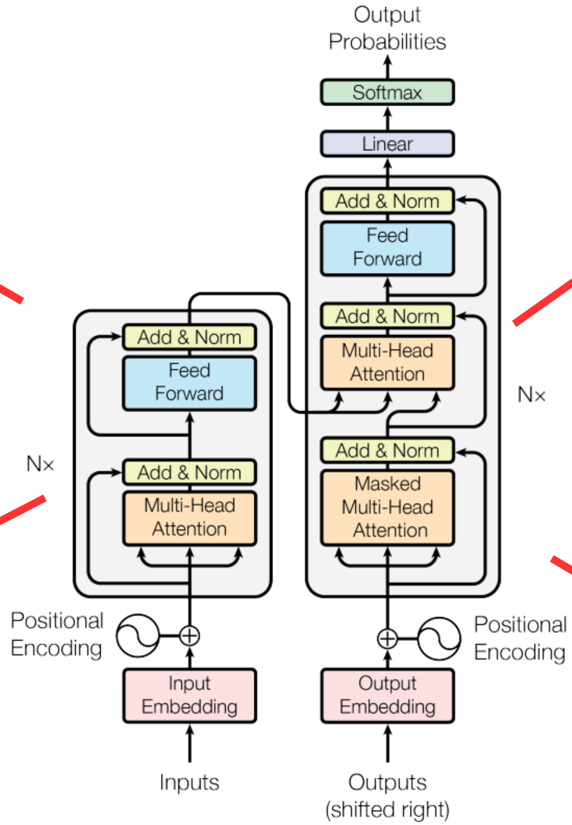
# Attention! The Transformers are coming!

Tim Niklas Witte

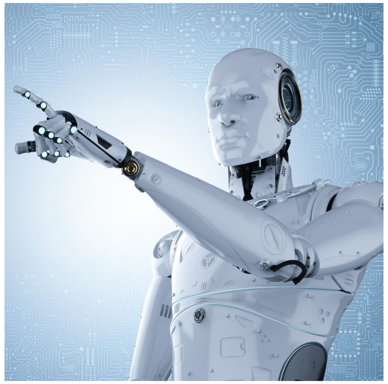
Image source: https://www.wallpaperflare.com/optimus-prime-the-city-weapons-fiction-robots-the-movie-wallpaper-wbsf/download (call date: 20.07.22)

Computer Vision





Natural Language Processing



Deep Reinforcement Learning

GANs

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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
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https://studip.uni-osnabrueck.de/sendfile.php?type=0&file_id=8a554d27d543b1ce06eb1a68a34e22ae&file_name=vqgan_4_i350.png
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# 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

8. Modifications of attention: Synthesizer, Linformer, Reformer

9. Conclusions

Discussion: Candy-wise attention

Image sources:
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https://emojipedia.org/de/toss-face/march-2022/gesicht-mit-umarmenden-h%C3%A4nden/
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# 1. Motivation

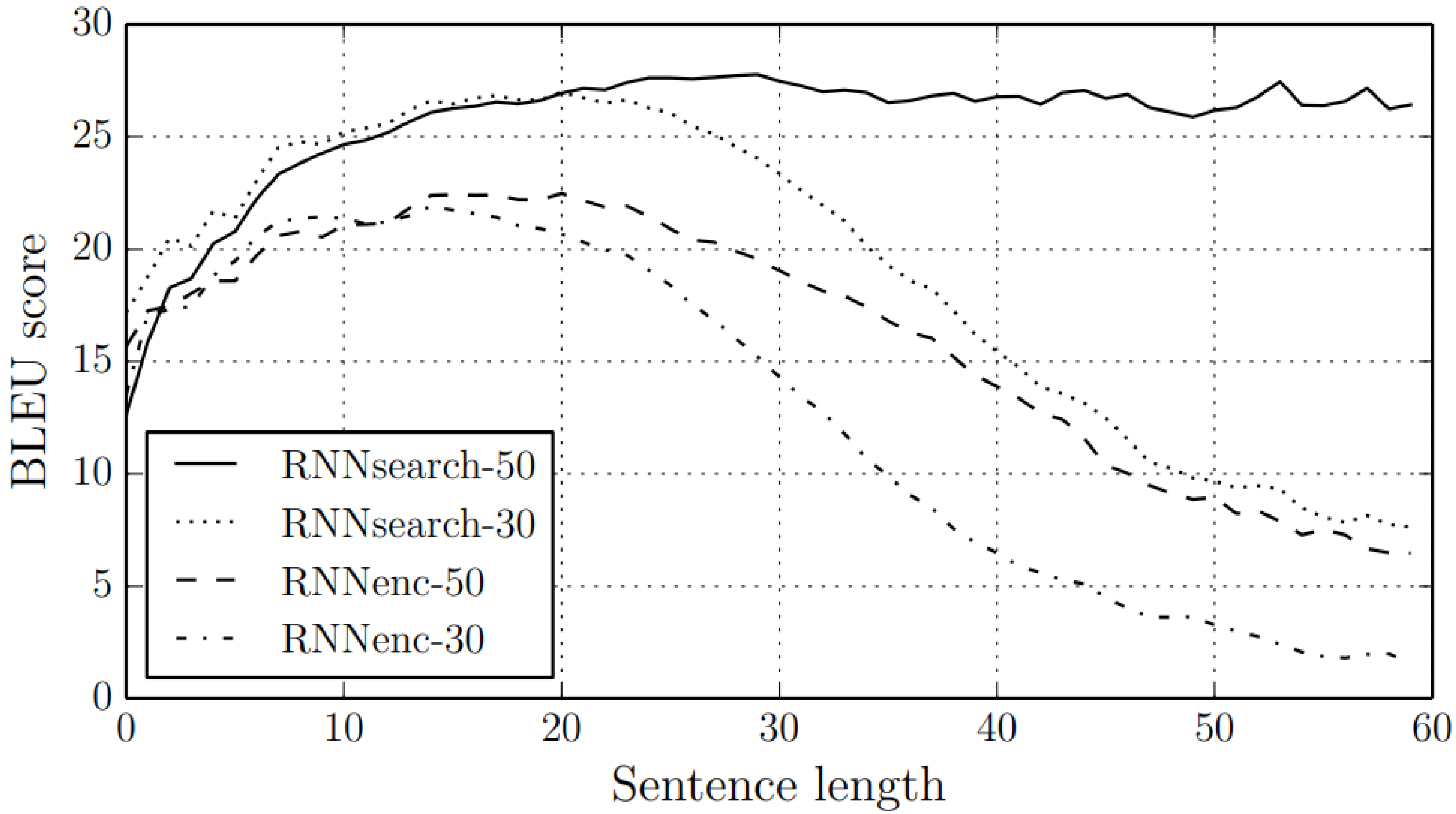


Figure 1: Performance (BLEU score) differences between RNN-based models for neural machine translation [1].

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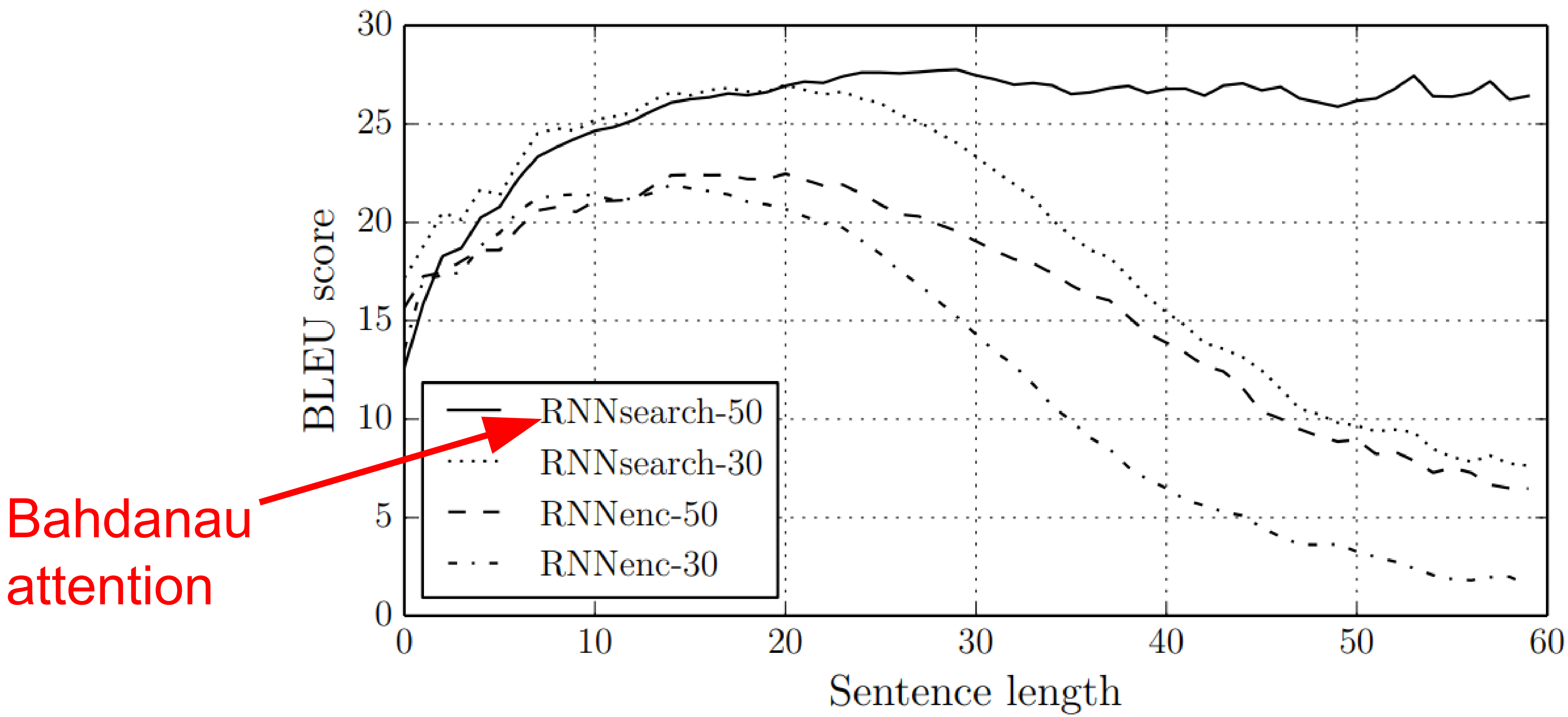


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https://upload.wikimedia.org/wikipedia/commons/thumb/7/7b/Attention_Sign.svg/2302px-Attention_Sign.svg.png
https://upload.wikimedia.org/wikipedia/commons/thumb/9/9a/Simple_Attention.svg/1024px-Simple_Attention.svg.png
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The server ...

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?

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
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This is the first book I did. → 

**Portuguese**
Este e o primerio livro que eu fiz.

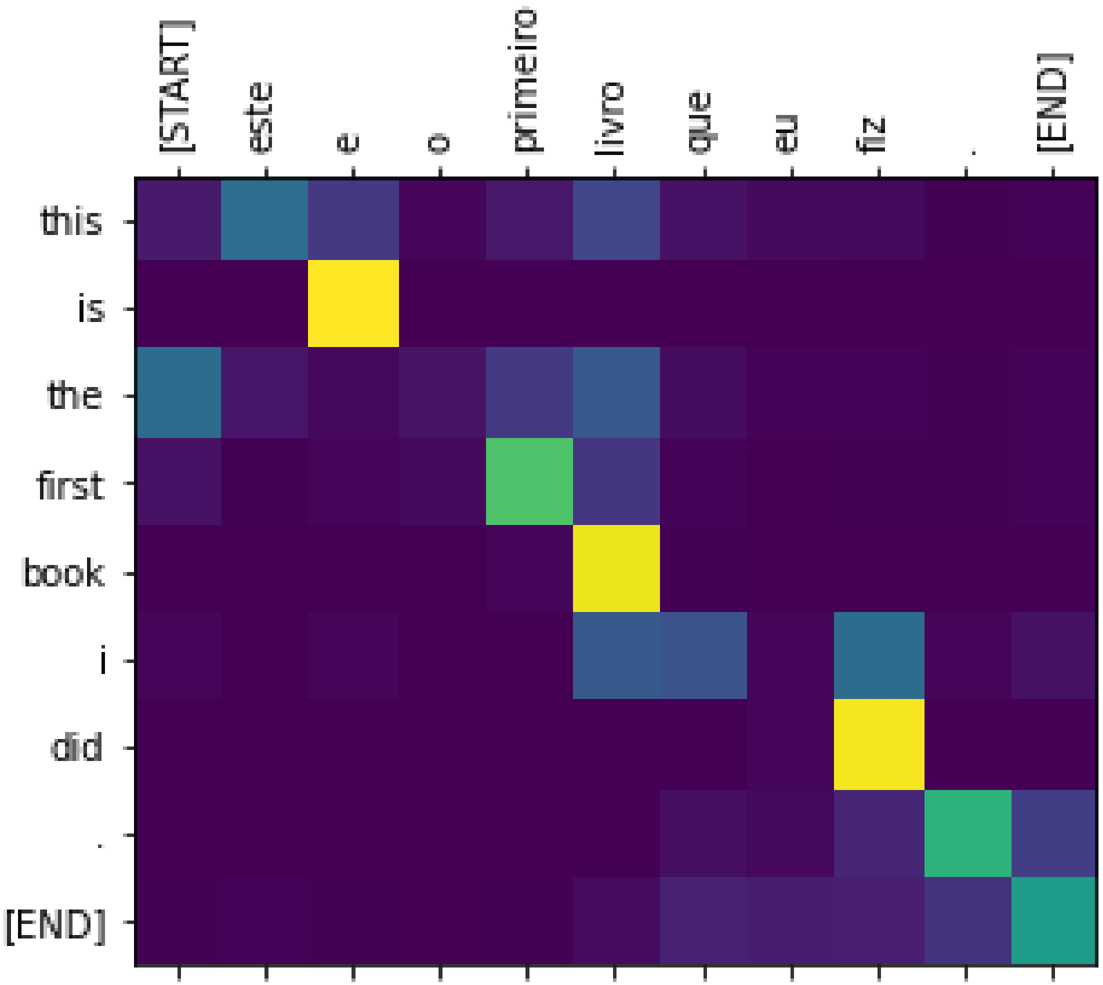


Figure 4: Self-attention heatmap.

Image source:
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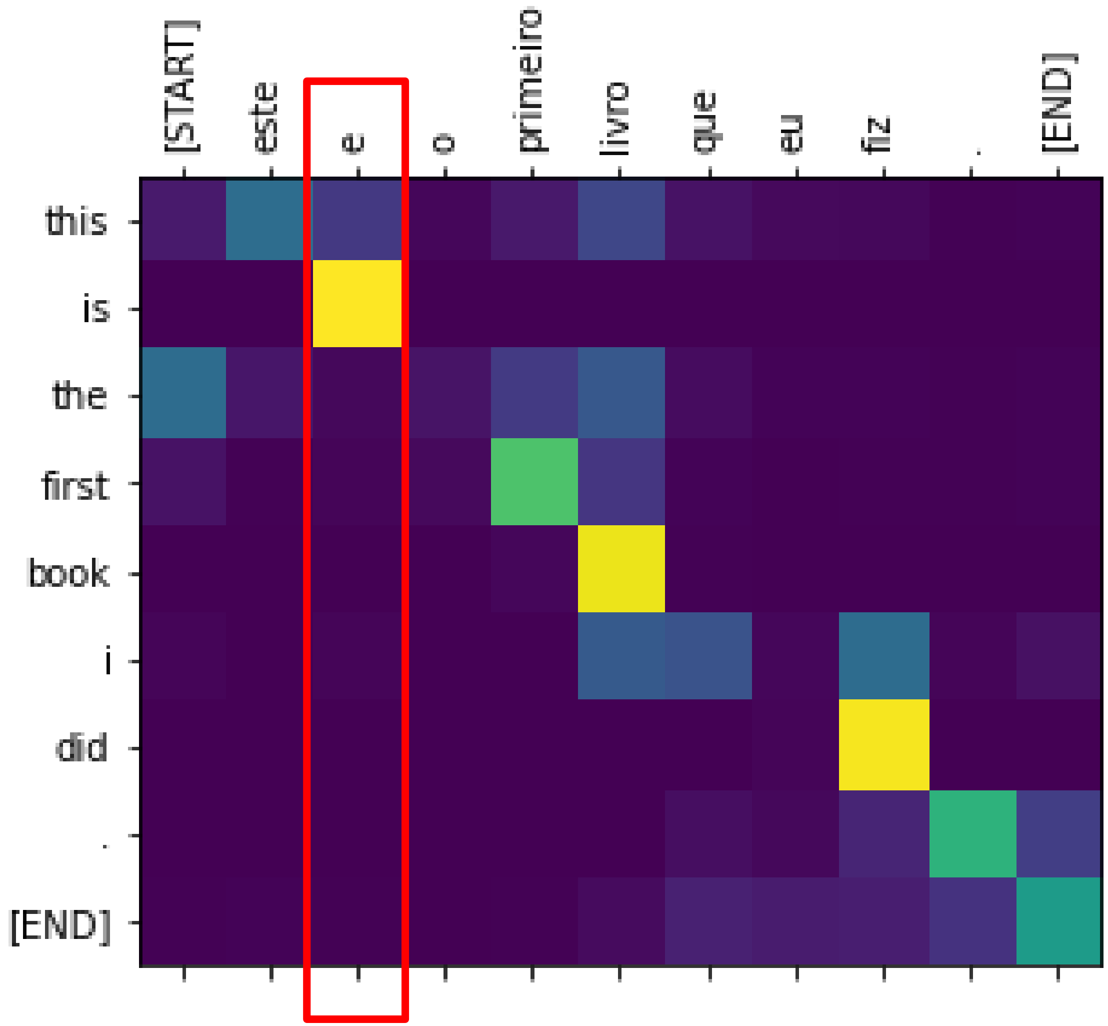


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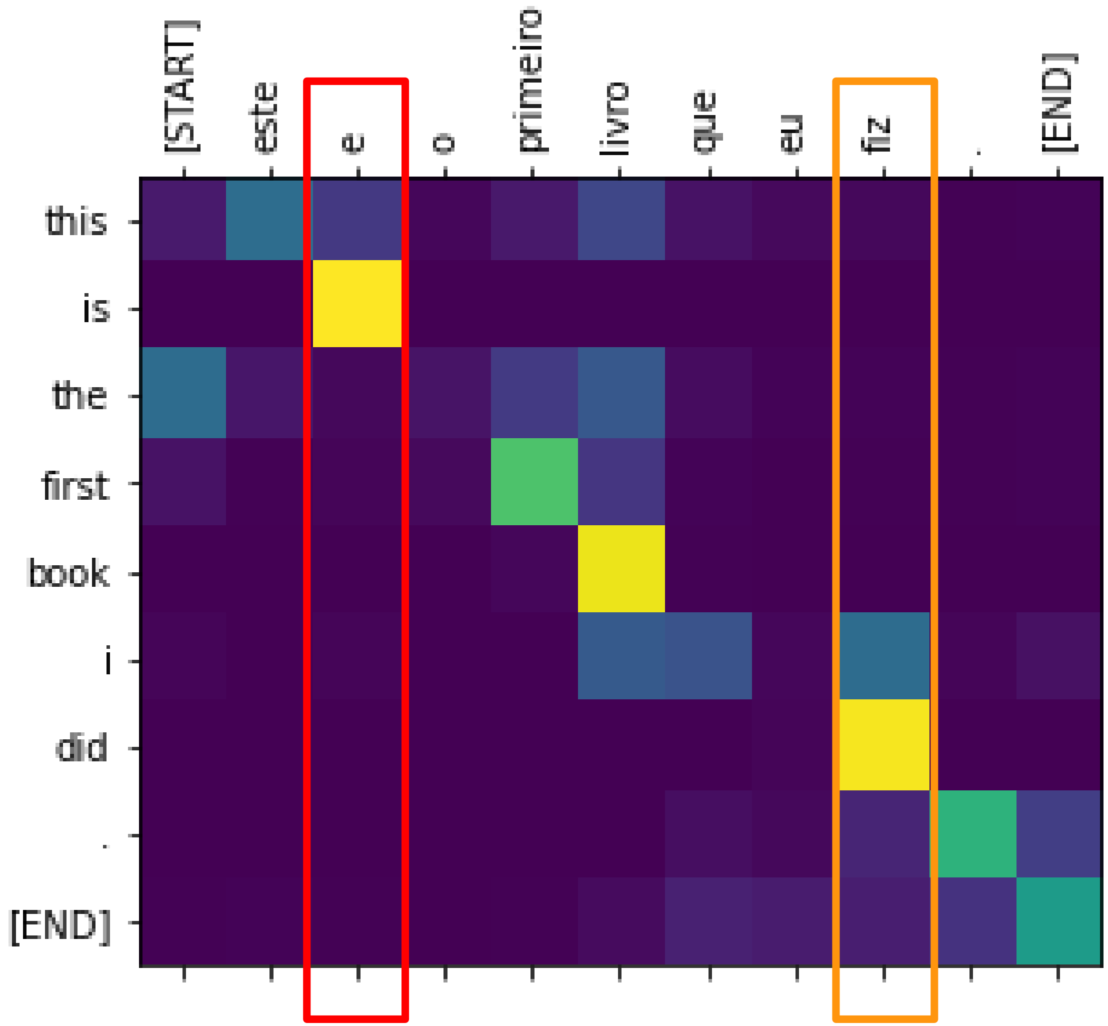


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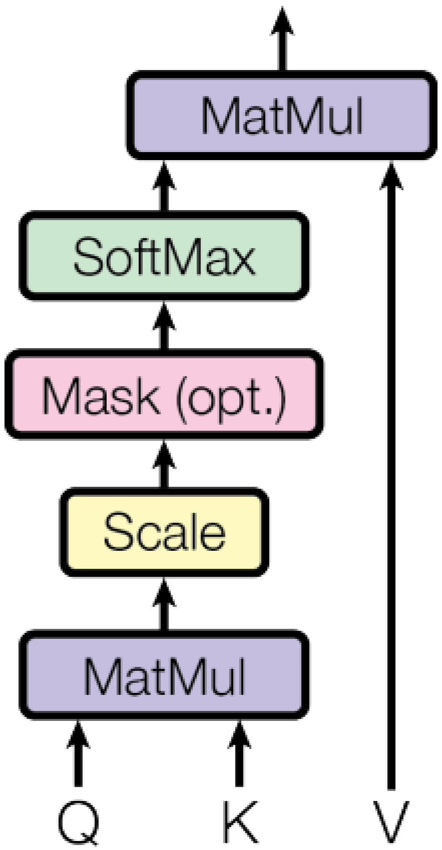


Figure 5: Self-attention [2].

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

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 $D_H$

## 2. Intuitive understanding of self-attention

Database

| Video title | Description | Video |
| --- | --- | --- |
| | | |

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

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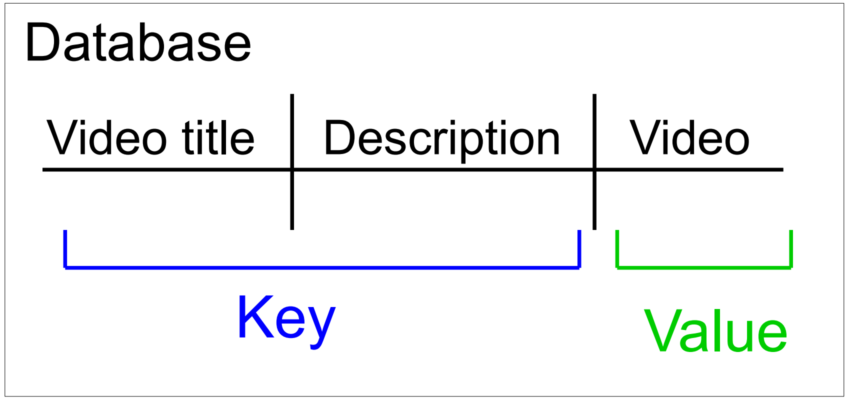


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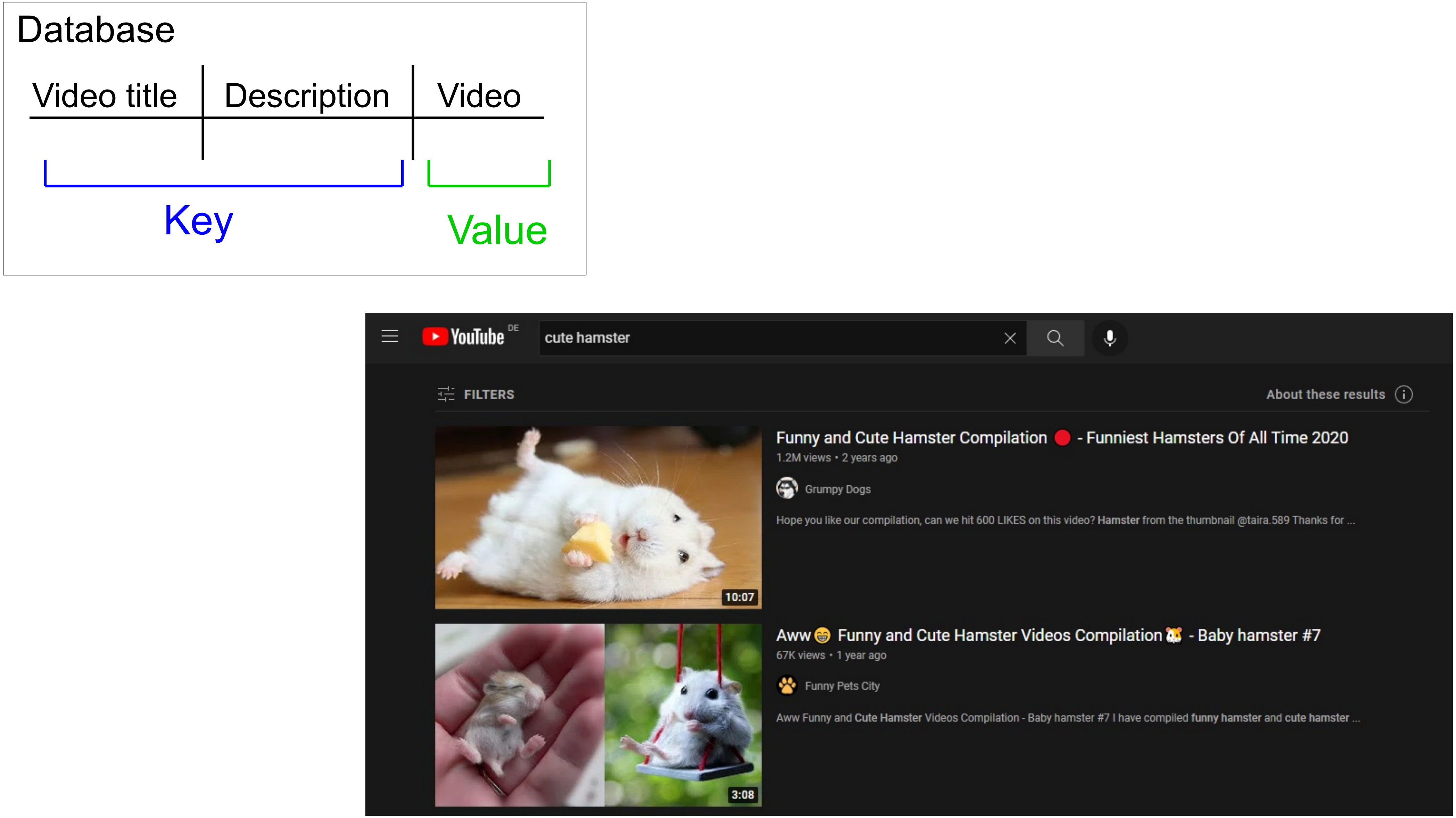


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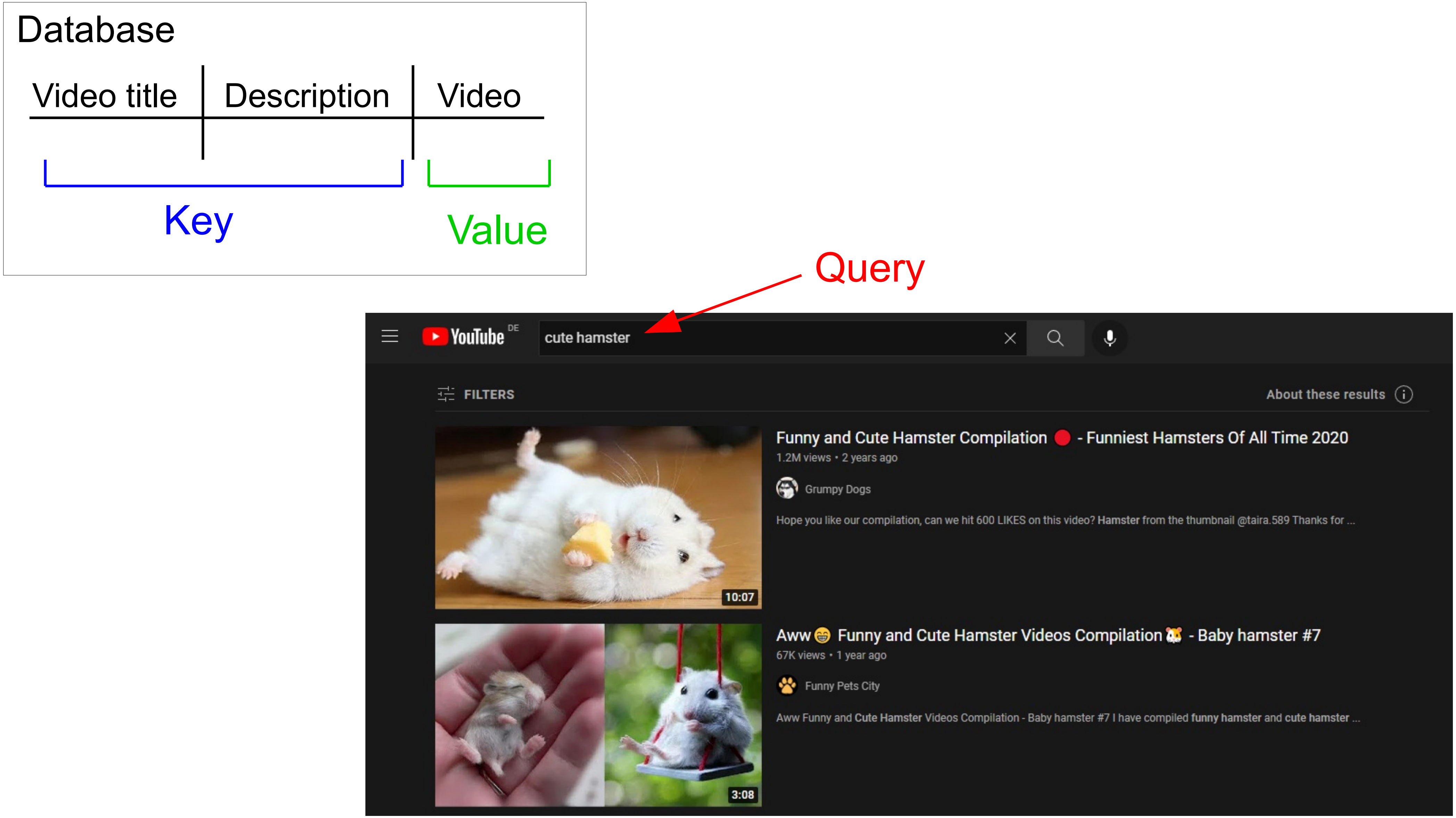


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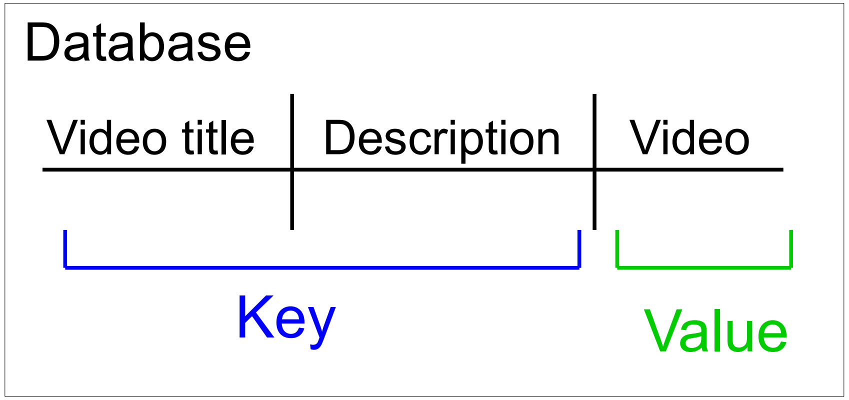
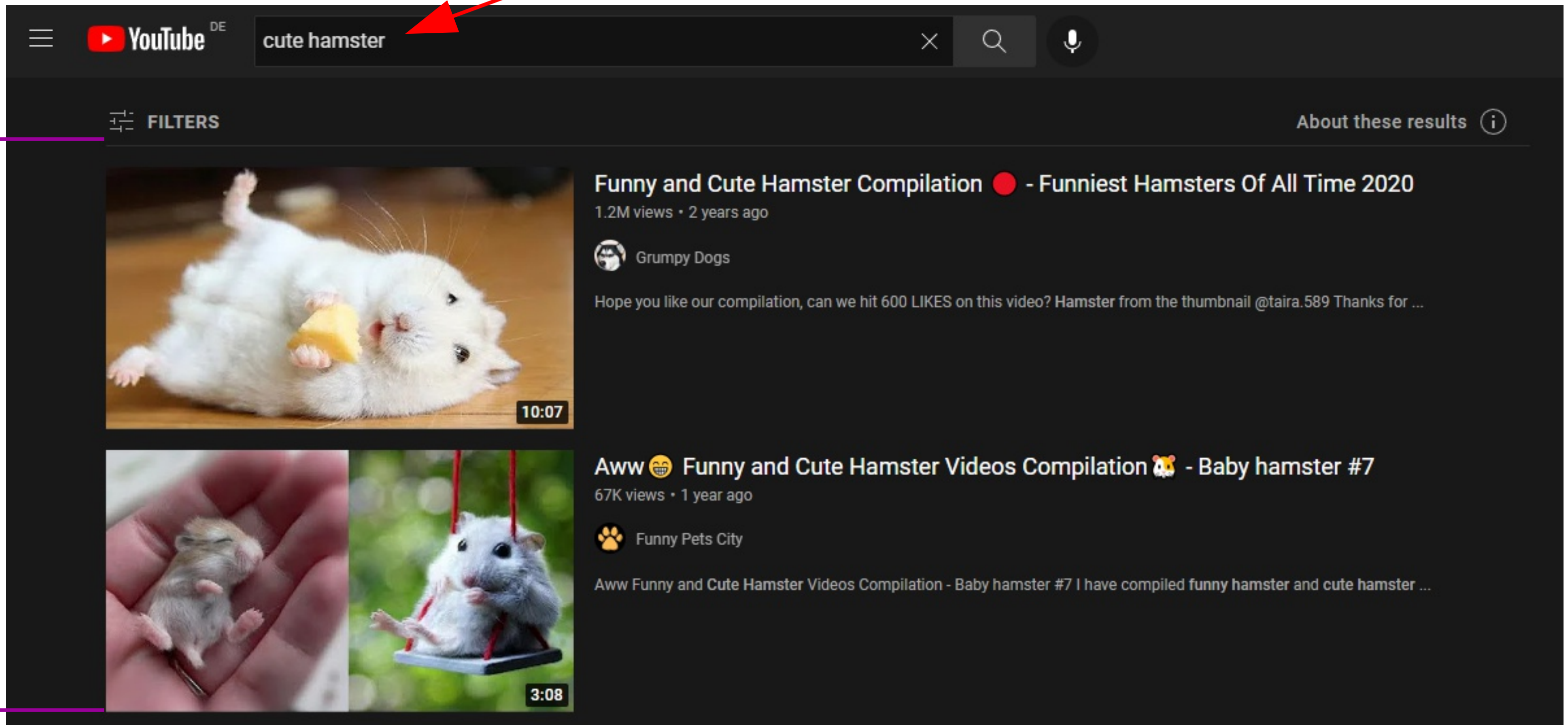



Query

$$\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

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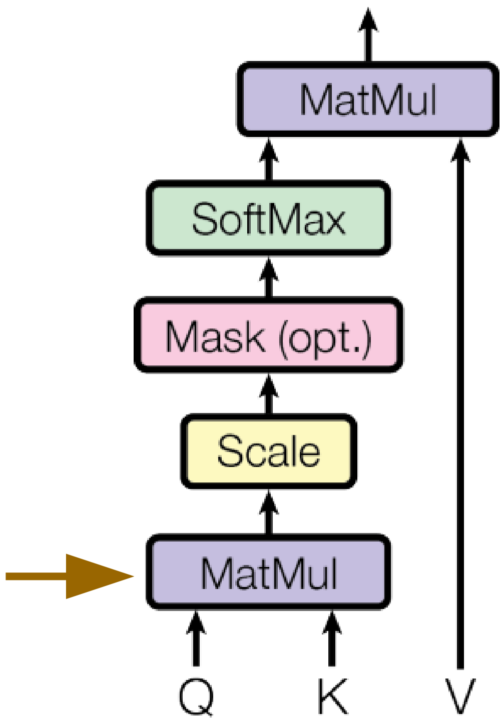


Figure 7: Self-attention visualised [2].

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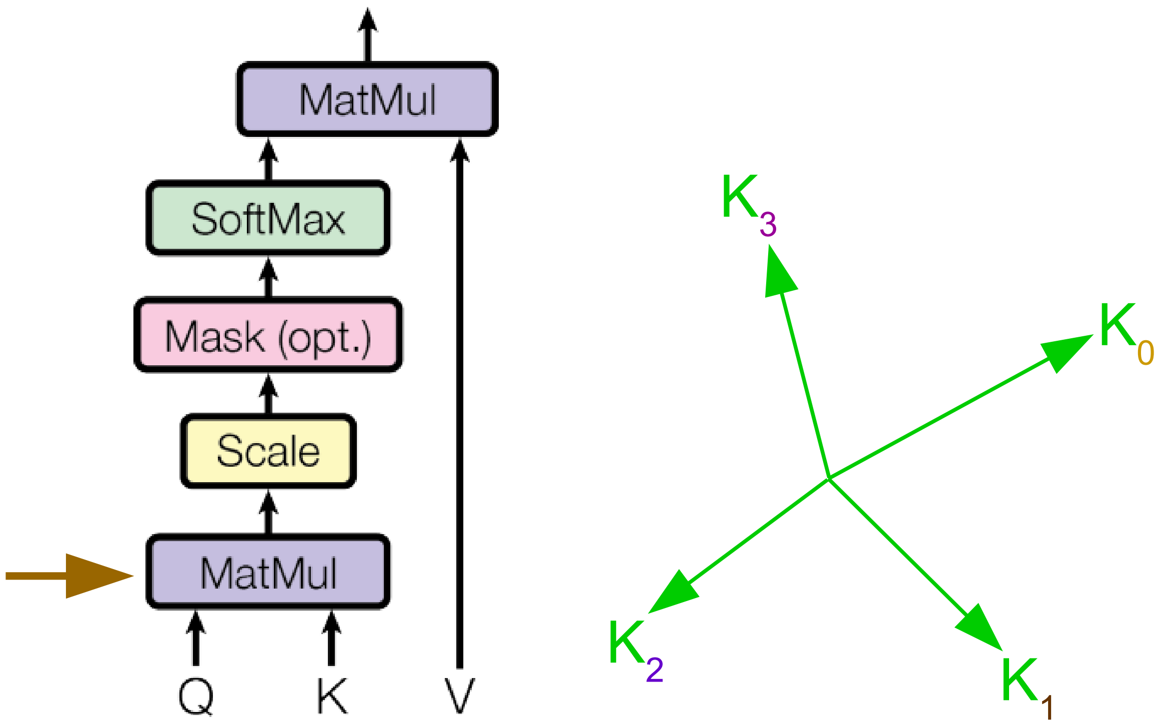


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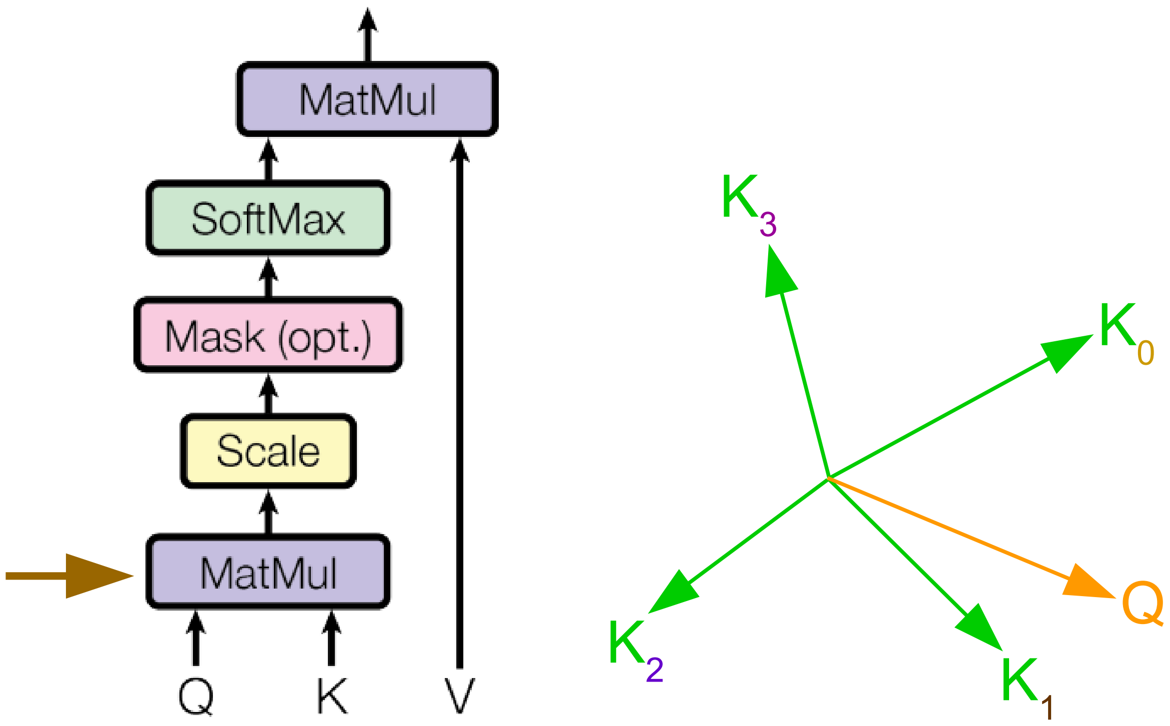


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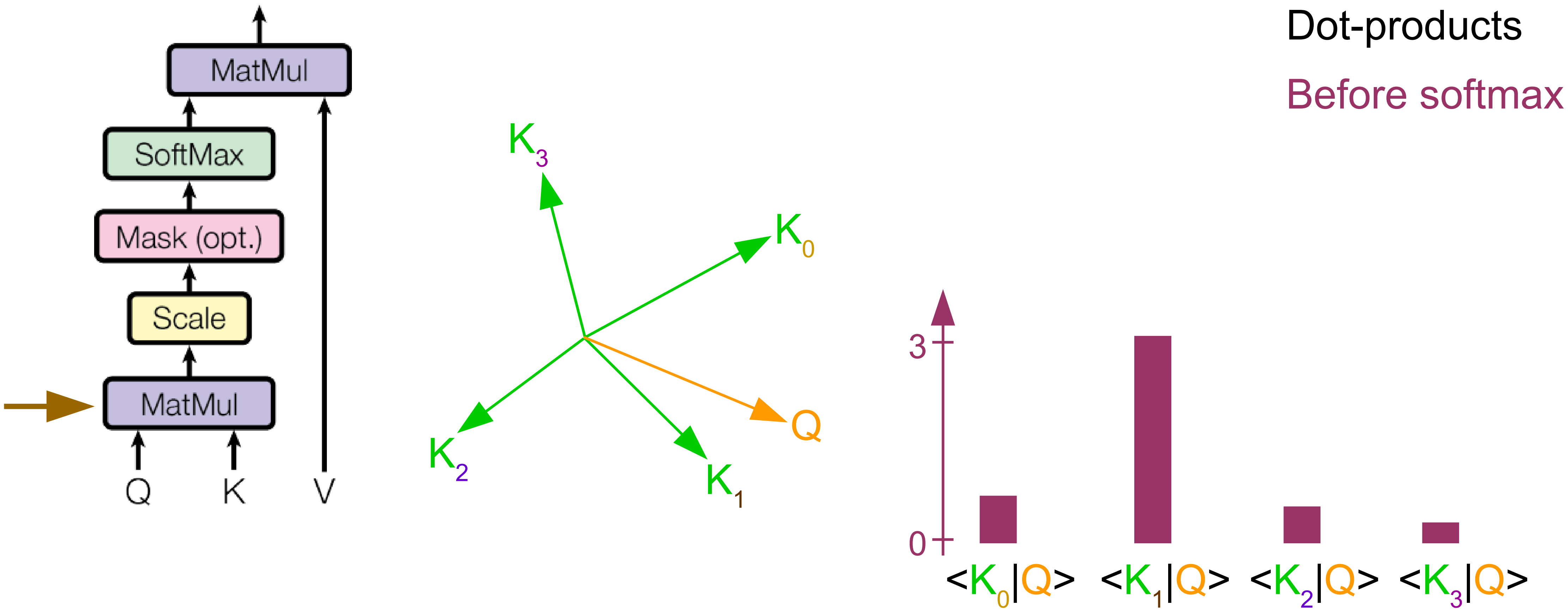


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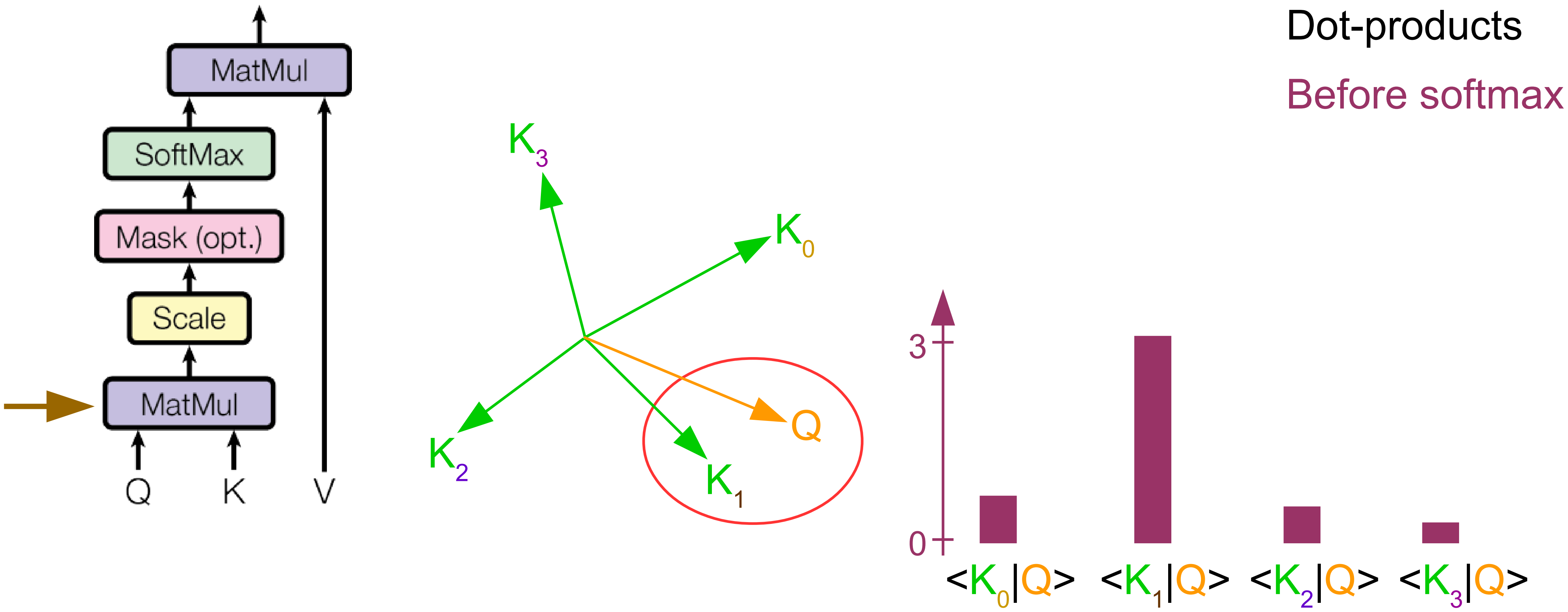


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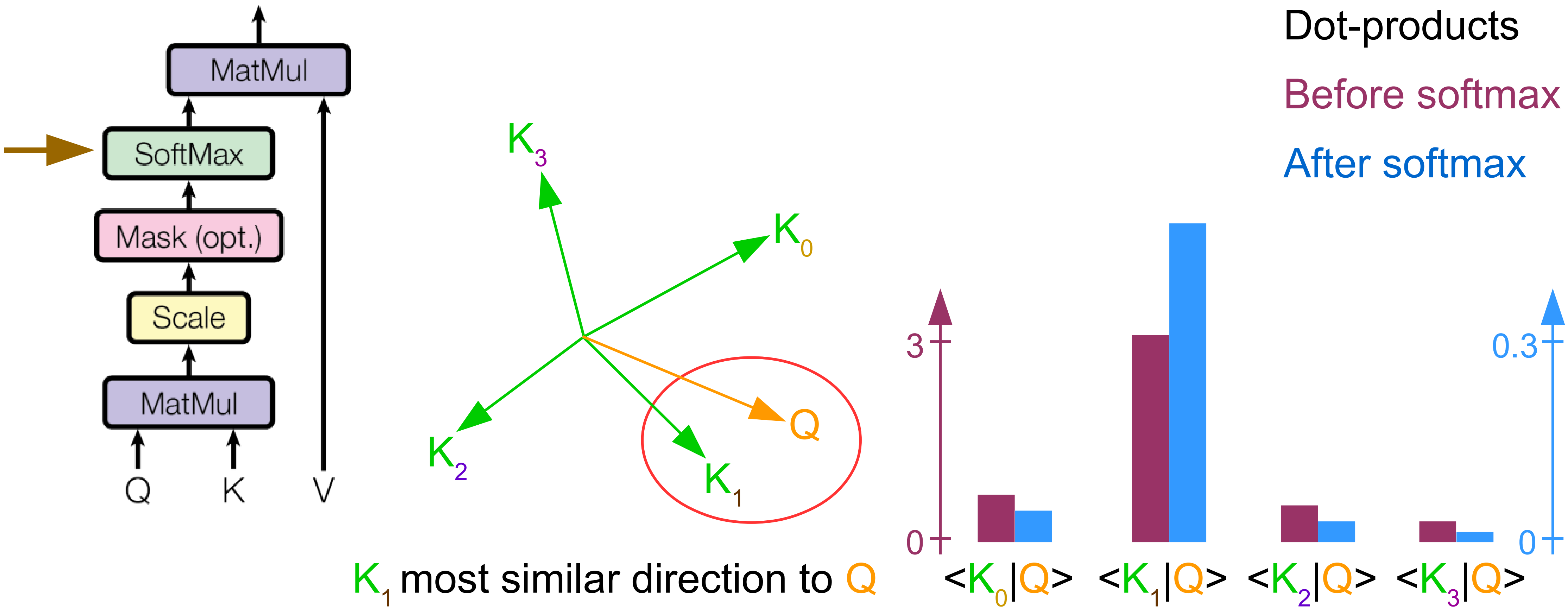


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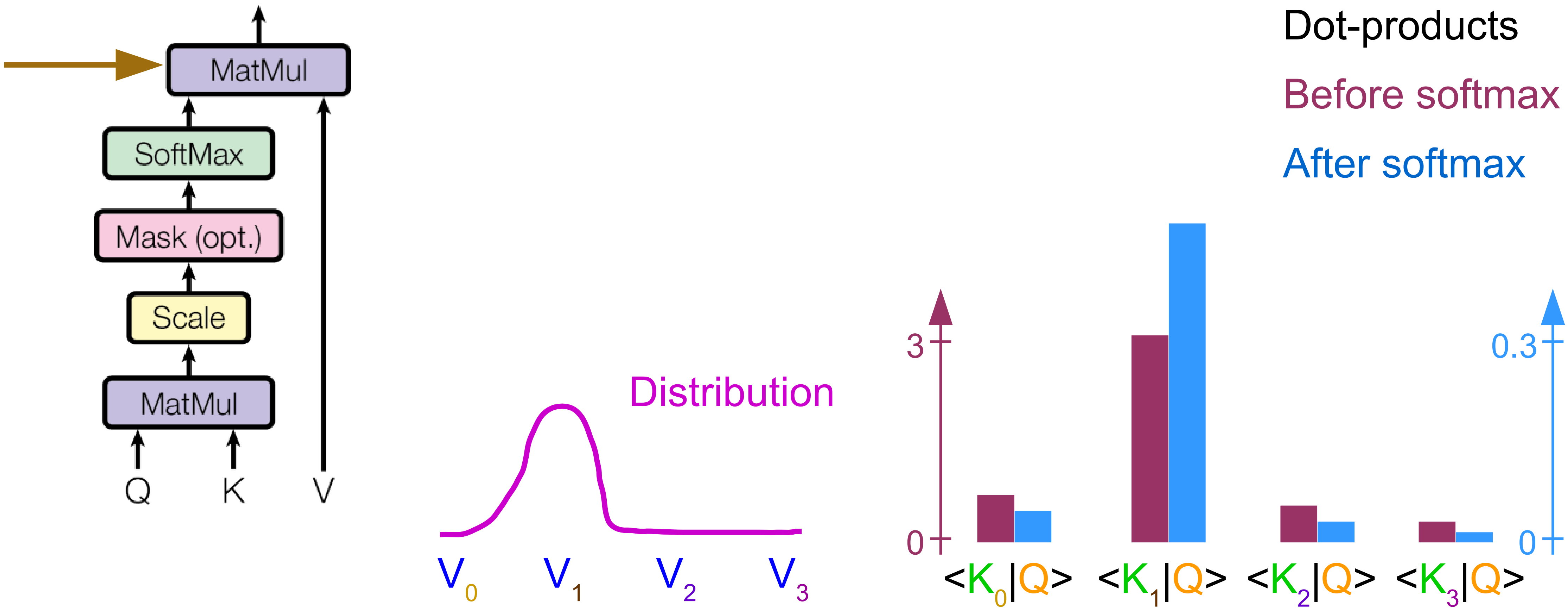


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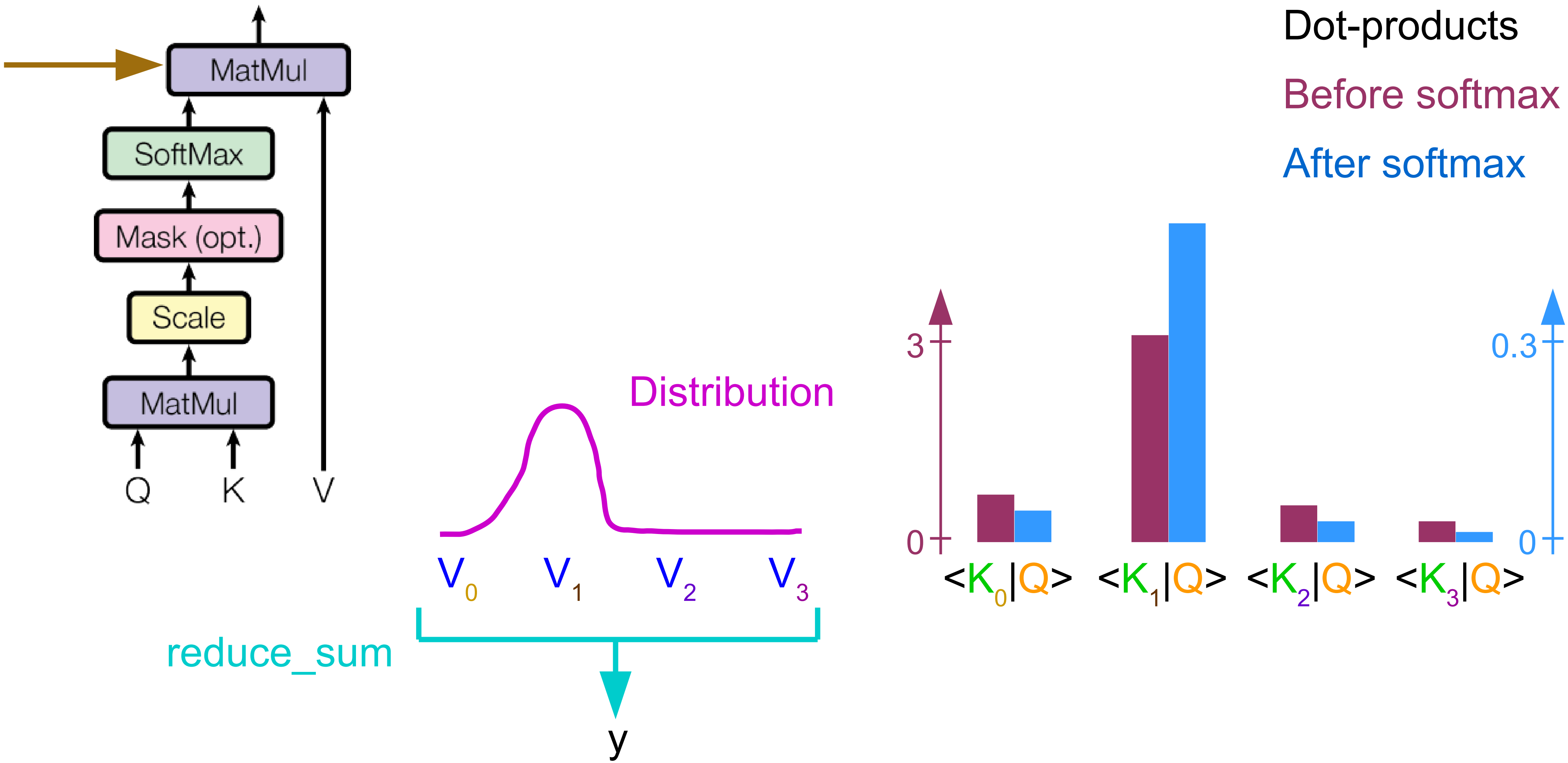


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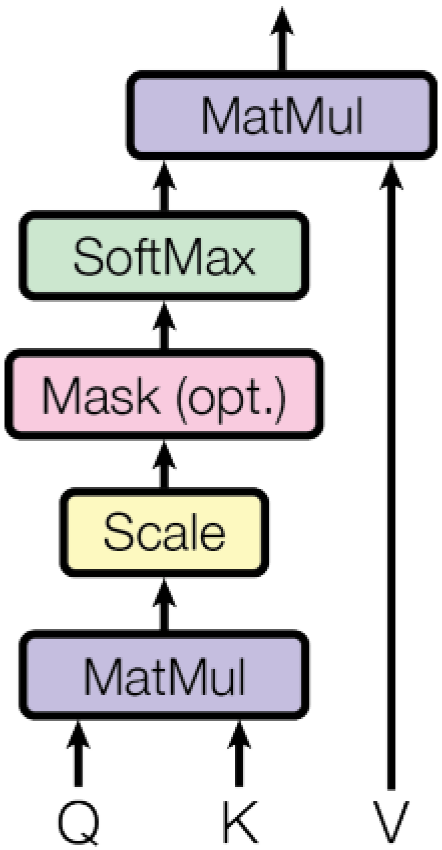


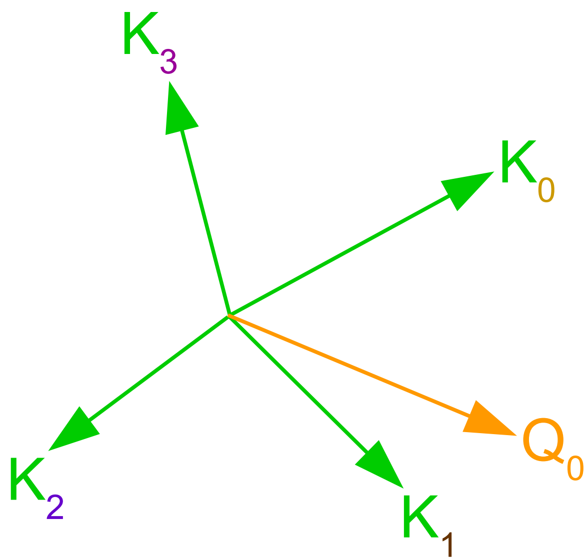


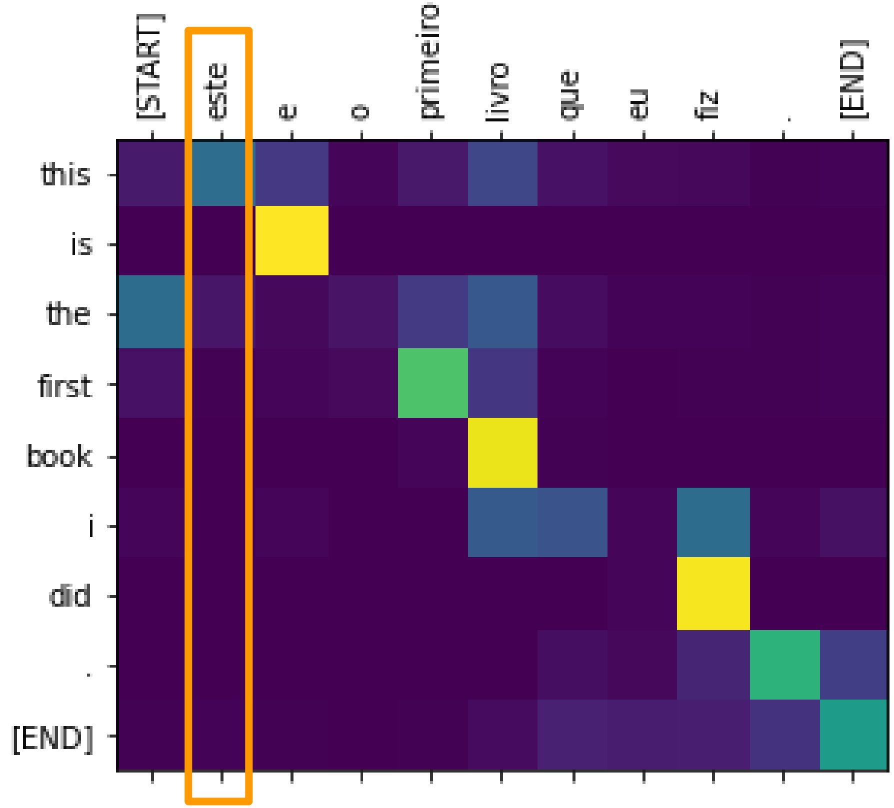


Figure 8: Self-attention – origin of the heatmap [2].

