



UNIVERSIDAD DE CHILE

Deep Learning

Deeper, Better, _____, Stronger than Machine Learning

Valentin Barriere

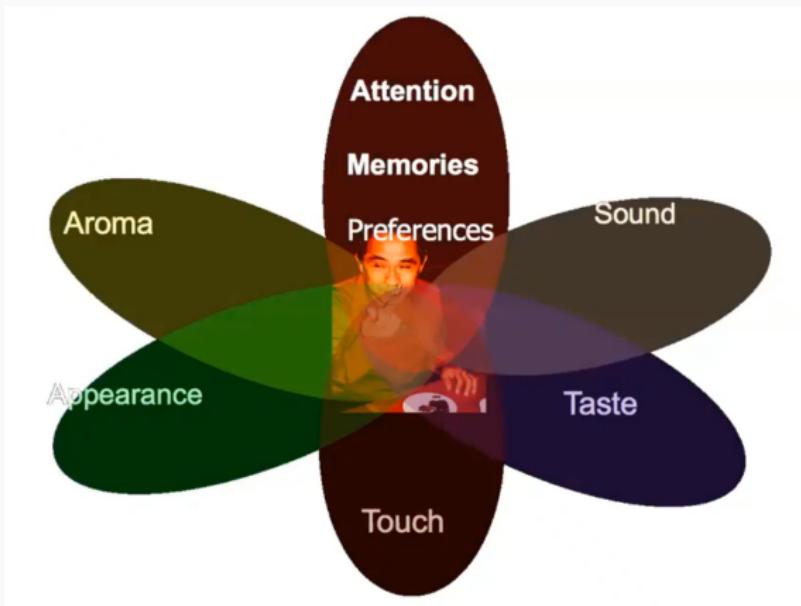
Universidad de Chile – DCC

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Multimodal Models

What is multimodal?

Modalities can refer to the human senses



Background: Multimodality

Human Intelligence and Artificial Intelligence, collect and process the information before taking a decision

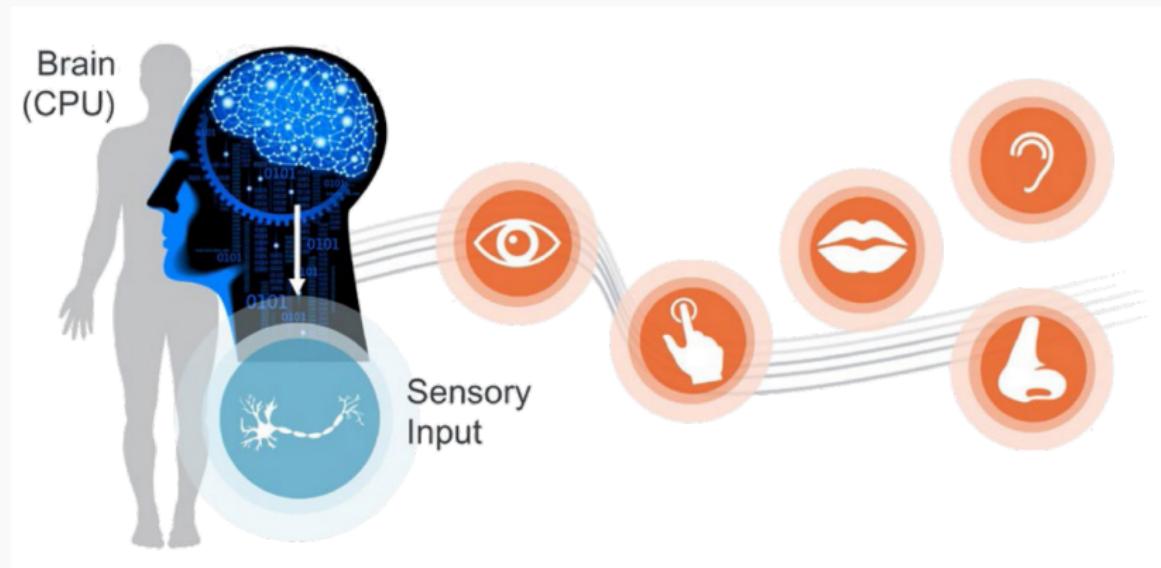


Figure 1: We use MModality in everyday life, this is how humans are communicating

Background: Multimodality

- **Language:** verbal content contains words, but also pragmatics and syntax



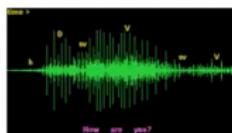
Language

- **Vision:** gesture, facial expressions, gaze, body language, ...



Vision

- **Speech:** prosody, vocal expressions, ...



Speech

But also: touch, physiological (ECG), mobile (location), social (friends in a network)...

Background: Multimodality

Basic definitions

Modality refers to a certain type of information, and its representation format in which information is stored. It is transmitted via a medium, which is a system of communication/transmission.

Human Communication

Transmission of a multimodal signal subject to the interpretation of individuals.

Depending on the different modalities that carry the information, we speak of vocal, verbal, facial, gestural signals, ...

Use of these signals to detect different aspects of the speaker: Emotion [25], Traits [15], or Employability [6].

They are heterogeneous and interconnected!

Modalities

Dimensions of Heterogeneity

Modality A



Modality B

1 Element representations:

Discrete, continuous, granularity



2 Element distributions:

Density, frequency



3 Structure:

Temporal, spatial, latent, explicit



4 Information:

Abstraction, entropy



5 Noise:

Uncertainty, noise, missing data

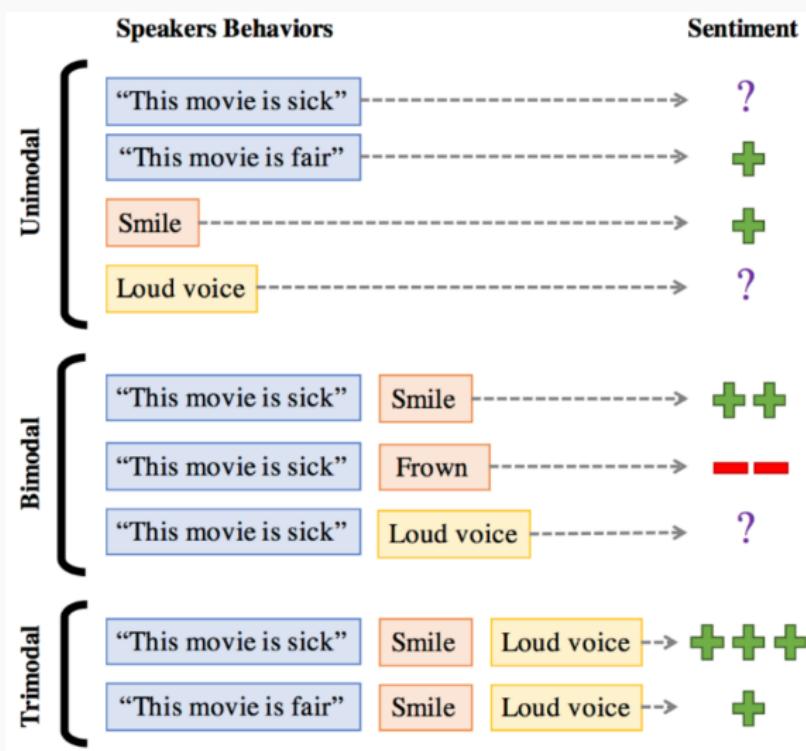


But they are also interconnected (McGurk effect):

<https://www.youtube.com/watch?v=2k8fHR9jKVM>

Complementarity

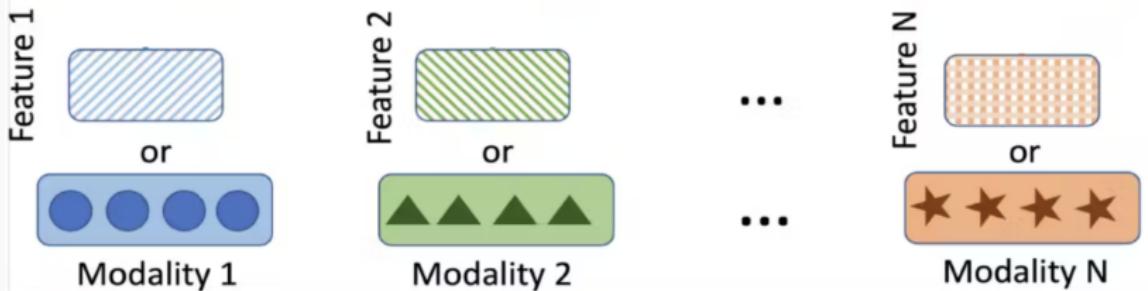
Different modalities can be consensual, complementary, one can help to reinforce the other, etc...



