# Cross-modal Information Flow in Multimodal Large Language Models

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# Project Objective

- **Objective:**

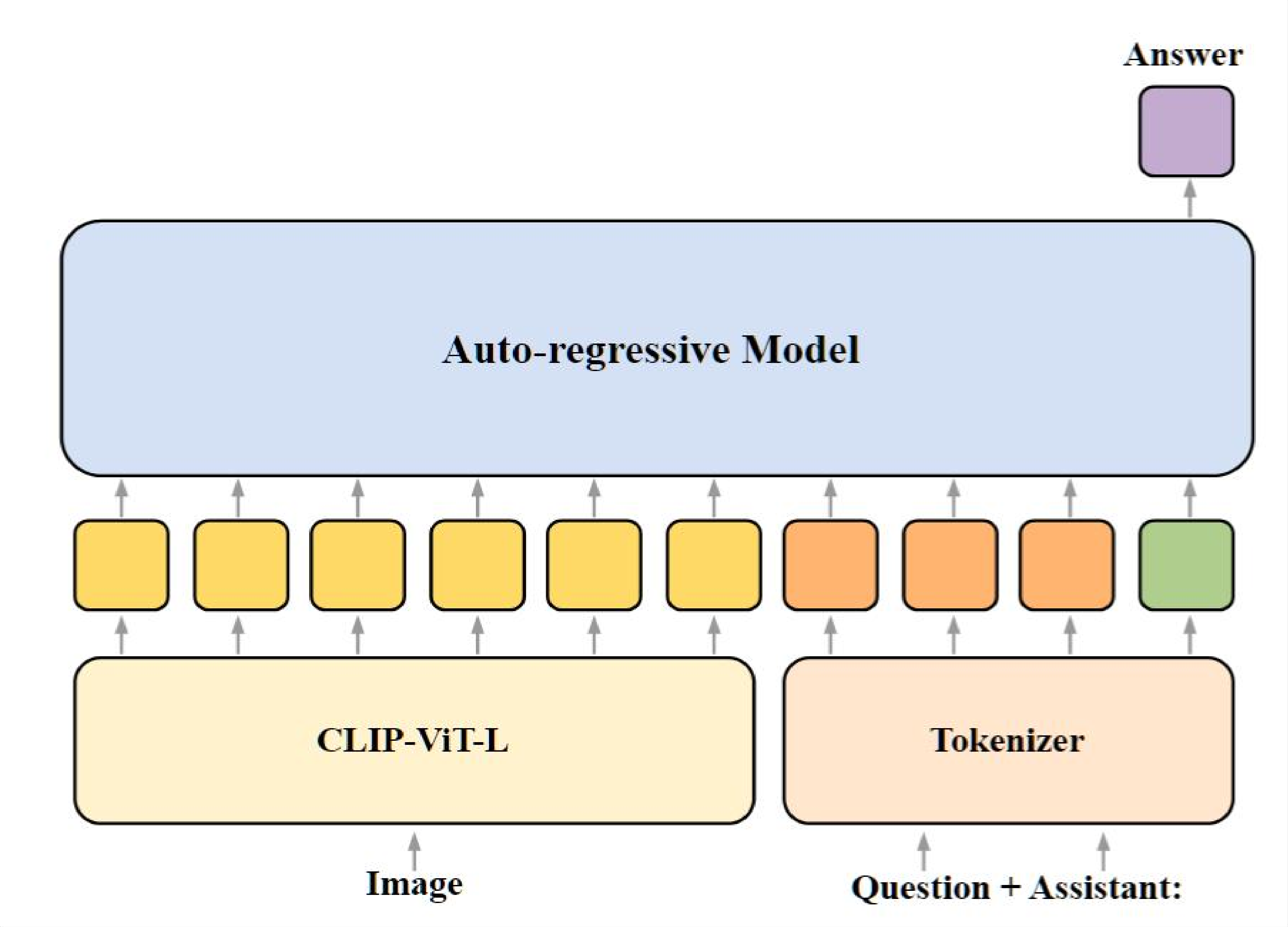
  Investigate the inner working mechanism of the multi-modal large language model (MLLM) when performing multi-modal tasks

- **Steps:**

  Within the auto-regressive MLLMs, we aim to answer the following questions:

