

Grounding Language Models for Visual Entity Recognition







Vicente Ordonez Sept 30th, 2024

Zilin Xiao¹



Ming Gong²



Paola Cascante-Bonilla¹



Xingyao Zhang²



Jie Wu²



Vicente Ordonez¹



Introduction

- > Task: Visual Entity Recognition
 - Input: an image and a query question
 - Output: a Wikipedia entity from a pre-defined set



Text Query

Who manufactured the plane?



What piece of equipment is placed on the animal in the image?



What is this building called?



Mcdonnell douglas

McDonnell Douglas was a major American aerospace manufacturing corporation and defense contractor formed by ...



Bridle

A bridle is a piece of equipment used to direct a horse. As defined in the Oxford English Dictionary, the "bridle" includes both the headstall that...



Skanderbeg Museum

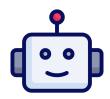
The National History Museum "Gjergj Kastrioti Skënderbeu" (Albanian: Muzeu Historik Kombëtar), also known as the Skanderbeg Museum...

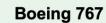
Introduction

- ➤ How it differs with Visual Question Answering?
 - Answers grounded to Wikipedia Entities.



What is the **model** of this aircraft?





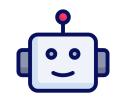
The Boeing 767 is an American wide-body airliner developed and manufactured by Boeing Commercial Airplanes. The aircraft was launched...

Introduction

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What is the **model** of this aircraft?



ARRIVA

Boeing 767

The Boeing 767 is an American wide-body airliner developed and manufactured by Boeing Commercial Airplanes. The aircraft was launched...

Fine-grained Recognition Capability Required.



Boeing 717



Douglas DC-8



Boeing 777



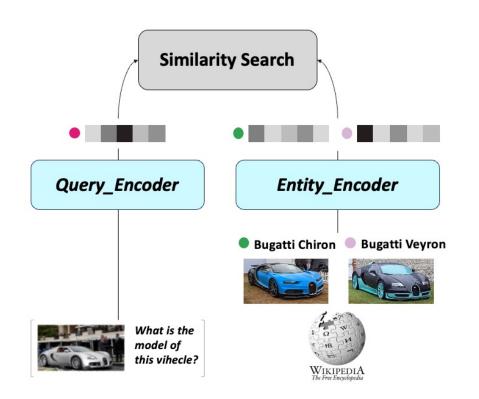
Airbus A320



Boeing 767

Prior Approach: Similarity Search

- > Similarity search: cross-modal retrieval
 - > Problem: hard to reason about spatial relations





What is the yellow item on top of truck?



Surfboard

A surfboard is a narrow plank used in surfing. Surfboards are relatively light but are strong enough to support an individual standing on them while riding an ocean wave....

Prior Approach: Multimodal LLM

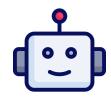
- > Multimodal LLM: LLM with Visual Instruction Tuning
 - > Problem 1: sometimes hallucinates a lot
 - > Problem 2: natural language response grounding to Wikipedia entities are not trivial



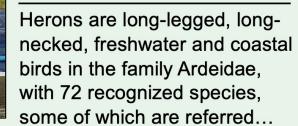


Which **category** of bird is shown in the image?

The bird in the image is likely to be an Australasian darter...

