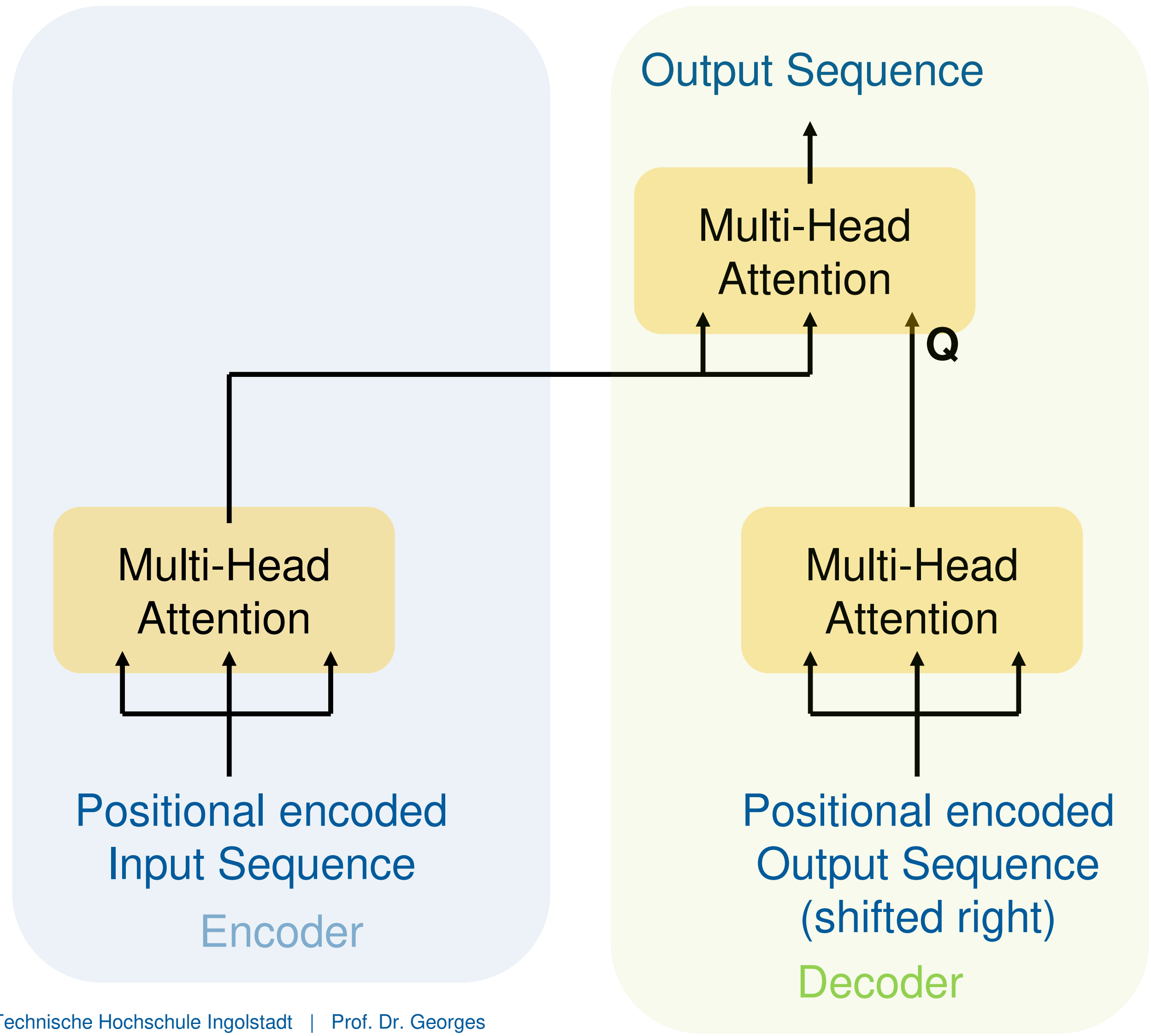
Transformer



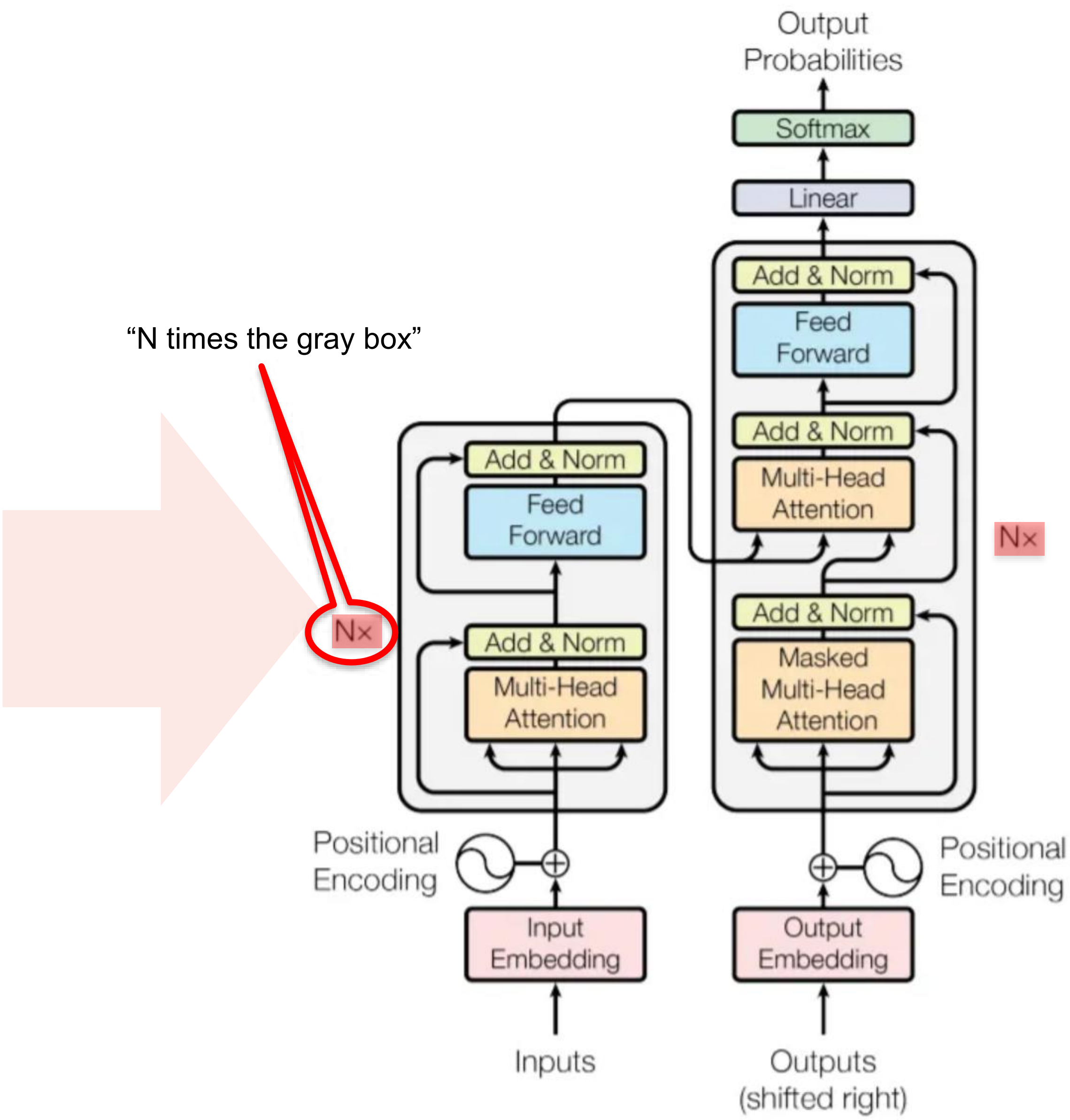


https://glassboxmedicine.com/2019/08/15/the-transformer-attention-is-all-you-need/

