# Computer Vision

## Week 10 – 11

2025-2

Mobile Systems Engineering

Dankook University

# Motivation & Bridge from Last Lecture

## Seq2Seq Model and Its Limitation

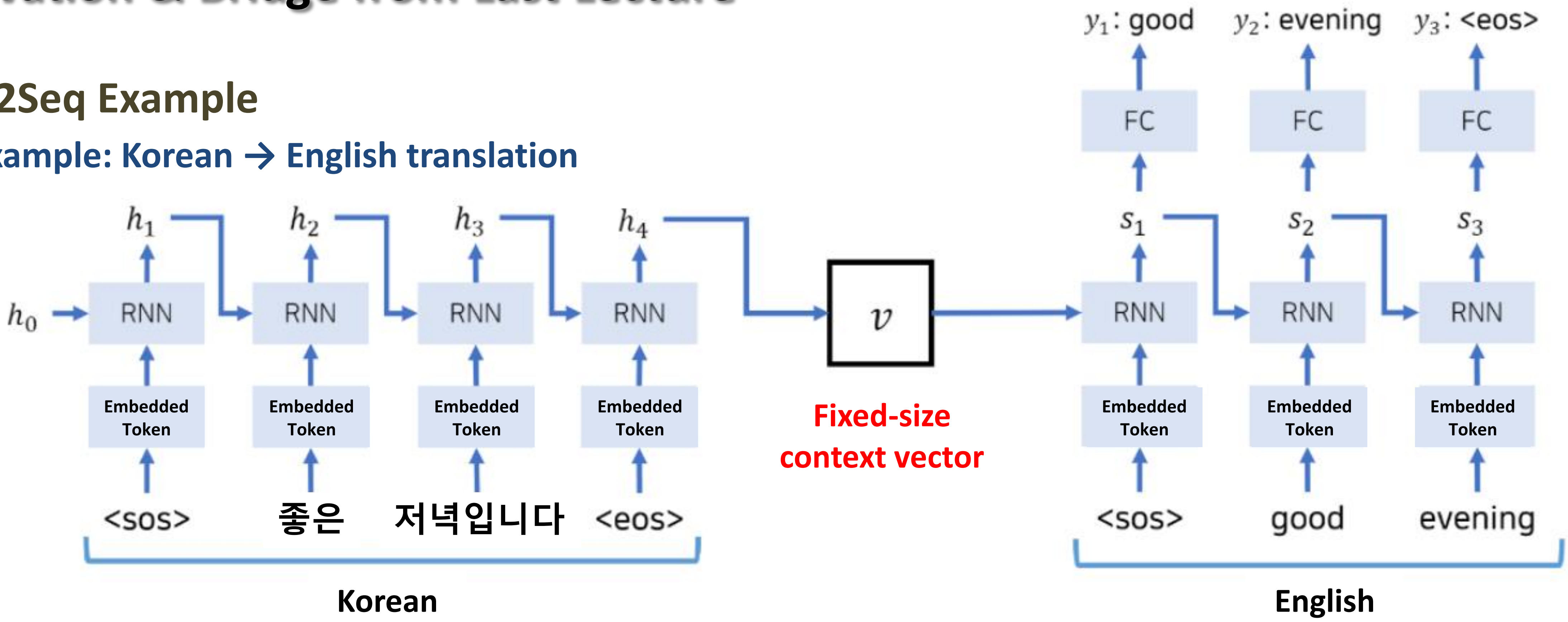
- **Seq2Seq (Sequence-to-Sequence)**
  - Converts one sequence into another sequence (ex: Korean → English translation).
  - Uses **encoder** (to read the source sentence) and **decoder** (to generate the target sentence).

- **Context Vector $v$**
  - The encoder compresses the entire source sentence into a **single fixed-size vector**.
  - This vector is then passed to the decoder to generate the target sentence.

- **Problem – Bottleneck**
  - All information from a long source sentence must fit into one vector.
  - This **bottleneck** causes **performance degradation** as sentence length increases.

# Motivation & Bridge from Last Lecture

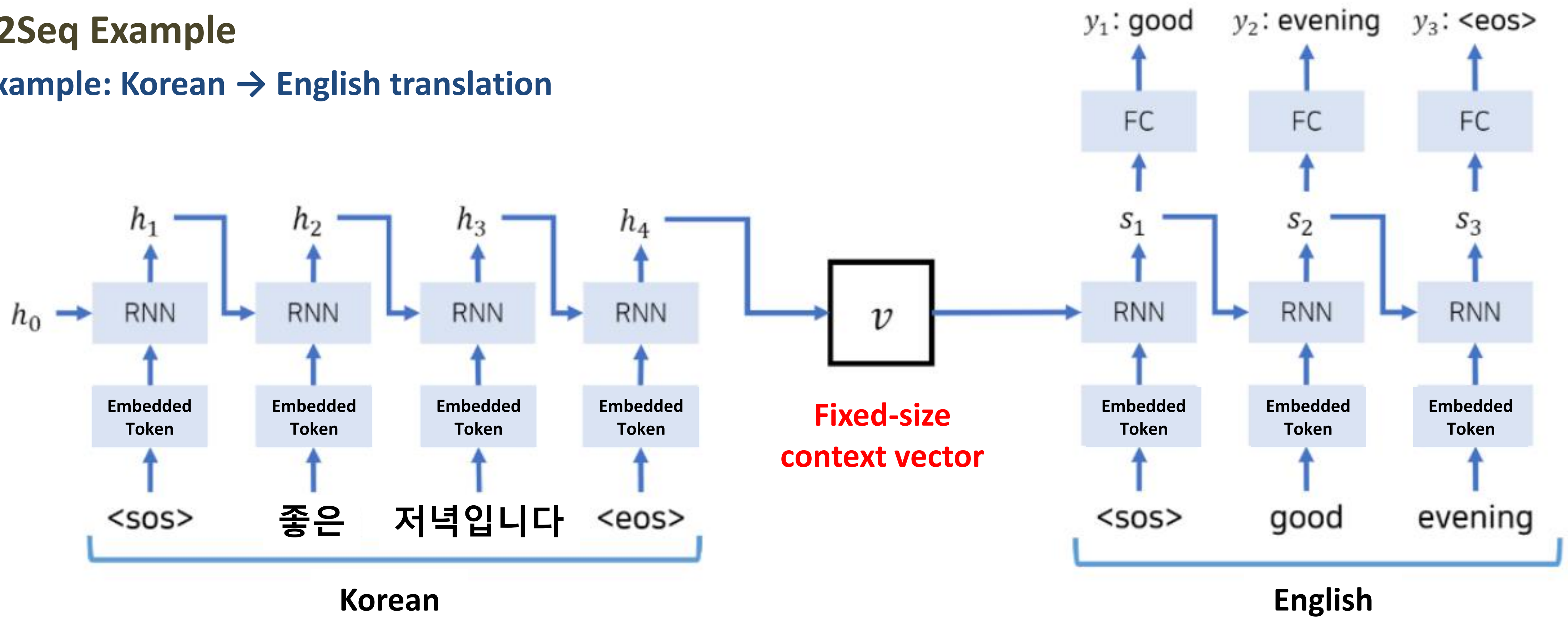
- **Seq2Seq Example**
  - **Example: Korean → English translation**




- **Source sentence (Korean)**
  - ✓"좋은 저녁입니다."
- **Encoder**
  - ✓Processes each word step by step → produces **hidden states** $h_1, h_2, h_3...$ →compresses into one **context vector** $v$.
- **Decoder**
  - ✓Uses $v$to generate English sentence: "Good evening."

# Motivation & Bridge from Last Lecture

- **Seq2Seq Example**
  - **Example: Korean → English translation**




- Process
  - ✓**Step 1.** Each Korean word updates the hidden state.
  - ✓**Step 2.** Final hidden state becomes the **context vector**.
  - ✓**Step 3.** Decoder uses $v$to produce hidden states $s_1, s_2, s_3, \ldots$.
  - ✓**Step 4.** Each step outputs one English word until <eos> token is reached.

# Motivation & Bridge from Last Lecture

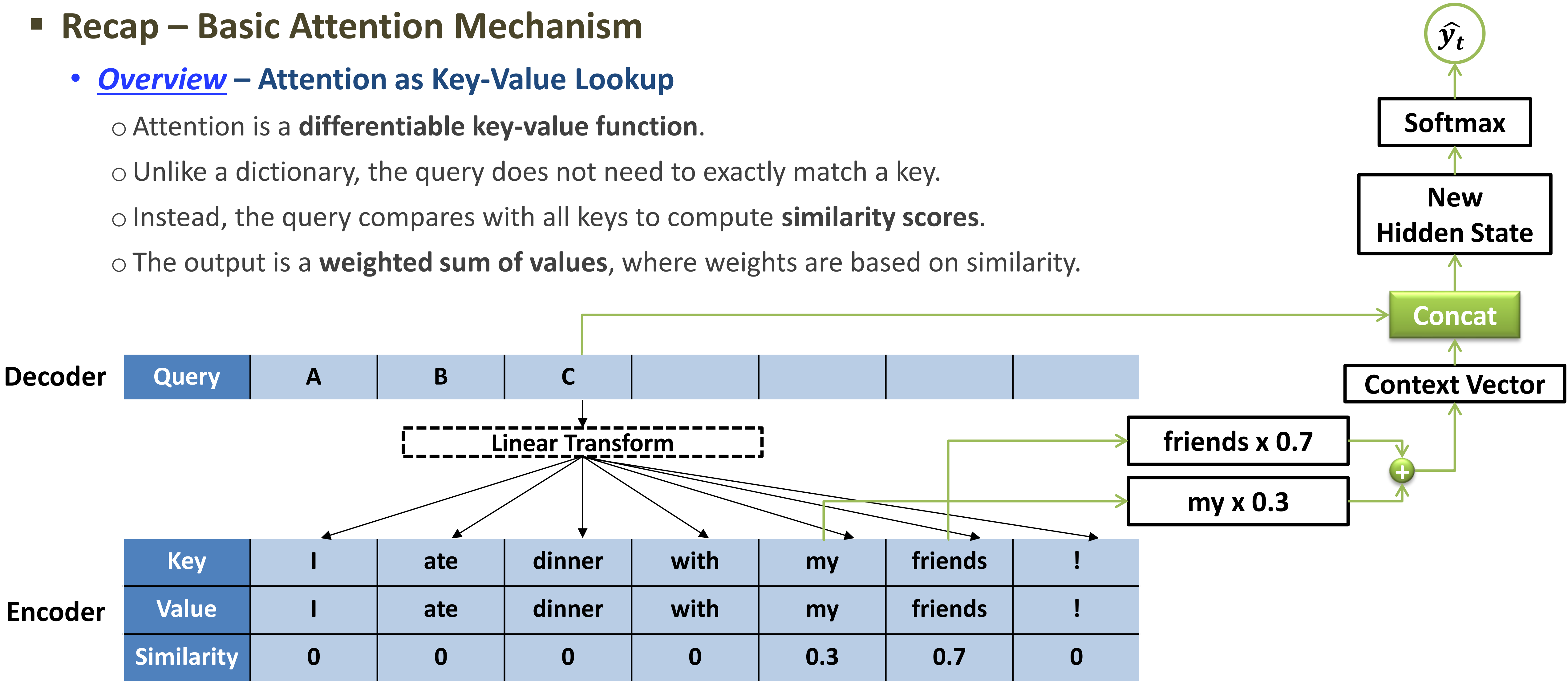
- **Why Attention Is Needed**
  - **1. Limitation of Recurrent Models (RNN, LSTM, GRU)**
    - They generate the hidden state $h_t$ as ***a function of the previous hidden state $h_{t-1}$ and the current input***.
    - This ***sequential dependency*** prevents ***parallelization*** across time steps, making training inefficient for long sequences.
    - Memory usage grows and ***batch processing becomes difficult*** as the sequence length increases.
  - **2. Seq2Seq with Fixed Context Vector**
    - Early neural machine translation used **Seq2Seq with LSTMs**.
    - The encoder ***compresses*** the entire input sentence into ***a single fixed-size context vector***.
    - The decoder then generates the output sequence word by word from this vector.
    - ***Problem:*** For long sentences, this ***bottleneck*** ***CANNOT*** capture all information → performance drops.
    - This also leads to a ***locality issue***: the decoder only sees the compressed context, losing global sentence structure.

**Motivation for Attention**
- Instead of relying on **one fixed vector**, what if the decoder could access **all encoder hidden states** dynamically?
- This allows the decoder to look back at the **entire input sequence**, not just a compressed summary.

