ComputerVision

Week9

2025-2

Mobile Systems Engineering

Dankook University

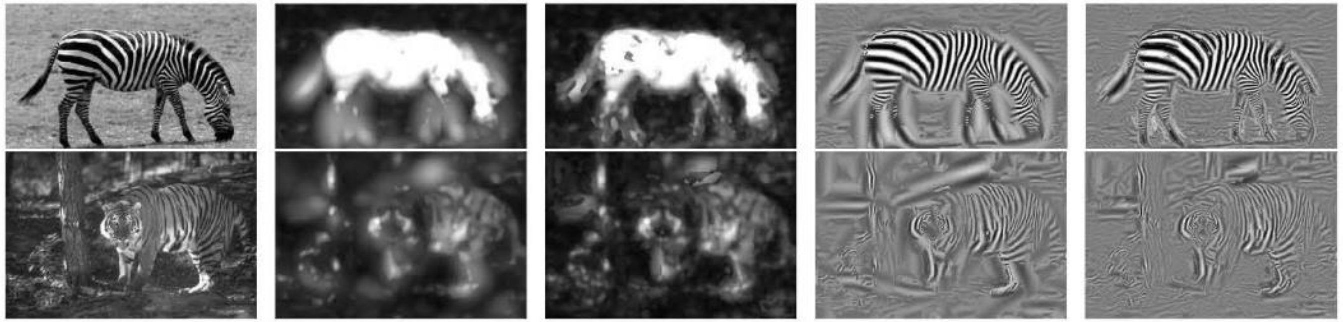
Attention Mechanism in Computer Vision

▪ Focusing on What Matters Most in an Image

- **Before Self-Attention & Transformers…**
  - o We first need to understand **the general concept of attention**.

- **Definition**
  - o **Attention** = A mechanism that enables models to **focus more on the most relevant parts of the input** while ignoring less important information.

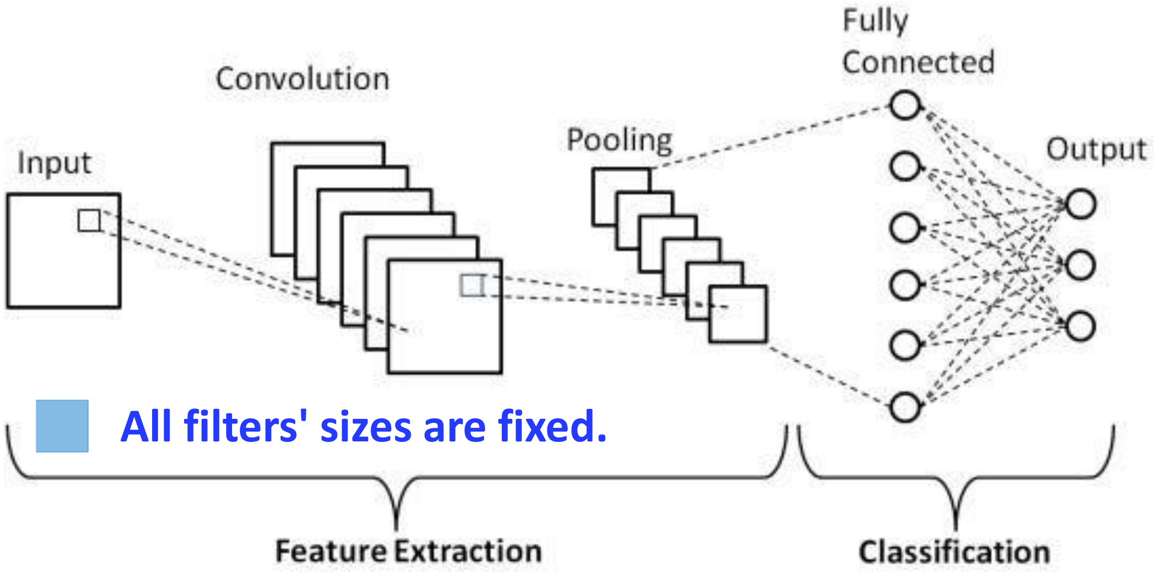
- In **Computer Vision**, this often means



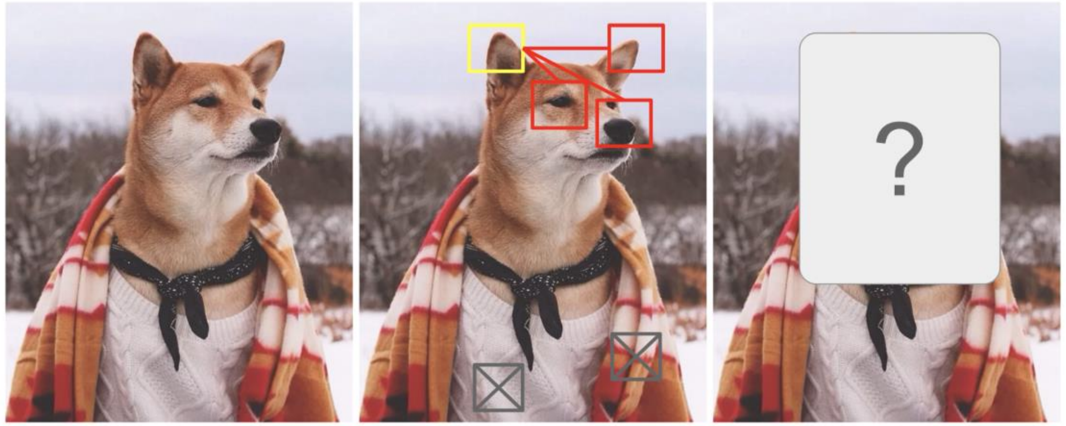
  - o Prioritizing **important regions** in an image (e.g., objects, edges, or textures)
  - o Ignoring irrelevant areas (e.g., plain background)

Attention Mechanism in Computer Vision

- **Motivation: Why Attention?**
  - **Why "focusing" matters in computer vision models**
    - **1. The Limitation of Traditional CNNs**



We cannot adaptively focus on the image content!



✓**Convolutional kernels** are *fixed-weight filters* applied uniformly across spatial locations.

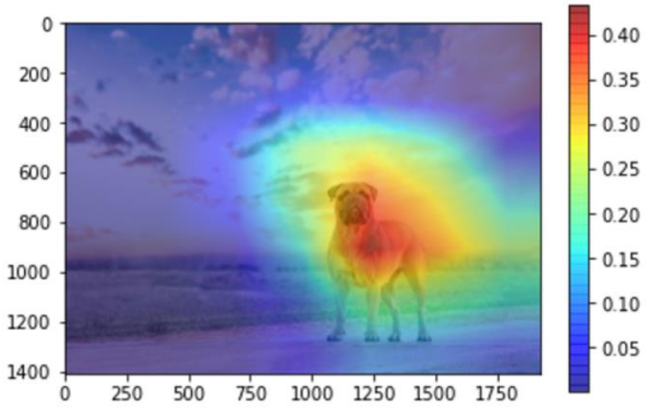
✓They **cannot adapt** their focus depending on the image content.

✓This can waste computational effort on irrelevant areas and dilute important cues.

Attention Mechanism in Computer Vision

- **Motivation: Why Attention?**
  - **Why “focusing” matters in computer vision models**
    - **2. Not All Information is Equal**
      - ✓In real-world images and videos, **only some regions carry critical information**.
      - ✓Example
        - ➢In a crowded street scene, detecting pedestrians and traffic lights matters more than every single background pixel.

(a) Original image

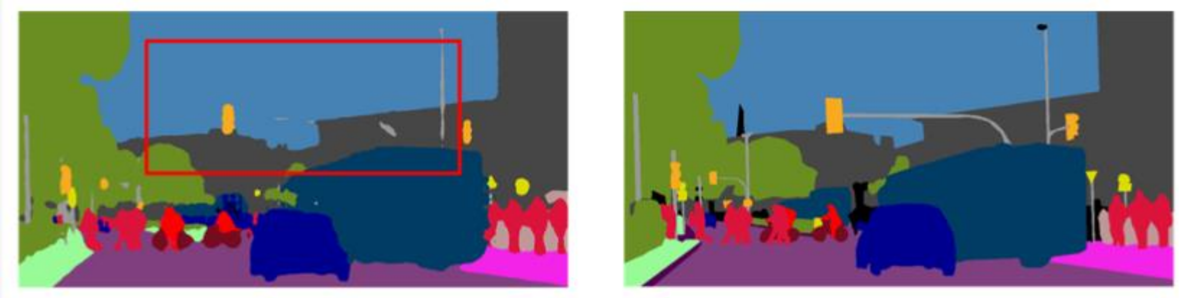


(b) Attention map

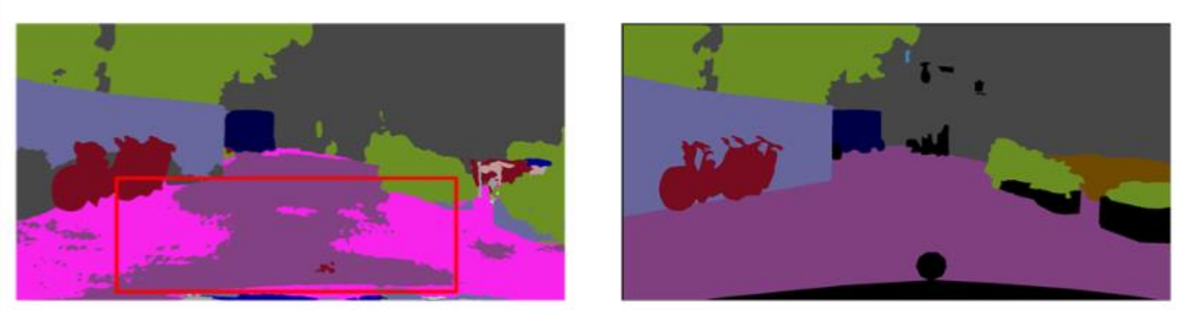
Attention Mechanism in Computer Vision

- **Motivation: Why Attention?**
  - **Why "focusing" matters in computer vision models**
    - **3.** Improves performance in tasks requiring **global context** (scene understanding, semantic segmentation, object detection)
      - ✓ **Need for Content-Dependent Processing**
        - Some tasks require the model to **dynamically decide where to look** based on the input.
        - Analogy to human vision
          Our eyes automatically focus on key regions and **ignore unimportant background**, while still being aware of it.

Some semantic segmentation issues observed in the Cityscapes dataset.



Case1. Missing small and thin objects



Case2. Incomplete segmentation of large objects (background)

Motivation: Why Attention?

- **Why "focusing" matters in computer vision models**
  - **Key Takeaway for Computer Vision**
    - **1. CNN → fixed & local**
    - **2. Attention → adaptive & global**
    - **3. Attention allows the model** to
      - ✓ Allocate **more capacity** to important areas.
      - ✓ Capture **long-range dependencies** in a single step.
      - ✓ Improve interpretability with attention maps.

Early Attention in AI

▪ Early Attention in Artificial Intelligence

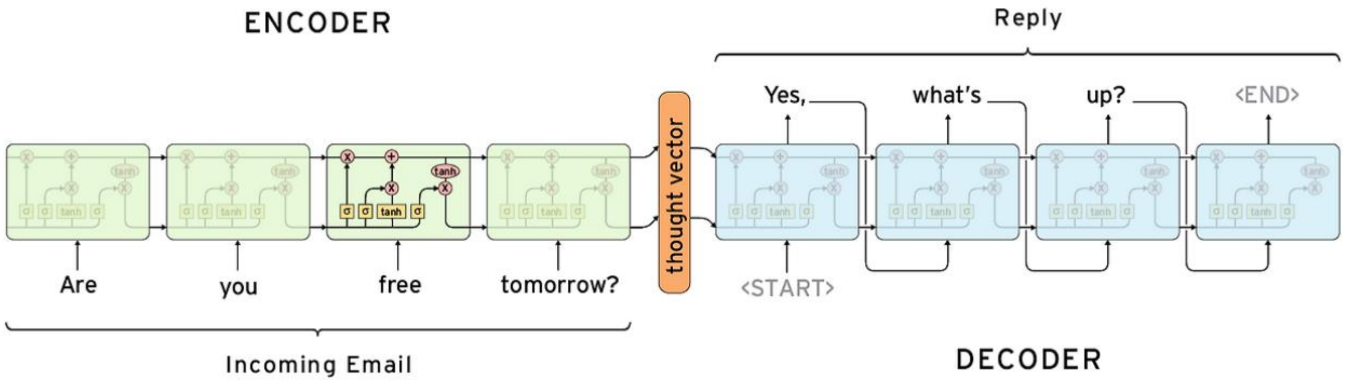
- Attention mechanisms were first introduced in the field of **Neural Machine Translation (NMT)** around 2014–2015 (Bahdanau et al., 2014; Luong et al., 2015).

