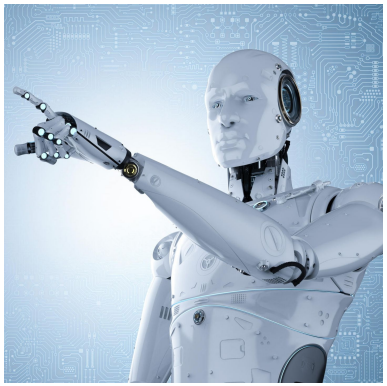
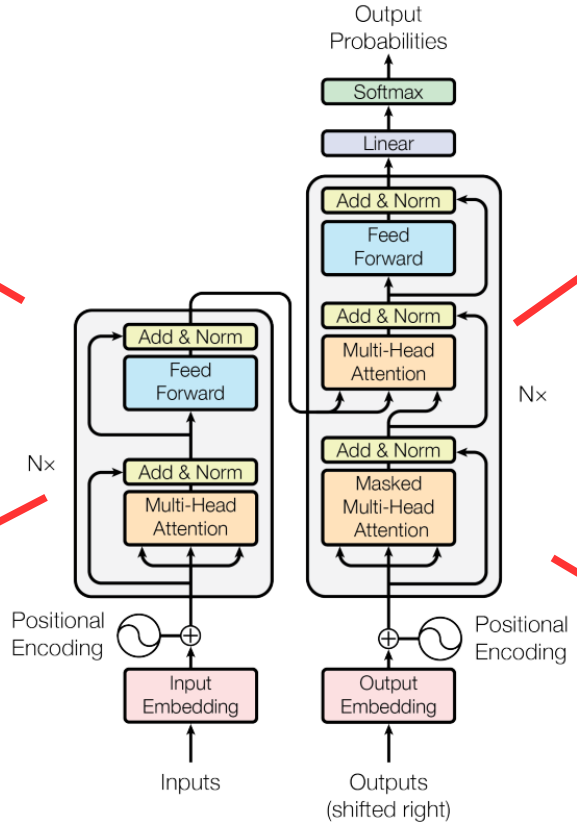
Image source:
https://www.wallpaperflare.com/optimus-prime-the-city-weapons-robots-the-movie-wallpaper-wbsf/download (call date: 20.07.22)

Computer Vision



Deep Reinforcement Learning



Natural Language Processing

Attention!
The Transformers are coming!

GANs

Tim Niklas Witte

Image sources:
https://machinelearningmastery.com/wp-content/uploads/2021/08/attention_research_1-727x1024.png
https://images.ctfassets.net/3viuren4us1n/1Ghw96A2tcYRfRezOwtmjx/e646778f3f53e50ea3e857e9cdb23120/Computer_vision.jpg
https://image.stern.de/7931130/t/NJ/v2/w1440/r1/-/roboter.jpg
https://www.studienscout-nl.de/fileadmin/_processed_/csm_Sprache-und-Sprachkurse_08f53ae680.jpg
https://studip.uni-osnabrueck.de/sendfile.php?type=0&file_id=8a554d27d543b1ce06eb1a68a34e22ae&file_name=vqgan_4_i350.png
(call dates: 20.07.22)

Structure

1. Motivation

2. Intuitive understanding of self-attention
3. Intuitive understanding of transformer architecture

4. Natural Language Processing
5. Computer Vision
6. GANs
7. Deep Reinforcement Learning

7. Modifications of attention: Synthesizer, Linformer, Reformer

8. Conclusions

Discussion: Candy-wise attention

Image sources:
https://www.flaticon.com/free-icon/candy-jar_10751352?related_id=10751352&origin=tag
https://emojipedia.org/de/toss-face/march-2022/gesicht-mit-umarmenden-h%C3%A4nden/
(call dates: 20.07.22)

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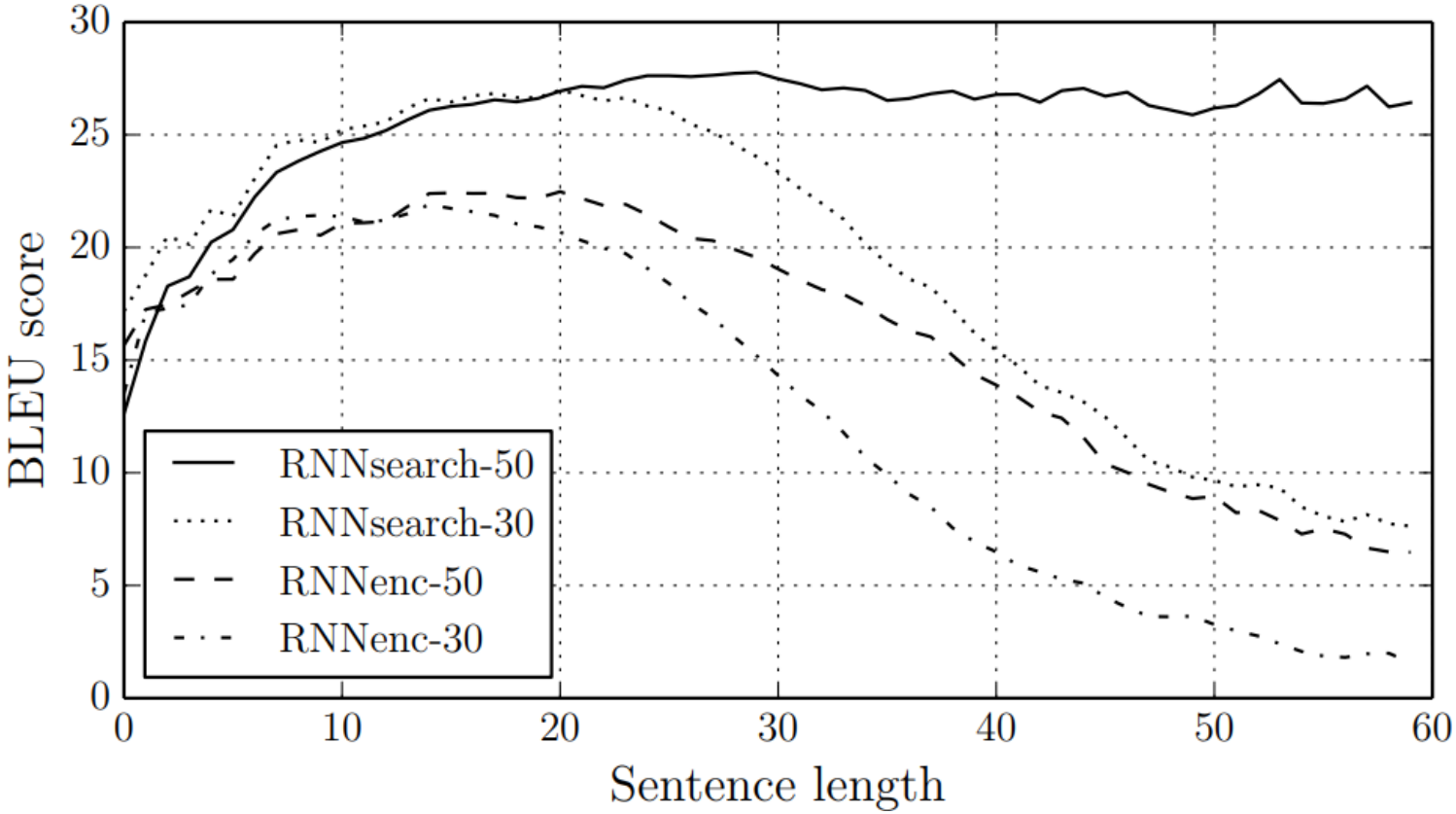

Figure 1: Performance (BLEU score) differences between RNN-based models for neural machine translation [1].

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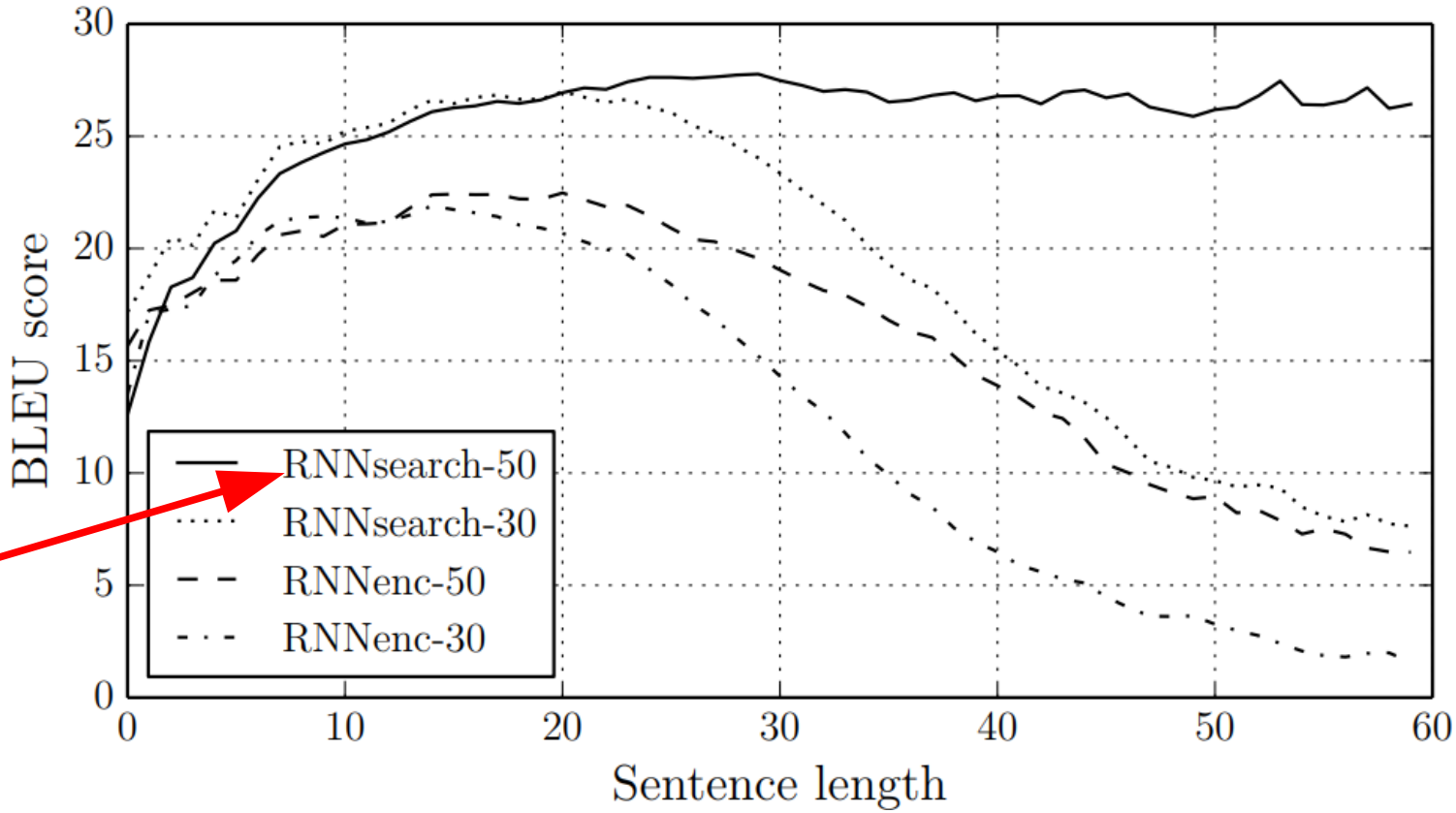

Bahdanau attention

Figure 1: Performance (BLEU score) differences between RNN-based models for neural machine translation [1].

2. Intuitive understanding of self-attention

Image sources:
https://www.campussafetymagazine.com/wp-content/uploads/2019/03/Bull-horn-announcement-PA-iStock-1000x500.jpg
https://upload.wikimedia.org/wikipedia/commons/thumb/7/7b/Attention_Sign.svg/2302px-Attention_Sign.svg.png
https://upload.wikimedia.org/wikipedia/commons/thumb/9/9a/Simple_Attention.svg/1024px-Simple_Attention.svg.png
(call dates: 20.07.22)

2. Intuitive understanding of self-attention

The server ...

2. Intuitive understanding of self-attention

The server ...

?

Figure 2: A Waiter.

Figure 3: Server in a data center.

Image sources:
https://content.gastivo.de/wp-content/uploads/2019/09/Der-Kellner-Knigge-Perfektes-Servieren-1024x576.jpg
https://i0.wp.com/blog.fyipe.com/wp-content/uploads/2020/01/servers-e1605085513709.jpeg
(call dates: 20.07.22)

2. Intuitive understanding of self-attention

The server is crashed.

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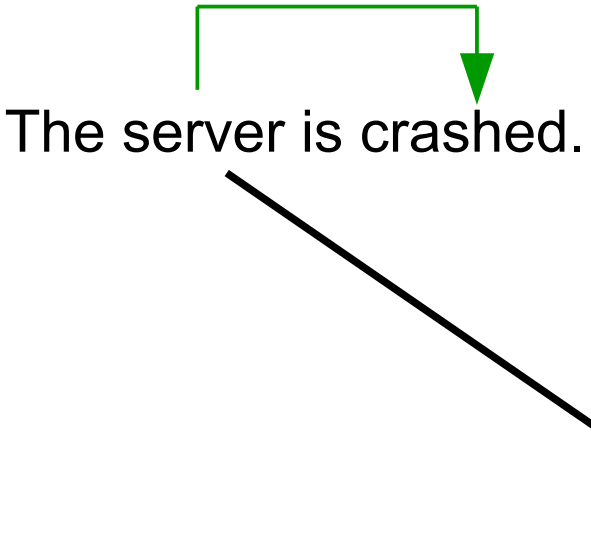

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English → **Portuguese**

This is the first book I did. → Este e o primerio livro que eu fiz.

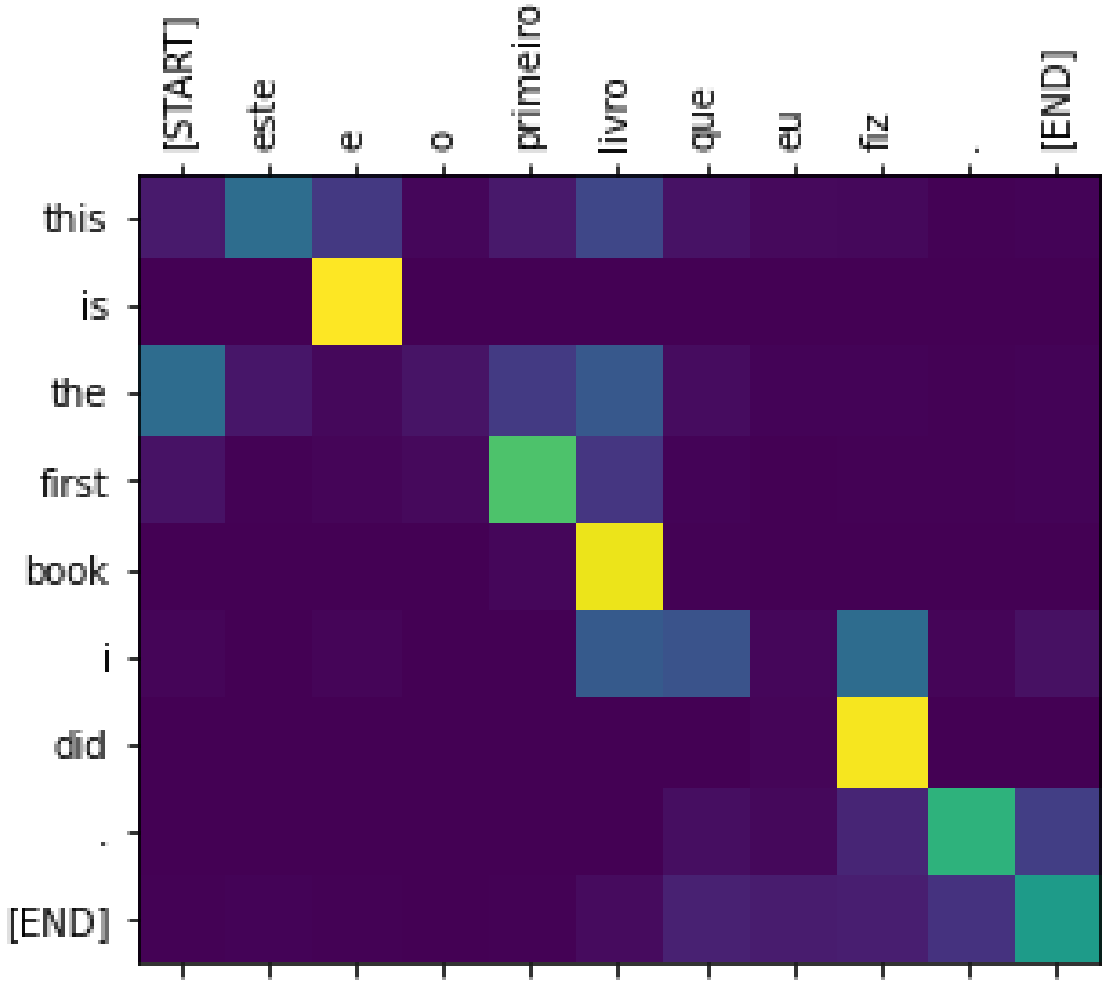

Figure 4: Self-attention heatmap.

Image source:
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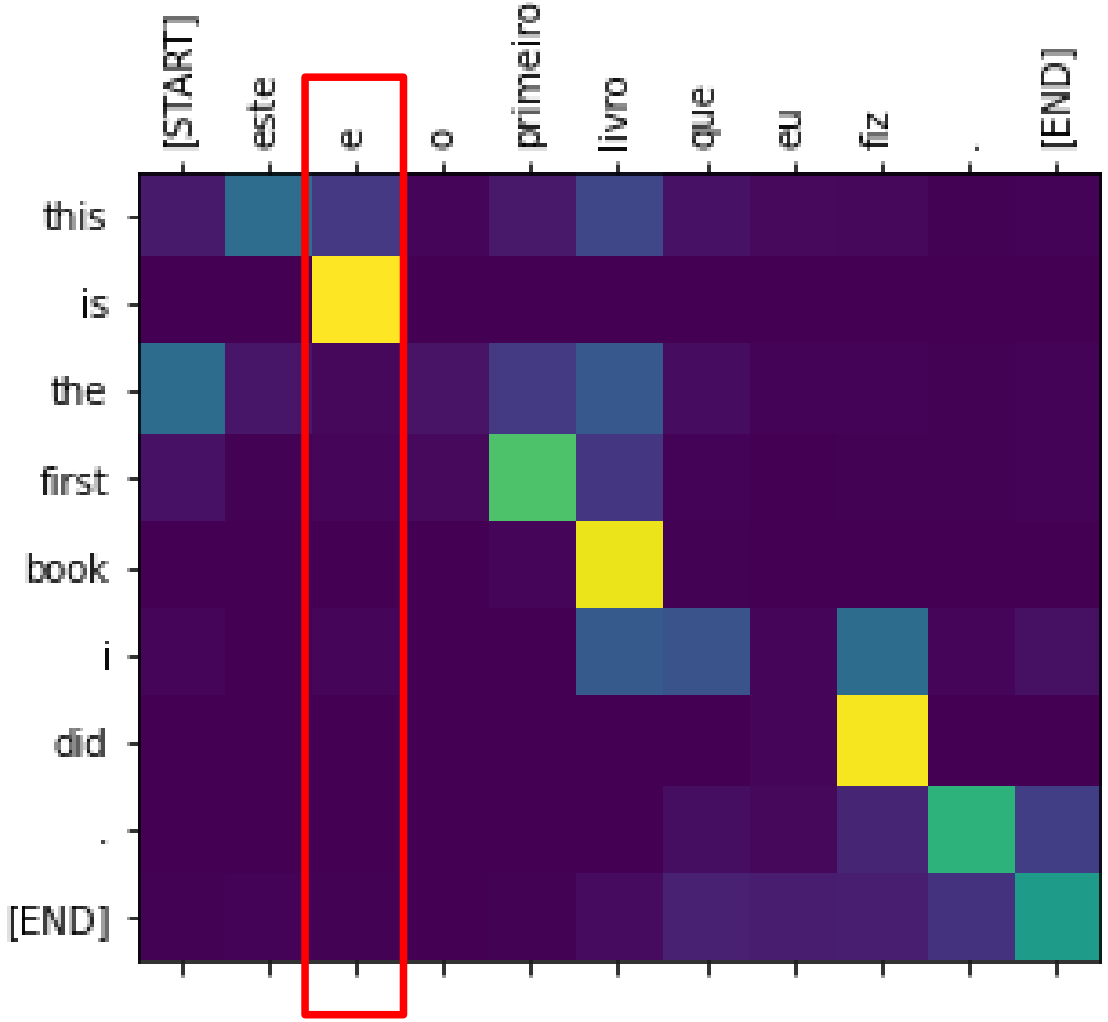

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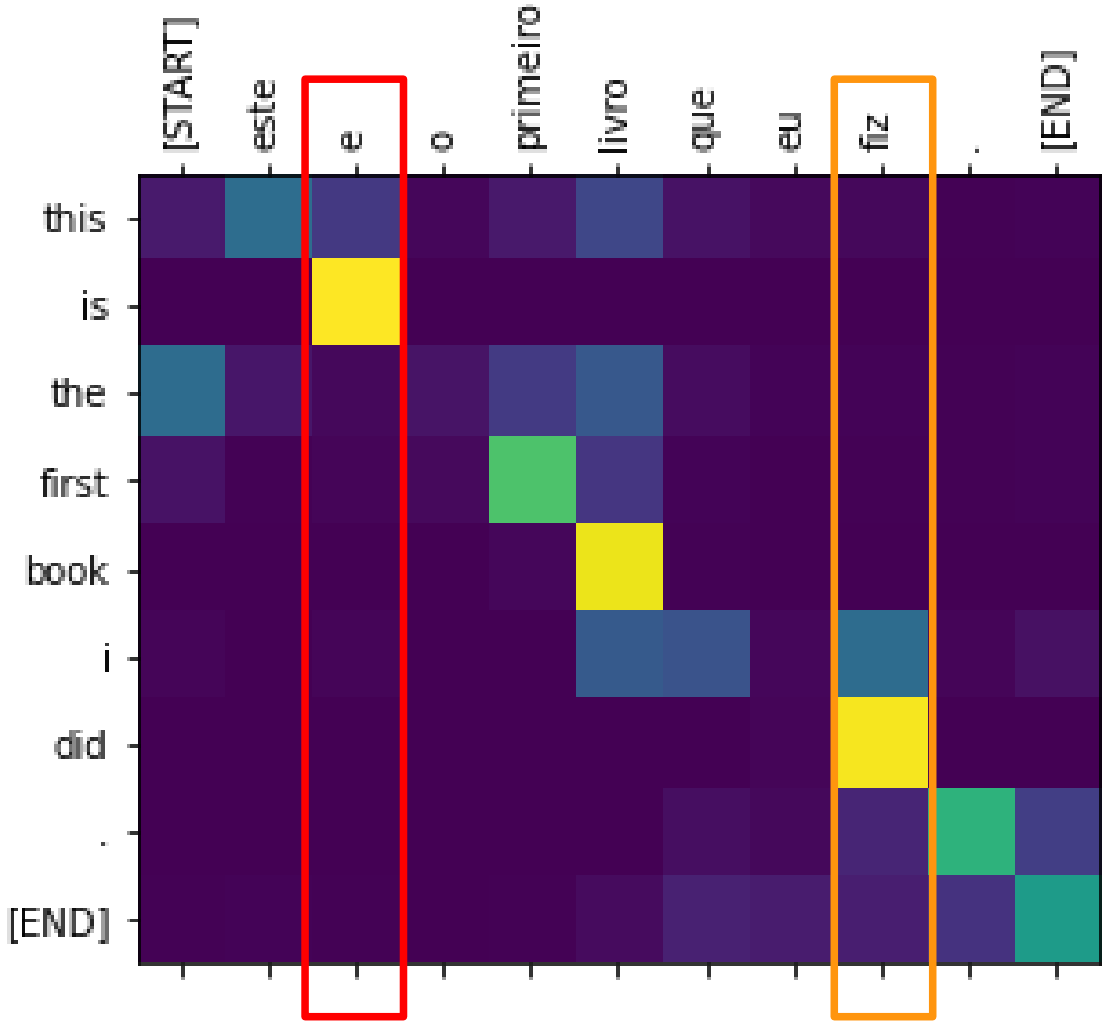

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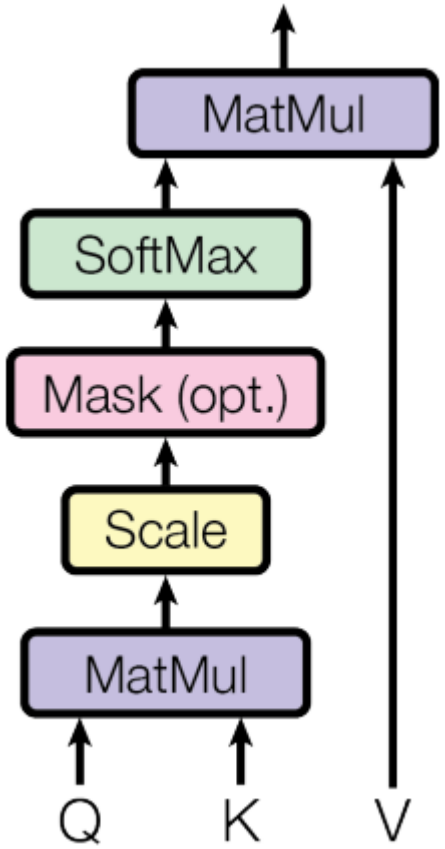


$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Q: Query matrix shape: d_k x D_H
K: Key matrix shape: d_k x D_H Hidden size
V: Value matrix shape: d_v x D_H

Figure 5: Self-attention [2].

2. Intuitive understanding of self-attention

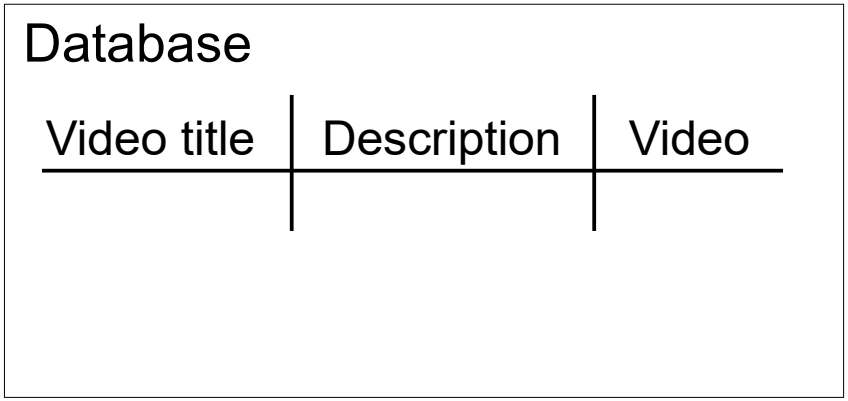


Figure 6: Self-attention example based on a YouTube search query.

2. Intuitive understanding of self-attention

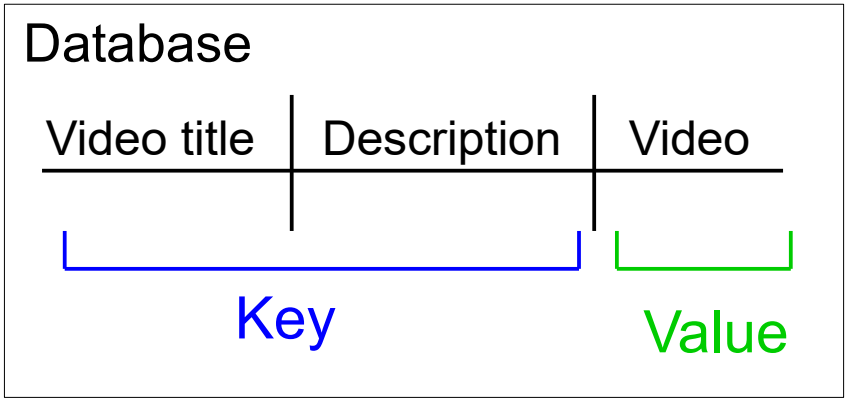


Figure 6: Self-attention example based on a YouTube search query.

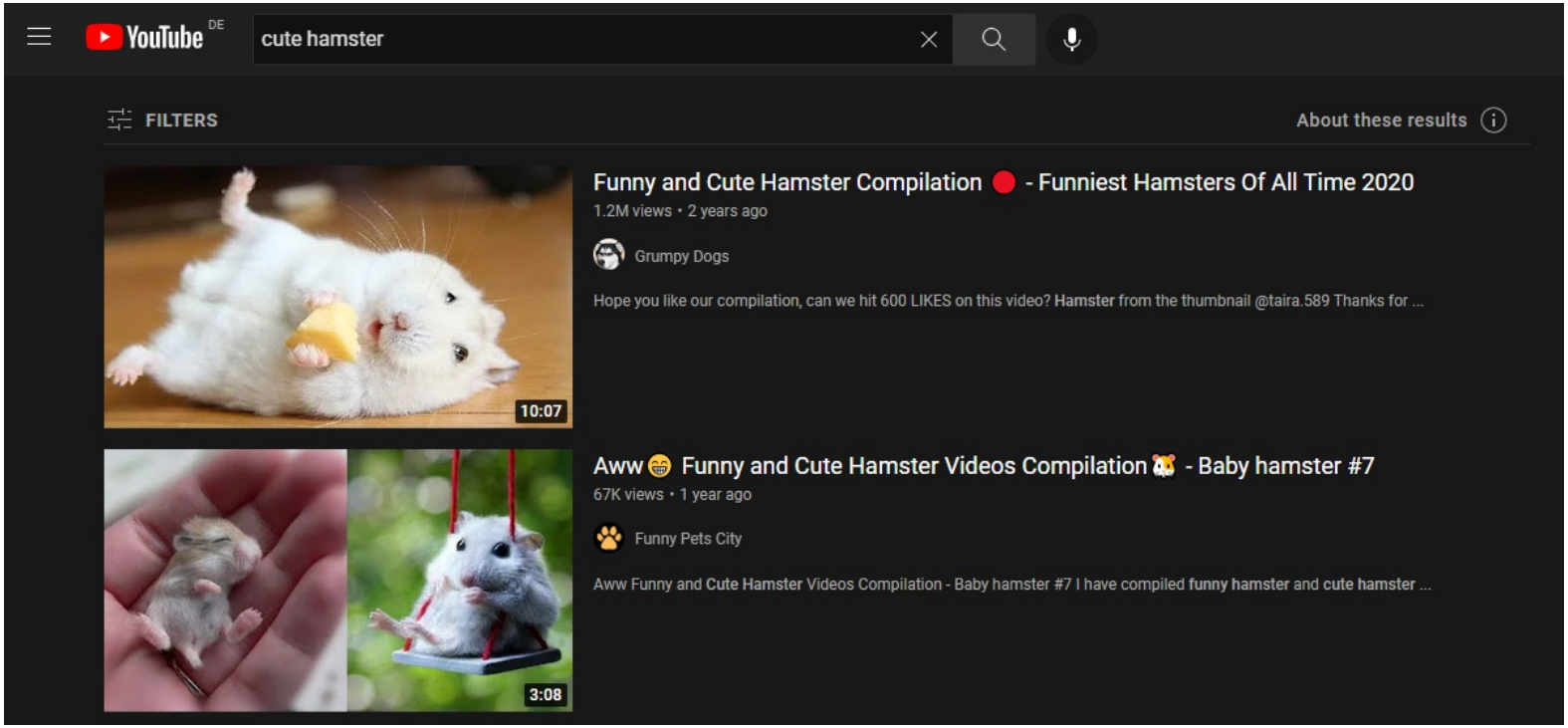
2. Intuitive understanding of self-attention

Database

Video title	Description	Video

Key

Value



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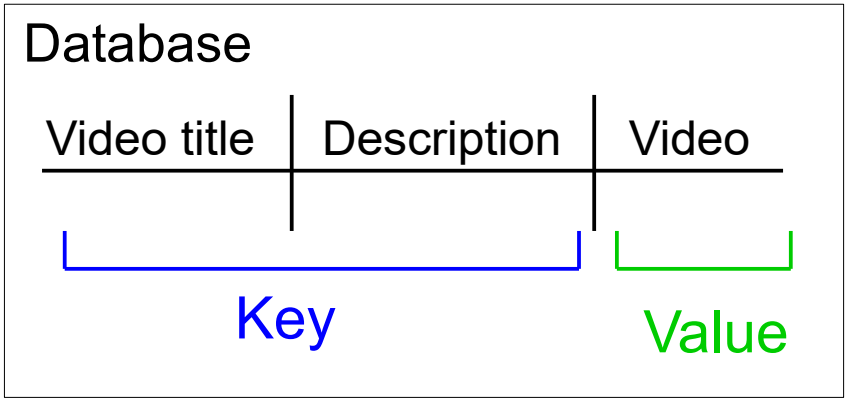

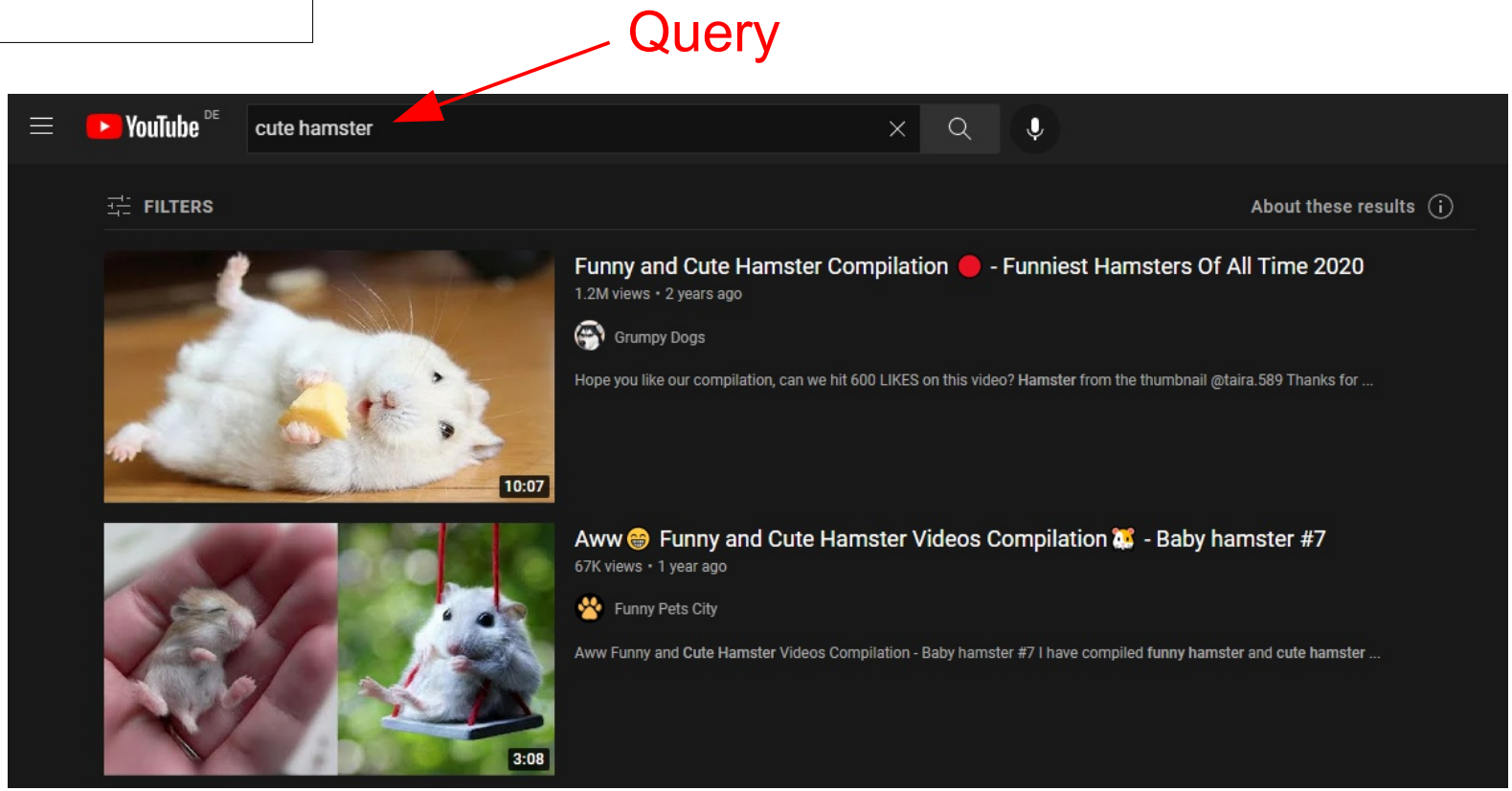

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2. Intuitive understanding of self-attention

Database

Video title	Description	Video

Key

Value

Query

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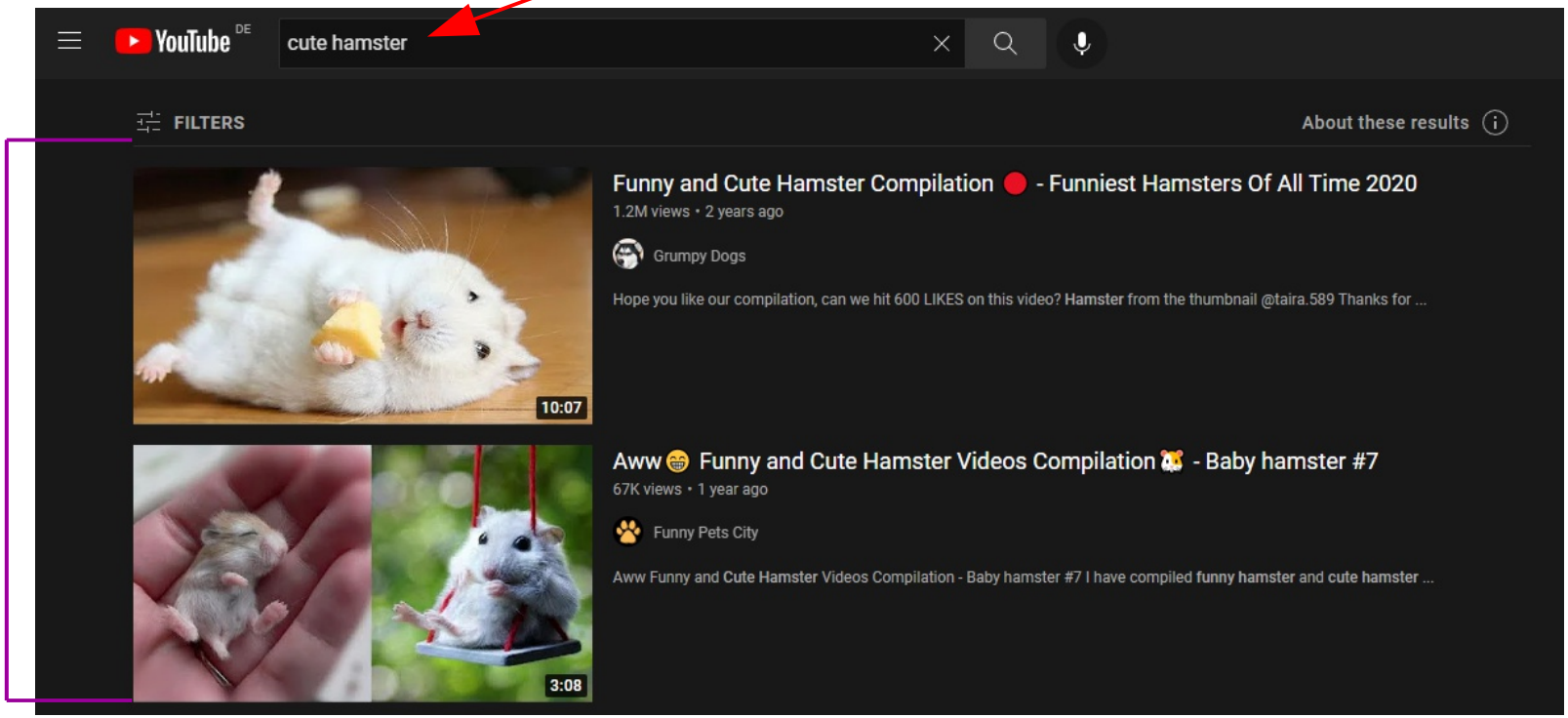

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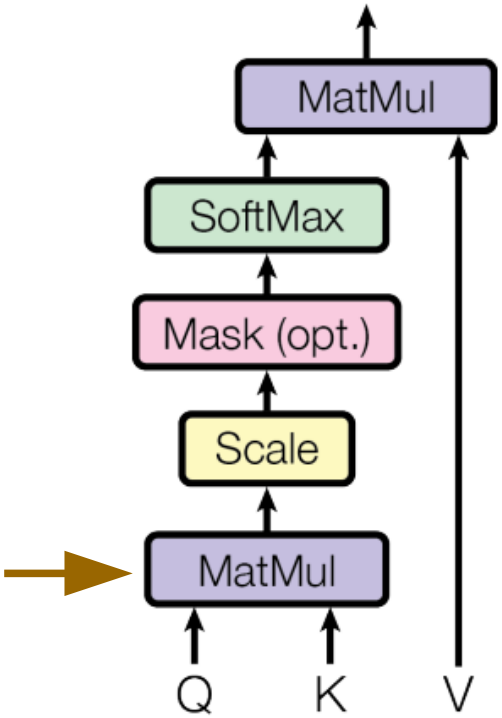
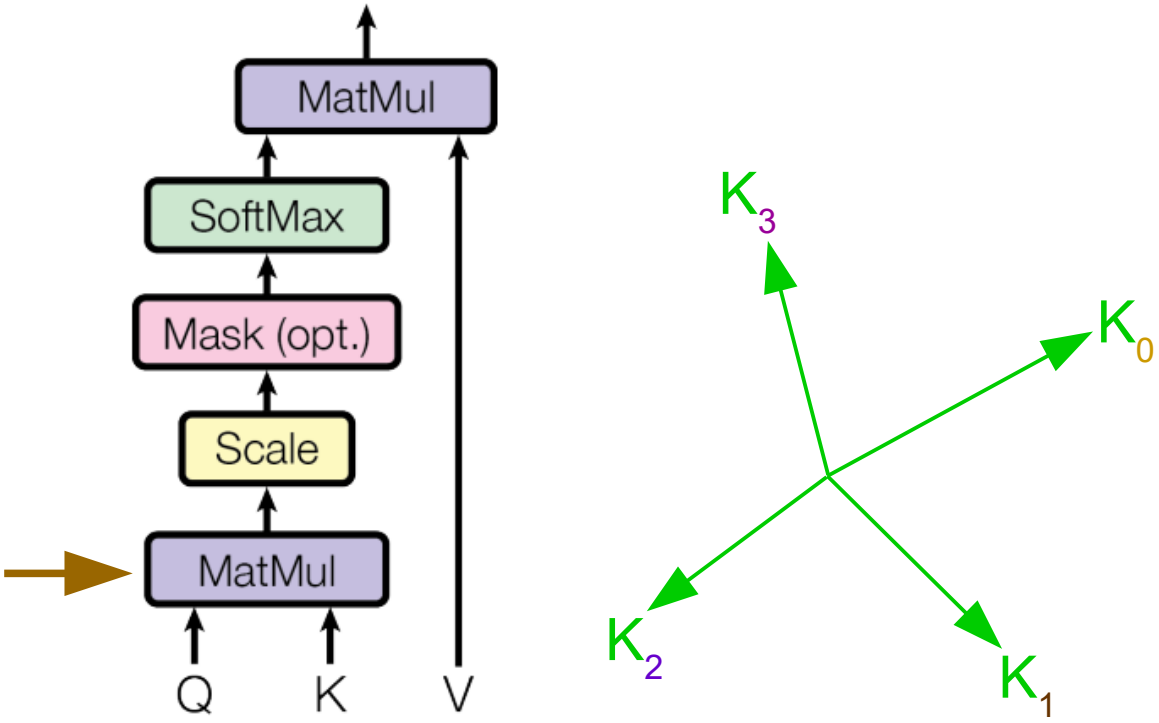


Figure 7: Self-attention visualised [2].

2. Intuitive understanding of self-attention



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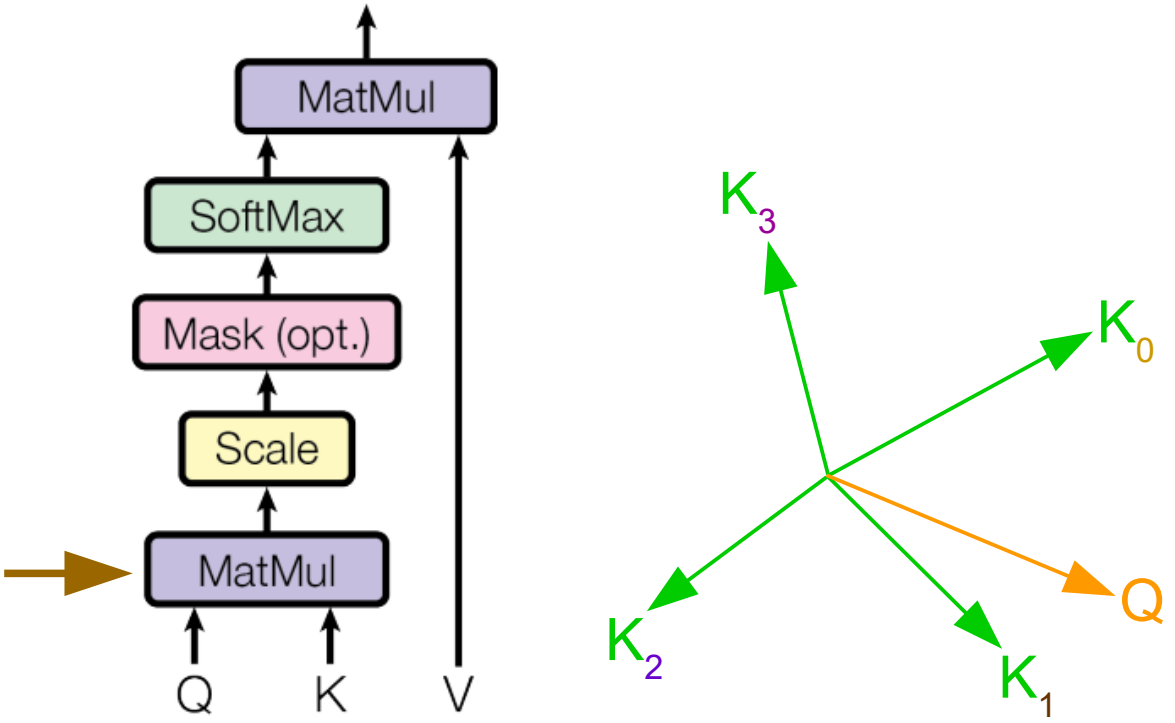

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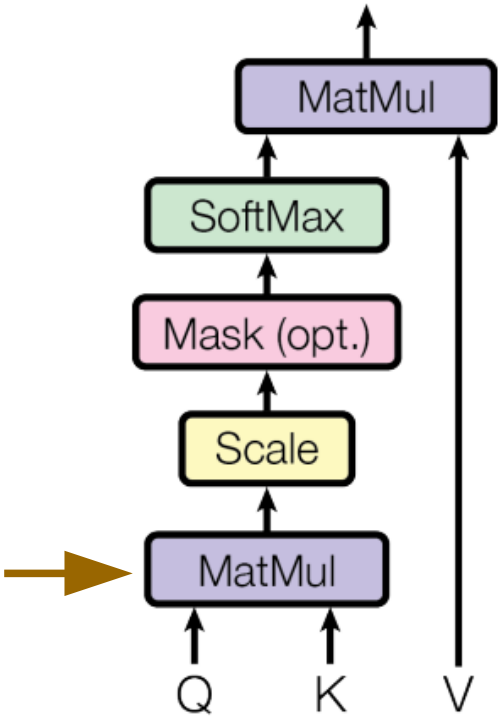

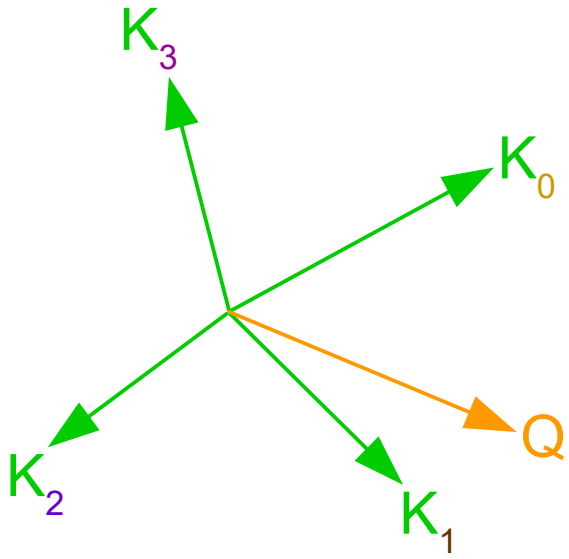

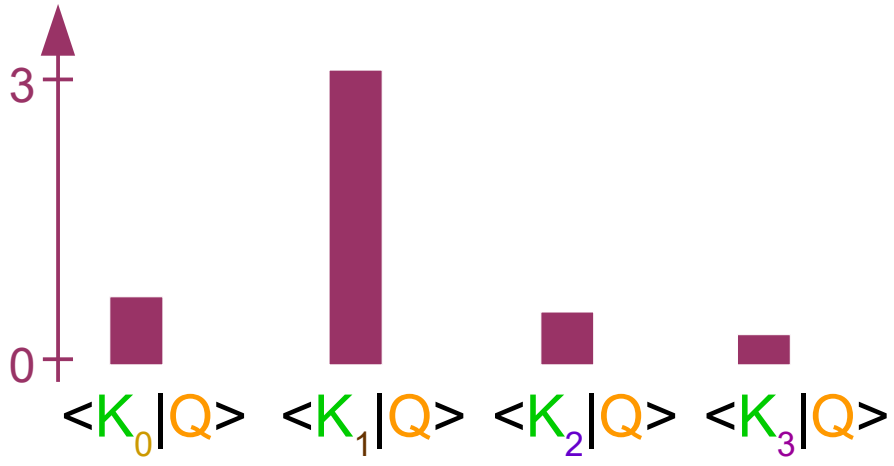

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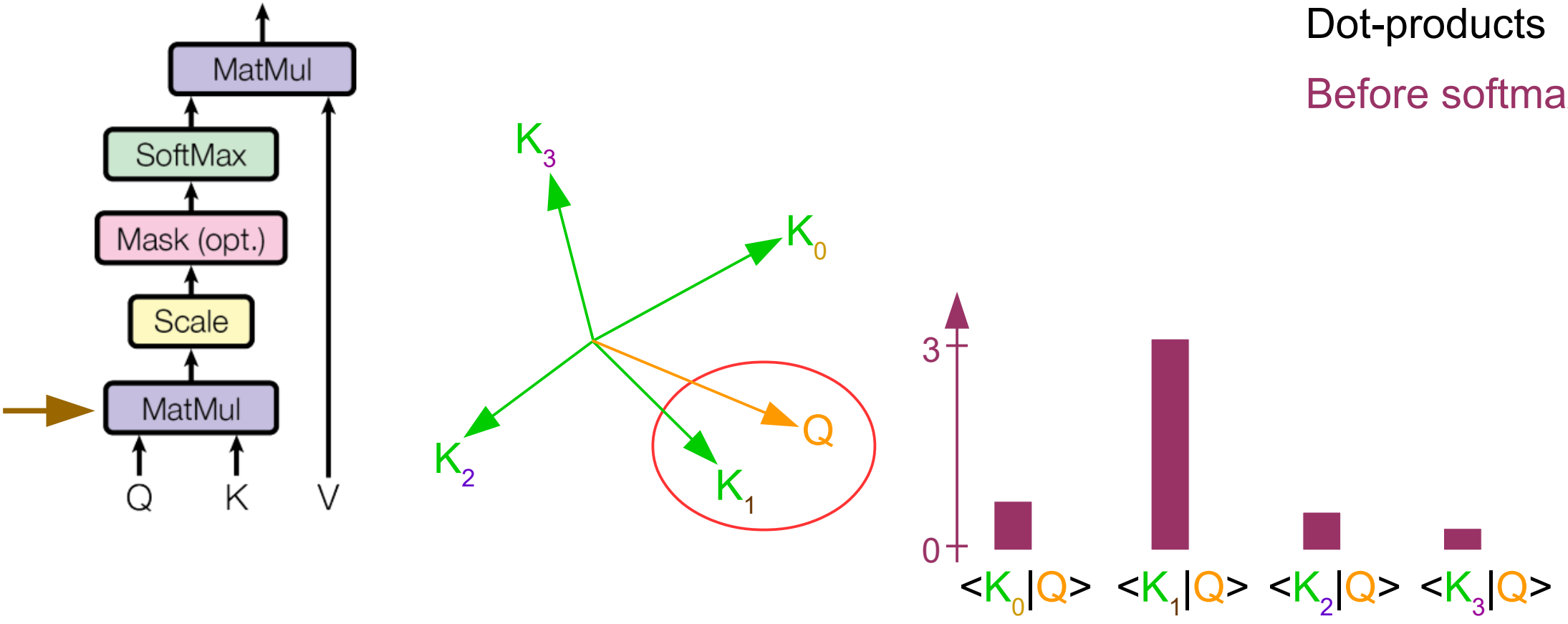

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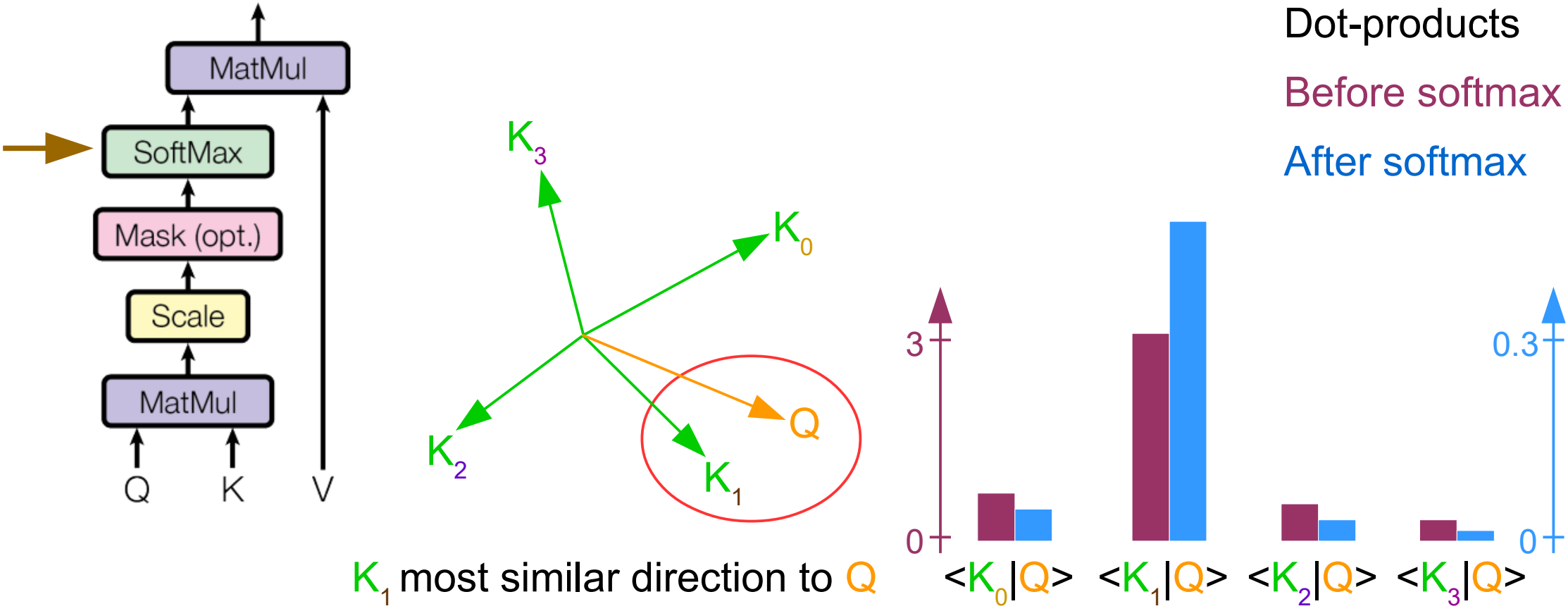

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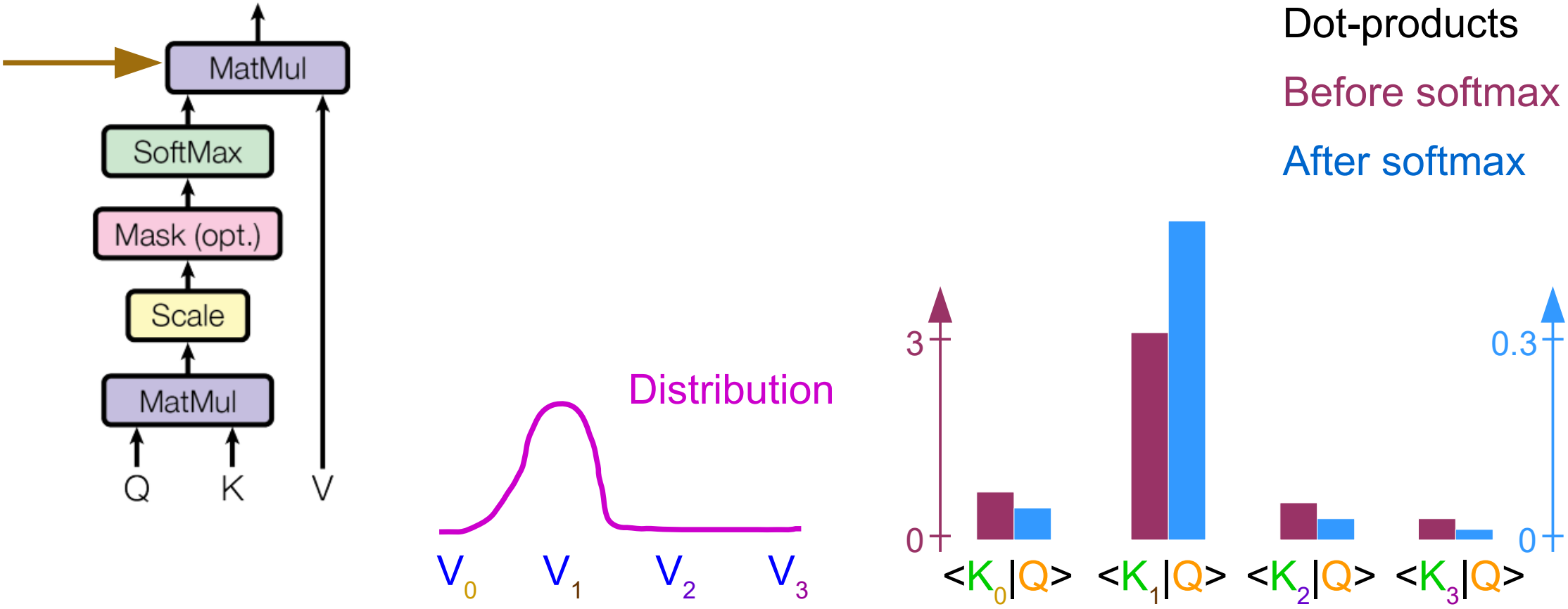

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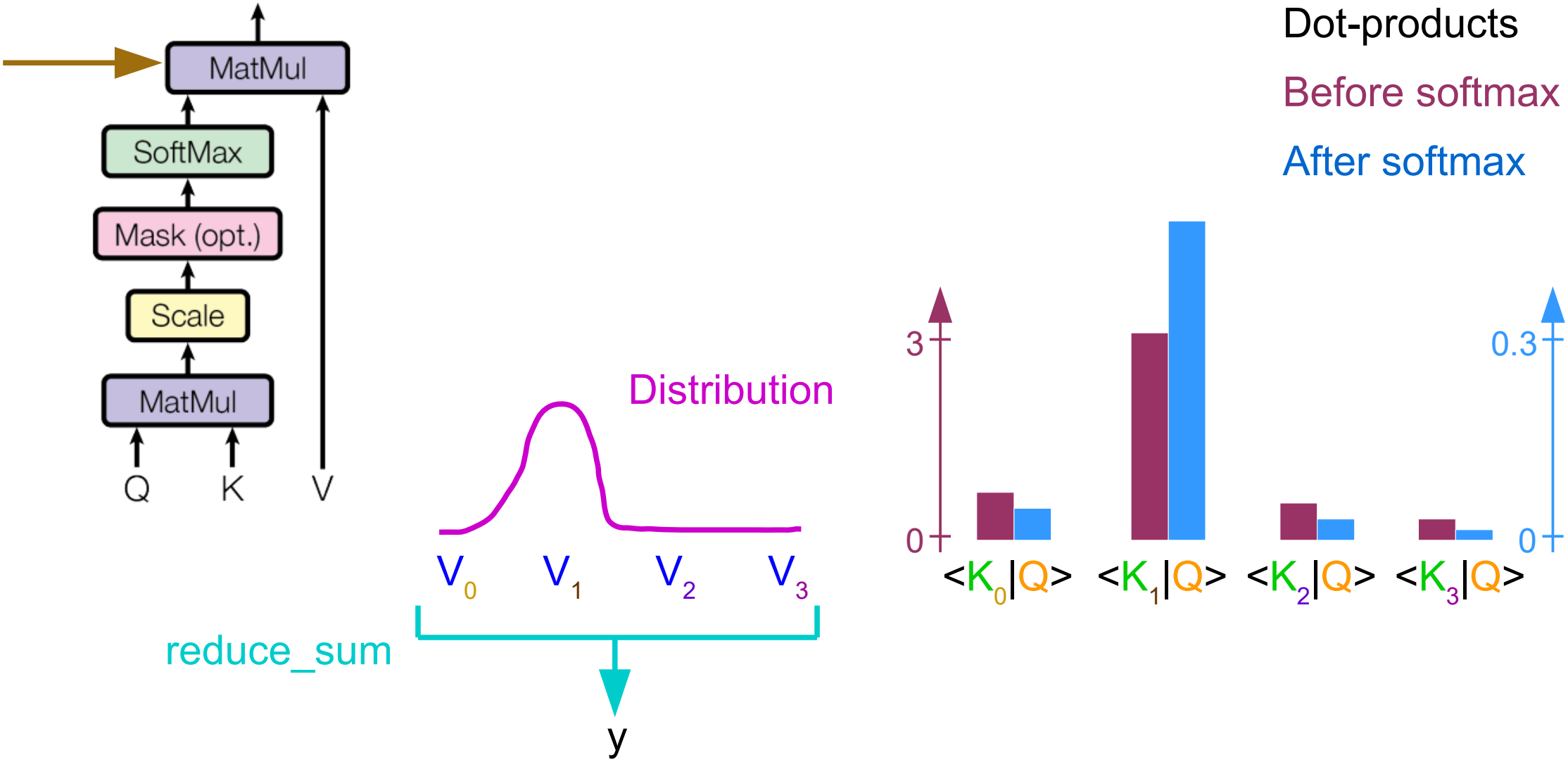