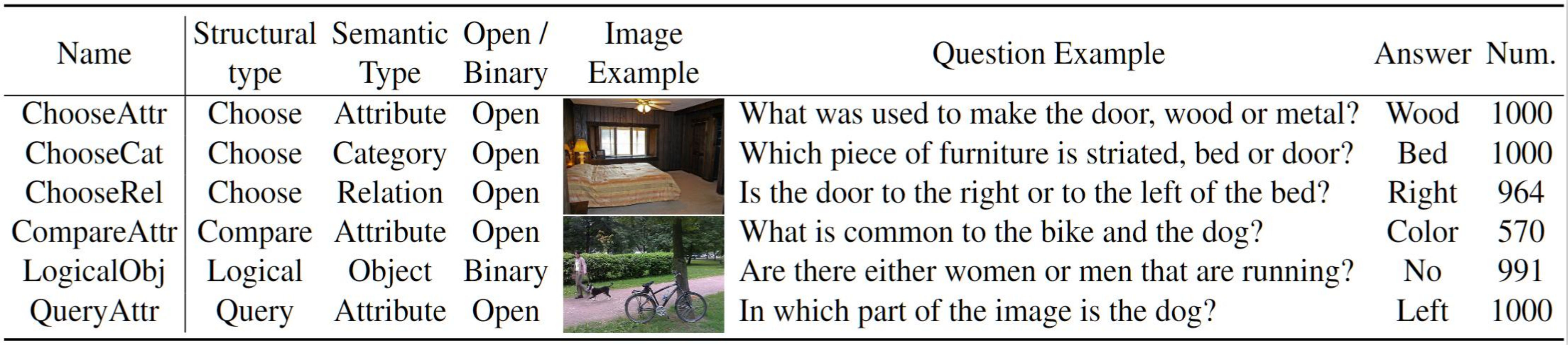
  - Where is visual and linguistic information integrated?
  - How is visual and linguistic information integrated?
  - How is the final prediction generated?

# Multi-modal large language model -- Llava



# Multi-modal task

- 6 VQA Tasks:



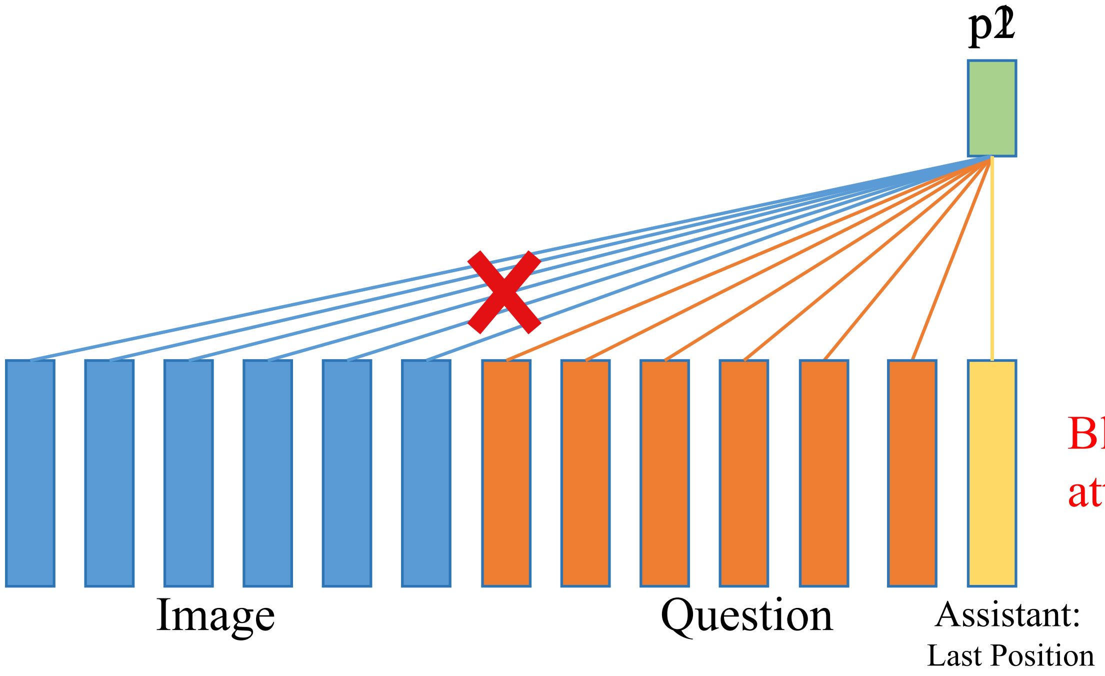
| Name | Structural type | Semantic Type | Open / Binary | Image Example | Question Example | Answer | Num. |
|---|---|---|---|---|---|---|---|
| ChooseAttr | Choose | Attribute | Open | | What was used to make the door, wood or metal? | Wood | 1000 |
| ChooseCat | Choose | Category | Open | | Which piece of furniture is striated, bed or door? | Bed | 1000 |
| ChooseRel | Choose | Relation | Open | | Is the door to the right or to the left of the bed? | Right | 964 |
| CompareAttr | Compare | Attribute | Open | | What is common to the bike and the dog? | Color | 570 |
| LogicalObj | Logical | Object | Binary | | Are there either women or men that are running? | No | 991 |
| QueryAttr | Query | Attribute | Open | | In which part of the image is the dog? | Left | 1000 |