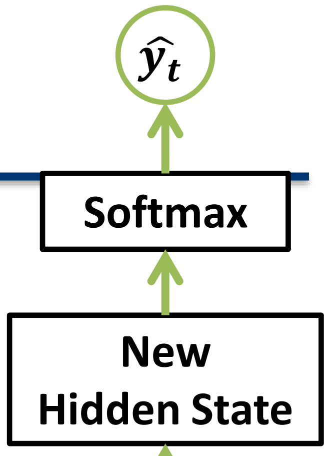
*→ This leads to **Seq2Seq with Attention (2015)**, where the decoder attends to all encoder outputs.*
*→ Later, the **Transformer (2017)** took this further by removing recurrence entirely and using only Attention, enabling **parallelization** and capturing **global dependencies** effectively.*

# Motivation & Bridge from Last Lecture

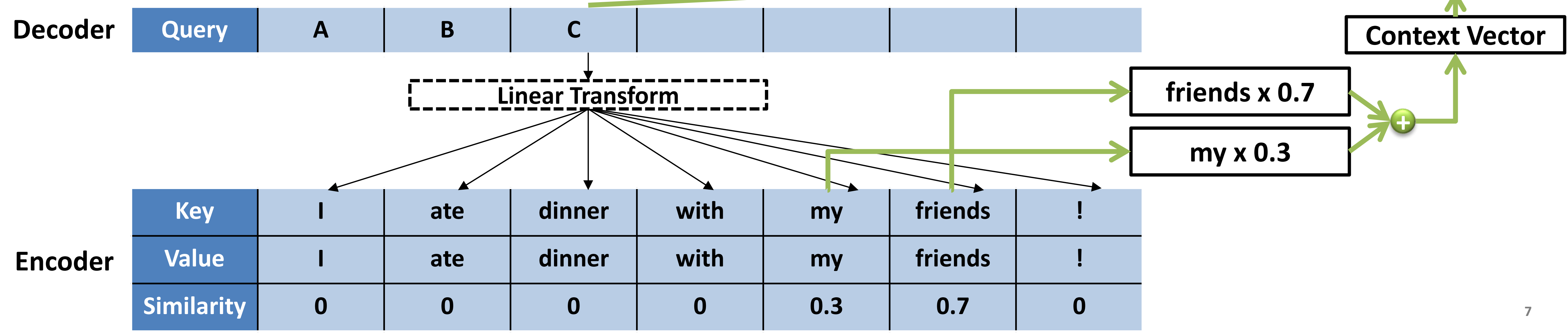
- Recap – Basic Attention Mechanism
  - *Overview* – Attention as Key-Value Lookup
    - Attention is a **differentiable key-value function**.
    - Unlike a dictionary, the query does not need to exactly match a key.
    - Instead, the query compares with all keys to compute **similarity scores**.
    - The output is a **weighted sum of values**, where weights are based on similarity.



# Motivation & Bridge from Last Lecture

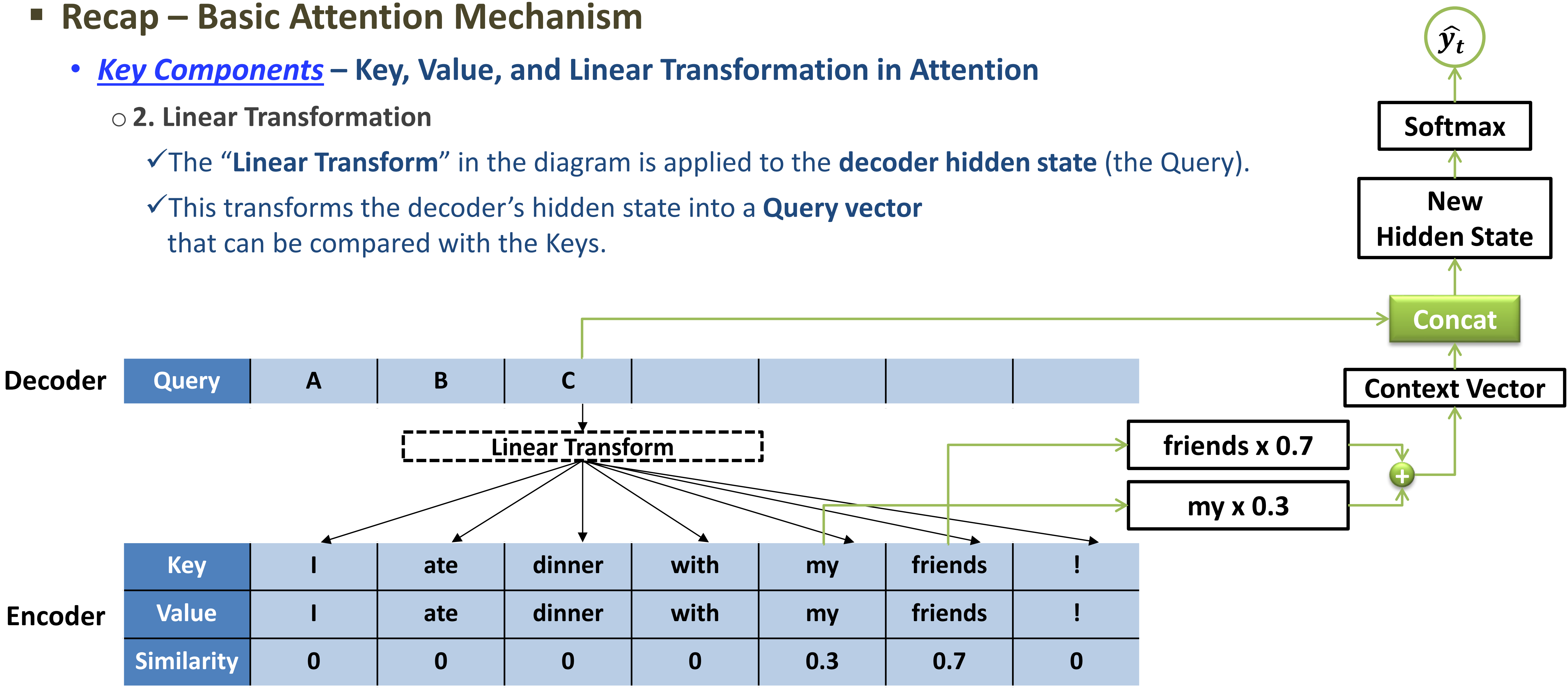



- **Recap – Basic Attention Mechanism**
  - ***Key Components*** **– Key, Value, and Linear Transformation in Attention**
    - **1. Key and Value**
      - ✓Each **Key** and **Value** can be seen as the **hidden state vectors** produced by the encoder (RNN/LSTM/GRU).
      - ✓They are **not just the original word embeddings**, but representations that contain **contextual information up to each token**.
      - ✓In most attention mechanisms, **Key** and **Value** come from the same encoder hidden states:
        - ➢ **Key:** used to measure similarity with the Query
        - ➢ **Value:** used to form the **context vector** through a weighted sum

# Motivation & Bridge from Last Lecture

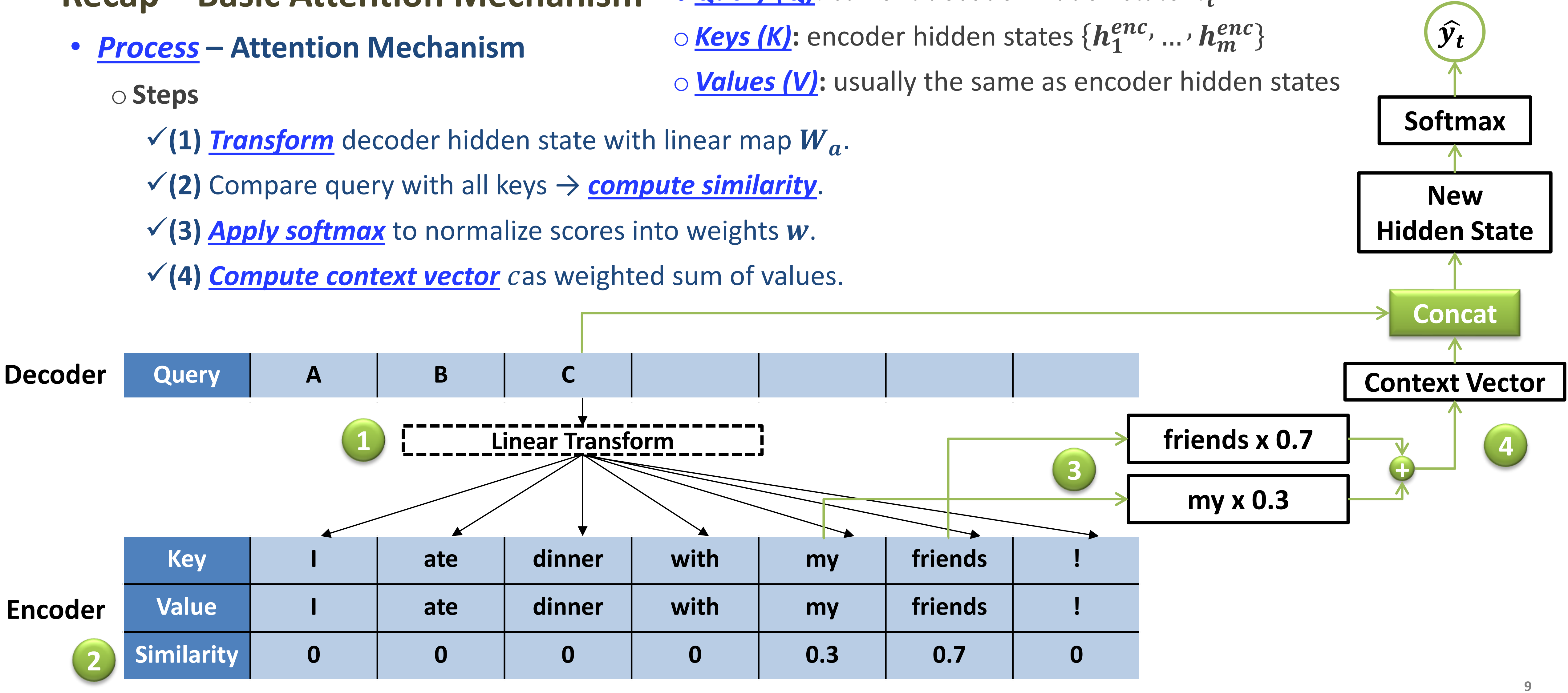
- Recap – Basic Attention Mechanism
  - *Key Components* – **Key, Value, and Linear Transformation in Attention**
    - 2. Linear Transformation
      - ✓The "**Linear Transform**" in the diagram is applied to the **decoder hidden state** (the Query).
      - ✓This transforms the decoder's hidden state into a **Query vector** that can be compared with the Keys.



# Motivation & Bridge from Last Lecture

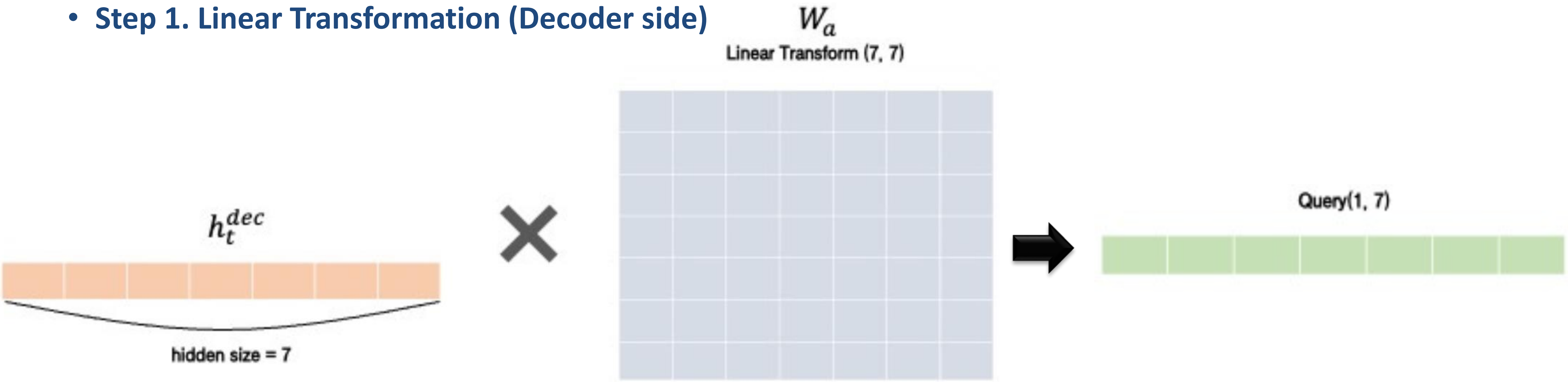
- **Recap – Basic Attention Mechanism**
  - ***Process*** **– Attention Mechanism**
    - **Steps**
      - ✓**(1)** ***Transform*** decoder hidden state with linear map $\boldsymbol{W_a}$.
      - ✓**(2)** Compare query with all keys → ***compute similarity***.
      - ✓**(3)** ***Apply softmax*** to normalize scores into weights $\boldsymbol{w}$.
      - ✓**(4)** ***Compute context vector*** $c$as weighted sum of values.

