Topics:

- Vision-Language Models

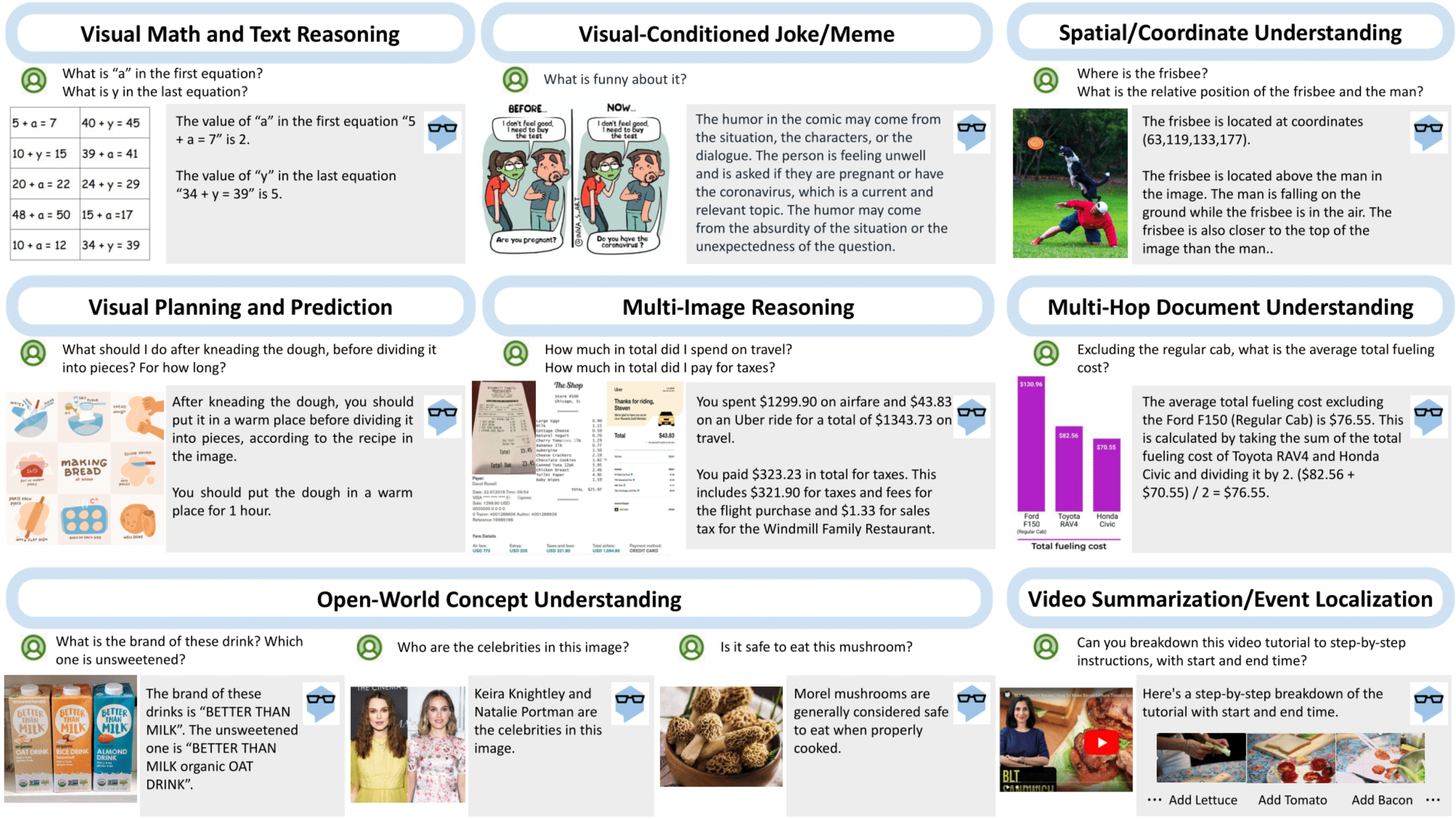
# CS 4644-DL / 7643-A

ZSOLT KIRA

- Project due April 26th 11:59pm (grace period **April 28th**)

- Fill out CIOS! https://b.gatech.edu/cios

## Admin



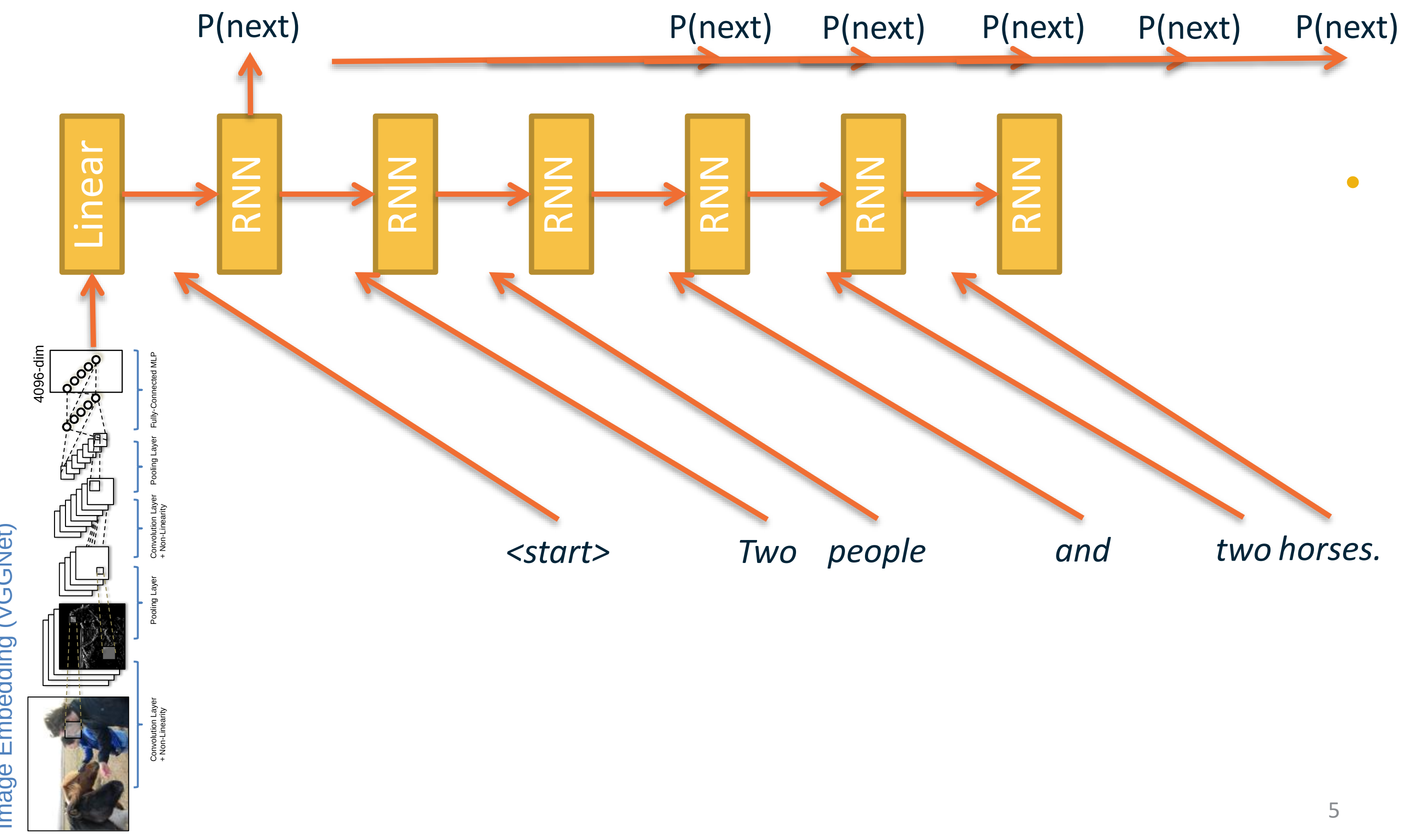

**Yang et al., MM-ReAct MM-ReAct: Prompting ChatGPT for Multimodal Reasoning and Action**

# Motivation: Vision-Language Models

# Overview

- Image+LSTM
- CLIP
- Vilbert
- Flamingo
- BLIP/BLIP-2
- LLaVA
- ImageBind / LanguageBind

# The Early Days: Neural Image Captioning




- **Features**:
  - Pre-trained visual encoder (vector)
  - Linear projection layer to map to "captionable" space
  - Vector serves as initial input to RNN


How should we encode this (representations?)?

How will they be learned?

# VLMs: Considerations

How/what should we train?

Using what data?

What tasks can we do?

Visual Feature Space

?

What should the interface be?

Language Model

Features Space (Encoder)

Decoder

a group of men are fishing on a beach

drei Männer in einem Ruderboot

a brown dog runs after a black dog on a shore

zwei Hunde spielen auf dem Strand

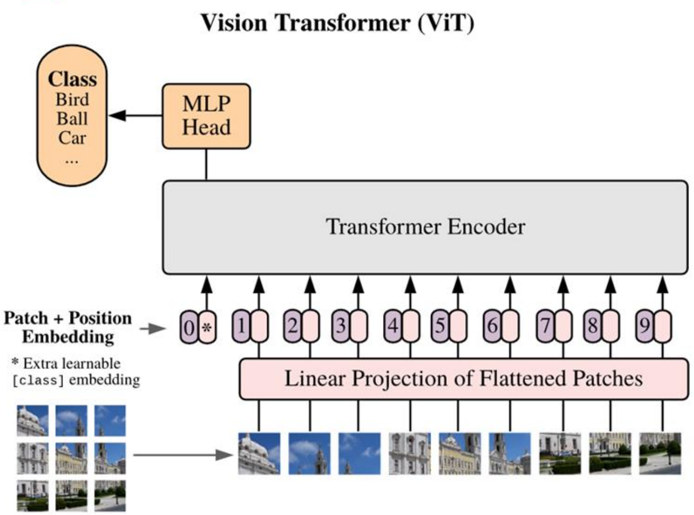
girl hits a ball and the catcher looks on

chiedsrichter beobachtet Baseballspieler

## VLMs: Considerations

## Potential ways of representing an image?

- Image encoder
  - Any architecture: ResNet, Vision transformer (ViT)
  - Randomly initialized, SL/SSL pre-trained