- Input form:

  [Image, Question, Assistant:]

# Method: Attention Knockout

- We use attention knockout method to investigate the information flow between diffenerent parts of the input



(p1- p2) /p1
relative change in probability

Block ***last position*** token from attending ***image*** for final prediction

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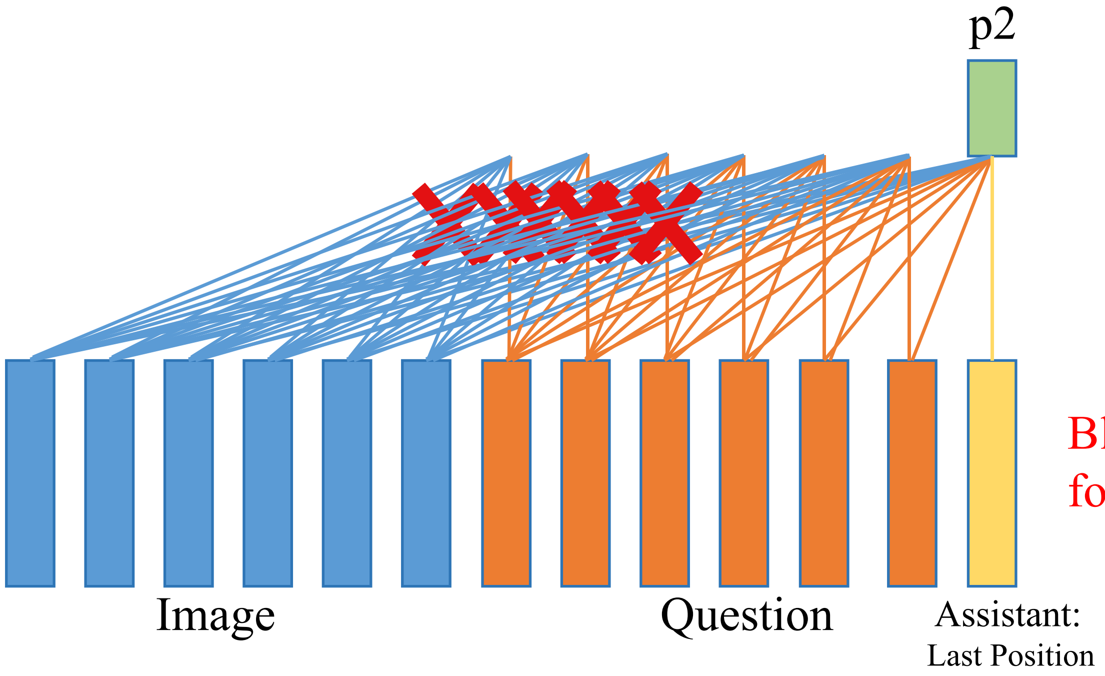


Block ***question*** from attending ***image*** for final prediction

# Information Flow: To *Last*

- ***Last-> Last***:

  Significant change in probability.

