CS 4824/ECE 4424: Attention and Transformers

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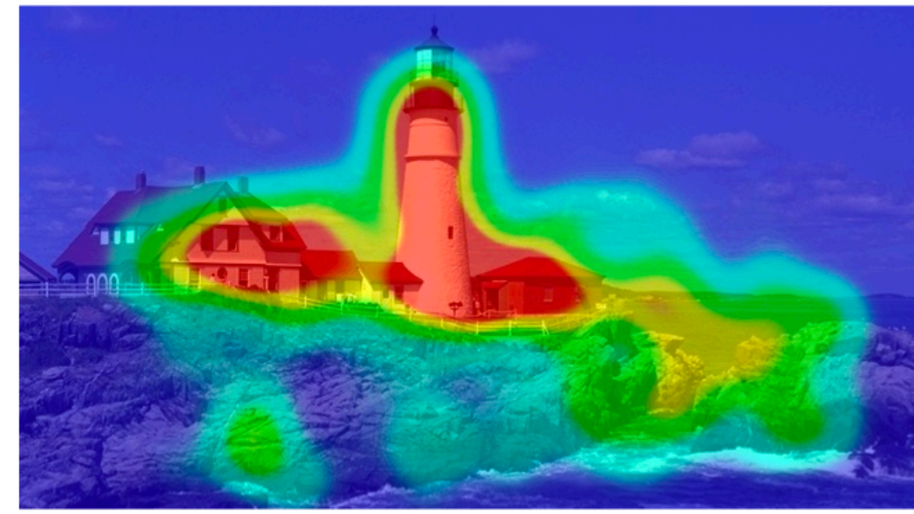
Attention

- **Key idea**: highlight important parts of the inputs
- Mechanism for alignment in machine translation, image captioning, etc.
- Attention in machine translation: align each output word with relevant input words by computing a softmax of the inputs

Attention

- Attention in Computer Vision
  - 2014: Attention used to highlight important parts of an image that contribute to a desired output



- Attention in NLP
  - 2015: machine translation
  - 2017: Language modeling with **Transformer networks**

Sequence Modeling

- **Challenges with RNNs**
  - Long range dependencies
  - Gradient vanishing (and explosion)
  - Large # of training steps
  - Recurrence prevents parallel computation