- **Motivation in NMT**
  - **Seq2Seq** models encode an input sentence into a **fixed-length vector** before decoding.
  - Problem: When the input sequence is long, **information loss** occurs (compression bottleneck).
  - RNN-based decoders also suffered from **vanishing gradients**, making it hard to learn long-range dependencies.

- **Core Idea**
  Allow the decoder to **dynamically attend** to different parts of the input sequence for each output word.

Early Attention in AI

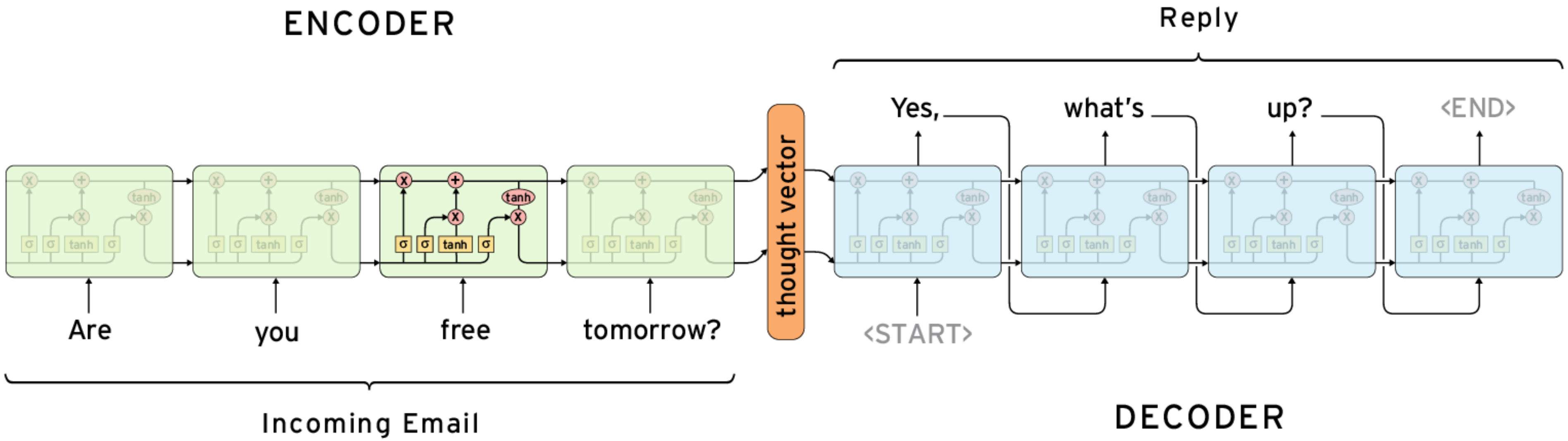
- **Fixed-Length Bottleneck Problem**
  - **Seq2Seq model without attention.**



  - o **Encoder** → compresses all input tokens into a single vector **c**.
  - o **Decoder** → uses **only c** to generate all output tokens.
  - o **Issues**
    - ✓1. Loss of fine-grained details for long sequences.
    - ✓2. Uniform treatment of all tokens regardless of relevance.
  - o **Example**
    - ✓*Summarizing a whole book into one sentence, then trying to answer detailed questions about it — impossible to recall all specific details.*

Early Attention in AI

- ## What is Seq2Seq?
  - **Definition**
    - **Seq2Seq (Sequence-to-Sequence)** models are deep learning architectures that transform one sequence into another.
    - Mostly used in **Natural Language Processing (NLP)** tasks such as machine translation, text summarization, and question answering.
  - **Structure**



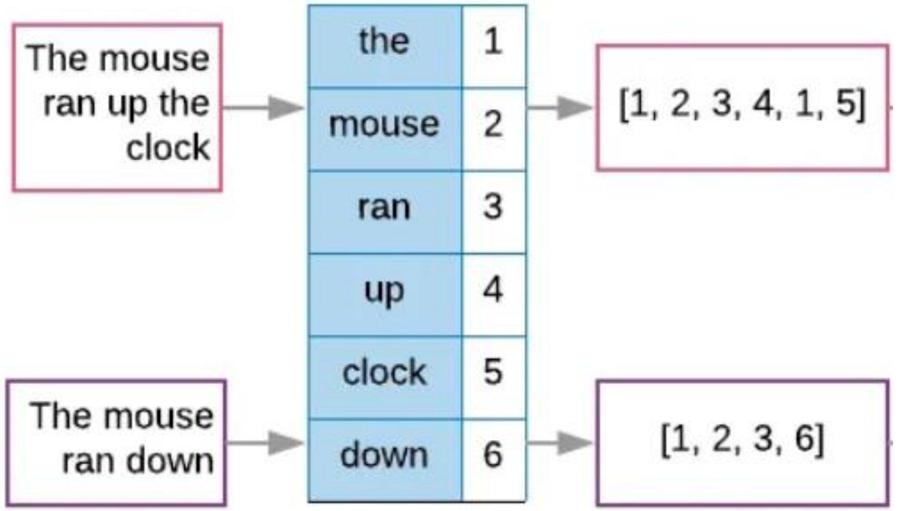
    - Two main components
      - ✓**Encoder** — processes the input sequence and produces a fixed-length **context vector**.
      - ✓**Decoder** — generates the output sequence using the context vector.

Early Attention in AI

▪ How the Encoder Works

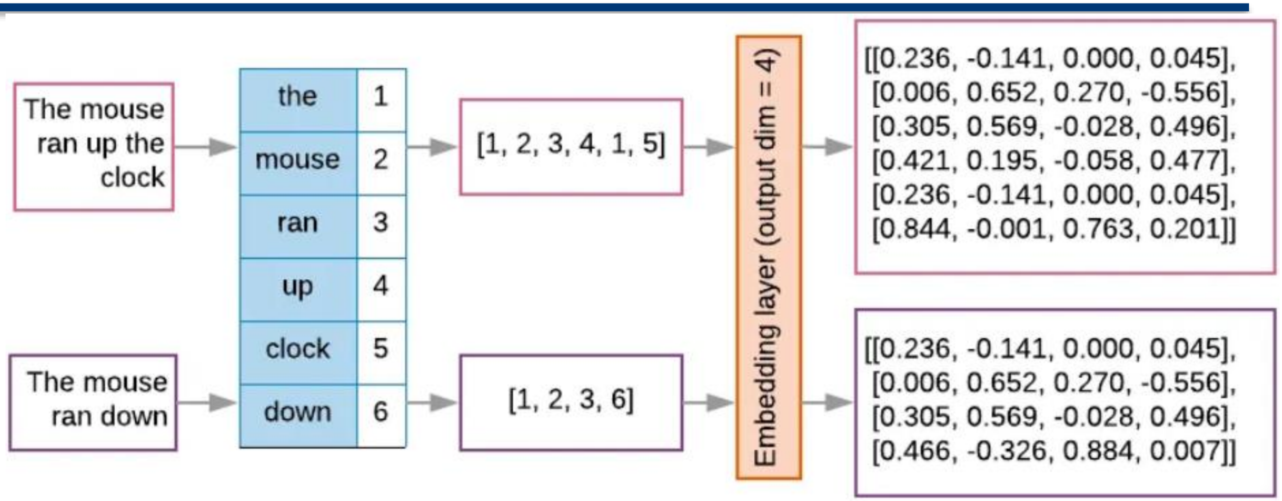
- The **encoder** transforms an input sequence (e.g., a sentence) into a compact representation that summarizes its meaning.
  - o We can break this process into **three main stages.**

- **Step 1. Tokenization**
  - o **Goal:** Break down a long text string into smaller units called **tokens**.
  - o Tokens can be **words**, **subwords**, or **characters** depending on the task.
  - o Example
    - ✓ "Hello, World!" → ["Hello", ",", "World", "!"]
  - o Each token represents a **basic unit of meaning**.
    - ✓ Tokenization converts **unstructured text** into a **structured list of symbols**.



Early Attention in AI

- **How the Encoder Works**
  - **Step 2. Vectorization**

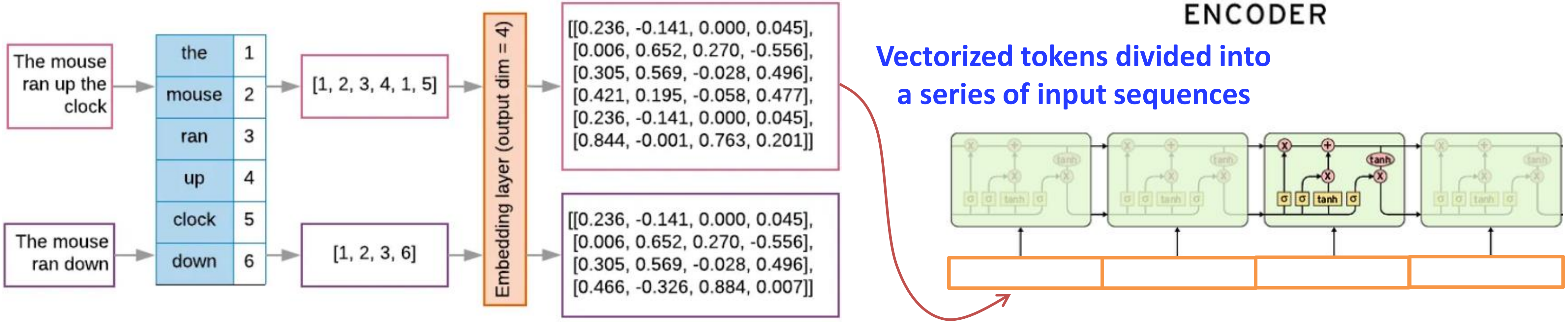


  - **Goal:** Convert each token into a **numeric vector** that the model can understand or process.
    - ✓This is called **word embedding**.
  - Each token is mapped to a **fixed-length dense vector** capturing
    - ✓**Semantic meaning** (similar words have similar vectors)
    - ✓**Syntactic roles** (e.g., verbs vs. nouns)
  - Examples of embedding techniques
    - ✓**Word2Vec**, **GloVe**, **FastText**
  - Benefit
    - ✓High-dimensional text data is transformed into **lower-dimensional, computationally efficient representations**.

Early Attention in AI

▪ How the Encoder Works

- **Step 3. Context Vector Generation**
  - **Goal:** Summarize the **entire input sequence** into a **single fixed-length vector** (the **context vector**).
    - ✓The encoder processes embeddings **sequentially** using **RNN, LSTM, or GRU**.
    - ✓At each step, the model updates a **hidden state**.
    - ✓The **final hidden state** represents the entire input — this is the **context vector**.
  - Limitation
    - ✓Compressing long sequences into a single vector can lead to **information loss**.
    - ✓This **bottleneck** is one of the main reasons why the **attention mechanism** was introduced.