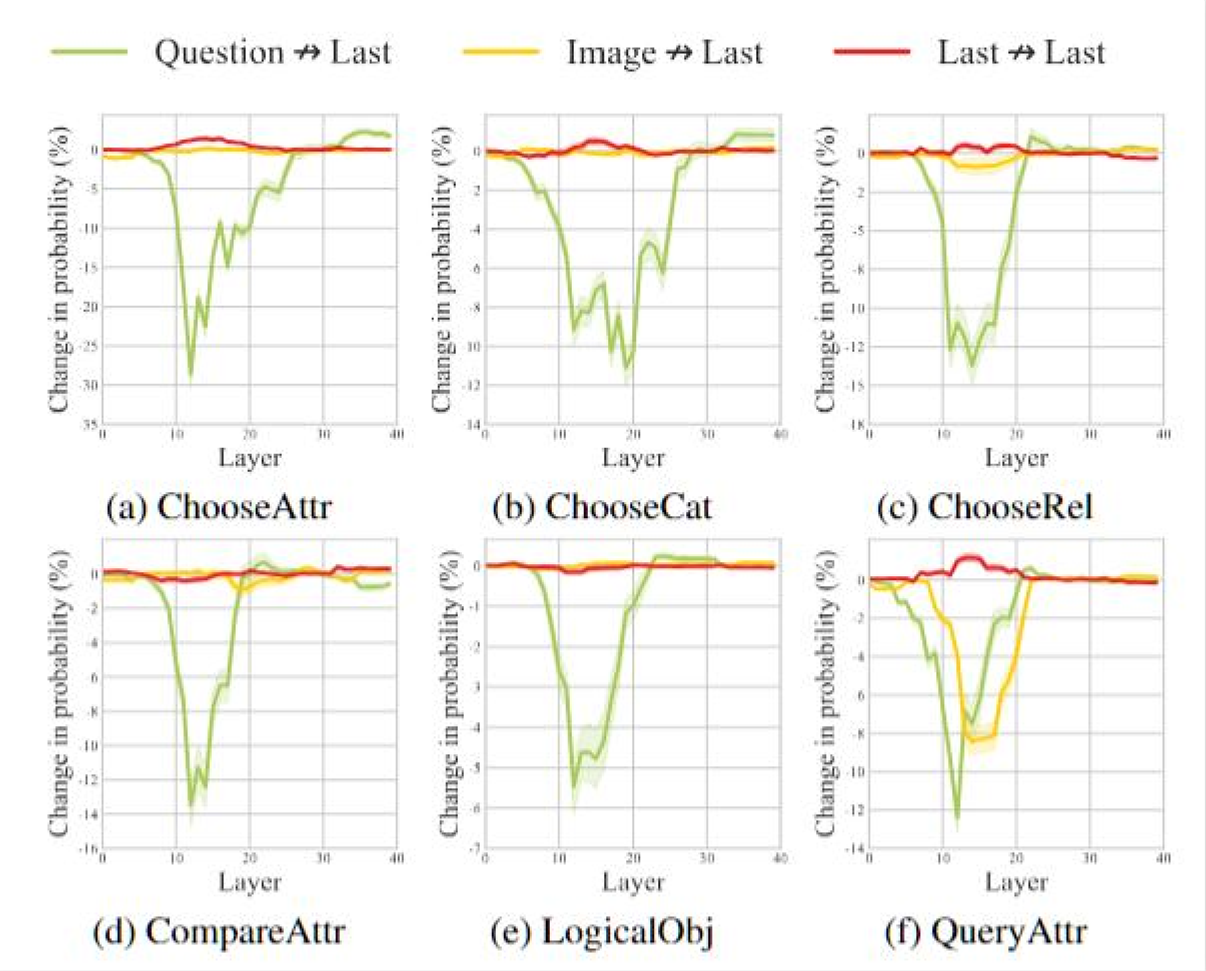
- ***Image -> Last***:

  No changes in the probability.

- ***Question->Last***:

  Significant change in probability.

Only the ***Question*** directly transfer crucial information to ***last position*** for the final prediction **in the middle layers.**