Transformer

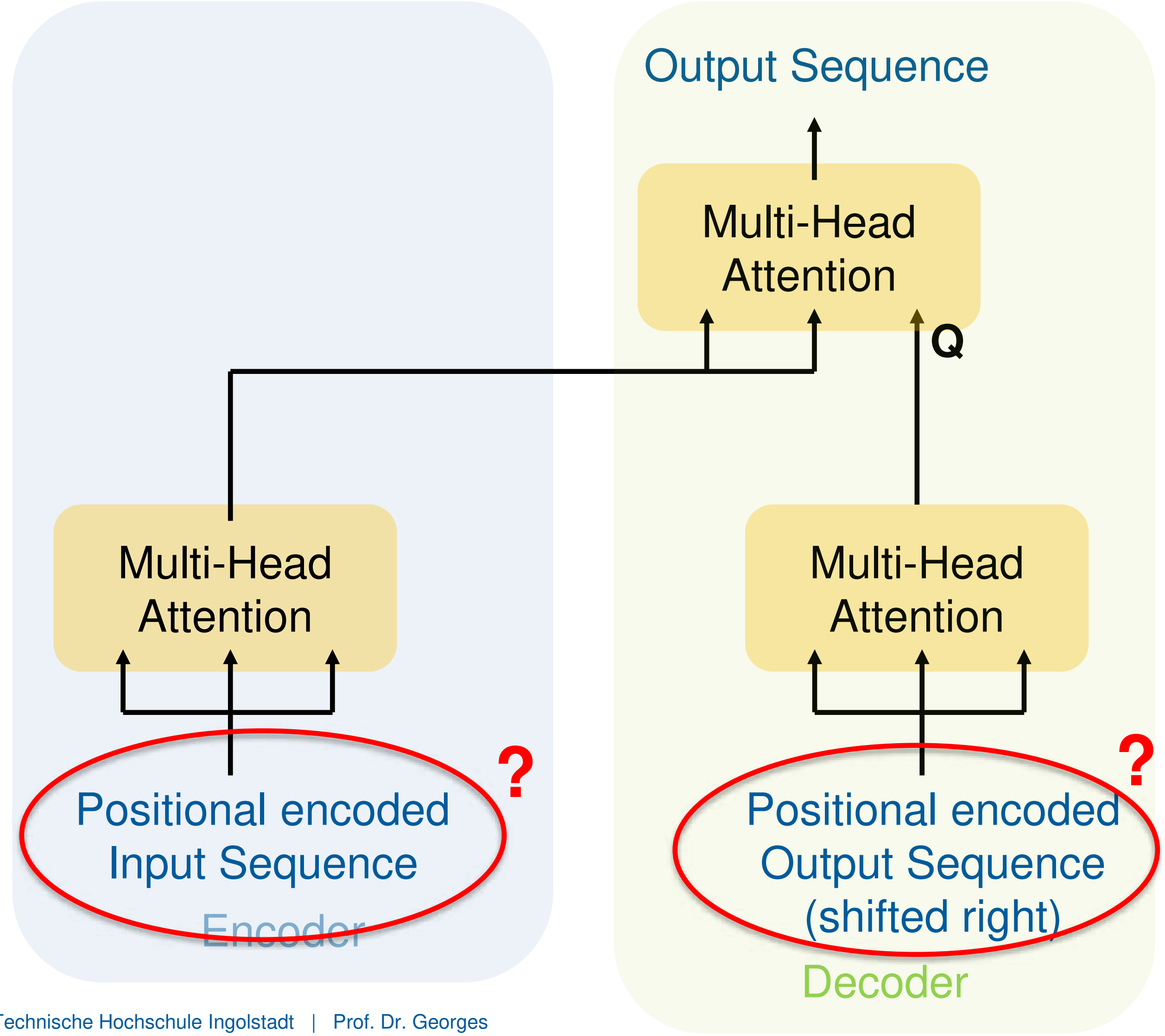


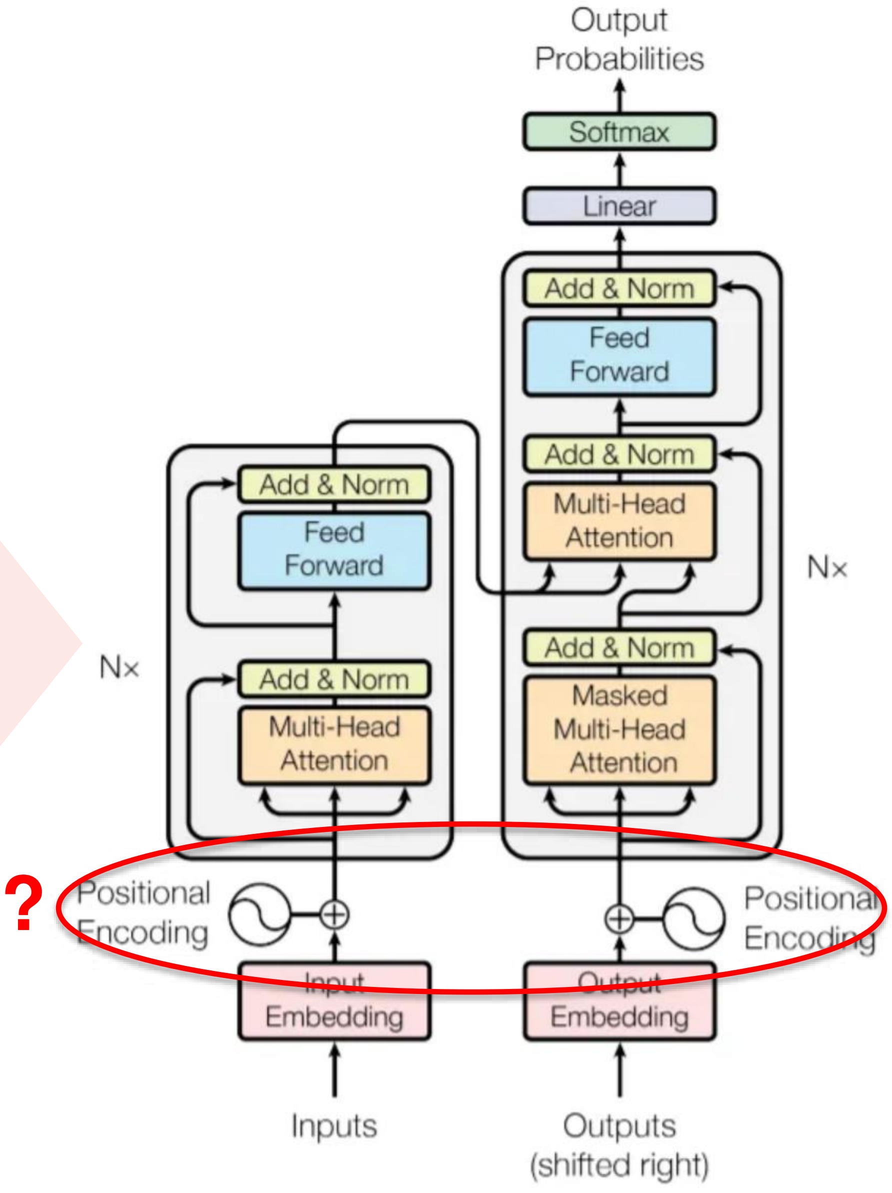
“N times the gray box”



