

# Multimodal Models Experimentation

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## OBJECTIVE/GOAL

To describe a screenshot of a webpage in as much detail as possible, including all its text, layout/positioning, color, etc. Ideally with only open source models, while using as minimal resources as possible (ideally CPU).

## IN SUMMARY (TOP MODELS RANKED)

- 1) BEST: GPT-4o — no hallucinations at all and describes the webpage just like a human would describe the page, able to read all the smaller text and very organized
  - Sometimes omits some text, but no longer an issue when add “Do not miss any text” to the prompt
  - Recognizes interactivity!—VERY GOOD FOR multi-image use cases / dynamic websites where users can click on links/dropdown menus!
- 2) LLaVA-Mistral through Huggingface
  - Actually able to read/identify the smaller text!!!
- 3) LLaVA-v1.6 through Ollama
  - Detailed description, but resolution curse, can’t recognize smaller text + can only read giant headers and images
  - Claims to support multi-image inputs, which would be useful for few-shot prompting—still figuring that out, to see if that means you can feed multi-image to a singular prompt (for few-shot) OR it just applies different prompts to each image fed
- worst = BLIP-2, LLaVA-Mistral through Ollama

## NEXT STEPS/RECOMMENDATIONS

- GPT-4o is still the best—WHY? It is a NATIVELY multi-modal, also the LARGEST/most complex model I tested. So to find an alternative to GPT that performs better than LLaVA and the other models (which are NOT natively multi-modal and only fine-tuned on text-only LLMs), could possibly experiment with other native multi-modal models
  - example: Anole- a native multi-modal model that is also open source
- **Try a larger model (13b? 34b?)**
- Resolution curse — image processing or resolution
  - LOOK INTO: how to increase resolution (currently supports three aspect ratios, up to 672x672, 336x1344, 1344x336 resolution) — what does this mean though, investigate resulting image quality when fed into model to generate response
- Prompt engineering
- Few-shot prompting with multi-image input
  - Resolve errors for multi-image input and prompt structure with LLaVA

- how to incorporate Few-shot into Ollama syntax + structure—LLaVA thankfully accepts multi-image inputs (but figuring out how to specify which one(s) are the examples)
- Concerns: LLaVA was not pre-trained with several images interleaved in one prompt, so it still might not perform well
- Try **LLaVA-NeXT-Interleave**- supports multi-image and multi-prompt generation!
- Incorporate Langchain? embeddings?

## OTHER FINDINGS/ANALYSIS

- Rankings of several multimodal LLMs on various tasks/metrics - <https://github.com/BradyFU/Awesome-Multimodal-Large-Language-Models/tree/Evaluation?tab=readme-ov-file>
  - LLaVA vs. BLIP-2: LLaVA (with all dif parameters) is always ranked higher in Perception compared to BLIP-2 (existence, count, position, color, poster, celebrity, scene, landmark, artwork, and OCR)
- Reducing hallucinations
  - What I tried:
    - reduce temperature — effective to a certain point (extremely high temperatures hallucinate more than lower temps, but effect of reducing temperature only does so much)
    - Prompt engineering:
      - increase prompt specify and detail — effective
      - “step by step” — varies
      - “Only describe what you can see” — varies, leads to response sometimes admitting that the image resolution is too blurry to be able to read
      - break down prompt into bite-sized tasks and ask about features individually/separately + combine descriptions later (for example - instead of asking everything about text, images, etc. all at once, ask one prompt that focuses on the text, then another about the images) — not very effective
      - BETTER models — LLaVA-1.5 with Vicuna base —> LLaVA-1.6 with Mistral base in both Ollama and Huggingface, LLaVA-Phi3, BakLLaVA, etc.
        - LLaVA-1.6 with Mistral in Huggingface was the most effective model change
    - TO TRY:
      - play around with: system, template, prompt—instead of squeezing it all into prompt
      - try CoT prompt engineering—using all text extracted from the prev step, describe this [next component]
      - ask multiple vision language models to reach a consensus + combine their descriptions after
  - Papers/Research
    - Mitigating hallucinations for image to text LLMs / VLMS / multi-modal models = still an ongoing, active area of research
      - most techniques = instruction tuning or training/finetuning on additional datasets, and/or require human ground truth (<https://arxiv.org/html/2405.09589v1#S3>)