Representation and Encoding

Encoding

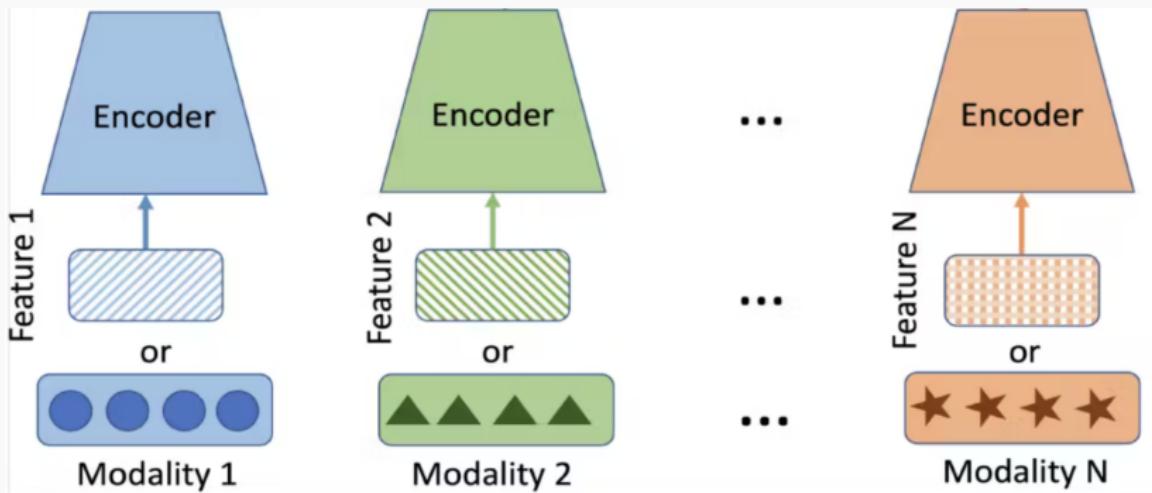
You can encode multimodal data using different methods: extract audio descriptors, extract image descriptors, text descriptors, etc...



Representation and Encoding

Encoding

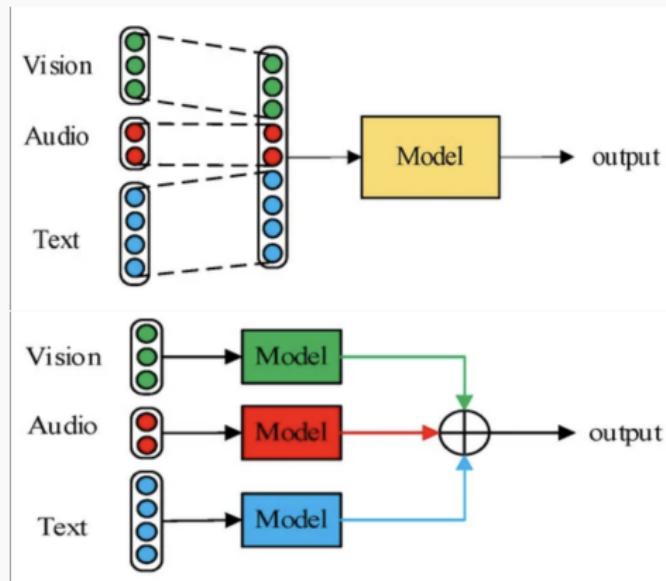
You can encode multimodal data using different methods: extract audio descriptors, extract image descriptors, text descriptors, etc...



Also possible using networks: a pre-trained CNN to encode the image, a pre-trained transformers or word embedding to encode the text, etc...

Basic Fusions

- Early Fusion: before processing
- Late Fusion: after the prediction

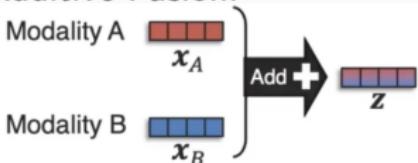


Historically

When the descriptors were extracted manually, the fusion of the unimodal representation before or after processing by a model. Nowadays, it is just big networks extracting the features and fusing them inside

Model-based Fusions I: Different type of fusions

- Additive Fusion:

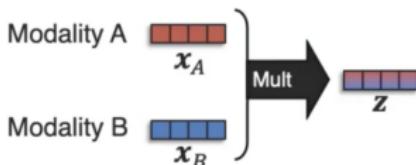


Additive fusion:

$$z = w_1 x_A + w_2 x_B$$

→ 1-layer neural network
can be seen as additive

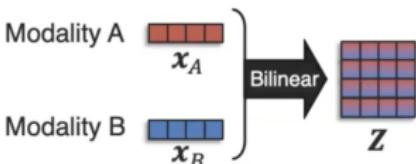
- Multiplicative Fusion:



Simple multiplicative fusion:

$$z = w(x_A \times x_B)$$

- Bilinear Fusion:



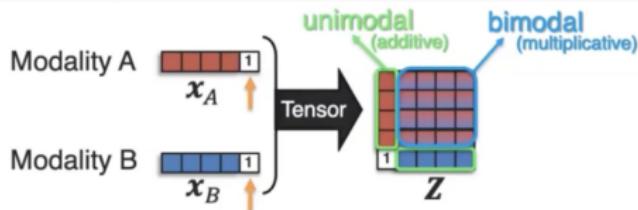
Bilinear Fusion:

$$Z = W(x_A^T \cdot x_B)$$

Remember: The data already has the interactions in it, the model is just trying to learn this

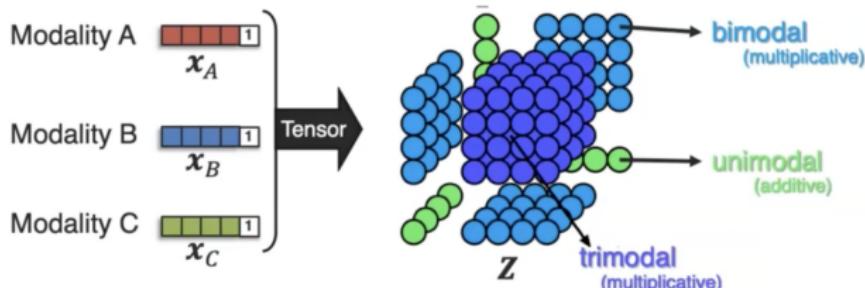
Model-based Fusions II

You can also create more complex fusion modules, but be careful about the complexity and number of parameters!



Tensor Fusion (bimodal):

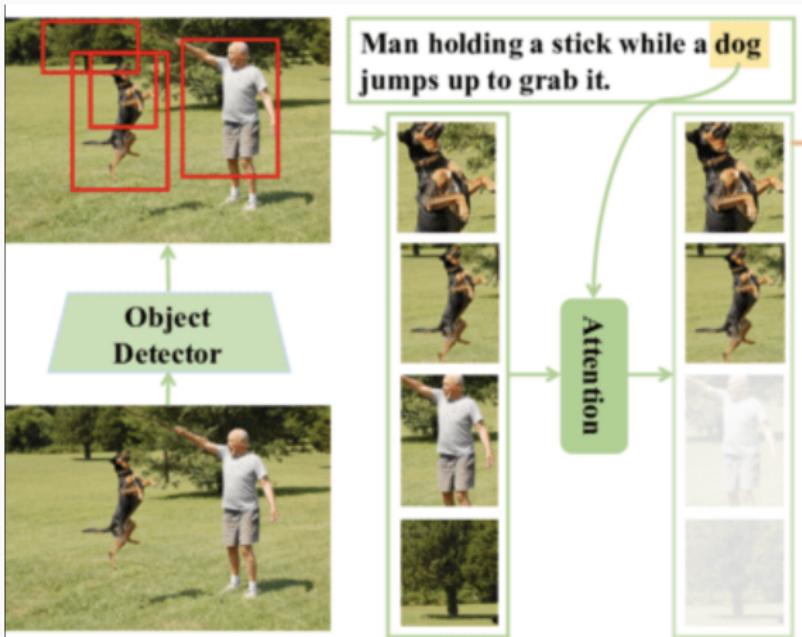
$$Z = w([x_A \ 1]^T \cdot [x_B \ 1])$$



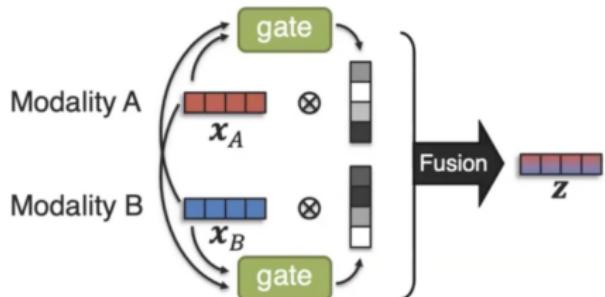
More in papers [17, 32, 8, 16, 19]

Model-based Fusions III

It is possible to use **attention-like gating mechanisms**, and in particular cros-modal attention. This helps to focus on the right part of the modalities when looking for something specific!



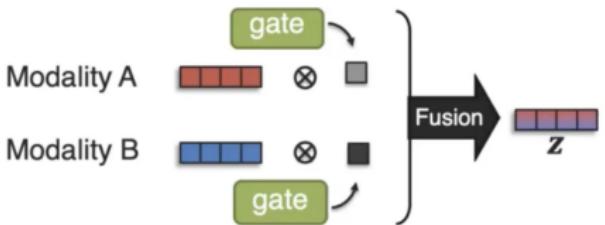
Model-based Fusions IV



Example with additive fusion:

$$z = g_A(x_A, x_B) \cdot x_A + g_B(x_A, x_B) \cdot x_B$$

→ g_A and g_B can be seen as attention functions



→ Gating output can be one weight
for the whole modality

Figure 2: Cross-modal gating attention [2]

It can be seen as a way to:

- prevent unwanted signal from propagating forward (negative; *gating*)
- select the preferable signal to move forward (positive; *attention*)

Tasks

Output	Input	Image	Text	Image & Text
Image	Vision tasks		<p>Text-based image generation, image retrieval</p> <p>Baby pandas walking on the grass</p> 	<p>Text-guided image editing, referring segmentation</p> <p>Panda on the far left</p> 
Text	Image captioning		<p>NLP tasks</p> <p>... world's rarest mammals, the giant [MASK]. Only about 1,500 of these black-and-white bears...</p>	<p>Visual question answering</p> <p>How many pandas are there?</p>  <p>There are 8 pandas</p>
Image & Text			<p>Visual Dialogue</p> <p>How many pandas are there?</p> <p>There are 8 pandas</p>	<p>Show me the image of a movie with a panda</p> 

"Old School" Datasets

MSCOCO



"The two people are walking down the beach."