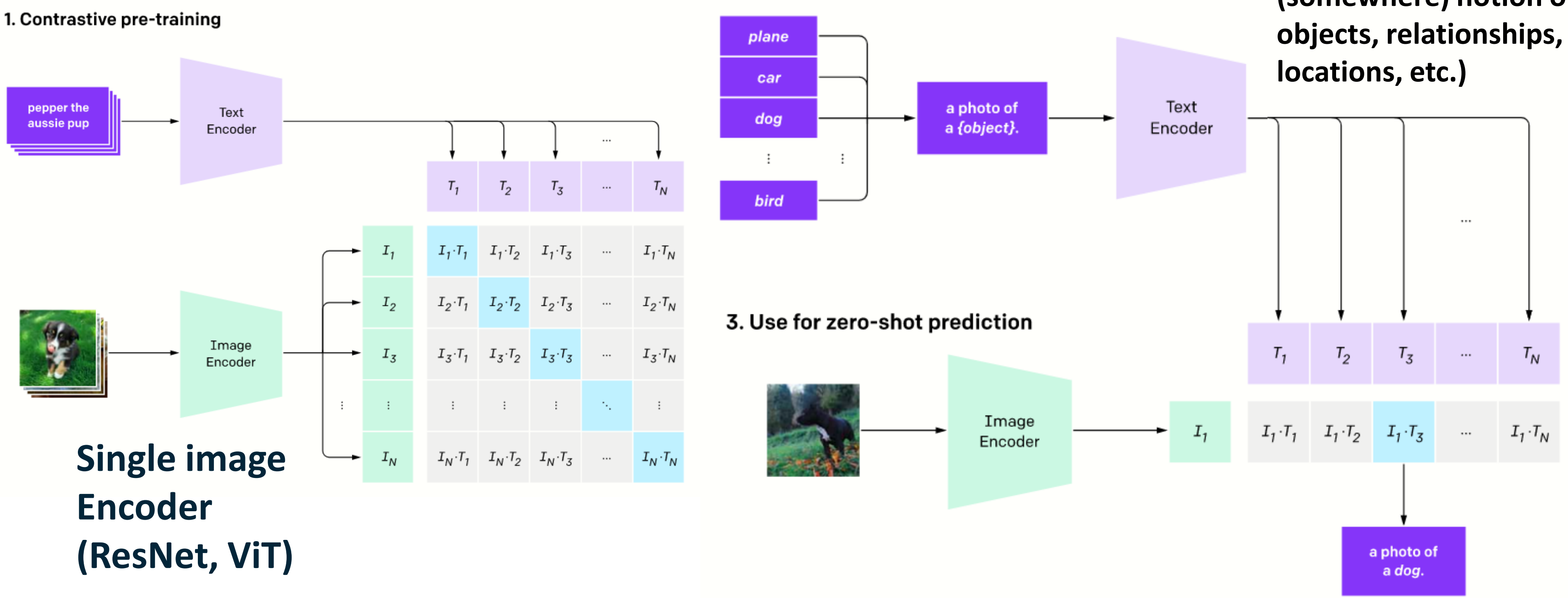


# Method of alignment: Contrastive Learning

**Data: 400M image-text pairs**

**Downside?**

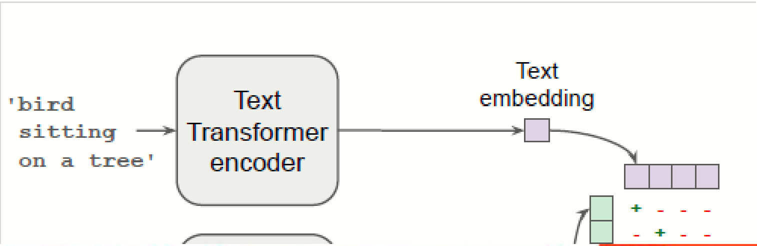
Coarse-grained.
Has to represent (somewhere) notion of objects, relationships, locations, etc.)



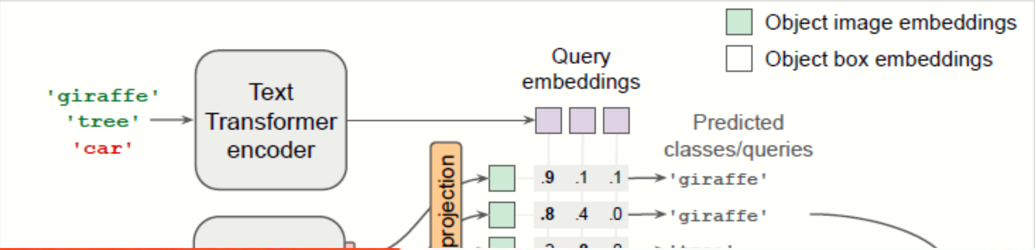

Single image Encoder (ResNet, ViT)

Radford et al., Learning Transferable Visual Models From Natural Language Supervision

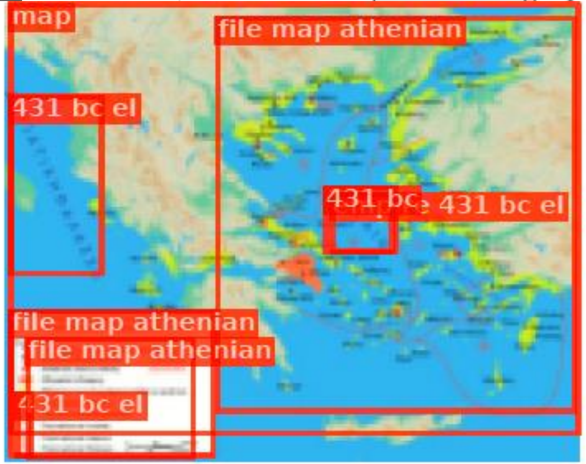
Image-level contrastive pre-training

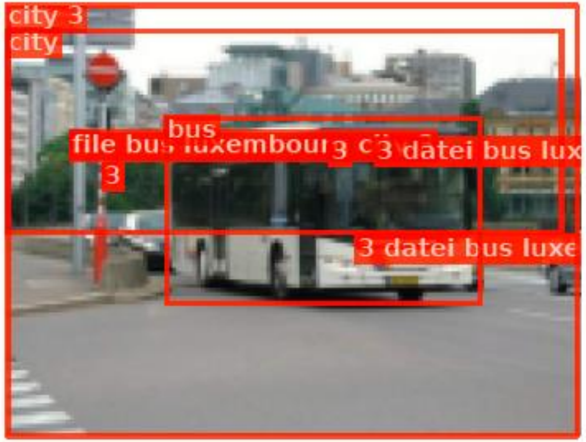



Transfer to open-vocabulary detection







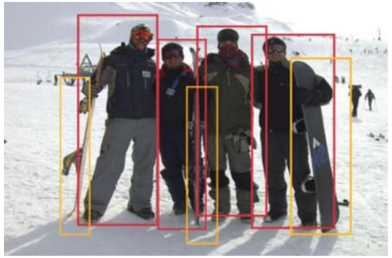

Minderer et al., Simple Open-Vocabulary Object Detection with Vision Transformers
Minderer et al., Scaling Open-Vocabulary Object Detection

# Open-Vocabulary Detection

Downside?

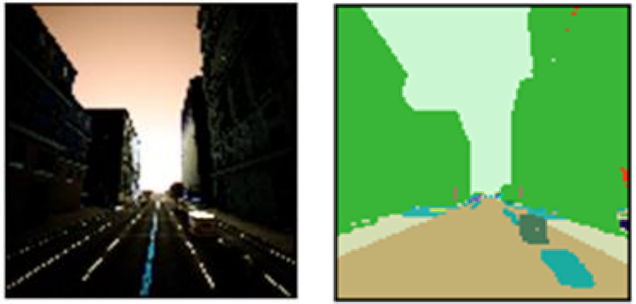
# Potential ways of representing an image?

- Image encoder
  - Randomly initialized, SL/SSL pre-trained
- **Alternative**:
  - Bounding boxes/segments/regions + features

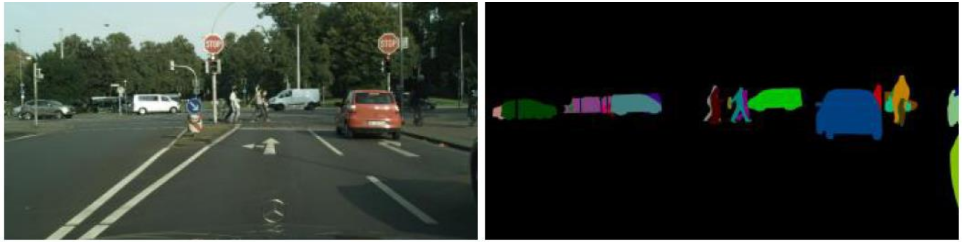


**Object Detection**

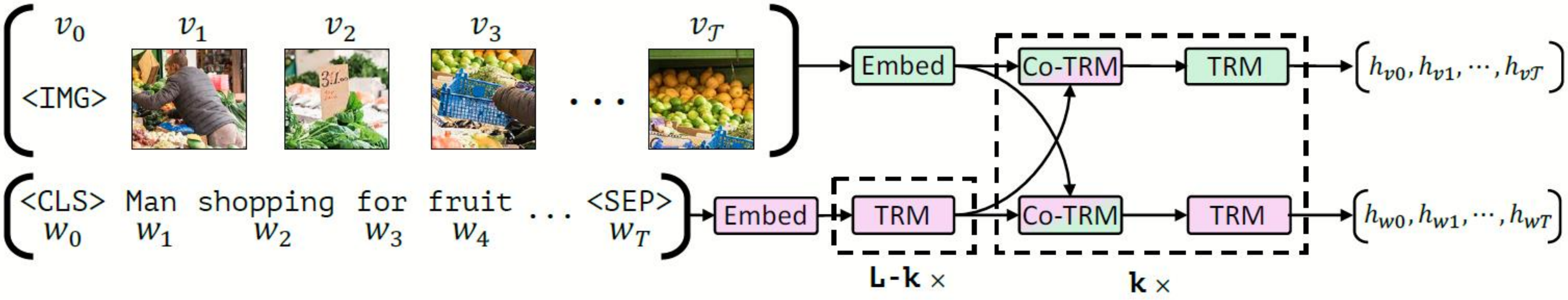
(List of bounding boxes with class distribution per box)



**Semantic Segmentation**

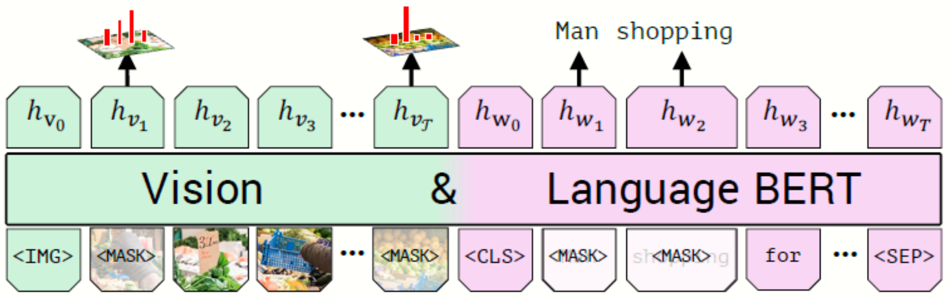


**Instance Segmentation**

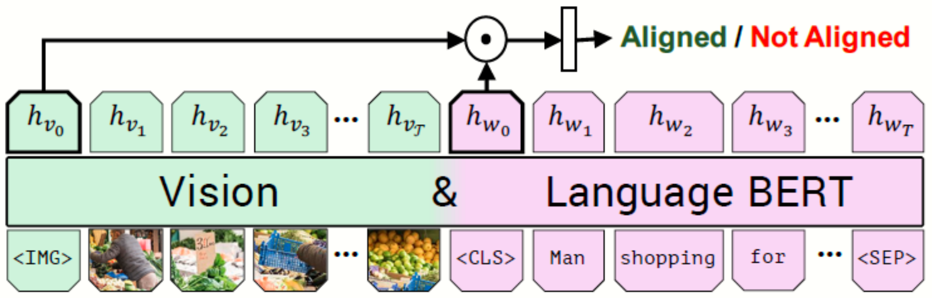



## Training: Masked Prediction + Alignment

## Interaction/Fusion: Cross-Attention




(a) Masked multi-modal learning

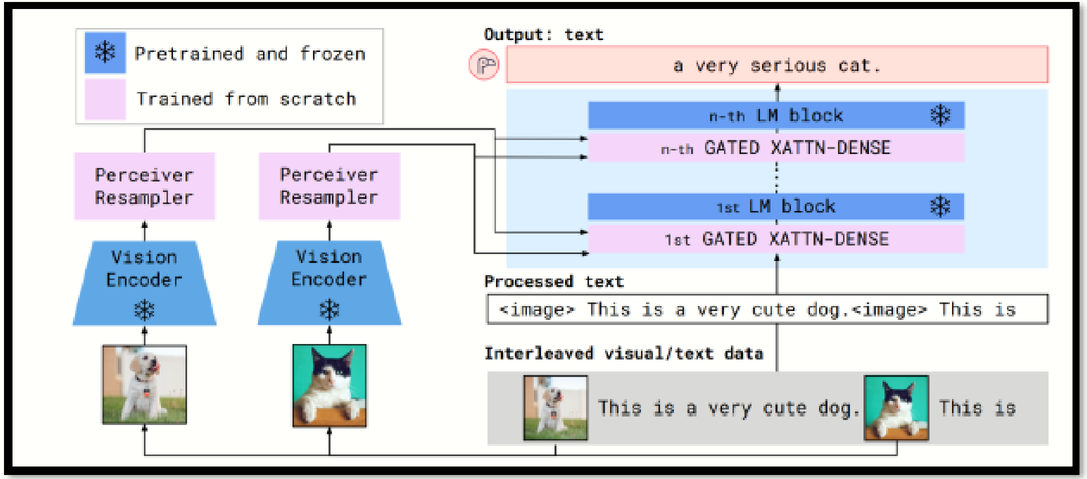



(b) Multi-modal alignment prediction

Lu et al., ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks

# Vilbert

- Flamingo:




Language Model

Connection Module

Vision Encoder

| |
|---|
| Pre-trained: 70B Chinchilla |
| Perceiver Resampler<br>Gated Cross-attention + Dense |
| Pre-trained: Nonrmalizer-Free ResNet (NFNet) |

NeurIPS 2021

# Multimodal Few-Shot Learning with Frozen Language Models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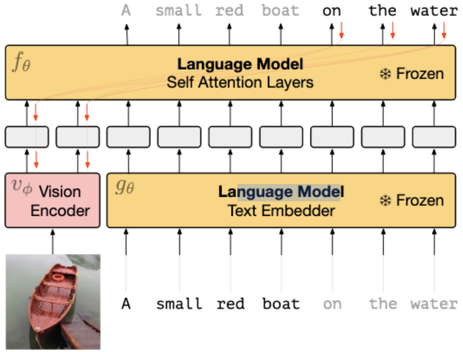
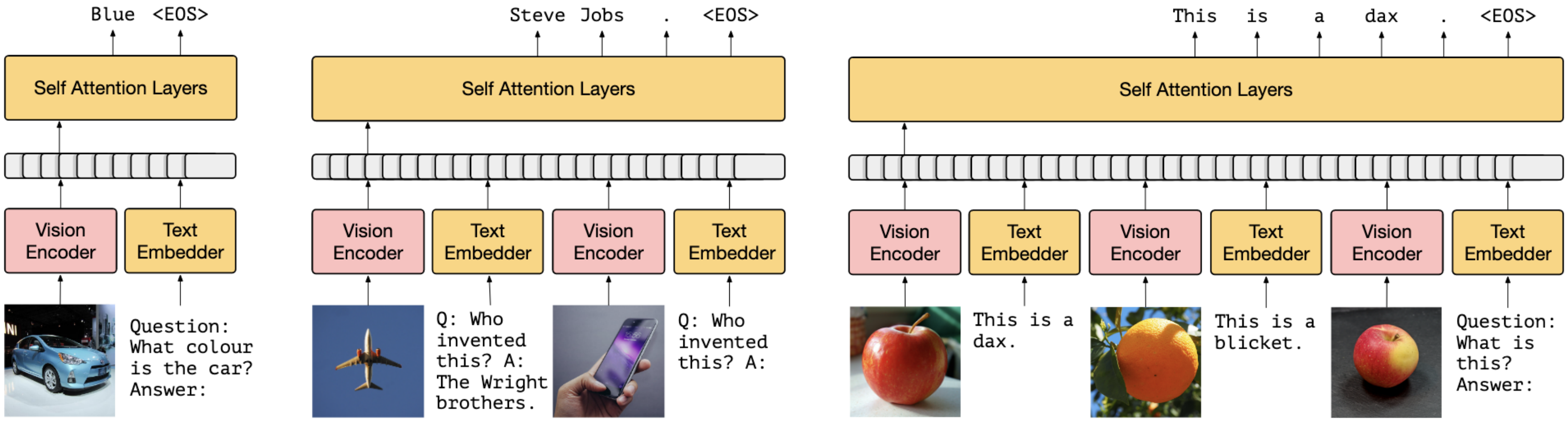
## Why Multi-Modal?

Training:




(a) **0-shot VQA** (b) **1-shot outside-knowledge VQA** (c) **Few-shot image classification**

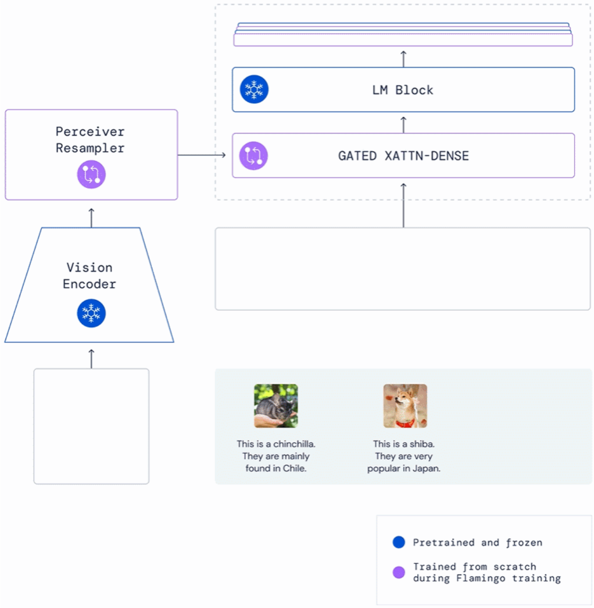
# Zero to Few-Shot

*Slide by Vicente Ordóñez*

Georgia Tech

# Flamingo VLM [4]

- What is Flamingo?
  - It's a Visual Language Model (VLM) for Few-Shot Learning that launched by DeepMind.
- Visual Language Model?
  - Processing images to generate reasonable text.
- What can it do?
  - Applicable to image and video understanding tasks via simply prompting it with a few examples
  - captioning, visual dialogue, classification, visual question answering



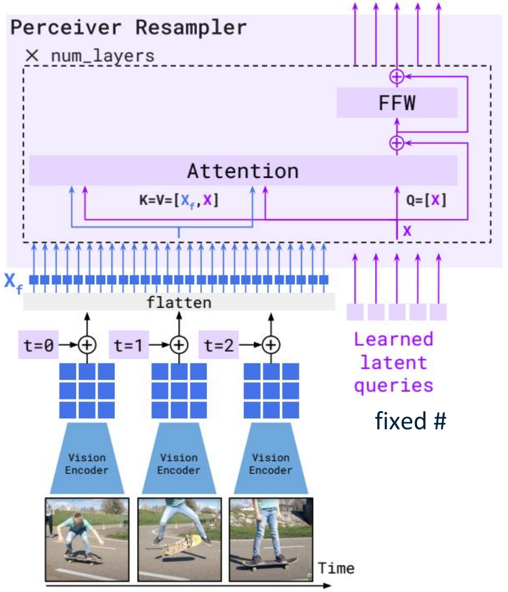

[4] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, et al.Flamingo: a Visual Language Model for Few-Shot Learning DeepMind 2022

# Flamingo VLM 🦩

- Three challenges for training with image/video and text.
  - **Supporting both images and videos**
    - Images /videos: 2D structure with high dimensionality.
    - Text: 1D sequence
    - Sol.: Introduce Perceiver Resample module.
  - **The interaction with image/video and text**
    - keep the pretrained model's language understanding and generation capabilities fully intact
    - Sol.: Interleave cross-attention layers with frozen self-attention. gating mechanism.
  - **Obtaining multimodal dataset to induce good generalist capabilities**
    - Dataset with weak matching problem
    - Sol.: combine dataset with standard strong related paired image/text and video/text datasets

# Flamingo VLM 🦩

- Model structure - **Supporting both images and videos**




```python
def perceiver_resampler(
    x_f,  # The [T, S, d] visual features (T=time, S=space)
    time_embeddings,  # The [T, 1, d] time pos embeddings.
    x,  # R learned latents of shape [R, d]
    num_layers,  # Number of layers
):
  """The Perceiver Resampler model."""

  # Add the time position embeddings and flatten.
  x_f = x_f + time_embeddings
  x_f = flatten(x_f)  # [T, S, d] -> [T * S, d]
  # Apply the Perceiver Resampler layers.
  for i in range(num_layers):
    # Attention.
    x = x + attention_i(q=x, kv=concat([x_f, x]))
    # Feed forward.
    x = x + ffw_i(x)
  return x
```

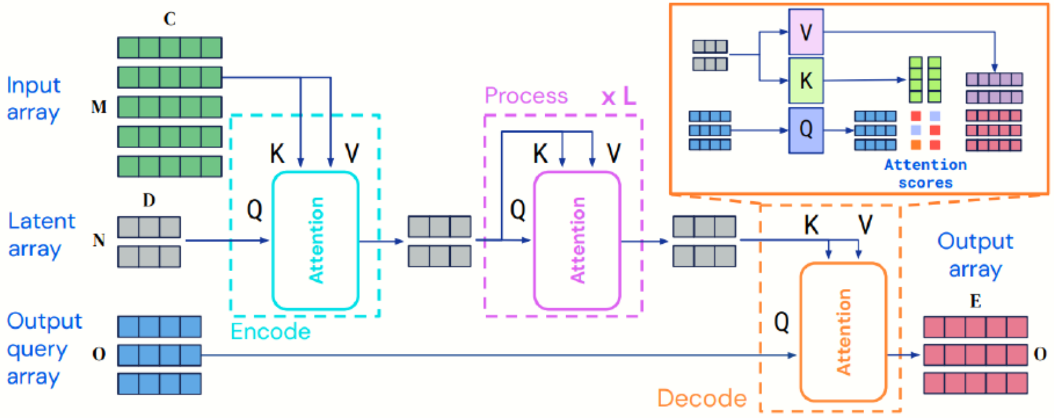
pseudo code

- Using pre-trained ResNet to get visual features $X_f$
- Compress the encode image into R tokens
- Core of this module : Attention .
  - Query: the learned latent token X
  - Key=Value: the concatenation of $X_f$, and the learned latent token X
  - Better performance by concatenating keys and values obtained from latent
- If the input is video
  - $X_f$ will add time embeddings

Maps **a variable size grid of visual features** from the Vision Encoder to **a fixed number of output token** (5 in the figure.)

# Perceiver / Perceiver IO:
## Transformer for general data perception

- General data processing method given data can be mapped into sequence of vectors
  - Use cross attention to fetch information from input
  - Self attention to process input.
  - Use cross attention to fetch relevant information and send to output.

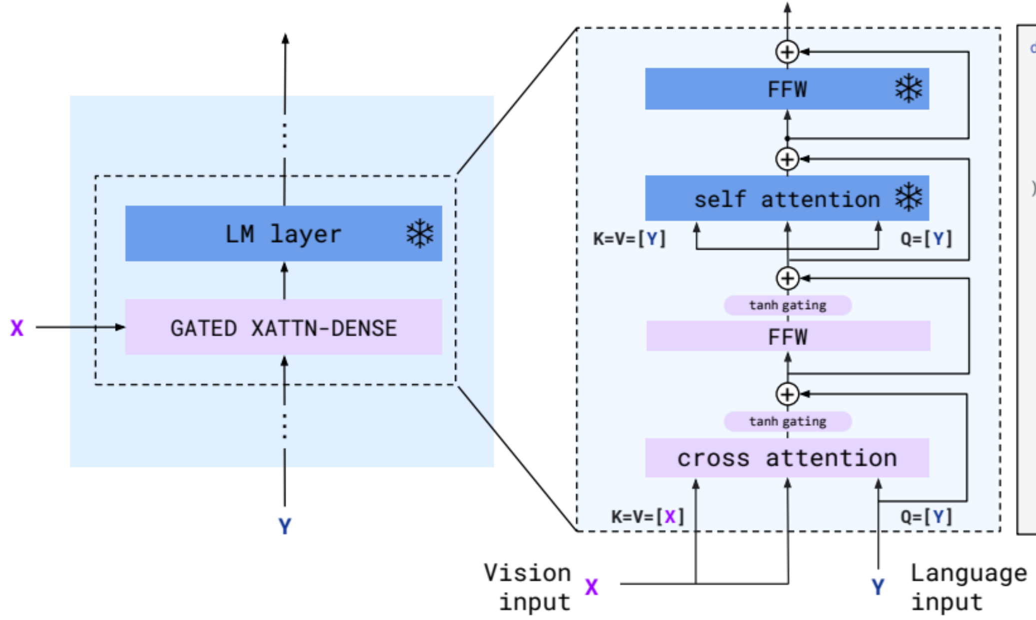




Jaegle, Andrew, et al. "Perceiver: General perception with iterative attention." *ICML*, 2021.
Jaegle, Andrew, et al. "Perceiver io: A general architecture for structured inputs & outputs." *ICLR*, 2021