Image source:
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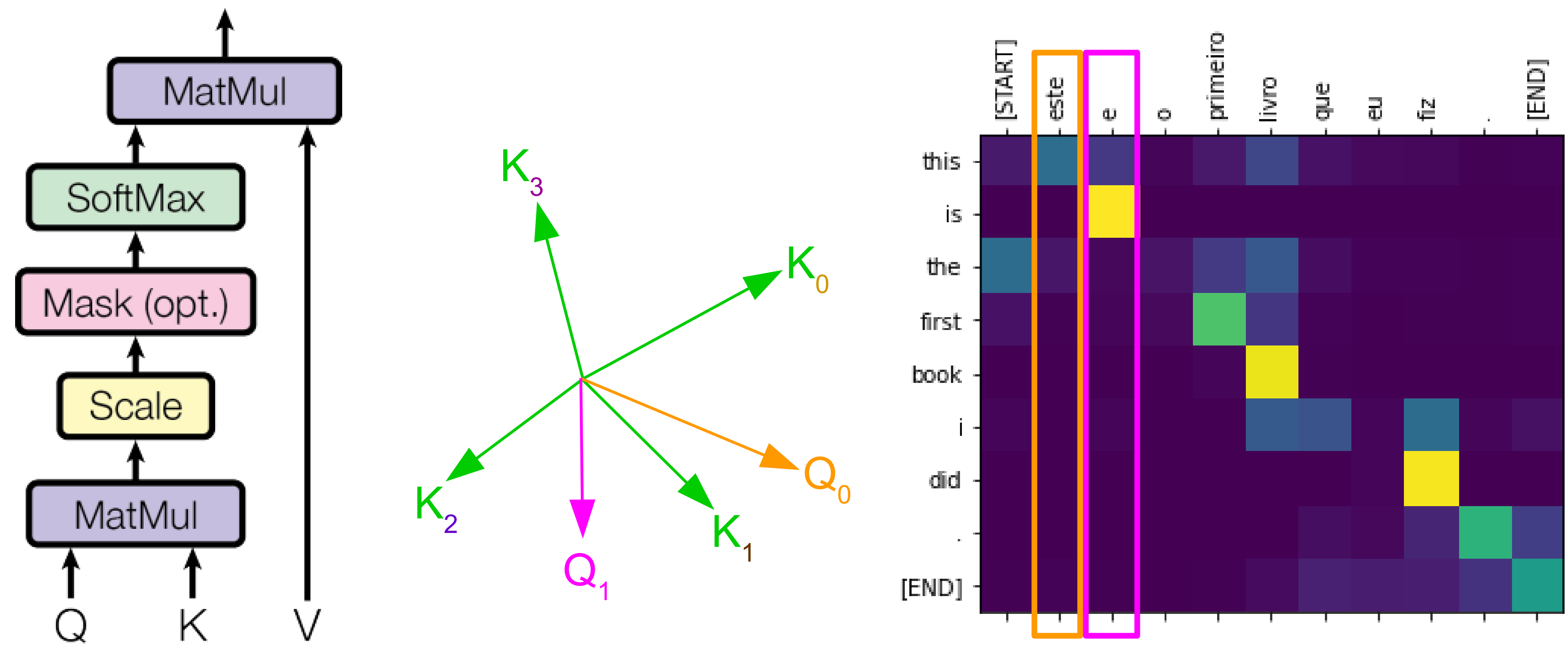


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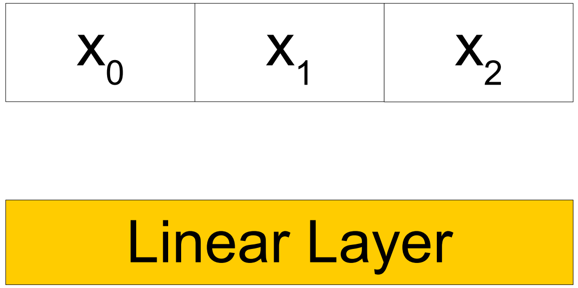

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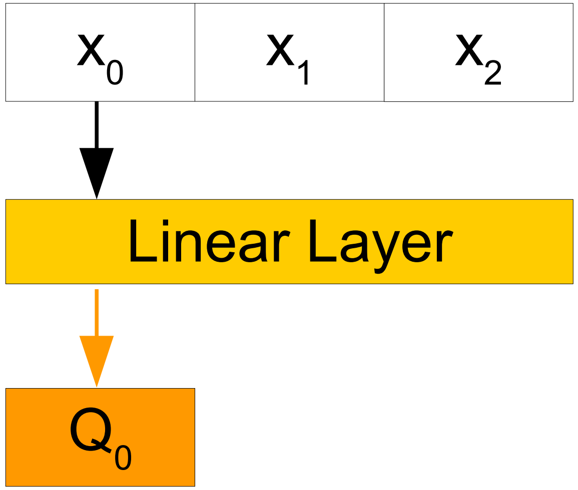

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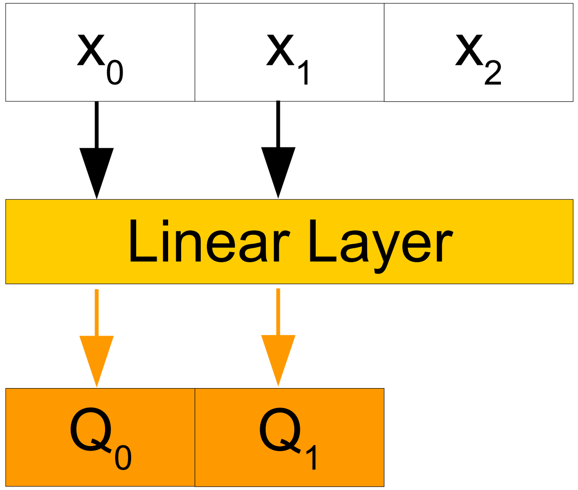

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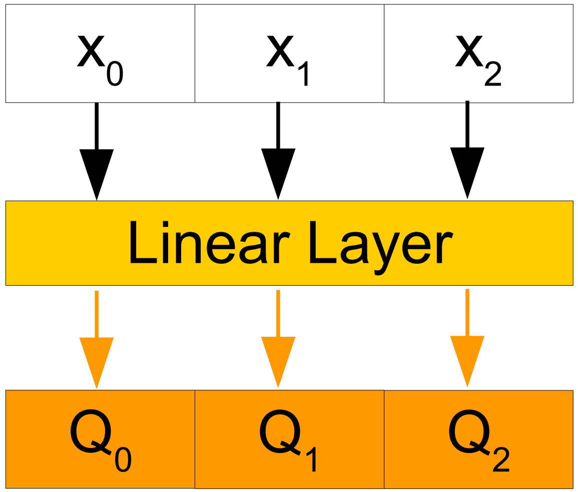

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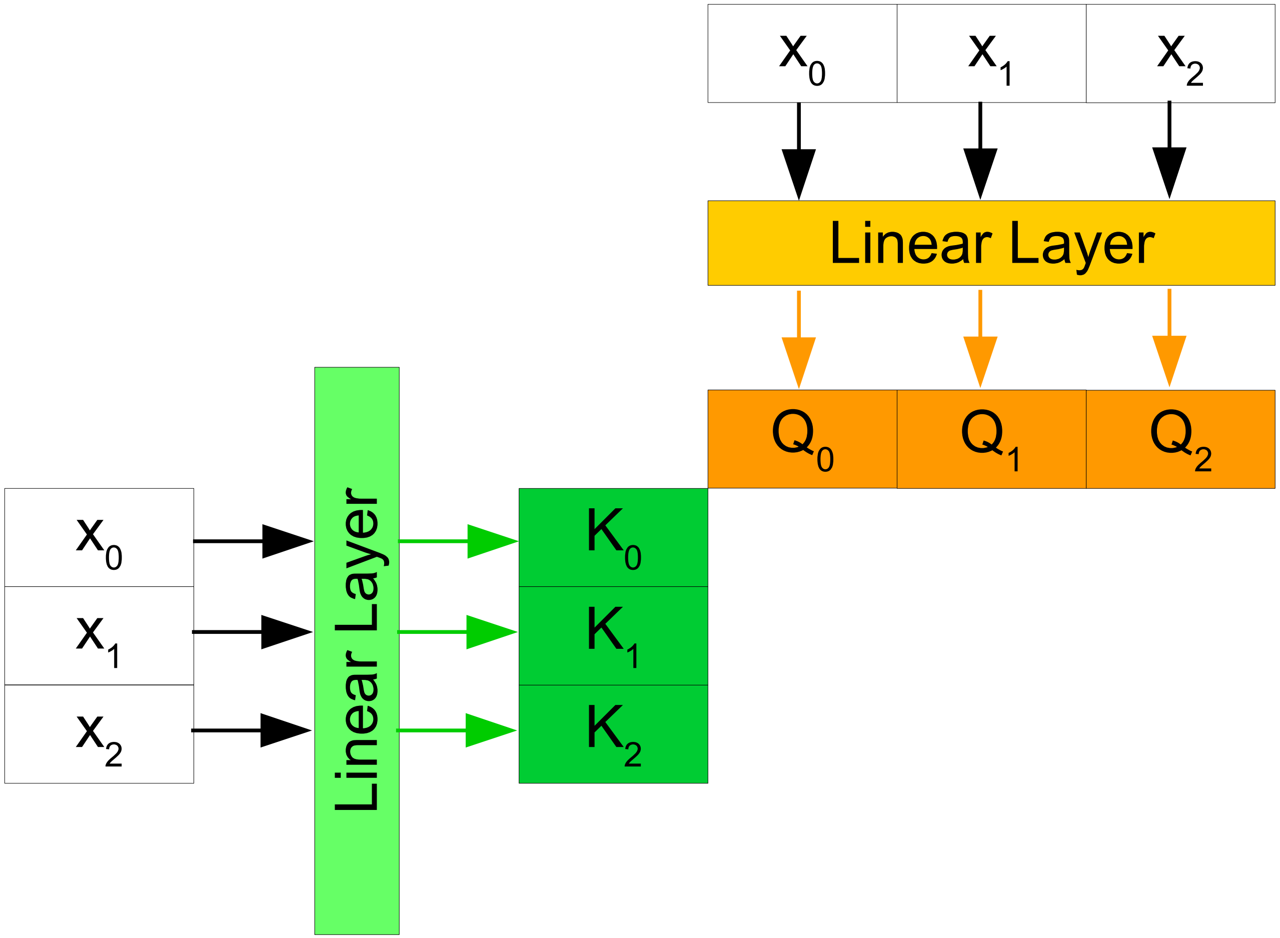

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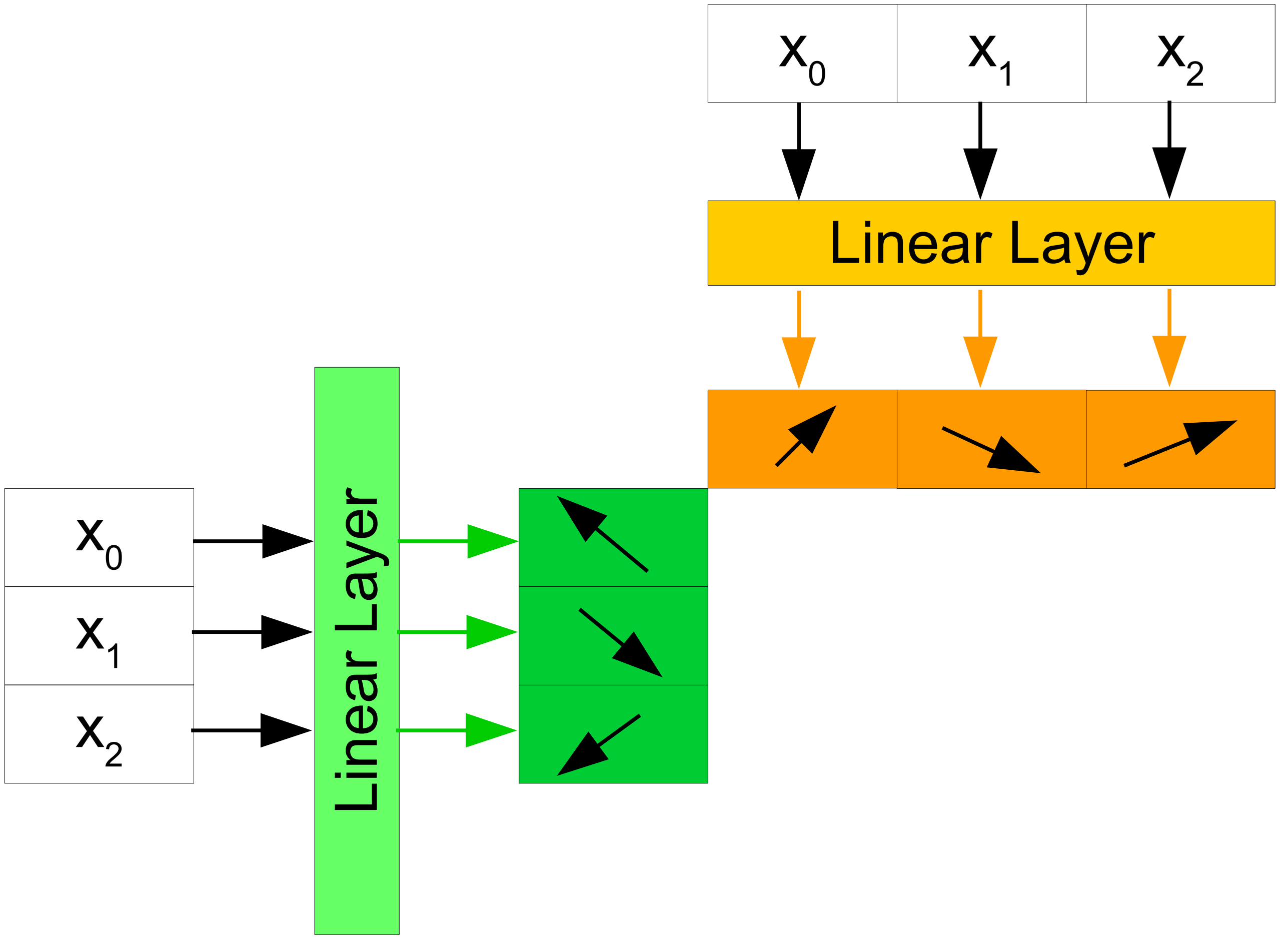

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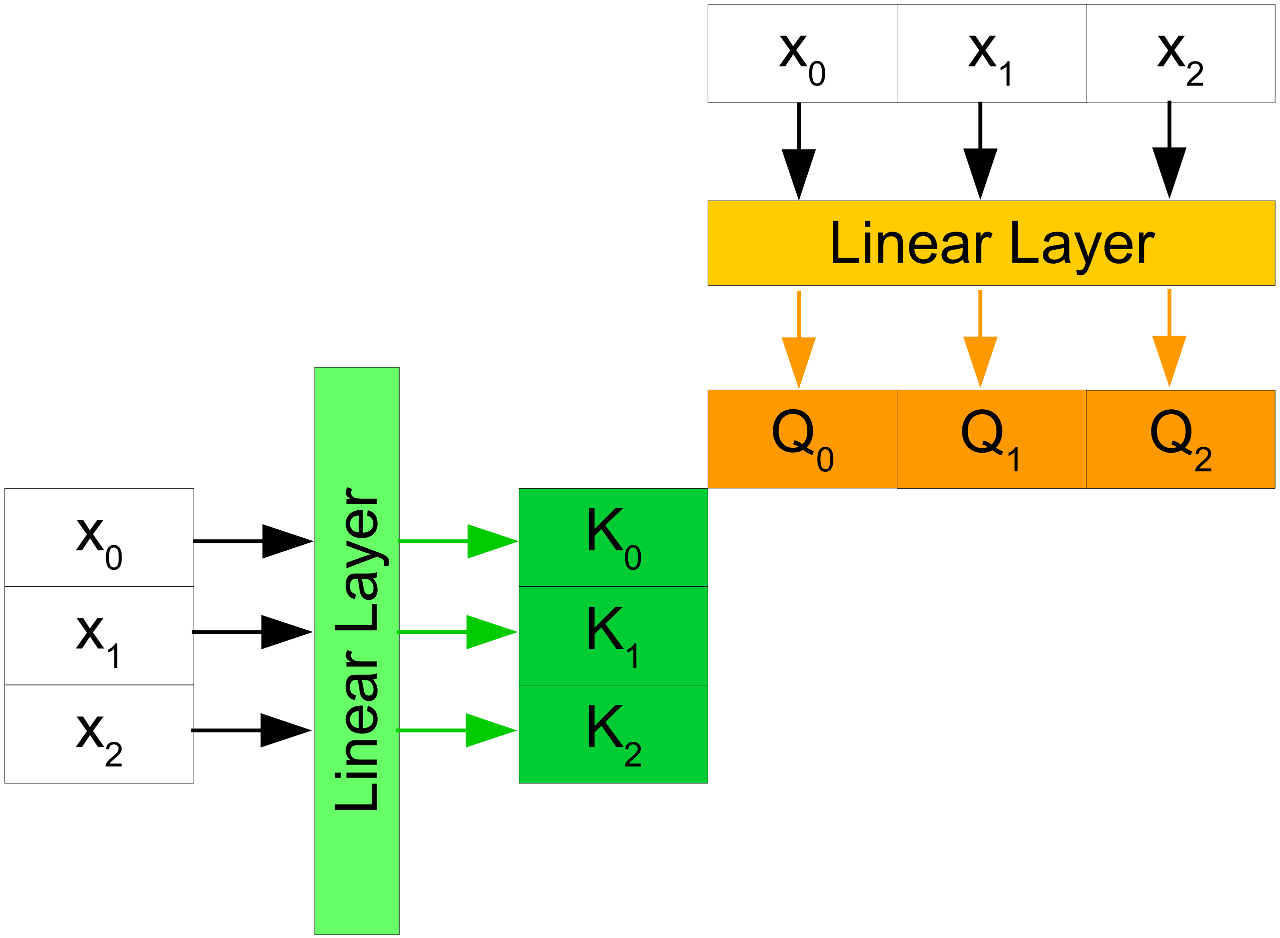

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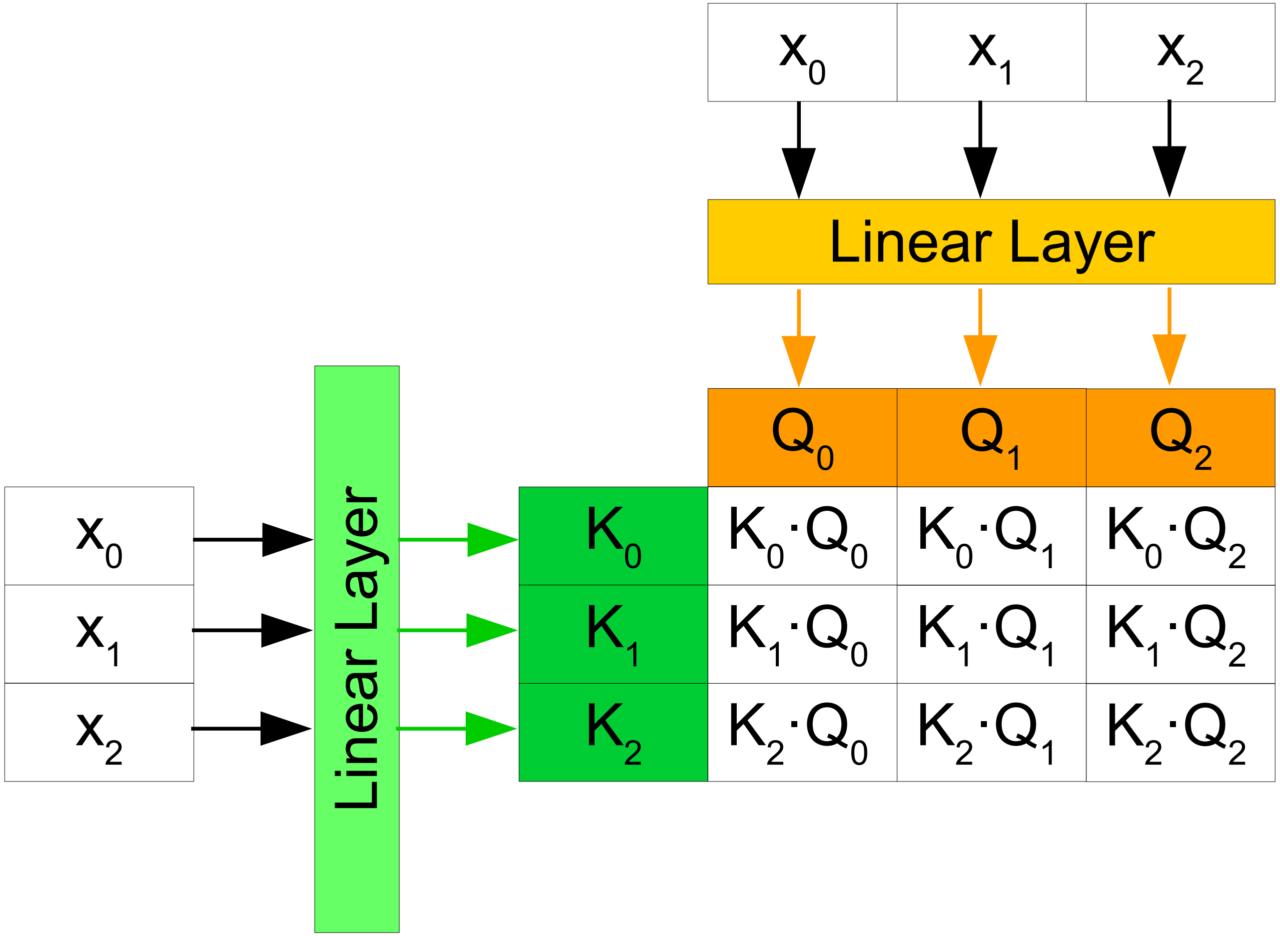

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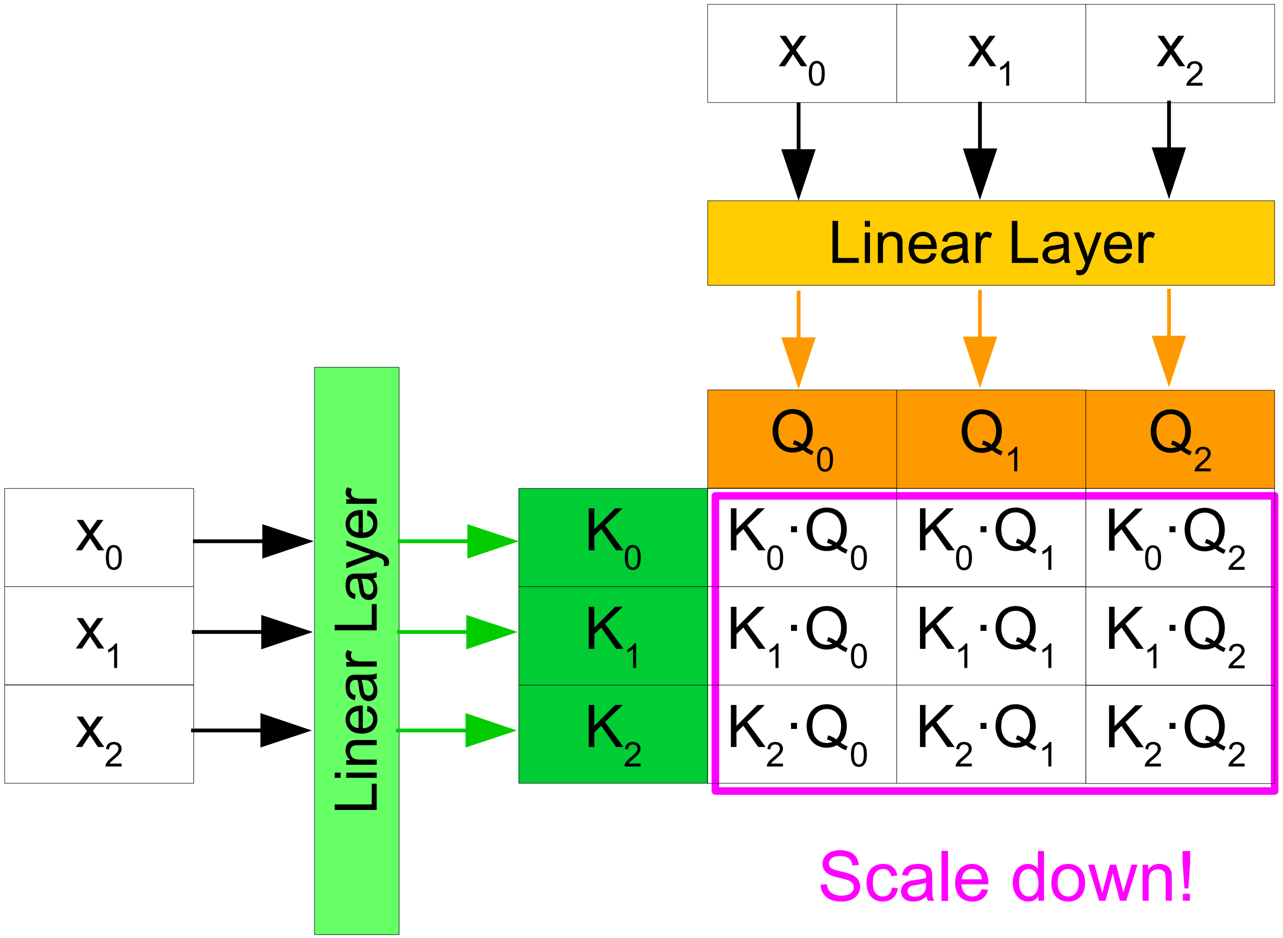
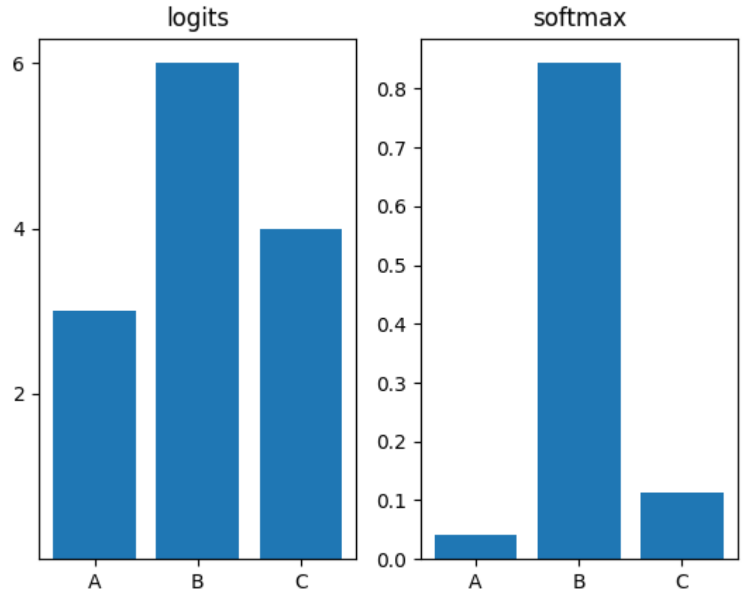



$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\boxed{\sqrt{d_k}}}\right)V$$

# Side note: softmax is not scale invariant



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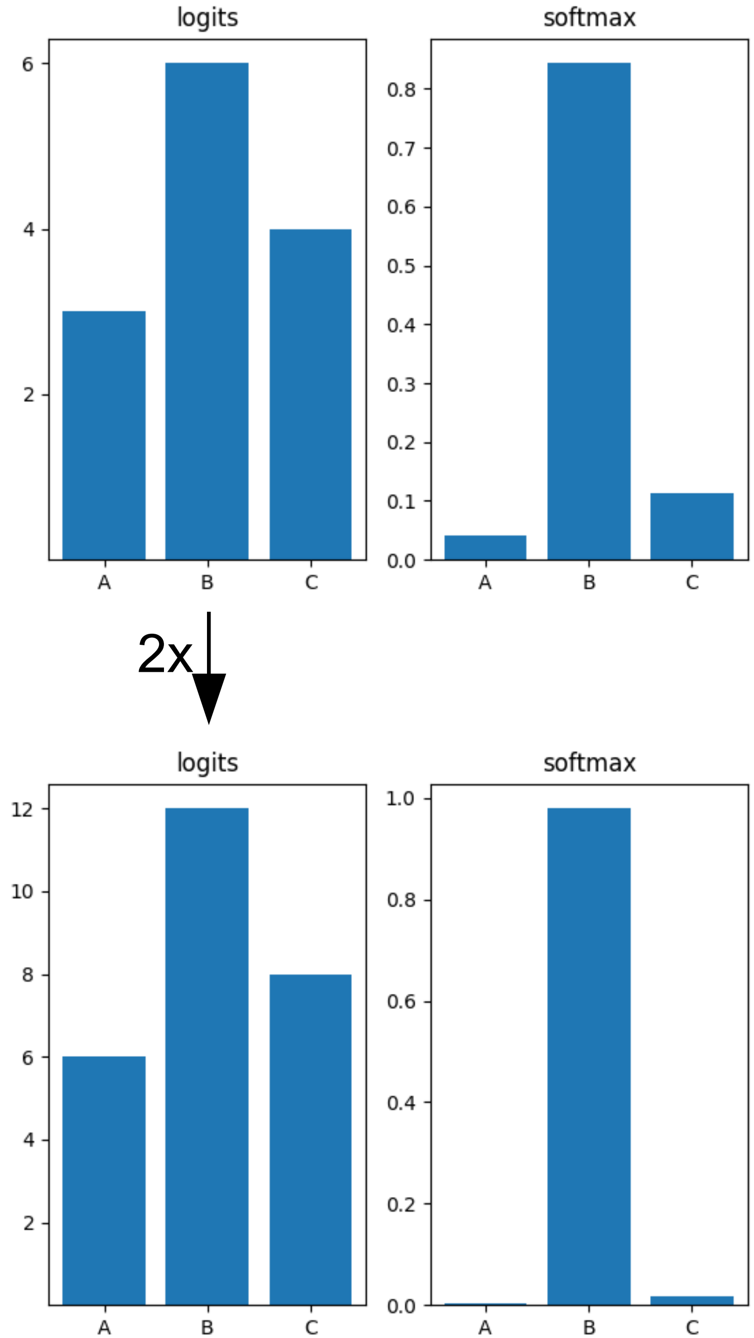

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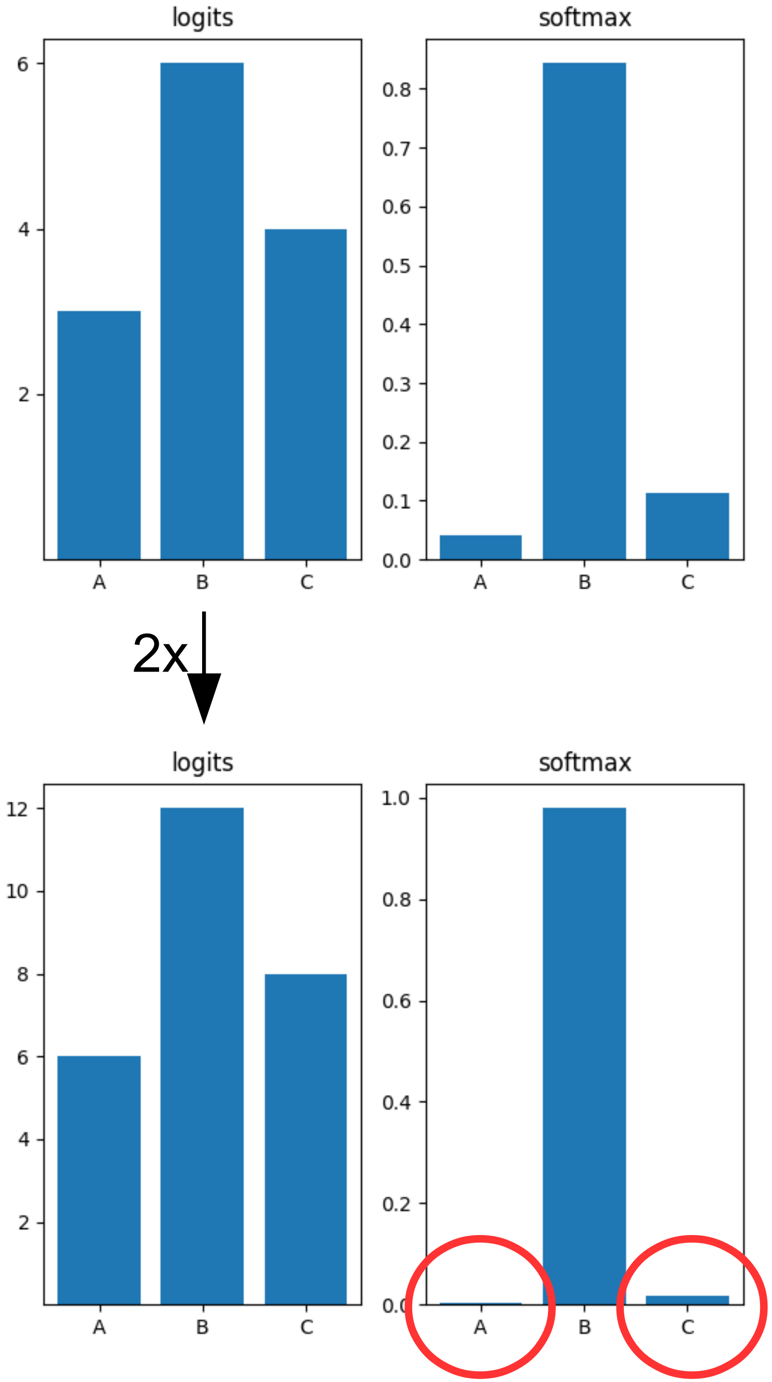

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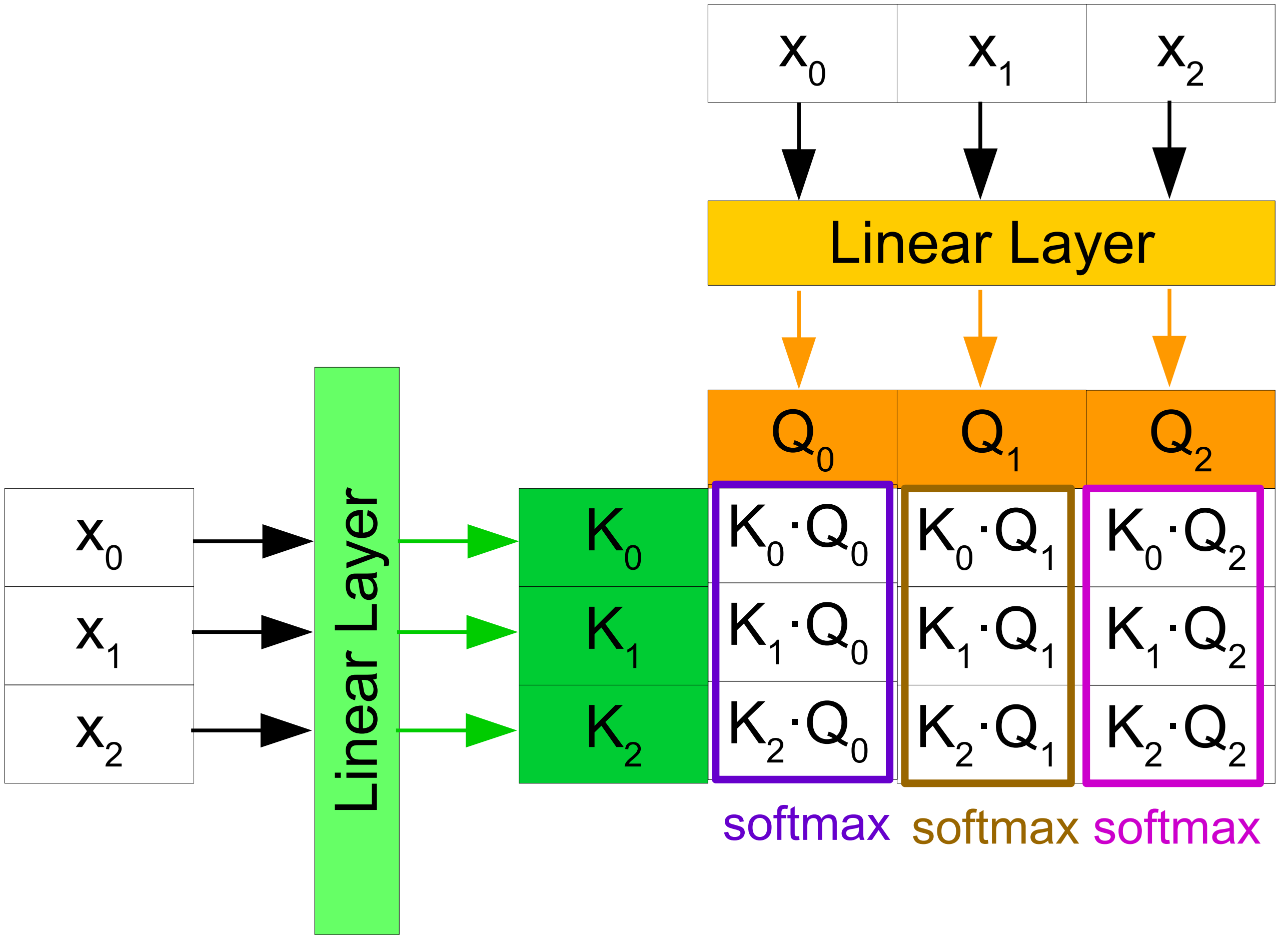

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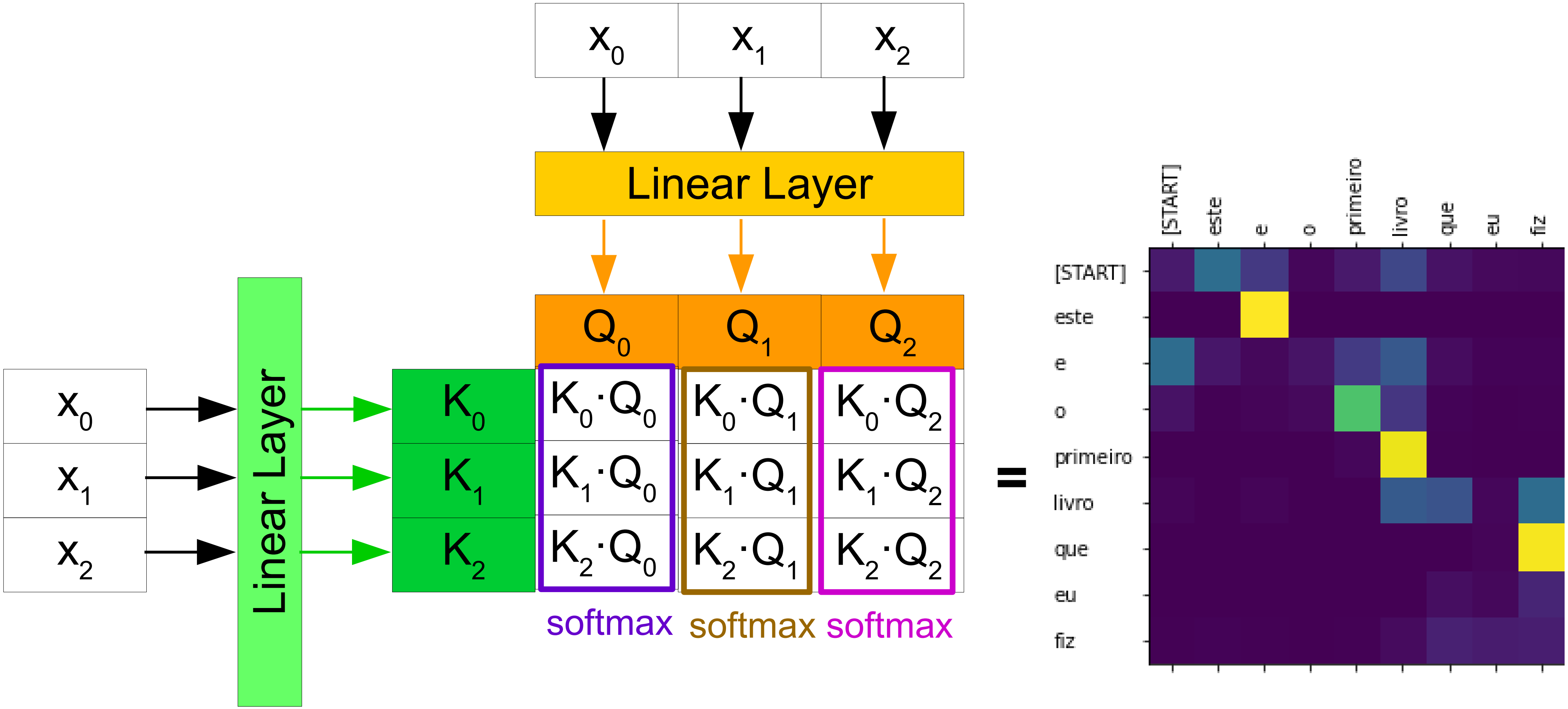


Here: 3 words instead of 9 ;)

Image source:
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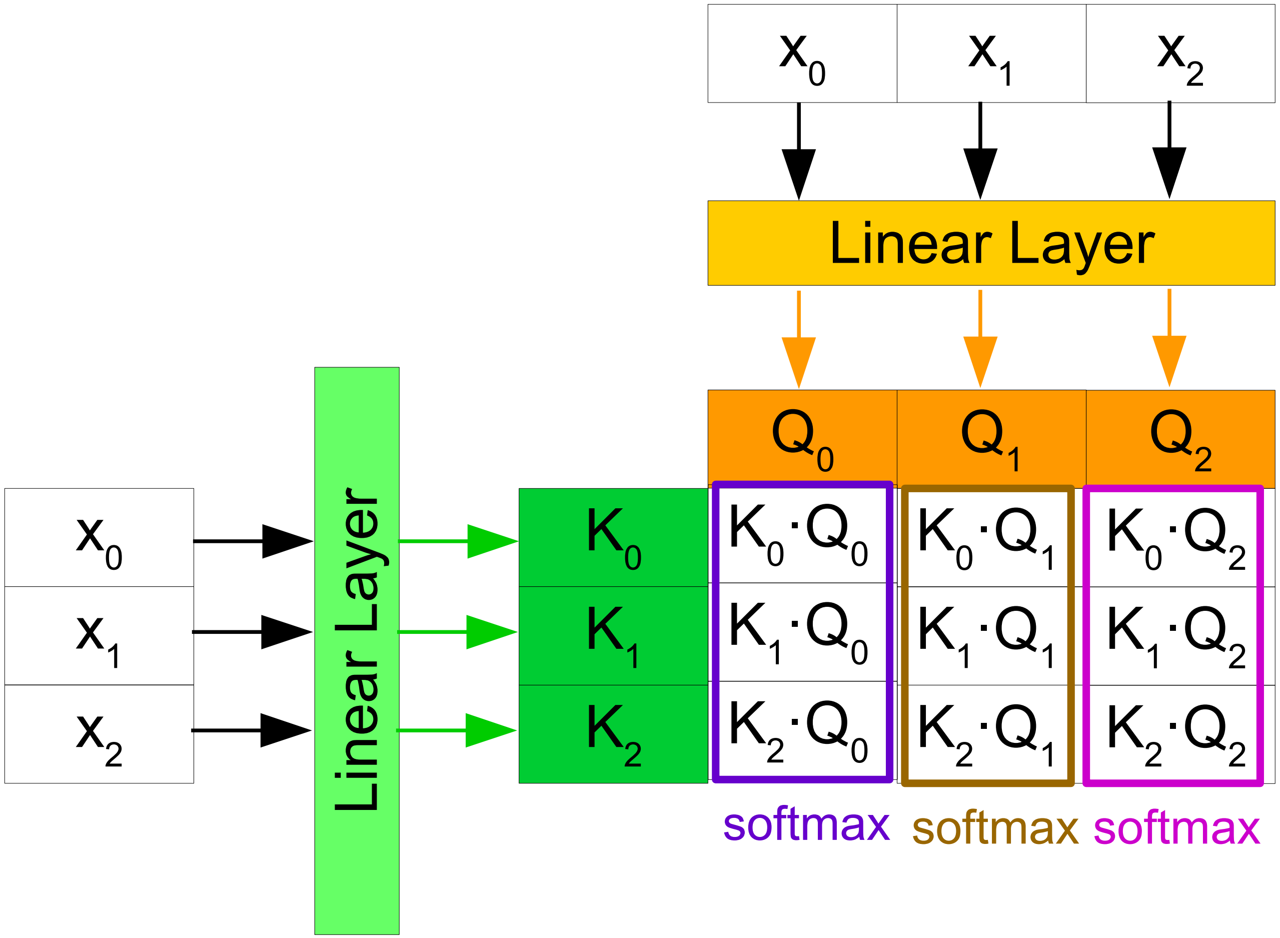

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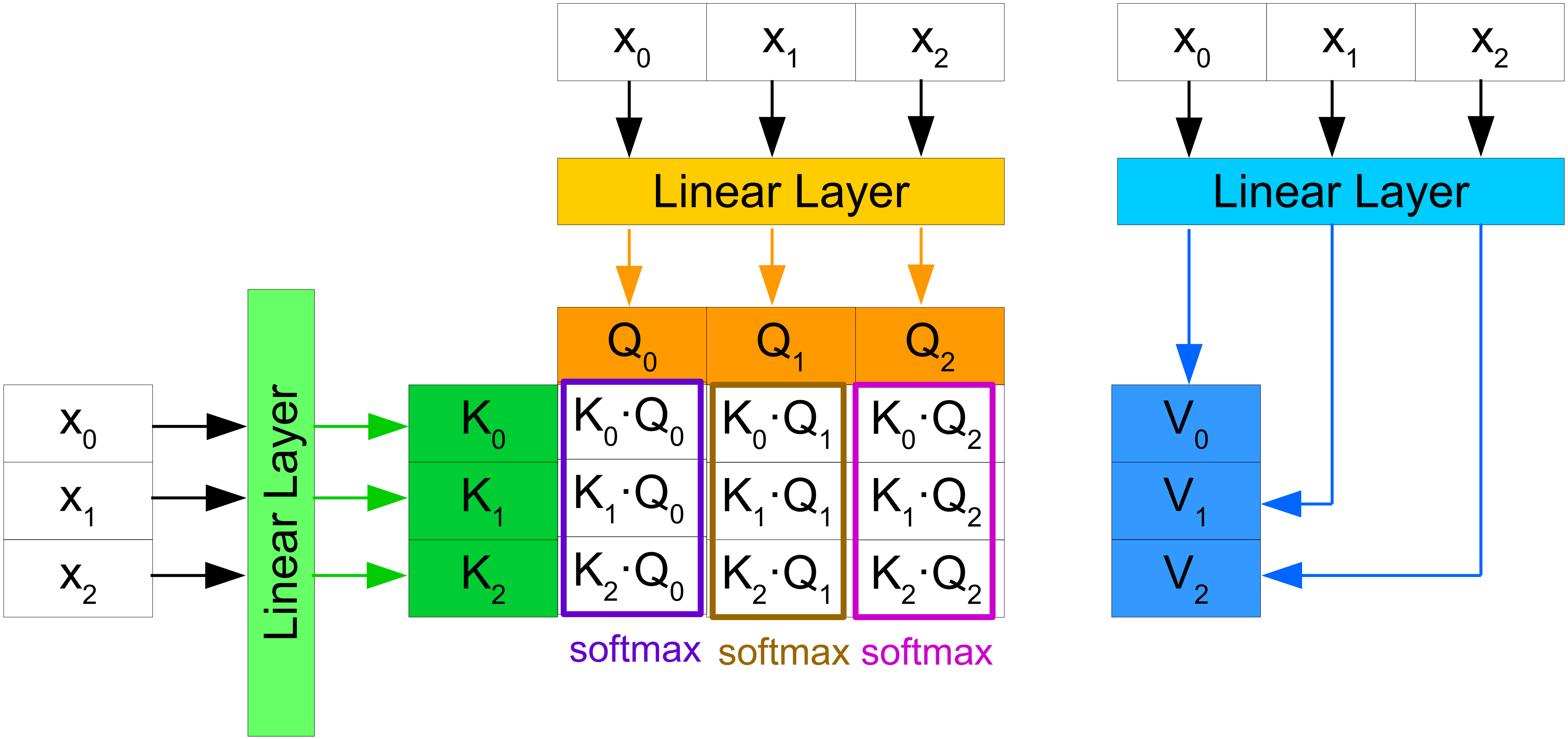

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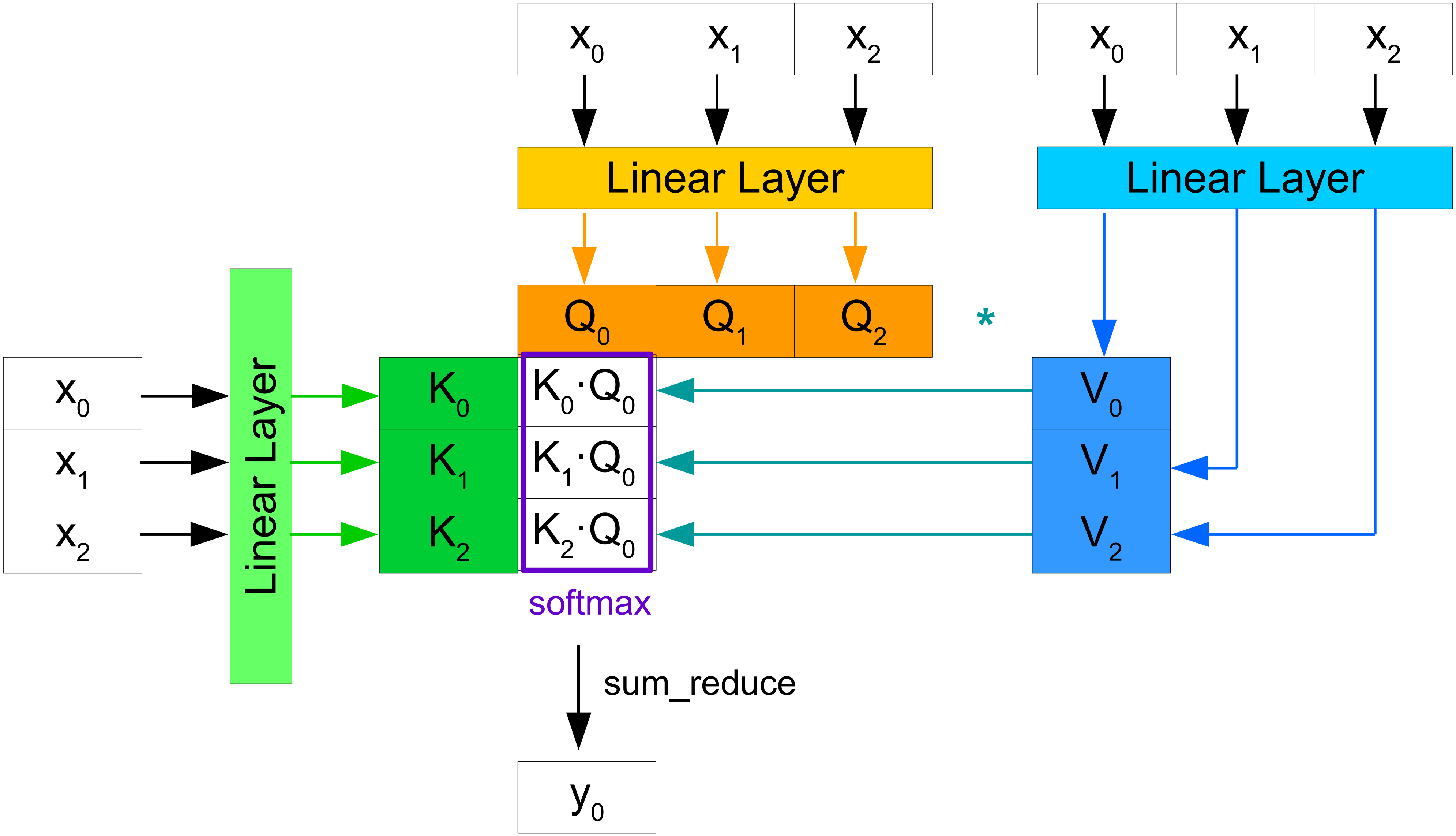

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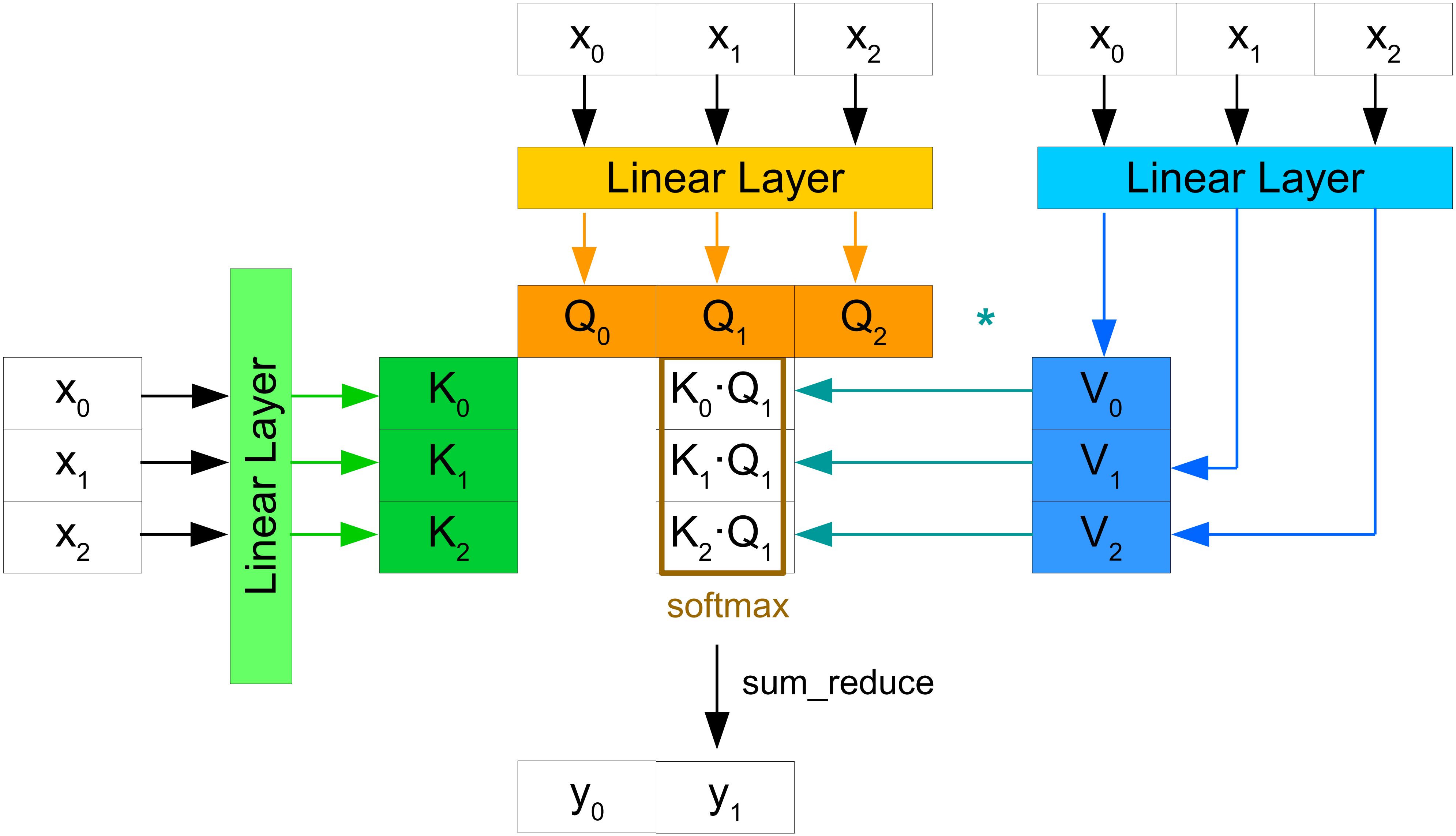

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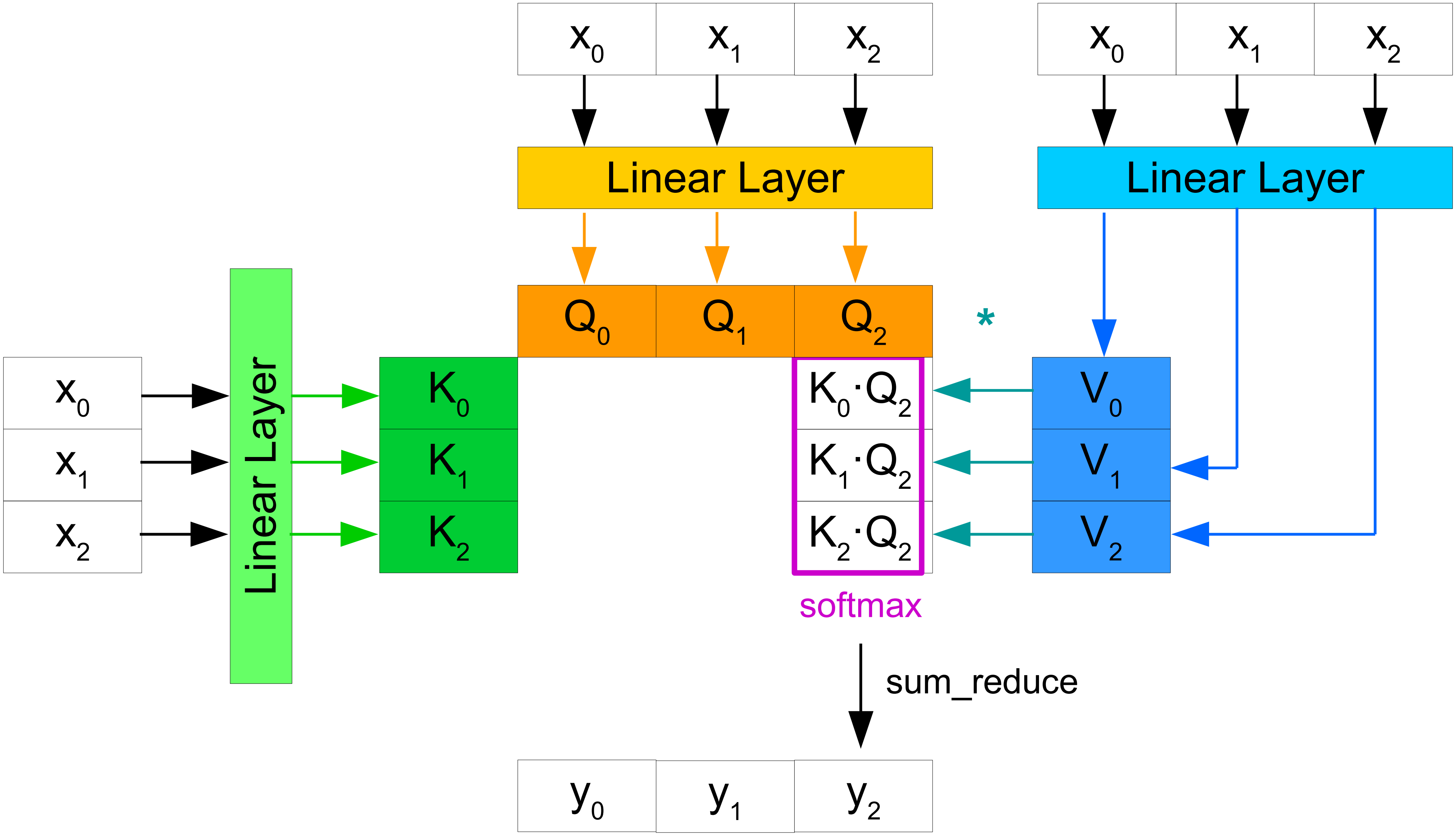

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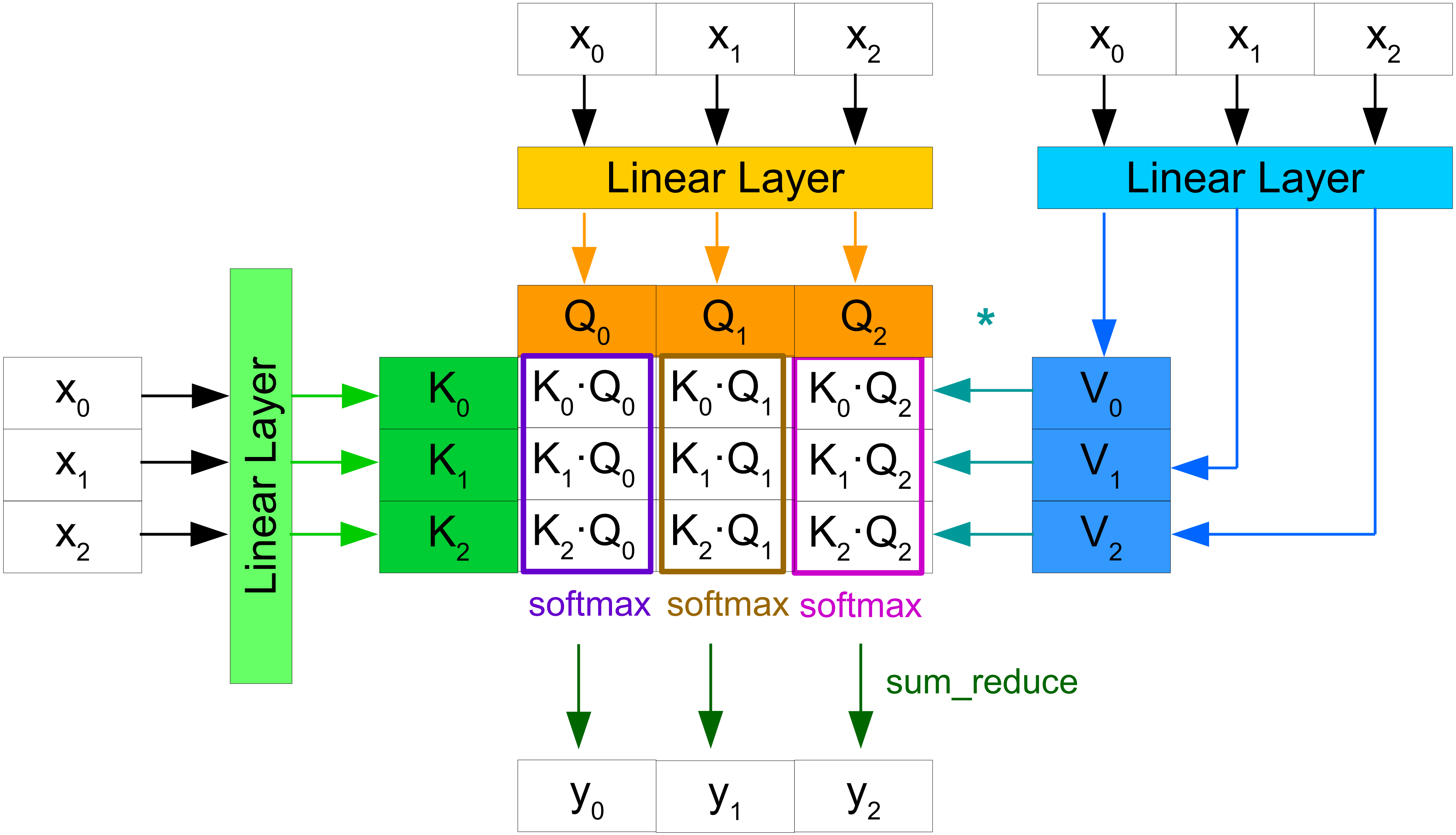

# 2.1 Multi-head attention

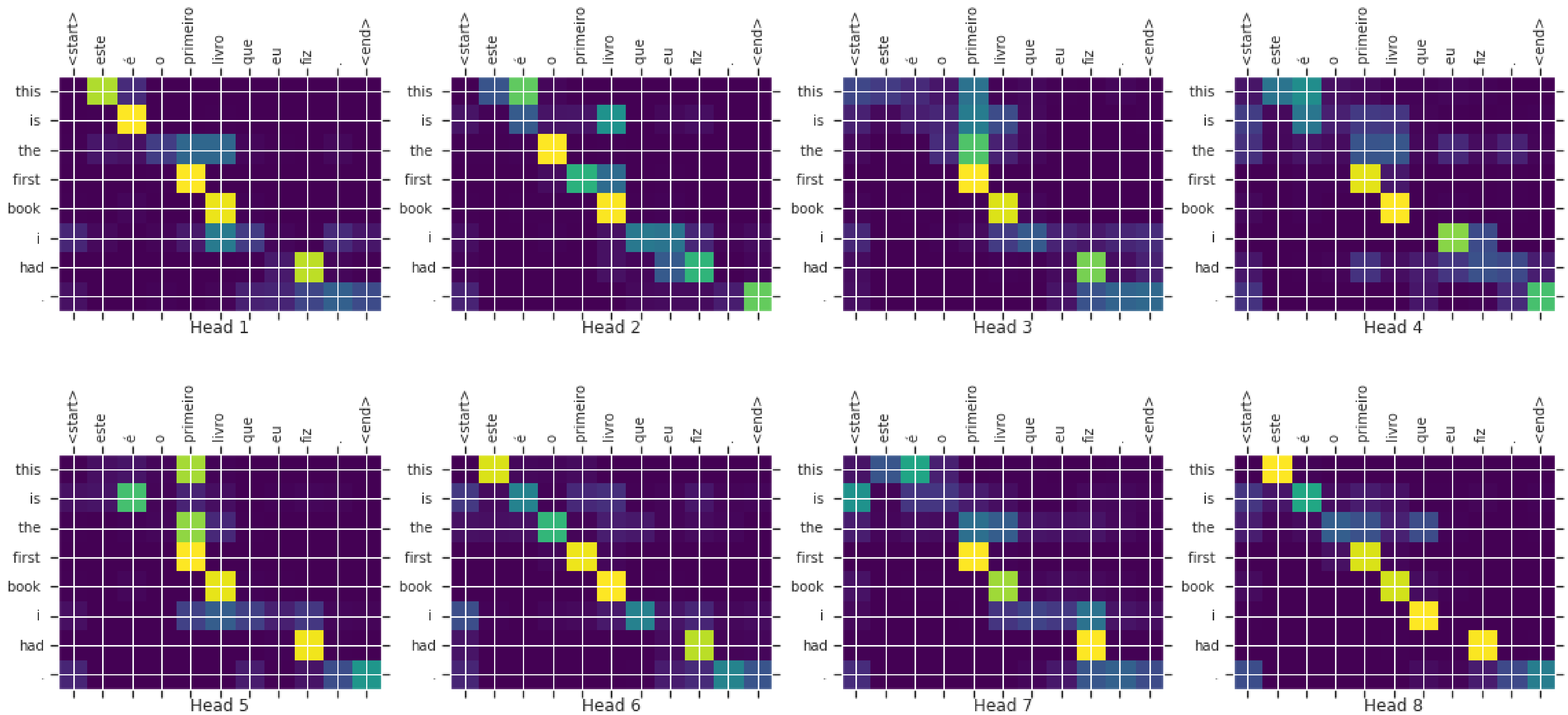


Figure 9: Heatmaps from Multi-head attention [2].

