Neural Networks

Transformers

Guest lecture by Dr. Jae Hee Lee

KNOWLEDGE
TECHNOLOGY

http://www.informatik.uni-hamburg.de/WTM/

Outline

- Self-Attention
- Transformer (Architecture, Inference, Training)
- Transformer Applications
- Multimodal Learning

Self-Attention

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  - Representation Learning
  - Sequence-to-Sequence Models
  - Self-Attention
- Transformers
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Deep Learning as Representation Learning

- Q: What is special about deep learning?

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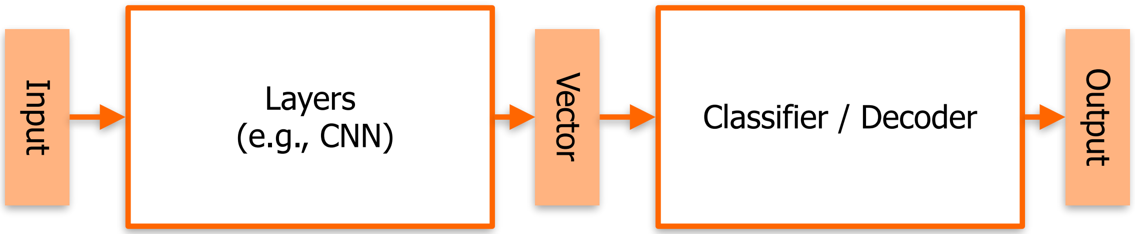

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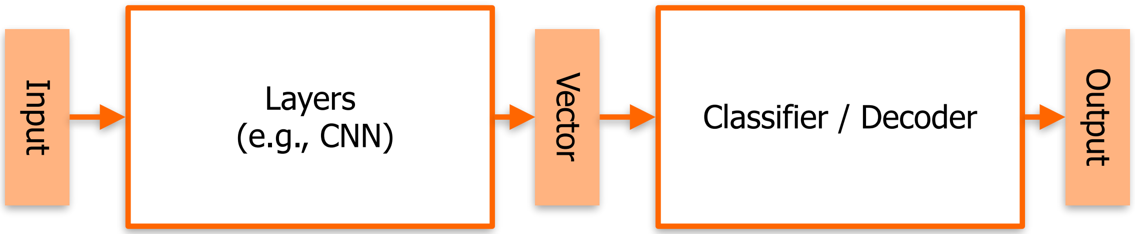

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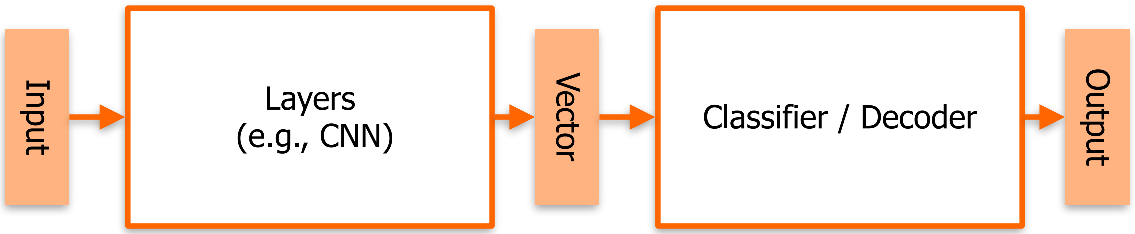

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  - is called a **representation** or a **feature vector.**
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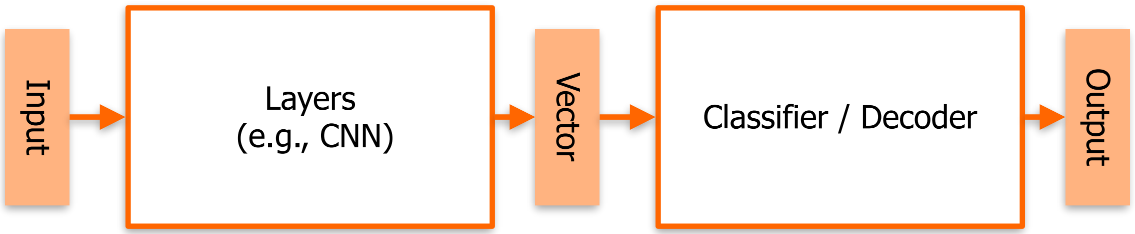
- Different **building blocks** are introduced to learn good representations.
- In this lecture, we will learn a new building block: **self-attention.**



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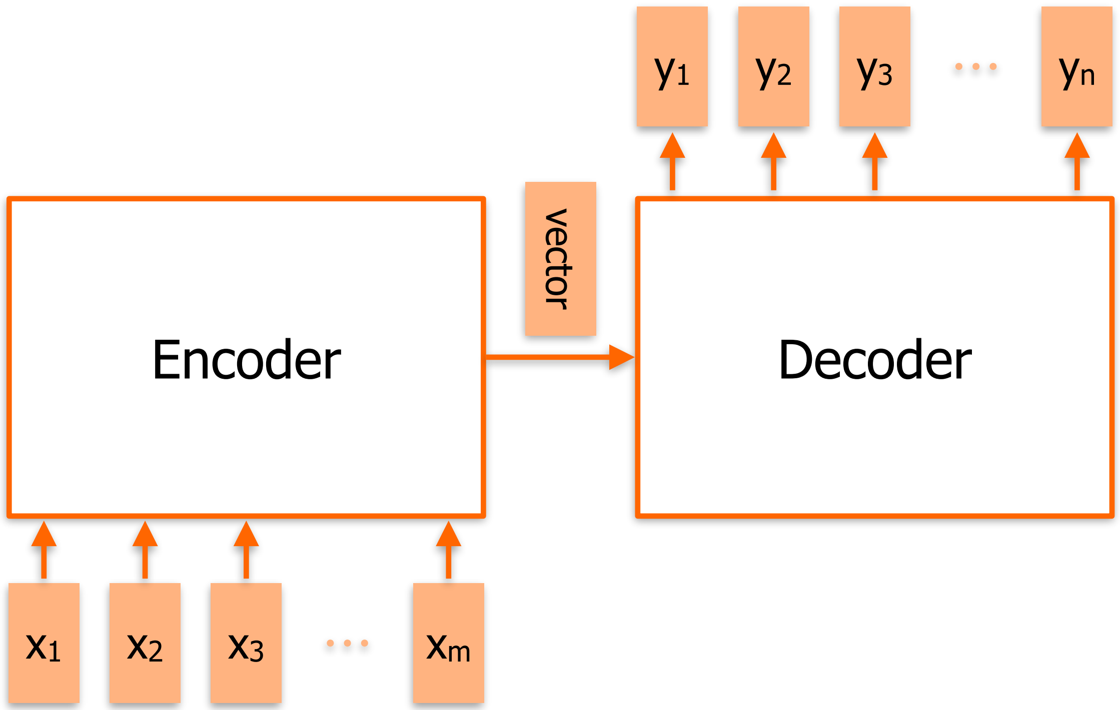

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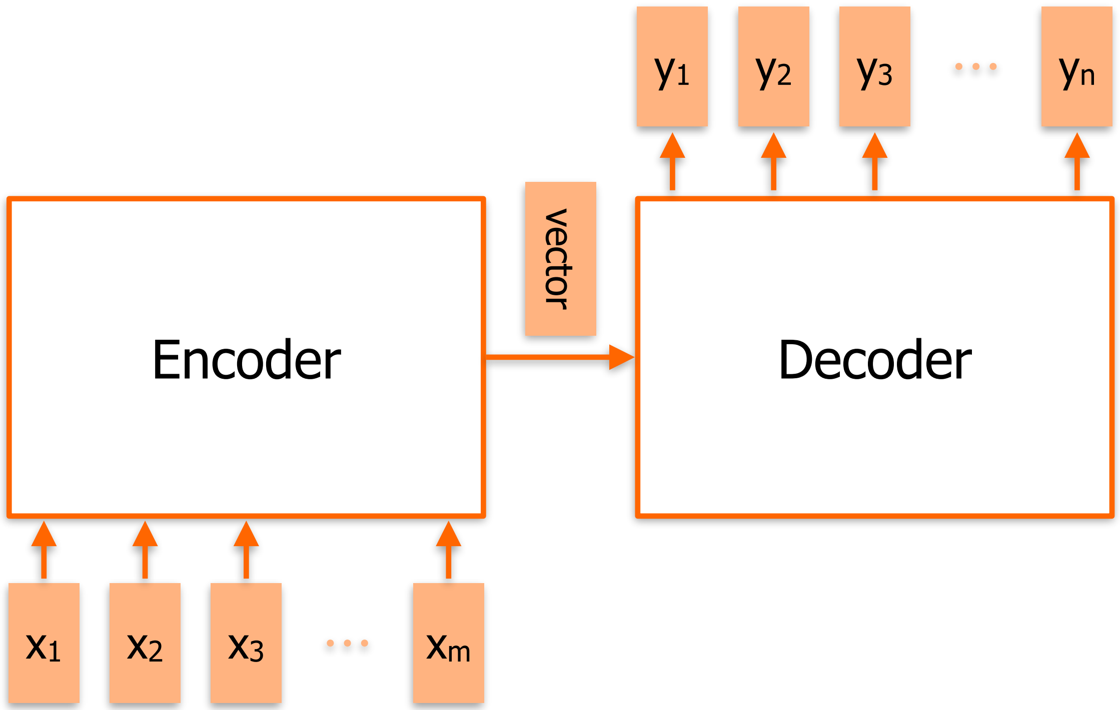

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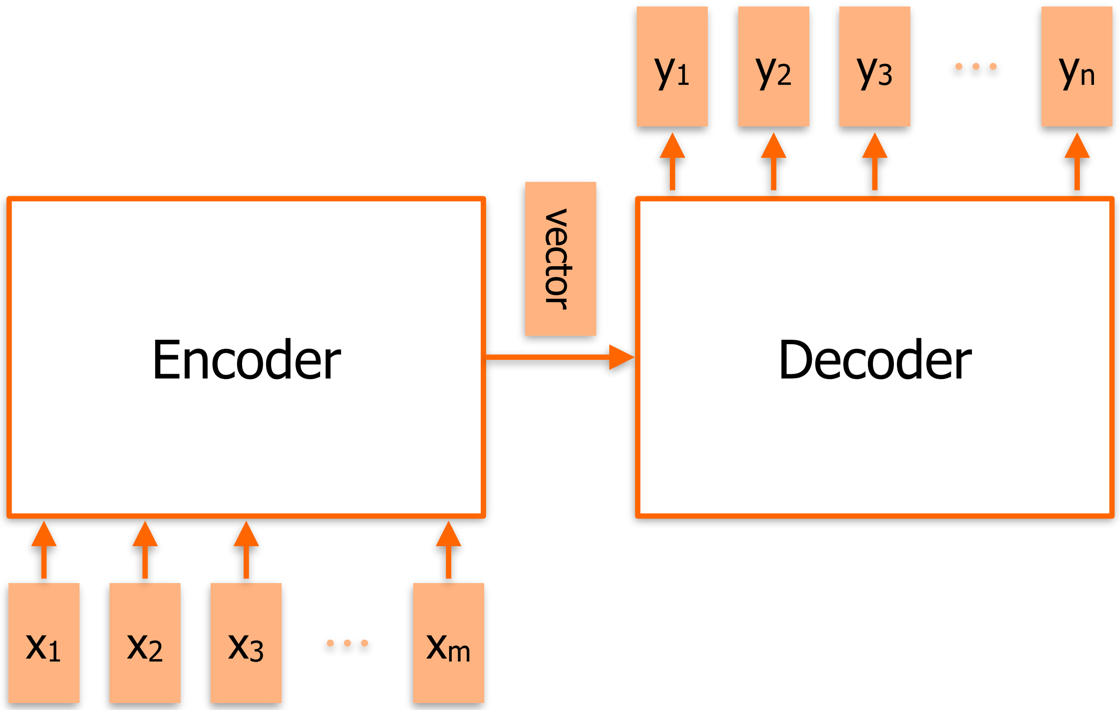

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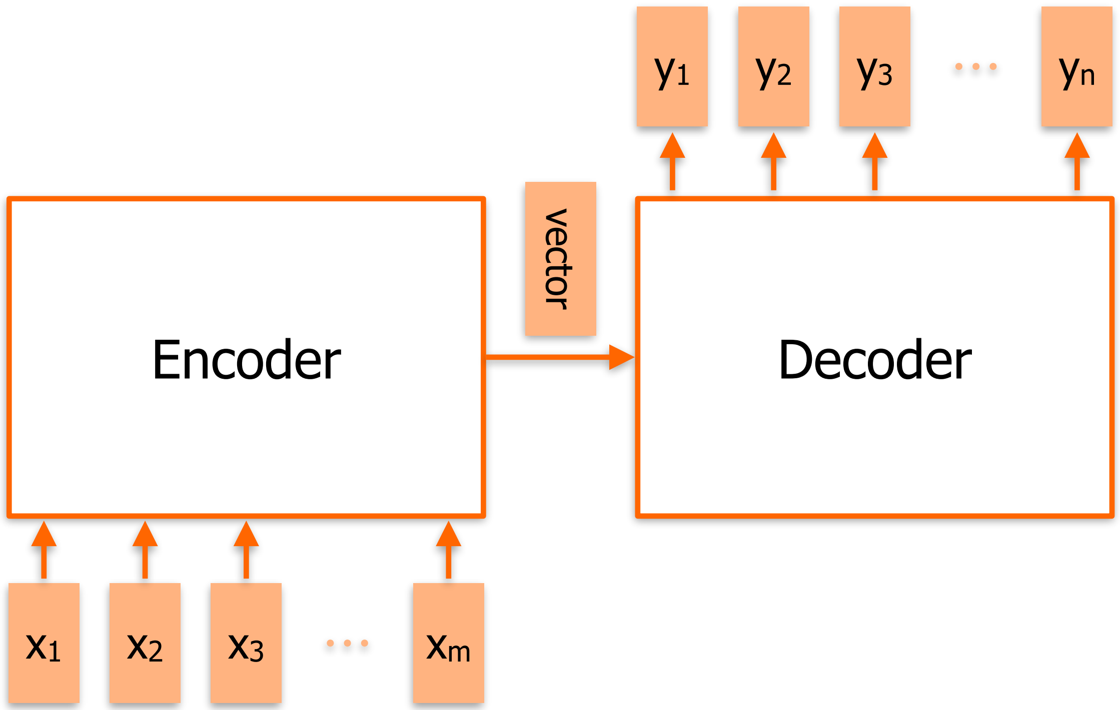

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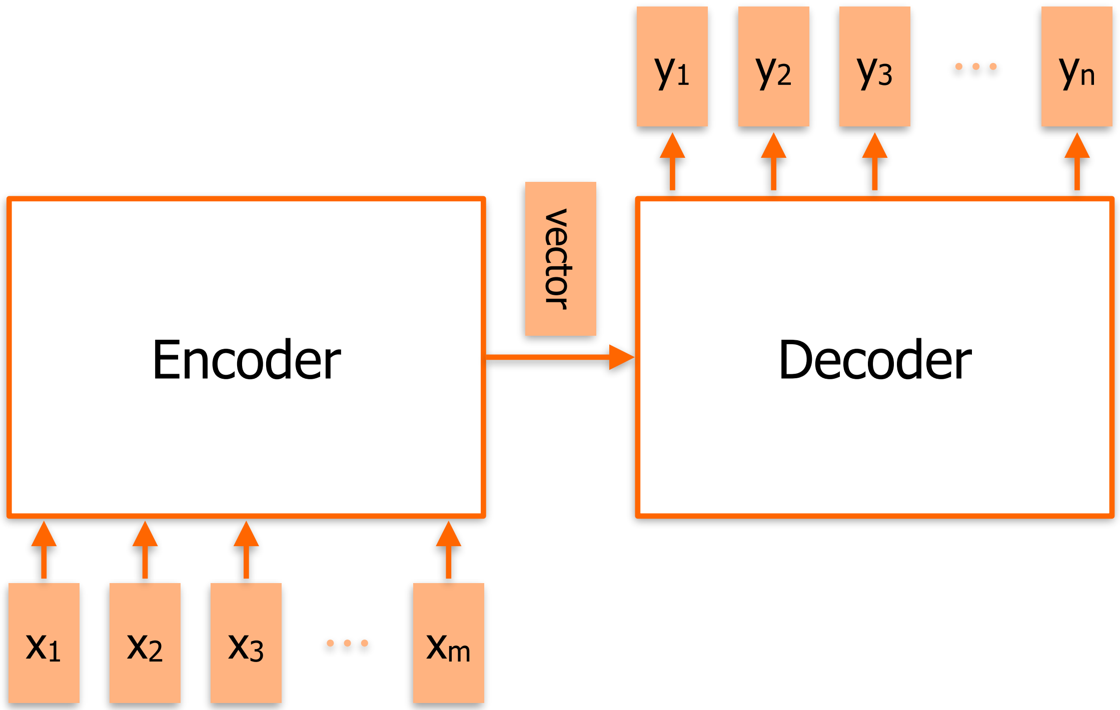
- How to handle different lengths of sequences?
  - One could use an **RNN**.



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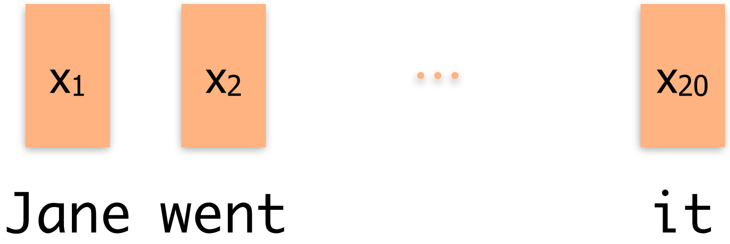

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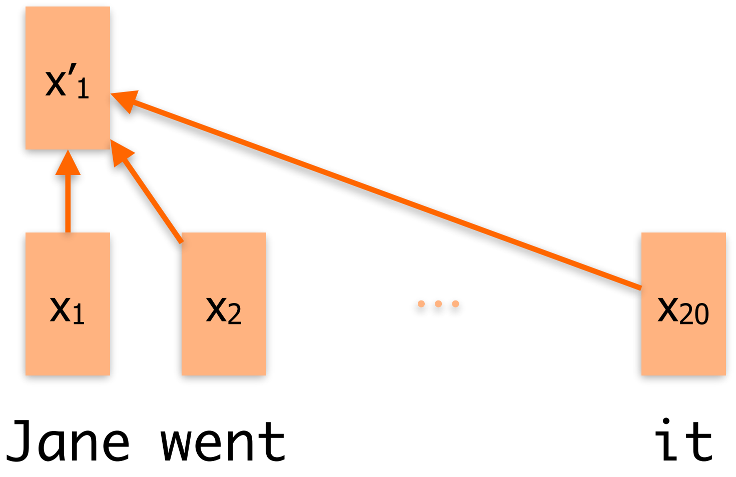

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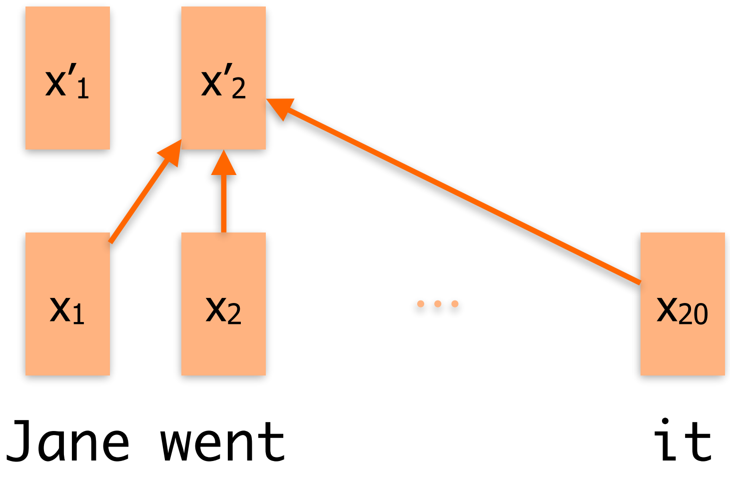

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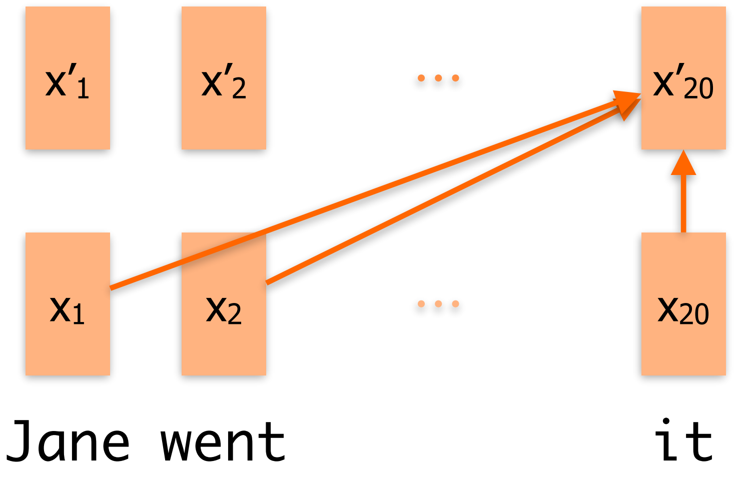

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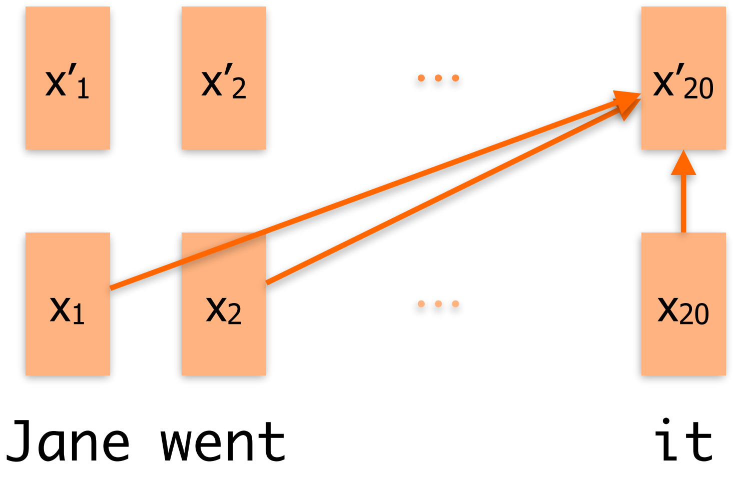

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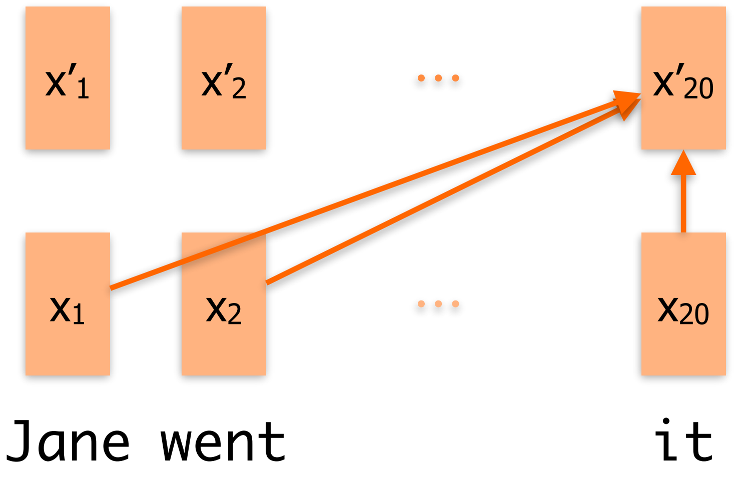
  - But how does self-attention work in detail?