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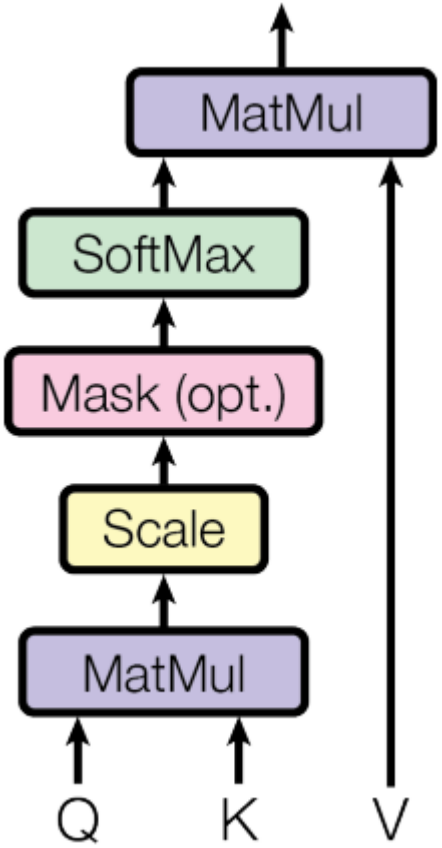

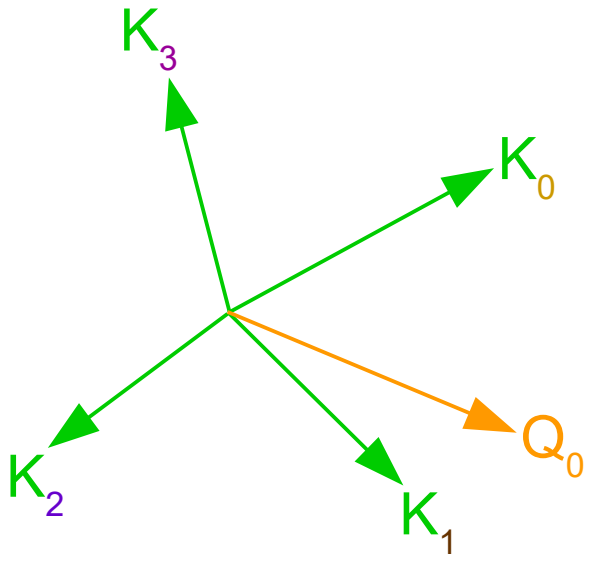

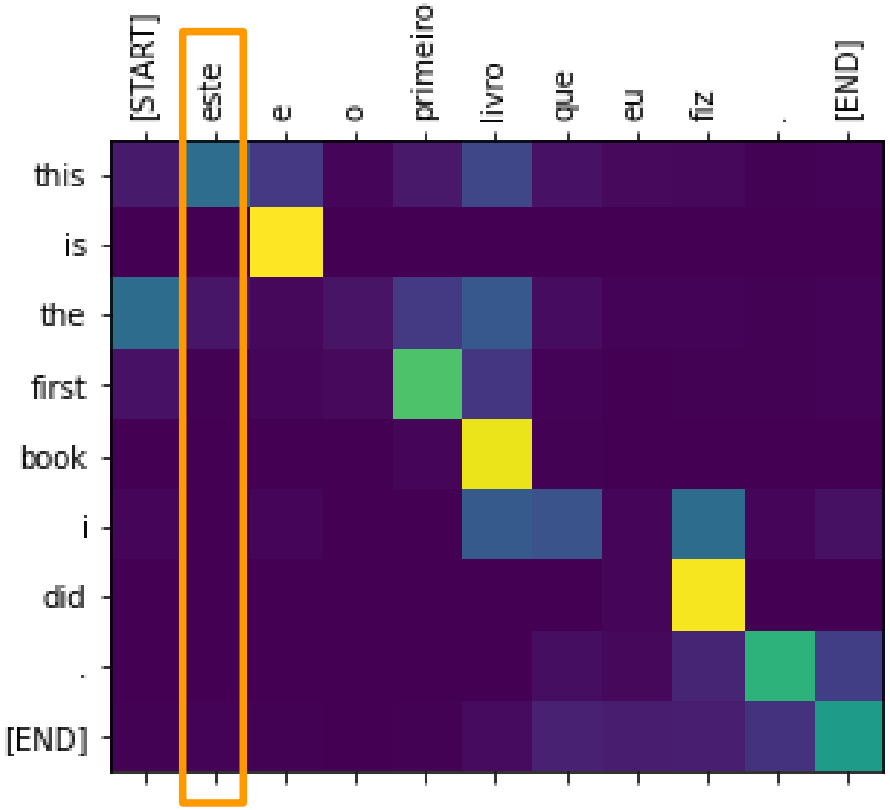

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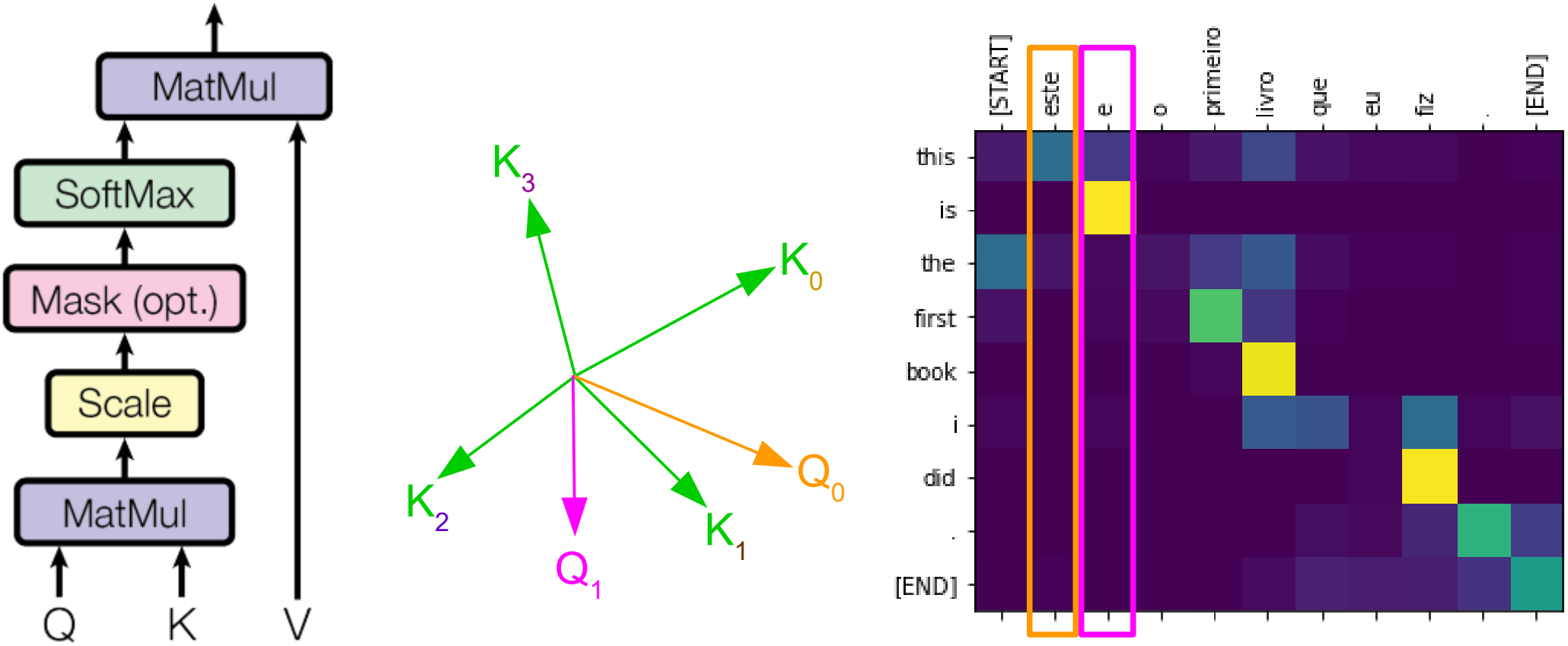

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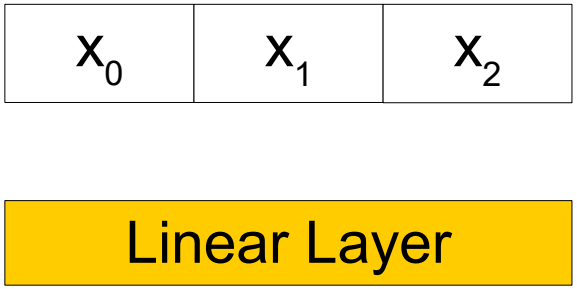

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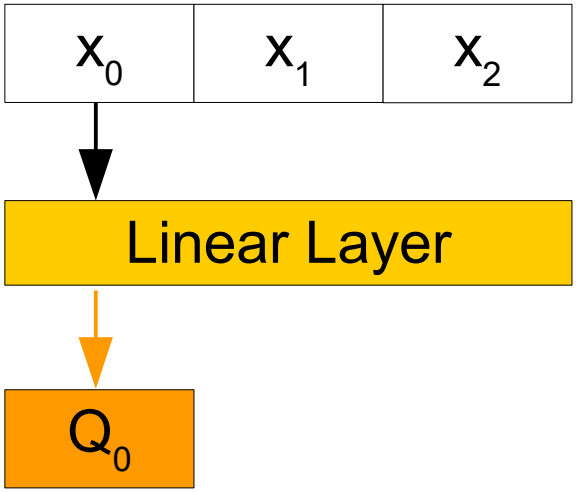

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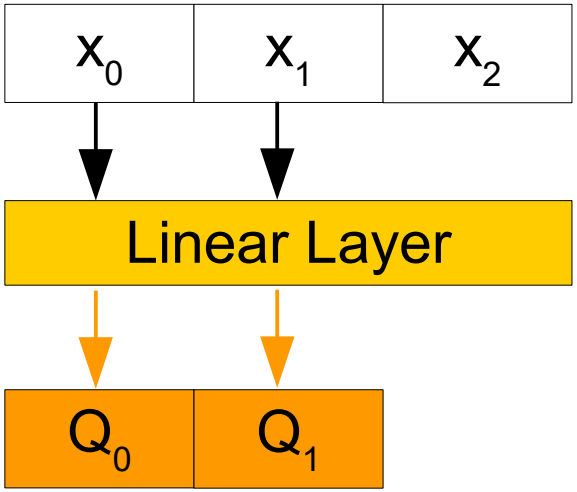

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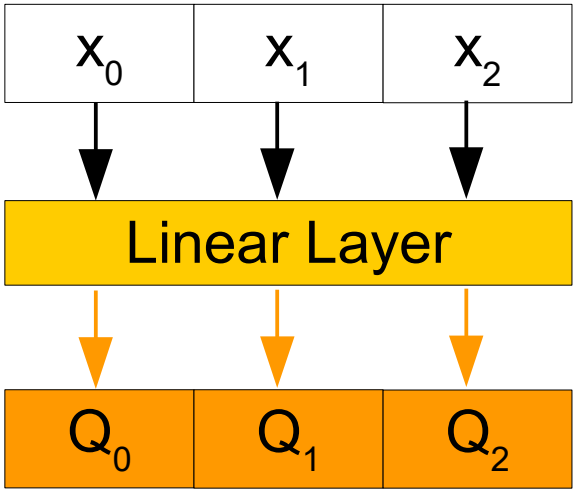

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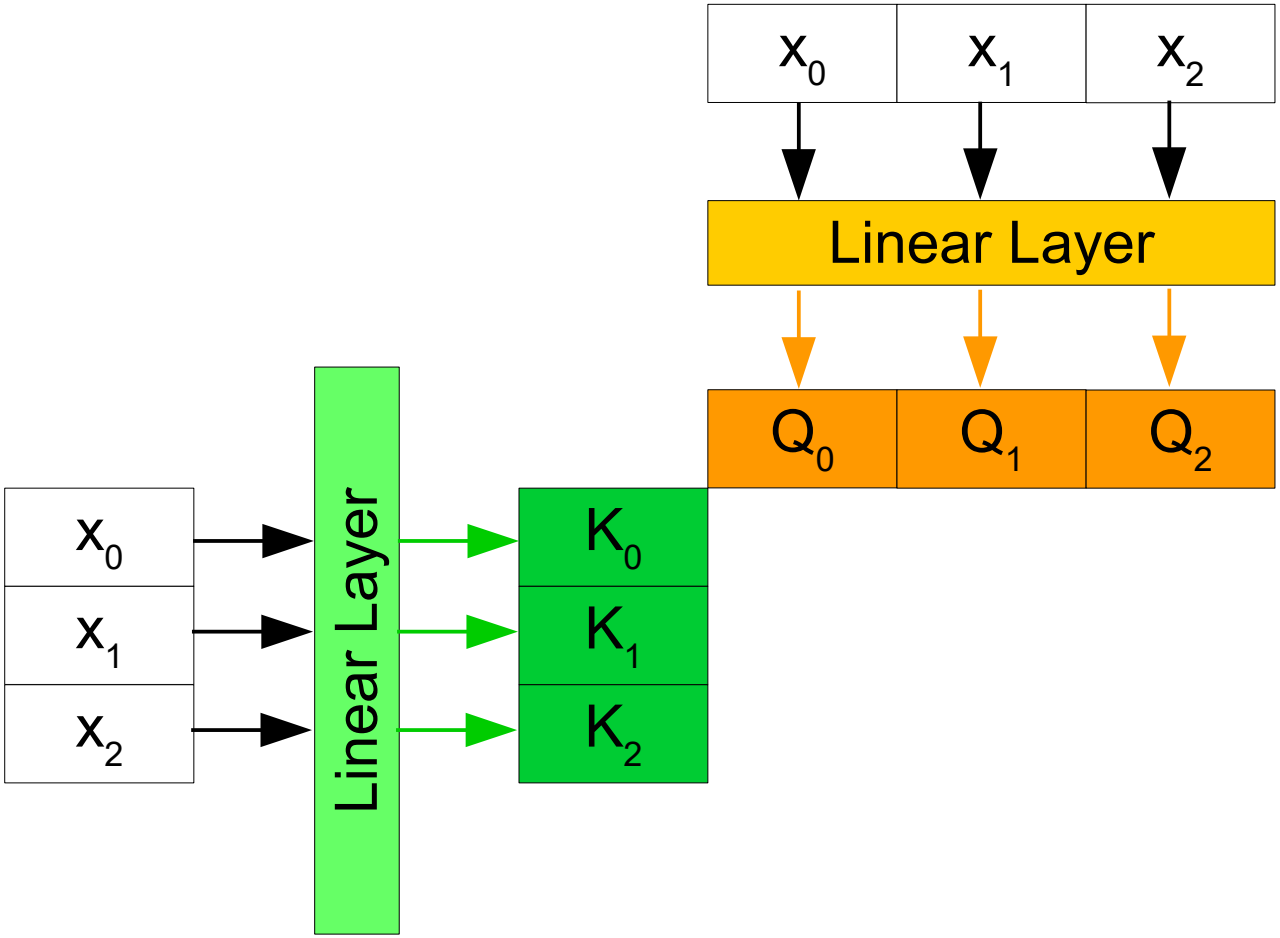

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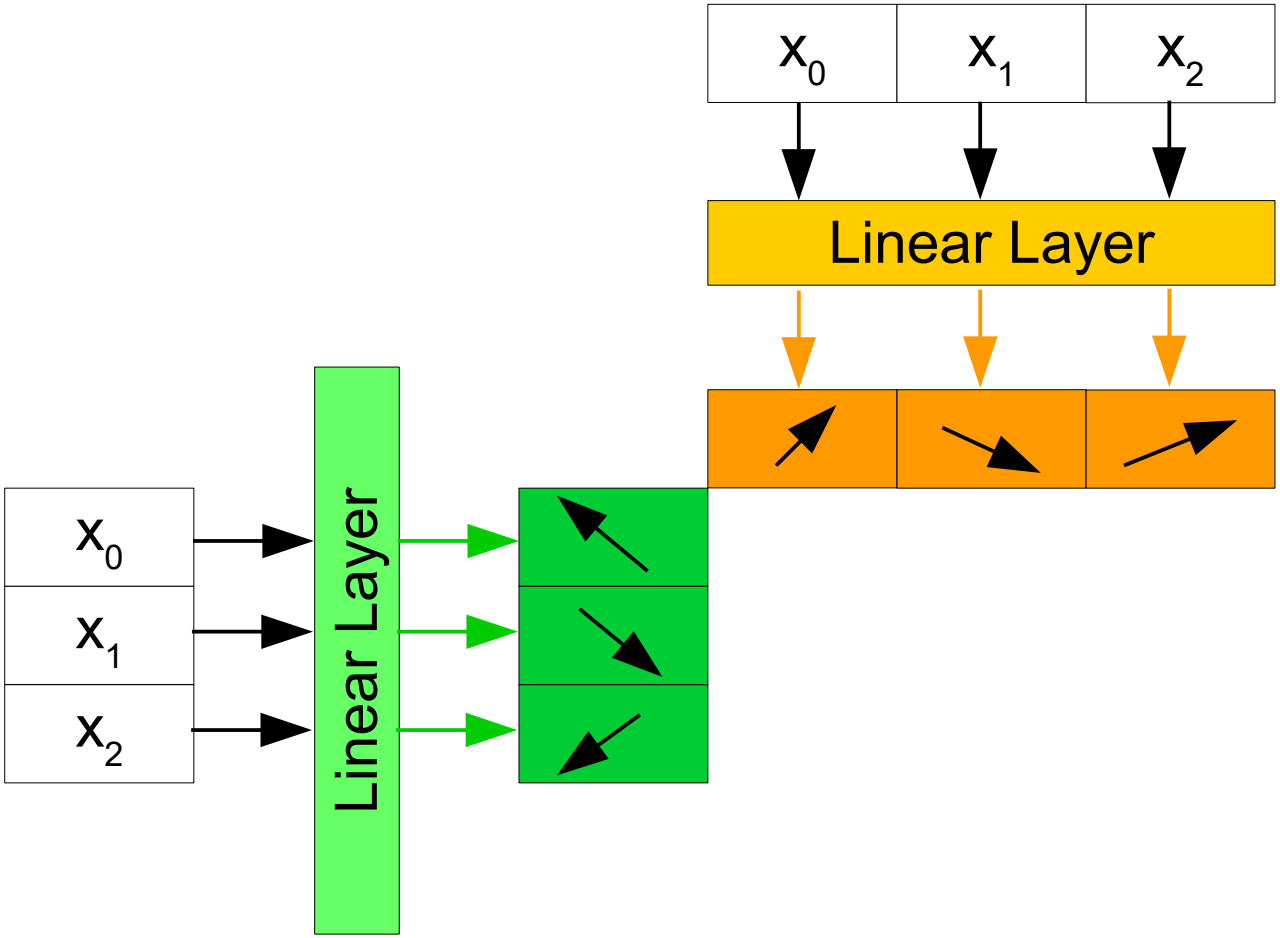

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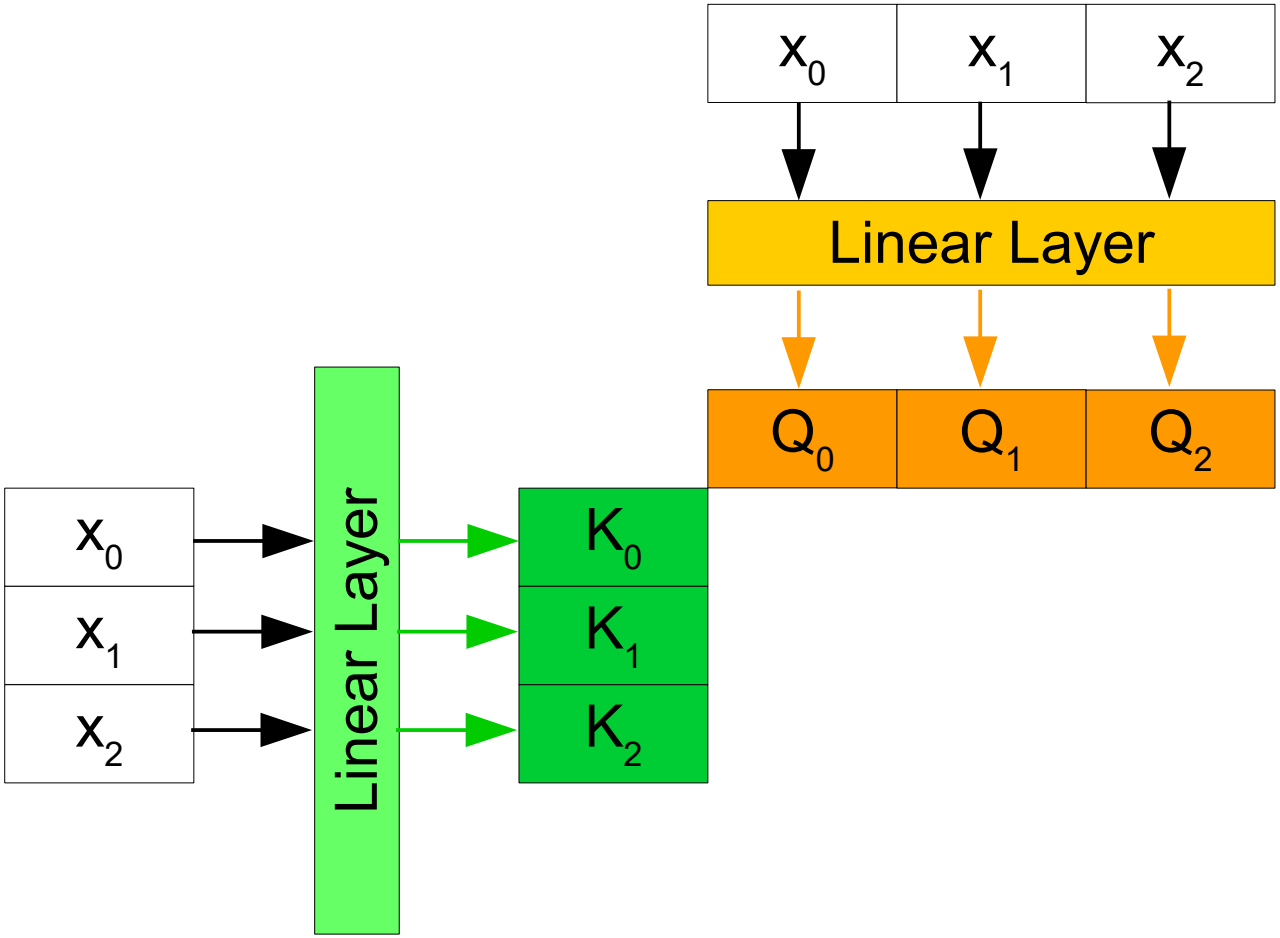

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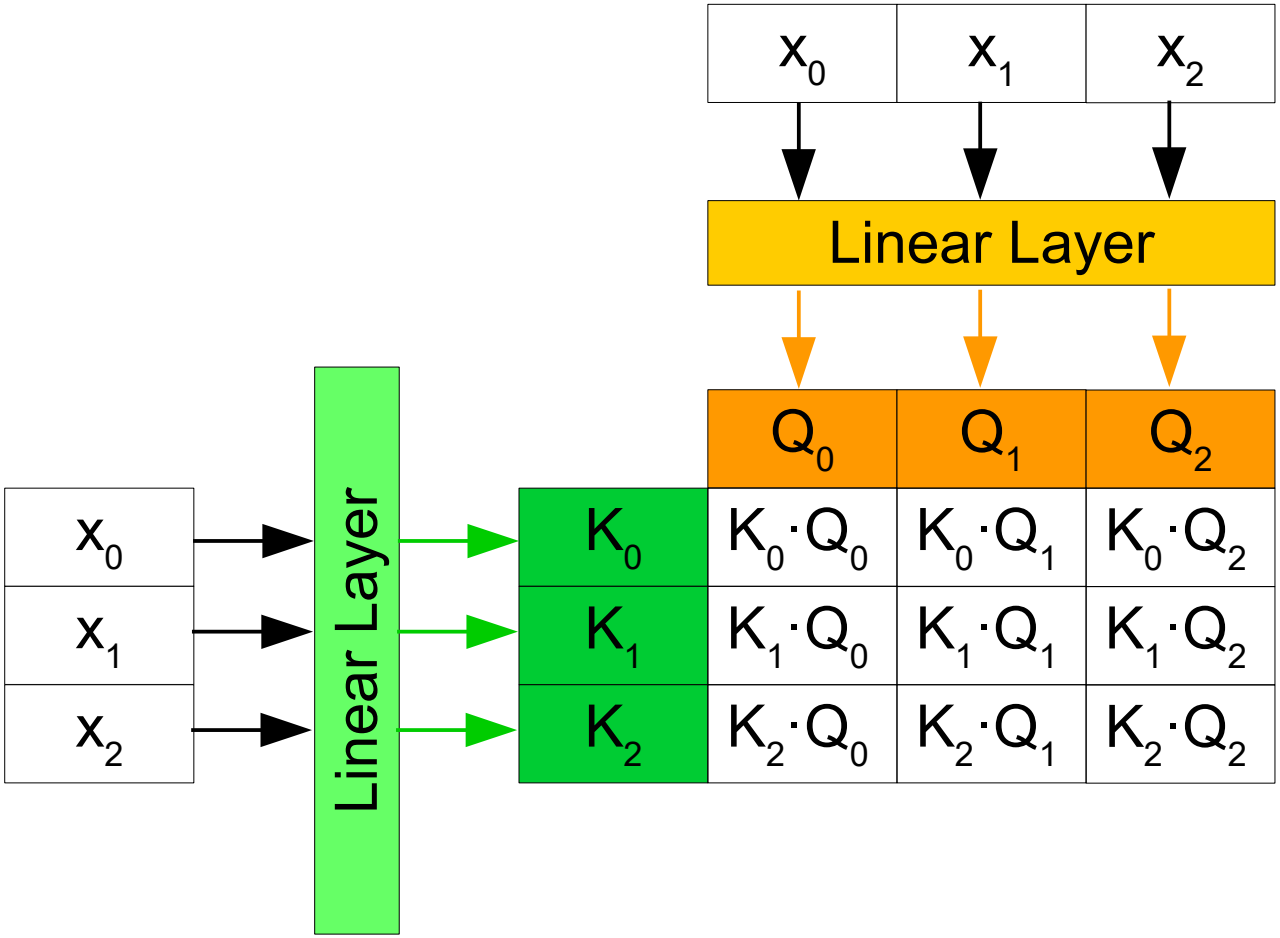

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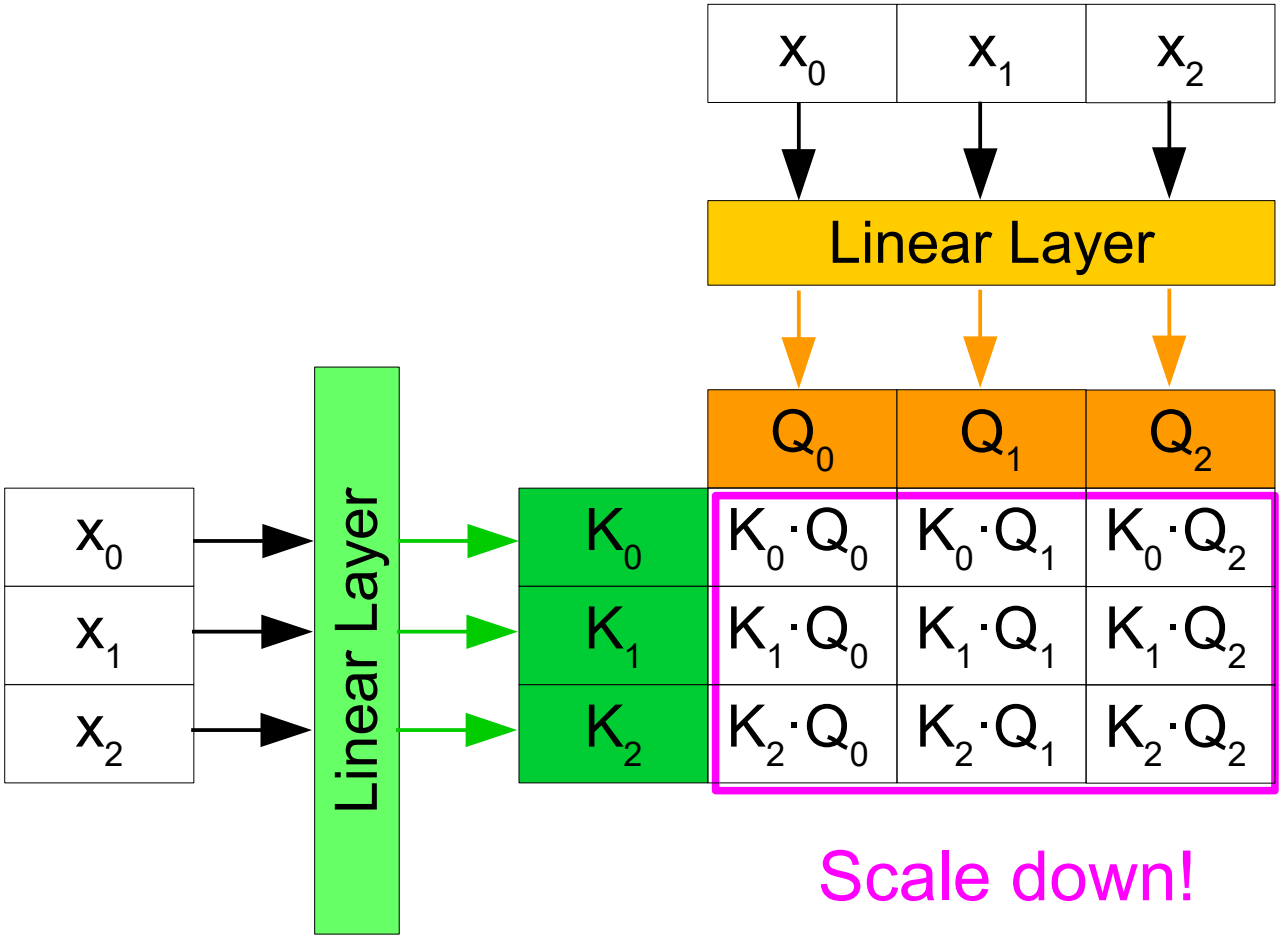
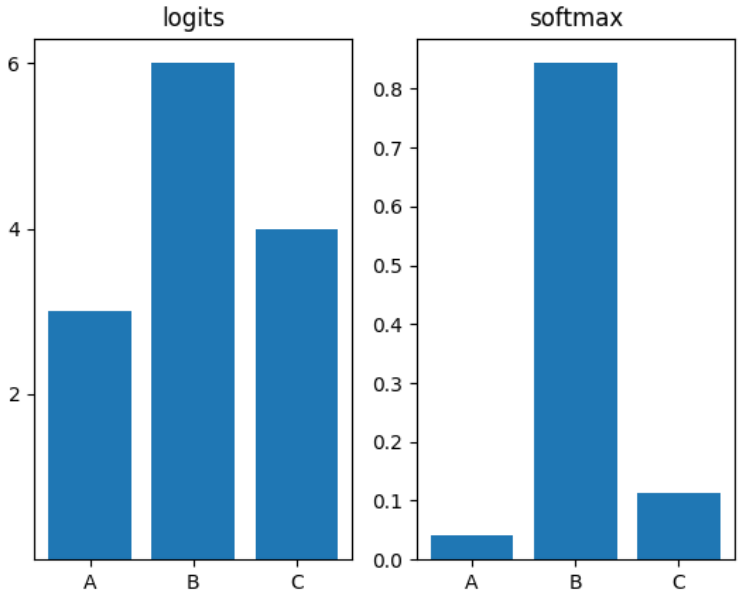
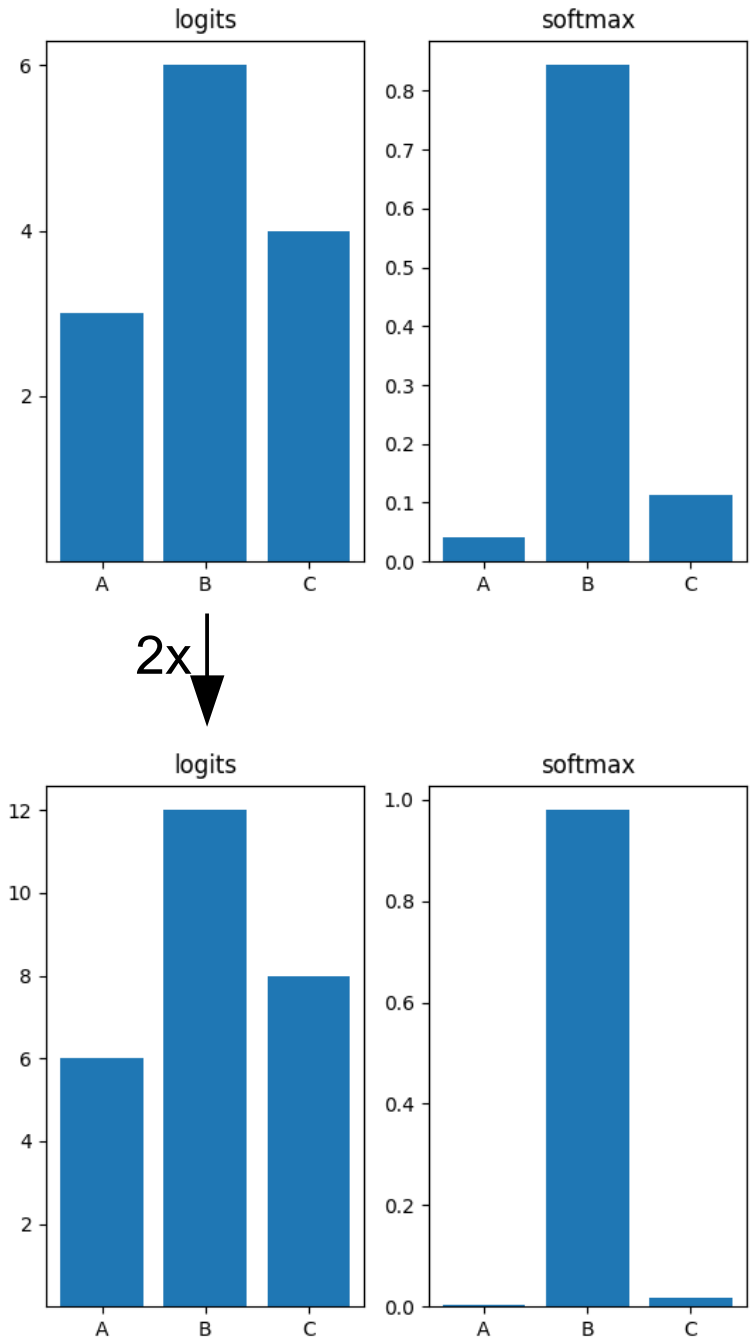


$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

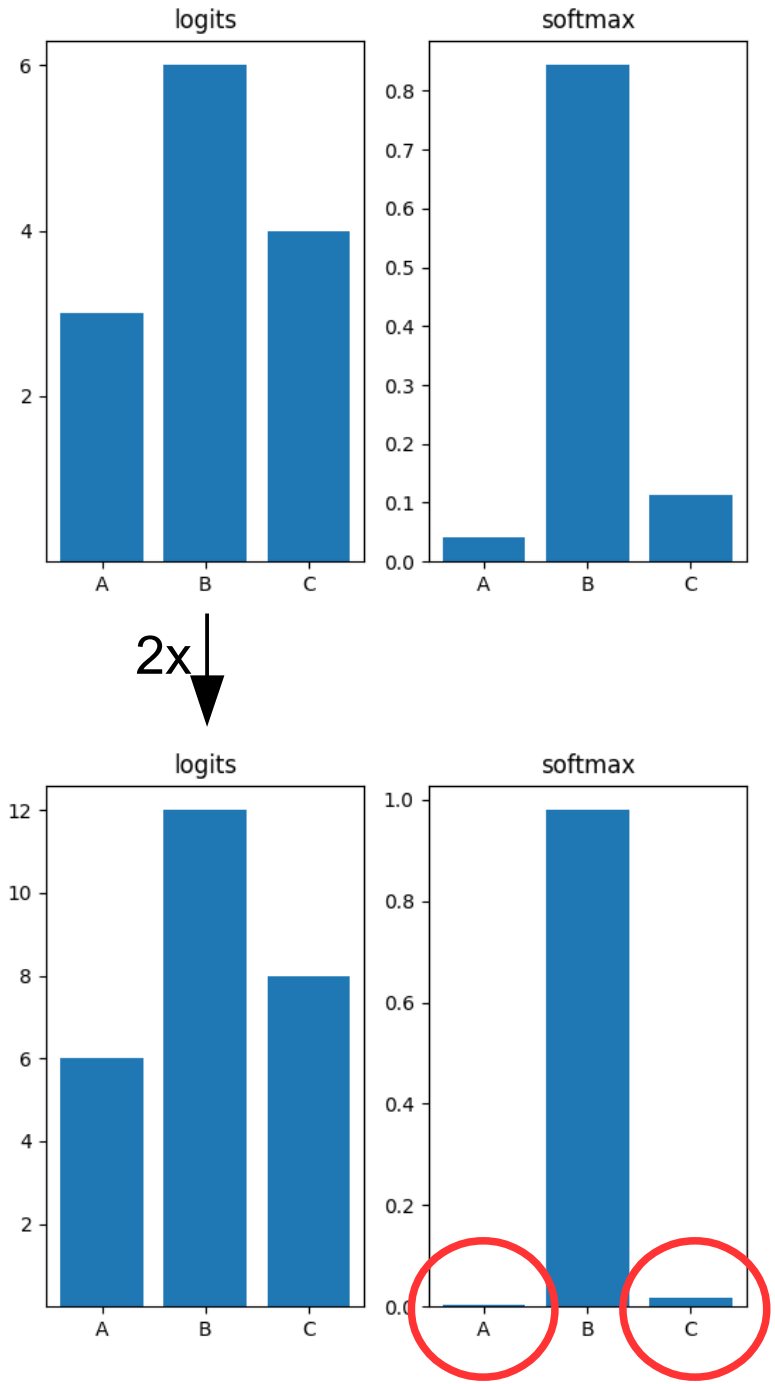
Side note: softmax is not scale invariant



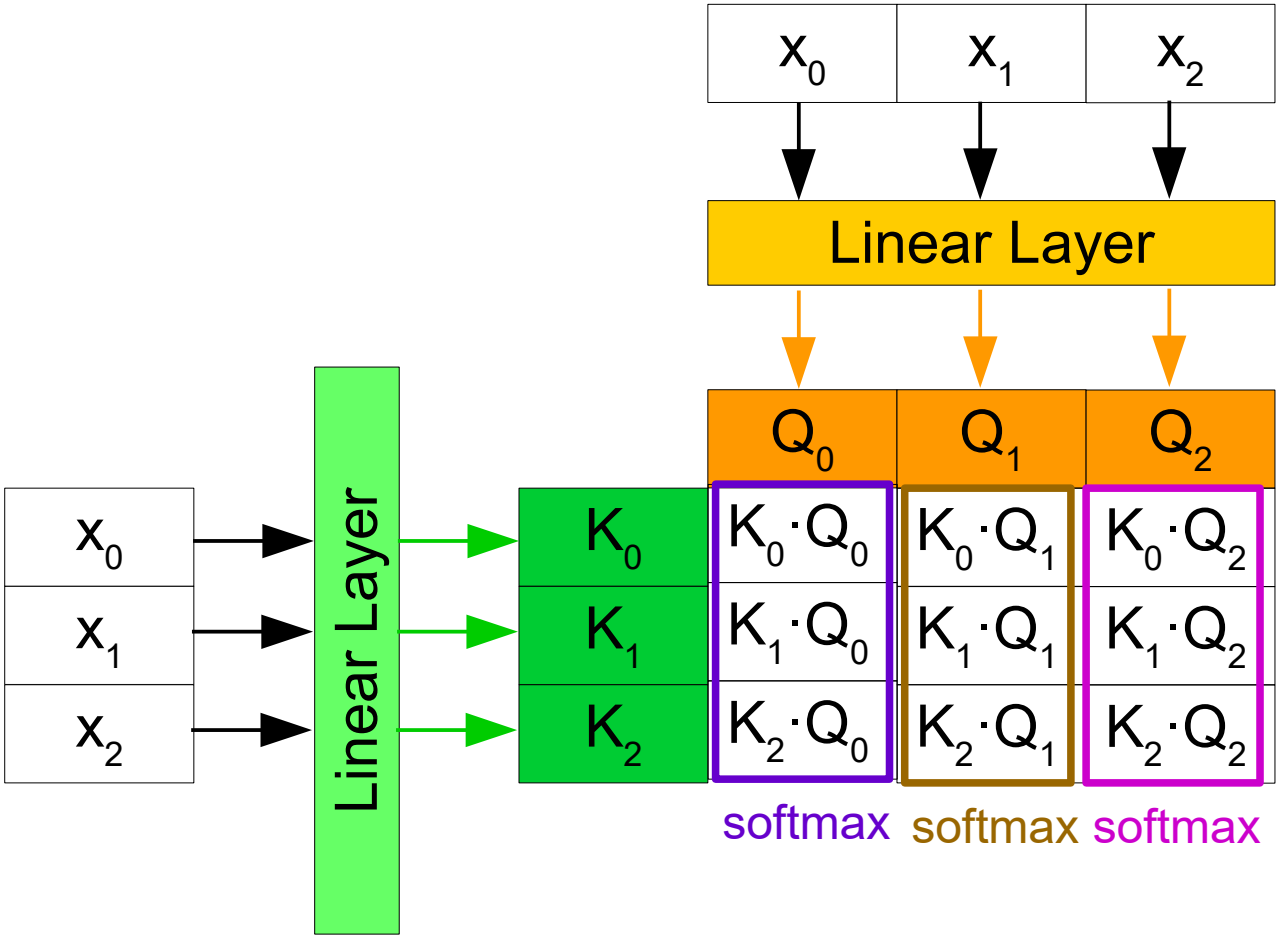
Side note: softmax is not scale invariant



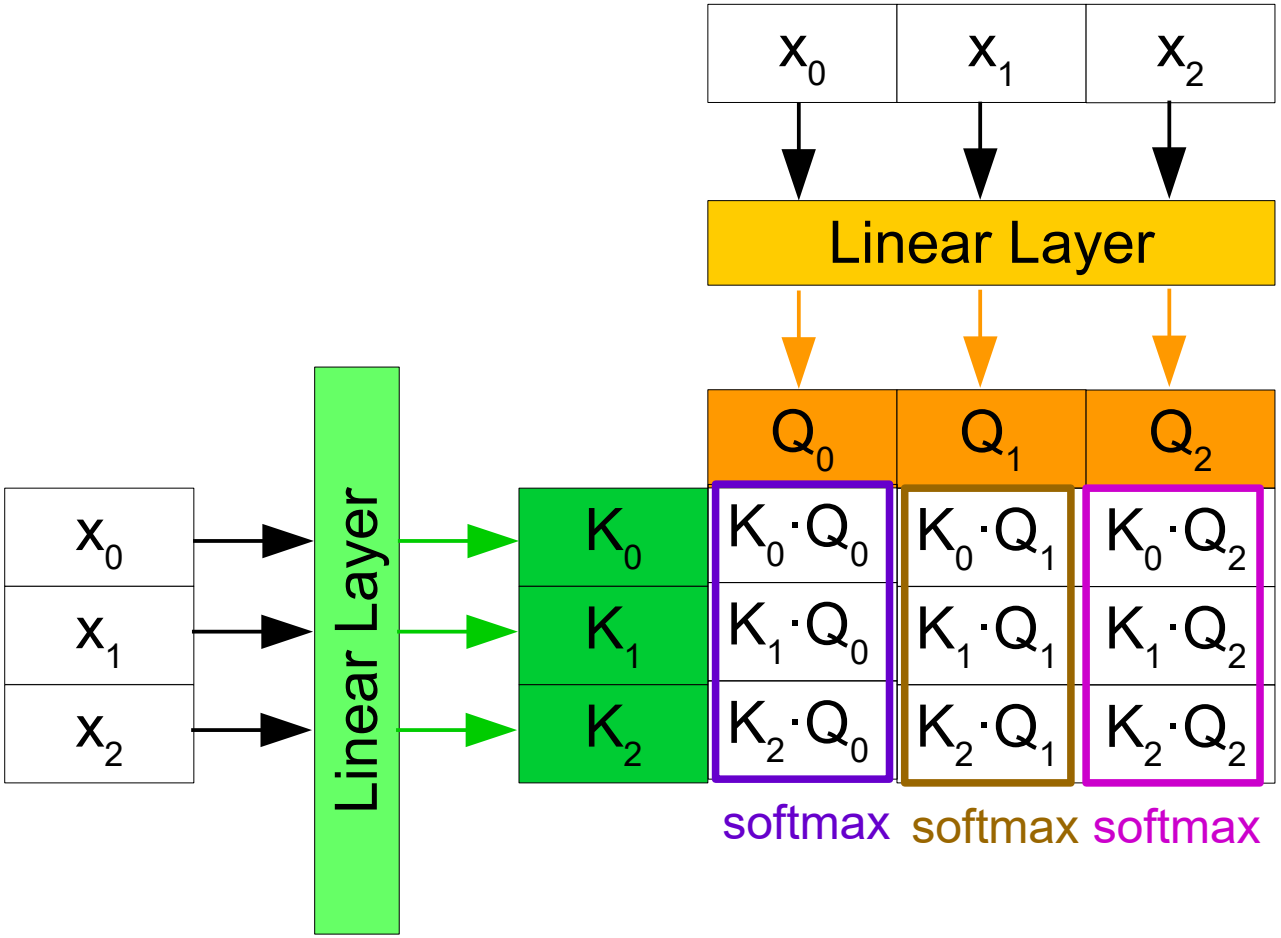
Side note: softmax is not scale invariant



2. Intuitive understanding of self-attention



2. Intuitive understanding of self-attention



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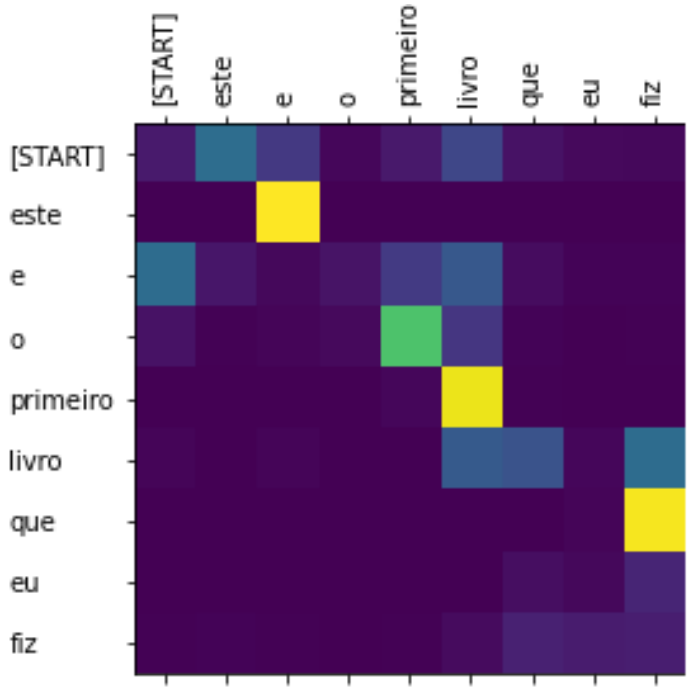
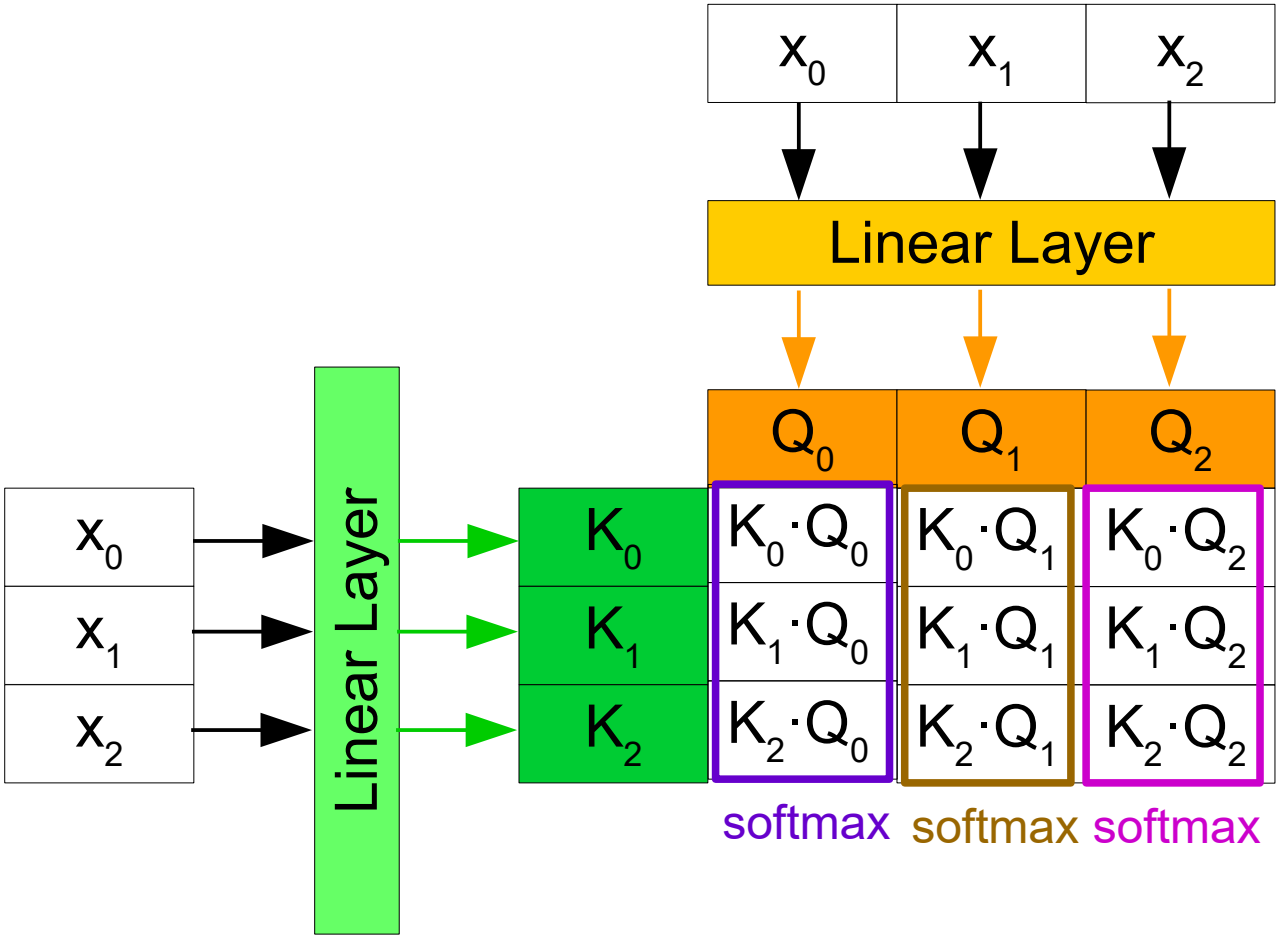


Here: 3 words instead of 9 ;)

Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

2. Intuitive understanding of self-attention



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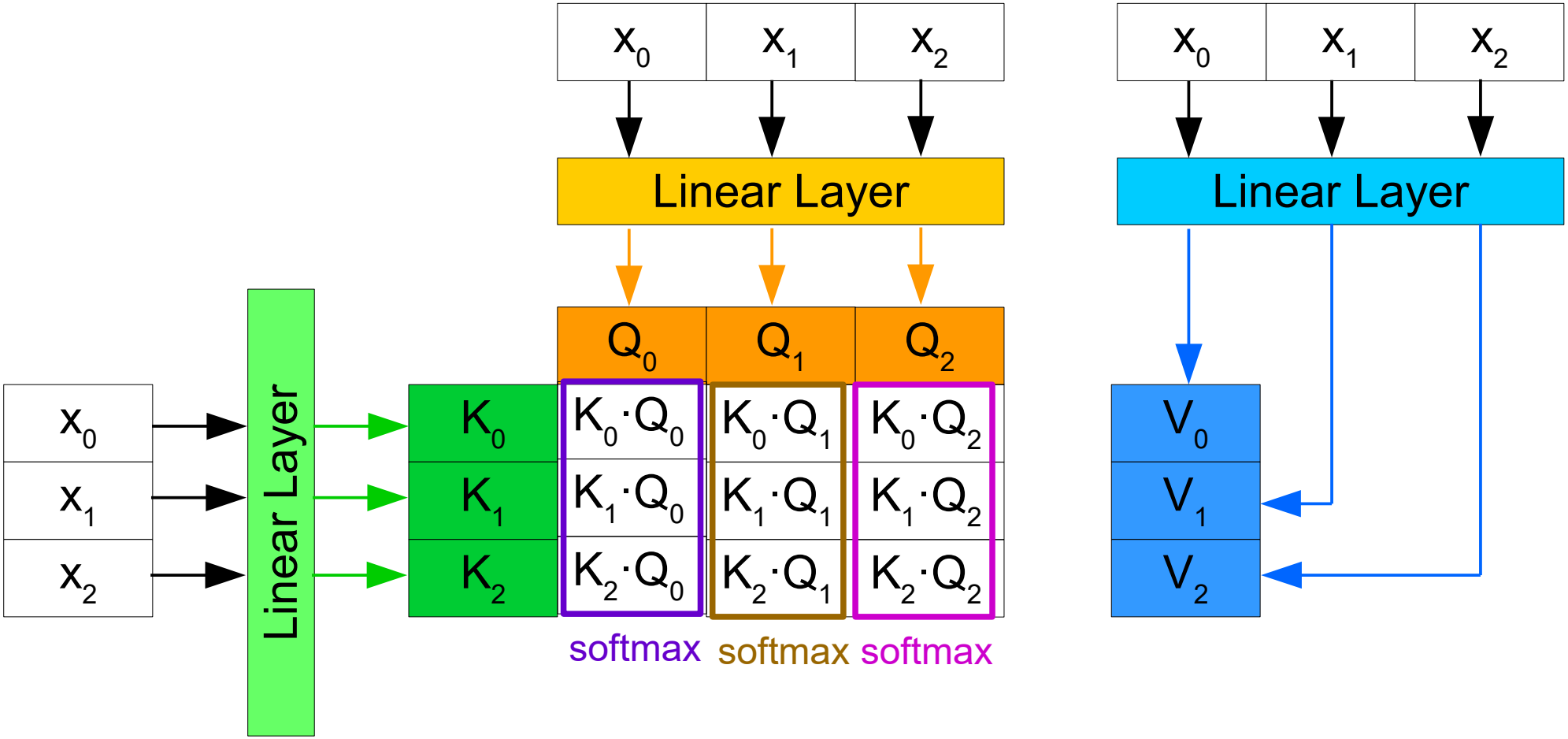

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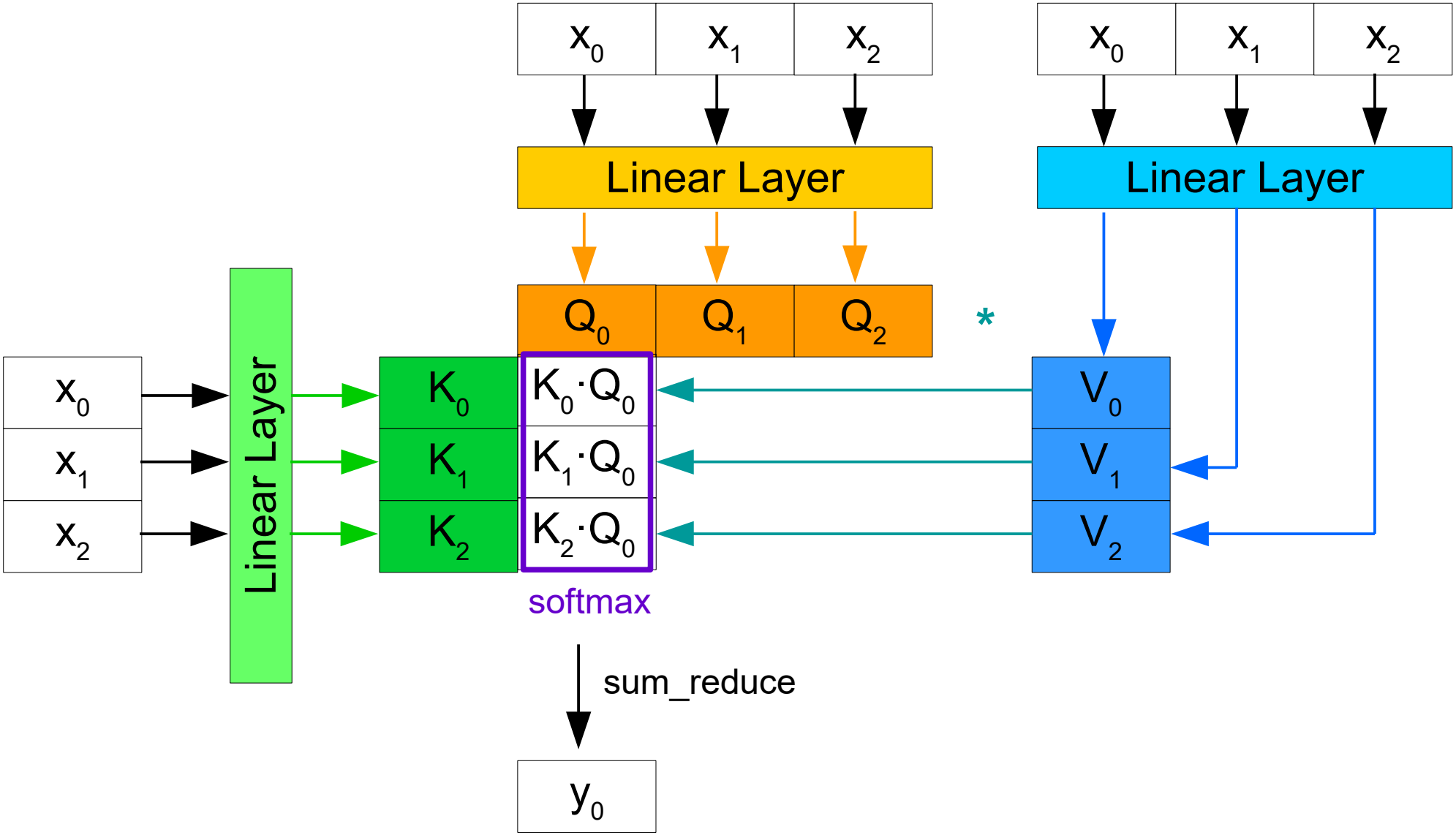

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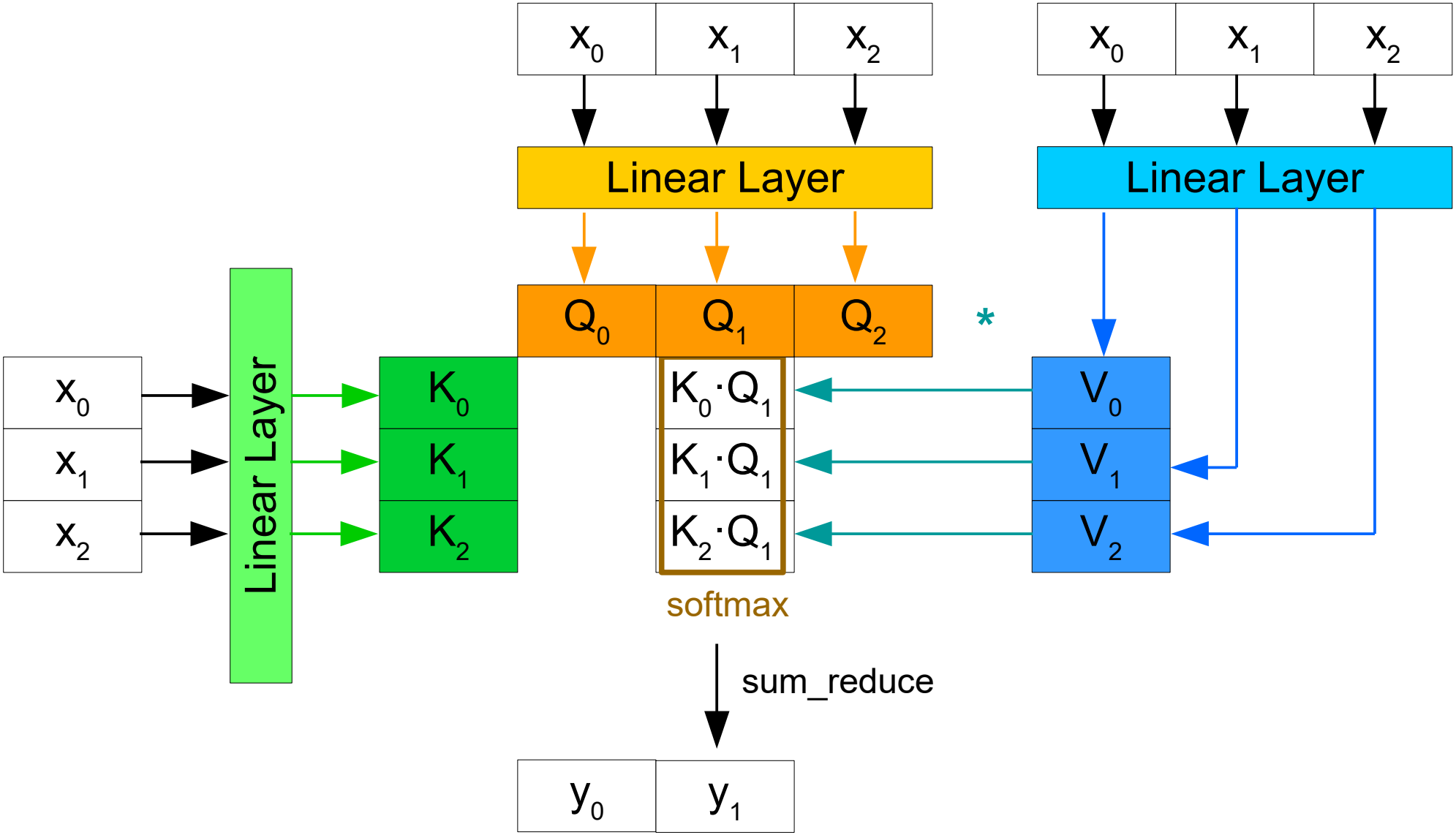