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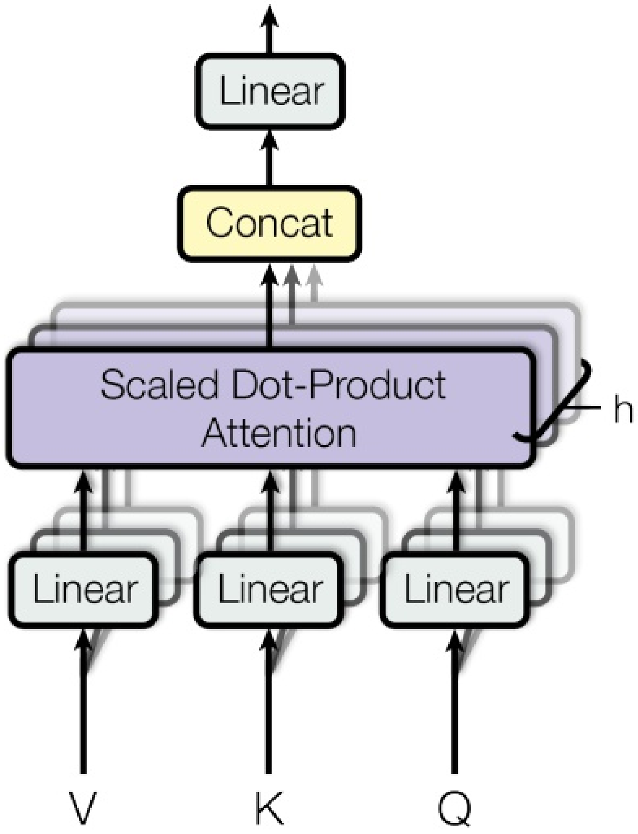
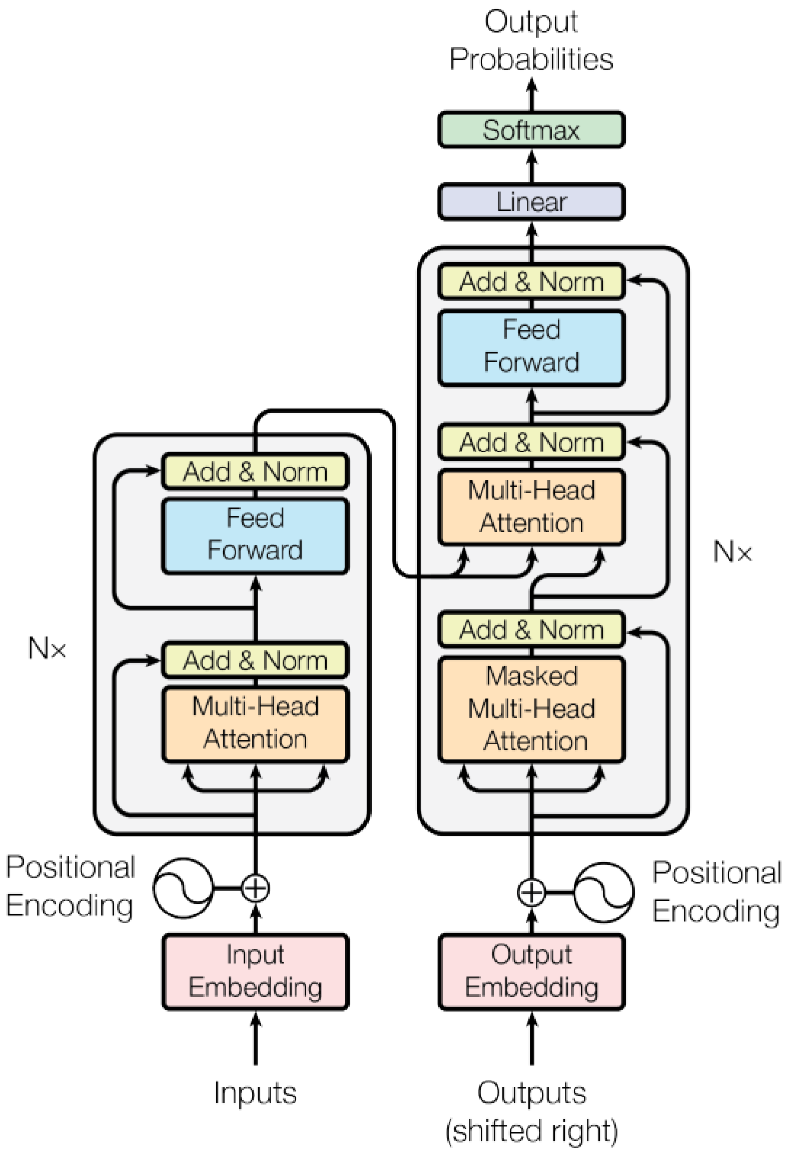



Figure 10: Overview of multi-head attention [2].




# 3. Intuitive understanding of the transformer architecture

Image sources:
https://machinelearningmastery.com/wp-content/uploads/2021/08/attention_research_1-727x1024.png
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## 3.1 Let's build a transformer

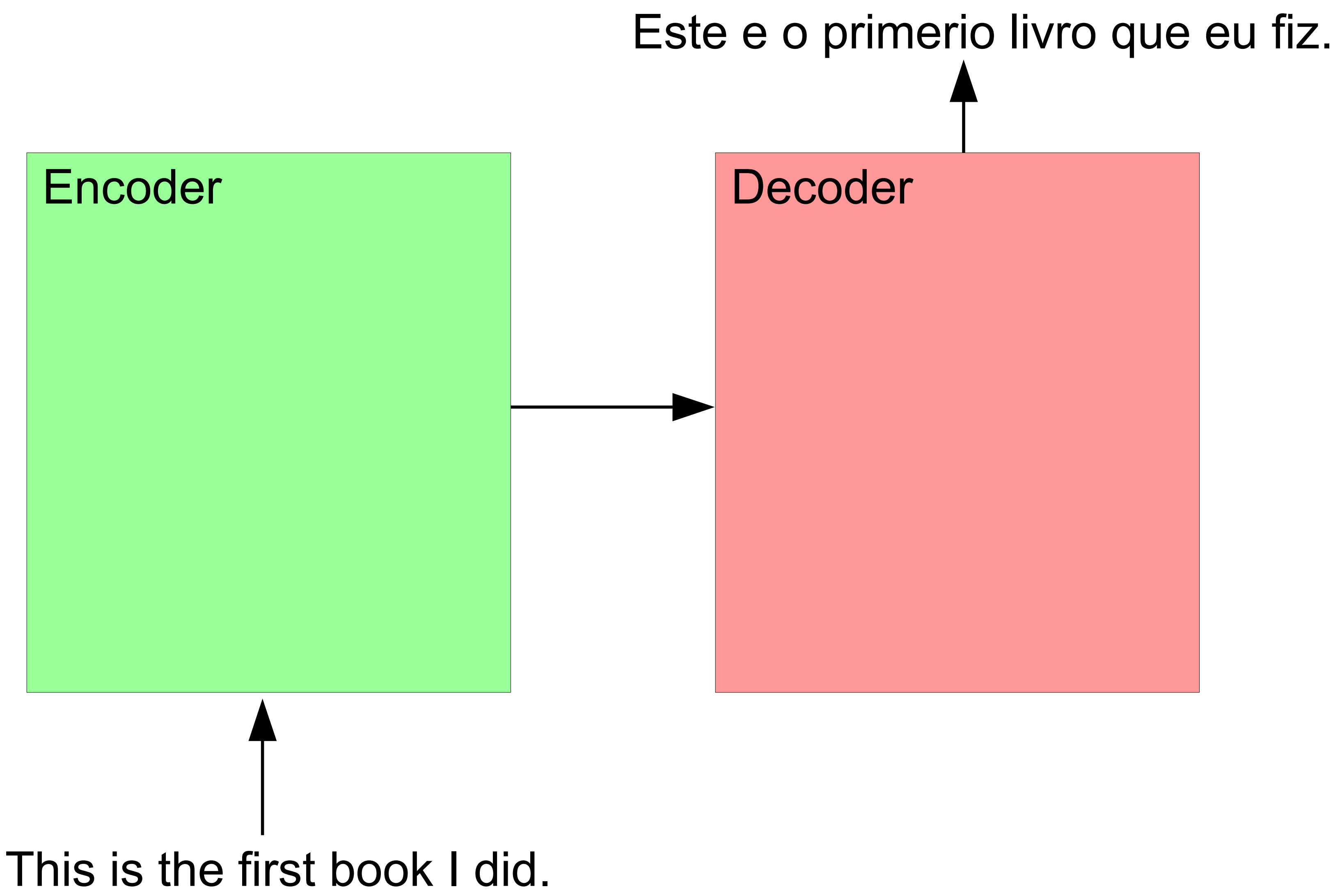


Figure 11: Neural machine translation based on a transformer [2].

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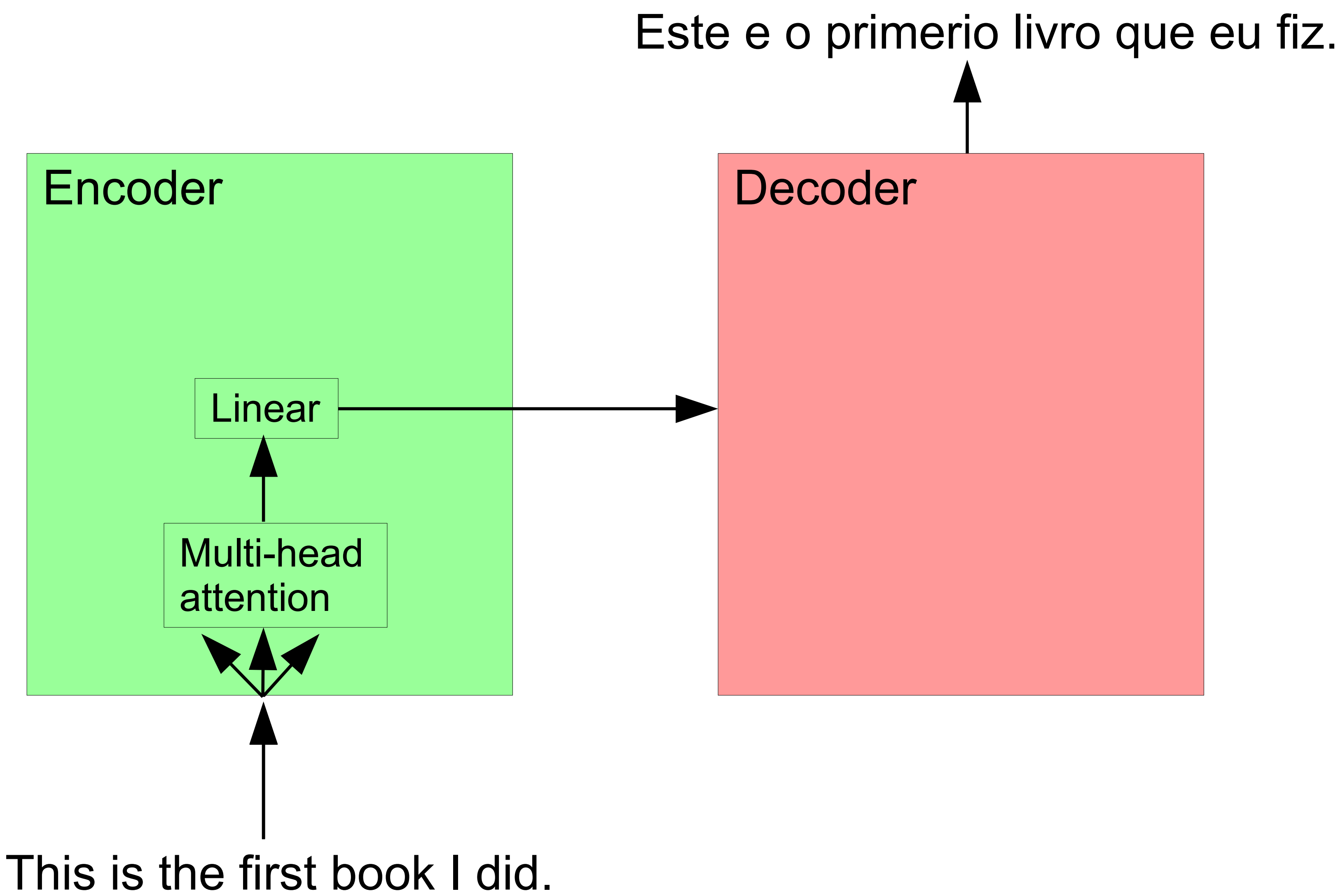


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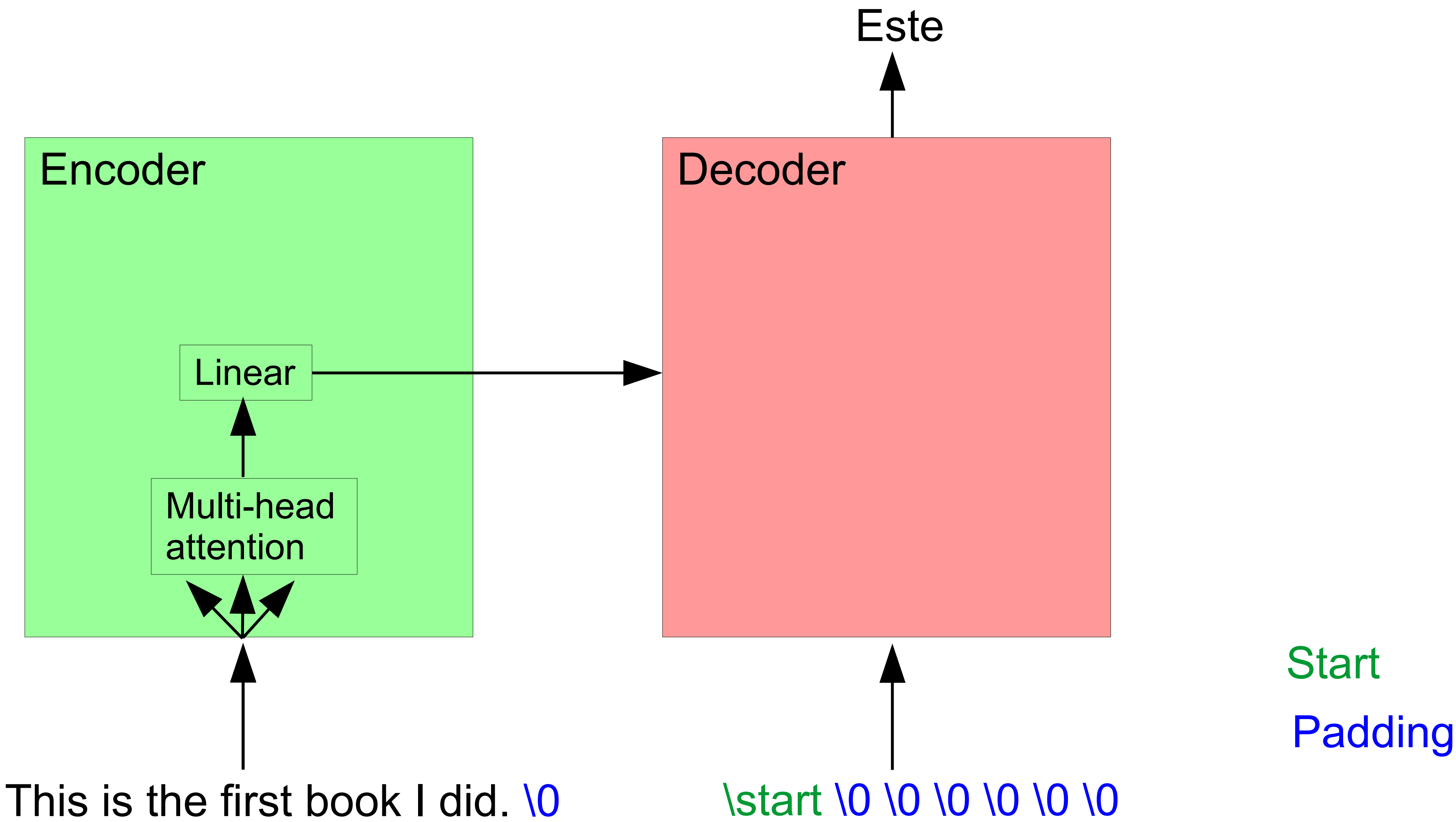


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# 3.1 Let's build a transformer

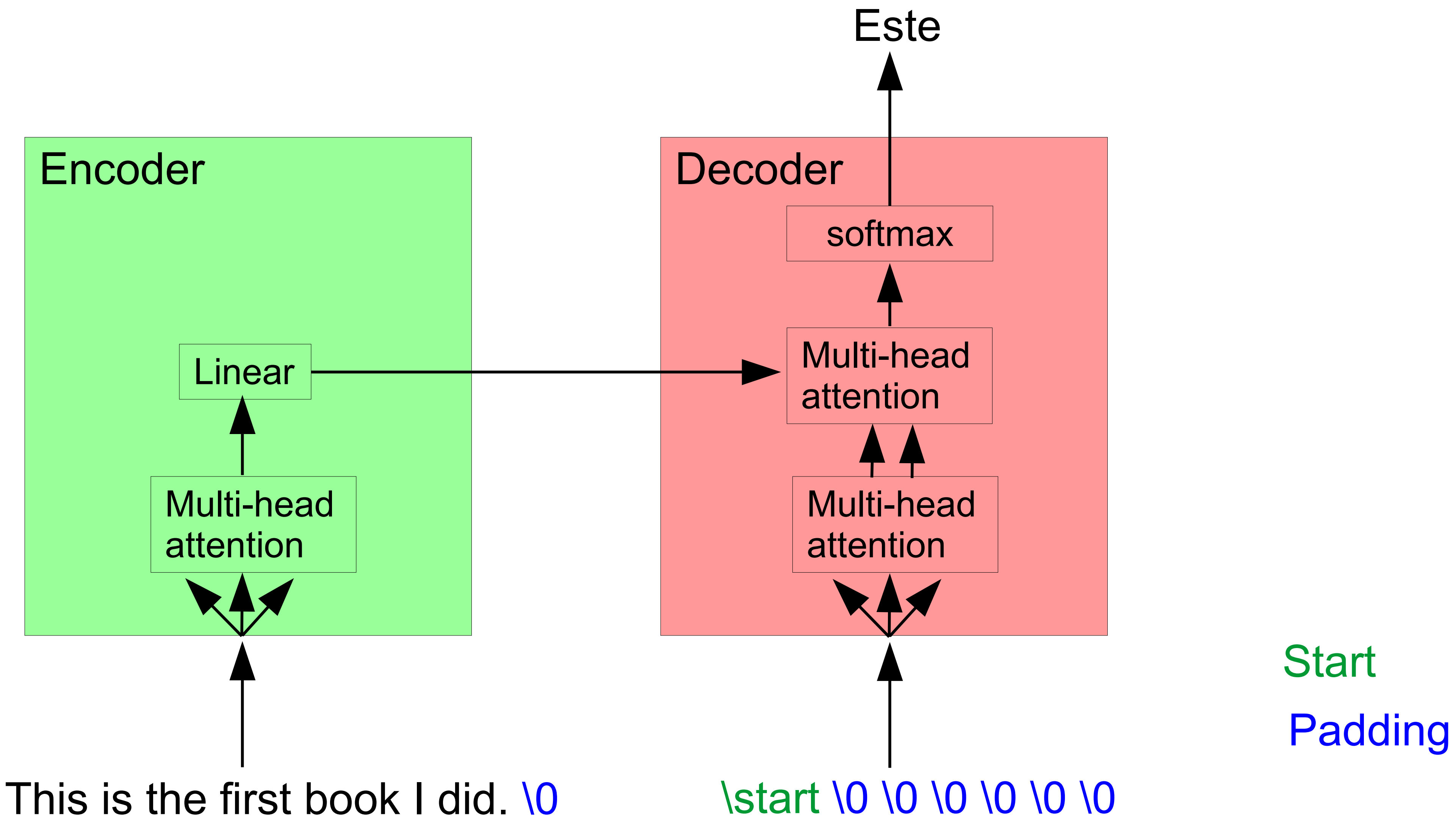


Figure 11: Neural machine translation based on a transformer [2].

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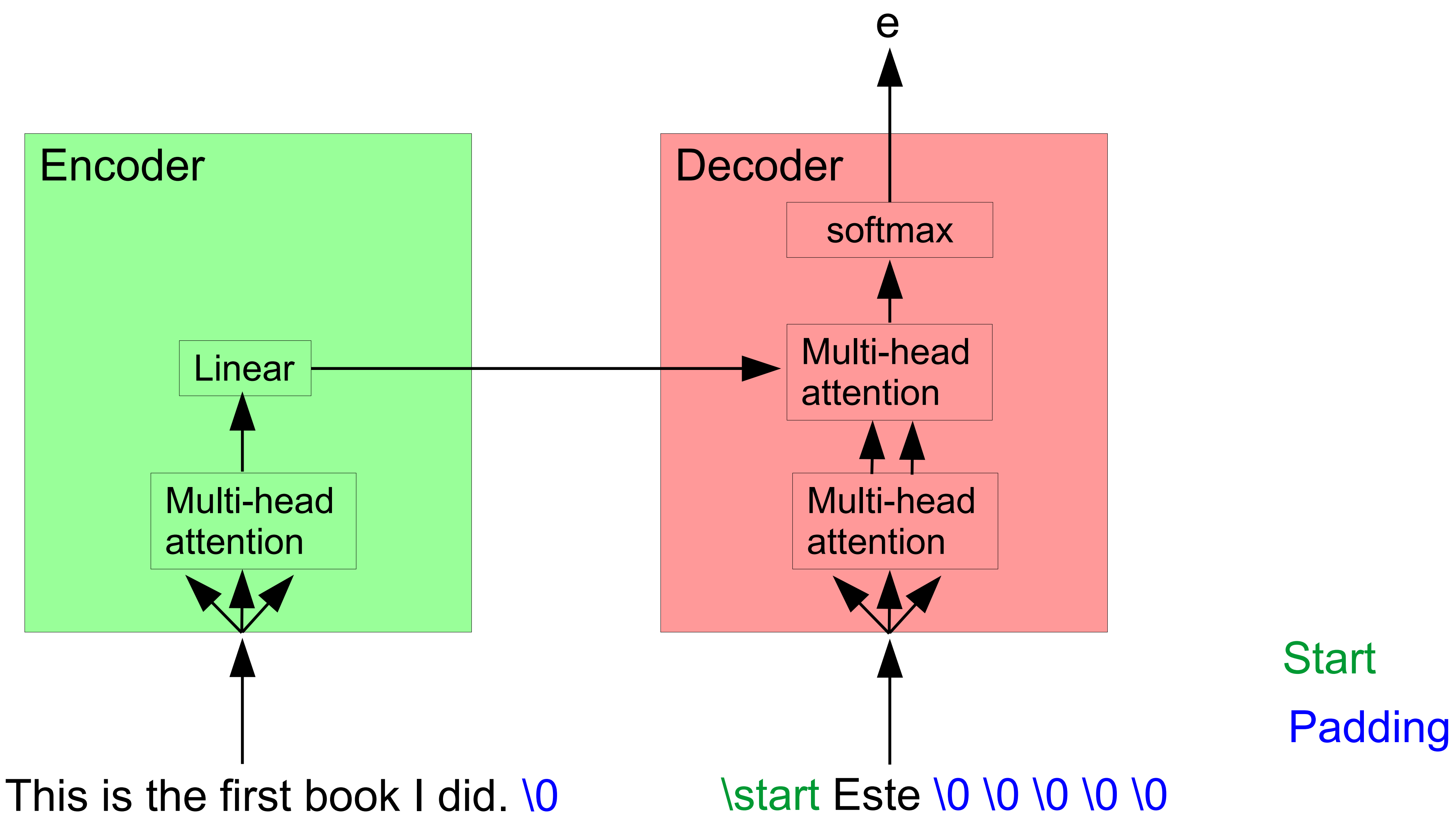


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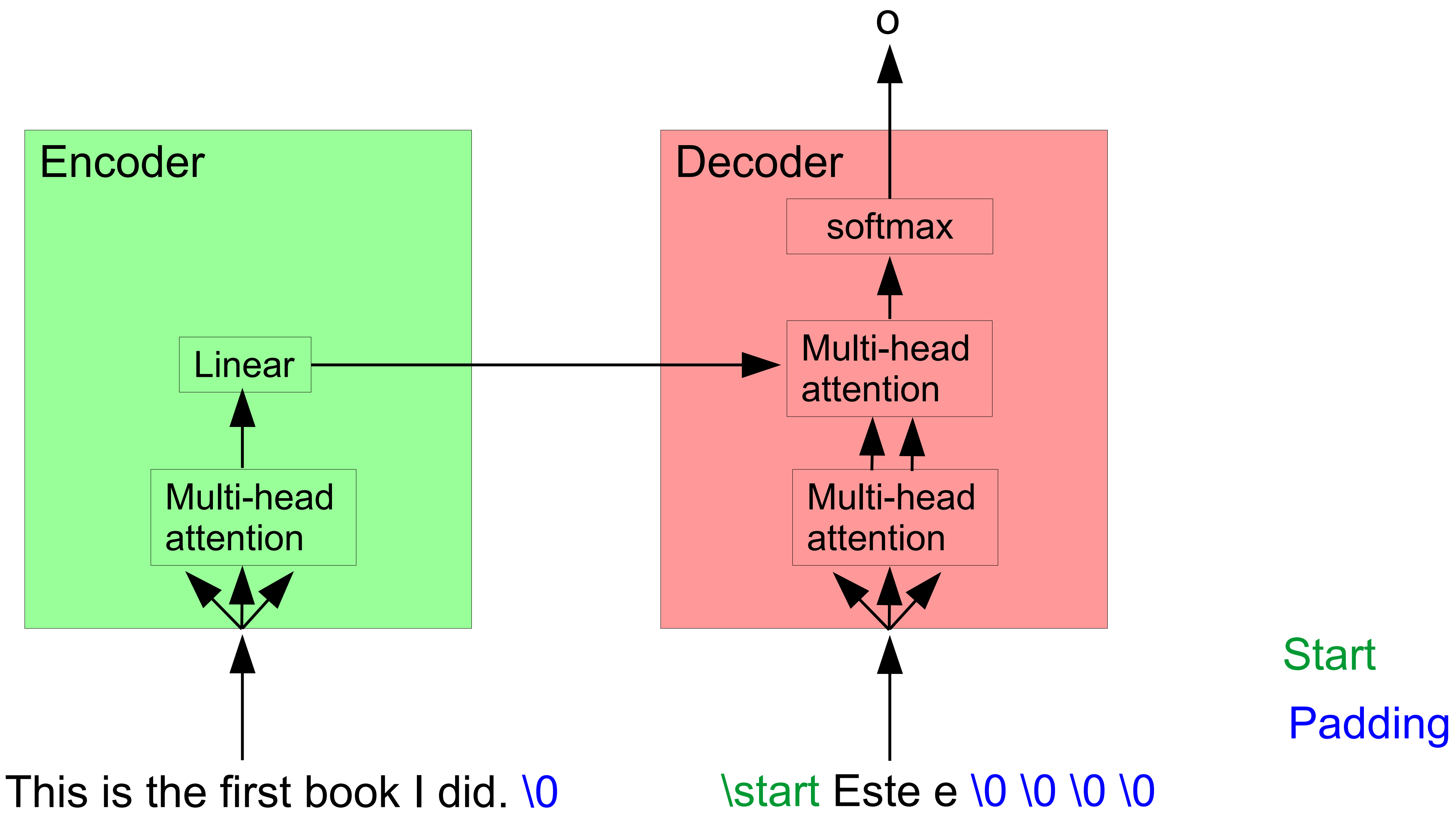


Figure 11: Neural machine translation based on a transformer [2].

# 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

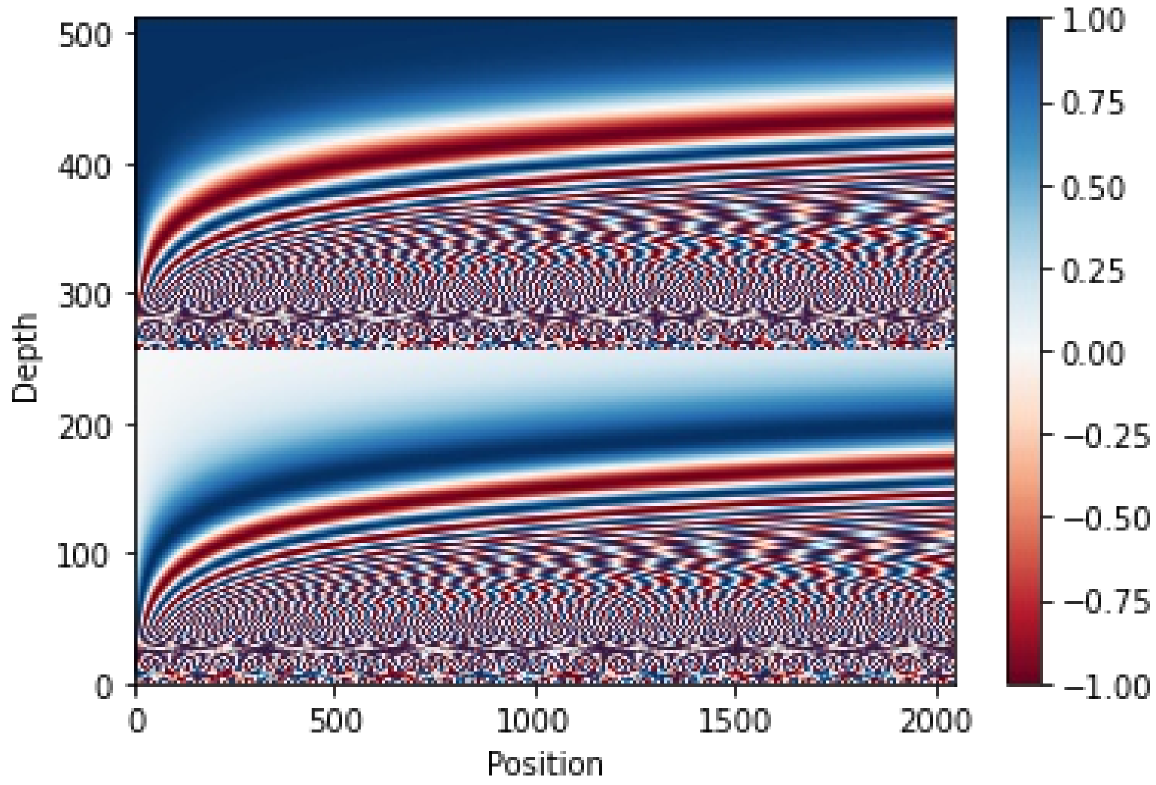


Figure 12: Positional encoding applied in a transformer [13].

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

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

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

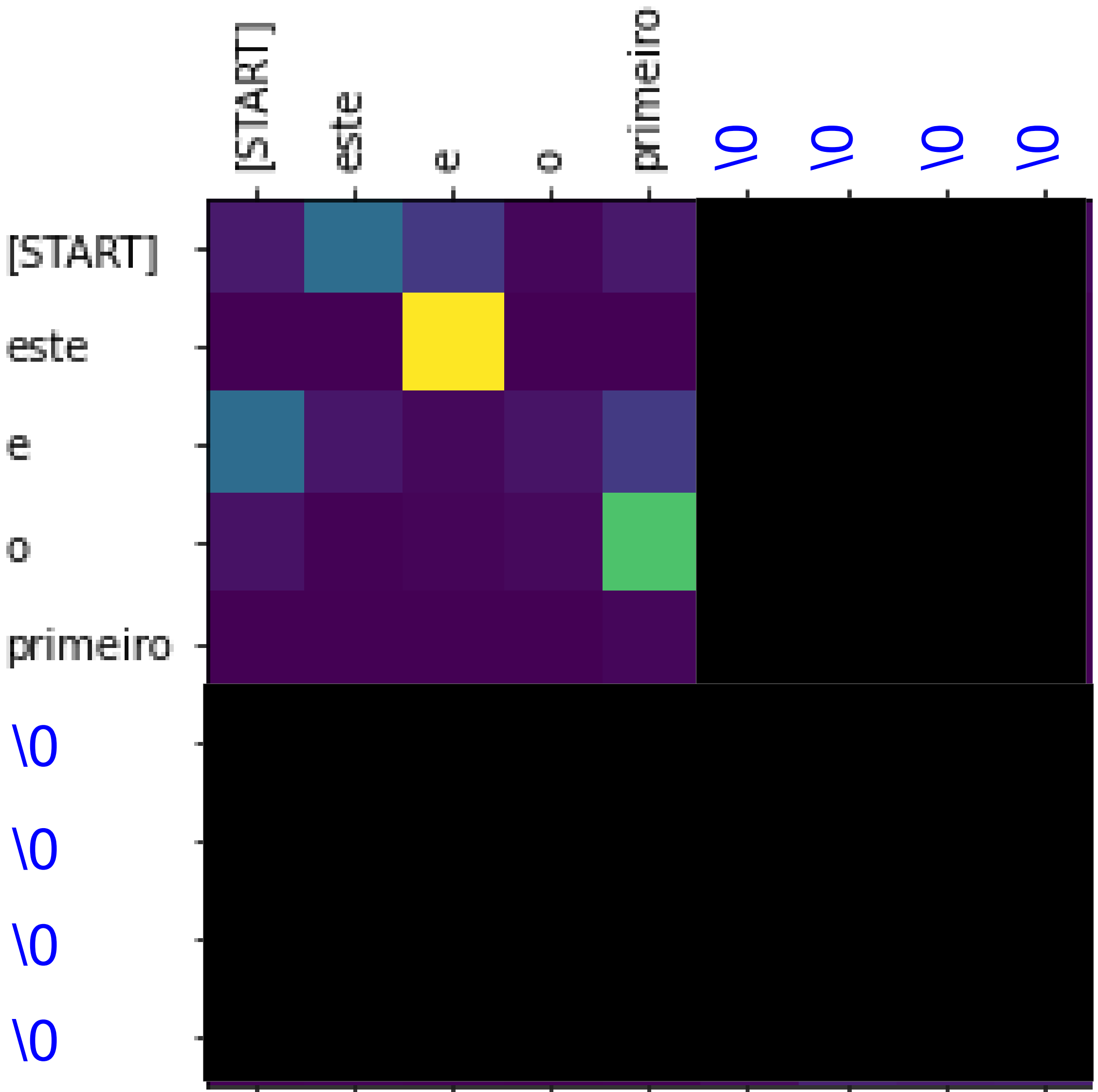


Figure 13: Masking padding words [11].

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.

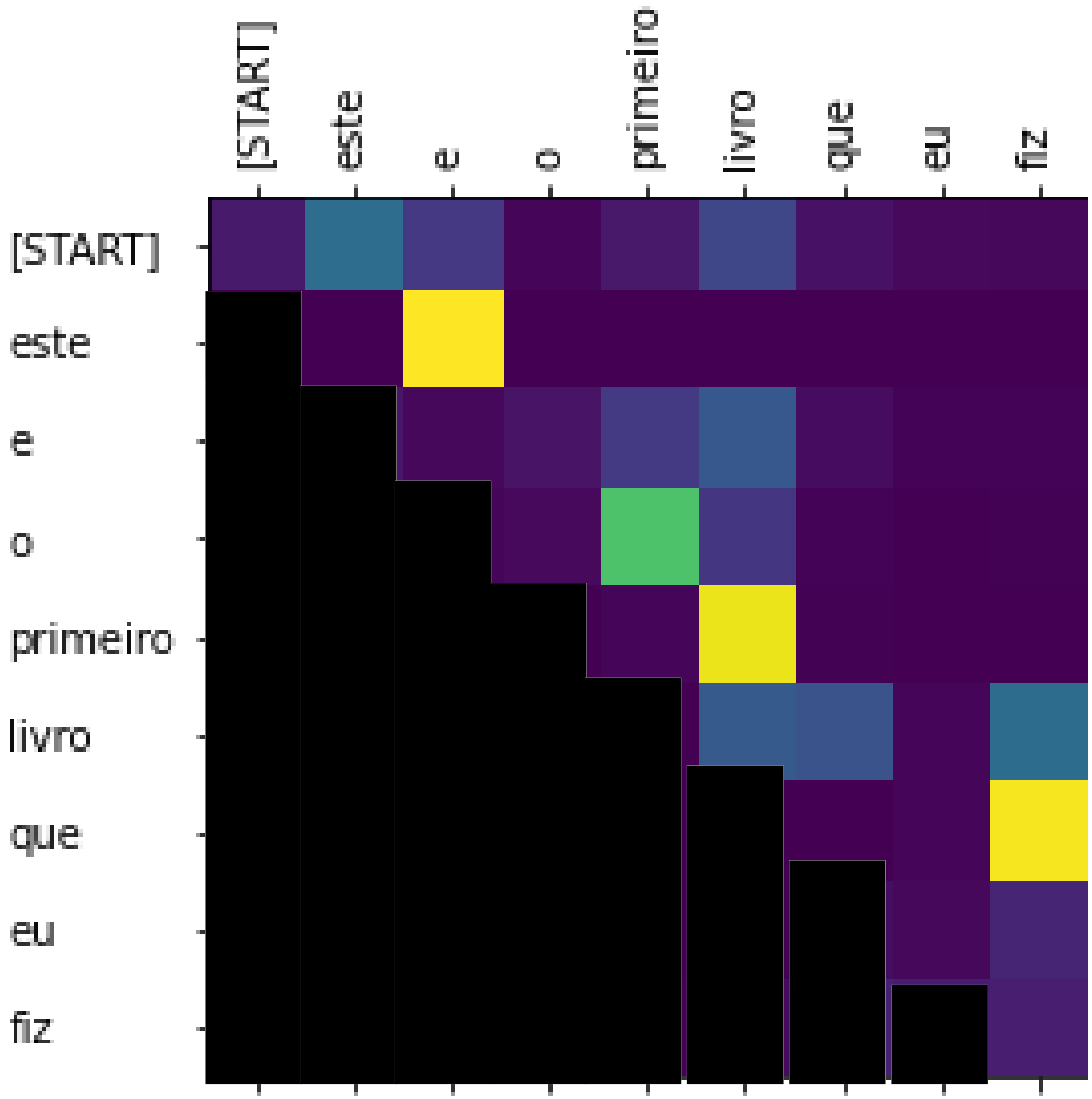


Figure 14: All values in the self-attention matrix above the diagonal are zero [11].

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

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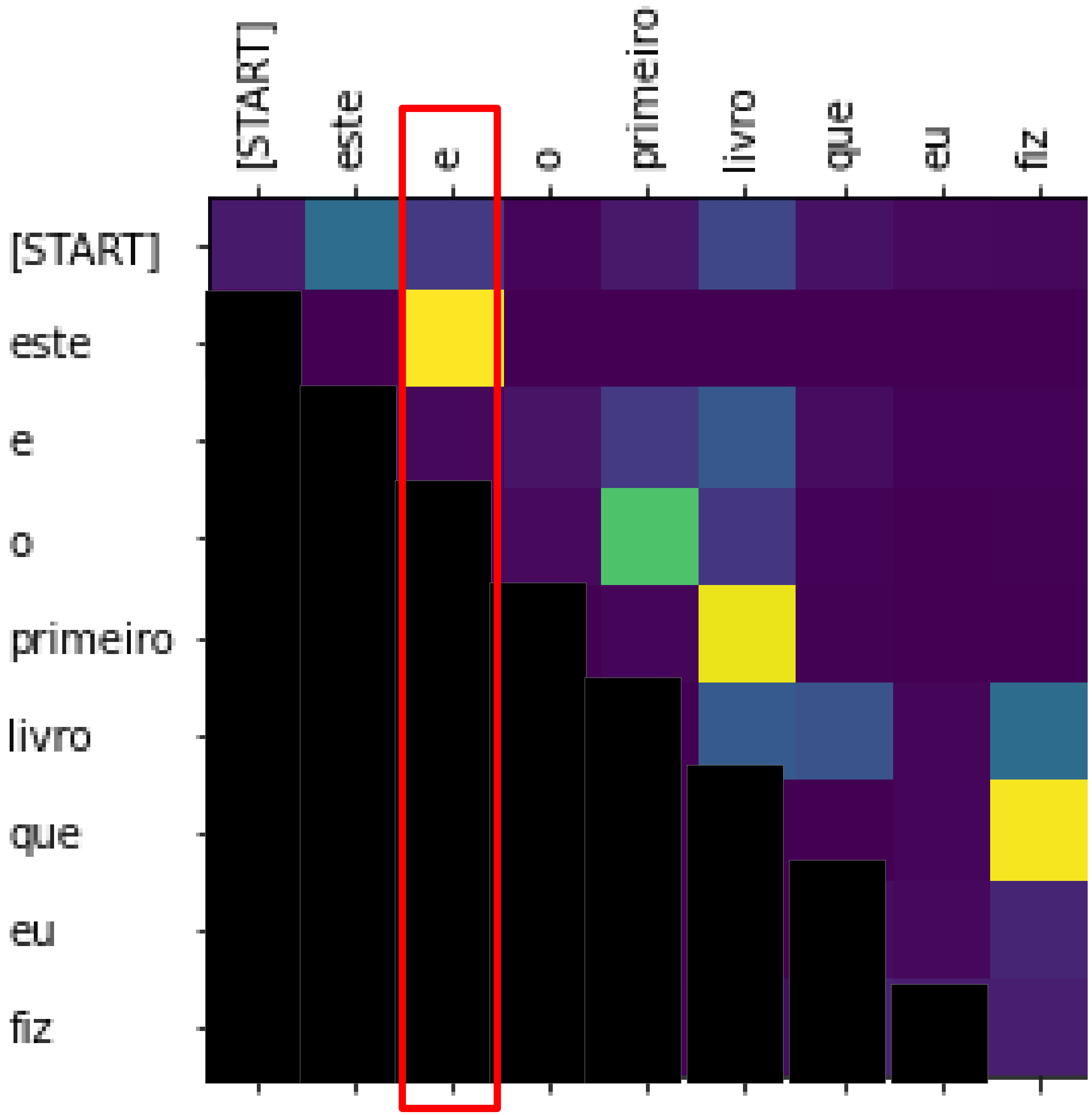



Figure 14: All values in the self-attention matrix above the diagonal are zero [11].

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

# 3.1 Let's build a transformer

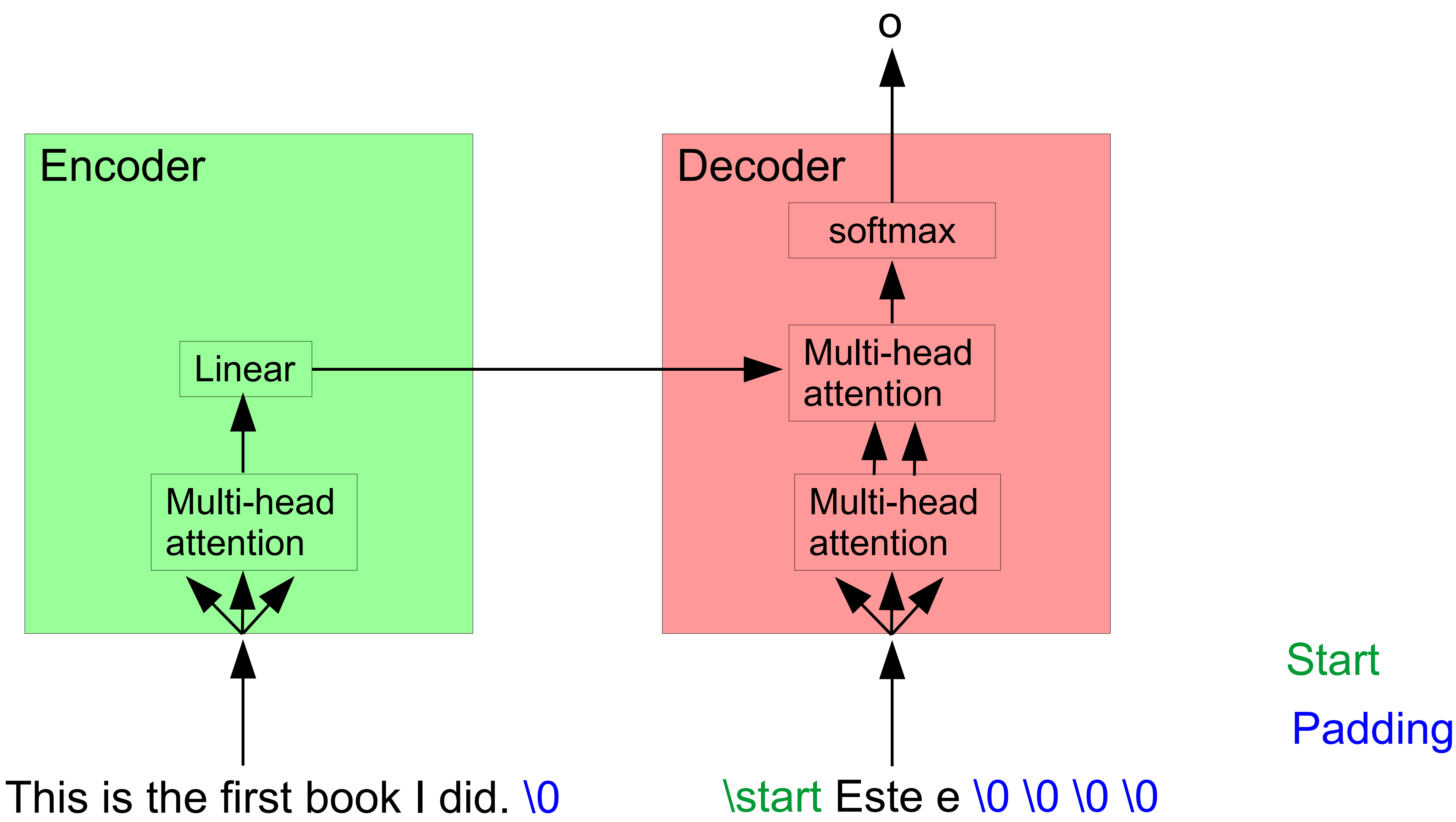



Figure 11: Neural machine translation based on a transformer [2].

## 3.4 Transformer

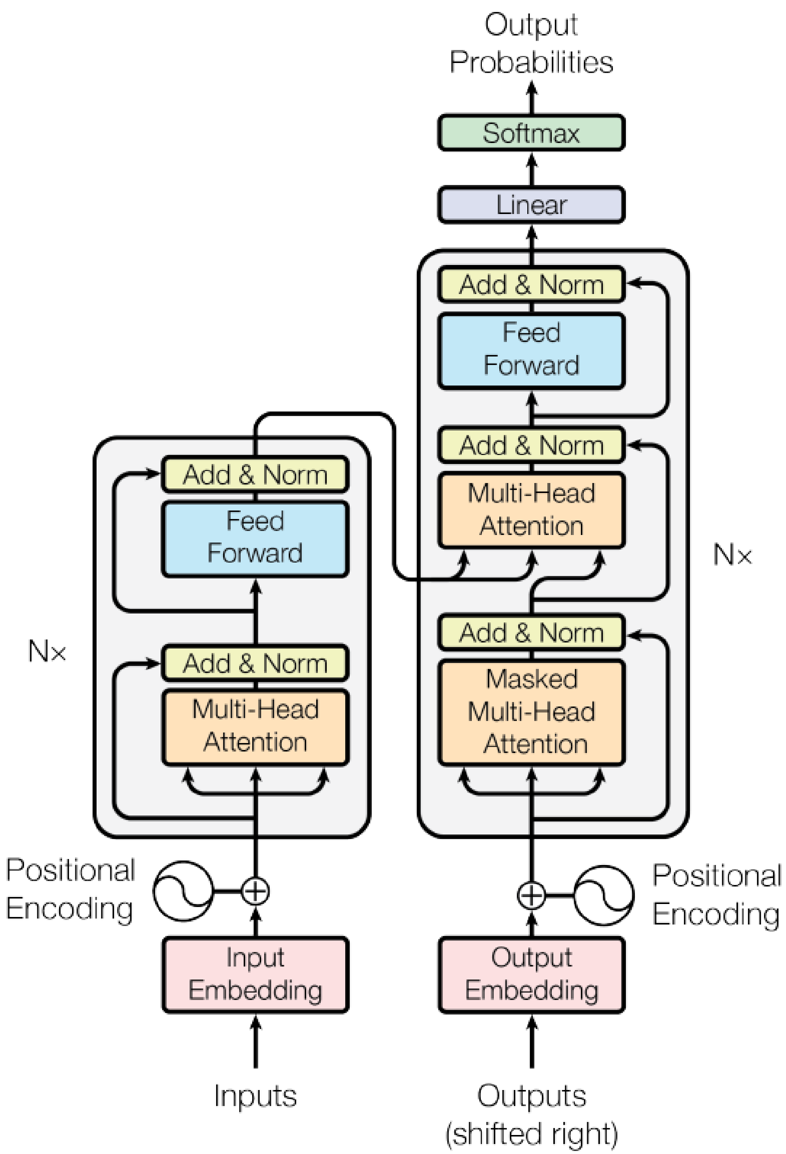



Figure 15: Transformer Architecture [2].

# 3.4 Transformer

Residual connection

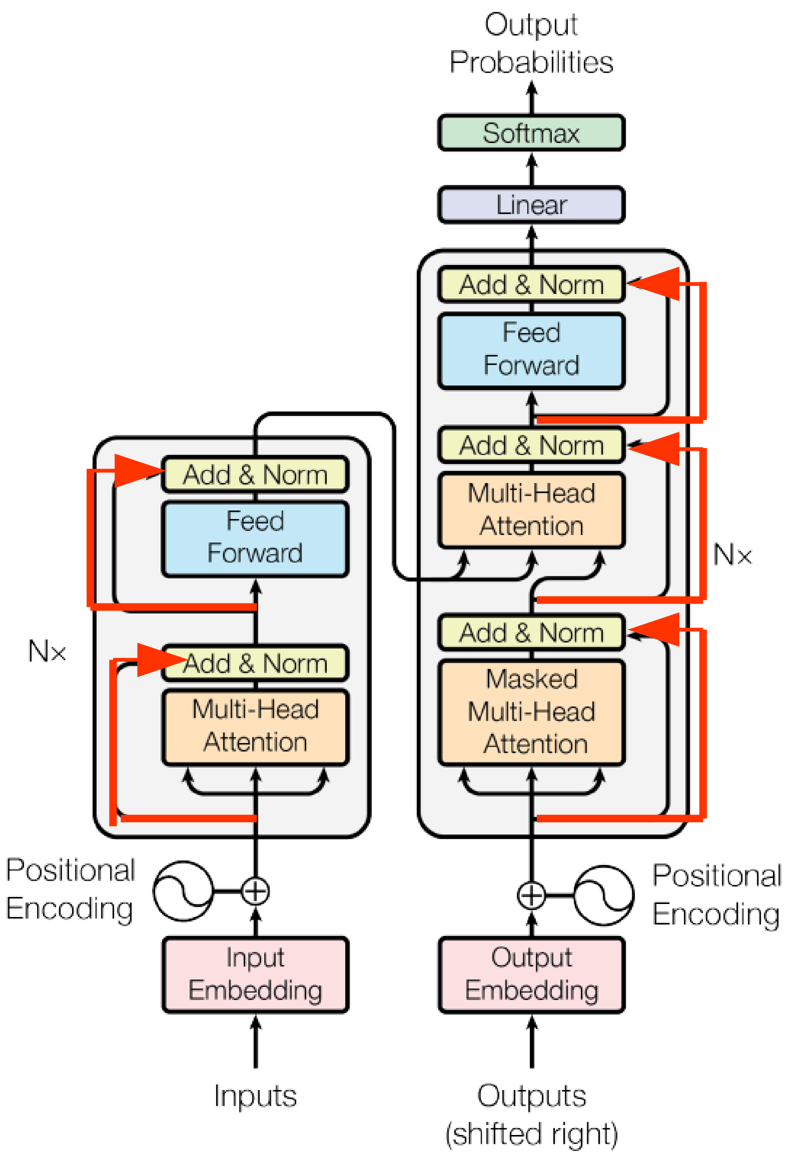



Figure 15: Transformer Architecture [2].