MSCOCO/OI Narratives



"In this image we can see a bridge and sea. In the background, we can see trees and the sky. We can see so many people on the bridge. At the bottom of the image, we can see two people. We can see stairs in the right bottom of the image ..."

Visual Genome



small round yellow frisbee, man has cast on his arm, concrete trail path in the park, man wearing black sunglasses

Conceptual Captions



"The **scenic route** through mountain ranges includes these unbelievably coloured mountains.

SBU Captions



"**King Arthur's** beheading rock - right on the sidewalk in the middle of **town**".

Human annotated

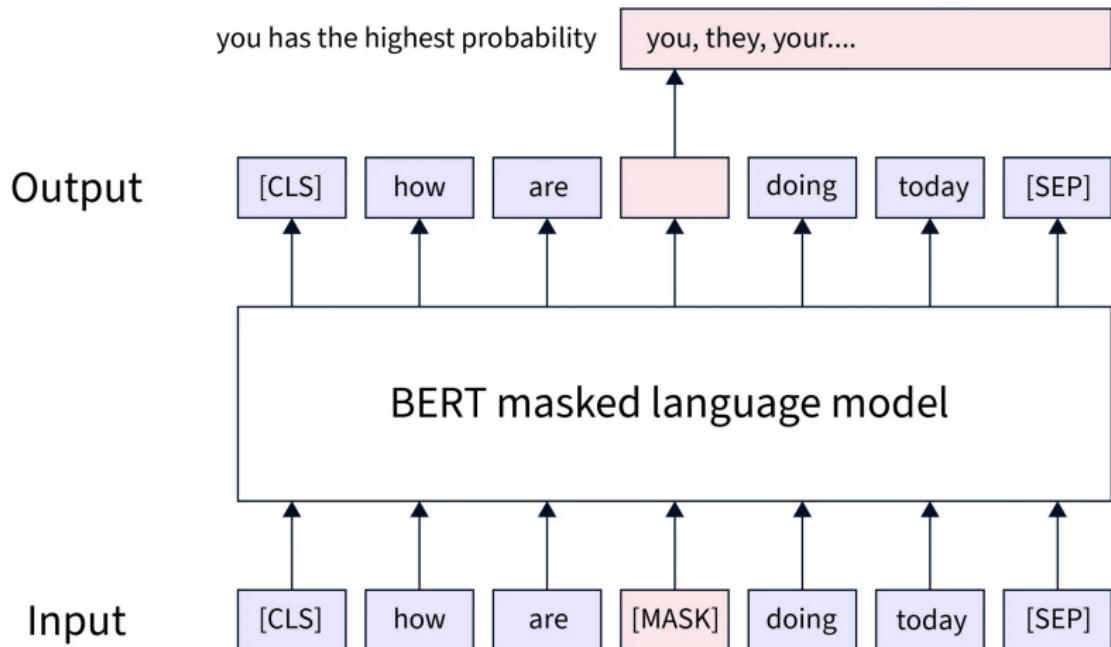
From the web

Figure 3: These datasets were used to train the multimodal models back in the days

For generative models, we will see that new data is available nowadays.

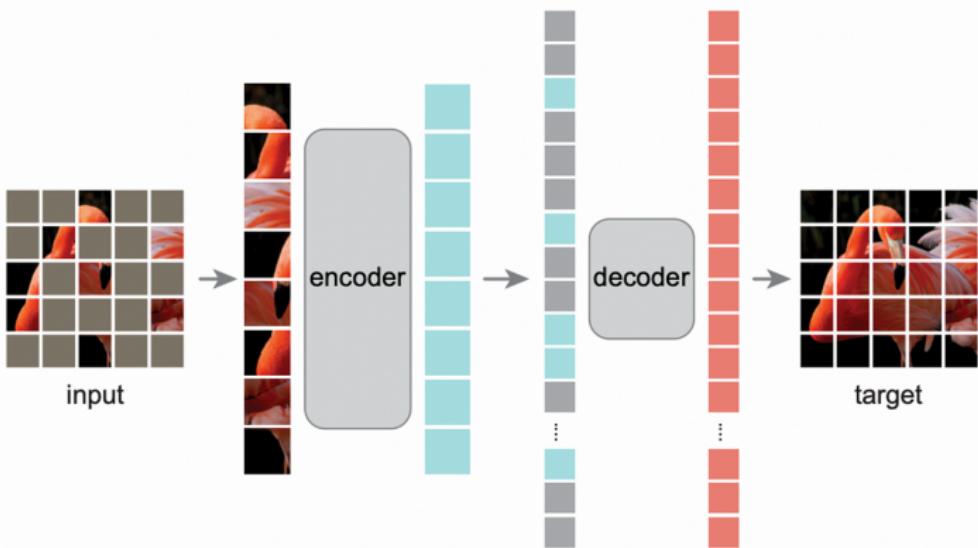
Fusion using Transformers

In the end, the transformers architecture functions well to fuse the different modalities, even their raw data is very different.



Fusion using Transformers

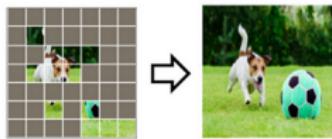
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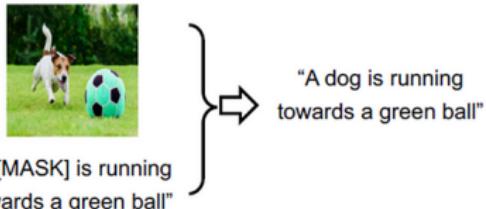
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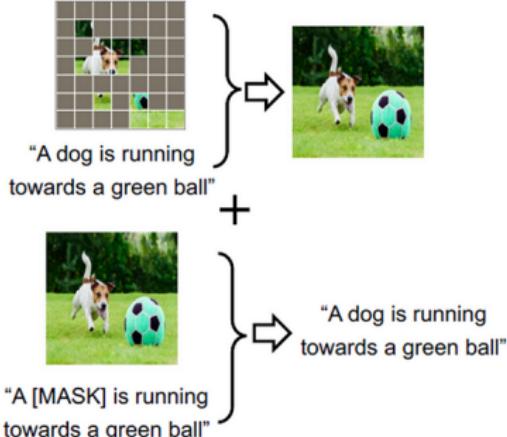
Masked Image Modeling



Masked Language Modeling in V+L Learning



Masked Vision and Language Modeling



First LMMs: LXMERT

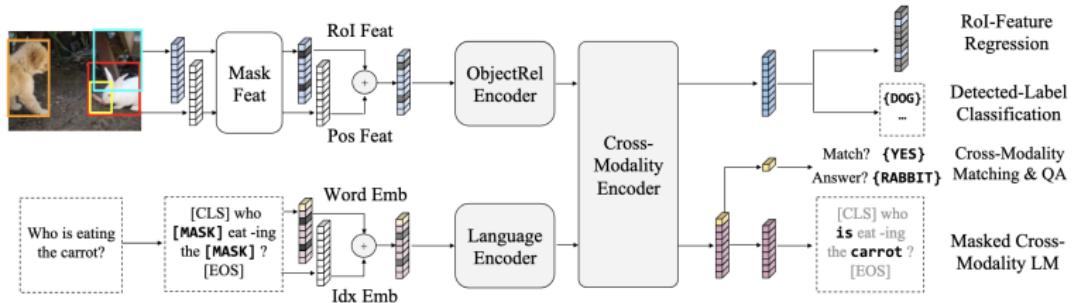
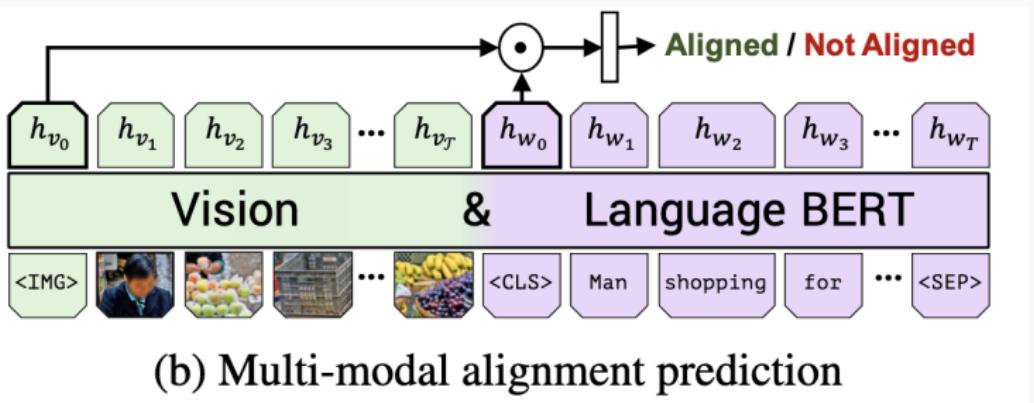
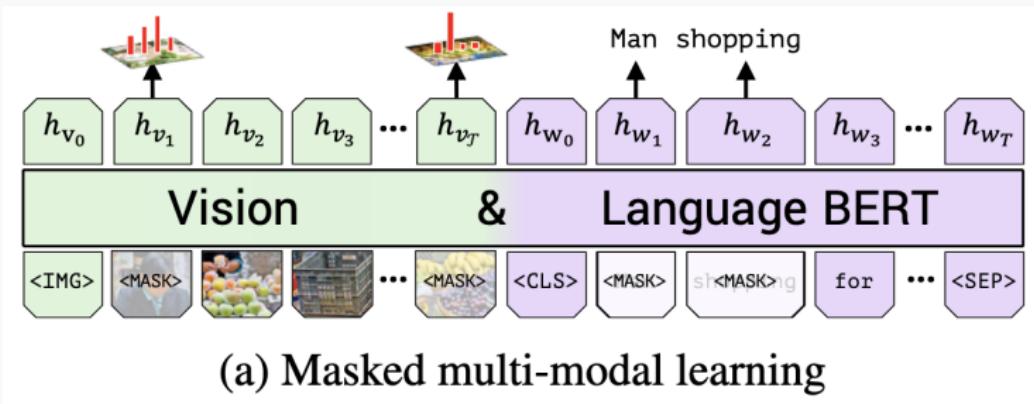