https://glassboxmedicine.com/2019/08/15/the-transformer-attention-is-all-you-need/

Transformer





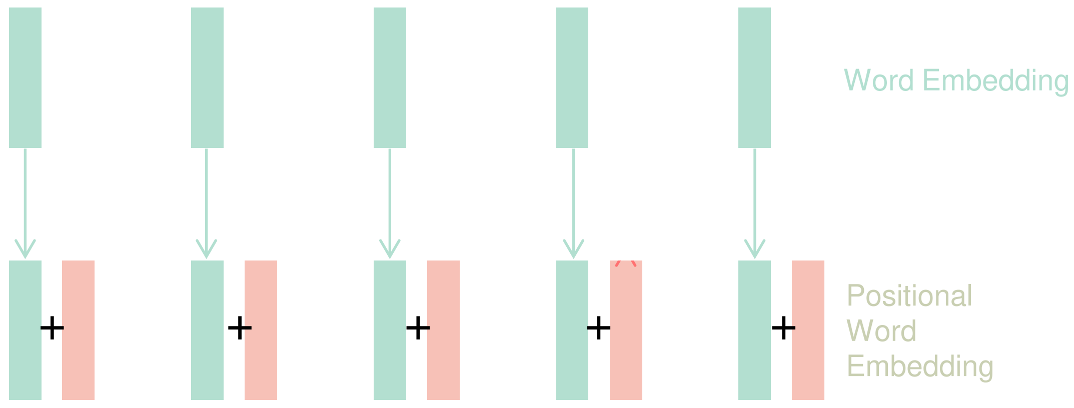
https://glassboxmedicine.com/2019/08/15/the-transformer-attention-is-all-you-need/