(a) ChooseAttr (b) ChooseCat (c) ChooseRel

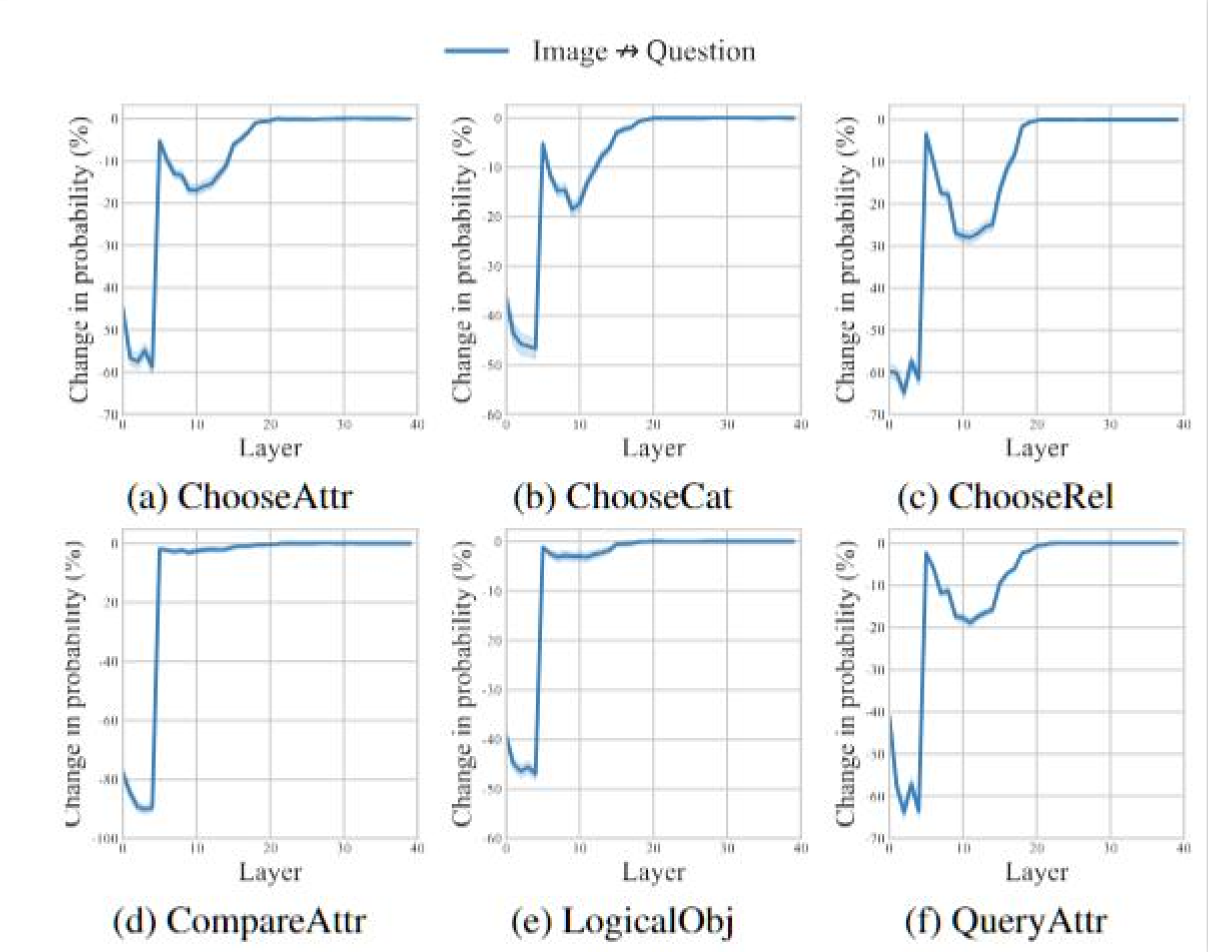
(d) CompareAttr (e) LogicalObj (f) QueryAttr

# Information Flow: *Image* To *Question*

***Image -> Question***

Image information flows twice:

- **lower layers**
- **lower-middle layers**

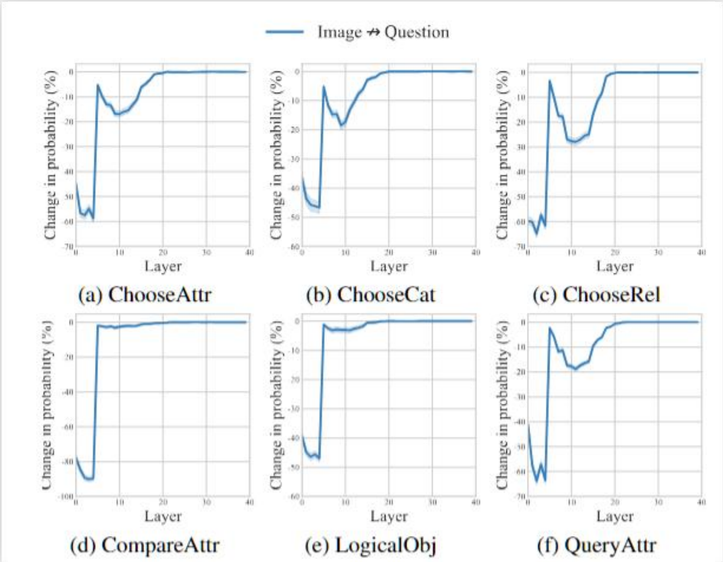


(a) ChooseAttr (b) ChooseCat (c) ChooseRel

(d) CompareAttr (e) LogicalObj (f) QueryAttr

# Information Flow Conclusion

- First, in **lower** layers, ***Image*** propagate information to ***Question***;
- Then, in **lower-middle** layers, same information flow from ***Image*** to ***Question***;
- Finally, in **upper-middle** layers, information in ***Question*** is transferred to ***last position*** for final prediction.