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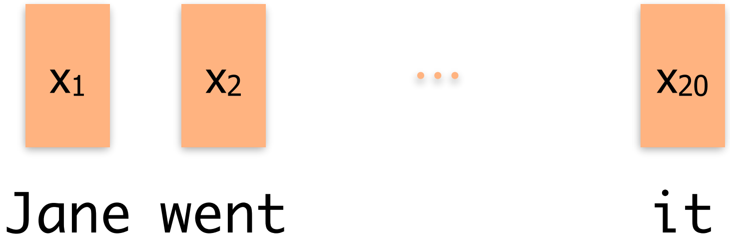

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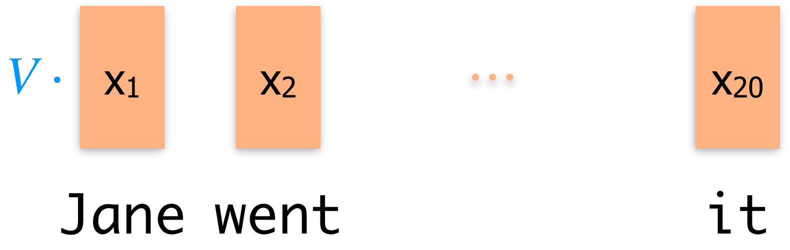

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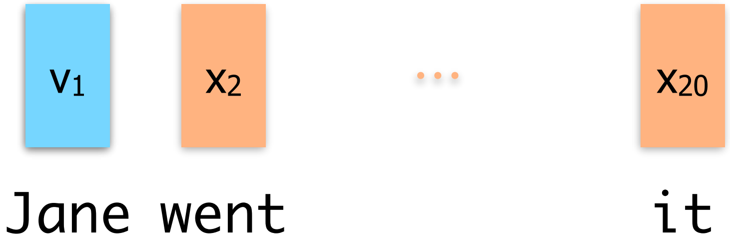

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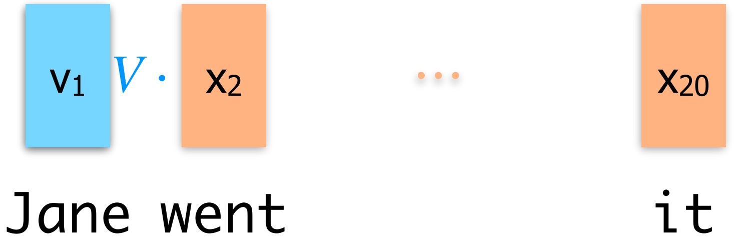

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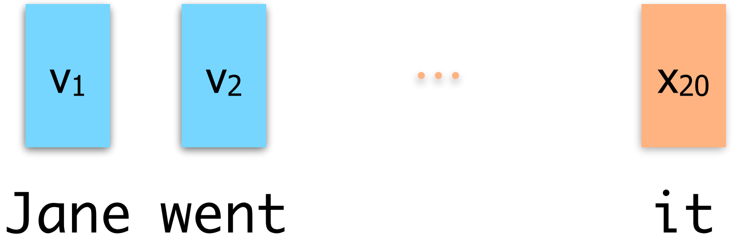

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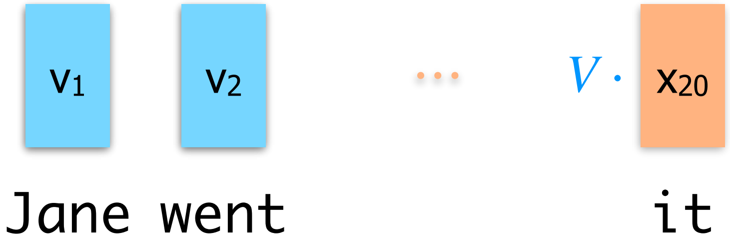

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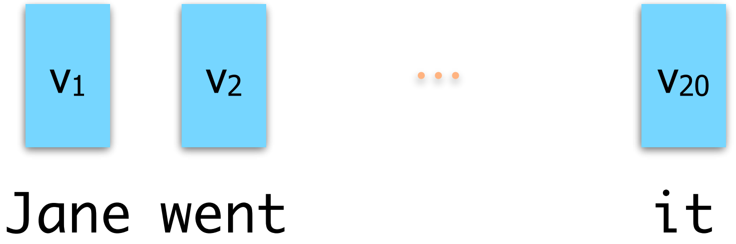

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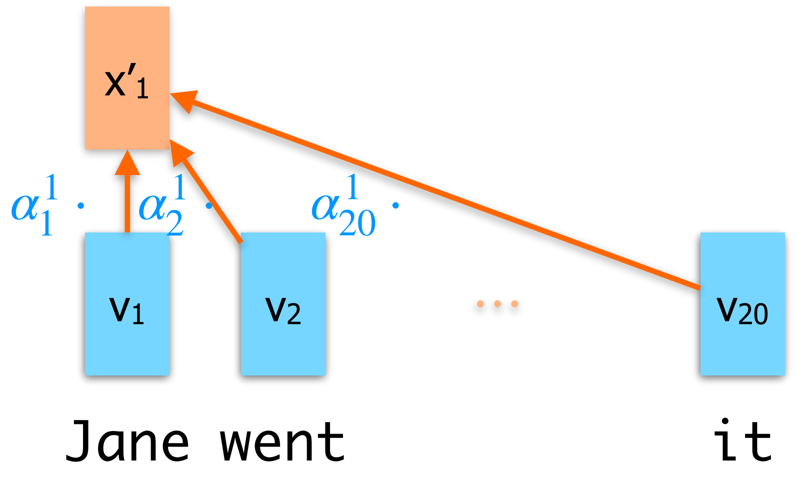

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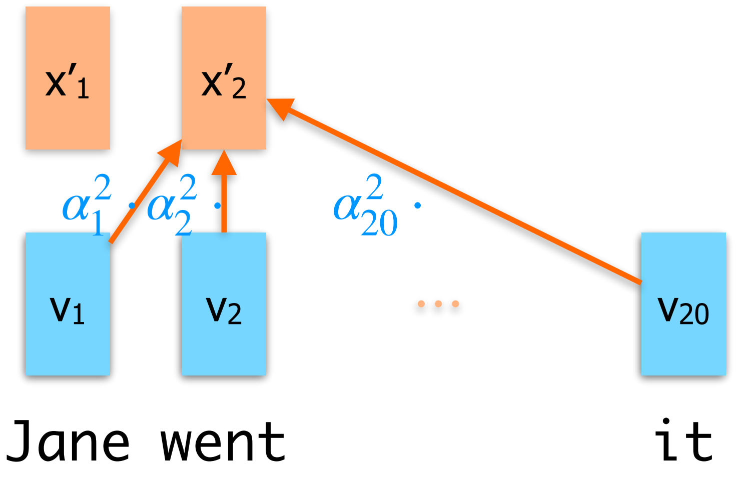

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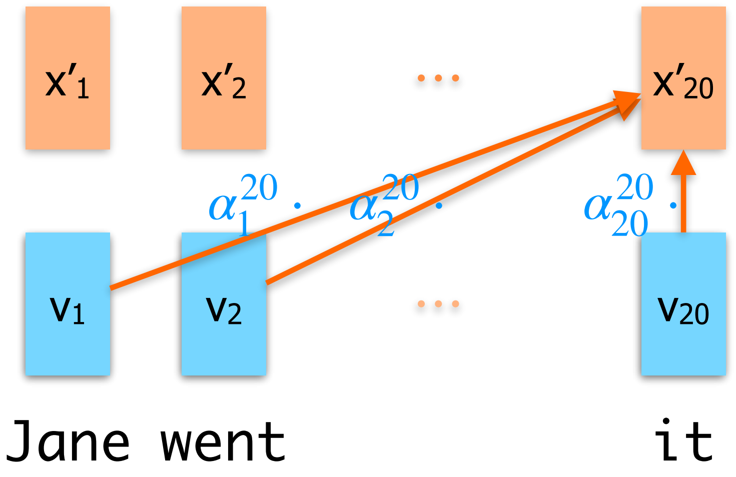

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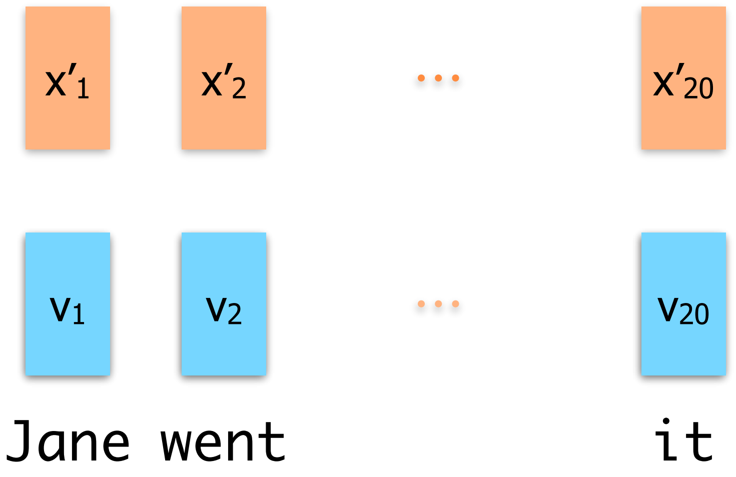

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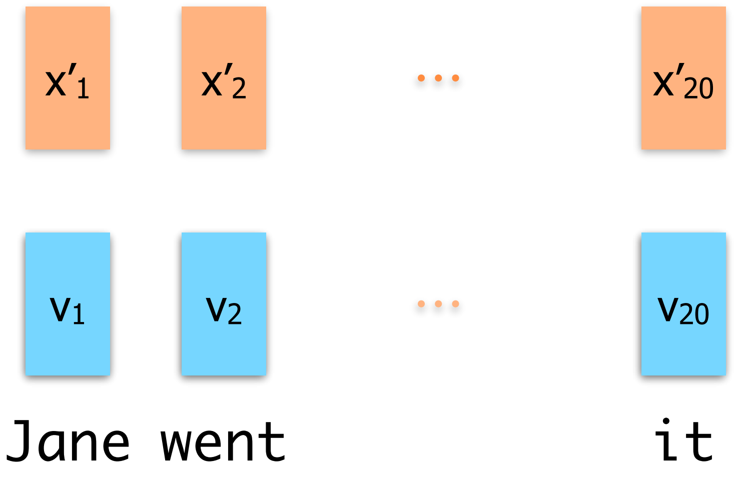

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Example

- $x_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, x_2 = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}, x_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 2 \end{bmatrix}$

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Summary

- Deep Learning allows for learning good representations.
- There are different DL building blocks for learning good representations.
- Self-attention is a DL building block that overcomes limitations of an RNN.

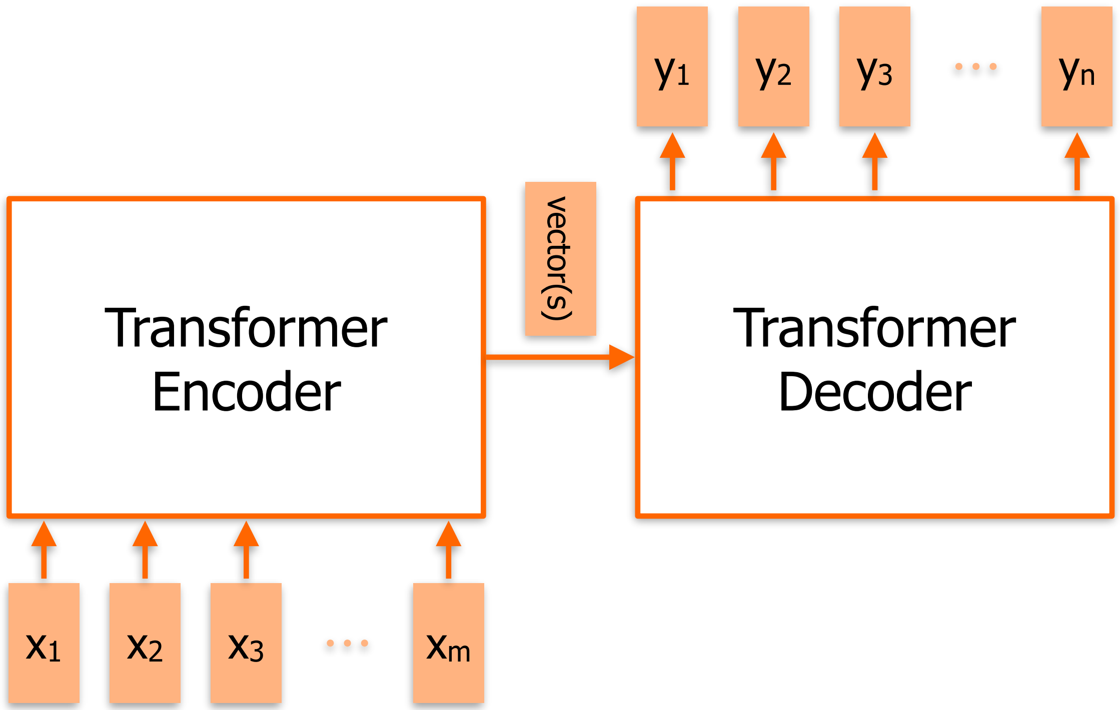
Questions?

Transformers

- Self-Attention
- Transformers
  - Introduction
  - Architecture
  - Inference
  - Training
- Transformer Applications
- Multimodal Learning

Transformer: Introduction

- Sequence-to-Sequence Model.



A. Vaswani et al., "Attention is All you Need," in Advances in Neural Information Processing Systems 30, 2017

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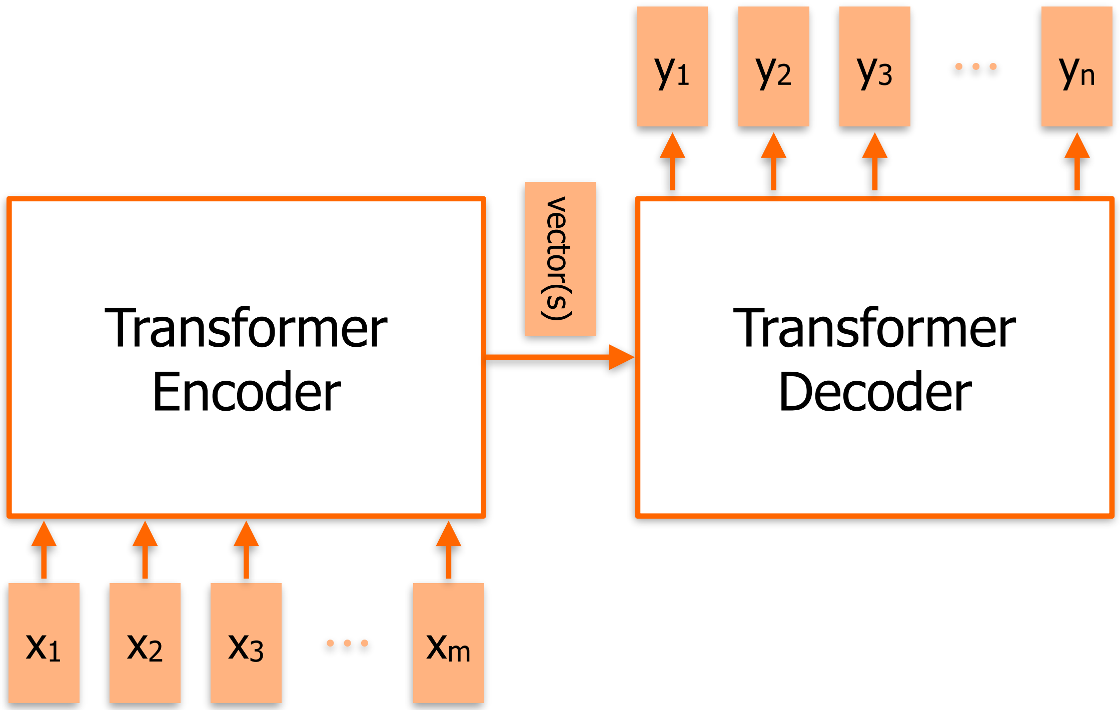

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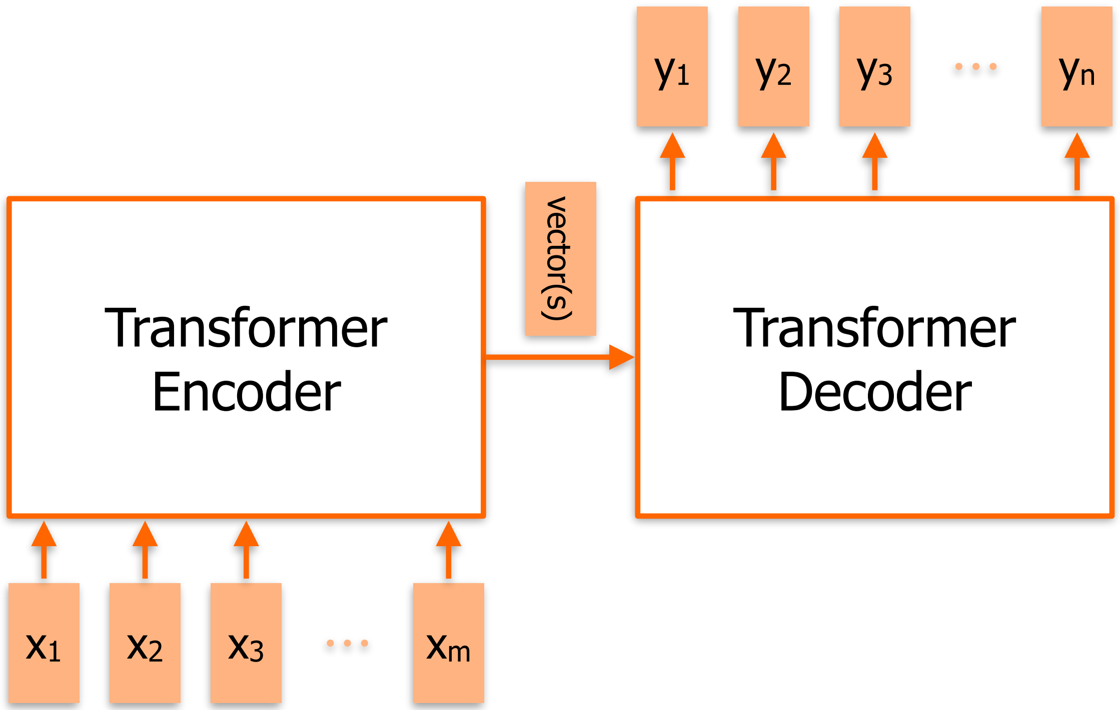
Transformer: Introduction

- Sequence-to-Sequence Model.
- Based on self-attention.
- Transformer literally “transformed” current deep learning architectures.
  - Natural Language Processing (ChatGPT!, BERT, GPT, …)
  - Vision (ViT, …)
  - Speech (Conformer, …)
  - Bioinformatics (AlphaFold, …)
  - Multimodal Learning (LXMERT, ViL-BERT, …)
  - …



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Transformer Variants

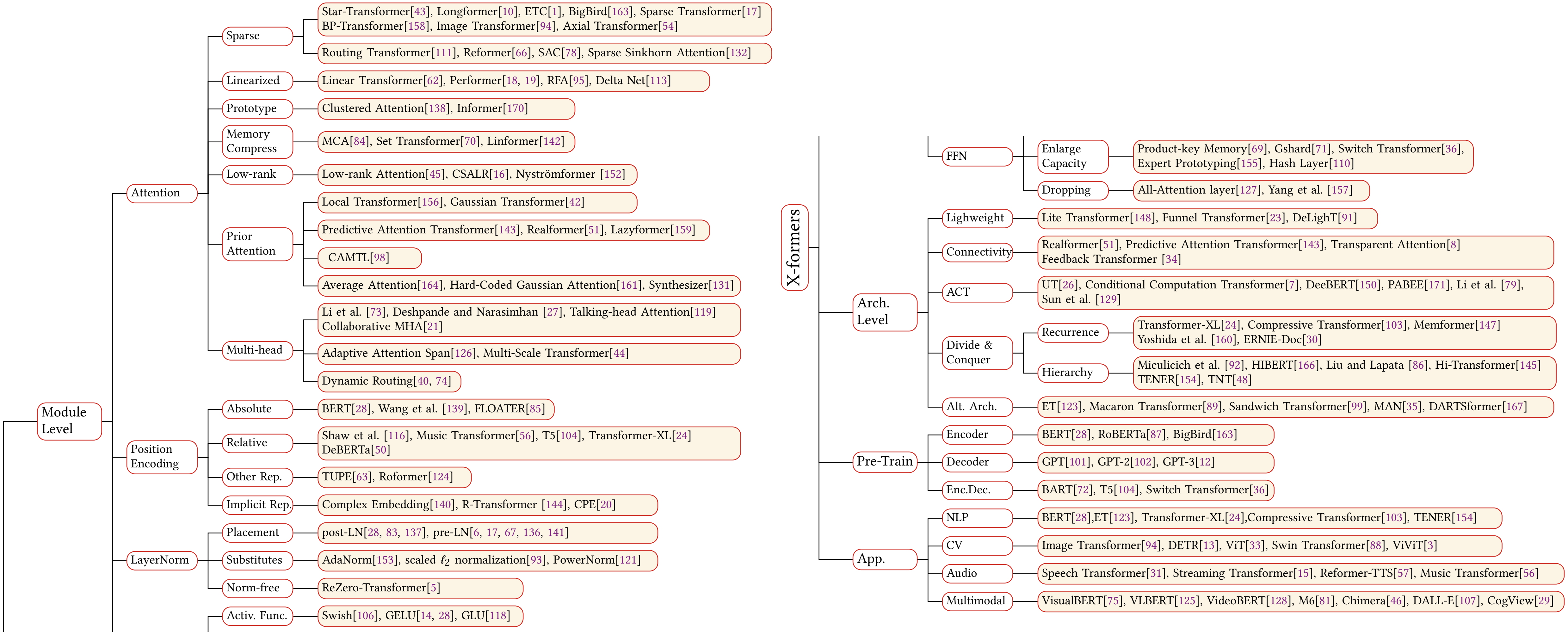
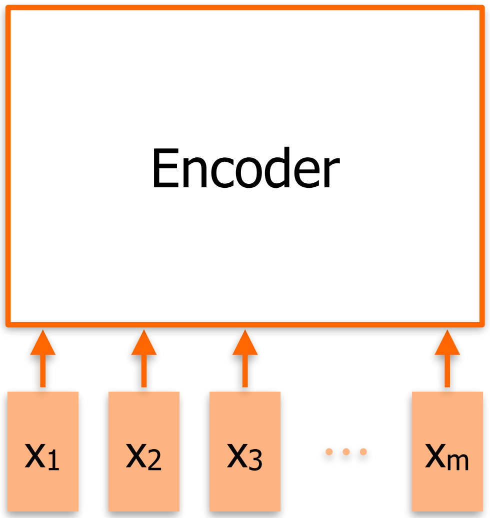


Fig. 3. Taxonomy of Transformers

 T. Lin, Y. Wang, X. Liu, and X. Qiu, “A Survey of Transformers.” 2021

Transformer Architecture: Encoder



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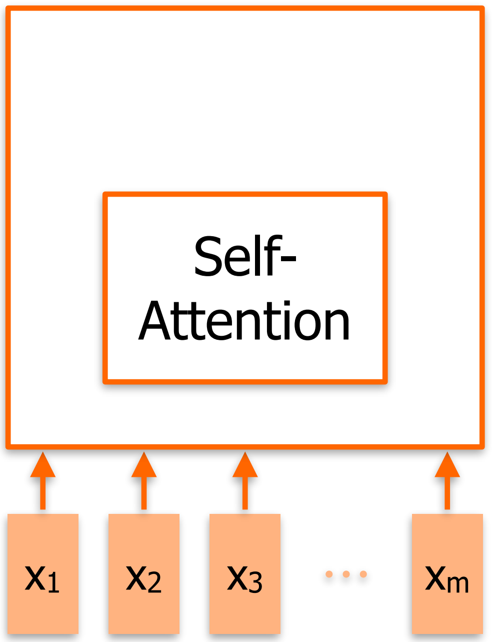
- **Self-Attention** is the main component of a Transformer.



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- **Self-Attention** is the main component of a Transformer.
- Another component in **FFN** (Feed-forward Network)
  - FFN(x) = Linear(ReLu(Linear(x)))
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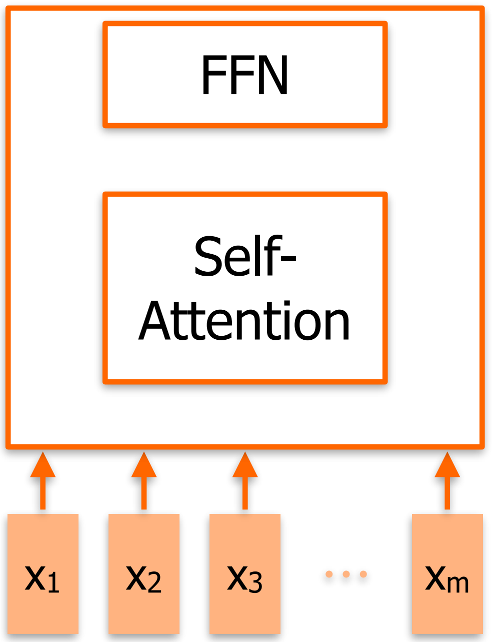

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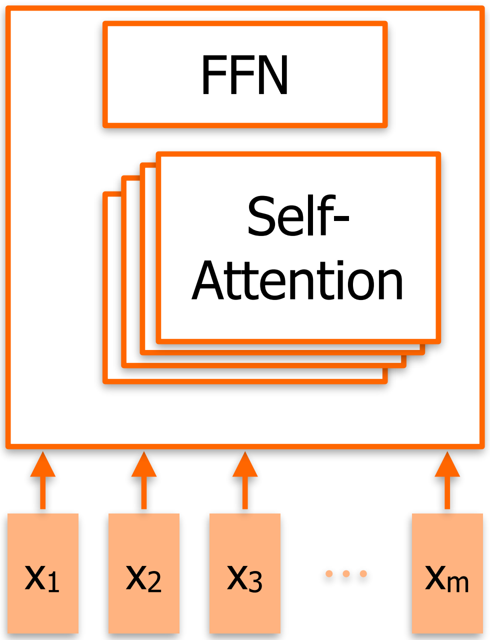

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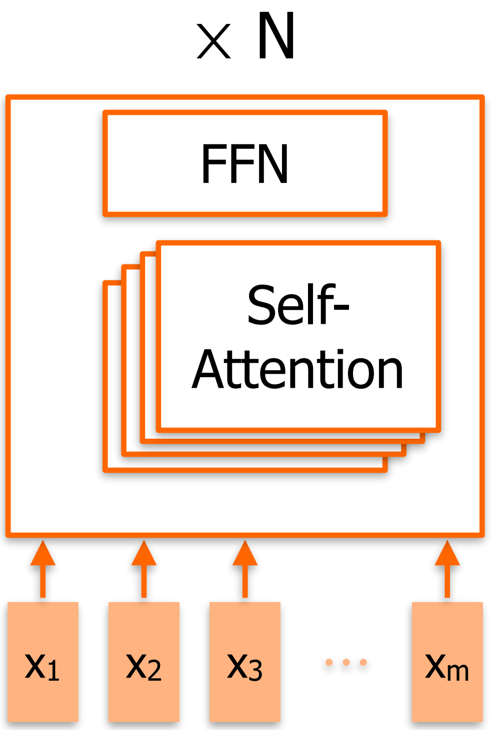

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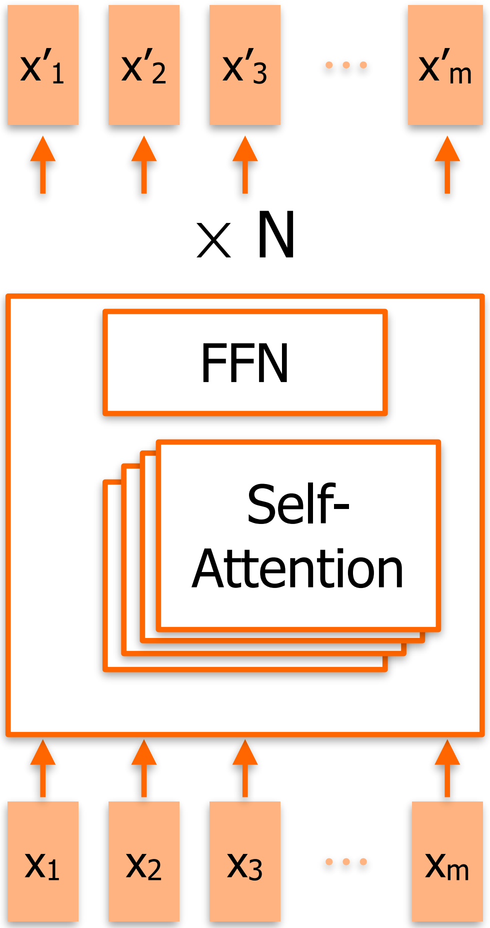

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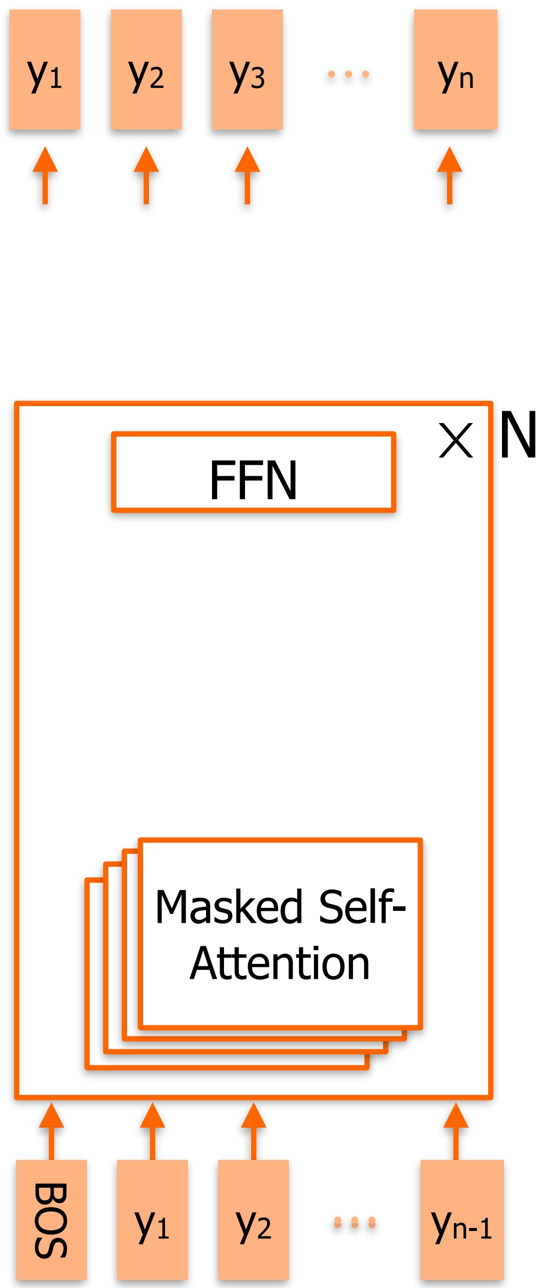