Figure 2: Pre-training in LXMERT. The object RoI features and word tokens are masked. Our five pre-training tasks learn the feature representations based on these masked inputs. Special tokens are in brackets and classification labels are in braces.

The first MModal Transformers [28]

- Use a trained faster-RCNN to extract Region of Interests (Rois) embeddings, and learn to classify it
- Mask words for language, or dimensions for vision
- Cross-modal matching and VQA tasks

First LMMs: VilBERT



First LMMs: ViLBERT

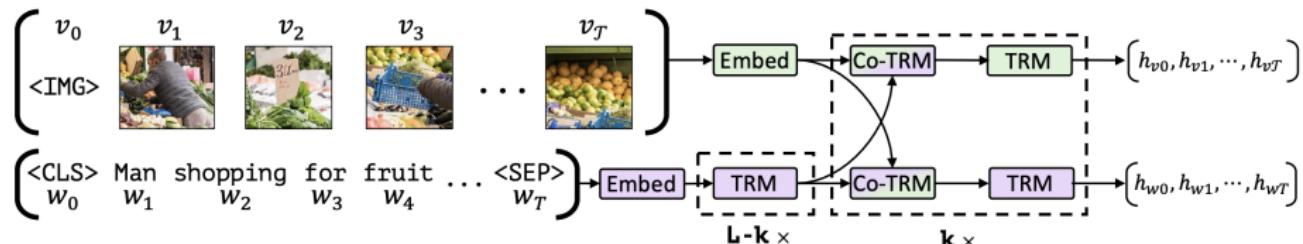
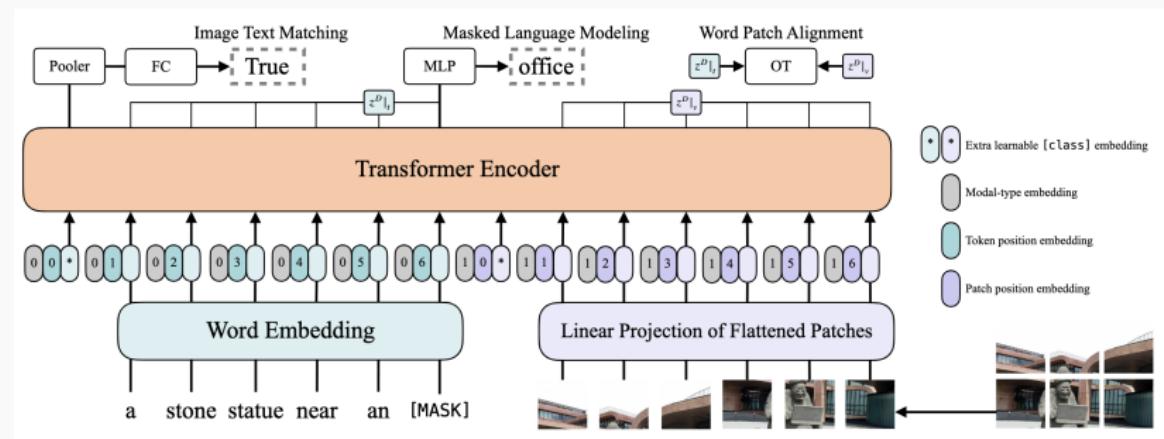


Figure 1: Our ViLBERT model consists of two parallel streams for visual (green) and linguistic (purple) processing that interact through novel co-attentional transformer layers. This structure allows for variable depths for each modality and enables sparse interaction through co-attention. Dashed boxes with multiplier subscripts denote repeated blocks of layers.

The ViLBERT model has a cross-attention transformers layers, using the queries and keys/values different modalities, allowing for **interaction between the modalities in the inside layers** [20]

First LMMs: ViLT

The Vision Language Transformers does not use any CNN to encode the image, showing that **flattening the image before transformer layers is good enough!** [9]



It uses three losses, similar to what we've seen beforehand.

Coordination

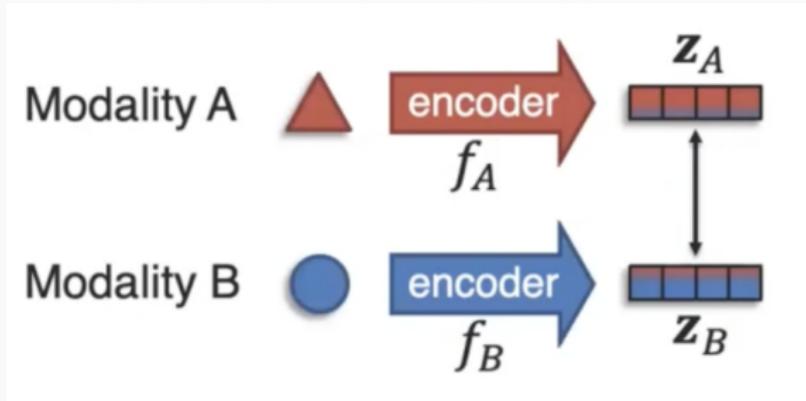


Figure 4: Coordination: align the modalities in a latent common space is a clever way to train a multimodal model in a self-supervised way.

Coordination

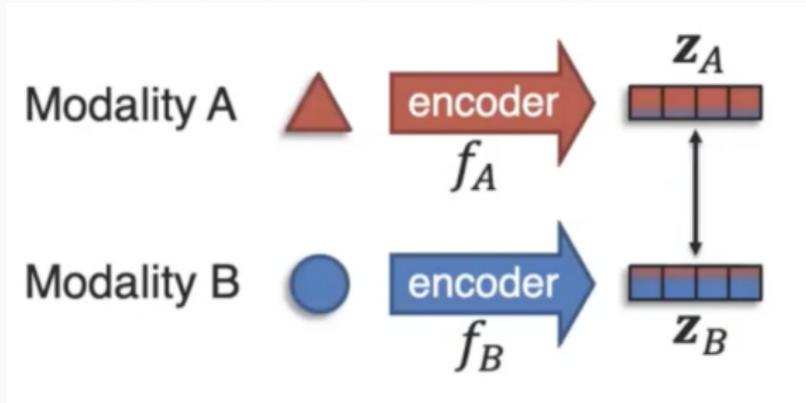


Figure 4: Coordination: align the modalities in a latent common space is a clever way to train a multimodal model in a self-supervised way.



Contrastive Learning: Example on Images

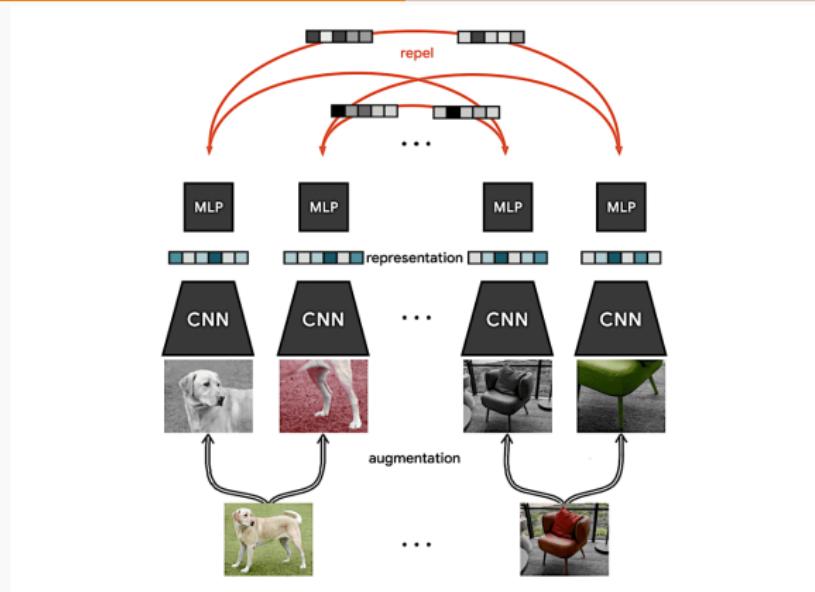


Figure 5: SimCLR is an example of pre-training on ImageNet

Principle

Representations from parts of the same images are getting closer while representations of the patches from different images are getting pushed apart. Can also work with classes!