(a) ChooseAttr (b) ChooseCat (c) ChooseRel

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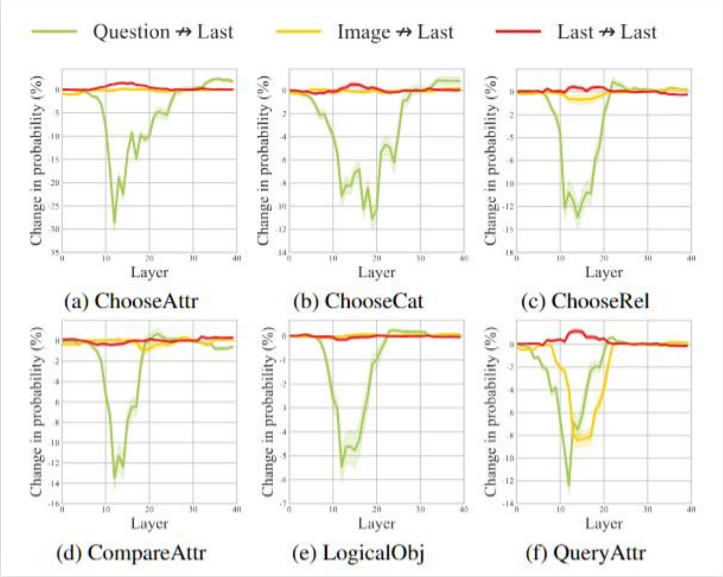

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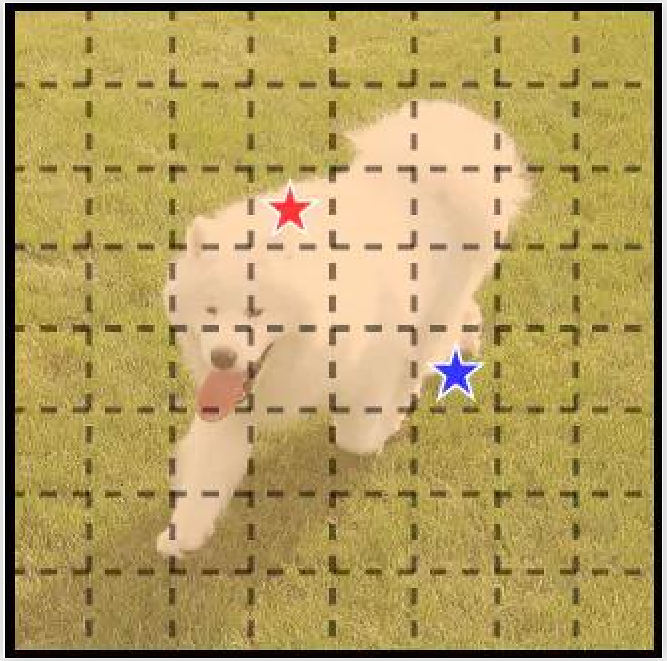
# What is the difference between the two image information flow

**Image patches**

- We split image patches into two groups:
  - image patches (***Related Image Patches***)
  - image patches (***Other Image Patches***)



