Cross-Modal Attention

Abdulkader Helwan · Follow
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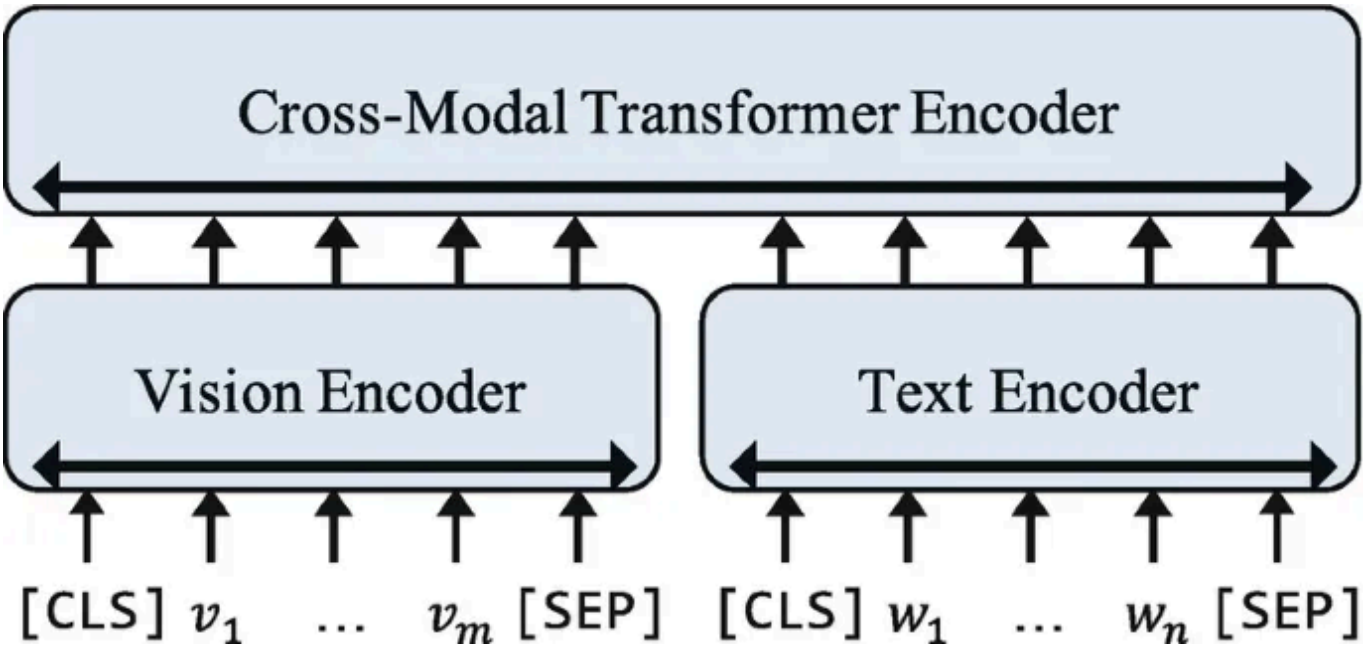

Cross-Modal Attention

Cross-modal attention is a mechanism used in multimodal models to dynamically align and fuse information from different modalities (e.g., text, images, audio). It allows the model to focus on the most relevant parts of one modality when processing another, enabling effective interaction between

modalities. Cross-modal attention is a key component in many state-of-the-art multimodal models, such as **DALL-E**, **CLIP**, and **ViLT**.

What is Cross-Modal Attention?

While self-attention computes relationships within a single modality (e.g., between words in a sentence or patches in an image), cross-modal attention computes relationships **between different modalities** (e.g., between text and image features).

The idea is to Use one modality as a **query** to attend to the other modality's **key-value pairs**.

This allows the model to dynamically align and combine information from both modalities.

How Does Cross-Modal Attention Work?

Cross-modal attention operates similarly to self-attention but involves two modalities. Here's how it works:

- **Modality A (Query):** Represents one modality (e.g., text embeddings).
- **Modality B (Key-Value):** Represents the other modality (e.g., image embeddings).

Projections:

The embeddings from both modalities are projected into three spaces:

- **Query (Q):** Derived from Modality A.

- **Key (K):** Derived from Modality B.
- **Value (V):** Derived from Modality B.

Attention Scores:

- Compute the dot product between the Query (Q) and Key (K) to measure the similarity between elements of Modality A and Modality B.
- This results in an **attention score matrix** that indicates how much each element of Modality A should attend to each element of Modality B.
- Apply a softmax function to the attention scores to normalize them into probabilities.

Weighted Sum:

- Use the attention probabilities to compute a weighted sum of the Values (V) from Modality B.
- This produces a **context vector** that represents the most relevant information from Modality B for each element of Modality A.

Output:

- The context vectors are combined with the original embeddings from Modality A to produce the final cross-modal representation.

Mathematical Formulation:

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

Where:

- Q: Query matrix (from Modality A).
- *K*: Key matrix (from Modality B).
- V: Value matrix (from Modality B).
- *dk*: Dimensionality of the key vectors (used for scaling).

Example: Cross-Modal Attention in DALL-E

In **DALL-E**, cross-modal attention is used to condition image generation on text:

Text Encoder:

- A Transformer encodes the input text into a dense embedding (Query).

Image Tokenizer:

- The input image is tokenized into discrete tokens (Key-Value).

Cross-Attention:

- The text embedding (Query) attends to the image tokens (Key-Value) to condition the image generation process.

Image Decoder:

- A VQ-VAE decoder generates the final image based on the conditioned tokens.