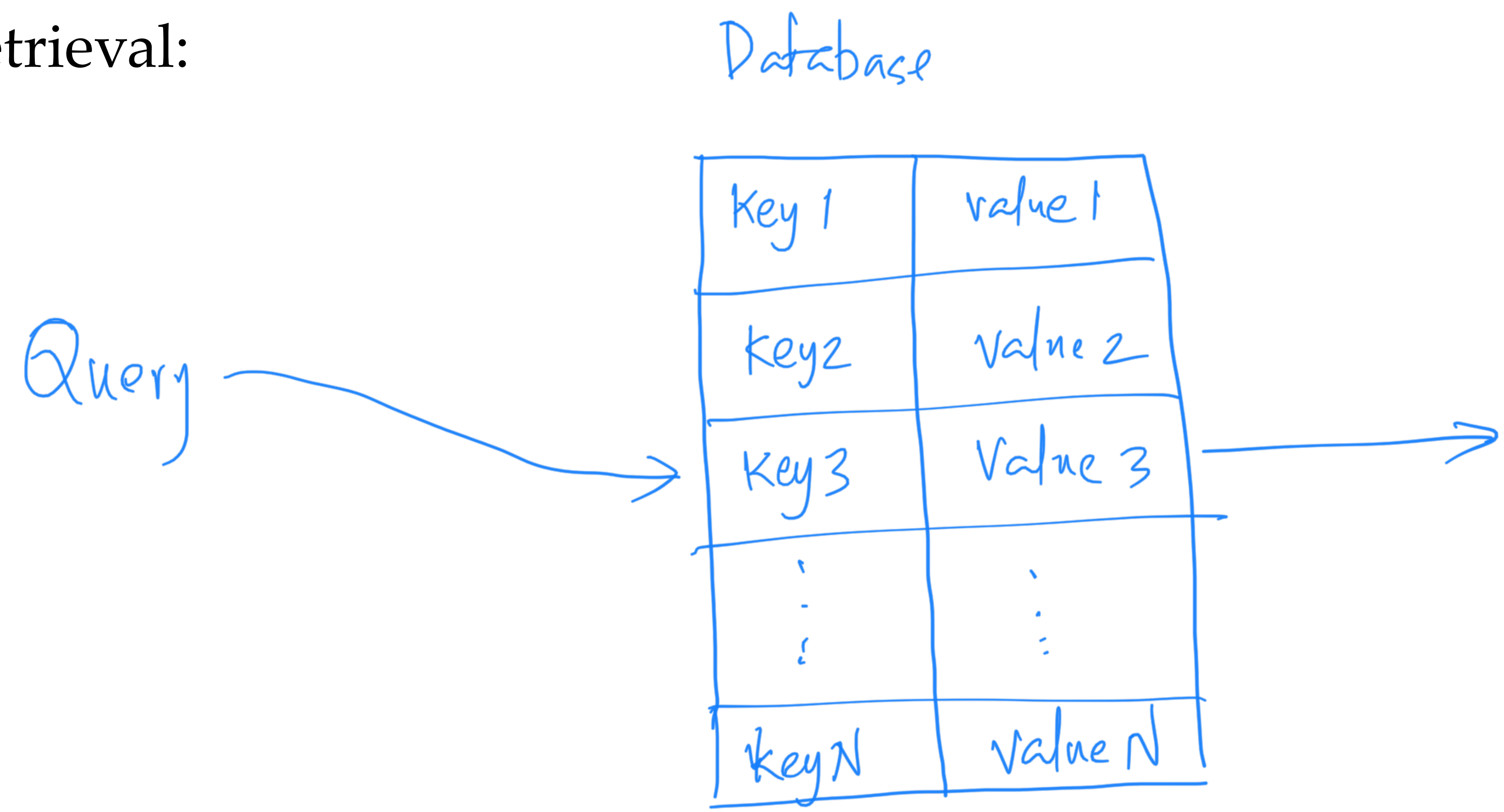
vs

- **Transformer Networks**
  - Facilitate long range dependencies
  - No gradient vanishing (and explosion)
  - Fewer training steps
  - No recurrence that facilitate parallel computation

Attention Mechanism

- Mimics the retrieval of a **value** v_i for a **query** q based on a **key** k_i in database

- Retrieval:

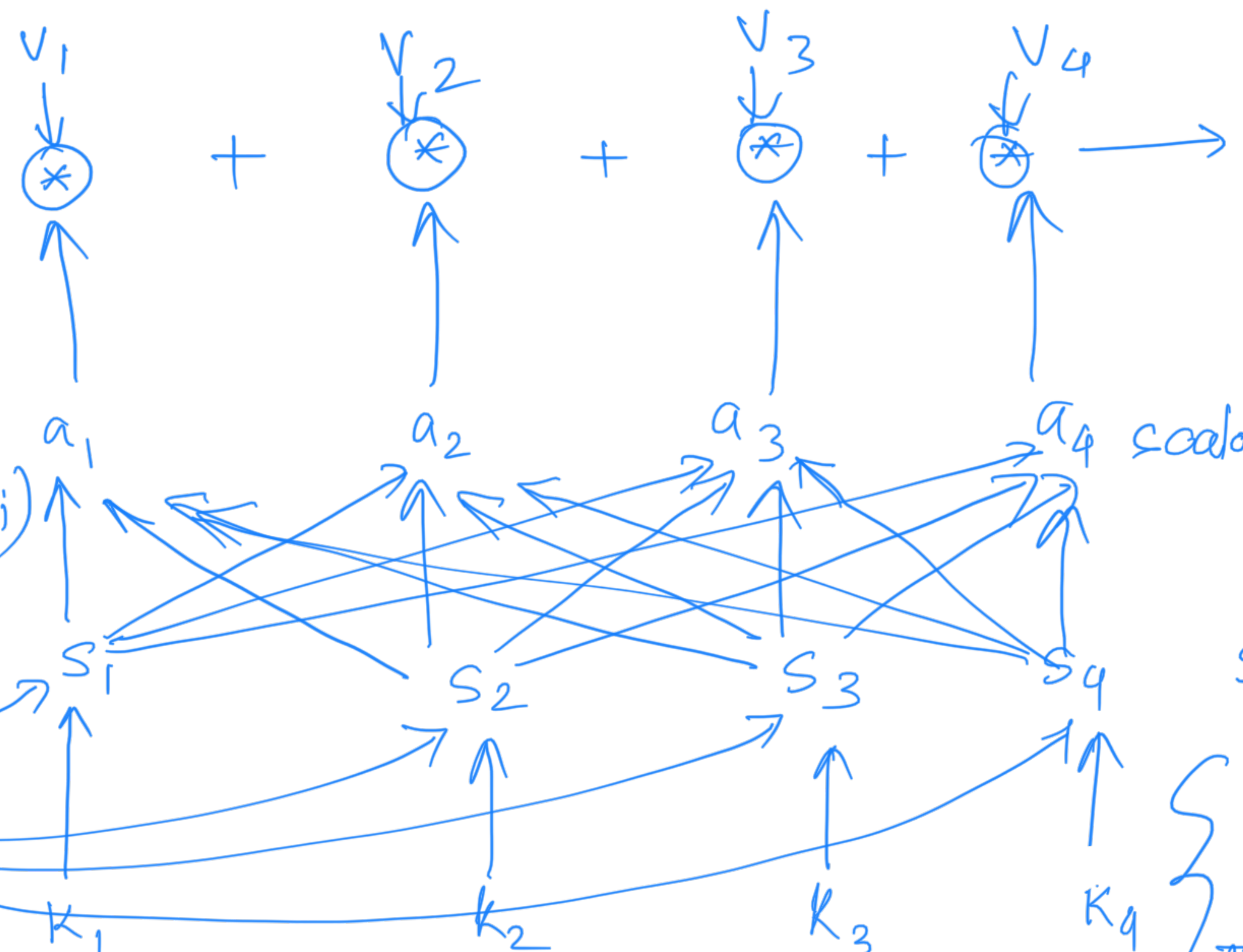


$$attention(q, \mathbf{k}, \mathbf{v}) = \sum_i similarity(q, k_i) \times v_i$$

Attention Mechanism

- Neural architecture

vectors



attention value $\sum_i a_i v_i$

softmax

$a_i = \frac{\exp(s_i)}{\sum_j \exp(s_j)}$

scalars

dot product