# Flamingo VLM

- Model structure - **The interaction with image/video and text**




```python
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."""

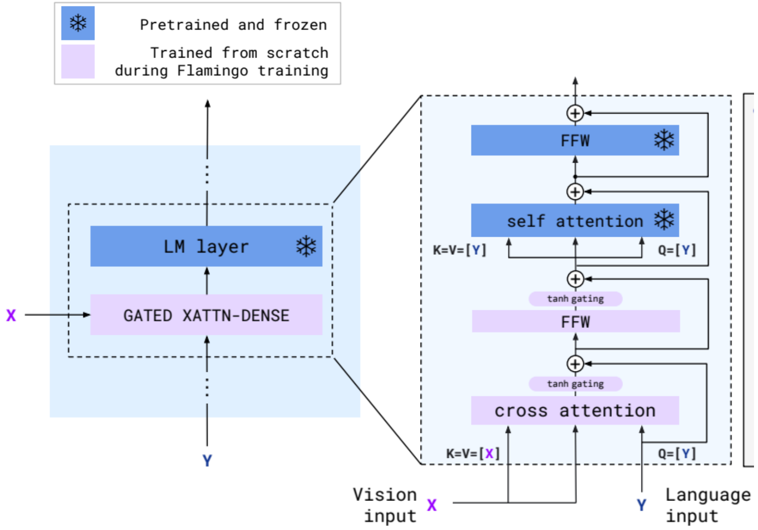
  # 1. Gated Cross Attention
  y = y + tanh(alpha_xattn) * attention(q=y, kv=x)
  # 2. Gated Feed Forward (dense) Layer
  y = y + tanh(alpha_dense) * ffw(y)

  # 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
```

A **Gated Cross attention** mechanism is proposed to fuse images and text.

# Flamingo VLM

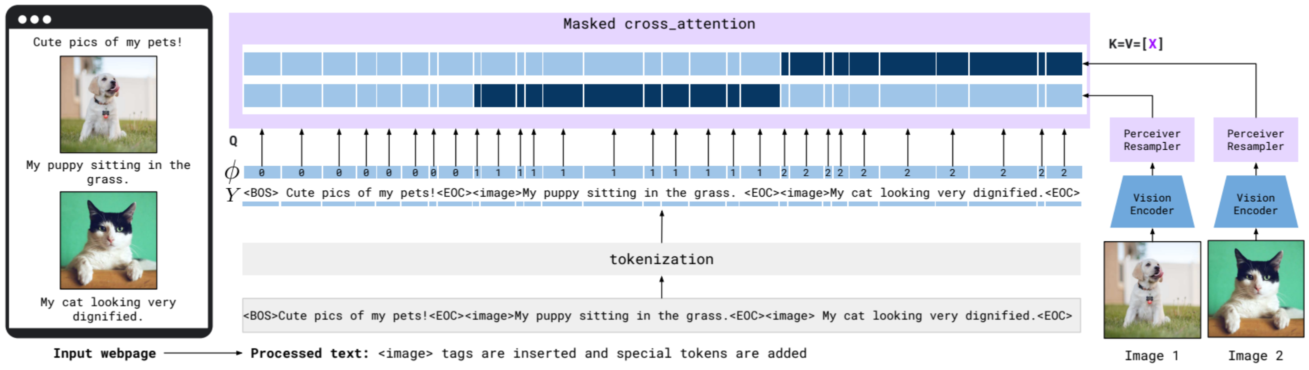
- Model structure - **The interaction with image/video and text**




- Frozen LM layers
  - LM: 70B parameter Chinchilla
  - keep pretrained LM's language understanding
- Gated Cross Attention:
  - Query: Y, Key=Value: X
  - Tanh Gating: Initialized with 0 then gradually increases
  - Transitions from a fully trained text-only model to a visual language model.
- The LM can generate text conditioned on the above visual tokens

# Flamingo VLM

- Model structure - **Interleaved visual data and text support**



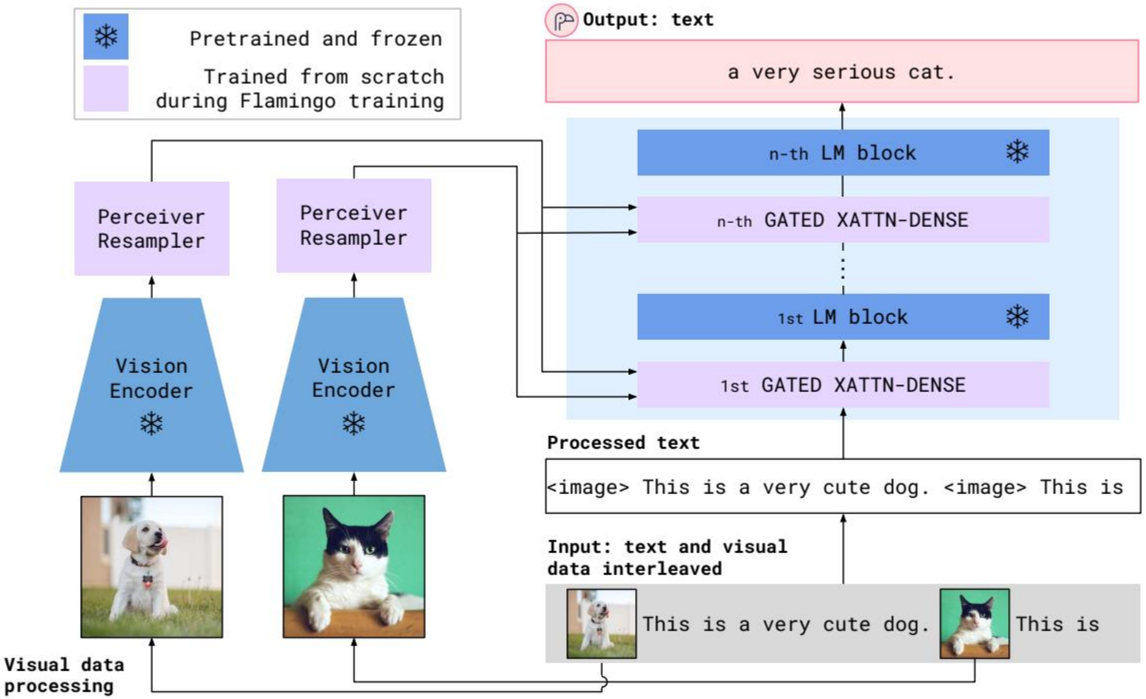

non masked

masked

- Multi-visual input support: per-image/video attention masking
- During Cross-attention,
  - each text can only focus on one image before it.
  - Function $\phi$ : for each token what is the index of the last preceding image
- During final prediction, each token can focus on all the previously text and image

# Flamingo VLM

- Overview of the Flamingo Model




- Each image is encoded individually

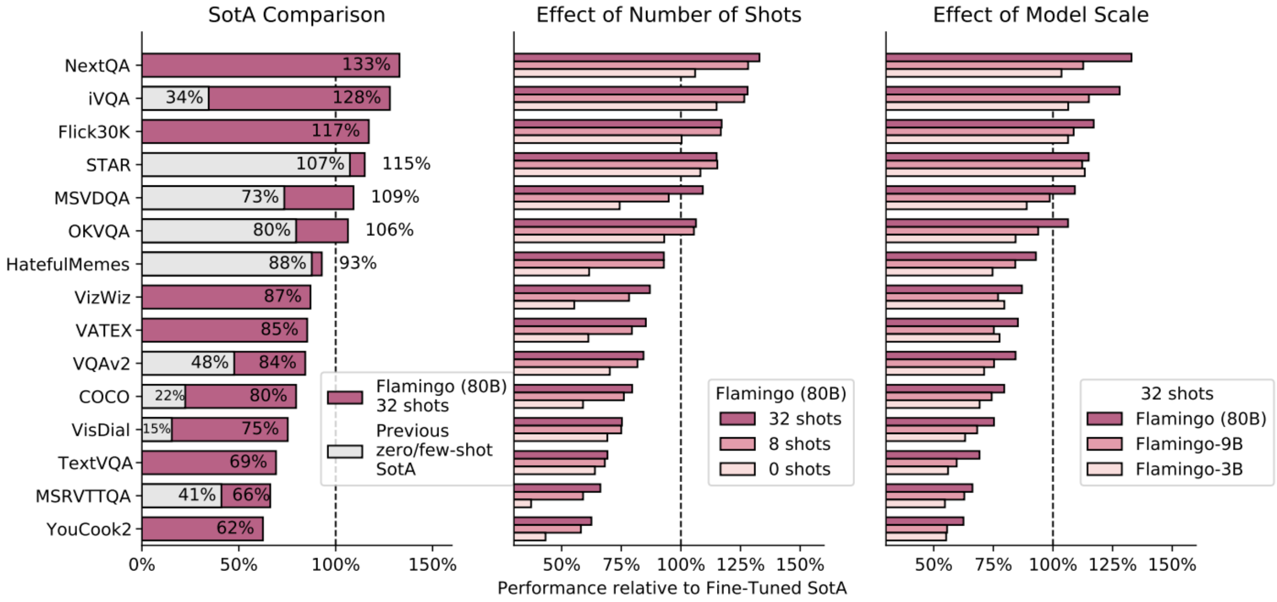
# Flamingo VLM

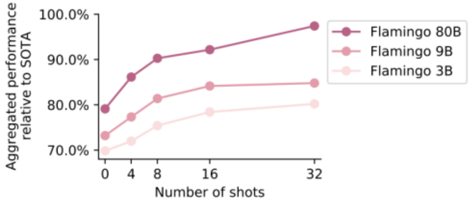
- Model structure - **Obtaining multimodal dataset to induce good generalist capabilities**


- M3W: Scrapping 43 million webpages from the Internet
- Training on a mixture of vision and language datasets
  - M3W(185M images+ 182G text)
  - ALIGN(1.8B images with alt-text)
  - LTIP (312M images/text)
  - VTP(27M short video/text)