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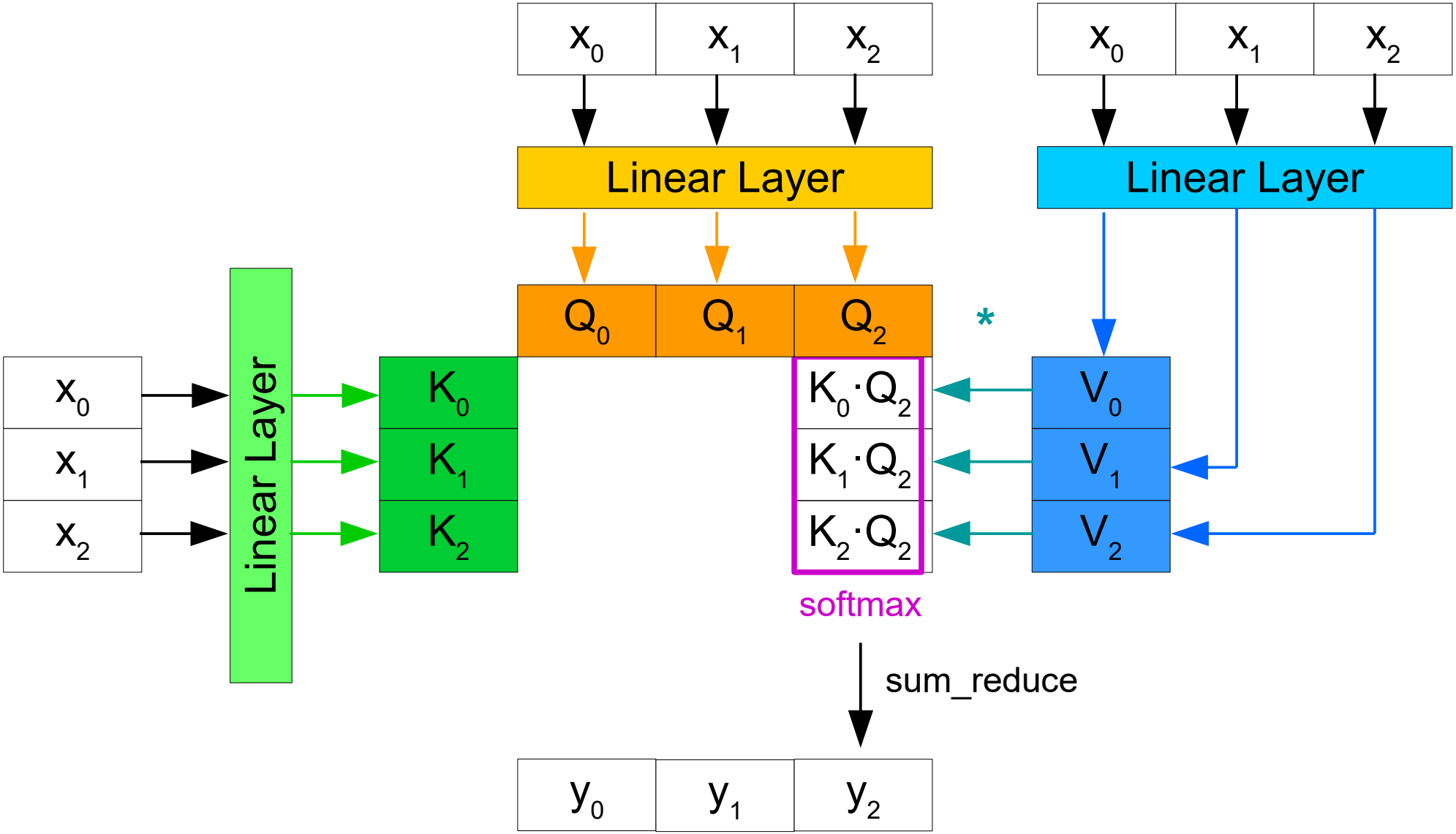
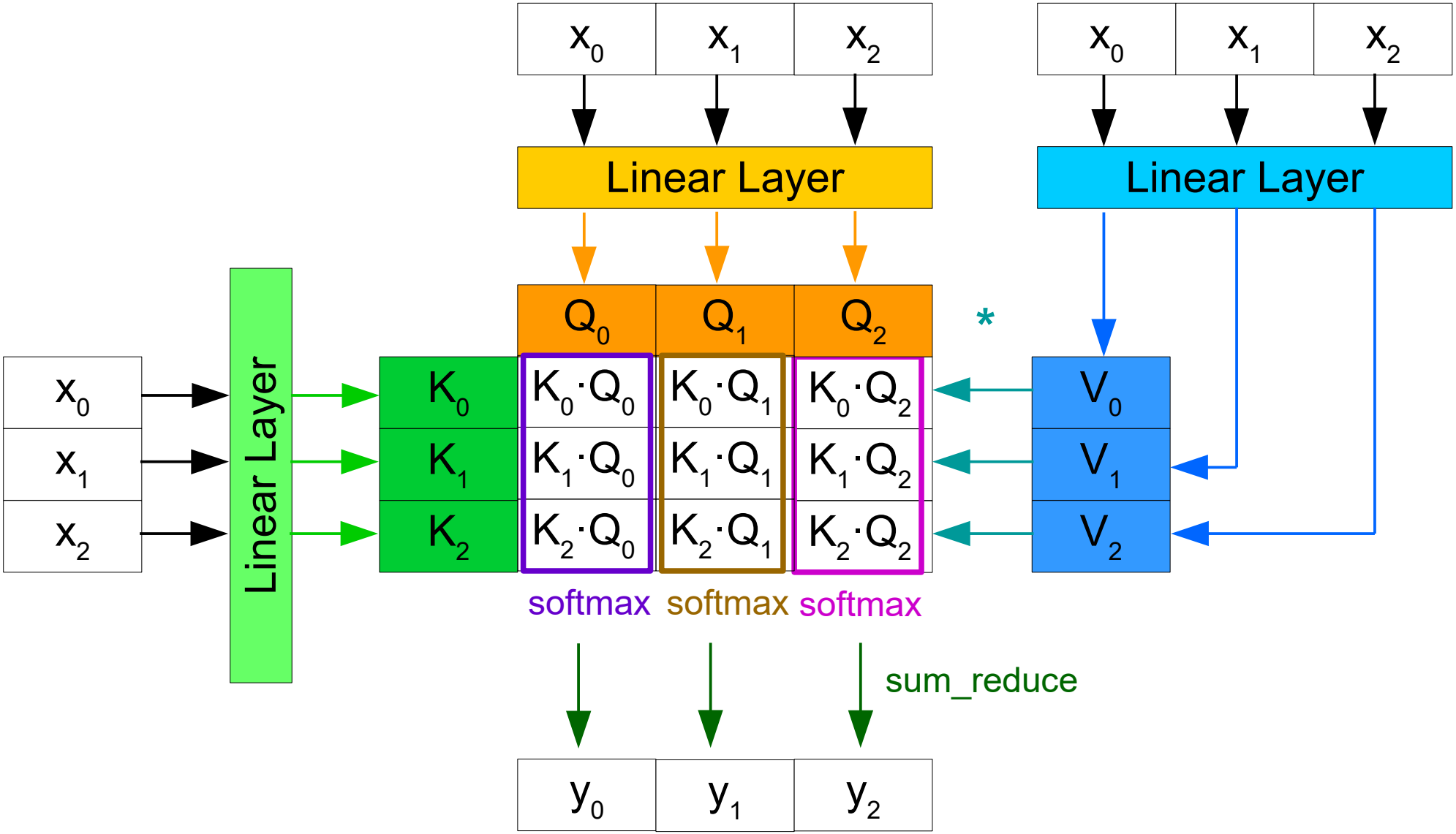


2. Intuitive understanding of self-attention



2.1 Multi-head attention

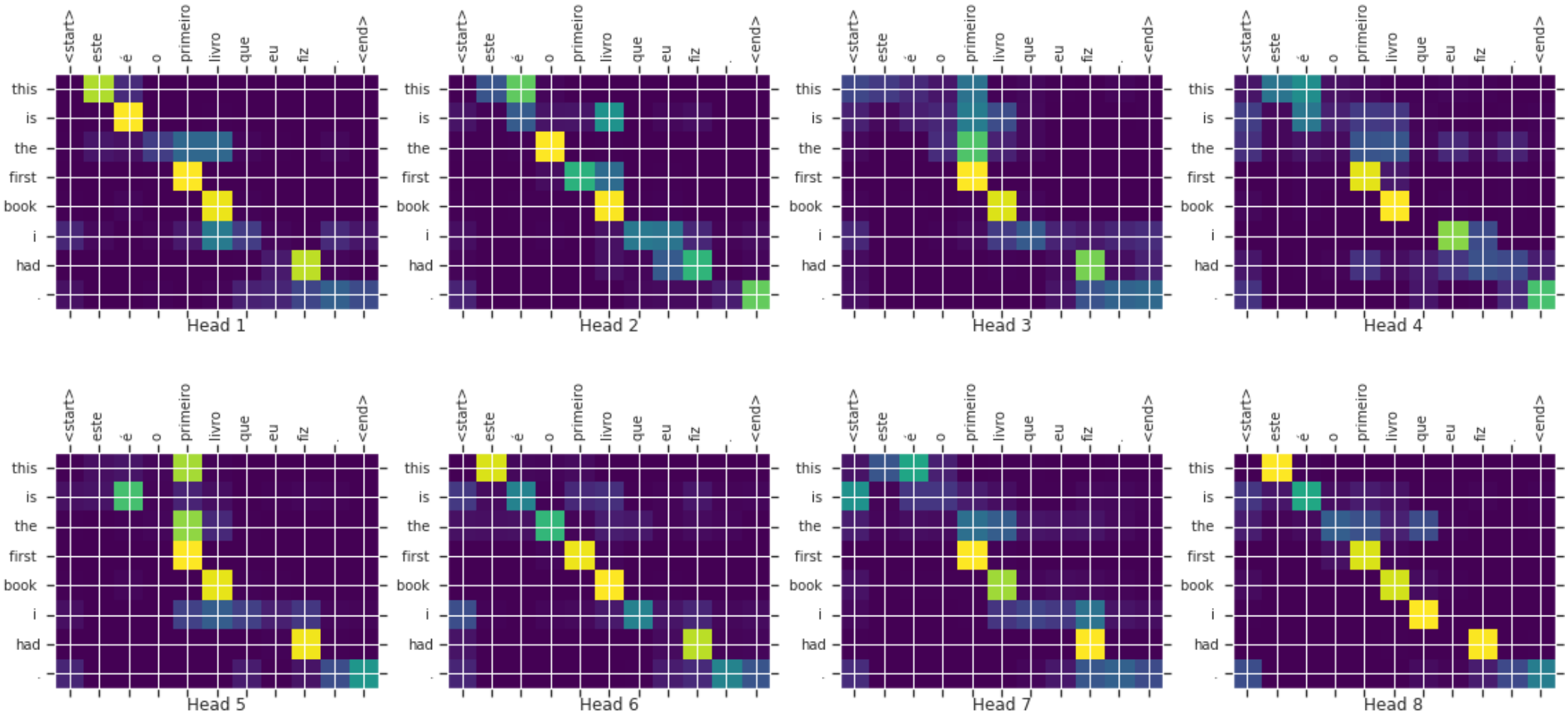


Figure 9: Heatmaps from Multi-head attention [2].

Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

2.1 Multi-head attention

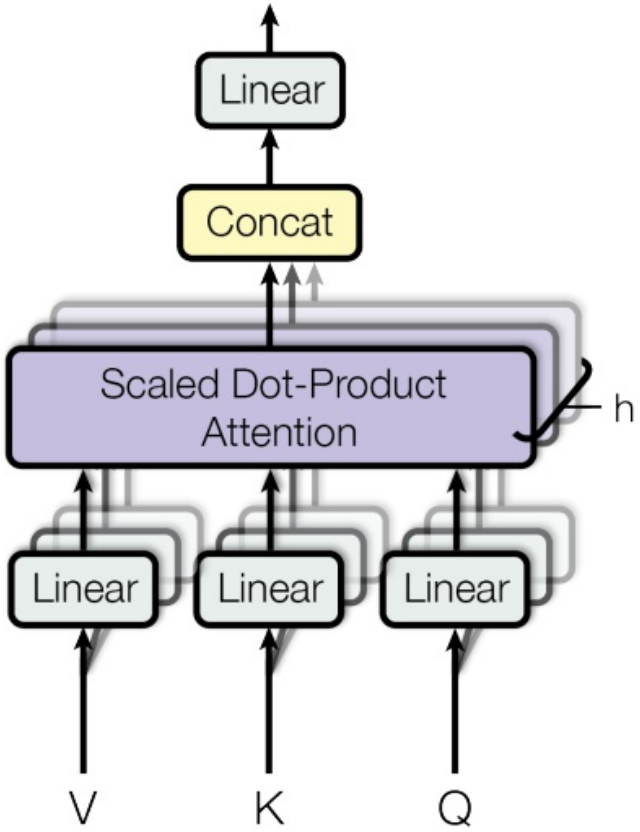
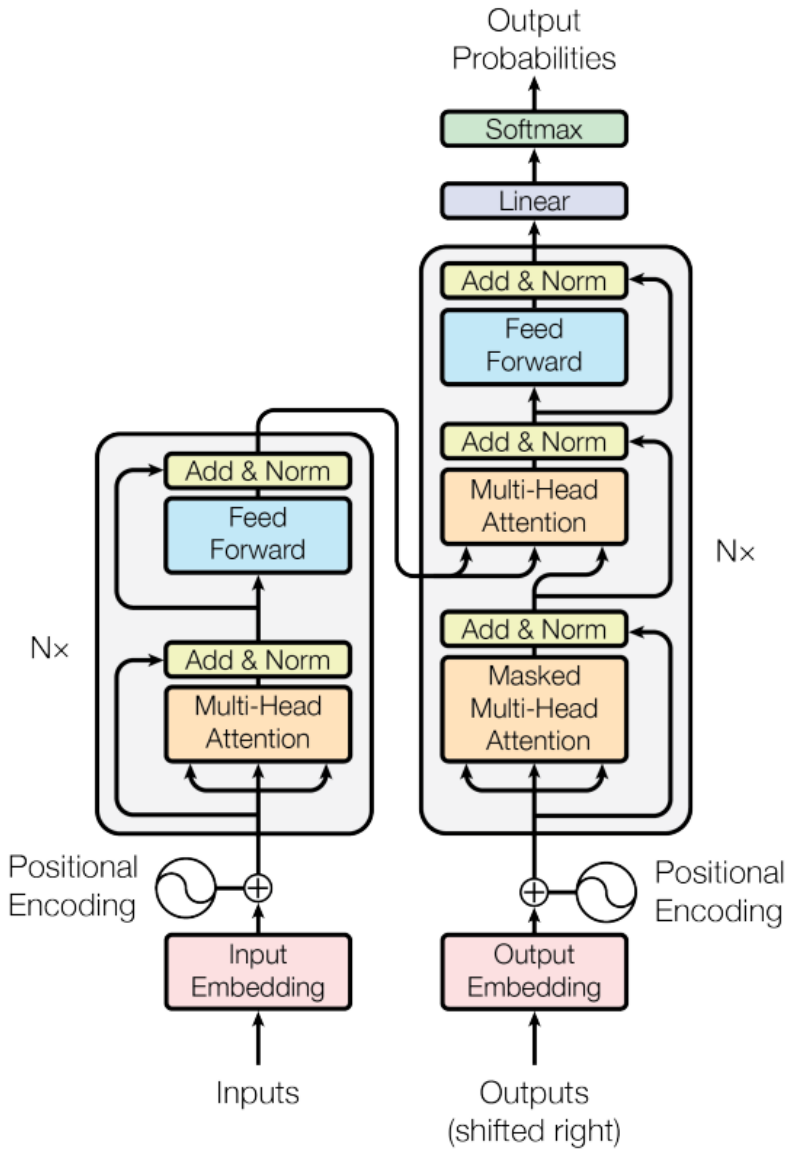


Figure 10: Overview of multi-head attention [2].



3. Intuitive understanding of the transformer architecture

Image sources:
https://machinelearningmastery.com/wp-content/uploads/2021/08/attention_research_1-727x1024.png
(call date: 20.07.22)

3.1 Let's build a transformer

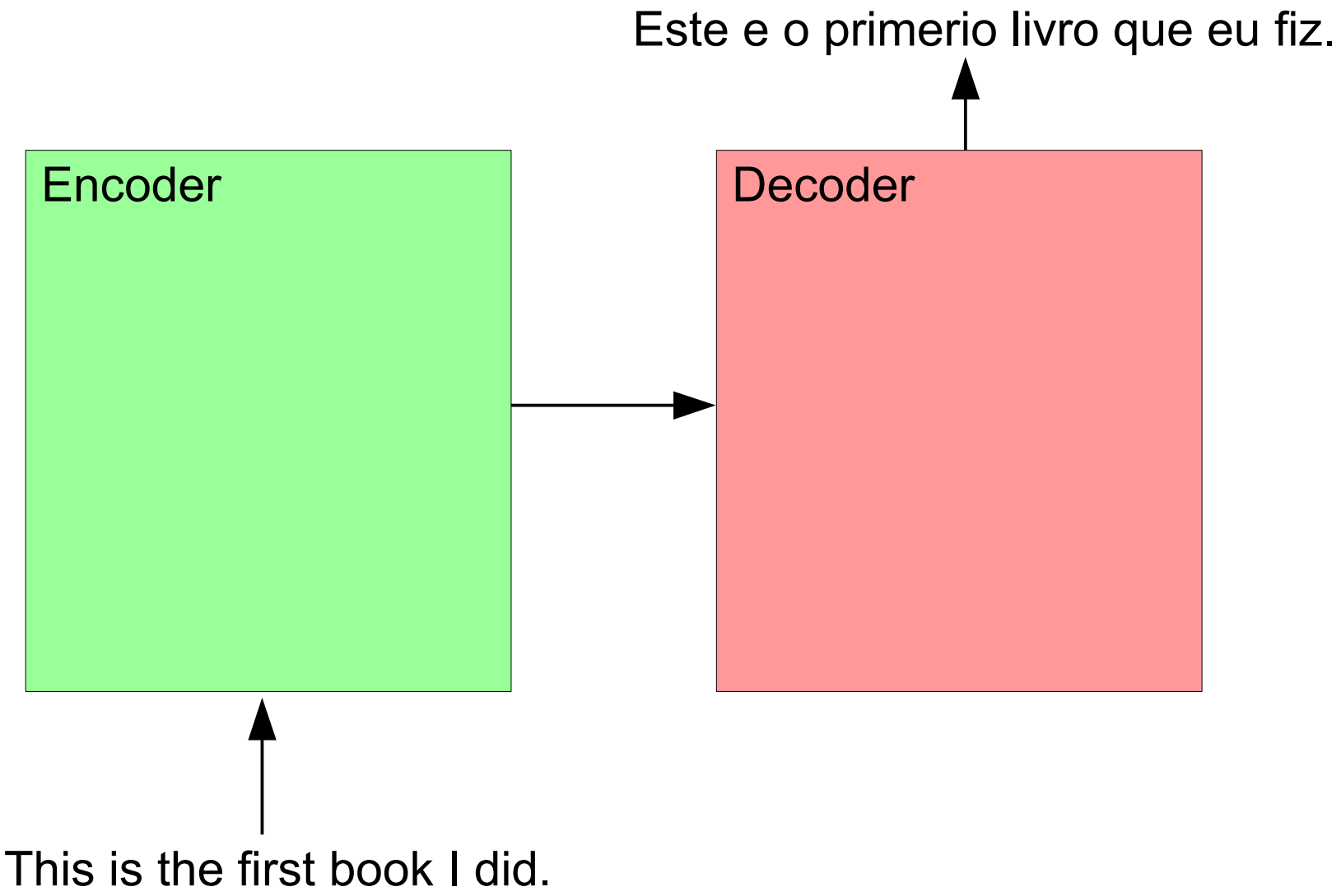


Figure 11: Neural machine translation based on a transformer [2].

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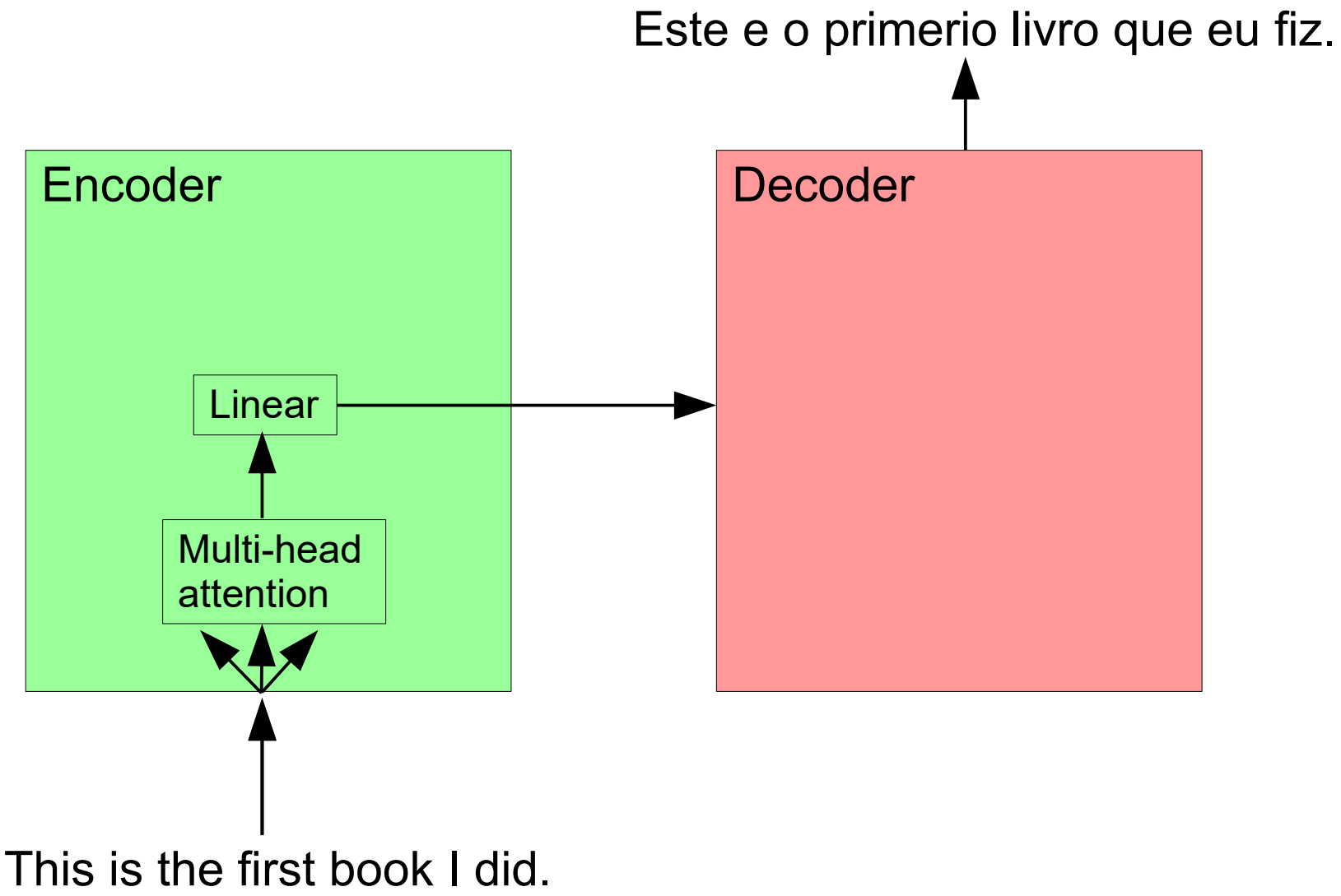

Figure 11: Neural machine translation based on a transformer [2].

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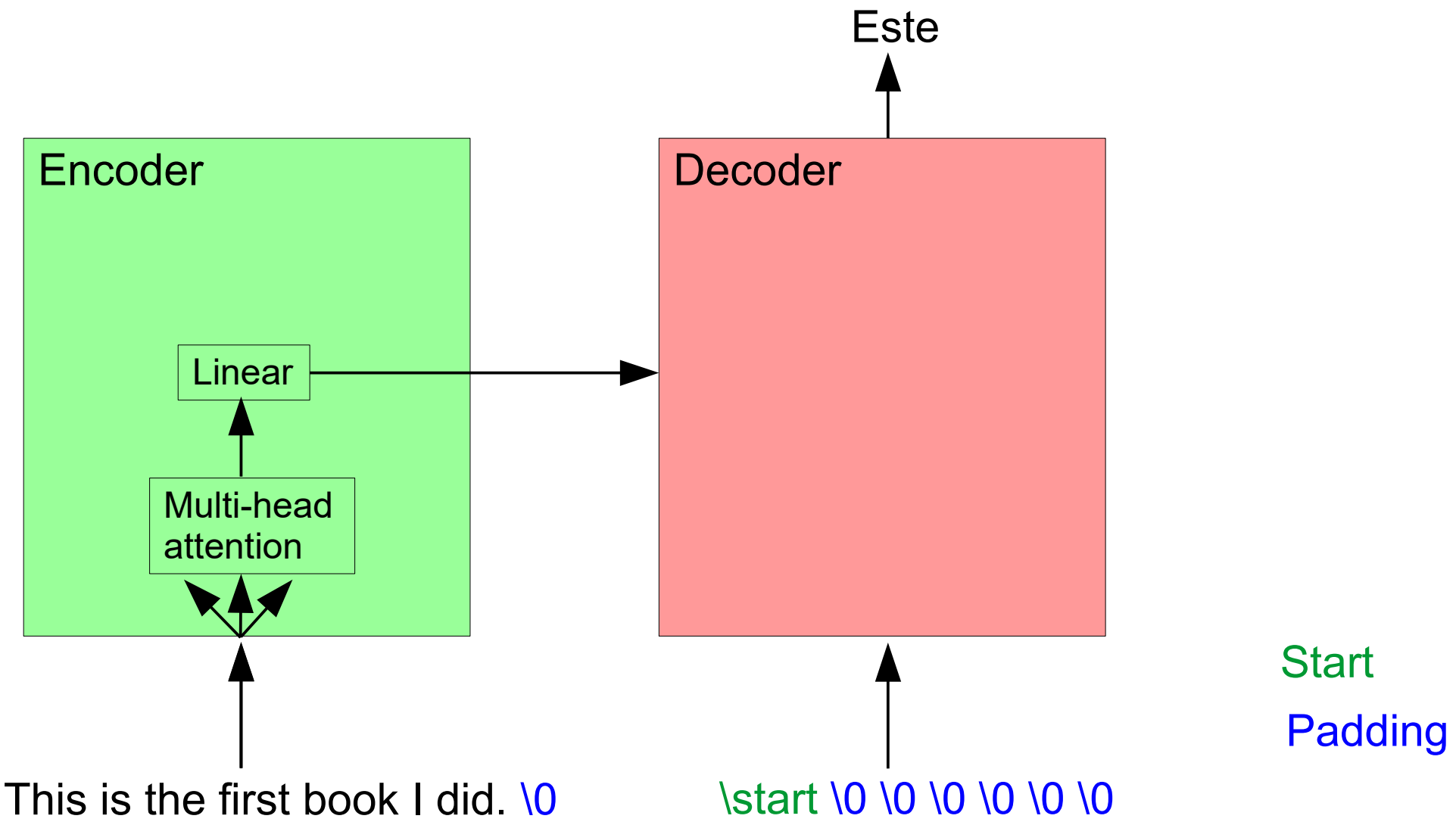

Figure 11: Neural machine translation based on a transformer [2].

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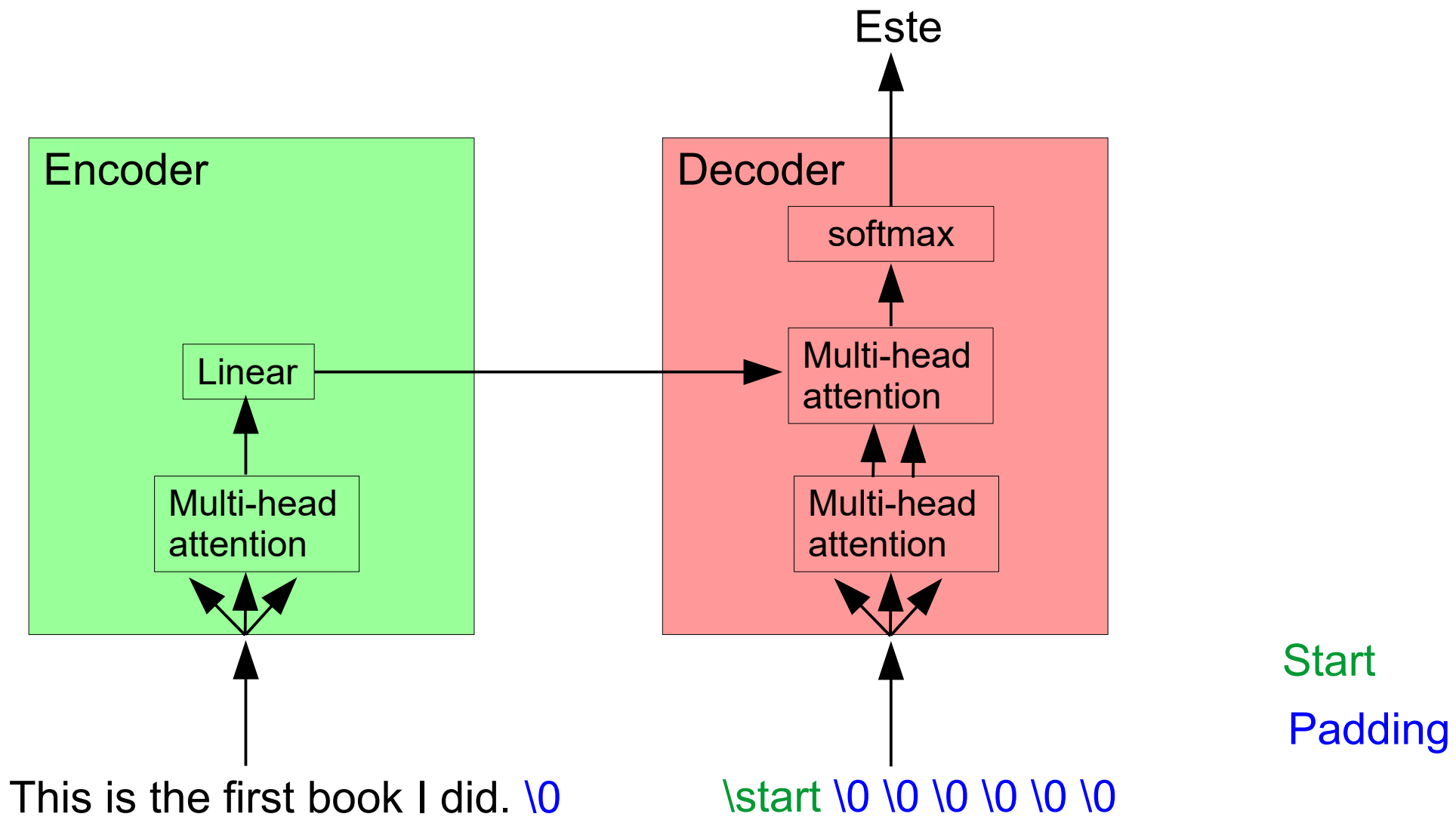

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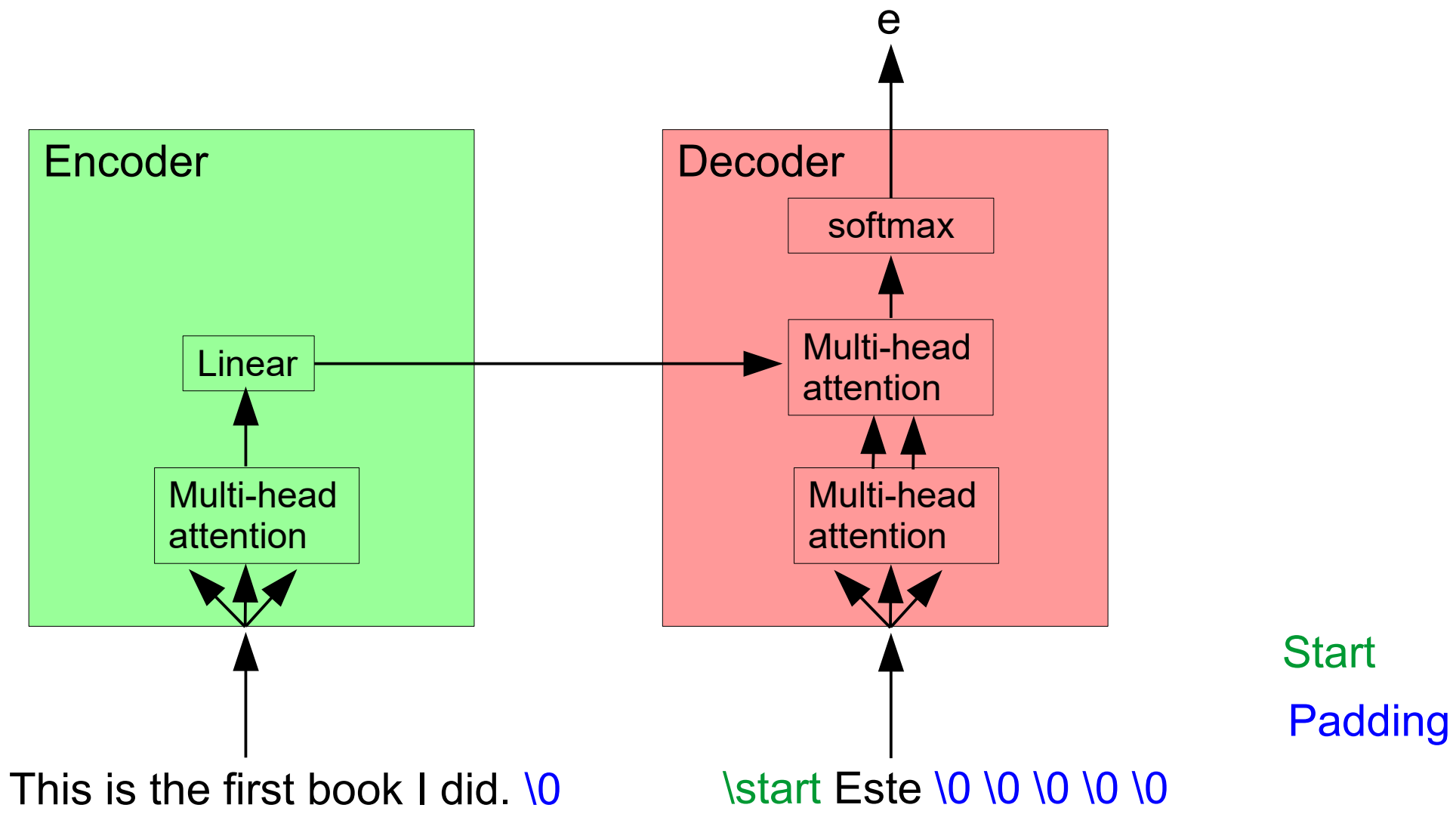

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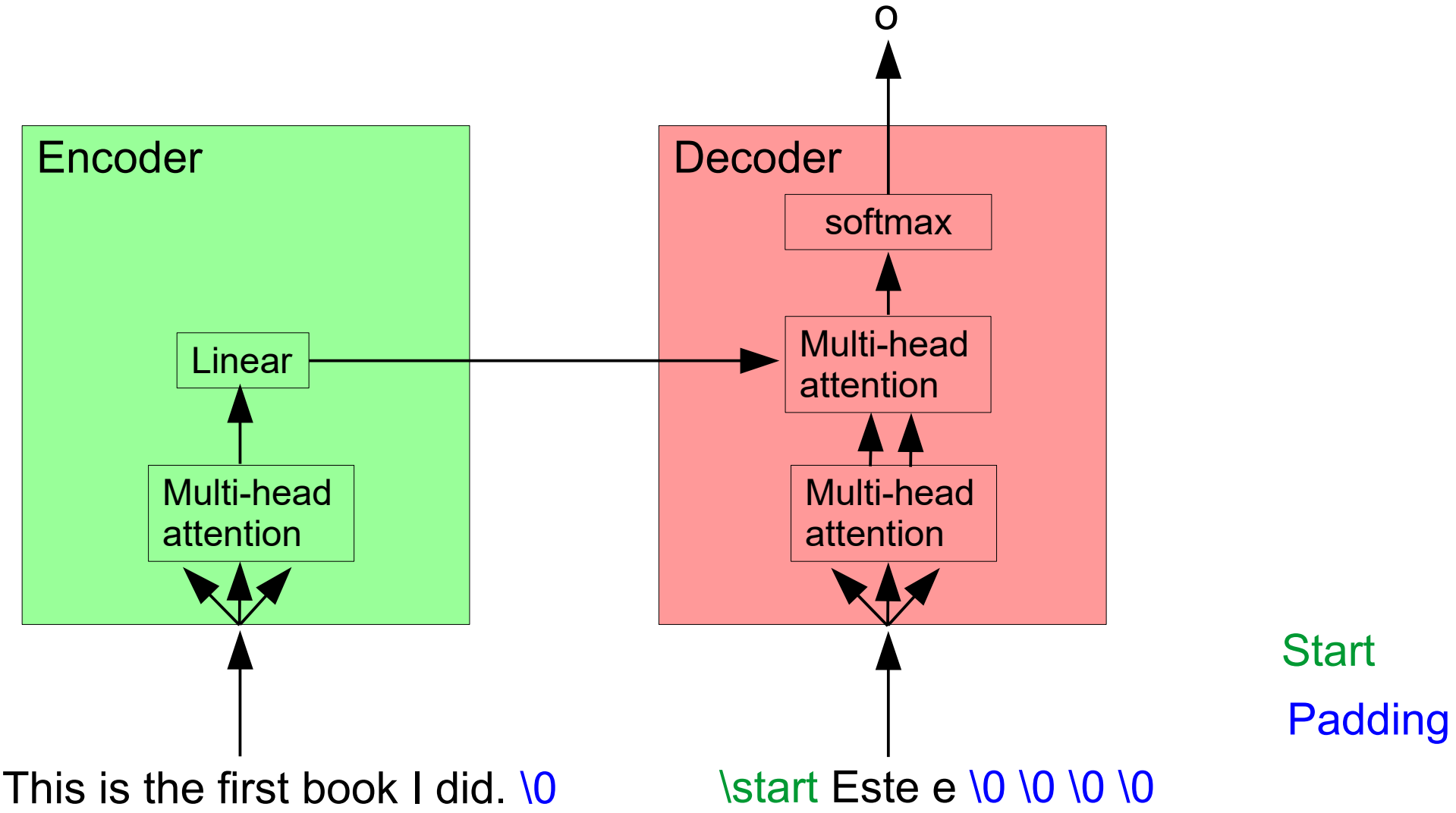

Figure 11: Neural machine translation based on a transformer [2].

3.2 Positional encoding

$$PE_{pos,2i} = \sin\left(pos/10000^{2i/d_{model}}\right)$$

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

depth/dimension index

3.2 Positional encoding

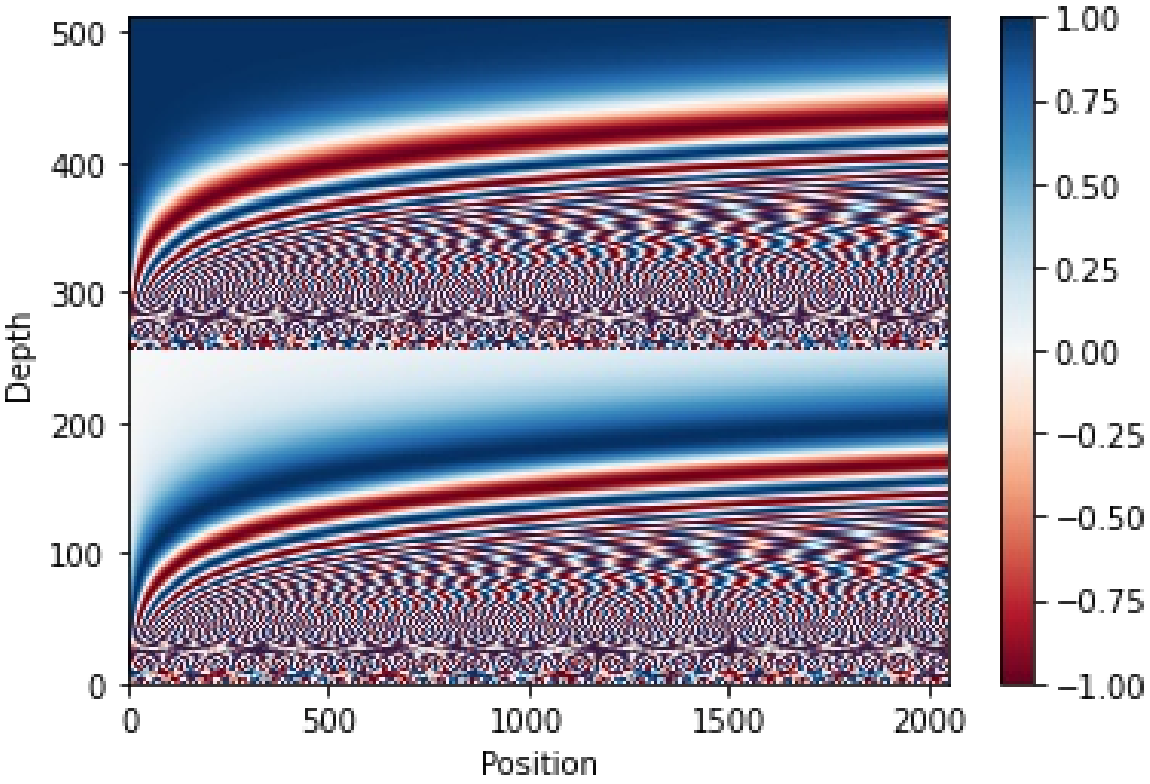

Figure 12: Positional encoding applied in a transformer [13].

$$PE_{pos,2i} = \sin\left(pos/10000^{2i/d_{model}}\right)$$

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

depth/dimension index

Image source:
https://www.tensorflow.org/static/text/tutorials/transformer_files/output_1kLCla68EloE_1.png
(call date: 20.07.22)

3.3 Masking – Encoder and Decoder Padding

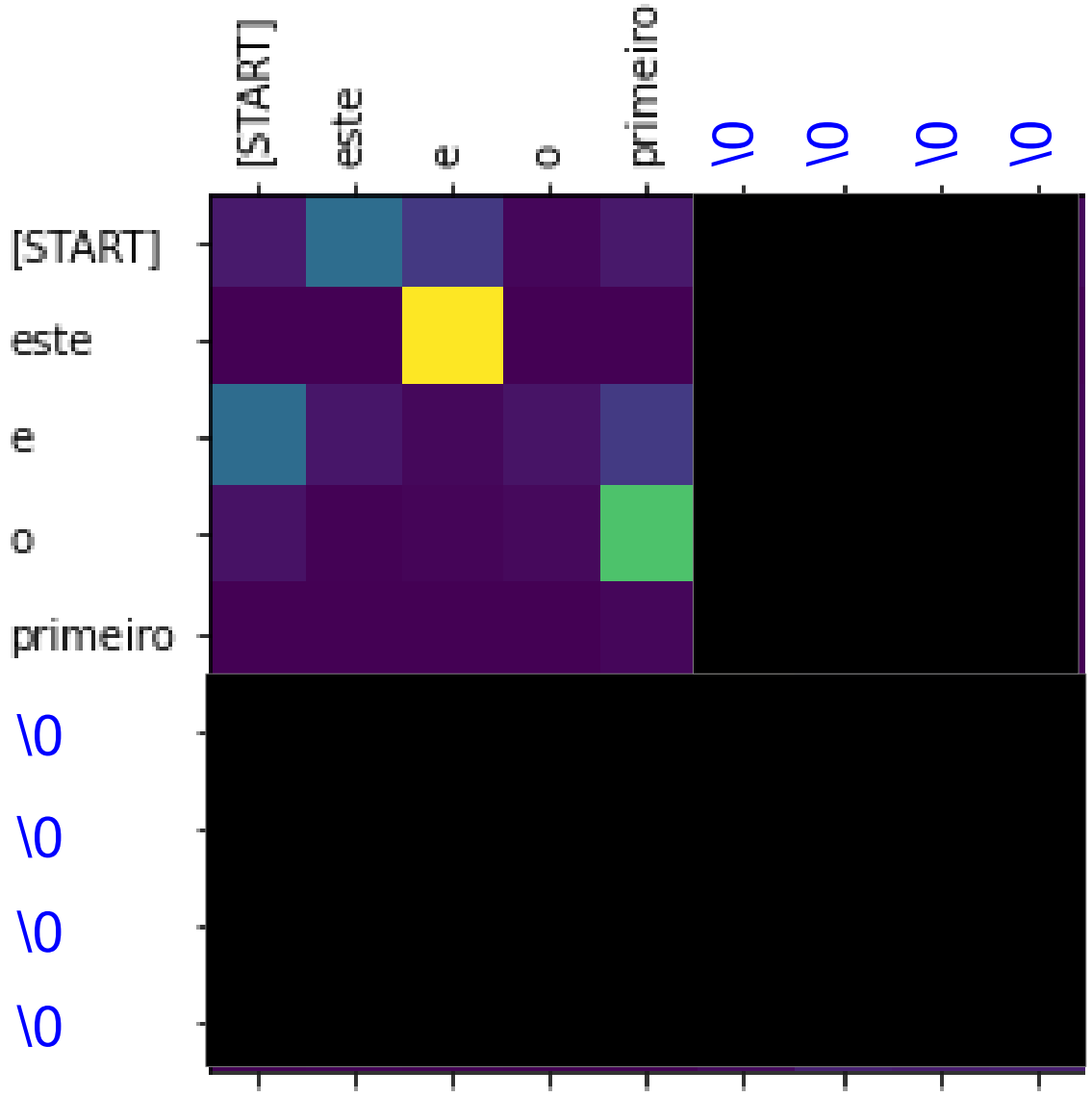

Figure 13: Masking padding words [11].

Image source:
https://www.tensorflow.org/static/text/tutorials/transformer_files/output_1kLCla68EloE_1.png
(call date: 20.07.22)

3.3 Masking – Decoder: Left to right information flow

A word in the output sequence is not allow to attend on words coming after it.

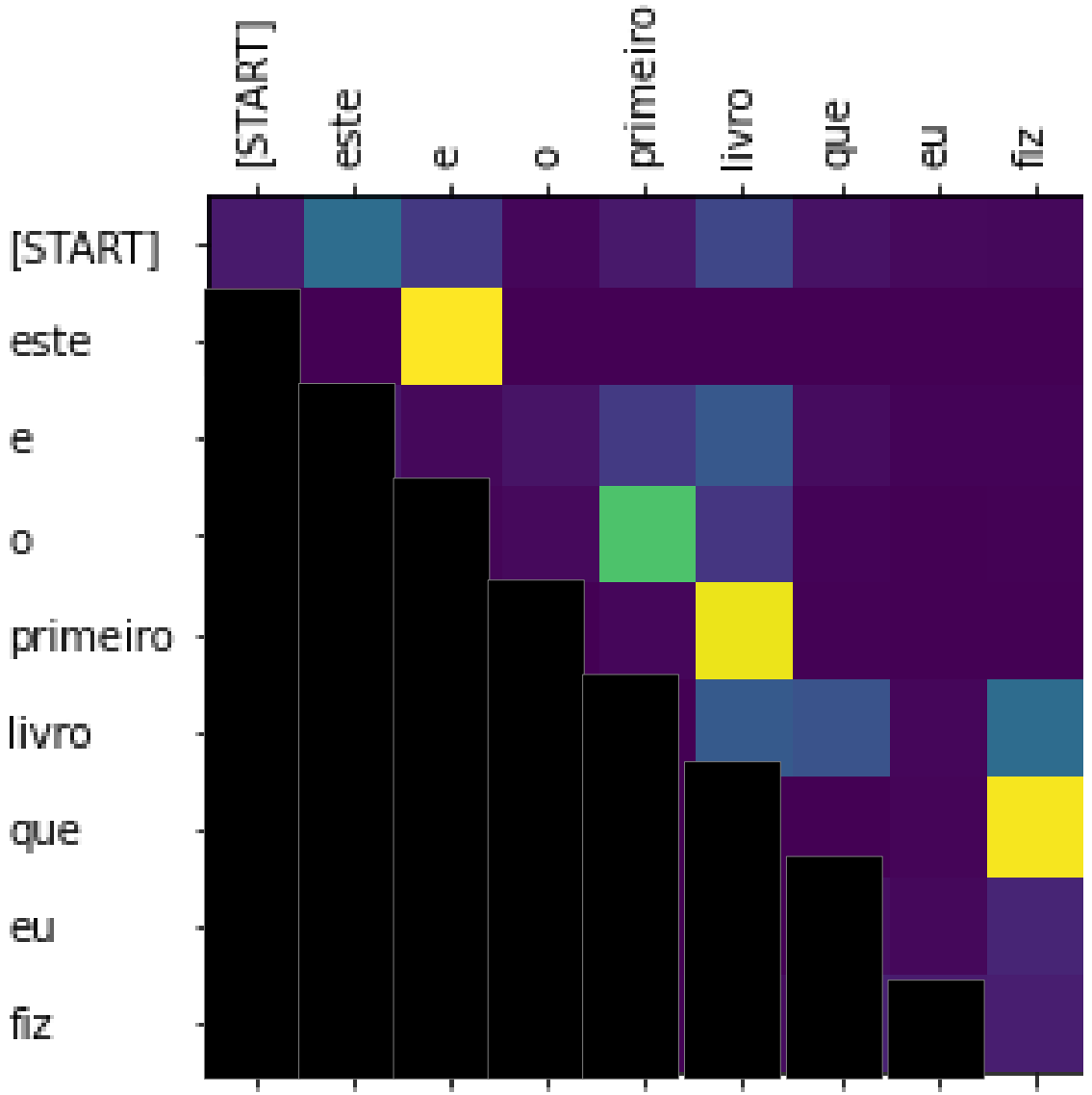

Figure 14: All values in the self-attention matrix above the diagonal are zero [11].

Image source:
https://www.tensorflow.org/static/text/tutorials/transformer_files/output_1kLCla68EloE_1.png
(call date: 20.07.22)

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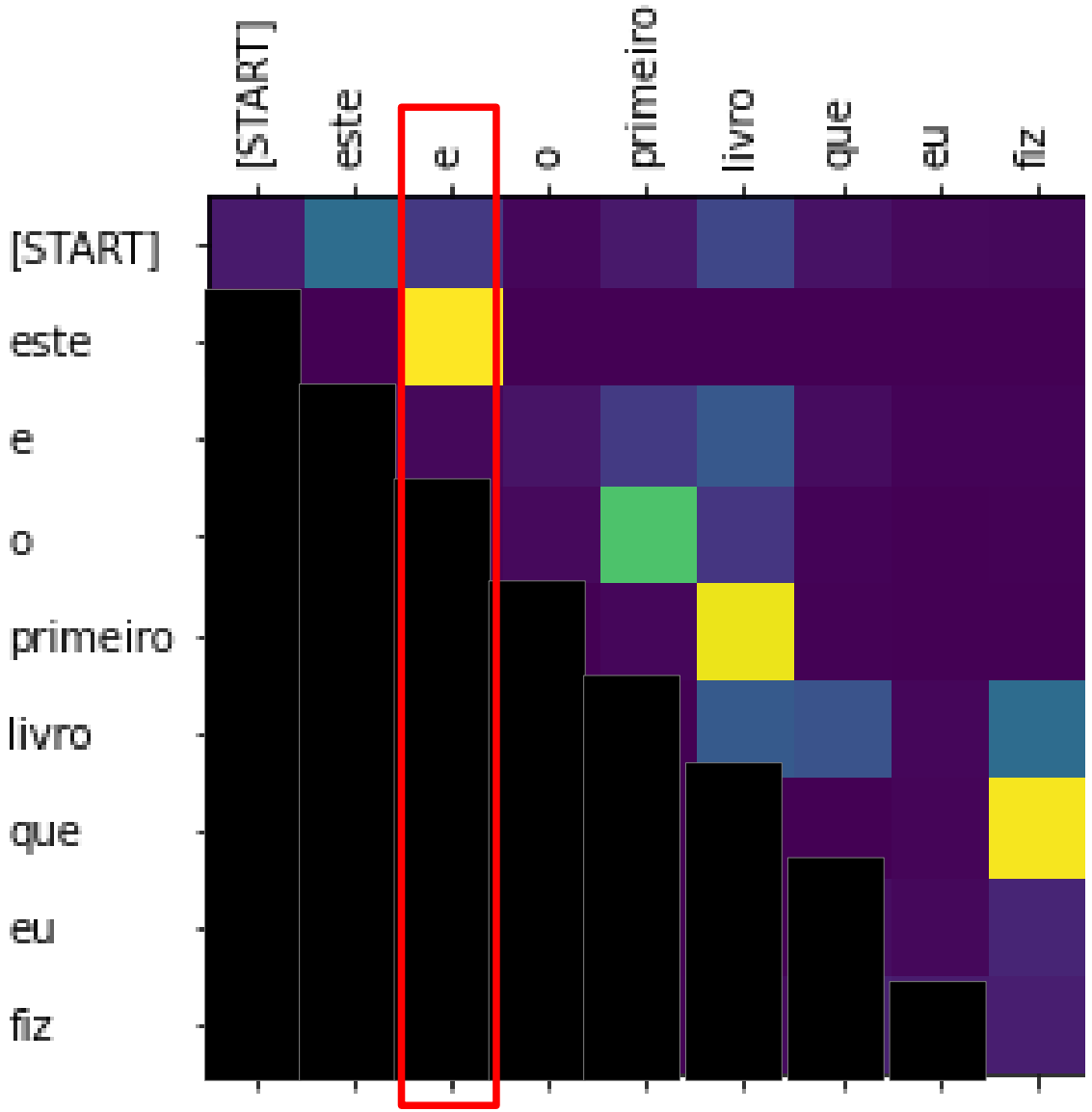

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(call date: 20.07.22)

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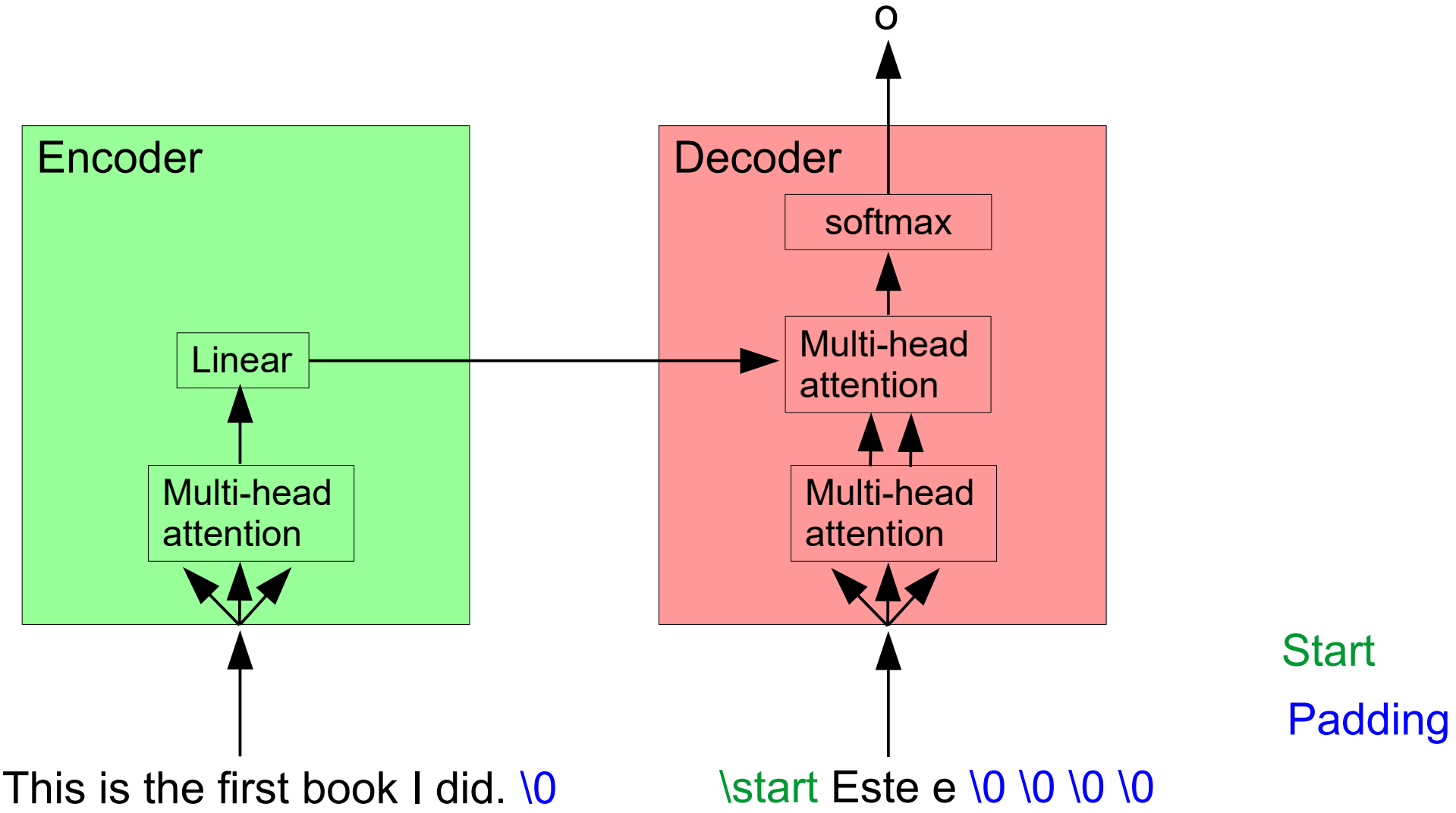

Figure 11: Neural machine translation based on a transformer [2].

3.4 Transformer

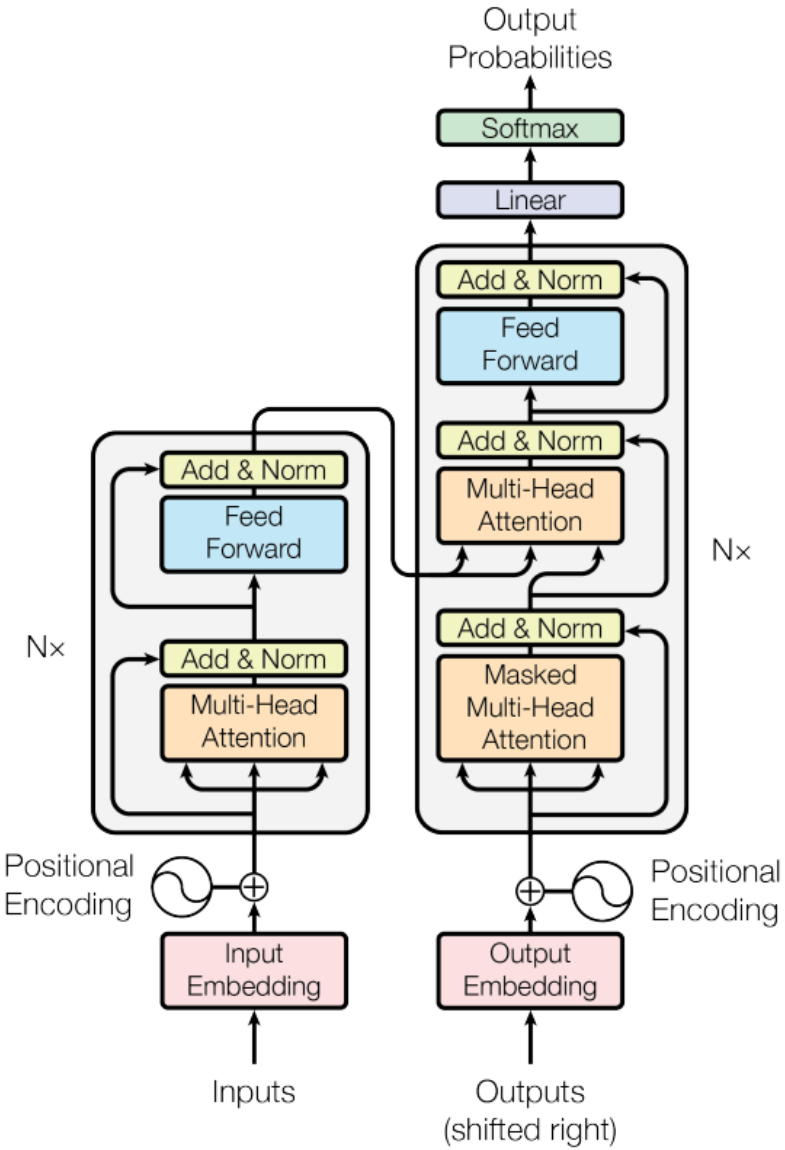

Figure 15: Transformer Architecture [2].

