Data deep-dive research

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Short recap

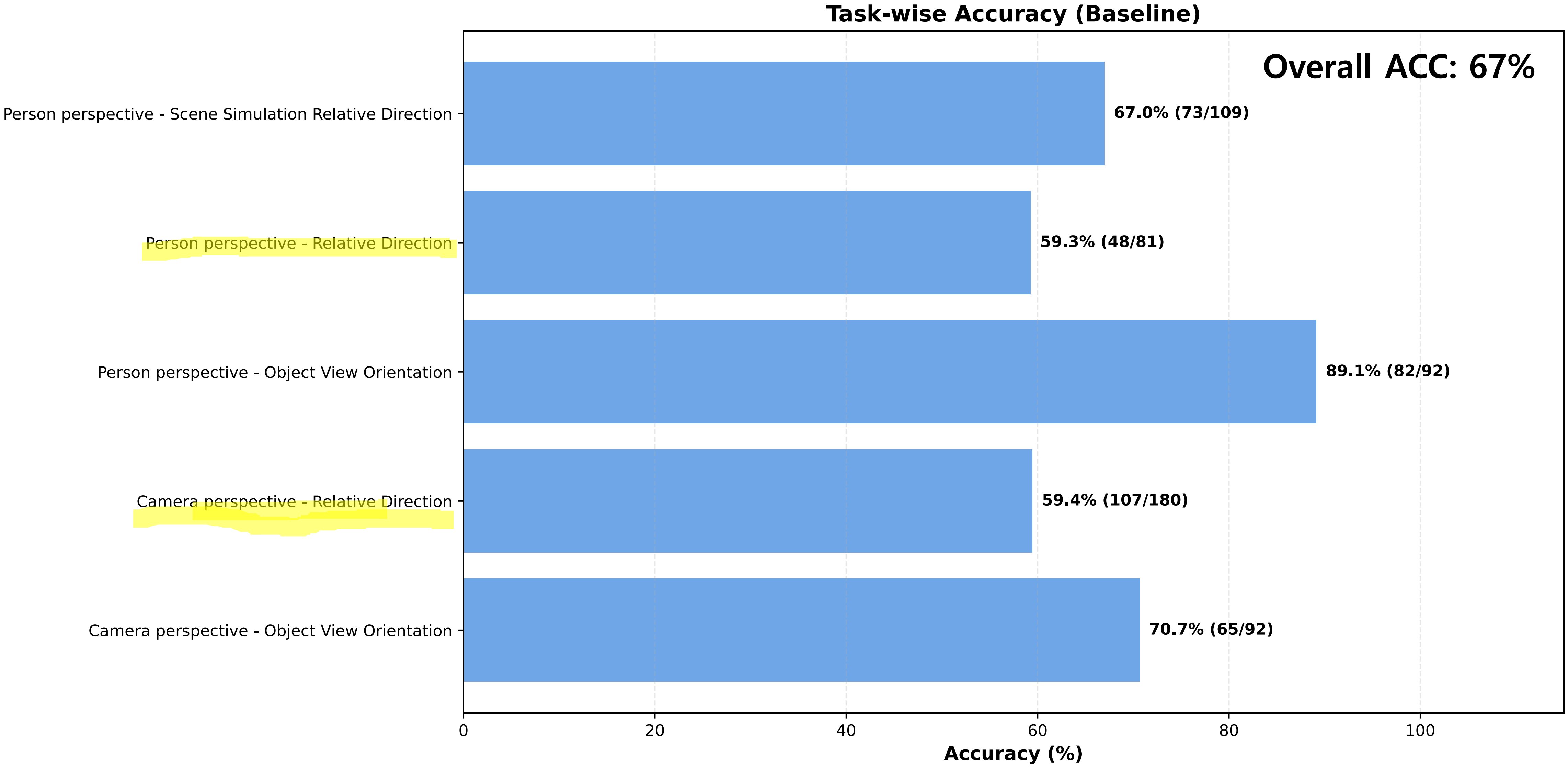
- Problems with the last research
  - Haven't looked into the data in detail.
  - A one-to-one comparison of a different model(MVSM) from the paper

Introduction

- Is there a task that you get more wrong than others? Why?