- LVLM Hallucination Revisor (LURE) algorithm ?
- “To mitigate object hallucination in LVLMs without resorting to costly training or API reliance, Zhao et al. (2024) introduced **MARINE**, a training-free and API-free solution. MARINE enhances LVLMs’ visual comprehension by combining existing open-source vision models and leveraging guidance without classifiers to incorporate object grounding features, thereby enhancing the precision of generated outputs” (<https://arxiv.org/html/2405.09589v1#S3>)
- CLIP-Guided Decoding (CGD) approach- a straightforward but effective training-free approach to reduce object hallucination at decoding time. CGD uses CLIP to guide the model’s decoding process by enhancing visual grounding of generated text with the image ? (<https://github.com/d-ailin/CLIP-Guided-Decoding>)
- Better models?
  - LLaVA: try greater parameter size? 13b? 34b?
  - natively multi-modal models vs. fine-tuned on text-only LLM
- Image resolution: LLaVA can't seem to read/recognize the smaller text (only very large text/headings + images)
- Try FEW-SHOT: The newer LLaVA 1.6 supports multi-image inputs — may be useful esp if we have multiple screenshots for capturing website interactions
- Few-Shot Prompting
  - Try LLaVA-NeXT-Interleave!?
  - <https://github.com/haotian-liu/LLaVA/issues/197>
- Resolution Curse
  - WHAT IS IT: VLMs are limited by the resolution of the vision encoder, and usually, it is not super large—as a result, might not be able to read/identify all the text
  - Possible solutions: Visual search, Visual cropping, MC-LLaVA (<https://huggingface.co/blog/visheratin/vlm-resolution-curse>)
  - <https://arxiv.org/abs/2312.14135>
  - <https://llava-vl.github.io/blog/2024-01-30-llava-next/> (HOW INCREASE IMAGE RESOLUTION!?)

## OTHER HELPFUL LINKS

- Collection of Multimodal Large Language Models: <https://github.com/BradyFU/Awesome-Multimodal-Large-Language-Models>
  - A Survey on Multimodal Large Language Models (<https://arxiv.org/pdf/2306.13549>)
- HALLUCINATIONS for VLMs / multi-modal models
  - PAPERS
    - Unveiling Hallucination in Text, Image, Video, and Audio Foundation Models: A Comprehensive Review (<https://arxiv.org/html/2405.09589v1#S3>)
    - Visual Hallucinations of Multi-modal Large Language Models (<https://arxiv.org/pdf/2402.14683>)
    - Detecting and Preventing Hallucinations in Large Vision Language Models (<https://arxiv.org/pdf/2308.06394>)

- Multi-modal hallucination control by visual information grounding (<https://www.amazon.science/publications/multi-modal-hallucination-control-by-visual-information-grounding>)
- Let there be a clock on the beach: Reducing Object Hallucination in Image Captioning ([https://openaccess.thecvf.com/content/WACV2022/papers/Biten\\_Let\\_There\\_Be\\_a\\_Clock\\_on\\_the\\_Beach\\_Reducing\\_Object\\_WACV\\_2022\\_paper.pdf](https://openaccess.thecvf.com/content/WACV2022/papers/Biten_Let_There_Be_a_Clock_on_the_Beach_Reducing_Object_WACV_2022_paper.pdf))
- Object Hallucination in Image Captioning (<https://aclanthology.org/D18-1437.pdf>)
- Mitigating Open-Vocabulary Caption Hallucinations (<https://assafbk.github.io/mocha/>)
- POSSIBLE SOLUTIONS:
  - Woodpecker: Hallucination Correction for Multimodal Large Language Models (<https://github.com/BradyFU/Woodpecker>, <https://arxiv.org/abs/2310.16045>)
  - Seeing is Believing: Mitigating Hallucination in Large Vision-Language Models via CLIP-Guided Decoding (<https://openreview.net/pdf/84e43111d901965aeb354a001699921796e8eaf0.pdf>, <https://github.com/d-ailin/CLIP-Guided-Decoding>)
  - ALOHa: A New Measure for Hallucination in Captioning Models (<https://arxiv.org/html/2404.02904v1>)
- FEW-SHOT LEARNING WITH MULTI-IMAGE
  - Self-Distillation for Few-Shot Image Captioning ([https://openaccess.thecvf.com/content/WACV2021/papers/Chen\\_Self-Distillation\\_for\\_Few-Shot\\_Image\\_Captioning\\_WACV\\_2021\\_paper.pdf](https://openaccess.thecvf.com/content/WACV2021/papers/Chen_Self-Distillation_for_Few-Shot_Image_Captioning_WACV_2021_paper.pdf))
  - LMCap: Few-shot Multilingual Image Captioning by Retrieval Augmented Language Model Prompting (<https://arxiv.org/abs/2305.19821>)
  - Re-ViLM: Retrieval-Augmented Visual Language Model for Zero and Few-Shot Image Captioning (<https://arxiv.org/abs/2302.04858>)
  - PM2 : A New Prompting Multi-modal Model Paradigm for Few-shot Medical Image Classification (<https://arxiv.org/abs/2404.08915>)
  - <https://huggingface.co/llava-hf/llava-v1.6-mistral-7b-hf/discussions/19>
  - <https://medium.com/@suvasism/multimodal-few-shot-learning-with-frozen-language-models-focus-on-understanding-implementation-of-065fb8a602cc>
- Vision LLM Resources: [https://github.com/jingyi0000/VLM\\_survey](https://github.com/jingyi0000/VLM_survey), <https://huggingface.co/blog/vlms>
  - <https://github.com/OpenGVLab/VisionLLM/tree/main/VisionLLMv2>, <https://arxiv.org/pdf/2406.08394>