  - ***Query (Q)***: current decoder hidden state $\boldsymbol{h_t^{dec}}$
  - ***Keys (K)***: encoder hidden states $\{\boldsymbol{h_1^{enc}}, \dots, \boldsymbol{h_m^{enc}}\}$
  - ***Values (V)***: usually the same as encoder hidden states



# Motivation & Bridge from Last Lecture

- **Recap – Basic Attention Mechanism**
  - **Step 1. Linear Transformation (Decoder side)**



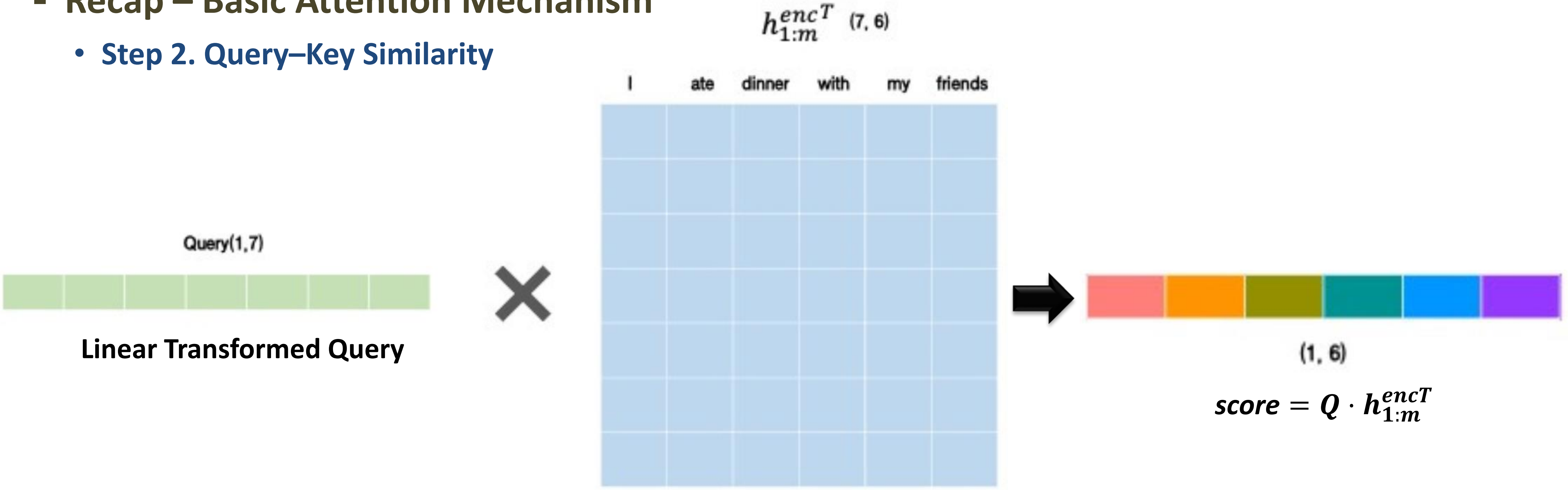

- The decoder hidden state $\boldsymbol{h_t^{dec}}$ has dimension **hidden size = 7**.
- Apply a linear transformation using matrix $\boldsymbol{W_a} \in \mathbb{R}^{7\times7}$.
- This produces the **Query vector**

$$\boldsymbol{Q} = \boldsymbol{h_t^{dec}} \boldsymbol{W_a}$$

- Shape: (1, 7)

# Motivation & Bridge from Last Lecture

- **Recap – Basic Attention Mechanism**
  - **Step 2. Query–Key Similarity**




**Linear Transformed Query**

$$\boldsymbol{score = Q \cdot h_{1:m}^{encT}}$$

- ○ Encoder hidden states $\boldsymbol{h_{1:m}^{enc}}$ act as **Keys**.
- ○ Compute similarity between Query and each Key

$$\boldsymbol{score = Q \cdot h_{1:m}^{encT}}$$

- ○ Shape: (1, m), where $\boldsymbol{m}$ = number of tokens in the source sentence.

# Motivation & Bridge from Last Lecture

- **Recap – Basic Attention Mechanism**
  - **Step 3. Attention Weights (Softmax)**
    - Apply softmax to the similarity scores


$$w\ (Attention\ Weights)$$

$$score = Q \cdot h_{1:m}^{encT} = h_t^{dec} \cdot W_a \cdot h_{1:m}^{encT}$$

$$w = softmax\left(h_t^{dec} \cdot W_a \cdot h_{1:m}^{encT}\right) = softmax\left(Q \cdot h_{1:m}^{encT}\right) = softmax(score)$$

    - These weights represent the **relevance of each source token** to the current decoder step.

  - **Step 4. Context Vector Construction**
    - Multiply weights with encoder **hidden states (Values)** and sum them up:

$$c = \sum_{i=1}^{m} w_i \cdot h_i^{enc}$$

    - This **context vector** $c$ encodes the most relevant information from the source sequence for predicting the next word.

# Motivation & Bridge from Last Lecture

- Recap – Basic Attention Mechanism
  - *Summary* – Attention Mechanism with Equations
    - Attention Weights, Context Vector, and Decoder Output

$$w = softmax\left(h_t^{dec} \cdot W_a \cdot h_{1:m}^{encT}\right) ; w = attention\ weights, W = linear\ transformed\ Query$$

$$c = w \cdot h_{1:m}^{enc} ; h = hidden\ states\ of\ Value$$

✓$c \in \mathbb{R}^{batch \times 1 \times hidden\_size}$ :context vector

✓$W_a \in \mathbb{R}^{hidden\_size \times hidden\_size}$: linear transform

$$\widetilde{h}_t^{dec} = tanh(\left[h_t^{dec}; c\right] \cdot W_{concat})$$

$$\widehat{y}_t = softmax(\widetilde{h}_t^{dec} \cdot W_{gen})$$

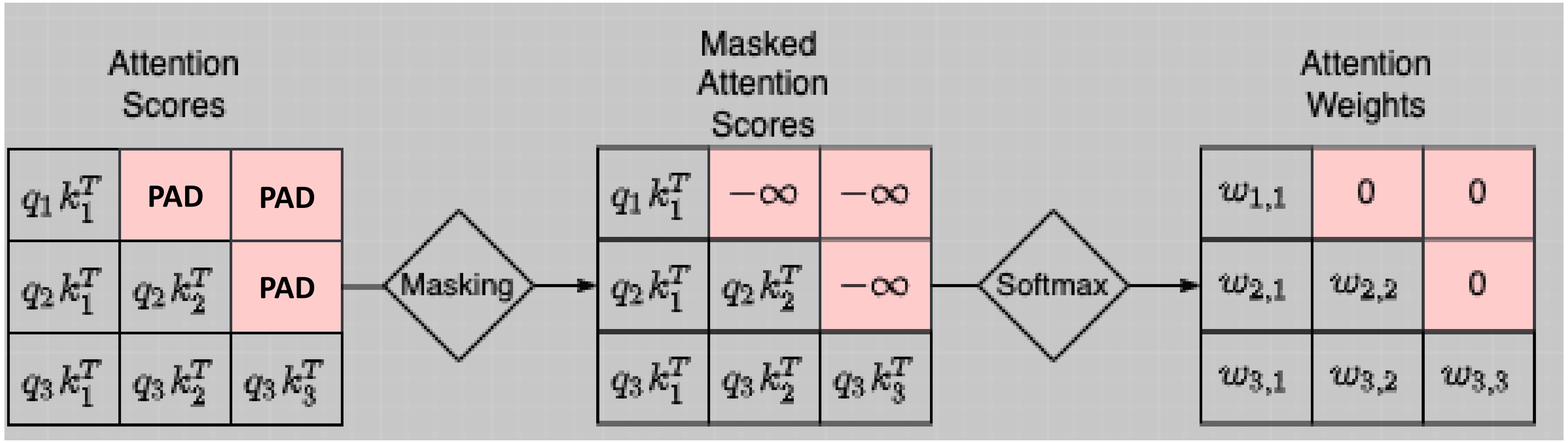
✓Combine decoder hidden state and context vector.

✓Transform back to hidden size with $W_{concat}$.

✓Generate prediction with softmax over vocabulary.

# Motivation & Bridge from Last Lecture

- **Recap – Basic Attention Mechanism**
  - **Masking in Attention**
    - **Problem**
      - ✓Sentences in a batch have different lengths. → Shorter sentences padded with <PAD> tokens.
        → If <PAD> contributes to attention, it introduces noise.
    - **Solution**
      - ✓Apply mask → replace <PAD> positions with $-\infty$ before softmax.
      - ✓***After softmax, weights for <PAD> become exactly 0.***



# Motivation & Bridge from Last Lecture

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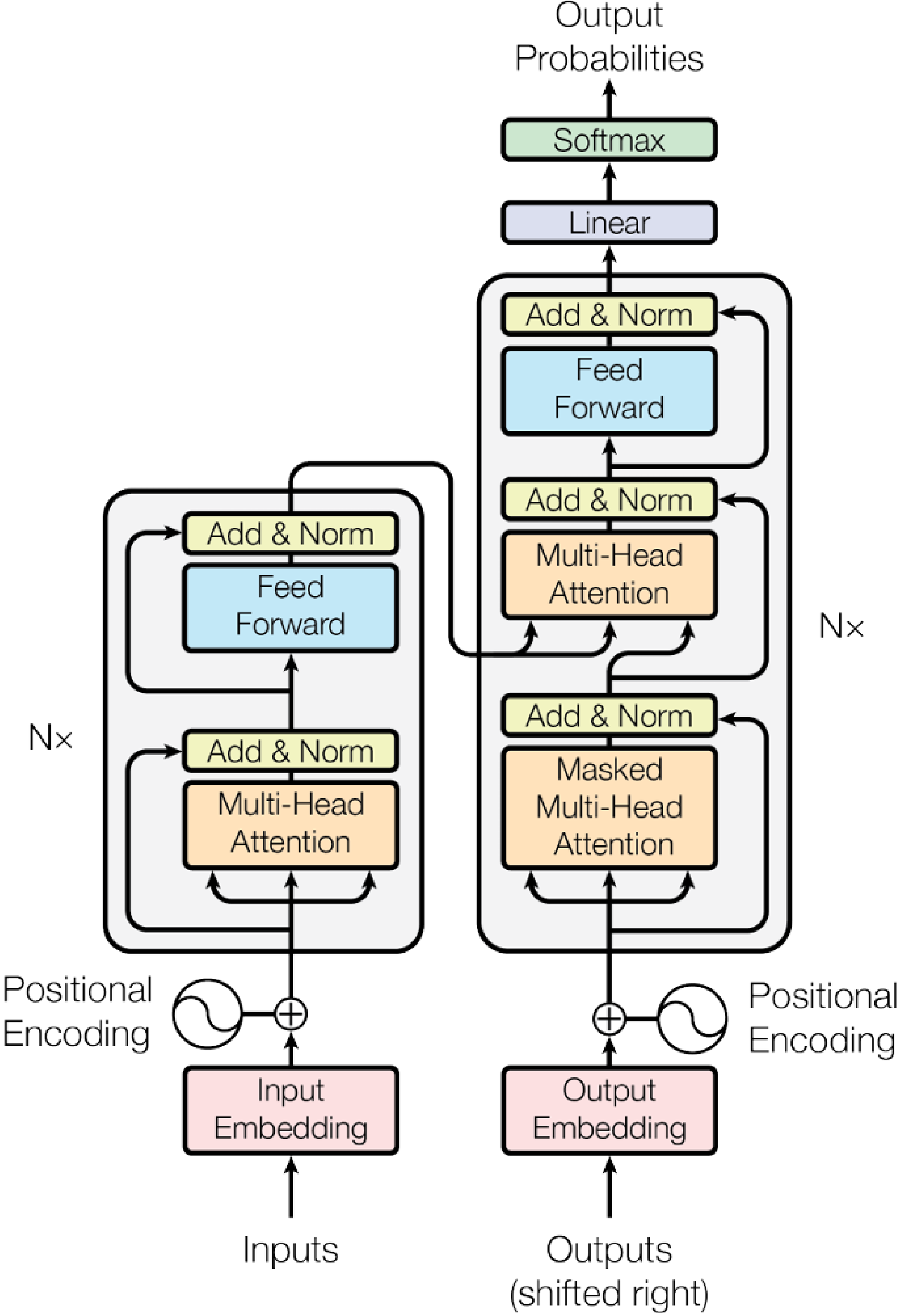
# Transformer Architecture

- **Architecture Overview**
  - The Transformer has an **Encoder–Decoder structure**, each built as a **stack of N identical layers** (originally $N = 6$).
  - **Encoder layer**
    - ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
    - Feed-Forward Network (FFN)
    - Residual connection & LayerNorm around each sublayer.
  - **Decoder layer**
    - ***Attention Type 2*** **– Masked Multi-Head Self-Attention**
    - ***Attention Type 3*** **– Encoder–Decoder Attention**
    - Feed-Forward Network
    - Residual connection & LayerNorm around each sublayer.
  - **Base model sizes**
    - $d_{model} = 512,\ d_{ff} = 2048,\ h = 8$