- If you get VQA wrong, is there a tendency for the model to give incorrect answers?
  - Left -> Right? Or is it completely wrong?

- Baseline : Vanilla MVSM (fine tuned Qwen2.5)


Task-wise Accuracy (Baseline)
Overall ACC: 67%
Person perspective - Scene Simulation Relative Direction
67.0% (73/109)
Person perspective - Relative Direction
59.3% (48/81)
Person perspective - Object View Orientation
89.1% (82/92)
Camera perspective - Relative Direction
59.4% (107/180)
Camera perspective - Object View Orientation
70.7% (65/92)
0
20
40
60
80
100
Accuracy (%)

Hypothesis 1

Data Augmentation

Hypothesis 1 : Data augmentation

- As demonstrated in Vision-Language research, focusing on **learning hard negatives** that confuse the model is key to improving performance, rather than simply augmenting data.

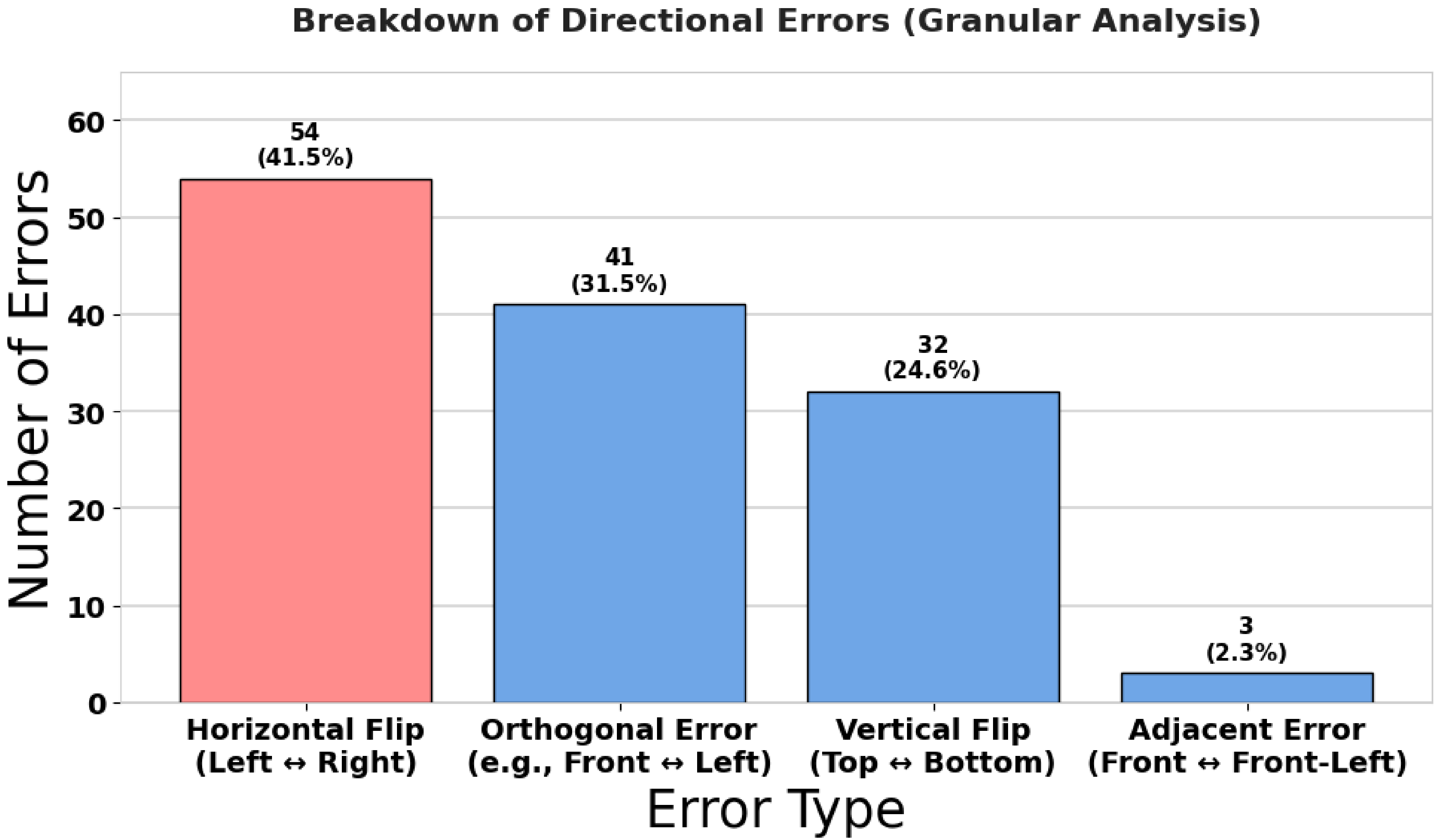
- Hard negative :
  - The most common incorrect answer the model gets wrong
  - image-text pair that is semantically similar but differs in fine-grained details.