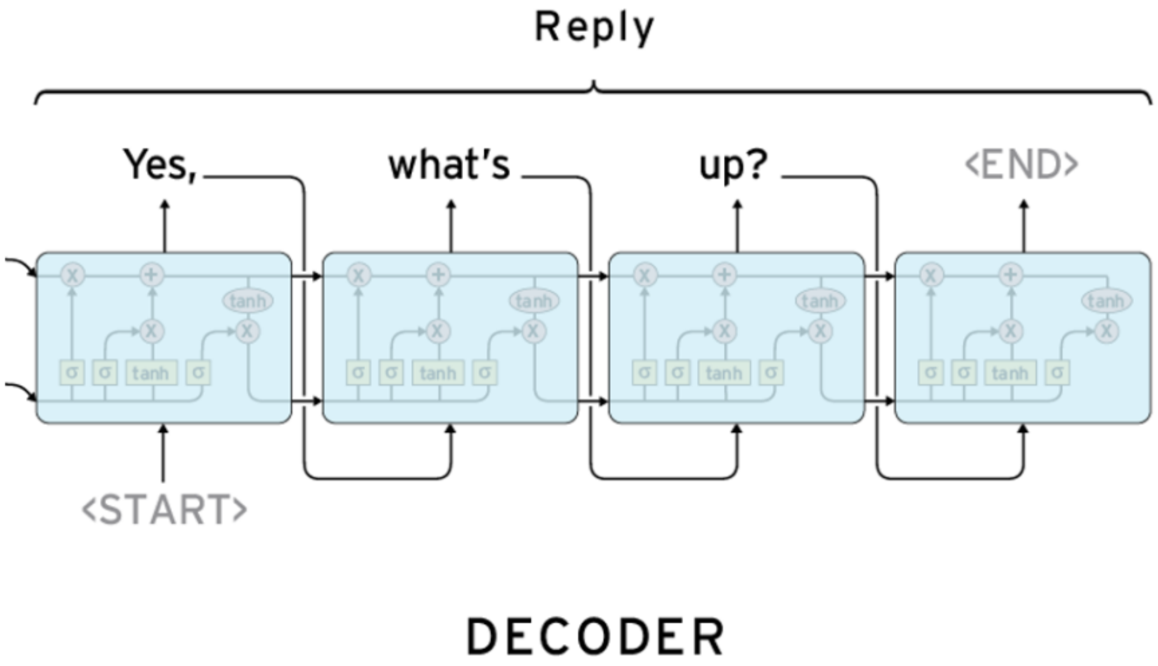


Early Attention in AI

How the Decoder Works

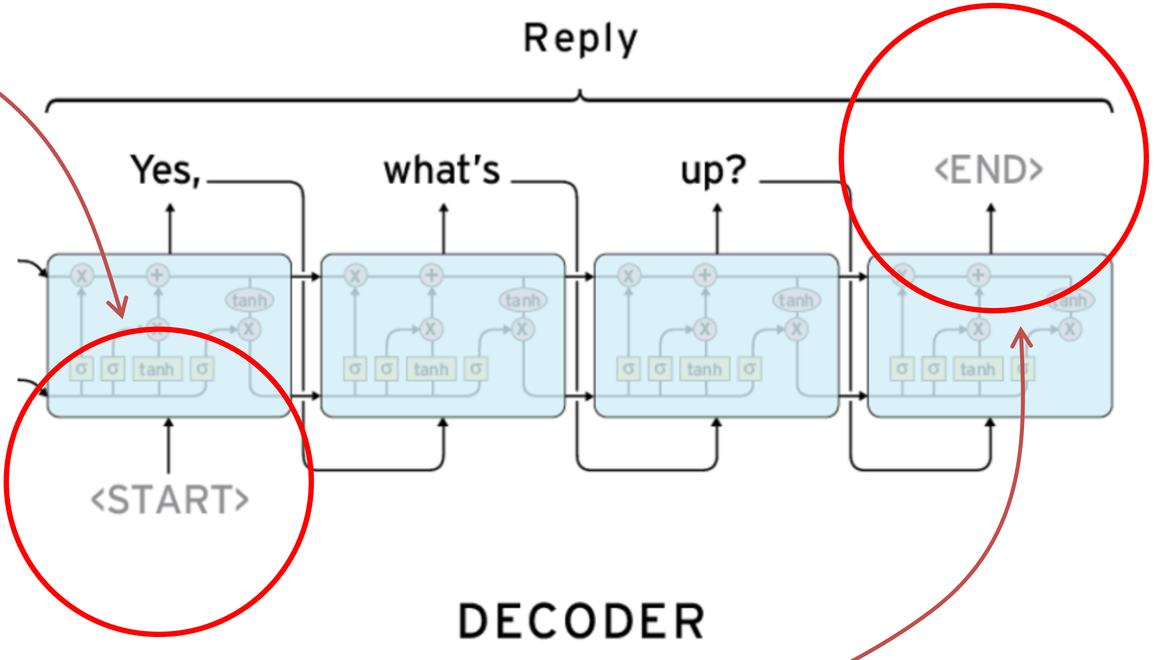
- The **decoder** takes the **context vector** and **hidden state** from the encoder, and generates the **output sequence** step-by-step.
  It works in a **recursive** manner until the complete output is formed.

- **Step-by-Step Sequence Generation**
  - **Input to the decoder**
    - ✓ **Context vector** from the encoder
    - ✓ **Hidden state** (summarizing the encoded sequence)
    - ✓ **Previous output token** (for all steps except the first)
  - The decoder predicts **one token at a time**.
  - Each predicted token becomes **input for the next step**.



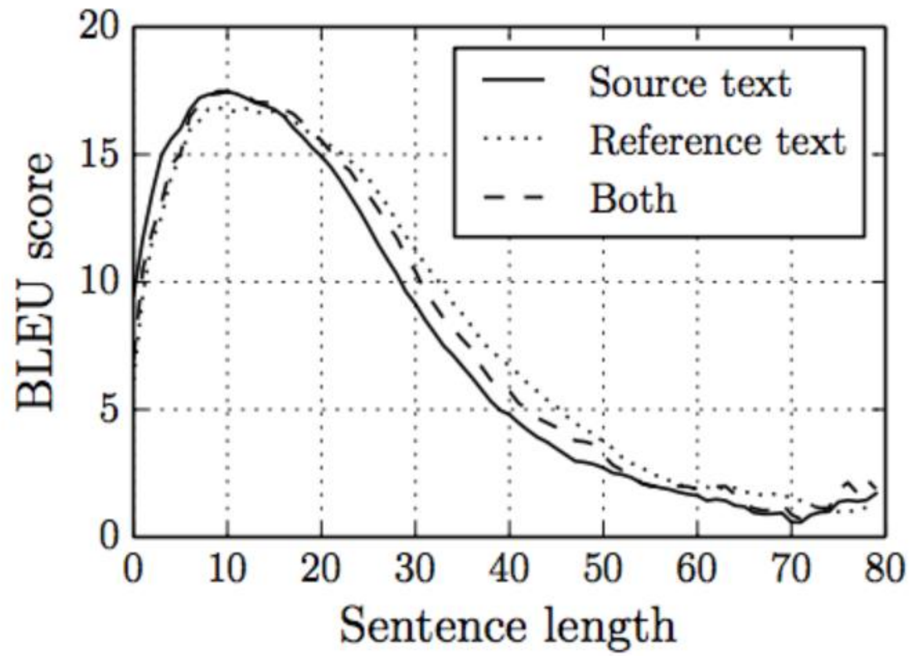
Early Attention in AI

- **How the Decoder Works**
  - **Special Start Token (<START>)**
    - At the **first step**, there is no previous output token.
      - ✓Instead, a special **start token** (e.g., <START>, <GO>, <s>) is fed into the decoder.
  - **Recurrent Prediction Process**
    - At each decoding step
      - ✓Combine **previous token embedding**, **context vector**, and **hidden state**.
      - ✓Pass through an RNN/LSTM/GRU cell.
      - ✓Apply **softmax** to produce a probability distribution over possible next tokens.
      - ✓Choose the token with the **highest probability**.
    - Continue until a special **end token** (<END>) is produced.



Early Attention in AI

- **Key Limitation of Fixed-Length Context Vector in Seq2Seq Models**
  - **Key Limitations**
    - In traditional Seq2Seq models, the decoder **relies entirely on a single fixed-length context vector** from the encoder.
    - This design **cannot effectively retain information for long sequences**.
    - As the entire sequence is compressed into one vector, the model tends to **forget early parts of the input sequence** when processing long inputs.
  - **Evidence – BLEU Score Degradation**
    - BLEU (Bilingual Evaluation Understudy) score measures similarity between generated translations and reference translations.
    - Graph shows
      - ✓For **short sentences**, Seq2Seq works well (high BLEU scores).
      - ✓For **long sentences**, BLEU score drops sharply → indicating loss of information from earlier tokens.



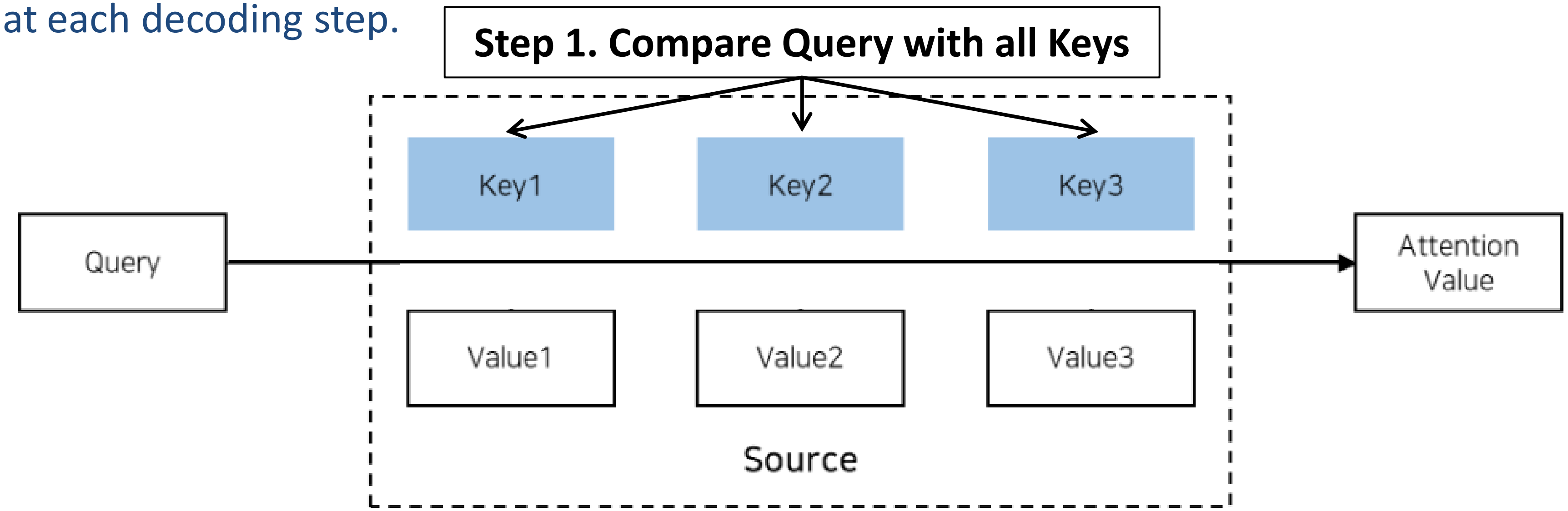
Early Attention in AI

- **Why Attention Became Necessary**
  - In traditional Seq2Seq
    - The decoder relies **only** on the single context vector.
    - Cannot “look back” at specific parts of the input sequence once encoding is done.
  - **Attention Mechanism** solves this by
    - Allowing the decoder to **access all encoder hidden states** at each decoding step.
    - Assigning **different weights** to different parts of the input depending on relevance.
  - This enables
    - Better handling of **long sequences**.
    - More accurate alignment between input and output.

Early Attention in AI

▪ Attention as a Solution

- **From a single bottleneck vector to step-wise, adaptive context retrieval**
  - **Key Idea**
    - ✓Instead of relying on **one fixed-length context vector**, the decoder can dynamically **refer back to all encoder hidden states** at each decoding step.
  - **How it works**

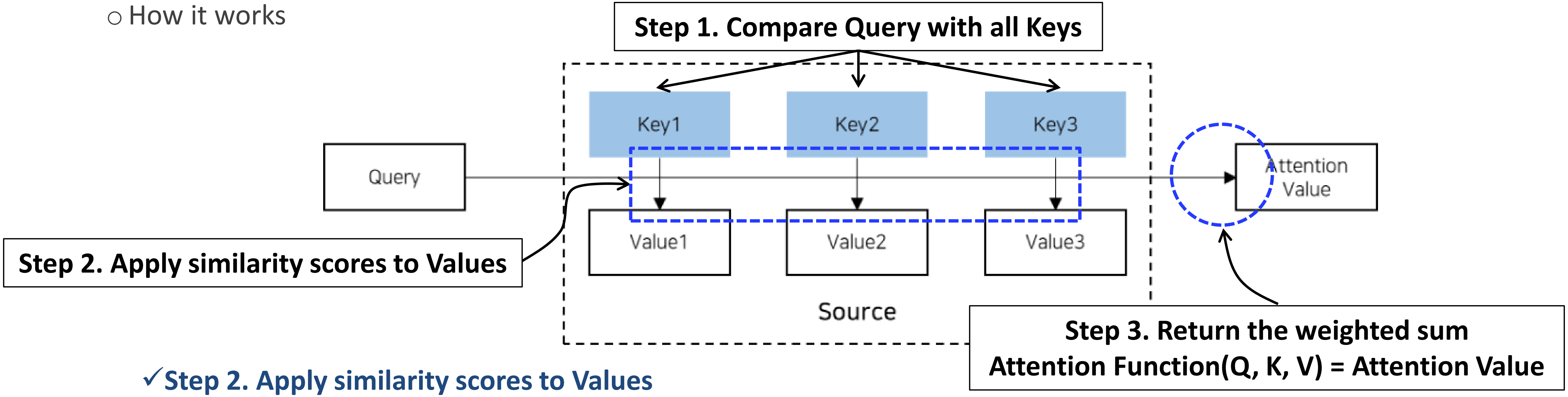


✓**Step 1. Compare Query with all Keys**

- ➢ **Query (Q):** the decoder’s current hidden state at time step *t*.
- ➢ **Keys (K):** all encoder hidden states representing each input token.
- ➢ Compute **similarity scores** between Q and every K.

Early Attention in AI

- **Attention as a Solution**
  - **From a single bottleneck vector to step-wise, adaptive context retrieval**
    - How it works



✓**Step 2. Apply similarity scores to Values**

➢**Values (V):** vectors associated with each Key (often the encoder hidden states themselves).