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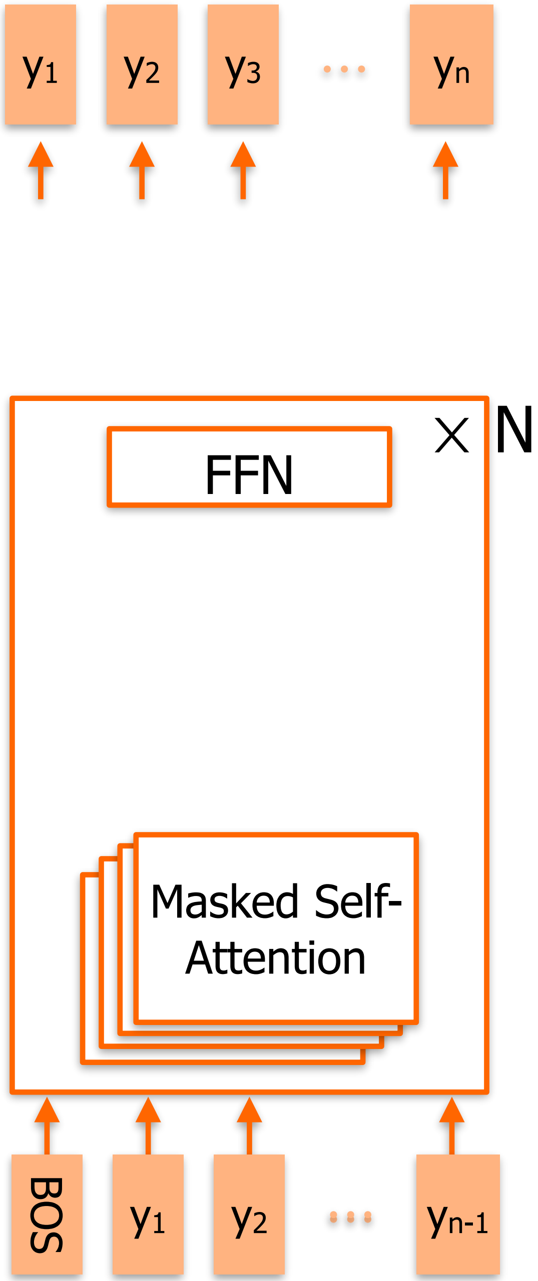

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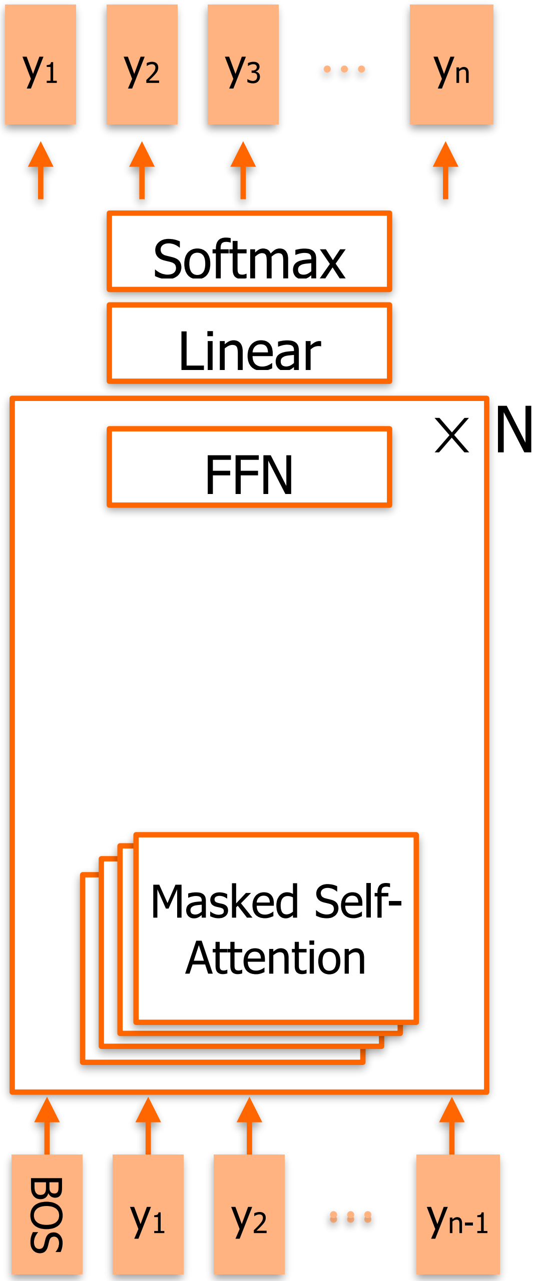

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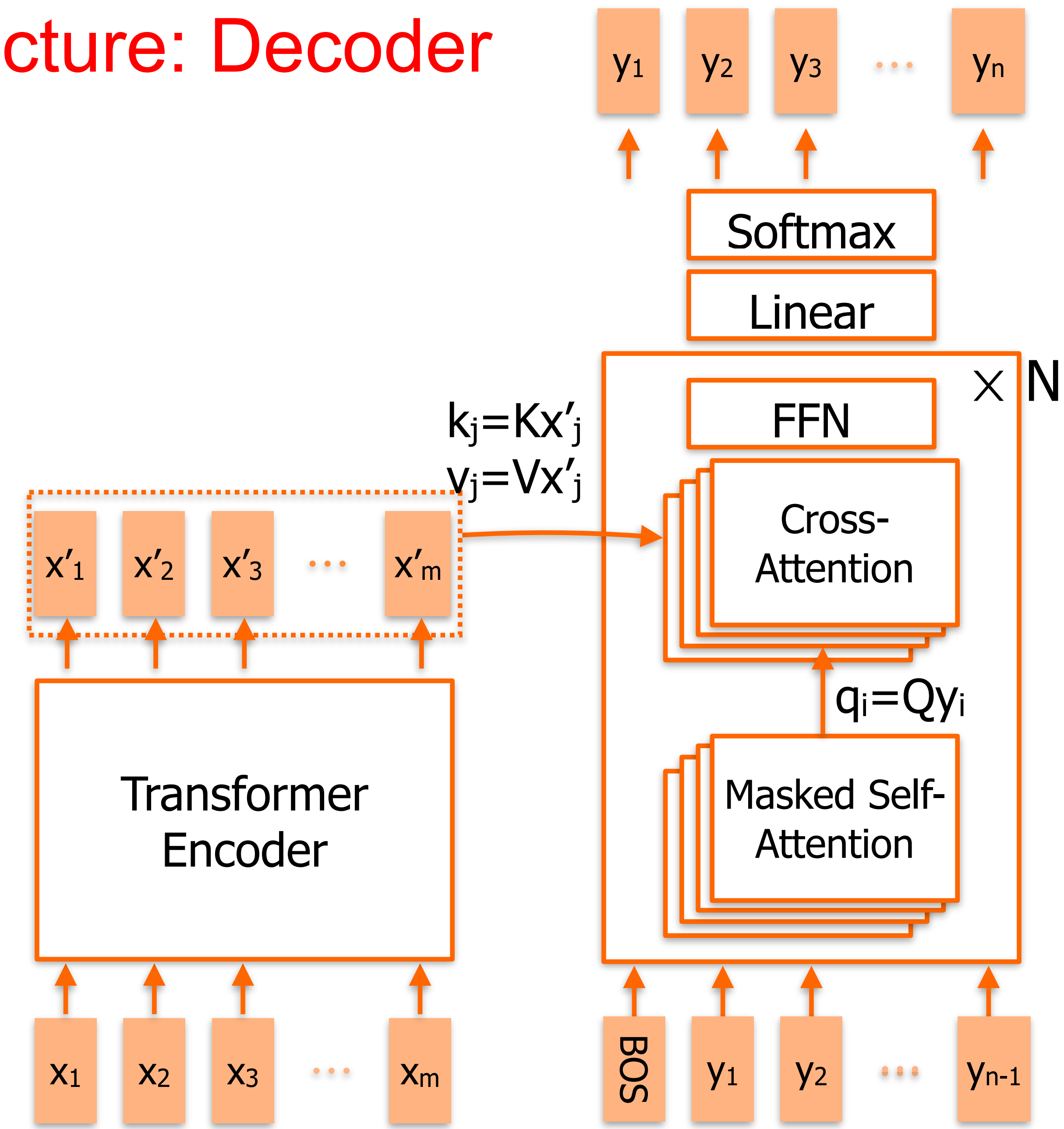

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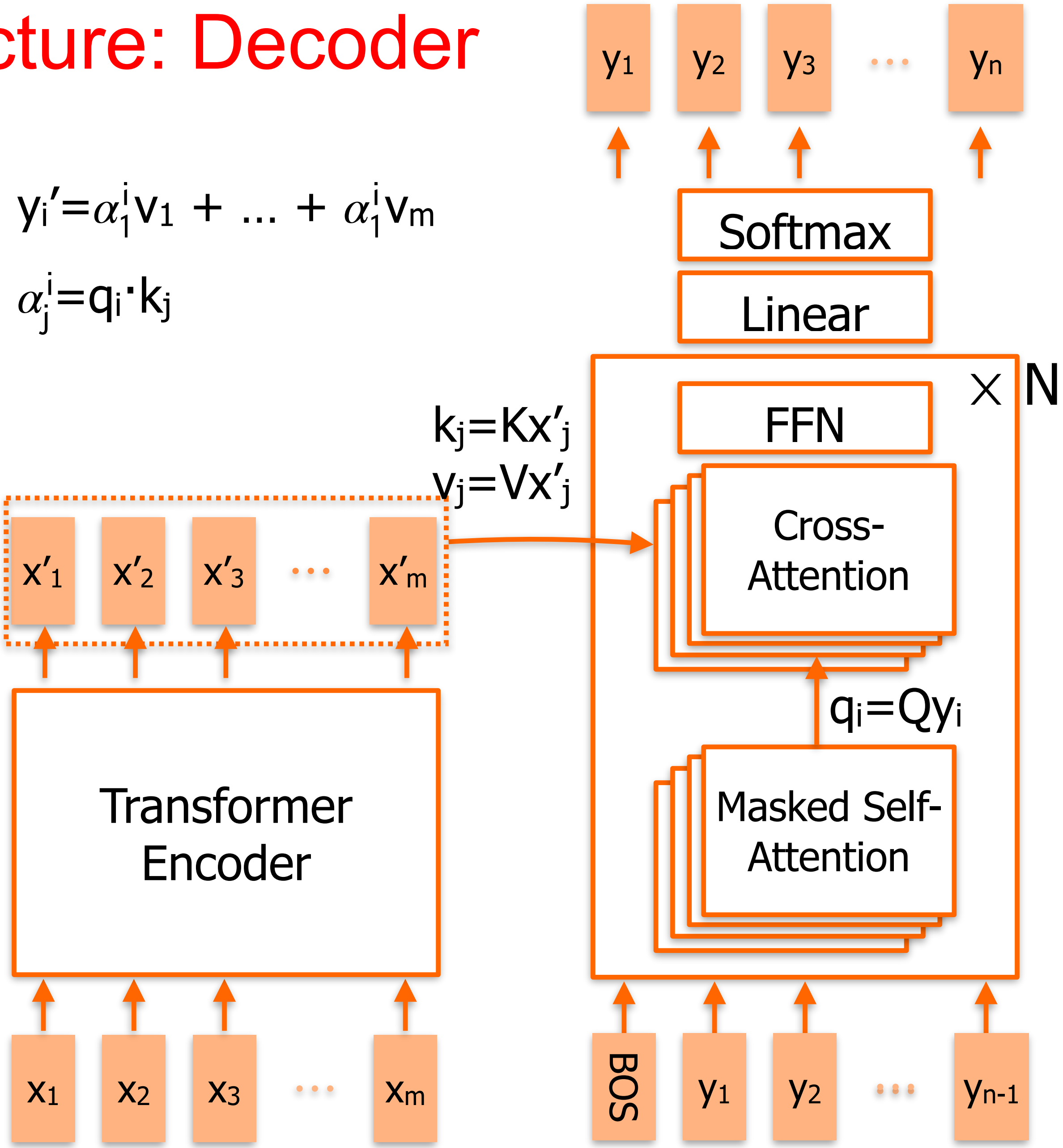

Transformer Architictre: Further details

1. https://towardsdatascience.com/residual-blocks-building-blocks-of-resnet-fd90ca15d6ec
2. https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Transformer Architictre: Further details

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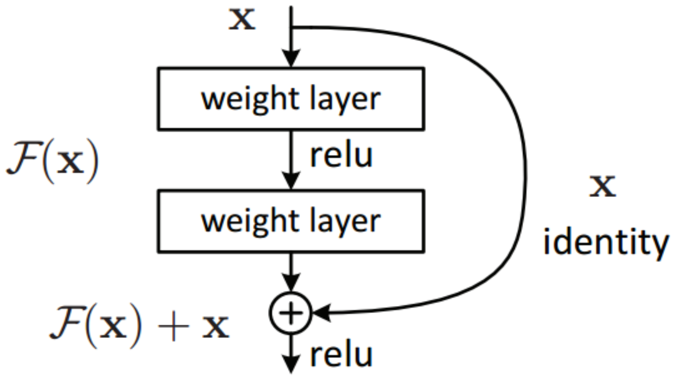

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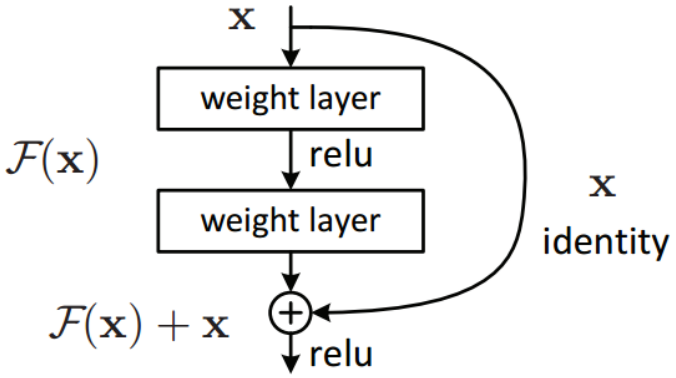

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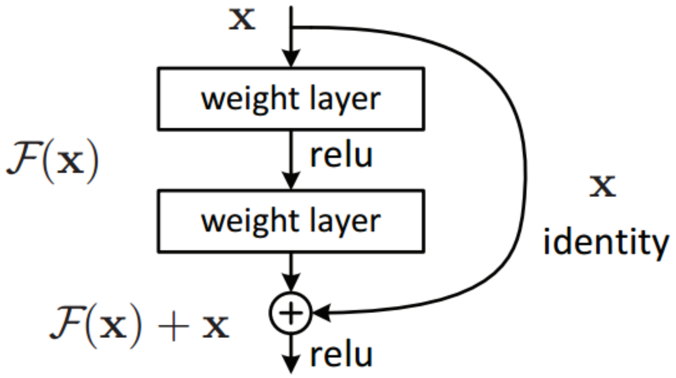

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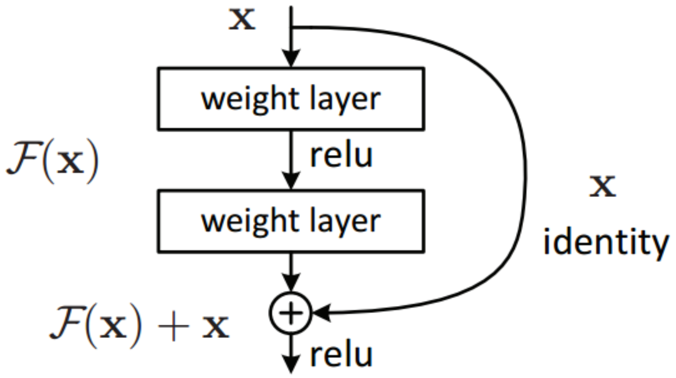

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- Residual connection
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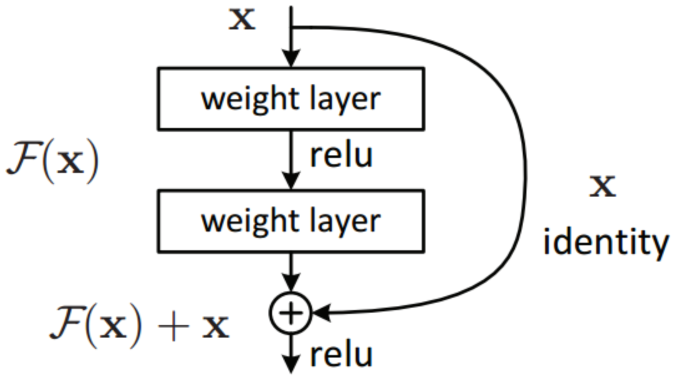

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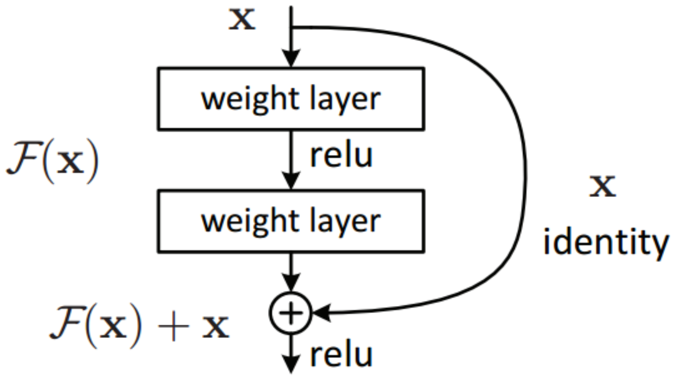

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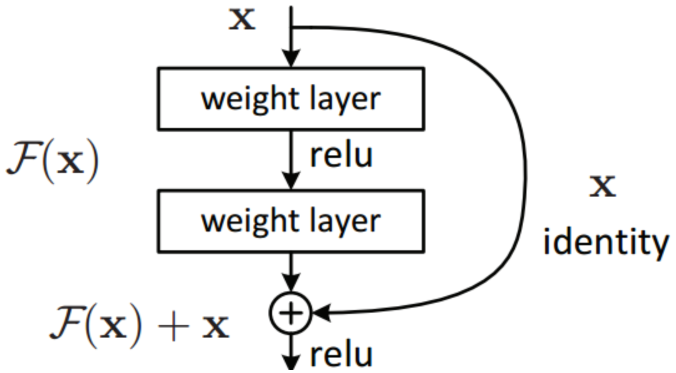

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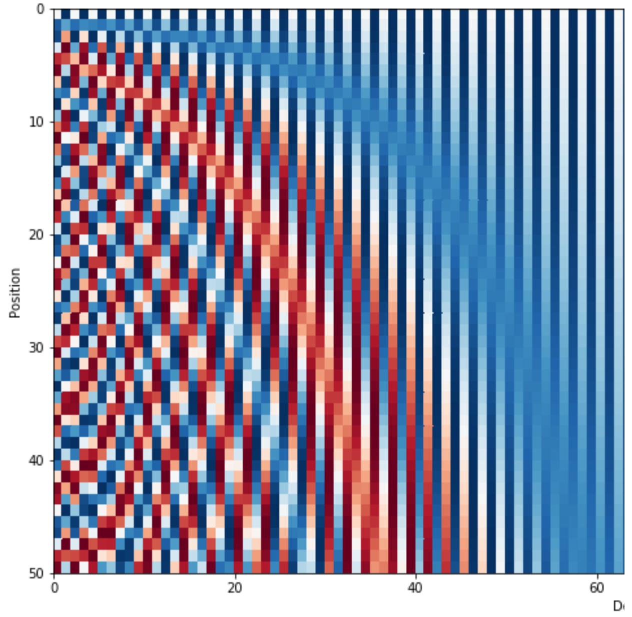

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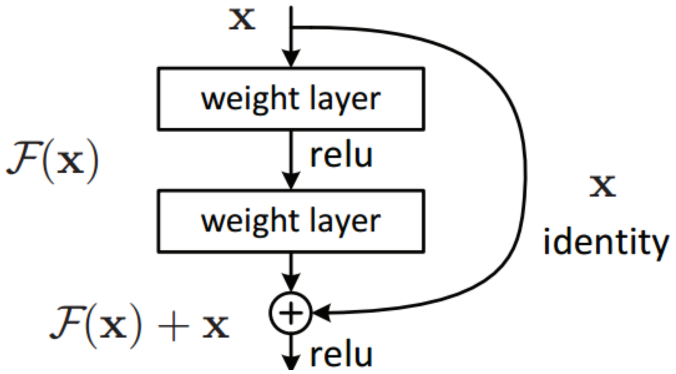
- Vectorization
  - Faster training and inference due to parallel processing.



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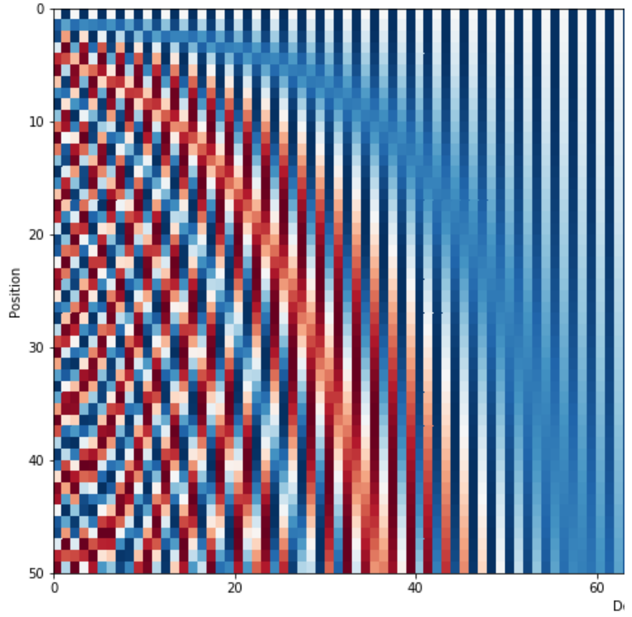

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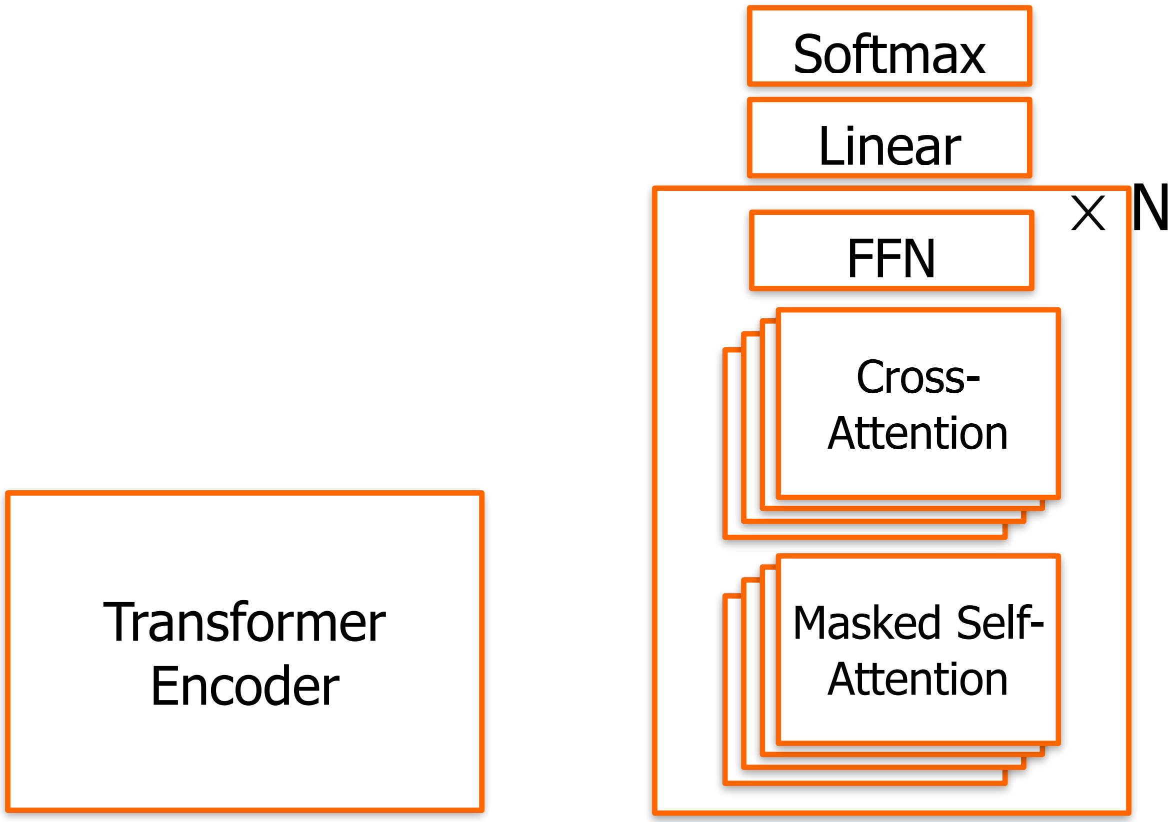
- First, encoder outputs $x'_1, x'_2, \ldots, x'_m$



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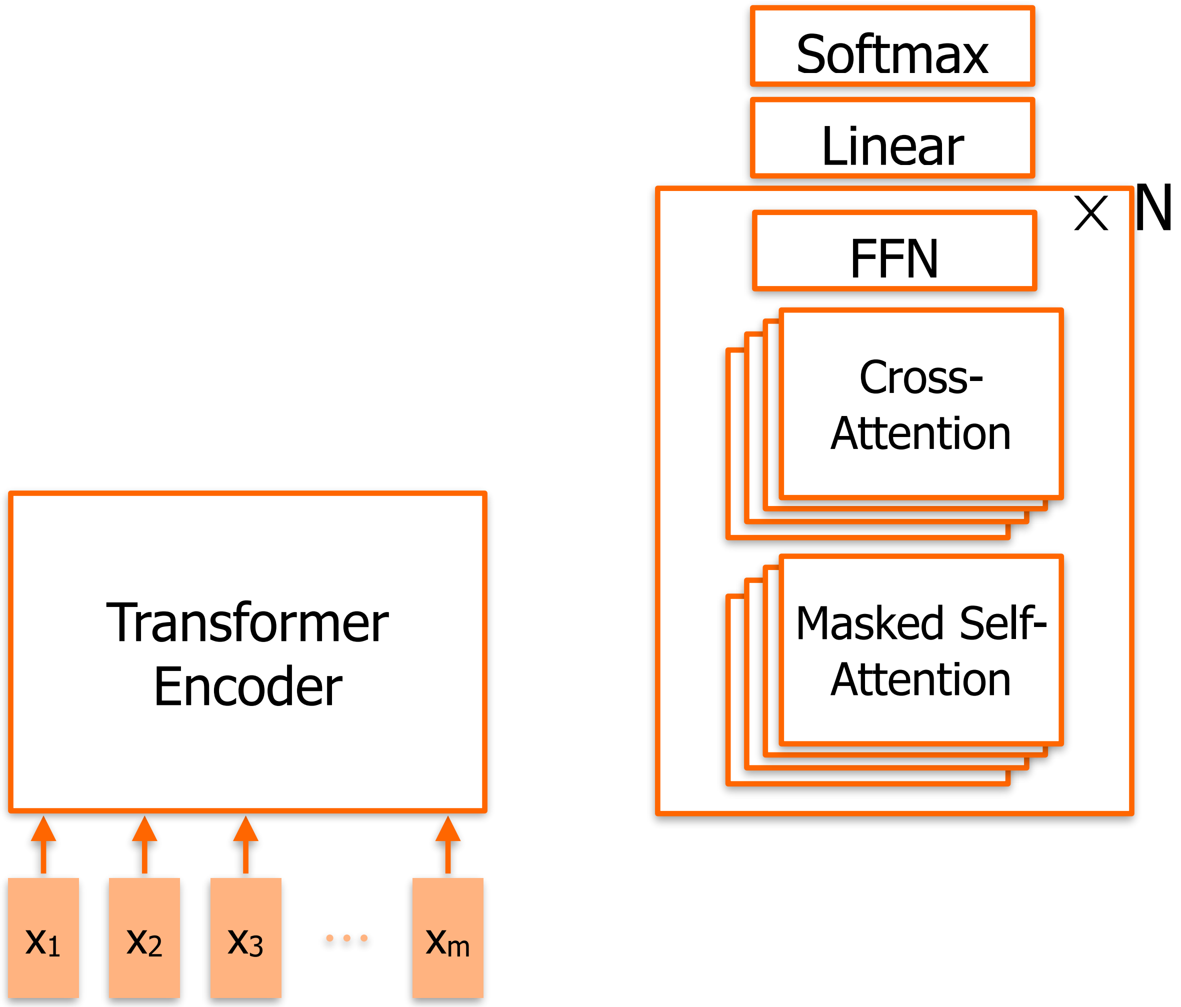