CLIP: Contrastive Language-Image Pre-training

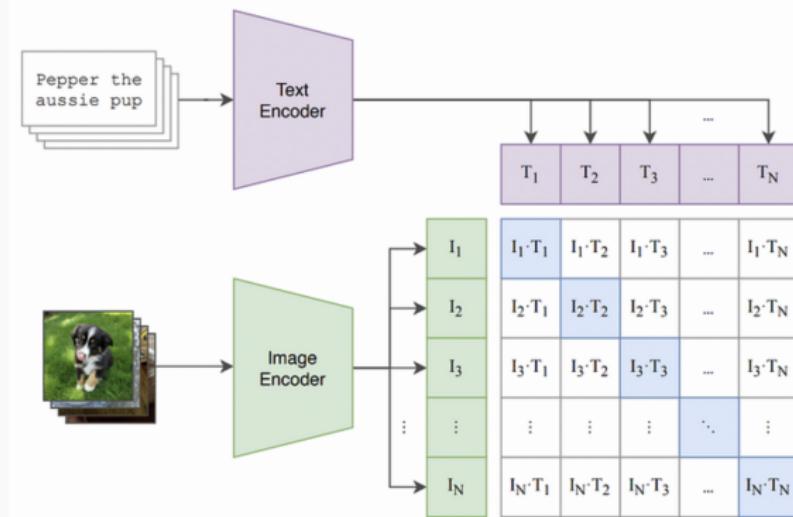


Figure 6: CLIP has been trained over 400M image-text pairs

Principle

Learn a shared multimodal embedding space, and maximize/minimize the distance between the embeddings belonging together. Loss equivalent to learn a function that maximizes the mutual information between the modalities [23].

CLIP: zero-shot

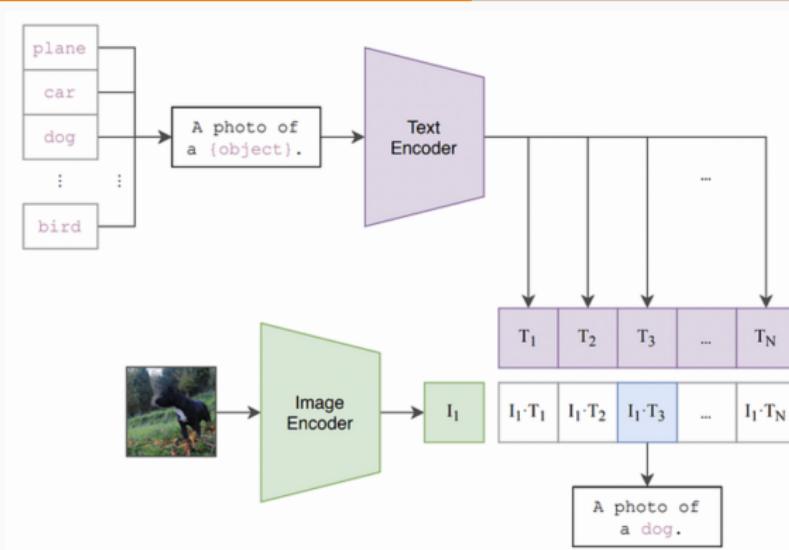


Figure 7: CLIP is very good at zero-shot using text templates

However, this is really dependant of the data and classes (it sucks for OOD such as Satellite data).

More on CLIP [here](#)

BLIP: Bootstrapping Language-Image Pre-training

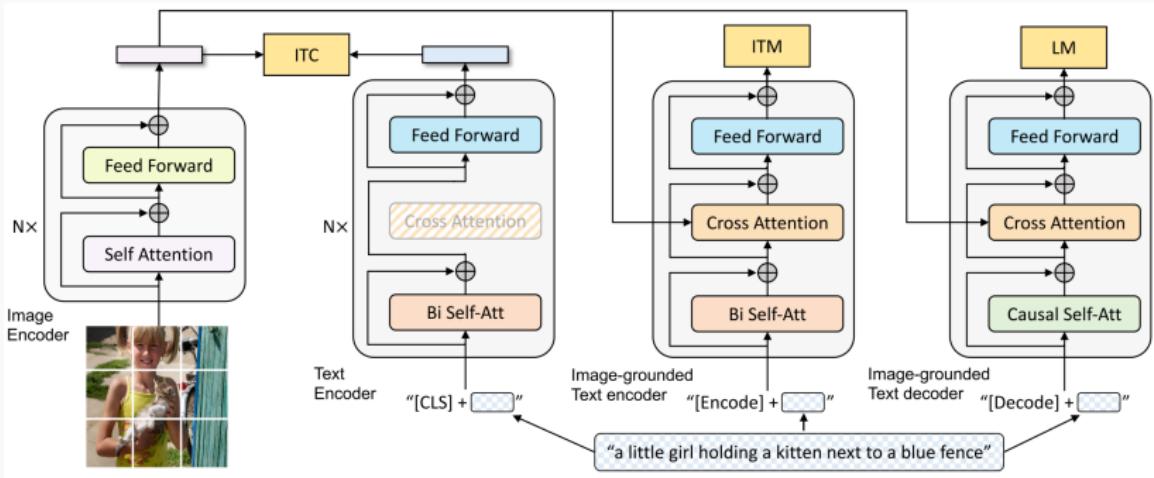


Figure 8: Unimodal encoders + multimodal image-grounded text-encoders [13]

Three losses

Image-text contrastive (ITC) loss for the unimodal encoders. For the multimodal encoders, an image-text matching (ITM) to distinguish between positive and negative image-text pairs, and a Language Model (LM) loss to generate text. **Also bootstraps the dataset to clean noisy examples** (filter bad captions).

Text to image generator: CLIP + VQ-GAN



Figure 9: Artificial images generation using CLIP + VQ-GAN

Text to image generator: CLIP + VQ-GAN

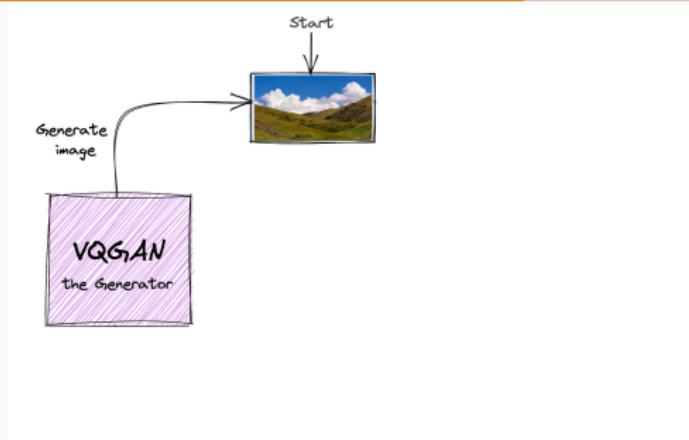


Figure 10: Artificial images generation conditioned on text

Text to image generator: CLIP + VQ-GAN

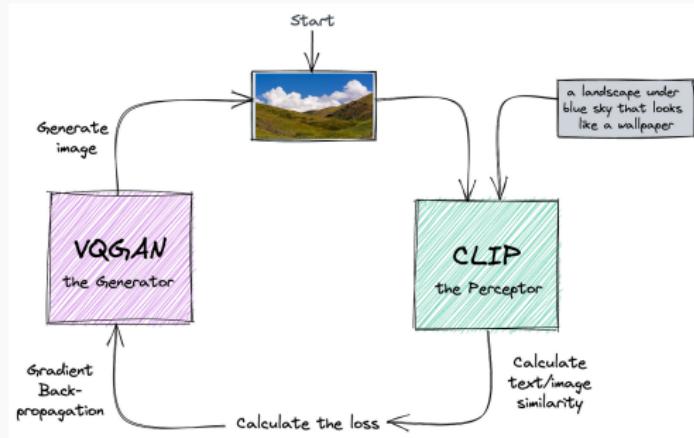


Figure 10: Artificial images generation conditioned on text

Text to image generator: CLIP + VQ-GAN

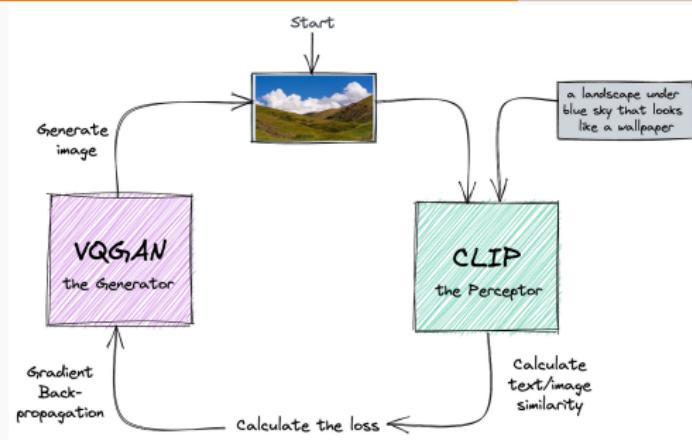
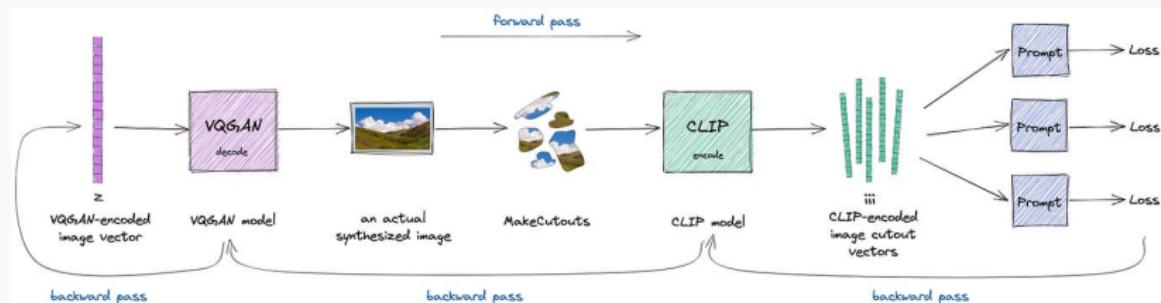