Attention Cross Attention Multimodal AI Transformers

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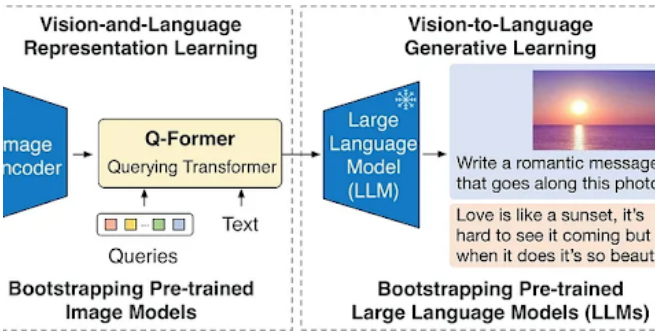

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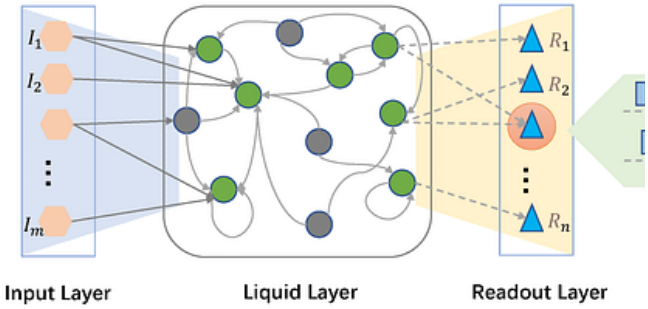

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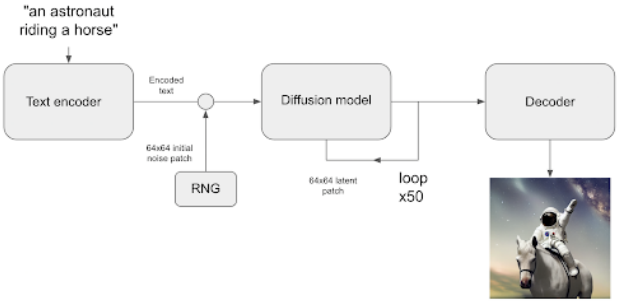

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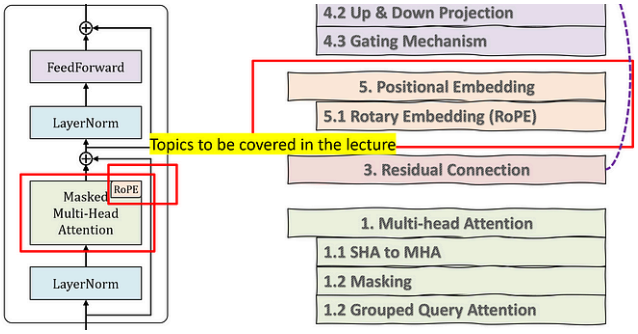

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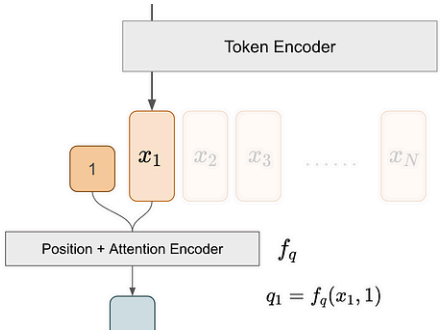

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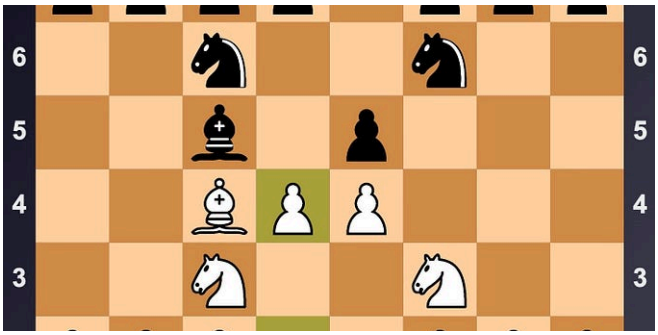

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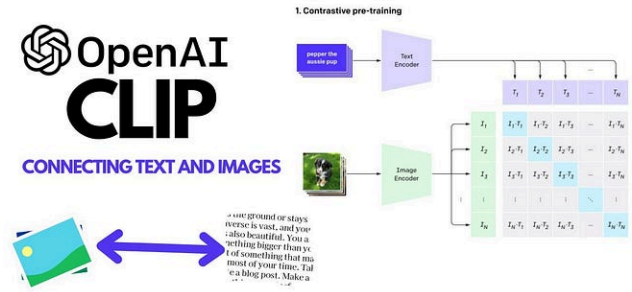

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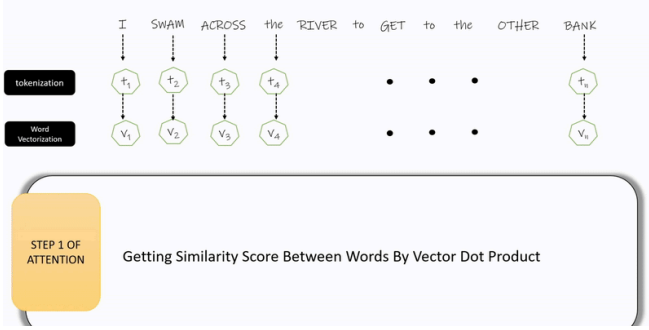

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