Positional Encoding in Transformer

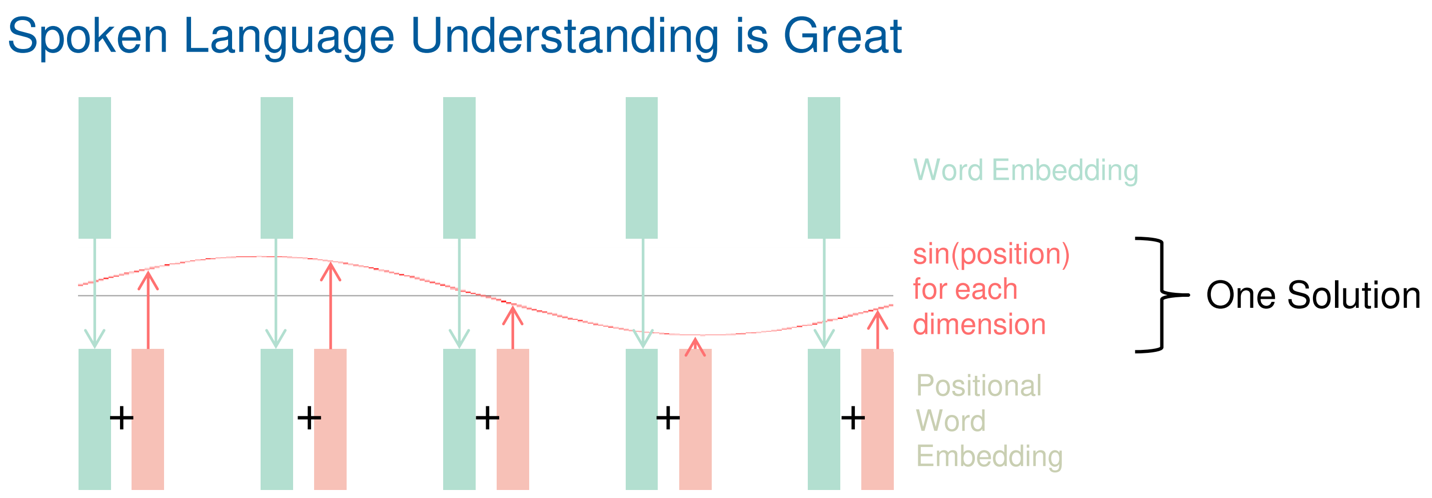
Spoken Language Understanding is Great

Positional Encoding in Transformer

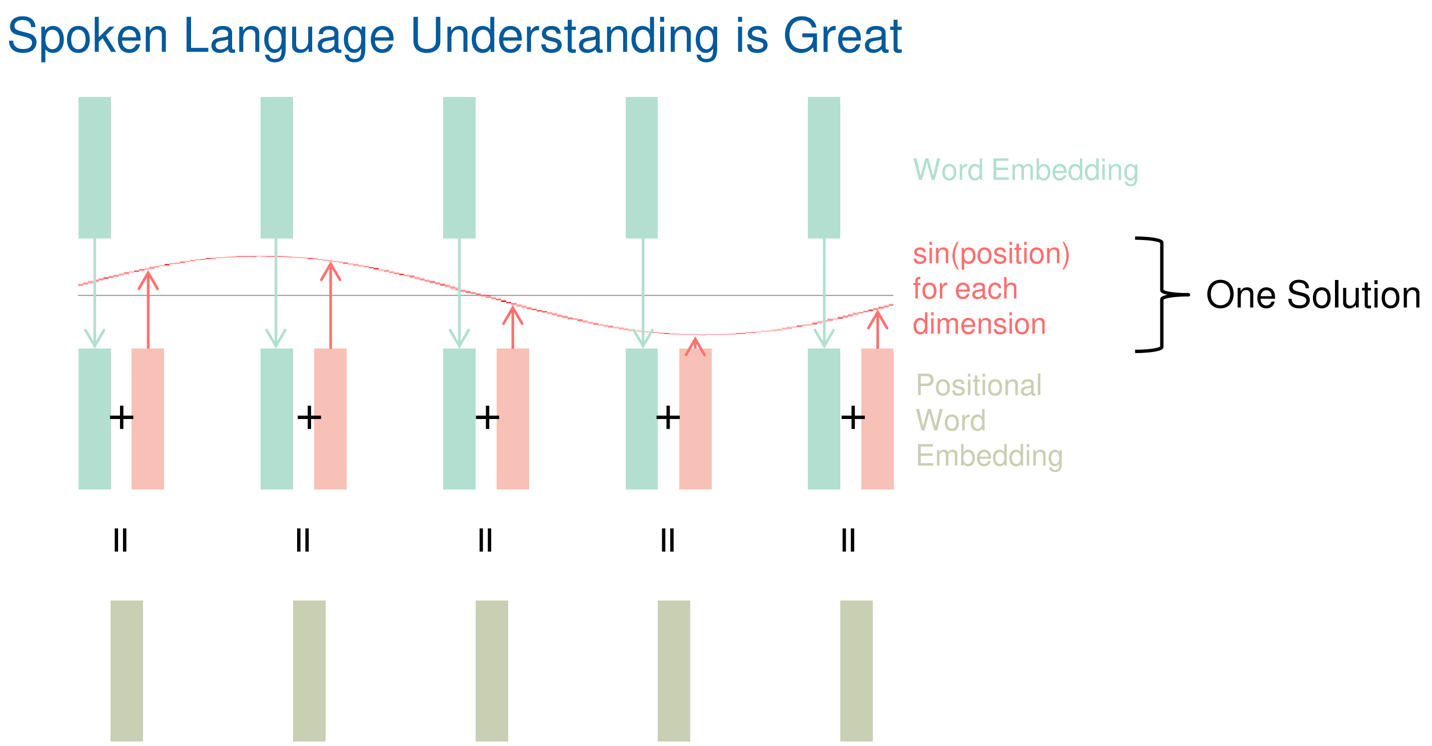
Spoken Language Understanding is Great



Positional Encoding in Transformer