NeurIPS 2021 : Align before Fuse: Vision and Language Representation Learning with Momentum Distillation (ALBEF)

Hypothesis 1 : Data augmentation

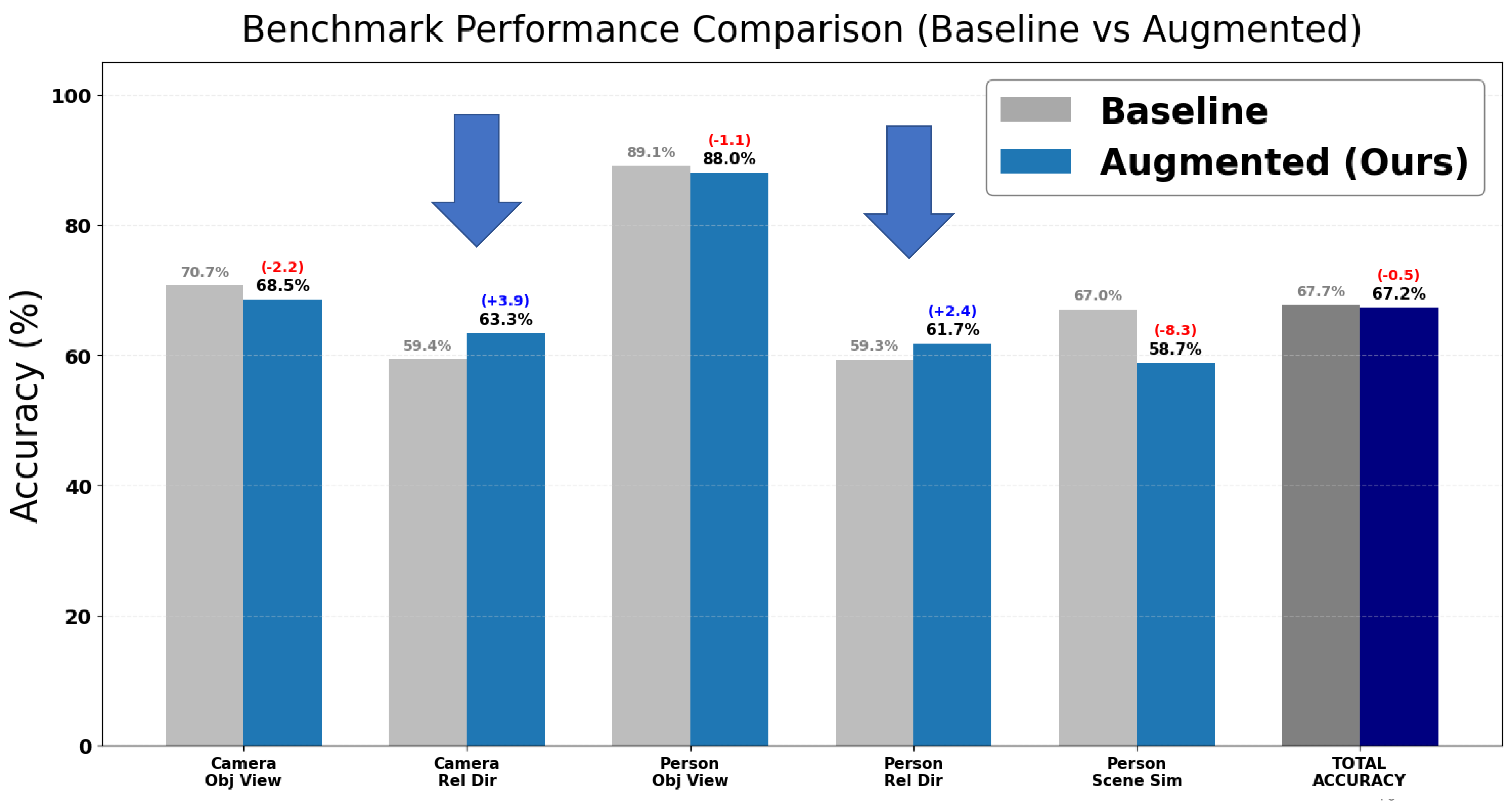
- **Horizontal Errors:**
  - (Front/Back)Left ⟷ (Front/Back)Right
- Orthogonal Errors:
  - Front ⟷ Left/Right
- Vertical Flip:
  - Top ⟷ Bottom
- Adjacent Error:
  - Angles that are not 90 or 180 degrees
  - Front ⟷ Front-left