➢Convert similarity scores into **weights** (e.g., via softmax) and multiply each Value by its corresponding weight.

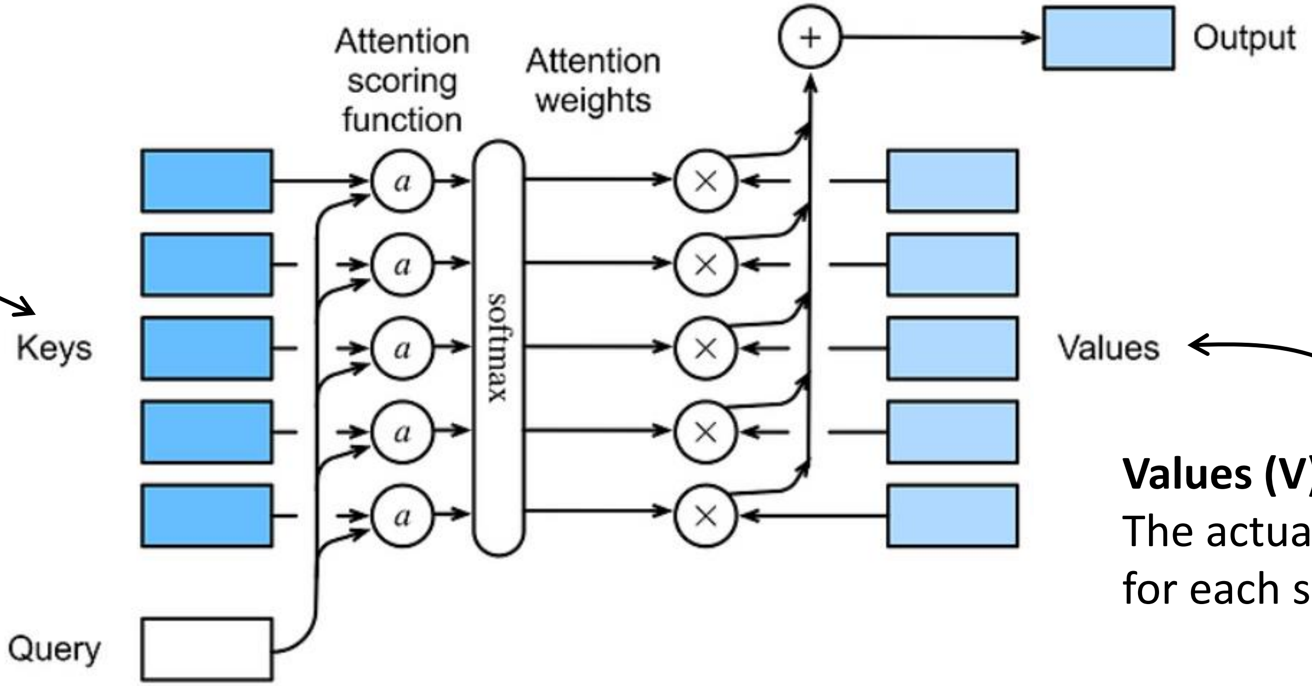
✓**Step 3. Return the weighted sum**

➢Add up the weighted Values to produce the **Attention Value** (context vector) for step *t*.

➢This context is **tailored** to what the decoder needs right now.

Early Attention in AI

- **Attention Mechanism — Step-by-Step**
  - **Goal**
    - Enable the decoder to focus on the most relevant parts of the encoder's output when generating each token.
  - **Step 1: Inputs**



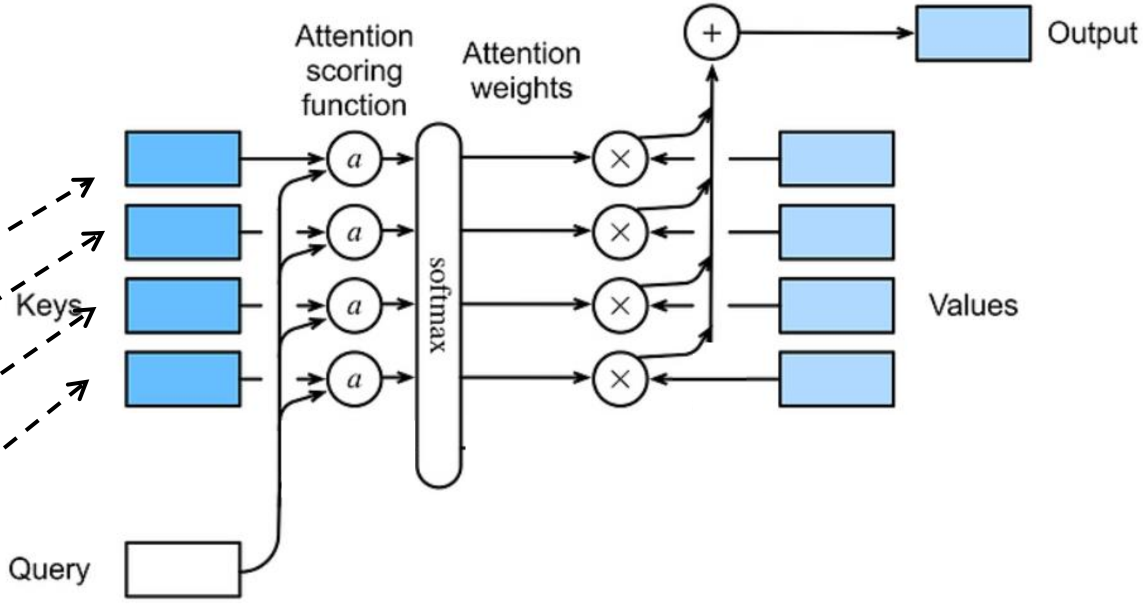
Keys (K)
All encoder hidden states — act like “labels” for each source token.

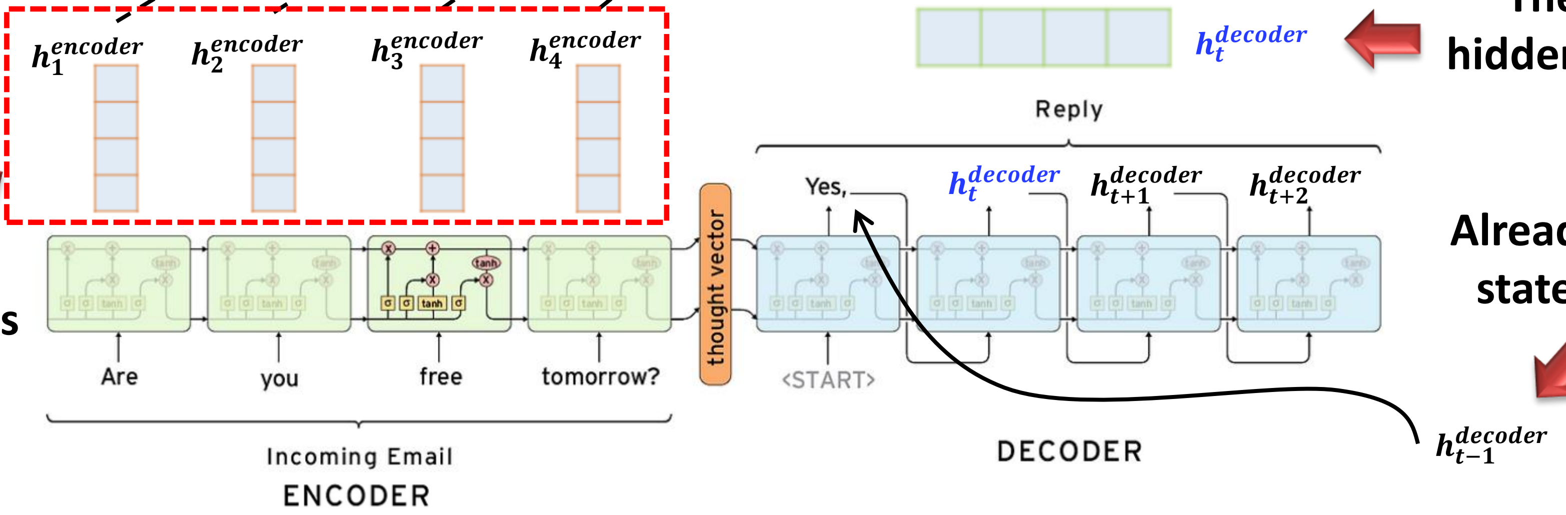
Values (V)
The actual encoded information for each source token.

Query (Q)
The current decoder hidden state at time step *t* — represents "what we're looking for" at this point in decoding.

Early Attention in AI

- **Attention Mechanism — Step-by-Step**
  - **Step 2: Compute Similarity (Attention Scores)**
    - **Compute Similarity (Attention Scores)**
    - Compare the **Query** with each **Key** to measure similarity.
    - Common similarity measure: **Dot Product**
      - ✓ $score(q, k_i) = q \cdot k_i$
    - Result
      - ✓ A set of raw scores indicating how much attention each source token should receive.





The current decoder hidden state at time step t

Already calculated hidden state at time step $t-1$

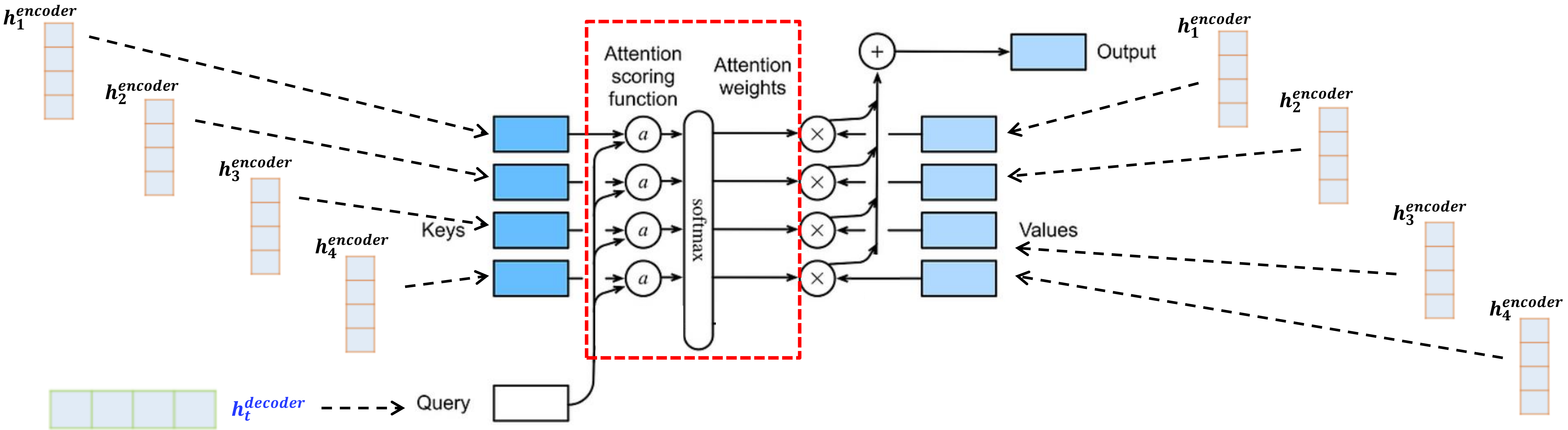
All encoder hidden states are used for Keys

Early Attention in AI

- **Attention Mechanism — Step-by-Step**
  - **Step 3: Normalize (Attention Weights)**
    - Apply **softmax** to scores so they sum to 1

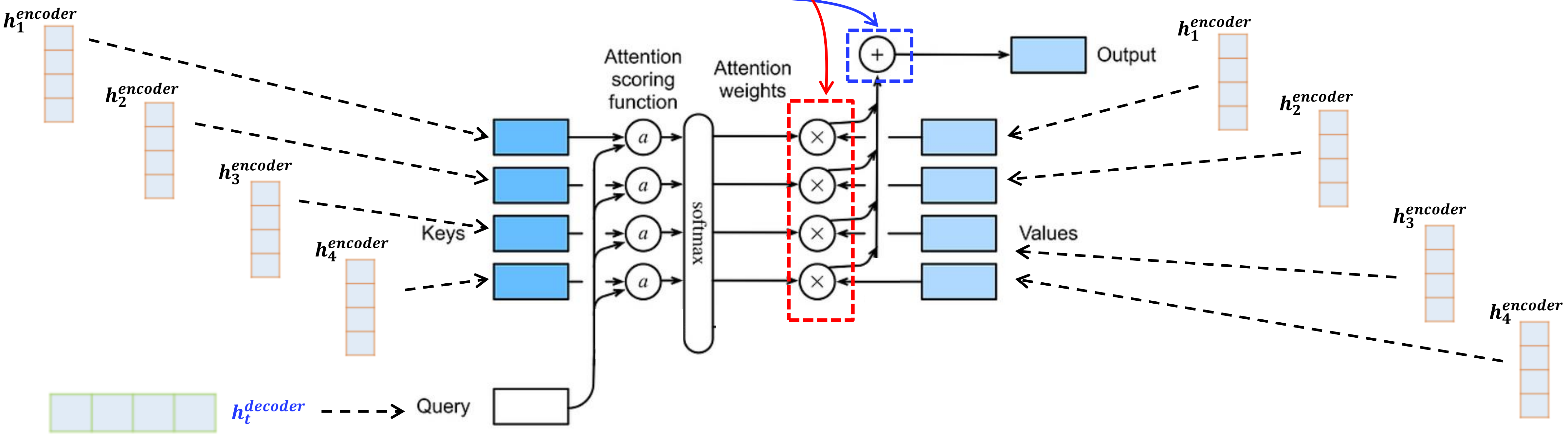
      ✓ $\alpha_i =$

    - Produces **attention weights** $\alpha_1, \alpha_2, \ldots, \alpha_n$ indicating relative importance of each token.