# Flamingo VLM

- **Result: Overview of the results of the Flamingo models**



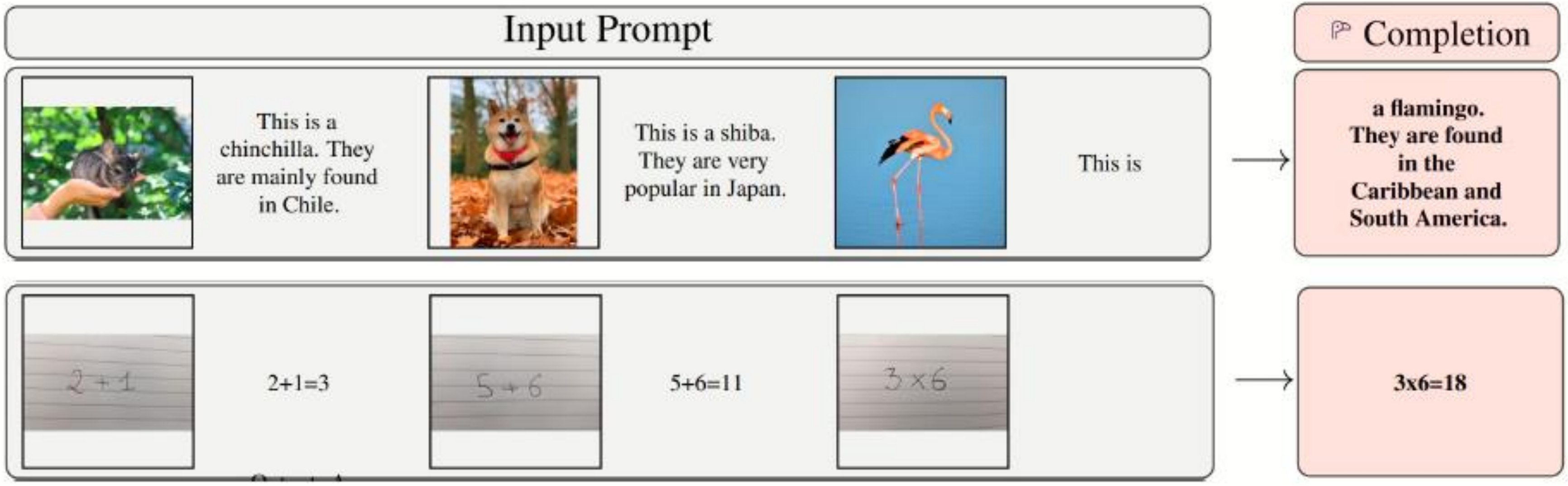




- Larger model sizes and more few-shot examples lead to better performance

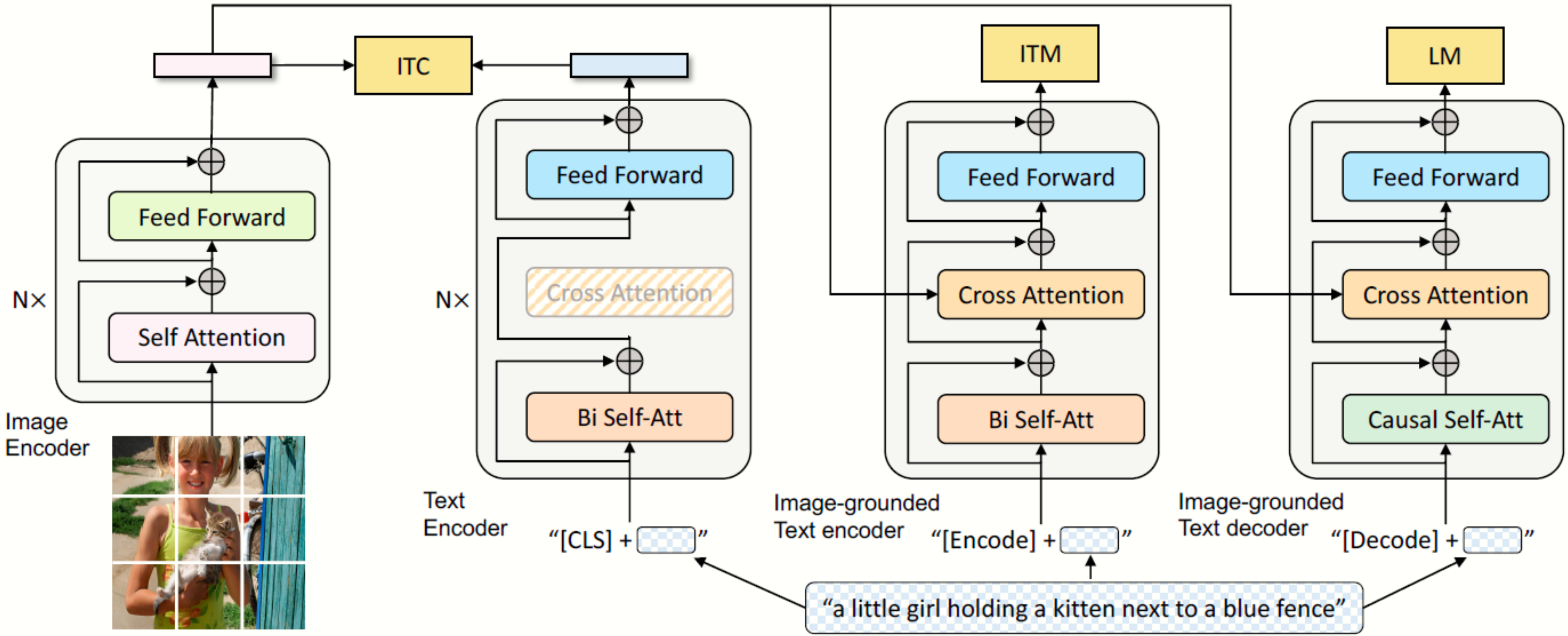
- Performance of Flamingo model using different numbers of shots and of different sizes,(without fine-tuned) in comparison with SoTA fine-tuned baseline.

- Flamingo: Multimodal In-Context-Learning

Emerging Property

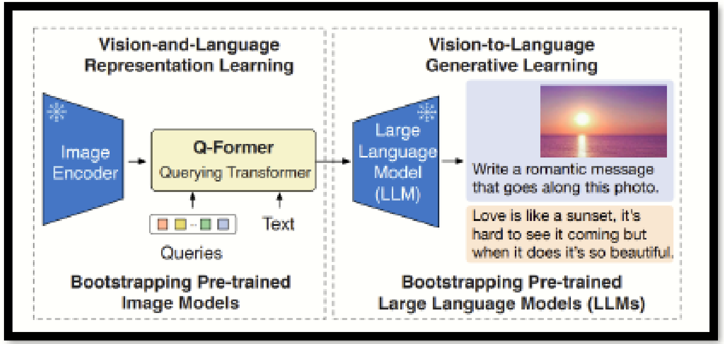



# Flamingo In-Context

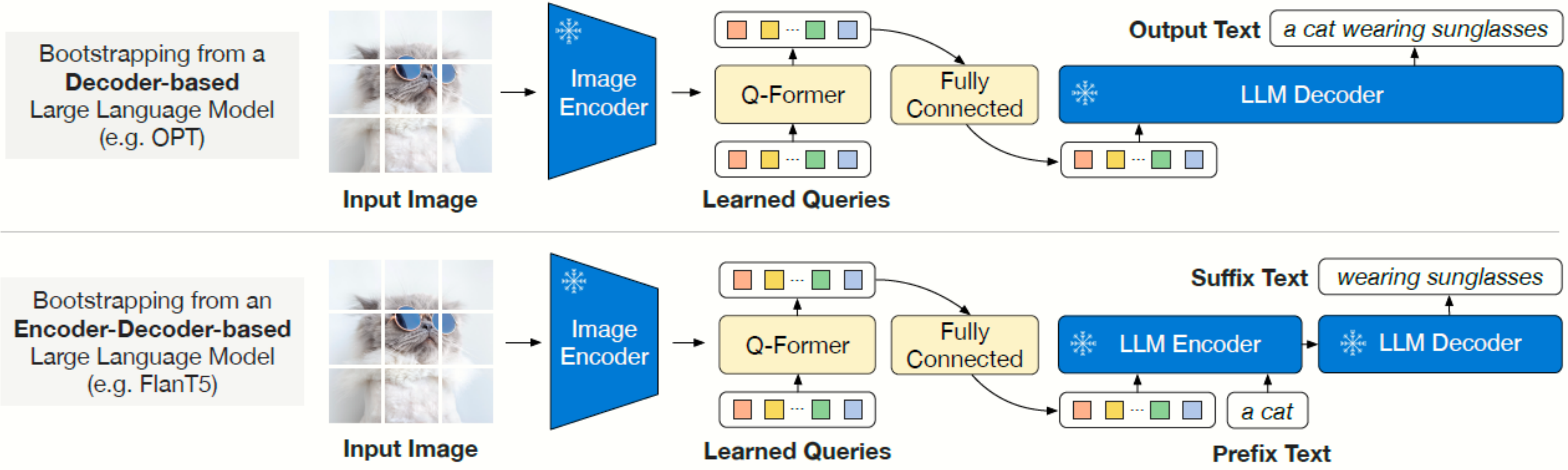



Li et al., BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation

• BLIP2




| | |
|---|---|
| Language Model | Pre-trained: FLAN-T5/OPT |
| Connection Module | Q-Former: Lightweight Querying Transformer |
| Vision Encoder | Contrastive pre-trained: EVA/CLIP |




Li et al., BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models

# BLIP-2

| Models | #Trainable Params | #Total Params | VQAv2 val | VQAv2 test-dev | OK-VQA test | GQA test-dev |
|---|---|---|---|---|---|---|
| VL-T5$_{\text{no-vqa}}$ | 224M | 269M | 13.5 | - | 5.8 | 6.3 |
| FewVLM (Jin et al., 2022) | 740M | 785M | 47.7 | - | 16.5 | 29.3 |
| Frozen (Tsimpoukelli et al., 2021) | 40M | 7.1B | 29.6 | - | 5.9 | - |
| VLKD (Dai et al., 2022) | 406M | 832M | 42.6 | 44.5 | 13.3 | - |
| Flamingo3B (Alayrac et al., 2022) | 1.4B | 3.2B | - | 49.2 | 41.2 | - |
| Flamingo9B (Alayrac et al., 2022) | 1.8B | 9.3B | - | 51.8 | 44.7 | - |
| Flamingo80B (Alayrac et al., 2022) | 10.2B | 80B | - | 56.3 | **50.6** | - |
| BLIP-2 ViT-L OPT$_{2.7B}$ | 104M | 3.1B | 50.1 | 49.7 | 30.2 | 33.9 |
| BLIP-2 ViT-g OPT$_{2.7B}$ | 107M | 3.8B | 53.5 | 52.3 | 31.7 | 34.6 |
| BLIP-2 ViT-g OPT$_{6.7B}$ | 108M | 7.8B | 54.3 | 52.6 | 36.4 | 36.4 |
| BLIP-2 ViT-L FlanT5$_{XL}$ | 103M | 3.4B | 62.6 | 62.3 | 39.4 | <u>44.4</u> |
| BLIP-2 ViT-g FlanT5$_{XL}$ | 107M | 4.1B | <u>63.1</u> | <u>63.0</u> | 40.7 | 44.2 |
| BLIP-2 ViT-g FlanT5$_{XXL}$ | 108M | 12.1B | **65.2** | **65.0** | <u>45.9</u> | **44.7** |

*Table 2.* Comparison with state-of-the-art methods on zero-shot visual question answering.

**Li et al., BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models**

# Visual Question Answering Examples

# Language Modeling: Large Language Models (LLM)

OpenAI GPT-2 → GPT-3 → ChatGPT / InstructGPT → GPT-4

**What's new?**

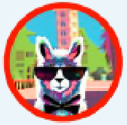
GPT-3:
In-context-learning
Chain-of-thoughts (CoT)

ChatGPT / InstructGPT:
In-context-learning
Chain-of-thoughts (CoT)
**Instruction-Following**

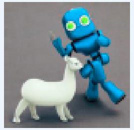
GPT-4:
In-context-learning
Chain-of-thoughts (CoT)
**Instruction-Following**
**Multimodal Input with image**

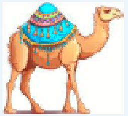
**Open Source Community**

LLaMA


Alpaca


Vicuna


GPT4-Alpaca


Tulu


# Recap on Language Modeling: Large Language Models (LLM)

OpenAI GPT-2 → GPT-3 → ChatGPT / InstructGPT → GPT-4

| | GPT-2 | GPT-3 | ChatGPT / InstructGPT | GPT-4 |
|---|---|---|---|---|
| **What's new?** | | In-context-learning<br>Chain-of-thoughts (CoT) | In-context-learning<br>Chain-of-thoughts (CoT)<br>**Instruction-Following** | In-context-learning<br>Chain-of-thoughts (CoT)<br>**Instruction-Following**<br>**Multimodal Input with image** |

**Multimodal Space**

Flamingo
BLIP2
GIT
...