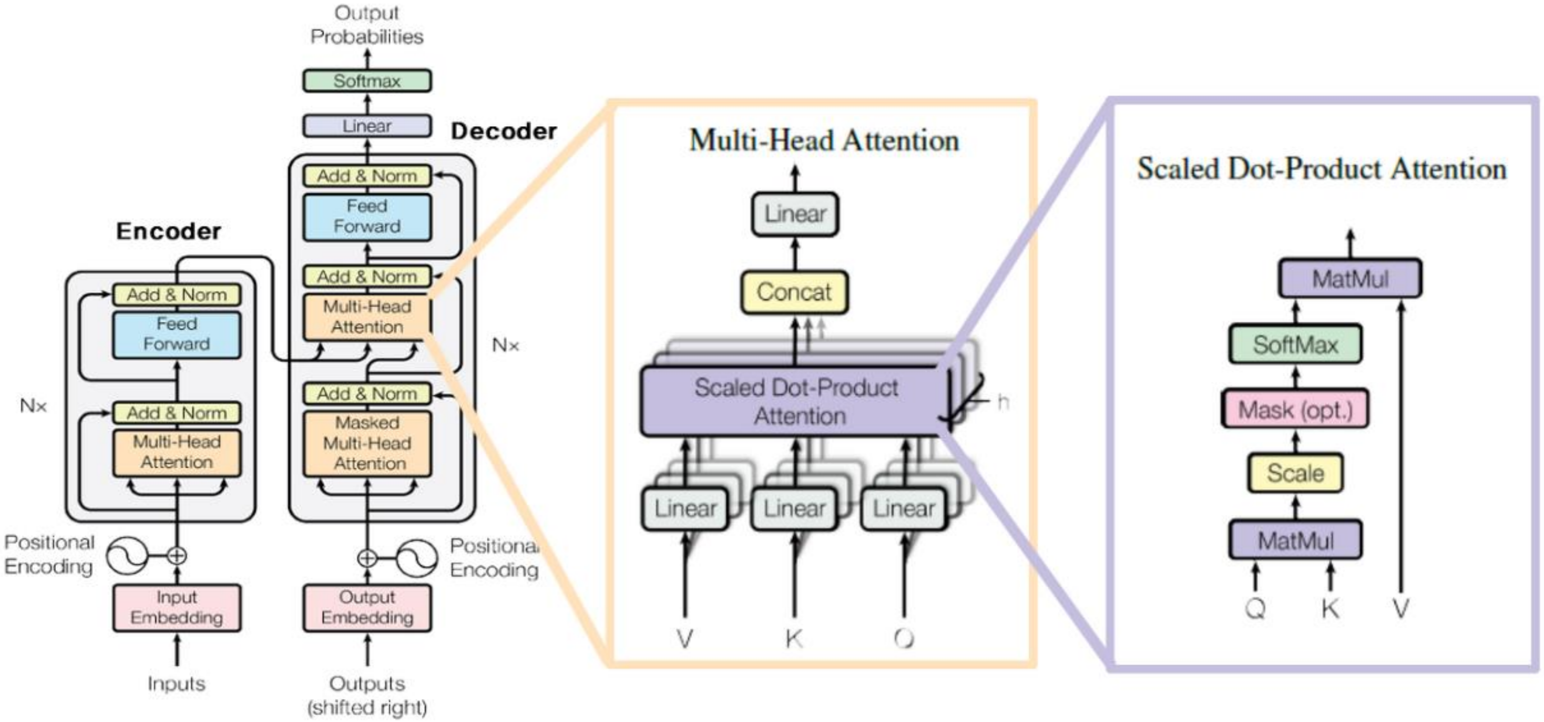


# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Self-Attention**
    - Before we dive into Multi-Head Attention, let's carefully understand how **Self-Attention** works.
    - **Problem**
      - ✓ Traditional models like RNNs and CNNs struggle when sequences get long
        - ➢ RNNs may forget earlier words due to the fixed hidden state.
        - ➢ CNNs capture local patterns well, but long-range dependencies are harder to learn.
    - **Goal**
      - ✓ Determine **how much each word in a sequence should attend to the other words**.

# Transformer – Key Components

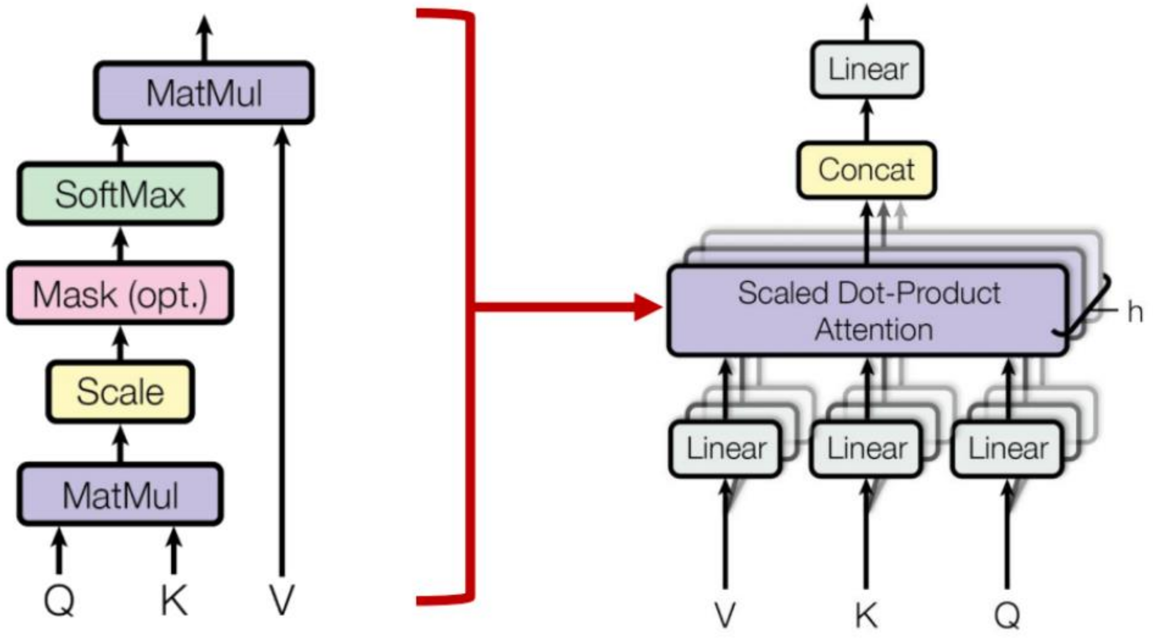
- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Self-Attention**
    - **Self-Attention** solves this by allowing **every word to directly attend to every other word** in the sequence.
      - ✓It answers the question: *“Which words should this word pay attention to, and by how much?”*




- **Example**
  - ✓In *“I love you”*, the representation of “I” is updated by looking at both “love” and “you,” weighted by their importance.

# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Queries, Keys, and Values**
    - To compute attention, we first generate three sets of vectors from our input embeddings




✓**Query (Q):** Represents the word we are focusing on – ***What am I looking for?***

✓**Key (K):** Represents how relevant each word is when queried – ***What do I contain that might be useful to others?***

✓**Value (V):** Contains the actual information that will be combined to produce the attention output – ***The actual information to be passed along.***

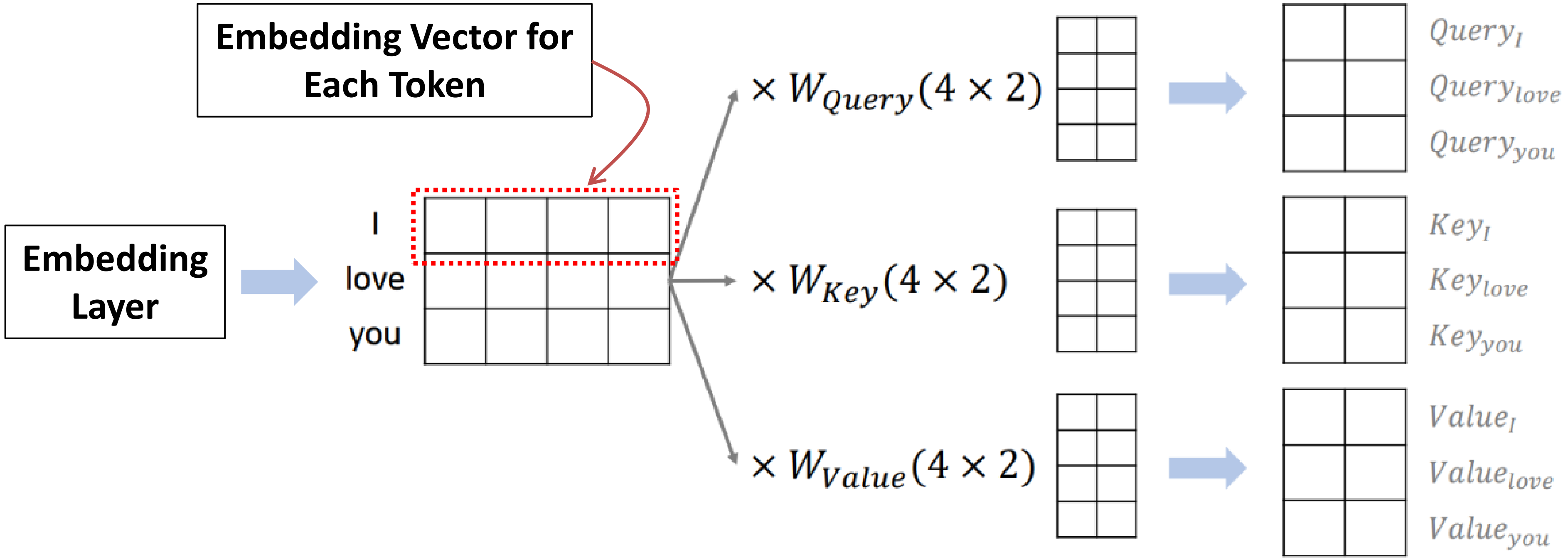
# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Queries, Keys, and Values**
    - Each word embedding $\boldsymbol{x_i}$ (e.g., 4-dimensional vector) is projected into three different spaces

$$\boldsymbol{Q_i = x_i W_{Query}},$$

$$\boldsymbol{K_i = x_i W_{Key}},$$

$$\boldsymbol{V_i = x_i W_{Value}}$$




✓The weight matrices $\boldsymbol{W_{Query}}, \boldsymbol{W_{Key}}, \boldsymbol{W_{Value}}$ are **learnable parameters**.

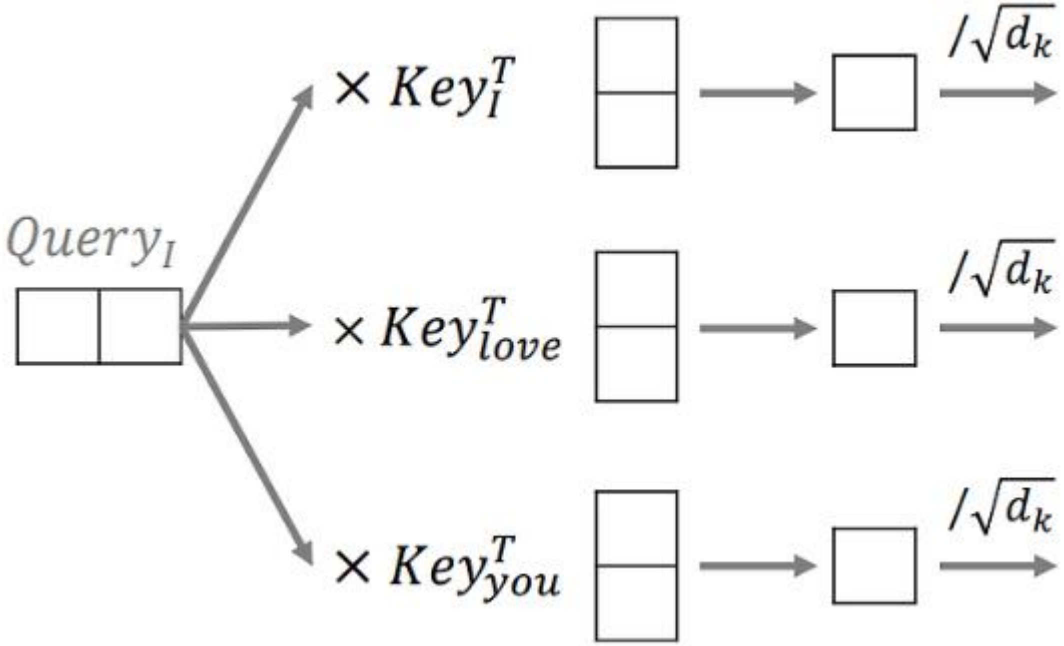
✓They are ***linear transformations***, not embeddings.

➢They map the same input into different roles for computing attention.

# Transformer – Key Components

- *Attention Type 1* – Multi-Head Self-Attention (MHSA)
  - **Scaled Dot-Product Attention**
    - The formula for attention is

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




    - **Step 1: Similarity**
      - ✓Compute the dot product between a Query and all Keys.
      - ✓This measures how relevant each word is to the Query word.
    - **Step 2: Scaling**
      - ✓Divide by $\sqrt{d_k}$ to keep values small.
      - ✓Prevents softmax from becoming too sharp when $d_k$ is large.

# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Scaled Dot-Product Attention**
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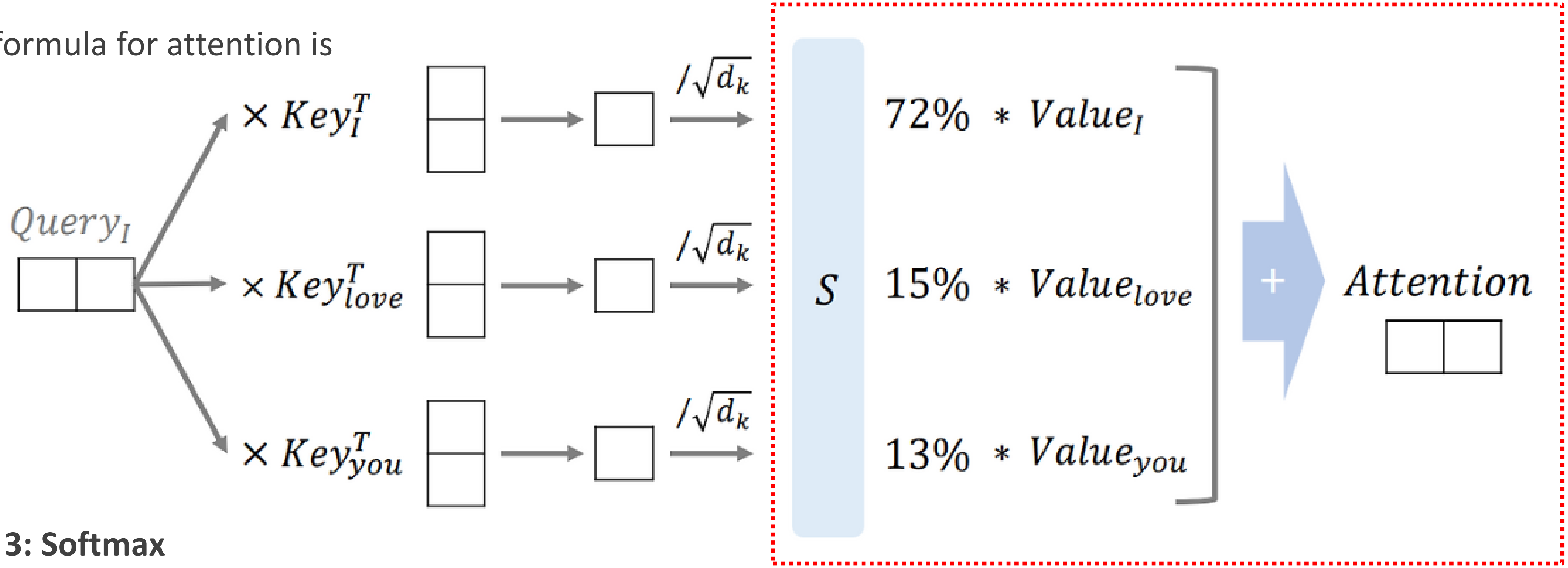
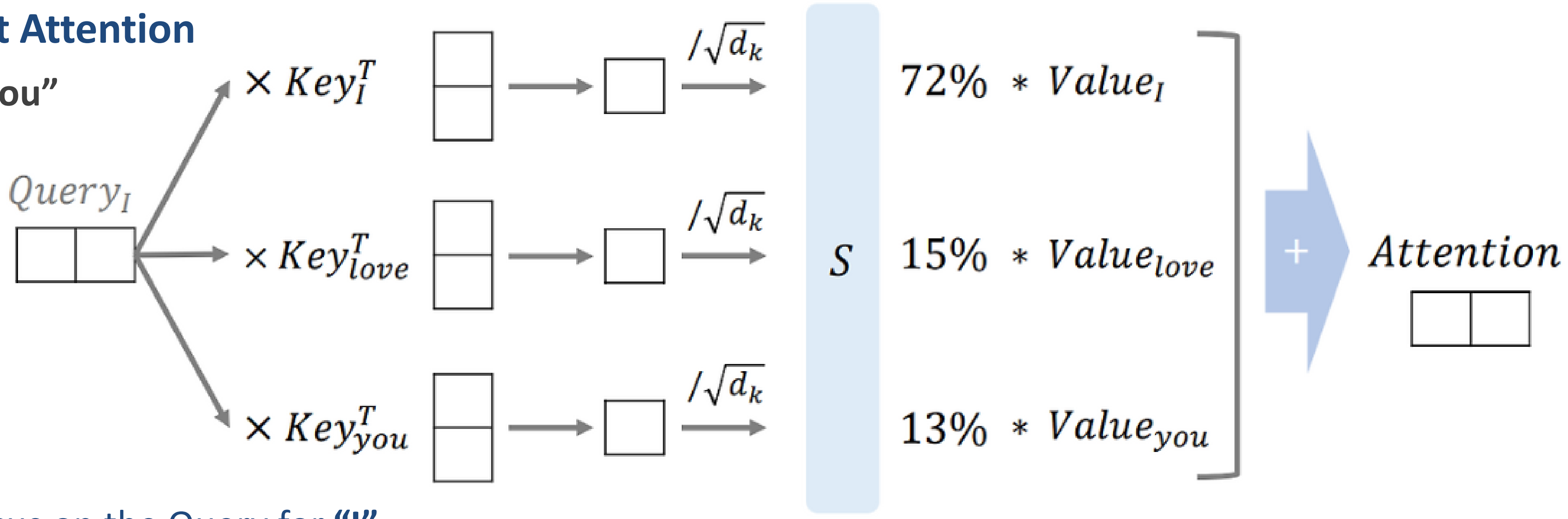



    - **Step 3: Softmax**
      - ✓Convert similarity scores into probabilities (attention weights).
    - **Step 4: Weighted sum**
      - ✓Multiply each Value vector by its attention weight.
      - ✓The result is the new representation for the word.

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

# Transformer – Key Components

- *Attention Type 1* – **Multi-Head Self-Attention (MHSA)**
  - **Scaled Dot-Product Attention**
    - Example: “I love you”




✓Suppose we focus on the Query for **“I”**

- ➢ Dot product with $Key_I$ → strong similarity → weight = 72%
- ➢ Dot product with $Key_{love}$ → moderate → weight = 15%
- ➢ Dot product with $Key_{you}$ → weaker → weight = 13%

✓Final output for **“I”**: $\mathbf{0.72 \cdot V_I + 0.15 \cdot V_{love} + 0.13 \cdot V_{you}}$

✓The word “I” is no longer just its original embedding.
It is now a **contextual embedding** that captures relationships with “love” and “you.”

# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Scaled Dot-Product Attention**
    - **Why Scaling is Necessary**
      - ✓Without scaling, the dot products can be very large if $\boldsymbol{d_k}$ is large.
        - ➢ When we compute self-attention, we use the dot product between a Query and a Key

$$\boldsymbol{s = q \cdot k = \sum_{i=1}^{d_k} q_i\, k_i}$$

        - ➢If the dimension $\boldsymbol{d_k}$ is large, this dot product tends to grow in magnitude.
        - ➢This can cause the softmax function to produce extremely peaked distributions, leading to very small gradients and unstable training.

      - ✓***Large values → softmax outputs are close to 0 or 1 → gradients vanish.***
      - ✓Scaling by $\sqrt{\boldsymbol{d_k}}$ stabilizes training and ensures smoother gradients.

# Transformer – Key Components

- *Attention Type 1* – **Multi-Head Self-Attention (MHSA)**
  - **Scaled Dot-Product Attention**
    - **Why Scaling is Necessary**
      - ✓ **Variance Analysis of the Dot Product**
        - ➢ Let us assume
          - Each element $\boldsymbol{q_i}$ and $\boldsymbol{k_i}$ is drawn from an independent distribution with mean 0 and variance 1.
          - That is, $\mathbb{E}[\boldsymbol{q_i}] = \mathbb{E}[\boldsymbol{k_i}] = \mathbf{0}$ and $\boldsymbol{Var}(\boldsymbol{q_i}) = \boldsymbol{Var}(\boldsymbol{k_i}) = \mathbf{1}.$
        - ➢ Then the variance of the dot product can be computed as

$$\boldsymbol{Var}(\boldsymbol{q} \cdot \boldsymbol{k}) = \boldsymbol{Var}\left(\sum_{i=1}^{d_k} \boldsymbol{q_i}\, \boldsymbol{k_i}\right)$$

        - ➢ Since $\boldsymbol{q_i}$ and $\boldsymbol{k_i}$ are independent

$$\boldsymbol{Var}(\boldsymbol{q} \cdot \boldsymbol{k}) = \sum_{i=1}^{d_k} \boldsymbol{Var}\,(\boldsymbol{q_i k_i})$$

$$= \sum_{i=1}^{d_k} \mathbb{E}\,[\boldsymbol{q_i^2}]\mathbb{E}[\boldsymbol{k_i^2}]$$

$$= \sum_{i=1}^{d_k} \mathbf{1} \cdot \mathbf{1} = \boldsymbol{d_k}$$

# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Scaled Dot-Product Attention**
    - **Why Scaling is Necessary**
      - ✓ **Variance Analysis of the Dot Product**
        - The variance of the dot product grows **linearly with $d_k$**.
        - When $d_k$ is large, dot products become very large in magnitude.
        - Feeding these large values directly into the softmax makes the output distribution very sharp (close to one-hot).
        - ***As a result, gradients become extremely small, which slows down or destabilizes training***.
    - **The Scaling Solution**
      - ✓ To address this, the Transformer introduces a **scaling factor**

$$s = \frac{q \cdot k}{\sqrt{d_k}}$$

      - ✓ By dividing by $\sqrt{d_k}$, we normalize the variance

$$Var\left(\frac{q \cdot k}{\sqrt{d_k}}\right) = \frac{1}{d_k} Var(q \cdot k) = \frac{1}{d_k} \cdot d_k = 1$$

    - This ensures that regardless of the dimensionality $d_k$, the variance of the scaled dot product remains stable (**≈1**).

# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **From Self-Attention to Multi-Head Attention**
    - So far, we learned that **self-attention** allows each word to attend to all the other words in a sequence.
    - But the original Transformer goes a step further by introducing **Multi-Head Attention**.
  - **Why Do We Need Multiple Heads?**
    - A **single attention head** projects Queries, Keys, and Values into one subspace.
    - This limits the variety of relationships it can capture.
    - By using **multiple attention heads**, the model can learn to focus on different aspects of relationships **in parallel**:
      - ✓One head may capture **syntactic structure** (e.g., subject–verb relationships).
      - ✓Another may capture **semantic meaning** (e.g., word similarity).
      - ✓Another may capture **positional dependencies**.
    - In short, multiple heads allow the model to **look at the sequence from different perspectives** at the same time.

# Transformer – Key Components

- *Attention Type 1* – **Multi-Head Self-Attention (MHSA)**
  - **How Multi-Head Attention Works**
    - For each head $\boldsymbol{i}$, we apply separate linear projections

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

    - where each projection matrix has size

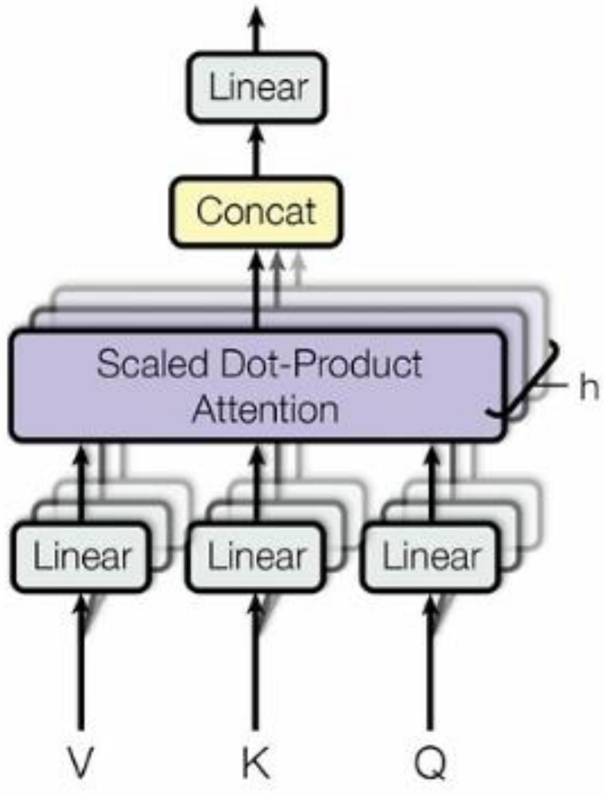
$$W_i^Q, W_i^K, W_i^V \in \mathbb{R}^{d_{model} \times d_k}$$

      - ✓ $d_{model}$: input embedding dimension (e.g., 512)
      - ✓ $h$: number of heads (e.g., 8)
      - ✓ $d_k = d_v = \frac{d_{model}}{h}$ (e.g., 64)
    - Each head computes its own attention output independently.

