

VisIT-Bench: A Benchmark for Vision-Language Instruction Following Inspired by **Real-World Use**

Yonatan Bitton*, Hritik Bansal*, Jack Hessel*, Rulin Shao, Wanrong Zhu, Anas Awadalla, Josh Gardner, Rohan Taori, Ludwig Schimdt

> Contextual **Knowledge of Events**

Figurative Speech Explanation

Art Knowledge

Recognition



Where is this?

Instruction-Conditioned Caption

There is a jeep parked on the street with

spare tire in the back with an inscription



Here is a photo of my

If you are going for a picnic at this location, what items should you carry with you?

bathroom. How can design it nicer?

Human-Verified GPT4 Response

"Tan Lines & Ticket Stubs: A Love Story Unbound" - A country song about the top down. There is a wheel cover on the leaving it all behind, finding love, and that says, "Quit your Job, Buy a Ticket, Get a embracing the freedom of the open road.

1. Why VisIT-Bench?

- Diverse tasks and human-chatbot interactions
- Converts 25 datasets into chatbot-friendly formats

G

• Reflect the dynamic demands of modern chatbots:

Wish-list' instructions

~70 tested skills



Tell me what is notable Someone said that this or important about the man is an angel. Why? event in this photo.

ples

Exam



Instruction

Create a catchy title

advice printed on the

for a country song

based upon the

T





Location



Repurposing of existing datasets (+multi-image tasks)

2. Data Collection

- Create "wish-list" instructions for desired **V&L** chatbot capabilities
- Use these as inspiration for instructions annotation
- Collect instruction-conditioned dense captions
- Generate human-verified chatbot responses from GPT-4 outputs



Quit your Job

Buy a Ticket

Tan, Fall in Love, Never Return."



3. Instruction-Conditioned Captions







GPT-4

It is not possible to determine if a disabled wheelchair-bound individual would find it easy to go into the store based on the image of "a sign on a brick wall." Additional information about the store's entrance, accessibility features, and layout is needed to make that assessment.

- 91.5% success rate in single-image scenarios
- Data collection demonstrates the effectiveness of instruction-conditioned dense captions.
- Showcases the necessity of VisIT-Bench dense captions over generated captions from a SoTA **BLIP2 captioning model.**

Would a disabled wheelchair bound individual find it easy to go into this store? a sign on a brick wall

Instruction-Conditioned Caption

This image is of an exterior store front and sidewalk, showing two portable wedge ramps, one green and one red. The ramps are positioned against the step to two retail doorways, and seem to bridge the vertical distance between the level of the sidewalk and the step up to the doorway. The ramps are printed with "STOPGAP.CA" on the top surface.

Overall Success: 31%



more accessible for them.

Overall Success: 91%

4. Results

- VisIT-Bench facilitates the comparison of different V&L models.
- How good is our automatic metric?
- \succ Correlations of automatic metrics vs. human preferences, with reference free (GPT-4-no-ref)
- > Showing strong alignment

LlamaAdapter-v2 (7B)

InstructBLIP (13B)

mPLUG-Owl (7B)

Otter (9B)

Single Image

Single Image

Single Image

Single Image

top orange line - upper bound, bottom blue line - random chance (50%)



OpenFlamingo

Human-preferences based Leaderboard

Instruction: What is the person doing looking at the laser ?

A: The person is examining the red laser, possibly trying to figure out its purpose or how to avoid it. He might be in a high-security area or facing an obstacle.

B: The person is standing in front of a laser with their back to the camera. They are looking at the laser, possibly ssessing or examining its features

Which model better fully follows the instruction, providing factual, helpfull and accurate response, and adhering to all of the instruction details? Model A

Model B

| | Model | Elo | matches | Win-rate vs. reference (w/ # ratings) |
|-----------------|---------------------------------|------|---------|---------------------------------------|
| Single Image | Human Verified GPT-4 Reference | 1223 | 1439 | — |
| 0 | LLaVA (13B) | 1085 | 1462 | 26.23% (n=244) |
| | LlamaAdapter-v2 (7B) | 1061 | 1507 | 27.41% (n=259) |
| | mPLUG-Owl (7B) | 995 | 1345 | 14.95% (n=214) |
| | InstructBLIP (13B) | 957 | 1315 | 12.37% (n=194) |
| | MiniGPT-4 (7B) | 893 | 1513 | 14.72% (n=299) |
| | PandaGPT (13B) | 786 | 1441 | 10.48% (n=229) |
| Multiple Images | Unman Warifod CDT 4 Deferrer of | 1102 | 210 | |

763

1192

995

911

902

5450

180

180

180

180

0.18% (n=544)

6.67% (n=60)

1.69% (n=59)

1.67% (n=60)



| Reference | 1370 | 5442 | - | | OpenFlamingo (9B) PandaGPT (13B) Multimodal GPT |
|-----------|------|------|----------------|-----------------|---|
| | 1106 | 5446 | 17.81% (n=494) | Multiple Images | |
| | 1082 | 5445 | 13.75% (n=502) | | |
| | 1081 | 5452 | 15.29% (n=497) | | Human Verified GPT-4 Reference mPLUG-Owl Otter |
| | 1011 | 5444 | 13.73% (n=517) | | |
| | | | | | |

6.84% (n=512)

991

5450