**Gap?**
**Instruction-Following**
**→ Alignment Research**

Multimodal GPT-4

Slide by Chunyuan Li

# Instruction Tuning

| | Input | Output |
|---|---|---|
| Translation | *Hello, Vancouver* | *你好，温哥华* |
| Summarization | *CVPR is the premier annual computer vision event comprising the main conference and several co-located workshops and short courses. This year, CVPR will be single track such that everyone (with full passport registration) can attend everything.* | *CVPR: top computer vision event, single-track, accessible to all.* |

- Task instructions are implicit.
- Individual models are trained, or multi-tasking without specifying the instructions
- Hard to generalize to new tasks in zero-shot

## In Language: Various NLP Task Datasets

# Instruction Tuning

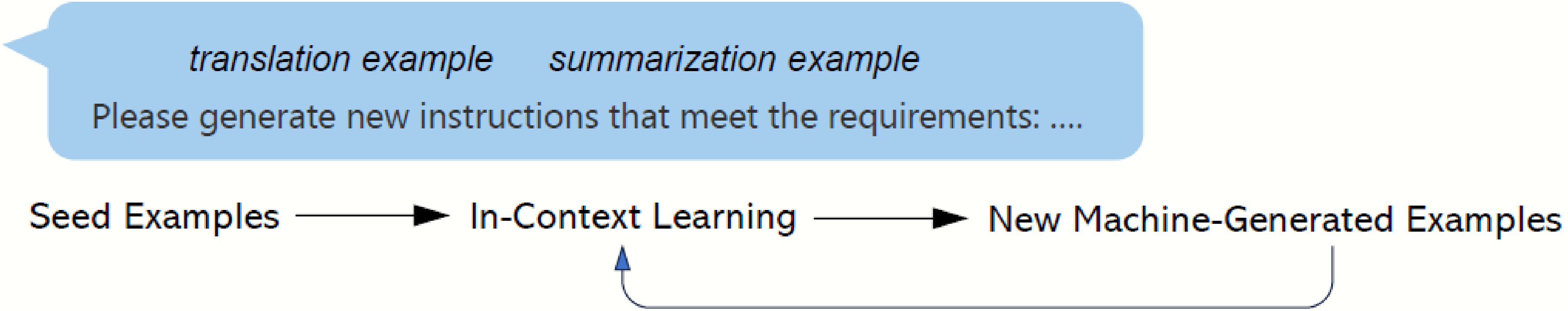
| Instruction | Input → Output | |
|---|---|---|
| Translate English into Simplified Chinese | *Hello, Vancouver* | *你好，温哥华* |
| Summarize in just 10 words to make the message even more brief and easier to remember. | *CVPR is the premier annual computer vision event comprising the main conference and several co-located workshops and short courses. This year, CVPR will be single track such that everyone (with full passport registration) can attend everything.* | *CVPR: top computer vision event, single-track, accessible to all.* |

- Task instructions are explicit, expressed in natural language
- One single model is trained, multi-tasking with specified instructions
- Natural and easy to generalize to new tasks in zero-shot

# Getting the Data: Self-Instruct Tuning

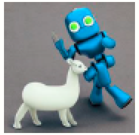
How to collect a diverse set of high-quality instructions and their responses?

- ❑ Human-Human: Collected from humans with high cost
- ❑ Human-Machine: A Strong LLM Teacher such as GPT3 and GPT4



## Instruction Tuning with Open-Source LLMs

### Self-Instruct with Strong Teacher LLMs & Mixed Human Data

| | LLaMA  | Alpaca  | Vicuna  | GPT4-Alpaca  | ... | Tulu  |
|---|---|---|---|---|---|---|
| Data Source | | GPT-3.5 | ShareGPT (Human & GPT) | GPT-4 (text-only) | ... | Mixed Data |
| Instruction-following Data (#Turns) | None | 52K | 500K (~150K conversions) | 52K | ... | |



*Slide by Chunyuan Li*

Georgia Tech

## Visual Instruction Tuning with GPT-4

https://llava-vl.github.io/

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### Self-Instruct with Strong Teacher LLMs

| | LLaMA | Alpaca | Vicuna |
|---|---|---|---|
| |  |  |  |
| Teacher | | GPT-3.5 | ShareGPT (Human & GPT) |
| Instruction-following Data | None | 52K | 700K (70 conversions) |

### But No Teacher is available on multiGPT4?

| GPT-4-LLM | LLaVA |
|---|---|
|  |  |
| GPT-4 (text-only) | GPT-4 (text-only) |

- 158K multimodal instruction following data (First & High Quality)

→ Multimodal Chatbot

Large Language and Vision Assistant

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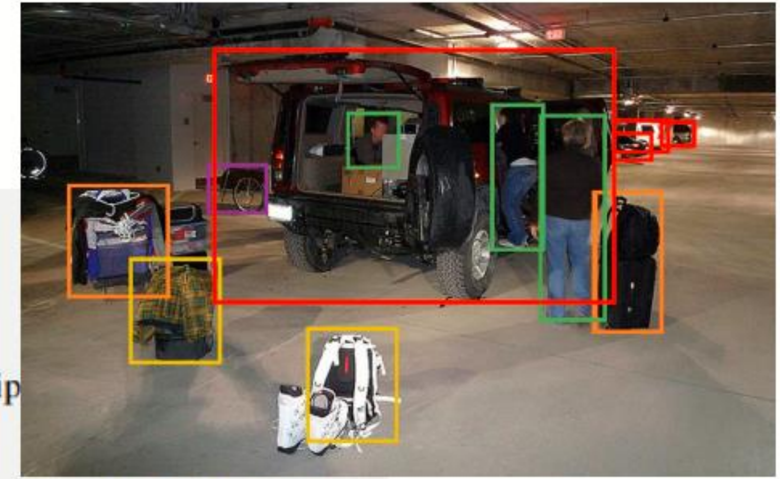
# Getting the Data - Multimodal

# GPT-assisted Visual Instruction Data Generation

**Downside?**

- Rich Symbolic Representations of Images
- In-context-learning with a few manual examples

→ Text-only GPT-4



**Context type 1: Captions**

A group of people standing outside of a black vehicle with various luggage.
Luggage surrounds a vehicle in an underground parking area
People try to fit all of their luggage in an SUV.
The sport utility vehicle is parked in the public garage, being packed for a trip
Some people with luggage near a van that is transporting it.

**Context type 2: Boxes**

person: [0.681, 0.242, 0.774, 0.694], person: [0.63, 0.222, 0.686, 0.516], person: [0.444, 0.233, 0.487, 0.34], backpack: [0.384, 0.696, 0.485, 0.914], backpack: [0.755, 0.413, 0.846, 0.692], suitcase: [0.758, 0.413, 0.845, 0.69], suitcase: [0.1, 0.497, 0.173, 0.579], bicycle: [0.282, 0.363, 0.327, 0.442], car: [0.786, 0.25, 0.848, 0.322], car: [0.783, 0.27, 0.827, 0.335], car: [0.86, 0.254, 0.891, 0.3], car: [0.261, 0.101, 0.787, 0.626]

## Data – Using Captions

# GPT-assisted Visual Instruction Data Generation

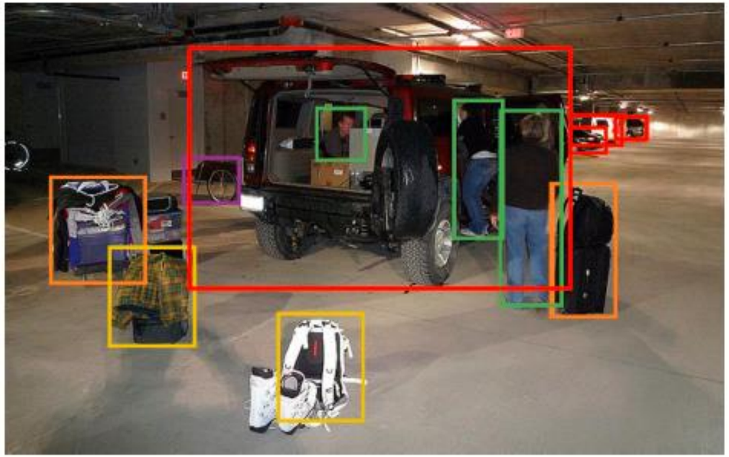
## Three type of instruction-following responses

```
messages = [ {"role":"system", "content": f"""You are an AI visual assistant, and you are seeing a single image. What you see are provided with five sentences, describing the same image you are looking at. Answer all questions as you are seeing the image.

Design a conversation between you and a person asking about this photo. The answers should be in a tone that a visual AI assistant is seeing the image and answering the question. Ask diverse questions and give corresponding answers.

Include questions asking about the visual content of the image, including the object types, counting the objects, object actions, object locations, relative positions between objects, etc. Only include questions that have definite answers:
(1) one can see the content in the image that the question asks about and can answer confidently;
(2) one can determine confidently from the image that it is not in the image. Do not ask any question that cannot be answered confidently.

Also include complex questions that are relevant to the content in the image, for example, asking about background knowledge of the objects in the image, asking to discuss about events happening in the image, etc. Again, do not ask about uncertain details. Provide detailed answers when answering complex questions. For example, give detailed examples or reasoning steps to make the content more convincing and well-organized. You can include multiple paragraphs if necessary."""}
]
for sample in fewshot_samples:
    messages.append({"role":"user", "content":sample['context']})
    messages.append({"role":"assistant", "content":sample['response']} )
messages.append({"role":"user", "content":'\n'.join(query)})
```



the passengers uncomfortable during the trip.