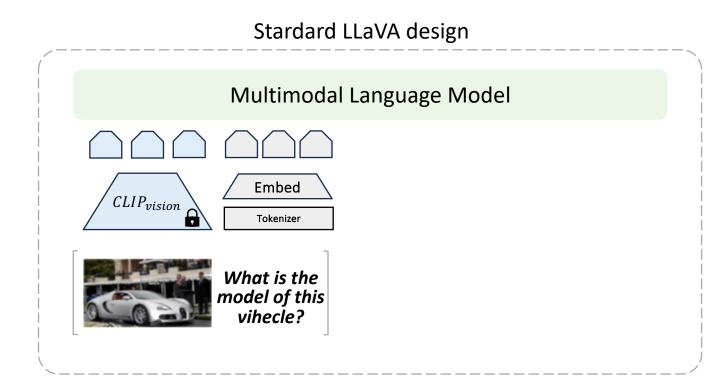


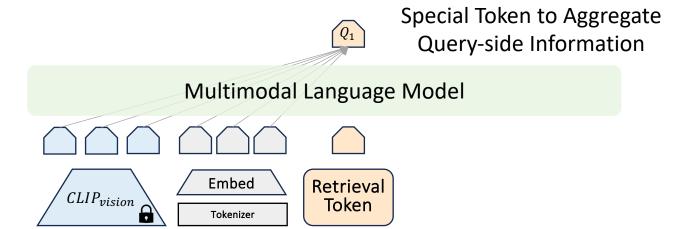
Heron



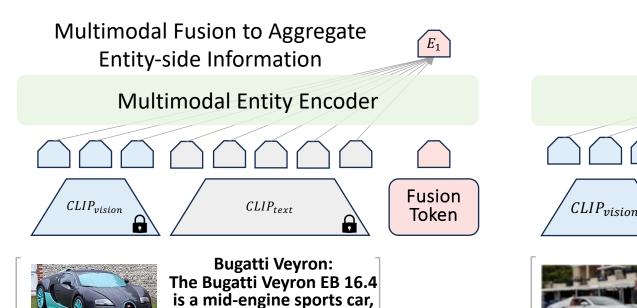
Our Approach

- > Can we take advantage of both similarity search and MLLM inherent reasoning ability?
 - > Yes!
- > We can use similarity search to do a coarse **retrieval**, narrowing down the candidates.
- Then ask an Multimodal LLM to further "re-ranking" the candidates.

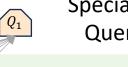




What is the model of this vihecle?

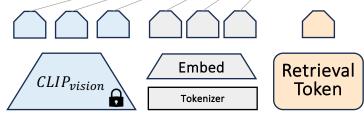


designed and



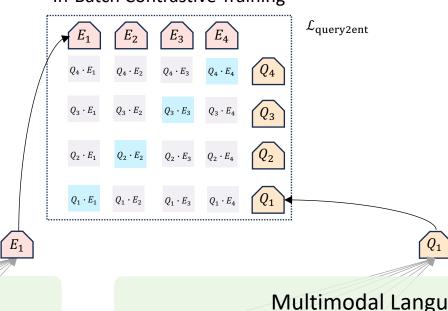
Special Token to Aggregate Query-side Information

Multimodal Language Model

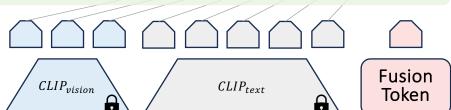




In-Batch Contrastive Training



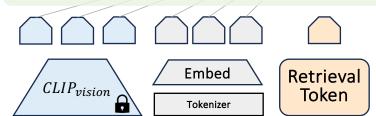
Multimodal Entity Encoder





designed and

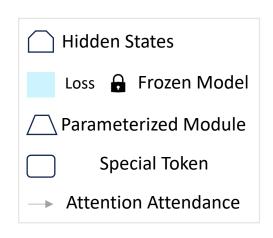
Multimodal Language Model

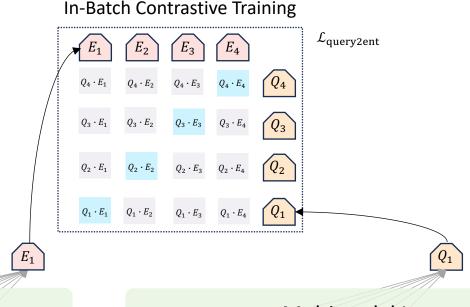


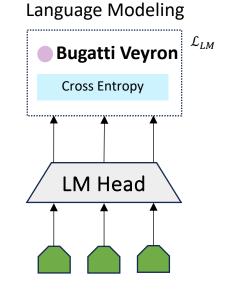


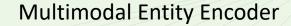
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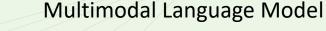