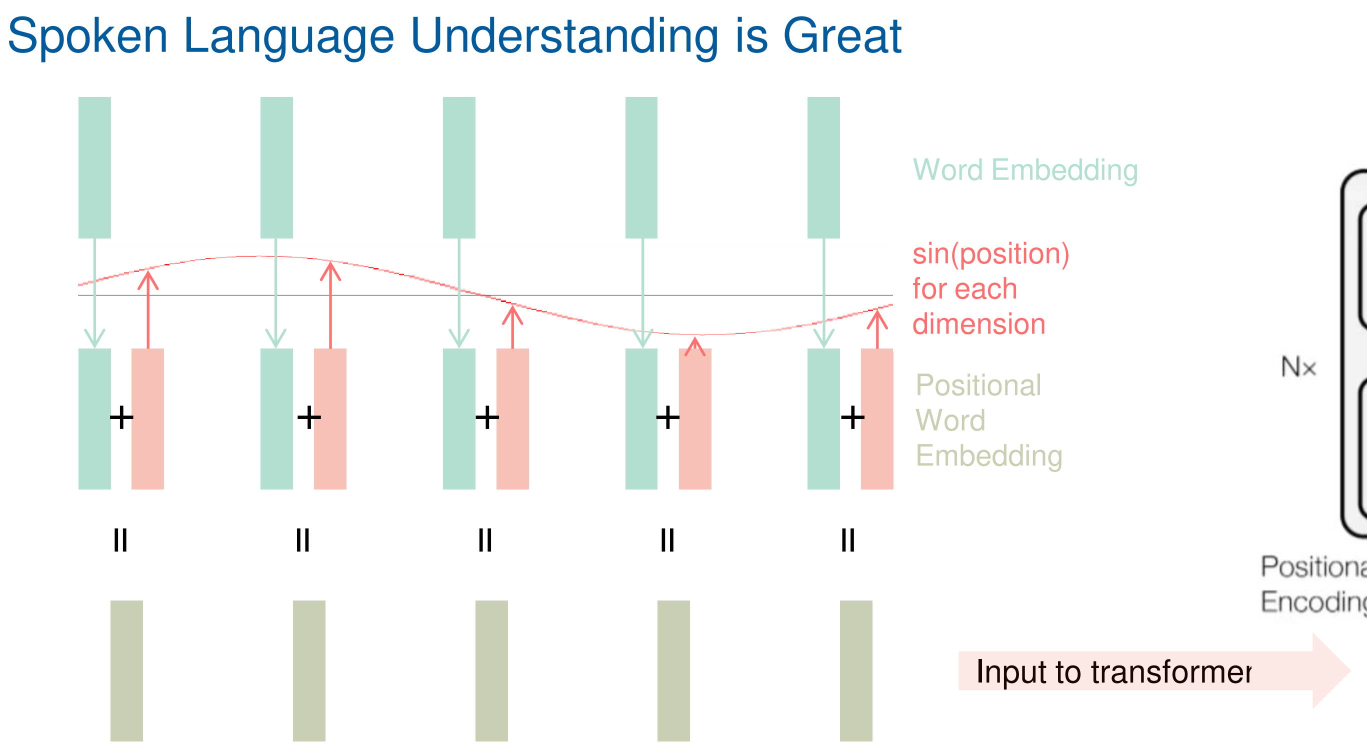


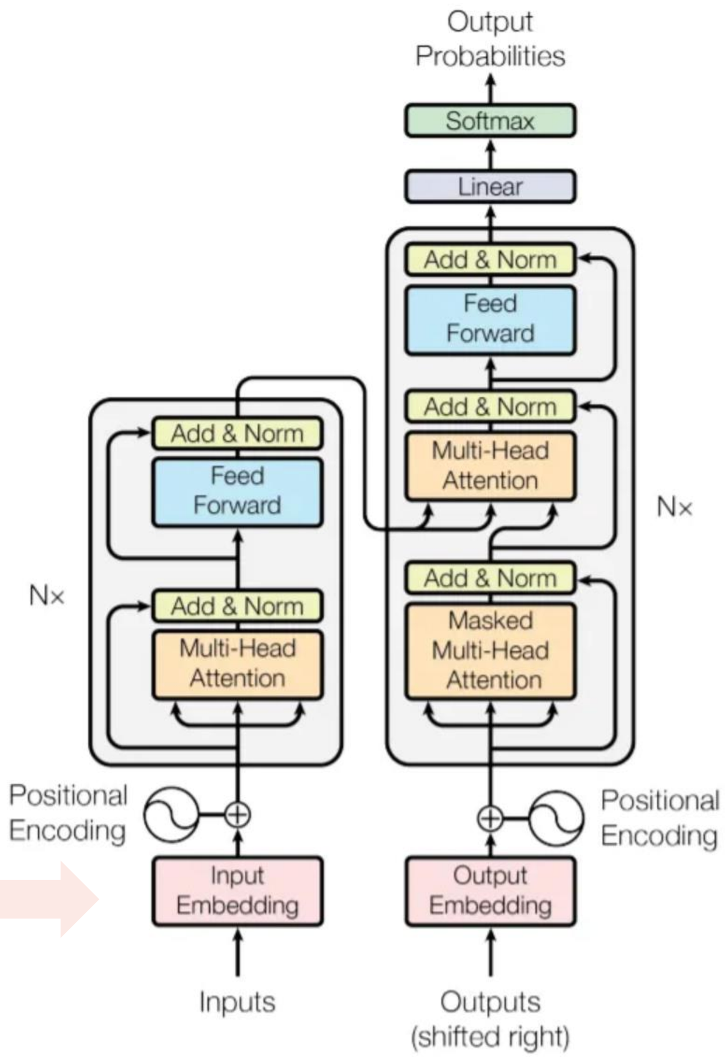
Positional Encoding in Transformer



https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Positional Encoding in Transformer





Examples

Question Classification

“weather” := Will it rain tomorrow?