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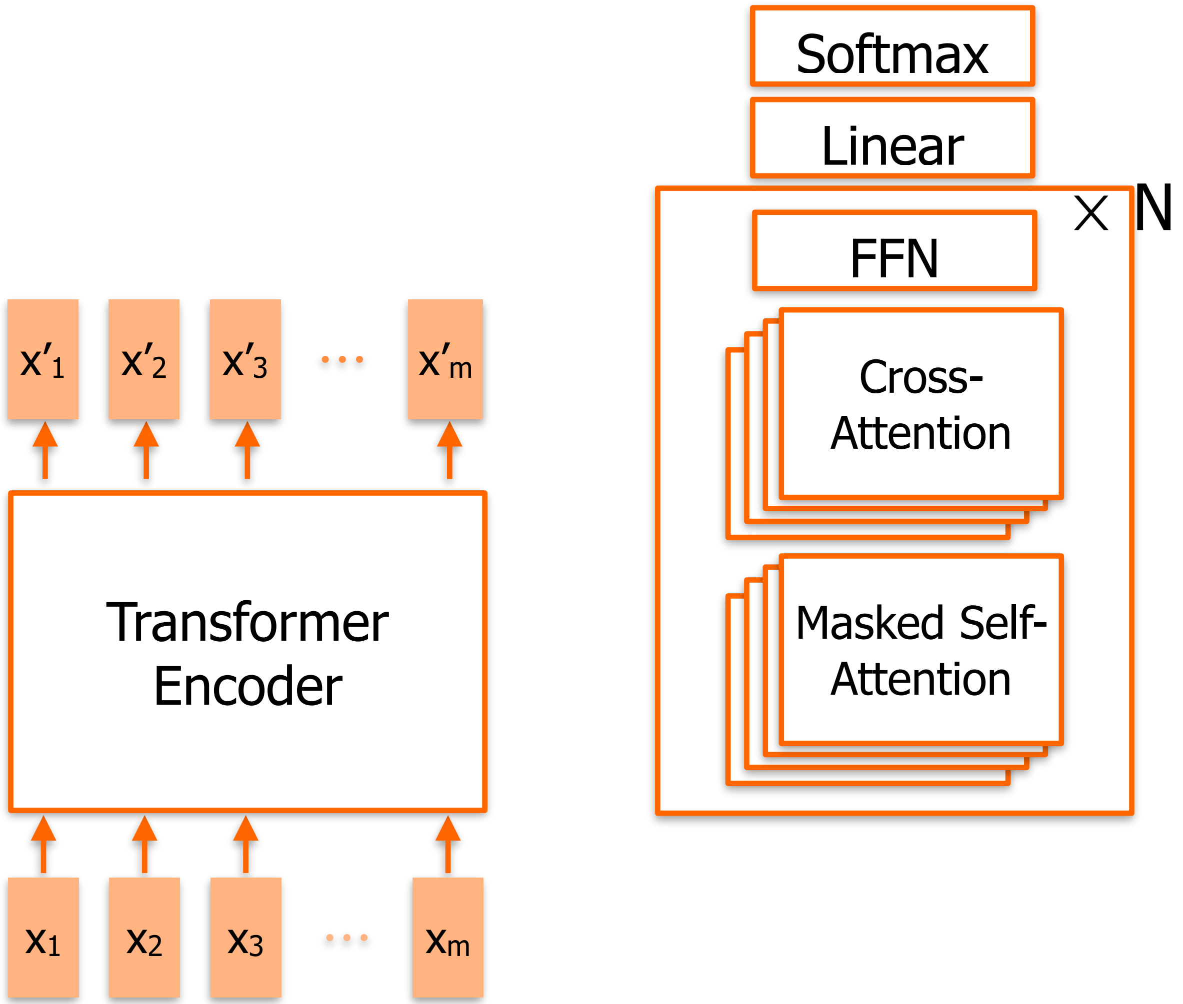

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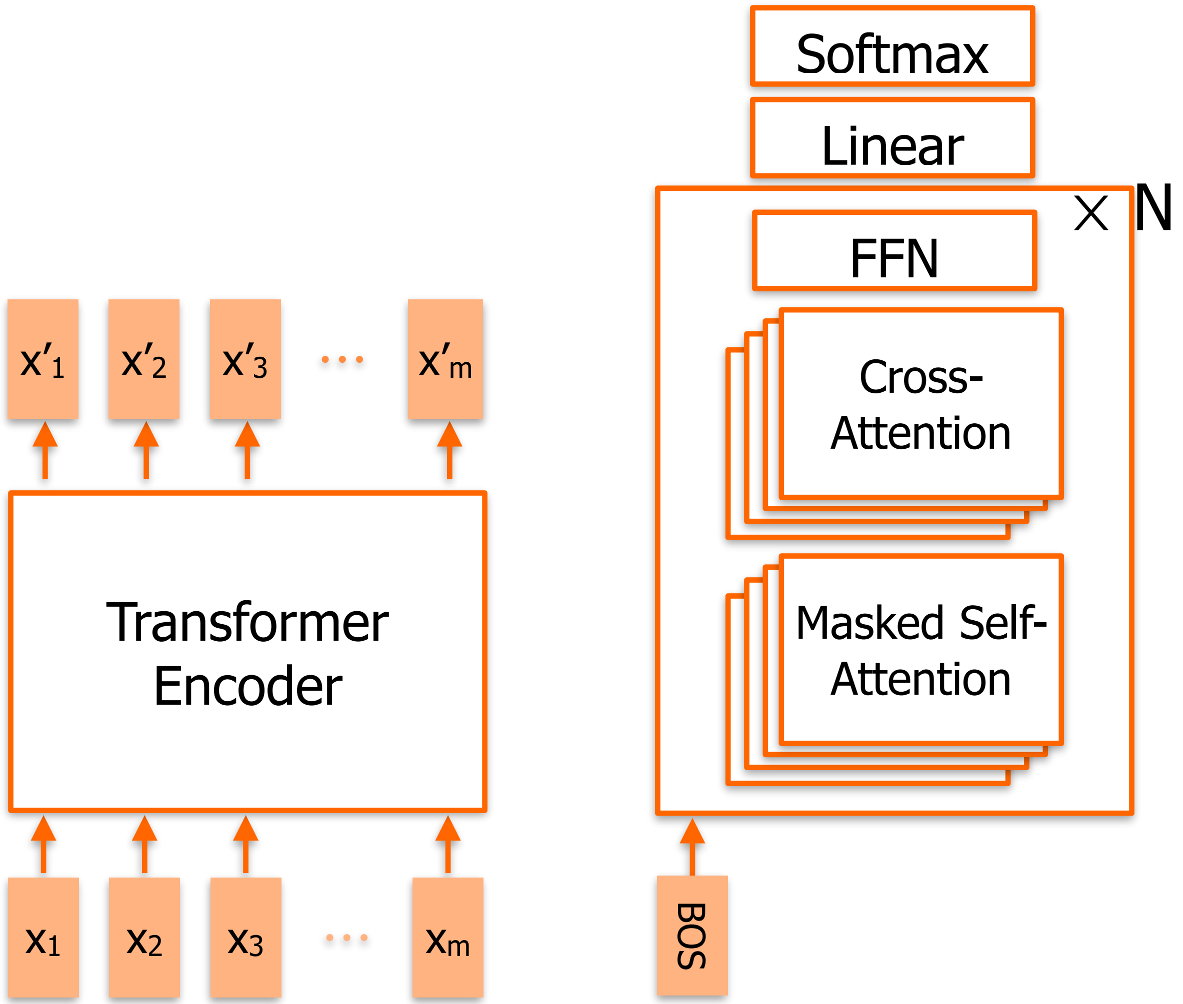

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- Decoder is **autoregressive**, i.e.,
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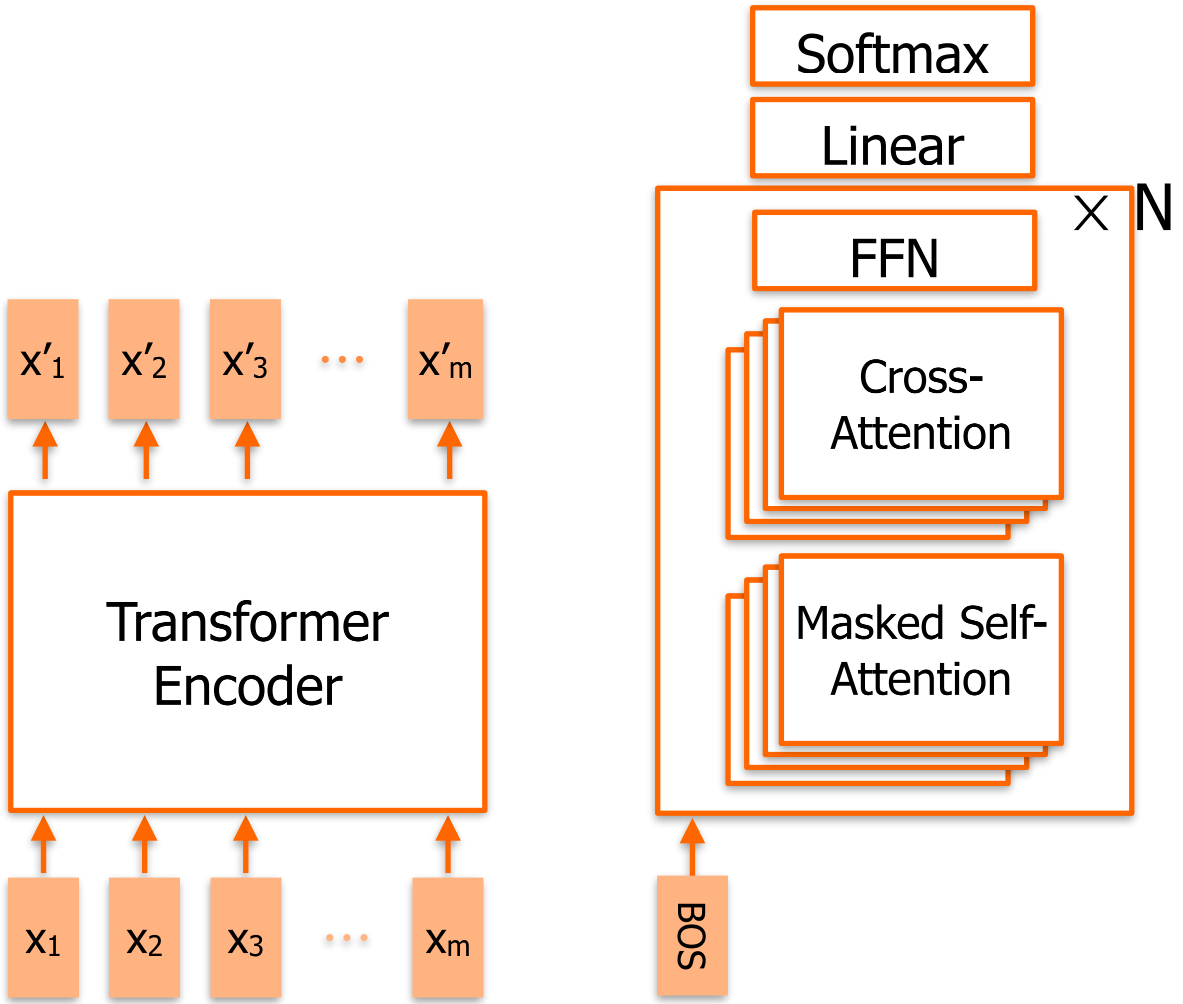

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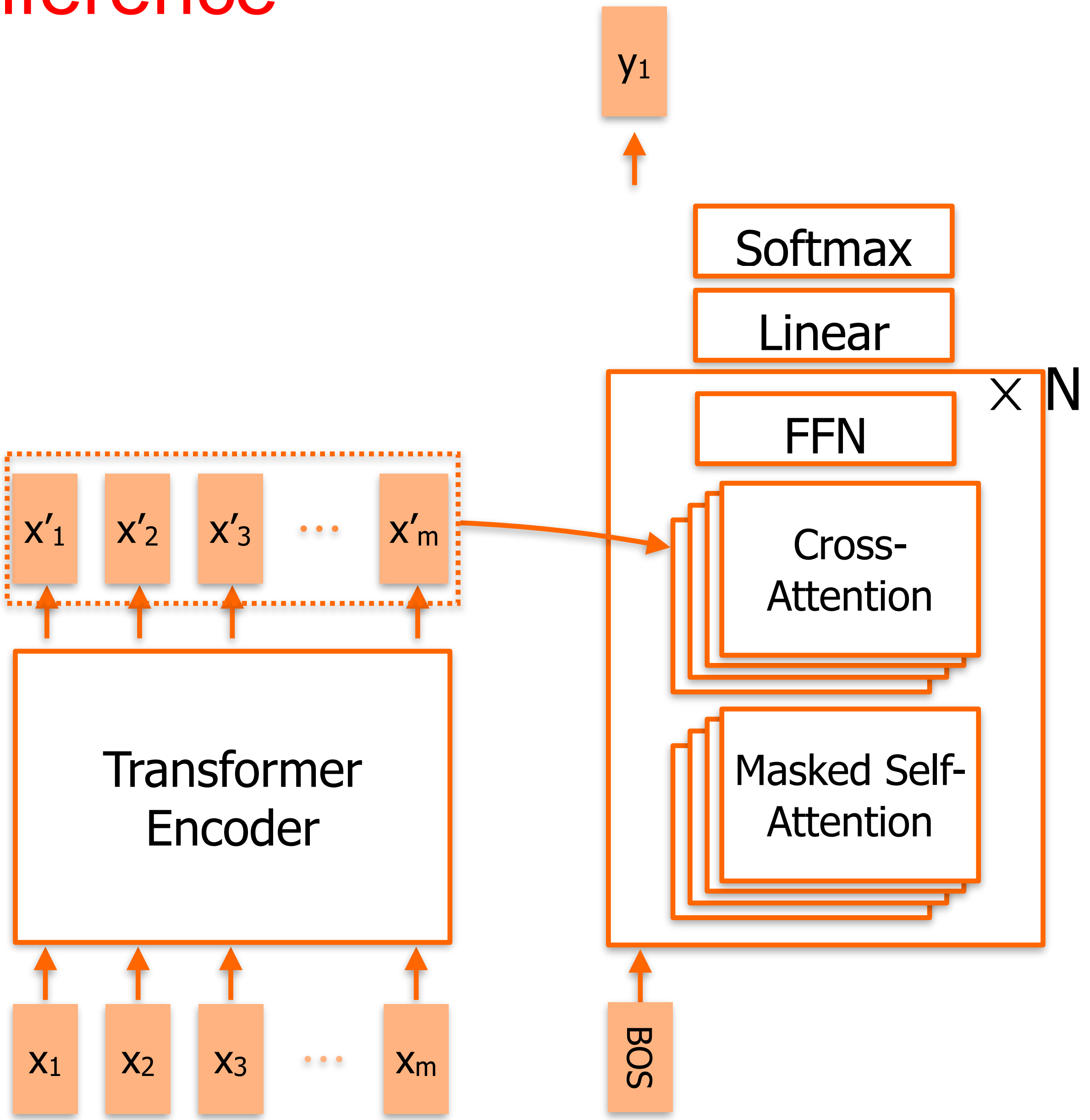

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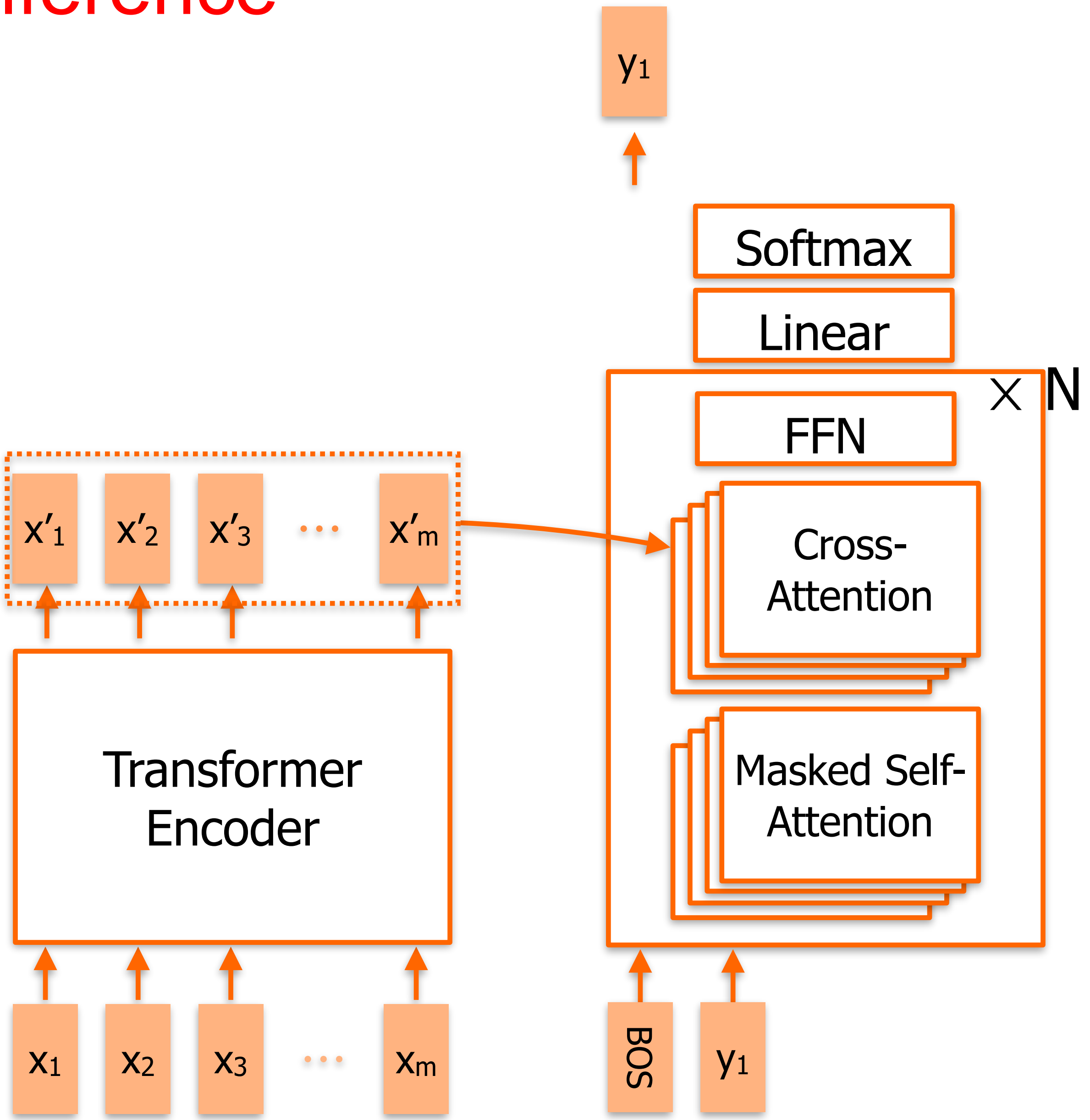

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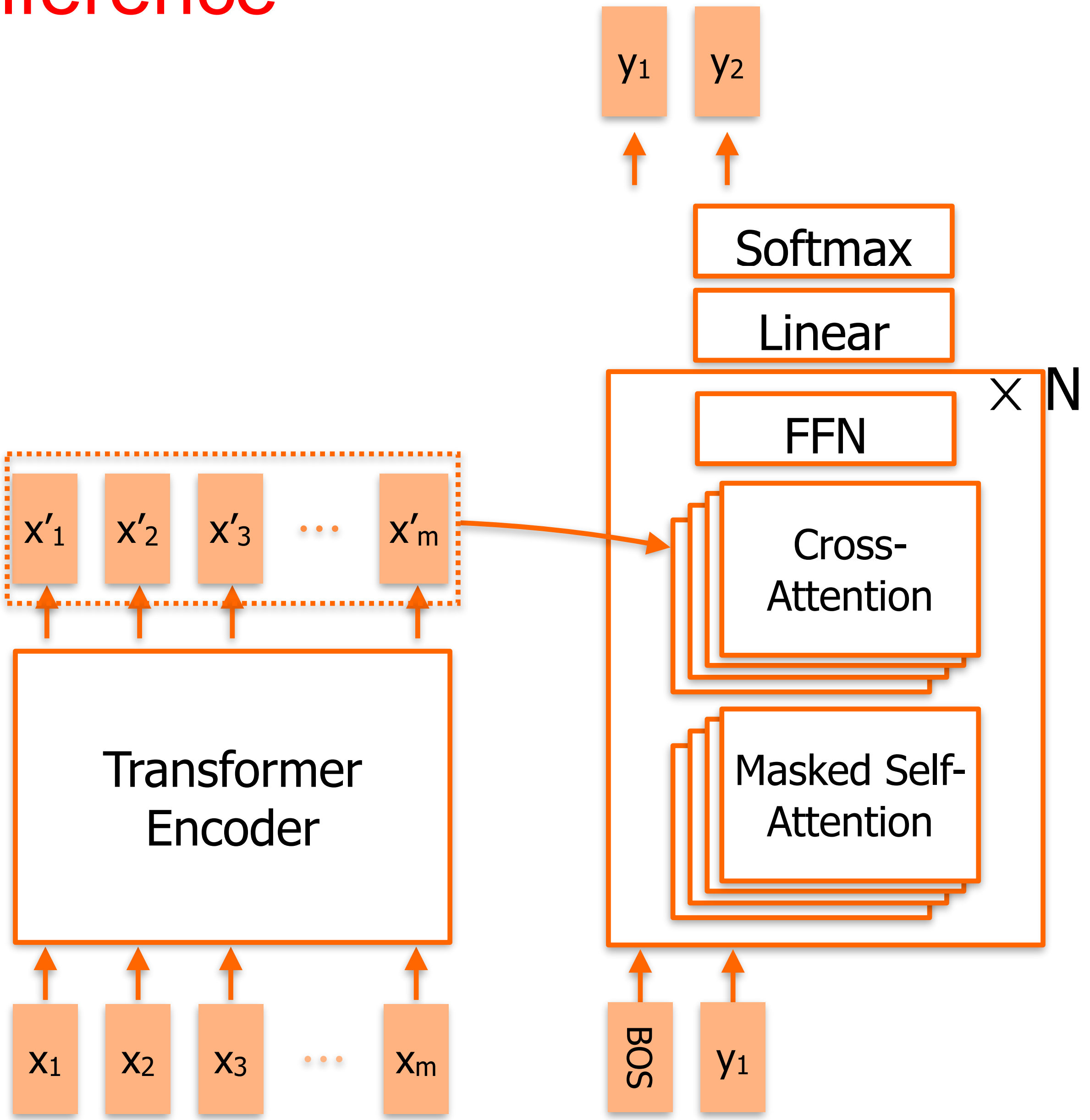

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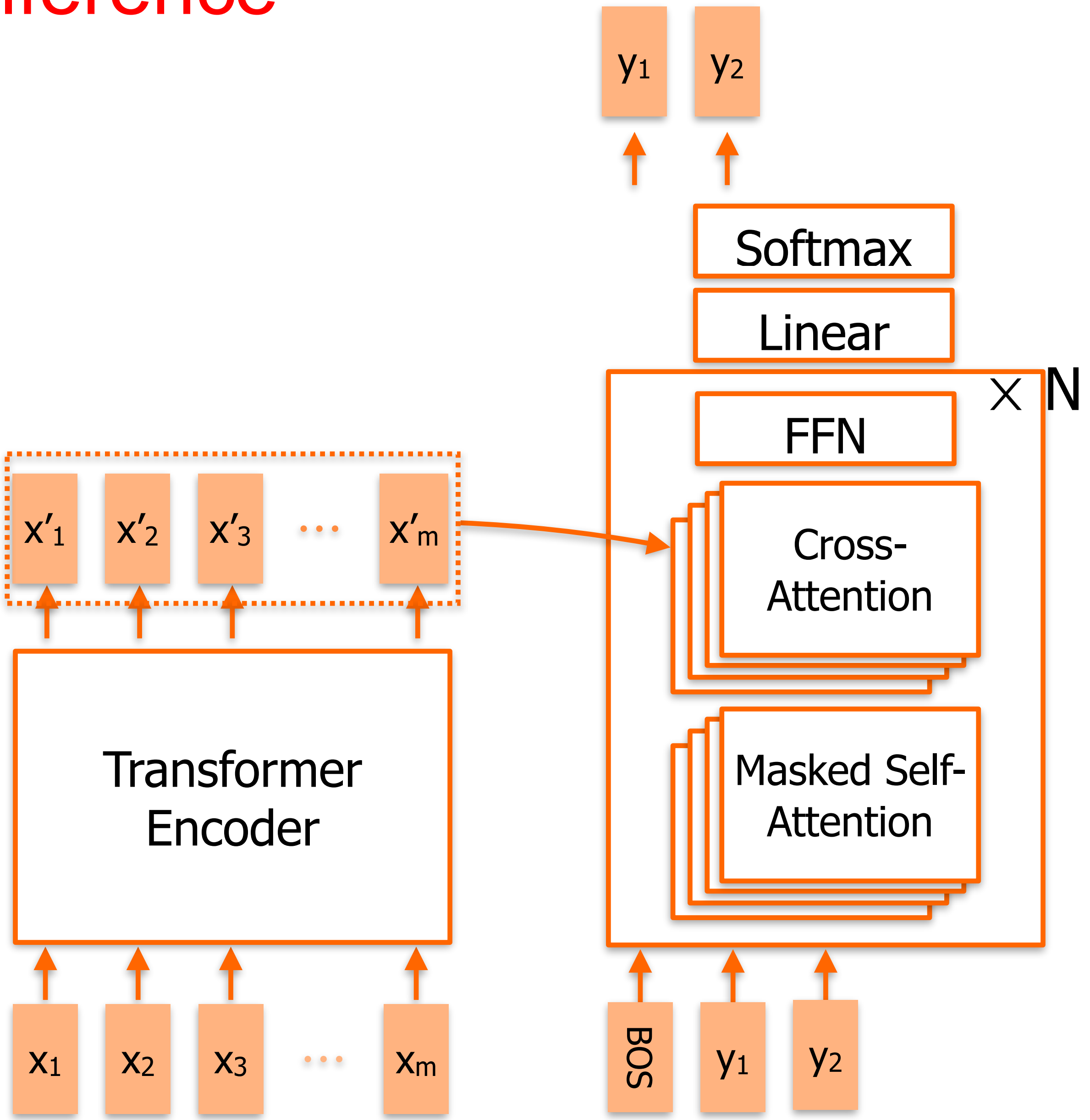