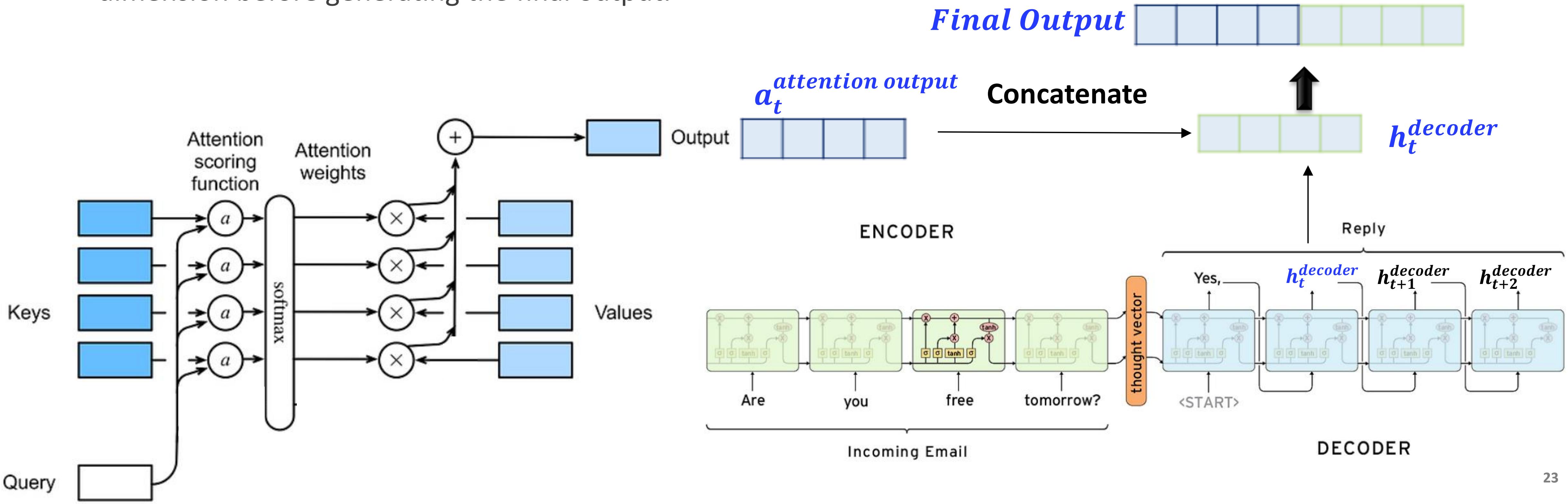
Early Attention in AI

- **Attention Mechanism — Step-by-Step**
  - **Step 4: Weighted Sum**
    - Multiply each **Value** vector by its corresponding attention weight.
    - Sum the results to obtain the **Attention Value**
      - ✓ $Attention\,(Q, K, V) = \sum_{i=1}^{n} a_i V_i$



Early Attention in AI

- **Attention Mechanism — Step-by-Step**
  - **Step 5: Output to Decoder**
    - The Attention Value is passed to the decoder along with its own state.
    - Allows the decoder to incorporate **context-specific information** for the current output token.
    - **Note:** The combined vector can be multiplied by a specific weight matrix to project it back to the original output dimension before generating the final output.

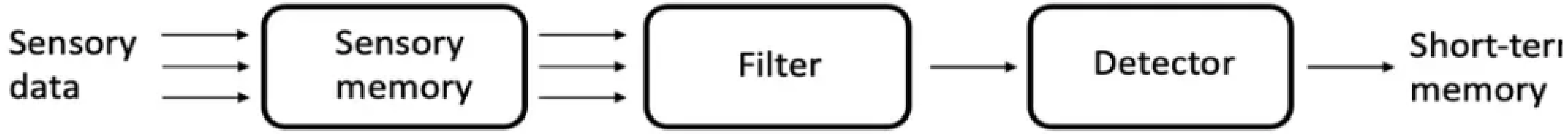


Attention in Computer Vision

▪ Origins of Attention in Cognitive Psychology

- In cognitive psychology, attention is defined as a **cognitive process that selectively focuses on the most important parts of information**.
  - Human visual attention operates as a combination of **low-level visual features** and **high-level cognitive guidance**.

- **Broadbent's Early Selection Model**

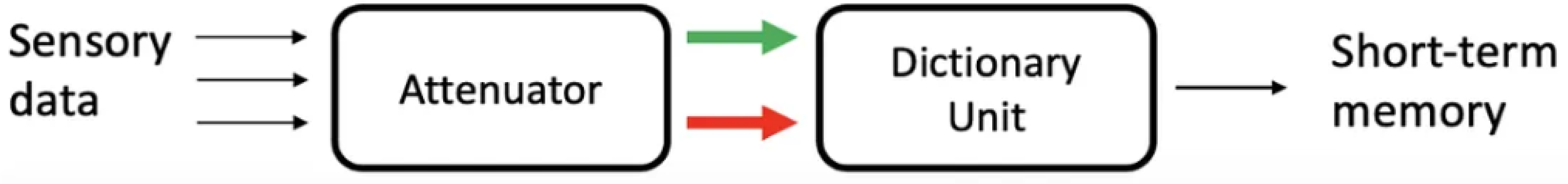


Broadbent's model of cognitive attention.

  - Sensory data is first stored briefly in **sensory memory** and then filtered based on physical features (e.g., pitch of sound, color, shape).
  - The **filter** selects only the relevant information, which is then passed to the **detector** and stored in **short-term memory**.
  - Selection is based primarily on low-level physical characteristics, and higher-level semantic information is processed later.

Attention in Computer Vision

- **Origins of Attention in Cognitive Psychology**
  - **Treisman's Late Selection Model**



Treisman's model of cognitive attention.

  - o Incoming data is not completely blocked but rather attenuated based on importance through an **attenuator**.
  - o Highly important data (green arrow) is passed strongly, while less important data (red arrow) is passed weakly. The **dictionary unit** determines whether the information is activated based on meaning and context.
  - o For example, one's own name can be activated with minimal signal strength, while irrelevant words require much higher activation levels.

Attention in Computer Vision

▪ Origins of Attention in Cognitive Psychology

- **Role in Artificial Intelligence (Deep Learning)**
  - The human **selective attention mechanism** has inspired its integration into deep learning, where it is used to ***assign higher weights to important parts of the input data***.
  - ***Role***: ***Suppress irrelevant information*** and ***emphasize important information***, enabling more efficient learning.
  - **Effect:** Reduces information loss and improves performance, particularly for long input sequences or complex visual data.

- **Role in Computer Vision**
  - **1. Concept & Role**
    - ✓In CV, attention is a **dynamic weight adjustment process** applied to feature maps between convolution layers.
    - ✓**Purpose**: Guides the model to focus on the **most relevant features** for the task.
    - ✓**Applications**: Almost tasks
      - ➢Image Classification · Object Detection · Semantic Segmentation · Video Understanding · Image Generation · 3D Vision · Multi-modal Tasks · Self-supervised Learning

Attention in Computer Vision

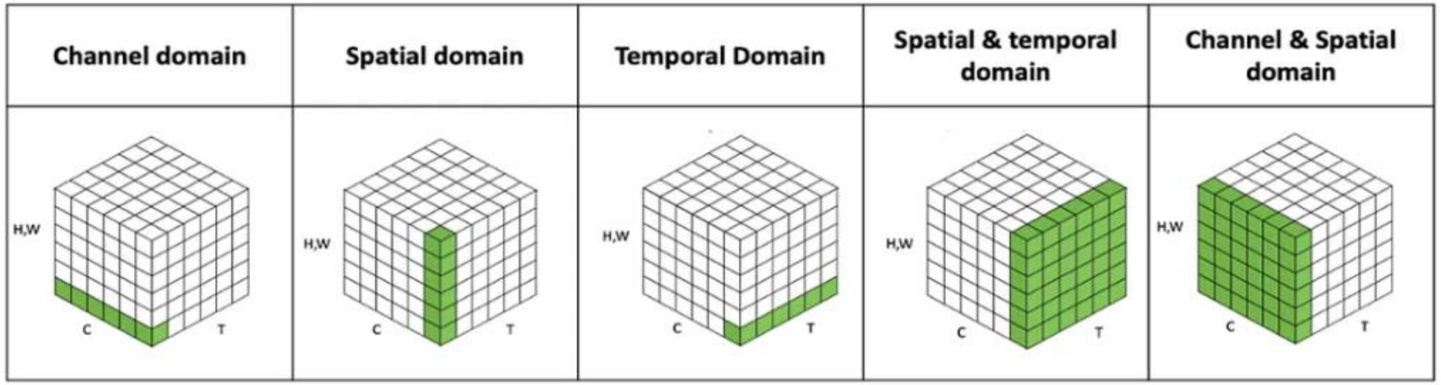
▪ Data Domain Categories in Computer Vision Attention

• General Concept

- In computer vision, an **attention mechanism** is a **dynamic weight adjustment function** applied to a feature map **between convolutional layers**.
- Purpose: Guide the next network layer to focus on **more important features** while suppressing less relevant ones.
- Formally: $\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{g}(\boldsymbol{x}), \boldsymbol{x})$
  - ✓ where $\boldsymbol{g}(\boldsymbol{x})$ generates an attention map for important regions and $\boldsymbol{f}(\boldsymbol{g}(\boldsymbol{x}), \boldsymbol{x})$ processes the input feature map $\boldsymbol{x}$ accordingly.

• Four Fundamental Attention Domains

- Channel Attention, Spatial Attention, Temporal Attention, Branch Attention, Hybrid

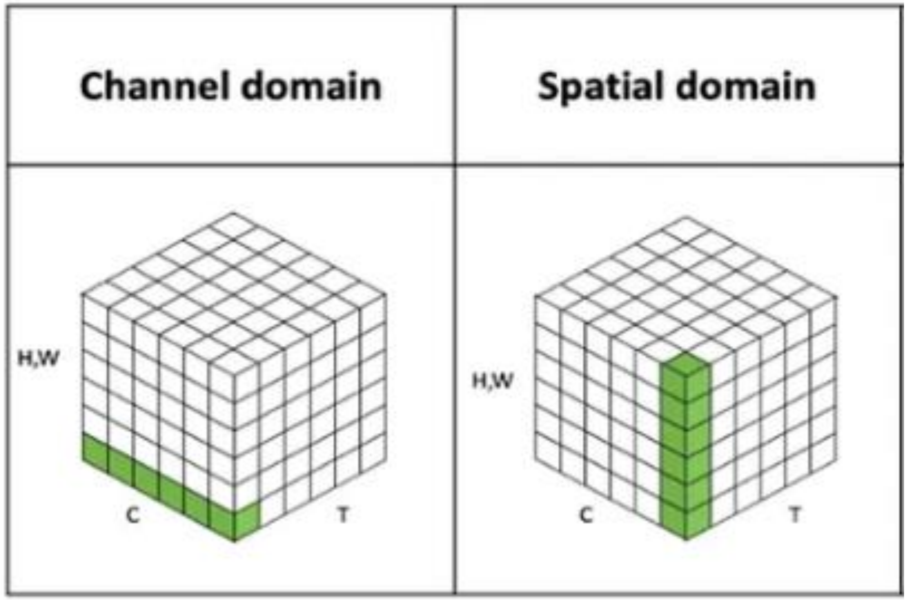


Dimensions of input tensor: H = height, W = width, C = channel, T = time.

Data domains that different attention mechanisms operate on.

Attention in Computer Vision

- **Data Domain Categories in Computer Vision Attention**
  - **Four Fundamental Attention Domains**
    - **1. Channel Attention – "What to Attend to"**
      - ✓Focuses on **feature channels** that are most relevant for the task.
      - ✓Learns channel-wise weights to emphasize informative features and suppress less useful ones.
      - ✓Example Applications: Object classification, fine-grained recognition.
    - **2. Spatial Attention – "Where to Attend to"**
      - ✓Highlights important **spatial regions** in the feature map.
      - ✓Often used to localize objects or important regions in an image.
      - ✓Example Applications: Object detection, segmentation.



