



# **Bridging Vision and Language: Overview of Multimodal Large Language Models**

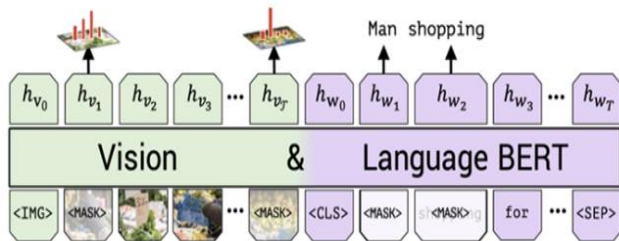
Adel Ahmadyan

Meta



## Earlier ...

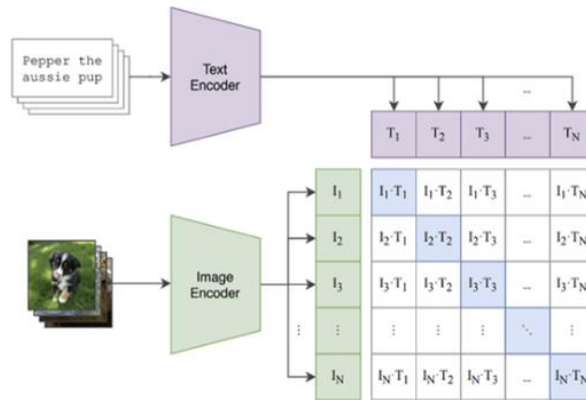
## Bert-based Models



VilBERT, VisualBERT, VL-BERT, UNITER, ALBERF, HERO, ...

Text models are usually very small  
Limited language understanding

## Dual-encoder Contrastive Models



CLIP, ALIGN, CoCa,  
Florence, MIL-NCE,  
BASIC, LiT, FILIP, MMV,

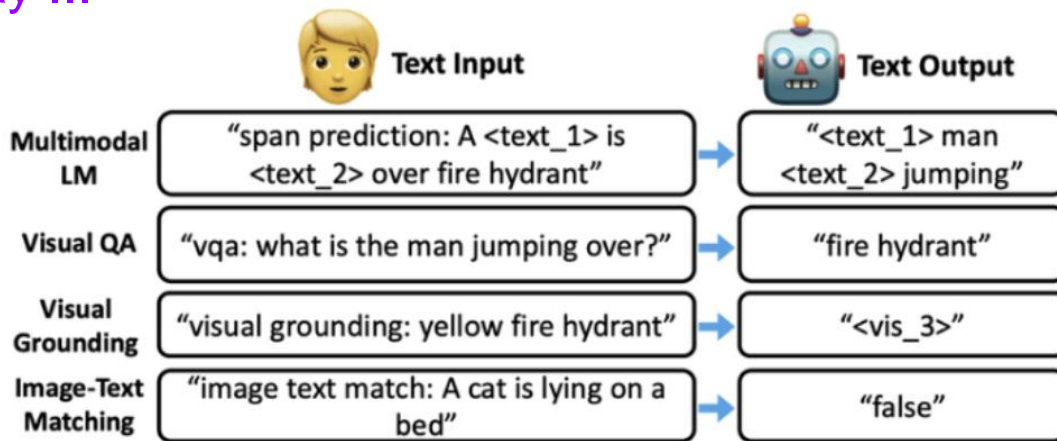
...

[paperswithcode.com/methods/category/vision-and-language-pre-trained-](https://paperswithcode.com/methods/category/vision-and-language-pre-trained)

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# Vision Language Model Overview

Today ...



## Vision Language Model

- Capable of performing different tasks, including VQA.
- Additional knowledge and intelligence comes from adding a large language model to the VLM

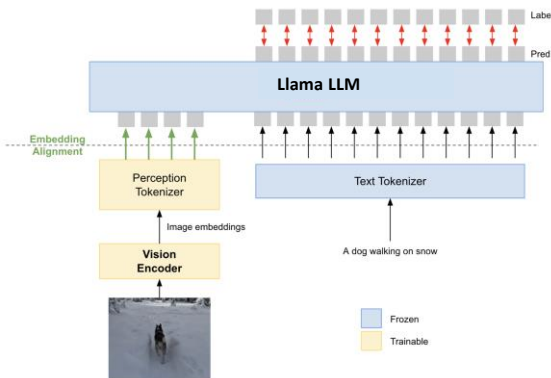
# How LLMs Understand Images?

## Fusing vision tokens with Large Language Models

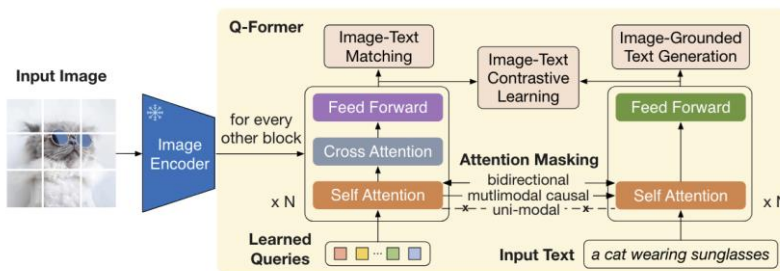
### Why is the vision encoder important for MM-LLM?

- Allows LLMs to input/ understand images

### How to fuse and align modality tokens with the large language model?

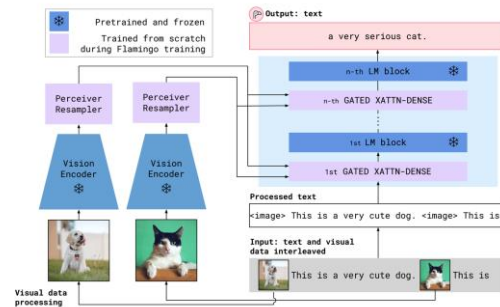


AnyMAL | LLaVa | Fuyu

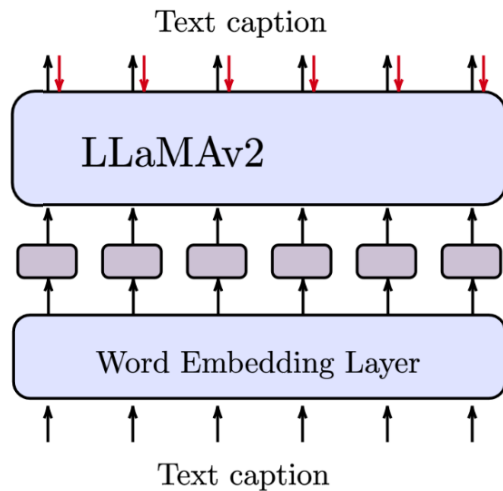


BLIP-v2

Li et. al, BLIP-2: Bootstrapping Language-Image Pre-training.  
Moon et. al, AnyMAL: An Efficient and Scalable Any-Modality Augmented Language Model  
Liu et. al, Flamingo: a Visual Language Model for Few-Shot Learning



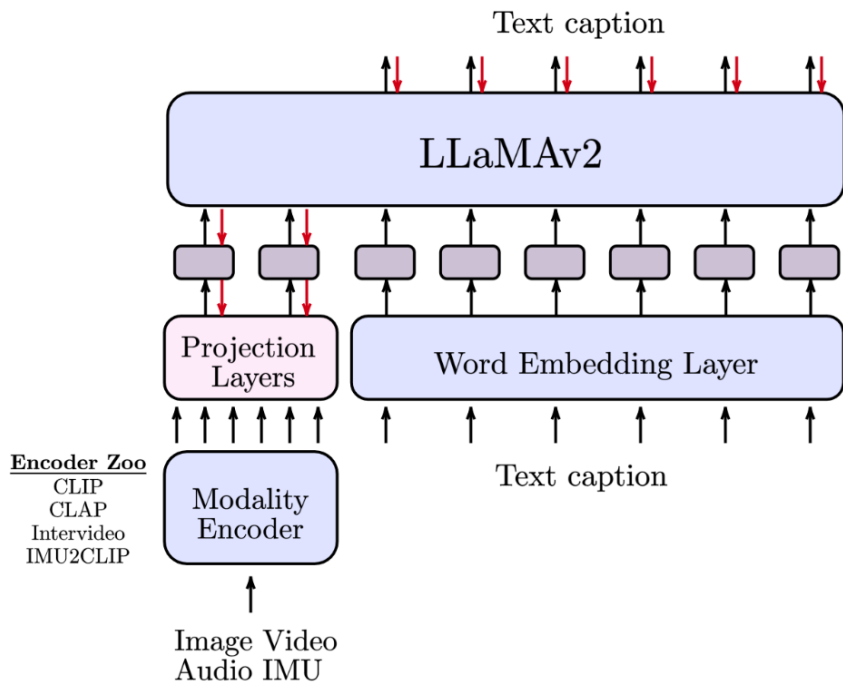
Flamingo



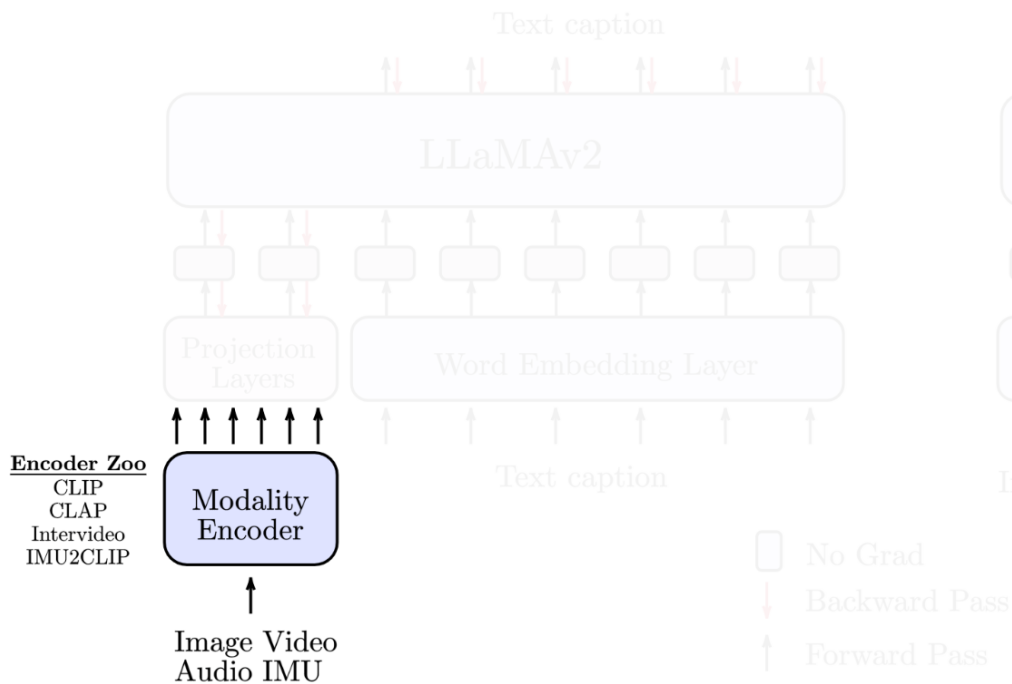
## Base Language Model

- Preserves the strong language-based capabilities
- Variations
  - OPT
  - FlanT5
  - Llama
  - Llama-2-chat

# AnyMAL Overview (2)

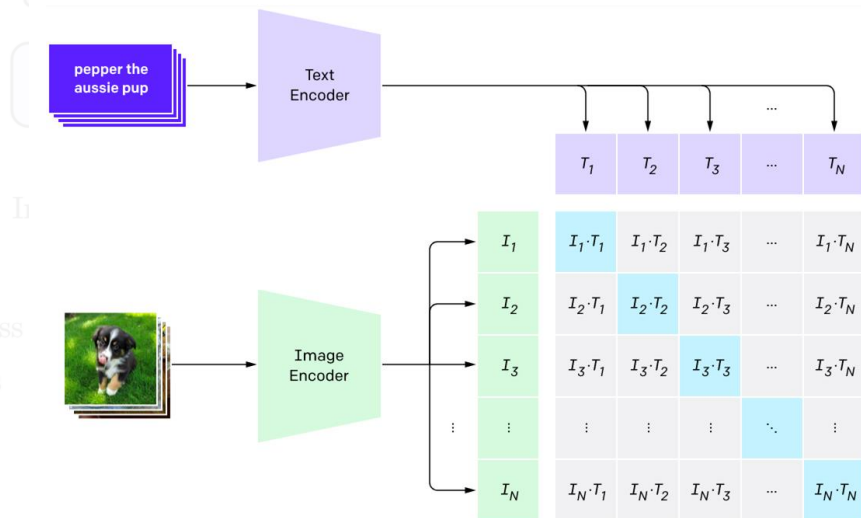


# AnyMAL Overview (3)

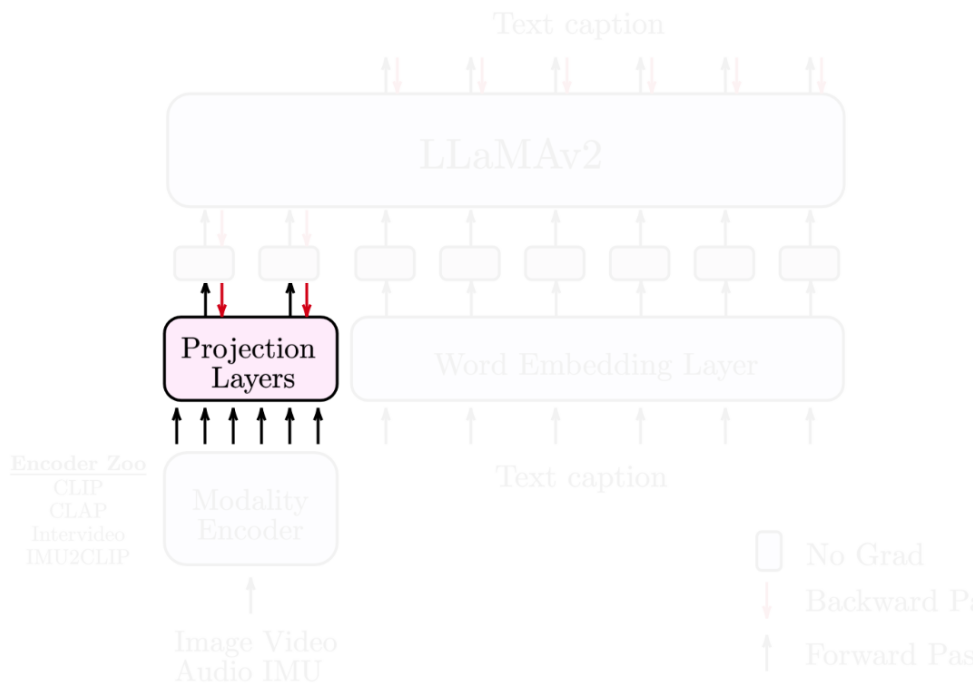


## Modality Encoder

- Trained with contrastive loss (text & other modality) for the best alignment in the text space

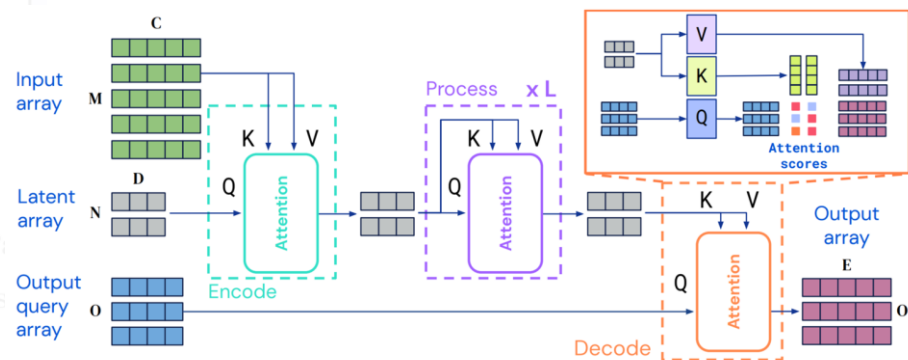


# AnyMAL Overview (4)



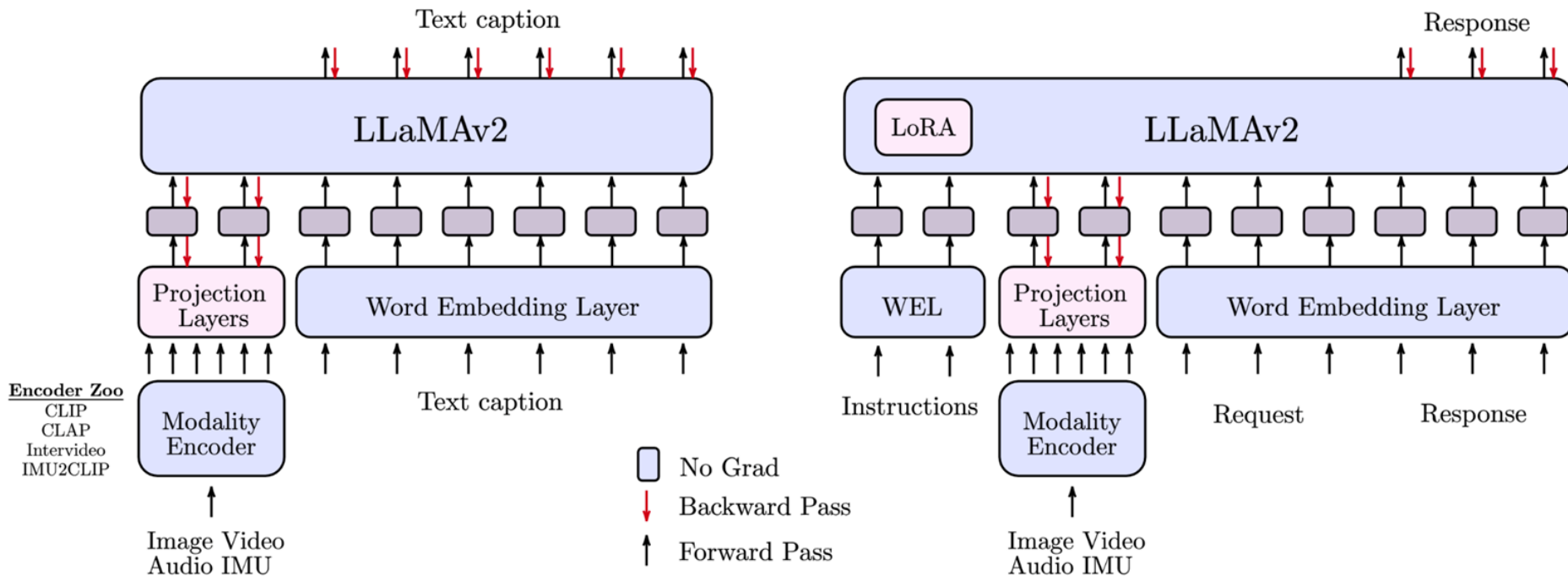
## Projection Layers

- Perceiver Resampler to resample patch embeddings into a sequence of Llama-compatible tokens





# Training: Pre-training & Fine-tuning



a) Modality Alignment

b) Multimodal Instruction Tuning

**Vision language model training**  
**=**  
**Vision encoder with language alignment**

# What Does the Vision Encoder See?



Look at that person



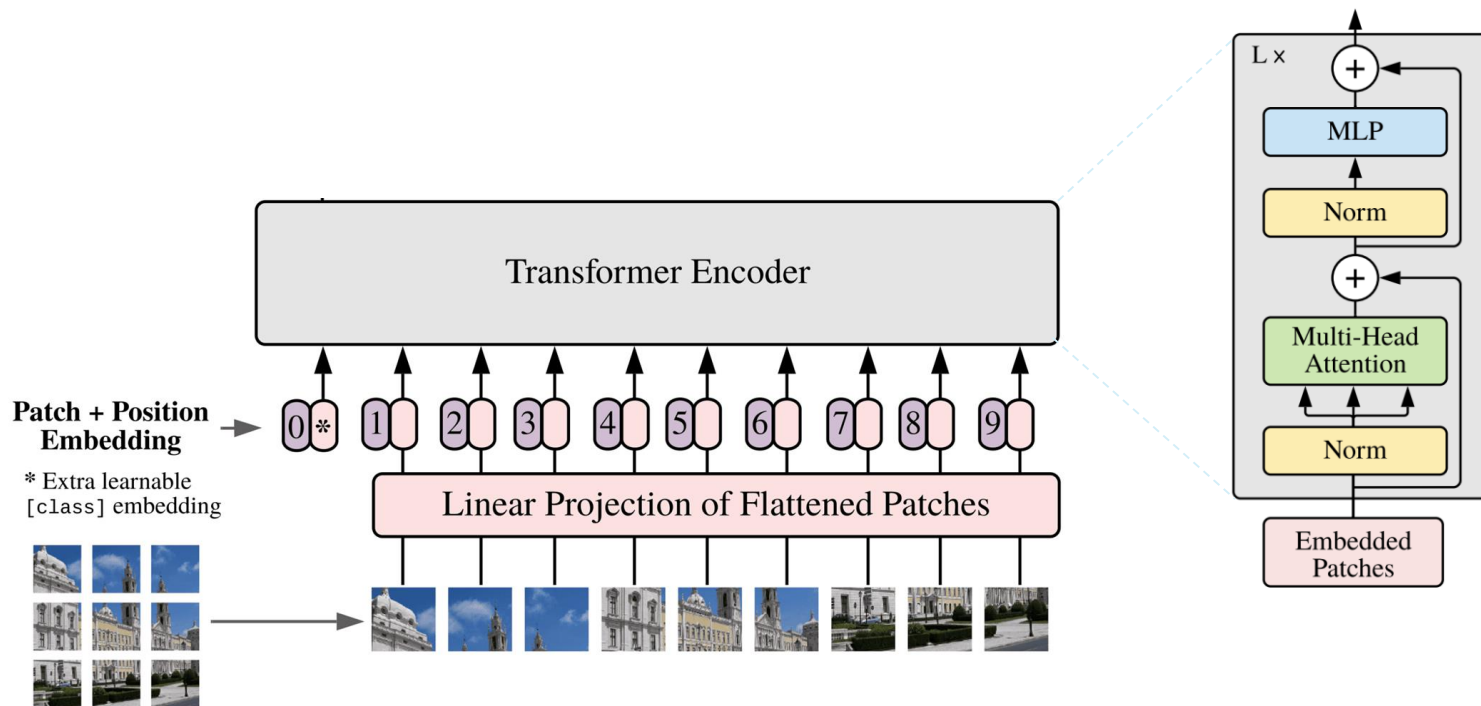
What is the name of that hotel?



What is that?

Li et. al. CLIP Surgery for Better Explainability with Enhancement in Open-Vocabulary Tasks

# Vision Transformer Backbone



Dosovitskiy et. al. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

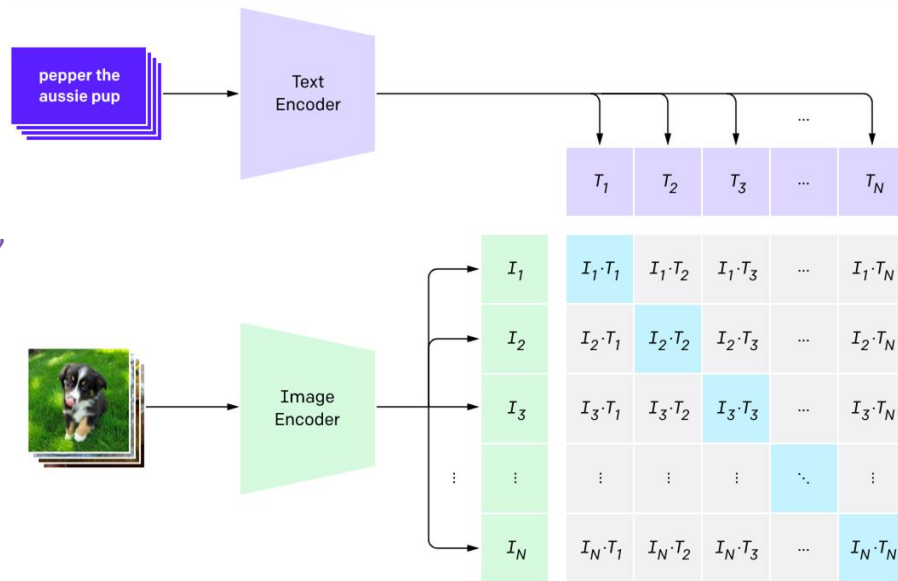
# Training a High Quality CLIP Vision Encoder (1)

## Key ingredients:

- Data volume and quality
- Model scale (number of parameters)
- Efficient pre-training recipes
- Domain fine-tuning: higher resolutions, diverse data, better caption quality

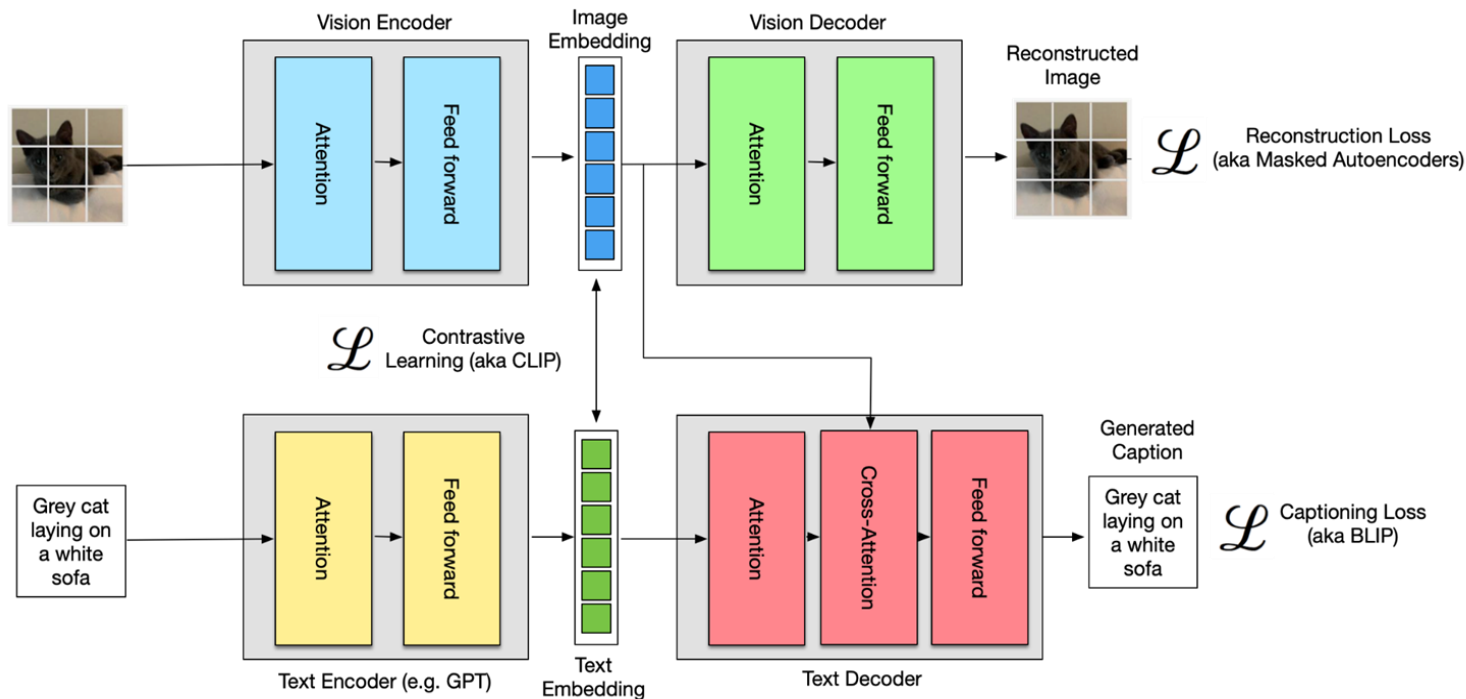
## Measuring quality:

- Zero-shot ImageNet (IN1k-0 shot)
- Post-alignment metrics
  - VQA accuracy
  - Captioning accuracy



Radford et. al, Learning Transferable Visual Models From Natural Language Supervision  
Li et. al, An Inverse Scaling Law for CLIP Training

# Training a High Quality CLIP Vision Encoder (2)



## Auxiliary loss functions

Improving alignment performance with LLM

Yu et. al. CoCa: Contrastive Captioners are Image-Text Foundation Models

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## **AnyMAL**

Any-Modality Augmented Language Model

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