# Image patches To Question

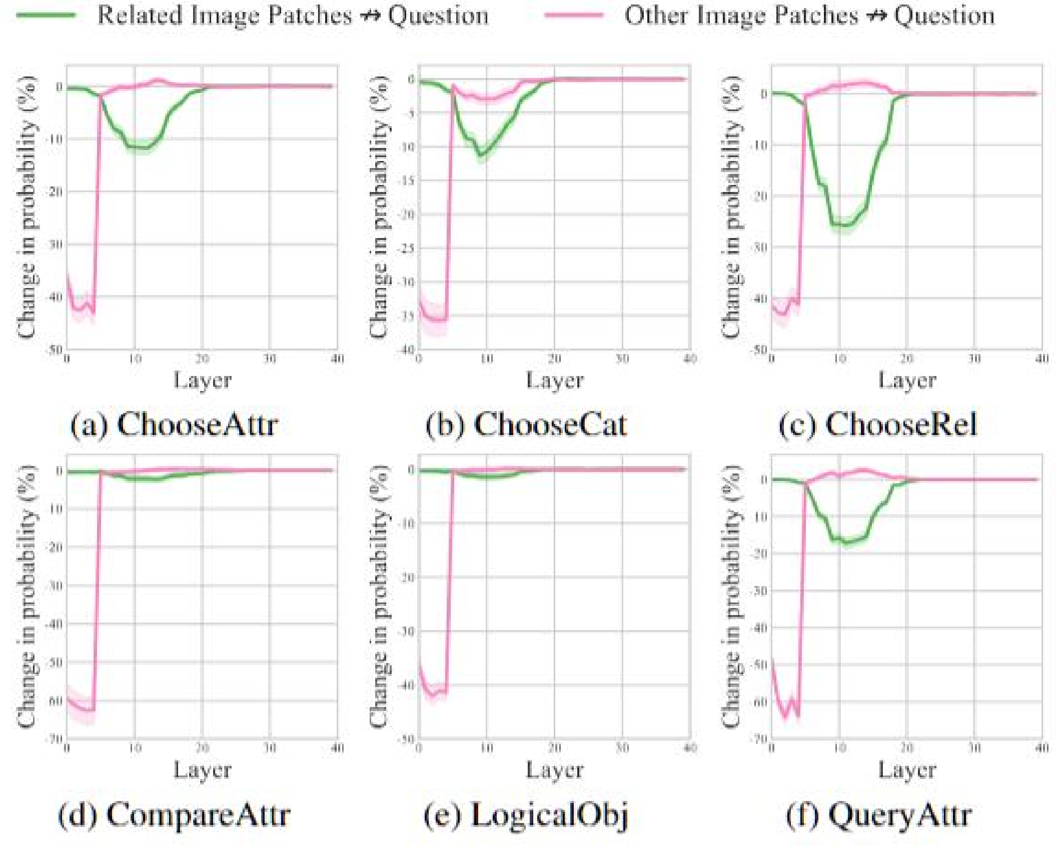
**Clear difference:**

- ***Other image patches*** propagate image information during first image information flow

- ***Related Image Patches*** propagate image information during second image information flow

**Conclusion:**

- **First**, in lower layer, the model integrates the whole image information to full question building a more generic representation,
- **Then**, in the subsequent layer (upper-middle layers), the model starts only to pay attention to the related parts to the object in the image fusing the features of the object with the full question.



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# Answer word generation

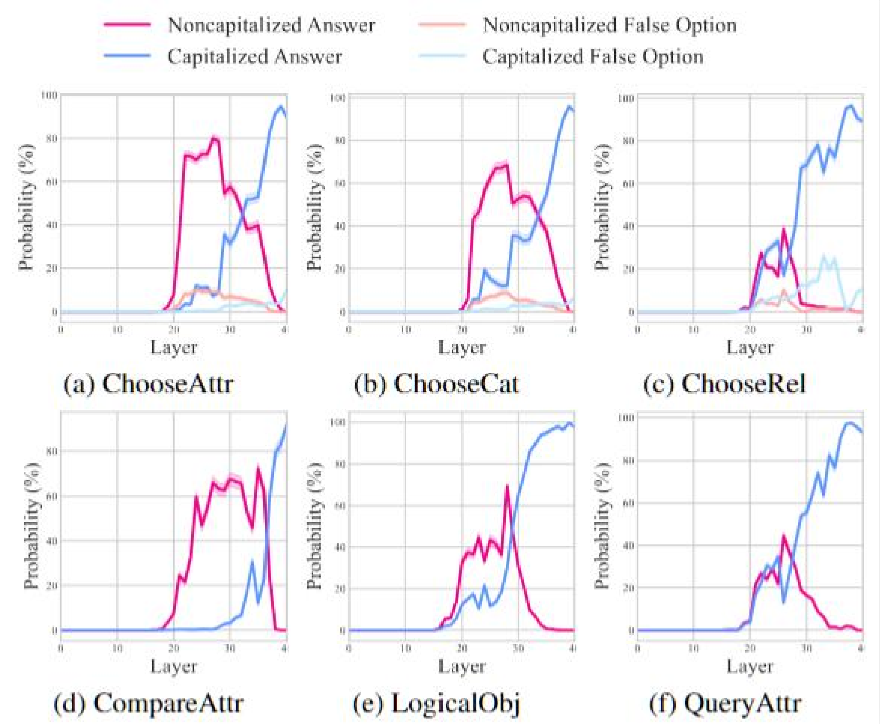
- ***Capitalized Answer***: Answer word with capital initial letter
- ***Noncapitalized Answer***: Answer word with lower-case for all letters