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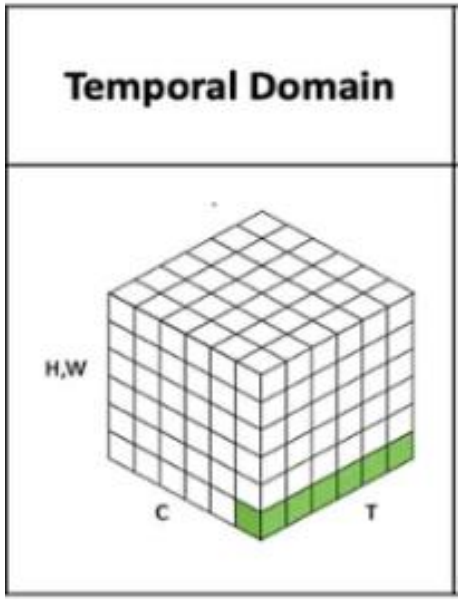
Data domains that different attention mechanisms operate on.

Attention in Computer Vision

- **Data Domain Categories in Computer Vision Attention**
  - **Four Fundamental Attention Domains**
    - **3. Temporal Attention – "When to Attend to"**
      - ✓Determines which **time frames** (in video or sequential data) contain critical information.
      - ✓Often combined with spatial attention for video understanding.
      - ✓Example Applications: Action recognition, video captioning.
    - **4. Branch Attention – "Which Path to Attend to"**
      - ✓Chooses among **multiple network branches** or kernels adaptively.
      - ✓Enables dynamic routing of information through different processing paths.
      - ✓Example Applications: Multi-scale feature extraction, adaptive convolution.



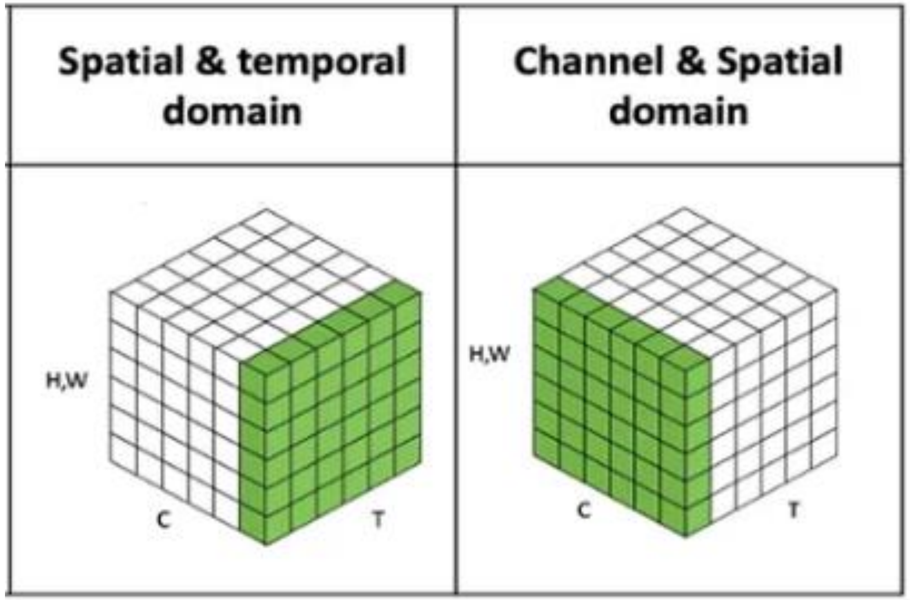
Dimensions of input tensor: H = height, W = width, C = channel, T = time.

Data domains that different attention mechanisms operate on.

Attention in Computer Vision

▪ Data Domain Categories in Computer Vision Attention

- **Four Fundamental Attention Domains**
  - **5. Hybrid Attention Mechanisms**



Dimensions of input tensor: H = height, W = width, C = channel, T = time.

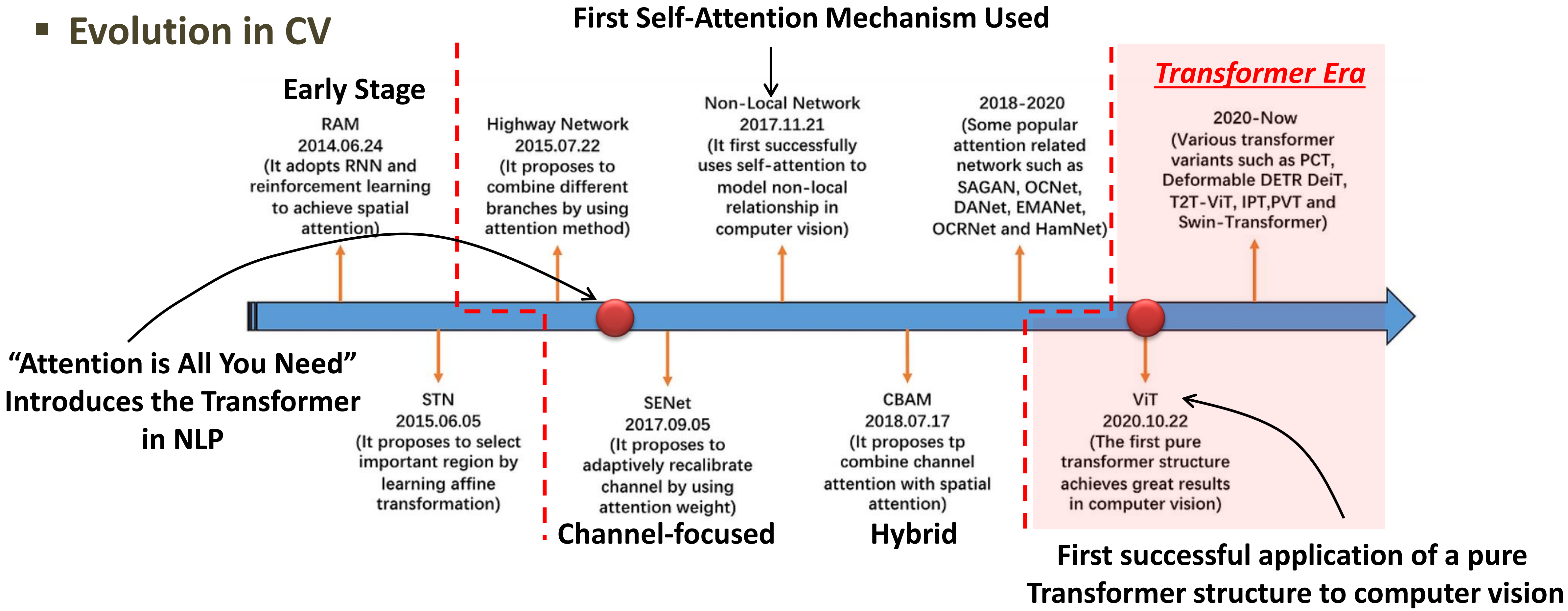
Data domains that different attention mechanisms operate on.

✓**Channel + Spatial** → Leverages both **what** and **where** to attend (e.g., combined weighting for channels and pixels).

✓**Spatial + Temporal** → Integrates **where** and **when** to attend (e.g., spatiotemporal attention in video models).

Attention in Computer Vision

- Evolution in CV



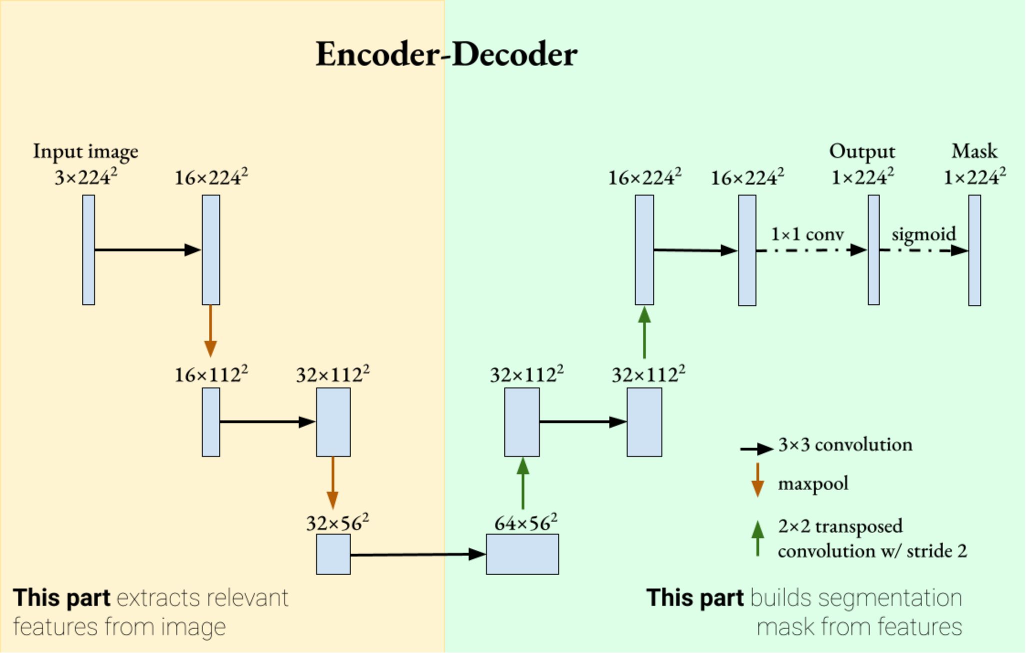
- We will explore the **Transformer architecture** in detail and study various **Transformer-based CV models** such as ViT, Swin Transformer, and PVT.

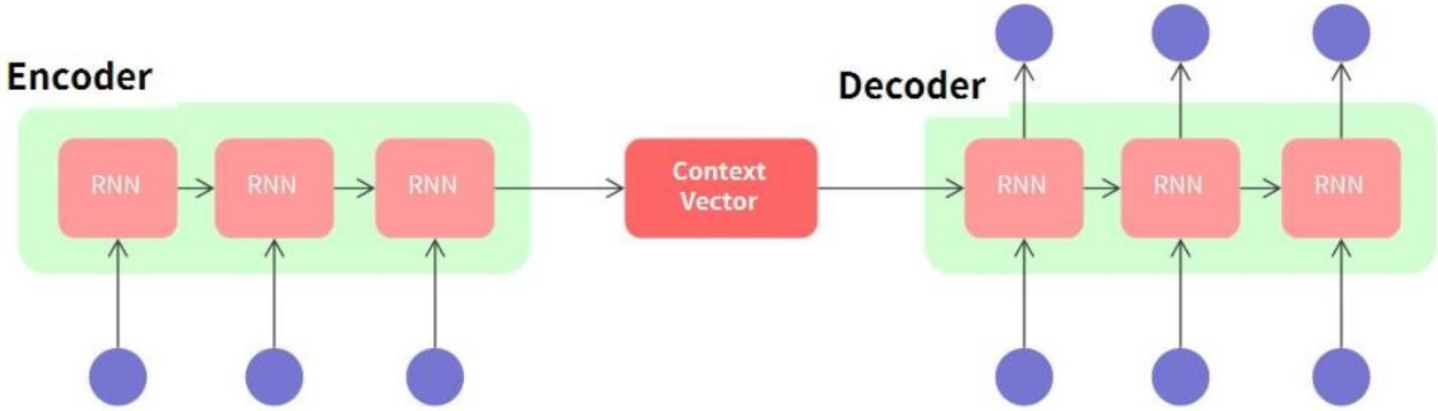
Why a Deeper Look at Encoder–Decoder?

- We’ve already met **U-Net** (CV) and **Seq2Seq** (NLP).
- Before we study **Transformers**, let’s solidify the **Encoder–Decoder pattern**: what it is, how information flows, and where it breaks.
- Learning objectives
  - Understand the data pipeline (tokens/patches → embeddings → latent/context)
  - See how **decoders** generate outputs (sequence vs. image)
  - Identify bottlenecks that motivate **attention** and **Transformers**

Why a Deeper Look at Encoder–Decoder?

- We've already met U-Net (CV) and Seq2Seq (NLP).