Problem 1 : Direction analysis



Hypothesis 1

- Augment Train dataset
  - 4548(baseline train data) -> 9048 (augmented train data)
  - Flip the image, flip the label(left , right)



Benchmark Performance Comparison (Baseline vs Augmented)
Baseline
Augmented (Ours)
Accuracy (%)
100
80
60
40
20
0
70.7%
(-2.2)
68.5%
59.4%
(+3.9)
63.3%
89.1%
(-1.1)
88.0%
59.3%
(+2.4)
61.7%
67.0%
(-8.3)
58.7%
67.7%
(-0.5)
67.2%
Camera
Obj View
Camera
Rel Dir
Person
Obj View
Person
Rel Dir
Person
Scene Sim
TOTAL
ACCURACY

Result 1 : Data Augmentation

- Although we achieved accuracy improvement in the targeted relative direction,

- We confirmed that the performance of other tasks actually decreased.
  - Which is called **Catastrophic Forgetting***
  - -> To solve this, we can try “cognitive replay”
  - It is a method of repeatedly learning previous data.

Kirkpatrick, James, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, et al. "Overcoming Catastrophic Forgetting in Neural Networks." *Proceedings of the National Academy of Sciences* 114, no. 13 (2017): 3521–3526

Hypothesis 2

Bounding box + Visual prompting

Problem 2 : Object detection fail

WRONG

[Question]

From the perspective of the boy, where is the TV located?

[Options]

A. back-left B. front C. right D. left

Problem 2 : Object detection fail

- The question is about “person perspective” but the model is likely looking at "the entire image"

Hypothesis 2 : Bounding box + Visual prompting

- The model may not be good at recognizing **reference objects.**
  - “From the perspective of **the boy**, where is the TV located?”

- -> Then let's make the reference point recognition more certain!
  - Maybe Bounding box might be helpful!
  - Used “Ultralytics YOLO-World*”