  - **Combining the Heads**
    - Once all heads are computed

$$MultiHead(Q, K, V) = Concat(head_1, \ldots, head_h)W^O$$

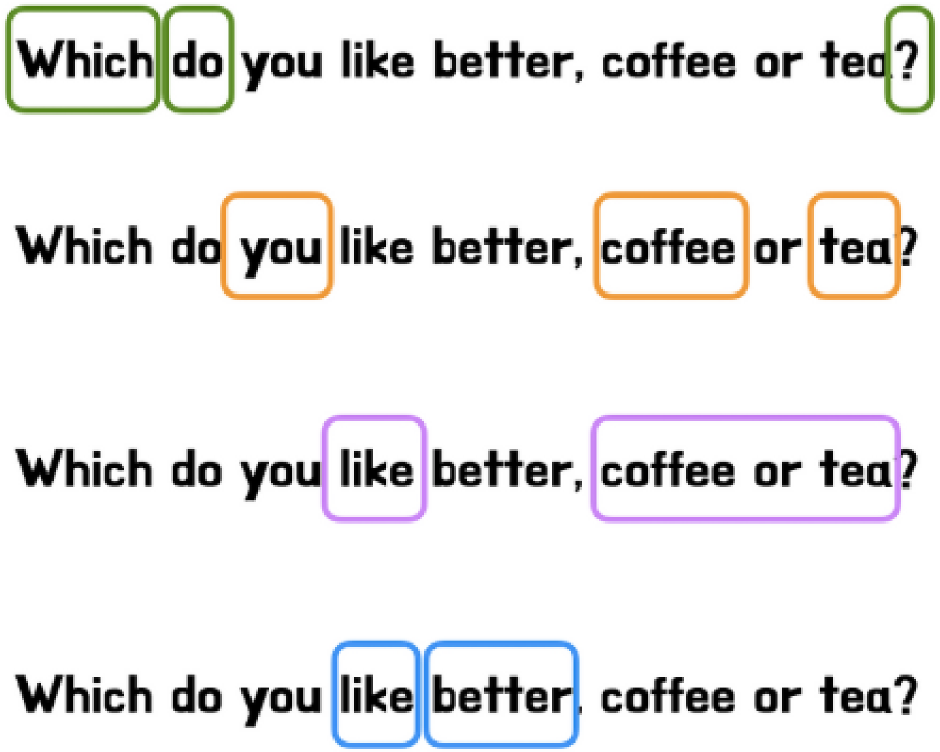
    - The outputs of all heads are concatenated along the feature dimension.
    - Then, a final projection $W^O \in \mathbb{R}^{hd_v \times d_{model}}$ brings the dimension back to $d_{model}$.




Multi-Head Attention

# Transformer – Key Components

- *Attention Type 1* – Multi-Head Self-Attention (MHSA)
  - **The Role of Multi-Head Attention – Different Heads, Different Focus**
    - The following examples illustrate that different attention heads specialize in different roles
    - **1. Sentence Type & Structure Attention**
      - ✓ Some heads focus on functional words and punctuation, helping the model understand the **overall sentence form**.
    - **2. Noun-Focused Attention**
      - ✓ Other heads attend strongly to nouns, helping the model capture **entities** in the sentence.
    - **3. Relation Attention**
      - ✓ Certain heads capture **relations** between words, such as verb-object or subject-predicate dependencies.
    - **4. Sentiment or Emphasis Attention**
      - ✓ Some heads highlight emotionally charged words or intensifiers, focusing on the **tone of the sentence**.



# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **The Role of Multi-Head Attention – Different Heads, Different Focus**
    - ***Interpretability of Attention***
      - ✓Another advantage of attention is **interpretability**.
      - ✓By visualizing attention weights, we can see **which words influence the prediction the most**.
      - ✓Different colors in the visualization represent different heads.
      - ✓This reveals that each head is not redundant but instead complements others.

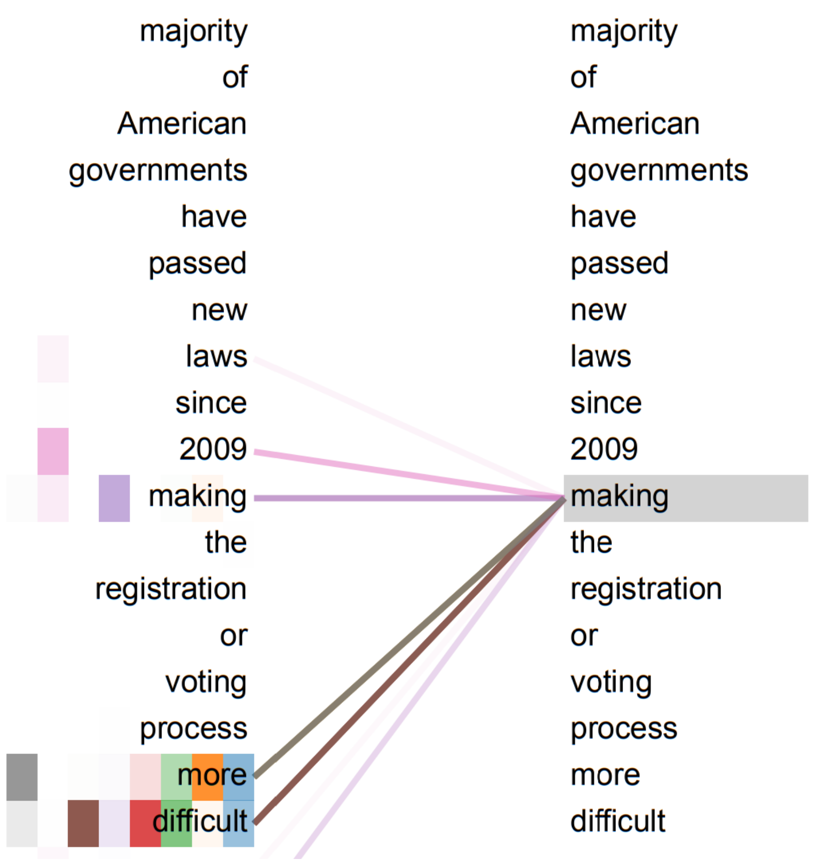
# Transformer – Key Components

- **[Attention Type 1](#) – Multi-Head Self-Attention (MHSA)**
  - **The Role of Multi-Head Attention – Different Heads, Different Focus**
    - ***Case Studies - Interpretability of Attention***

✓ **1. Long-Distance Dependency (Making example)**

➢ In one head, the verb **"making"** attends to words far earlier in the sentence.

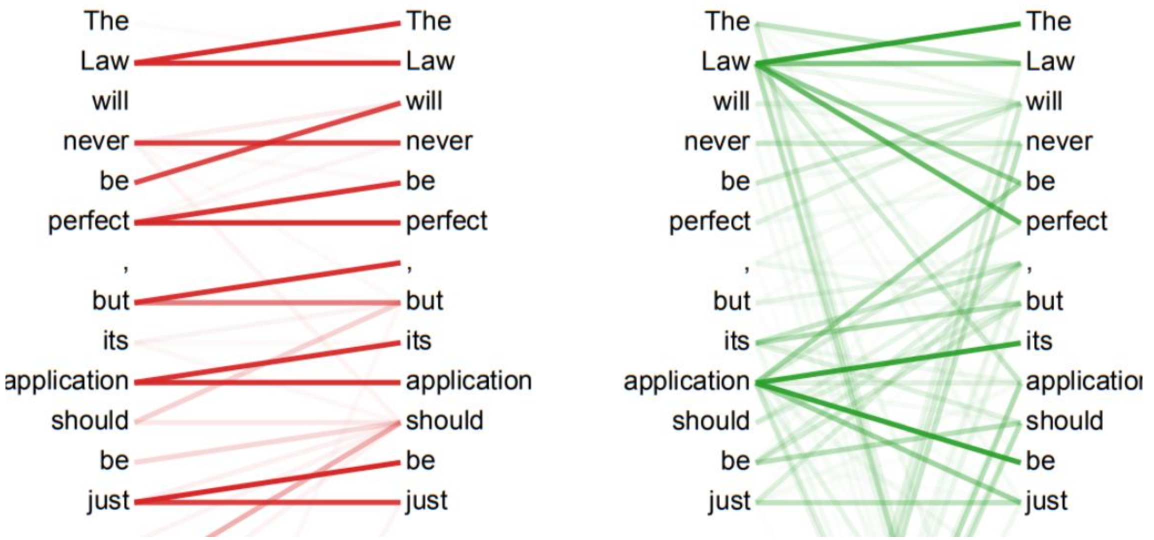
→ This shows how the model captures **long-range dependencies** that RNNs struggle with.




✓ **2. Sentence Structure (Parallel Examples)**

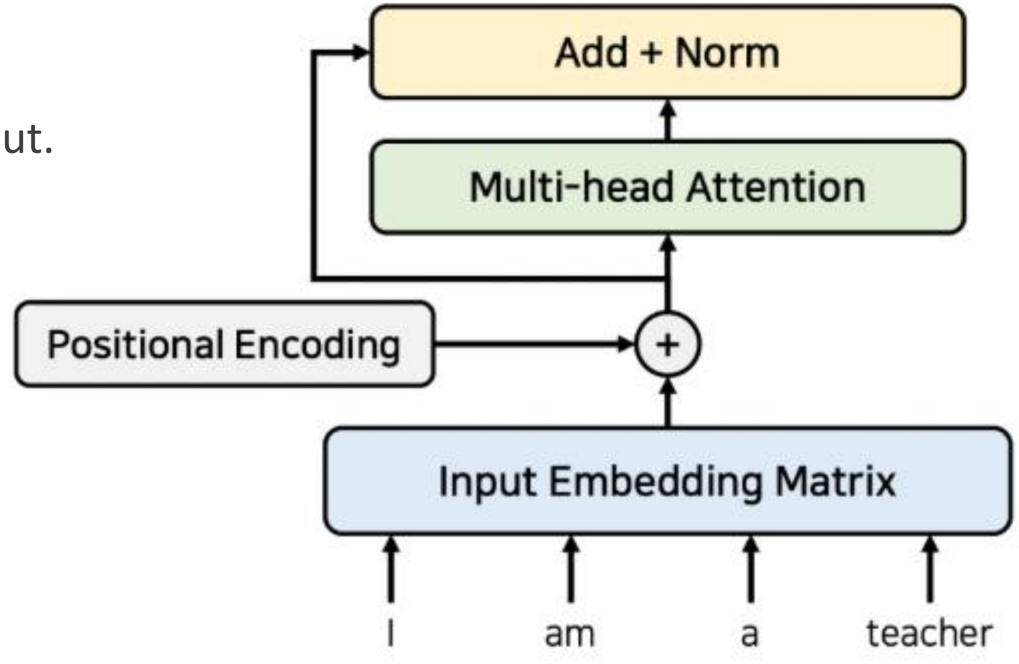
➢ Some heads align multiple words with their repeated counterparts in translation or generation.

→ This reflects the model's ability to learn **syntactic alignment**.



# Transformer – Key Components

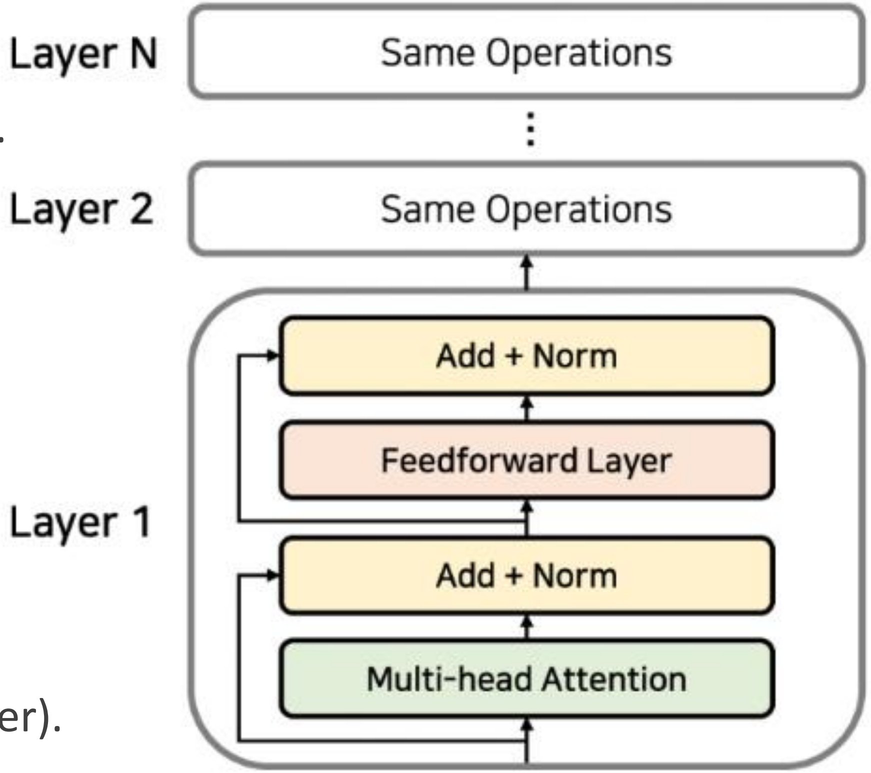
- *Attention Type 1* – Multi-Head Self-Attention (MHSA)
  - **Multi-Head Attention in the Encoder**
    - **Residual Connections in Transformers**
      - ✓ In the Transformer encoder, each sub-layer (such as **Multi-Head Attention** or the **Feedforward Network**) is wrapped with a residual connection
        - ➢ **1.** Input goes into the sub-layer.
        - ➢ **2.** Output of the sub-layer is added back to the original input.
        - ➢ **3.** This sum is then normalized (LayerNorm).




    - **Why Do We Use Residual Learning Here?**
      - ✓ It makes training more stable for deep architectures (Transformers often use 6–12 layers or more).
      - ✓ It allows the original input information to **flow through the network unaltered**, even if the sub-layer changes only a little.
      - ✓ It improves gradient flow during backpropagation, making optimization easier.