# 3.4 Transformer

Layer normalization

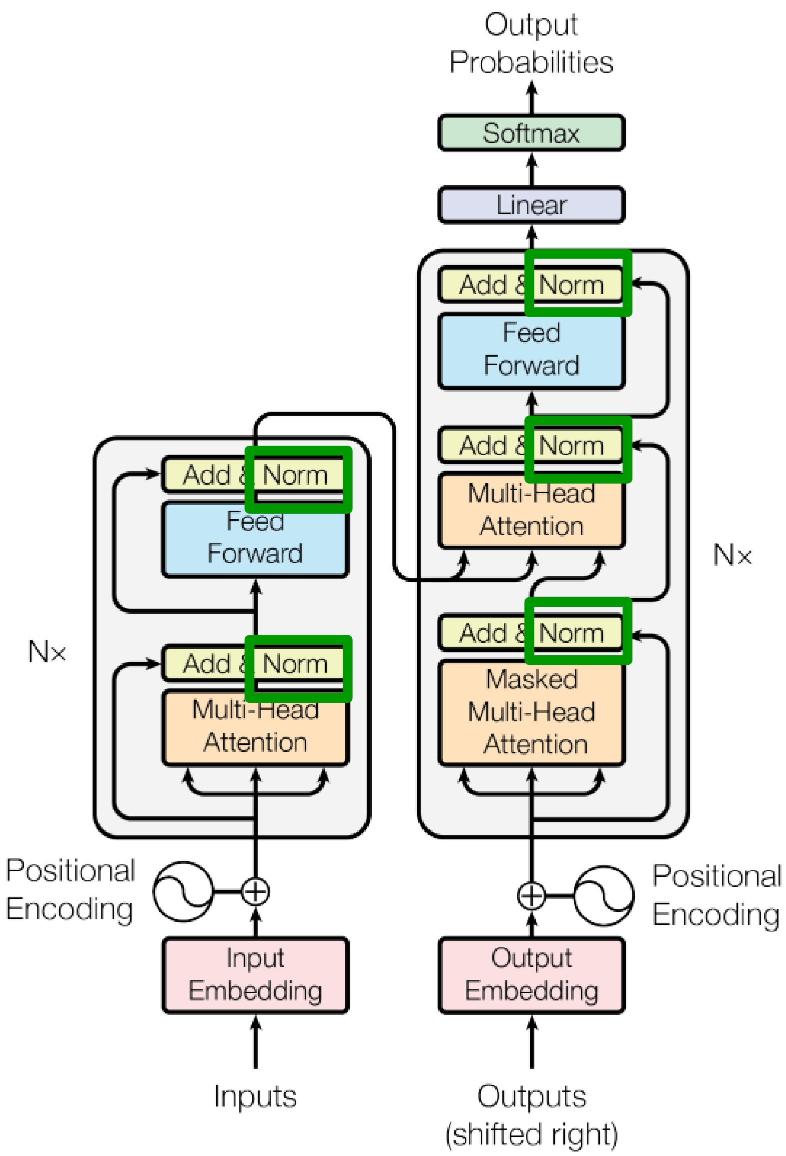



Figure 15: Transformer Architecture [2].

# 4. Transformers in Natural Language Processing

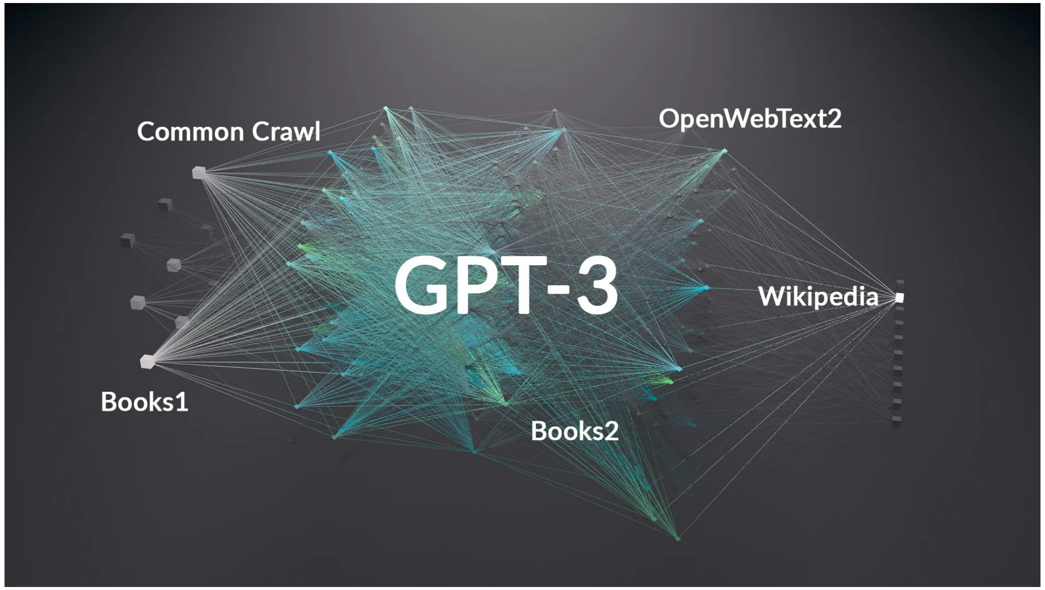



Image sources:
https://cdn-images-1.medium.com/max/428/1*lMlwRSQfzaYw1ckgS-jgZw.jpeg
https://i0.wp.com/katzlberger.ai/wp-content/uploads/2021/04/GPT-3-Datenquellen.jpg?resize=1400%2C800&ssl=1
(call dates: 20.07.22)

# 4.1 BERT: Bidirectional Encoder Representations from Transformers

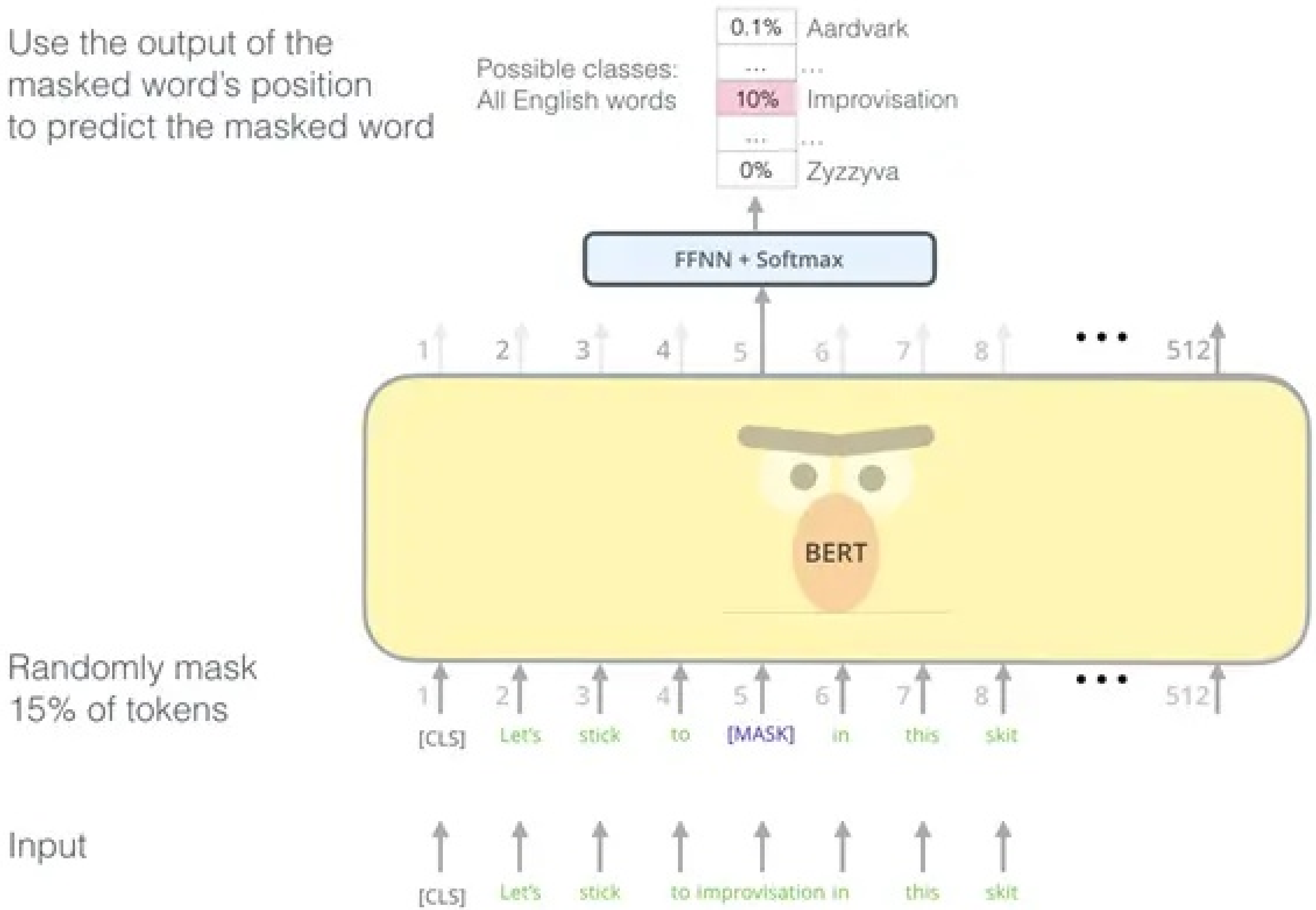



Figure 16: BERT Architecture [8].

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

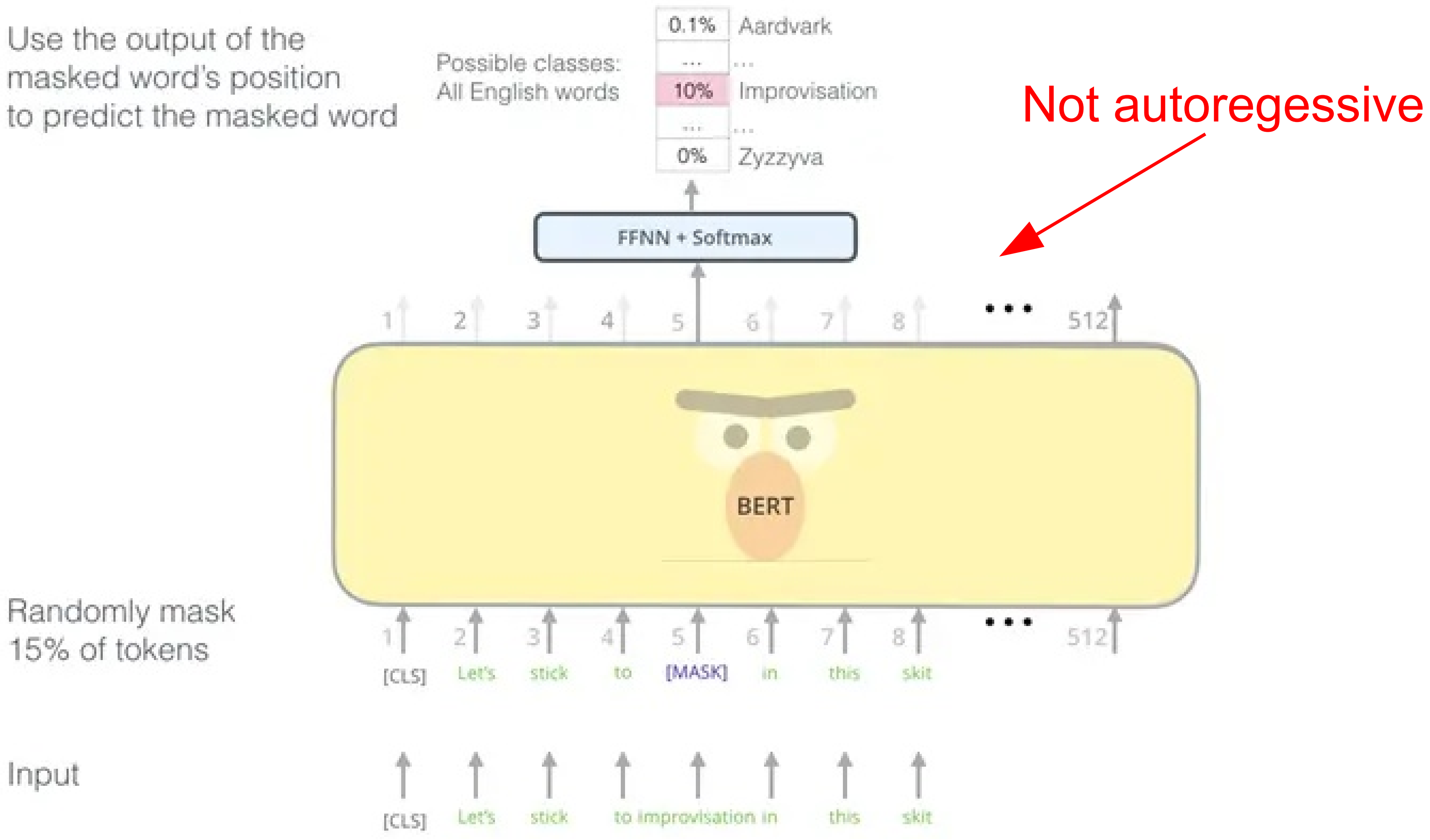



Figure 16: BERT Architecture [8].

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

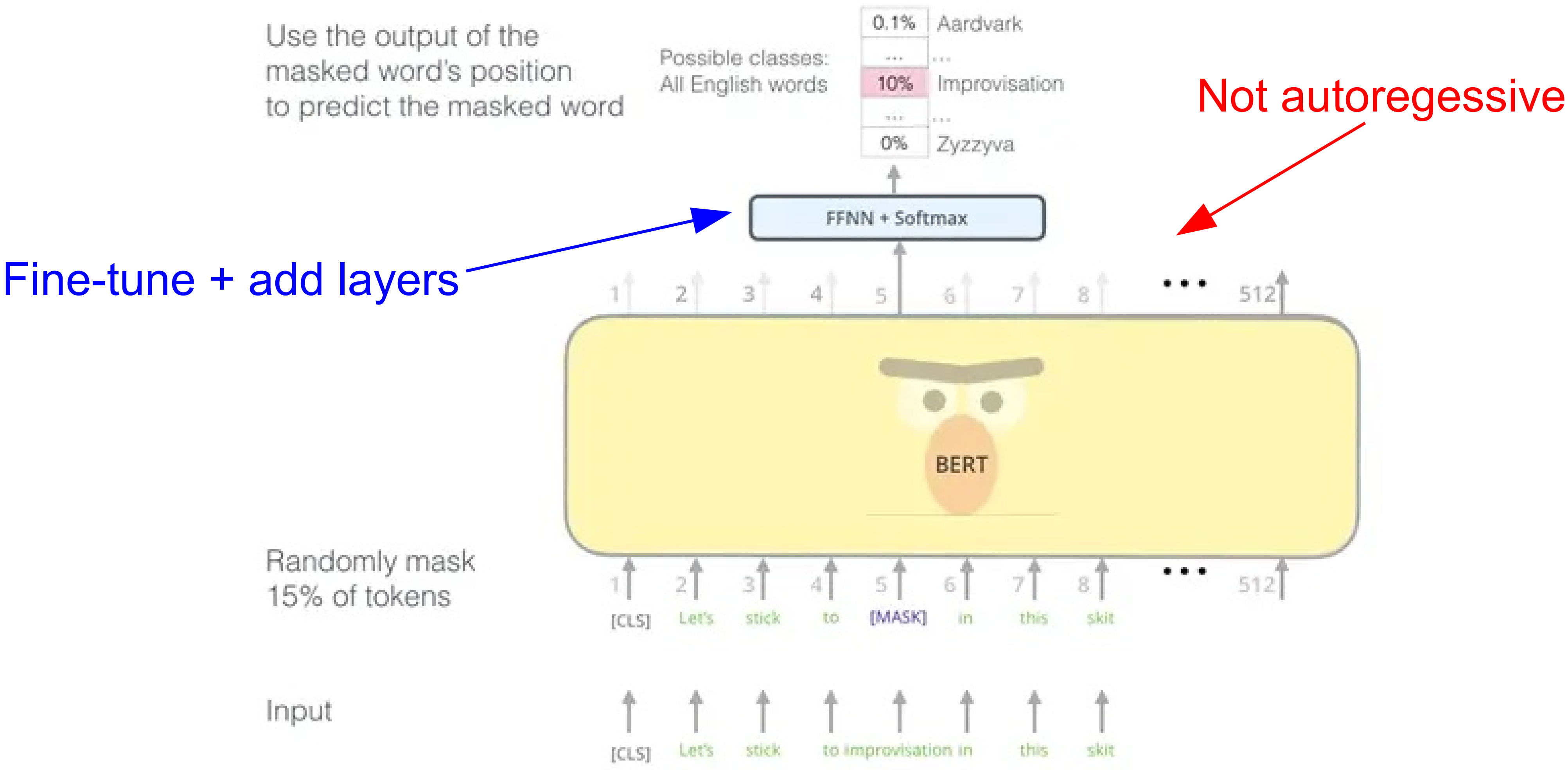



Figure 16: BERT Architecture [8].

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

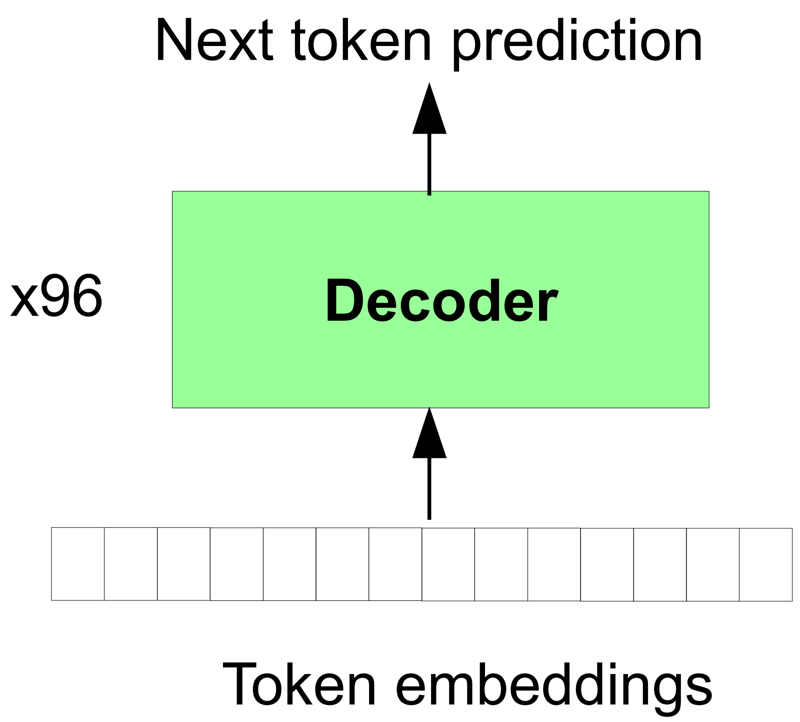



Figure 17: GPT-3 Overview [9].

# 4.2 GPT-3: Generative Pre-trained Transformer 3

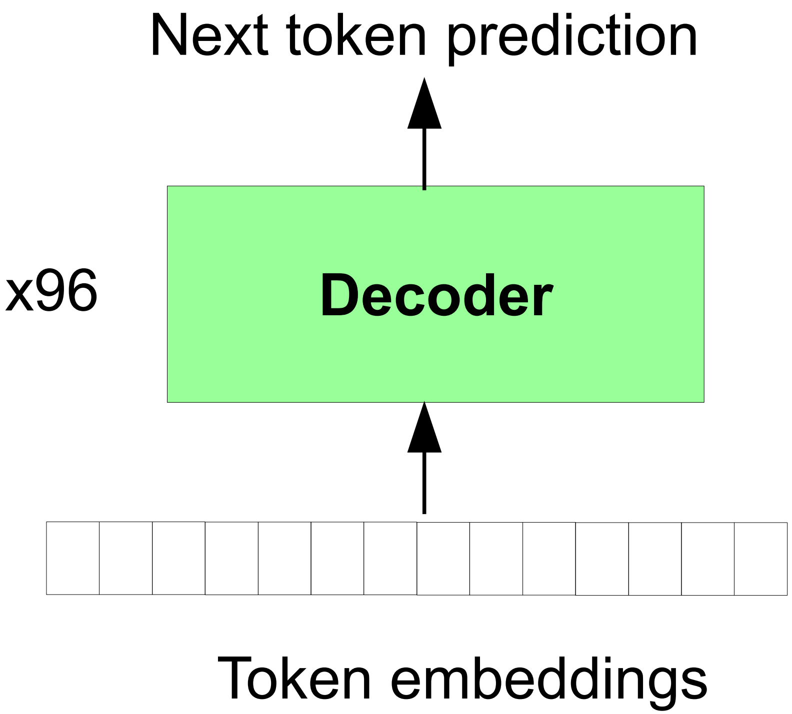



Figure 17: GPT-3 Overview [9].

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

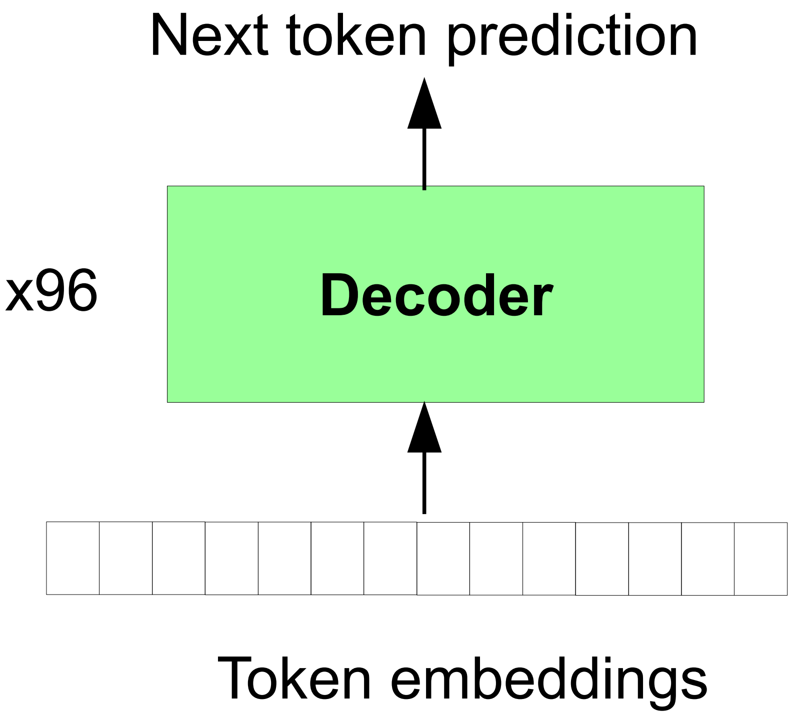




Figure 17: GPT-3 Overview [9].

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

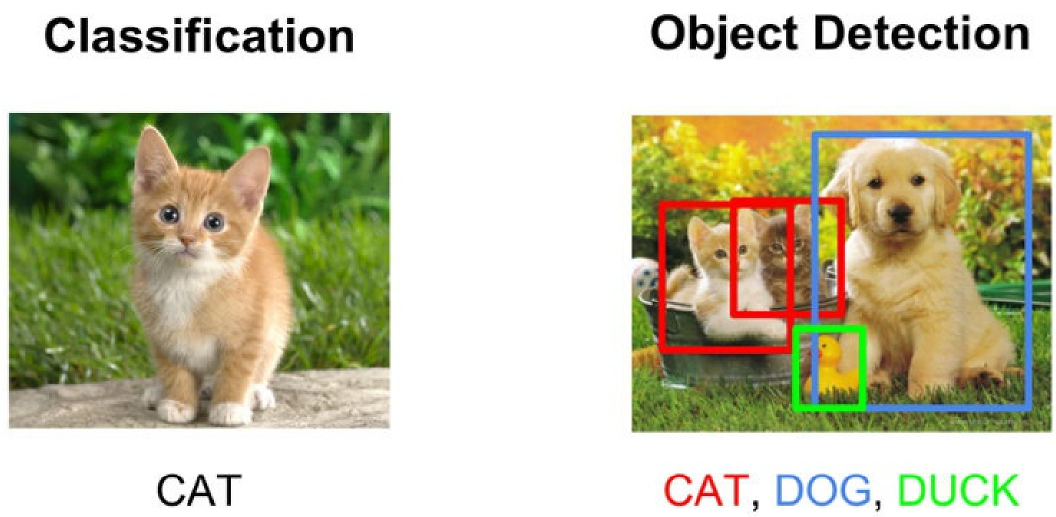



Image source:
https://res.cloudinary.com/dyd911kmh/image/upload/f_auto,q_auto:best/v1522766480/1_6j34dAOTijqP6HDFnjxPFA_udggex.png (call date: 20.07.22)

## 5.1.1 ViT: Vision Transformer – Image Classification

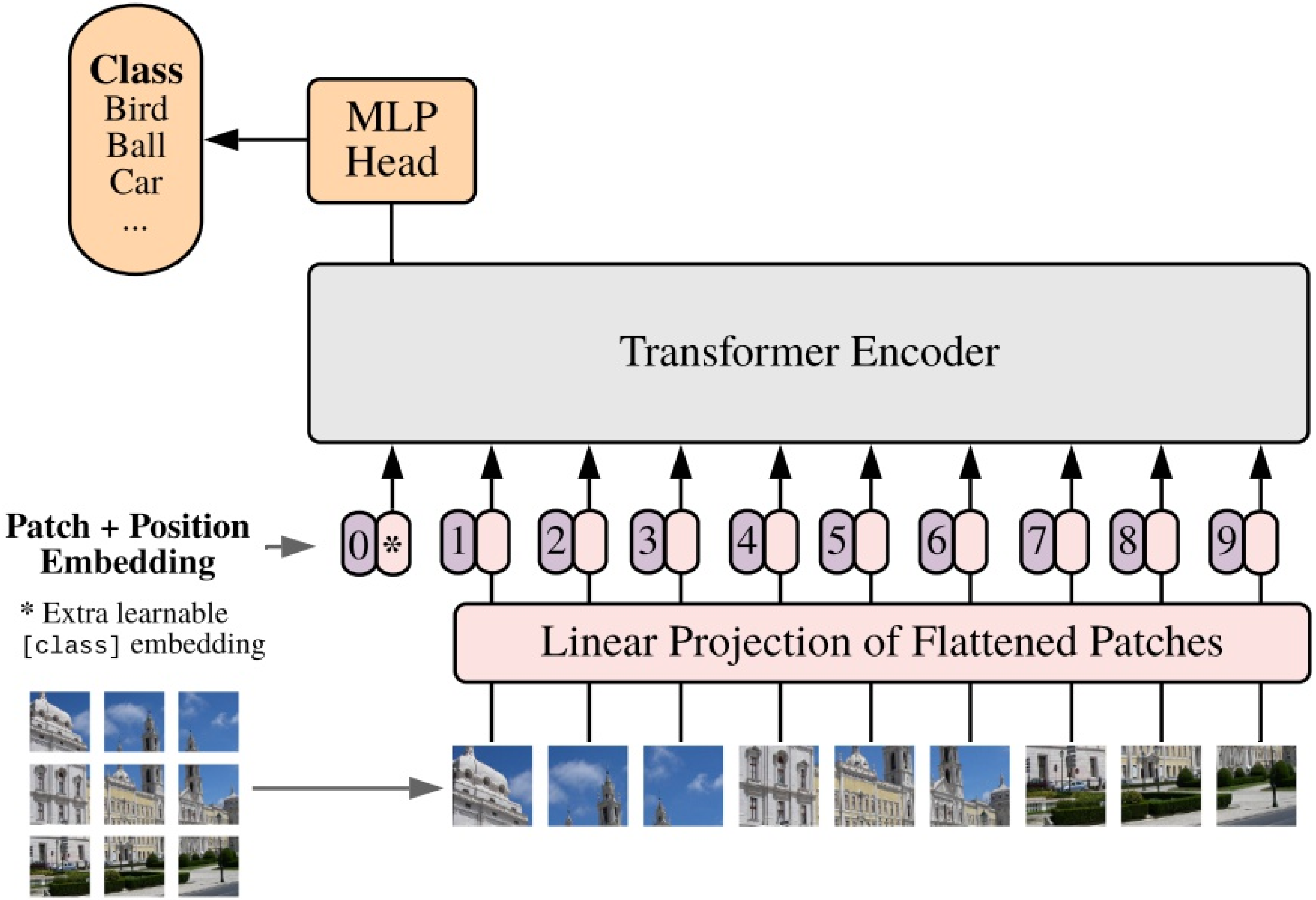



Figure 18: ViT Architecture [3].

## 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”

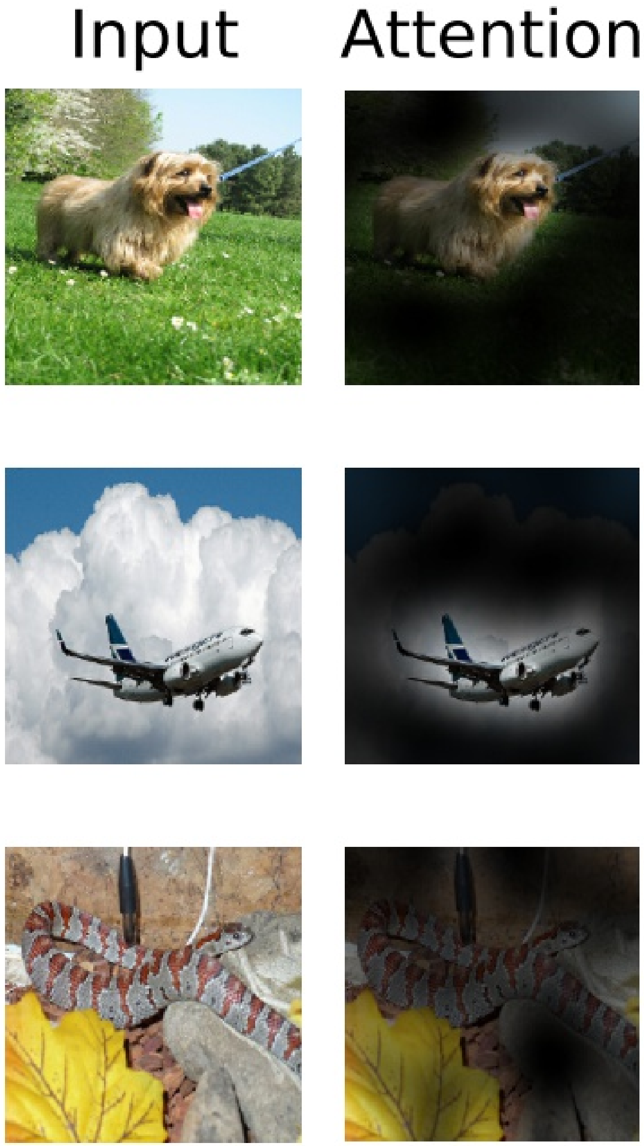



Figure 19: Visualization of self-attention
in an image [3].

# Side note: Feature Attribution with Occlusion

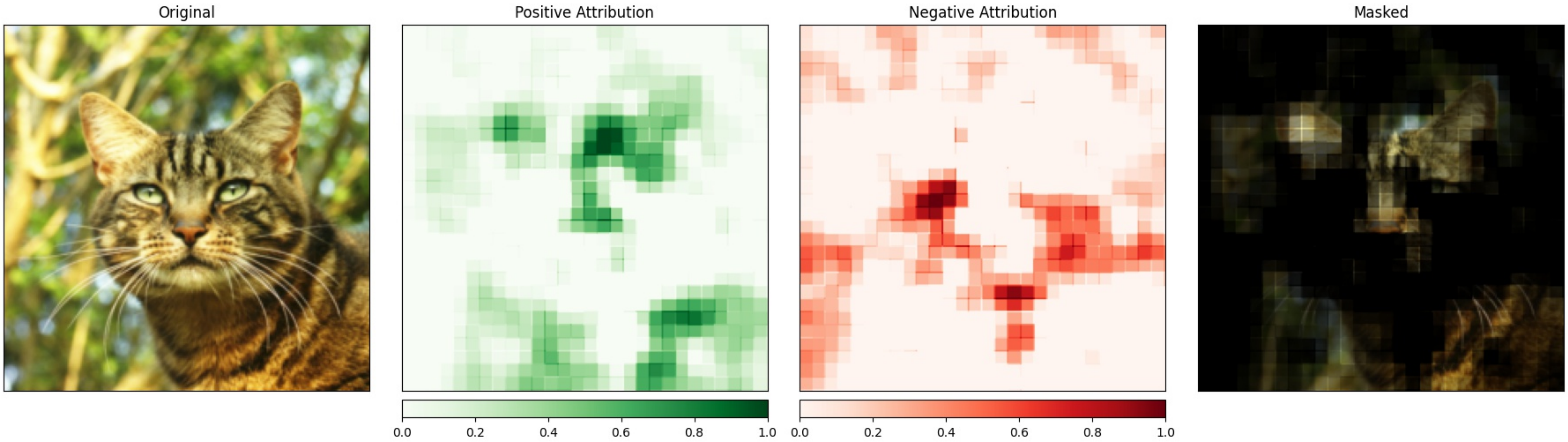



Image source:
https://www.youtube.com/watch?v=Am2EF9CLu-g&list=PL_lsbAsL_o2CTlGHgMxNrKhzP97BaG9ZN&index=7&ab_channel=PyTorch (call date: 26.01.23)

# 5.1.4 ViT: Vision Transformer – "Learn to be a CNN"

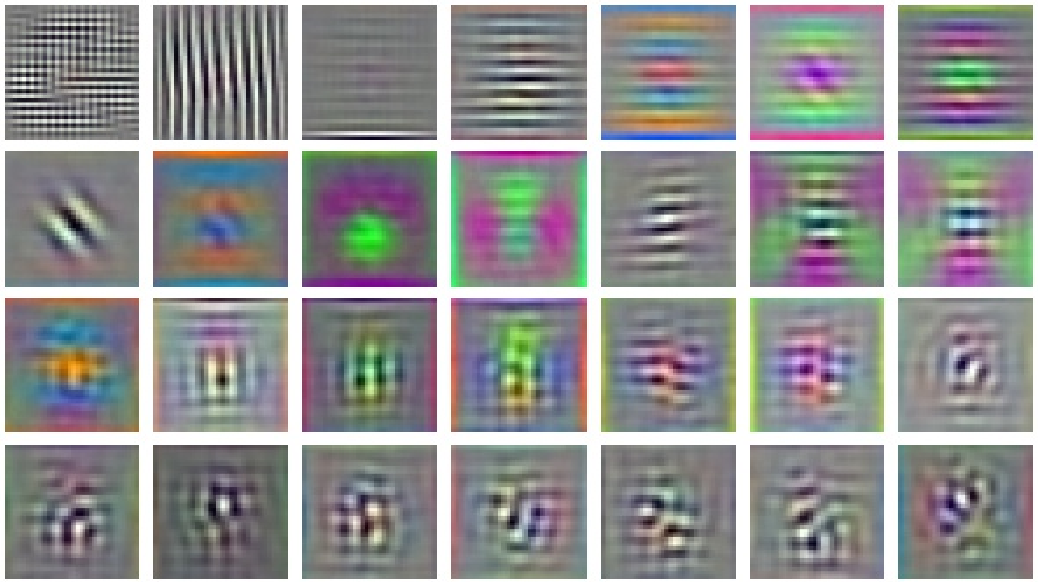


Figure 20: Learned patterns to which the self-attention mechanism reacts to [3].

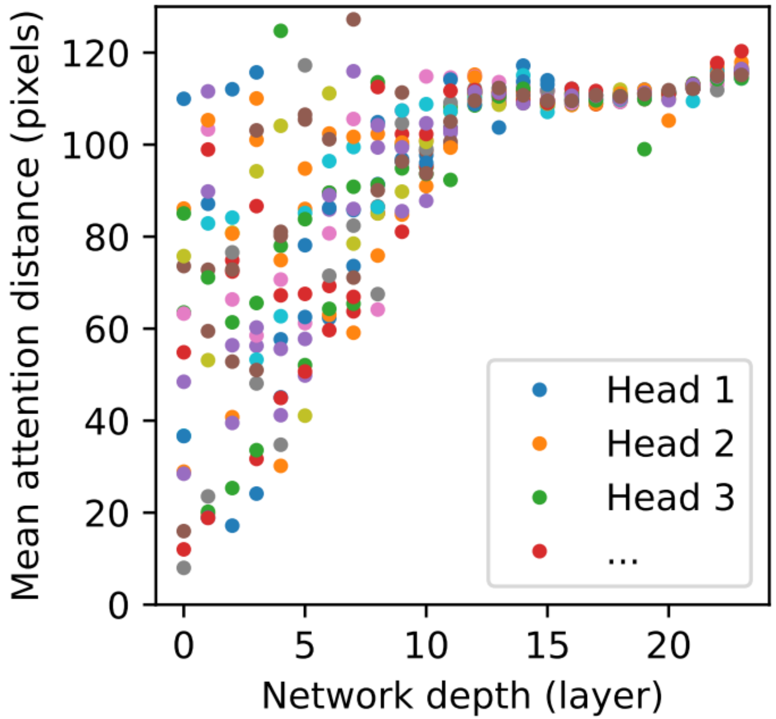



Figure 21: Mean attention distance of each layer [3].

# Side note: Receptive Field in a CNN

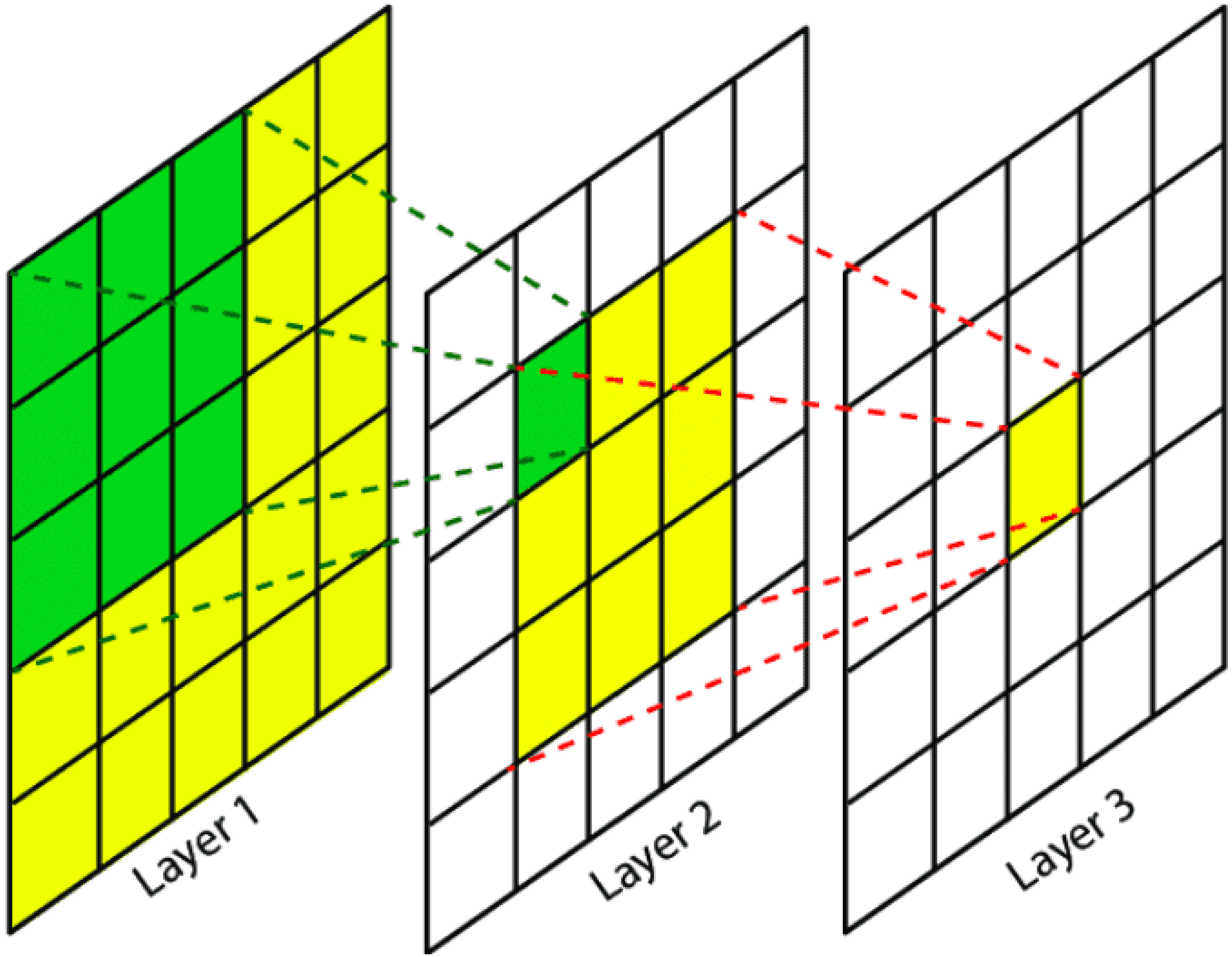



Image source: https://theaisummer.com/static/490be17ee7f19b78003c3fdf5a6bbafc/83b75/receptive-field-in-convolutional-networks.png (call date: 20.07.22)

# 5.2.1 DETR: DEtection Transformer – Object detection

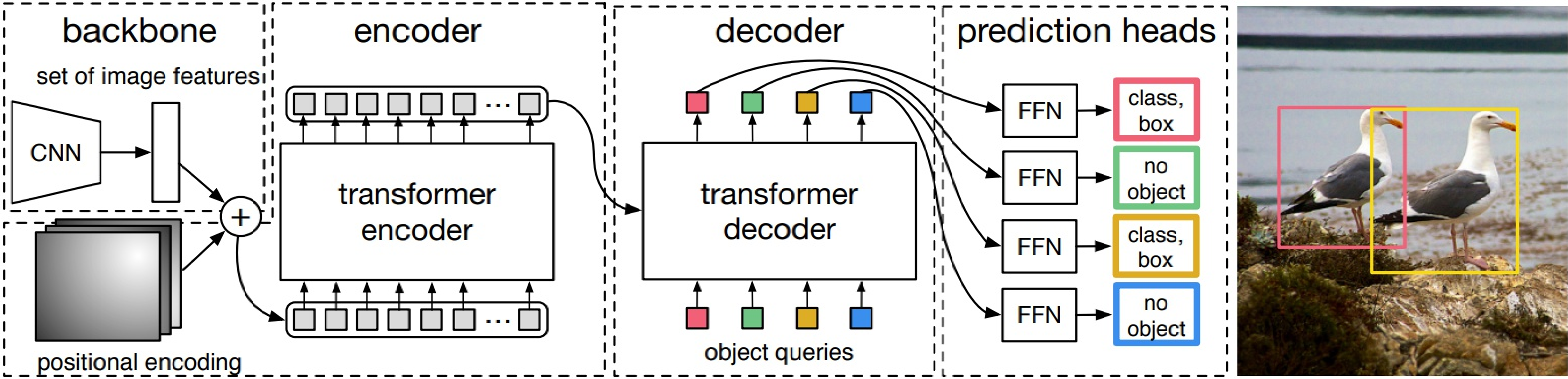



Figure 22: DETR architecture [4].

# 5.2.1 DETR: DEtection Transformer – Object detection

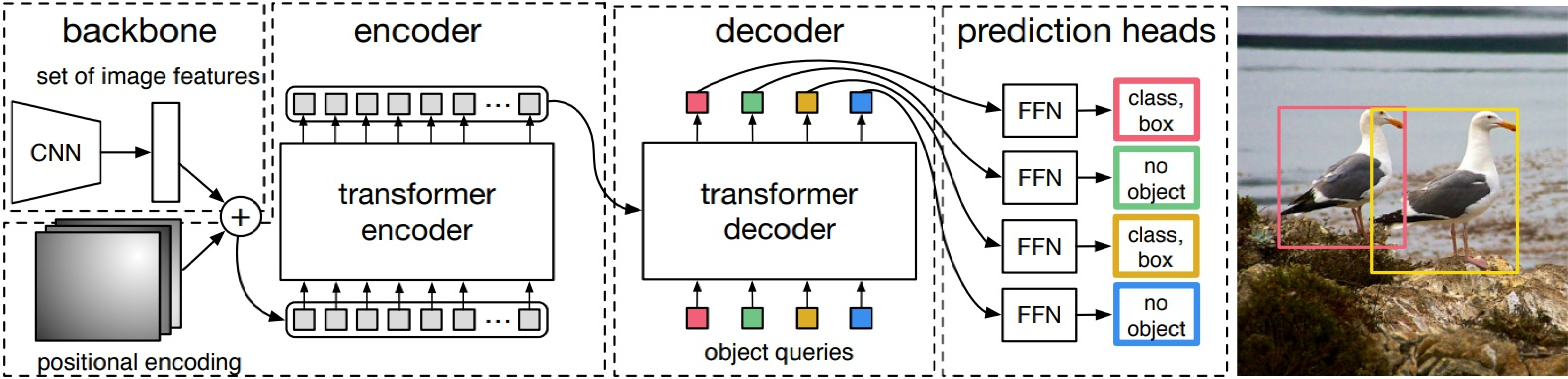



Figure 22: DETR architecture [4].

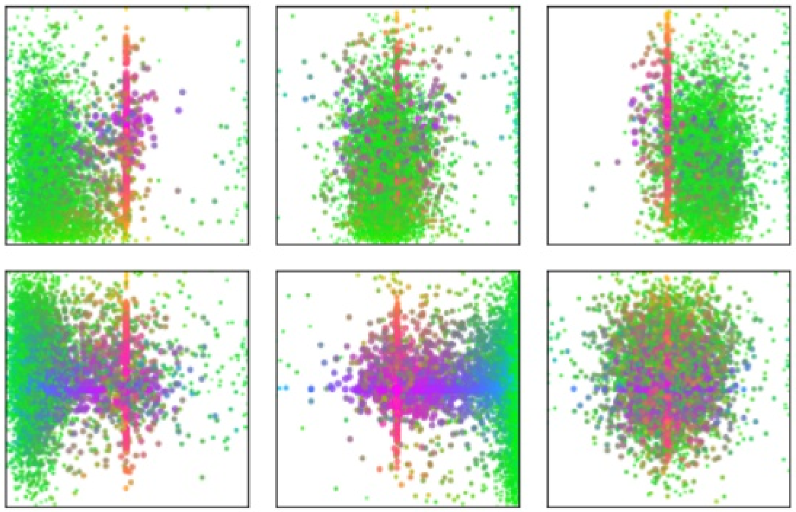


Figure 23: Object queries [4].

# 5.2.1 DETR: DEtection Transformer – Object detection

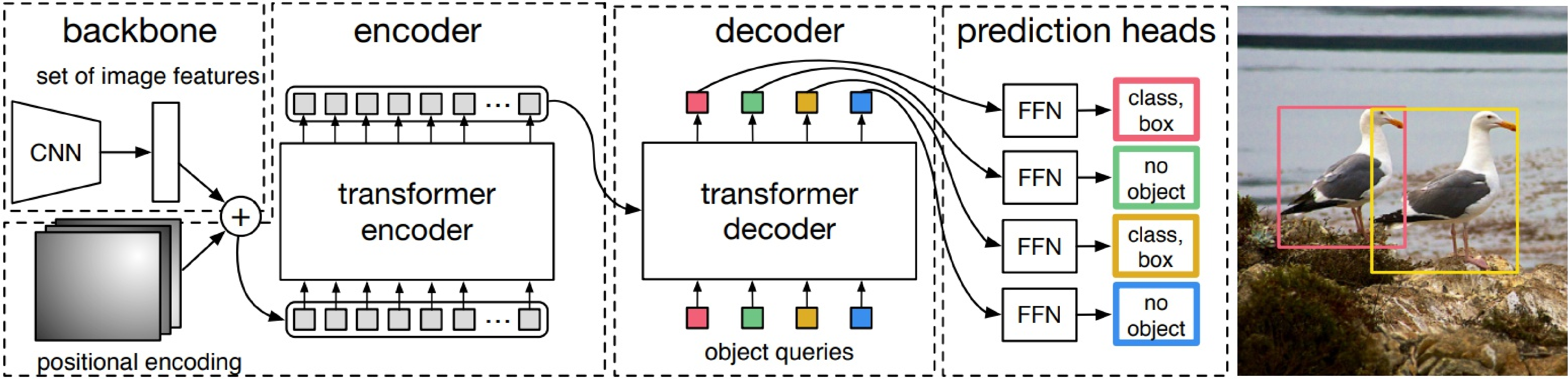



Figure 22: DETR architecture [4].

**Training:**

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

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

N = amount of boxes

# 5.2.1 DETR: DEtection Transformer – Object detection

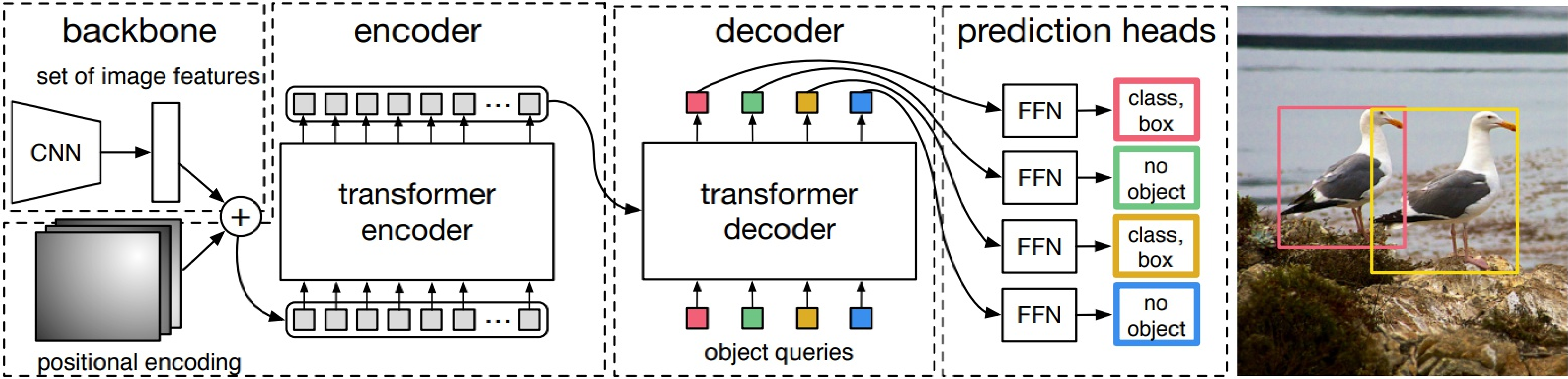



Figure 22: DETR architecture [4].

**Training:**

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

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

N = amount of boxes

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

# 5.2.2 DETR: DEtection Transformer "Attention-head communication"

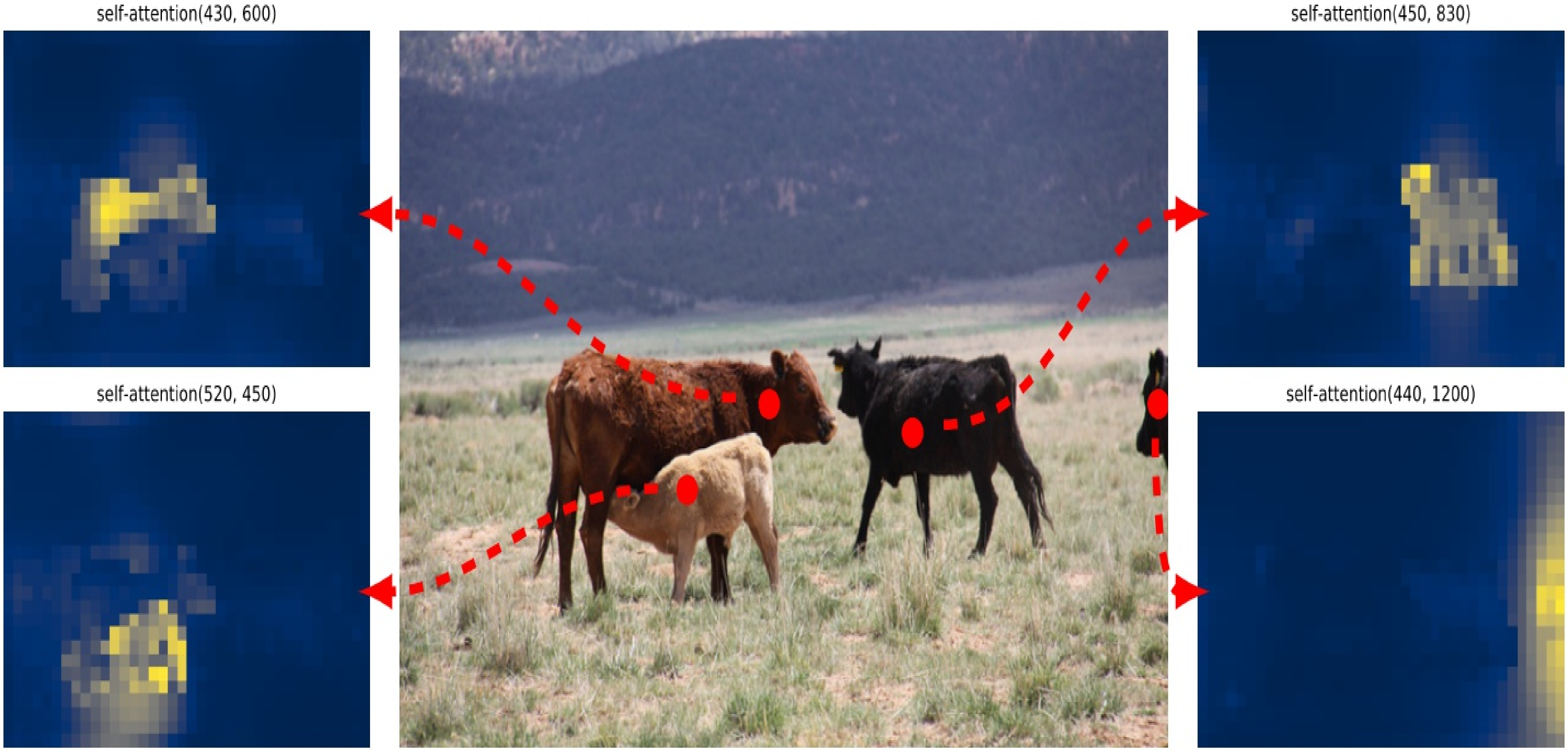



Figure 24: Different attention-heads attend to different objects in the image [4].

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

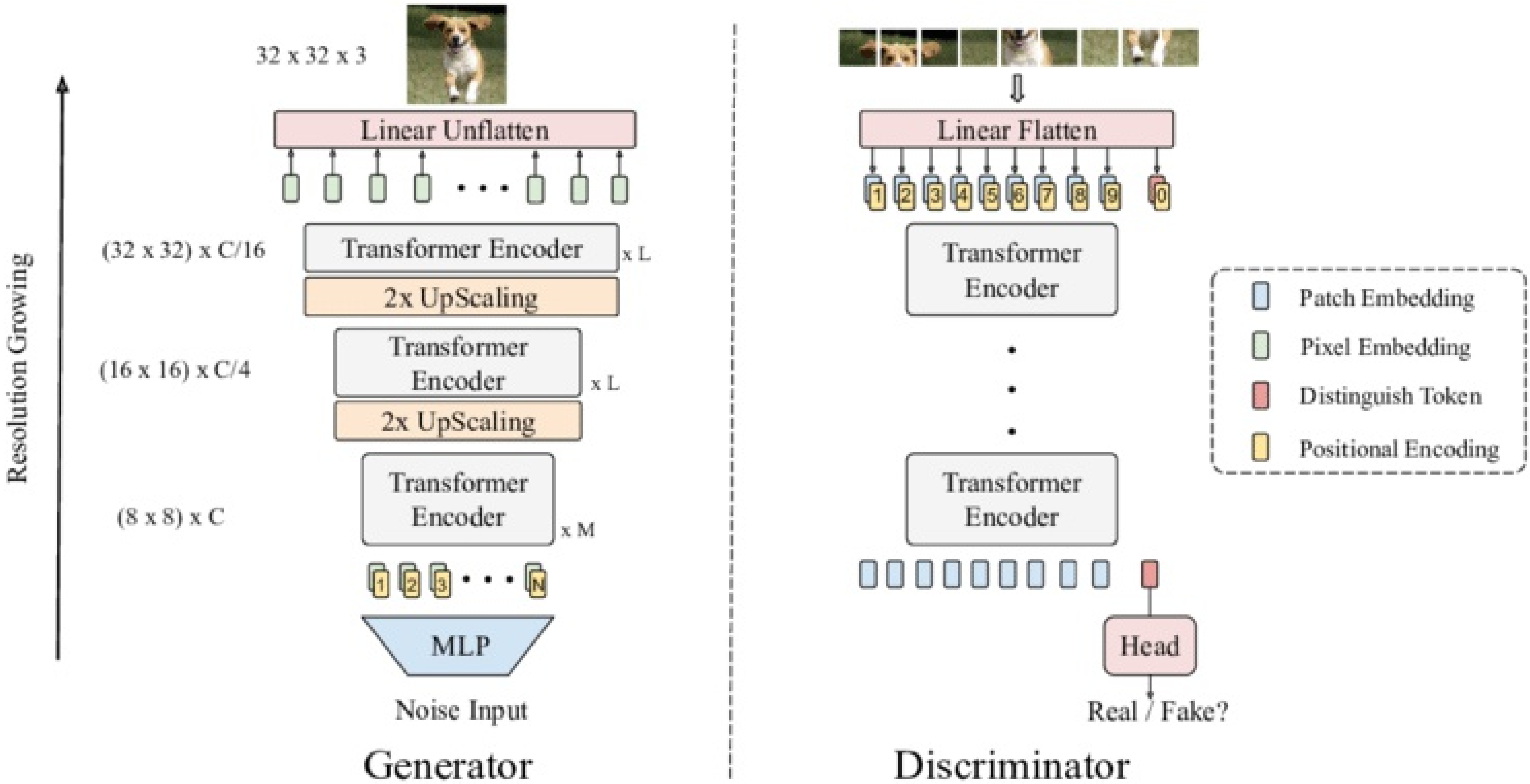



Figure 25: TransGAN architecture [5].

# Side note: PixelShuffle

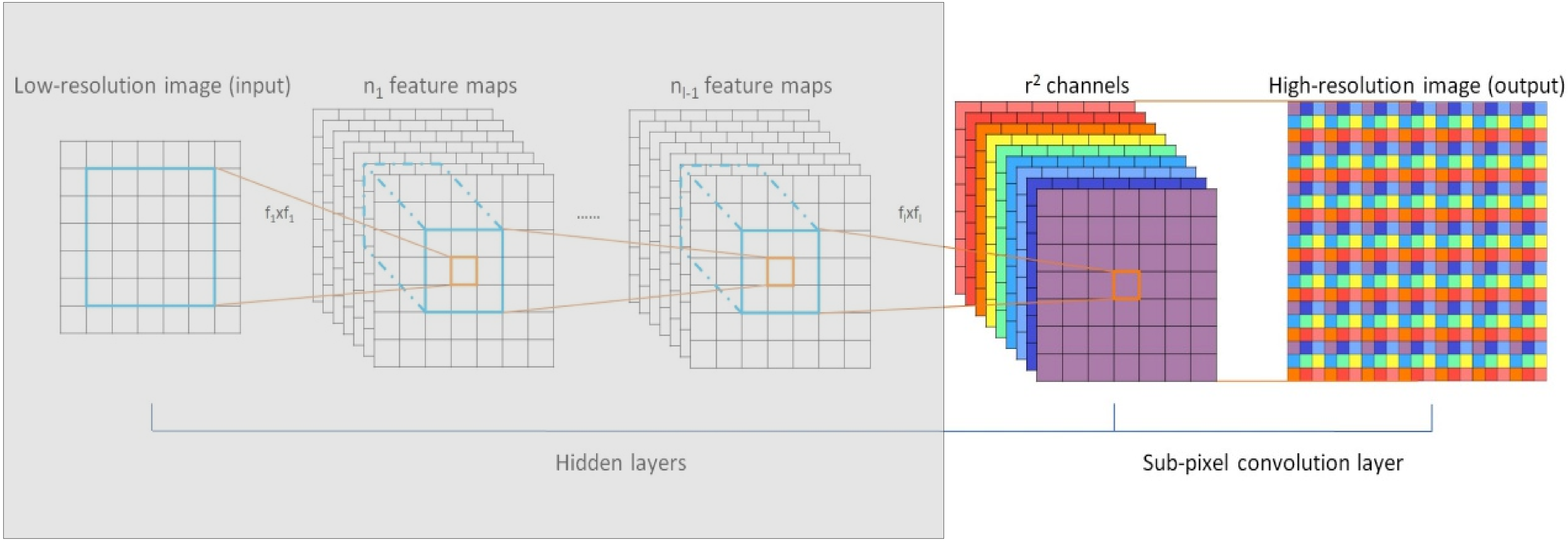



Image source:
Shi, Wenzhe et al. "Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016): 1874-1883.