Figure 10: Artificial images generation conditioned on text



[Interesting explanations](#) and [a notebook](#) with [code explanations](#)

Diffusion: New advances in text-to-image I

Diffusion models allow to generate images conditioned on text

Demo [Stable Diffusion 3 Medium](#)

Learn more about the [Stable Diffusion 3 series](#). Try on [StabilityAI API](#), [Stable Assistant](#), or on Discord via [Stable Artisan](#). Run locally with [ComfyUI](#) or [diffusers](#)

A delicious ceviche cheesecake slice

Run



Figure 11: Examples of funny images obtained with diffusion models

Diffusion: New advances in text-to-image II

Definition

Probabilistic models that learn the data distribution by modeling the reverse of a diffusion process (adding noise step-by-step) to generate new data points.

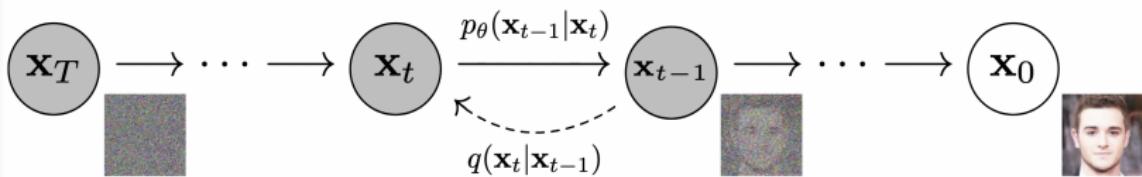


Figure 12: Denoising an image [7]

Process

- **Forward:** Add small amounts of noise to the data, which gradually becomes noisier over time steps, until resembling random noise
- **Reverse:** Learn to gradually remove noise to recover the original data, starting from pure noise and generating realistic data.

Diffusion: Stable Diffusion

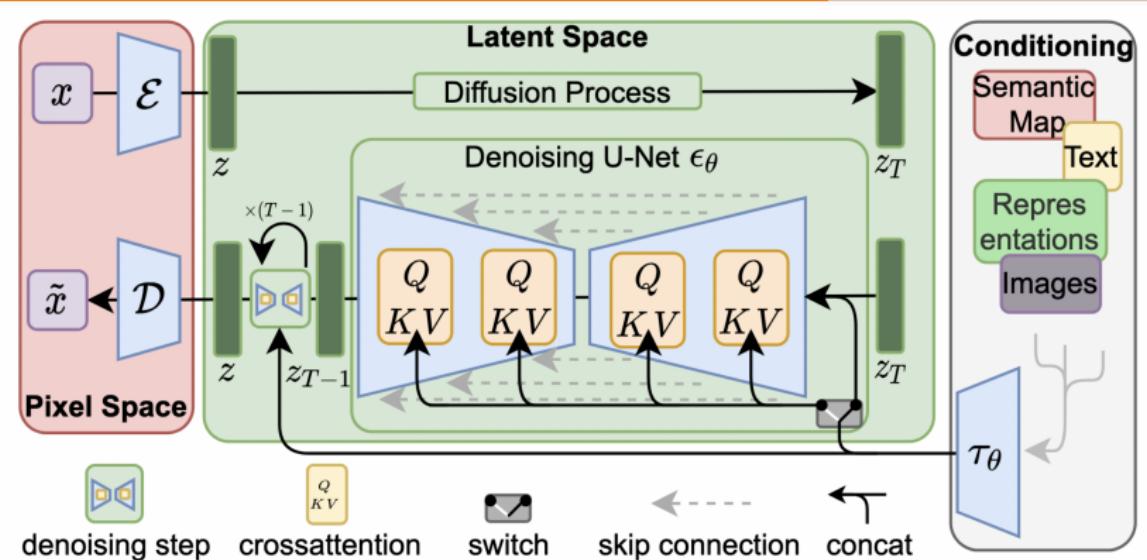


Figure 13: Stable Diffusion architecture [24]

- Use a Denoising Network (e.g., U-Net) to reduce the noise at each step.
- Conditioning (e.g., text embedding) helps guide the model to generate a specific output using x -attention mechanism.

LLM-based: Frozen encoders

- Learn image embeddings to be aligned with a **frozen language model**
- Goal: encode images **into the word embedding space of a LLM**
- The LLM should generate captions for those images
- Very good a few-shot

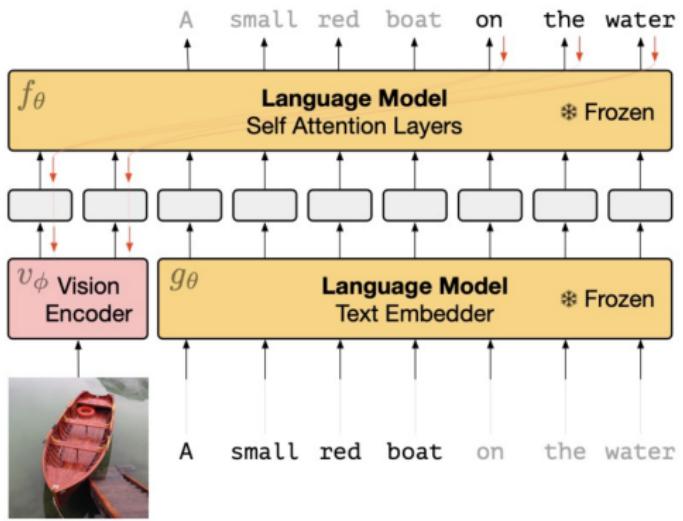


Figure 14: Few shot examples from the model called Frozen [29]

LLM-based: BLIP2 and BLIP3

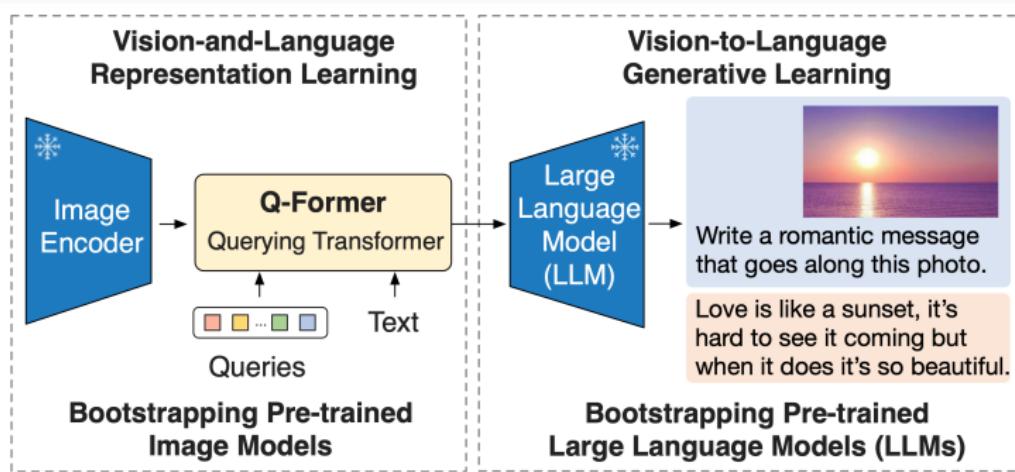


Figure 15: BLIP 2/3 [12, 31] use frozen encoders, just learning the Q-Former

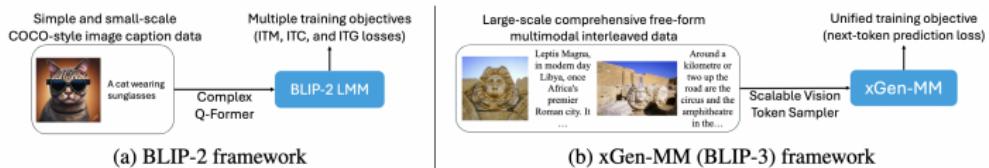


Figure 1: We introduce **xGen-MM (BLIP-3)**, a framework (b) for developing Large Multimodal Models (LMMs). Our framework improves upon BLIP-2 (a) [1] by (1) increasing the richness, scale, and diversity of training data, (2) replacing the Q-Former layers with a more scalable vision token sampler, and (3) simplifying the training process via the unification of the training objectives to a single loss at every training stage. The resulting suite of LMMs can perform various visual language tasks and achieve competitive performance across benchmarks.