# Transformer – Key Components

- ***Attention Type 1*** **– Multi-Head Self-Attention (MHSA)**
  - **Multi-Head Attention in the Encoder**
    - In the **Transformer Encoder**, Multi-Head Attention is used in every layer.
    - Each Encoder layer consists of
      - ✓**1.** Multi-Head Self-Attention
      - ✓**2.** Add & Norm (Residual Connection + Layer Normalization)
      - ✓**3.** Feedforward Network
      - ✓**4.** Another Add & Norm
    - These layers are stacked **N times** (e.g., 6 layers in the original Transformer).
    - The input embeddings are enriched step by step as they pass through each stacked layer.
    - Importantly, **self-attention in the encoder** lets each word look at all the other words in the same sentence, helping the encoder build contextualized word representations.



# Transformer – Key Components

- ***Attention Type 2*** **– Masked Multi-Head Self-Attention**
  - **Motivation**
    - The **goal** of Decoder Self-Attention is the same as in the Encoder:
      → To capture relationships between tokens in the sequence.
  - **Difference**
    - Encoder operates on the **input sentence** (all tokens available).
    - Decoder operates on the **output sentence** (generated tokens so far).

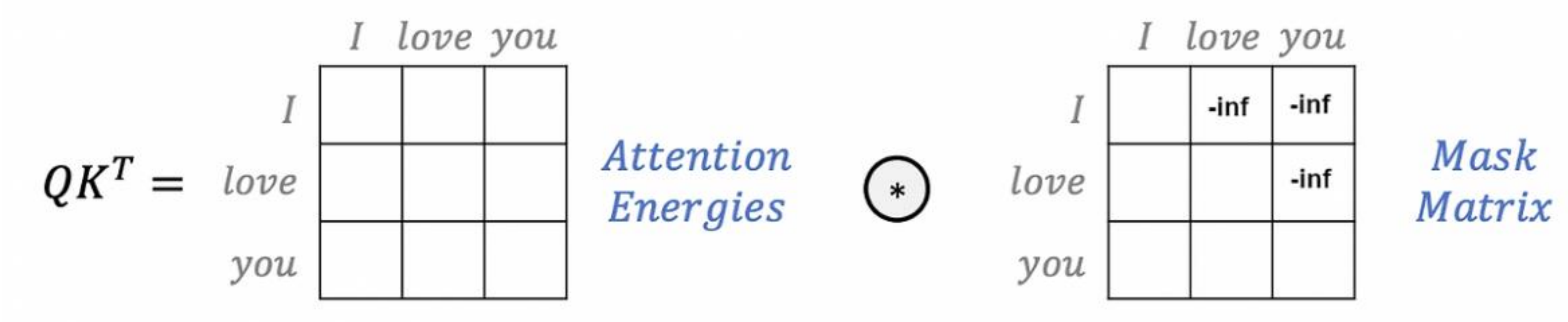
  →This means the decoder must ***not look at future words*** — otherwise it would be cheating.

  - **Auto-Regressive Property**
    - In sequence generation, the model predicts words **one by one**.
    - At time step $t$, the prediction must depend **only on words before** $t$.
    - **Example**
      - ✓Query = “I”, Key = [“I”]
      - ✓Query = “love”, Key = [“I, love”]
      - ✓Query = “you”, Key = [“I, love, you”]

    → The decoder must not use information from future tokens when predicting the next word.

# Transformer – Key Components

- ***Attention Type 2*** **– Masked Multi-Head Self-Attention**
  - **Masking Mechanism**
    - To prevent access to future tokens, we use a **mask matrix**.
    - Mask values are set to $-\infty$for forbidden positions.
    - When passed through the **softmax function**, these positions become 0, meaning they are ignored.



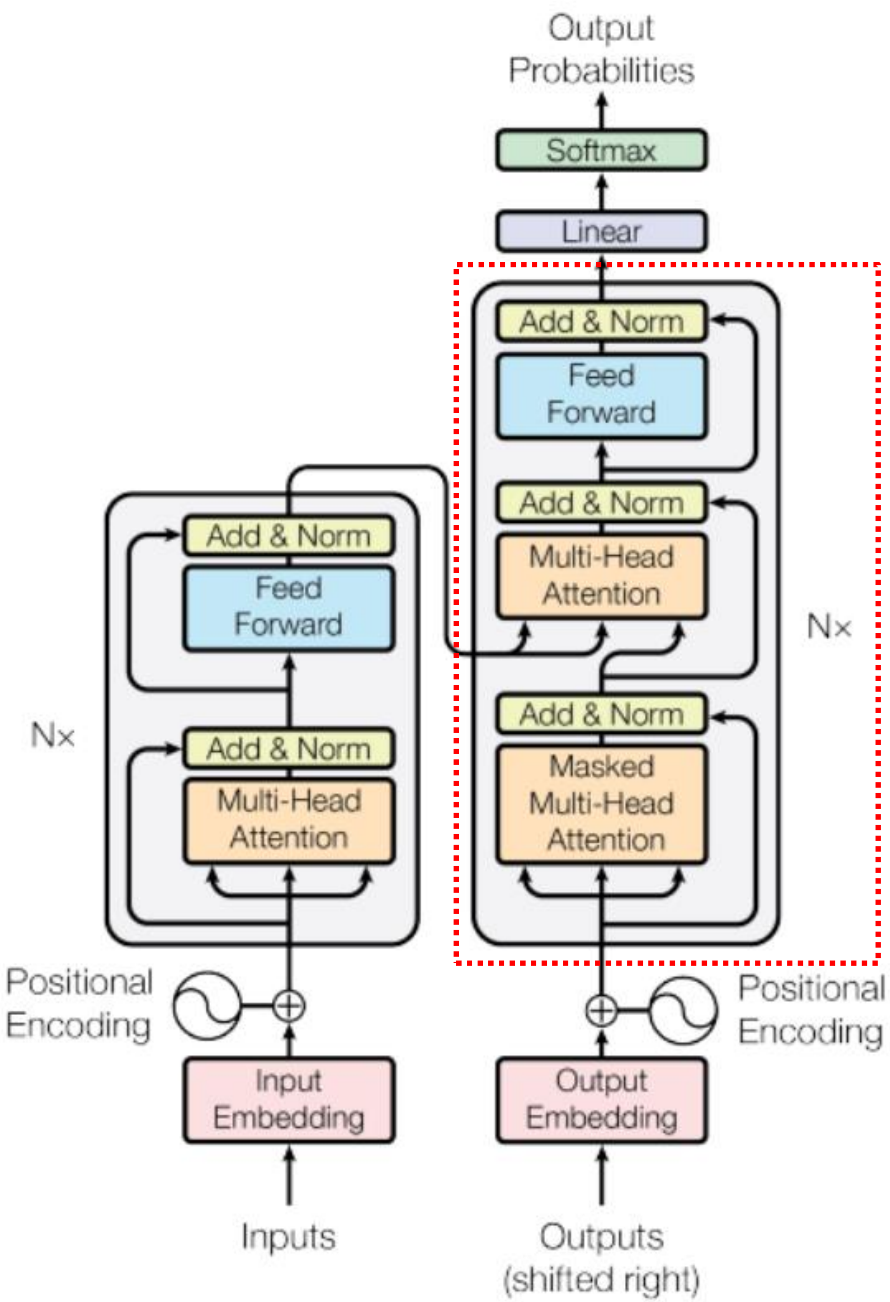

$$QK^T \xrightarrow{\textbf{+ Mask}} softmax\left(\frac{QK^T}{\sqrt{d_k}} + Mask\right)$$

→ This ensures that each token only attends to itself and earlier tokens.

# Transformer – Key Components

- **Attention Type 3 – Encoder–Decoder Attention**
  - **What is Encoder–Decoder Attention?**
    - In the decoder, there are **two types of attention**
      - ✓**Masked Self-Attention** (prevents looking at future words).
      - ✓**Encoder–Decoder Attention** (focuses on the input sequence).
    - In **Encoder–Decoder Attention**
      - ✓**Queries (Q)** come from the decoder.
      - ✓**Keys (K)** and **Values (V)** come from the encoder.

→ This allows the decoder to decide ***which parts of the source sentence are most relevant*** when generating each target word.

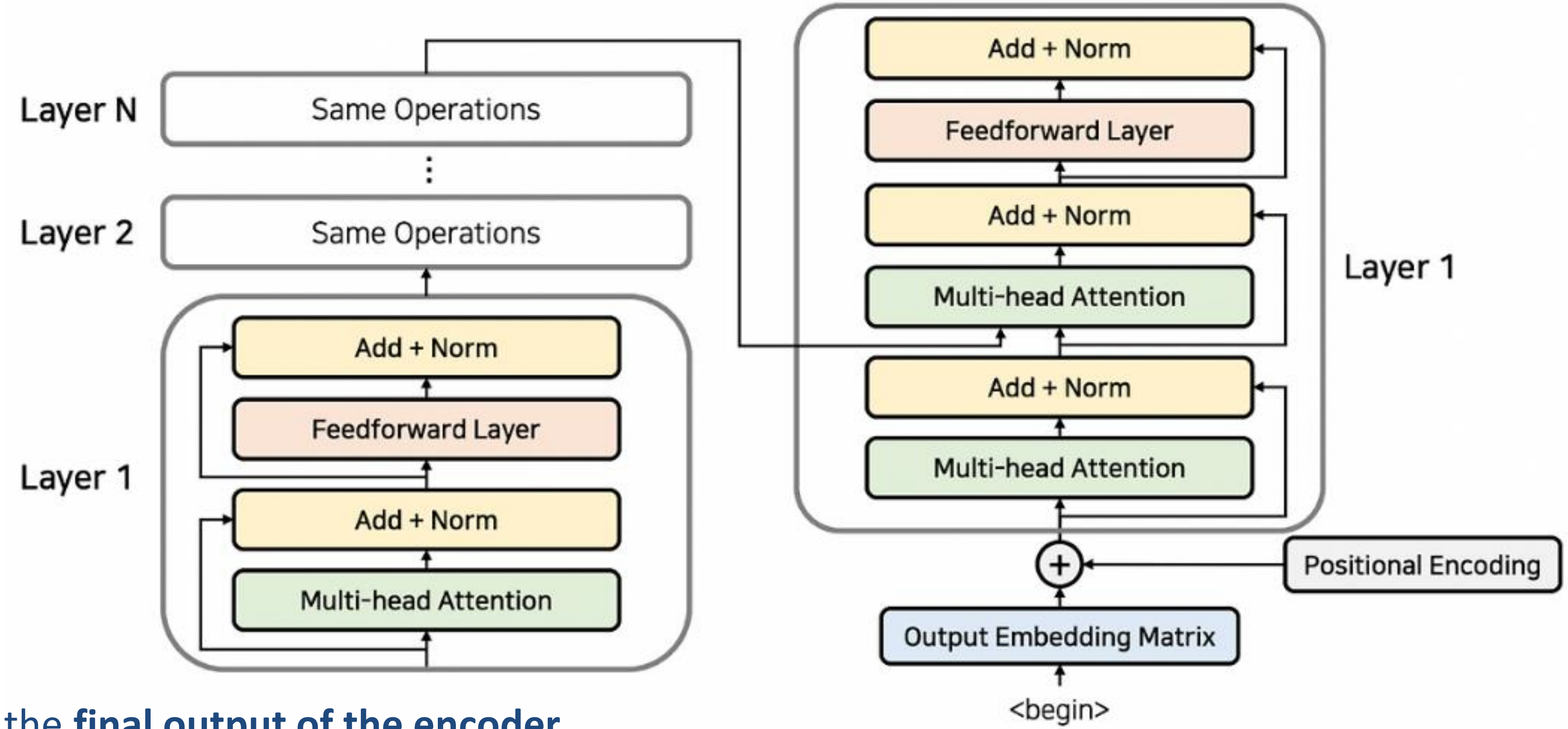


# Transformer – Key Components

- ***Attention Type 3*** **– Encoder–Decoder Attention**
  - **Why Do We Need It?**
    - Self-attention in the encoder learns ***contextual representations*** of the input sentence.
    - The decoder needs to know: *"When generating this word, which input words should I focus on?"*
    - Encoder–Decoder Attention provides this mechanism by ***linking each decoder word to the encoder's representations***.
  - **Example**
    - When translating *"guten abend"* → *"good evening"*
      - ✓The decoder word "good" should attend strongly to "guten."
      - ✓The decoder word "evening" should attend strongly to "abend."

# Transformer – Key Components

- ***Attention Type 3*** **– Encoder–Decoder Attention**
  - **How It Works**
    - At each decoding step




✓**1.** The decoder takes the **final output of the encoder**.

✓**2.** It computes attention scores between the decoder's Query and the encoder's Keys.

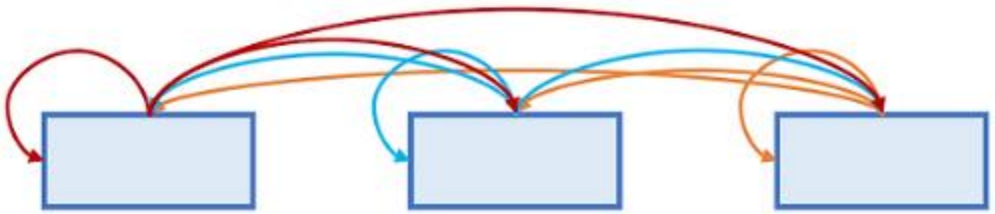
✓**3.** These scores weight the encoder's Values, producing a context vector.