## 6.2 TransGAN: Evaluation

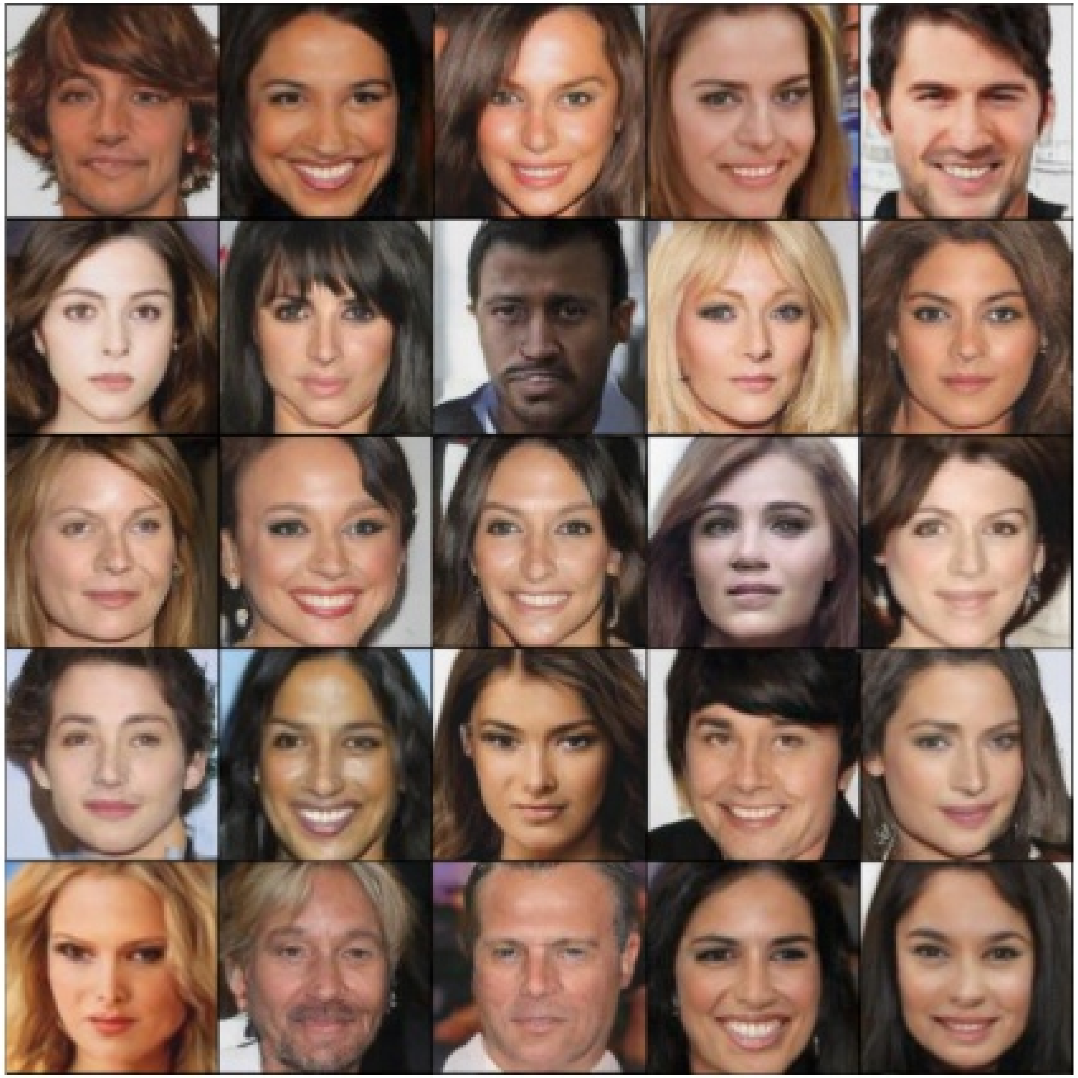


Figure 26: Generated images by the TransGAN [5].

# 6.2 TransGAN: Evaluation

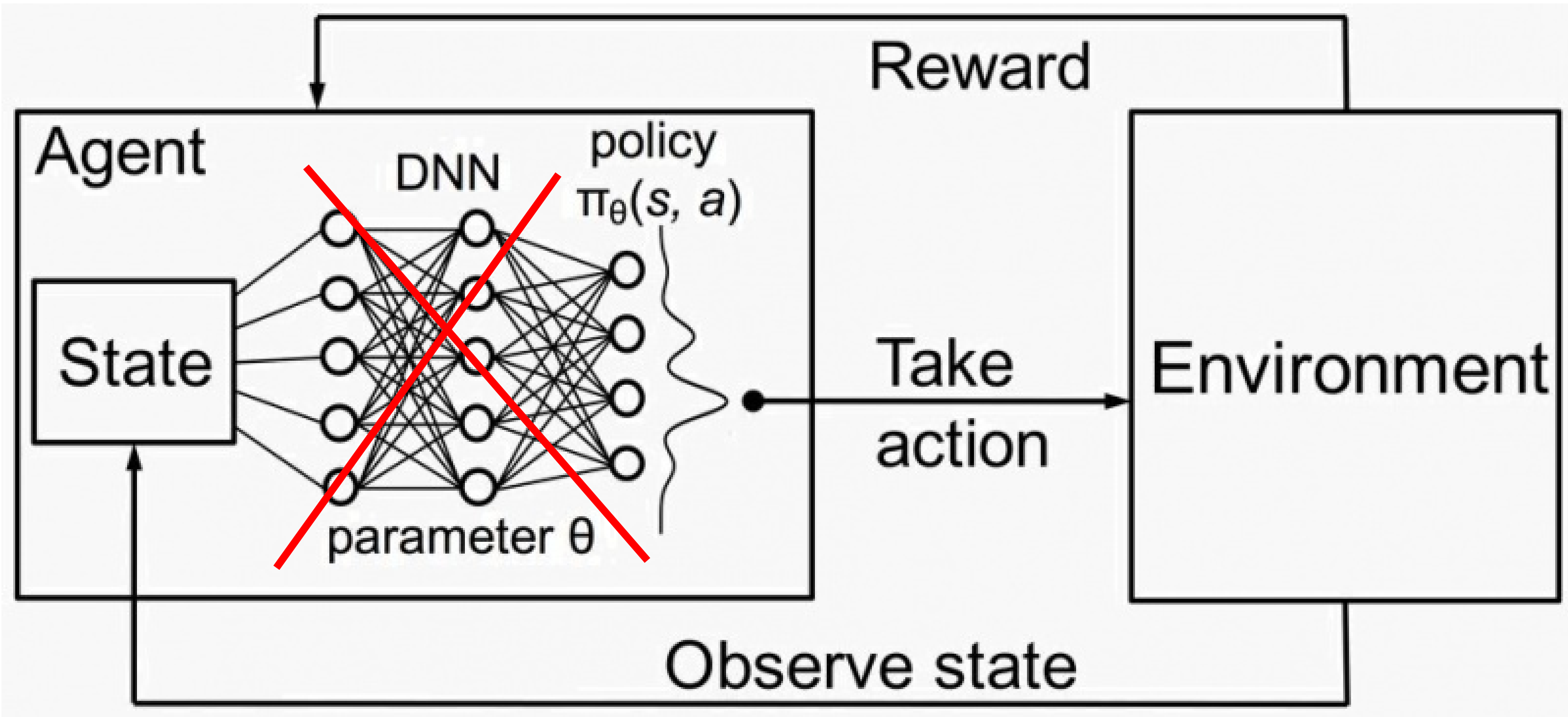
| Methods | WGAN-GP | | AutoGAN | | StyleGAN-V2 | | TransGAN | |
|---|---|---|---|---|---|---|---|---|
| | IS ↑ | FID ↓ | IS ↑ | FID ↓ | IS ↑ | FID ↓ | IS ↑ | FID ↓ |
| Original | **6.49** | 39.68 | 8.55 | **12.42** | 9.18 | 11.07 | 8.36 | 22.53 |
| + DiffAug [69] | 6.29 | **37.14** | **8.60** | 12.72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

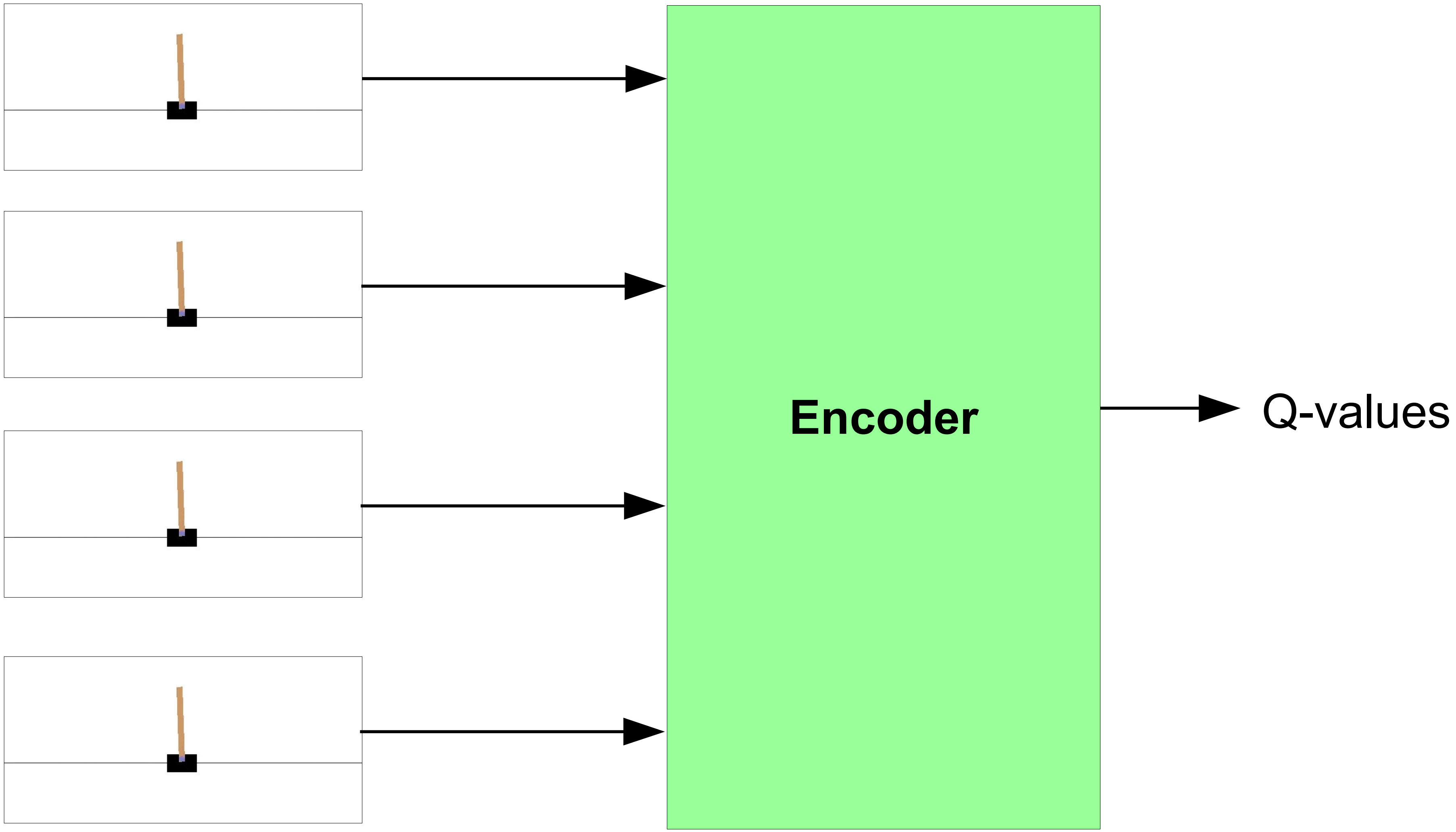



Figure 27: DTQN architecture [6].

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

# 7.1.2 DTQN: Evaluation

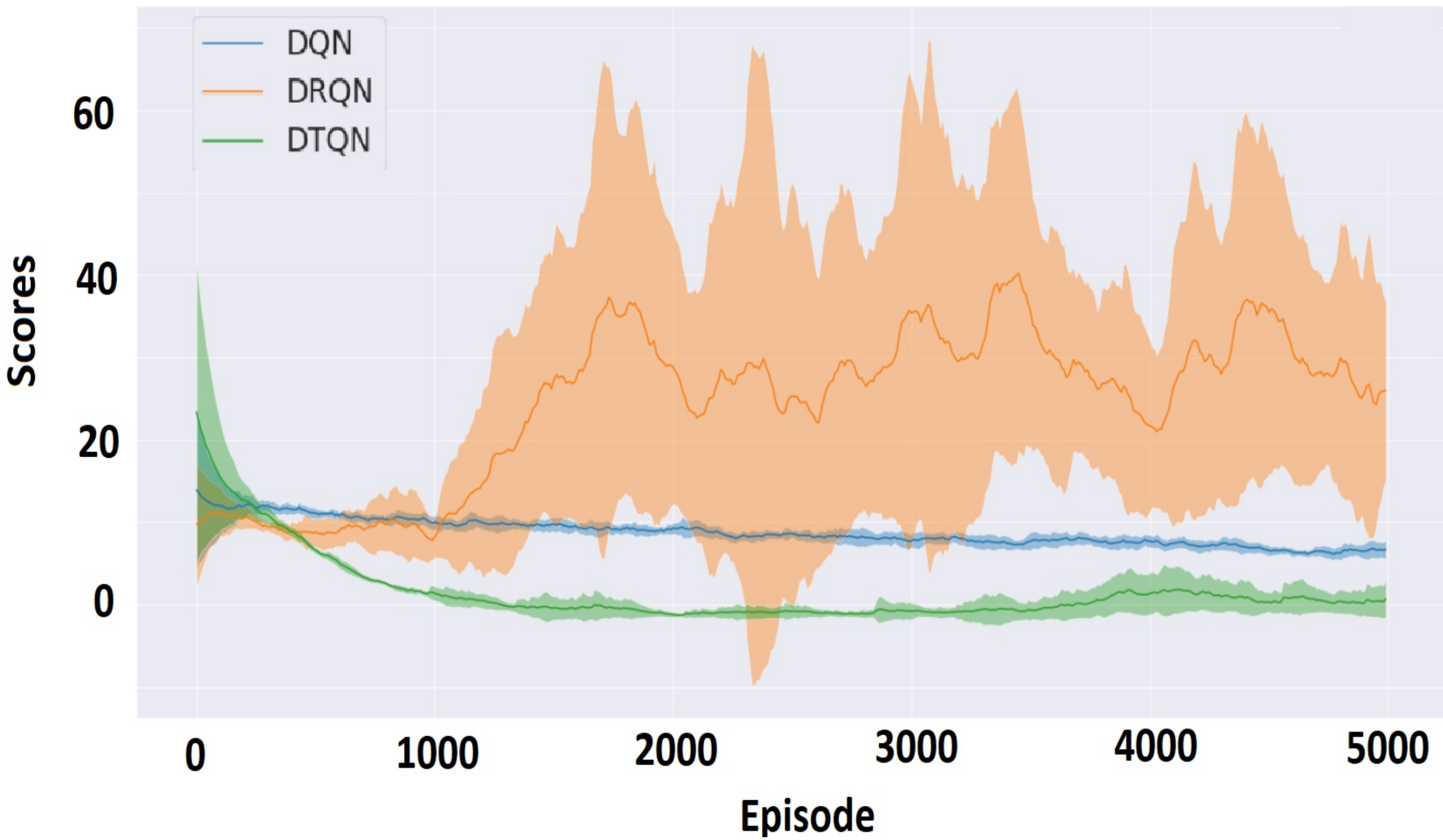
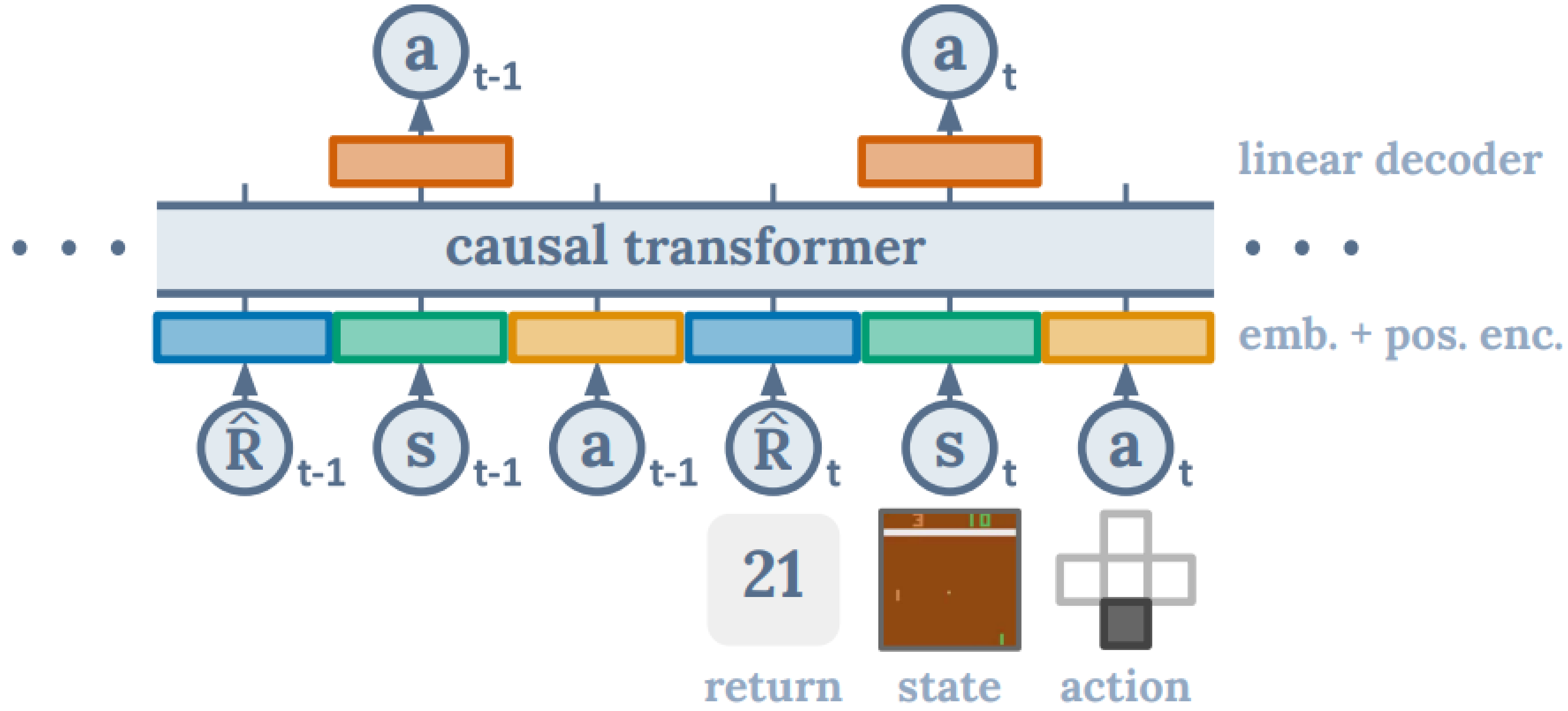



Figure 28: DTQN performance [6].

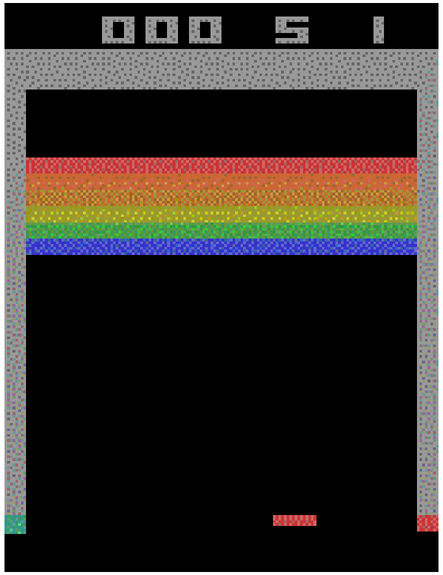
# 7.2.1 Decision Transformer: Architecture



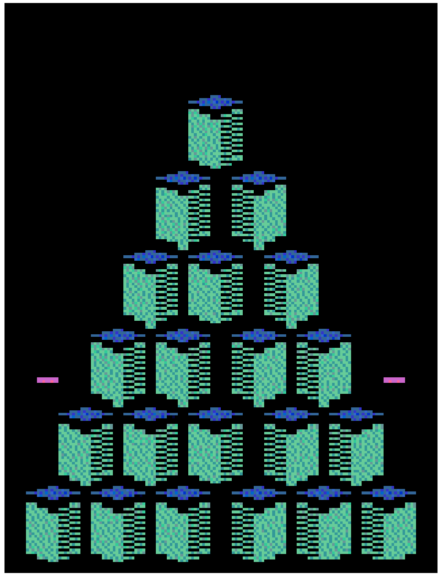

$$G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}.$$

Figure 29: Decision Transformer architecture [7].

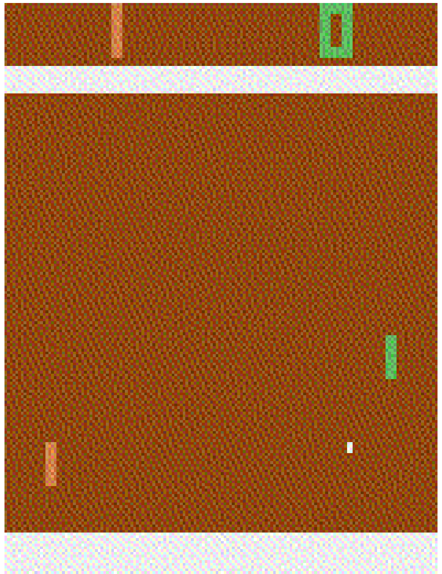
# 7.2.2 Decision Transformer: Evaluation



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?

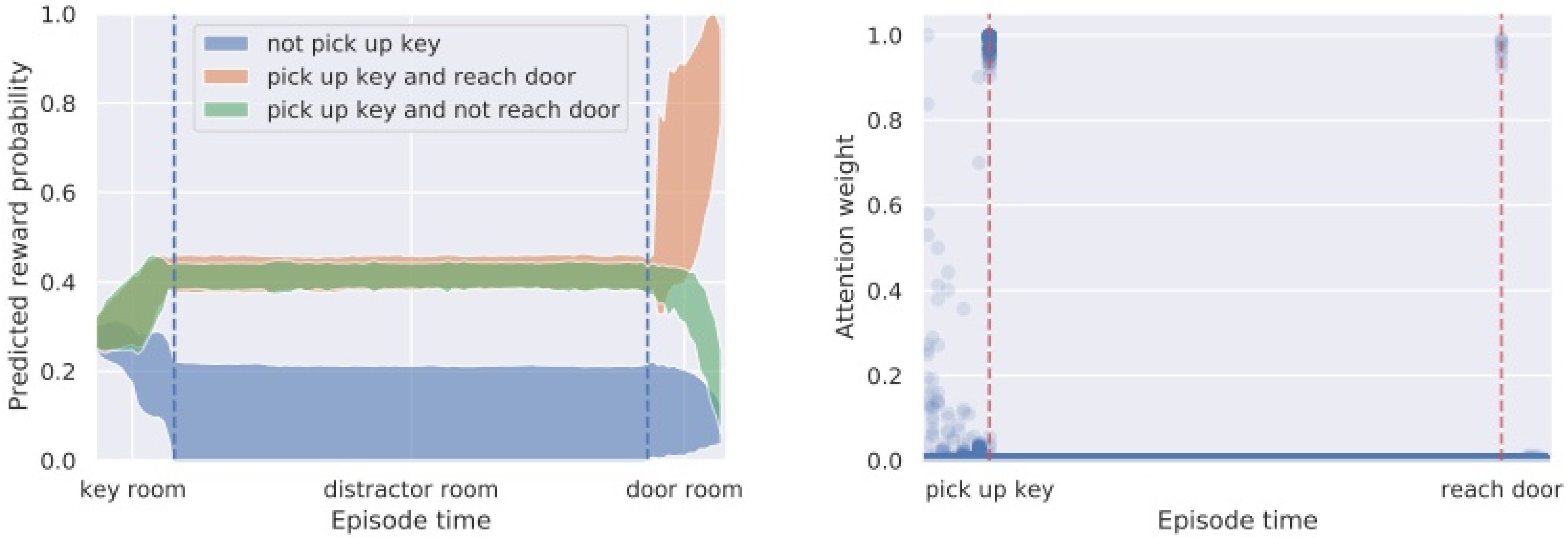
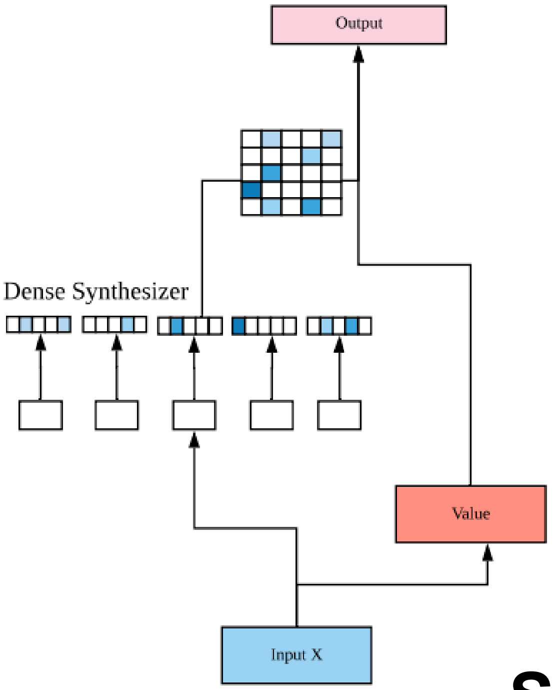
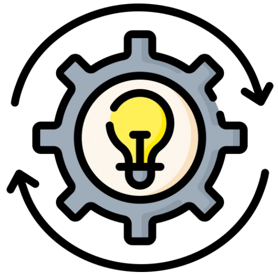
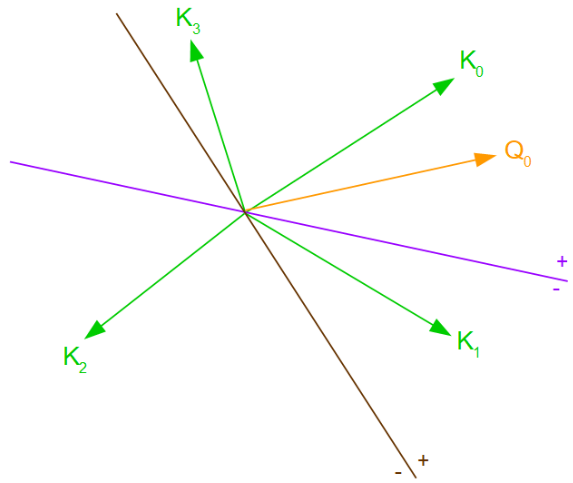



Figure 31: Decision Transformer attend to pivotal events [7].






Reformer

# 8. Modifications of attention: Synthesizer, Linformer, Reformer

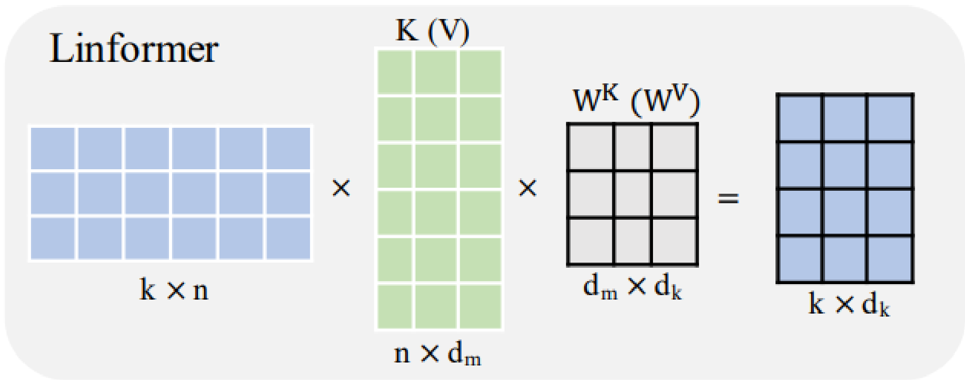
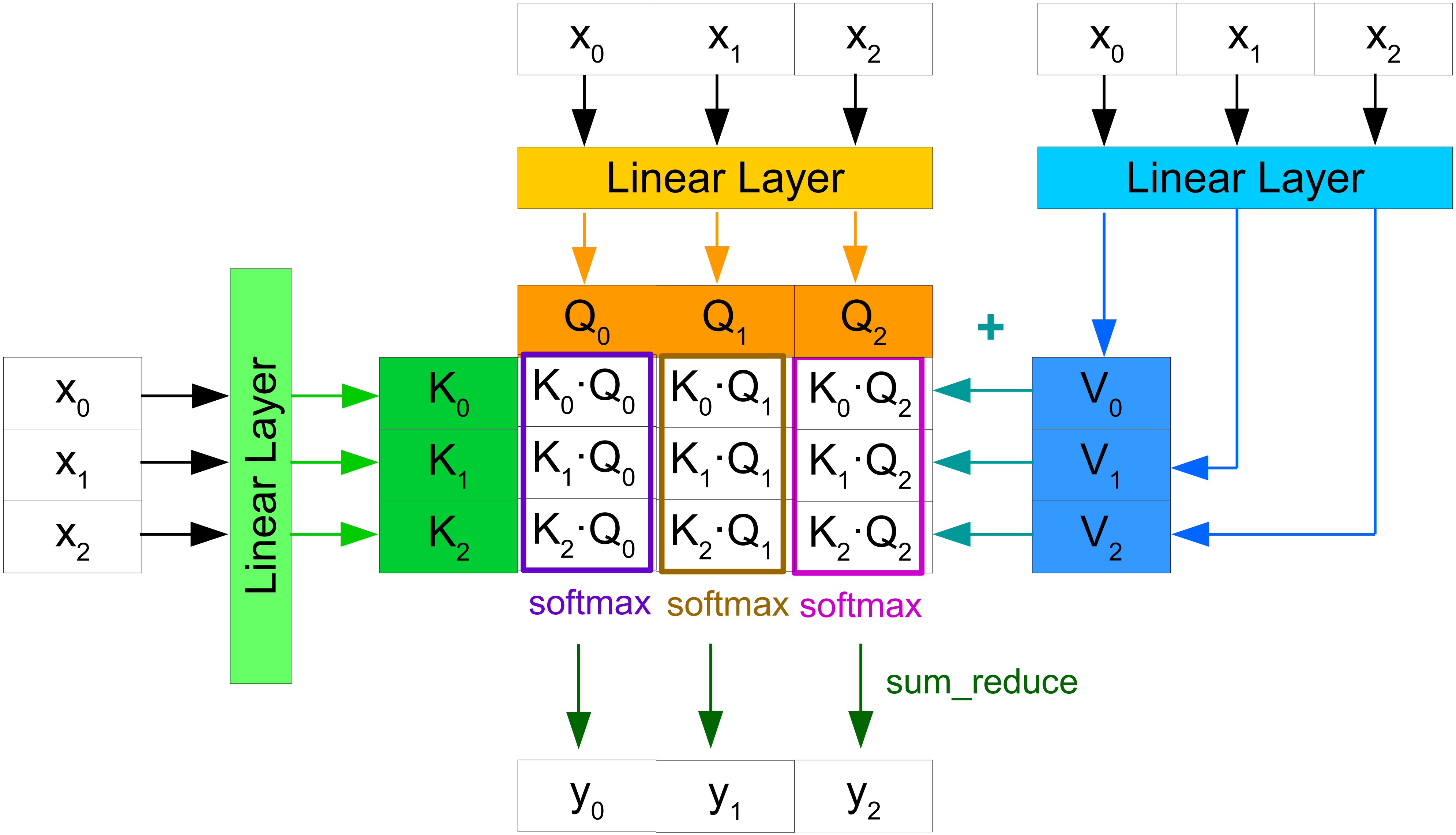
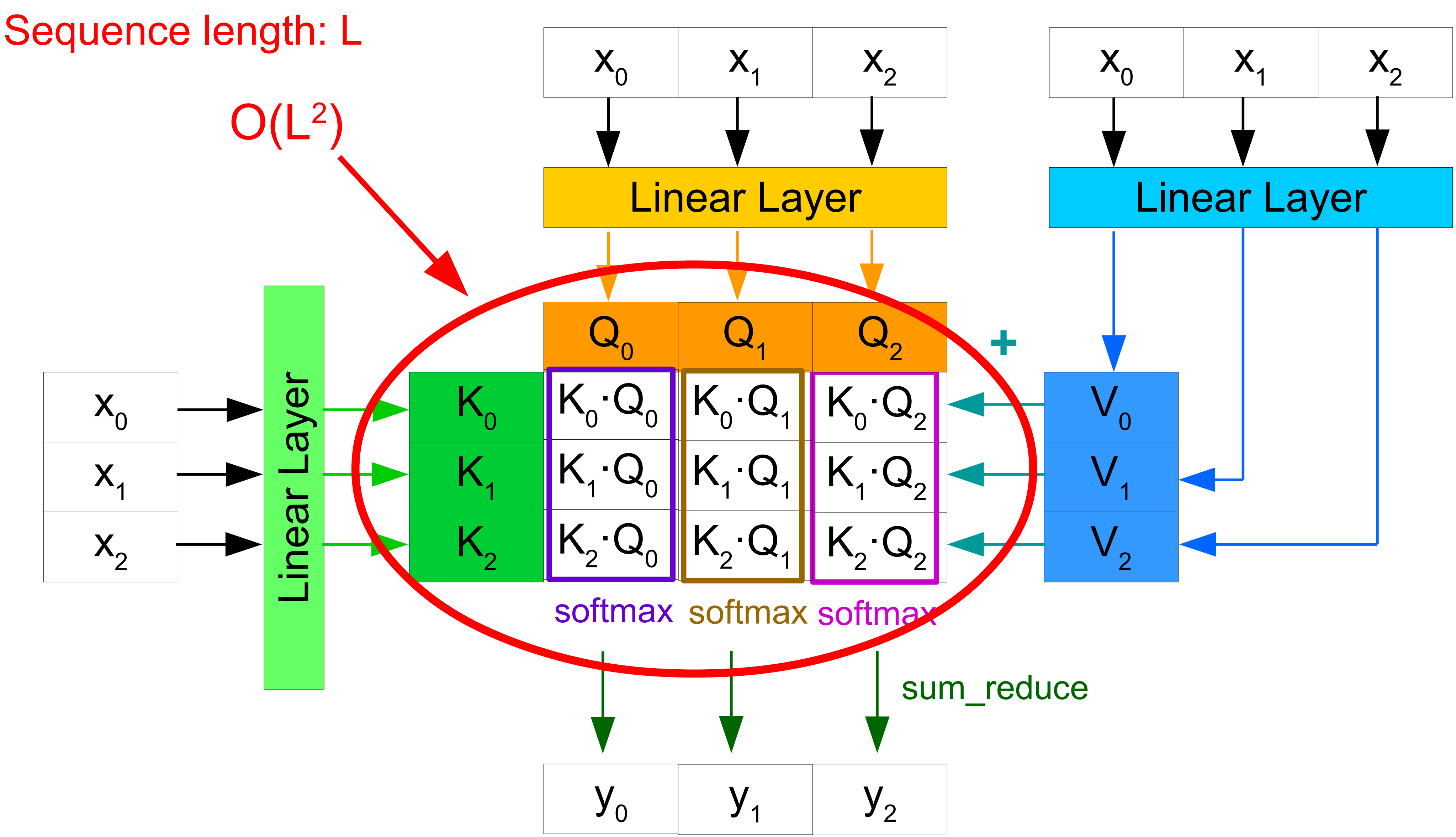



Image sources:
https://cdn-icons-png.flaticon.com/512/5116/5116423.png
(call dates: 21.01.23)
Tay, Yi et al. “Synthesizer: Rethinking Self-Attention in Transformer Models.” International Conference on Machine Learning (2020).
Wang, Sinong et al. “Linformer: Self-Attention with Linear Complexity.” ArXiv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

# 8. Self-attention: Time and Space Complexity



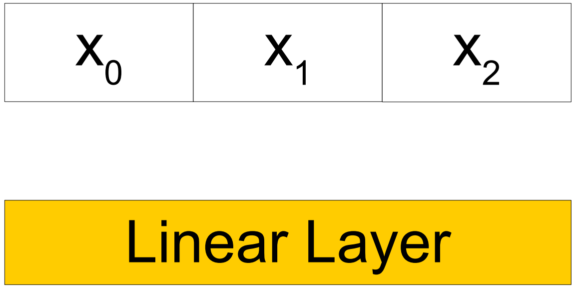
# 8. Self-attention: Time and Space Complexity



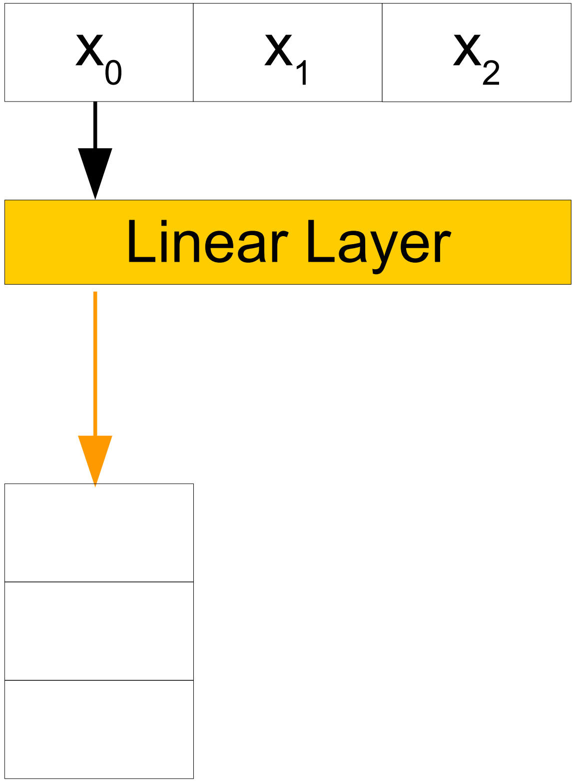
# 8.1 Synthesizer: *Dense* variant

| | | |
|---|---|---|
| $x_0$ | $x_1$ | $x_2$ |

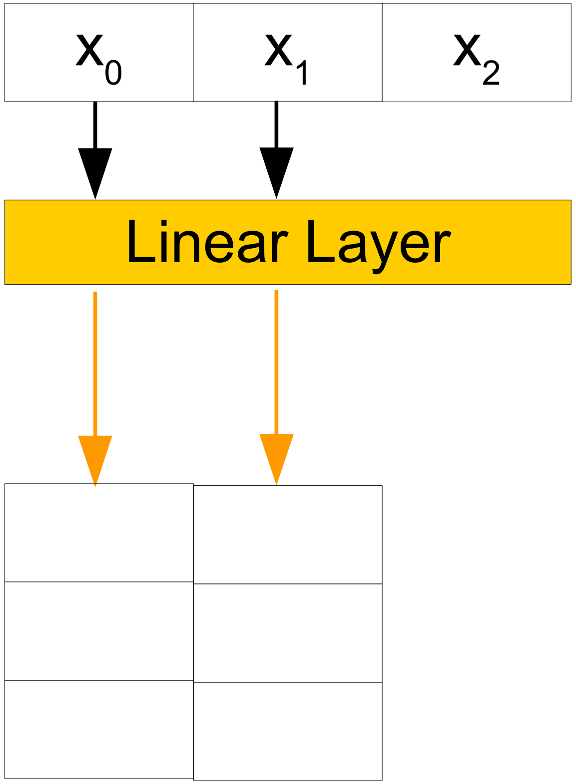
# 8.1 Synthesizer: *Dense* variant



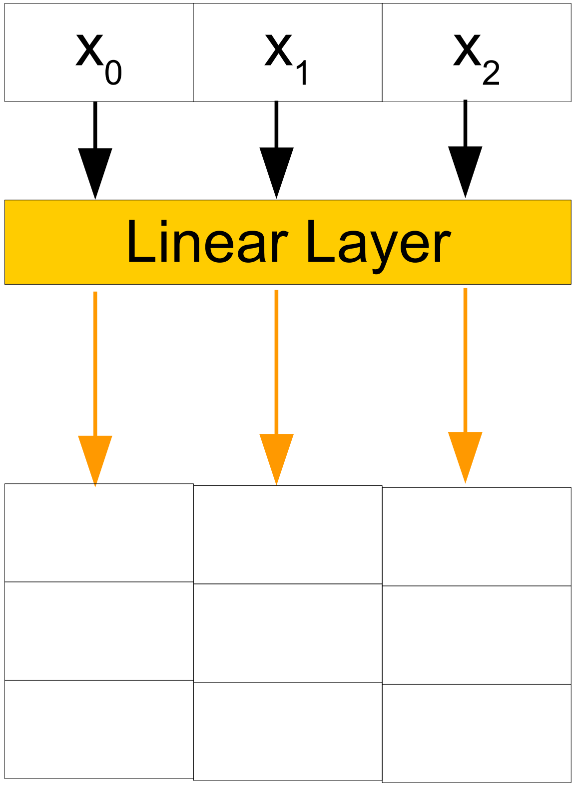
# 8.1 Synthesizer: *Dense* variant



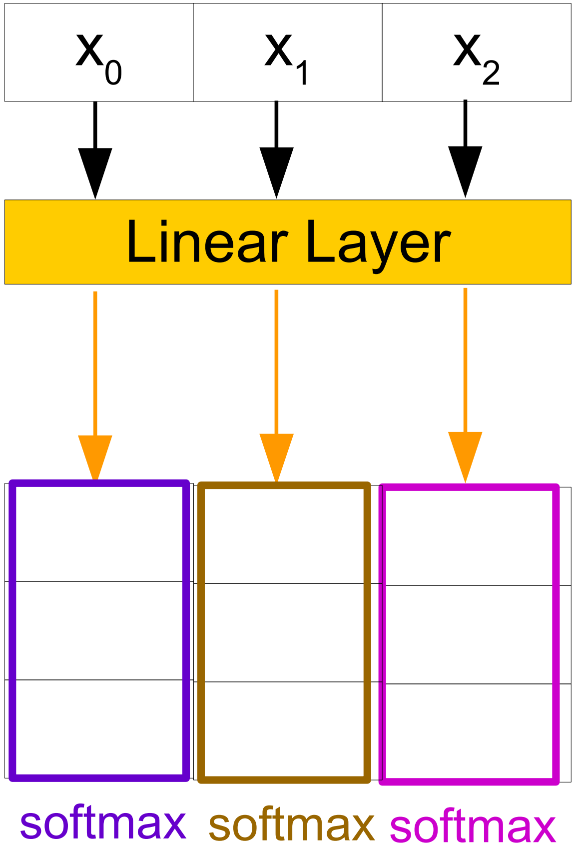
# 8.1 Synthesizer: *Dense* variant



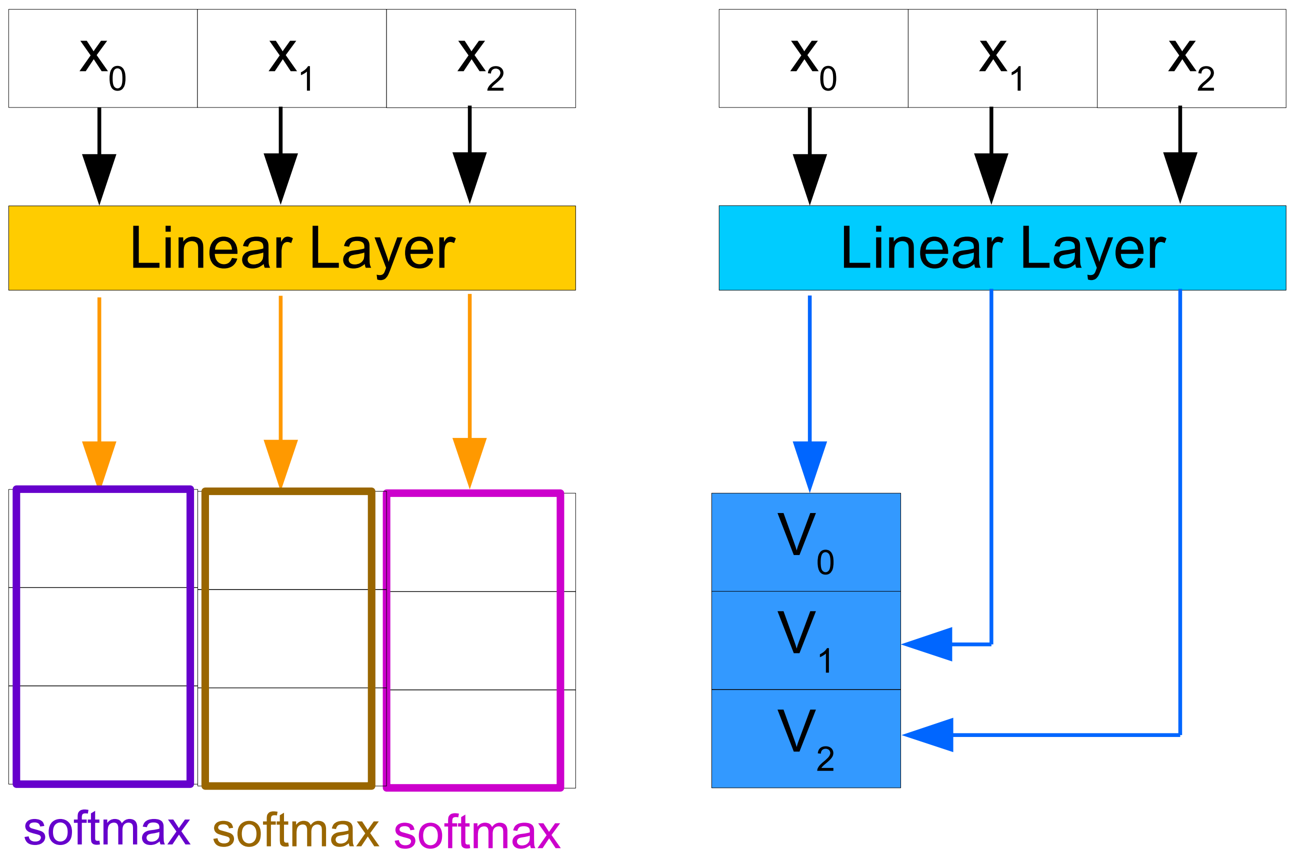
# 8.1 Synthesizer: *Dense* variant



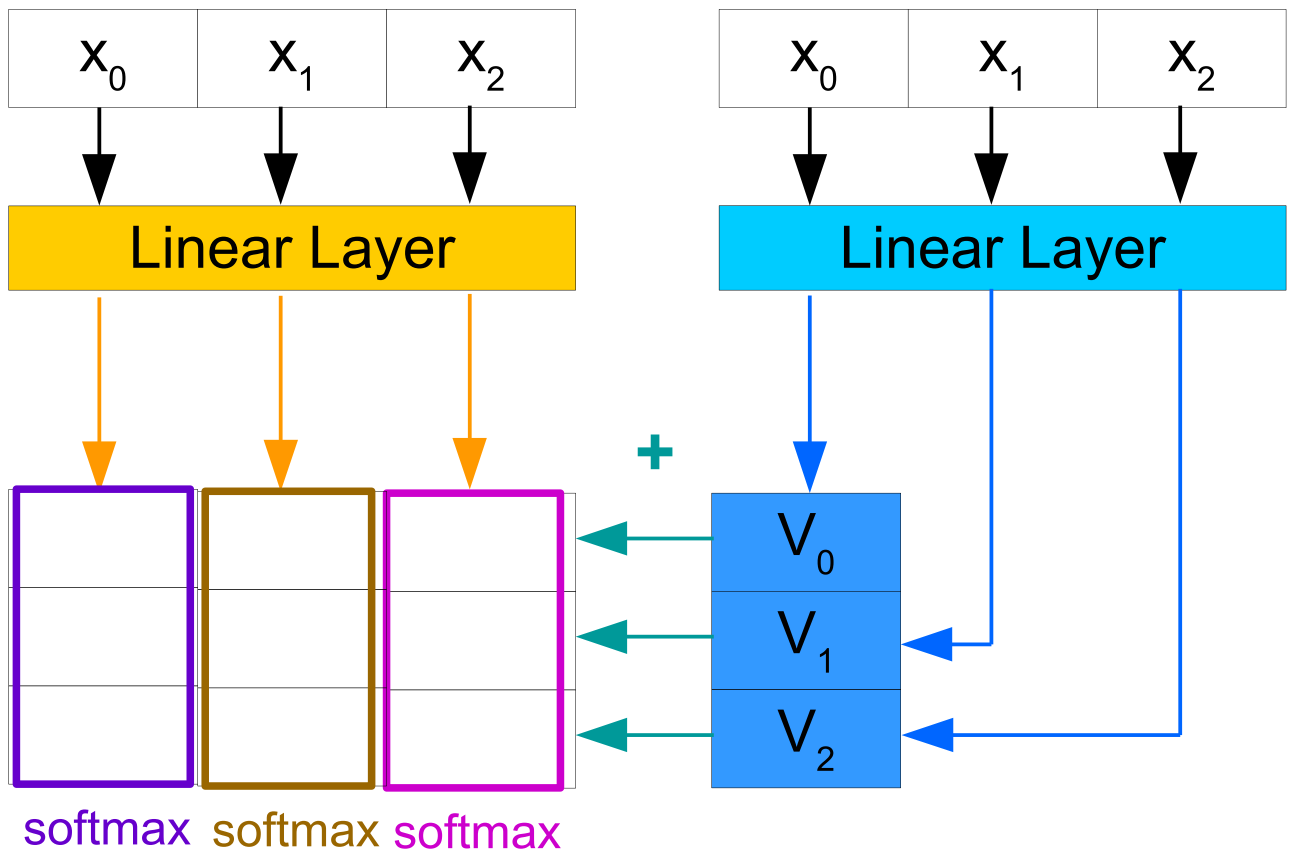
# 8.1 Synthesizer: *Dense* variant



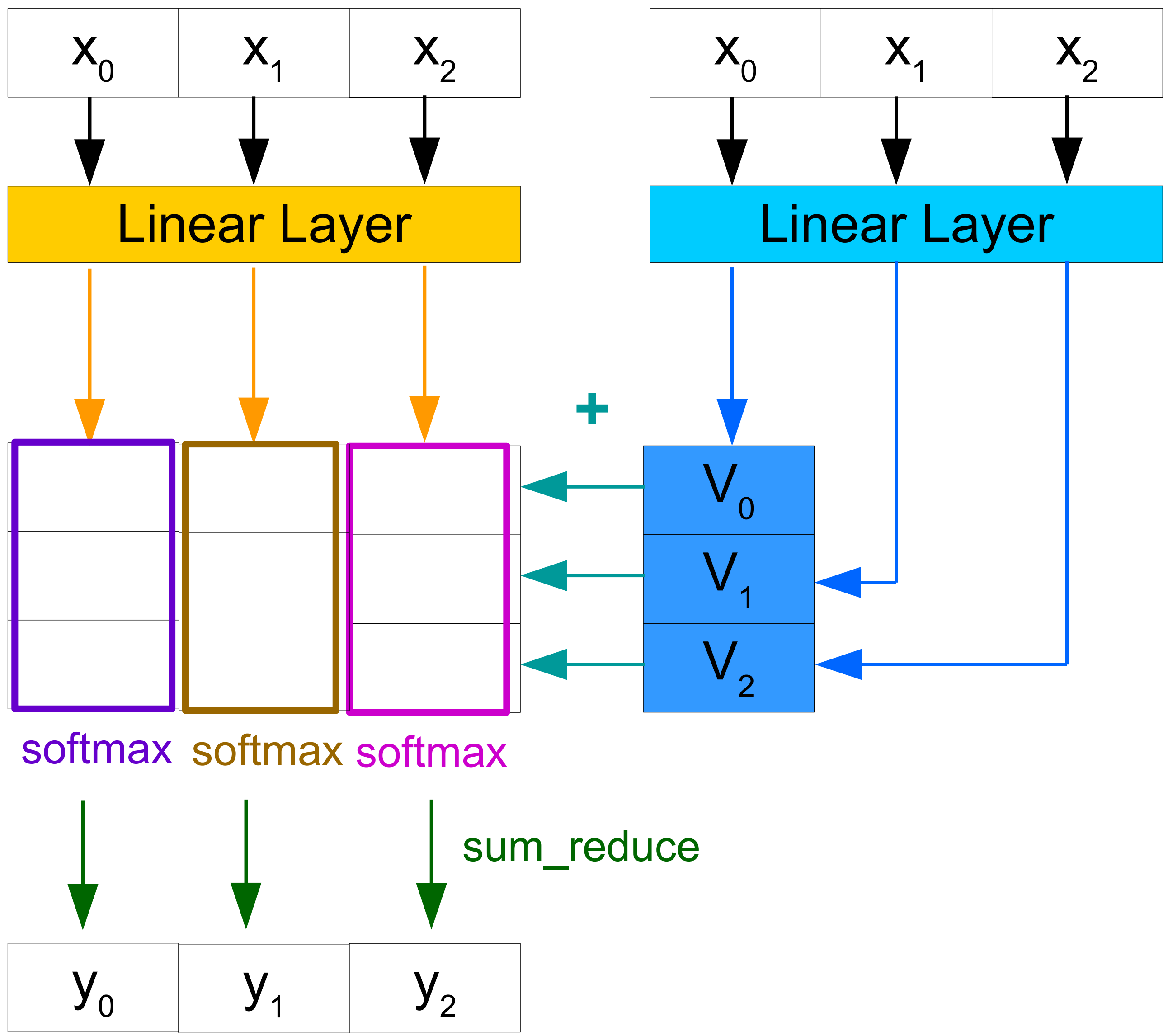
# 8.1 Synthesizer: *Dense* variant



# 8.1 Synthesizer: *Dense* variant



# 8.1 Synthesizer: *Dense* variant



# 8.1 Synthesizer: *Random* variant

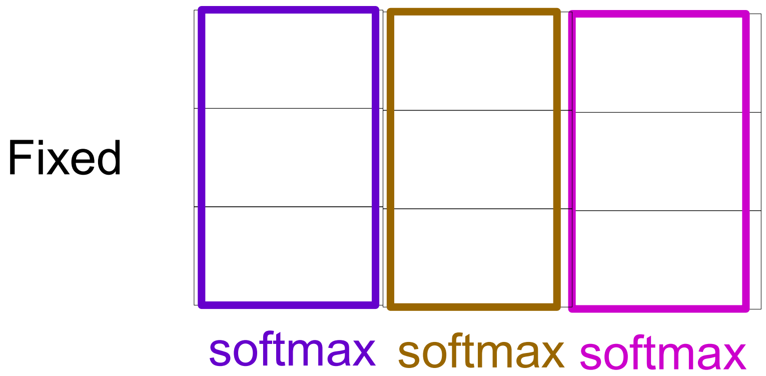
| | | |
|---|---|---|
| $x_0$ | $x_1$ | $x_2$ |

Fixed

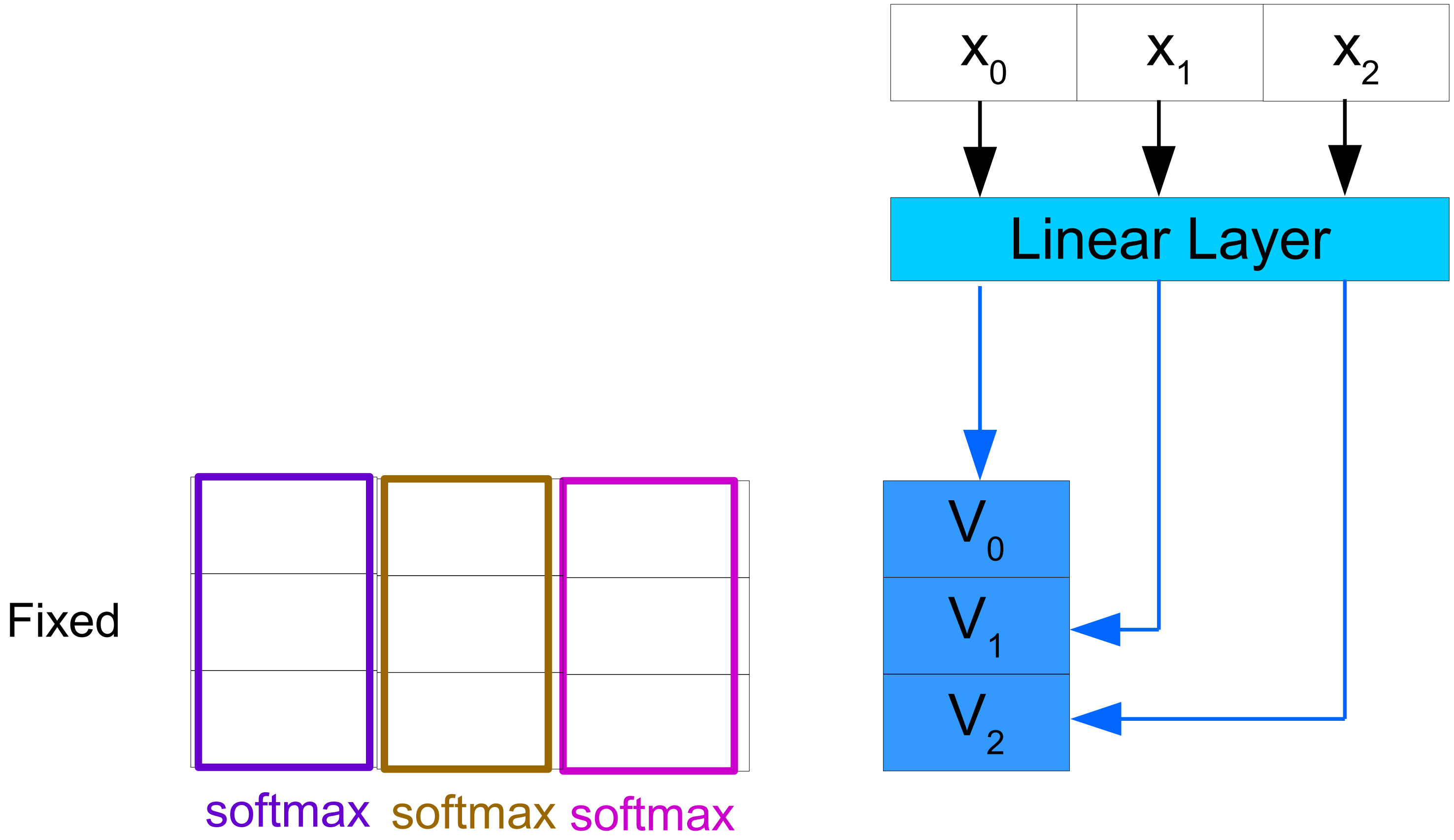
| | | |
|---|---|---|
| | | |
| | | |
| | | |

# 8.1 Synthesizer: *Random* variant

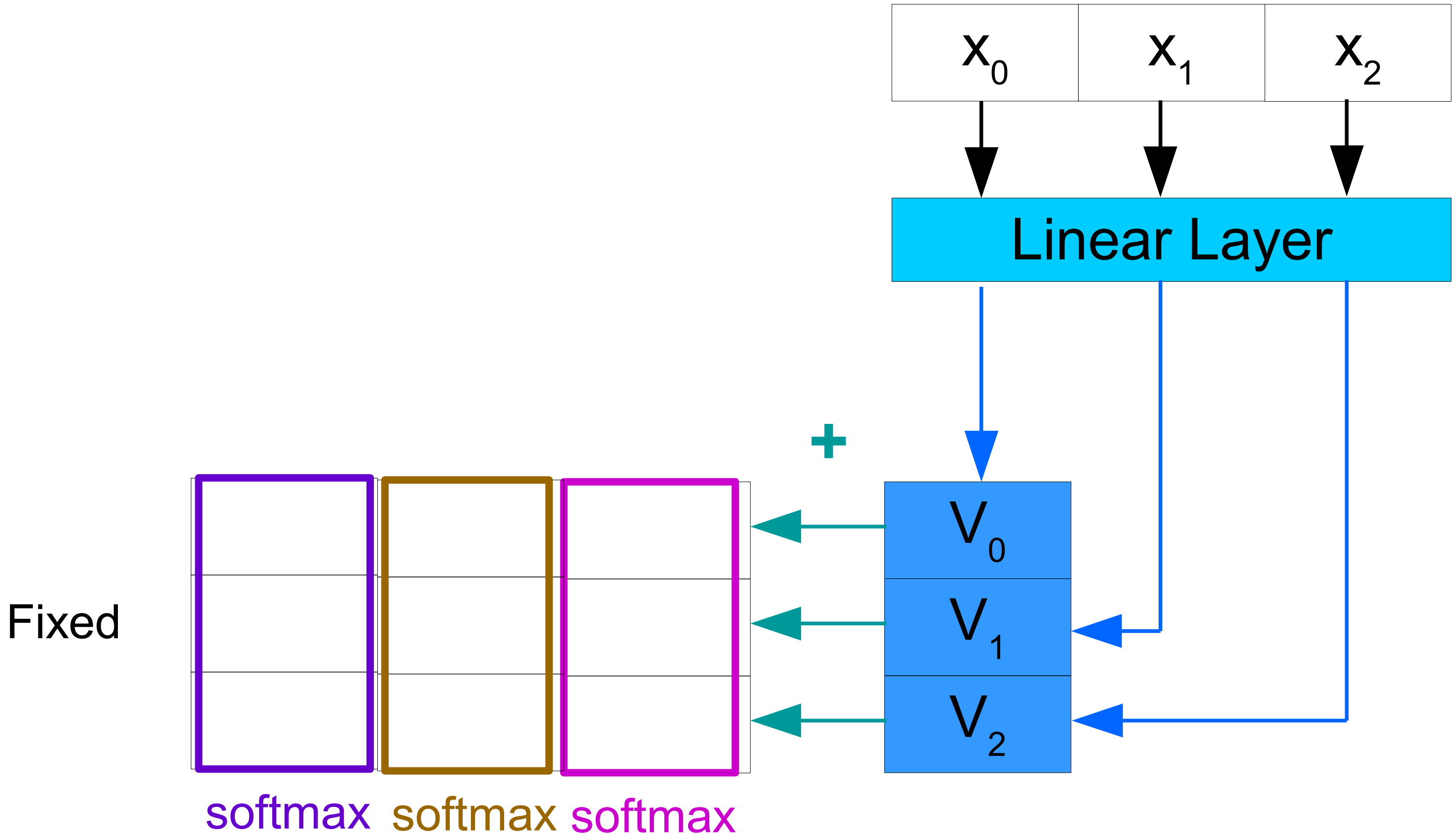
| | | |
|---|---|---|
| $x_0$ | $x_1$ | $x_2$ |