3.4 Transformer

Residual connection

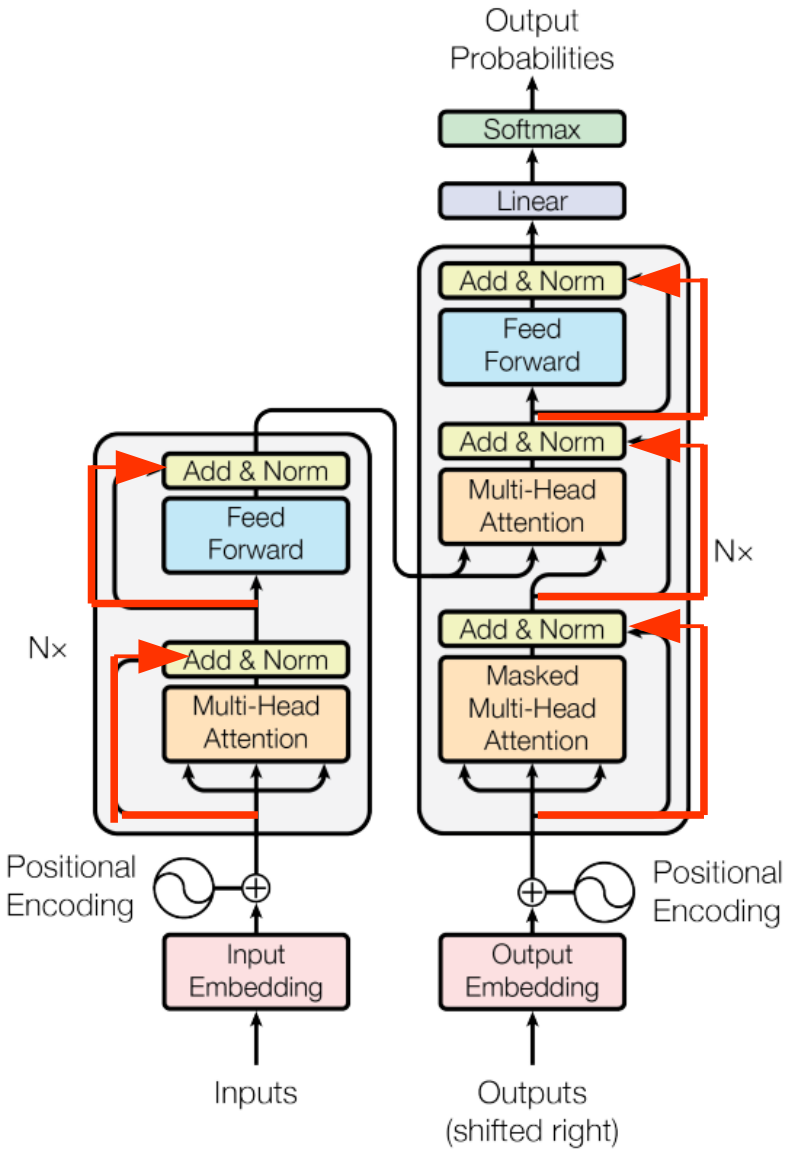

Figure 15: Transformer Architecture [2].

3.4 Transformer

Layer normalization

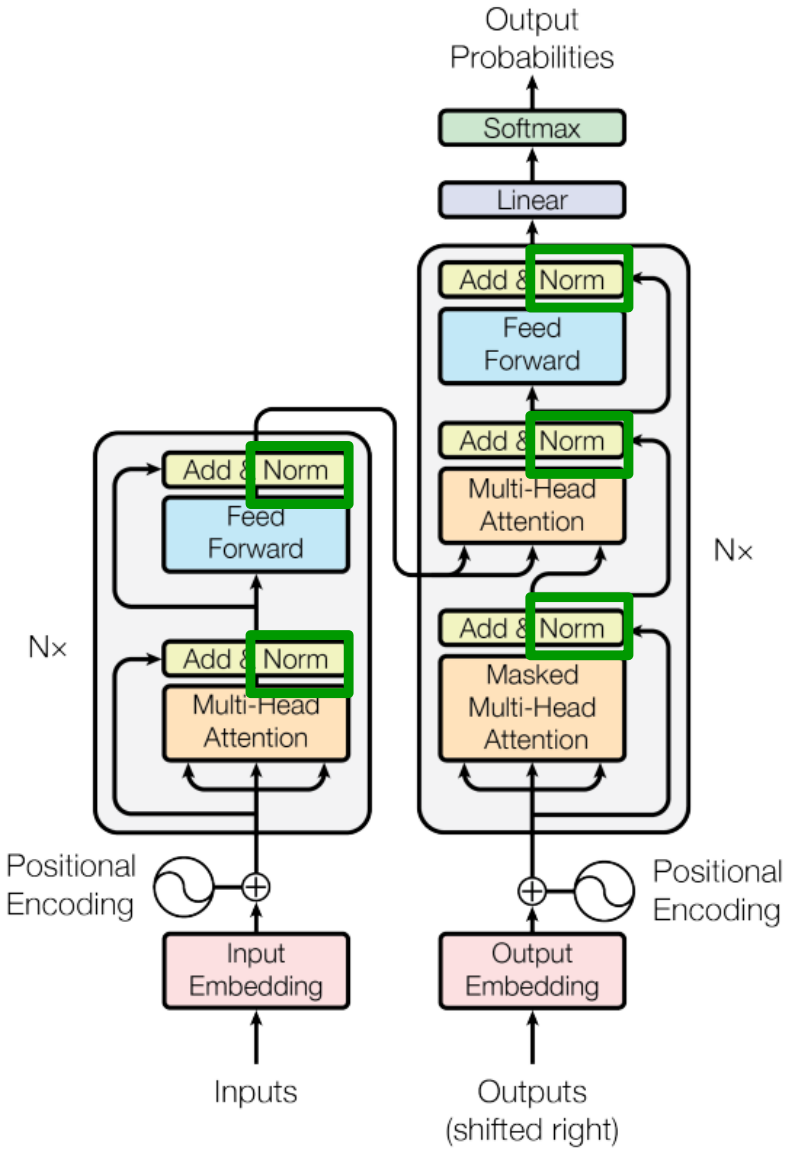

Figure 15: Transformer Architecture [2].

4. Transformers in Natural Language Processing

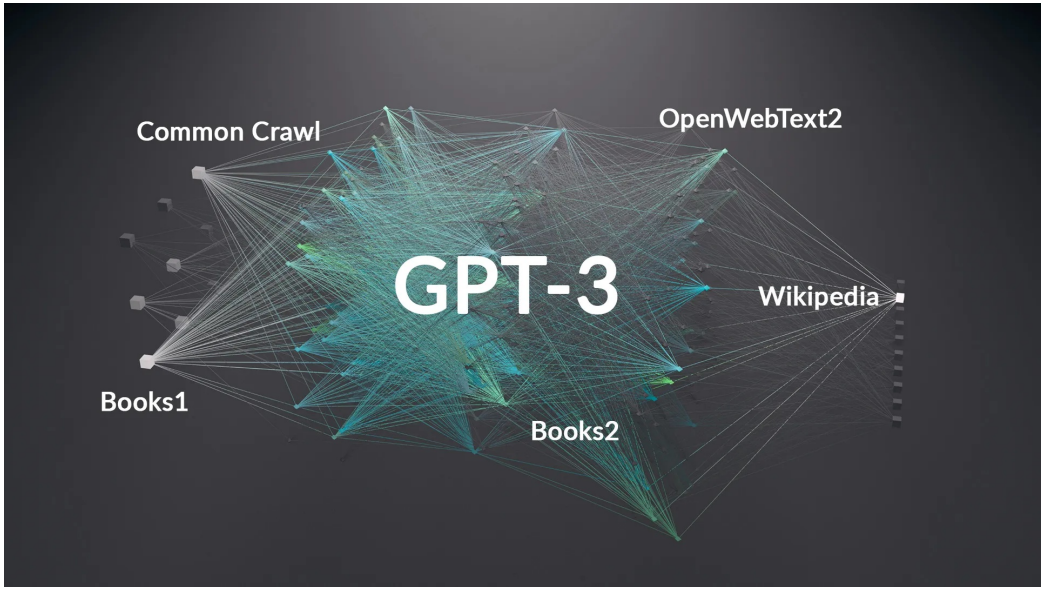

Image sources:
https://cdn-images-1.medium.com/max/428/1*lMlwRSQfzaYw1ckgS-jgZw.jpeg
https://i0.wp.com/katzlberger.ai/wp-content/uploads/2021/04/GPT-3-Datenquellen.jpg?resize=1400%2C800&ssl=1
(call dates: 20.07.22)

4.1 BERT: Bidirectional Encoder Representations from Transformers

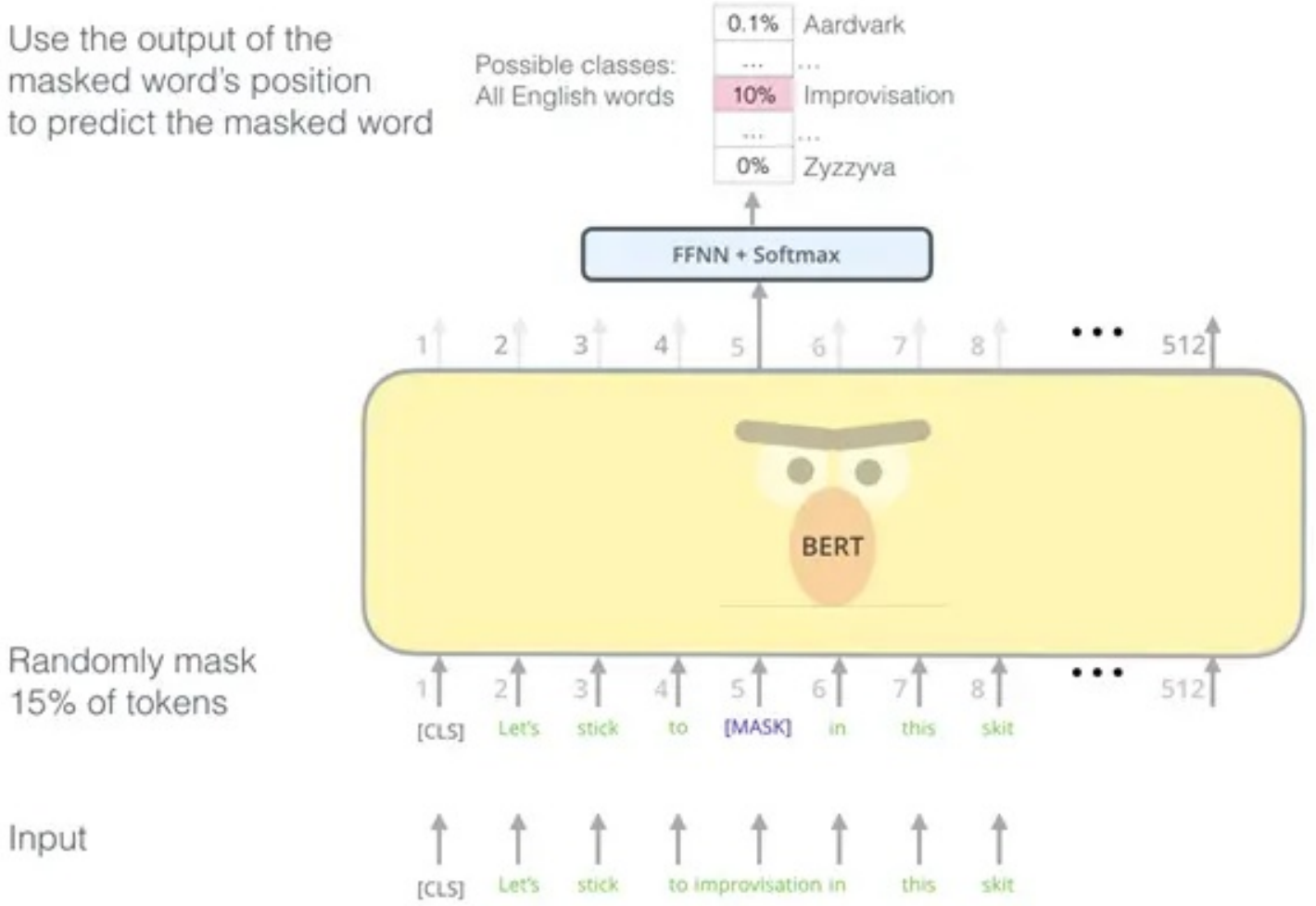

Figure 16: BERT Architecture [8].

Image source: https://www.alexanderthamm.com/wp-content/uploads/High-level-architecture-of-BERT-1.png.webp (call date: 20.07.22)

4.1 BERT: Bidirectional Encoder Representations from Transformers

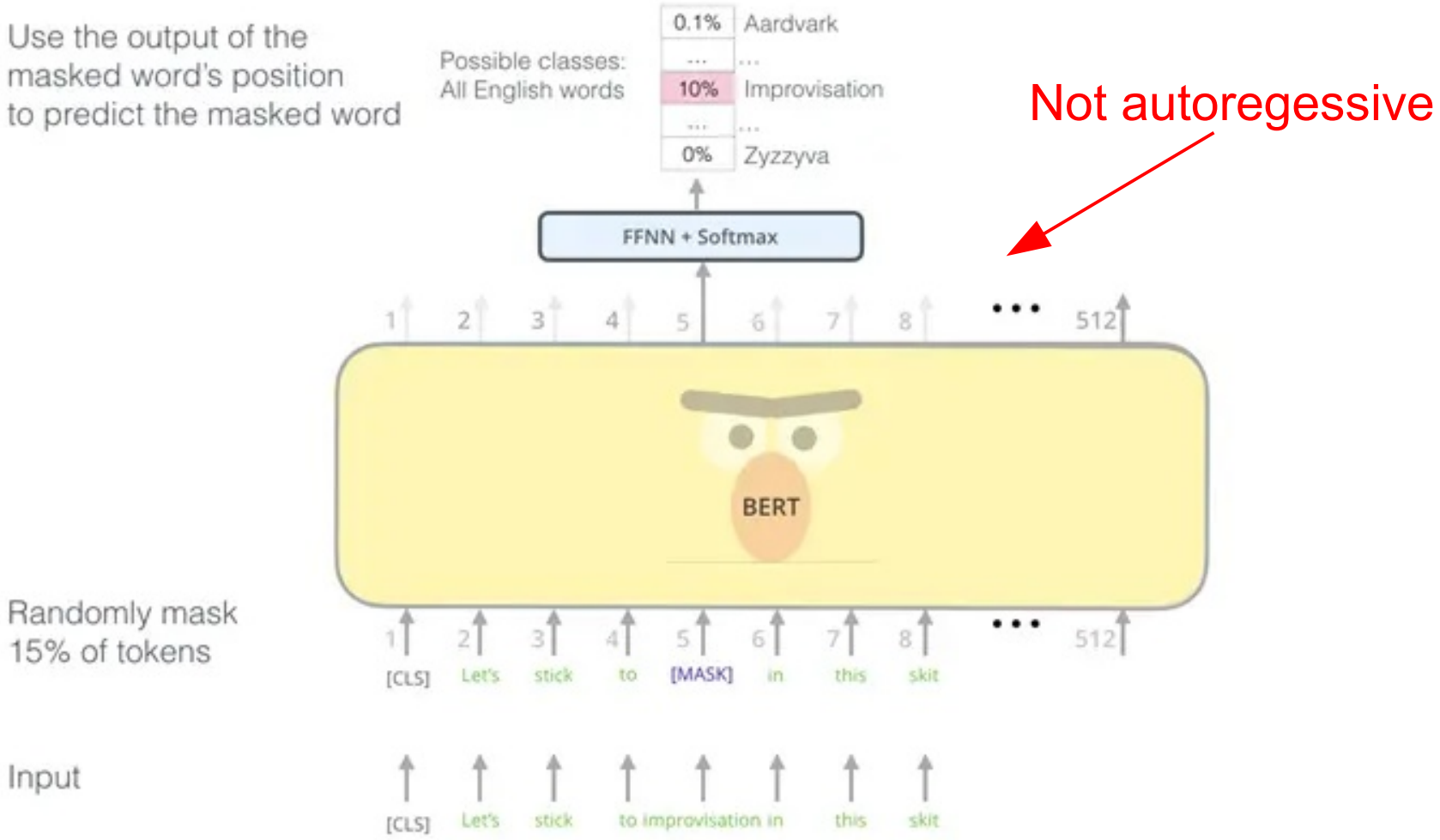

Figure 16: BERT Architecture [8].

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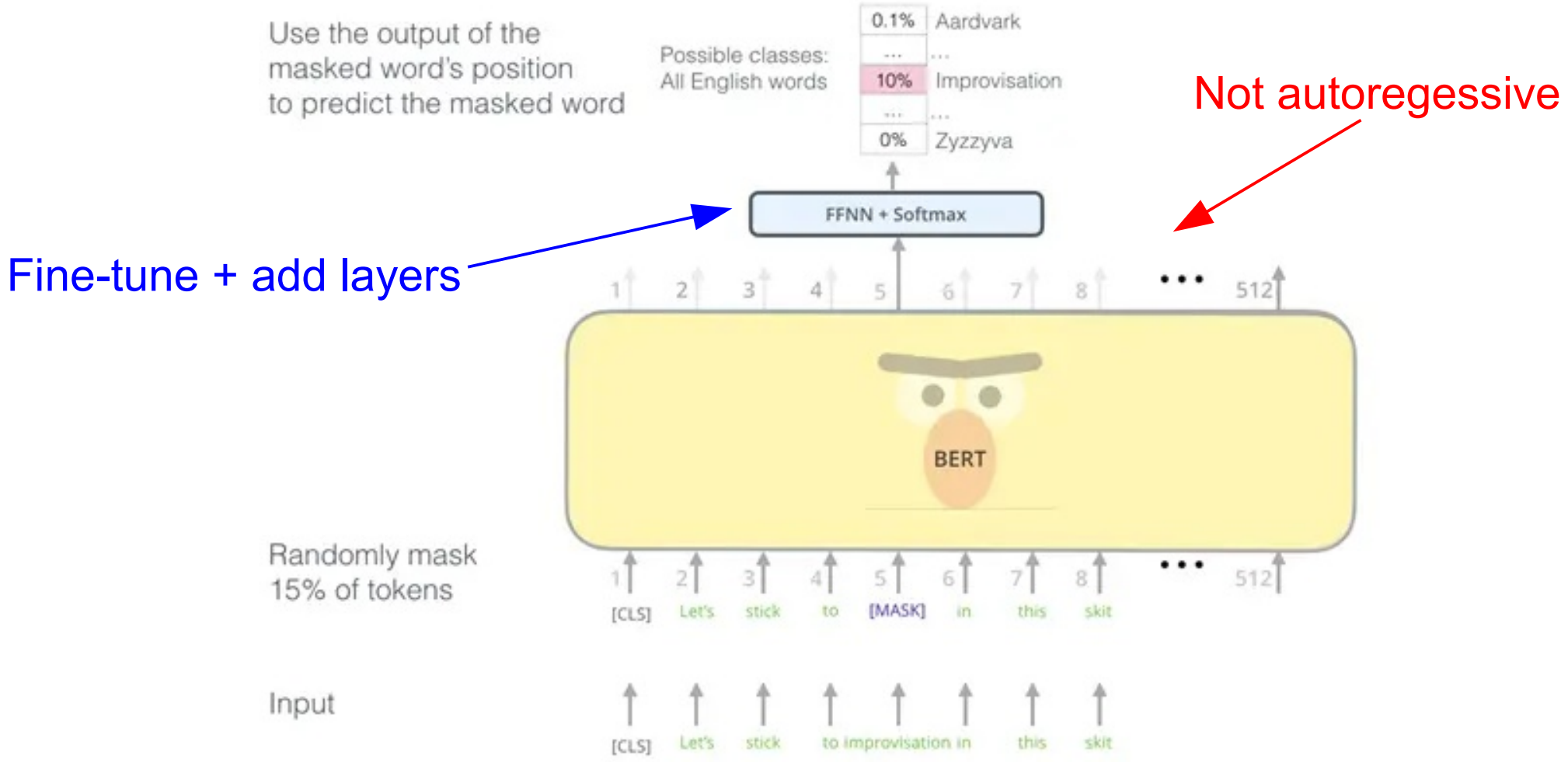


Figure 16: BERT Architecture [8].

Image source: https://www.alexanderthamm.com/wp-content/uploads/High-level-architecture-of-BERT-1.png.webp (call date: 20.07.22)

4.2 GPT-3: Generative Pre-trained Transformer 3

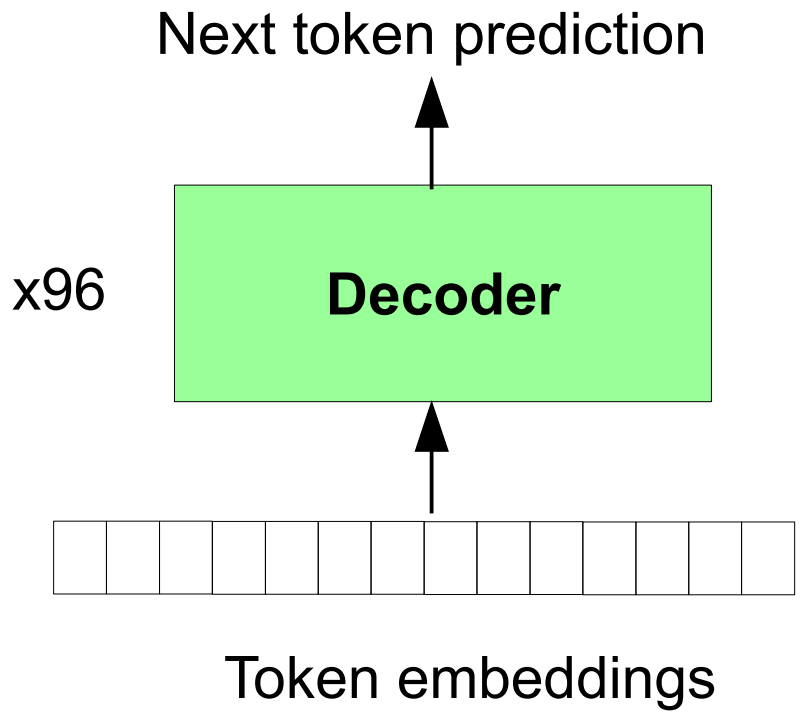


Figure 17: GPT-3 Overview [9].

4.2 GPT-3: Generative Pre-trained Transformer 3

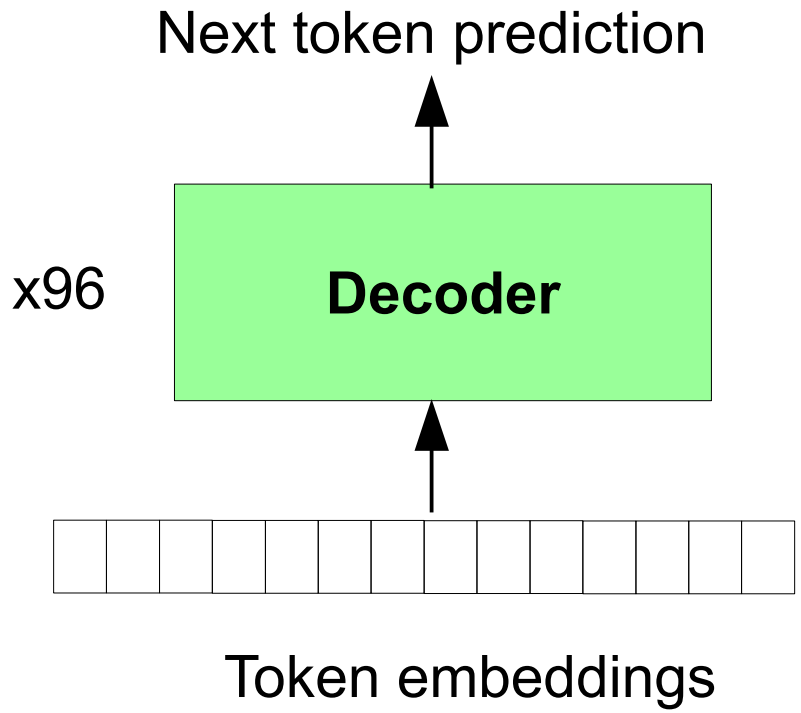


Figure 17: GPT-3 Overview [9].

Image sources:
https://upload.wikimedia.org/wikipedia/commons/thumb/8/80/Wikipedia-logo-v2.svg/250px-Wikipedia-logo-v2.svg.png
https://cdn-icons-png.flaticon.com/512/29/29302.png
https://cdn-icons-png.flaticon.com/512/493/493805.png
(call dates: 20.07.22)

4.2 GPT-3: Generative Pre-trained Transformer 3

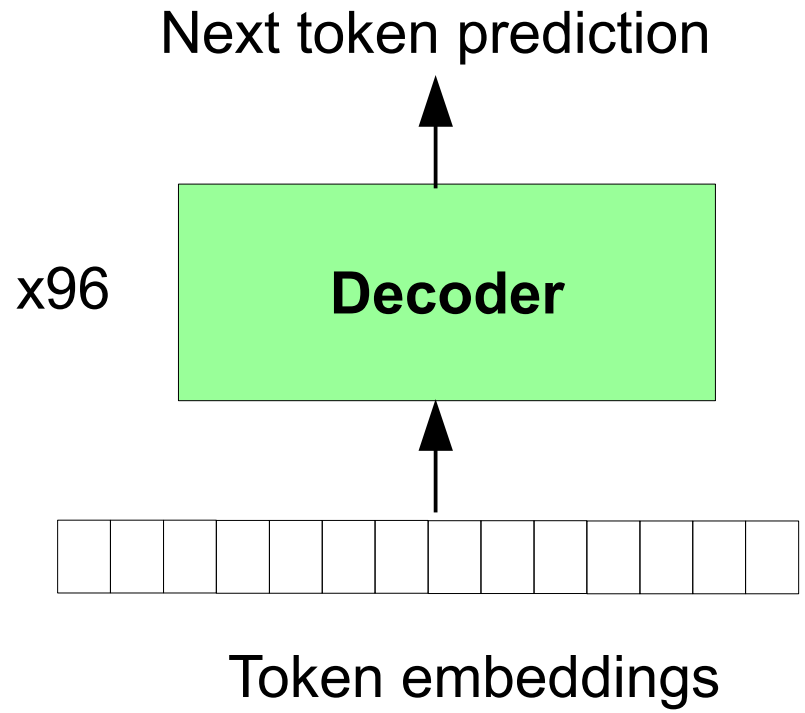


Figure 17: GPT-3 Overview [9].

Fine-tuning: **No gradient updates**
Input:
Translate English to French:
cheese =>

Image sources:
https://upload.wikimedia.org/wikipedia/commons/thumb/8/80/Wikipedia-logo-v2.svg/250px-Wikipedia-logo-v2.svg.png
https://cdn-icons-png.flaticon.com/512/29/29302.png
https://cdn-icons-png.flaticon.com/512/493/493805.png
(call dates: 20.07.22)

4.3 BERT vs. GPT-3

	BERT	**GPT-3**
release year	2018	2020
#params	340M	175B
#attention heads	16	96
hidden size	1024	12288
stacked transformer blocks	encoder (non-autoregressive)	decoder (autoregressive)
attention direction	bidirectional	left-to-right
#stacked transformer blocks	12	96
input	512 token embeddings	2048 token embeddings
output	512 token embeddings + classifiers	1 token embedding + classifier

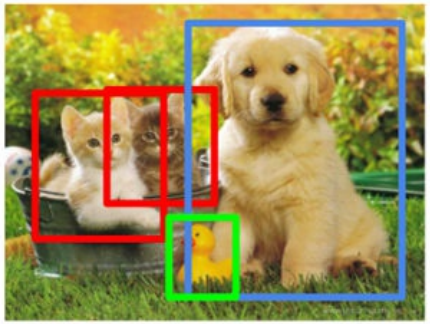
Table 1: Differences between BERT and GPT-3 [8,9].

5. Transformers in Computer Vision

Classification

CAT

Object Detection



CAT, DOG, DUCK

Image source:
https://res.cloudinary.com/dyd911kmh/image/upload/f_auto,q_auto:best/v1522766480/1_6j34dAOTijqP6HDFnjxPFA_udggex.png (call date: 20.07.22)

5.1.1 ViT: Vision Transformer – Image Classification

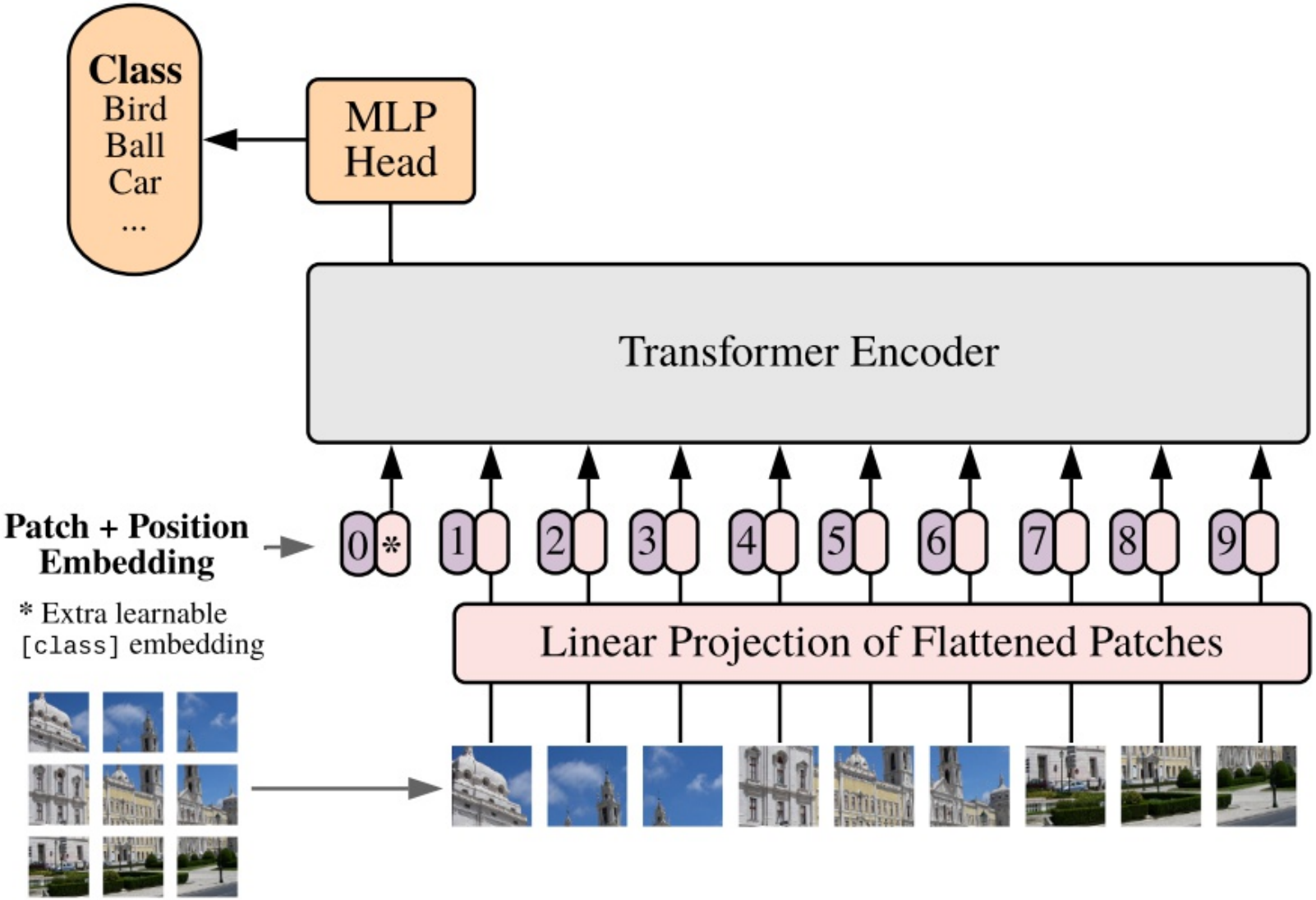


Figure 18: ViT Architecture [3].

5.1.2 ViT: Vision Transformer – Evaluation

	ViT-H/14	ResNet152x4
ImageNet	**88.55**	87.54
ImageNet ReaL	**90.72**	90.54
CIFAR-10	**99.50**	99.37
CIFAR-100	**94.55**	93.51
Oxford-IIIT Pets	**97.56**	96.62
Oxford Flowers-102	**99.68**	99.63
VTAB (19 tasks)	**77.63**	76.29
#param	632M	14M
TPUv3-core-days	2.5k	9.9k

Table 2: Performance of the ViT and ResNet [3].

5.1.3 ViT: Vision Transformer – “Attention in an image”

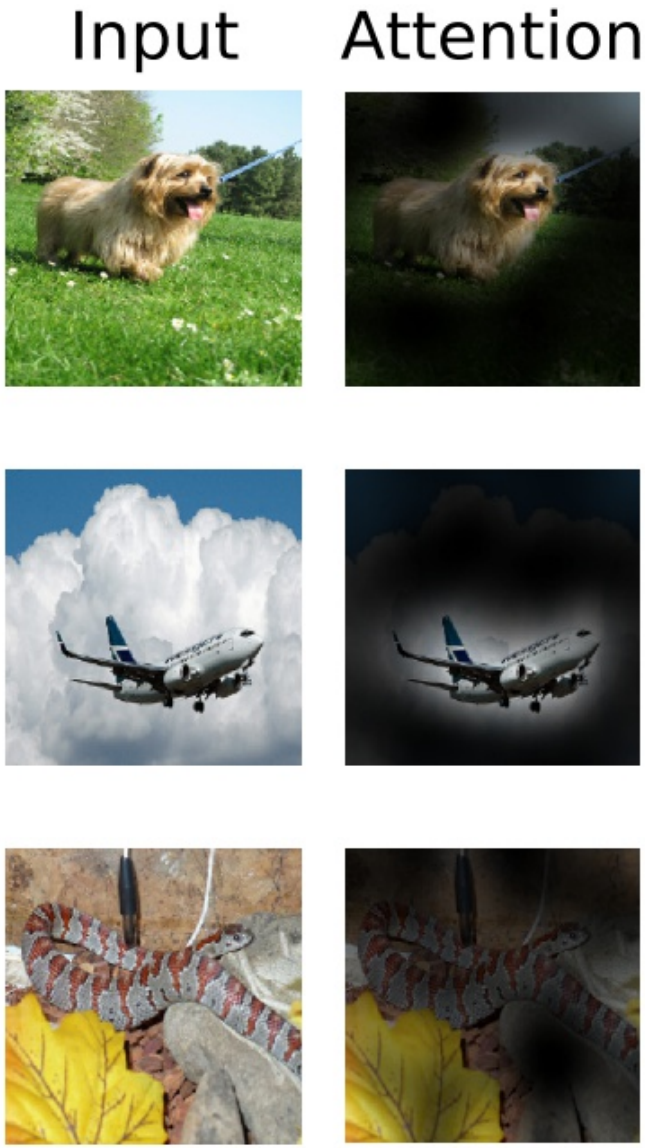


Figure 19: Visualization of self-attention in an image [3].

Side note: Feature Attribution with Occlusion

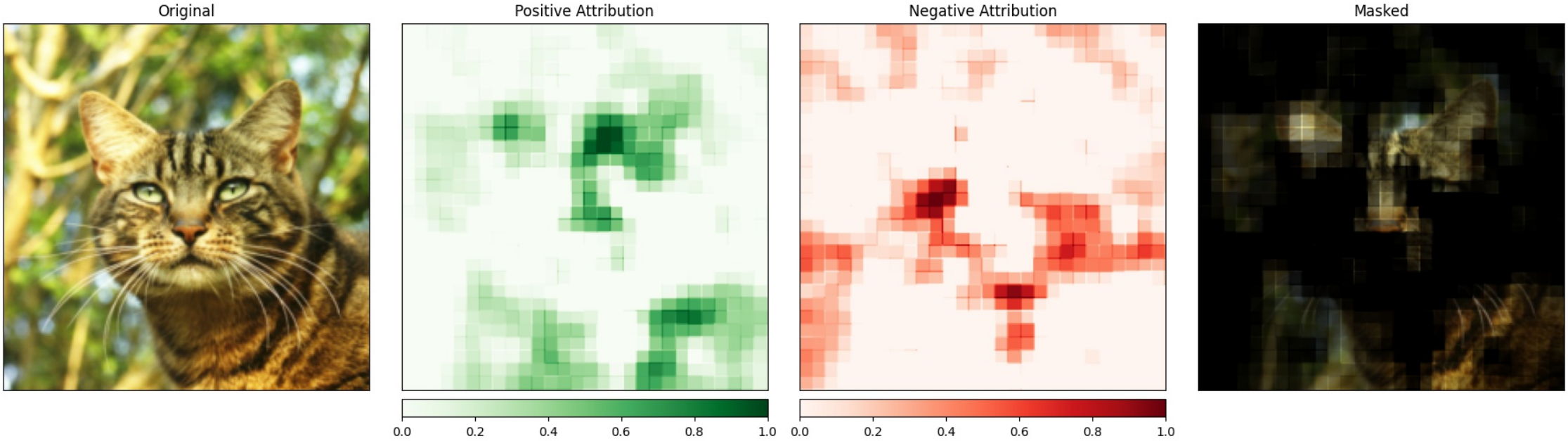


Image source:
https://www.youtube.com/watch?v=Am2EF9CLu-g&list=PL_lsbAsL_o2CTlGHgMxNrKhzP97BaG9ZN&index=7&ab_channel=PyTorch (call date: 26.01.23)

5.1.4 ViT: Vision Transformer – “Learn to be a CNN”

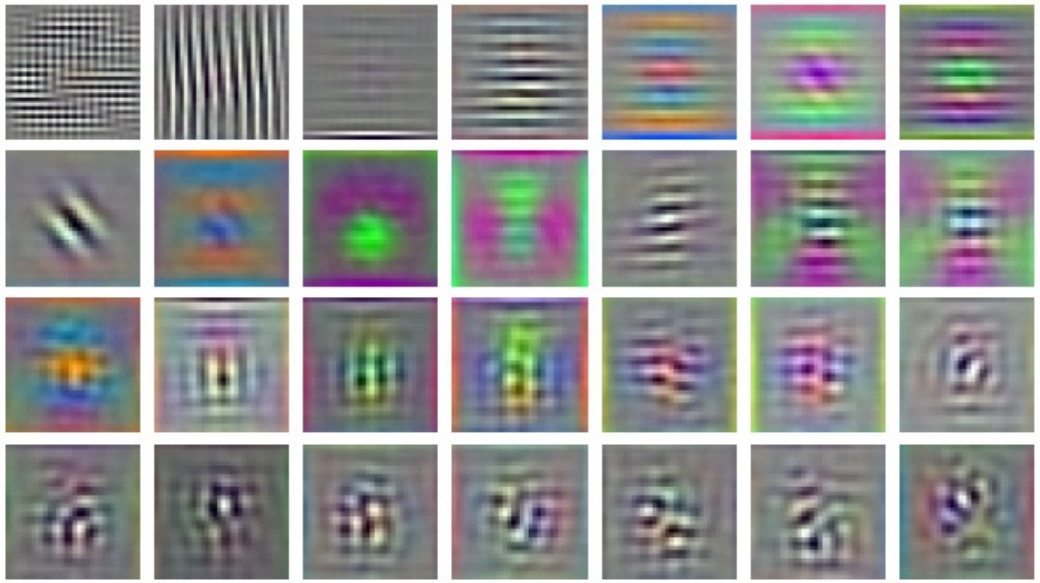


Figure 20: Learned patterns to which the self-attention mechanism reacts to [3].

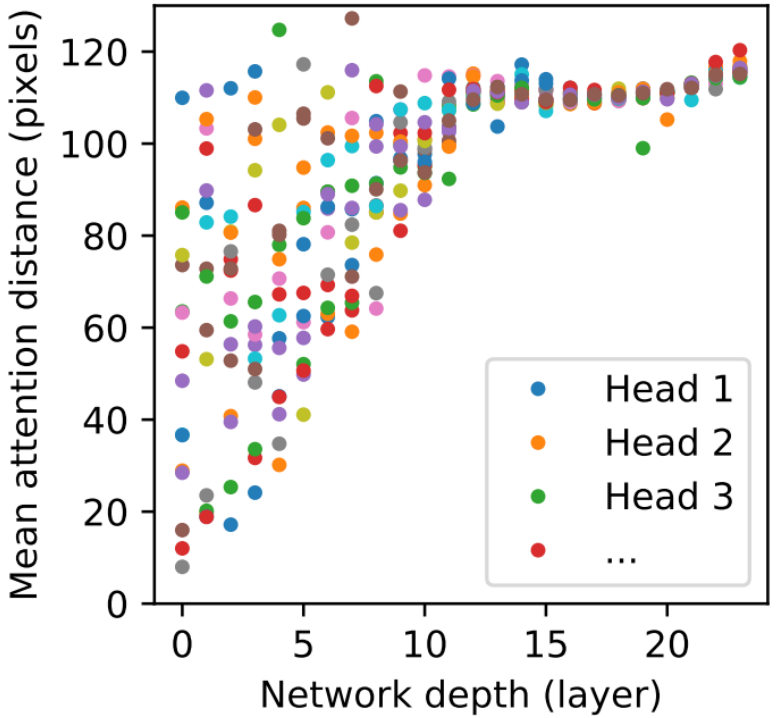


Figure 21: Mean attention distance of each layer [3].

Side note: Receptive Field in a CNN

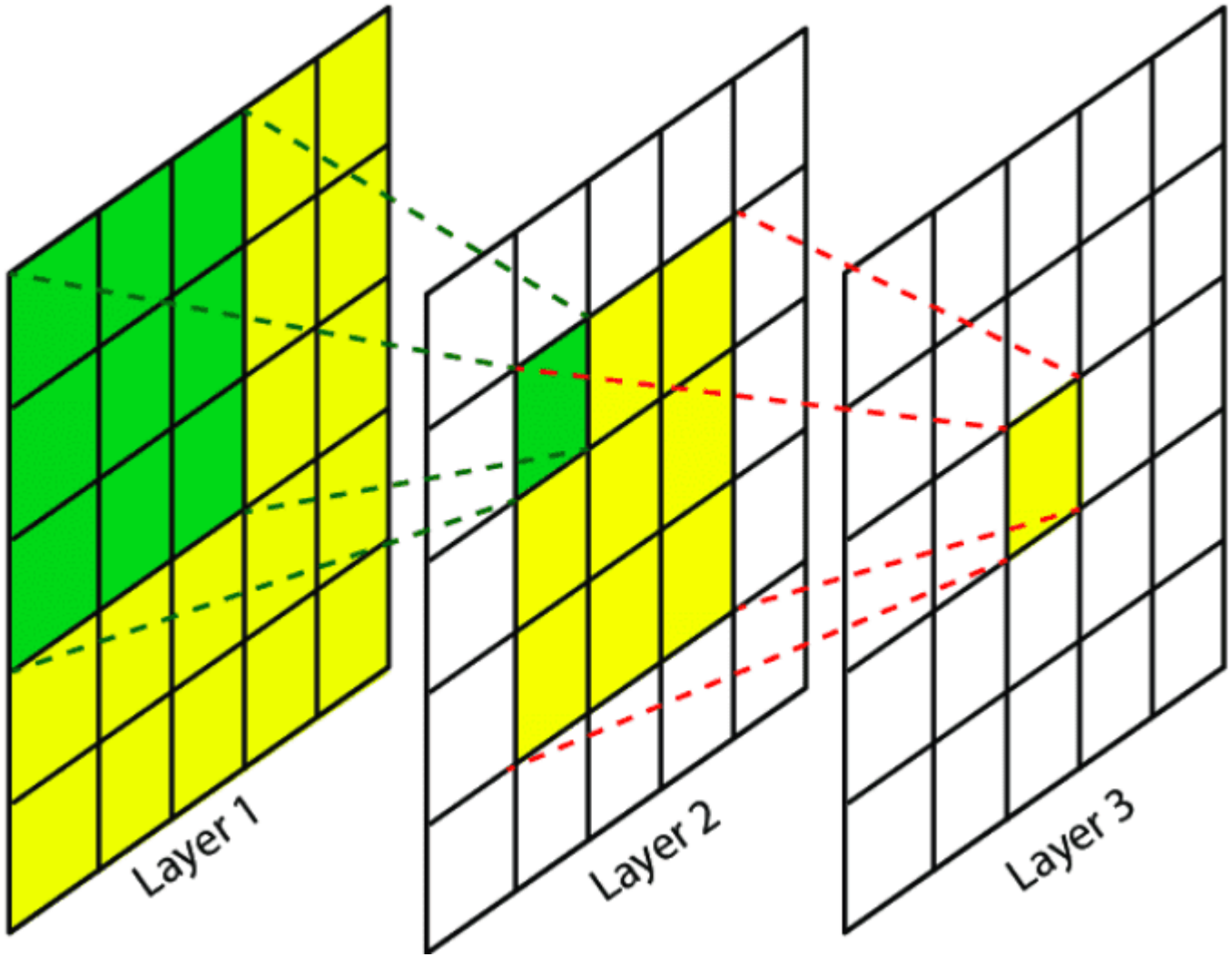


Image source:
https://theaisummer.com/static/490be17ee7f19b78003c3fdf5a6bbafc/83b75/receptive-field-in-convolutional-networks.png (call date: 20.07.22)

5.2.1 DETR: DEtection Transformer – Object detection

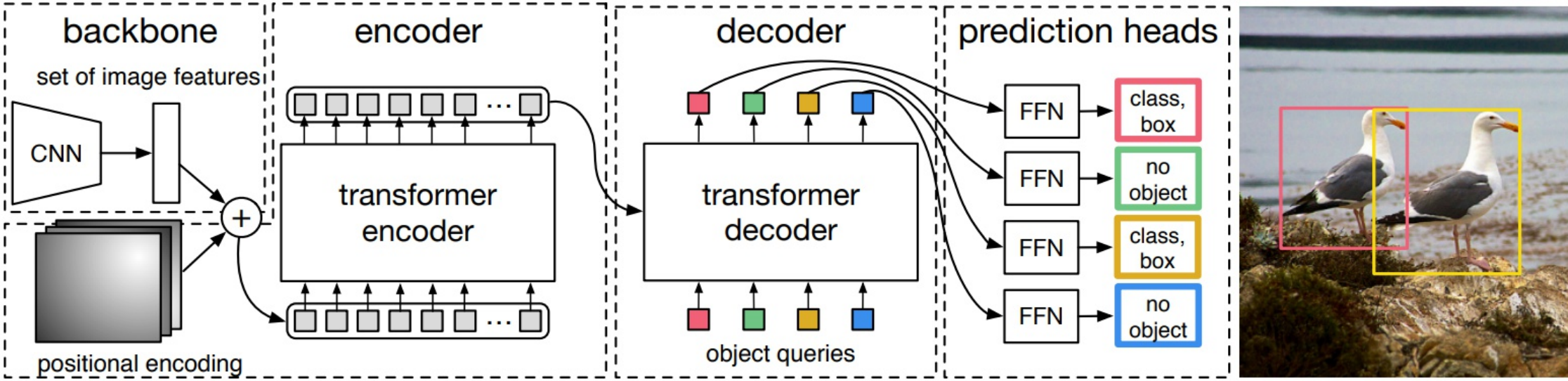


Figure 22: DETR architecture [4].

5.2.1 DETR: DEtection Transformer – Object detection

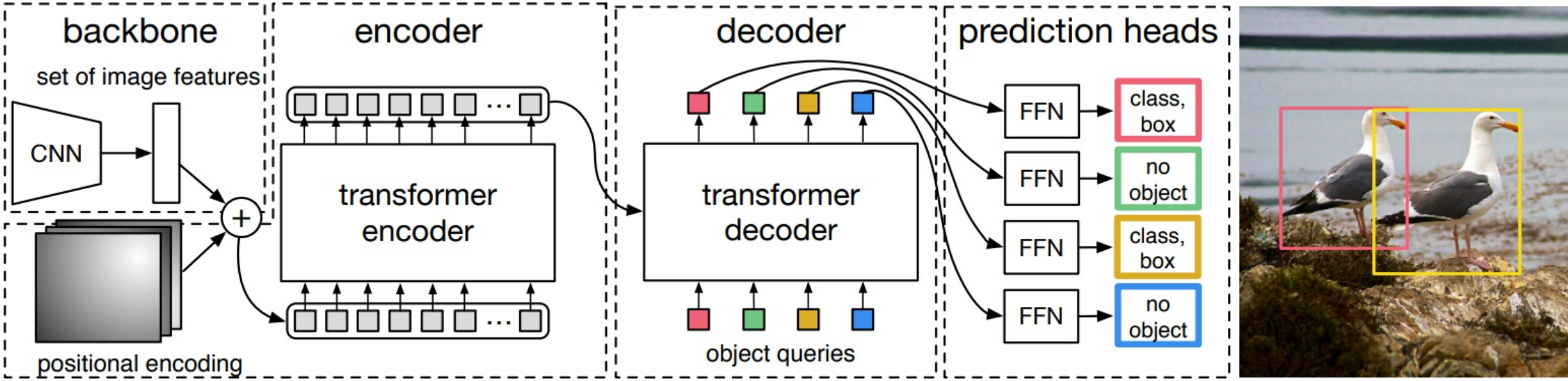


Figure 22: DETR architecture [4].

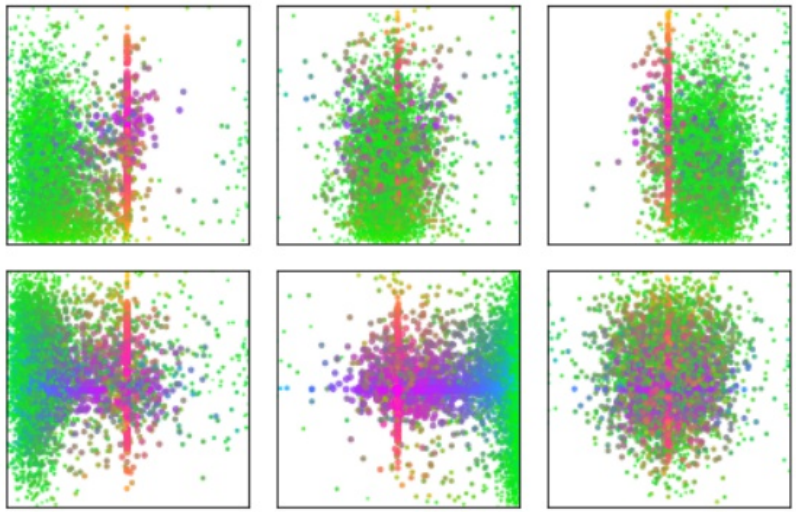


Figure 23: Object queries [4].

5.2.1 DETR: DEtection Transformer – Object detection

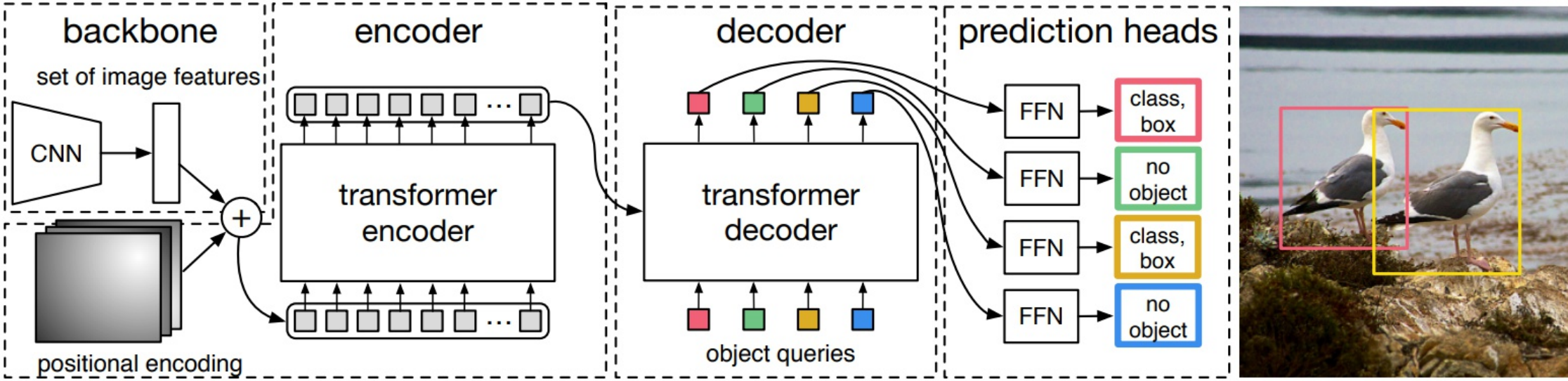


Figure 22: DETR architecture [4].

Training:

Loss = best matching loss between target and prediction → Hungarian Algorithm

$$\hat{\sigma} = \arg\min_{\sigma \in \mathfrak{S}_N} \sum_{i}^{N} \mathcal{L}_{\text{match}}(y_i, \hat{y}_{\sigma(i)})$$

N = amount of boxes

5.2.1 DETR: DEtection Transformer – Object detection

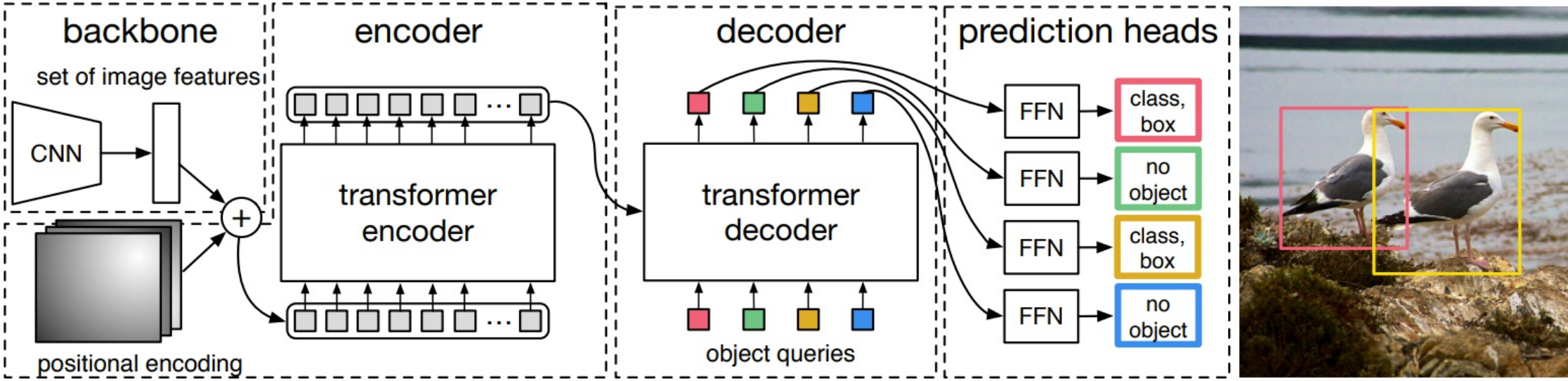


Figure 22: DETR architecture [4].

Training:

Loss = best matching loss between target and prediction → Hungarian Algorithm

$$\hat{\sigma} = \arg\min_{\sigma \in \mathfrak{S}_N} \sum_{i}^{N} \mathcal{L}_{\text{match}}(y_i, \hat{y}_{\sigma(i)})$$

N = amount of boxes

$$\mathcal{L}_{\text{Hungarian}}(y, \hat{y}) = \sum_{i=1}^{N} \left[-\log \hat{p}_{\hat{\sigma}(i)}(c_i) + \mathbb{1}_{\{c_i \neq \varnothing\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\hat{\sigma}}(i)) \right]$$

Classification loss (cross entropy loss)

Box loss (intersection over union loss)

5.2.2 DETR: DEtection Transformer
“Attention-head communication”

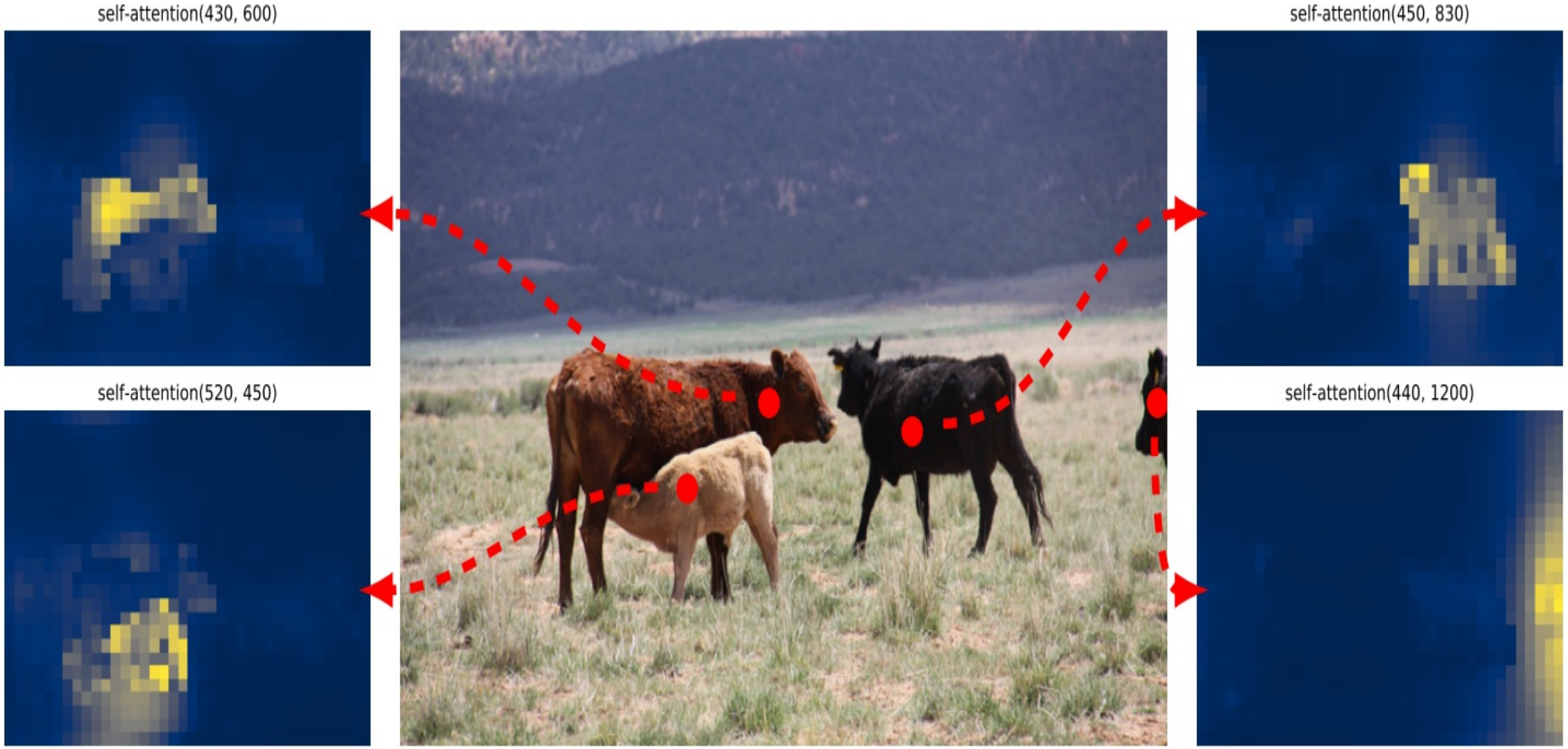


Figure 24: Different attention-heads attend to different objects in the image [4].

This Person Does Not Exist [25].

6. GAN based on a Transformer

Without transposed convolutions!!!