inverse distance
cosine similarity

(scalar)
query

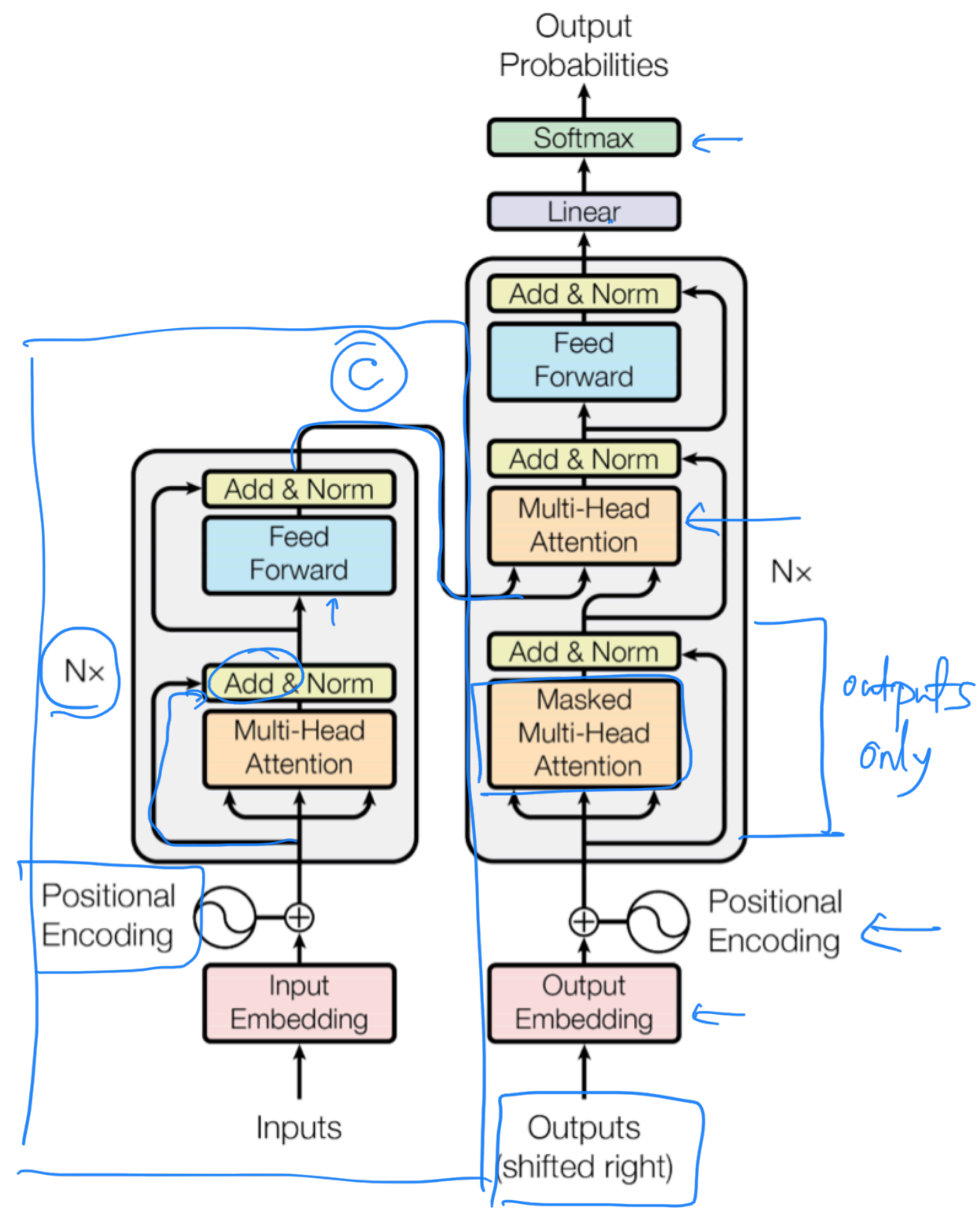
$s_i = f(q, k_i)$

q (vector)

$q^T k_i$ (dot product)
$q^T k_i / \sqrt{d}$ (scaled dot product)
$q^T W k_i$ (general d.p.)
(additive simi) $w_q^T q + w_k^T k_i$

“Attention is all you need”