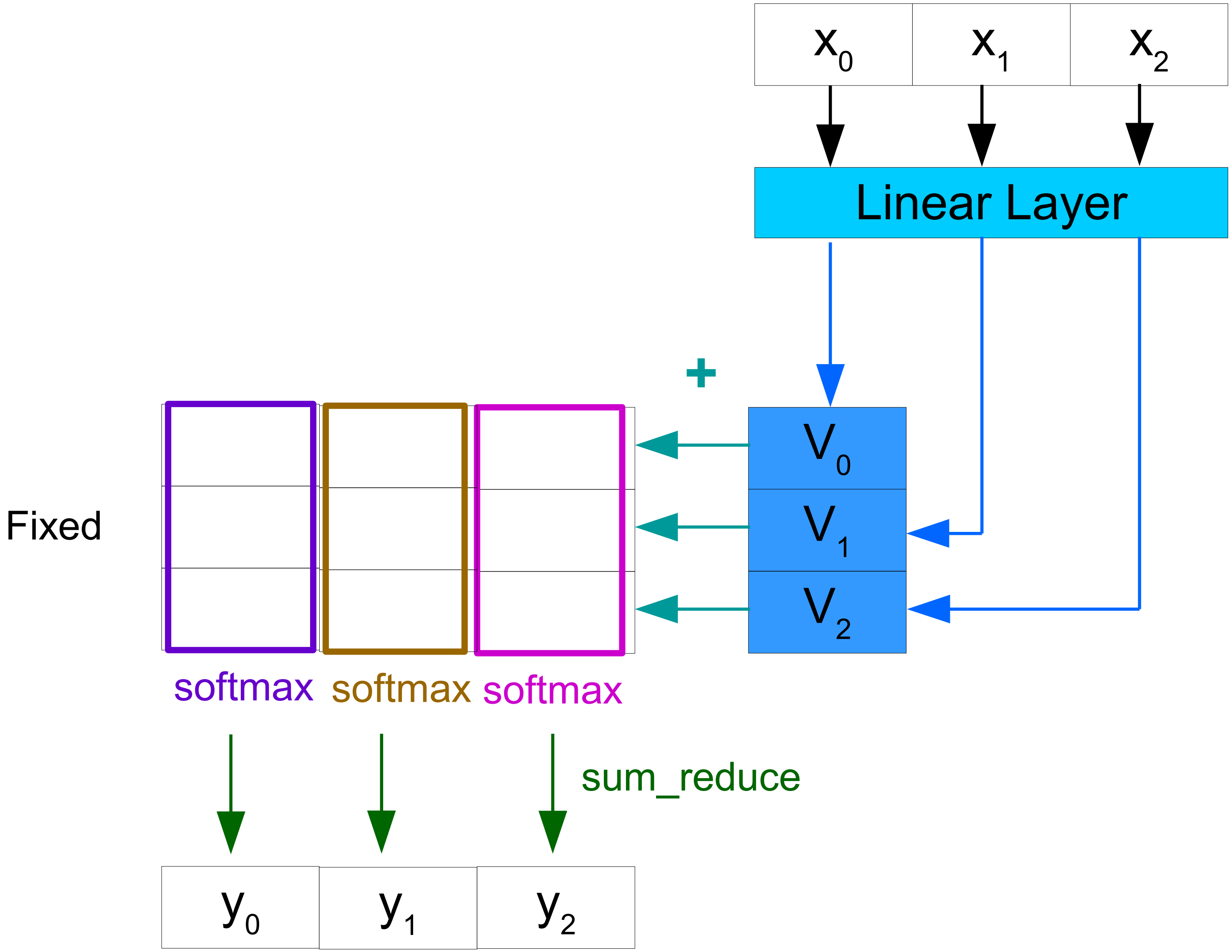
# 8.1 Synthesizer: *Random* variant



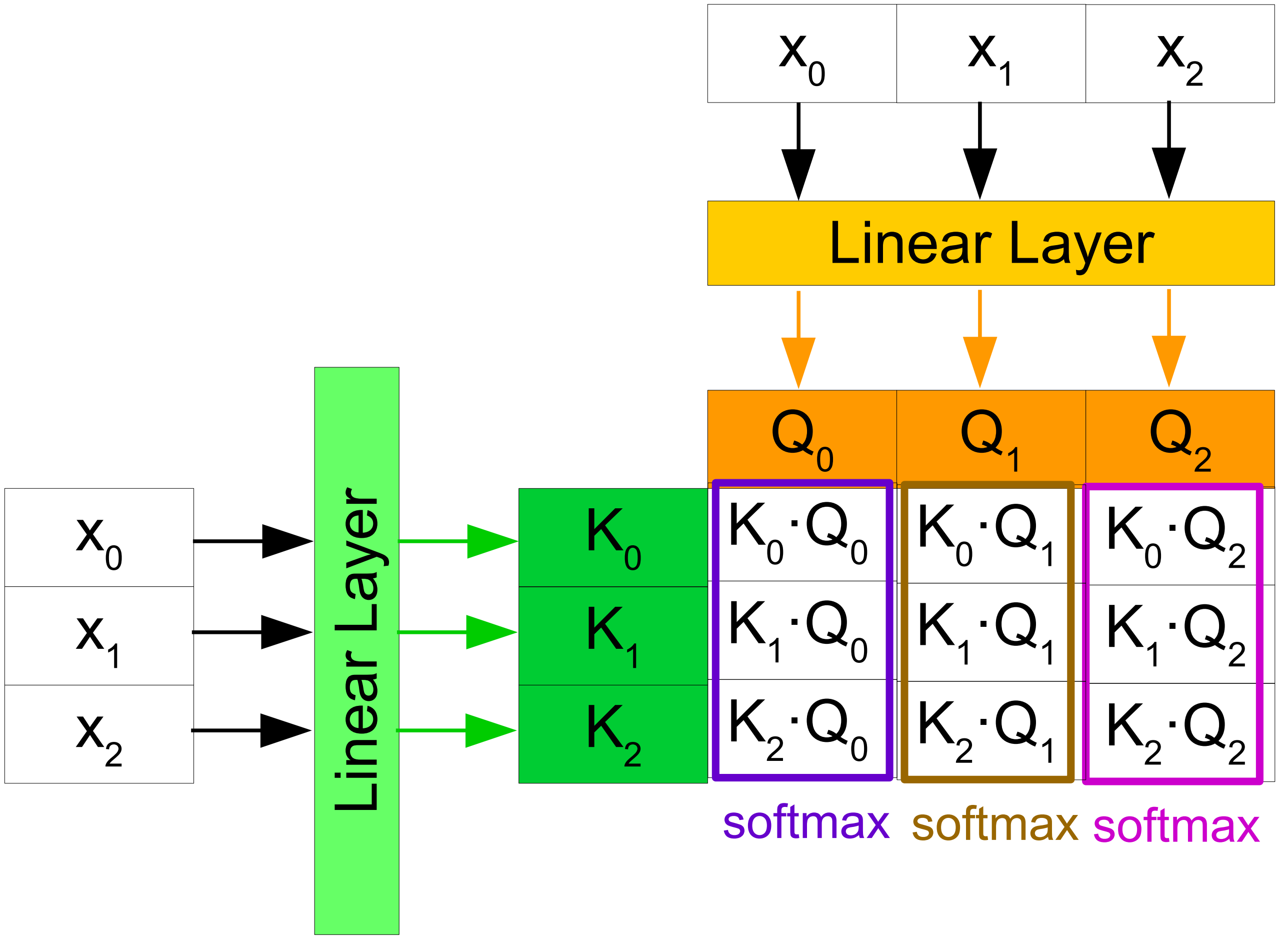
# 8.1 Synthesizer: *Random* variant



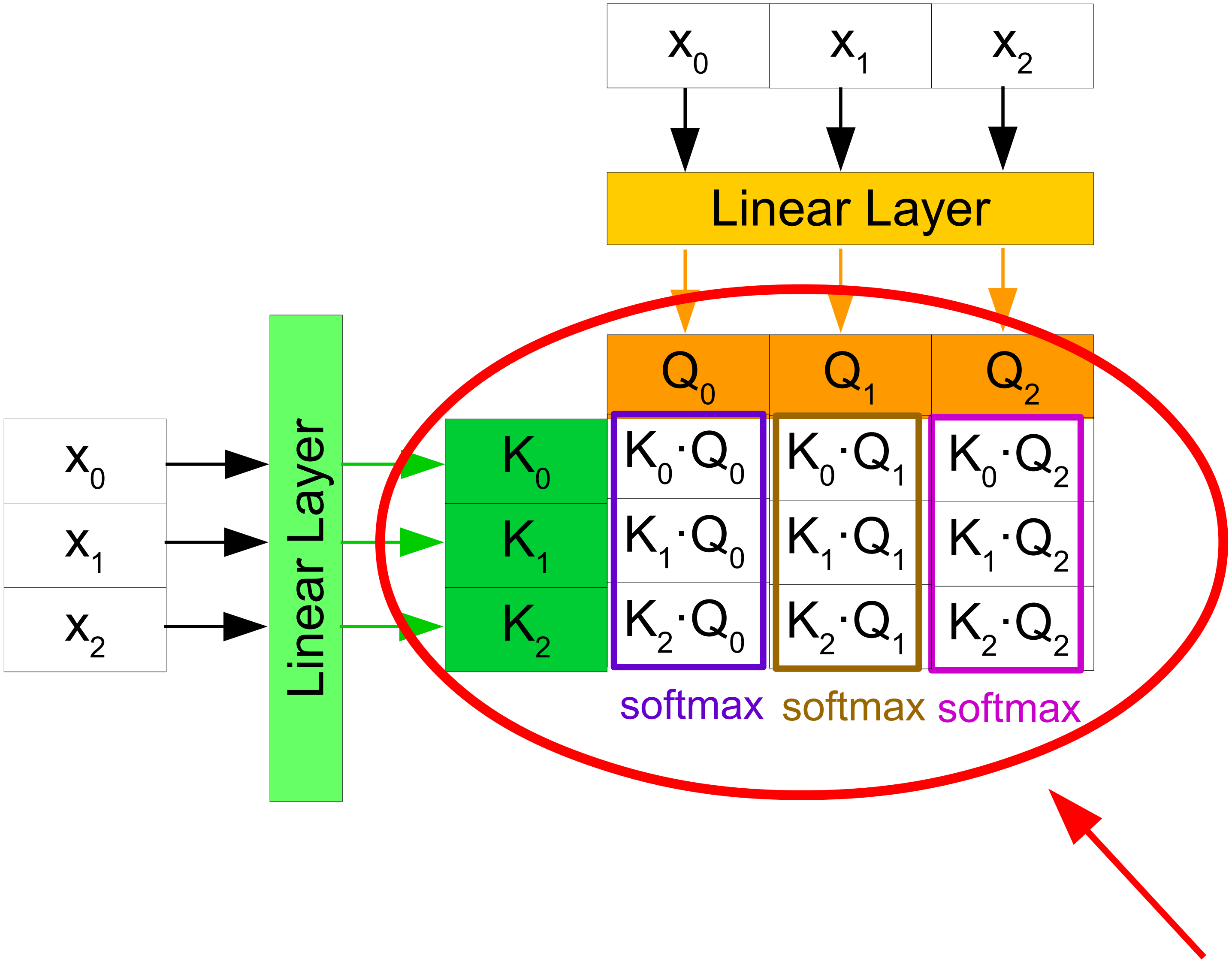
# 8.1 Synthesizer: *Random* variant



# 8.2 Linformer: Self-Attention with Linear Complexity

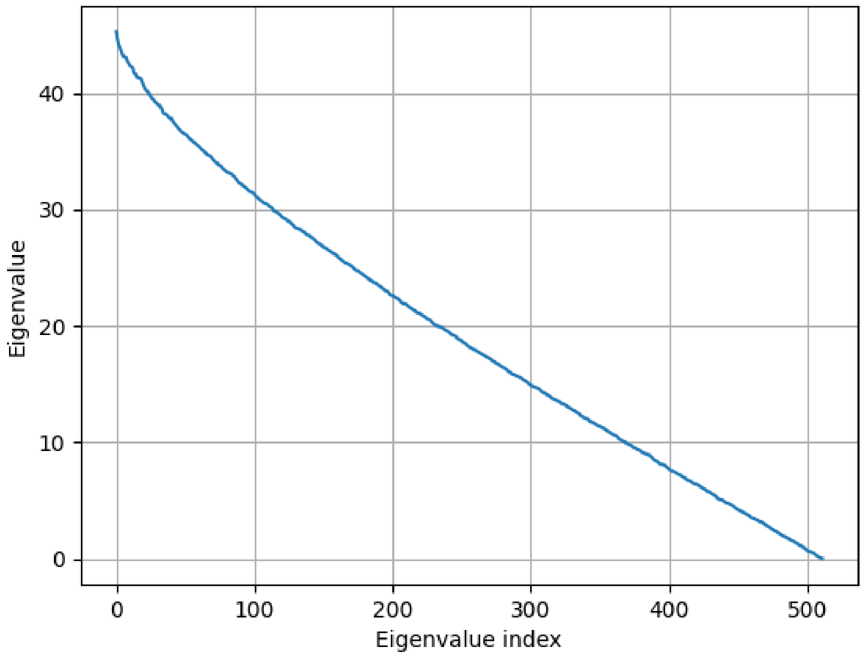


# 8.2 Linformer: Self-Attention with Linear Complexity




Self-Attention is Low Rank

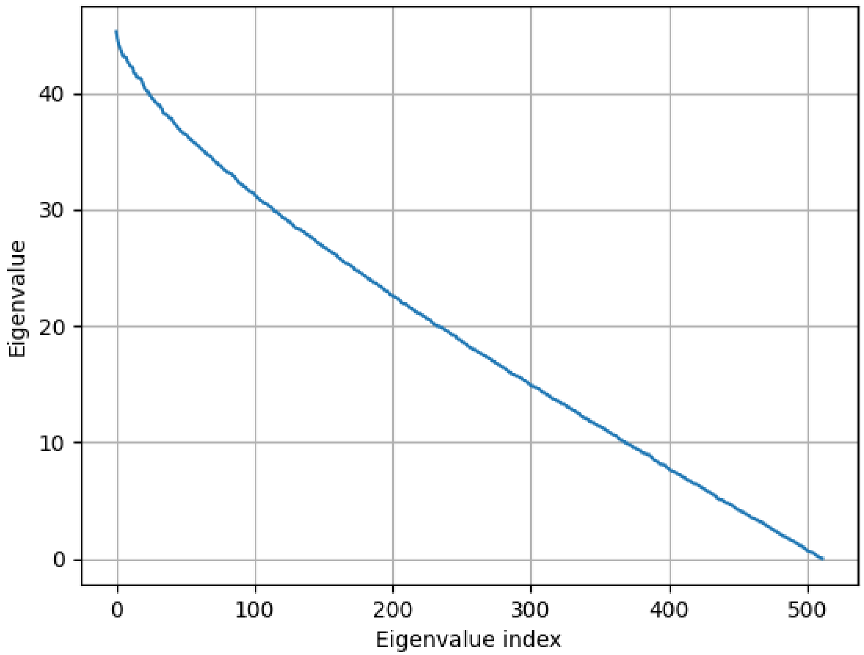
# 8.2 Linformer: Self-Attention with Linear Complexity




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

# 8.2 Linformer: Self-Attention with Linear Complexity

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




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

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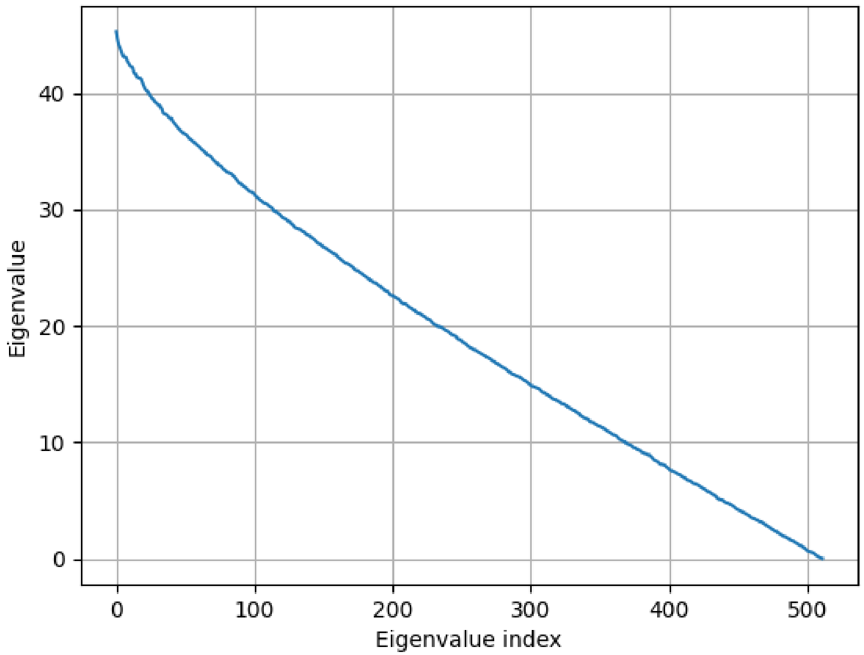
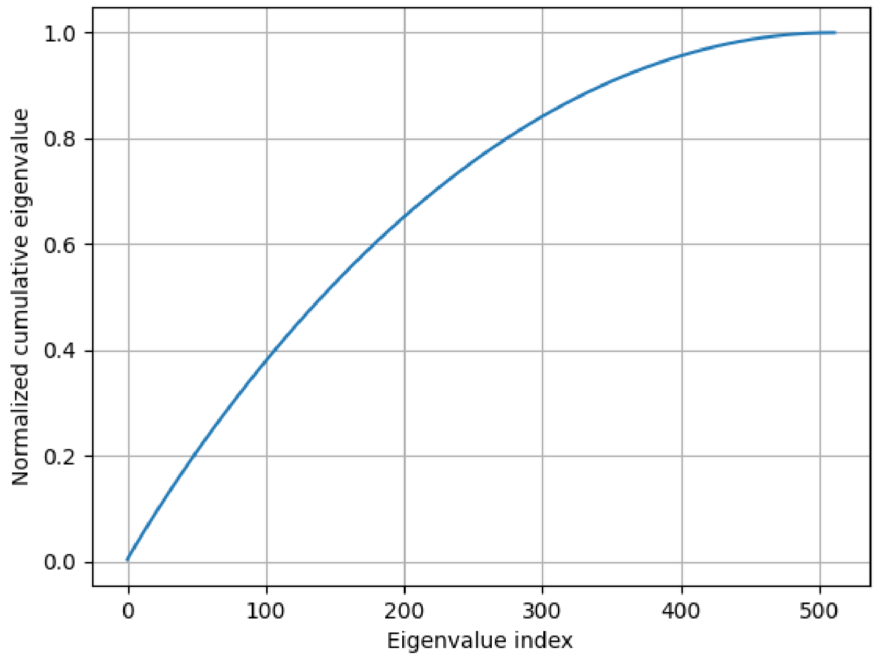
→ All dimensions have the same amount of information

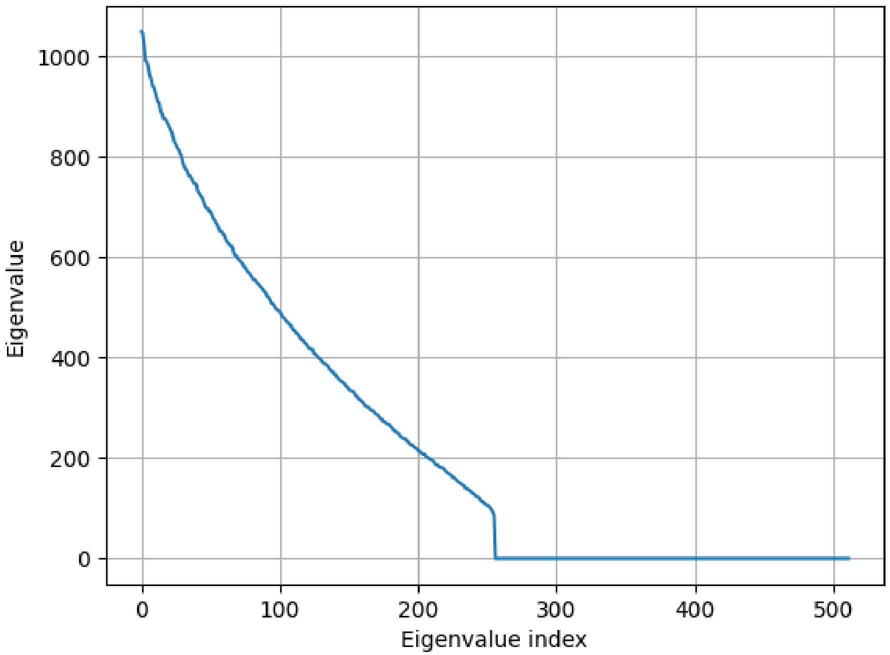



Eigenvalue spectrum of a 256x256 matrix (full rank).

# 8.2 Linformer: Self-Attention with Linear Complexity

A = 256 x 128
B = 128 x 256
M = A · B

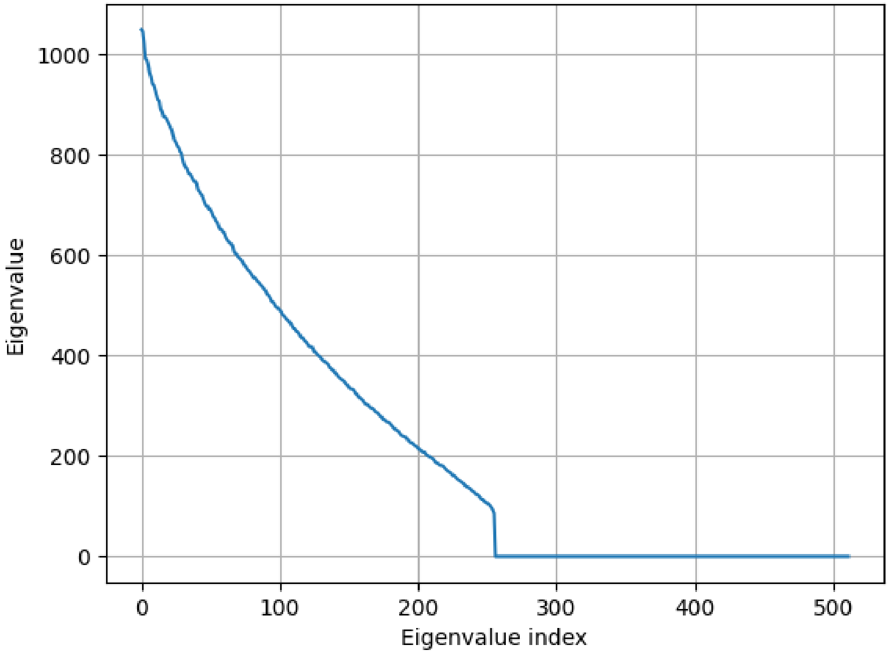



Eigenvalue spectrum of a 256x256 matrix (low rank).

# 8.2 Linformer: Self-Attention with Linear Complexity

A = 256 x 128
B = 128 x 256
M = A · B

Information is concentrated along few dimensions

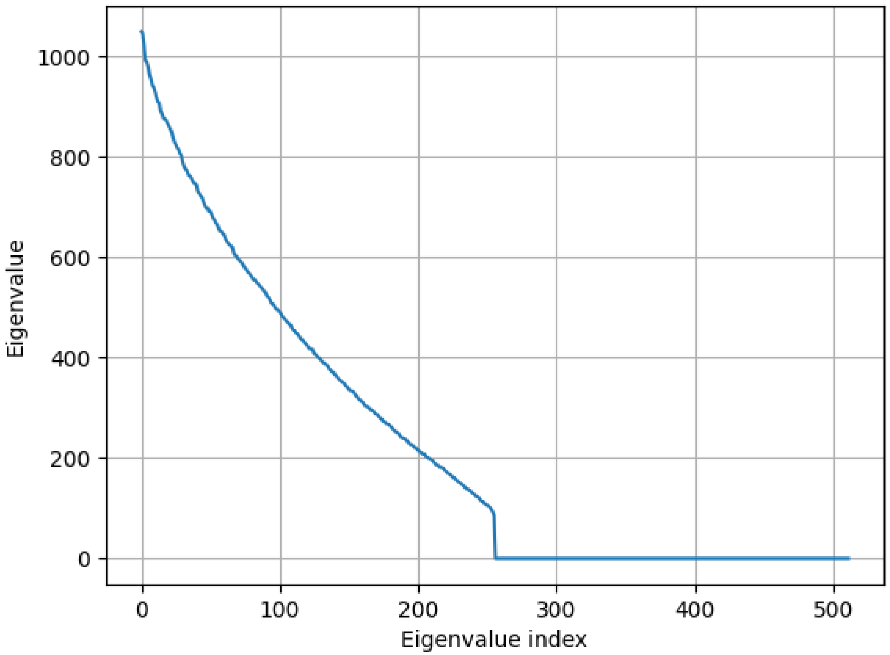


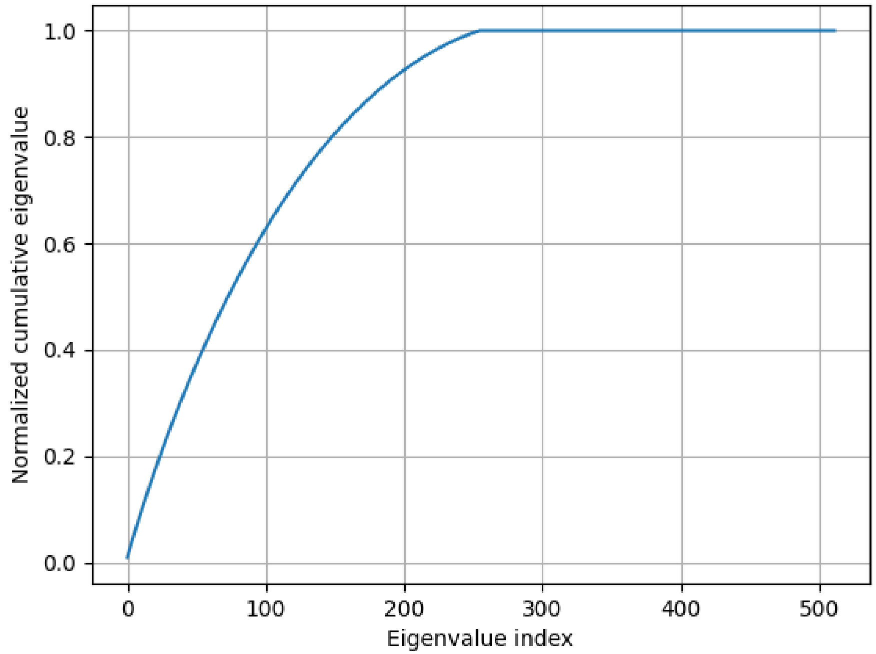

Eigenvalue spectrum of a 256x256 matrix (low rank).

# 8.2 Linformer: Self-Attention with Linear Complexity

A = 256 x 128
B = 128 x 256
$M = A \cdot B$

Information is concentrated along few dimensions




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

# 8.2 Linformer: Self-Attention is Low Rank

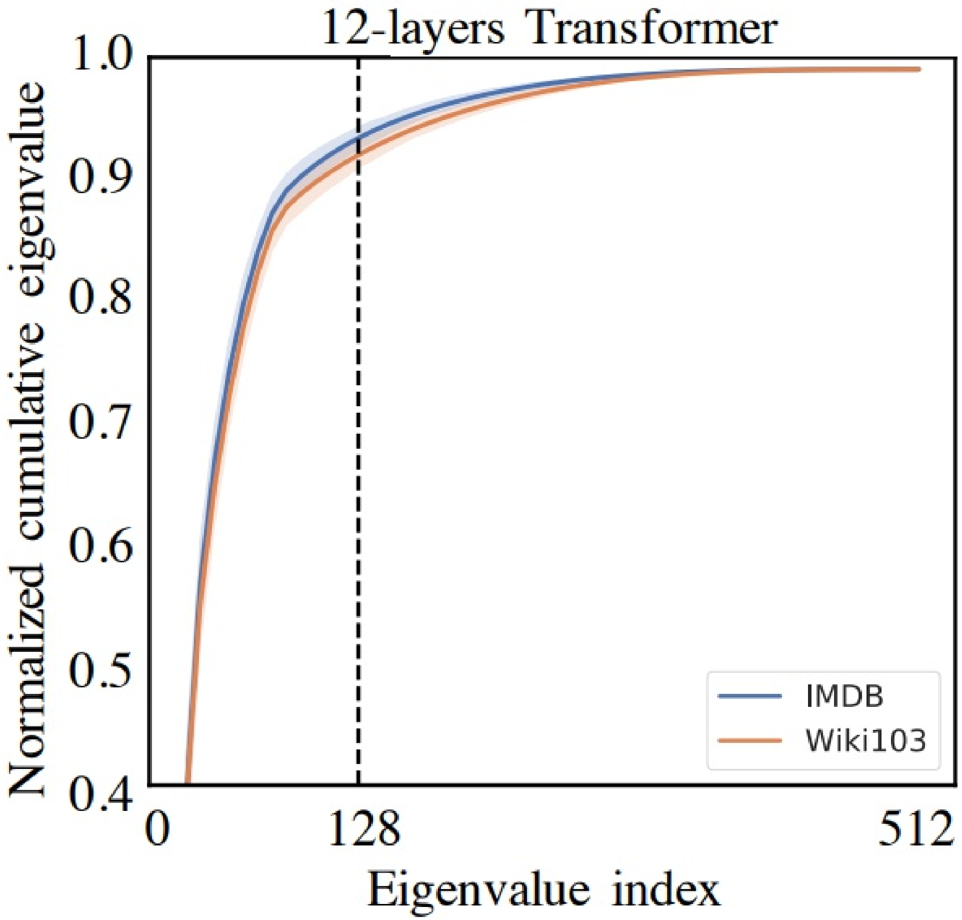
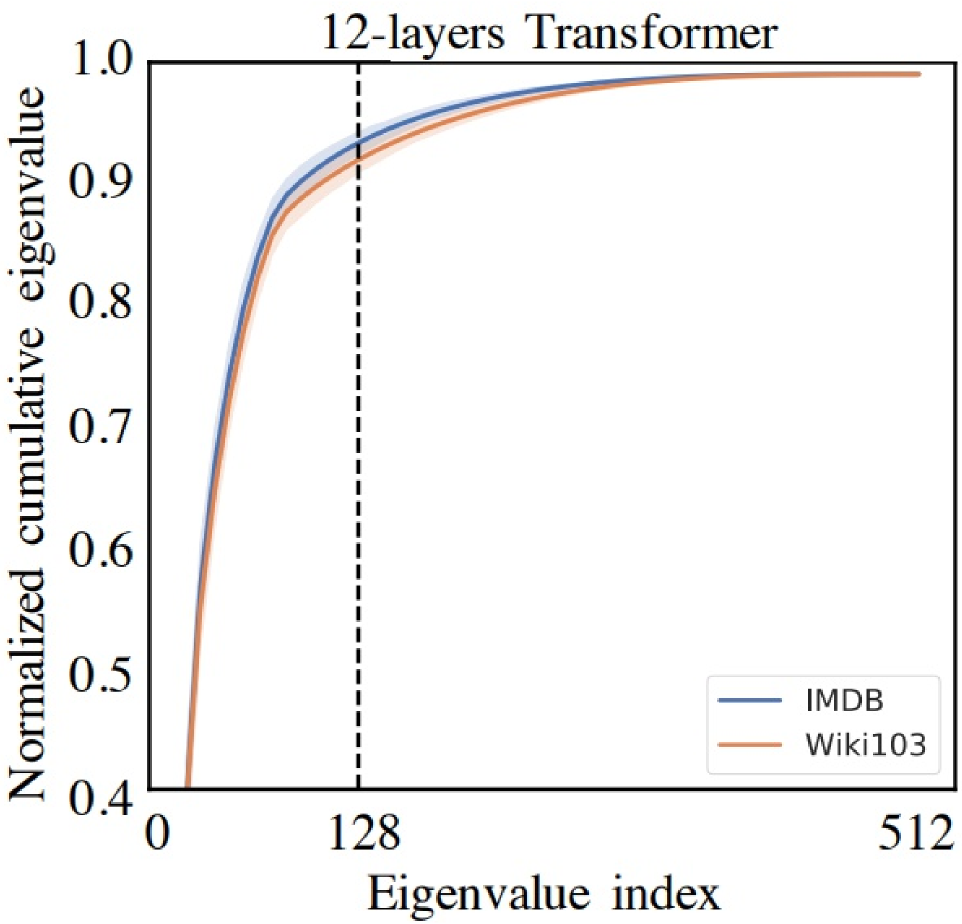
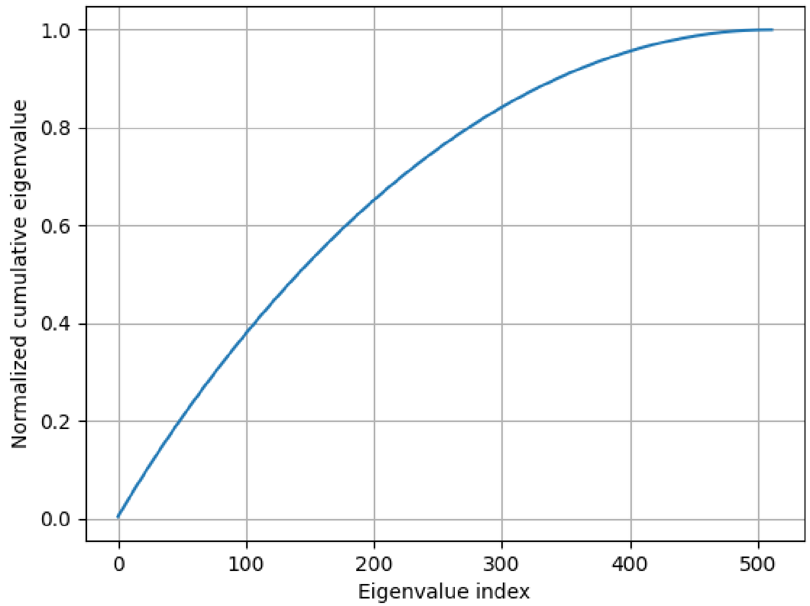



Image sources:
Wang, S., Li, B.Z., Khabsa, M., Fang, H., & Ma, H. (2020). Linformer: Self-Attention with Linear Complexity. ArXiv, abs/2006.04768.

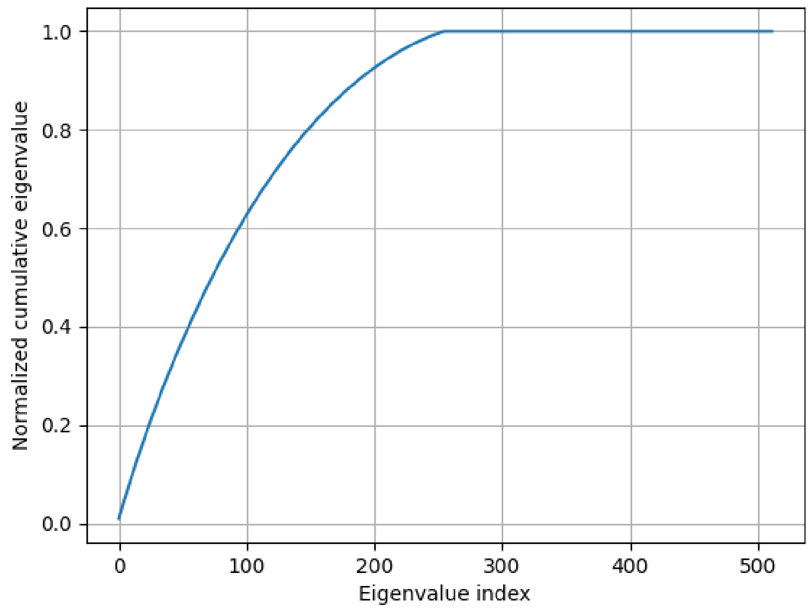
# 8.2 Linformer: Self-Attention is Low Rank




**Full rank**




**Low rank**

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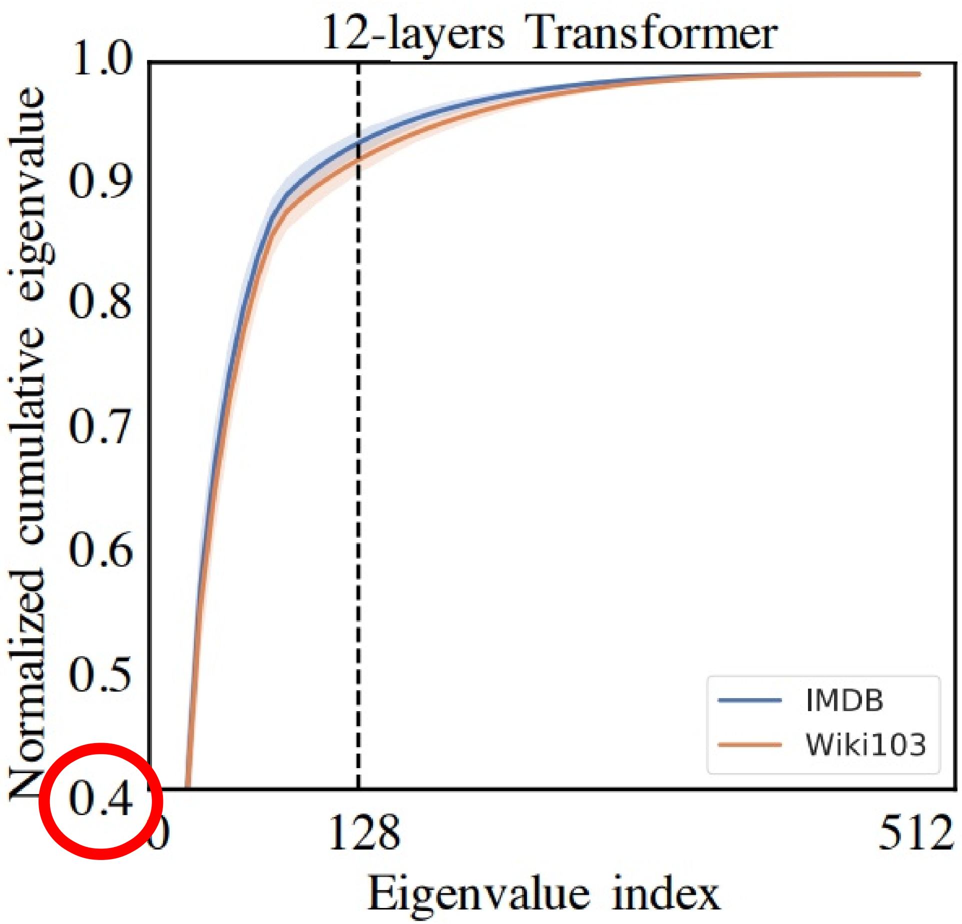
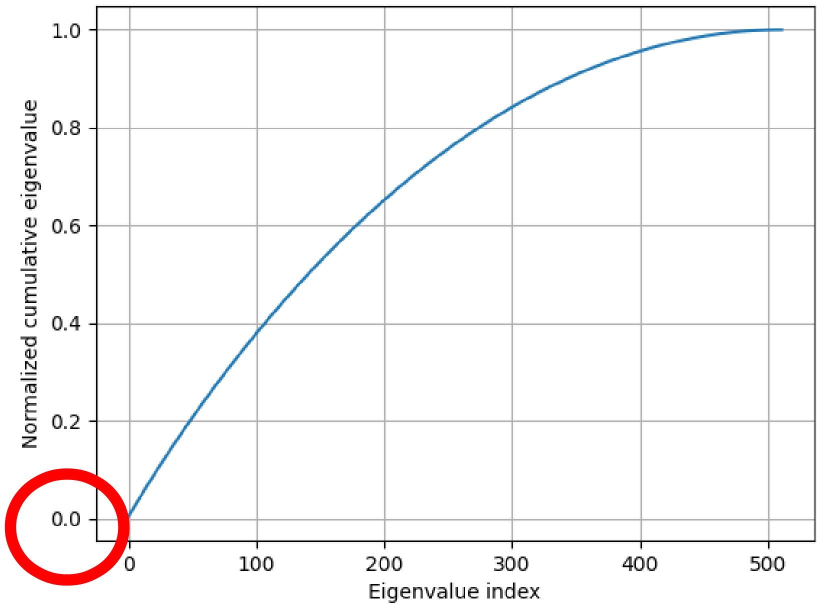
Wang, S., Li, B.Z., Khabsa, M., Fang, H., & Ma, H. (2020). Linformer: Self-Attention with Linear Complexity. ArXiv, abs/2006.04768.

# 8.2 Linformer: Self-Attention is Low Rank




Full rank




Low rank

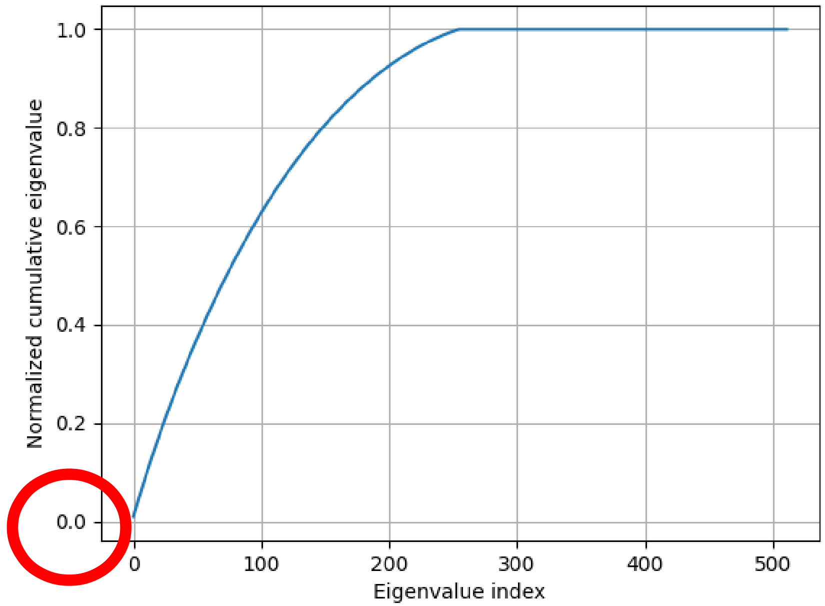
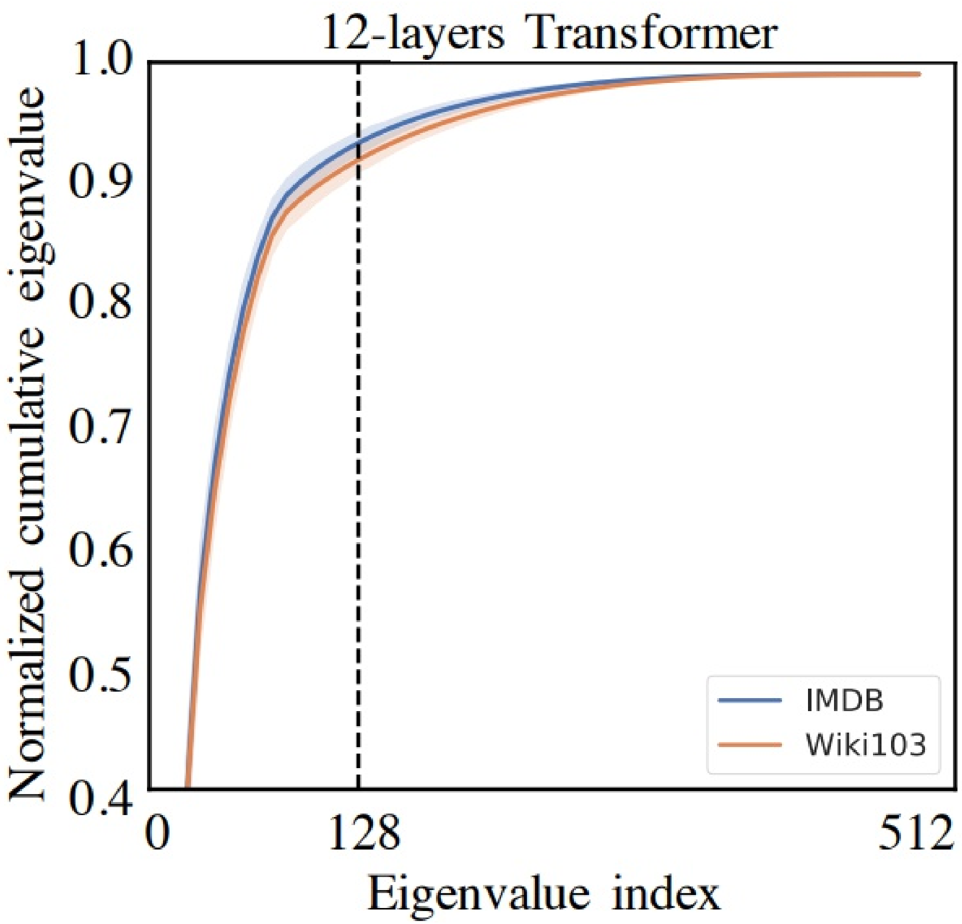



Image sources:
Wang, S., Li, B.Z., Khabsa, M., Fang, H., & Ma, H. (2020). Linformer: Self-Attention with Linear Complexity. ArXiv, abs/2006.04768.

# 8.2 Linformer: Self-Attention with Linear Complexity

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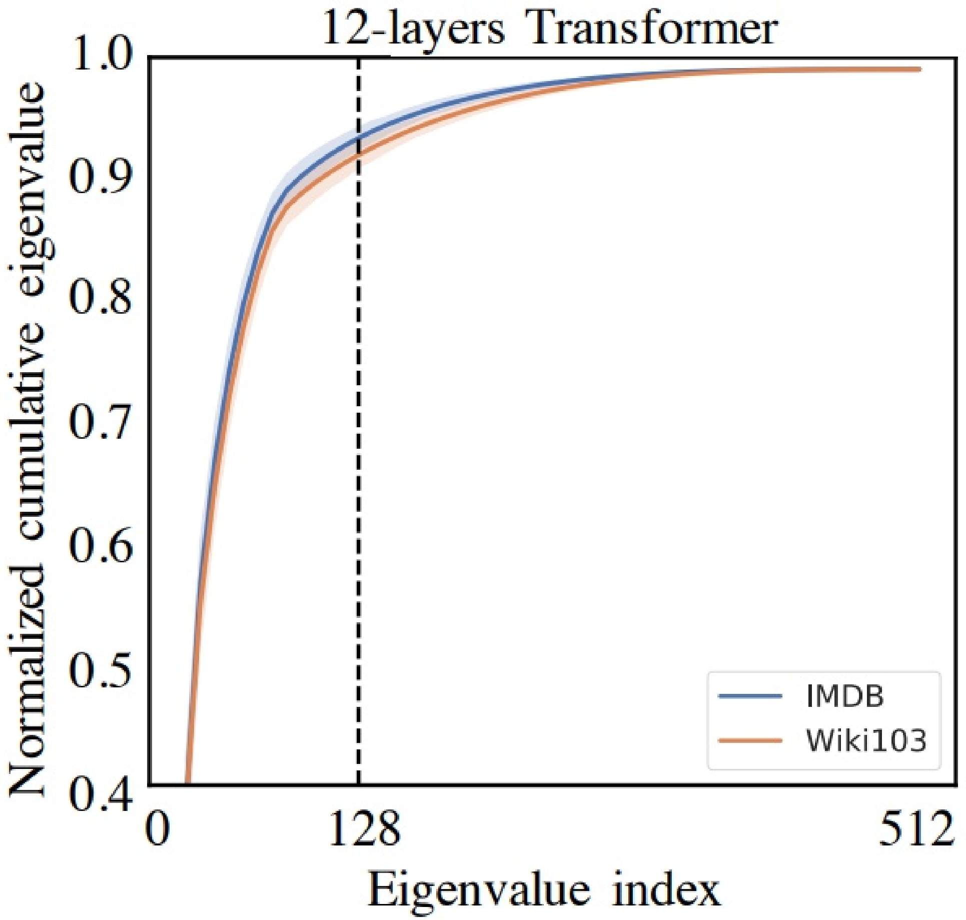


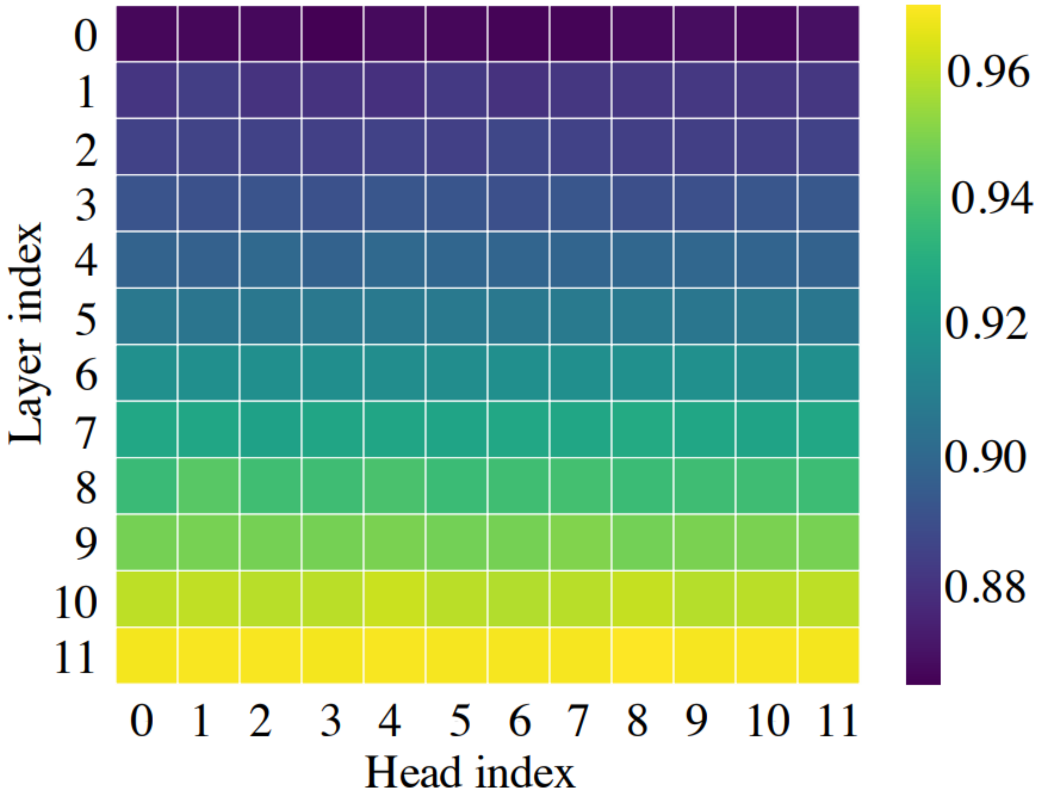


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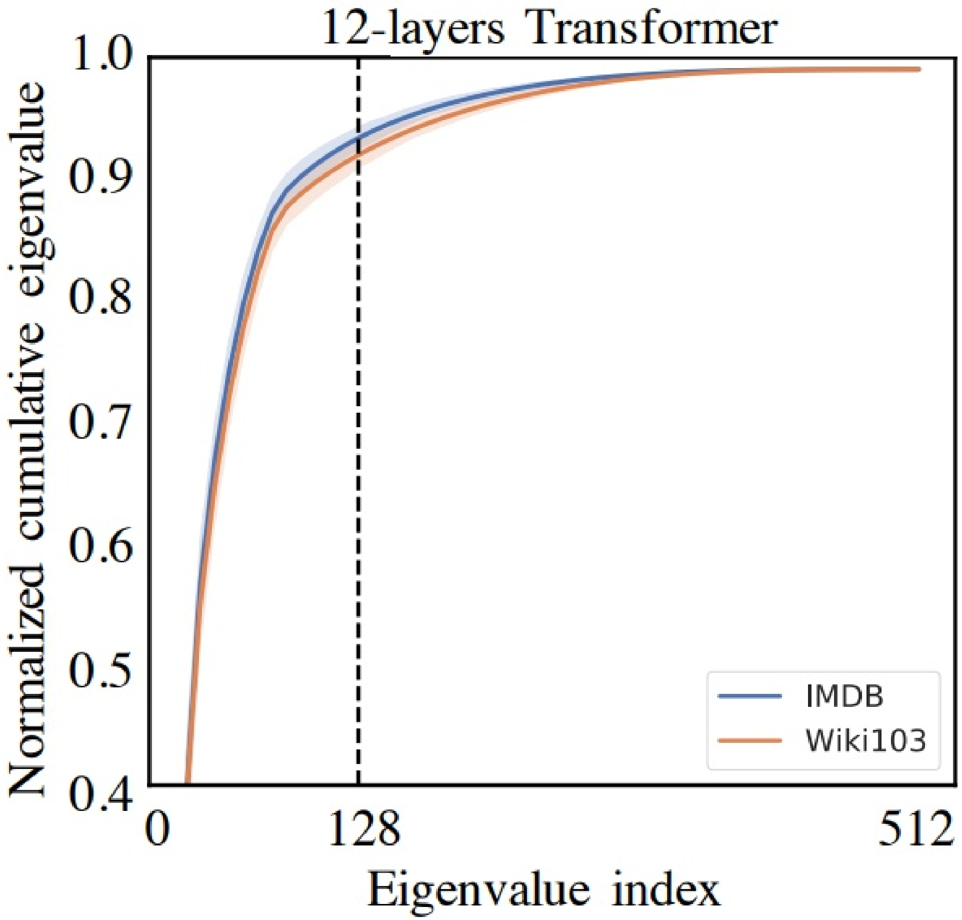
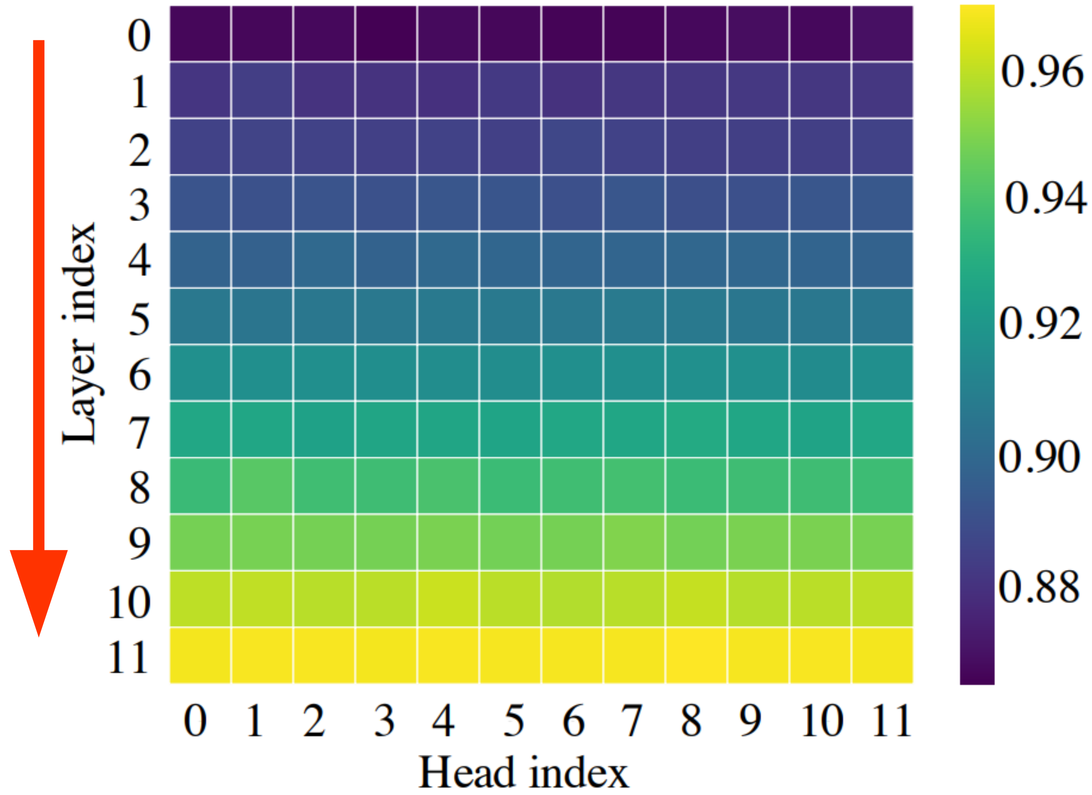



**Eigenvalue index: 128**

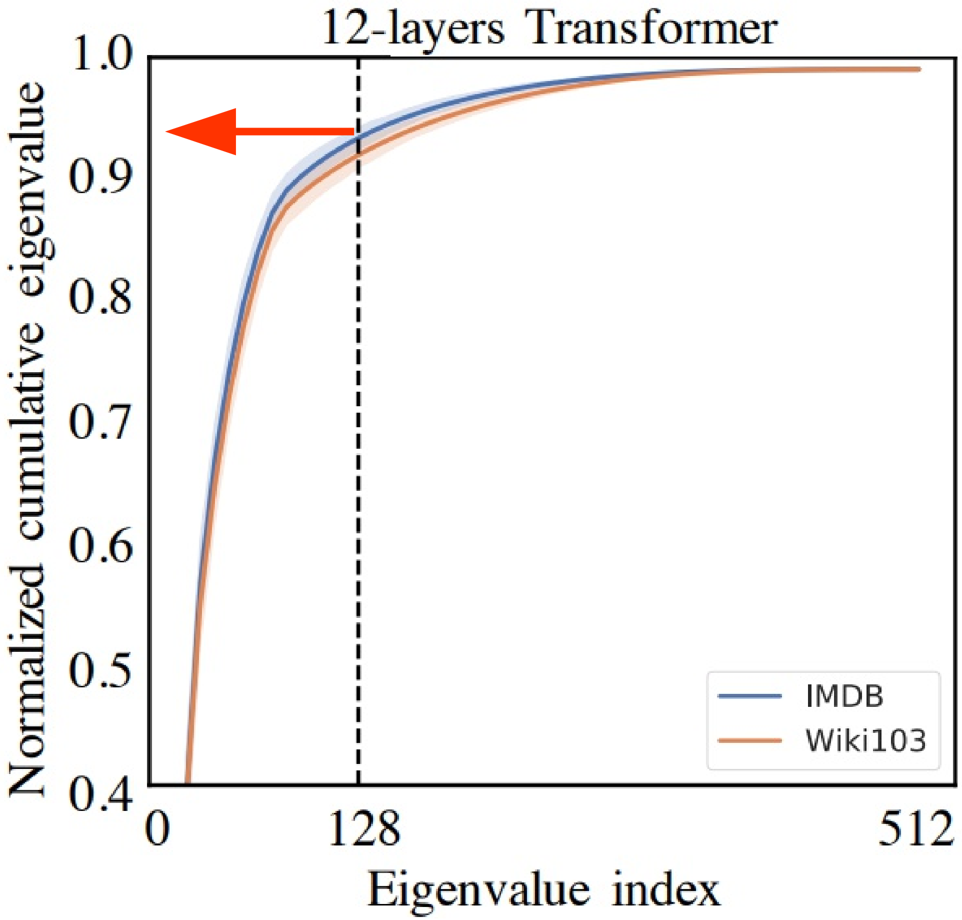


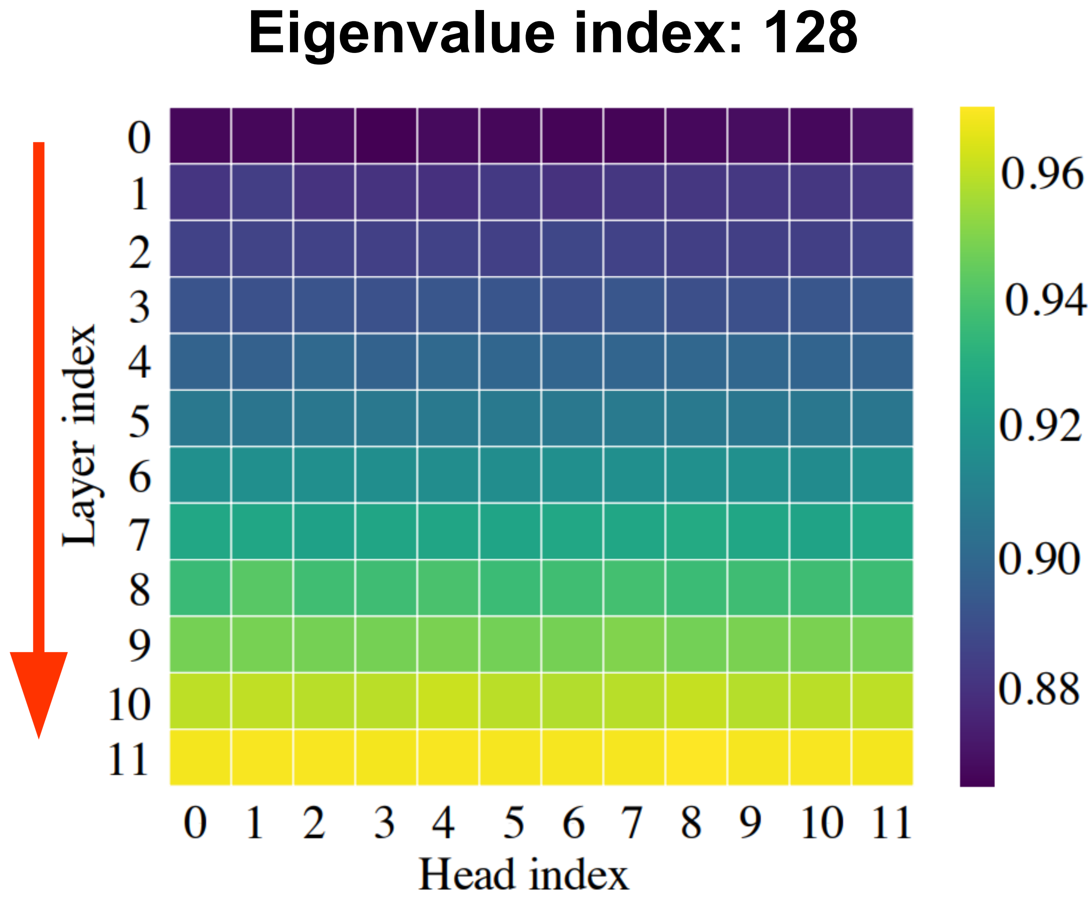

With increasing deep:
Put more and more information into fewer and fewer dimensions