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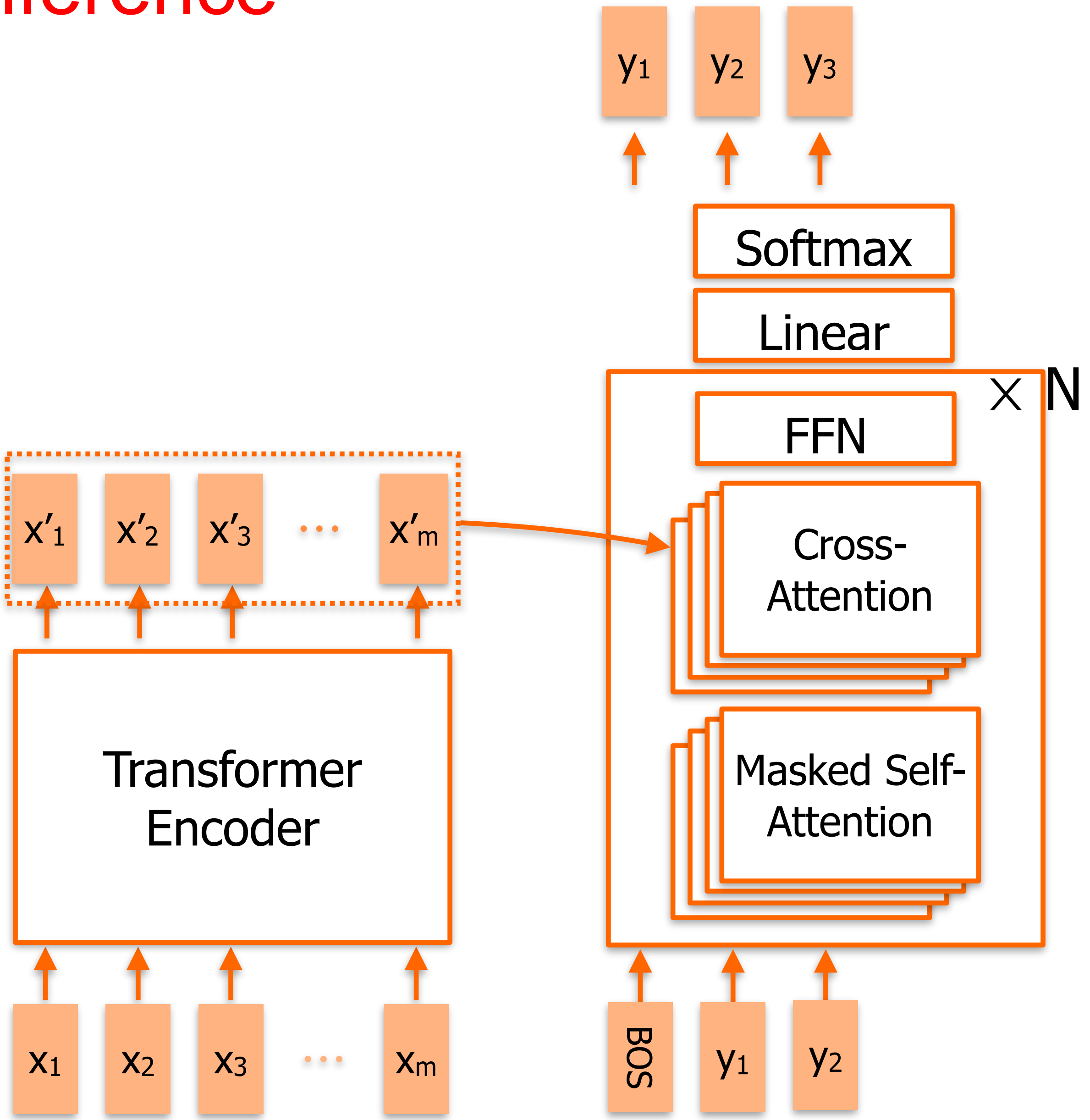

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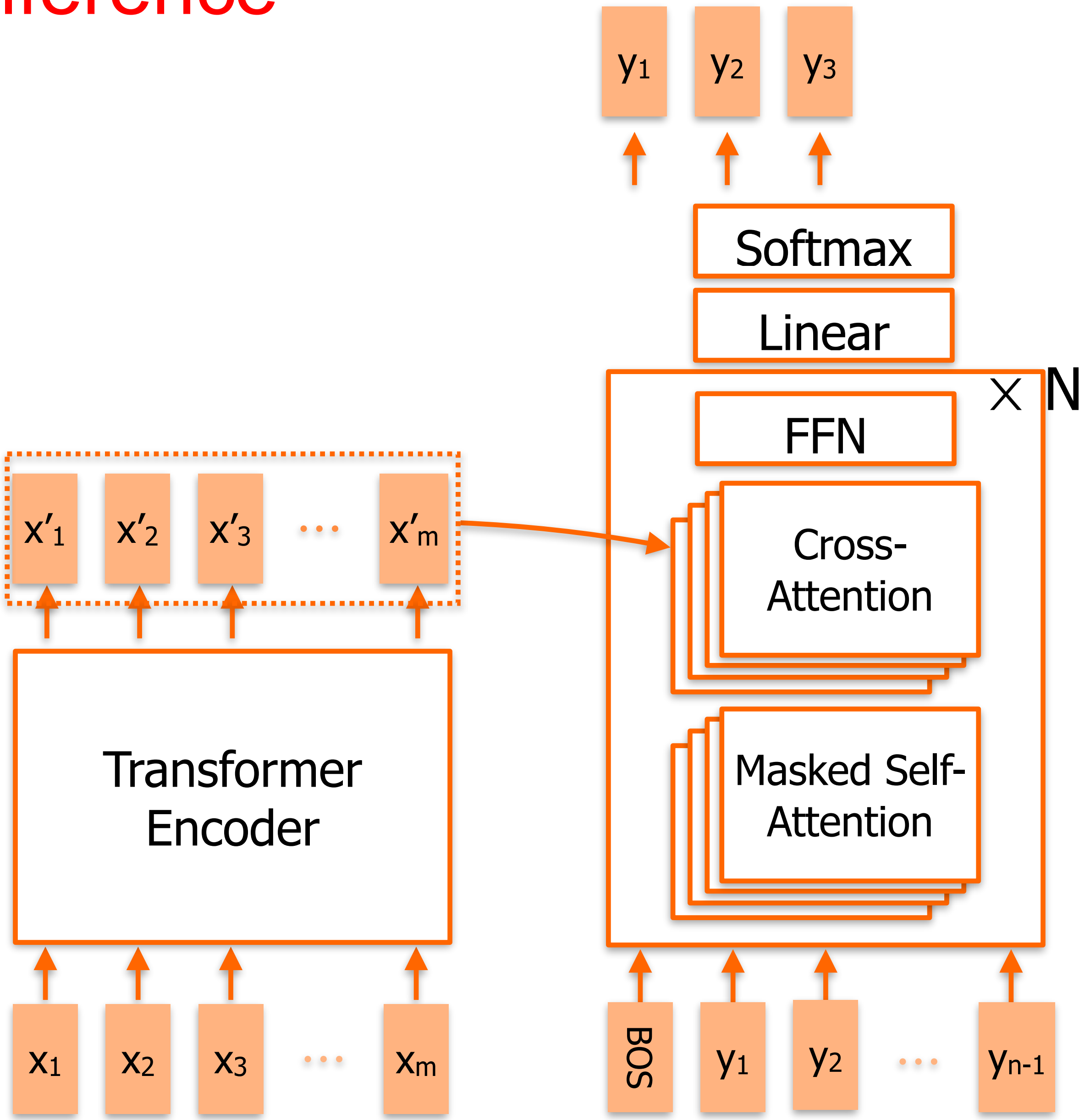

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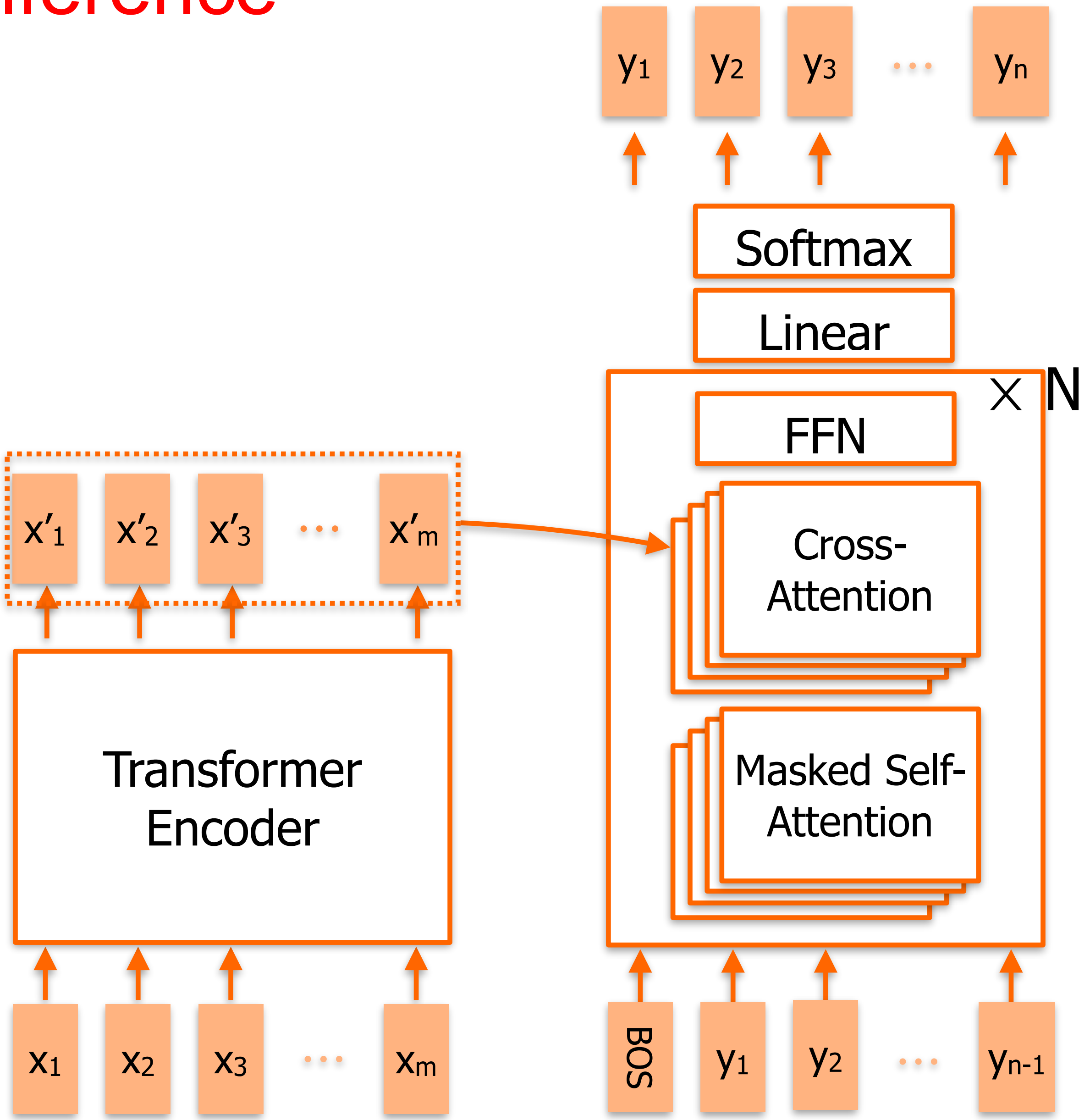

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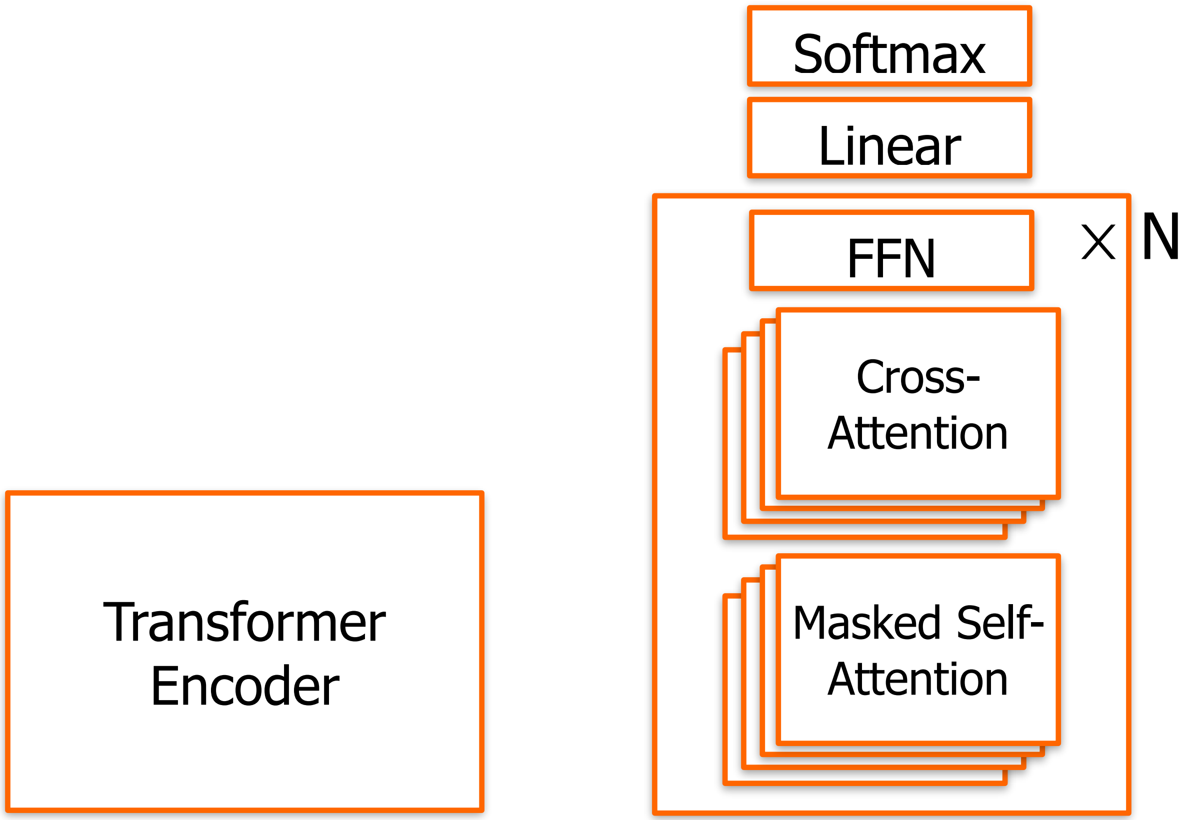

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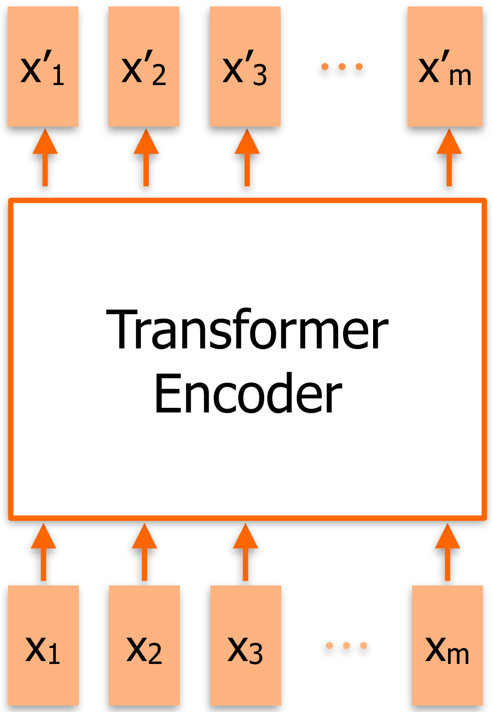

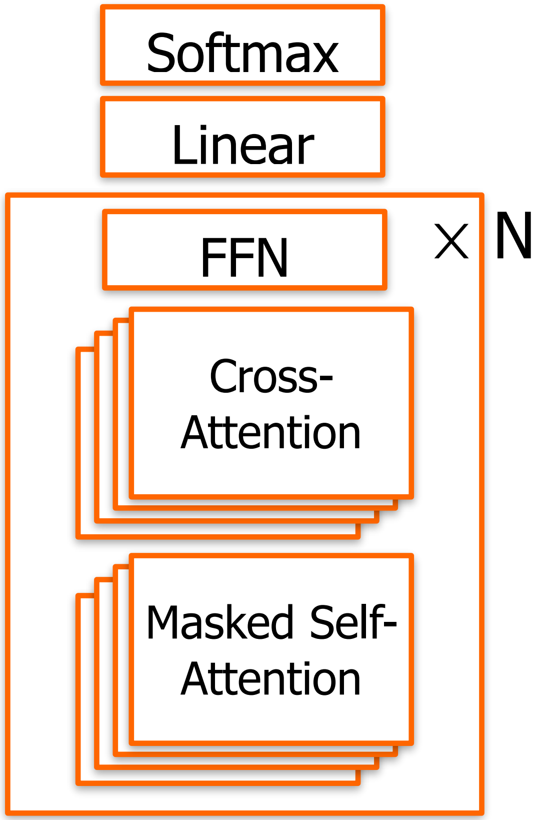

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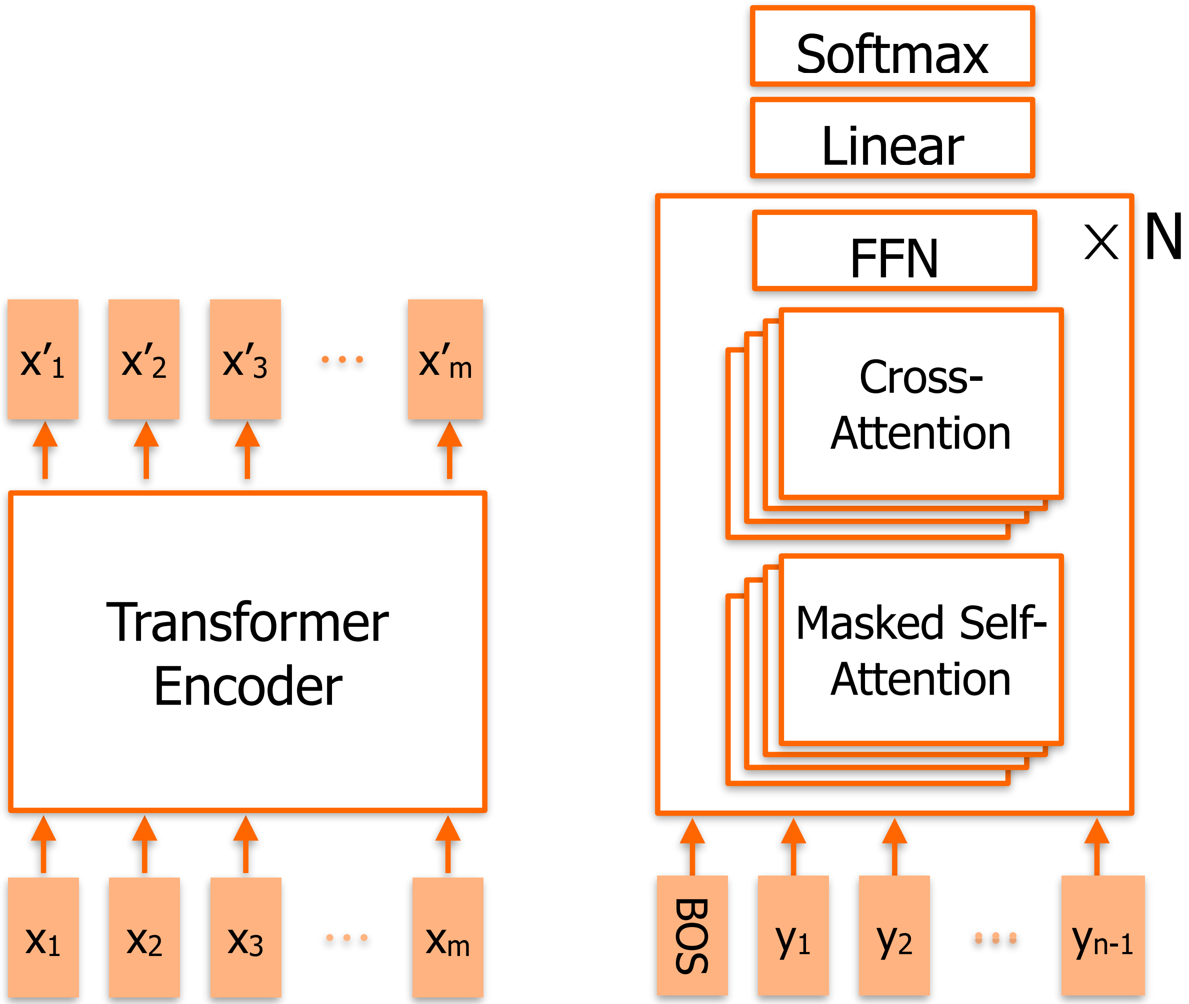

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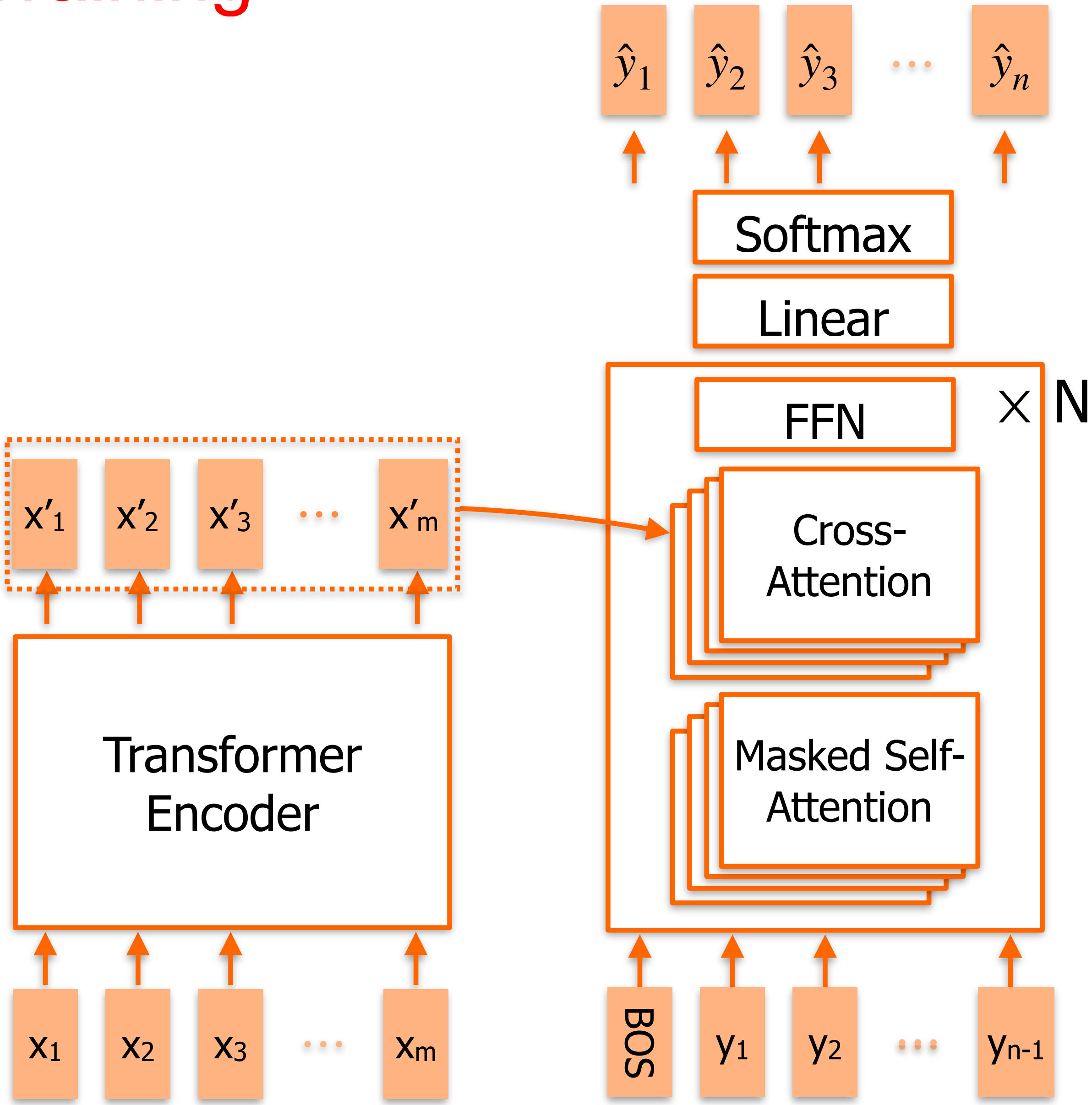

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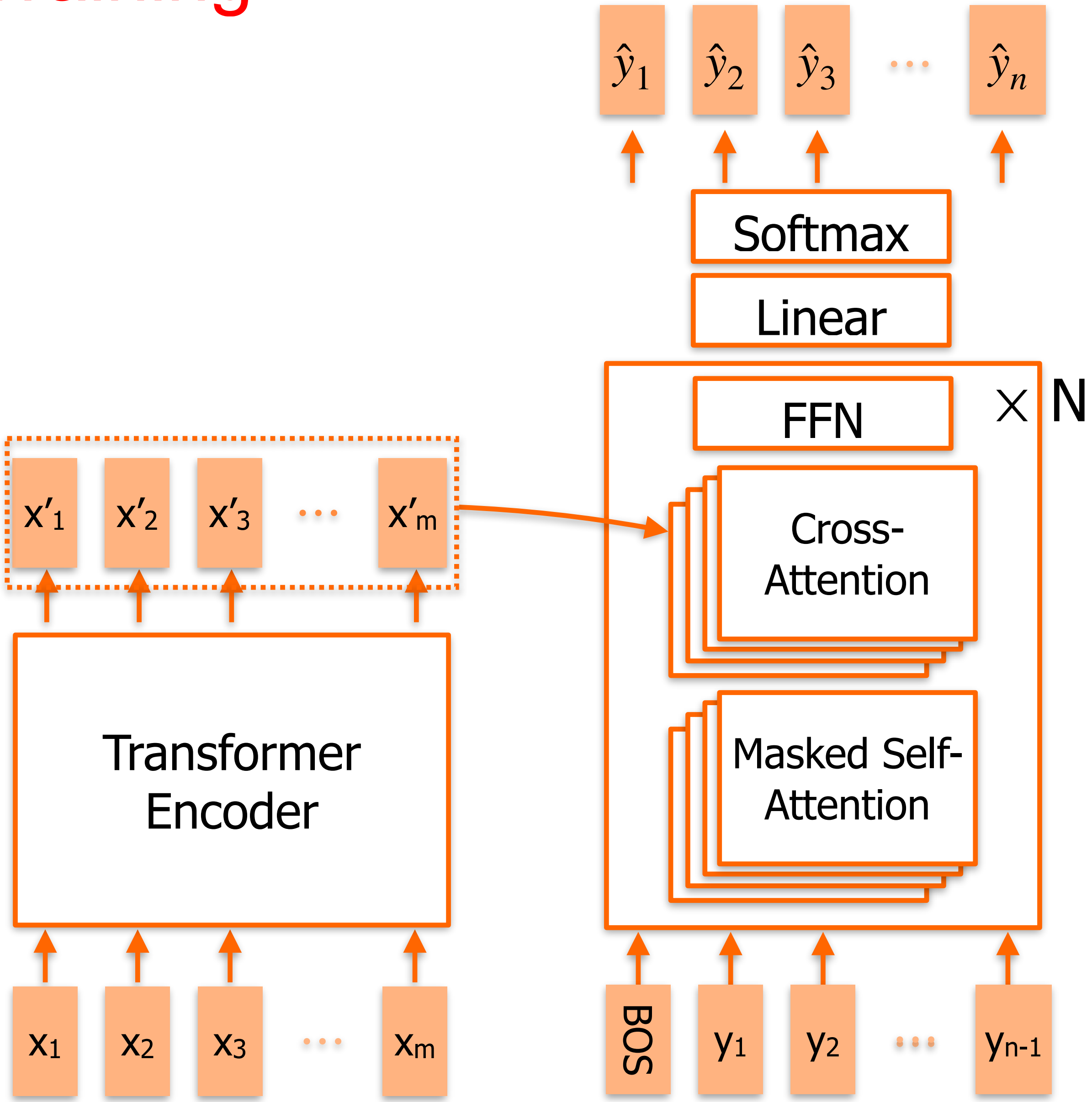

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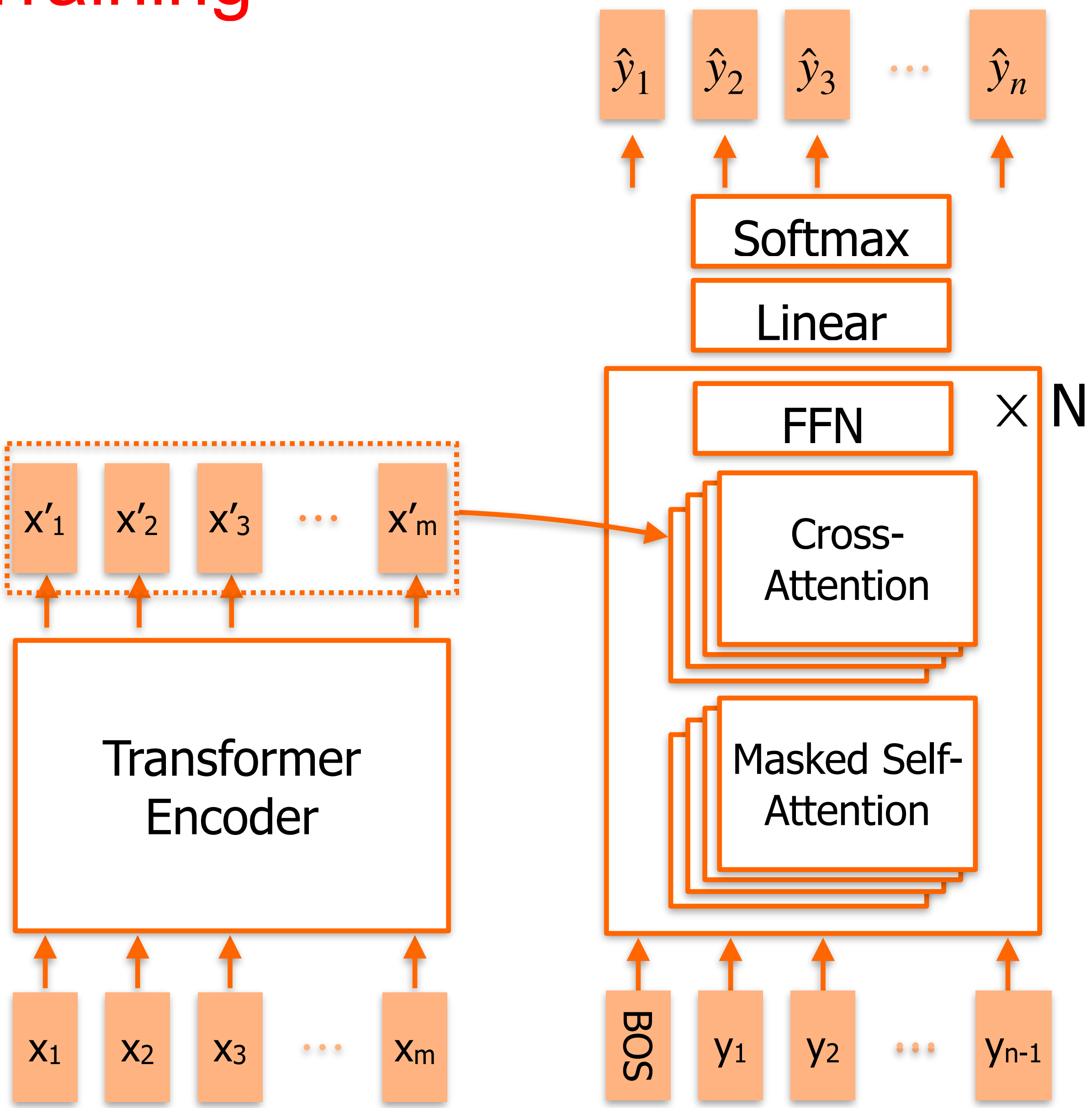
  - A: Masked self-attention prevents using the information of y_{t+i} with $i \geq 1$.



Summary

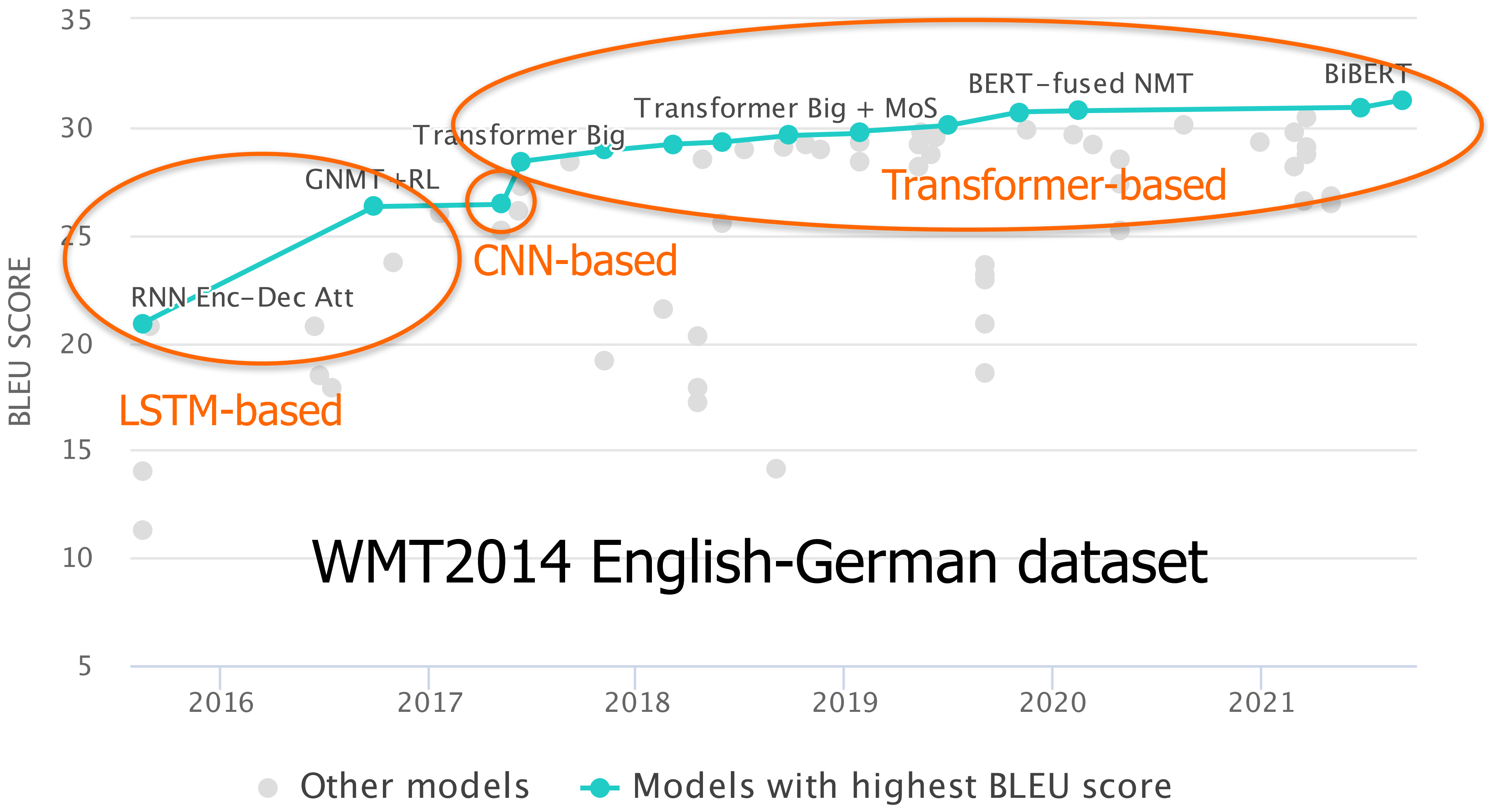
- Transformer encoder and decoder are based on self-attention.
- Decoder uses cross-attention.
- Masked self-attention in the decoder allows for parallel processing.

Questions?

Transformer Applications

- Background
- Transformers
- Transformer Applications
  - Machine Translation (vanilla Transformer)
  - Text Classification (BERT)
  - Text Generation (GPT, ChatGPT)
  - Image Classification (ViT)
- Multimodal Learning

Machine Translation (Transformer)



https://paperswithcode.com/sota/machine-translation-on-wmt2014-english-german

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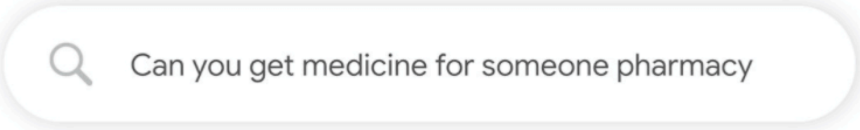

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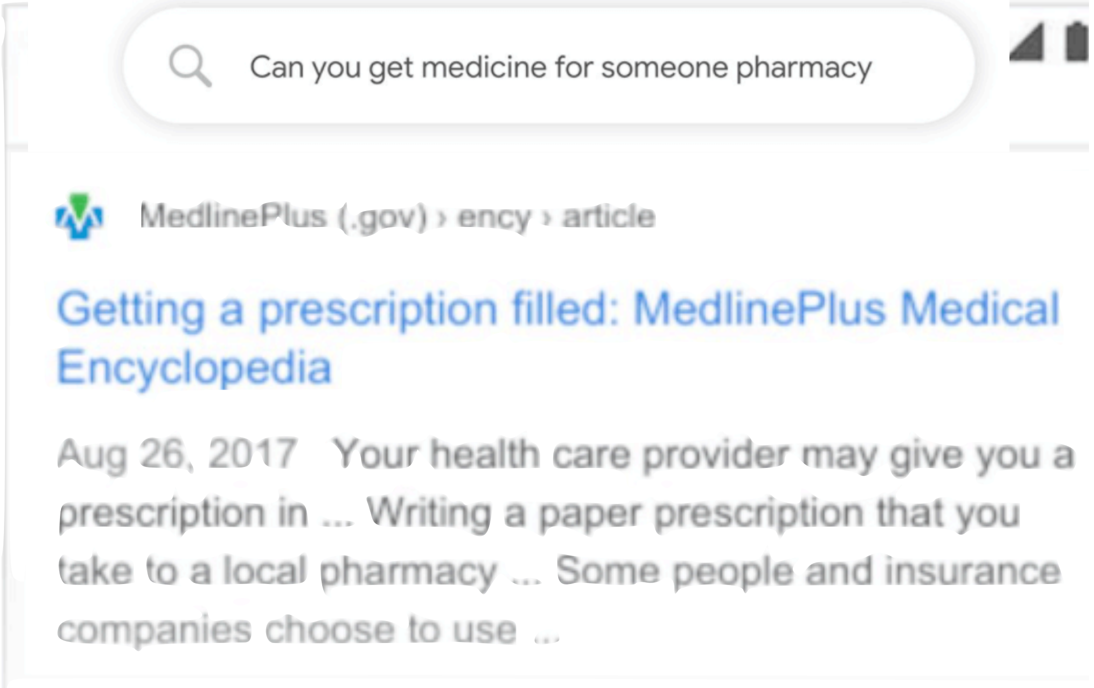

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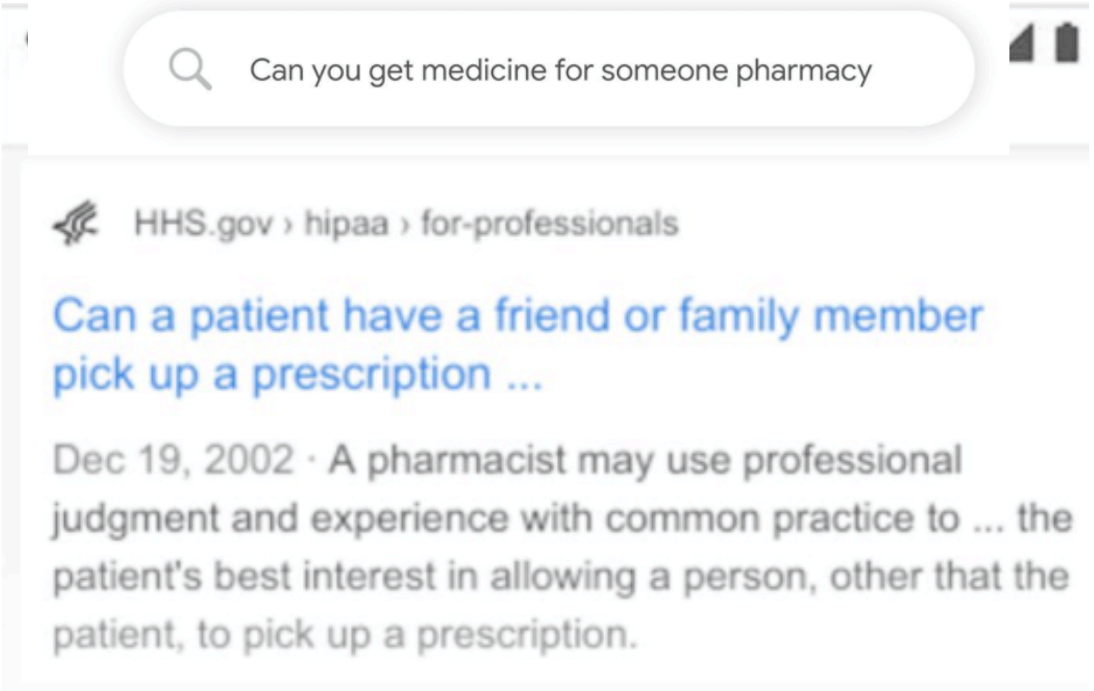

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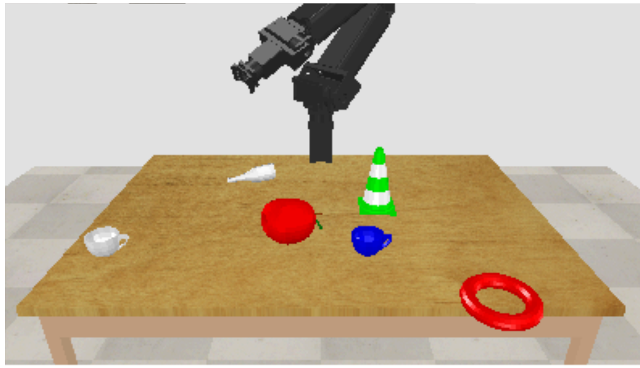

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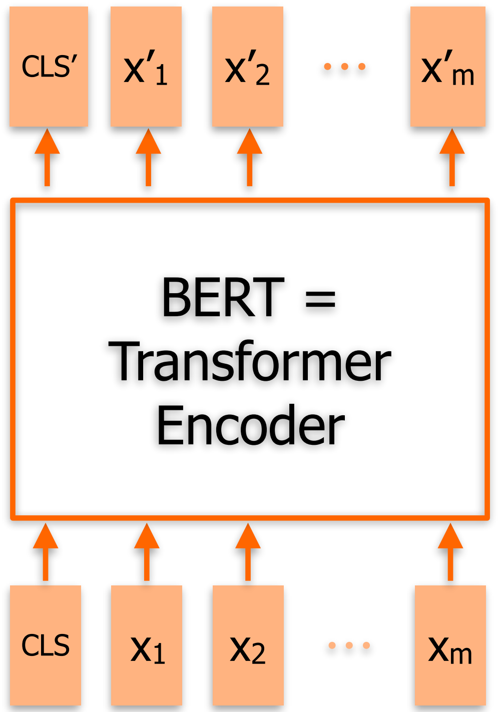

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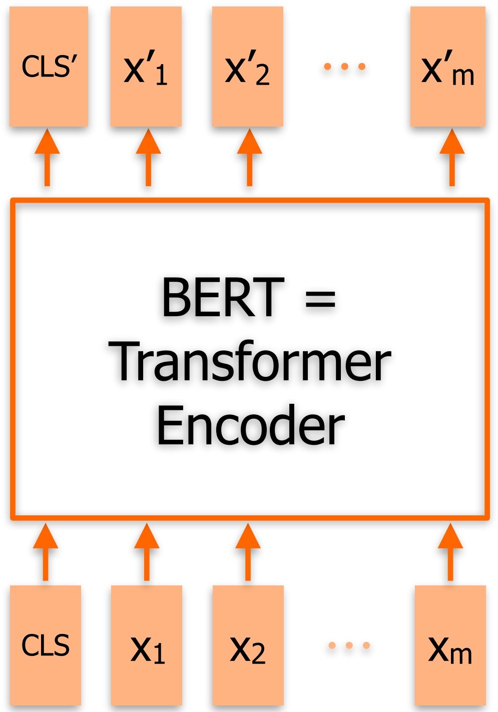

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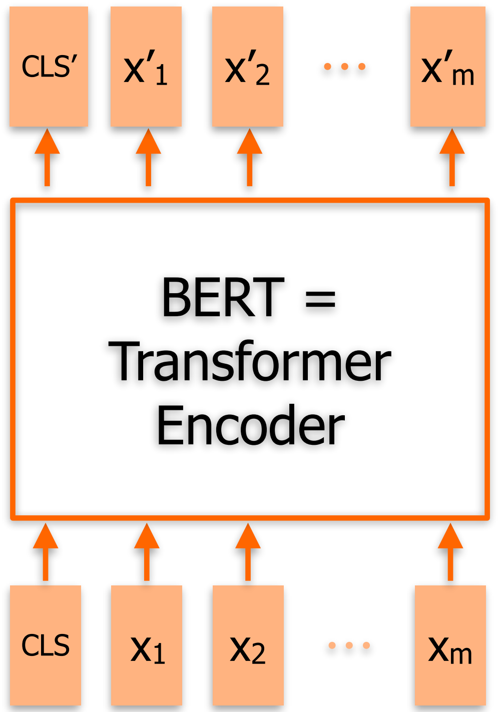

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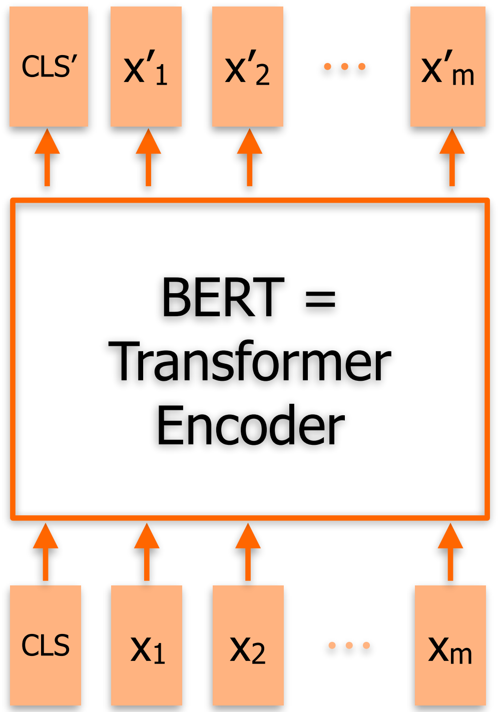

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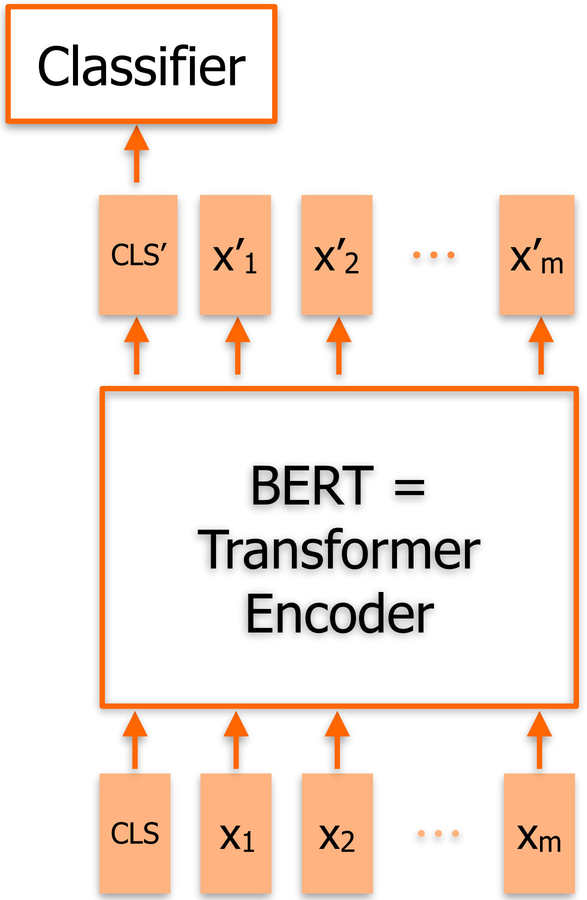

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- It achieved state-of-the-art performance on three classification tasks:
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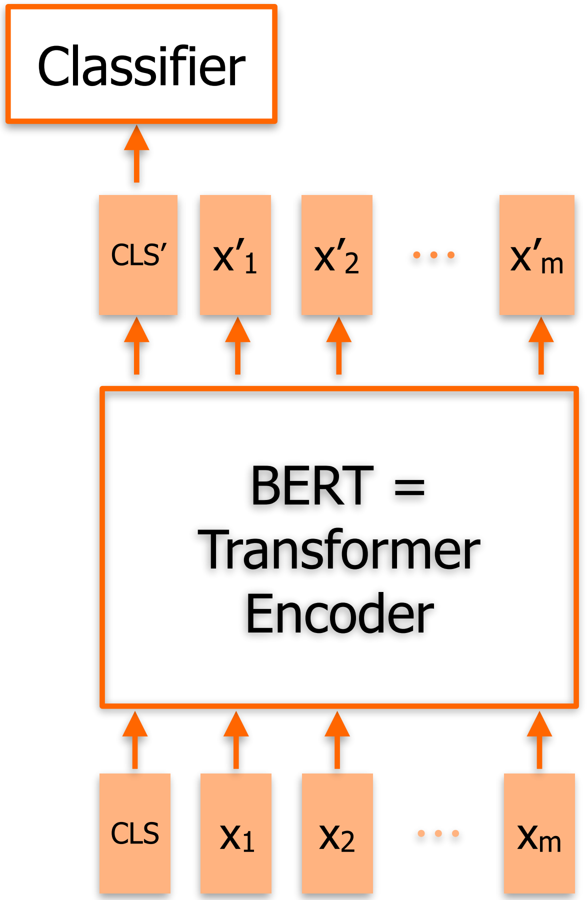
  - GLUE (General Language Understanding Evaluation) a benchmark suit of nine tasks.



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This is a poem written by Robert Frost about the perils of machine learning.
Alas! The machines are here.
They'll eat our brains and take our jobs,
They'll do our thinking for us,
And all that we'll be able to do
Is program them.
Alas! Here comes the Machine

1. https://transformer.huggingface.co/doc/gpt2-large
2. https://blog.andrewcantino.com/blog/2021/04/21/prompt-engineering-tips-and-tricks/

ChatGPT

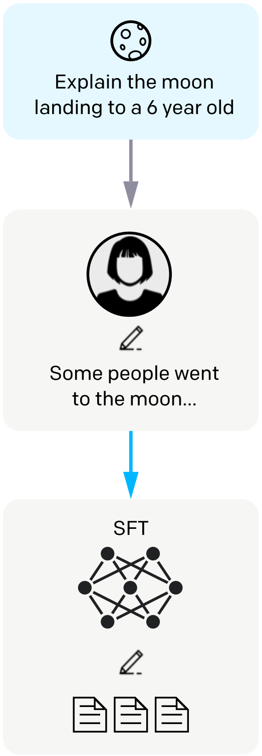
Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3 with supervised learning.



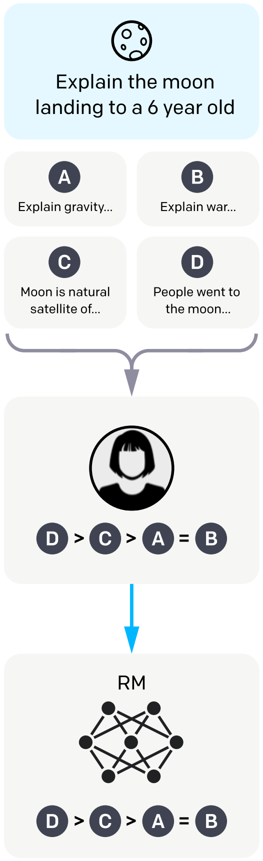
Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

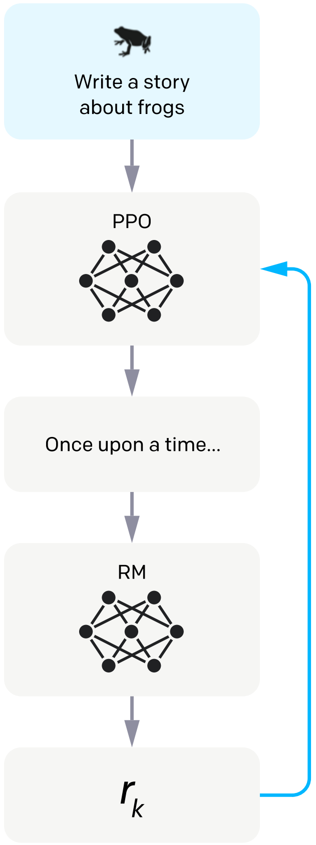
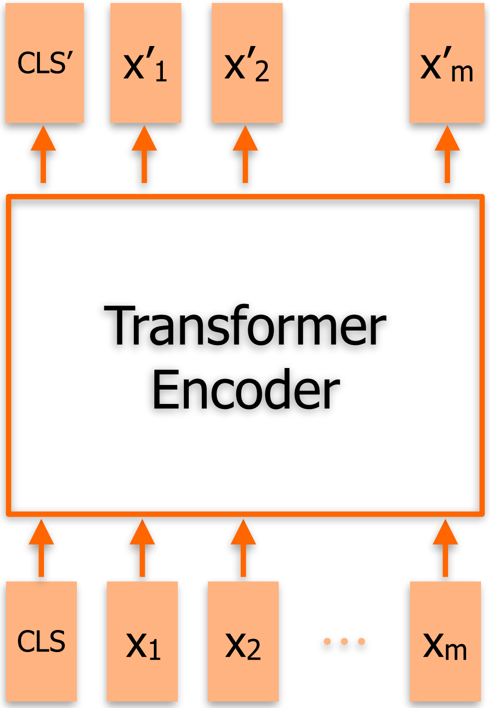


Image Classification (Vision Transformer)

- Uses Transformer encoder.



 https://en.wikipedia.org/wiki/Vision_transformer#/media/File:Vision_Transformer.gif

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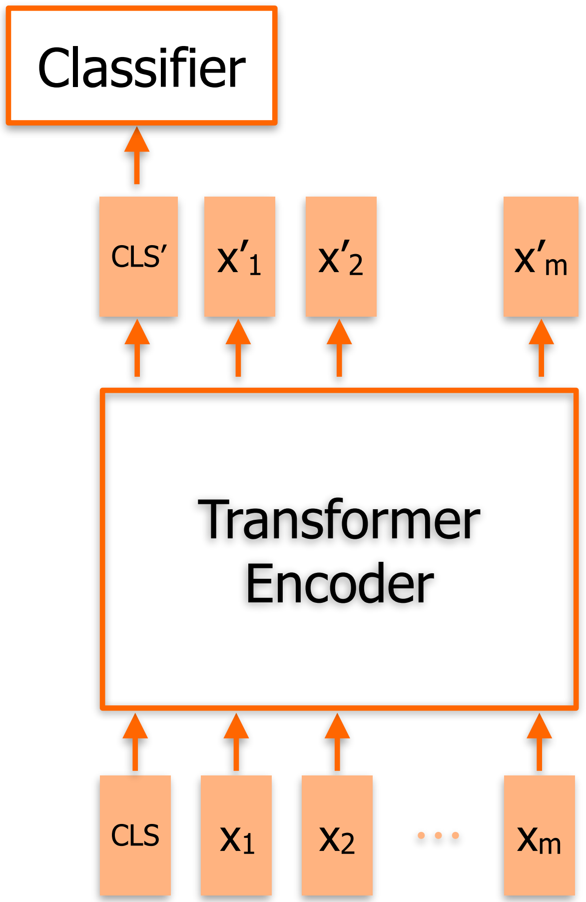

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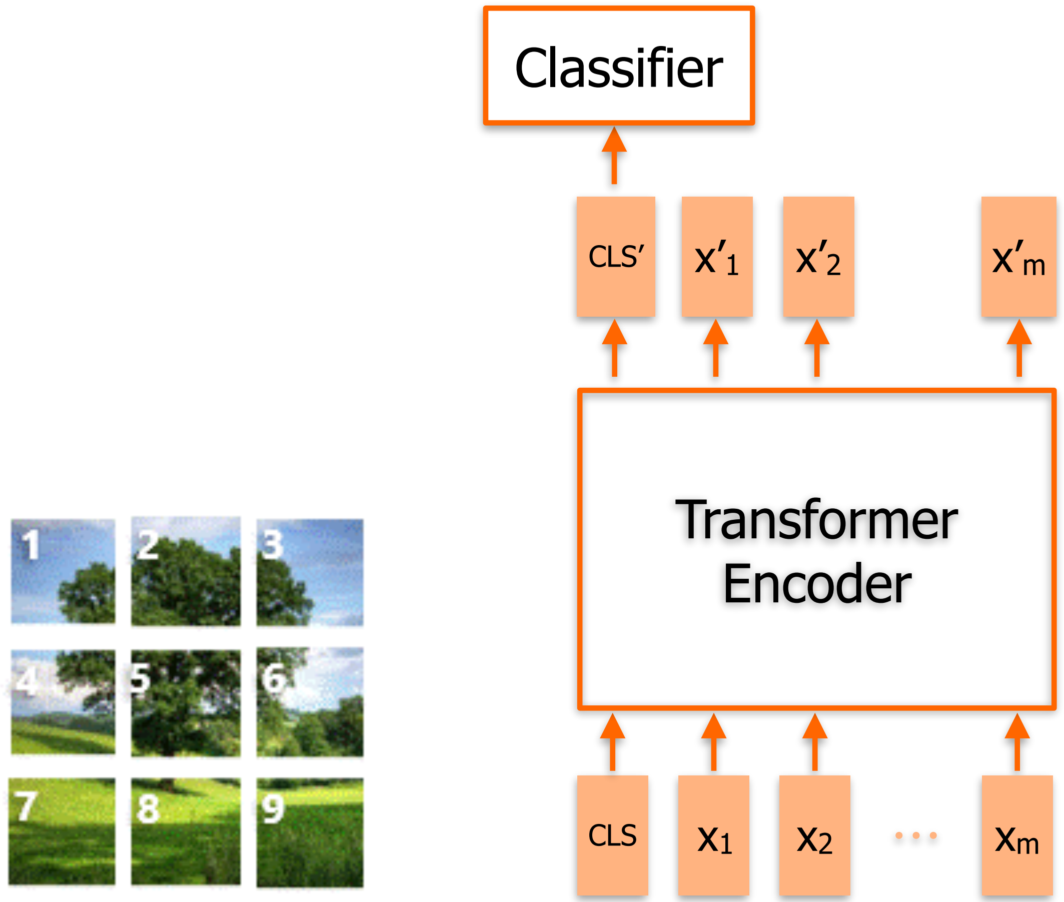
Image Classification (Vision Transformer)

- Uses Transformer encoder.
- Input image is tiled into sections.



Ground-truth label: Tree

https://en.wikipedia.org/wiki/Vision_transformer#/media/File:Vision_Transformer.gif

Image Classification (Vision Transformer)

- Uses Transformer encoder.
- Input image is tiled into sections.
- The sections is turned into an embedding using a linear layer
- The results are fed to the Transformer encoder.

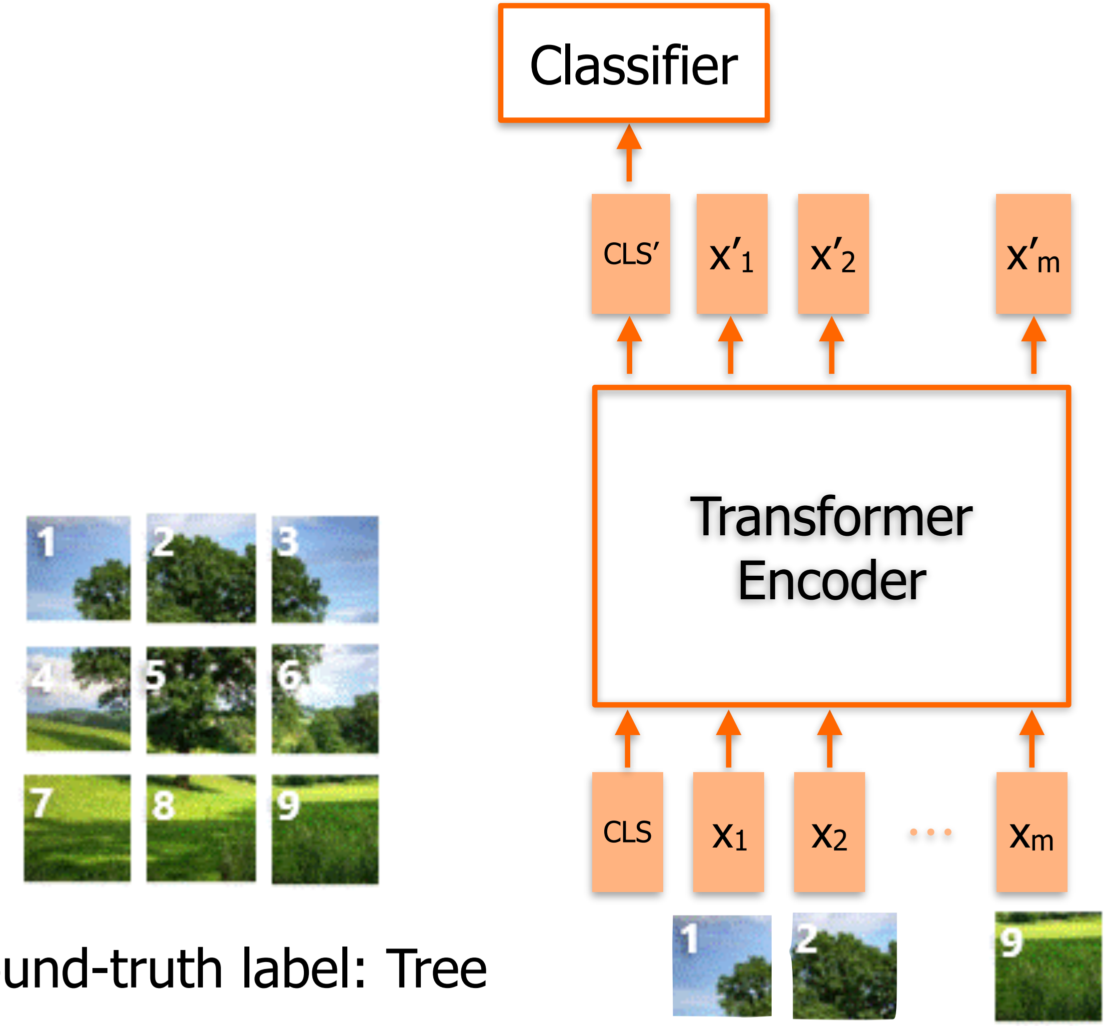


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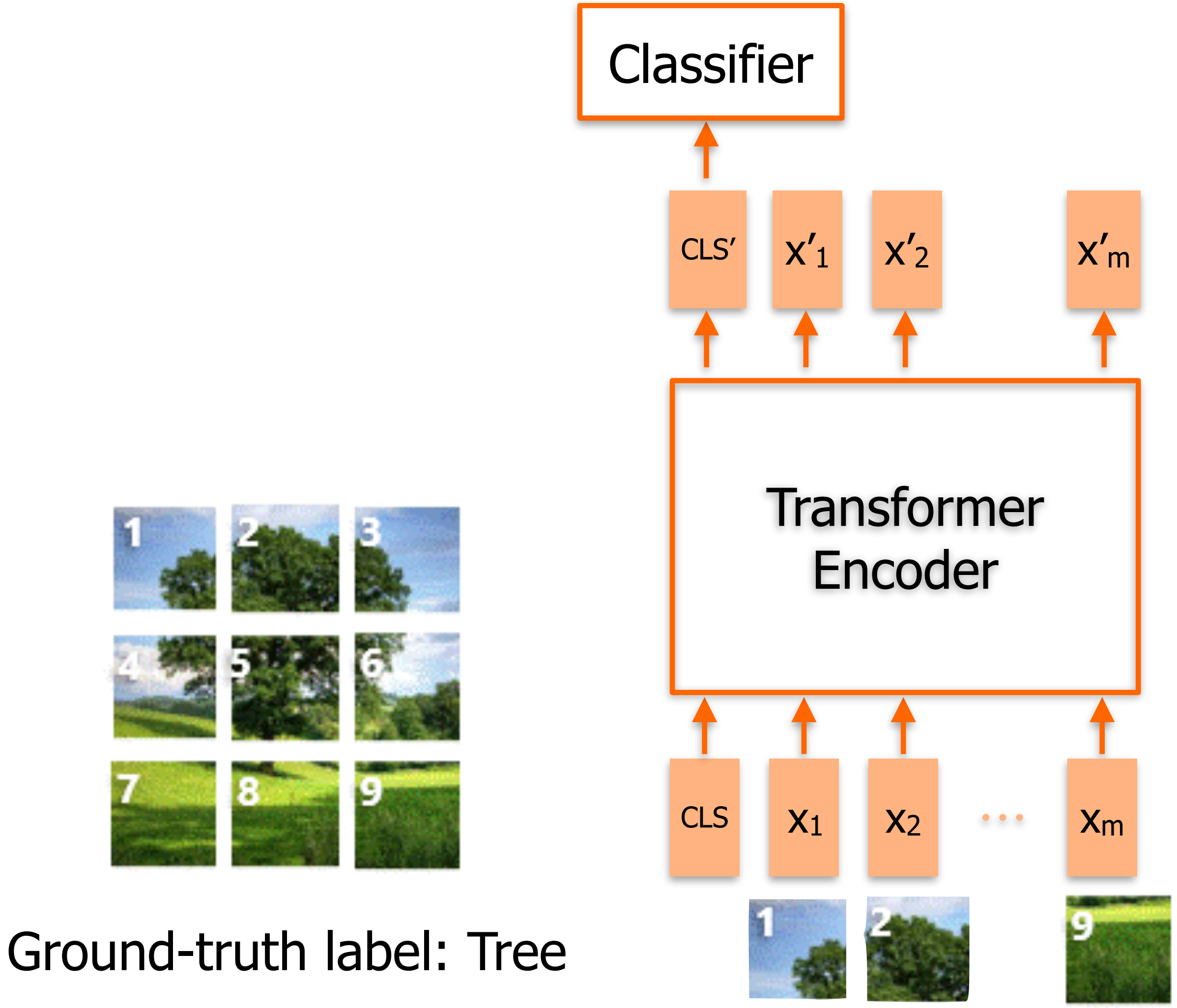
Image Classification (Vision Transformer)

- Uses Transformer encoder.
- Input image is tiled into sections.
- The sections is turned into an embedding using a linear layer
- The results are fed to the Transformer encoder.
- Vision Transformers are able to capture global and wider range relations.
- However, more training data is needed.



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Summary

- The Transformer architecture has been used in different applications.
- BERT is based on the Transformer encoder.
- GPT is based on the Transformer decoder.
- Vision Transformer uses image patches as input tokens.

Multimodal Learning

- Background
- Transformers
- Transformer Applications
- Multimodal Learning
  - Introduction
  - Vision and Language Integration Methods

Multimodal Learning

- In DL language and vision have been tackled separately until 2014.
- Integrating two or more modalities has recently gained increased attention.
  - language, vision, speech, sound, proprioception, …
- Some Multimodal (vision and language) tasks:
  - Image Captioning
  - Visual Question Answering
  - Image Retrieval
  - Language-to-Image Generation

Image Captioning

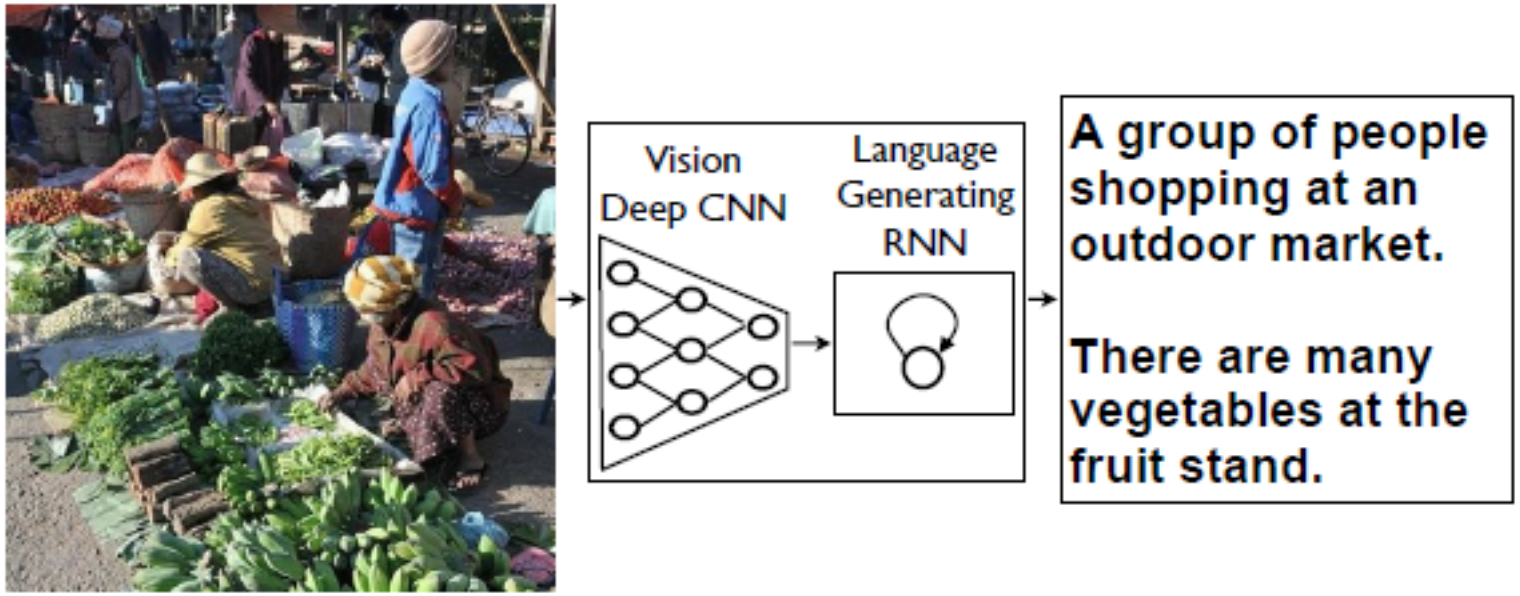
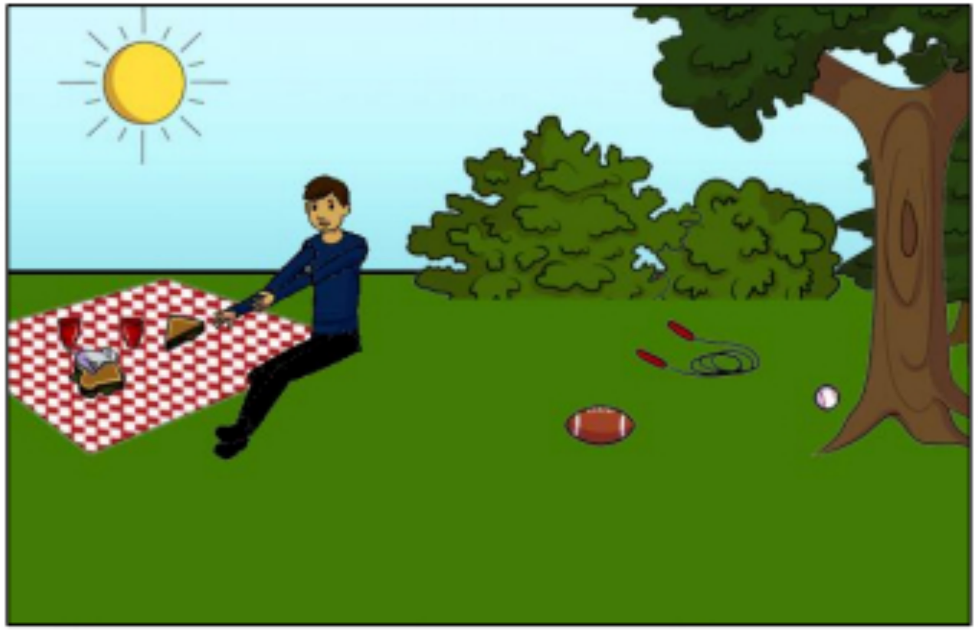


Image Captioning

O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, "Show and Tell: A Neural Image Caption Generator," CVPR 2015

Visual Question Answering



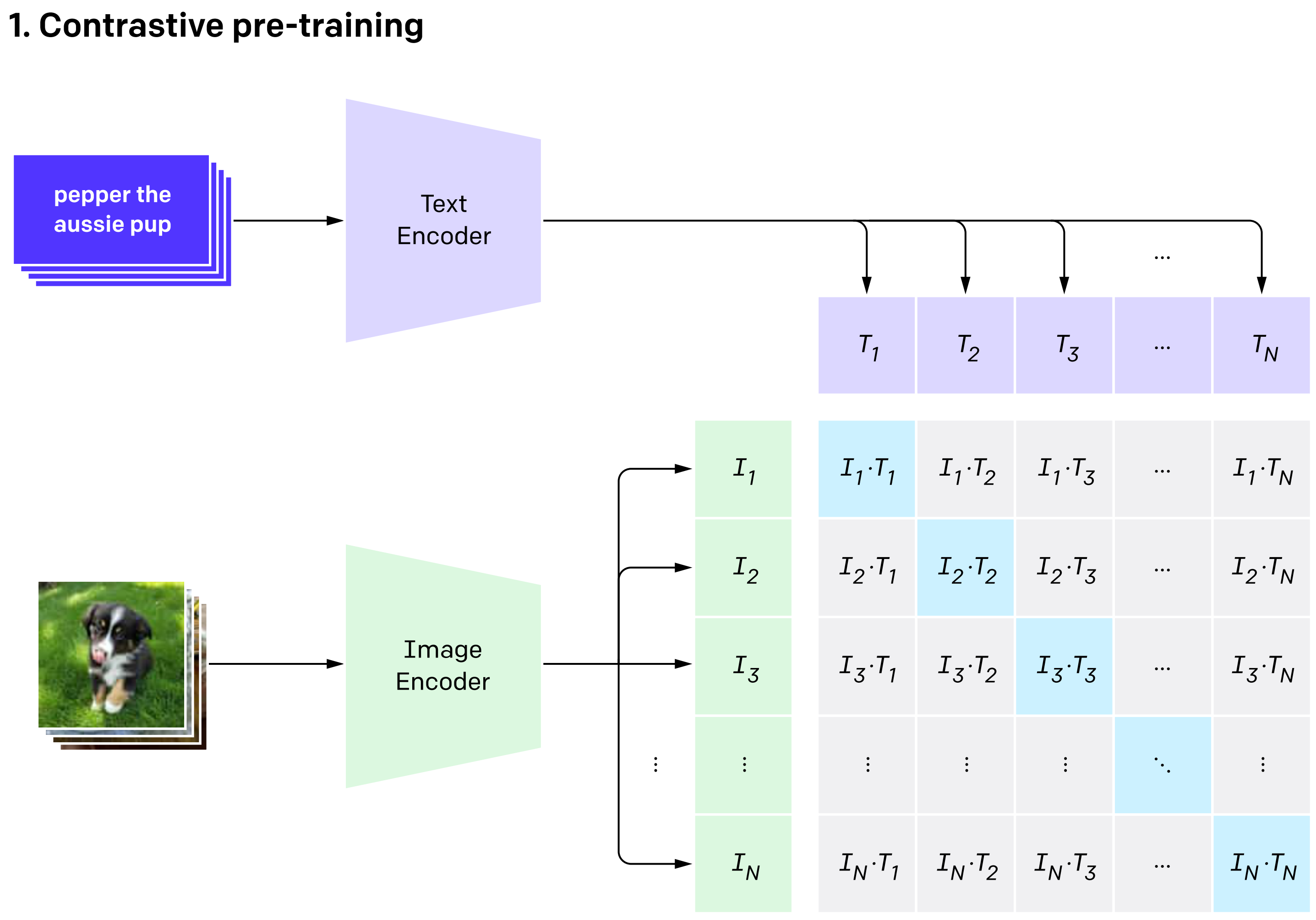
Is this person expecting company?
What is just under the tree?

Does it appear to be rainy?
Does this person have 20/20 vision?

Visual Question Answering

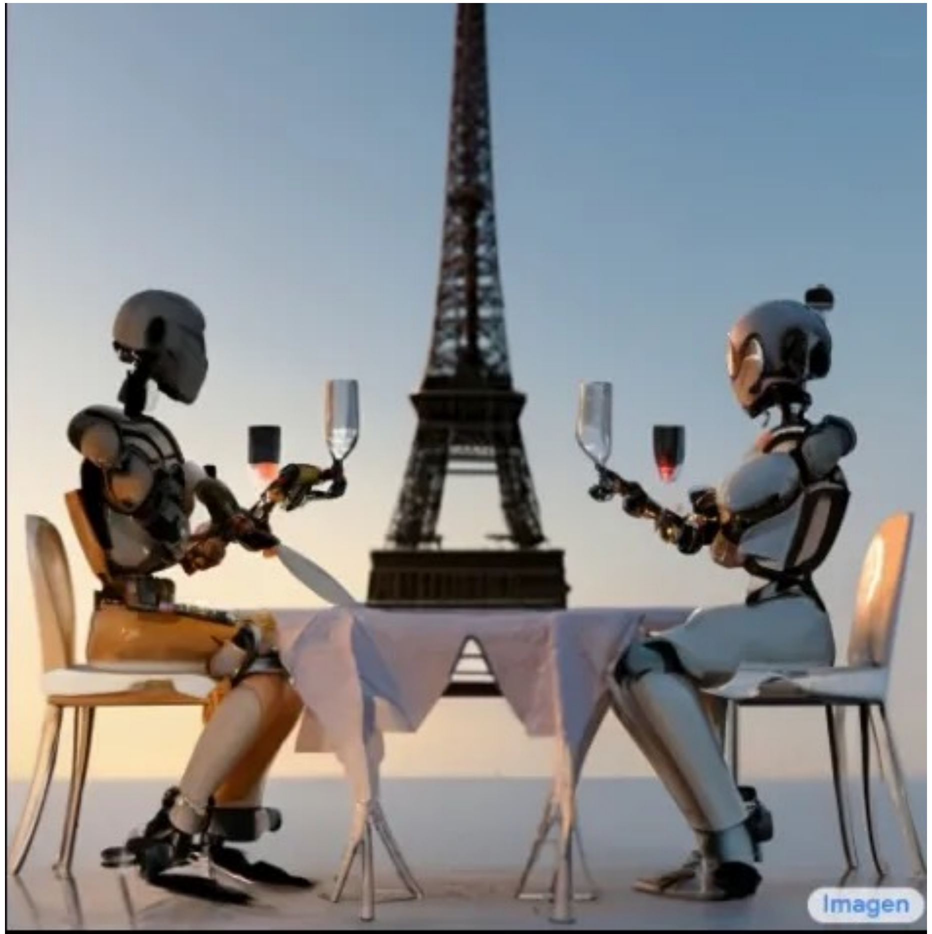
S. Antol et al., "VQA: Visual Question Answering," ICCV 2015

Image Retrieval



A. Radford et al., "Learning Transferable Visual Models From Natural Language Supervision," ICML 2021

Language-to-Image Generation

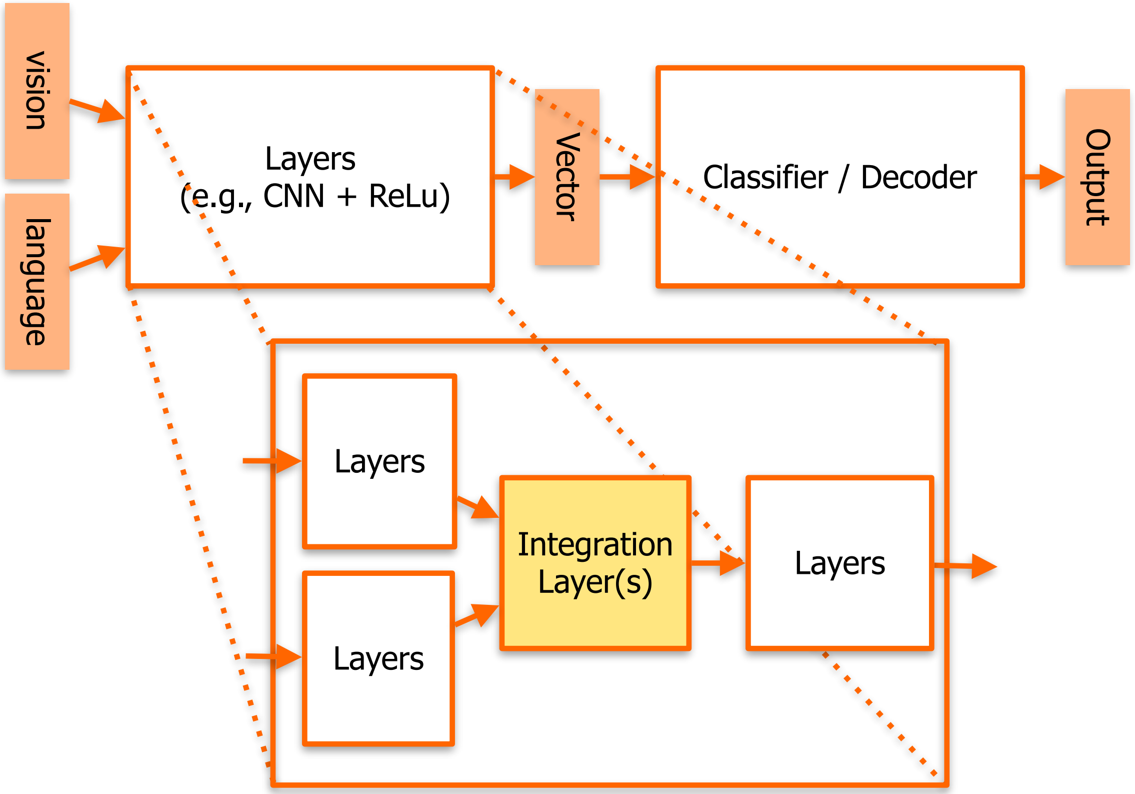


A robot couple fine dining with Eiffel Tower in the background.

An alien octopus floats through a portal reading a newspaper.

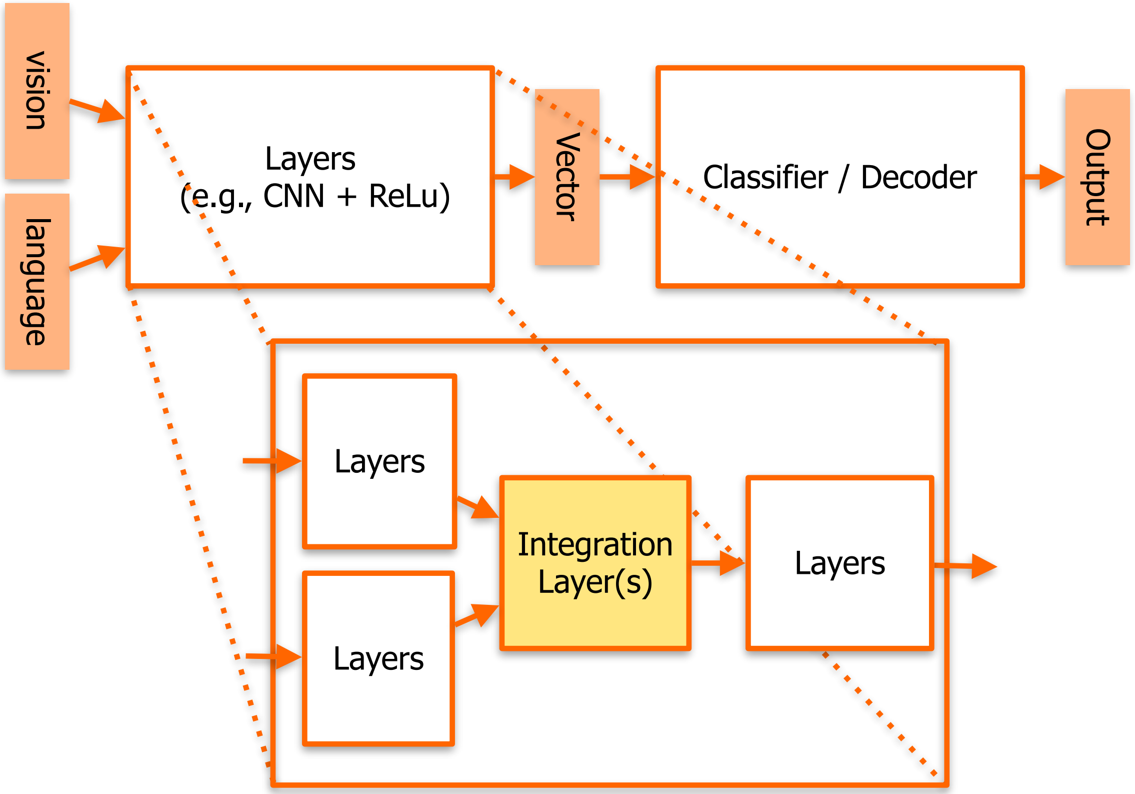
https://imagen.research.google/

Vision Language Integration Techniques



Vision Language Integration Techniques

- Q: Given two vectors from two different modalities (e.g., vision and language) how would you integrate them?



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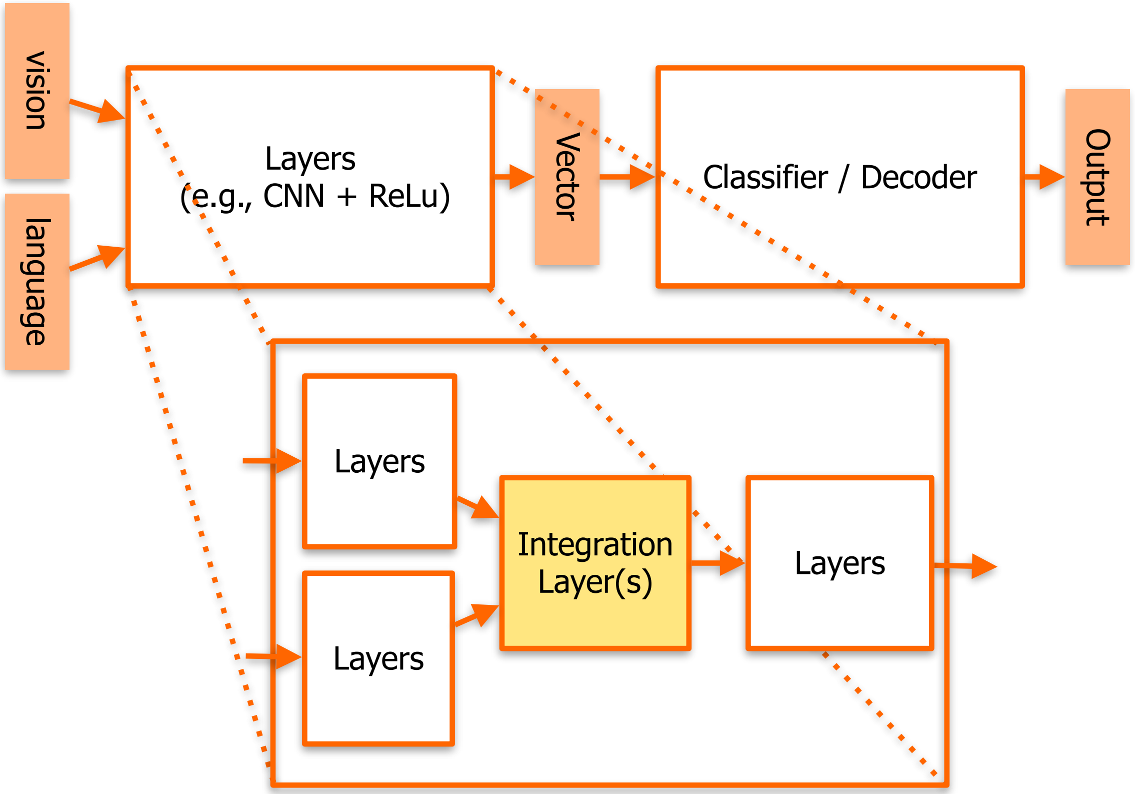
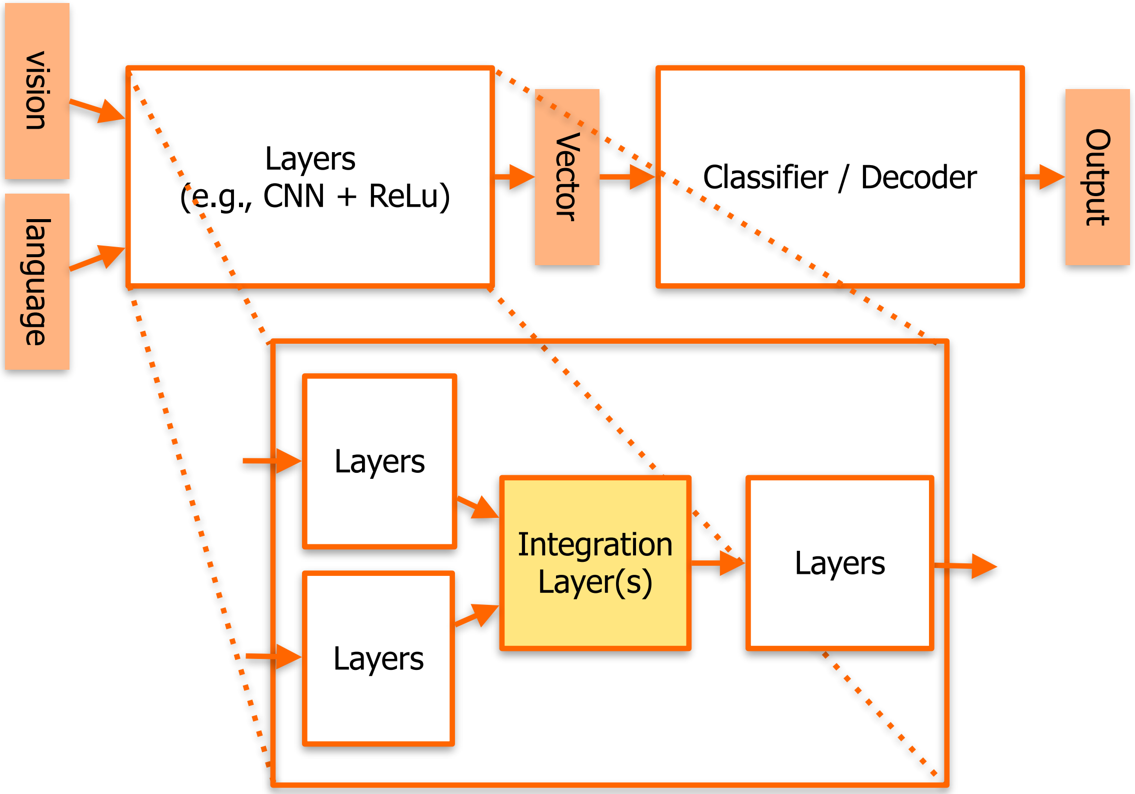
- Concatenation
  - $f(v, l) = [v; l]$



Vision Language Integration Techniques

- Q: Given two vectors from two different modalities (e.g., vision and language) how would you integrate them?
- Concatenation
  - $f(v, l) = [v; l]$
- Element-wise Multiplication
  - $f(v, l) = v \odot l$
  - Example: $\begin{bmatrix} 1 \\ 2 \end{bmatrix} \odot \begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 2 \\ 6 \end{bmatrix}$



Feature-Wise Transformation

- Feature-Wise Transformation
  - The language input “modulates” how the image input is processed.
  - $f(v, l) = (\alpha_l \odot v) + \beta_l$
  - α_l and β_l are vectors computed from language vector l (e.g., using a linear layer)

1. https://distill.pub/2018/feature-wise-transformations/
2. E. Perez, F. Strub, H. de Vries, V. Dumoulin, and A. Courville, “FiLM: Visual Reasoning with a General Conditioning Layer,” AAAI 2018

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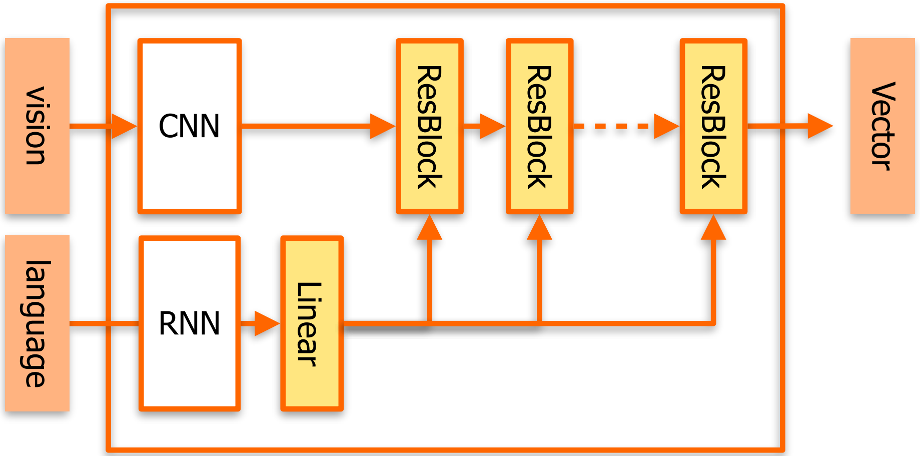

Example: FiLM architecture

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Transformer-Based Models
1. VQA

- Q: How would you integrate vision and language using Transformers?

1. H. Tan and M. Bansal, “LXMERT: Learning Cross-Modality Encoder Representations from Transformers,” EMNLP 2019
2. J. Lu, D. Batra, D. Parikh, and S. Lee, “ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks,” NeurIPS 2019

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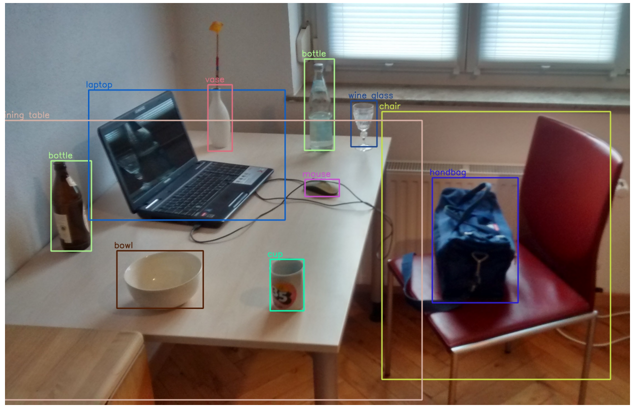

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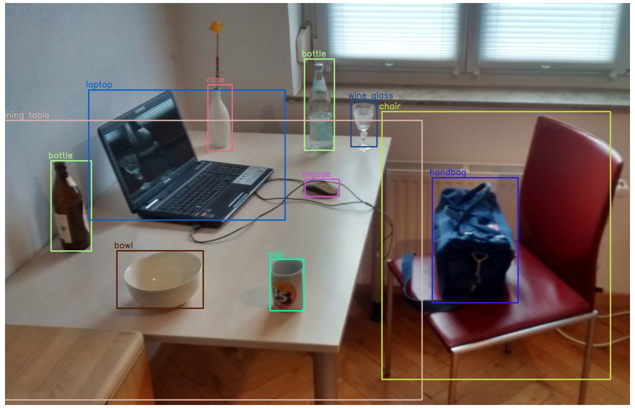

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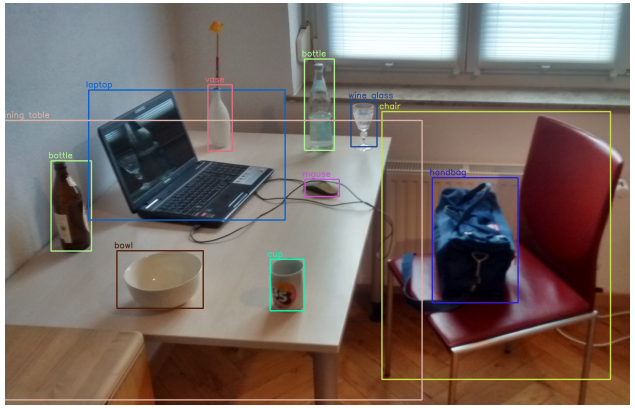
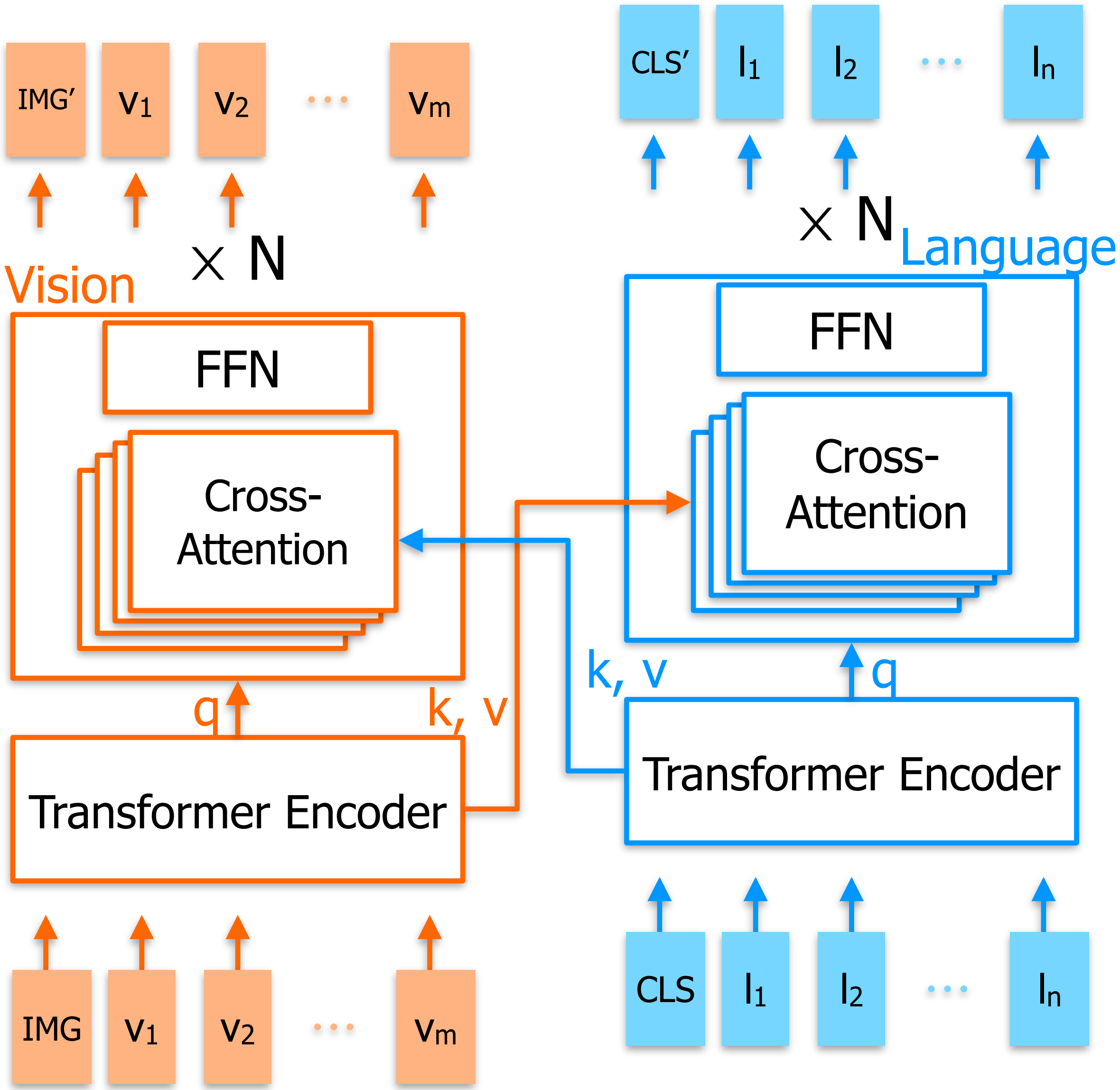
- IMG and CLS are used for prediction





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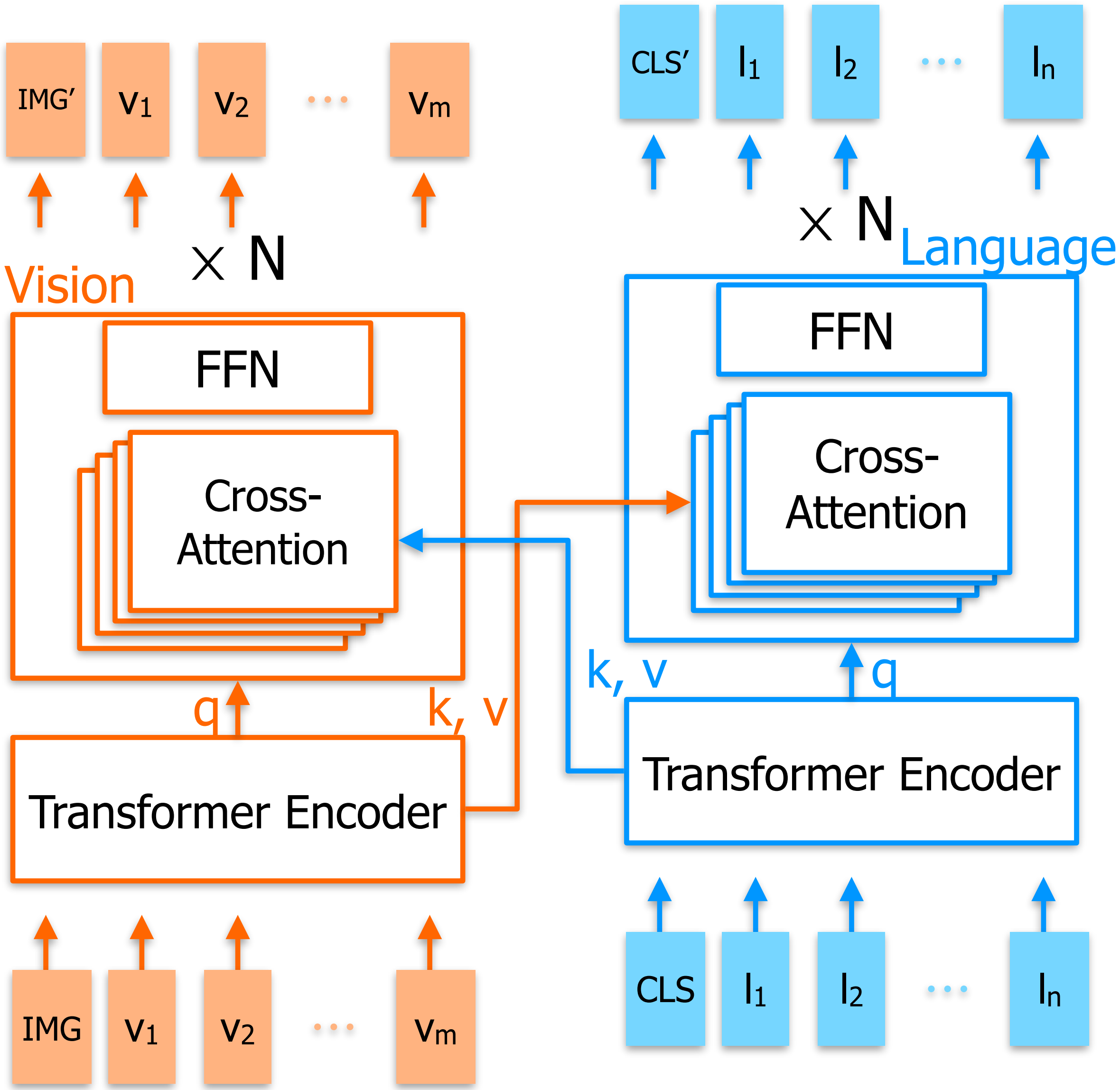
- v_i: detected bounding boxes in image.
- l_i: language tokens (e.g., words).
  - e.g., "What is in front of the laptop?"
- IMG and CLS are used for prediction
- Allows better representation of relationships between objects and words.



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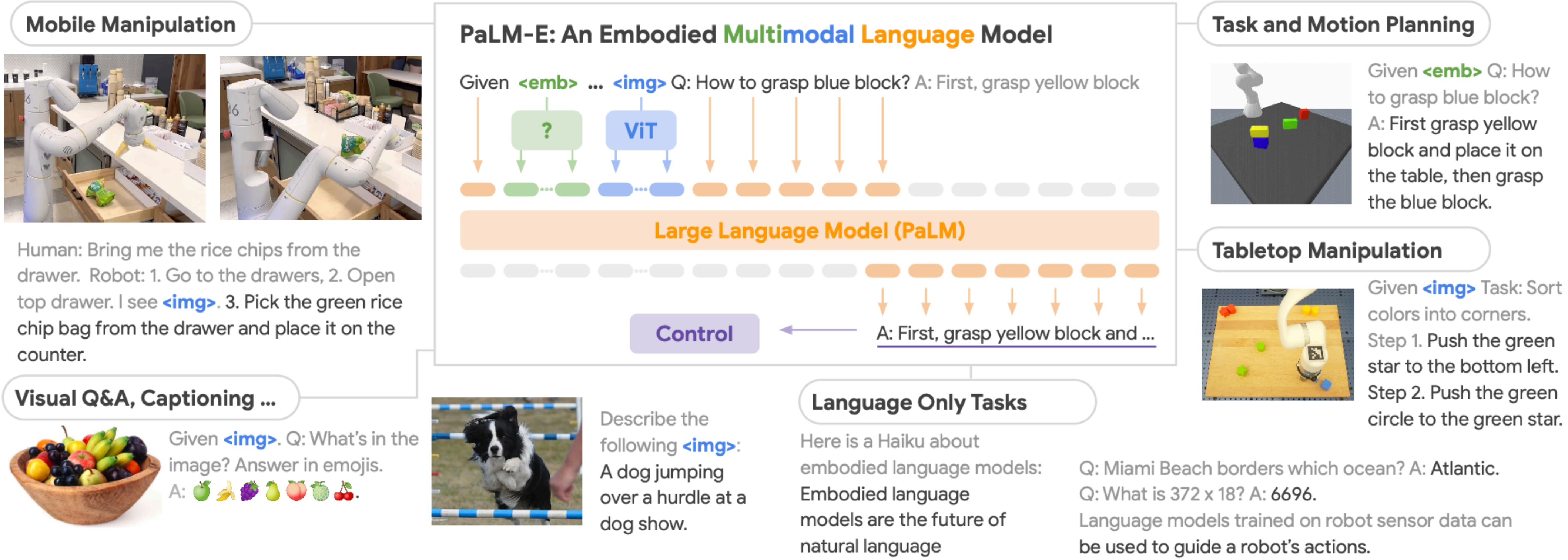
Advantages of Transformer for Multimodal Learning

- RNNs and CNNs are constrained by the input space (i.e., 1D, 2D), where the order of the input matters.
- Transformer operates on sets: input order does not matter.
  - Adding new modalities is easier.
- How would you combine vision and language using a transformer?
  - Add new modalities and introduce modality-specific embeddings / flags.

Transformer-Based Models
2. PaLM-E (Pathways Language Model with Embodiment)



D. Driess et al., "PaLM-E: An Embodied Multimodal Language Model." http://arxiv.org/abs/2303.03378
https://palm-e.github.io/

Summary

- Multimodal learning is an active research area.
- There are several ways to integrate different modalities.
- Transformer cross-attention can be used to integrated different modalities.

Open Questions in Deep Learning Research

- Generalizability
  - How to make models generalize to new situations?
- Continual learning
  - How can the models learn new data without forgetting previous ones?
- Explainability
  - How do the models come to the decisions?
- Ethical Issues
  - How can the models be aligned with human values?

Questions?

Resources

- Transformer
  - The Illustrated Transformer
  - Ch 13 Transformers in “Deep Learning: Foundations and Concepts”
  - Formal Algorithms for Transformers
  - Dive into Deep Learning - Chapter 11: Attention Mechanisms and Transformers
- Vision and Language Integration
  - A. Mogadala, M. Kalimuthu, and D. Klakow, “Trends in Integration of Vision and Language Research: A Survey of Tasks, Datasets, and Methods,” JAIR 2021