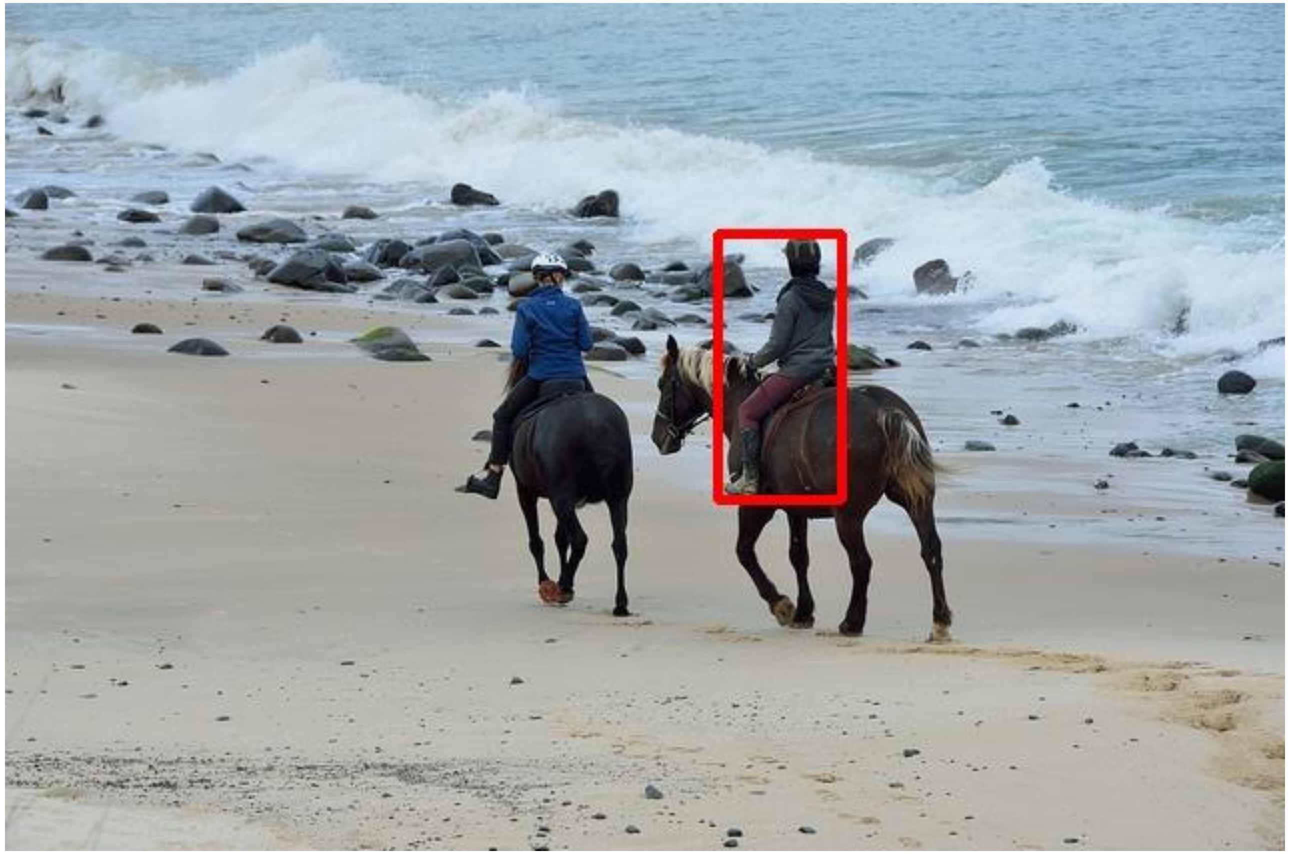
CVPR 2024 : Cheng, Tianheng, Lin Song, Yixiao Ge, Xuchao Liu, Xinggang Wang, and Ying Shan. "Yolo-world: Real-time open-vocabulary object detection." *arXiv preprint arXiv:2401.17270* (2024).

How does “Yolo world” works?

- Existing YOLO (v5, v8, etc.) could only find fixed, pre-trained classes (e.g. 80 classes including people, cars, dogs, cats, etc.).

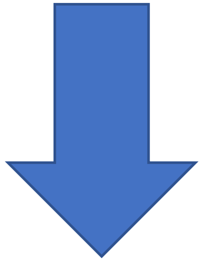
- 1. Text Encoder : Convert user-entered text (e.g., "cat") into vector that the computer can understand. This process utilizes CLIP, a large-scale language-image model, to extract the meaning of the text.
- 2. Image Encoder : Analyzes the input image to extract visual features
- 3. Fusion : If a specific area of the image has a high similarity to the text vector, we determine that it is the object the user is looking for and draw a bounding box there.

Example



MS-CoCo Example

From the perspective of the person wearing the grey clothes, where is the person wearing the blue clothes?



From the perspective of the person **in the red bounding box** wearing the grey clothes, where is the person wearing the blue clothes?