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

# 8.2 Linformer: Self-Attention with Linear Complexity

More and more skewed

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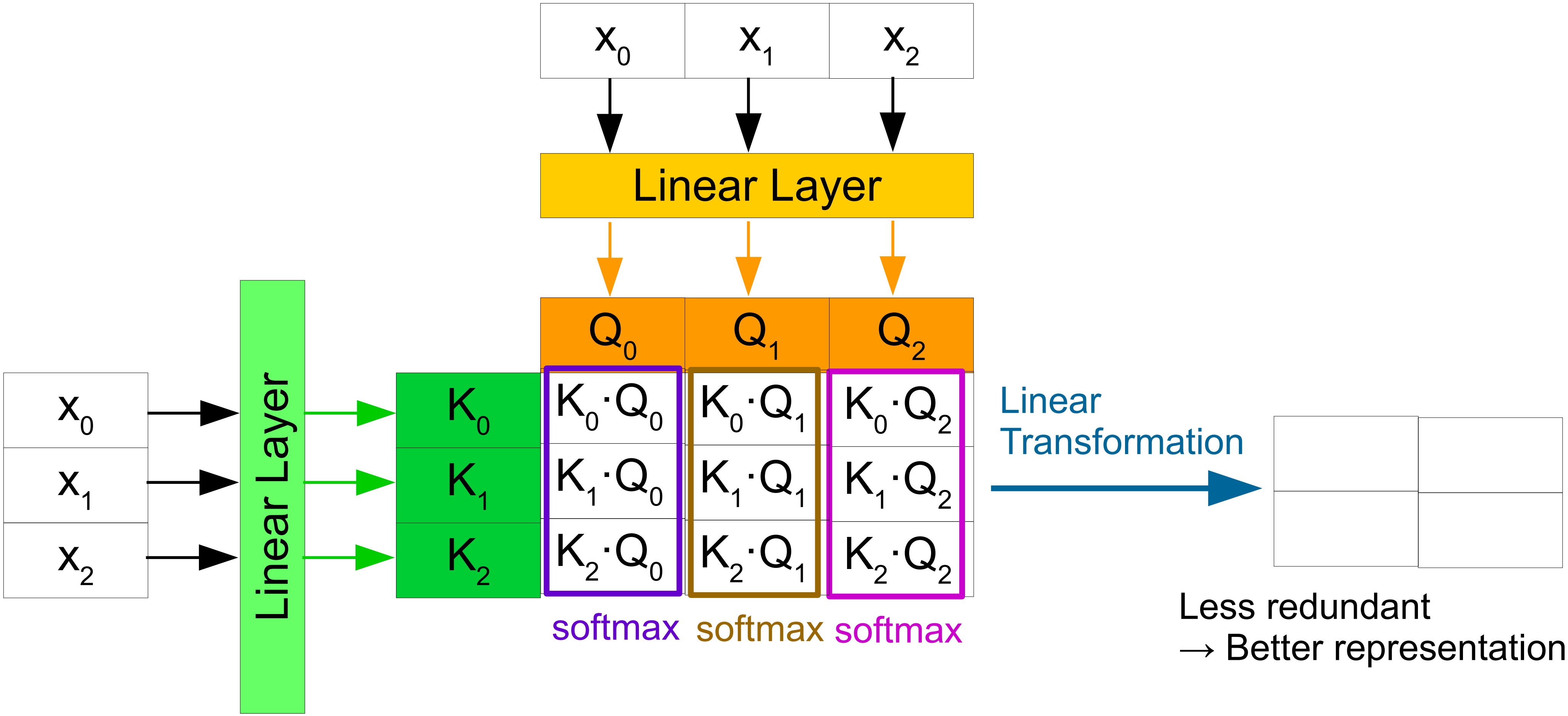
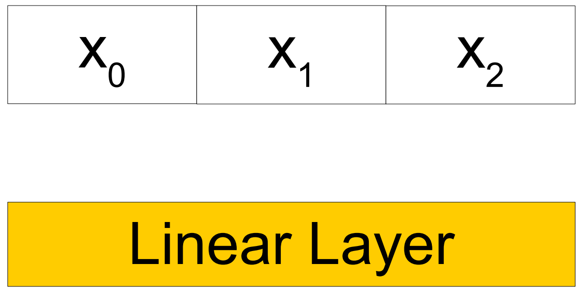
# 8.2 Linformer: Self-Attention with Linear Complexity



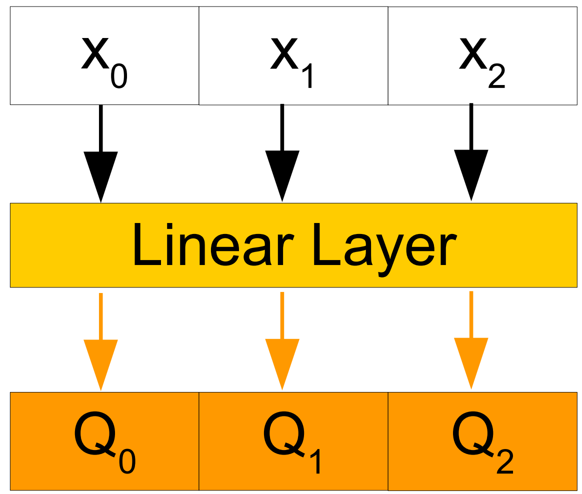
# 8.2 Linformer: Self-Attention with Linear Complexity

| | | |
|---|---|---|
| $x_0$ | $x_1$ | $x_2$ |

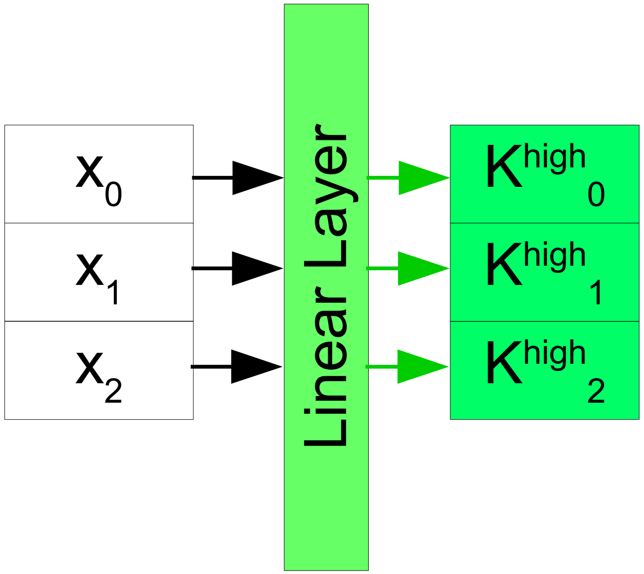
# 8.2 Linformer: Self-Attention with Linear Complexity

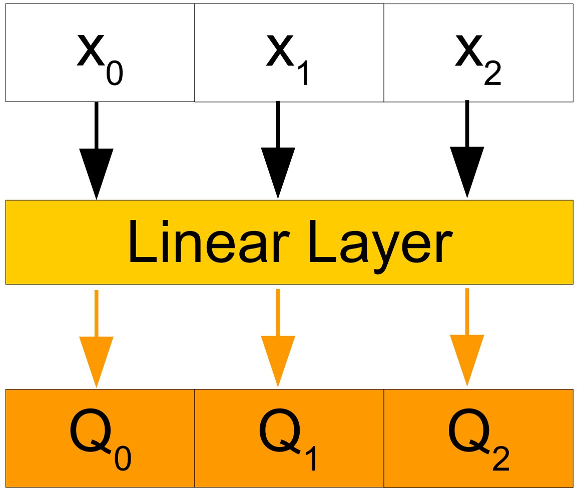


# 8.2 Linformer: Self-Attention with Linear Complexity

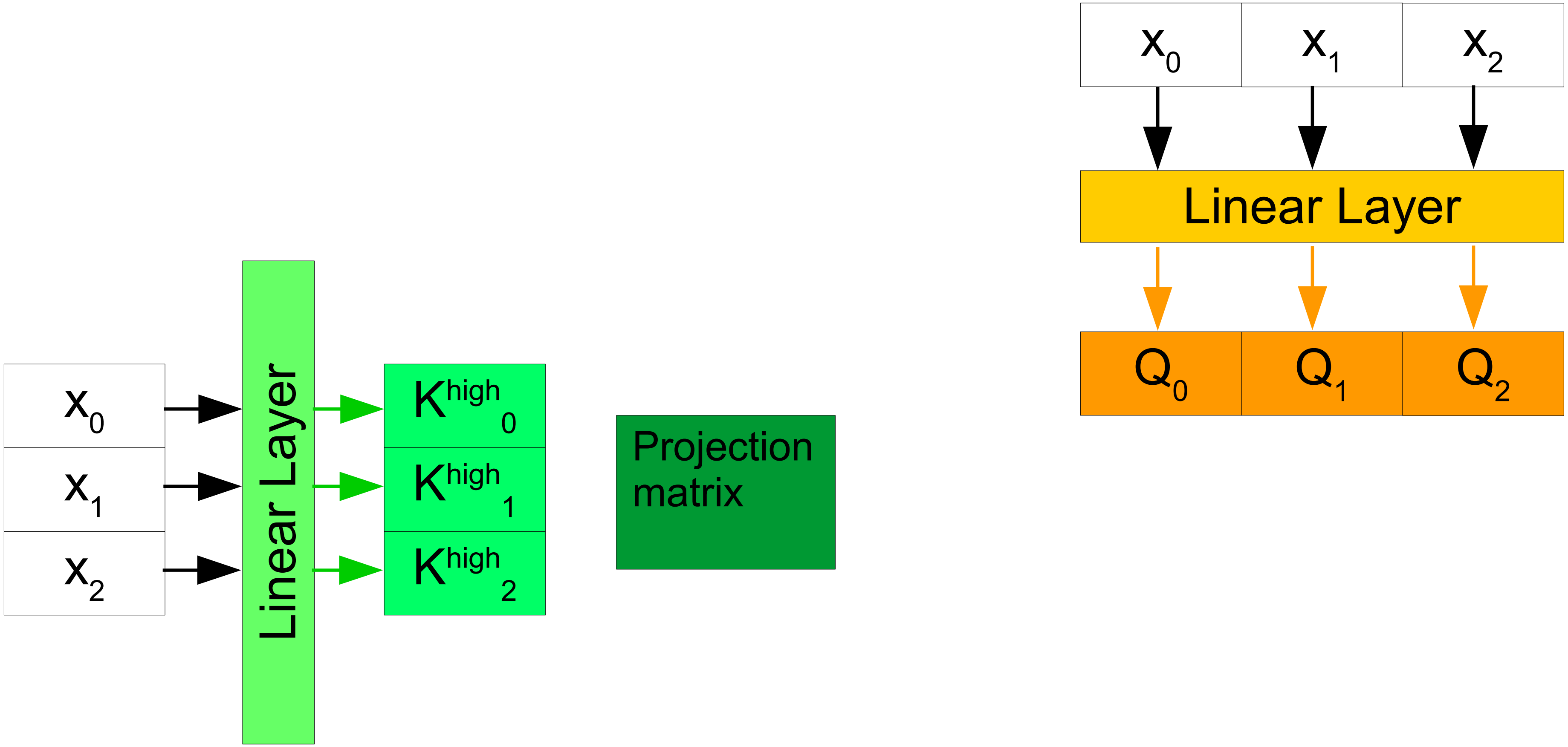


# 8.2 Linformer: Self-Attention with Linear Complexity

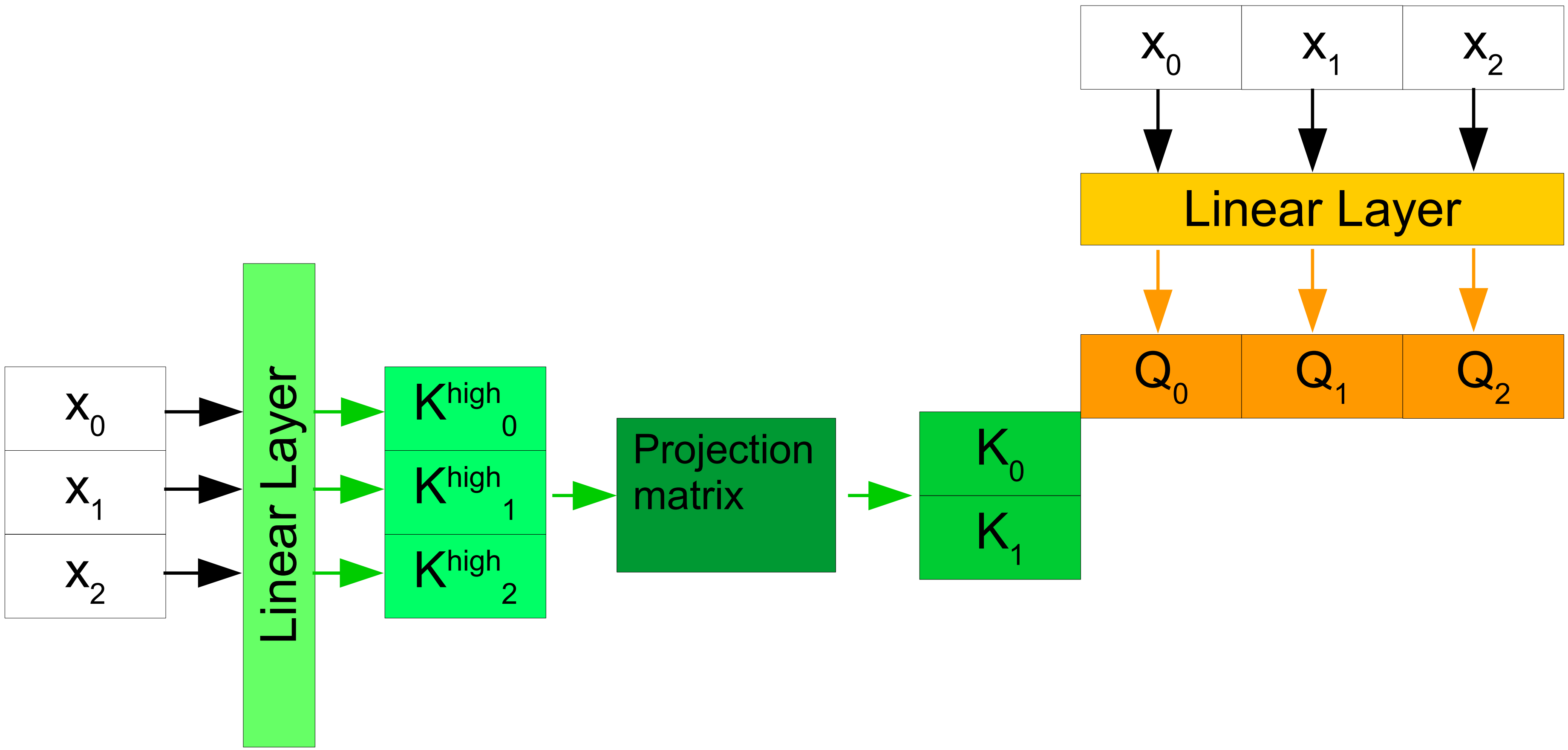


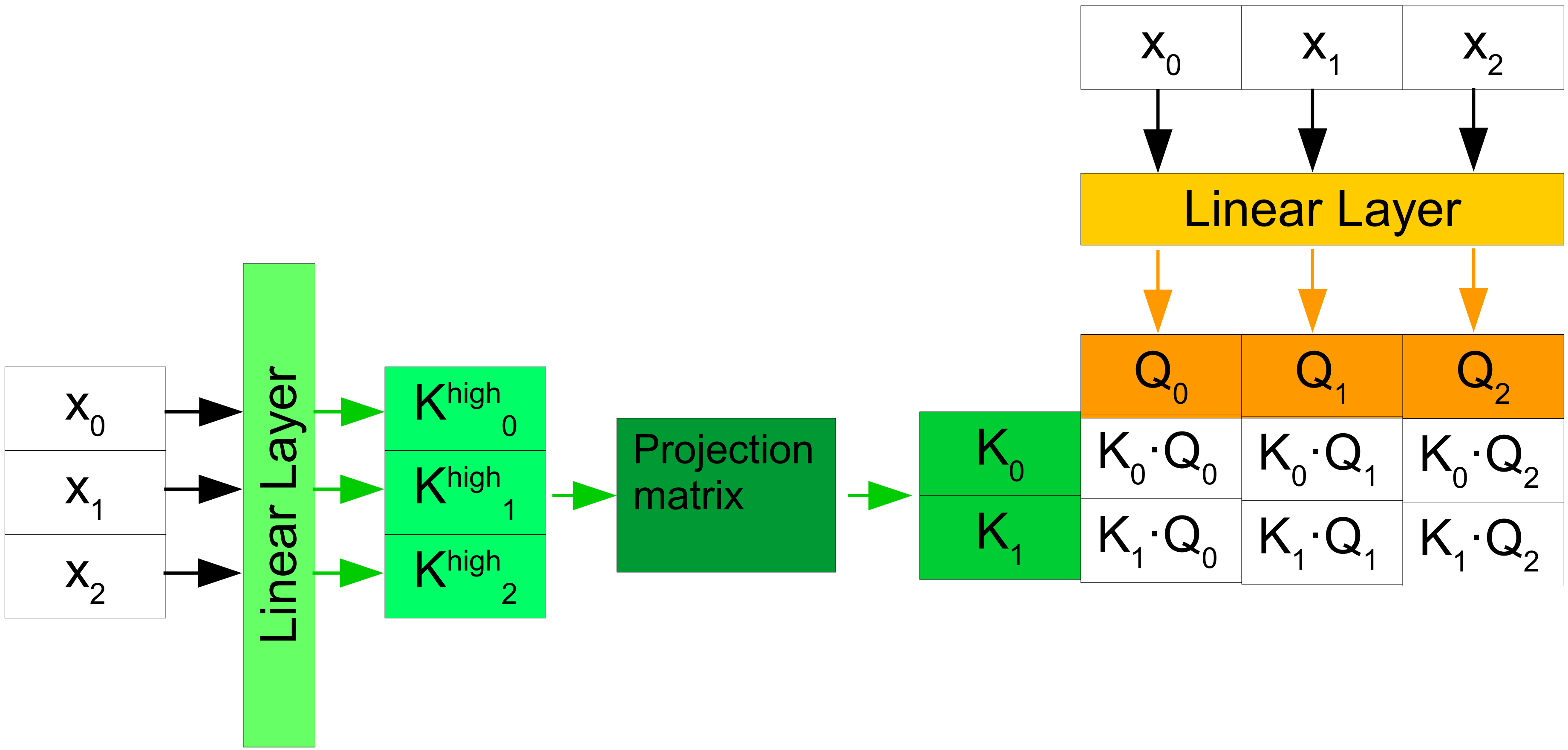
# 8.2 Linformer: Self-Attention with Linear Complexity



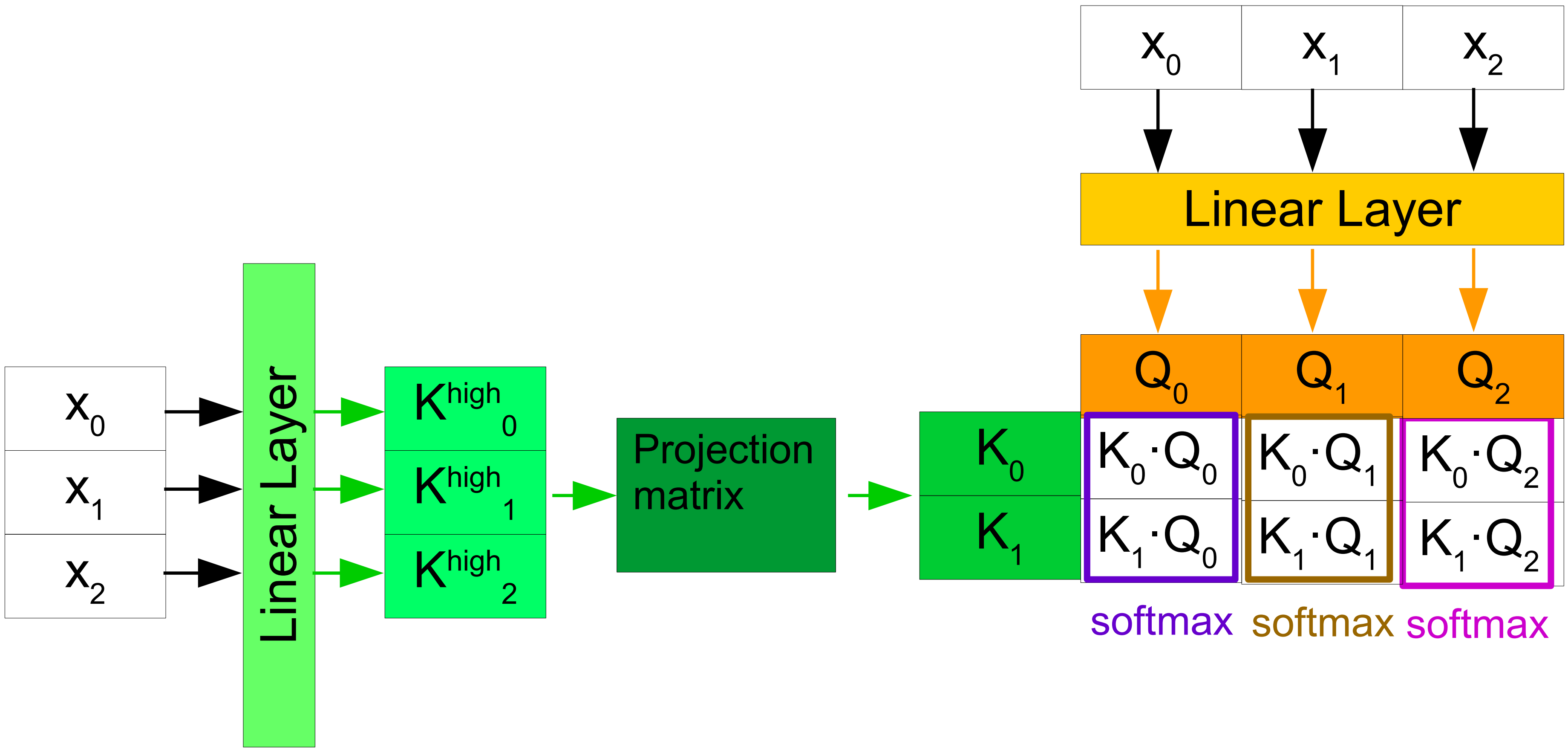
# 8.2 Linformer: Self-Attention with Linear Complexity



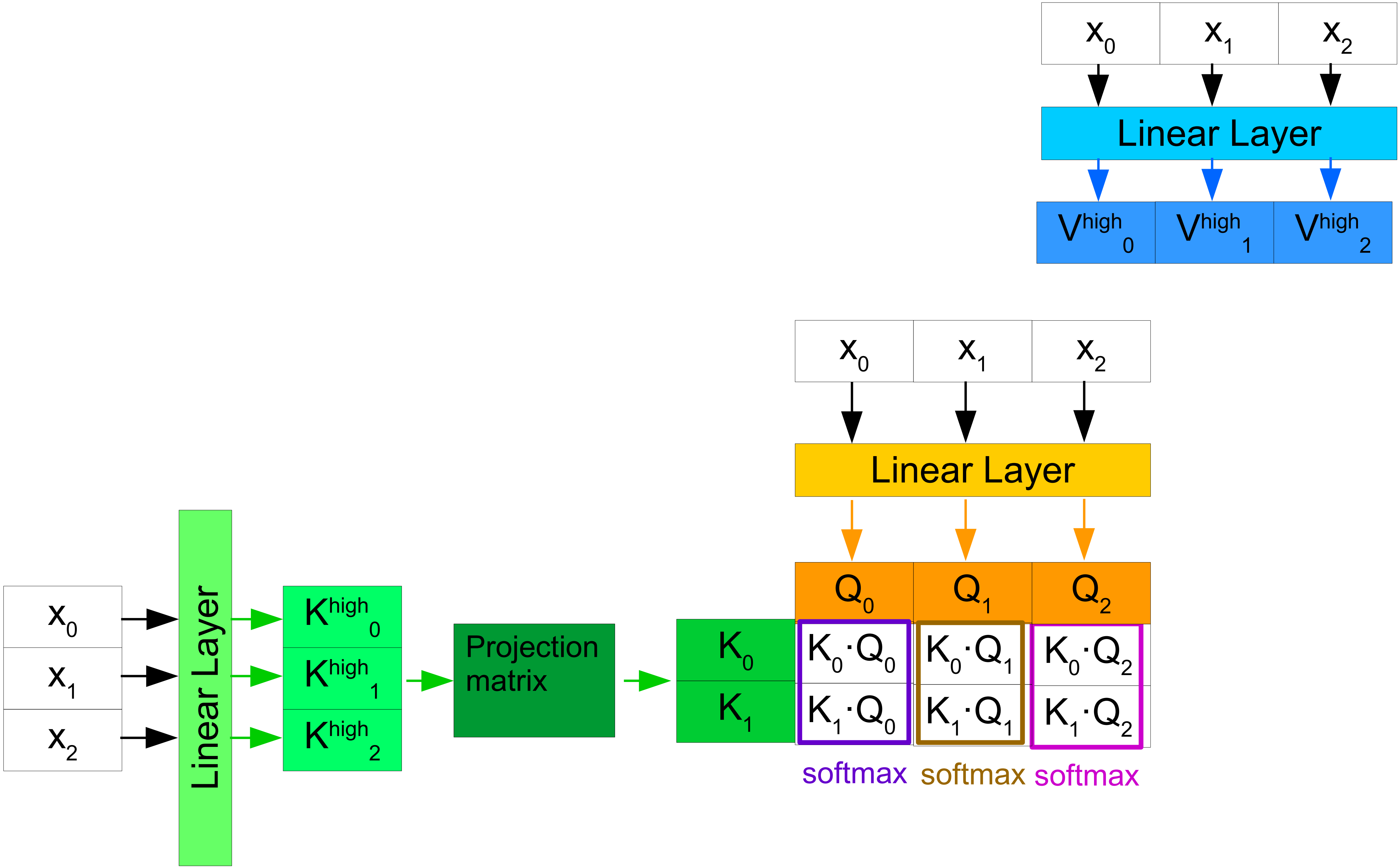
# 8.2 Linformer: Self-Attention with Linear Complexity



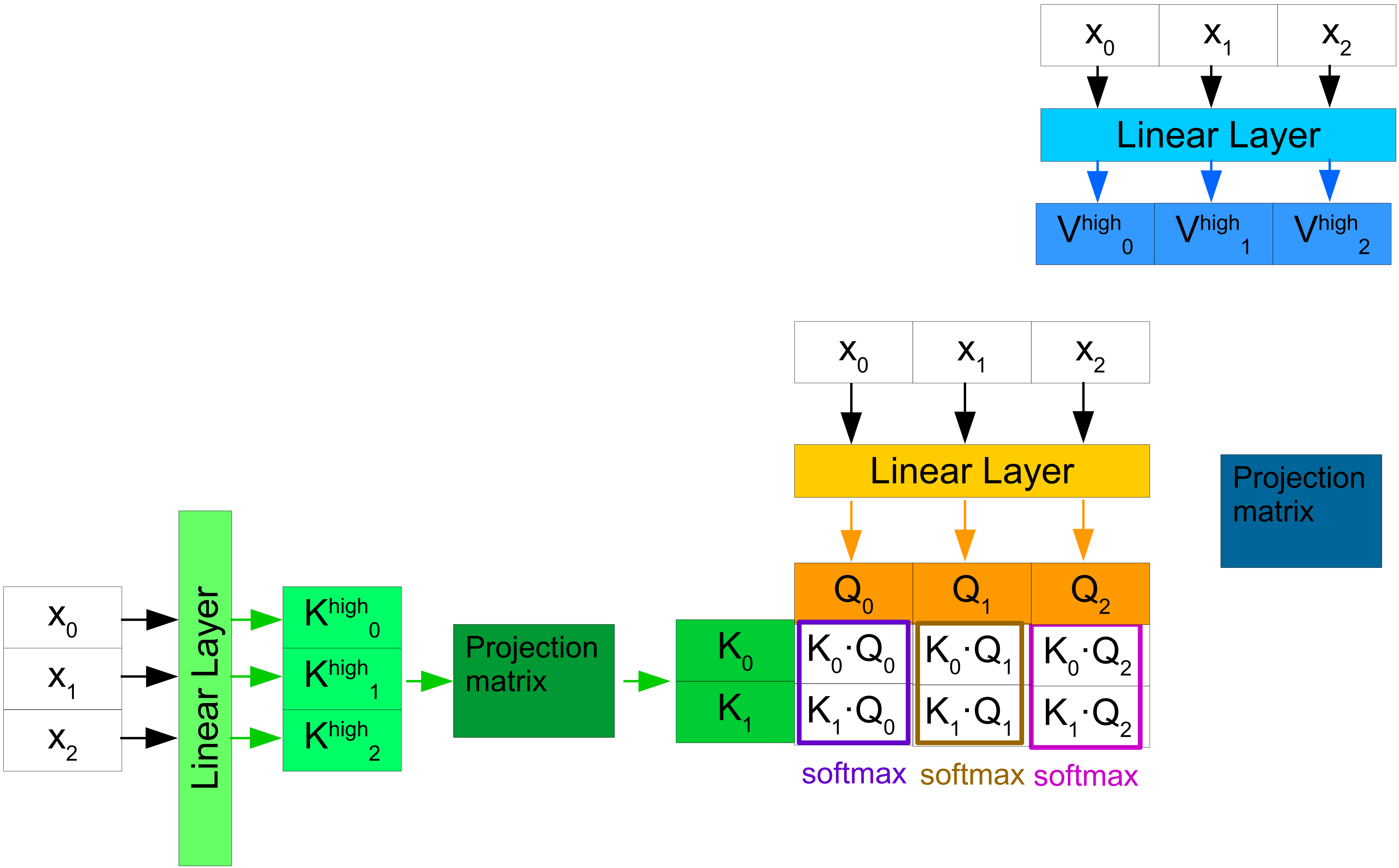
# 8.2 Linformer: Self-Attention with Linear Complexity



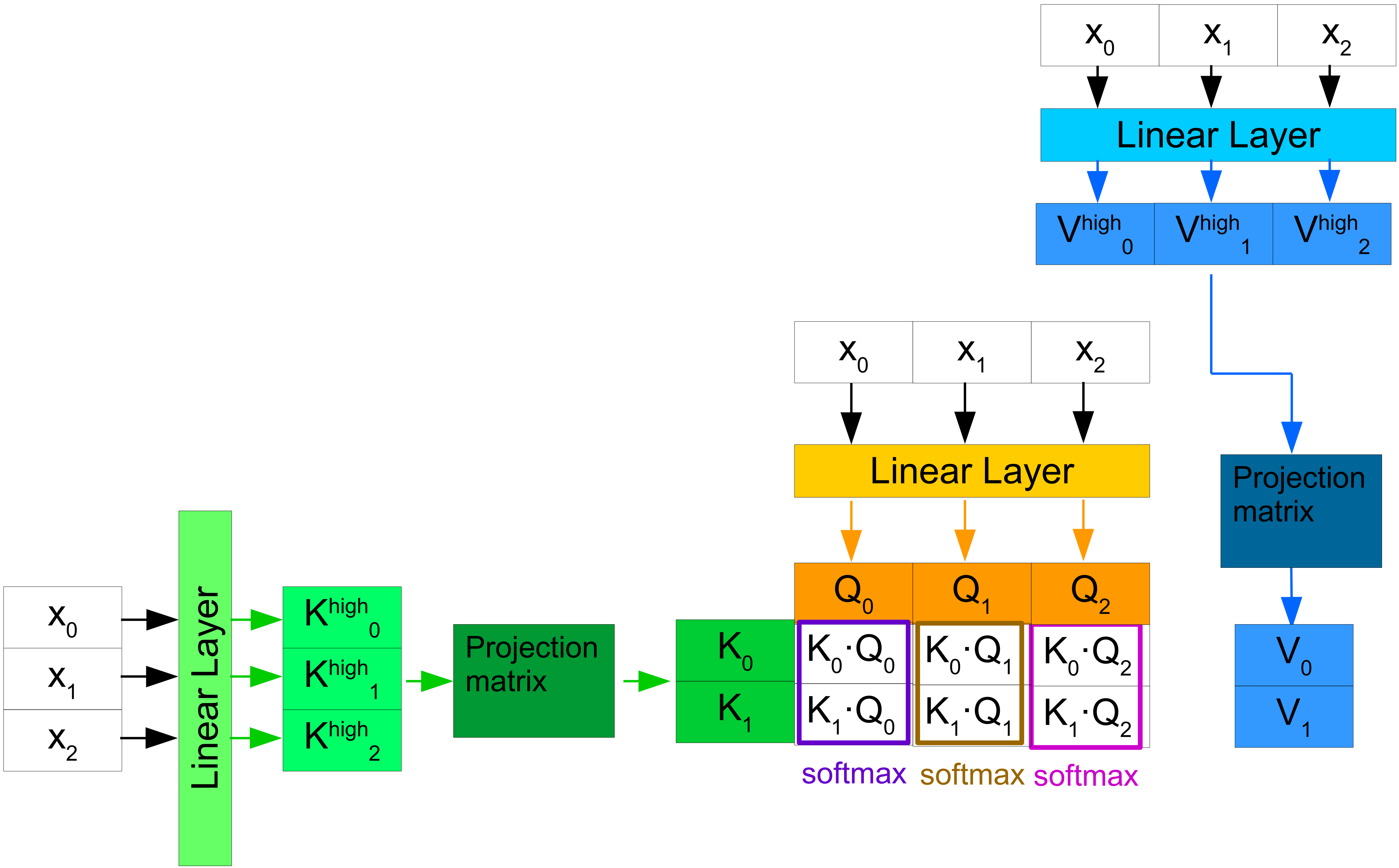
# 8.2 Linformer: Self-Attention with Linear Complexity



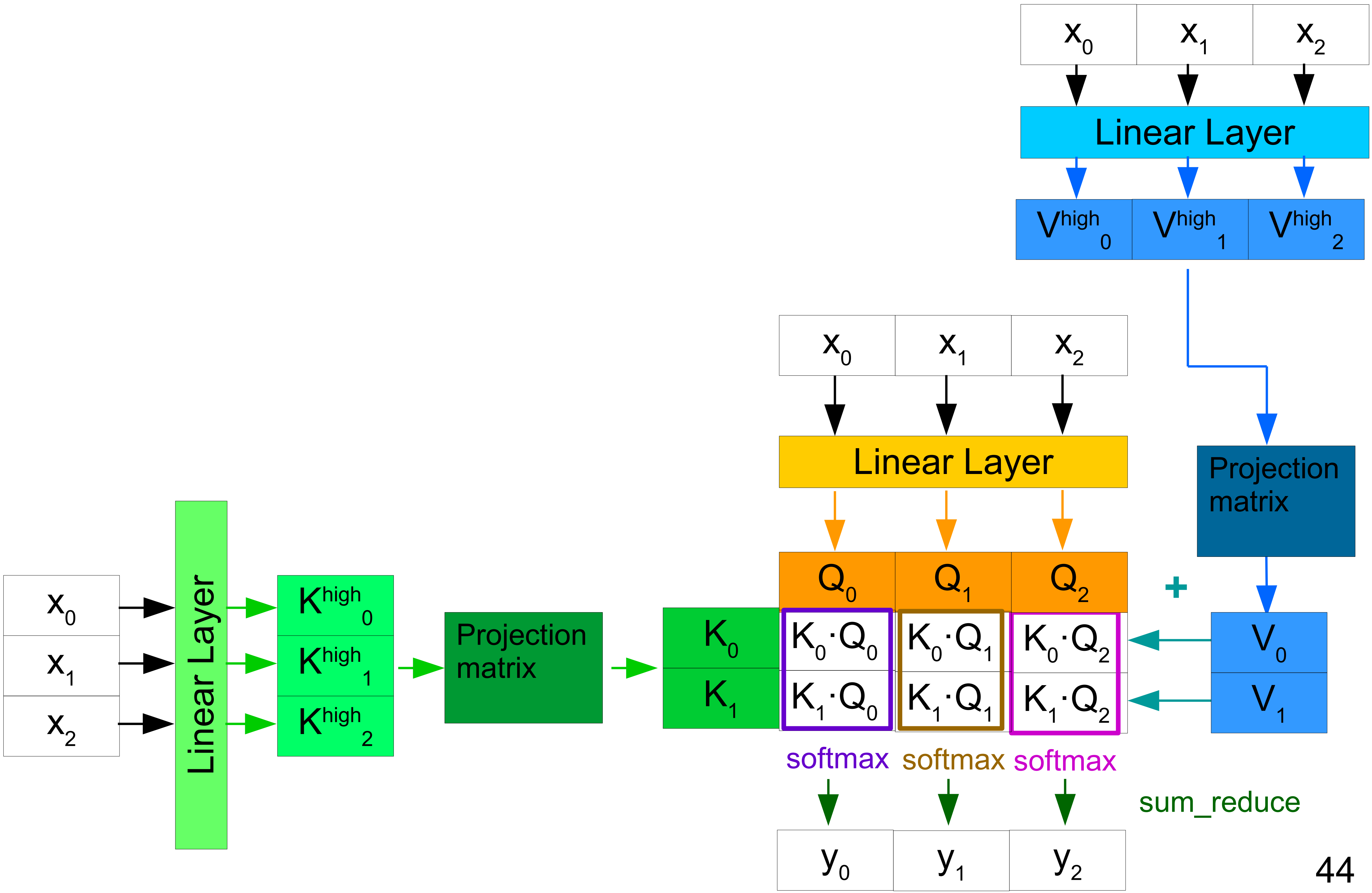
# 8.2 Linformer: Self-Attention with Linear Complexity



# 8.2 Linformer: Self-Attention with Linear Complexity



# 8.2 Linformer: Self-Attention with Linear Complexity



# 8.3 Reformer: The Efficient Transformer

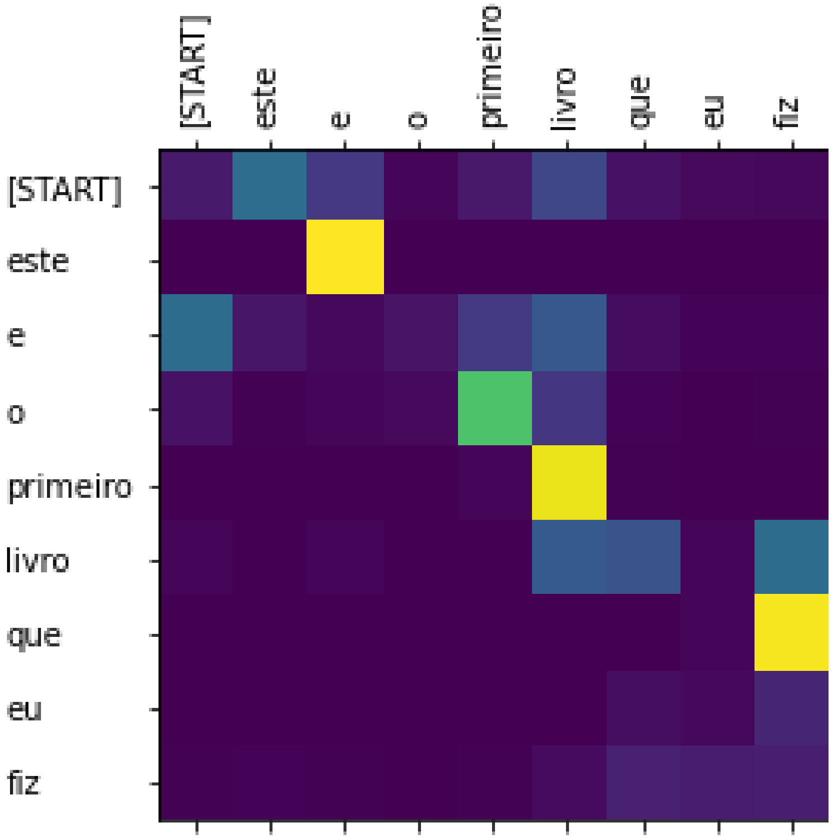



Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

# 8.3 Reformer: The Efficient Transformer

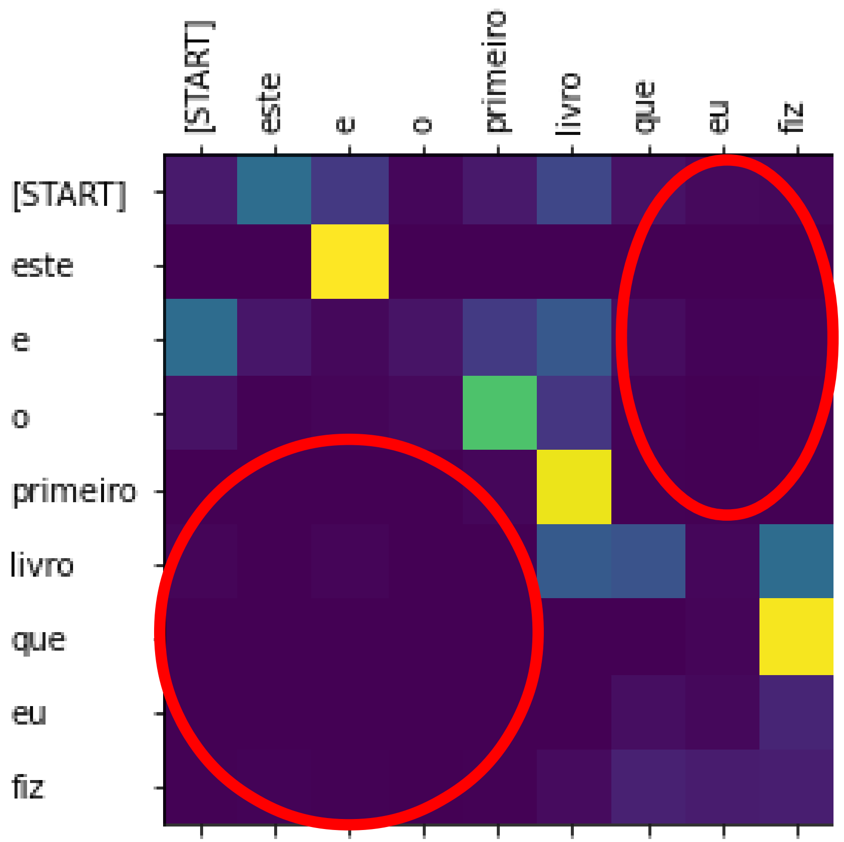
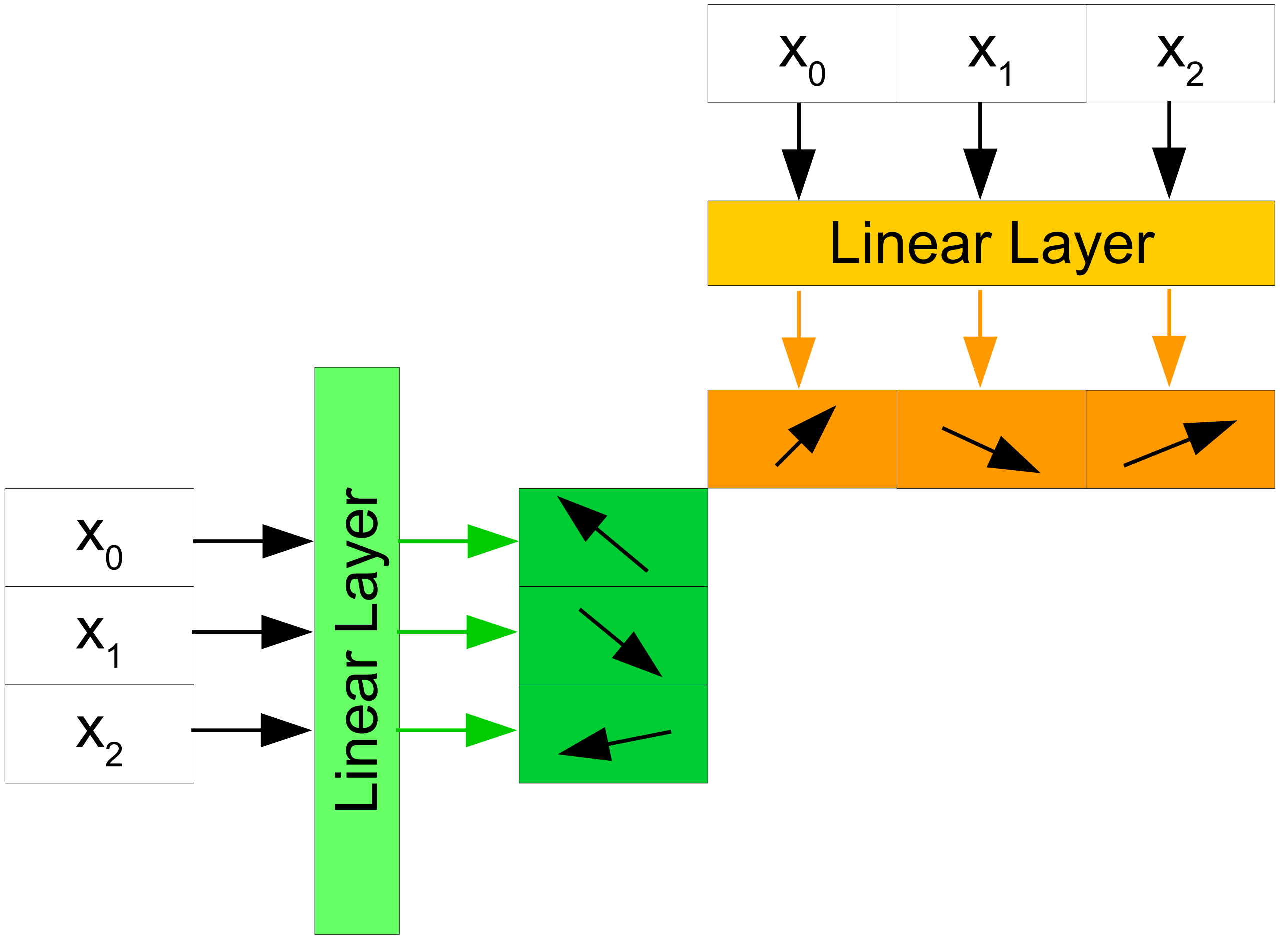
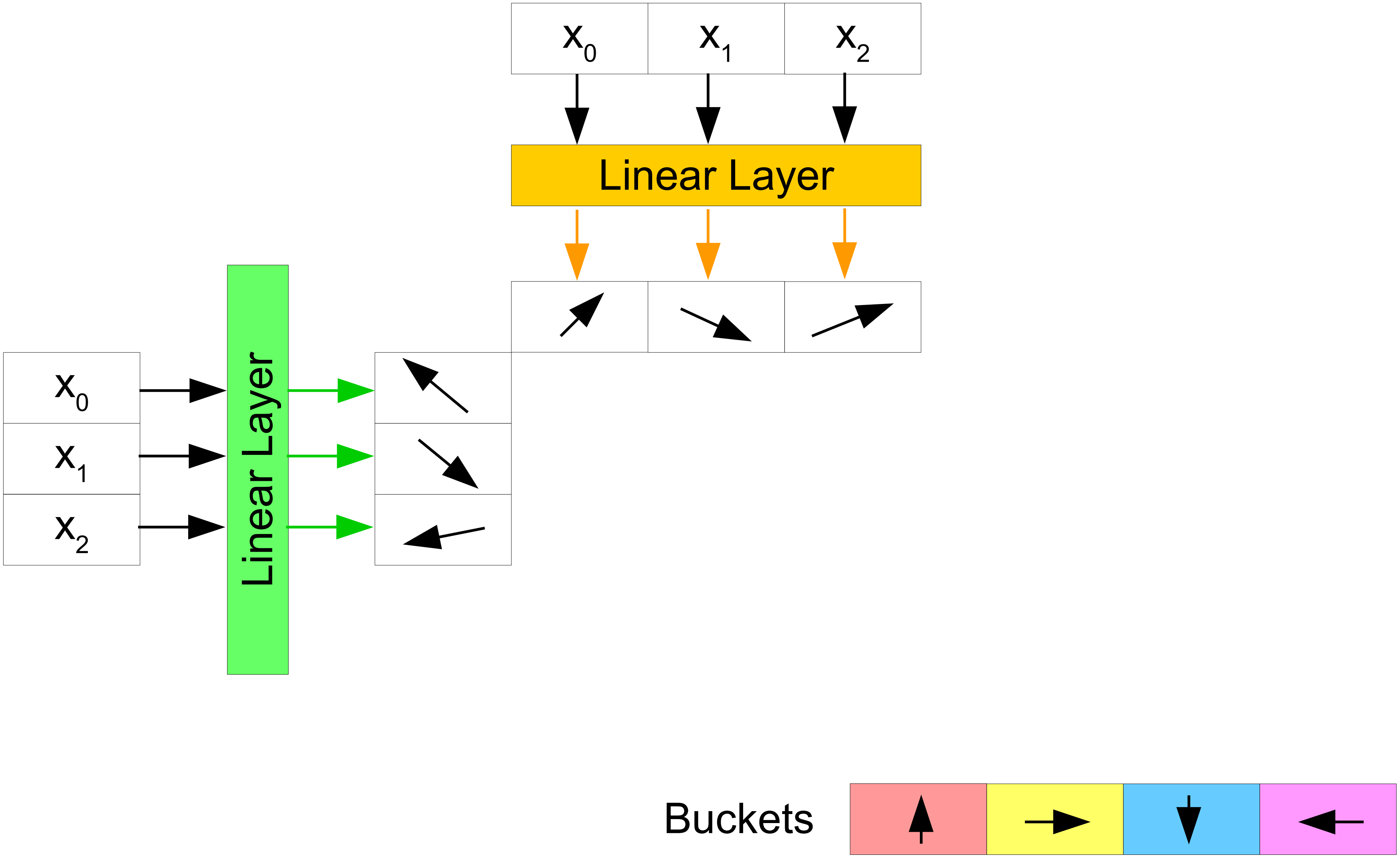



Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

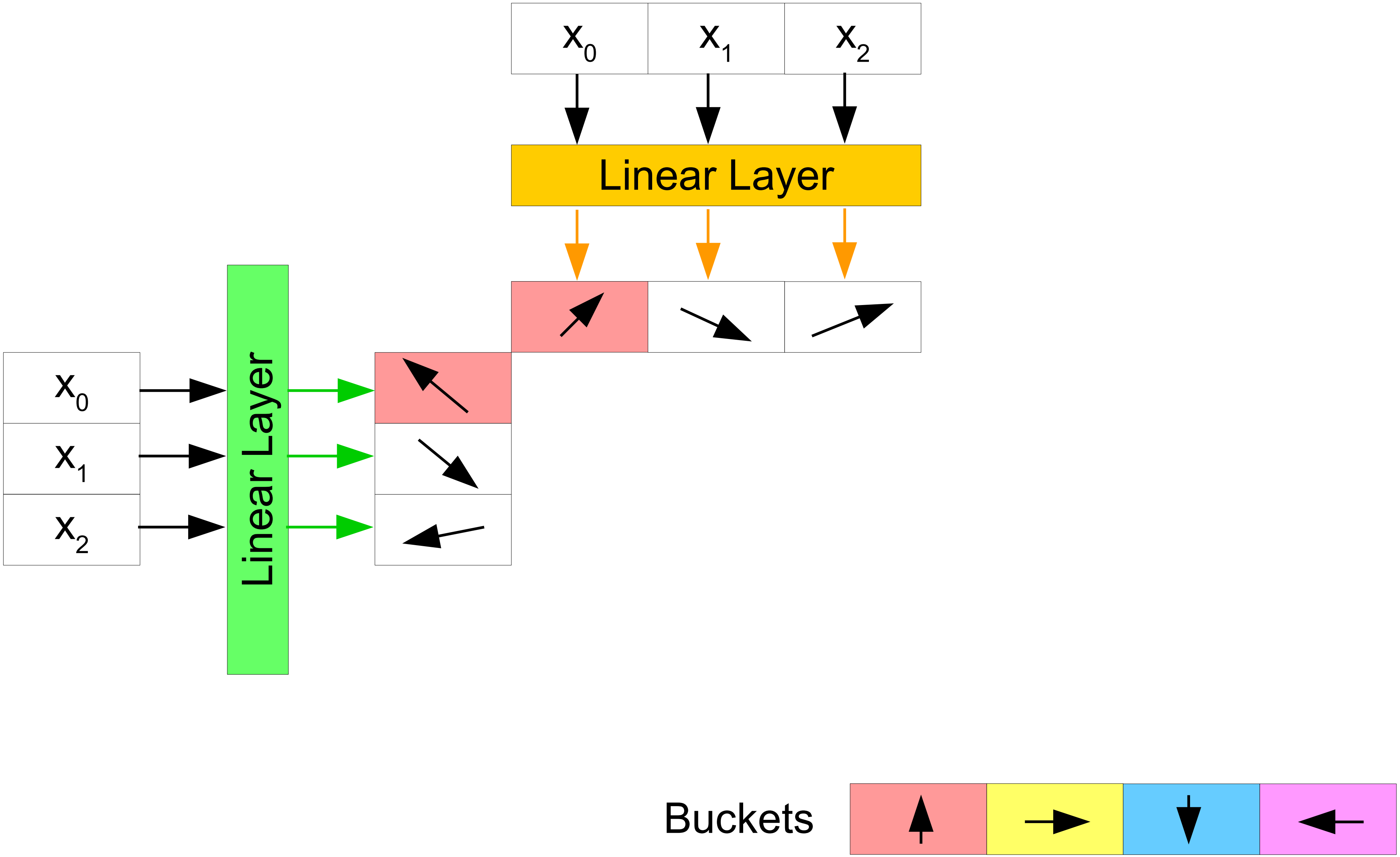
# 8.3 Reformer: The Efficient Transformer



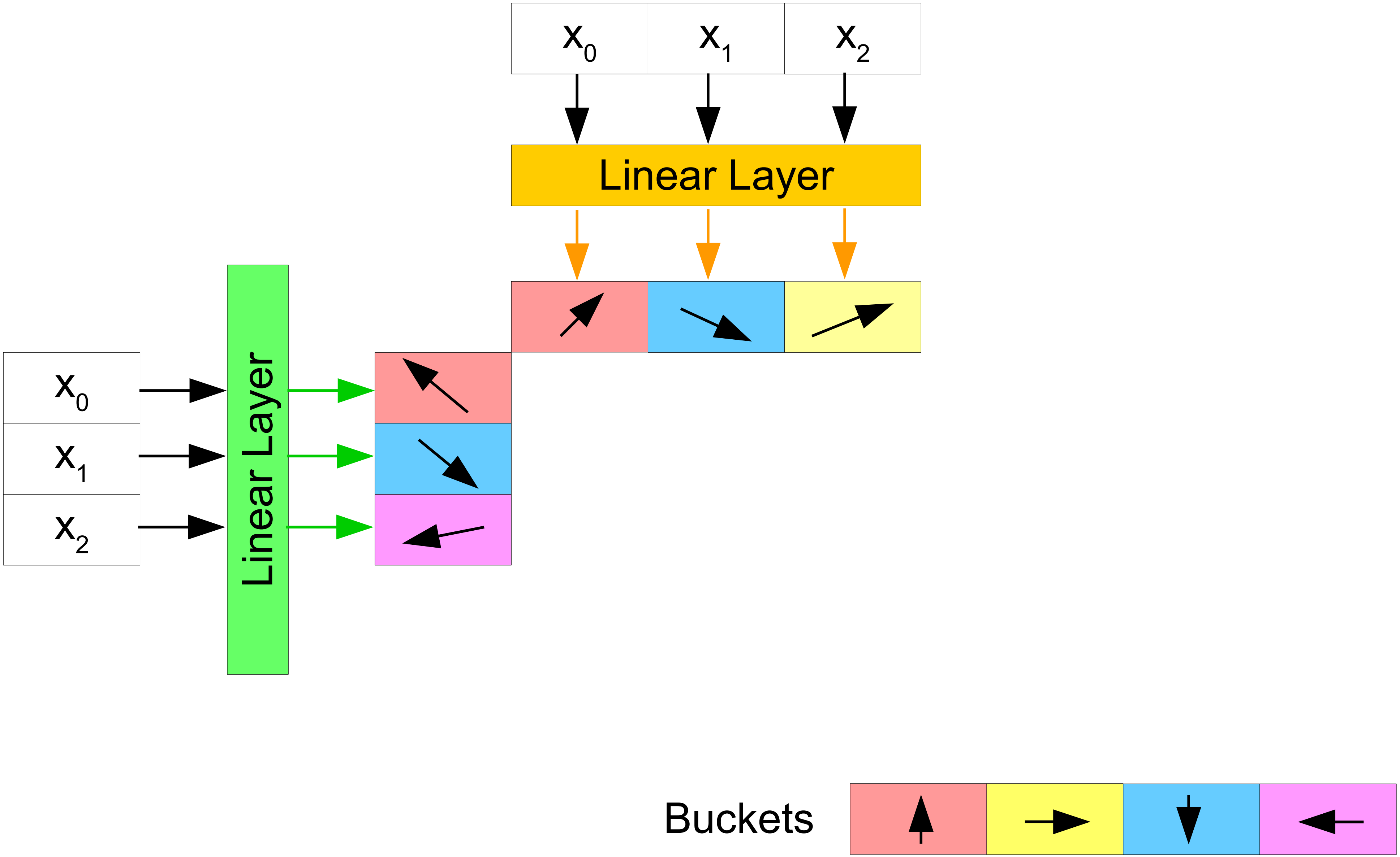
# 8.3 Reformer: The Efficient Transformer