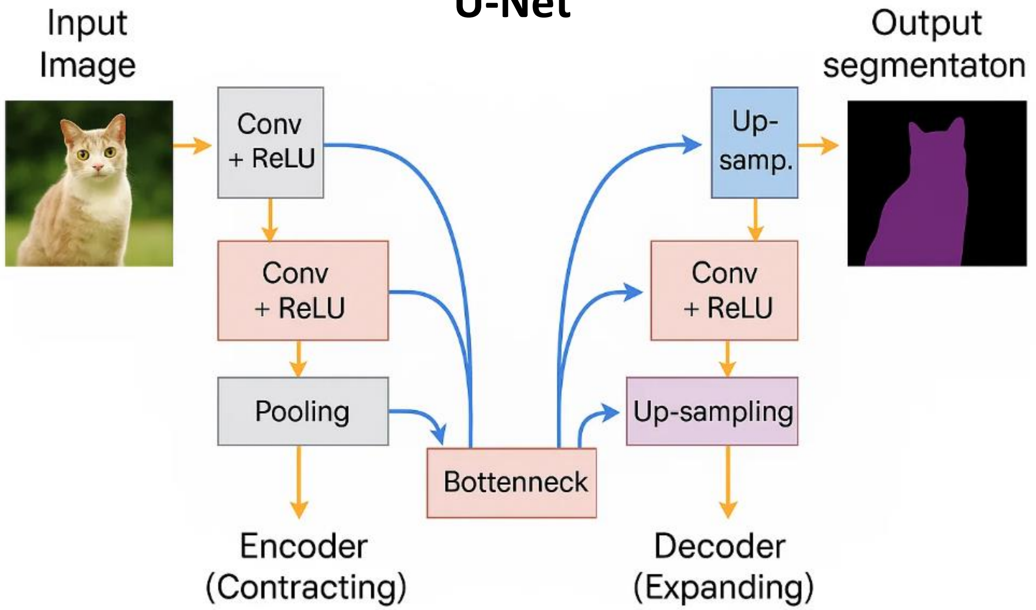


- Before we study Transformers, let's solidify the Encoder–Decoder pattern: what it is, how information flows, and where it breaks.
  - Learning objectives
    - Understand the data pipeline (tokens/patches → embeddings → latent/context)
    - See how **decoders** generate outputs (sequence vs. image)
    - Identify bottlenecks that motivate **attention** and **Transformers**

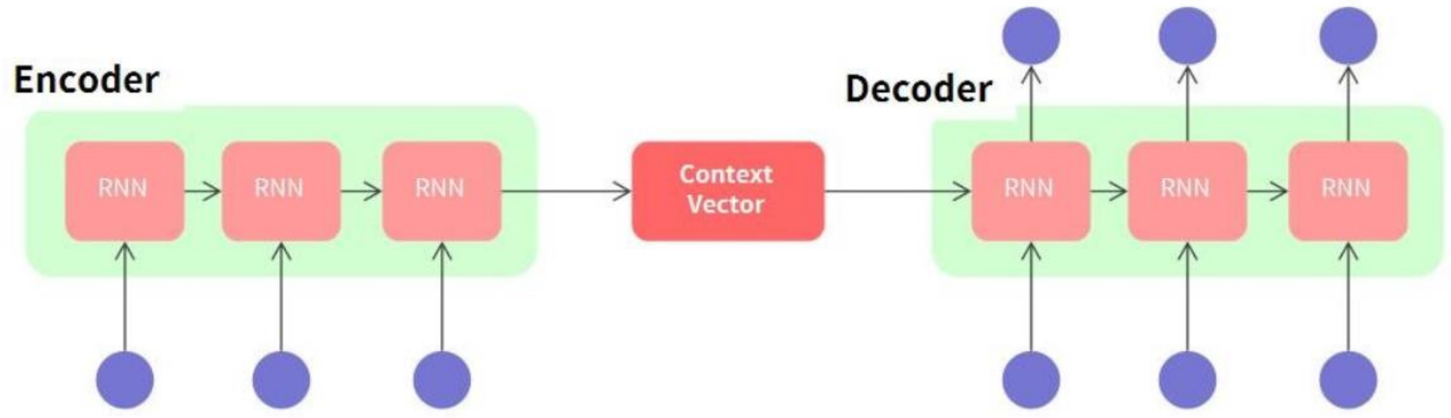
Why a Deeper Look at Encoder–Decoder?

- **The Encoder–Decoder Mental Model**
  - **Mapping $x \rightarrow z \rightarrow y$**

U-Net



Seq2Seq



Latent space (=representation) z → Context Vector

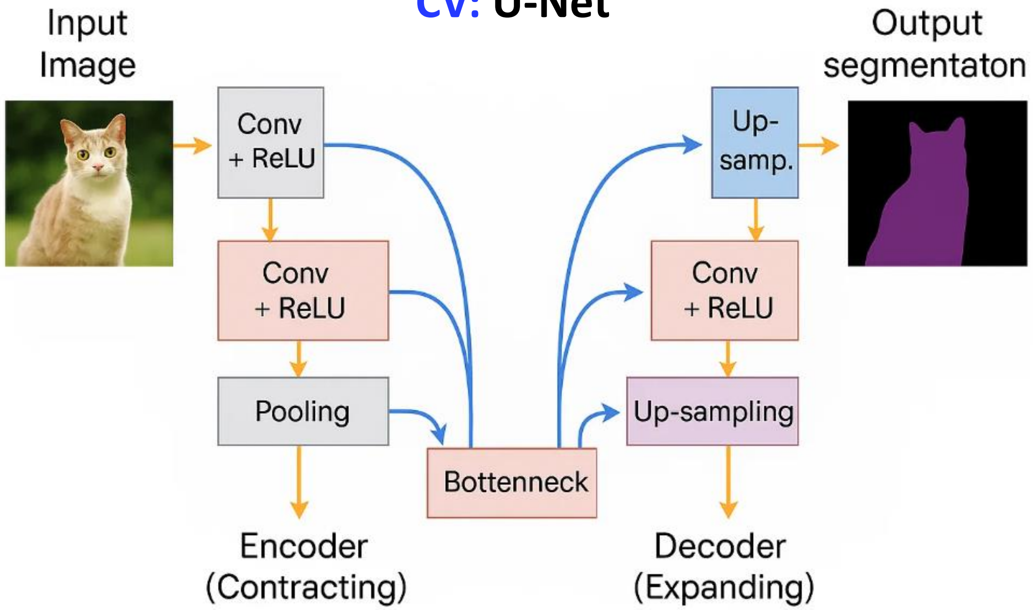
Latent space (=representation) z → Bottleneck

- **Encoder**: compresses input into a **latent** representation z (a vector, grid, or pyramid).
- **Decoder**: expands z into an output with task-specific structure y (sequence, mask, image).

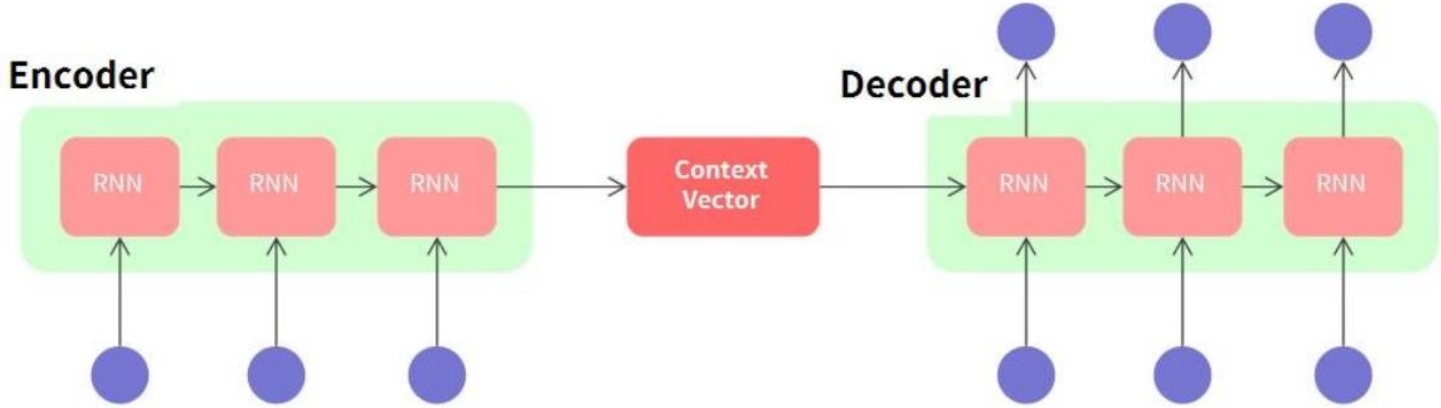
Why a Deeper Look at Encoder–Decoder?

- **The Encoder–Decoder Mental Model**
  - **Same idea, different instantiations**

CV: U-Net



NLP: Seq2Seq



Latent space (=representation) z → Context Vector

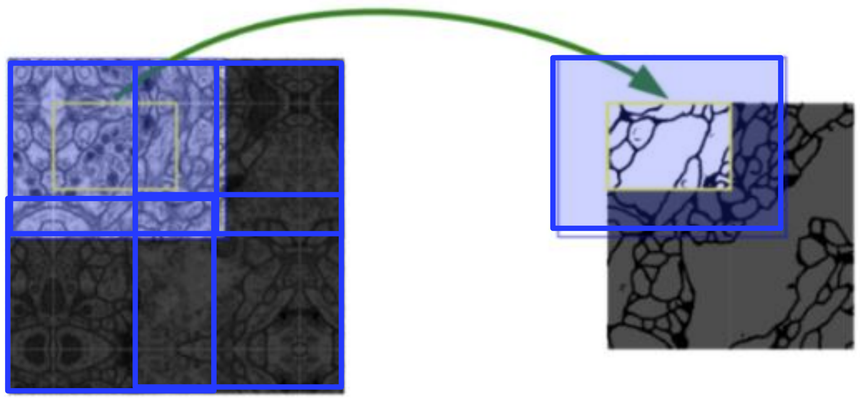
Latent space (=representation) z → Bottleneck

- **NLP**: RNN/GRU/LSTM encoder → vector → RNN decoder (Seq2Seq)
- **CV**: CNN encoder (downsampling) → feature pyramid → CNN decoder (upsampling)
- Optional: **skip connections** (e.g., U-Net) to restore spatial detail.=

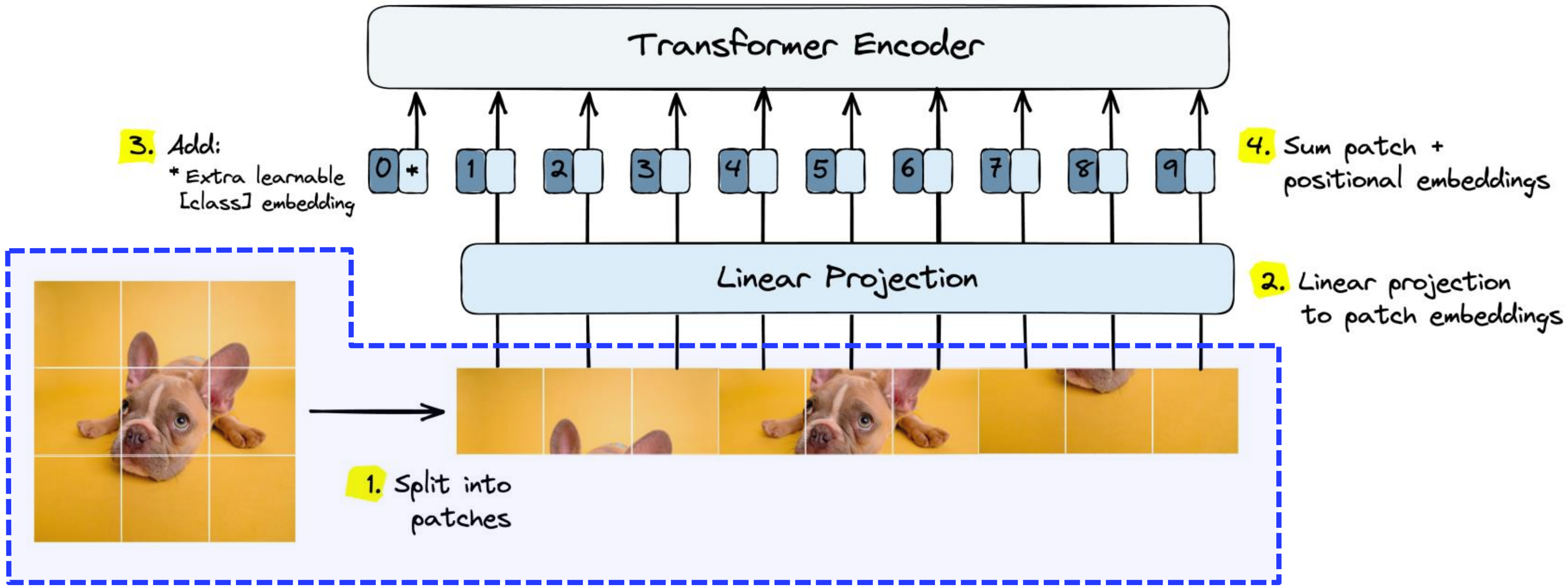
Why a Deeper Look at Encoder–Decoder?