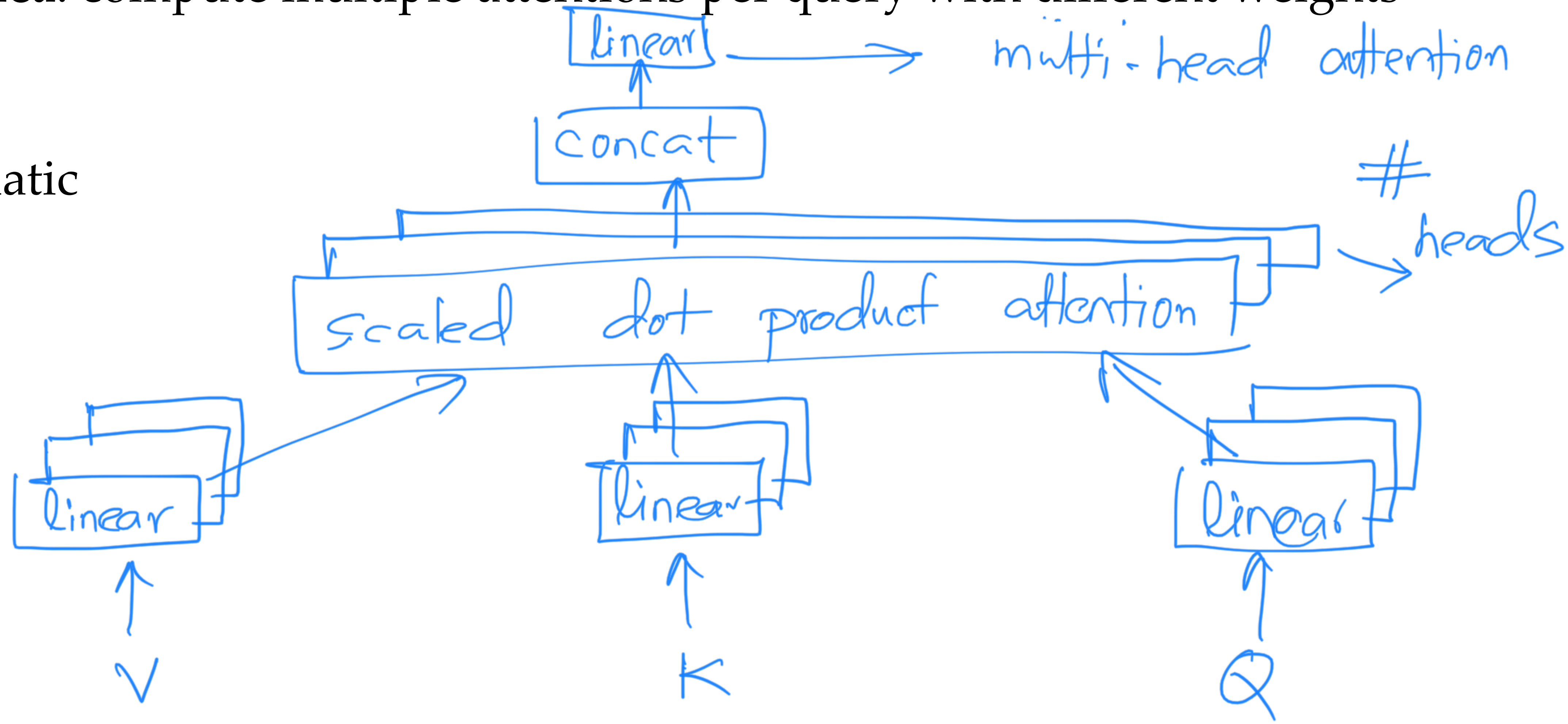
- Vaswani et al. (2017) – Transformer Network



- Encoder-decoder based on attention (no recurrence)

Multihead attention

- **Key idea**: compute multiple attentions per query with different weights
- Schematic



$$multihead(Q, K, V) = W^0 contact(head_1, head_2, \ldots, head_h)$$

$$head_i = attention(W_i^0 Q, W_i^K K, W_i^V V)$$

$$attention(Q, K, V) = softmax\left(\frac{q^T K}{\sqrt{d_k}}\right) V$$

Masked Multi-head attention

- **Key idea**: multi-head where some values are masked (i.e., probabilities of masked values are nullified to prevent them from being selected)

- When decoding, an output value should only depend on previous outputs (not future outputs). Hence we mask future outputs

$$attention(Q, K, V) = softmax\left(\frac{q^T K}{\sqrt{d_k}}\right) V$$

$$MaskedAttention(Q, K, V) = softmax\left(\frac{q^T K + \boxed{M}}{\sqrt{d_k}}\right) V$$

where M is a mask matrix of 0's and $-\infty$'s

Layer normalization and positional embedding

- Layer normalization
  - Normalize values in each layer to have 0 mean and 1 variance

- Positional embedding
  - Embedding to distinguish each position