Image source: https://www.thispersondoesnotexist.com/image (call date: 20.07.22)

6.1 TransGAN: Architecture

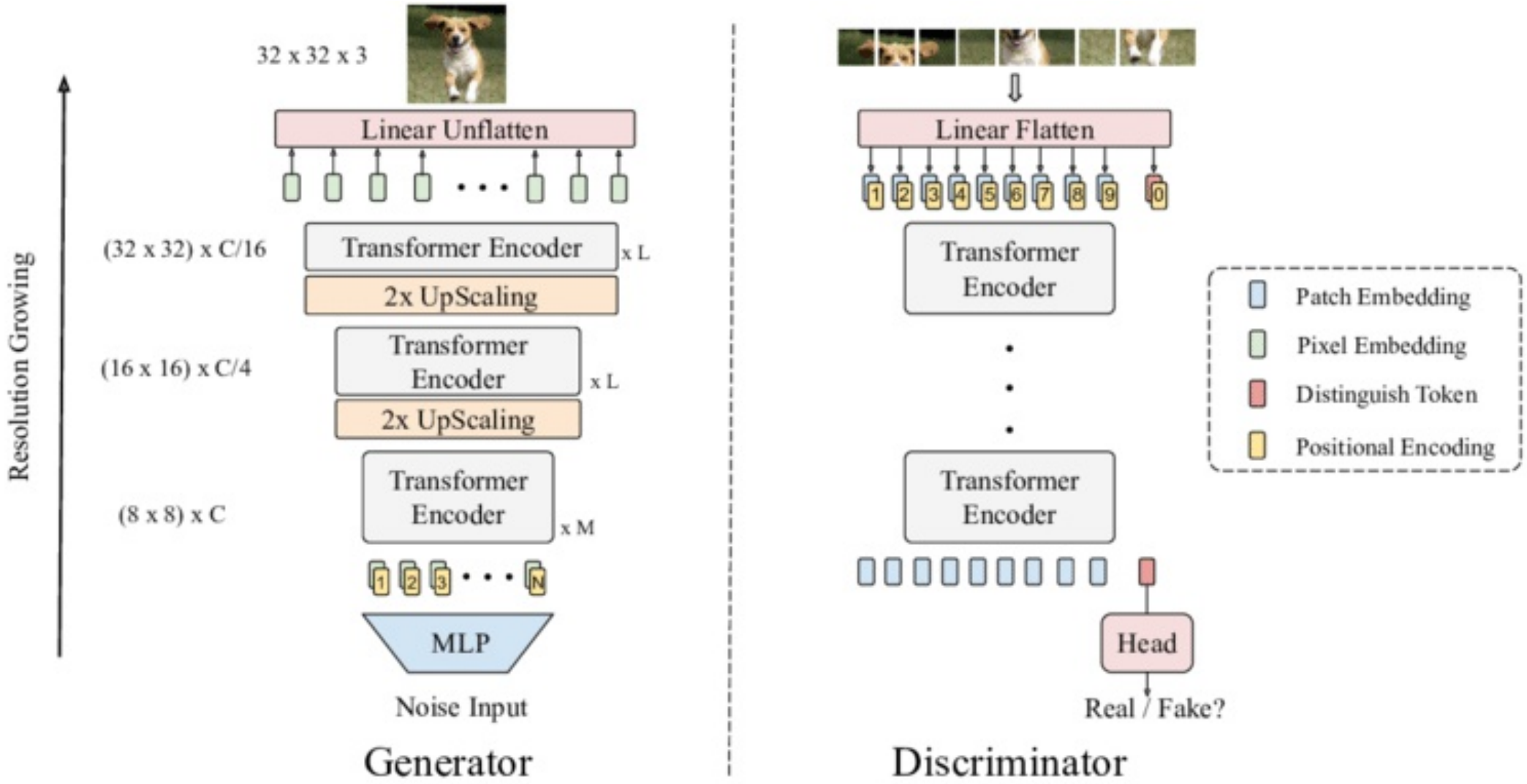


Figure 25: TransGAN architecture [5].

Side note: PixelShuffle

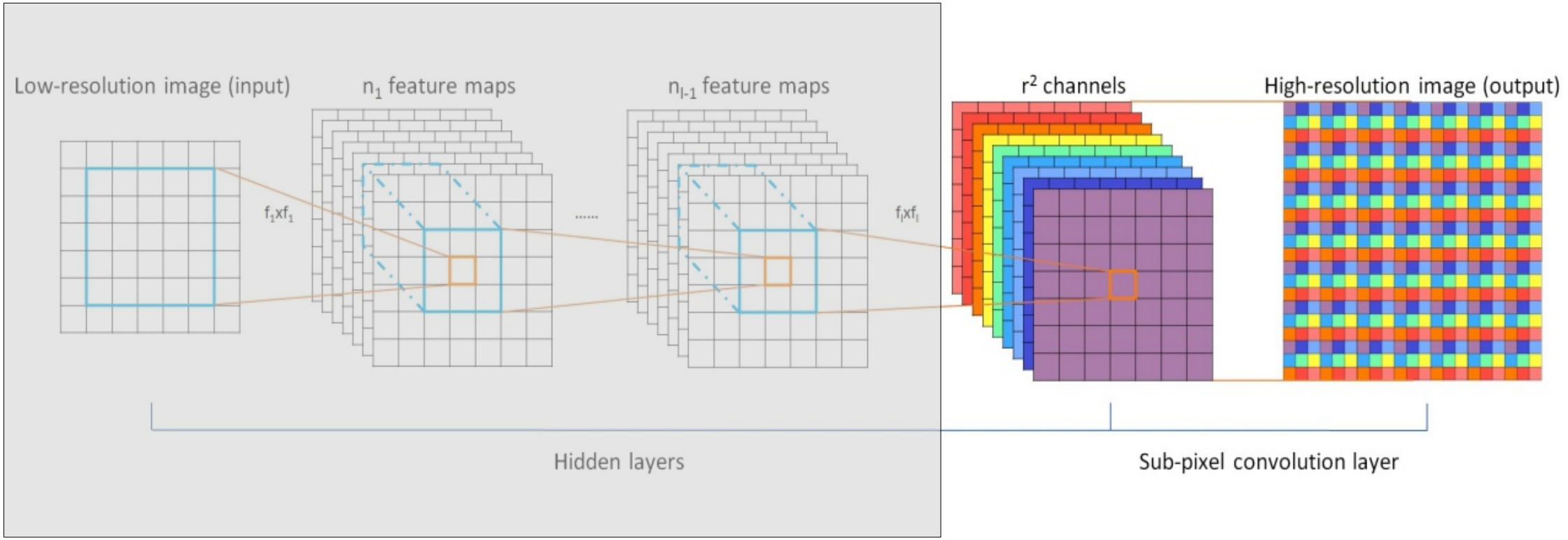


Image source:
Shi, Wenzhe et al. “Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network.” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016): 1874-1883.

6.2 TransGAN: Evaluation

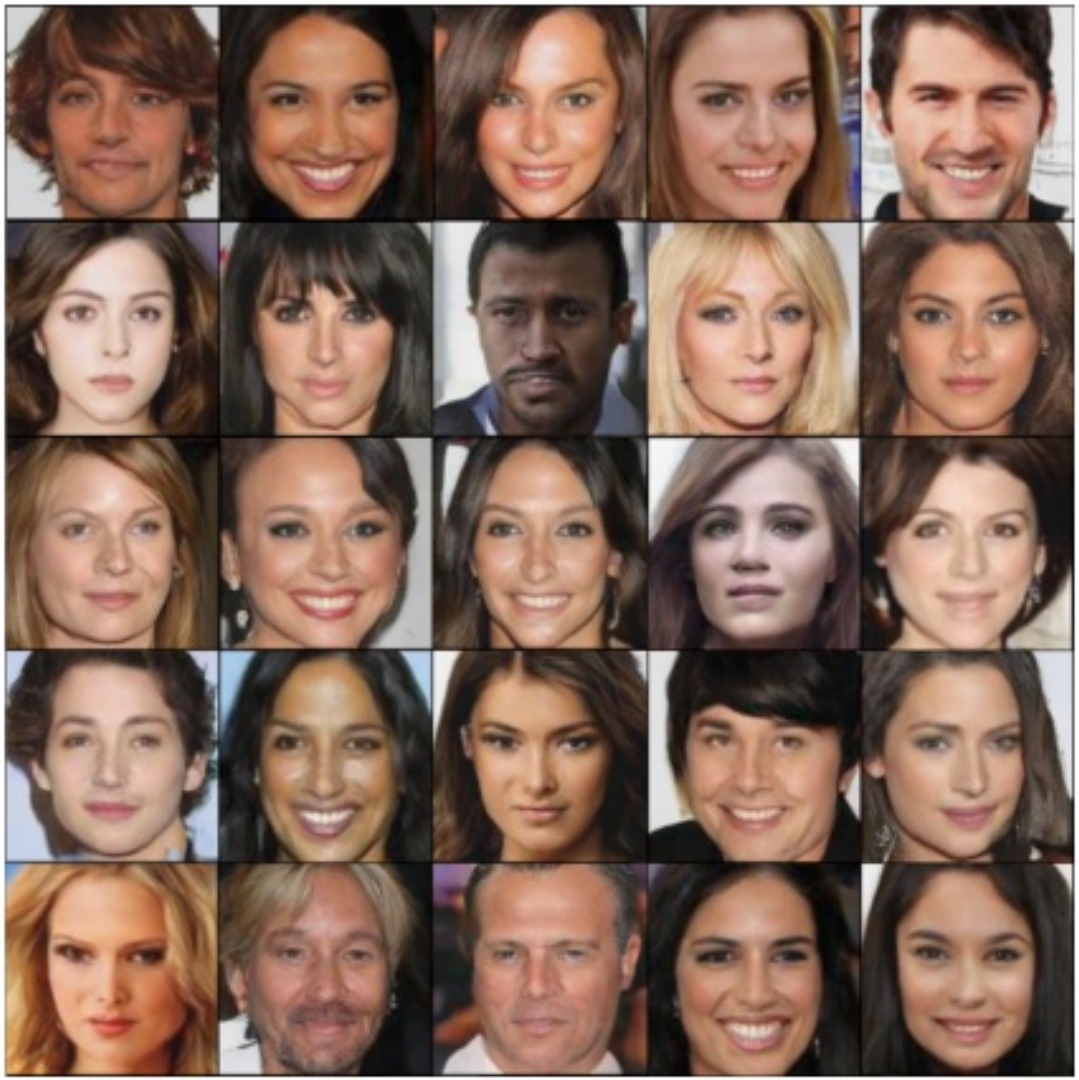


Figure 26: Generated images by the TransGAN [5].

6.2 TransGAN: Evaluation

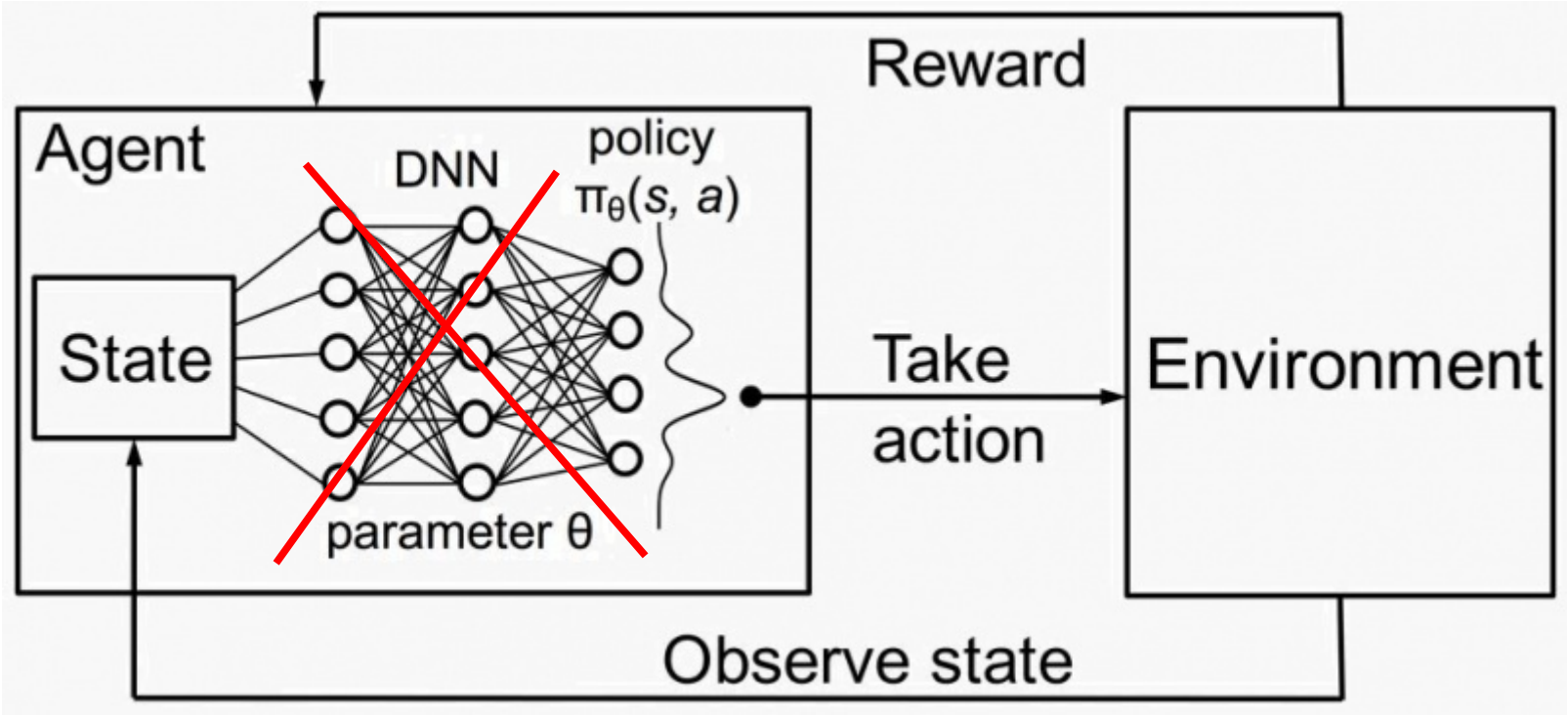
Methods	WGAN-GP		AutoGAN		StyleGAN-V2		TransGAN	
	IS ↑	FID ↓	IS ↑	FID ↓	IS ↑	FID ↓	IS ↑	FID ↓
Original	**6.49**	39.68	8.55	**12.42**	9.18	11.07	8.36	22.53
+ DiffAug [69]	6.29	**37.14**	**8.60**	12.72	**9.40**	**9.89**	**9.02**	**9.26**

Table 3: Performance of the TransGAN compared with state-of-the-art GANs [5].

IS: Inception score “high = good”

FID: Frechet Inception Distance “low = good”

7. Transformers in Deep Reinforcement Learning



Now: Transformer

Image source:
https://miro.medium.com/max/1400/1*ZZJ2FJFDNB9W-kdA2CfmTQ.png (call date: 20.07.22)

7.1.1 DTQN: Deep Transformer Q-network

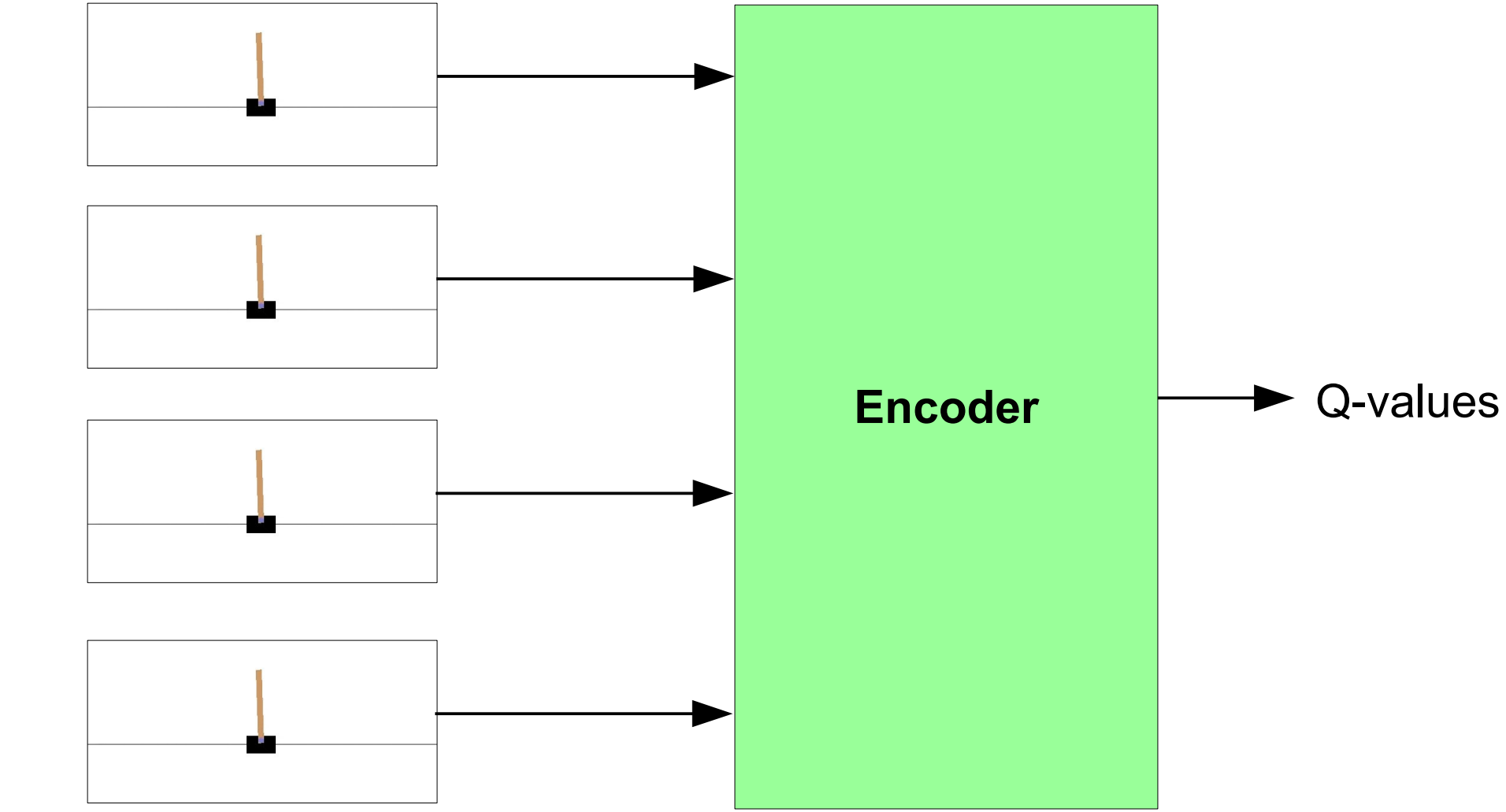


Figure 27: DTQN architecture [6].

Image source:
https://miro.medium.com/freeze/max/600/1*C6T-7ytta7KRbejnCfOtXQ.gif (call date: 20.07.22)

7.1.2 DTQN: Evaluation

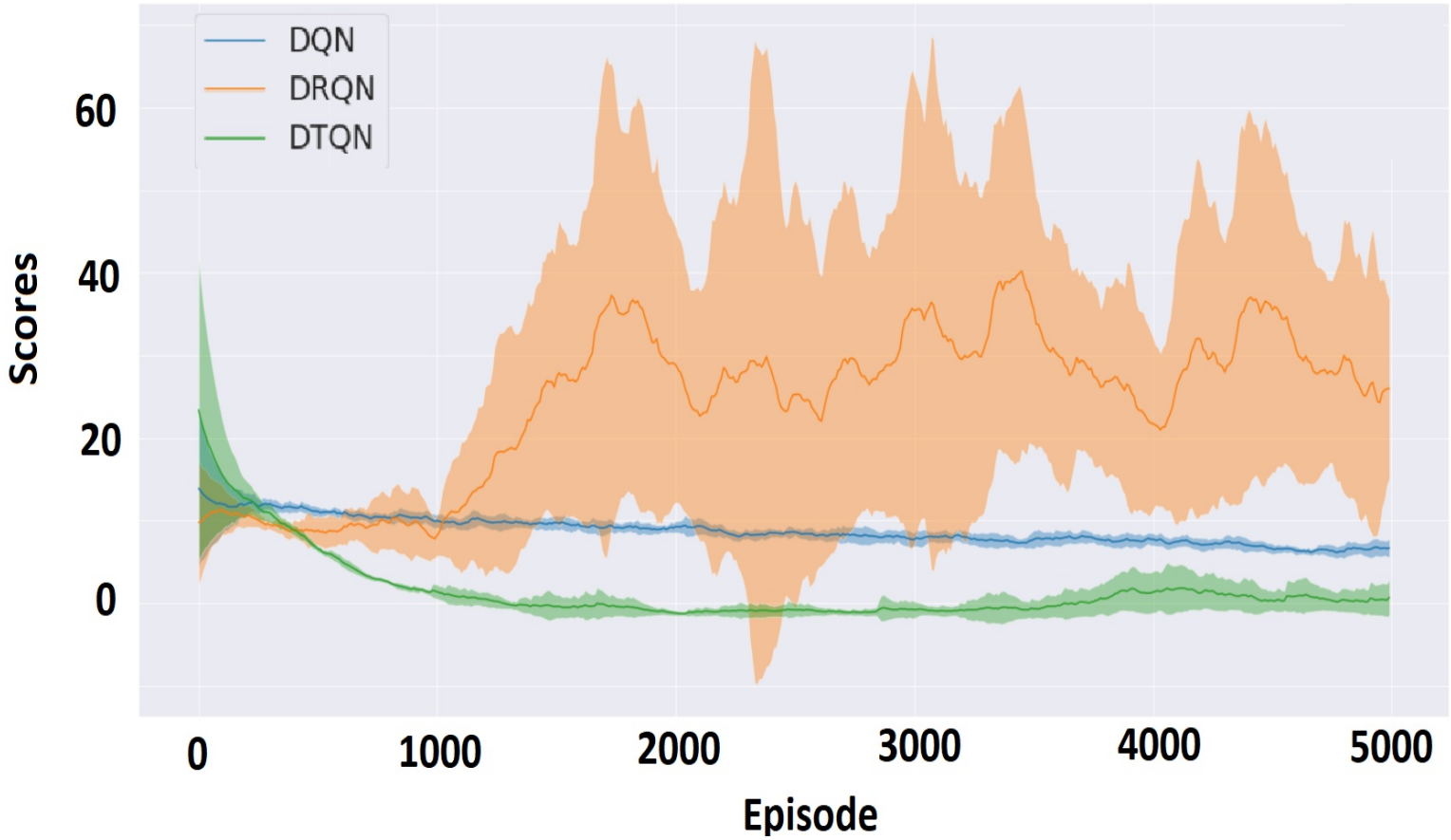


Figure 28: DTQN performance [6].

7.2.1 Decision Transformer: Architecture

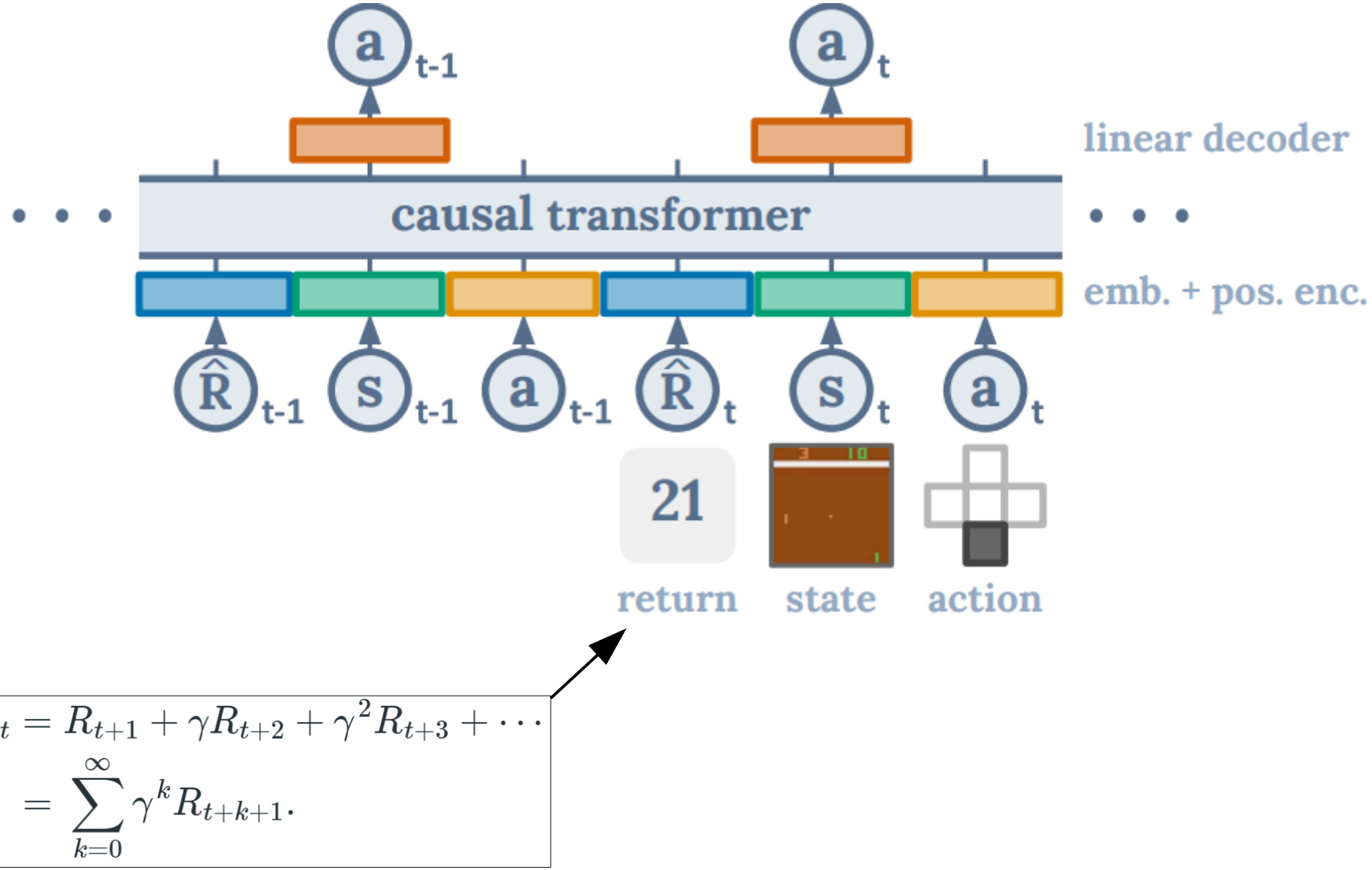
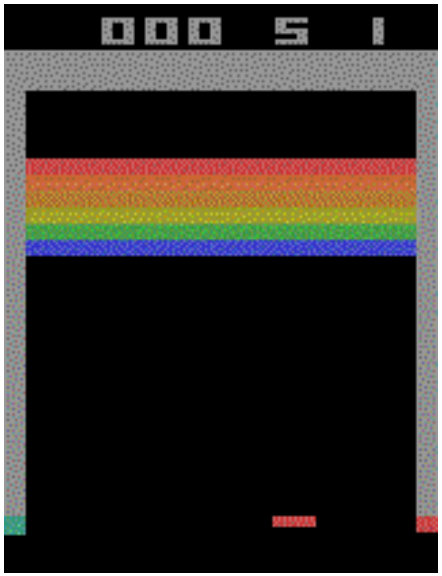
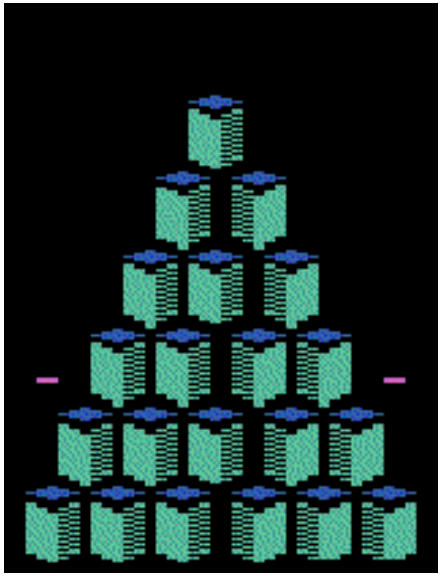


Figure 29: Decision Transformer architecture [7].

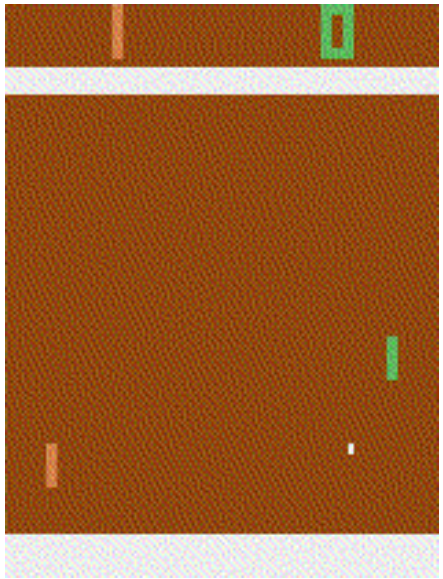
7.2.2 Decision Transformer: Evaluation



Breakout



Qbert



Pong

Seaquest

Figure 30: Evaluated environments.

Image sources:
https://www.gymlibrary.ml/_images/breakout.gif
https://www.gymlibrary.ml/_images/qbert.gif
https://www.gymlibrary.ml/_images/pong.gif
https://www.gymlibrary.ml/_images/seaquest.gif (call dates: 20.07.22)

7.2.3 Decision Transformer: Evaluation

CQL: conservative Q-Learning
QR-DQN: distributional RL
REM: random ensemble mixture

Game	DT	CQL	QR-DQN	REM
Breakout	**267.5 ± 97.5**	211.1	21.1	32.1
Qbert	25.1 ± 18.1	**104.2**	1.7	1.4
Pong	106.1 ± 8.1	**111.9**	20.0	39.1
Seaquest	**2.4 ± 0.7**	1.7	1.4	1.0

Table 4: Performance of the Decision Transformer compared with state-of-the-art DRL methods [7].

7.2.4 Decision Transformer: Why attention?

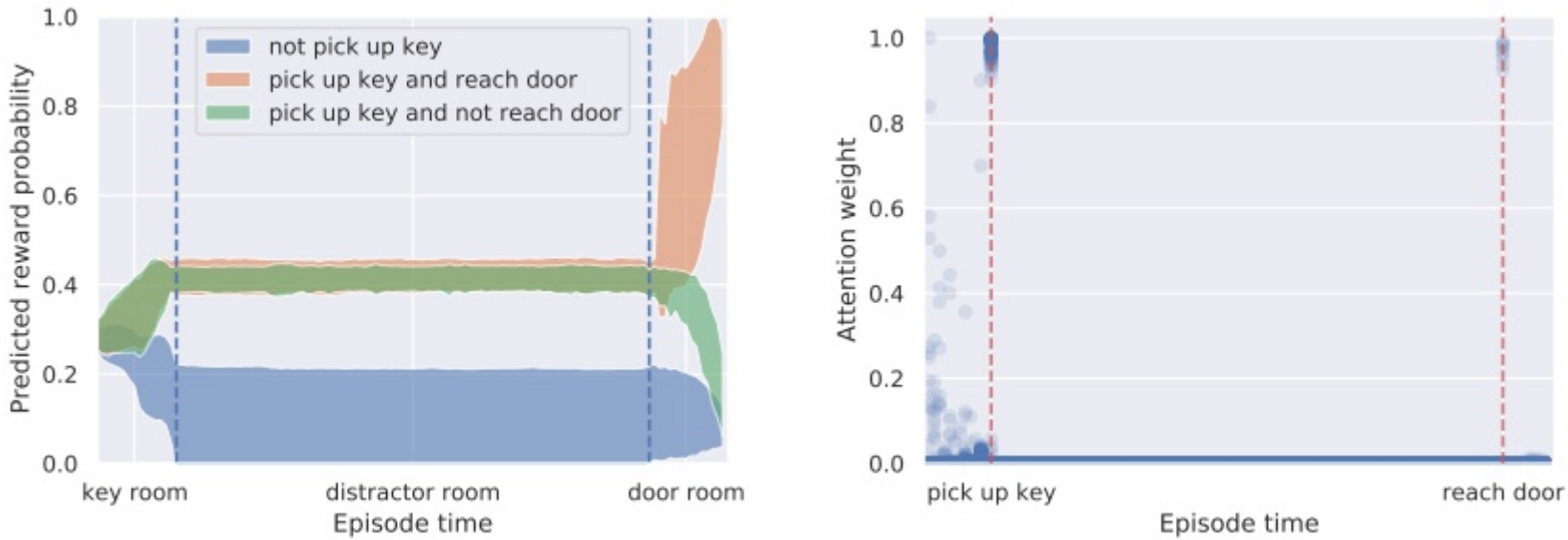
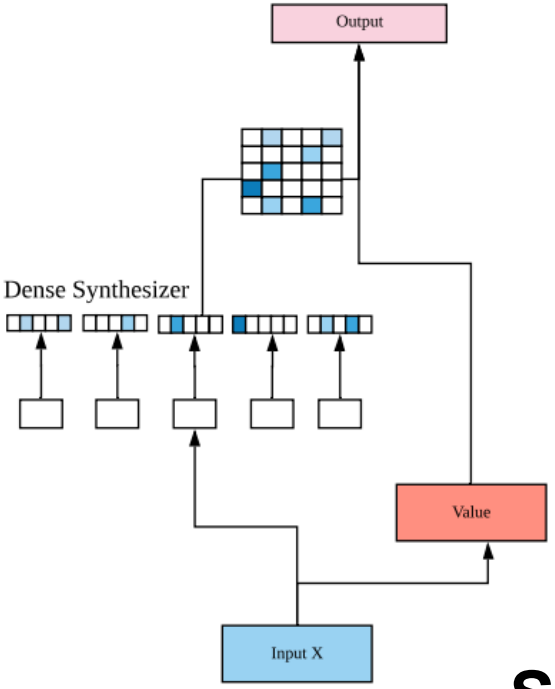
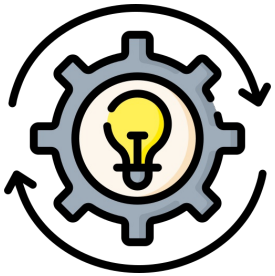
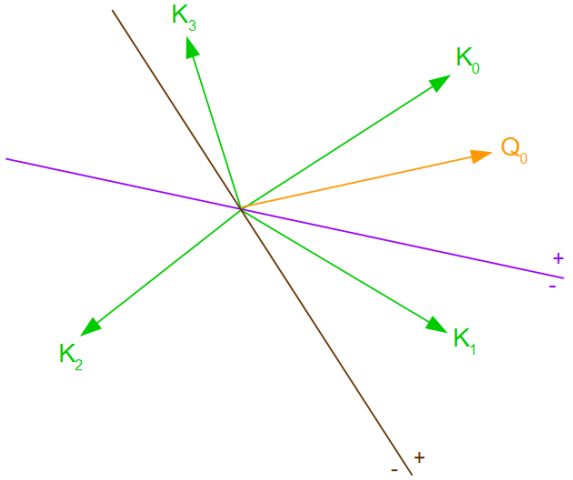


Figure 31: Decision Transformer attend to pivotal events [7].







Reformer

7. Modifications of attention: Synthesizer, Linformer, Reformer

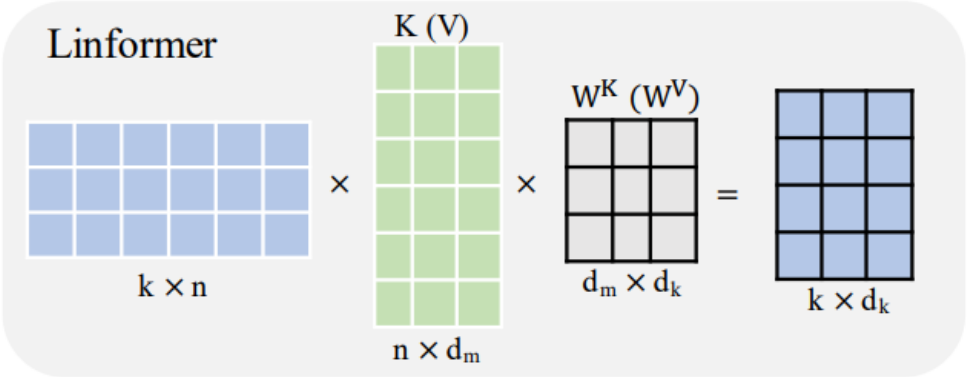
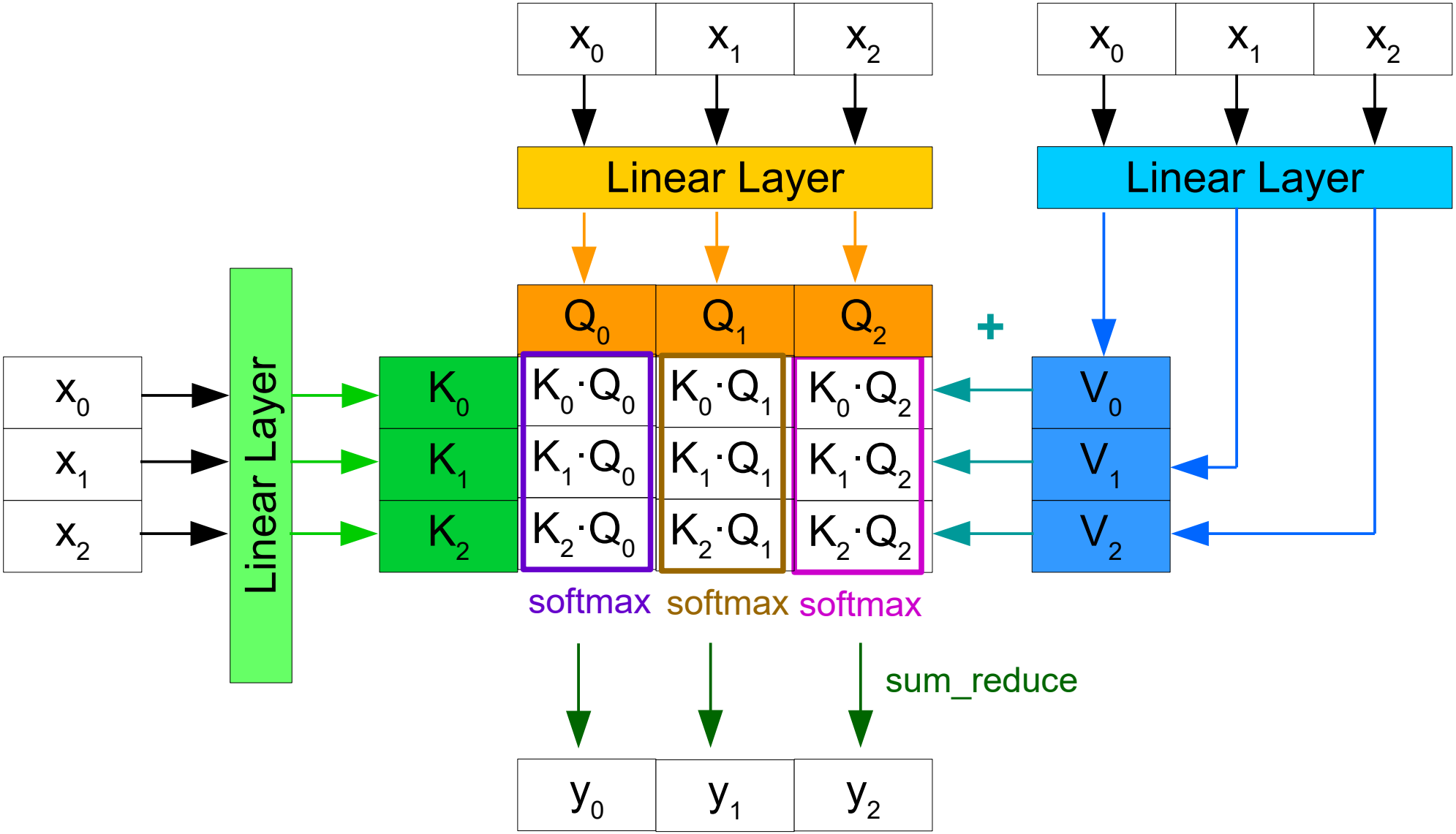
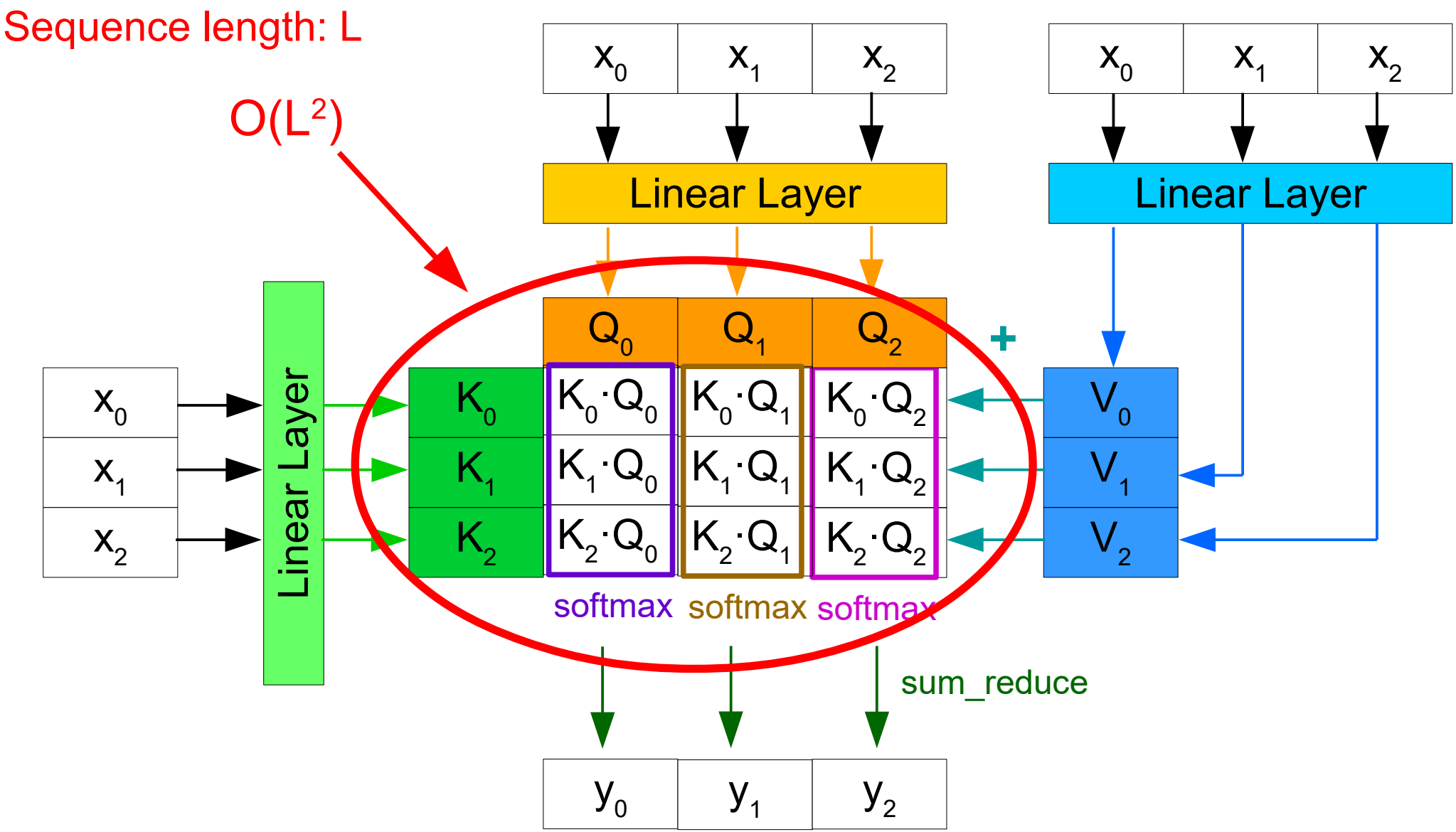


Image sources:
https://cdn-icons-png.flaticon.com/512/5116/5116423.png
(call dates: 21.01.23)
Tay, Yi et al. "Synthesizer: Rethinking Self-Attention in Transformer Models." International Conference on Machine Learning (2020).
Wang, Sinong et al. "Linformer: Self-Attention with Linear Complexity." ArXiv abs/2006.04768 (2020): n. pag.

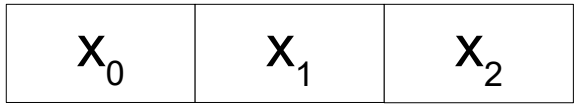
7. Self-attention: Time and Space Complexity



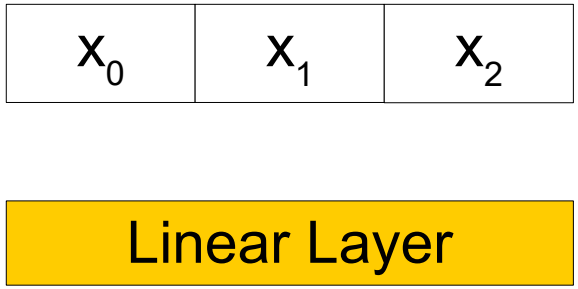
7. Self-attention: Time and Space Complexity