“location” := Where is Munich?

Sentimental Analysis

Objectivity vs. Subjectivity

“A TDNN is a feed forward neuronal network.” vs.

“I believe in neuronal networks.”

Positive- vs. Negative-Polarity

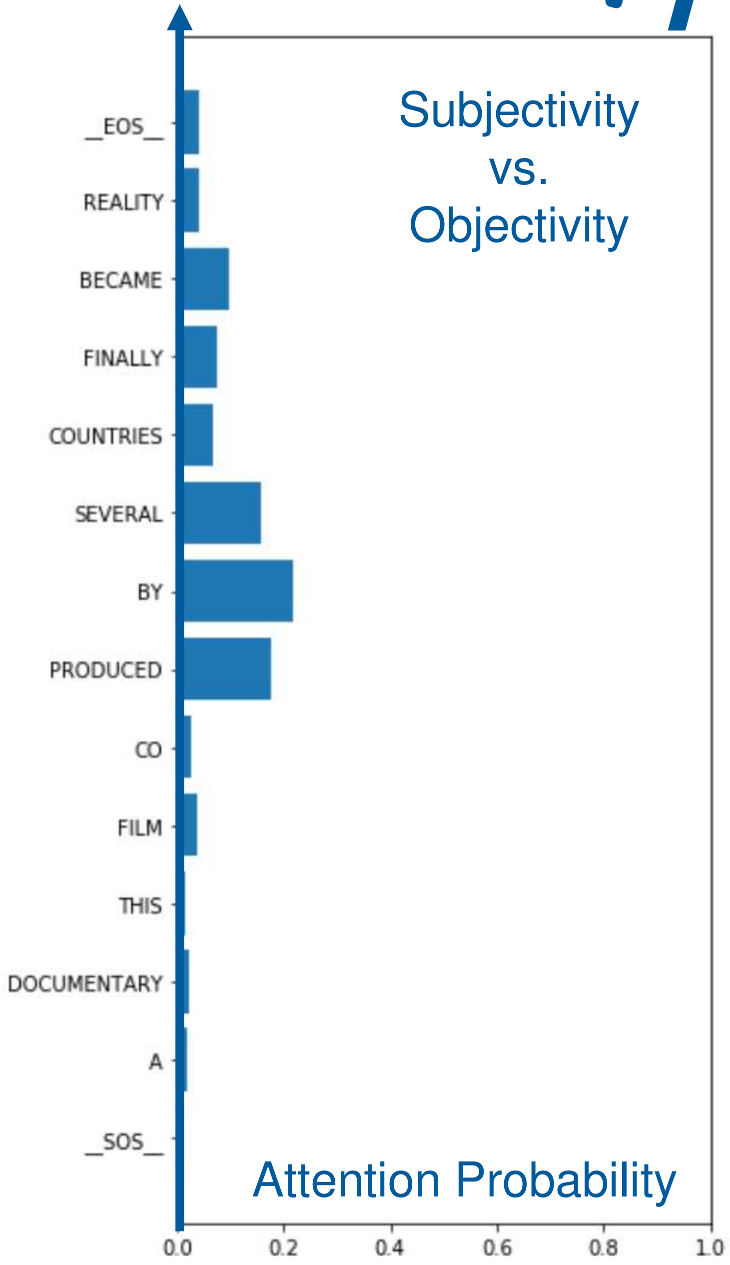
“This was a great talk. I love NLP.” vs.

“Text processing is not my favorite topic.”

Newsgroup Classification

“NLP” := Information Retrieval is about …

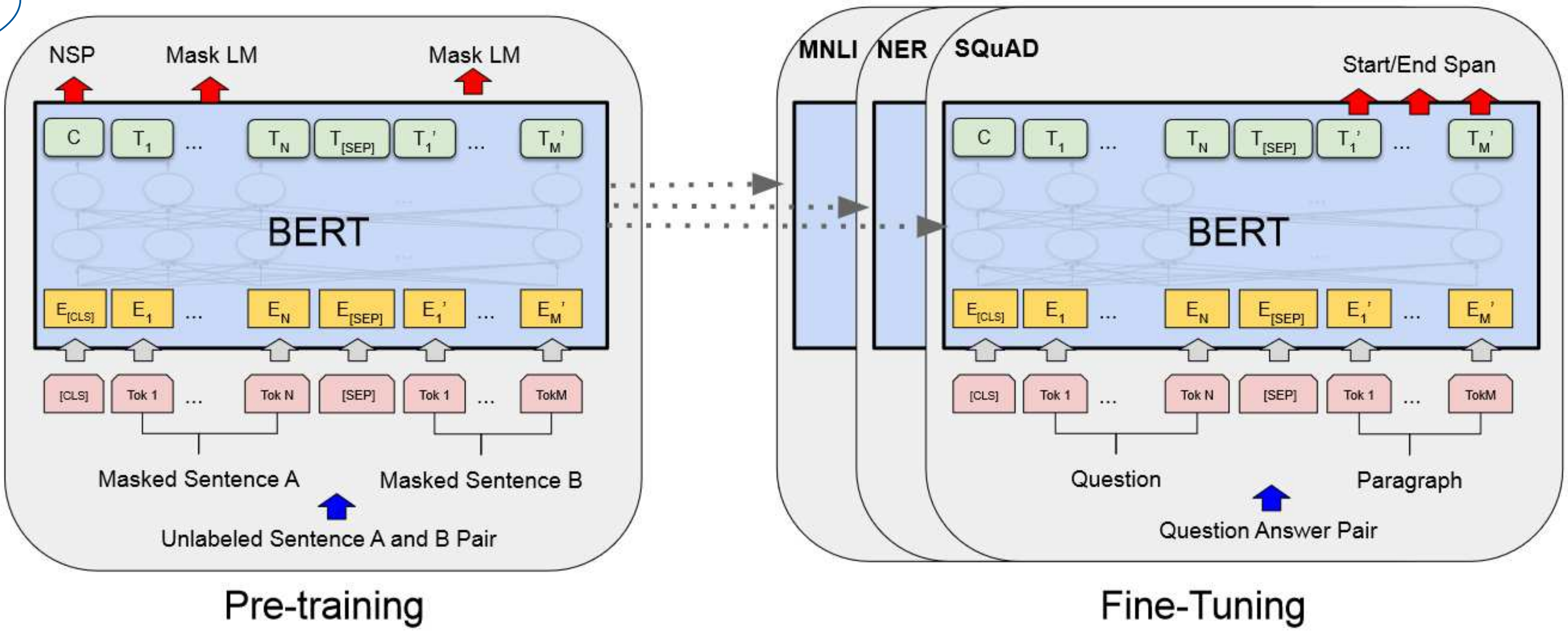
“car” := The gear of a car ….



Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT := Bidirectional Encoder Representations from Transformers

Bidirectional representations from unlabeled text



https://arxiv.org/pdf/1810.04805.pdf

Take-away: Attention mechanism in RNNs

1. **Unrolling of RNNs**

   Matrix, Vector Notation of Neuronal Networks and graphical representation

2. **Sequence to Sequence with RNNs and use-cases:**

   No-, Partial, Full-Delay. Part-Of-Speech Tagging, Grapheme to Phoneme Conversion, Machine Translation, Intent Extraction, …

3. **Attention: Focus on Relevant Section in the Encoder-Sequence given current output**

4. **Dot-Product Attention and the generalization:**

   Important key-words: “Key”, “Value” and “Query”, “Energy-”, “Attention-” and “Context-vector”, “Compatibility- ” and “Distribution-function”, “Self-” and “Multi-head attention”

5. **https://arxiv.org/pdf/1706.03762.pdf**