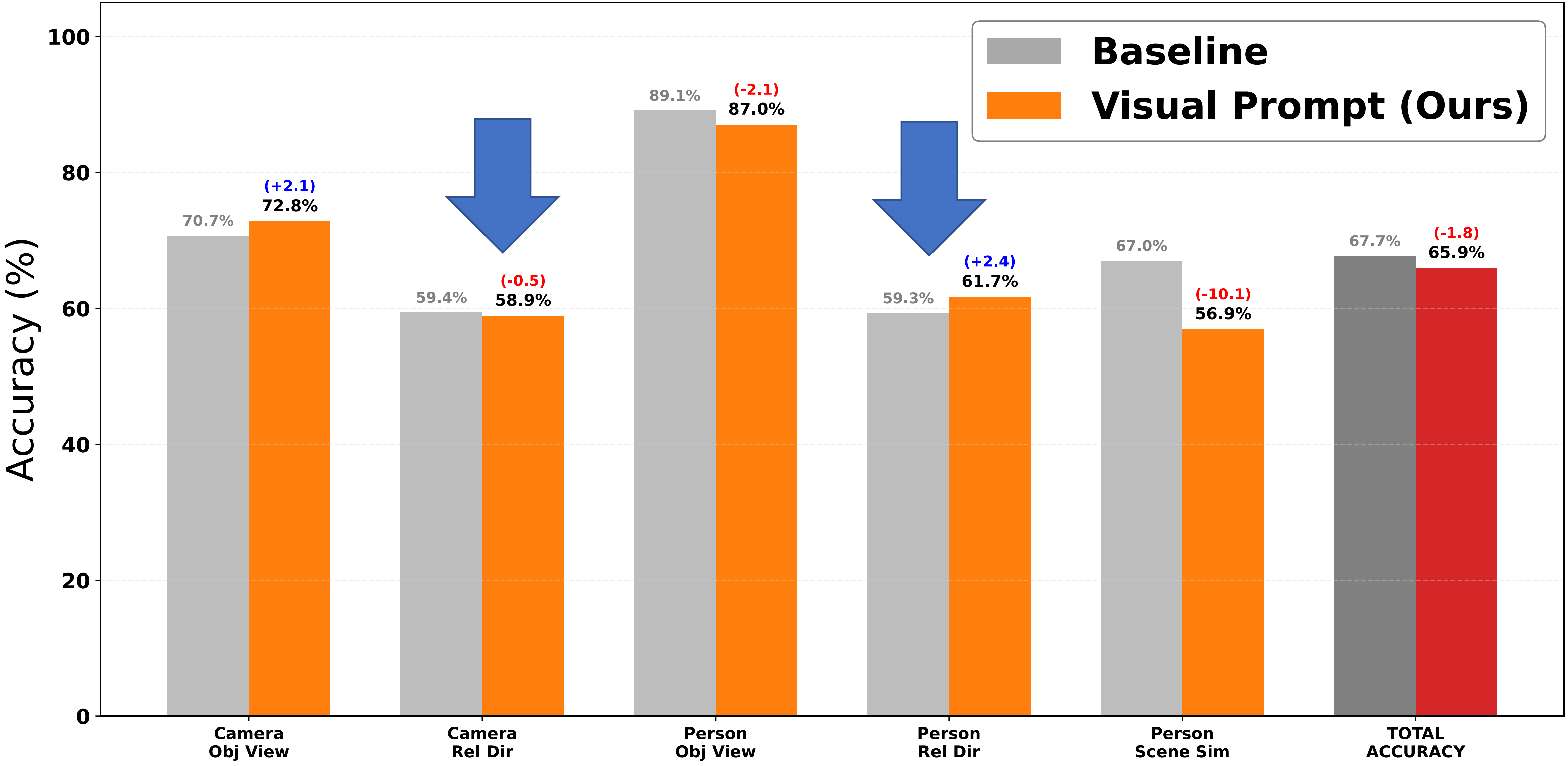
Example

ScanNet Example

How is the sofa positioned with respect to the table?

How is the sofa positioned with respect to the table in the **red bounding box?**

Performance Comparison: Baseline vs Visual Prompting



Result 2 : Bounding Box

- Result :
  - [Per] Rel dir ($+2.4\%$), [Camera] Obj ori ($+2.1\%$): Performance improved in problems where the anchor point must be clear.

- Limitations:
  - [Per] Scene simulation (-10.1%) : The surrounding environment (walls, obstacles, spatial structure) must be grasped as a whole, but this is interpreted as a kind of **tunnel vision** phenomenon where the model's gaze is trapped within a red box.

Do bounding boxes induce tunnel vision?

$$S_i = \left| \frac{\partial f(x)}{\partial x_i} \right|$$

$f(x)$: Logit of prediction

x_i : pixel value

- Used Saliency map
  - A saliency map is a way to visualize how sensitive each element of the input is to the prediction by calculating the gradient of the input x with respect to the model output y.
  - “If this pixel value changes even a little, how much does the correct answer (Logits) change?”