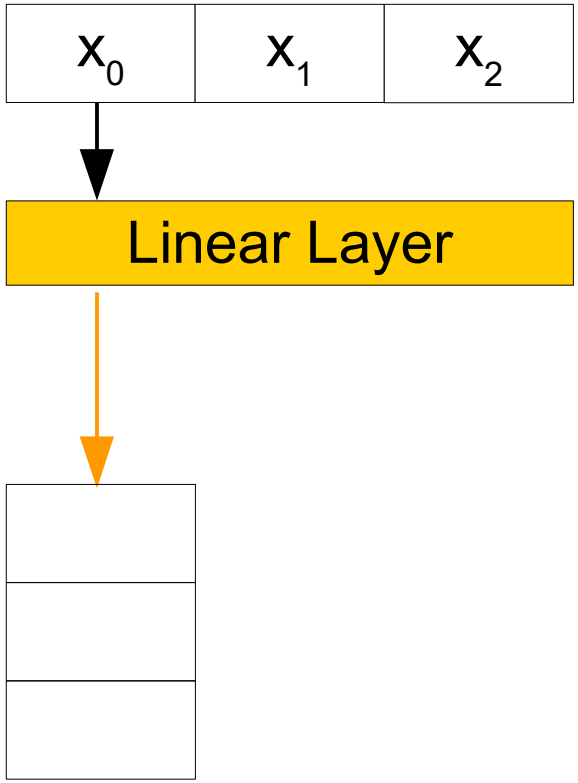
7.1 Synthesizer: *Dense* variant



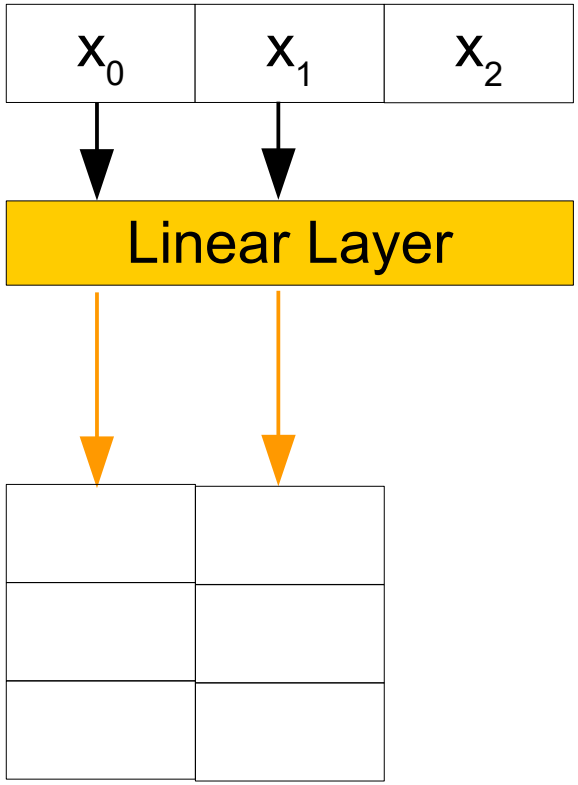
7.1 Synthesizer: *Dense* variant



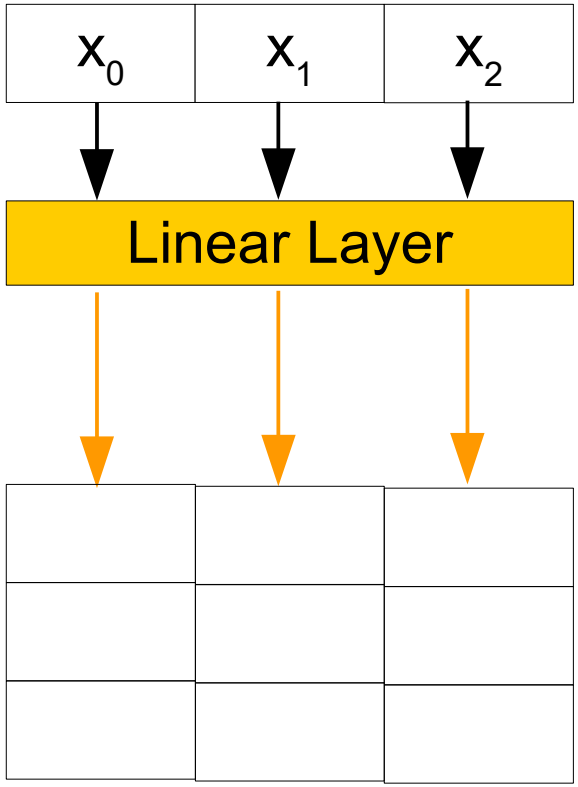
7.1 Synthesizer: *Dense* variant



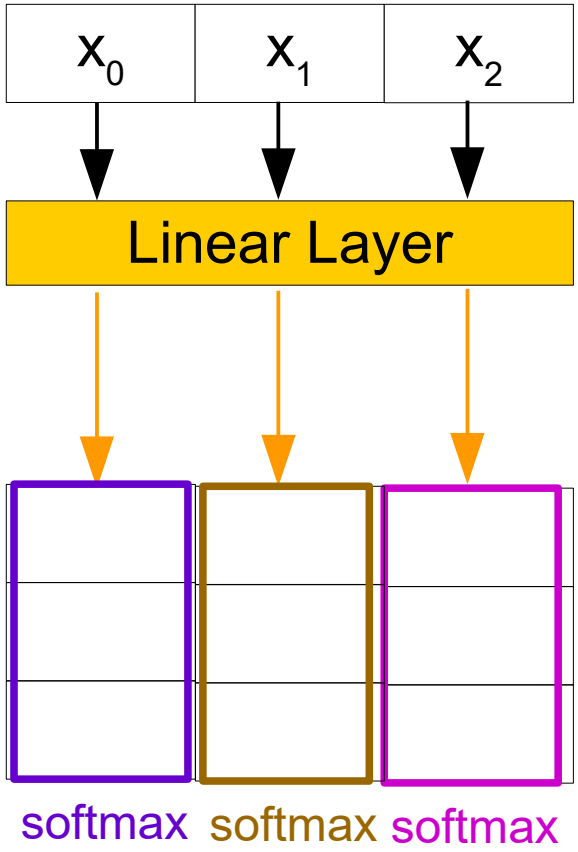
7.1 Synthesizer: *Dense* variant



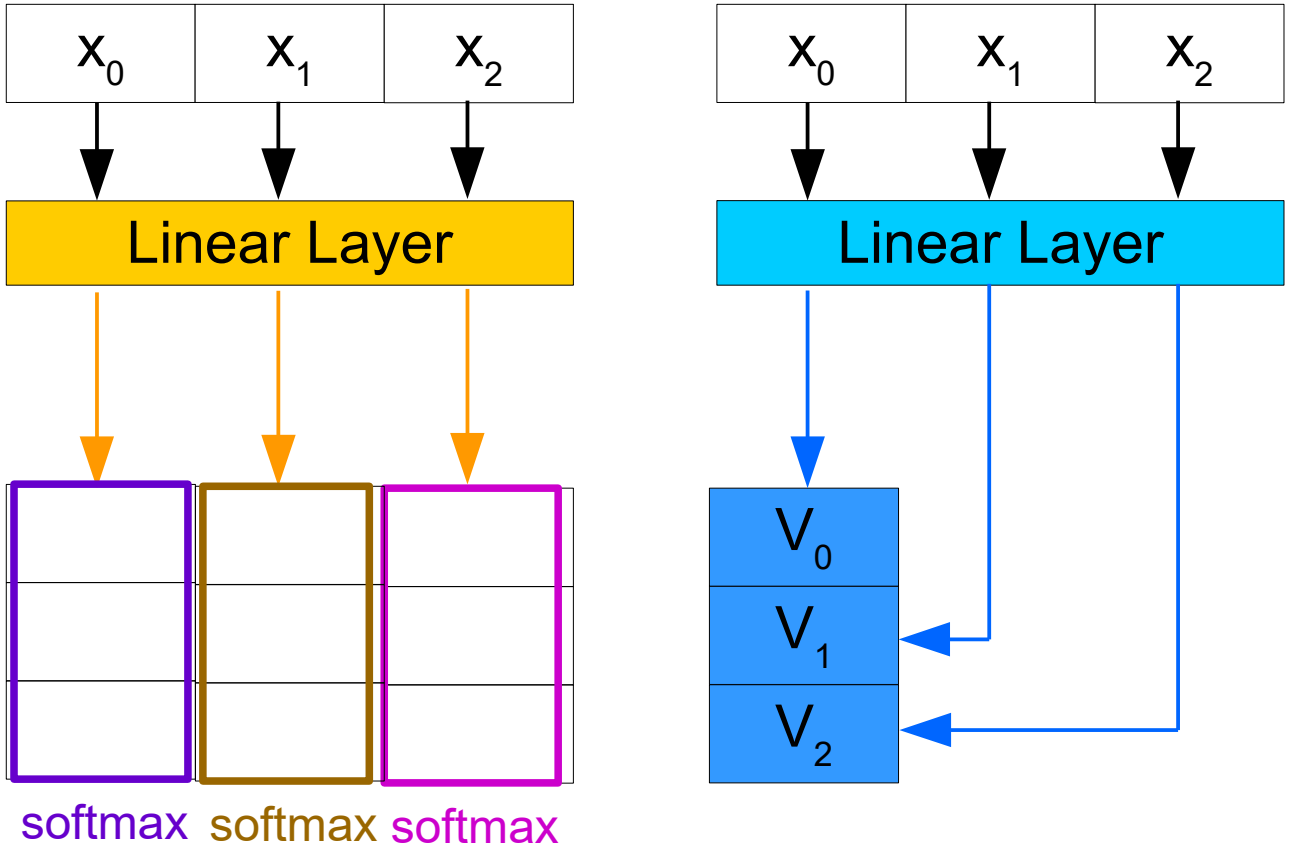
7.1 Synthesizer: *Dense* variant



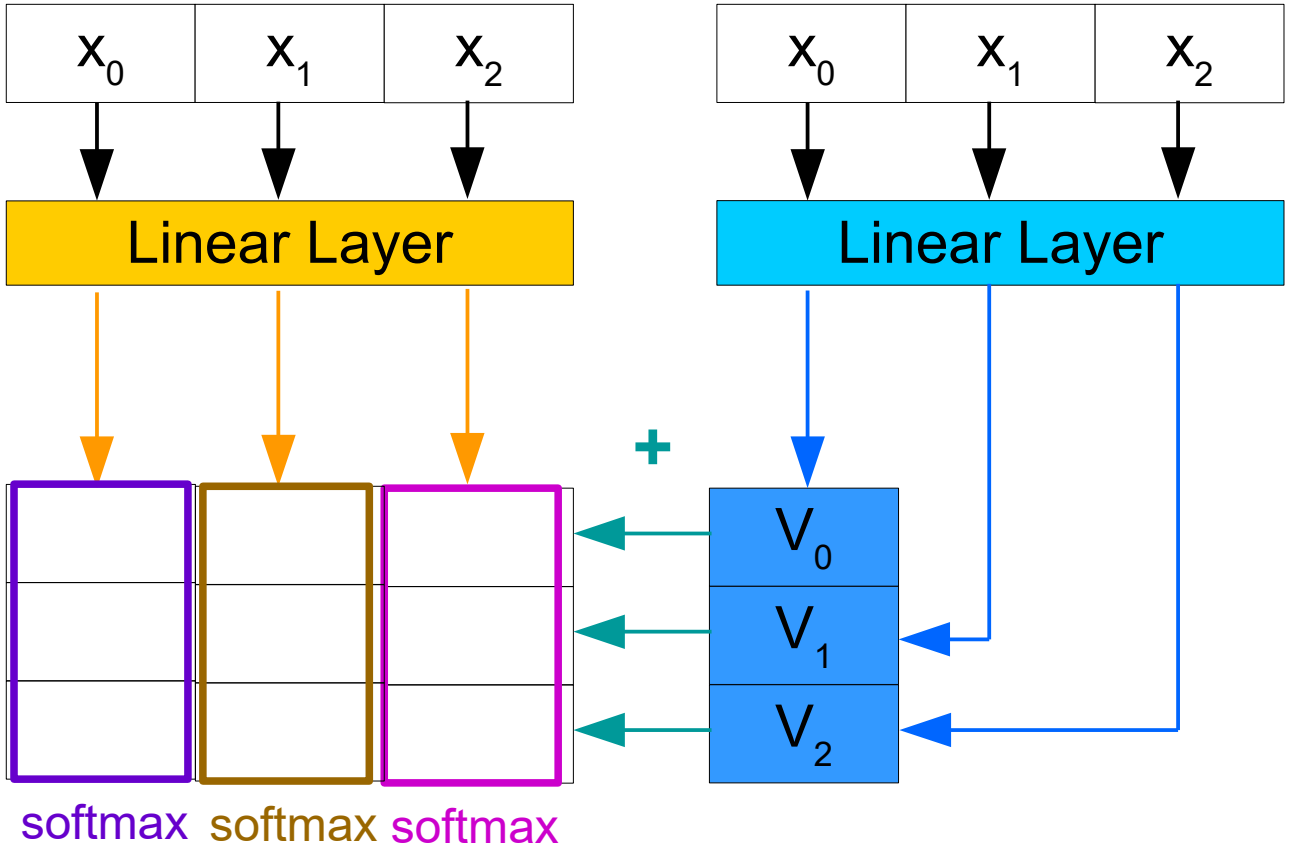
7.1 Synthesizer: *Dense* variant



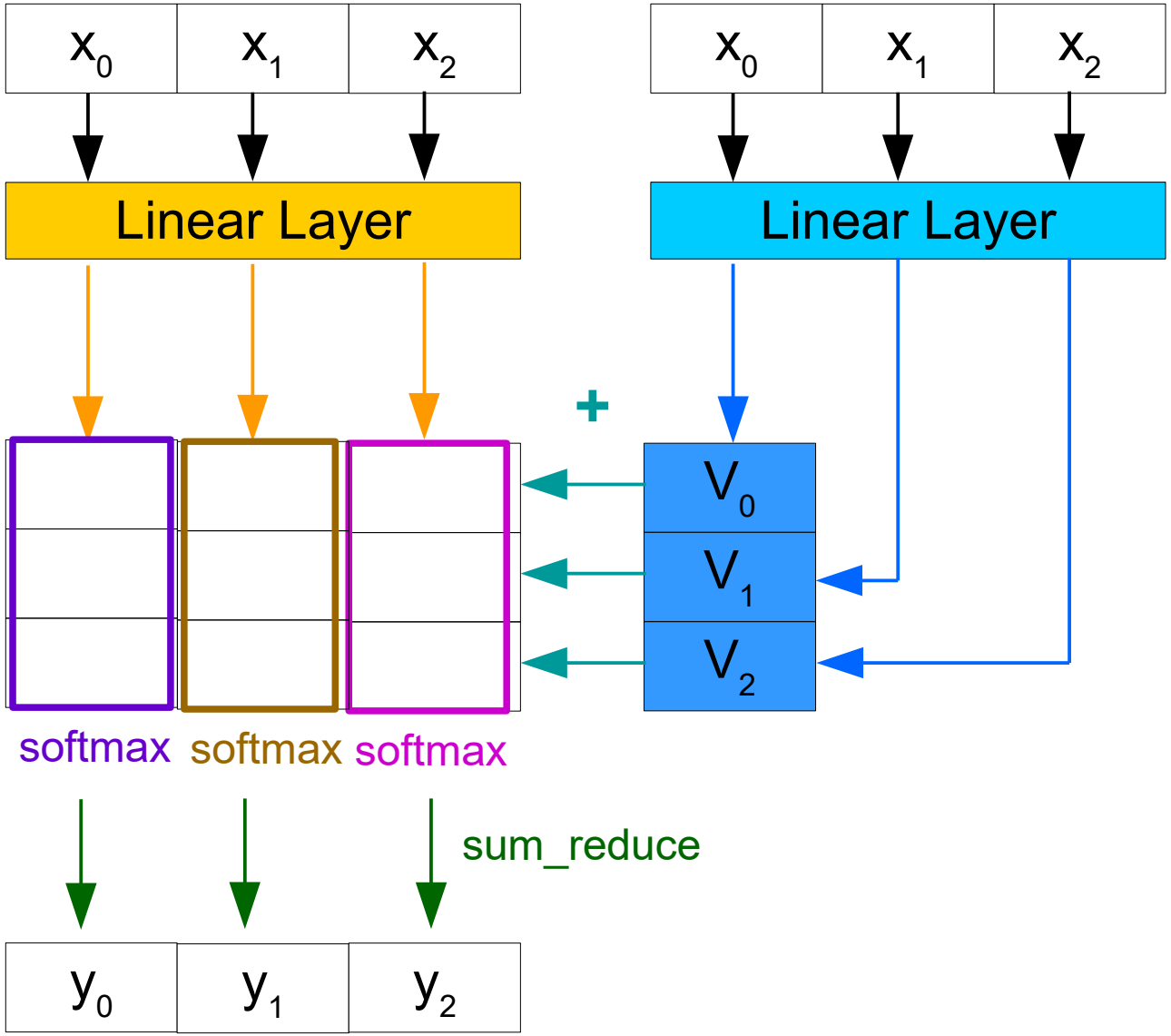
7.1 Synthesizer: *Dense* variant



7.1 Synthesizer: *Dense* variant



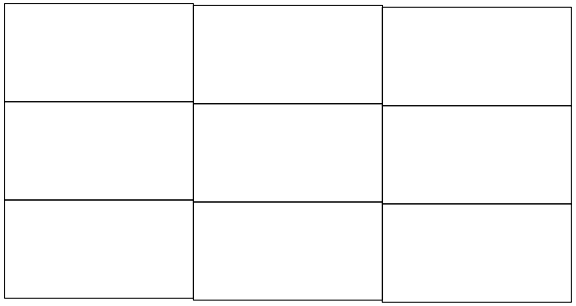
7.1 Synthesizer: *Dense* variant



7.1 Synthesizer: *Random* variant

x_0	x_1	x_2

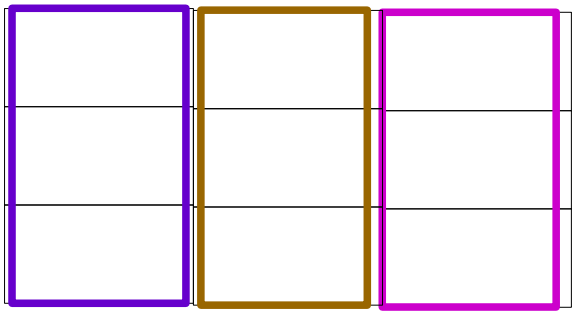
Fixed



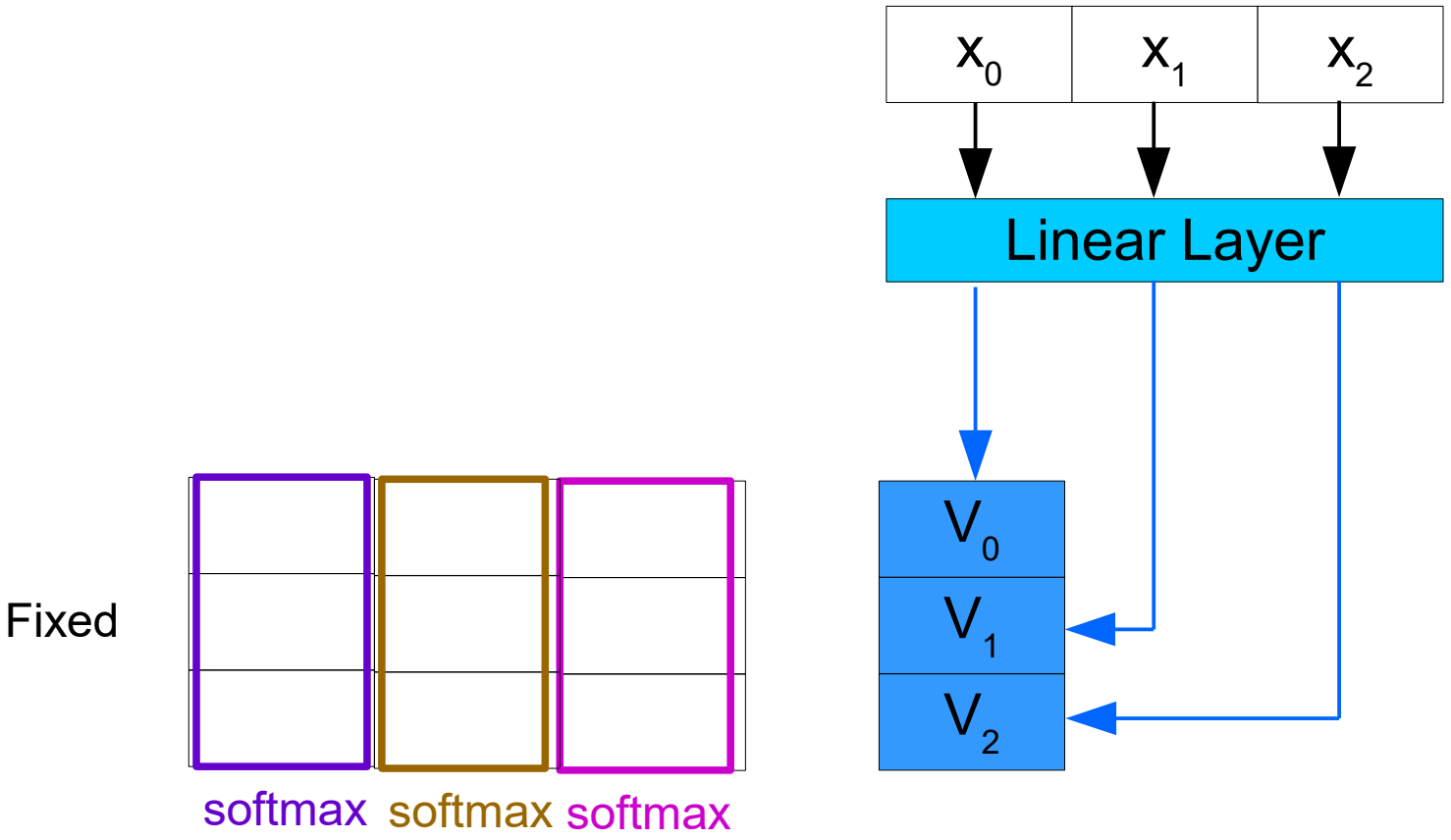
7.1 Synthesizer: *Random* variant

x_0	x_1	x_2

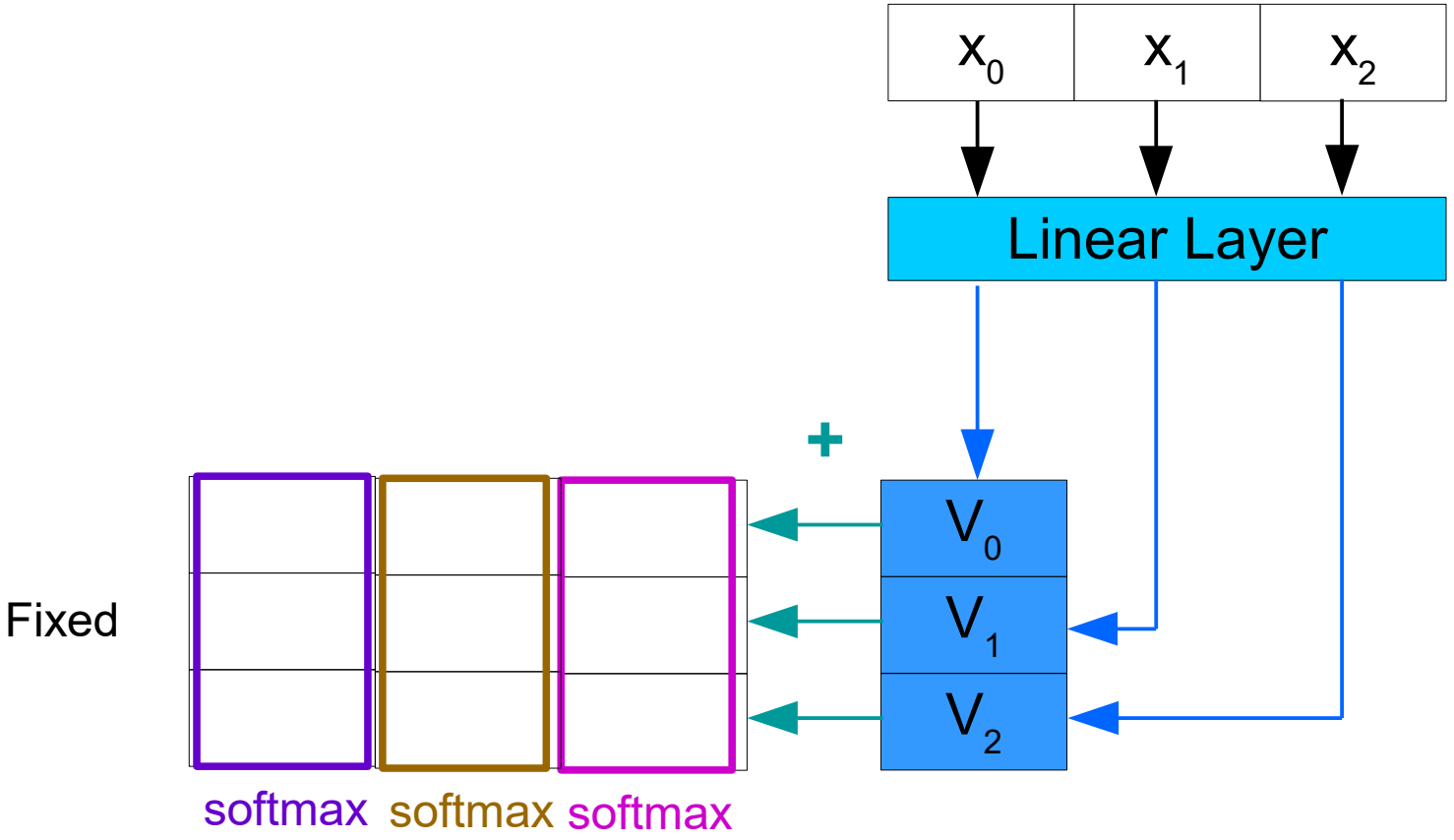
Fixed



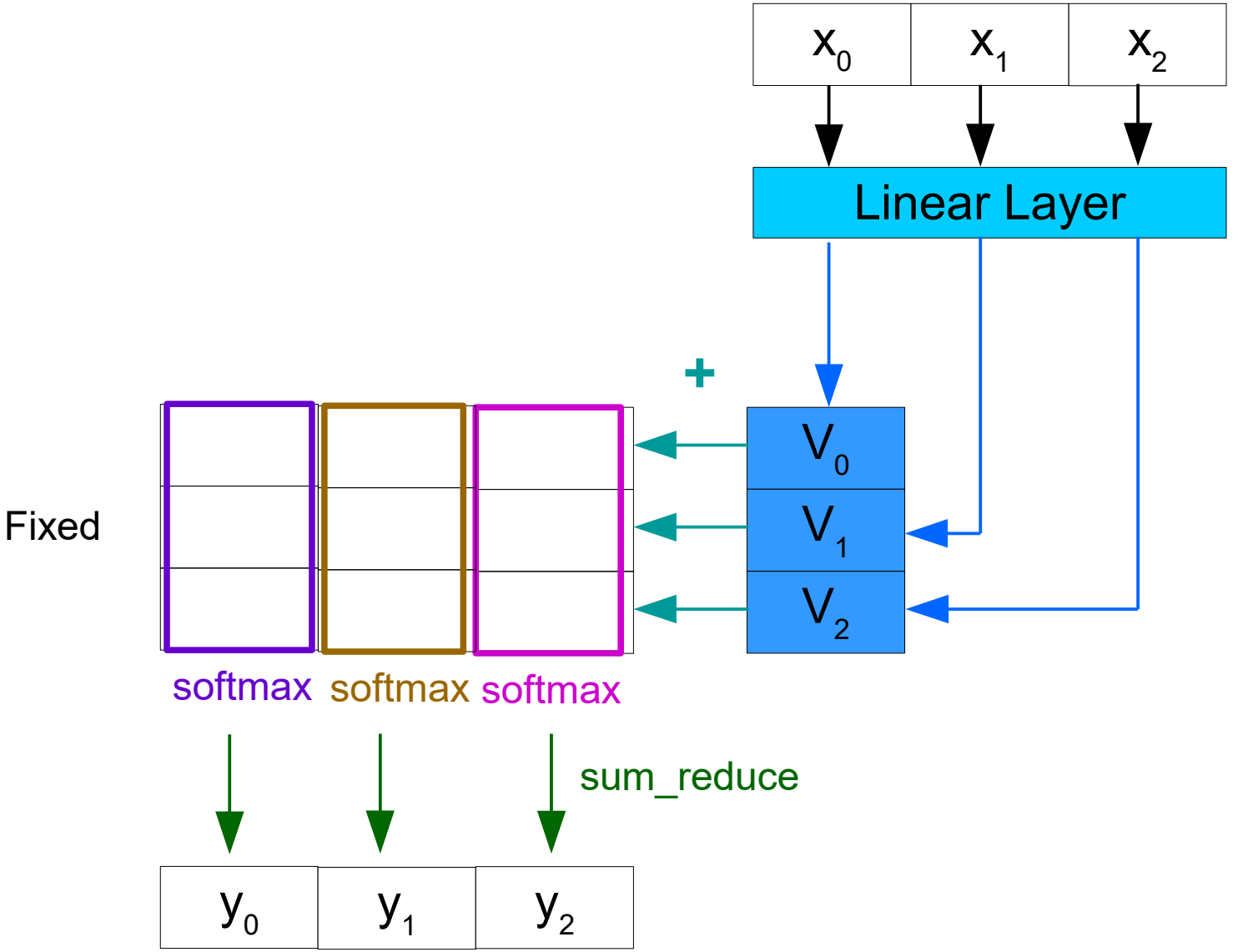
7.1 Synthesizer: *Random* variant



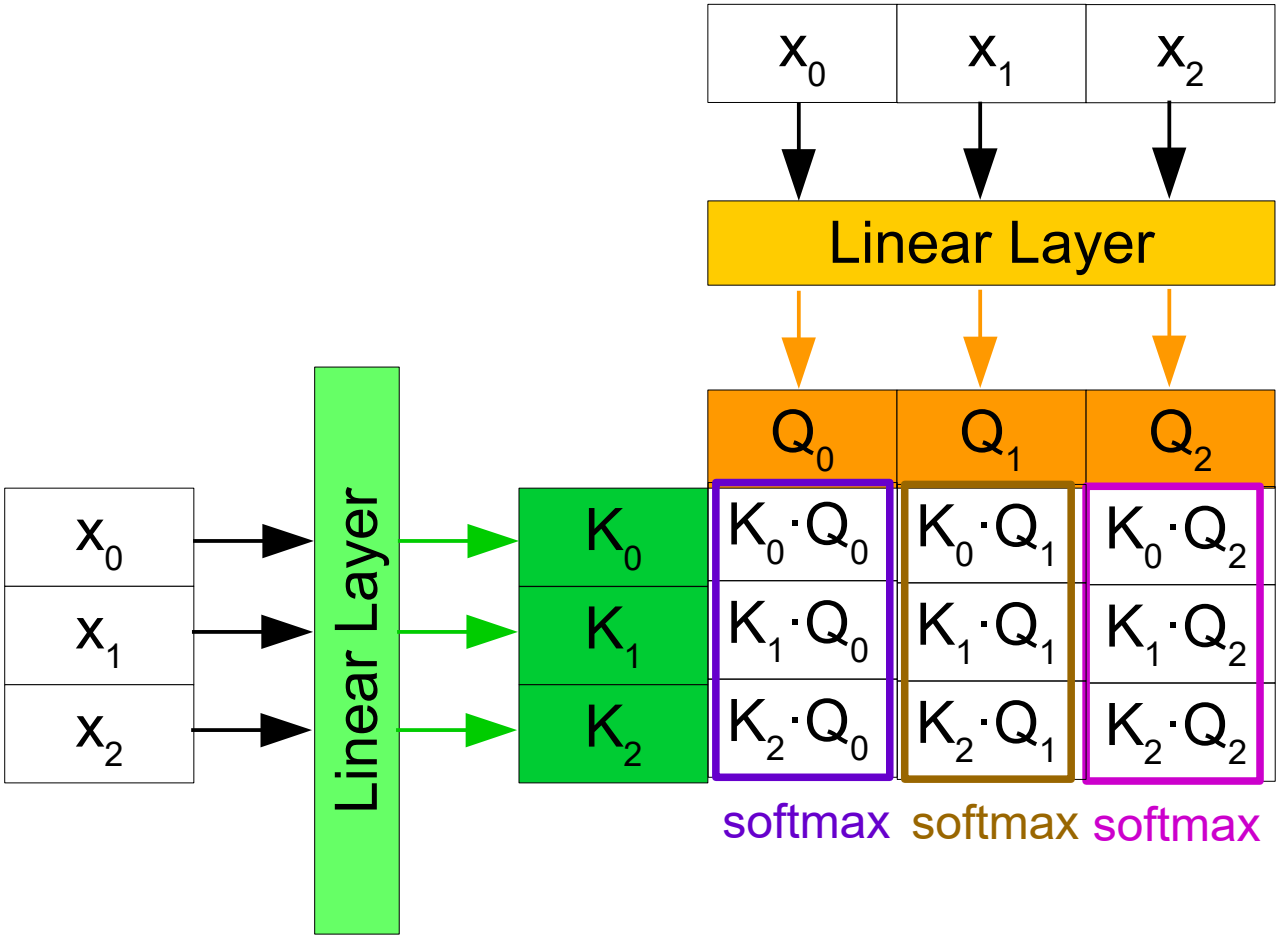
7.1 Synthesizer: *Random* variant



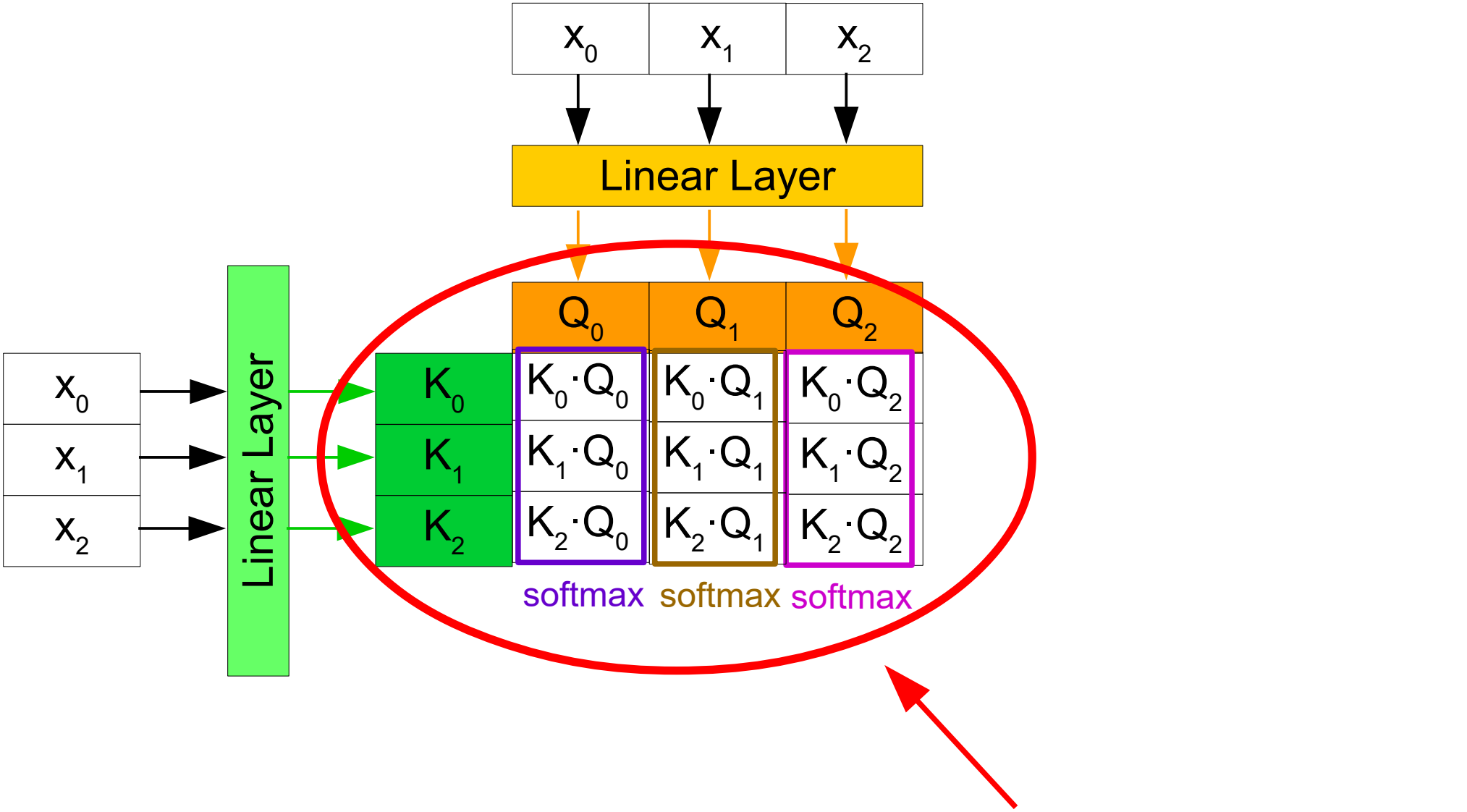
7.1 Synthesizer: *Random* variant



7.2 Linformer: Self-Attention with Linear Complexity



7.2 Linformer: Self-Attention with Linear Complexity



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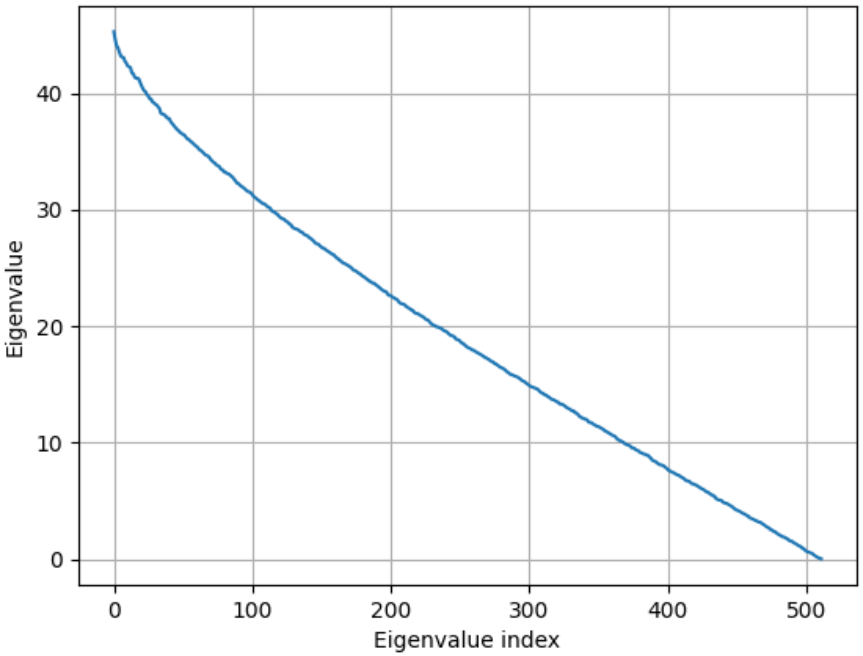
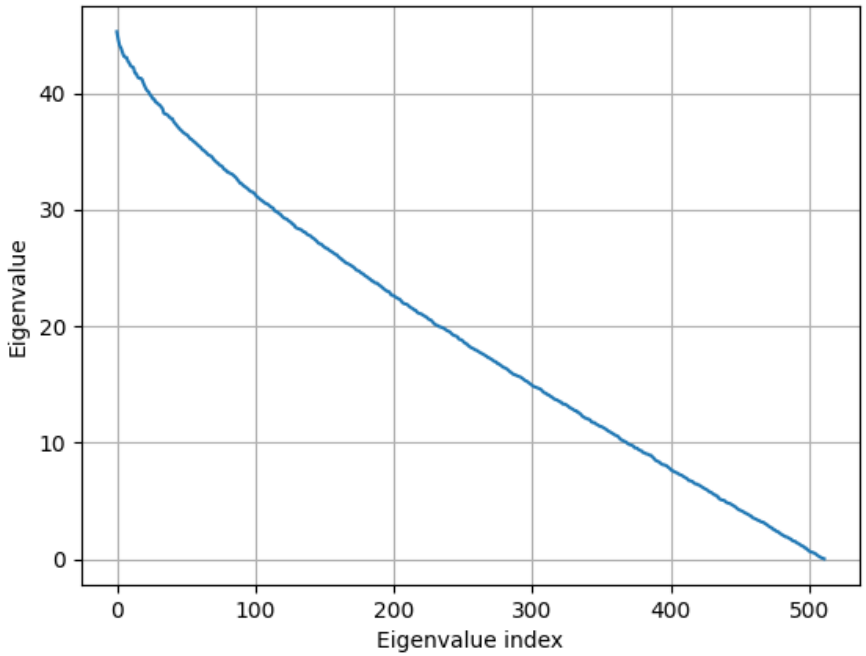


Eigenvalue spectrum of a 256x256 matrix (full rank).

7.2 Linformer: Self-Attention with Linear Complexity

“Order a set of uniform distributed numbers”
→ All dimensions have the same amount of information



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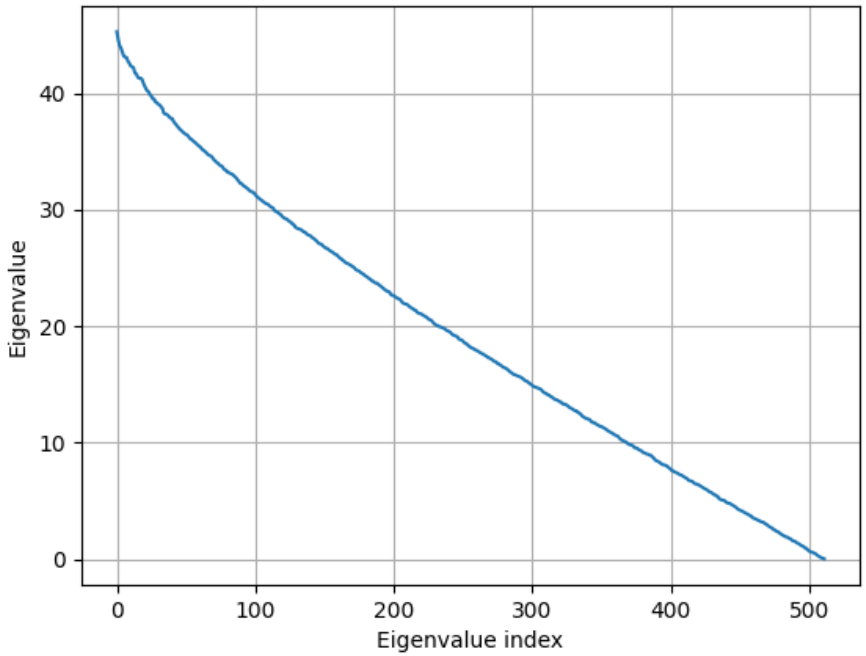
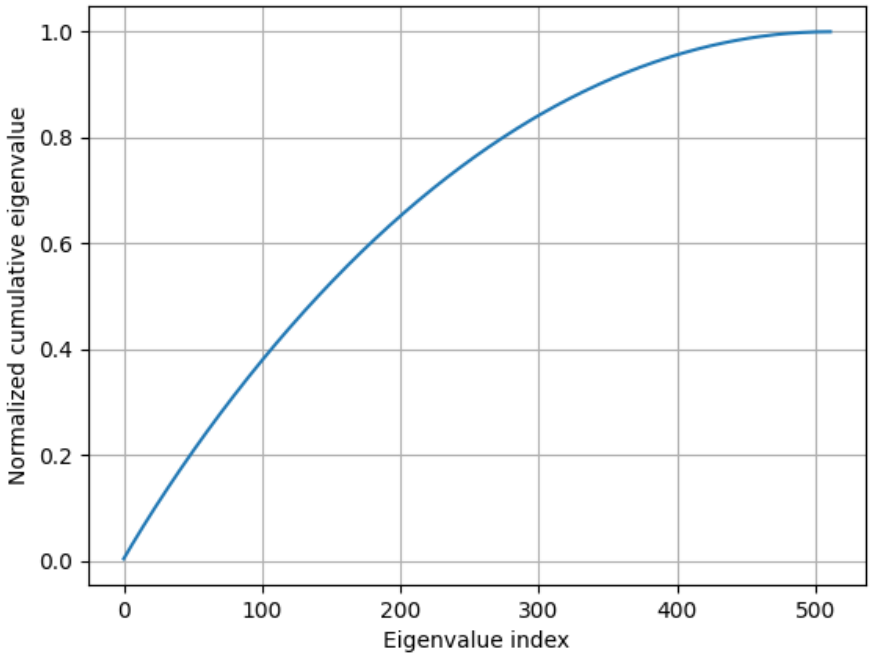
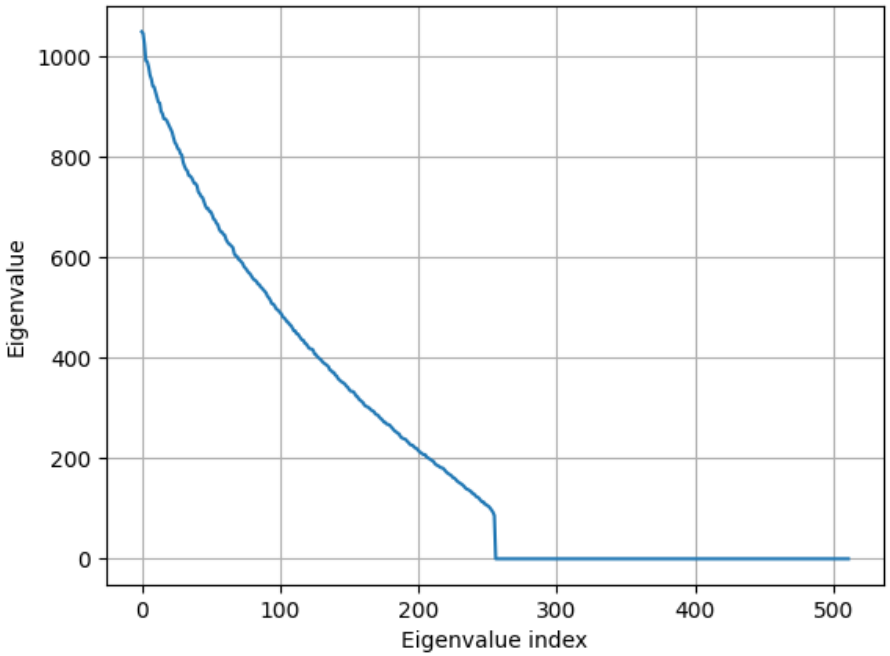




Eigenvalue spectrum of a 256x256 matrix (full rank).

7.2 Linformer: Self-Attention with Linear Complexity

A = 256 x 128
B = 128 x 256
M = A · B

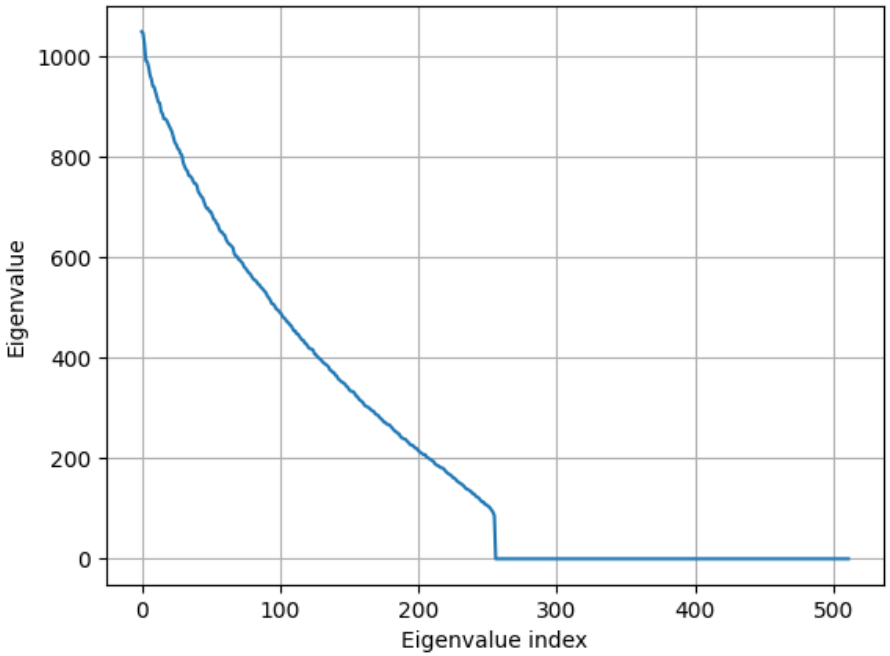


Eigenvalue spectrum of a 256x256 matrix (low rank).

7.2 Linformer: Self-Attention with Linear Complexity

A = 256 x 128
B = 128 x 256
M = A · B

Information is concentrated along few dimensions



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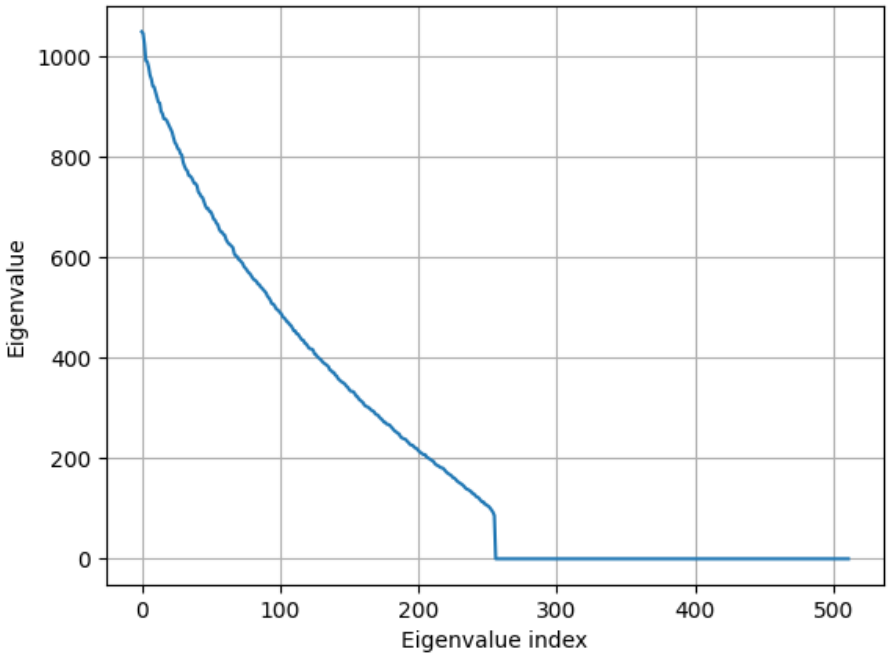
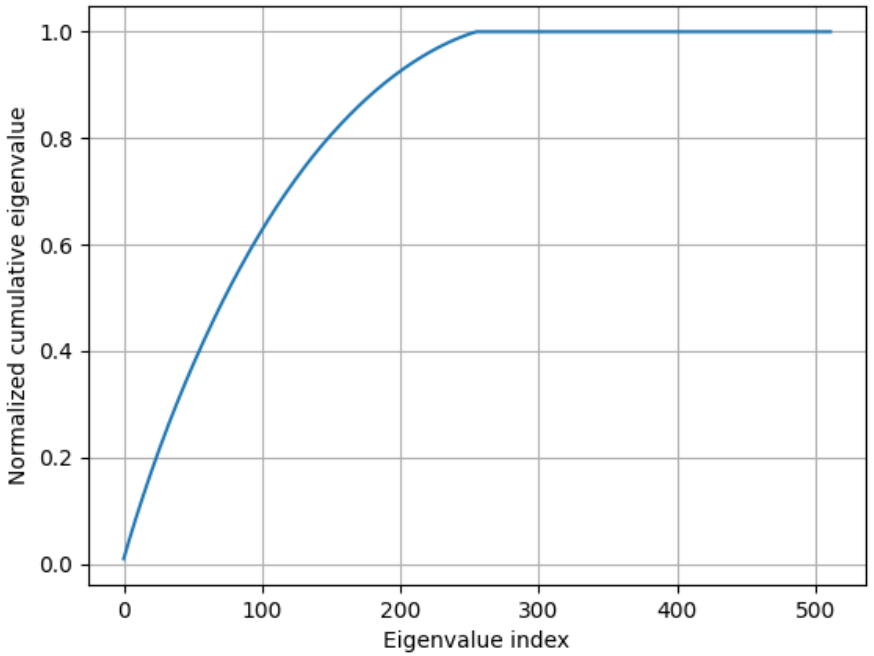
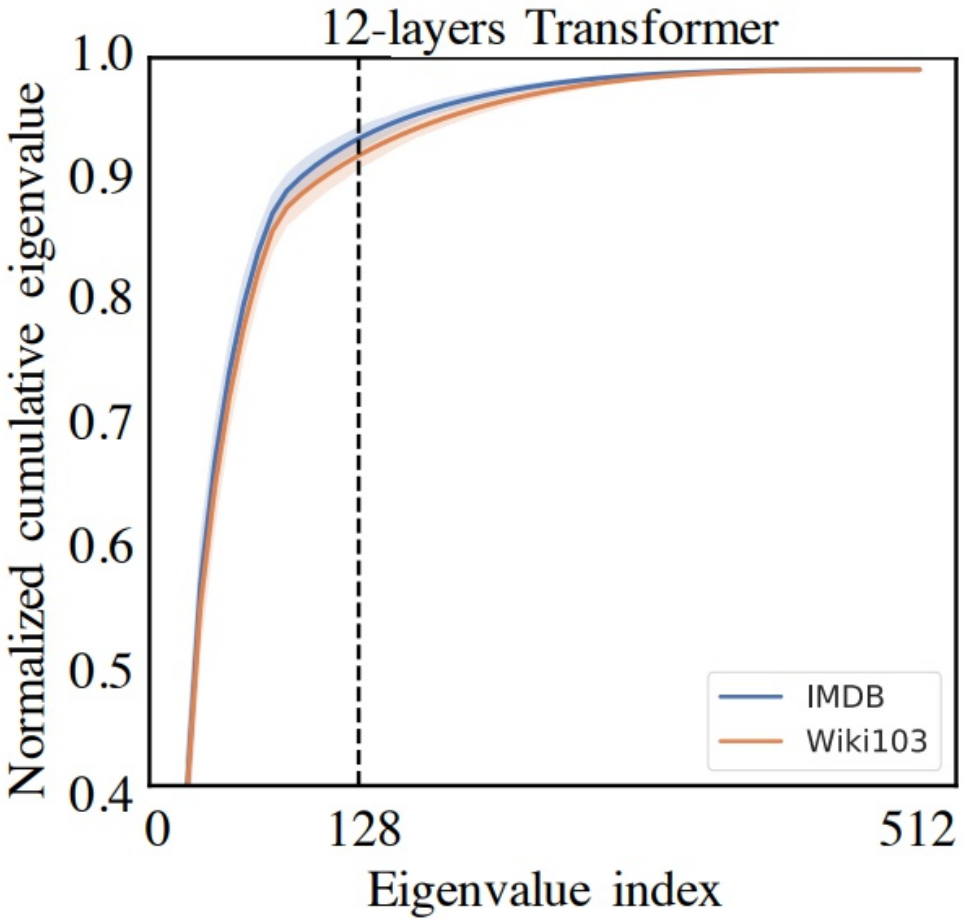




Eigenvalue spectrum of a 256x256 matrix (low rank).

7.2 Linformer: Self-Attention is Low Rank



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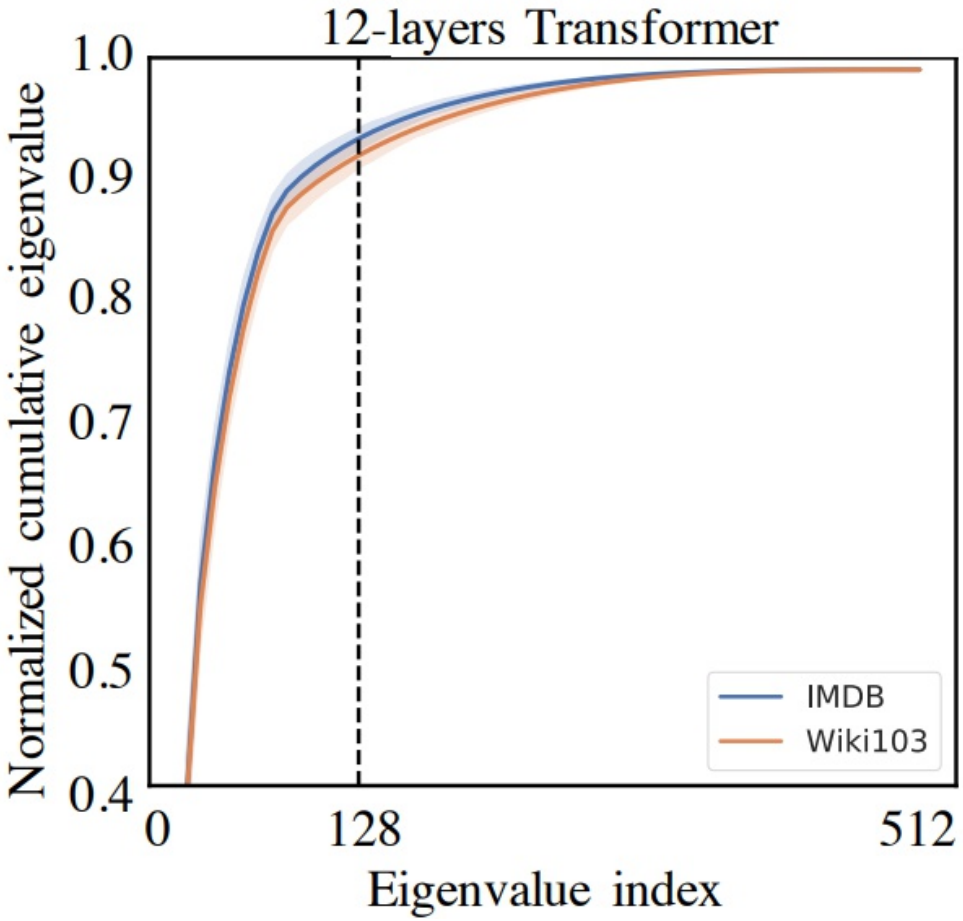
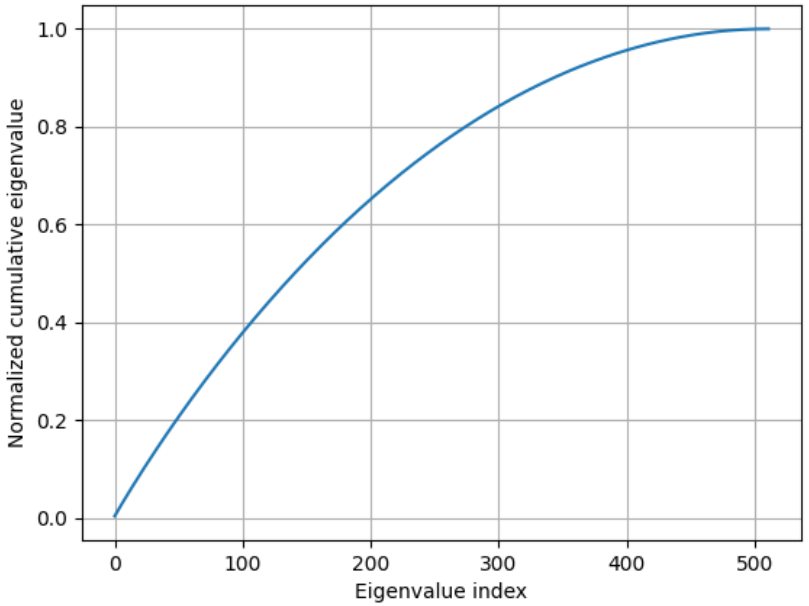
Wang, S., Li, B.Z., Khabsa, M., Fang, H., & Ma, H. (2020). Linformer: Self-Attention with Linear Complexity. ArXiv, abs/2006.04768.

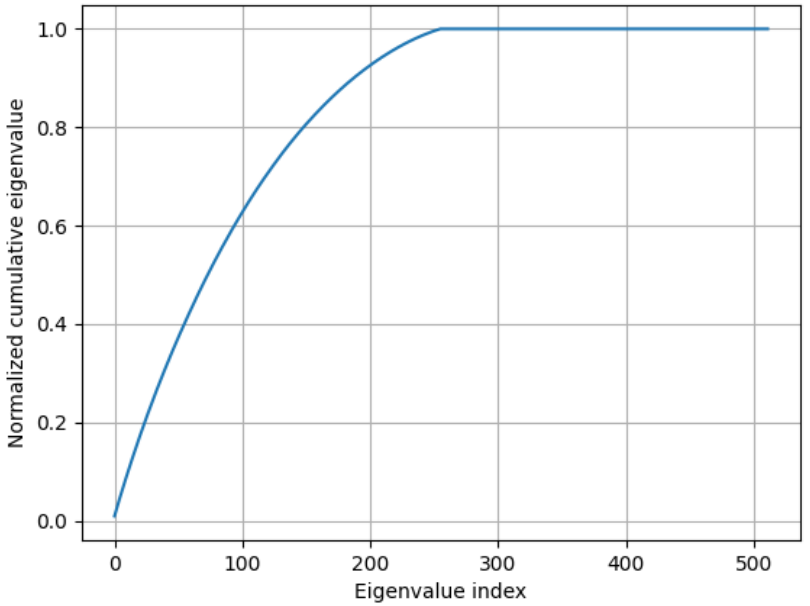
7.2 Linformer: Self-Attention is Low Rank



Full rank



Low rank



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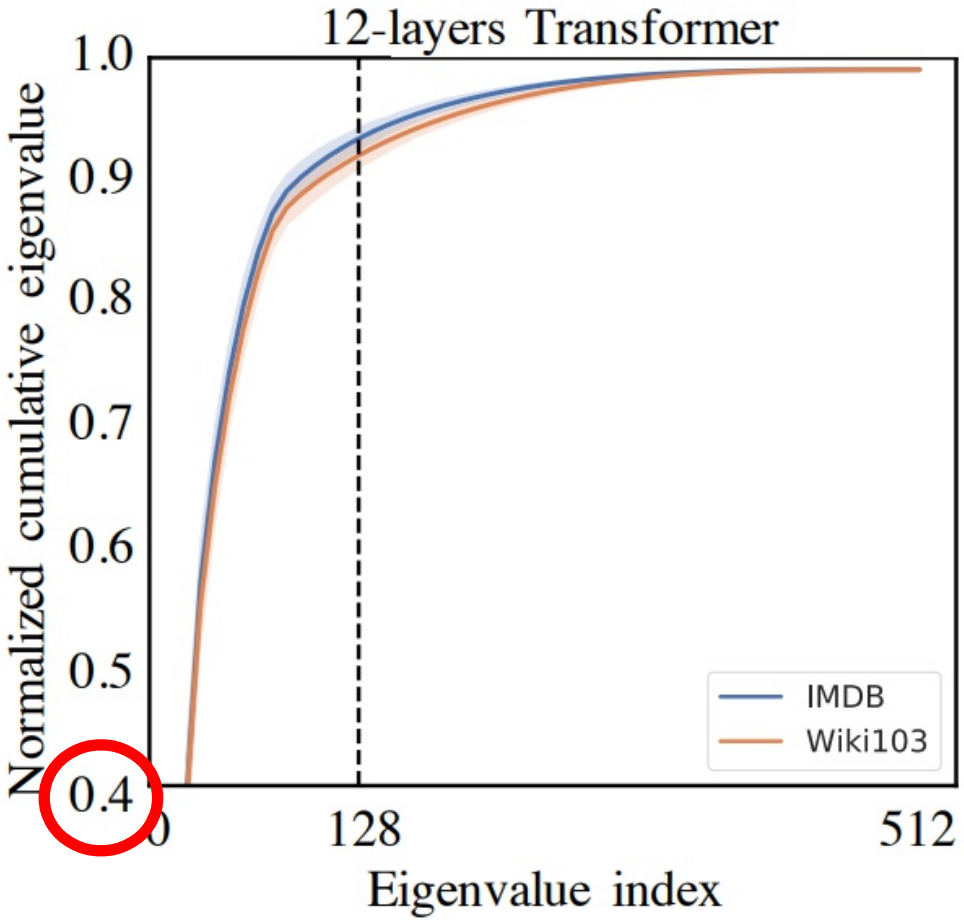
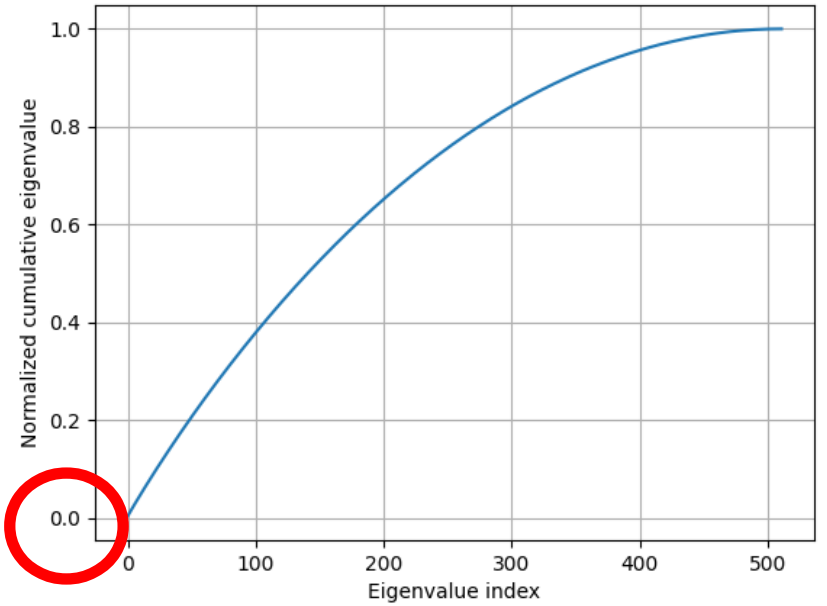


Full rank



Low rank

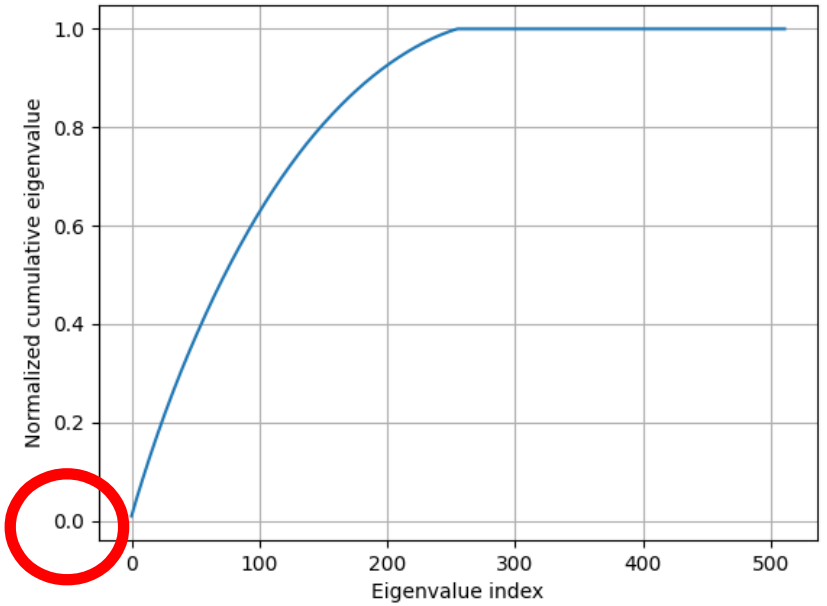


Image sources:
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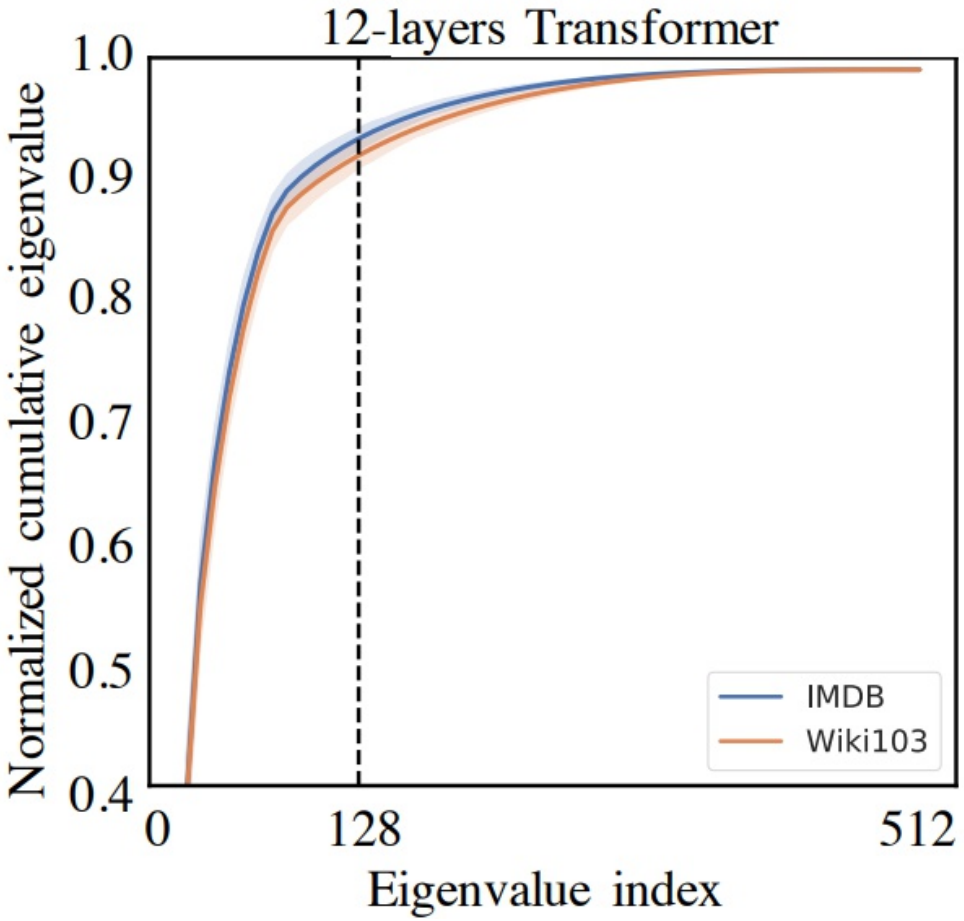
7.2 Linformer: Self-Attention with Linear Complexity



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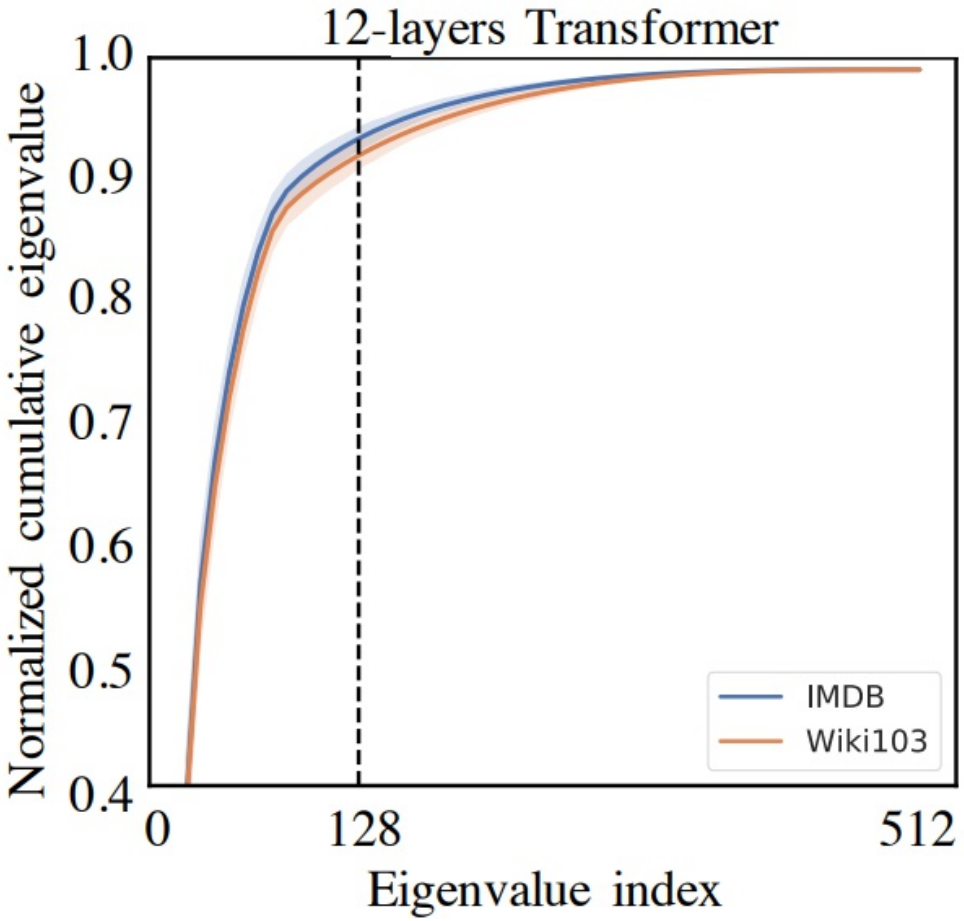

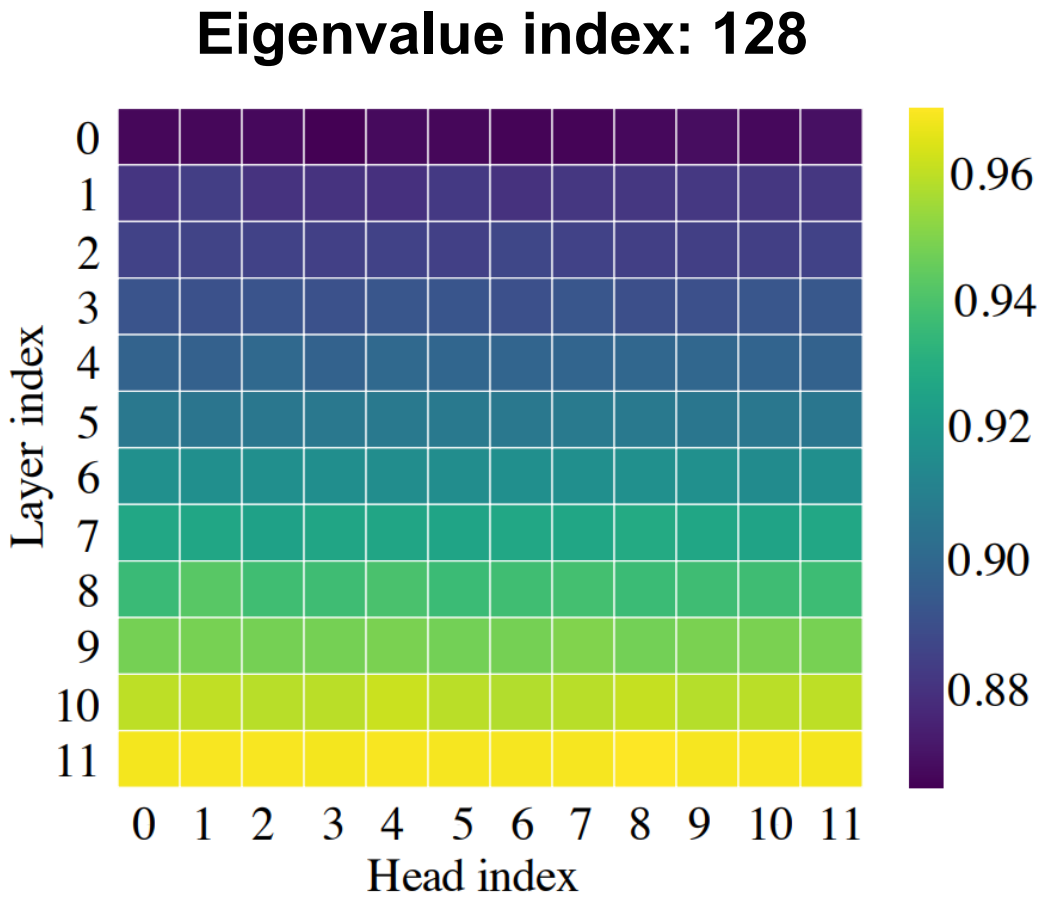

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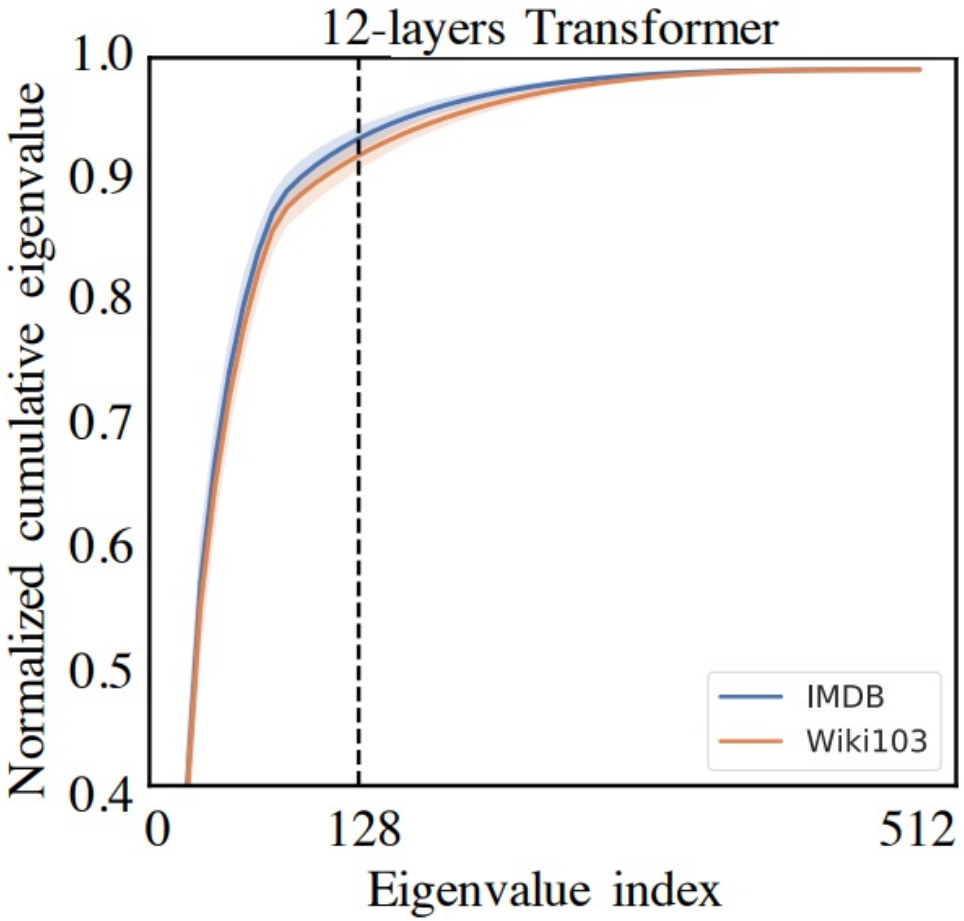
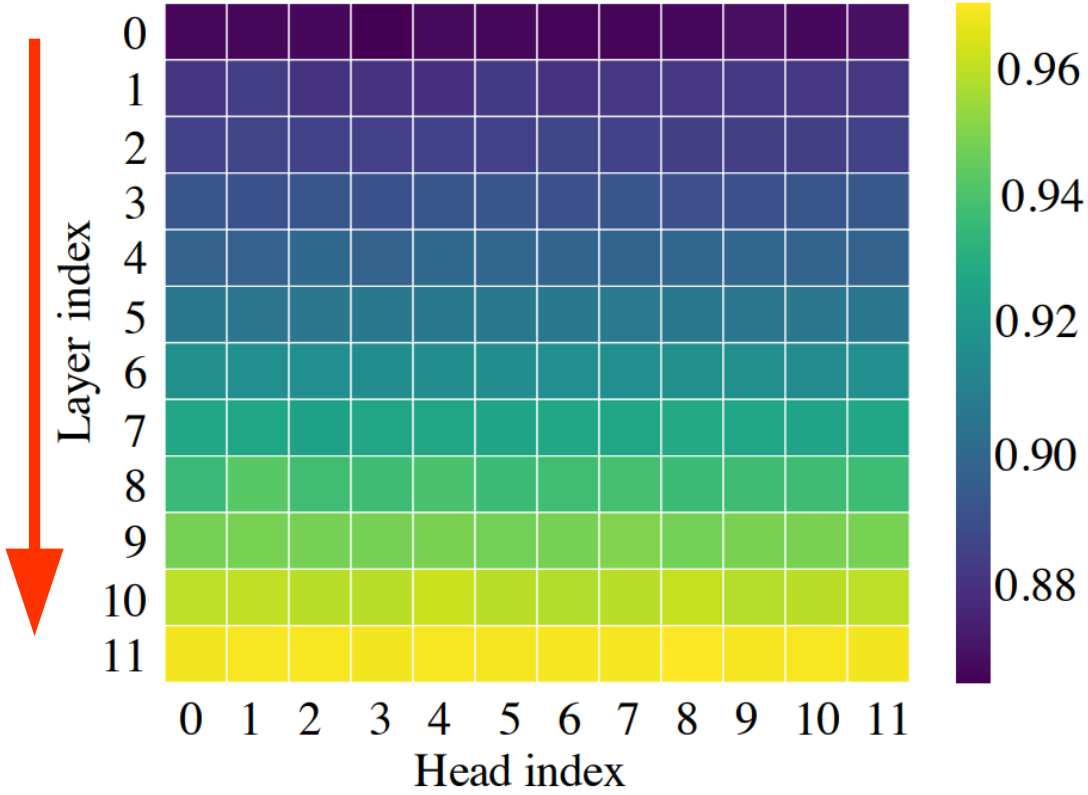