**Observation:**

- ***Capitalized Answer*****:** probability increase and then decrease
- ***Noncapitalized Answer***: probability increase when the probability of ***Capitalized Answer*** decrease

**Conclusion**:

- The model has already **semantically** inferred the answer in the **middle layers**
- Then, the model starts to refine the syntactic correctness of the answer in **higher layers**



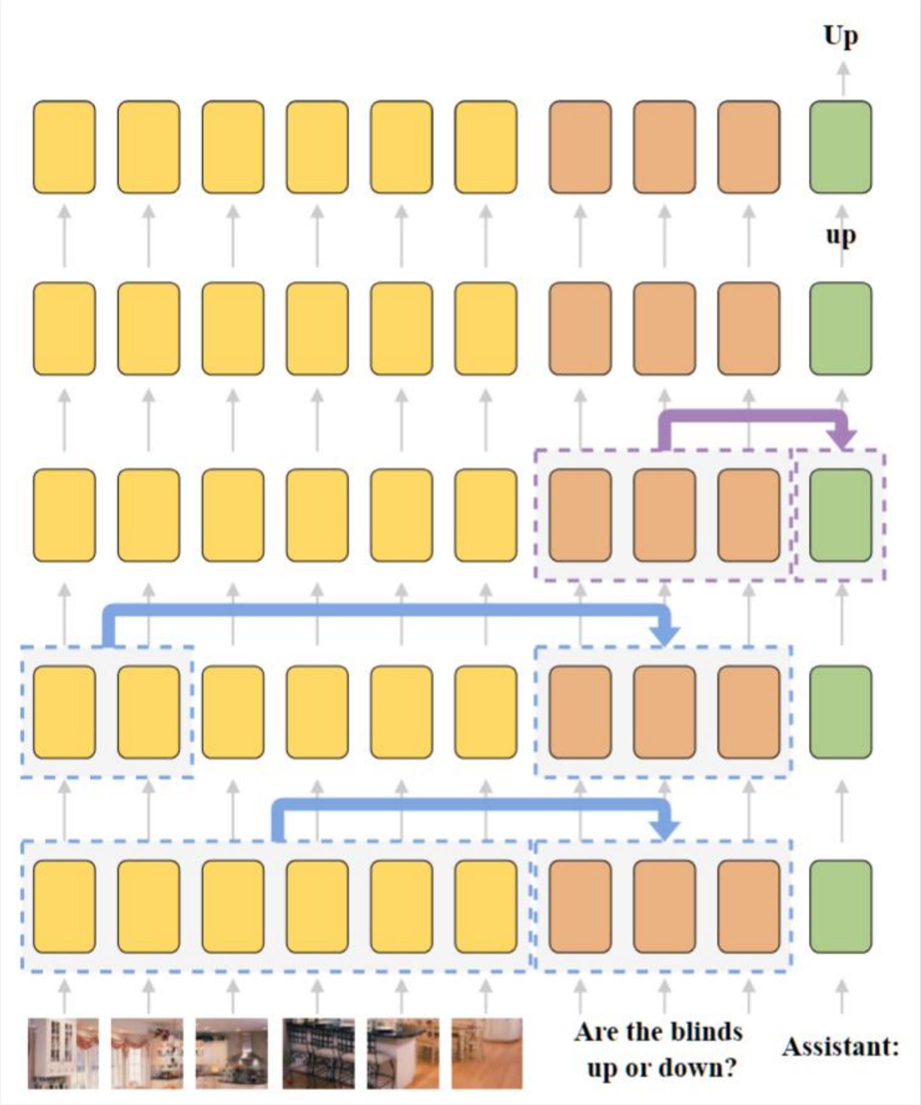
(a) ChooseAttr (b) ChooseCat (c) ChooseRel

(d) CompareAttr (e) LogicalObj (f) QueryAttr

# Conclusion

**From bottom to top layers:**

1. **First**, the model propagates general visual information from the whole image into the linguistic hidden representation;
2. **Next**, selected visual information relevant to answering the question is transferred to the linguistic representation;
3. **Finally**, the integrated multimodal information within the hidden representation of the question flows to last position facilitating the final prediction.
4. **In addition**, the answers are initially generated in lowercase form and then converted to uppercase for the first letter.


Up
up
Are the blinds up or down?
Assistant: