

Vision Language Models

Important Concepts

Supervised: Model is trained on a labeled dataset

Self-Supervised: Model generates its own labels from the input data

Zero-Shot: Model makes predictions about new classes that it hasn't seen during training

Few shot: Model learns from only a very small number of training example

Image Encoder: ViT CLIP...

Text Encoder: T5, BERT...

LLM: GPT, LaMA

Loss or Objective function: Contrastive, Captioning, Image-Text Matching

Tasks: Recognition(Accuracy), Retrieval(T2I, I2T : Recall), VQA (Accuracy), Captioning (BLEU,...)

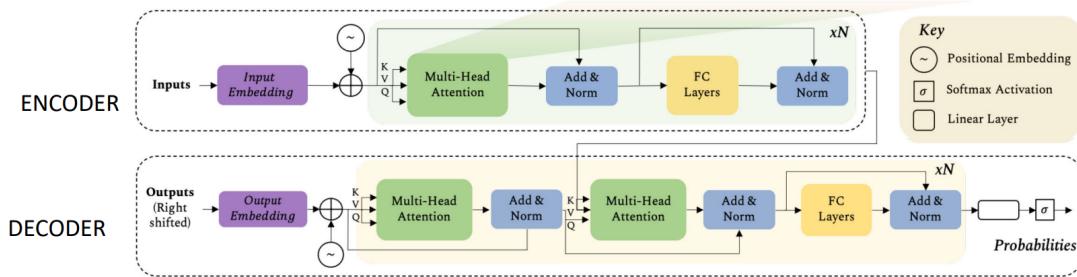
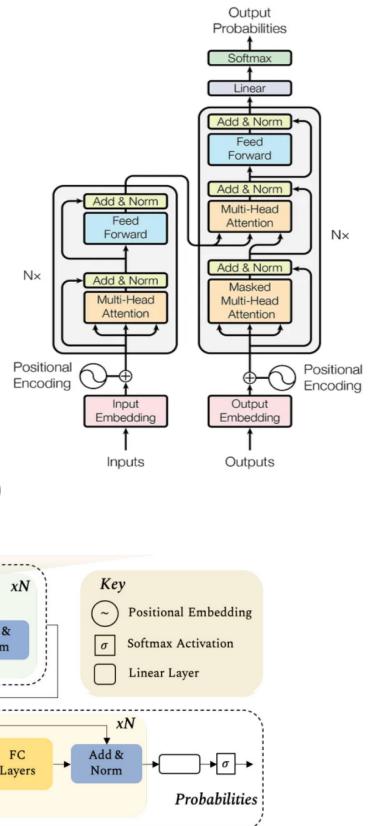
Transformer

Used for modelling long dependencies between input sequence elements. Allows processing multiple modalities (images, videos, text, speech) using similar processing blocks.

Pre-trained using pretext tasks on large-scale (unlabelled) datasets.

Vision Applications:

- Recognition Tasks (Image Classification, Object Detection, action recognition and segmentation)
- Generative modelling, multi-modal tasks (Visual Question answering, visual reasoning)
- Video Processing (Activity recognition, Video forecasting)
- Low-level Vision (Image super resolution, Image enhancement)
- 3D Analysis (Point cloud classification)

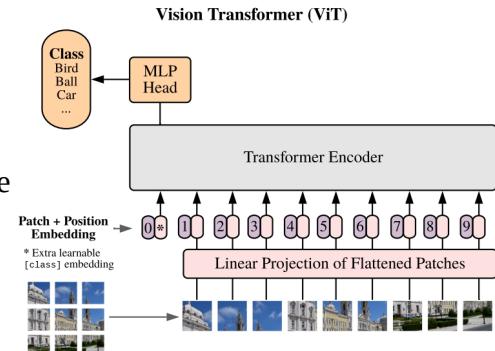


Vision Transformer

Take 16×16 patch, form an embedding of dimension 768.

Can be done with single convolution (in channels = 3, out channels = 768, kernel size = (16,16), stride = (16,16))

For a 224×224 RGB image, the output will be 196×768 , add 1 classification token to it. Resultant embedding will be 197×768 dimensional

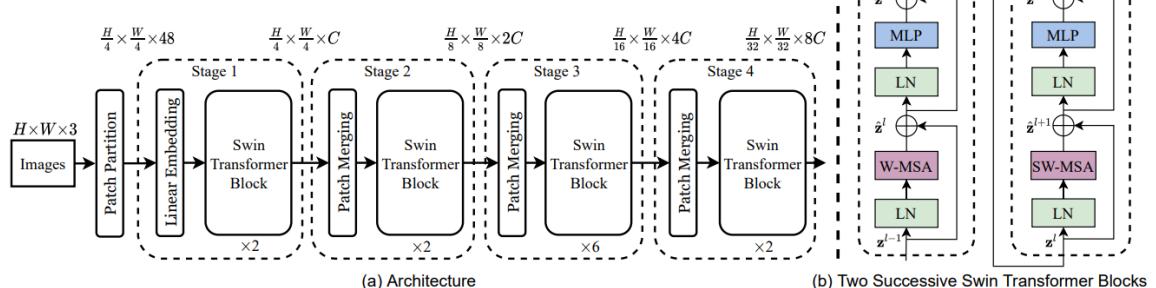
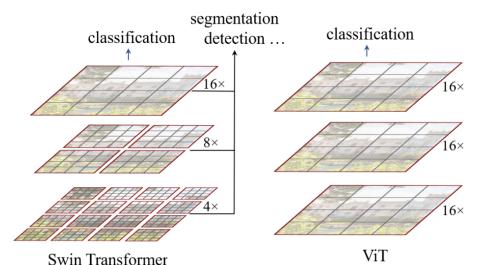


SWIN Transformer

“Shifted Windows”

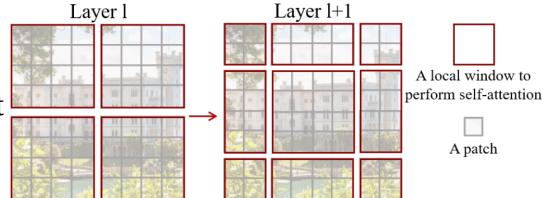
A hierarchical transformer who representation is computed with shifted windows. Shifted windowing limit attention:

- To local window
- Allowing cross window connections



Initially, you have patches of 4×4 RBG channel, you pass them through linear embedding, which convert them to C-dimensional vector. In patch embedding you merge the 2×2 neighbouring patches into 1 while increasing the embedding dimension by twice.

The paper uses W-MSA instead of MSA, because computing attention of every patch with every other patch will be computationally expensive, as well we don't need that much of global information. Instead in W-MSA/SW-MSA, we compute self-attention within a window. For SW-MSA, the paper proposes cyclic shift of patches.

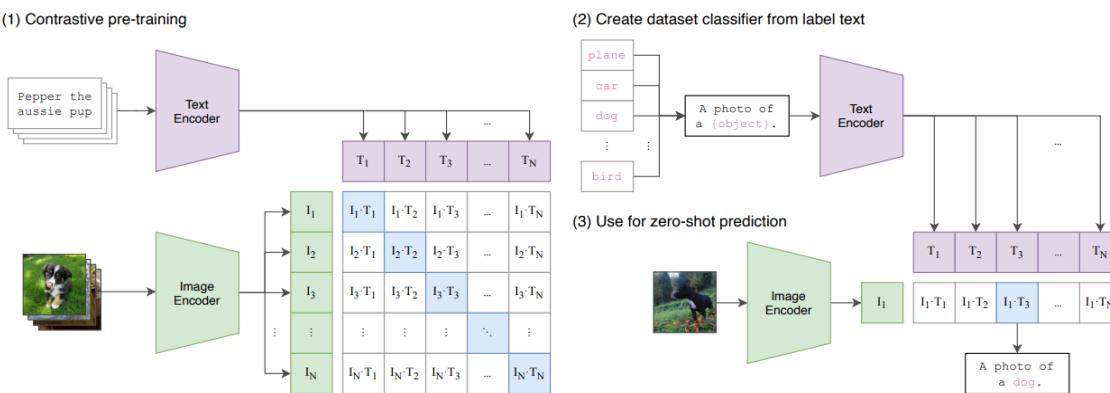


$$\begin{aligned}\hat{z}^l &= \text{W-MSA}(\text{LN}(\hat{z}^{l-1})) + \hat{z}^{l-1} \\ z^l &= \text{MLP}(\text{LN}(\hat{z}^l)) + \hat{z}^l\end{aligned}$$

$$\begin{aligned}\hat{z}^{l+1} &= \text{SW-MSA}(\text{LN}(\hat{z}^l)) + \hat{z}^l \\ z^{l+1} &= \text{MLP}(\text{LN}(\hat{z}^{l+1})) + \hat{z}^{l+1}\end{aligned}$$

Contrastive Language Image Pre-Training

Pair an image with its caption using contrastive learning.



m_i = one-hot encoded label vector for i^{th} image sample

y_i^m = cosine similarities vector for i^{th} image sample

t_i = one-hot encoded label for i^{th} text sample

y_i^t = cosine similarities vector for i^{th} text sample

ϕ = cross entropy loss

$$\begin{aligned}\mathcal{L}_m &= \frac{\sum_{i=1}^N \phi(y_i^m, m_i)}{N} & \mathcal{L}_t &= \frac{\sum_{i=1}^N \phi(y_i^t, t_i)}{N} \\ \mathcal{L} &= \frac{\mathcal{L}_m + \mathcal{L}_t}{2}\end{aligned}$$

Supervised Learning	Zero Shot Learning
Labelled Data	Data can be labelled/unlabelled
Training Phase	No Training
Final Prediction on Labelled data	Accuracy on the final result

Motivation: Image classification models are limited with fixed number of labels and Generalization. CLIP overcomes these limitations.

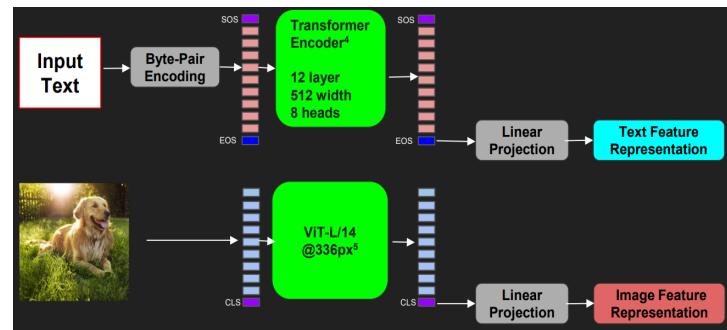
Training:

- Trained on 400M image-text pairs from internet.
- Batch size 32768
- 32 epochs over the dataset

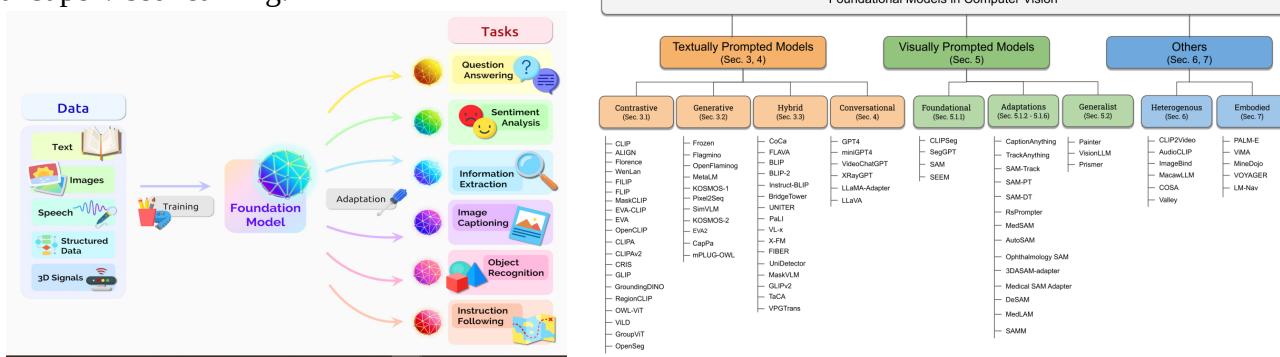
- Cosine learning rate decay

Architecture:

- ResNet-based or ViT-based image encoder
 - Transformer based text encoder



Foundation Models: AI Neural network trained on mountain of raw data generally with unsupervised learning.



Contrastive Captioners (CoCa)

Contrastive Captioners Pre-training

$$\mathcal{L}_{CoCa} = \lambda_{con}\mathcal{L}_{con} + \lambda_{cap}\mathcal{L}_{cap}$$

Encode Decoder Captioning

$$\mathcal{L}_{cap} = -\sum_{t=1}^T \log P_\theta(y_t | y_{<t}, x)$$

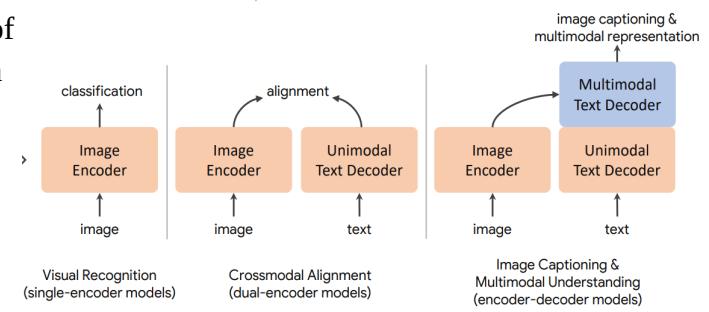
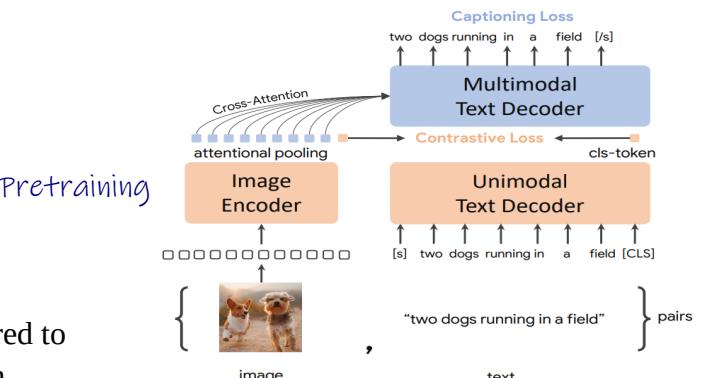
Dual Encoder Contrastive Learning: Compared to pretraining with single-encoder classification,

which requires human-annotated labels and data cleaning, the dual-encoder approach exploits noisy web-scale text descriptions and introduces a learnable text tower to encode free-form texts

$$\mathcal{L}_{CON} = -\frac{1}{N} \left(\underbrace{\sum_{i=1}^N \log \frac{\exp(x_i^T y_i / \sigma)}{\sum_{j=1}^N \exp(x_i^T y_j / \sigma)}}_{\text{image-to-text}} + \underbrace{\sum_{i=1}^N \log \frac{\exp(y_i^T x_i / \sigma)}{\sum_{j=1}^N \exp(y_i^T x_j / \sigma)}}_{\text{text-to-image}} \right)$$

where x_i and y_j are normalized embeddings of the image in the i^{th} pair and that of the text in the j^{th} pair

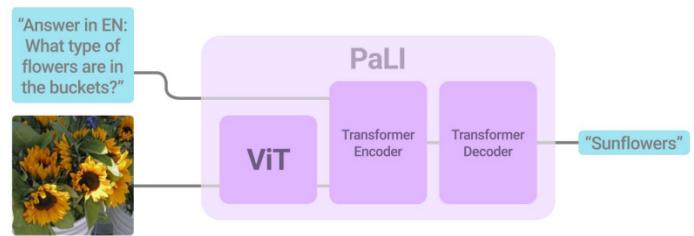
The pretrained CoCa can be used for downstream tasks including visual recognition, vision-language alignment, image captioning and multimodal understanding with zero-shot transfer, frozen-feature evaluation or end-to-end finetuning.



Pathways Language and Image (PaLI)

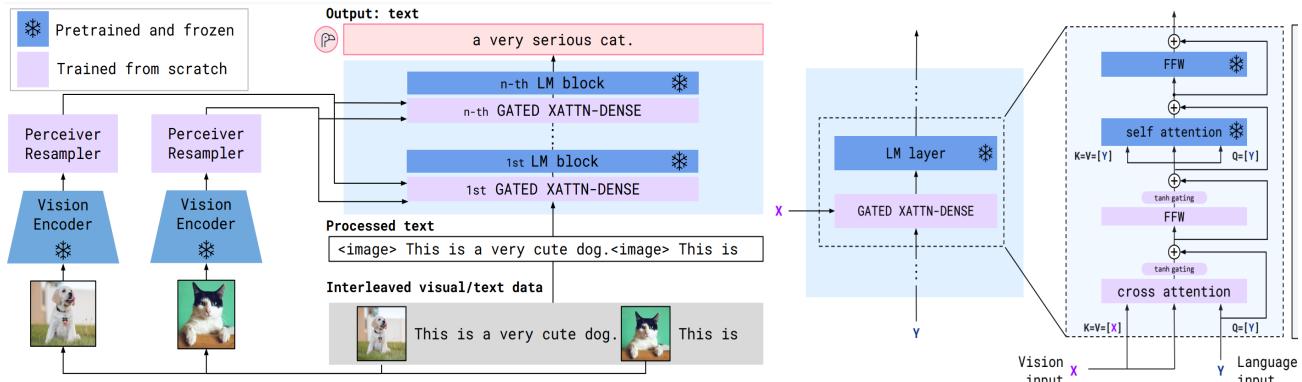
Training Mixture:

- Span corruption on text only data
- Split captioning on WebLI alt-text data
- Captioning on CC3M-35L
- OCR on WebLI OCR-text data
- English and Cross lingual VQA
- English and Cross lingual VQG(visual question generation)
- English-only Object-Aware (OA) VQA
- Object Detection



Model	Components	Image Encoder	Mutimodal Encoder-Decoder	Total
PaLI-3B	ViT-G, mT5-L	1.8B	1.2B	3B
PaLI-15B	ViT-G, mT5-XXL	1.8B	13B	14.8B
PaLI-17B	ViT-e, mT5-XXL	3.9B	13B	16.9B

Flamingo



Objective:

$$p(y|x) = \prod_{l=1}^L p(y_l|y_{<l}, x_{\leq l}) \quad y_l \text{ is the } l^{\text{th}} \text{ language token of input text; } y_{<l} \text{ is set of preceding token;}$$

$x_{\leq l}$ set of images/videos preceding token y_l in the interleaved sequence and p is parametrized by Flamingo model.

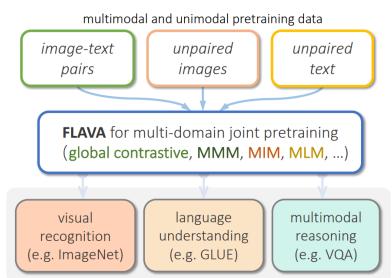
Dataset:

- Training on mixture of vision and language datasets
MultiModal MassiveWeb (M3W) : 43M webpages
- Pairs of image/video and text
Long Text and Image Pair (LTIP) consist 312M image & text pair. Video and Text Pair (VTP) consist 27M short video paired with sentence description.

FLAVA

Foundational Language and Vision Alignment Model

The model involves an image encoder to extract unimodal image representations, a text encoder to obtain unimodal text representations, and a multimodal encoder to fuse and align the image and text representations for multimodal reasoning.



Loss functions:

1) Masked Image Modeling (MIM)

Loss: This loss function is used for pretraining the vision model by predicting masked regions in an image.

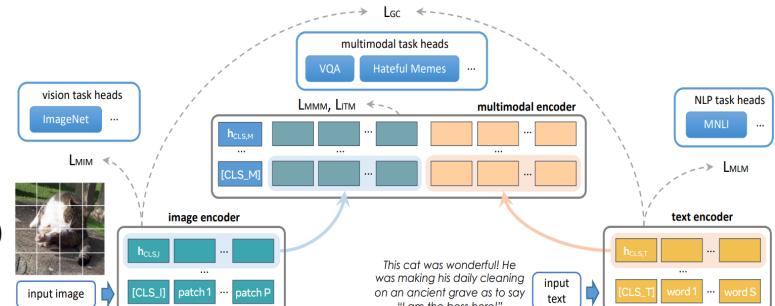
2) Masked Language Modeling (MLM)

Loss: This loss function is used for pretraining the language model by predicting masked words in a sentence.

3) Multimodal Masked Modeling (MMM) Loss: This loss function combines both MLM and MIM to ensure that the model learns to understand and generate both text and images together.

4) Image-Text Matching (ITM) Loss: This loss function is used to ensure that the model can correctly match corresponding pairs of images and texts.

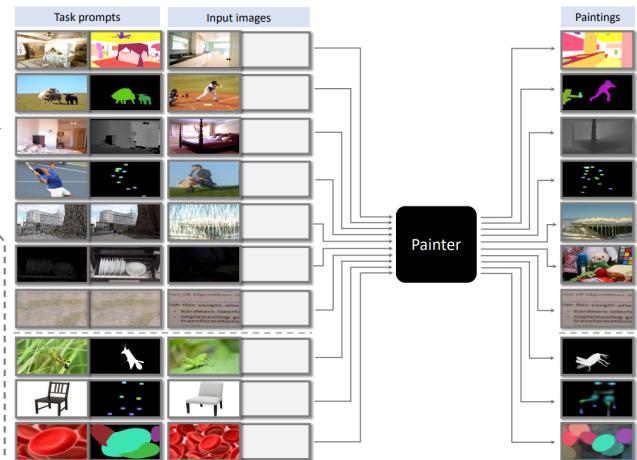
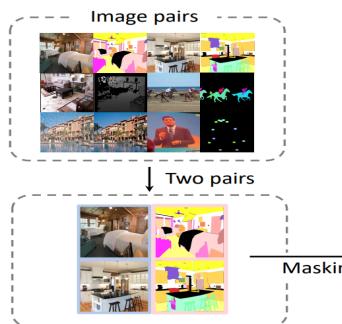
5) Contrastive Loss: This loss function helps in aligning the representations of different modalities (e.g., text and image) by bringing similar pairs closer and pushing dissimilar pairs apart.



Painter

In context Learning. Given an i/p image inpaint the desired but missing o/p image

Tasks: Semantic Segmentation, Instance Segmentation, Depth Resomation, keypoint detection, De-noising, Deraining, Image Enhancement.



BLIP-2 Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models

Used lightweight Querying transformer to serve as bottleneck between frozen image and text encoder.

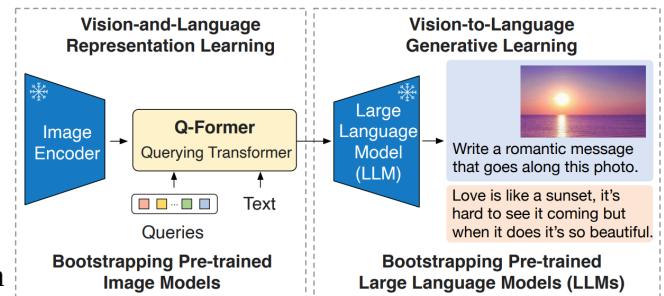
Q-Former uses a set of learnable querying vectors and is pre-trained in 2 stages:

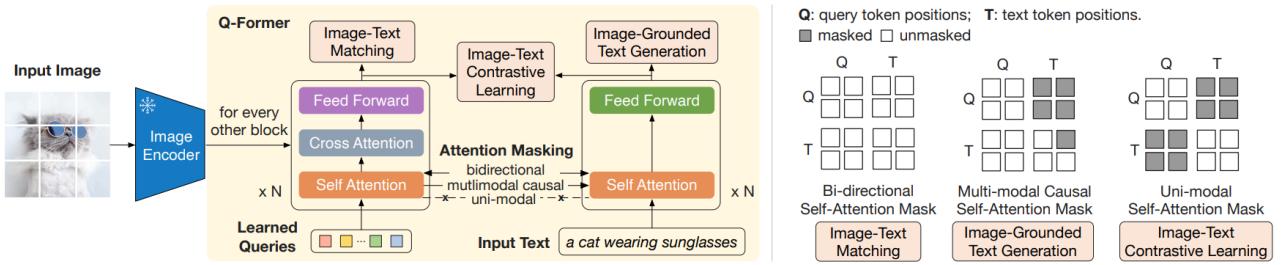
1) Vision-Language representation learning with frozen image encoder.

2) Vision-Language generative learning with frozen text encoder.

Vision-Language representation learning

- Image-Text Contrastive Learning: Align image representation with text representation
- Image-Text Matching: Binary classification of image-text pair
- Image-grounded Text generation: condition Q-Former to generate text by accepting images as input





Vision-Language Generative Learning

Two variants of LLM architectures. Q-Former is connected to frozen LLM and pre-trained s.t. LLM generative ability is fully harnessed.

The output query embeddings from image transformer are linearly projected to same dimension as text embedding the language model expects. The projected query embedding are then concatenated to text embedding to serves as soft visual prompts forcing LM to focus on visual features extracted by Q-Former.

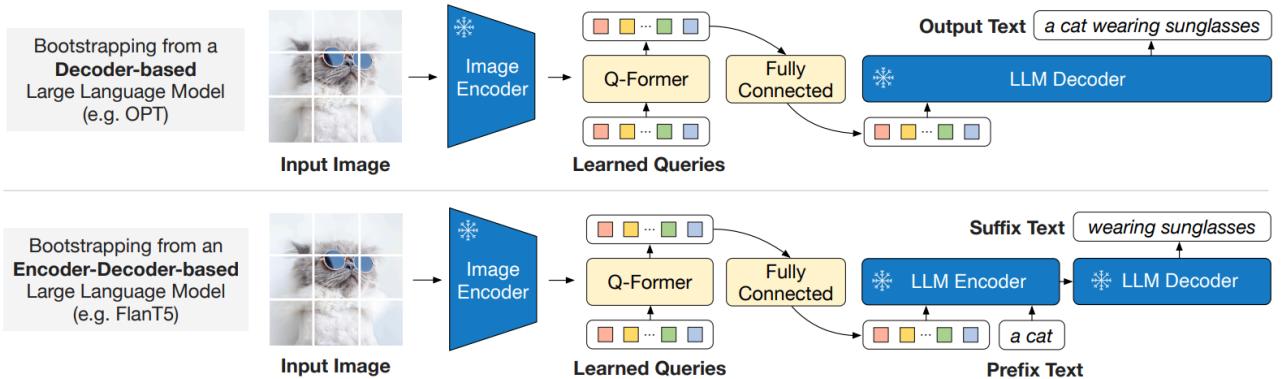
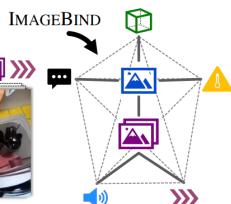


Image-Bind

Learn a joint embedding across six different modalities:

- Image
- Text
- Audio
- Depth
- Thermal
- IMU



Naturally Paired Datasets

- Video, audio pairs from Audioset dataset
- Image, depth pairs from SUN RGB-D dataset
- Image, thermal pairs from the LLVIP dataset
- Video IMU pairs from Ego4D datasets

ViT-H for Images/Videos

OpenCLIP for Text

ViT-B for Audio

ViT-S for Thermal

InfoNCE loss:

$$L_{I,M} = -\log \frac{\exp(q_i^T k_i)/\tau}{\exp(q_i^T k_i)/\tau + \sum_{j \neq i} \exp(q_j^T k_j)/\tau}$$

q_i : Normalized Embedding for Image, k_i : Normalized embedding for other modality

Images and Text Encoder are frozen during training; Audio, depth, thermal, IMU encoder are updated

Language-Bind

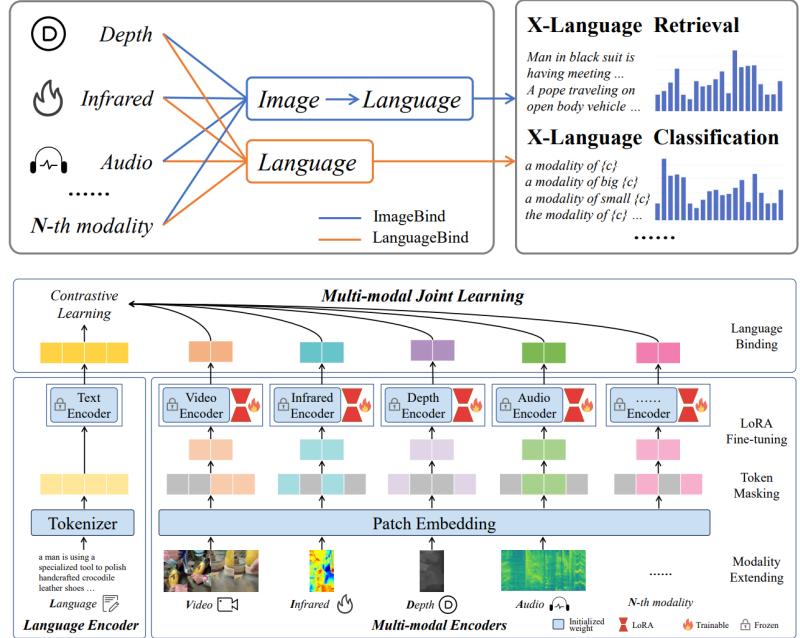
- 1) 24 layer, 1024-dim ViT with patch size of 14
 - 2) Initialize with OpenCLIP-large
 - 3) Depth and infrared are treated as RGB image
 - 4) Audio data is transformed to spectrogram of duration 10sec
 - 3) Low Rank Adaptation (LoRA) for FineTuning, maintain weight W_0 frozen while learning new weight matrix BA.
- In case of modality-agnostic encoder $h(\cdot)$ and x , forward process can be represented as:

$$h(x) = W_0 x + BAx$$

Contrastive learning to bind individual modalities to language

$$L_{M2T} = -\frac{1}{K} \sum_{i=1}^K \log \frac{\exp(x_i^T y_i / \tau)}{\sum_{j=1}^K \exp(x_i^T y_j / \tau)}$$

$$L_{T2M} = -\frac{1}{K} \sum_{i=1}^K \log \frac{\exp(y_i^T x_i / \tau)}{\sum_{j=1}^K \exp(y_i^T x_j / \tau)}$$



LlaVa Visual Instruction Tuning

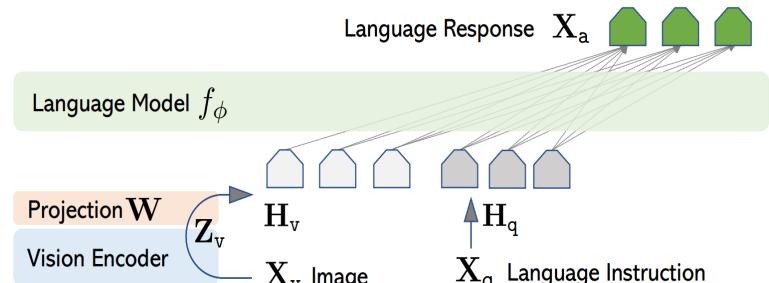
$$H = W \cdot Z_v \text{ with } Z_v = g(X_v)$$

Stage 1: Pretaining for feature Alignment

Filter CC3M to 595K image-text pairs, keep both the visual encoder and LLM weight frozen, train for W (projection matrix)

Stage 2: Fine-tuning End-to-End

$$\text{Train } \theta = \{W, \phi\}$$



Instruction Tuning For each image X_v , generate multi-turn conversation data $(X_q^1, X_a^1, \dots, X_q^T, X_a^T)$. Organise them as sequence, by treating all answers as the assistant's response. Instruction at the t^{th} turn:

$$X_{instruct}^t = \begin{cases} \text{Randomly choose } [X_q^1, X_v^1] \text{ or } [X_v, X_q^1] & \text{the first turn } t=1 \\ X_q^t, & \text{the remaining turn } t>1 \end{cases}$$

Perform instruction tuning of LLM on the prediction tokens, using original auto-regressive training objective.

$$p(X_a | X_v, X_{instruct}) = \prod_{i=1}^L p_\theta(x_i | X_v, X_{instruction, <i}, X_{a,<i})$$

Video ChatGPT

Video Sample $V_i \in \mathbb{R}^{T \times H \times W \times C}$, using CLIP generate $x_i \in \mathbb{R}^{T \times h \times w \times D}$.

No. of tokens $N = h \times w$

Temporal representation $t_i \in \mathbb{R}^{T \times D}$

Spatial representation $z_i \in \mathbb{R}^{N \times D}$

Both concatenated to form video-level feature

$$v_i = [t_i \ z_i] \in \mathbb{R}^{(T+N) \times D}$$

Trainable layer g , projects these video-level features into language decoder's embedding space

$$Q_v = g(v_i) \in \mathbb{R}^{(T+N) \times K}$$

Text Queries $Q_t \in \mathbb{R}^{L \times K}$ is concatenated with Q_v

Video Instruction Set creation

- Human Assisted Annotations: Videos and captions from ActivityNet-200. Annotators enrich original captions by adding information about: Physical appearance and Spatial and temporal localization
- Semi-Automatic Annotation Framework: Use BLIP-2 and GriT for key frame analysis. Also use Tag2Text to generate tags for each key-frame.
- GPT-Assisted PostProcessing

PG-Video-LlaVa

Incorporates audio context that enhances video understanding.

1)Frozen LLM: Vicuna-13b-v1.5

2)Voice activity Detection: Identifies speech segments, filter out noise, cuts and merges audio into batches.

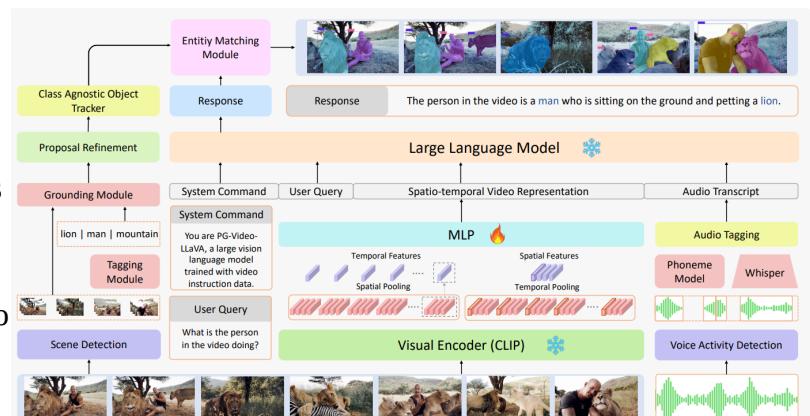
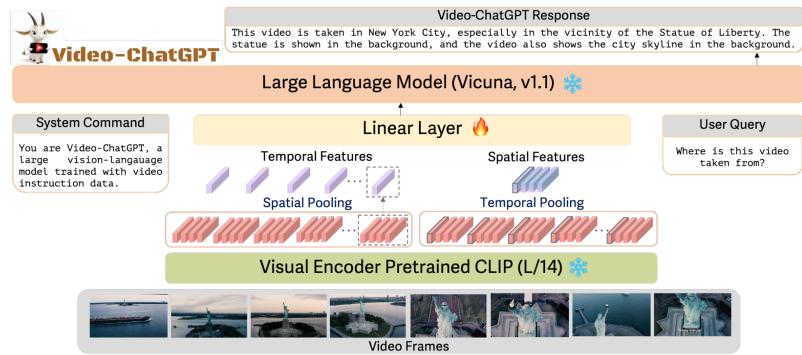
3)Whisper models converts speech to transcript. Audio Tagging produce audio-tagging o/p from sliced original audio, consider top 3 audio

classes predicted. If speed is not among them segment is ignored. Phoneme classifies the smallest unit of speech, temporary aligns transcript with matching phonemes.

4)Spatial Temporal Video Representation same as Video-Chat GPT

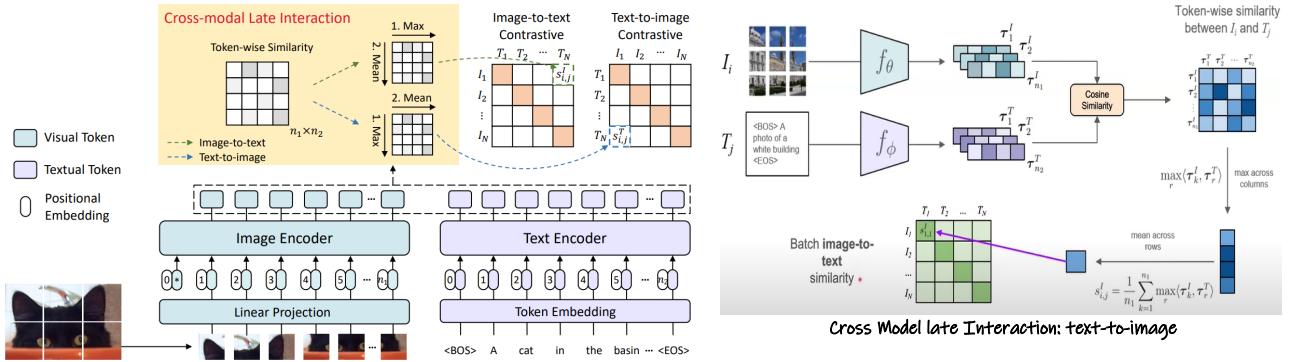
5)Scene Detection (PyScene Detect): to group frames from same scene; Tagging Module (RAM SWIN) generate objects in that image; Grounding Module (GroundingDINO-T) Produces Bounding boxes in the image; Proposal Refinement (SAM): o/p segmentation; Class Agnostic Object Tracker (DEVA Tracker) decouples segmentation and tracking tasks to be class agnostics

6) Entity Matching Module (Vicuna 1.5) takes LLM response and list of objects to filter out objects

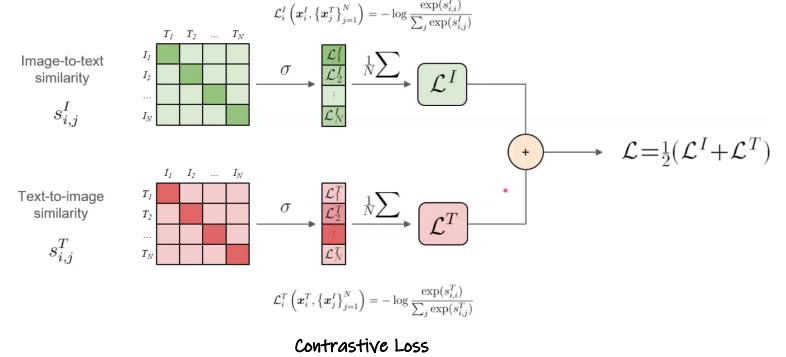


FILIP Fine-Grained Interactive Language-Image Pre-Training

CLIP is not able to capture fine-grained interactions, also cannot capture relationship between image patches and textual words.

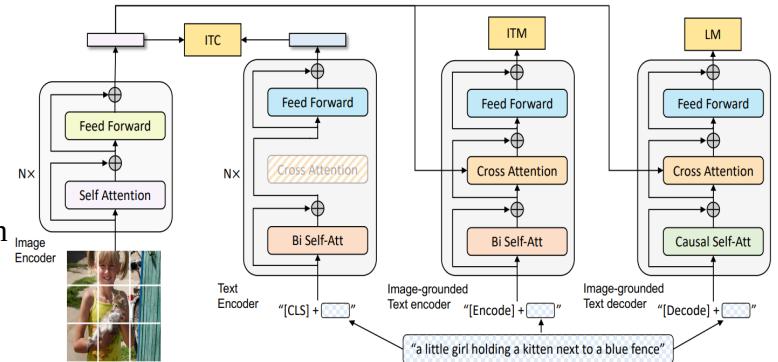


n_1 and n_2 be the no. of non-padded tokens in i^{th} image and j^{th} text, corresponding encoded feature τ_1^I and τ_j^T . Compute the similarity matrix. For image-to-text similarity, take max along columns and mean it to get s_{ij}^I . Similarly for text-to-image similarity, take max along row and mean it to get s_{ij}^T



BLIP

Pre-training model architecture and objectives of BLIP (same parameters have the same color).



1) Unimodal encoder (ViT-B/16 and ViT-L/16; BERT base) is trained with an image-text contrastive (ITC) loss to align the vision and language representations.

2) Image-grounded text encoder uses additional cross-attention layers to model vision-language interactions, and is trained with a image-text matching (ITM) loss to distinguish between positive and negative image-text pairs.

3) Image-grounded text decoder replaces the bi-directional self-attention layers with causal self-attention layers, and shares the same cross-attention layers and feed forward networks as the encoder. The decoder is trained with a language modeling (LM) loss to generate captions given images.