Eigenvalue index: 128



With increasing deep:
Put more and more information into fewer and fewer dimensions

Image sources:
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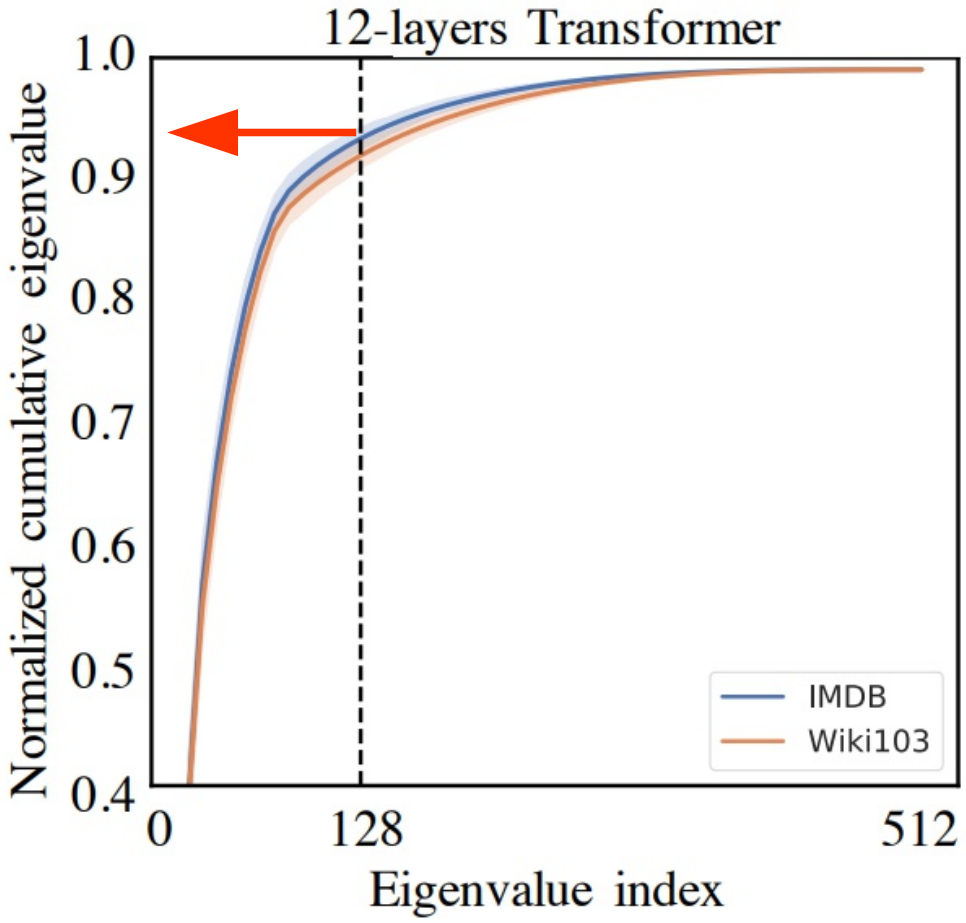
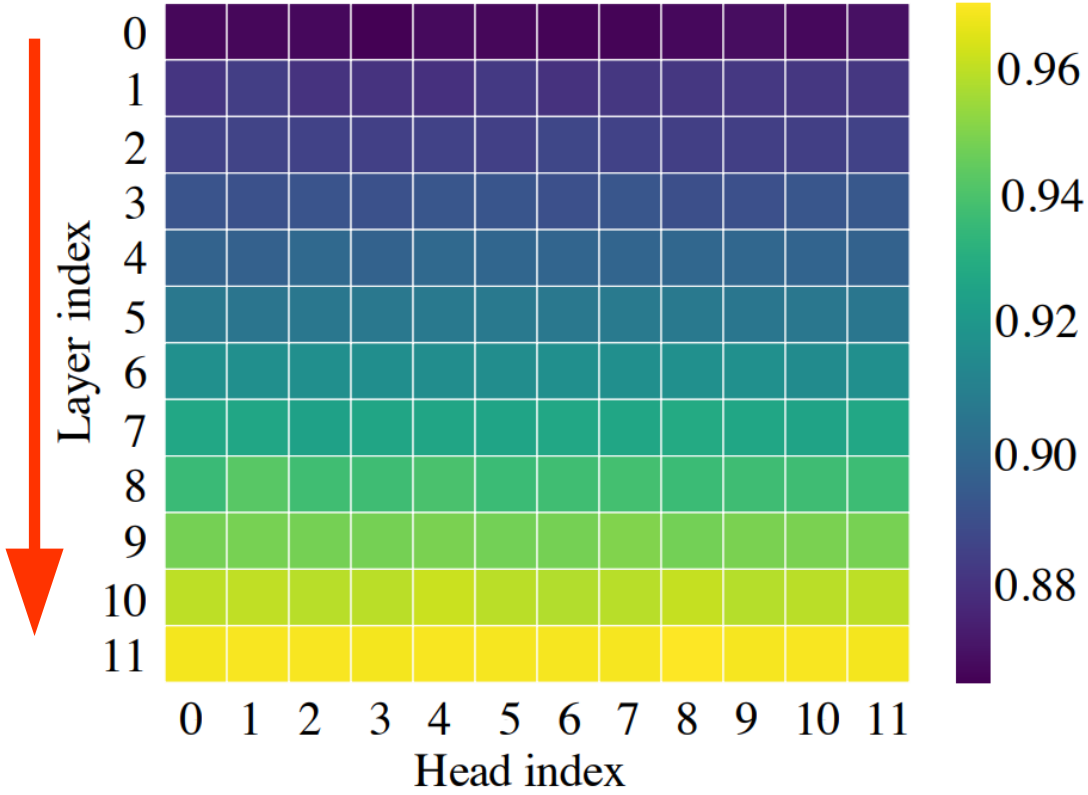
7.2 Linformer: Self-Attention with Linear Complexity

More and more skewed



Eigenvalue index: 128



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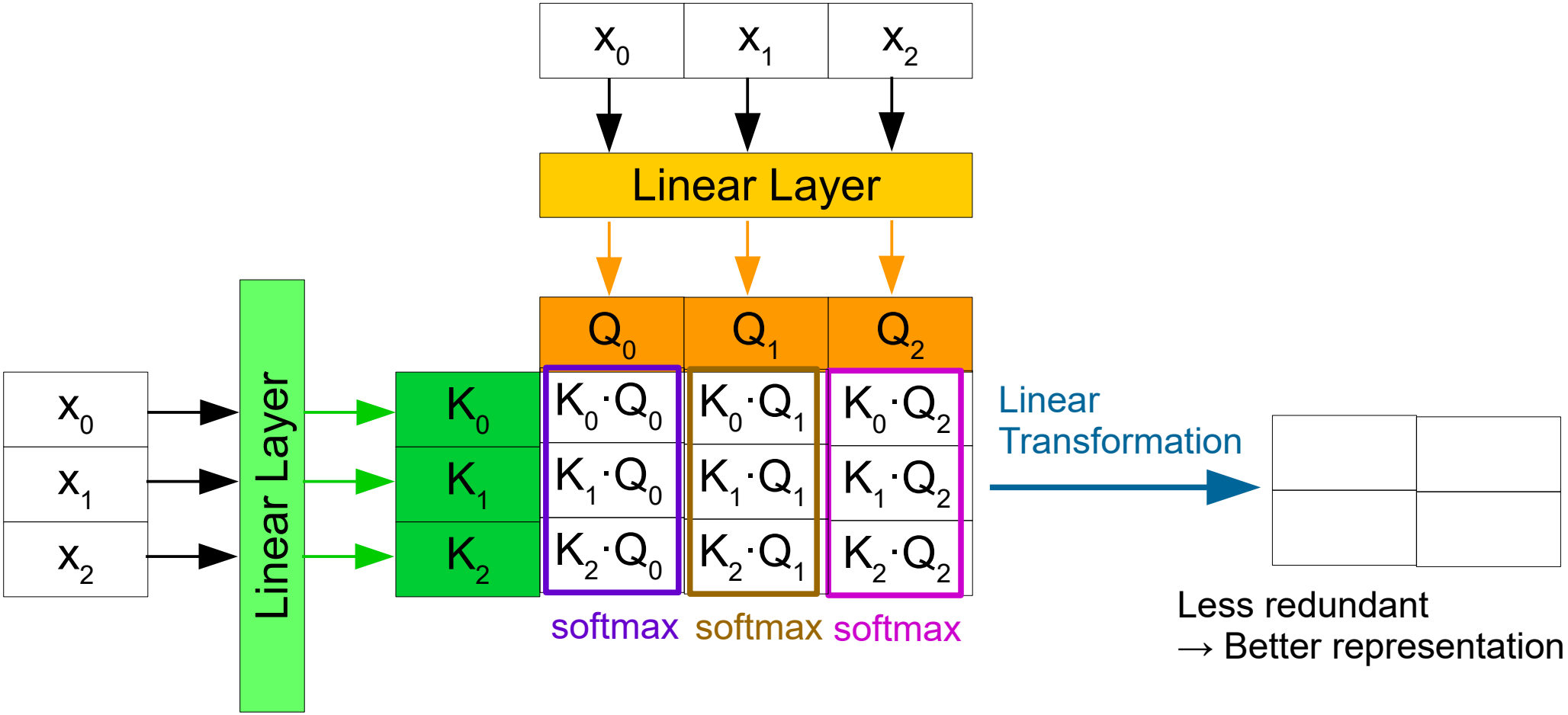

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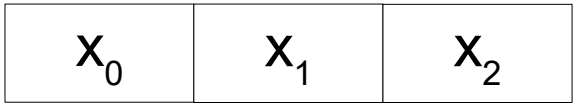

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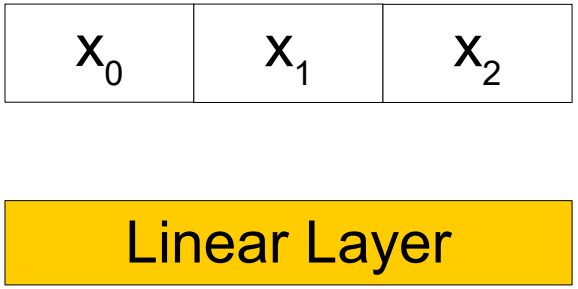
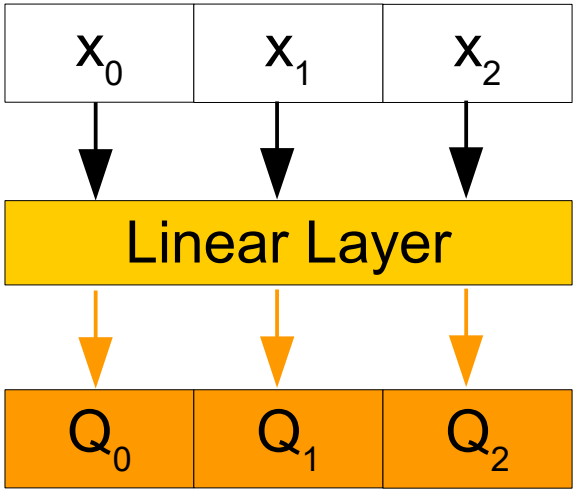


7.2 Linformer: Self-Attention with Linear Complexity



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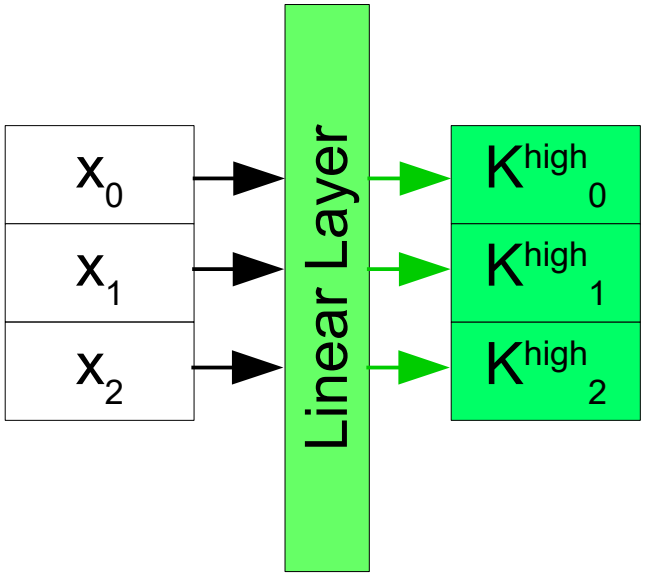

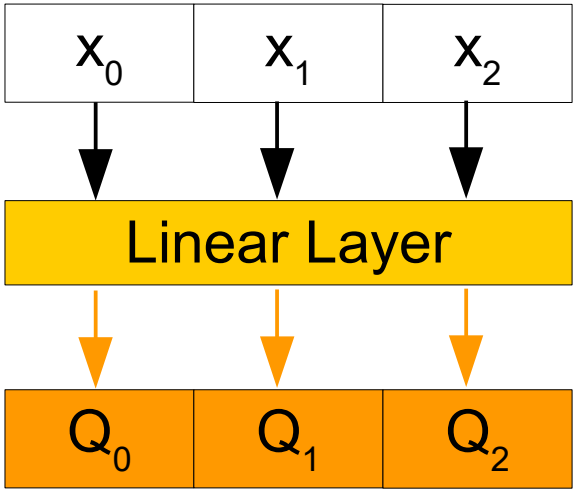

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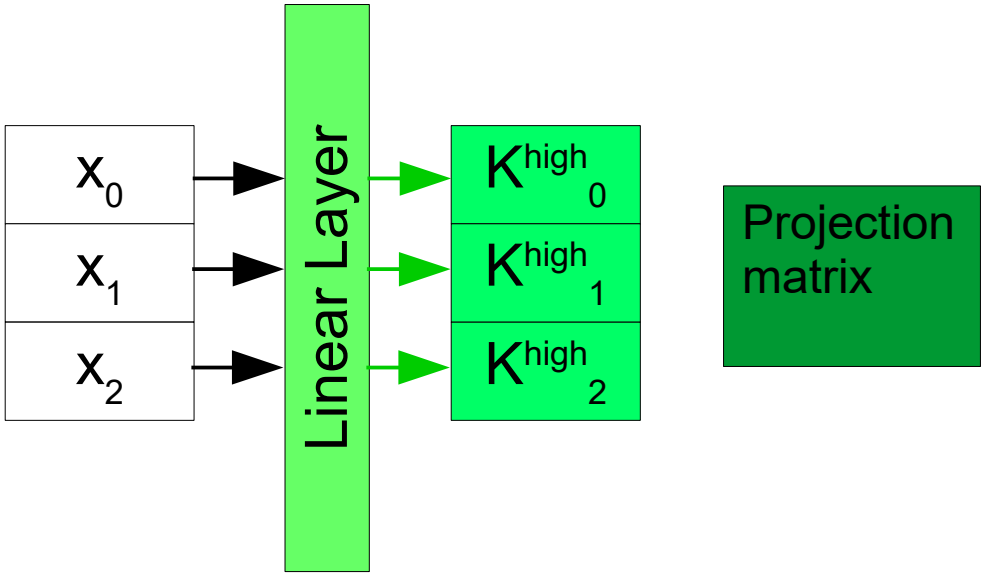
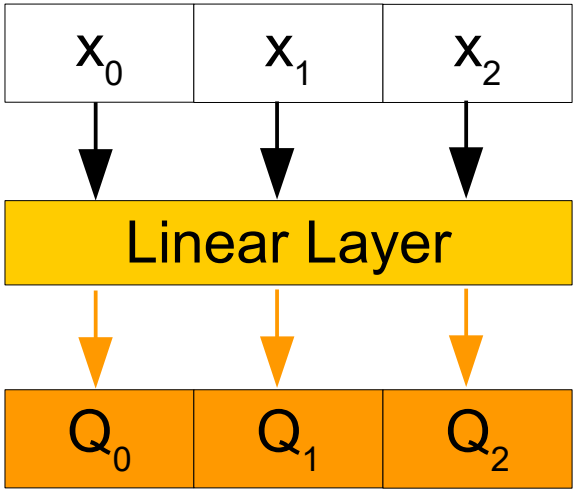


Projection matrix



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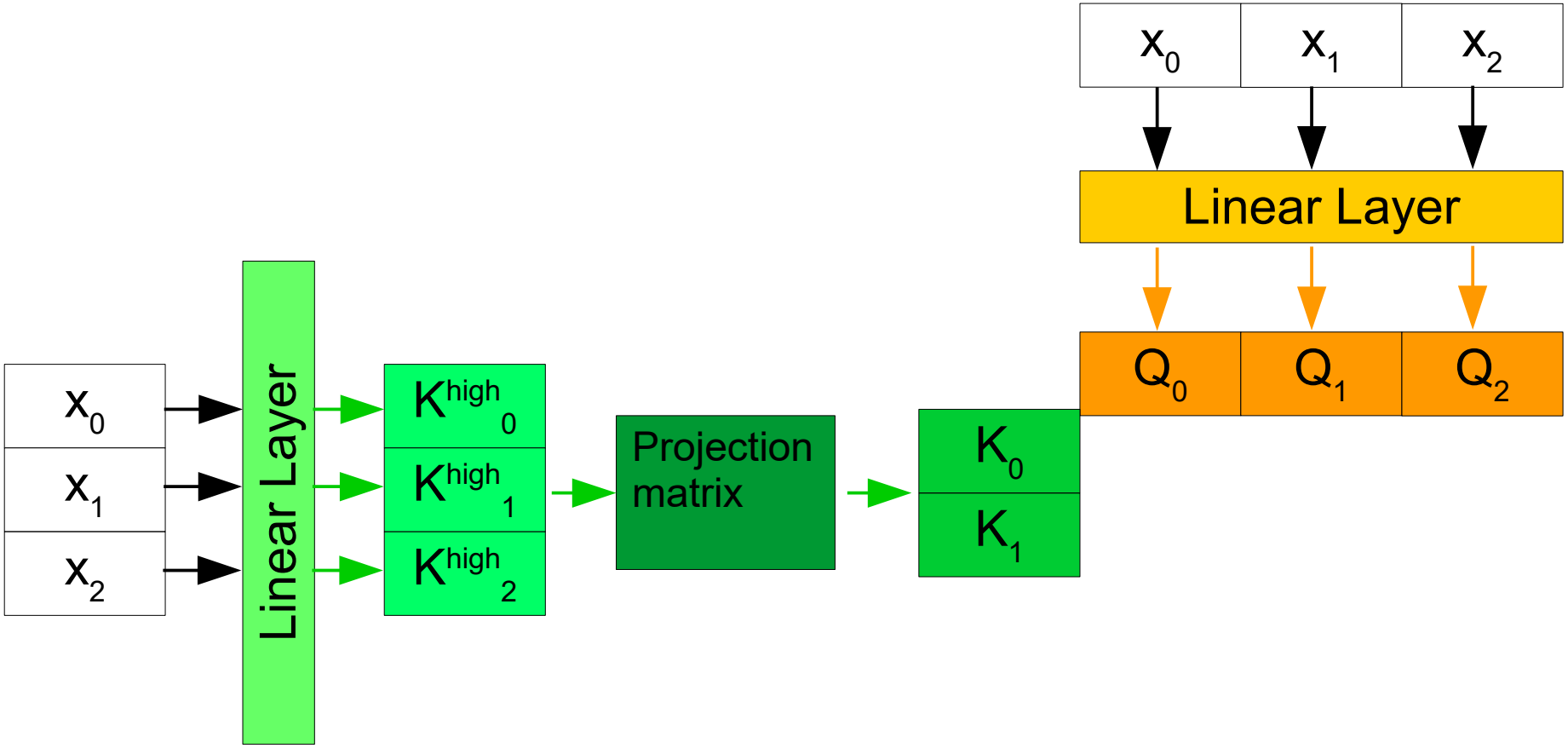

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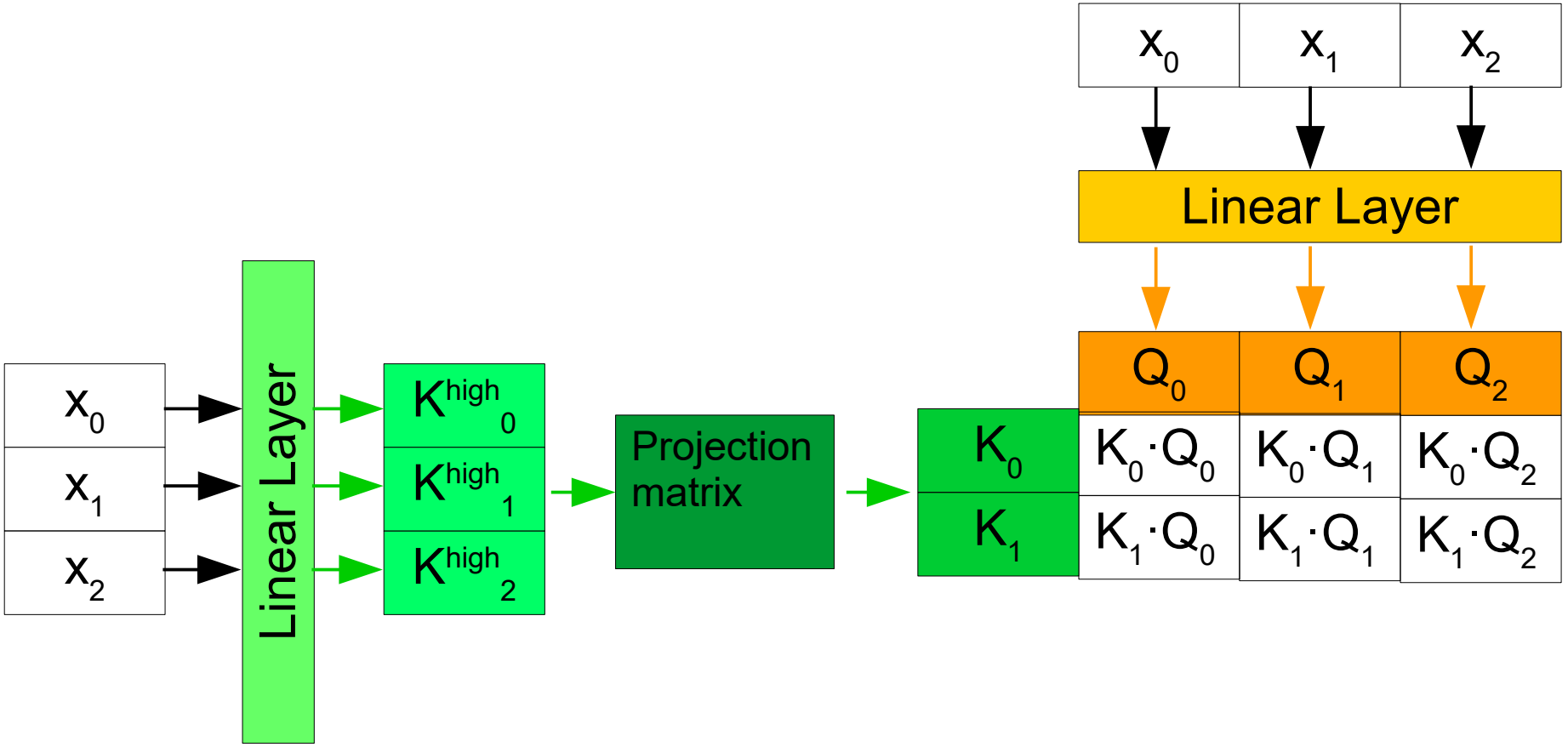

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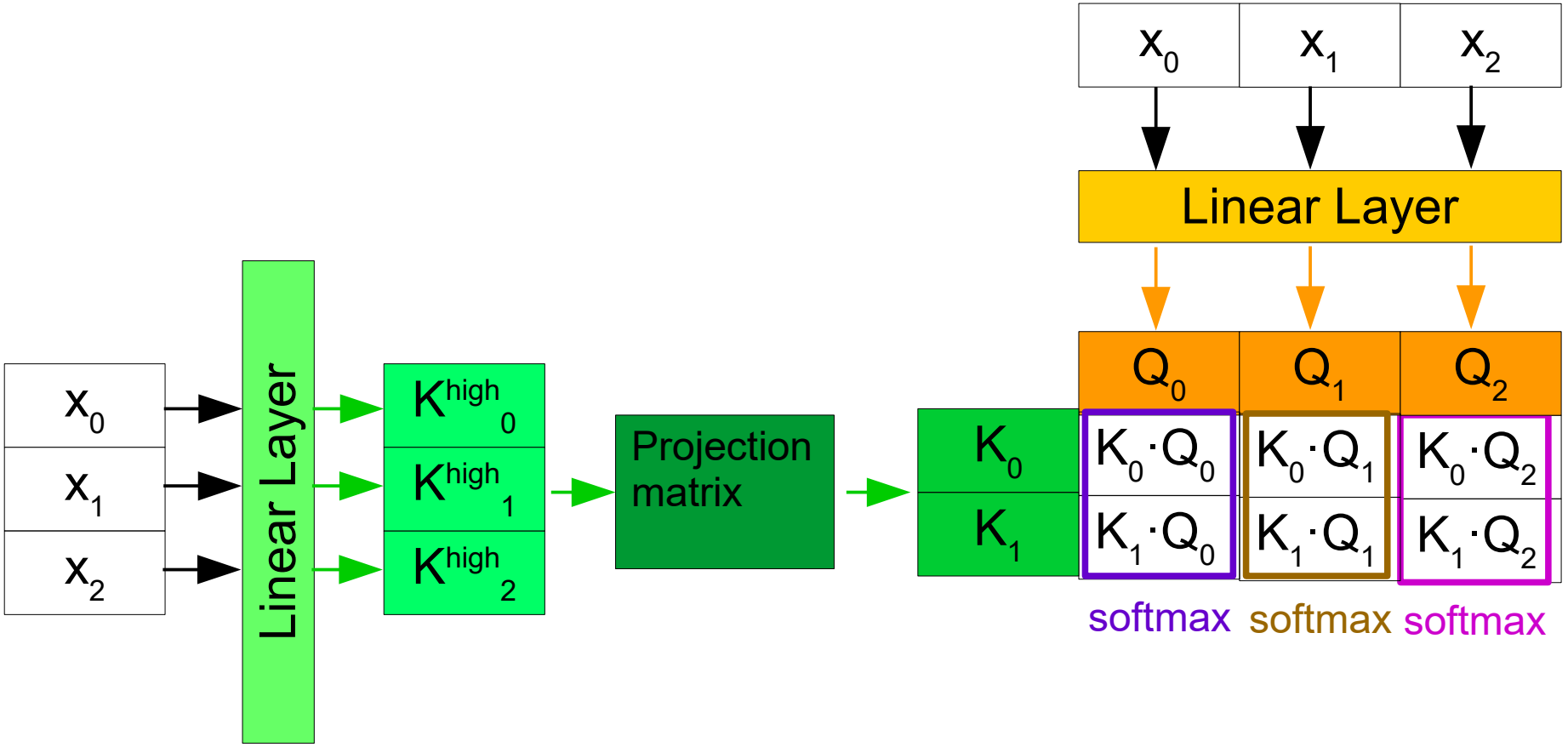

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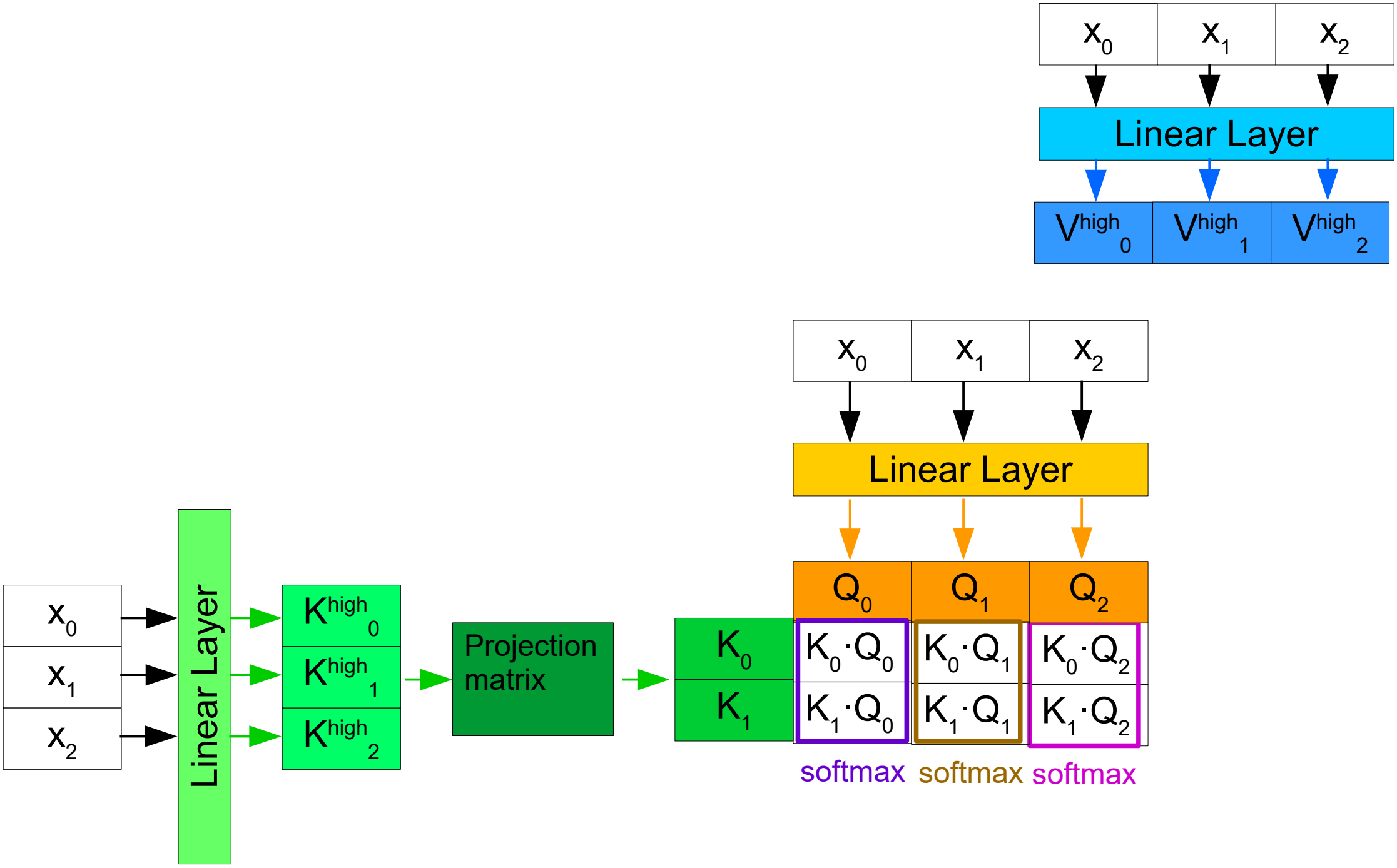

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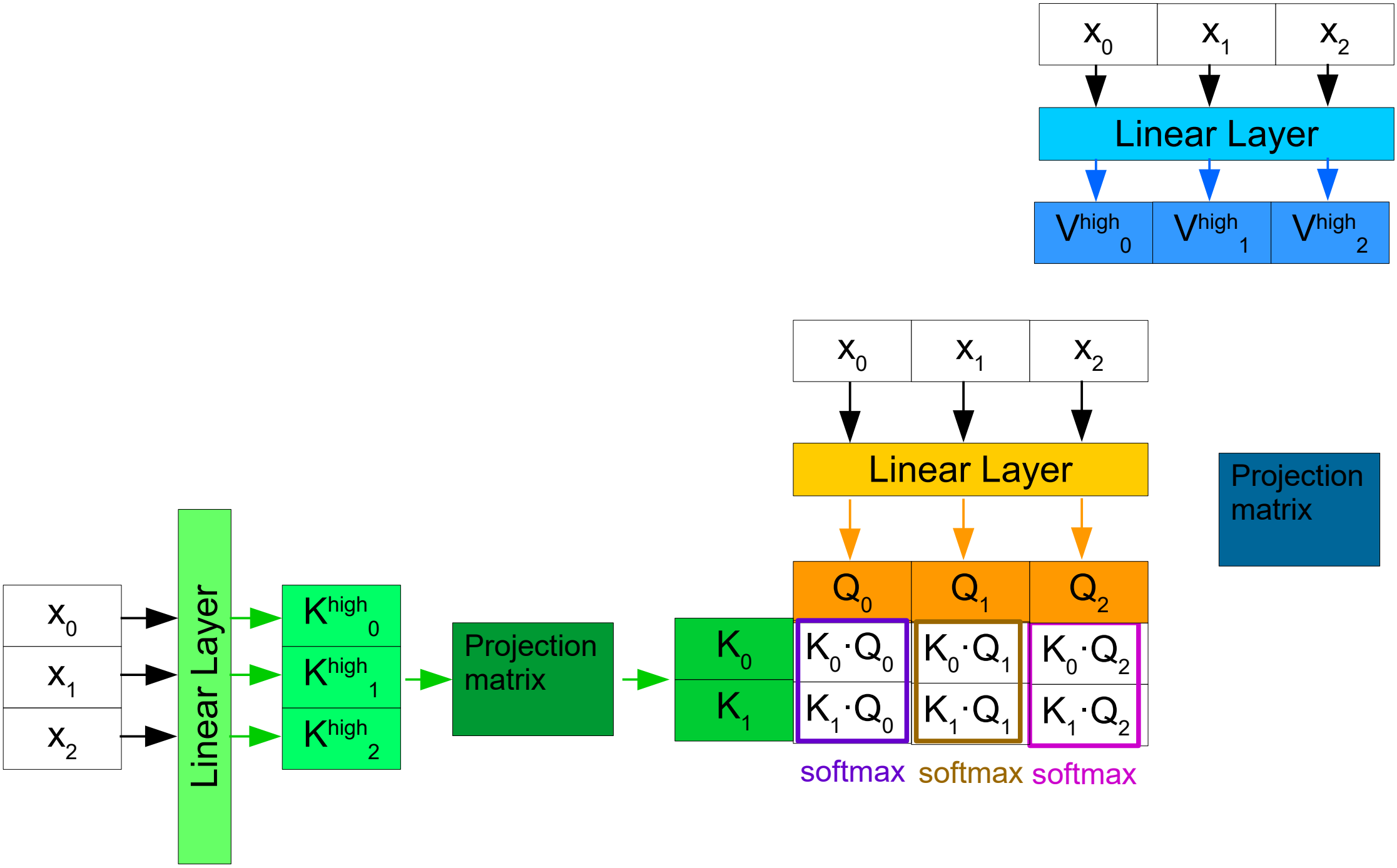

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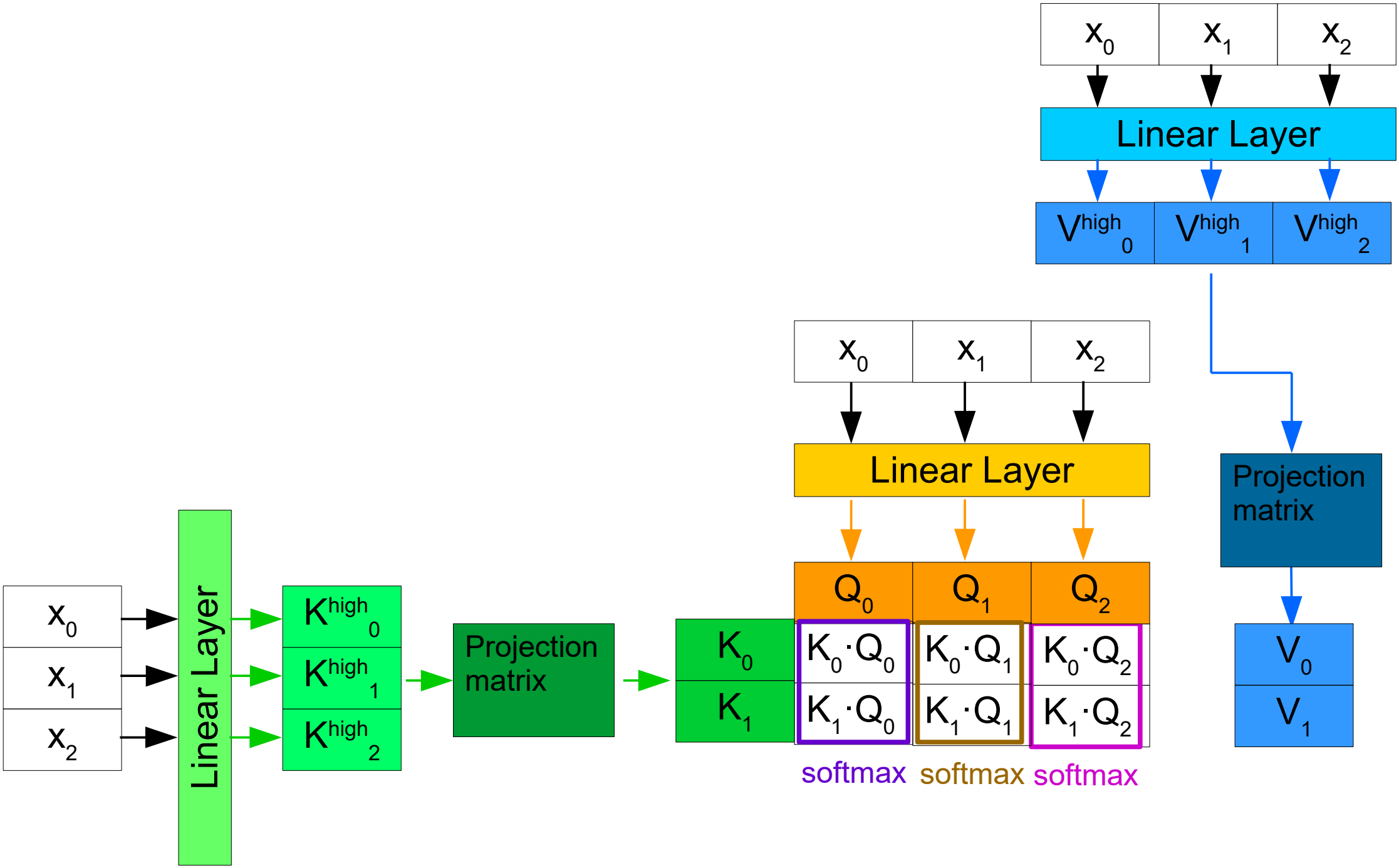

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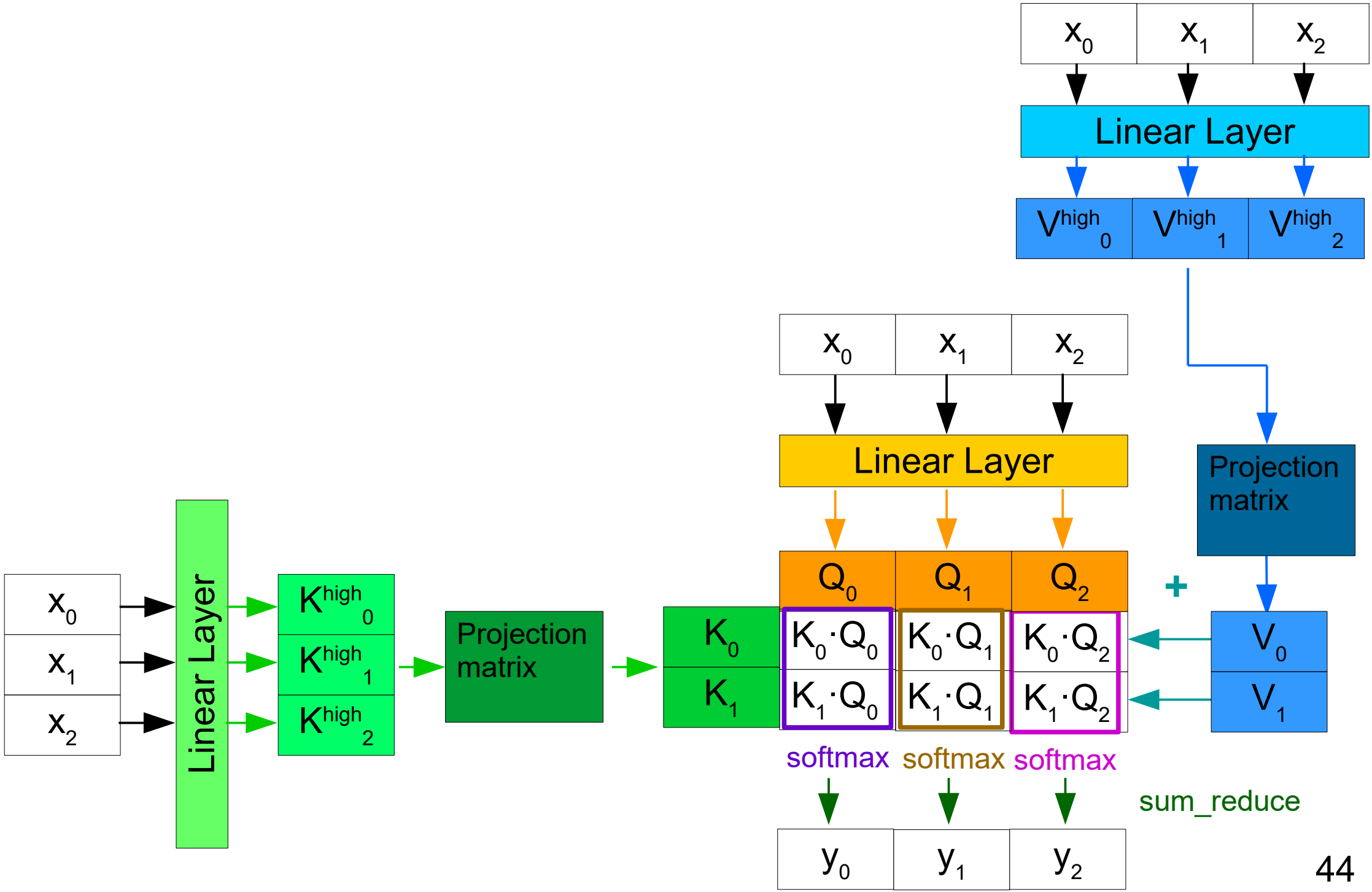

7.3 Reformer: The Efficient Transformer

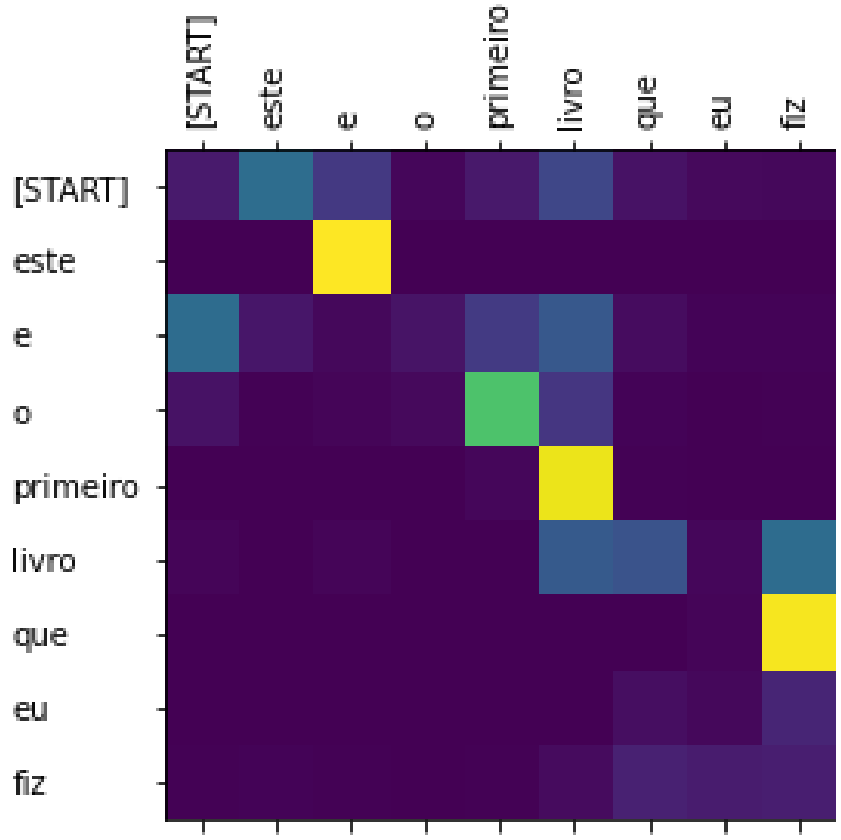

Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

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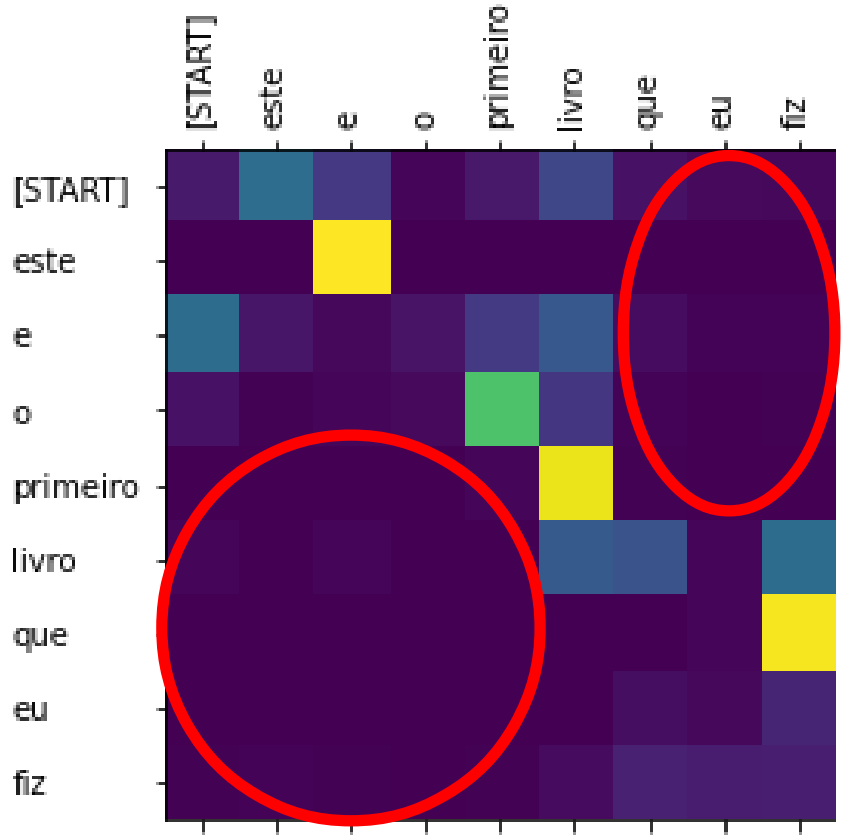

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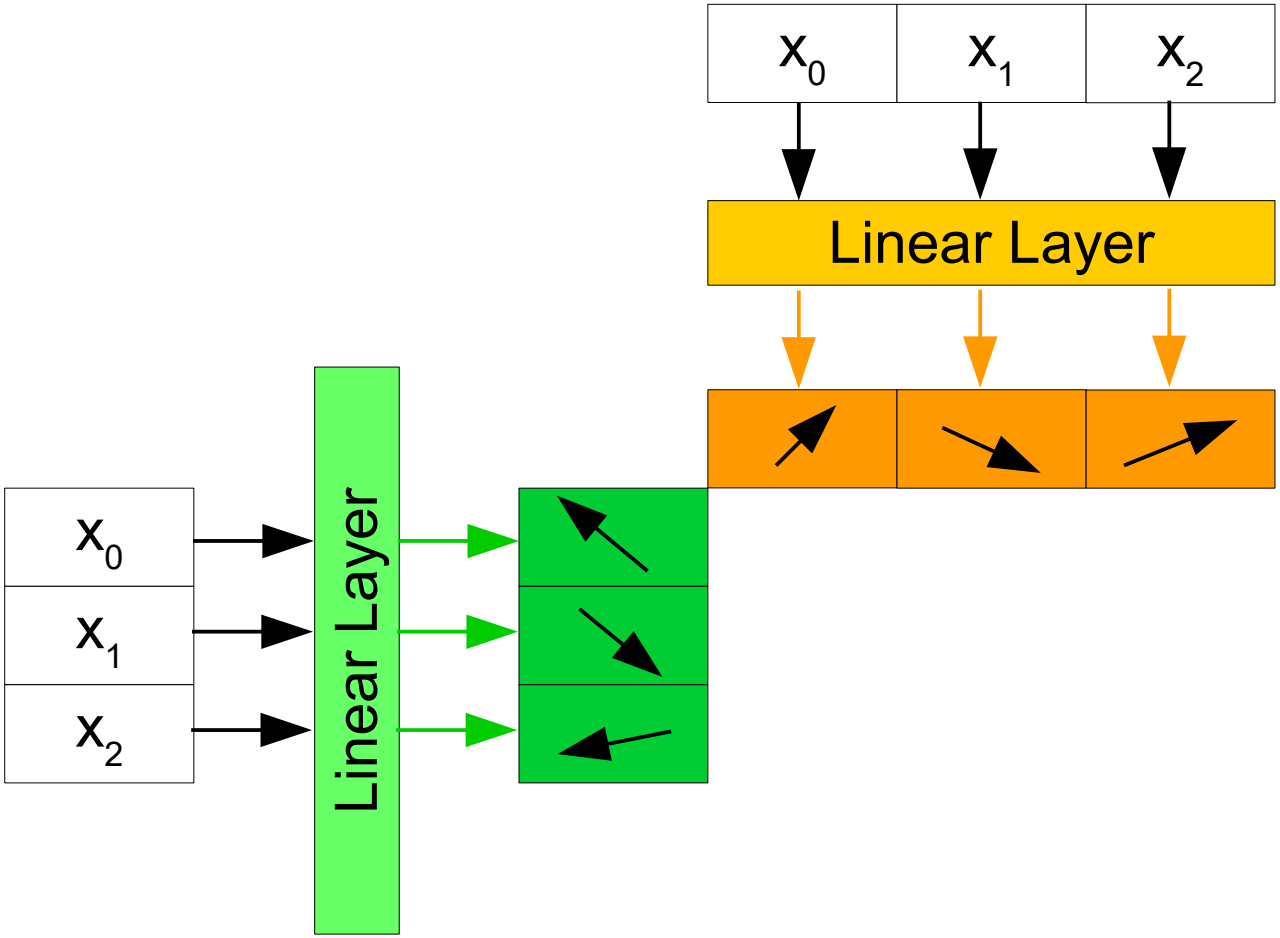

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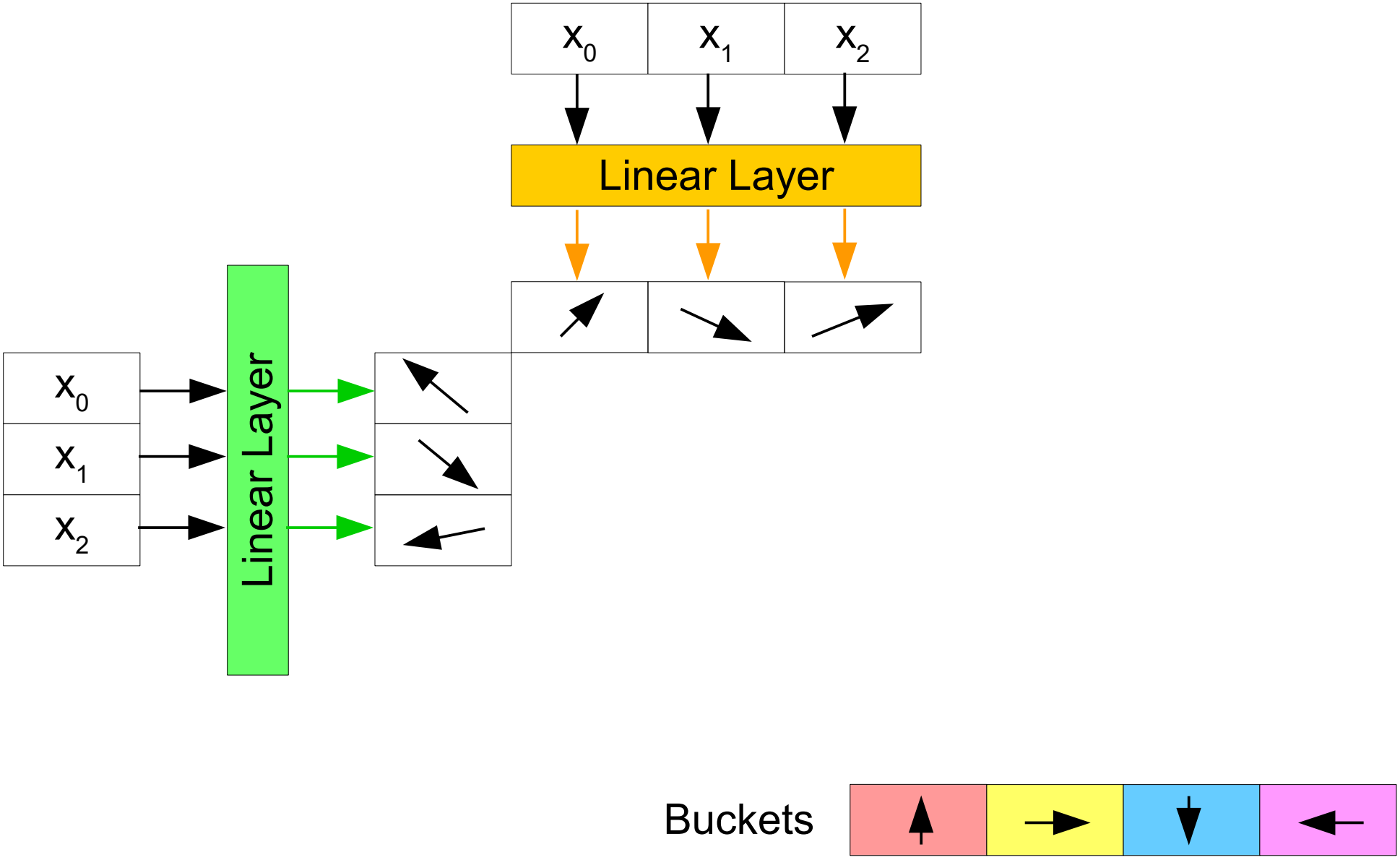
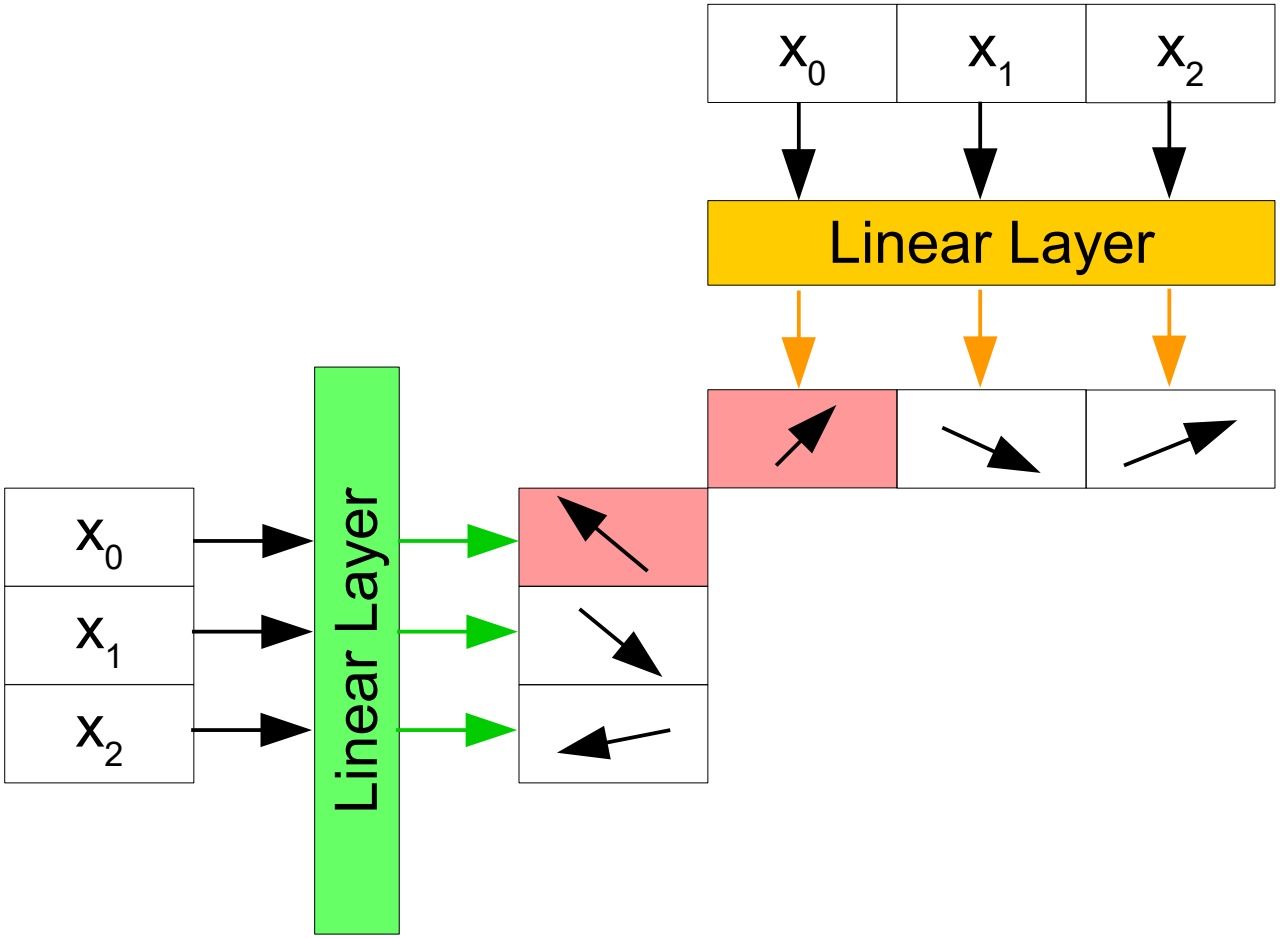
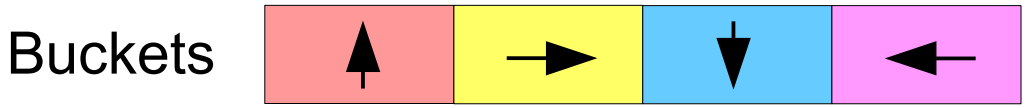
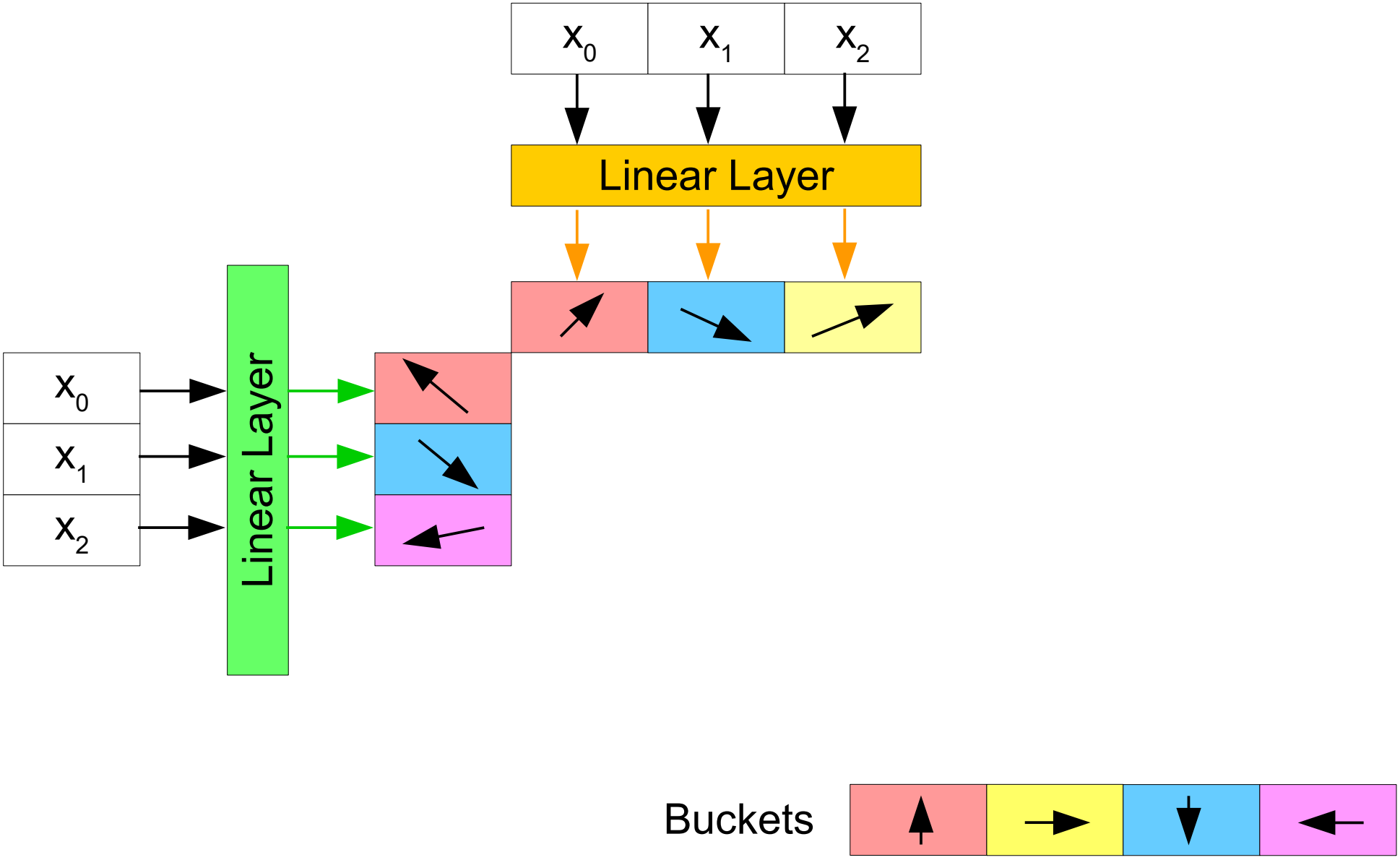