- Why not attention map?
  - It shows where the model "routed" during its computation, doesn't guarantee that it influenced the correct answer.

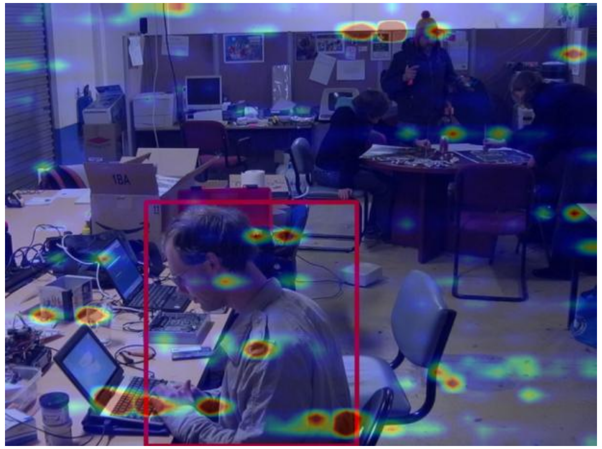
ICLR 2014 : Simonyan et al. "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps." arXiv preprint arXiv:1312.6034 (2013).

[Rel Dir] From the perspective of the man who is looking at the computer, where is the man wearing a hat positioned?

Original Image

Original Saliency

Visual Prompt Image

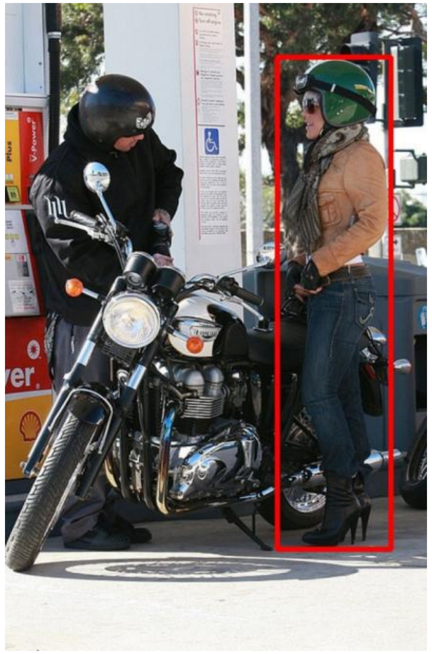


Boxed Saliency

[Rel Dir] From the perspective of the woman wearing the green helmet, where is the person in black clothes?

Original Image

Original Saliency



Visual Prompt Image

Boxed Saliency

Hypothesis 3

Chain of thought

Hypothesis 3 : Chain of Thought

Q : With the camera's viewpoint as the front, which direction is the elephant facing in the image? A. right B. front C. back-left D. left Answer with the option letter.

"A"