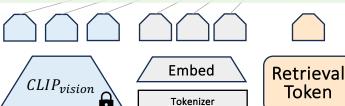












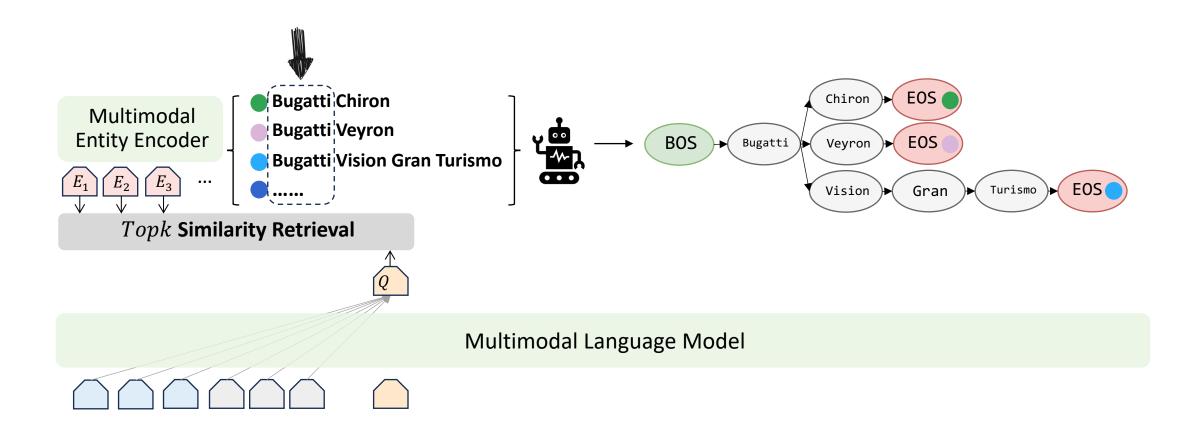


Bugatti Veyron: The Bugatti Veyron EB 16.4 is a mid-engine sports car, designed and

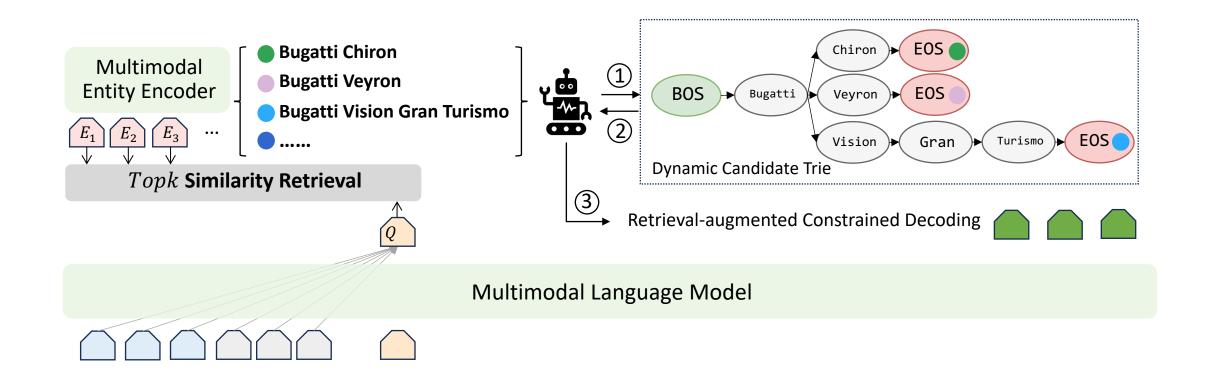


What is the model of this vihecle?