7.3 Reformer: The Efficient Transformer

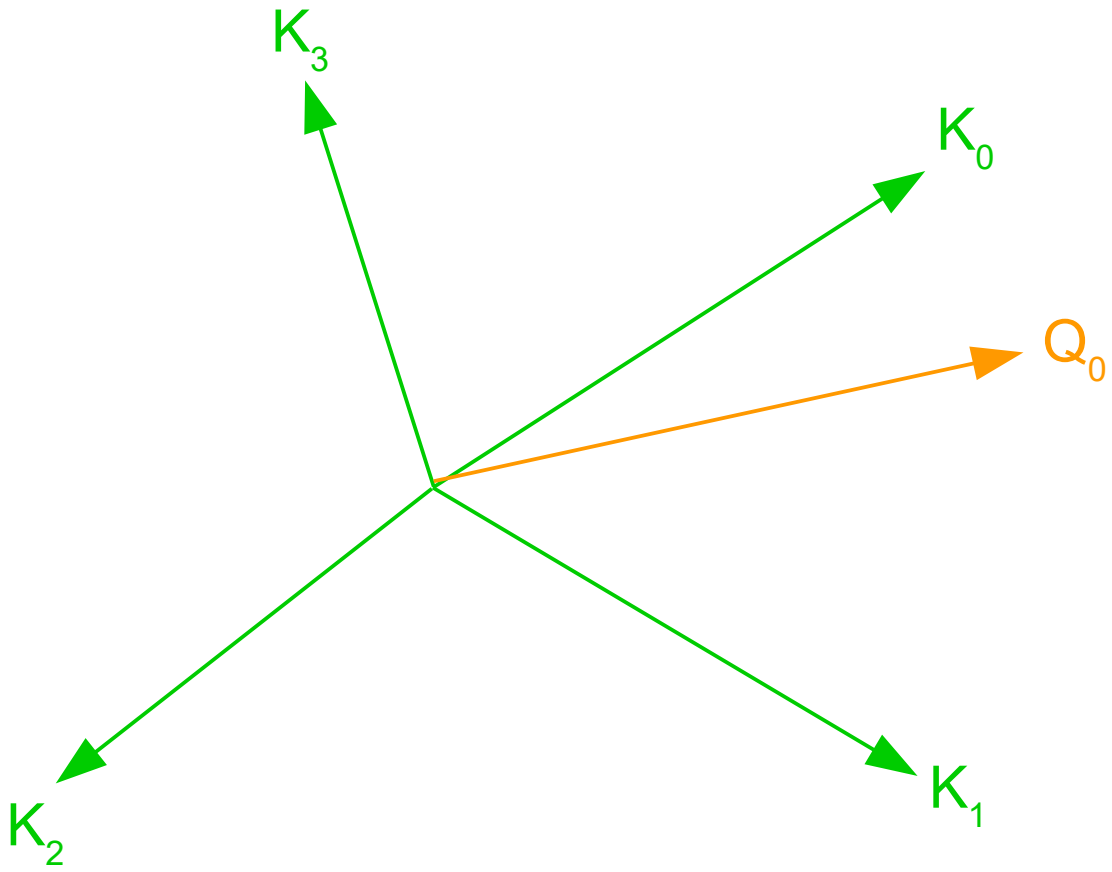




7.3 Reformer: The Efficient Transformer

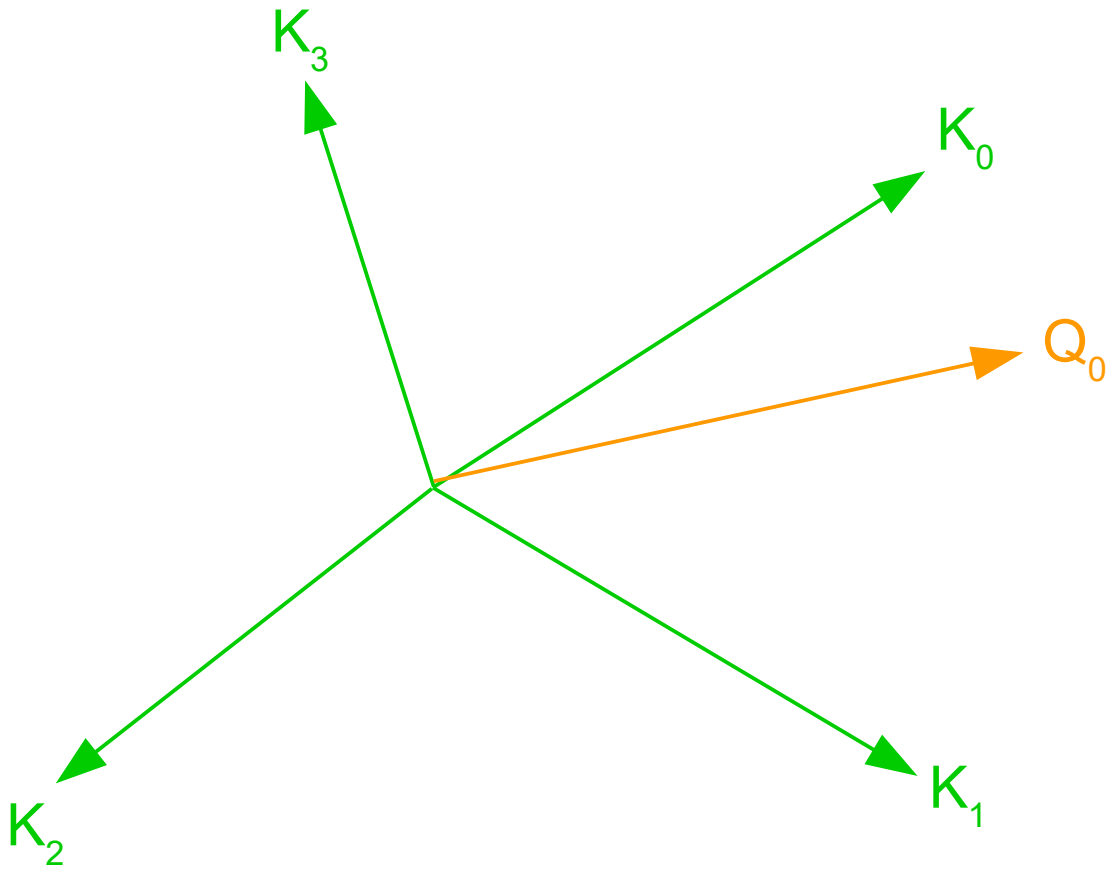


7.3.1 Random Plane Projections



7.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes



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Four buckets
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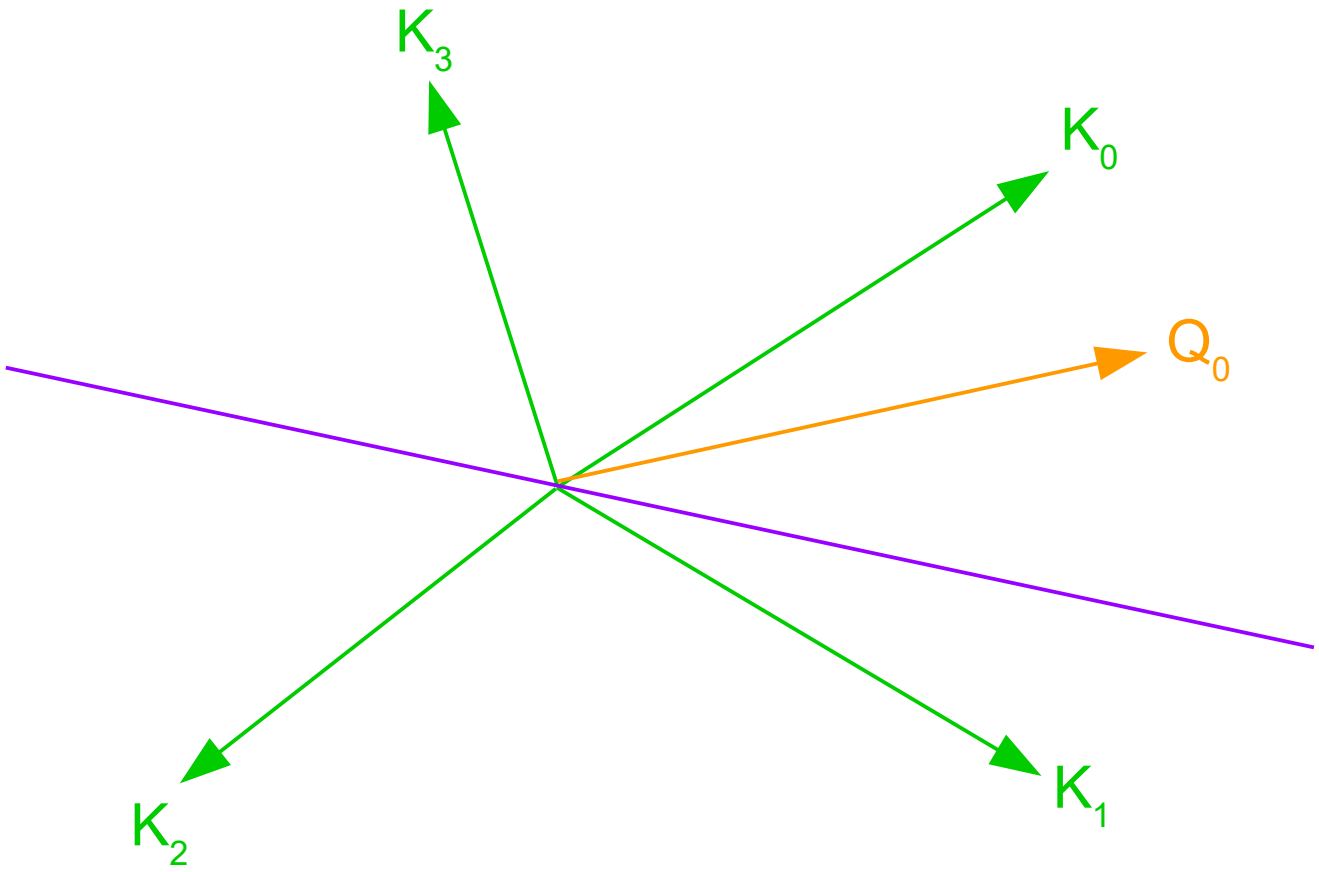
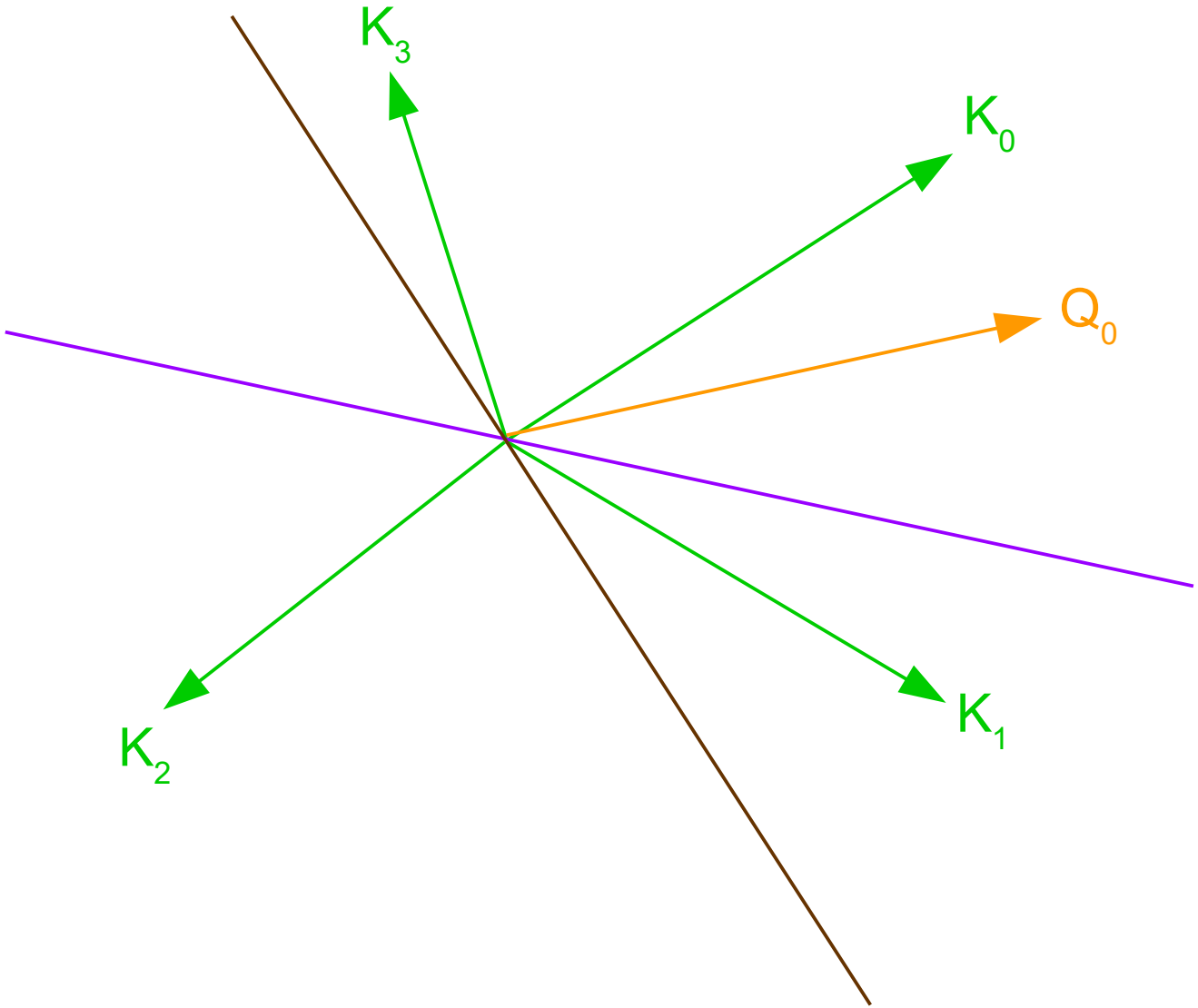


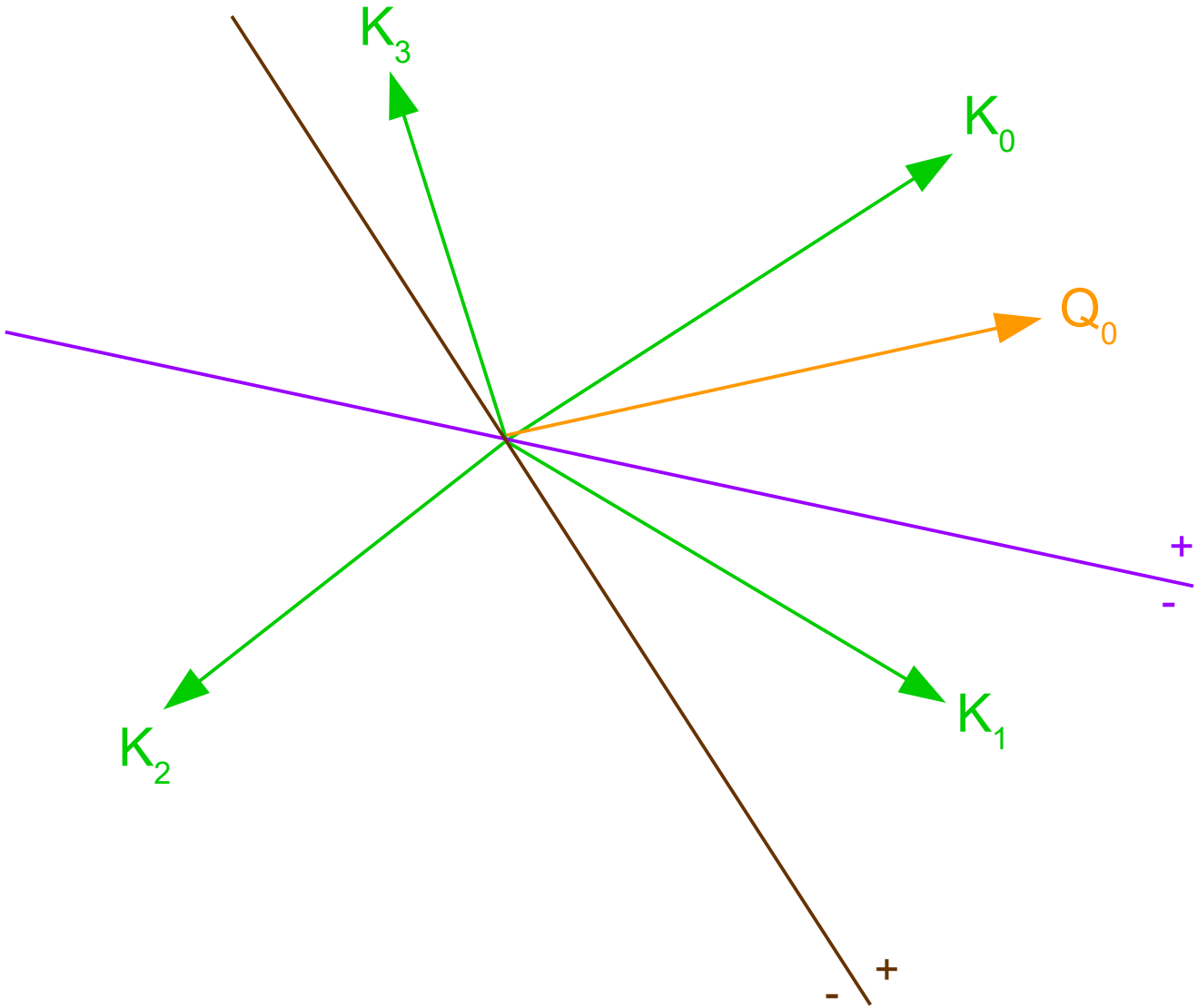
7.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes

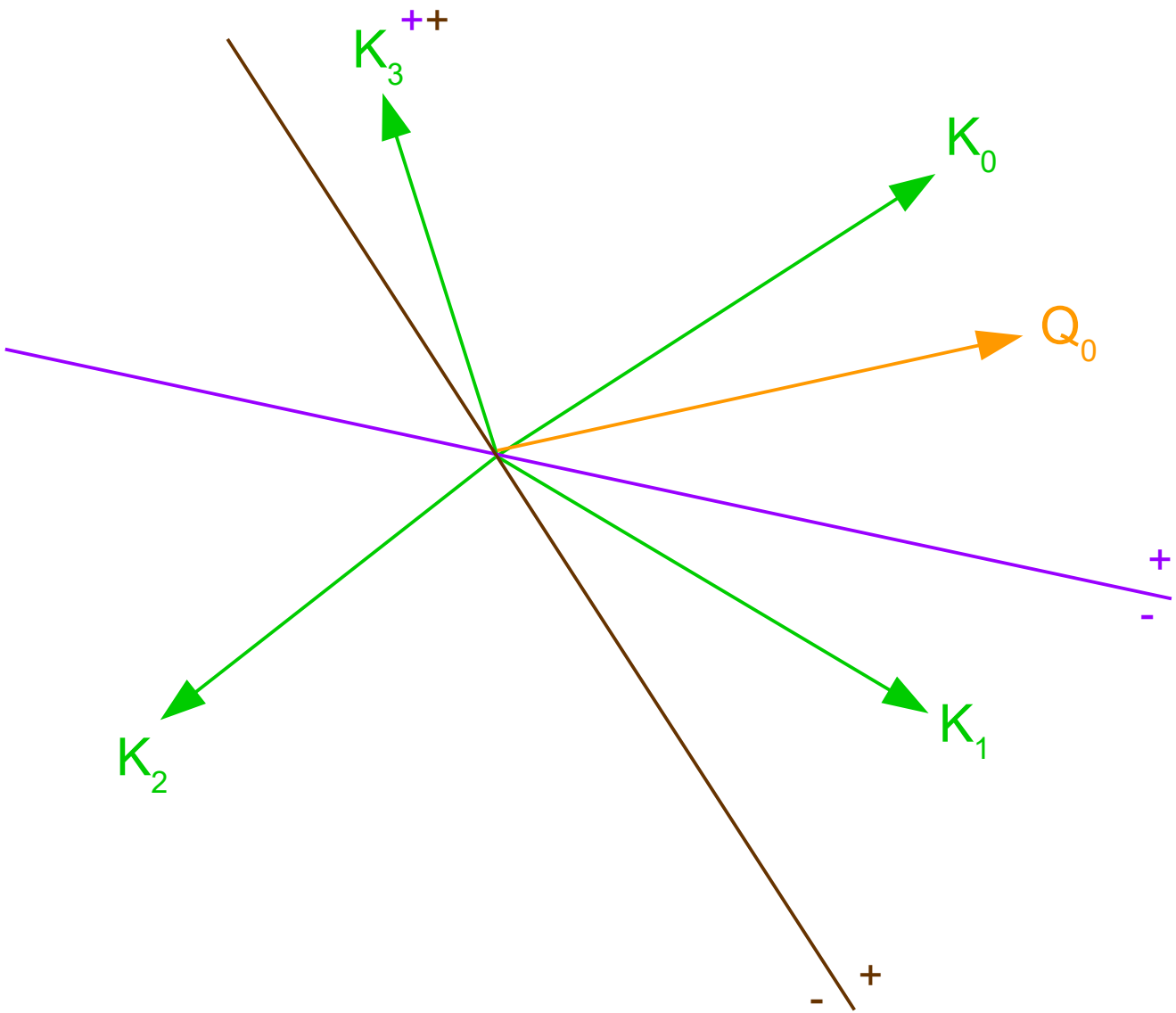


7.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes



7.3.1 Random Plane Projections



Four buckets
→ Two hyperplanes

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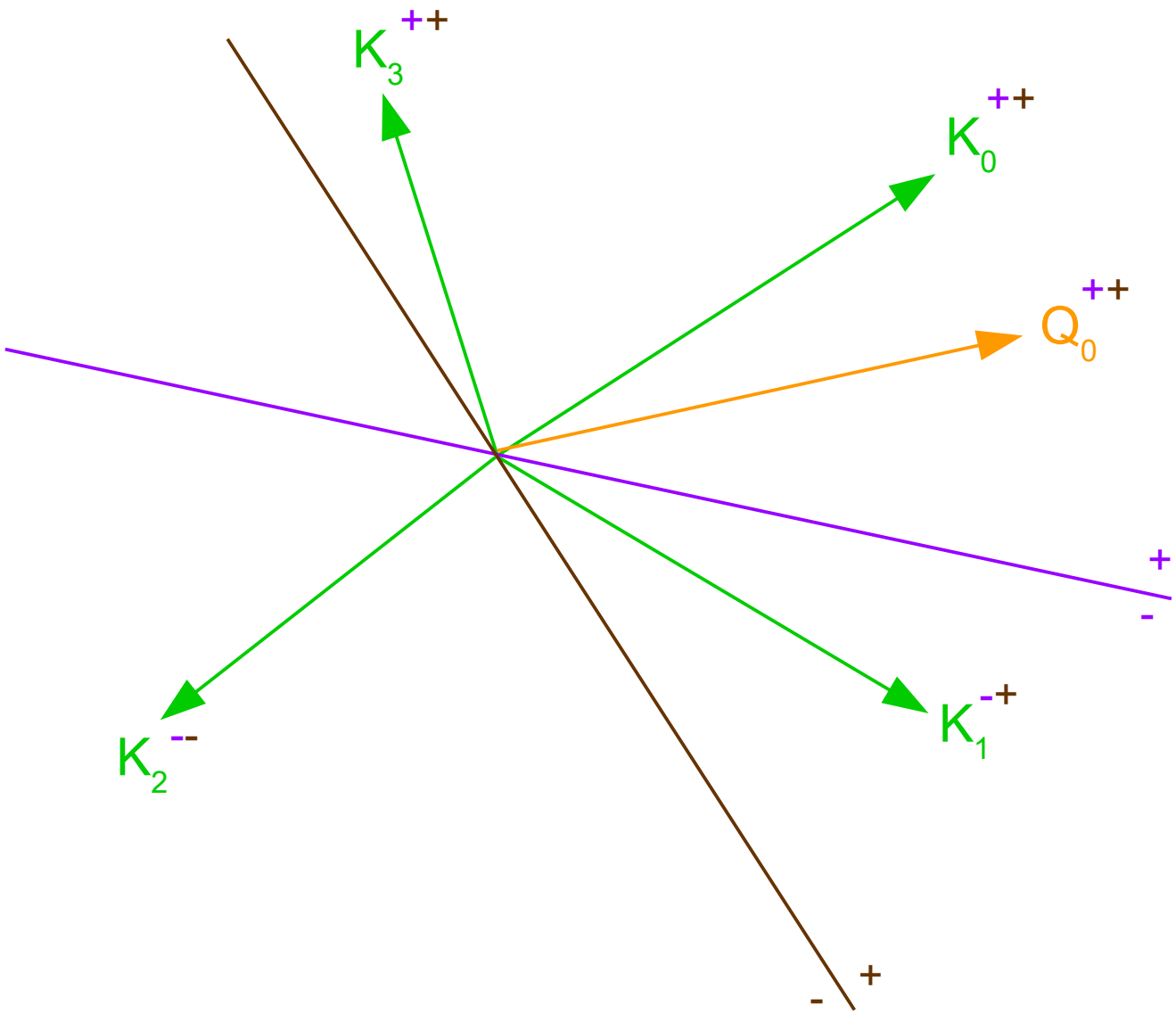

Four buckets
→ Two hyperplanes

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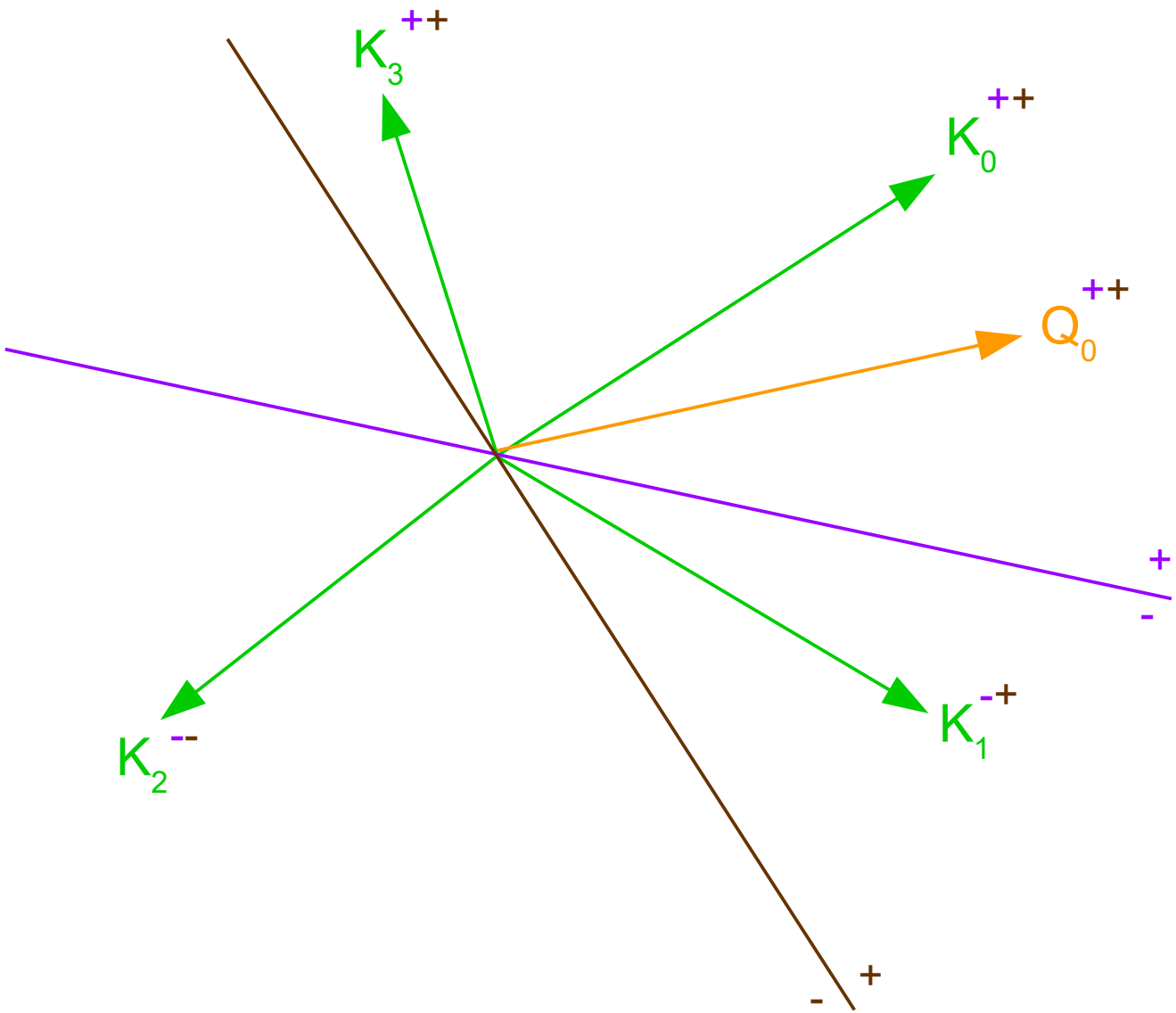


Four buckets
→ Two hyperplanes

Buckets

++	+-	-+	--
K_0		K_1	K_2
K_3			
Q_0			

7.3 Reformer: The Efficient Transformer

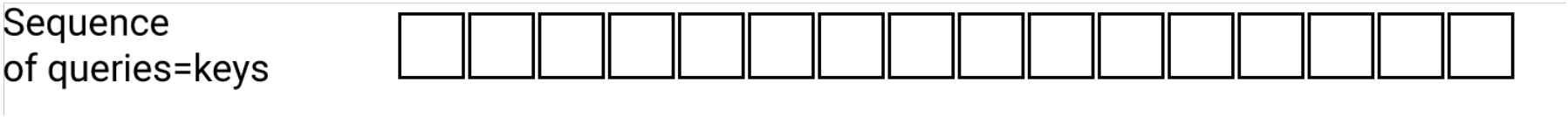
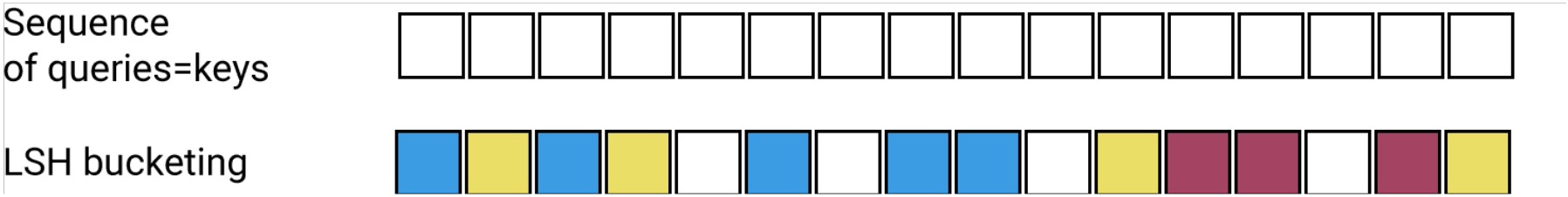


Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

7.3 Reformer: The Efficient Transformer



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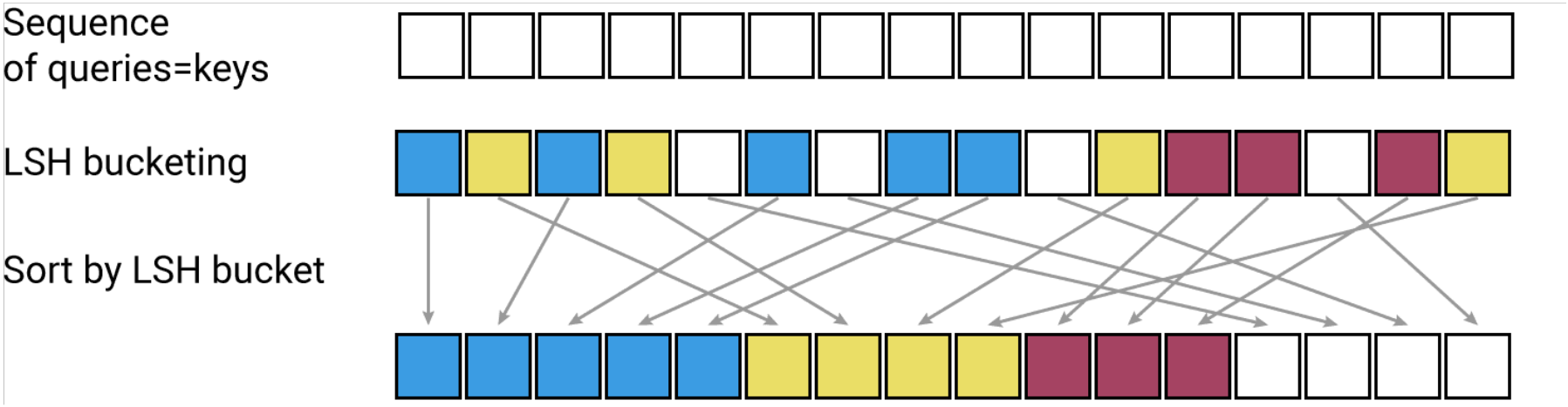

Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
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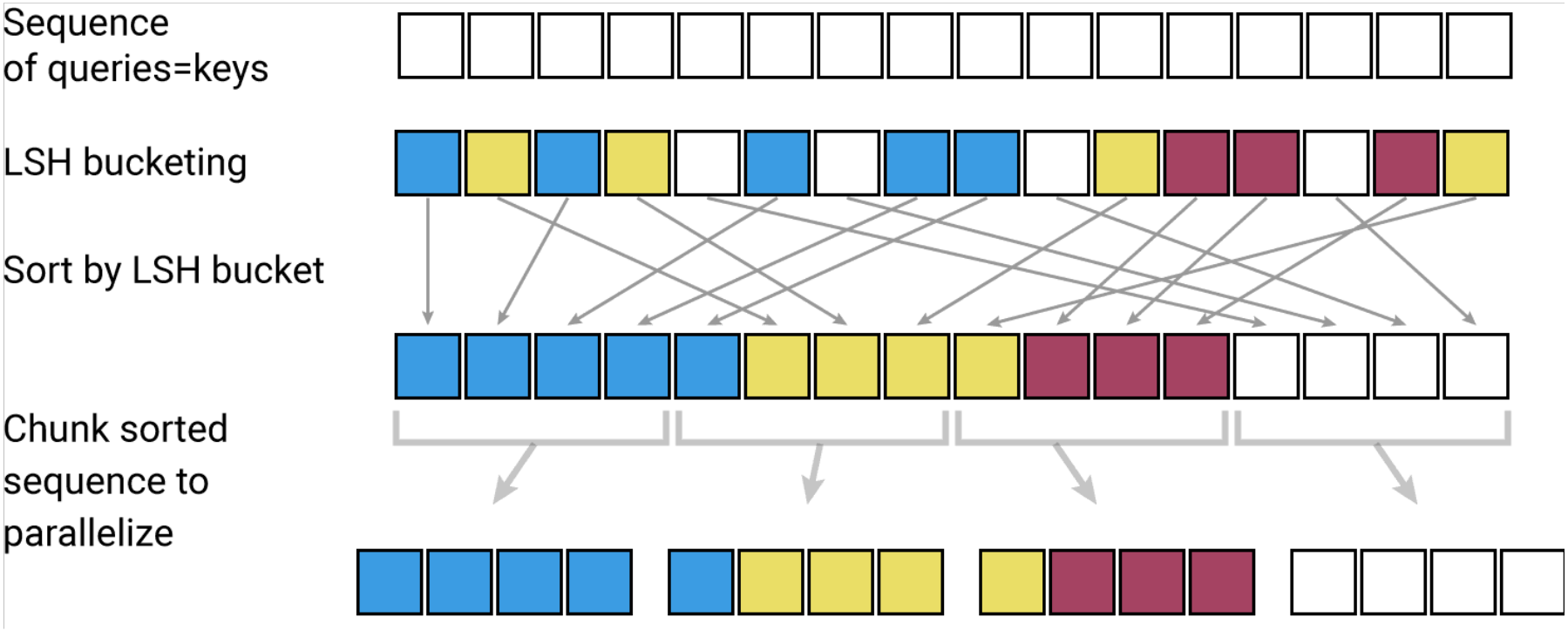


Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

7.3 Reformer: The Efficient Transformer

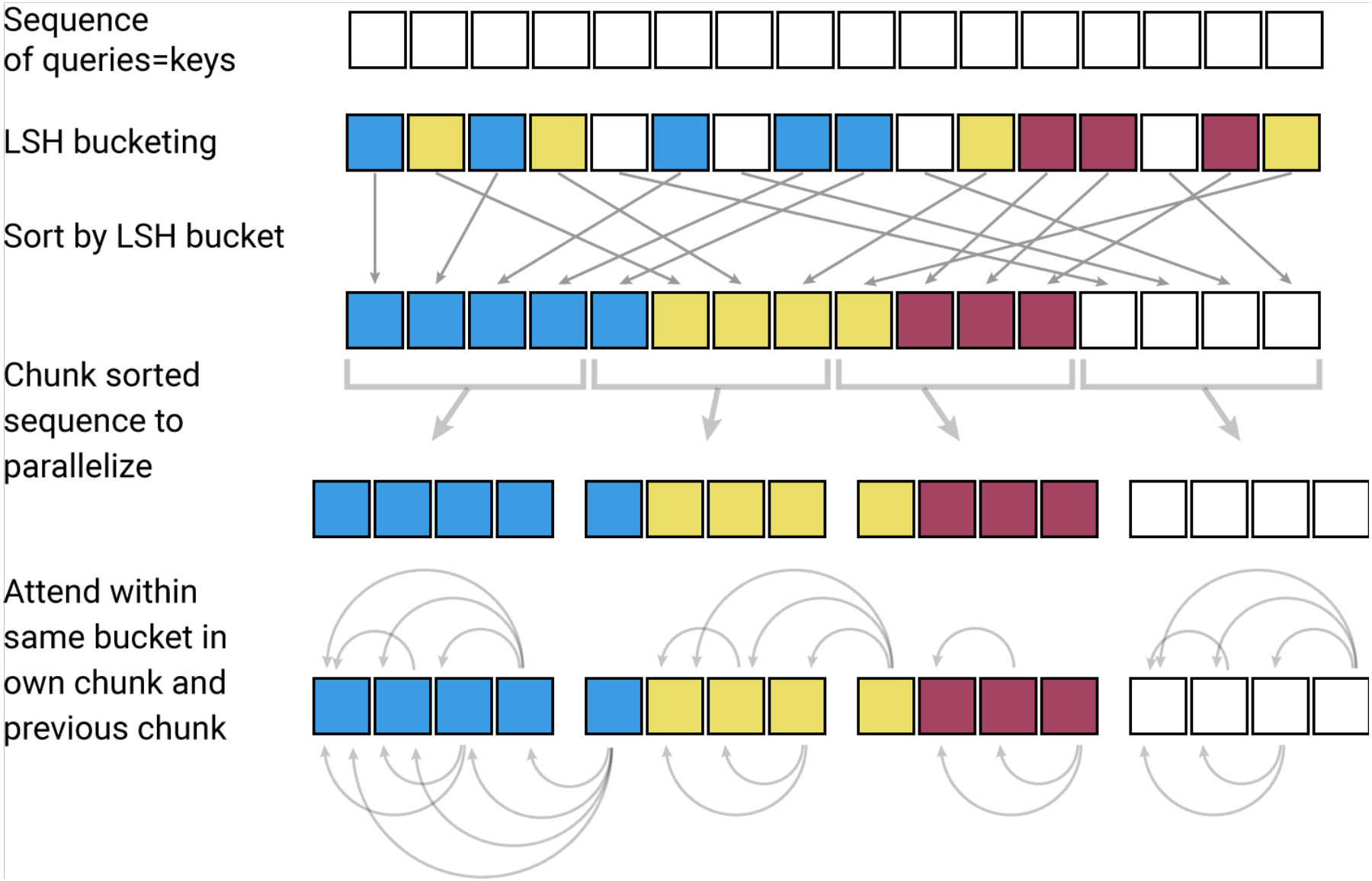
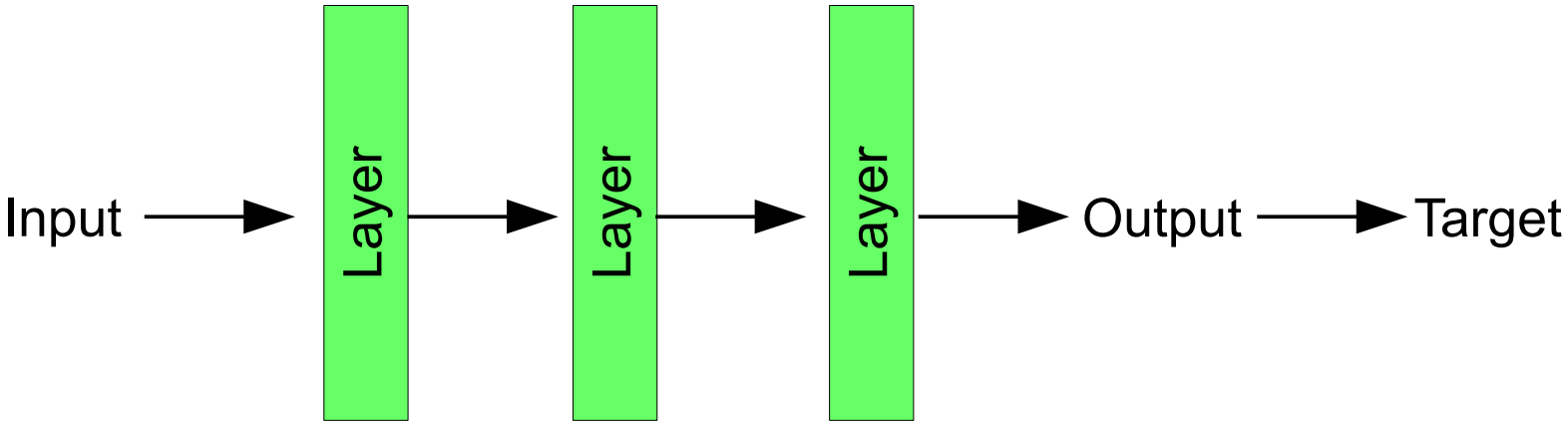
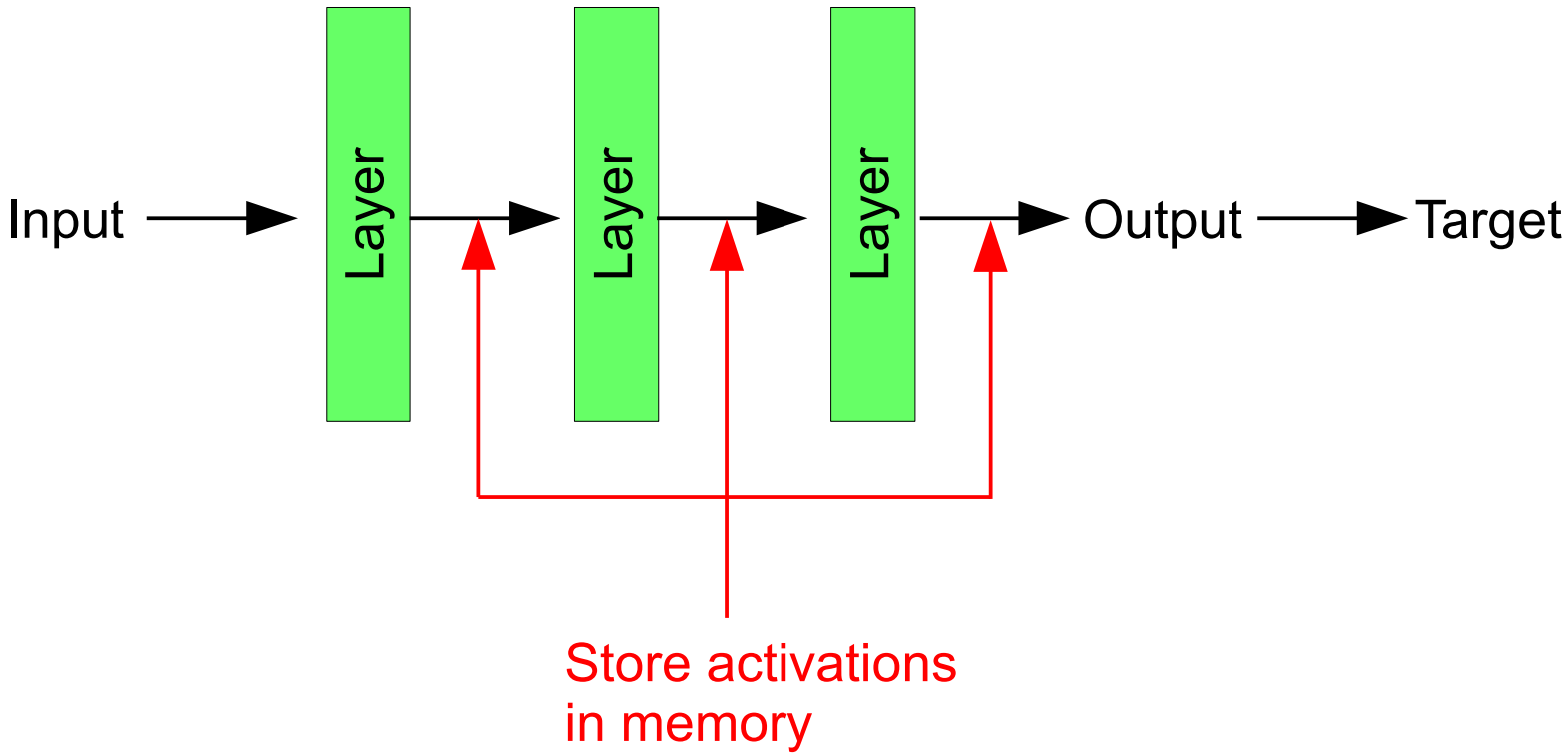


Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer. ArXiv, abs/2001.04451.

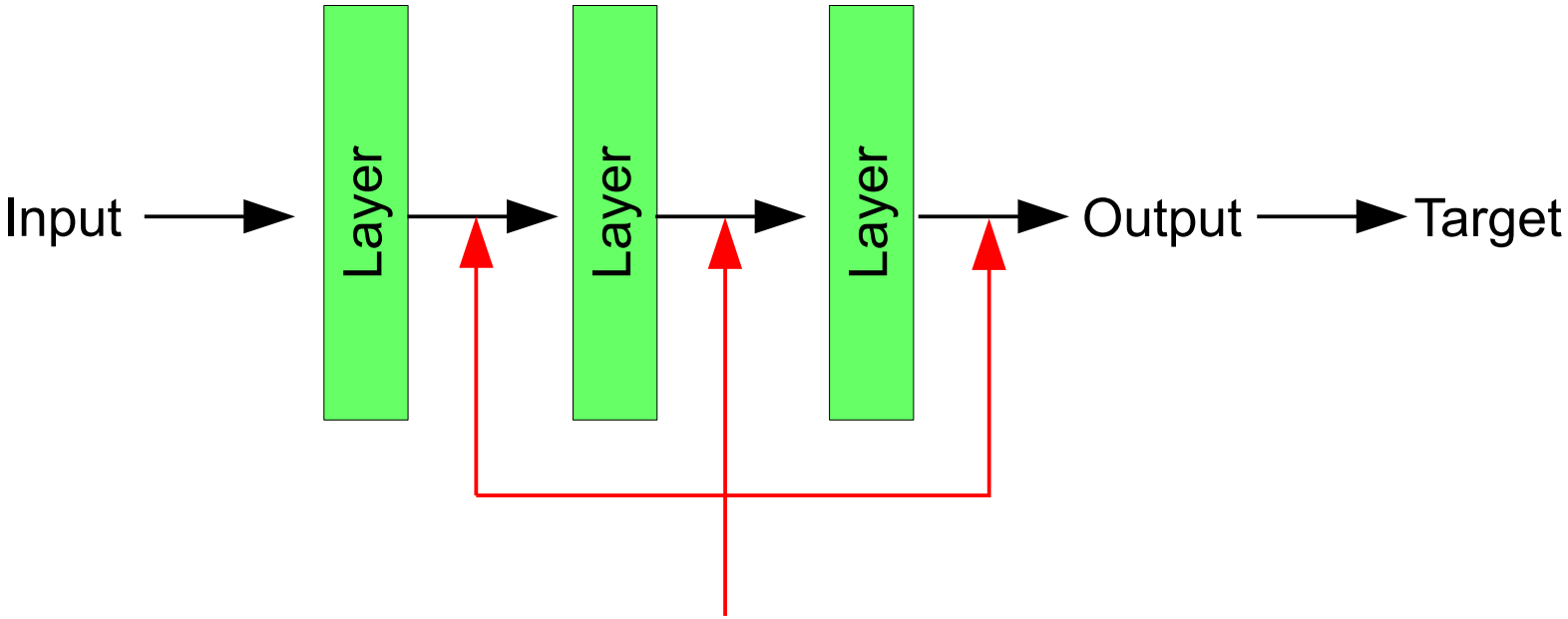
7.3 Memory problem – Backpropagation



7.3 Memory problem – Backpropagation



7.3 Memory problem – Backpropagation



Store activations in memory

including:

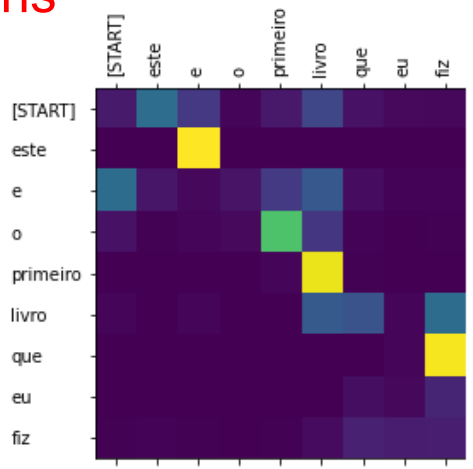
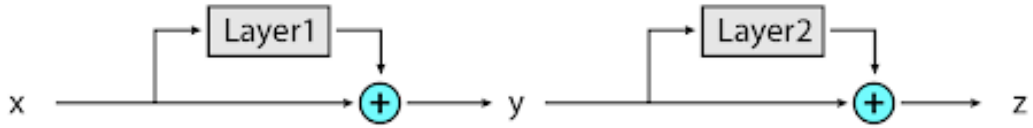


Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

7.3 Reformer: The Efficient Transformer

Residual connection



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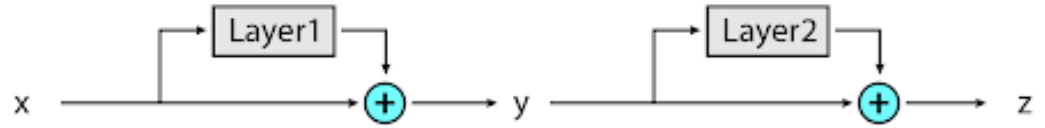
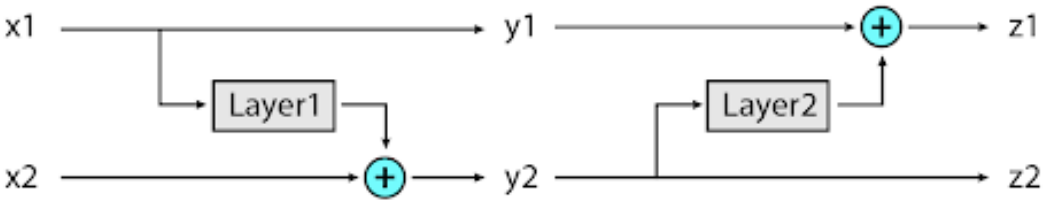
7.3 Reformer: The Efficient Transformer

Residual connection



Reversible layer
(forward pass)



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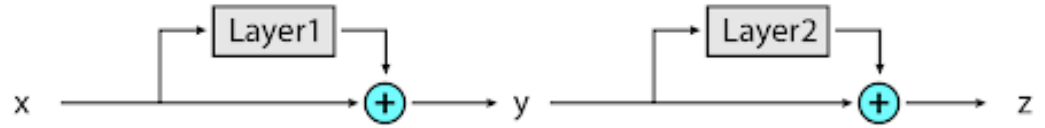
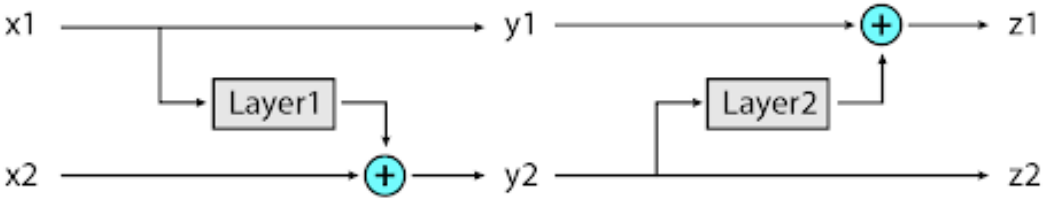
7.3 Reformer: The Efficient Transformer

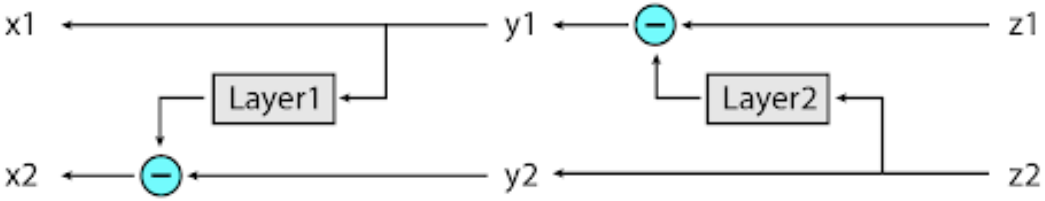
Residual connection



Reversible layer (forward pass)



Reversible layer (backward pass)



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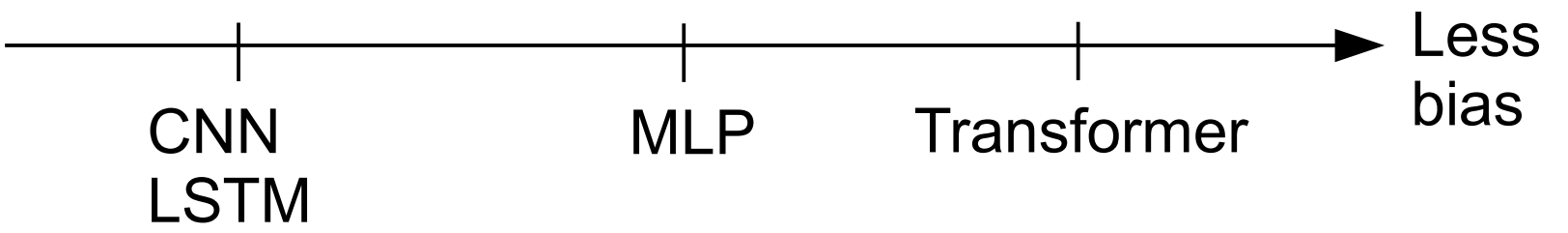
8. Conclusions

- Transform data into a sequence
- More general



- Data hungry 
- Quadratic scale of self-attention
- Outside of context window
- Performance depends on the situation → RNN better? 🤔

Image sources:
https://www.flaticon.com/free-icon/fangs_2068587?term=fangs&page=1&position=3&page=1&position=3&related_id=2068587&origin=search
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https://emojipedia-us.s3.dualstack.us-west-1.amazonaws.com/thumbs/120/whatsapp/326/thinking-face_1f914.png
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AlphaCandy

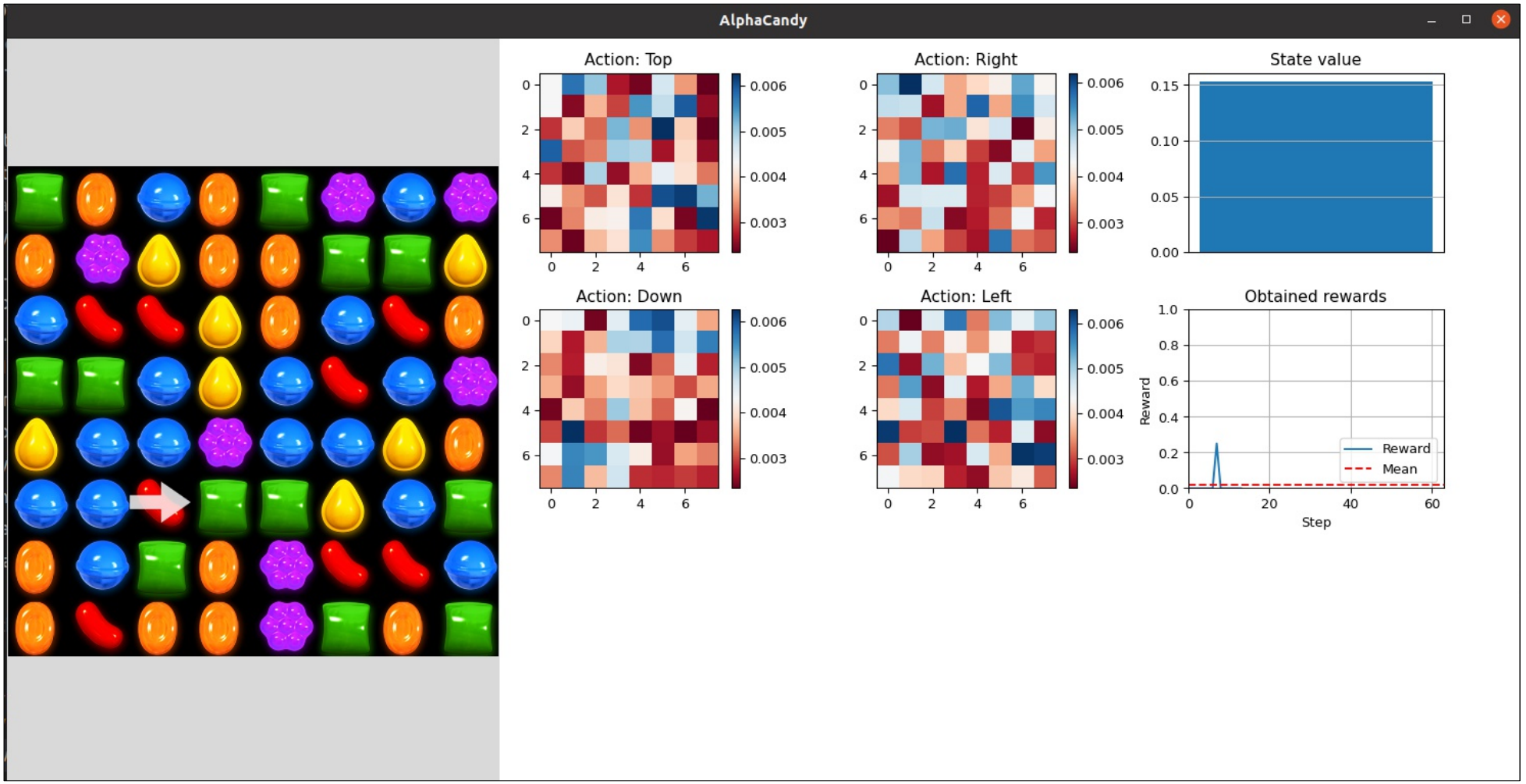

Figure 35: AlphaCandy UI.

Image sources:
https://www.flaticon.com/free-icon/candy-jar_10751352?related_id=10751352&origin=tag
https://emojipedia.org/de/toss-face/march-2022/gesicht-mit-umarmenden-h%C3%A4nden/
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