- CV: Patchification / NLP: Tokenization (Input → Units)
  - Vision (U-Net & friends)

Patch : image recognition unit



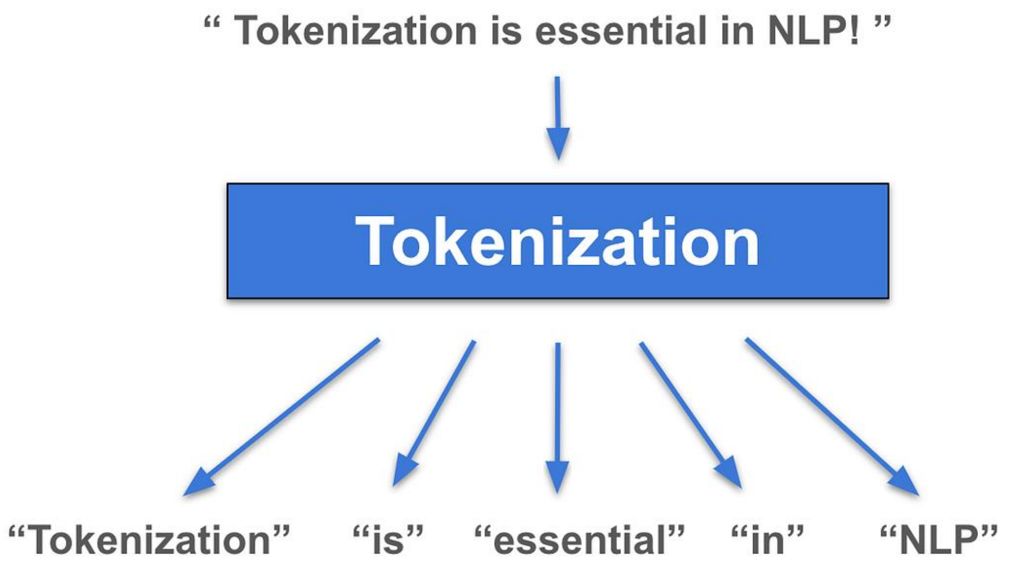
U-Net: Overlap-tile
(i.e., Overlapped Multiple Patches)

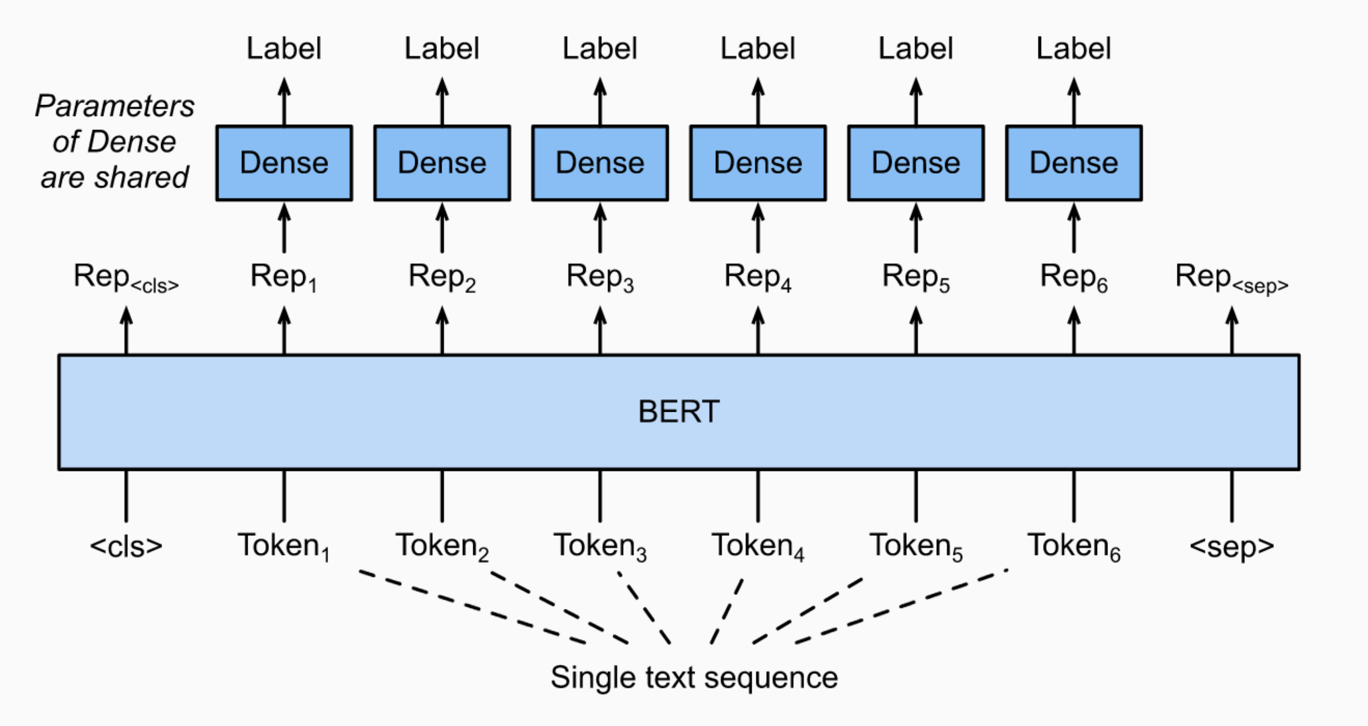


- Convolutions split the image into a **feature grid** (implicit tokens).
- (Preview for ViT) Images can be **patchified** into fixed-size tokens (e.g., 16×1616\times1616×16).

Why a Deeper Look at Encoder–Decoder?

- **CV: Patchification / NLP: Tokenization (Input → Units)**
  - **Text (Seq2Seq)**



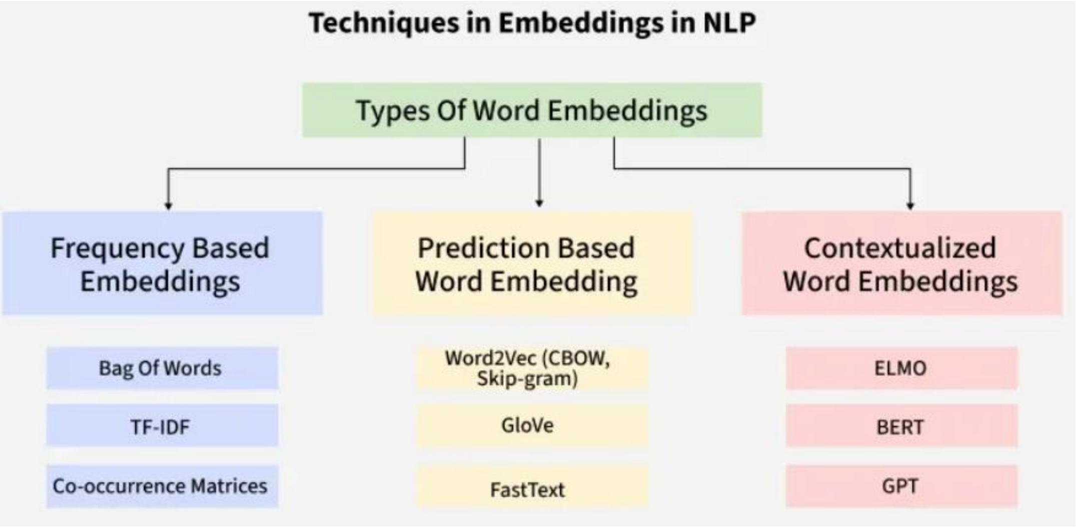


  - Tokenize into words/ subwords / characters.
  - Add special tokens: <START>, <END>, <PAD>.

- **Outcome**: a sequence or grid of ***units (i.e., patches or tokens)*** that the encoder can embed.

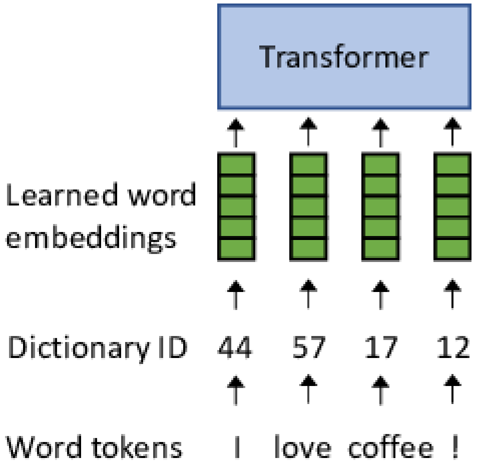
Why a Deeper Look at Encoder–Decoder?

- **Embedding (Units → Vectors)**

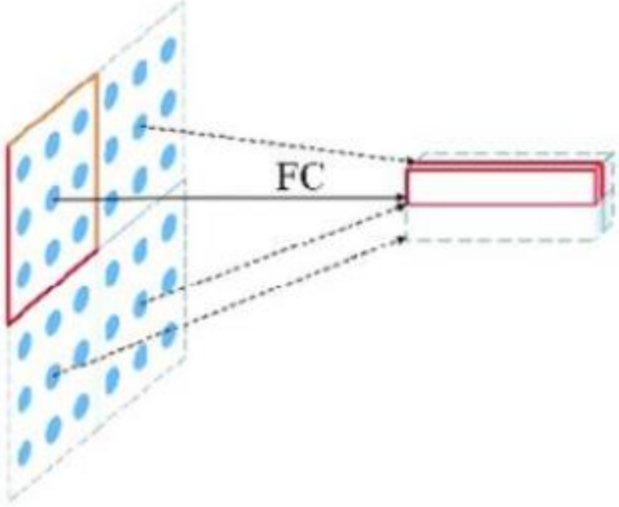


Word Embedding in NLP

Domain: NLP



Patch Embedding in NLP



- **Text:** map tokens to dense vectors (Word2Vec/GloVe/FastText or learned embeddings).

- **Vision:** first conv layers act as **learned embedding** of local patches; in ViT, a linear "patch embedding" projects flattened patches.

- ***Why embeddings matter***:
    - Move from symbolic space to a **continuous, learnable geometry** where proximity encodes meaning/appearance.

Why a Deeper Look at Encoder–Decoder?

- **General Encoder-Decoder Architecture**
  - **1. The Encoder (Compress & Organize Information)**
    - **Text (RNN encoder)**
      - ✓Processes embeddings left→right; final hidden state(s) summarize input.
    - **Vision (CNN encoder)**
      - ✓Stacks conv + pooling/strides → **lower H×W, higher channels**; captures multi-scale semantics.
    - Output forms
      - ✓**(1) Single vector** (classic Seq2Seq), **(2) Sequence of states** (one per token), and **(3) Feature maps/pyramids** (for images)
  - **2. Context Vector (The Bottleneck)**
    - **Classic Seq2Seq:** a **fixed-length vector** c (e.g., last hidden state) is the only conduit to the decoder.
      - ✓Pros: simple; Cons: **information bottleneck**, especially for long inputs.
    - **CV contrast:** U-Net mitigates a similar bottleneck with **skip connections** (high-res features passed directly to the decoder).
    - This sets up the need for **attention** (dynamic, content-aware access to encoder states).

Why a Deeper Look at Encoder–Decoder?

- **General Encoder-Decoder Architecture**
  - **3. The Decoder (Generate the Output)**
    - **Text (sequence decoder)**
      - ✓Initialize with context; at time t, use previous token + hidden state → predict next token (softmax).
      - ✓Training tricks: **teacher forcing**, **scheduled sampling**, **beam search** at inference.
    - **Vision (image/segmentation decoder)**
      - ✓Upsampling (transpose conv / interpolation + conv) to reconstruct spatial detail.
      - ✓May fuse **skip connections** for sharp boundaries (U-Net).
  - **Putting It Together (Two Pipelines)**
    - **NLP pipeline:** Tokens → Embeddings → RNN Encoder → (Context or Attention) → RNN Decoder → Sequence
    - **CV pipeline:** Image → Conv Encoder → Feature Pyramid (+ Skips) → Conv Decoder → Mask/Image
    - *Shared idea:* ***encode structure → decode structure****; differences are the* ***unit type*** *(tokens vs. pixels/features) and* ***decoder objective****.*

Why a Deeper Look at Encoder–Decoder?

- **Where Things Break (Motivation for Attention/Transformer)**
  - **1.** Fixed-length **context vectors** struggle with long or complex inputs.
  - **2.** Sequential RNN decoders limit **parallelism** and **long-range** reasoning.
  - **3.** In CV, plain upsampling can miss **global context** without extra links.
  - **4. Attention** (cross-/self-) fixes the access problem; **Transformers** replace recurrence with **parallel attention blocks**.
- **Quick Recap & Transition**
  - We now understand **Encoder–Decoder** across NLP & CV
    - Tokens/patches → embeddings → encoder states → (context/attention) → decoder.
  - Next up
    - **Transformers** — same high-level blueprint, but replace recurrence with **multi-head self-attention**, add **positional encodings**, and scale with **parallel computation**.