LLM-based: xGen-MM (BLIP3) I

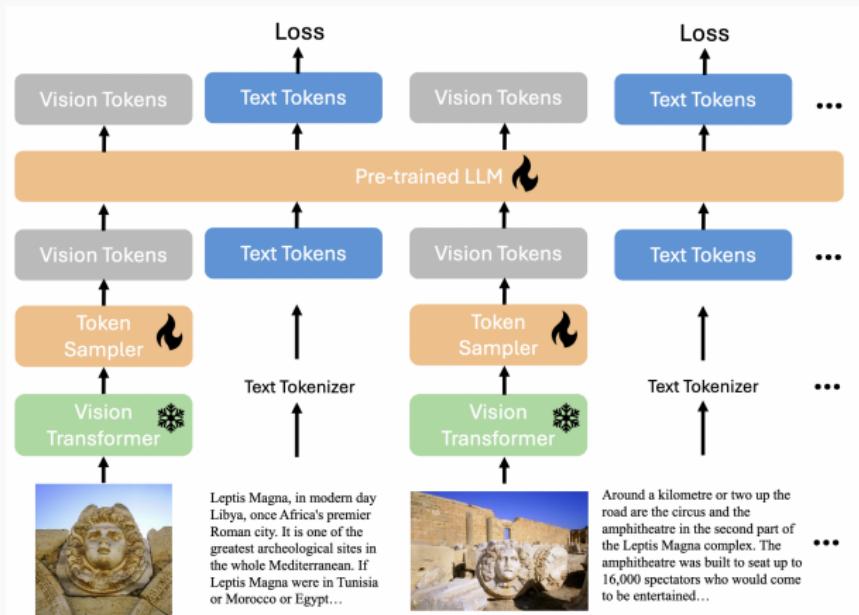


Figure 2: Overview of the xGen-MM (BLIP-3) framework. Free-form interleaved images and texts from the ensembled interleaved and caption datasets are input into the framework, with each modality undergoing a separate tokenization process to be fed into the pre-trained LLM in natural order. A standard auto-regressive loss is then applied to the text tokens. The Vision Transformer is kept frozen during training, while all other parameters, including the token sampler and the pre-trained LLM, are trained.

Figure 16: BLIP 3 use frozen encoders, but now relies only on one task of Language Modeling. Models available [here](#)

LLM-based: xGen-MM (BLIP3) II

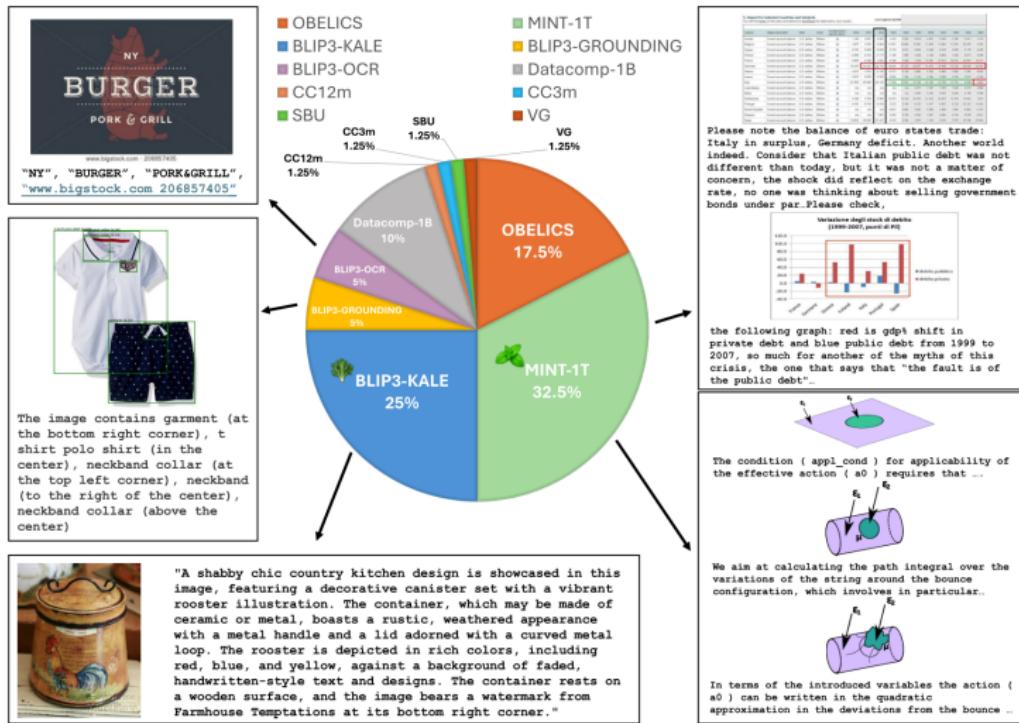


Figure 17: BLIP3 training set contains interleaved multimodal data (mix of sequences of images and text) of very diverse content

LLM-based: Flamingo

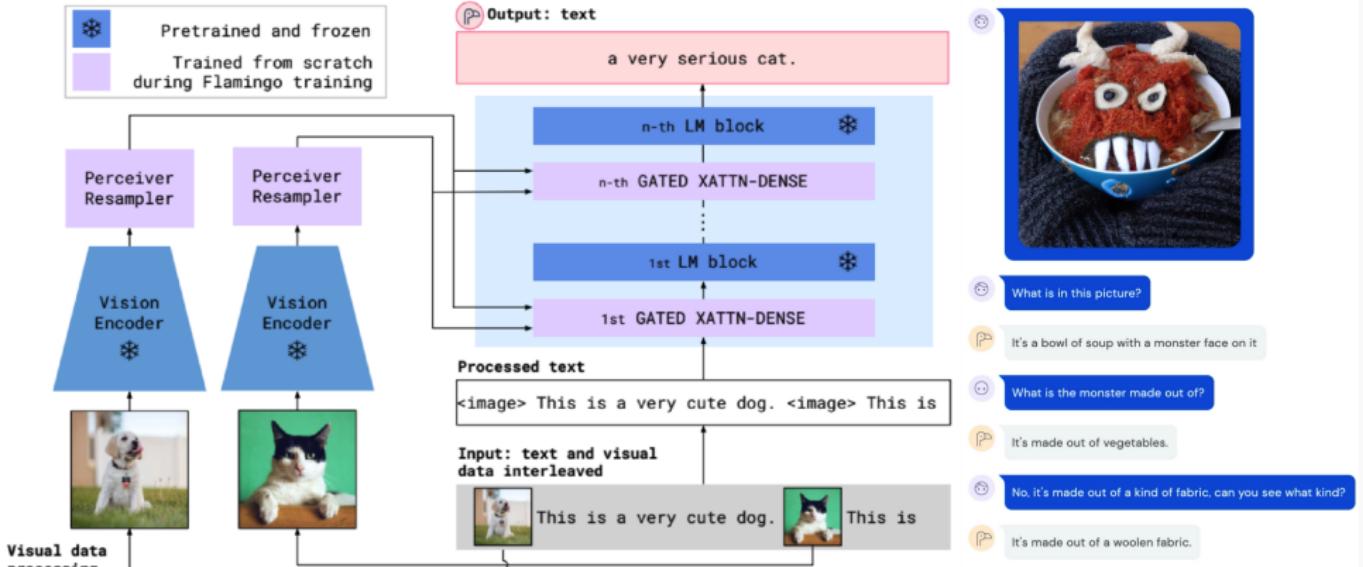
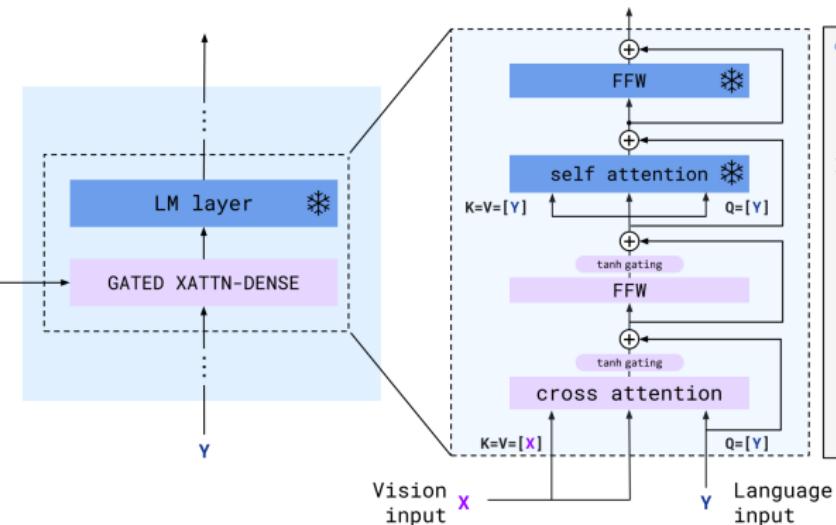


Figure 18: Flamingo was the first LMM that can converse with a human [1]

- Parts trained from scratch, part pre-trained and frozen
- Cross-modal gating mechanism
- Interleaved text with images