✓**4.** This context vector guides the decoder in generating the next word.

$$\boldsymbol{Attention}(Q_{decoder}, K_{encoder}, V_{encoder})$$

# Transformer – Key Components

- Summary – Three Types of Attention in the Transformer
  - ***Attention Type 1*** **– Encoder Multi-Head Self-Attention (MHSA)**
    - Each word in the **input sequence** attends to **all other words** in the same sentence.
    - Purpose: Build **contextual embeddings** that capture global relationships.

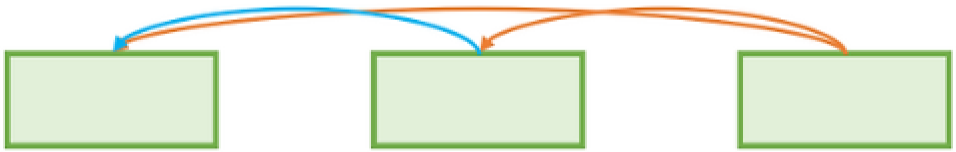


***→ Global context inside the encoder.***

**: Encoder**

**: Decoder**

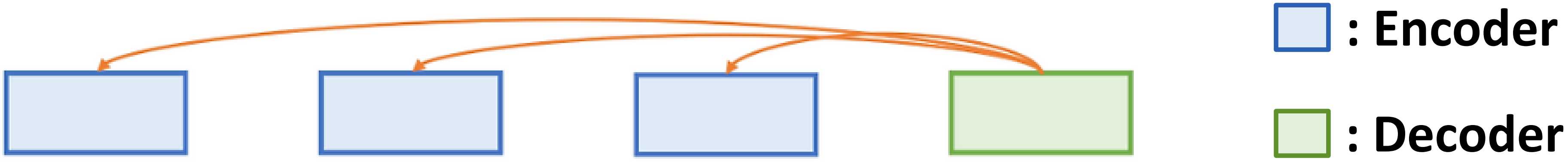
  - ***Attention Type 2*** **– Decoder Masked Multi-Head Self-Attention (Masked MHSA)**
    - Used in the **decoder** when generating output.
    - Each word can only attend to **itself and previous words**.
    - Future words are **masked** to preserve the **auto-regressive property**.



***→ Prevents cheating by blocking future tokens.***

# Transformer – Key Components

- **Summary – Three Types of Attention in the Transformer**
  - ***Attention Type 3*** **– Encoder–Decoder Attention**
    - Queries come from the **decoder**, while Keys and Values come from the **encoder**.
    - Allows the decoder to focus on the **most relevant parts of the input sentence**.




***→ Links the input sentence to the output generation.***

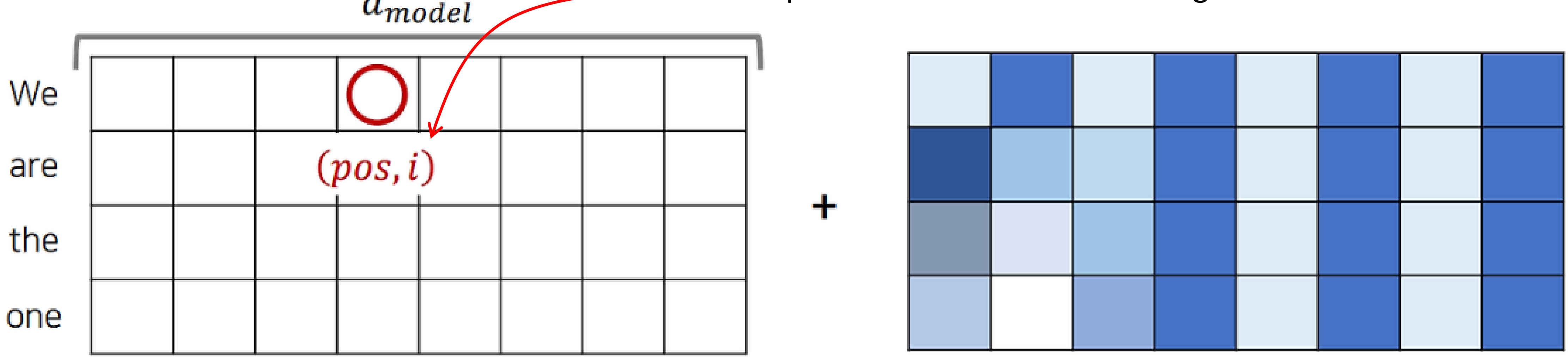
- ***"Together, these three types of attention form the core of the Transformer architecture"***

# Transformer – Other Components

- **Positional Encoding**
  - **Why Do We Need Positional Information?**

$\boldsymbol{pos}$: word index,

$\boldsymbol{i}$: position within the embedding dimension of the word



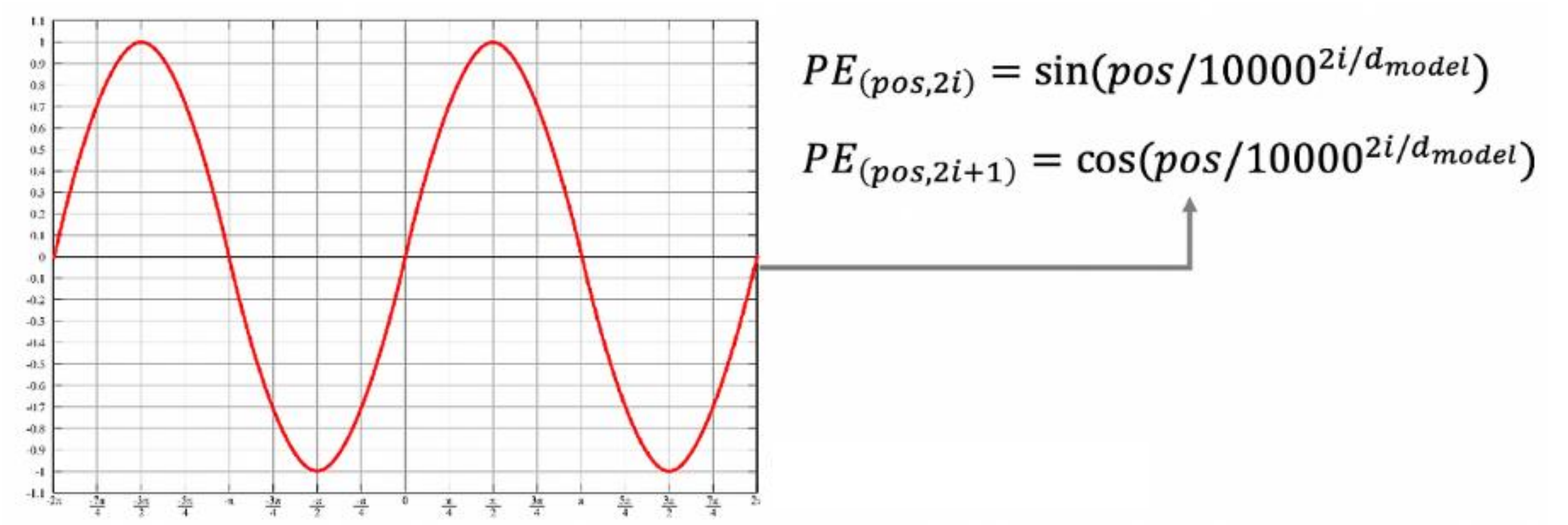

**Normal Embedding** **Positional Encoding**

- Unlike RNNs or LSTMs, **Transformers process the entire input sequence in parallel**.
- This parallelization is powerful but **loses the natural order of tokens** that RNNs inherently have.
- To give the model a sense of sequence order, we add **Positional Encoding** to input embeddings.

# Transformer – Other Components

- **Positional Encoding**
  - **The Idea of Positional Encoding**
    - Each token embedding **does not contain position by itself**.
    - We generate a **positional vector** that encodes the position of each token in the sequence.
    - Then, we simply **add this positional vector** to the word embedding before feeding it into the Transformer.

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



# Transformer – Other Components

- ## Positional Encoding
  - **Why Use Sine and Cosine?**
    - o Using **integers (1, 2, 3, …)** as positional indices is unstable for training.

→ ***As the sequence length grows, indices become very large, which makes learning difficult.***

- o Using **ratios in [0, 1]** also fails.
  - ✓ For example, the value 0.9 represents the 9th element in a sequence of length 10, but the 90th element in a sequence of length 100.

→ ***Thus, the same value has different meanings depending on sequence length.***

- o Using **binary vectors (e.g., [0, 1, 0, 1, 0, 0, 0, 1])** can also cause problems.

→ ***In high-dimensional spaces, distance metrics may treat them inconsistently, leading to incorrect similarity judgments.***

- o Instead, sine and cosine functions provide **continuous, smooth, and periodic signals** that are stable across different sequence lengths.

# Transformer – Other Components

- ## Positional Encoding
  - **Why Use Sine and Cosine?**
    - Using both of sine and cosine.

    →If we only use sine (or only cosine), ***positions can overlap*** because the function ***repeats values periodically***.

  - **Properties of Positional Encoding**
    - Sine and cosine positional encodings are used because they satisfy four essential conditions:
    - **Uniqueness** – Each token position is assigned a unique value.
    - **Consistency of distance** – The relative distance between tokens is preserved.
      - ✓e.g., the difference between token 1 and token 2 is the same as between token 2 and token 3.
    - **Scalability** – The encoding can generalize to sequences longer than those seen during training, without causing errors.
    - **Predictability** – Since sine and cosine are deterministic functions, the position values can always be reconstructed.

# Transformer

- **Why Self-Attention? – From [Quantitative Analysis]**
  - Traditional RNNs, LSTMs, and Seq2Seq models have been powerful, but **Transformers replaced them with Self-Attention**. Why?
  - There are three main reasons.
    - **1. Computational Complexity per Layer**

$n$: Sequence length, $d$: Representation dimension, $k$: kernel size

| Layer Type | Complexity per Layer | Sequential Operations | Maximum Path Length |
|---|---|---|---|
| Self-Attention | $O(n^2 \cdot d)$ | $O(1)$ | $O(1)$ |
| Recurrent | $O(n \cdot d^2)$ | $O(n)$ | $O(n)$ |
| Convolutional | $O(k \cdot n \cdot d^2)$ | $O(1)$ | $O(log_k(n))$ |
| Self-Attention (restricted) | $O(r \cdot n \cdot d)$ | $O(1)$ | $O(n/r)$ |

✓**RNNs:** Complexity = $\boldsymbol{O(n \cdot d^2)}$, because computation is sequential across all tokens.

✓**Self-Attention:** Complexity = $\boldsymbol{O(n^2 \cdot d)}$.

✓When the sequence length $\boldsymbol{n}$ is not too large compared to the representation dimension $\boldsymbol{d}$, Self-Attention is more efficient.

✓For natural language tasks with vocab sizes in the thousands, representation dimensions like 256 or 512 are typical. In such cases, Self-Attention is often computationally better.

# Transformer

- **Why Self-Attention? – *From Quantitative Analysis***
  - Traditional RNNs, LSTMs, and Seq2Seq models have been powerful, but **Transformers replaced them with Self-Attention**. Why?
  - **There are three main reasons.**
    - **2. Amount of Computation**

$n$: Sequence length, $d$: Representation dimension, $k$: kernel size

| Layer Type | Complexity per Layer | Sequential Operations | Maximum Path Length |
|---|---|---|---|
| Self-Attention | $O(n^2 \cdot d)$ | $O(1)$ | $O(1)$ |
| Recurrent | $O(n \cdot d^2)$ | $O(n)$ | $O(n)$ |
| Convolutional | $O(k \cdot n \cdot d^2)$ | $O(1)$ | $O(log_k(n))$ |
| Self-Attention (restricted) | $O(r \cdot n \cdot d)$ | $O(1)$ | $O(n/r)$ |

✓**RNNs:** Must process tokens sequentially — computation takes $O(n)$.

✓**Self-Attention:** Can process all positions **in parallel**, because all Attention Scores can be computed at once.

✓This parallelism makes Self-Attention significantly faster in modern GPU/TPU systems.

# Transformer

- **Why Self-Attention? – *From Quantitative Analysis***
  - Traditional RNNs, LSTMs, and Seq2Seq models have been powerful, but **Transformers replaced them with Self-Attention**. Why?
  - **There are three main reasons.**
    - **3. Path Length for Long-Range Dependencies**

$n$: Sequence length, $d$: Representation dimension, $k$: kernel size

| Layer Type | Complexity per Layer | Sequential Operations | Maximum Path Length |
|---|---|---|---|
| Self-Attention | $O(n^2 \cdot d)$ | $O(1)$ | $O(1)$ |
| Recurrent | $O(n \cdot d^2)$ | $O(n)$ | $O(n)$ |
| Convolutional | $O(k \cdot n \cdot d^2)$ | $O(1)$ | $O(log_k(n))$ |
| Self-Attention (restricted) | $O(r \cdot n \cdot d)$ | $O(1)$ | $O(n/r)$ |

✓RNNs struggle with **long-range dependencies** because information must flow through many recurrent steps.

➢Maximum Path Length = $O(n)$.

✓Self-Attention directly connects all tokens, so the path length = $O(1)$.

✓This allows Transformers to **capture long-distance relationships** much more effectively than RNNs or CNNs.

- What is attention map?
  - What kinds of information does the attention map include?