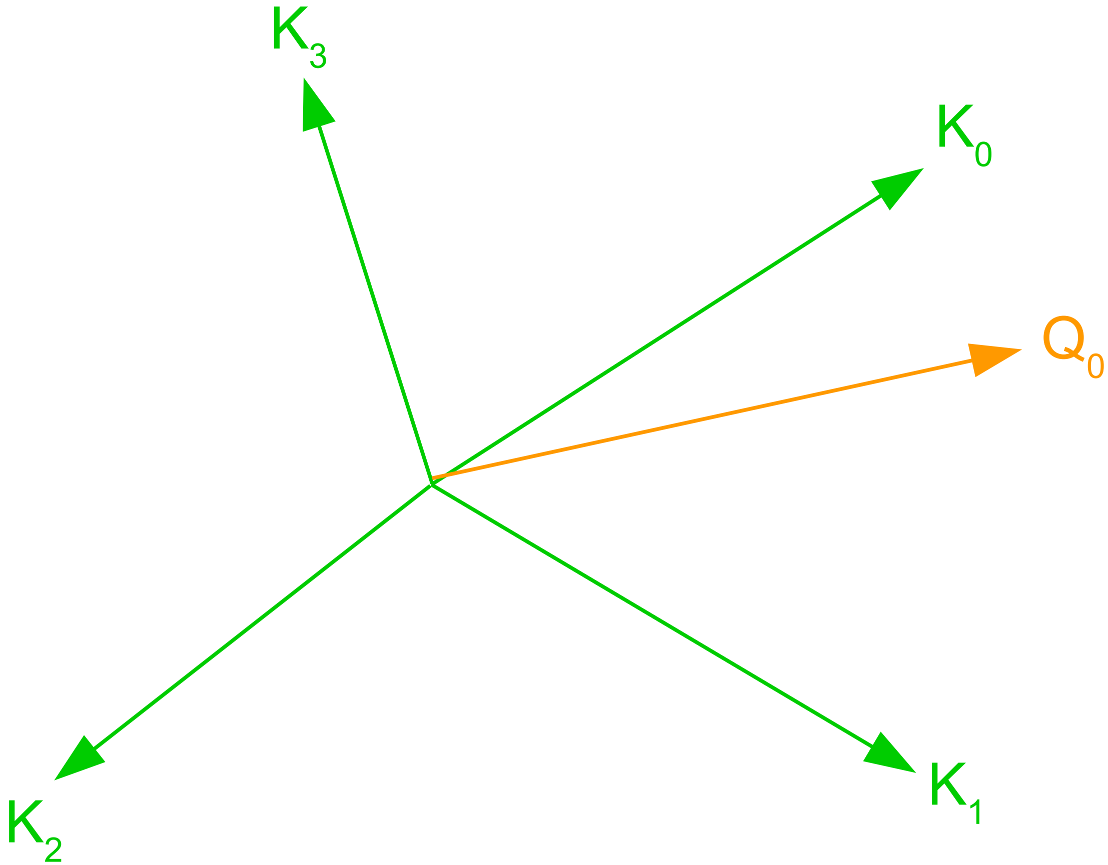
# 8.3 Reformer: The Efficient Transformer



# 8.3 Reformer: The Efficient Transformer

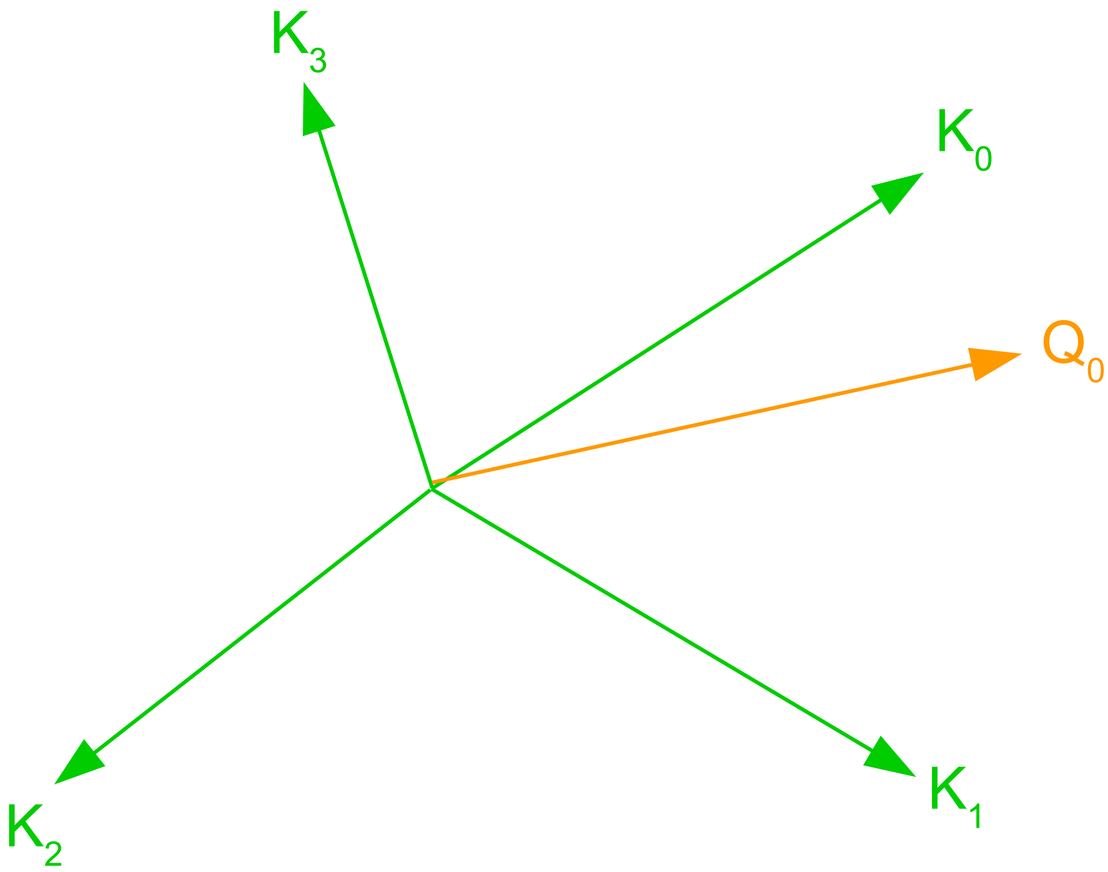


## 8.3.1 Random Plane Projections



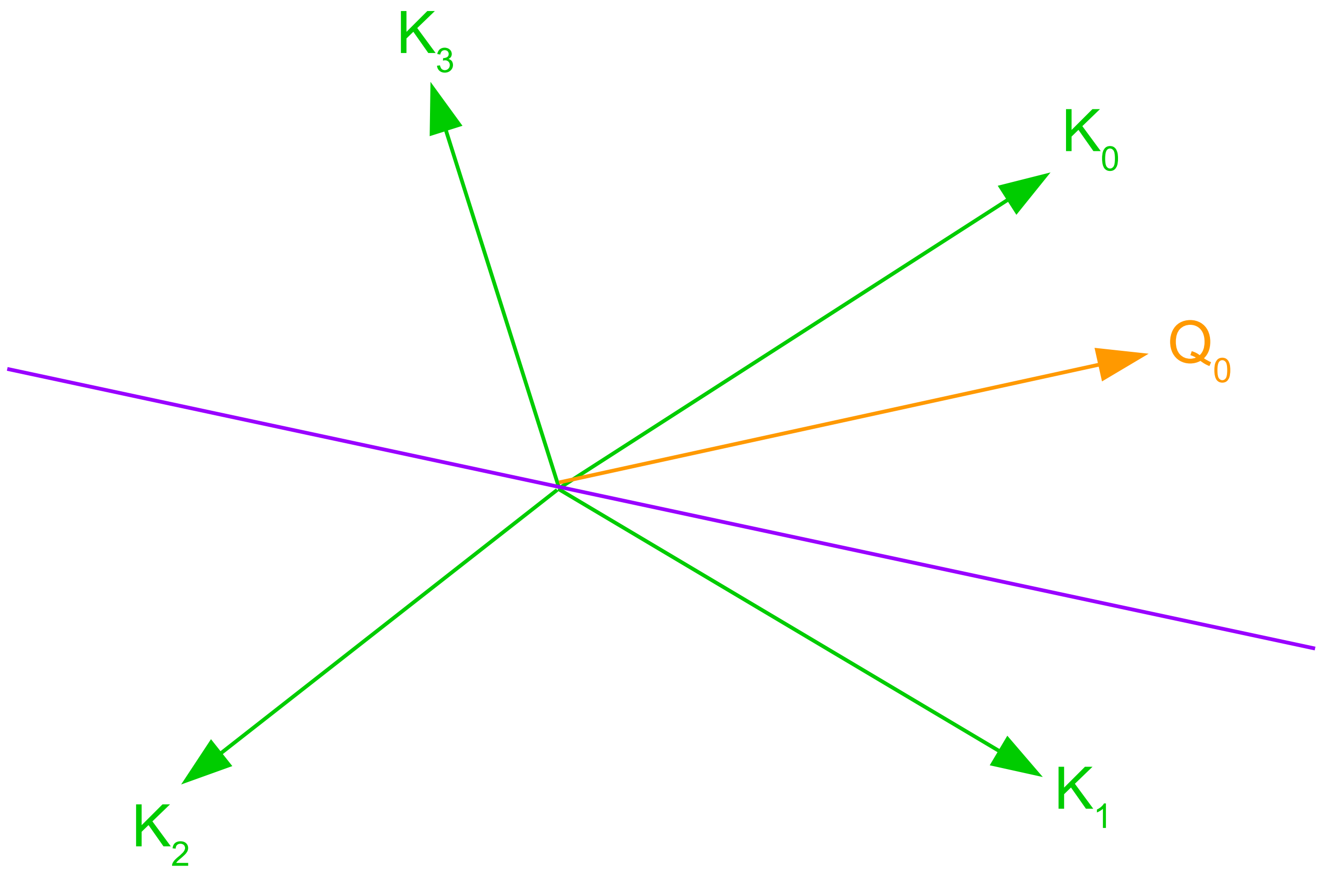
# 8.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes



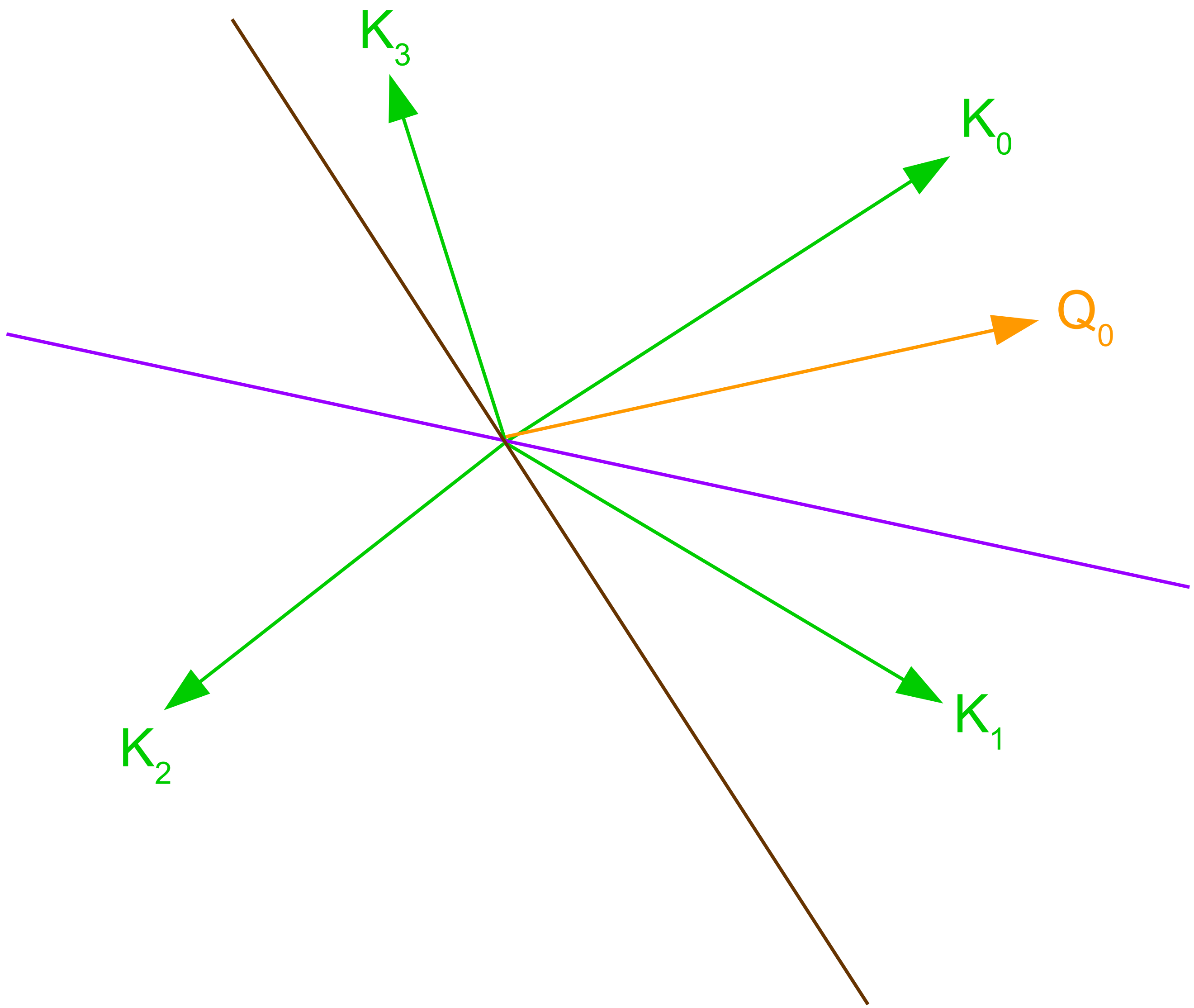
# 8.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes

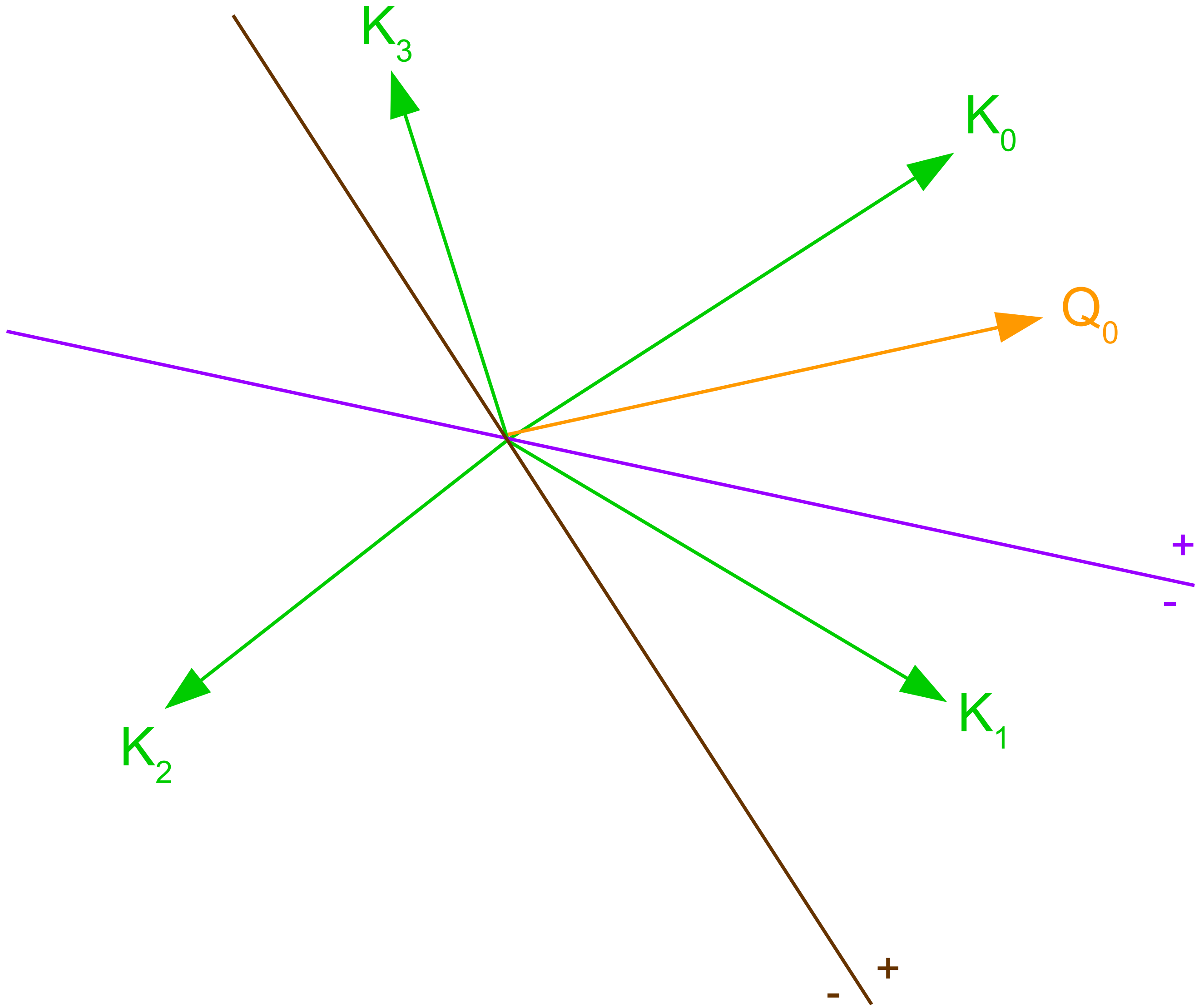


# 8.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes



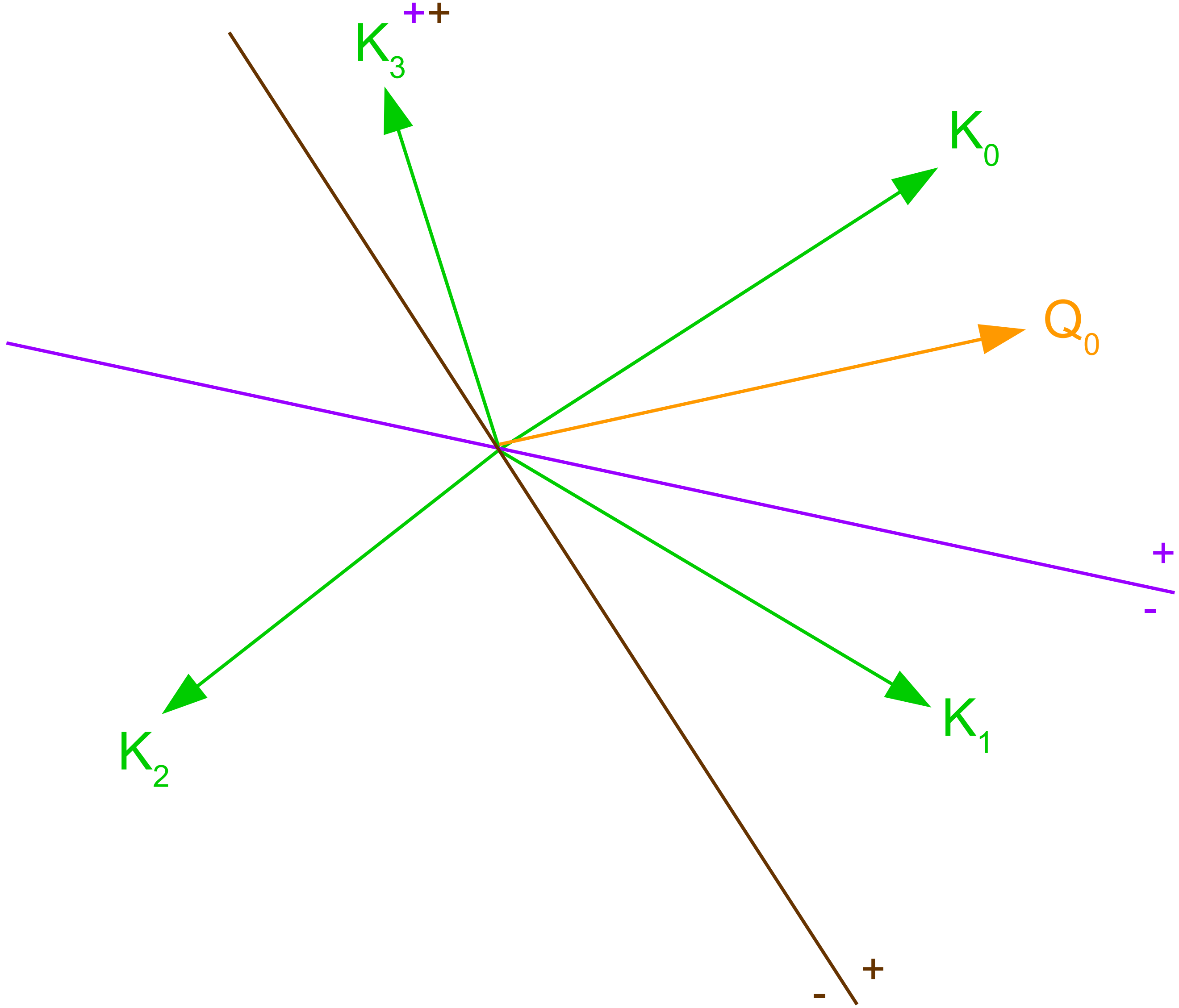
# 8.3.1 Random Plane Projections



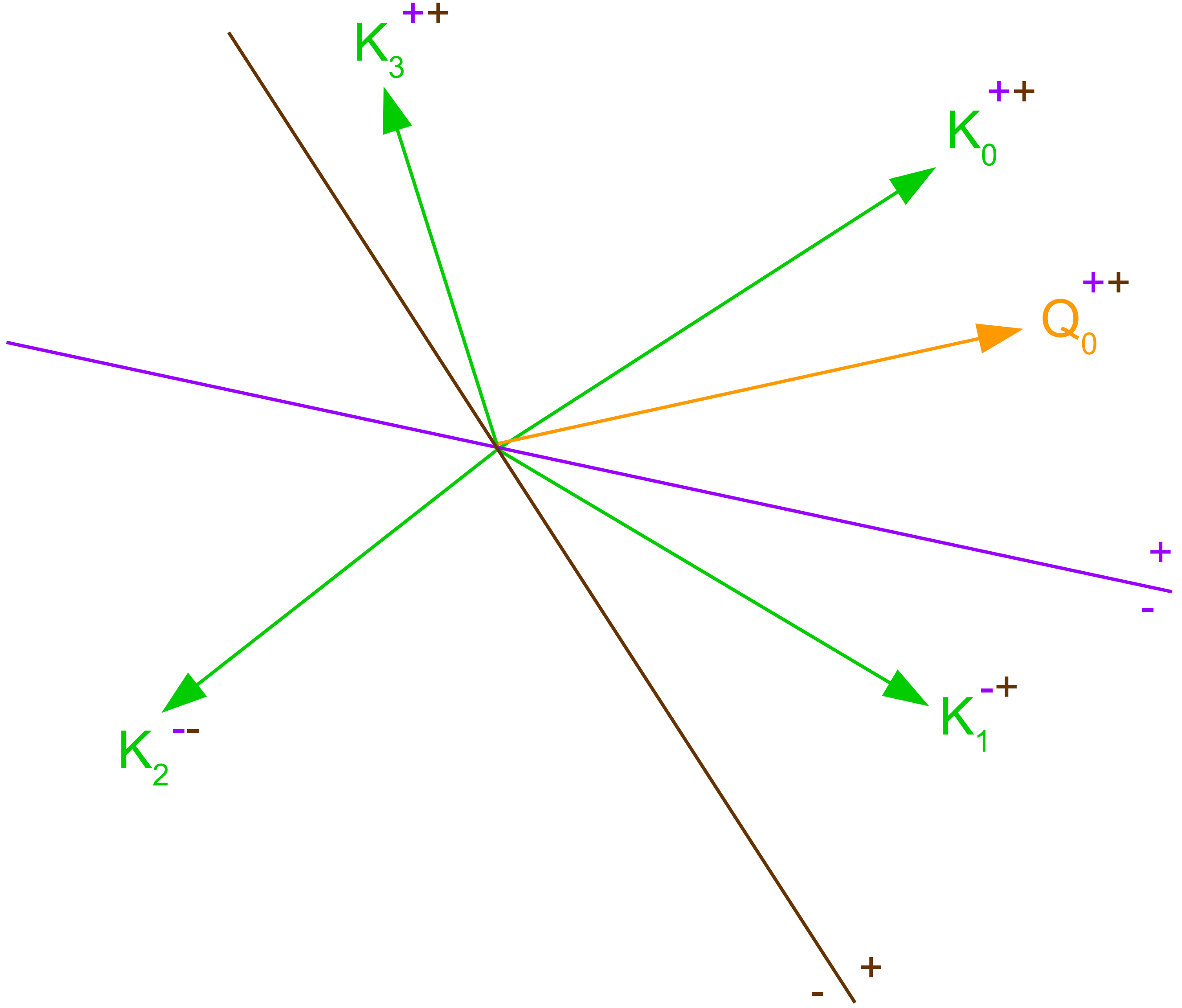

Four buckets
→ Two hyperplanes

## 8.3.1 Random Plane Projections

Four buckets
→ Two hyperplanes

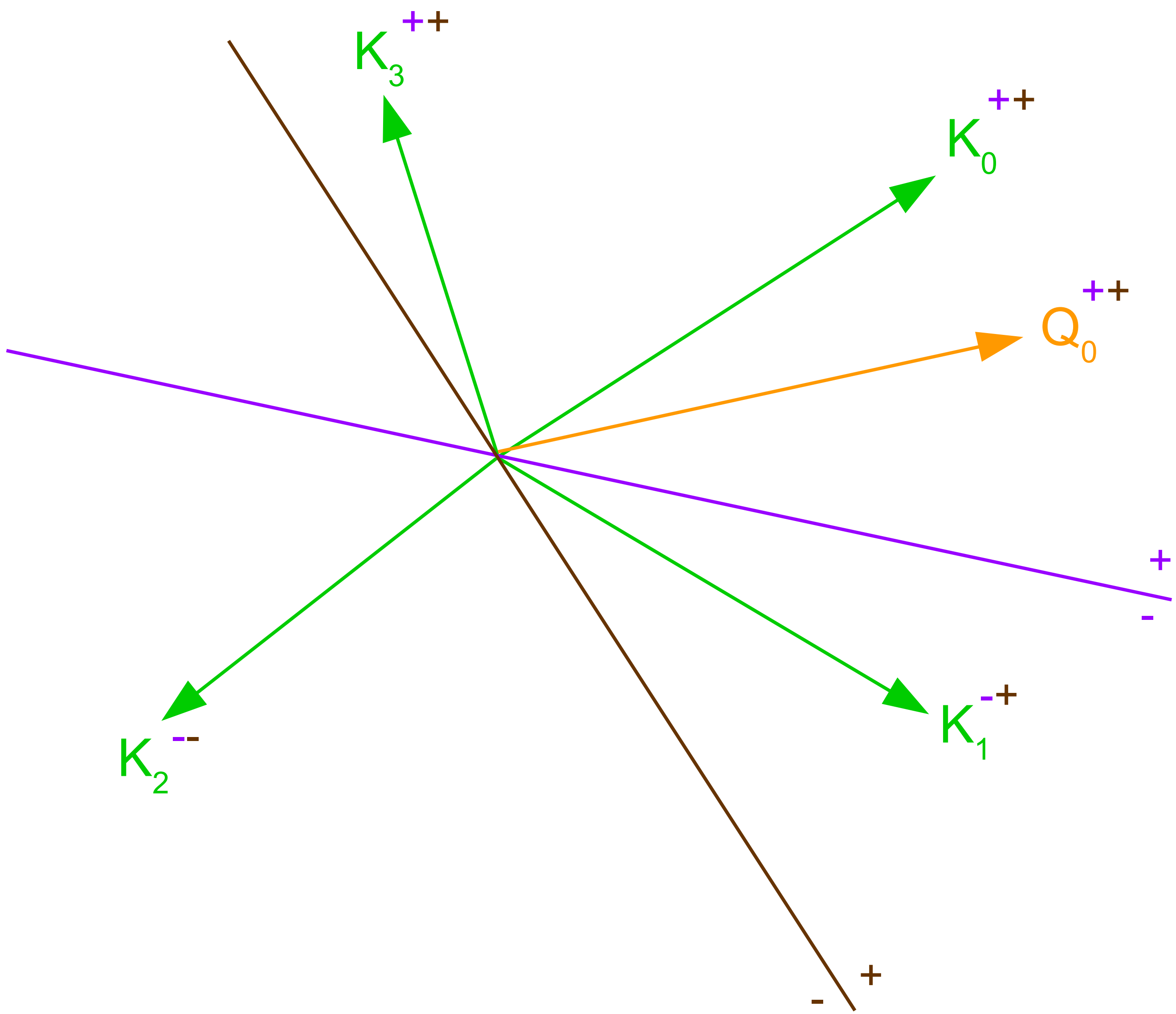


## 8.3.1 Random Plane Projections




Four buckets
→ Two hyperplanes

# 8.3.1 Random Plane Projections




Four buckets
→ Two hyperplanes

Buckets

| ++ | +- | -+ | -- |
|---|---|---|---|
| $K_0$ | | $K_1$ | $K_2$ |
| $K_3$ | | | |
| $Q_0$ | | | |

# 8.3.2 Reformer: The Efficient Transformer

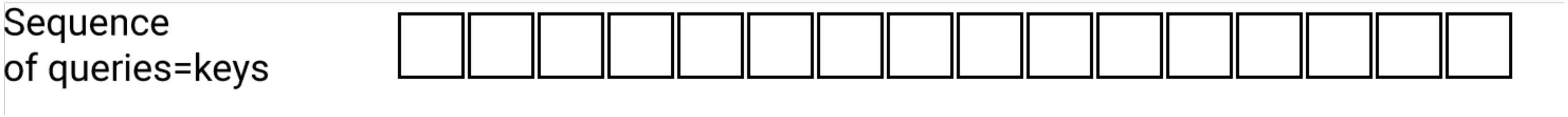



Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

# 8.3.2 Reformer: The Efficient Transformer

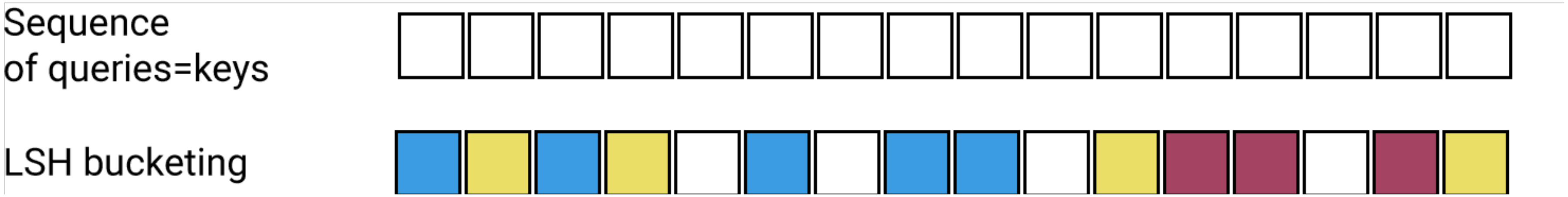



Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

# 8.3.2 Reformer: The Efficient Transformer

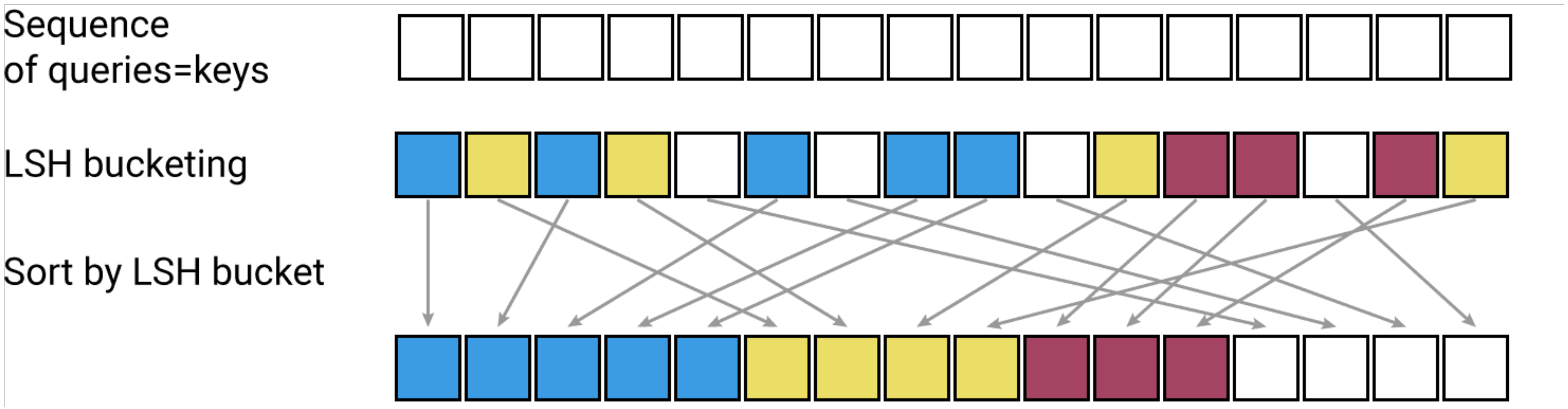



Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

# 8.3.2 Reformer: The Efficient Transformer

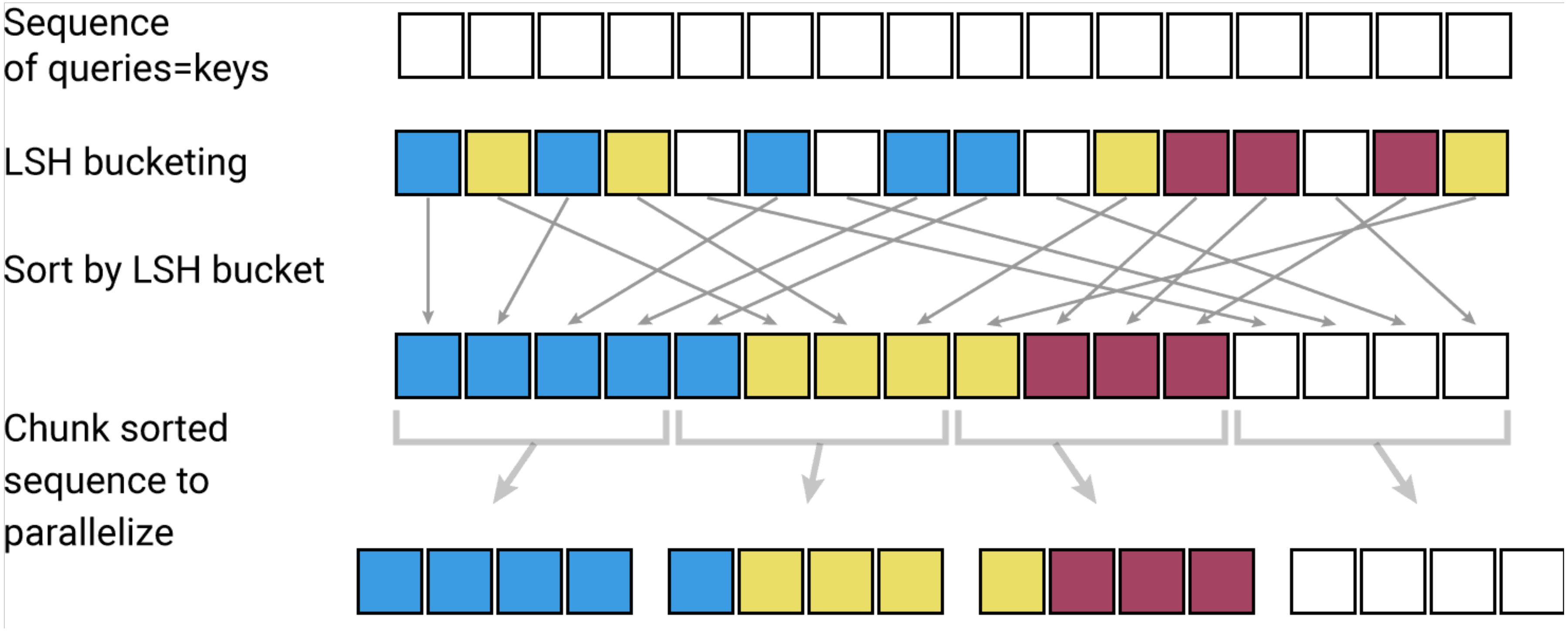



Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

# 8.3.2 Reformer: The Efficient Transformer

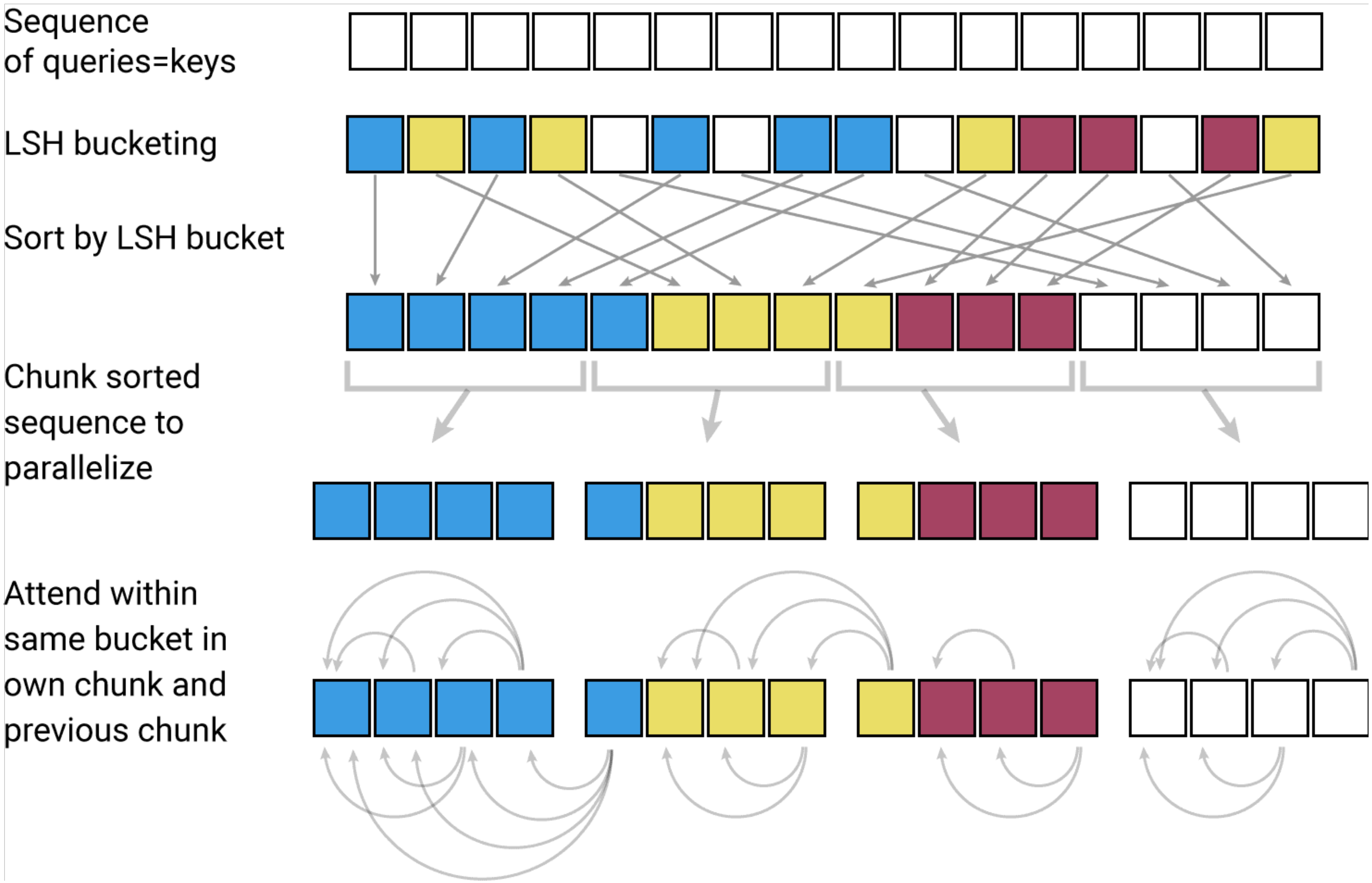
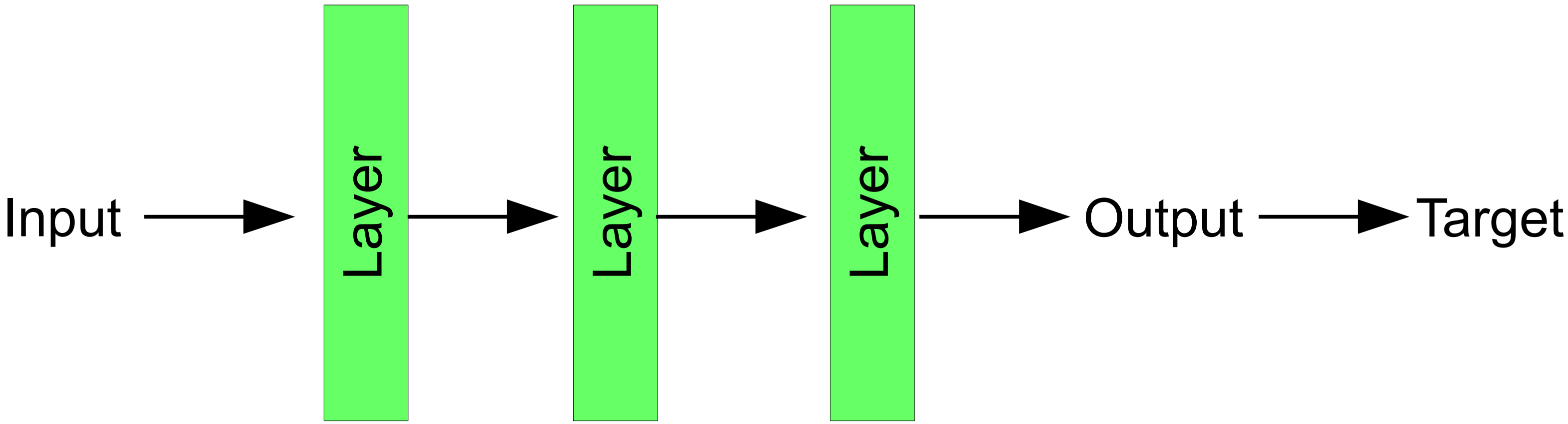
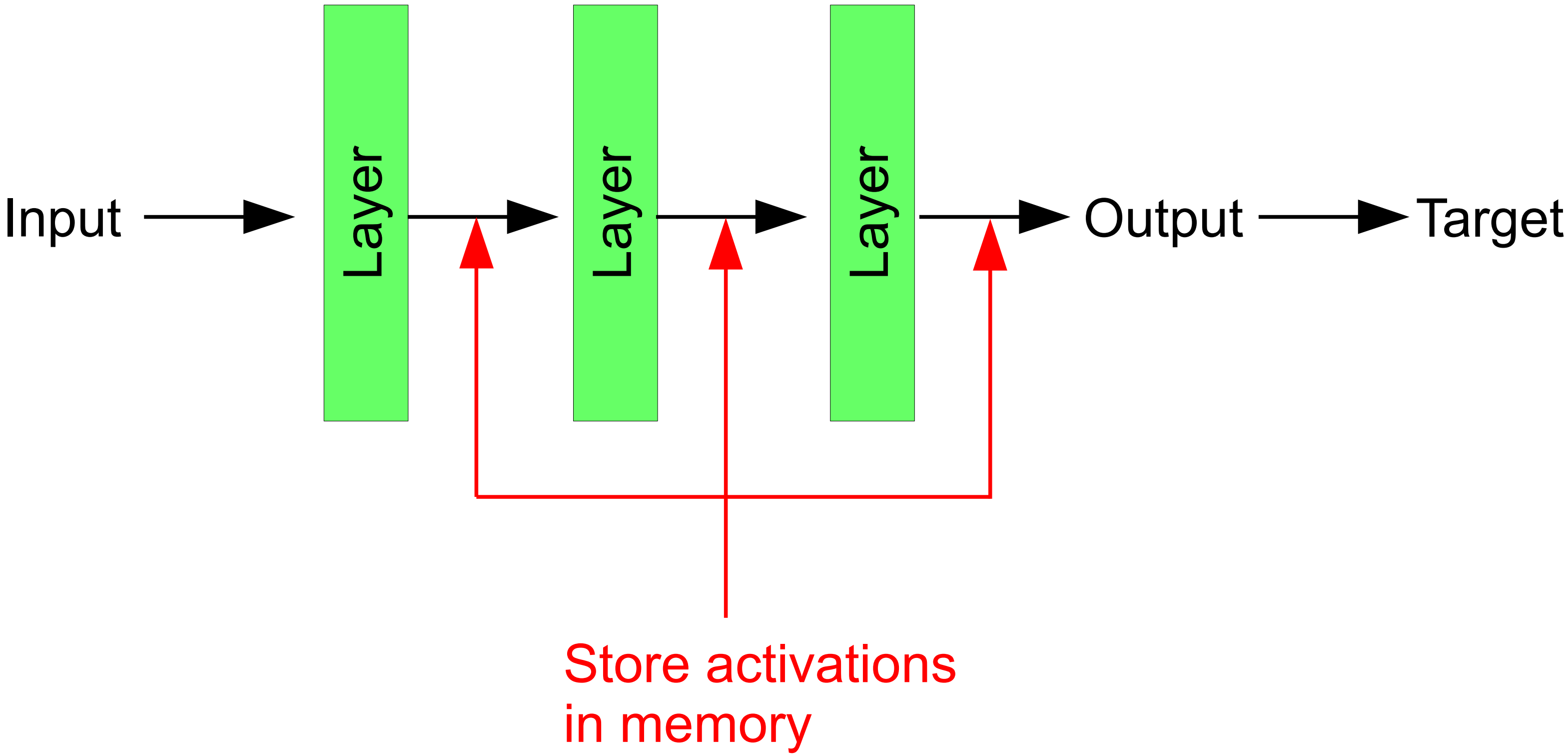



Image source:
Kitaev, N., Kaiser, L., & Levskaya, A. (2020). Reformer: The Efficient Transformer.
ArXiv, abs/2001.04451.

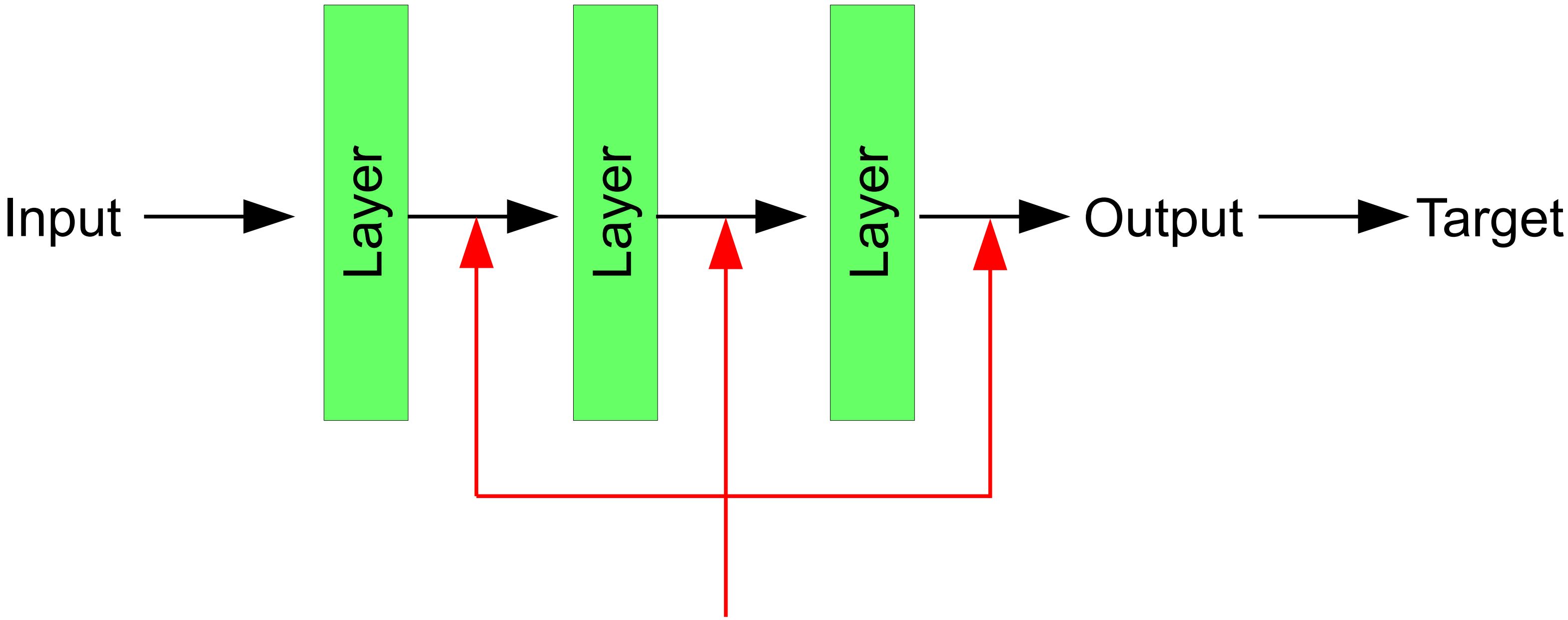
# 8.3.3 Memory problem – Backpropagation



# 8.3.3 Memory problem – Backpropagation



# 8.3.3 Memory problem – Backpropagation




Store activations
in memory

including:

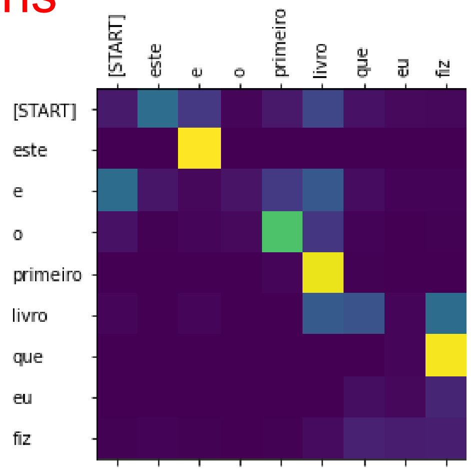



Image source:
https://www.tensorflow.org/images/tutorials/transformer/attention_map_portuguese.png
(call date: 20.07.22)

# 8.3.4 Reversible layer

Residual connection

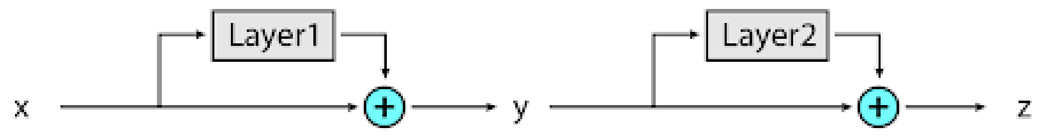
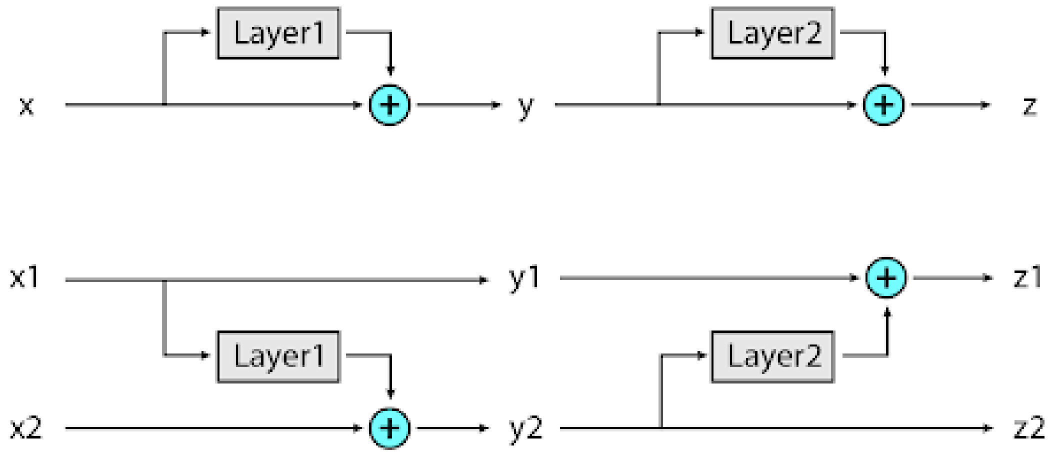



Image source:
https://1.bp.blogspot.com/-l3GO6OKfPPQ/Xh-9qQA6HvI/AAAAAAAAFNM/ioxl9LL_GoghLIjTVGLu2Pm8ghclT22egCEwYBhgL/s1600/image4.png (call date: 29.01.22)

# 8.3.4 Reversible layer

Residual connection

Reversible layer
(forward pass)

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# 8.3.4 Reversible layer

Residual connection

Reversible layer
(forward pass)

Reversible layer
(backward pass)

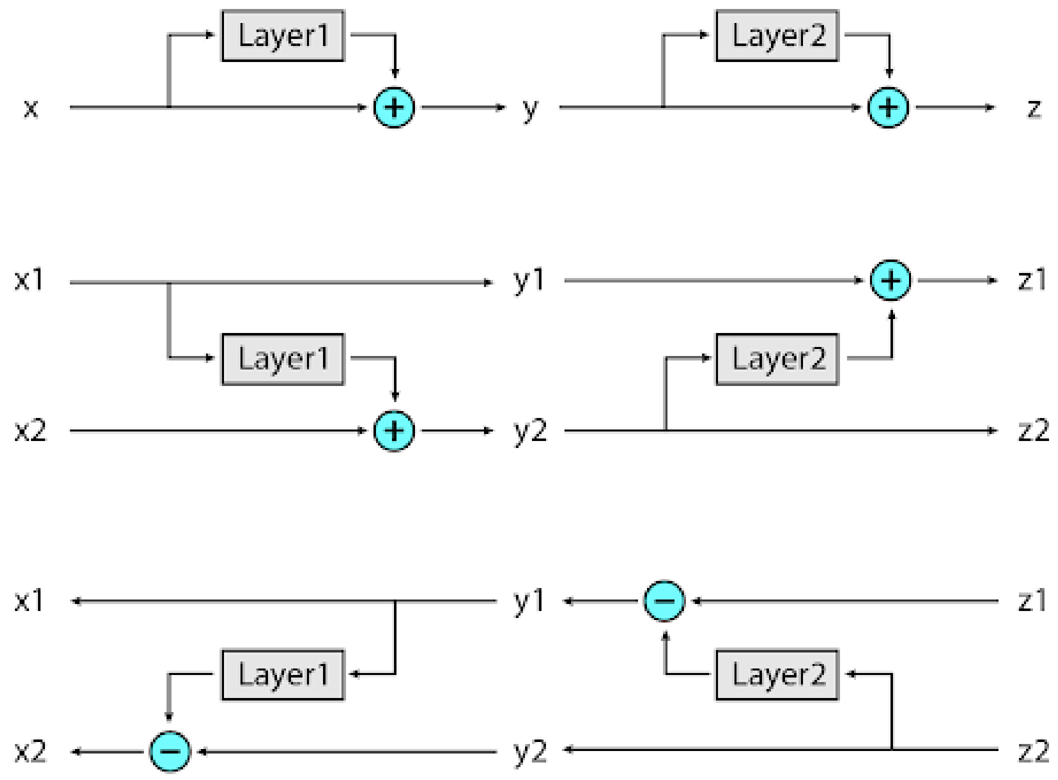
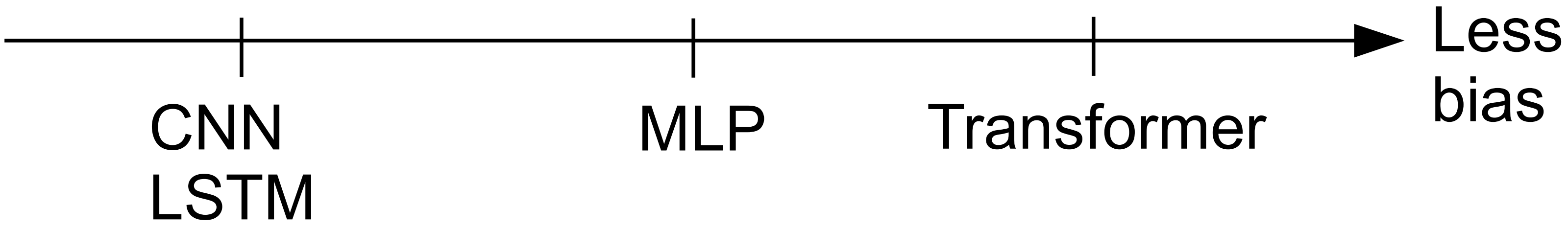



Image source:
https://1.bp.blogspot.com/-l3GO6OKfPPQ/Xh-9qQA6HvI/AAAAAAAAFNM/ioxl9LL_GoghLIjTVGLu2Pm8ghclT22egCEwYBhgL/s1600/image4.png (call date: 29.01.22)

# 9. 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
https://www.flaticon.com/free-icon/file-storage_3616558?term=data&page=1&position=37&page=1&position=37&related_id=3616558&origin=search
https://emojipedia-us.s3.dualstack.us-west-1.amazonaws.com/thumbs/120/whatsapp/326/thinking-face_1f914.png
(call dates: 20.07.22)

# AlphaCandy

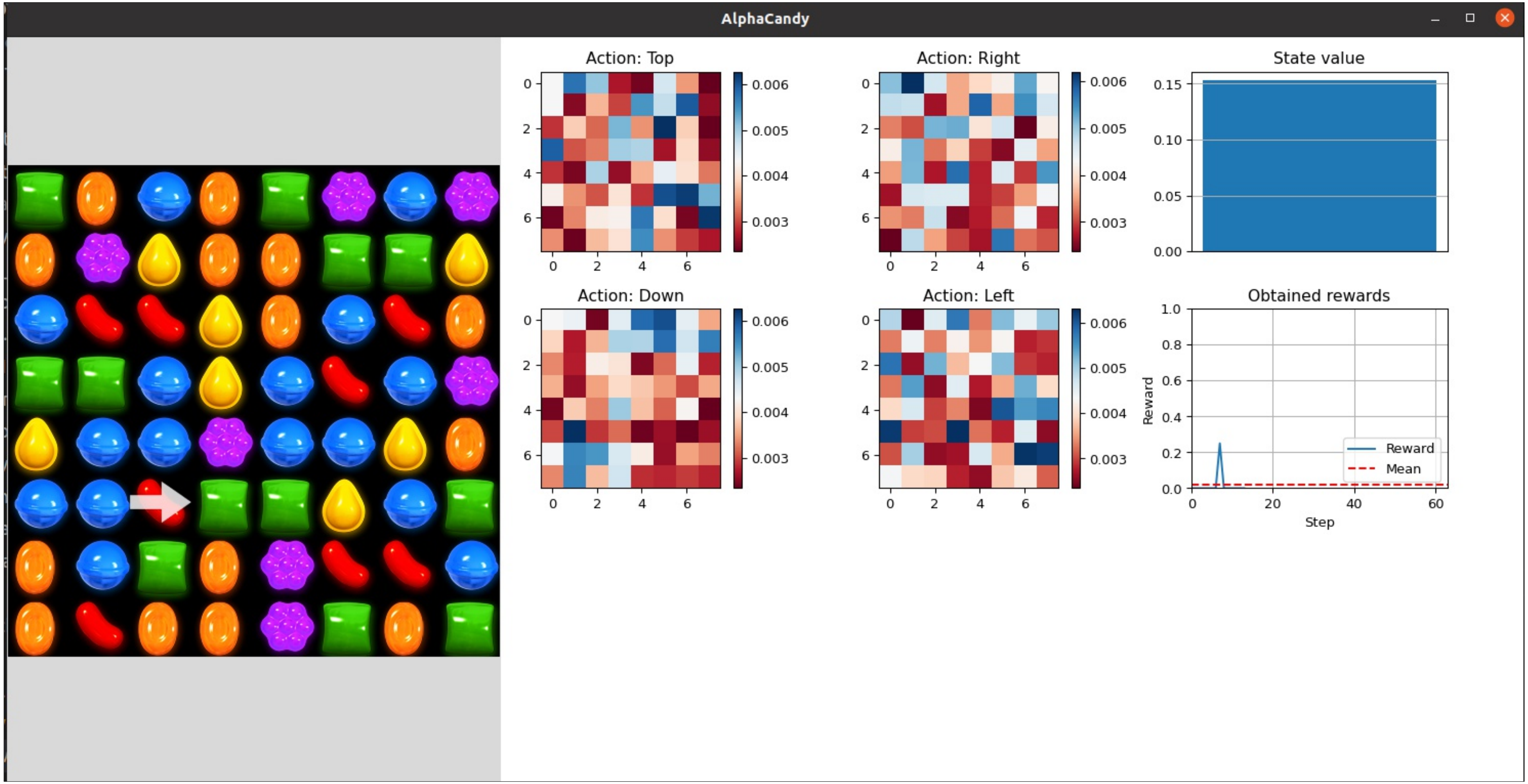



Figure 35: AlphaCandy UI.

Image sources:
https://www.flaticon.com/free-icon/candy-jar_1075135?related_id=1075135&origin=tag
https://emojipedia.org/de/toss-face/march-2022/gesicht-mit-umarmenden-h%C3%A4nden/
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