LLM-based: Flamingo II



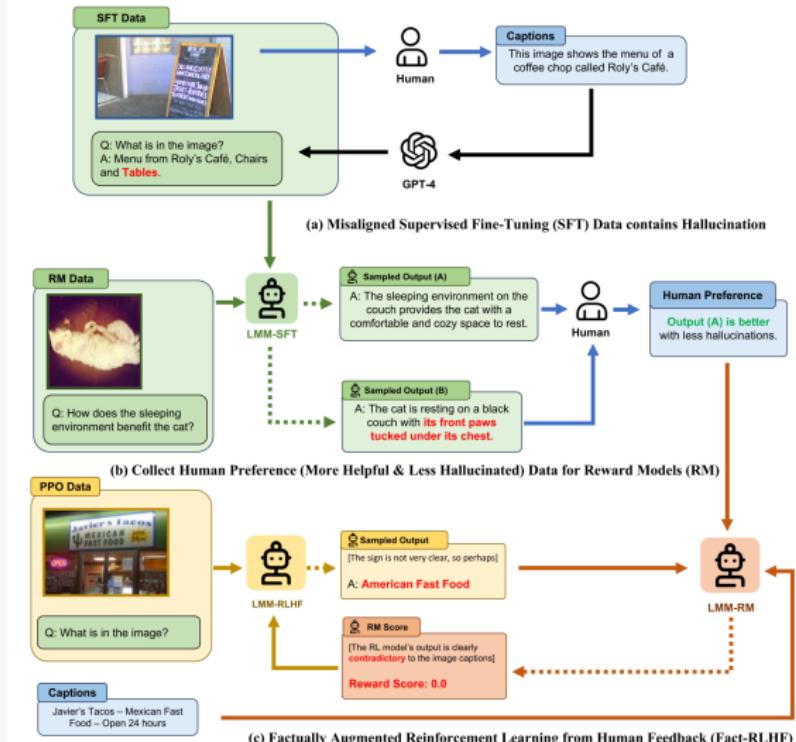
```
def gated_xattn_dense(  
    y, # input language features  
    x, # input visual features  
    alpha_xattn, # xattn gating parameter - init at 0.  
    alpha_dense, # ffw gating parameter - init at 0.  
):  
    """Applies a GATED XATTN-DENSE layer."""  
  
    # 1. Gated Cross Attention  
    y = y + tanh(alpha_xattn) * attention(q=y, kv=x)  
    # 2. Gated Feed Forward (dense) Layer  
    y = y + tanh(alpha_dense) * ffw(y)  
  
    # Regular self-attention + FFW on language  
    y = y + frozen_attention(q=y, kv=y)  
    y = y + frozen_ffw(y)  
    return y # output visually informed language features
```

Figure 19: Gated attention mechanism of Flamingo

The LM layers are frozen to preserve its quality obtained from a very large pre-training.

LLM-based: Large Language and Vision Assistant (LLaVA)

- Open-source model based on LLama, adapting it to multimodal data [18]
- Projection matrix from the supplied image using CLIP and feeds it to Llama
- Pre-training of the projection matrix, then fine-tuning adding the LLM weights
- Possible to RLHF [27]



Open-source datasets: OBELICS

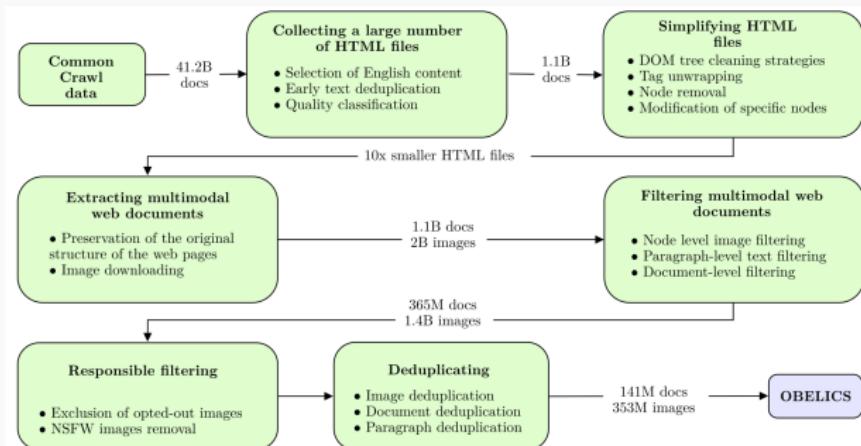


Figure 20: OBELICS [10] is an open, massive and curated collection of interleaved image-text web documents, containing 141M documents, 115B text tokens and 353M images

A series of models called IDEFICS that were trained on this dataset are available open-source [here](#).



Towards video

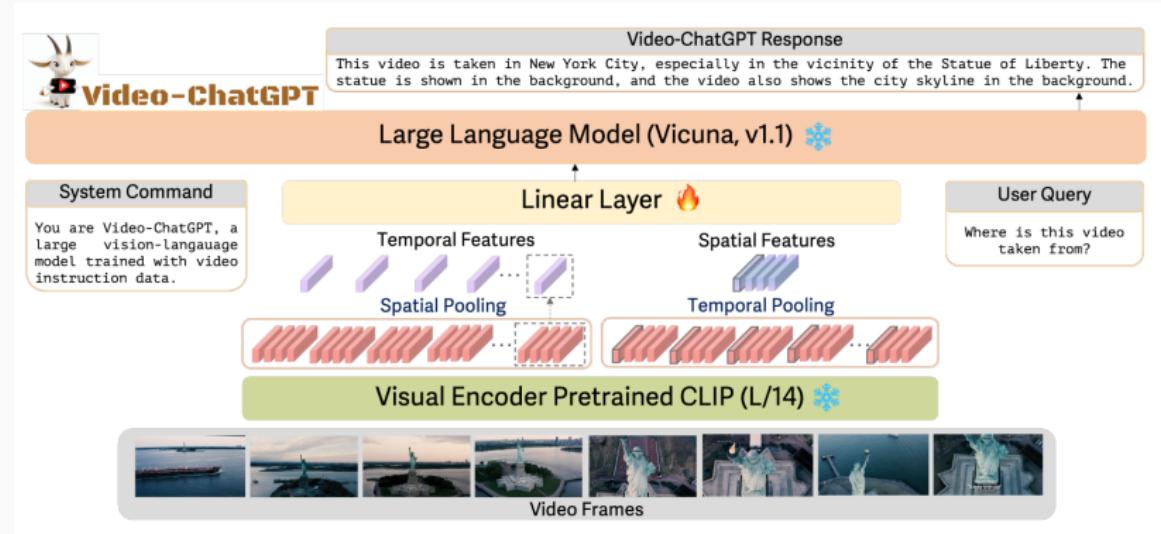
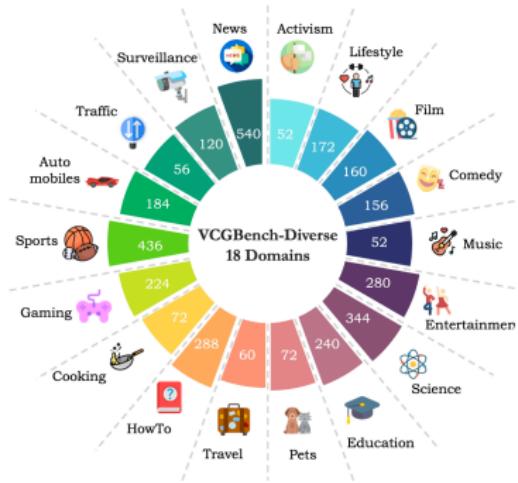


Figure 21: Architecture of Video-ChatGPT, visual encoder extract features that are pooled spatially and temporally [22]

Others architectures available including audio [5, 11, 35, 30, 3, 21]

How to evaluate the video generative LLM?



Category	Description	#	Domains
5 Video Capturing Methods			
Stable Settings	Videos shot in stable, predictable environments with minimal camera movement.	1200	Cooking, How-to, Education
Dynamic Settings	Videos with significant camera movement requiring adaptation to rapid context shifts.	448	Sports, Traffic, Travel
Fixed Cameras	Videos recorded from stationary cameras, providing consistent viewpoints for monitoring purposes.	124	Surveillance, Automobile
Professional Quality	Professionally produced videos with high visual and audio quality, and controlled lighting.	1608	News, Film
Variable Quality	Informal videos with varying quality, often using handheld devices, captured in spontaneous settings.	124	Lifestyle, Pets
6 Reasoning Complexities			
Sequential Understanding	Requires comprehension and following of a series of steps or actions in order.	828	Cooking, How-to, Education
Predictive Reasoning	Involves understanding and predicting outcomes of dynamic, intricate action sequences.	180	Sports, Gaming
World Knowledge	Demands integration of broader contextual information and world knowledge to interpret video content.	848	Science, News
Causal Reasoning	Focuses on understanding cause-and-effect relationships within the video.	340	Surveillance, Activism
Emotional Reasoning	Involves interpreting stories, character motivations, and emotional subtexts.	1080	Entertainment, Film, Comedy
Analytical Reasoning	Requires critical analysis and interpretation of complex information or situations.	228	Traffic, Automobile

Figure 22: VCGBench-Diverse video conversational benchmark [21]

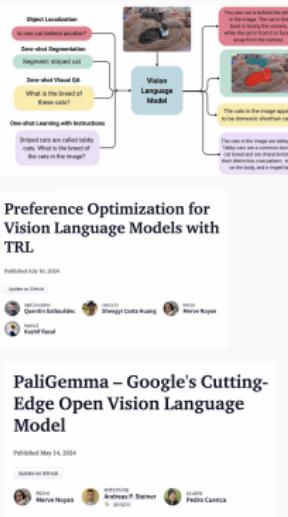
- 18 broad video categories, with 4,354 QA pairs
- tasks: dense video captioning, spatial and temporal understanding, and complex reasoning
- five video-capturing methods, ensuring diversity and robust generalization and six reasoning complexities

Today, everything is a token!

- Image tokenization with SEED: [4]
- SpeechTokenizer from [34]
- AnyGPT: [33]
- OmniVec: [26]

Want to learn more about MModal ML?

- You can check this [LMM tutorial](#) from huggingface
- This other one on [Preference Optimization for LMMs using DPO](#)
- Another tutorial on how to [use PaliGemma](#), with [a demo](#)



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Questions?

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