At Inference-Time: Retrieve then Generate with Guidance



At Inference-Time: Retrieve then Generate with Guidance



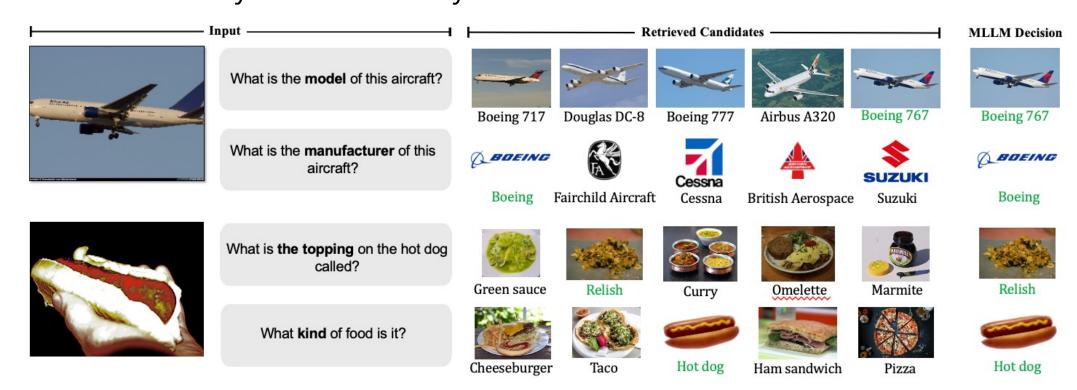
Quantitative Results

- ➤ We trained AutoVER 7B & 13B on 2.5M+ image-query pairs from OVEN-Train dataset and tested the model on val and test splits.
- > It demonstrates a consistent improvement in all data splits and subsets.
 - > with the exception for falling short of zero-shot GPT-4V on Query Unseen Split.

_		Entity Split			Query Split			Overall
Category	Method	SEEN	UNSEEN	HM	SEEN	UNSEEN	НМ	НМ
Discriminative	CLIP _{ViTL14} CLIP Fusion _{ViTL14} CLIP2CLIP _{ViTL14}	5.4 32.7 12.6	5.3 4.3 10.1	5.4 7.7 11.2	$0.8 \\ 33.4 \\ 4.1$	1.4 2.2 2.1	1.0 4.2 2.8	1.7 5.4 4.4
Generative	PaLI-3B PaLI-17B	$21.6 \\ 30.6$	$6.6 \\ 12.4$	10.1 17.6	$33.2 \\ 44.2$	$14.7 \\ 22.4$	$20.4 \\ 29.8$	13.5 22.1
Zero-shot	$\begin{array}{c} \mathrm{BLIP-2_{Flan-T5-XXL}} \\ \mathrm{GPT-4V} \end{array}$	8.6 29.8	3.4 19.3	4.9 23.4	24.6 56.5	17.7 52.7	20.6 54.5	7.9 32.9
Ours	AutoVER-7B AutoVER-13B	61.5 63.6	21.7 24.5	32.1 35.6	69.0 68.6	31.4 32.3	43.2 43.9	36.8 39.2

Qualitative Results

- > We visualize some retrieved entity candidates and the decision made by MLLM.
- > The model adeptly captures slight variations in the query text and retrieves entirely different entity candidates.



Ablation Study

- > Ablation experiments on a subset of training data shows that:
- > Retrieve-then-Generate paradigm heavily boost the performance on UNSEEN split of test dataset.
- > With constrained decoding design, AutoVER suffers fewer hallucination brought by ungrounded response.

Table 5: Ablation study of AutoVER-7B-0.1 on Oven-Wiki entity Split_(Val).

Method	SEEN	UNSEEN	НМ
AUTOVER-7B-0.1	48.9	19.0	27.4
+ w/o retrieval	50.7	0.6	1.2
+ w/o constrained decoding	46.8	0.6	1.2
+ w/ LoRA	43.5	2.8	5.3