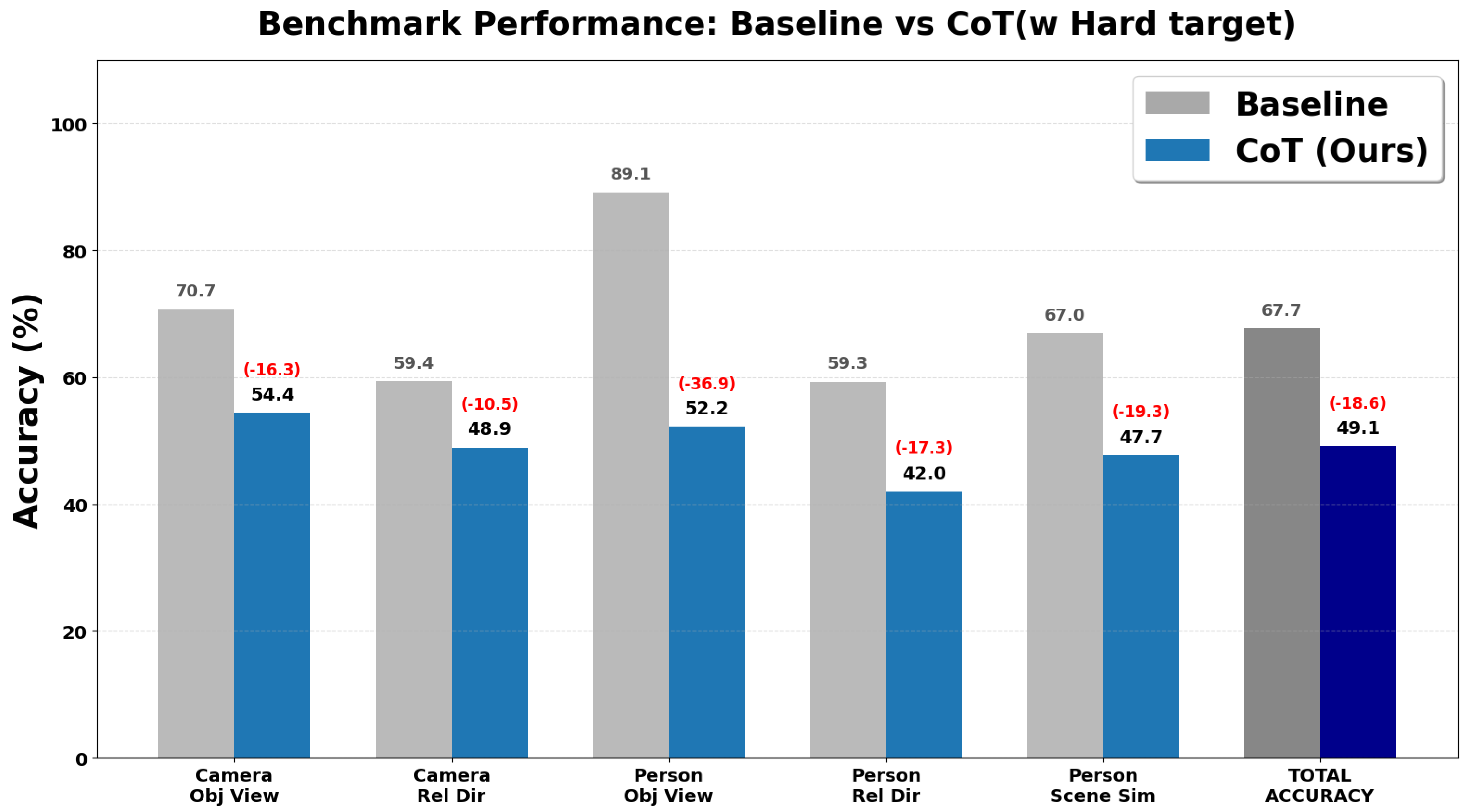
Let's think step by step to determine the spatial relationship.
1.First, I identify the reference point: the camera viewpoint.
2. Next, I locate the target object: man.
3. By analyzing their relative positions in the 3D space, man is positioned to the right of the camera viewpoint.

Therefore, the correct option is **A.**

Distilling the knowledge

- Used Qwen 2.5 **7B** model for **teacher** , and our Qwen 2.5 3B model will be a student
  - Qwen2.5 73B model was unusable due to OOM issue.

NIPS 2014 : Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. "Distilling the knowledge in a neural network." *arXiv preprint arXiv:1503.02531* (2015).



Benchmark Performance: Baseline vs CoT(w Hard target)
Baseline
CoT (Ours)
Accuracy (%)
0
20
40
60
80
100
70.7
(-16.3)
54.4
59.4
(-10.5)
48.9
89.1
(-36.9)
52.2
59.3
(-17.3)
42.0
67.0
(-19.3)
47.7
67.7
(-18.6)
49.1
Camera
Obj View
Camera
Rel Dir
Person
Obj View
Person
Rel Dir
Person
Scene Sim
TOTAL
ACCURACY

Result 3 : CoT

- Why is it so bad?
  - Used the Qwen 2.5 **7B** model instead of the 72B model or other higher end models.
  - Noise was mixed in during the process of creating **unnecessary forced logic.**
- How can we overcome this?
  - Better open source model (InternVL2-26B, Llama-3.2-11B-Vision, Qwen3)

Conclusion

- We confirmed that data augmentation(for hard negatives) and bounding boxes helped improve performance, but the CoT experiment failed.

Thank you!

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