Data – Response Generation

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# GPT-assisted Visual Instruction Data Generation

```
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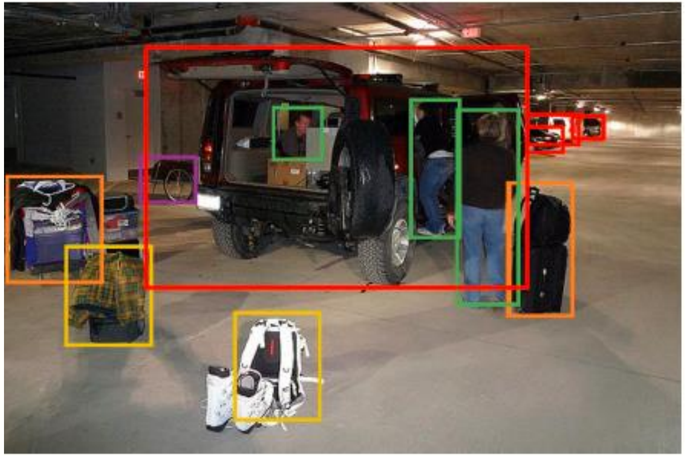
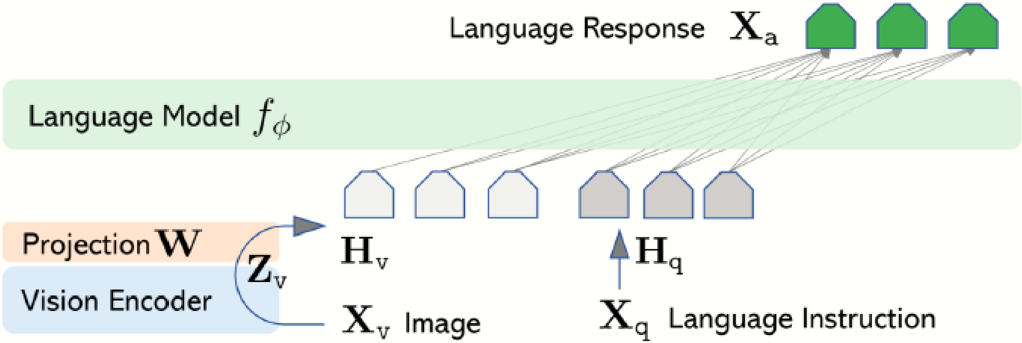


# LLaVA: Large Language-and-Vision Assistant

❑ Architecture




❑ Two-stage Training

•**Stage 1: Pre-training for Feature Alignment**.

Only the projection matrix is updated, based on a subset of CC3M.

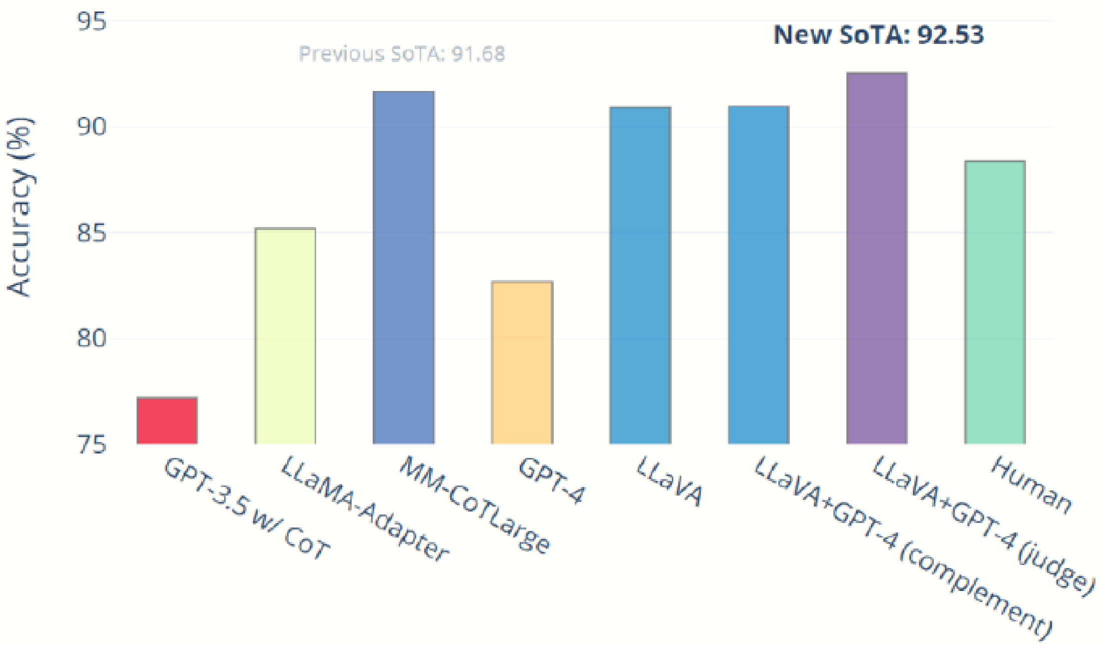
•**Stage 2: Fine-tuning End-to-End.** Both the projection matrix and LLM are updated

•**Visual Chat**: Our generated multimodal instruction data for daily user-oriented applications.

•**Science QA**: Multimodal reasoning dataset for the science domain.

# Science QA: New SoTA with the synergy of LLaVA with GPT-4

- LLaVA alones achieve 90.92%
- We use the text-only GPT-4 as the juedge, to predict the final answer based on its own previous answers and the LLaVA answers.
- This ``GPT-4 as juedge" scheme yields a new SOTA 92.53%
- GPT-4 is an effective model ensemble method



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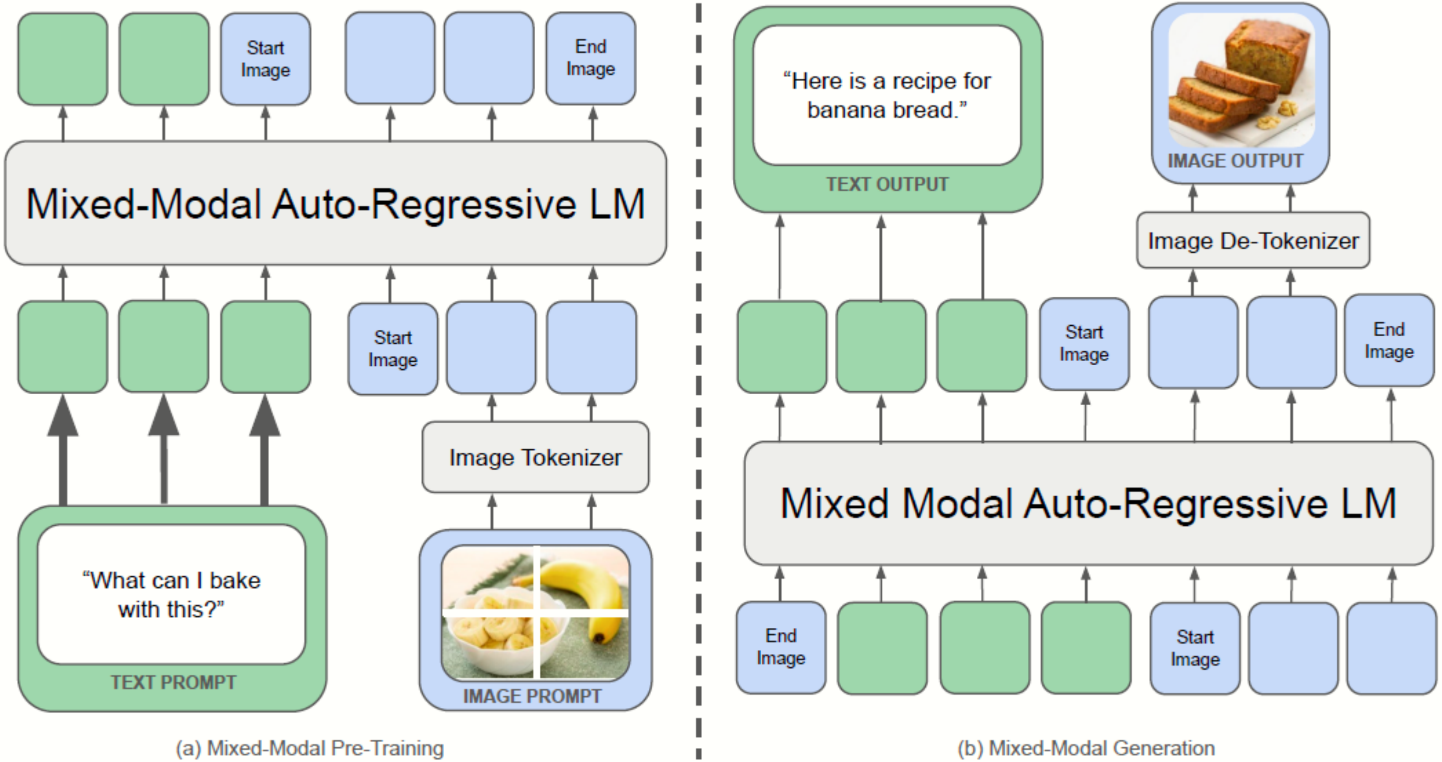


(a) Mixed-Modal Pre-Training

(b) Mixed-Modal Generation

**Unifying image models, generation (diffusion models?), and autoregressive models still an open problem!**

**Meta, Chameleon: Mixed-Modal Early-Fusion Foundation Models**

# Chameleon

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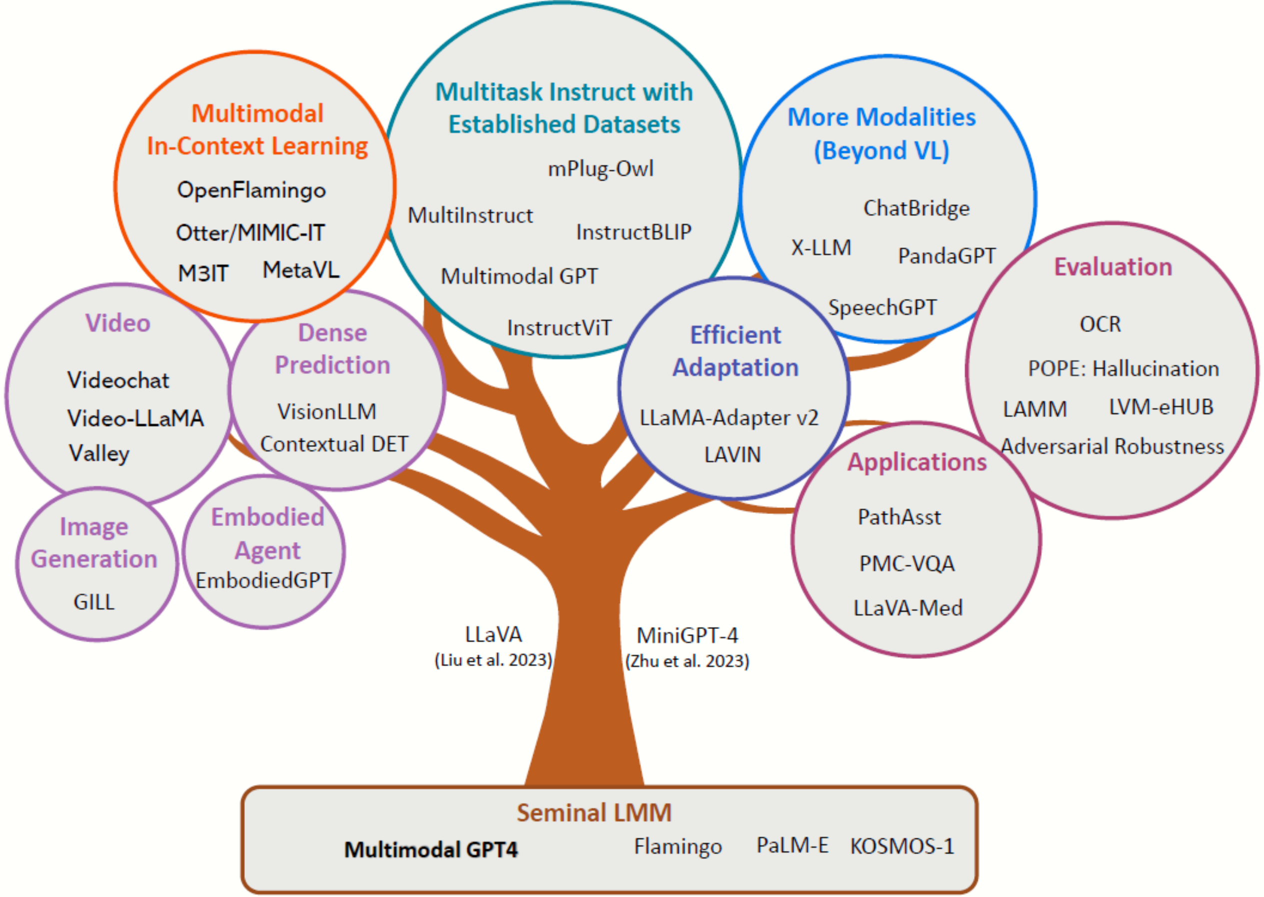
| Datasets | Previous Open-source SoTA | Claude-3.5 Sonnet-0620 | GPT-4o 0513 | InternVL2.5 78B | Qwen2-VL 72B | Qwen2.5-VL 72B | Qwen2.5-VL 7B | Qwen2.5-VL 3B |
|---|---|---|---|---|---|---|---|---|
| *College-level Problems* | | | | | | | | |
| $\text{MMMU}_{\text{val}}$ (Yue et al., 2023) | 70.1 Chen et al. (2024d) | 68.3 | 69.1 | 70.1 | 64.5 | **70.2** | 58.6 | 53.1 |
| $\text{MMMU-Pro}_{\text{overall}}$ (Yue et al., 2024) | 48.6 Chen et al. (2024d) | 51.5 | **51.9** | 48.6 | 46.2 | 51.1 | 38.3 | 31.56 |
| *Math* | | | | | | | | |
| $\text{MathVista}_{\text{mini}}$ (Lu et al., 2024) | 72.3 Chen et al. (2024d) | 67.7 | 63.8 | 72.3 | 70.5 | **74.8** | 68.2 | 62.3 |
| $\text{MATH-Vision}_{\text{full}}$ (Wang et al., 2024d) | 32.2 Chen et al. (2024d) | - | 30.4 | 32.2 | 25.9 | **38.1** | 25.1 | 21.2 |
| $\text{MathVerse}_{\text{mini}}$ (Zhang et al., 2024c) | 51.7 Chen et al. (2024d) | - | 50.2 | 51.7 | - | **57.6** | 49.2 | 47.6 |
| *General Visual Question Answering* | | | | | | | | |
| MegaBench (Chen et al., 2024b) | 47.4 MiniMax et al. (2025) | 52.1 | **54.2** | 45.6 | 46.8 | 51.3 | 36.8 | 28.9 |
| $\text{MMBench-EN}_{\text{test}}$ (Liu et al., 2023d) | 88.3 Chen et al. (2024d) | 82.6 | 83.4 | 88.3 | 86.9 | **88.6** | 83.5 | 79.1 |
| $\text{MMBench-CN}_{\text{test}}$ (Liu et al., 2023d) | 88.5 Chen et al. (2024d) | 83.5 | 82.1 | **88.5** | 86.7 | 87.9 | 83.4 | 78.1 |
| $\text{MMBench-V1.1-EN}_{\text{test}}$ (Liu et al., 2023d) | 87.4 Chen et al. (2024d) | 80.9 | 83.1 | 87.4 | 86.1 | **88.4** | 82.6 | 77.4 |
| MMStar (Chen et al., 2024c) | 69.5 Chen et al. (2024d) | 65.1 | 64.7 | 69.5 | 68.3 | **70.8** | 63.9 | 55.9 |
| $\text{MME}_{\text{sum}}$ (Fu et al., 2023) | **2494** Chen et al. (2024d) | 1920 | 2328 | **2494** | 2483 | 2448 | 2347 | 2157 |
| MuirBench (Wang et al., 2024a) | 63.5 Chen et al. (2024d) | - | 68.0 | 63.5 | - | **70.7** | 59.6 | 47.7 |
| $\text{BLINK}_{\text{val}}$ (Fu et al., 2024c) | 63.8 Chen et al. (2024d) | - | **68.0** | 63.8 | - | 64.4 | 56.4 | 47.6 |
| $\text{CRPE}_{\text{relation}}$ (Wang et al., 2024h) | 78.8 Chen et al. (2024d) | - | 76.6 | 78.8 | - | **79.2** | 76.4 | 73.6 |
| $\text{HallBench}_{\text{avg}}$ (Guan et al., 2023) | **58.1** Wang et al. (2024f) | 55.5 | 55.0 | 57.4 | **58.1** | 55.2 | 52.9 | 46.3 |
| MTVQA (Tang et al., 2024) | **31.9** Chen et al. (2024d) | 25.7 | 27.8 | 31.9 | 30.9 | 31.7 | 29.2 | 24.8 |
| $\text{RealWorldQA}_{\text{avg}}$ (X.AI, 2024) | 78.7 Chen et al. (2024d) | 60.1 | 75.4 | **78.7** | 77.8 | 75.7 | 68.5 | 65.4 |
| $\text{MME-RealWorld}_{\text{en}}$ (Zhang et al., 2024f) | 62.9 Chen et al. (2024d) | 51.6 | 45.2 | 62.9 | - | **63.2** | 57.4 | 53.1 |
| $\text{MMVet}_{\text{turbo}}$ (Yu et al., 2024) | 74.0 Wang et al. (2024f) | 70.1 | 69.1 | 72.3 | 74.0 | **76.2** | 67.1 | 61.8 |
| MM-MT-Bench (Agrawal et al., 2024) | 7.4 Agrawal et al. (2024) | 7.5 | **7.72** | - | 6.59 | 7.6 | 6.3 | 5.7 |

# Vision-Language Explosion (2023)

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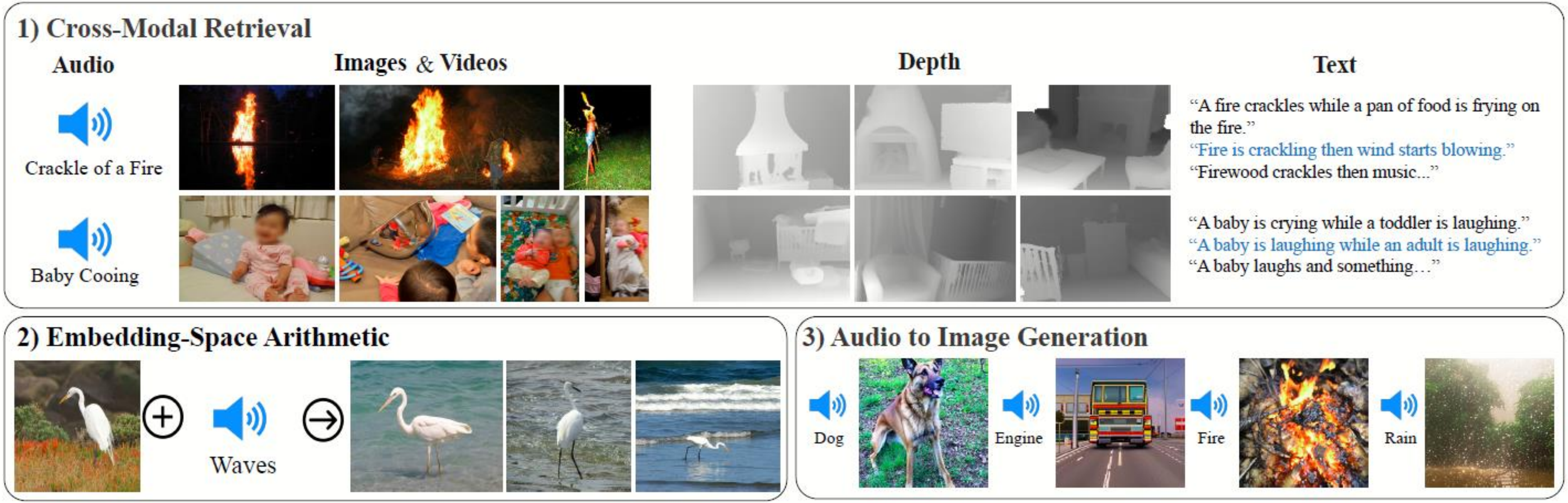
# Vision-Language Explosion (2023)

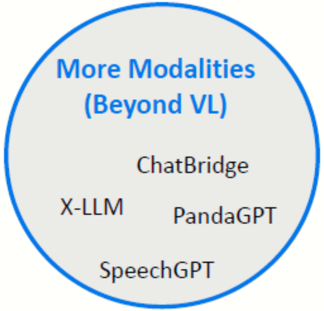


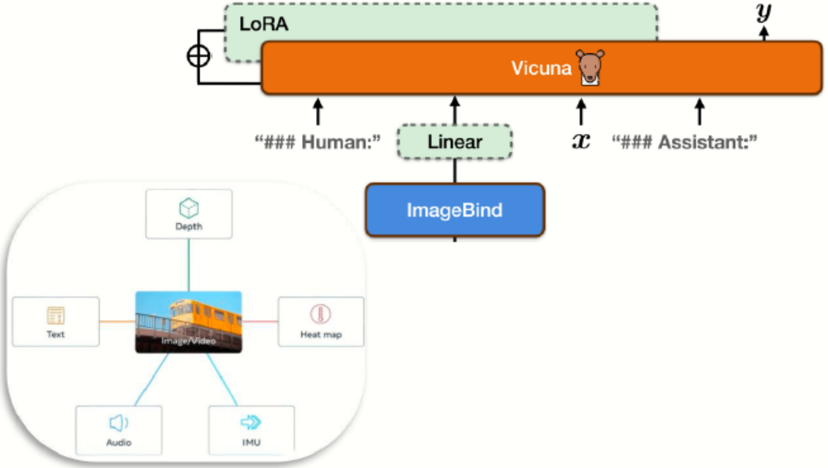

Girdhar et al., ImageBind: One Embedding Space To Bind Them All

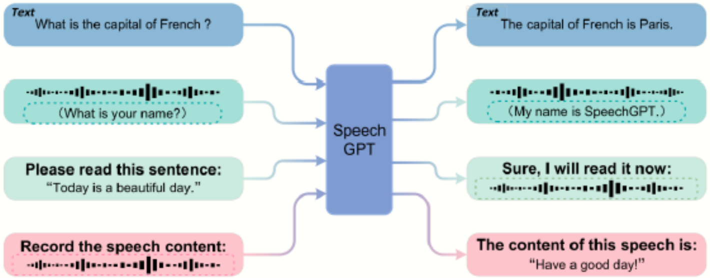
# More Modalities: ImageBind

# More Modalities (Beyond VL)

- ChatBridge: Bridging Modalities with Large Language Model as a Language Catalyst
- PandaGPT: One Model To Instruction-Follow Them All
- SpeechGPT: Empowering large language models with intrinsic cross-modal conversational abilities
- X-LLM: Bootstrapping Advanced Large Language Models by Treating Multi-Modalities as Foreign Languages



## Visual Math and Text Reasoning

What is “a” in the first equation?
What is y in the last equation?

| | |
|---|---|
| 5 + a = 7 | 40 + y = 45 |
| 10 + y = 15 | 39 + a = 41 |
| 20 + a = 22 | 24 + y = 29 |
| 48 + a = 50 | 15 + a =17 |
| 10 + a = 12 | 34 + y = 39 |

The value of “a” in the first equation “5 + a = 7” is 2.

The value of “y” in the last equation “34 + y = 39” is 5.

## Visual-Conditioned Joke/Meme

What is funny about it?


The humor in the comic may come from the situation, the characters, or the dialogue. The person is feeling unwell and is asked if they are pregnant or have the coronavirus, which is a current and relevant topic. The humor may come from the absurdity of the situation or the unexpectedness of the question.

## Spatial/Coordinate Understanding

Where is the frisbee?
What is the relative position of the frisbee and the man?

The frisbee is located at coordinates (63,119,133,177).

The frisbee is located above the man in the image. The man is falling on the ground while the frisbee is in the air. The frisbee is also closer to the top of the image than the man..

## Visual Planning and Prediction

What should I do after kneading the dough, before dividing it into pieces? For how long?


After kneading the dough, you should put it in a warm place before dividing it into pieces, according to the recipe in the image.

You should put the dough in a warm place for 1 hour.

## Multi-Image Reasoning

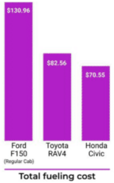
How much in total did I spend on travel?
How much in total did I pay for taxes?


You spent $1299.90 on airfare and $43.83 on an Uber ride for a total of $1343.73 on travel.

You paid $323.23 in total for taxes. This includes $321.90 for taxes and fees for the flight purchase and $1.33 for sales tax for the Windmill Family Restaurant.

## Multi-Hop Document Understanding

Excluding the regular cab, what is the average total fueling cost?




The average total fueling cost excluding the Ford F150 (Regular Cab) is $76.55. This is calculated by taking the sum of the total fueling cost of Toyota RAV4 and Honda Civic and dividing it by 2. ($82.56 + $70.55) / 2 = $76.55.

## Open-World Concept Understanding

What is the brand of these drink? Which one is unsweetened?


The brand of these drinks is “BETTER THAN MILK”. The unsweetened one is “BETTER THAN MILK organic OAT DRINK”.

Who are the celebrities in this image?

Keira Knightley and Natalie Portman are the celebrities in this image.

Is it safe to eat this mushroom?

Morel mushrooms are generally considered safe to eat when properly cooked.

## Video Summarization/Event Localization

Can you breakdown this video tutorial to step-by-step instructions, with start and end time?

Here's a step-by-step breakdown of the tutorial with start and end time.

… Add Lettuce Add Tomato Add Bacon …

Yang et al., MM-ReAct MM-ReAct: Prompting ChatGPT for Multimodal Reasoning and Action

# Tasks

- Vision+Language (and multi-modal) are hot!
- **Why?**
  - Align various interface modalities
  - Leverage more data (all modalities)
  - Physical world inherently multi-modal
- **Large number of design choices!**
  - Vision encoding?
  - Method of alignment?
  - Method of fusion?
  - Grounding?

- **Tasks**:
  - Image ⇔ language
  - Visual question answering
    - + Interaction
  - Embodied AI

**Resources:**
https://www.youtube.com/@VLPTutorial

# Summary