Look and Answer the Question: On the Role of Vision in Embodied Question Answering

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More research on embodied multi-modal agents is needed

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  - This is partially reflected in the increasing number of papers on multi-modality (Vinyals et al., 2015), grounding (Clark and Brennan, 1991), and interaction (Hill et al., 2021).

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- However, many existing multi-modal tasks do not have "embodied" component: Visual Question Answering (Antol et al., 2015), Visual Dialogue (Das et al., 2017).

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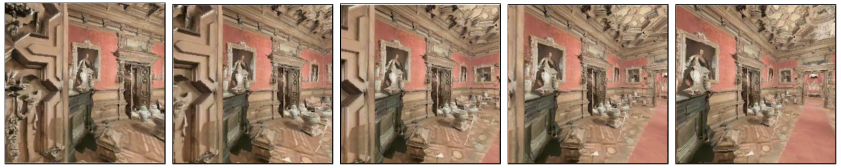
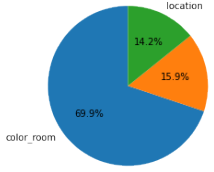
This paper focuses on the task of Embodied Question Answering (Das et al., 2018), which brings the aspects of **generation**, **real-world simulation** and **multi-modal interaction** together. We will specifically look at the **question answering** component of the task.

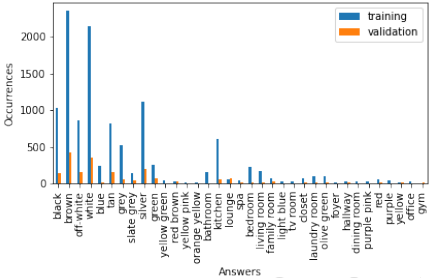
More about Question Answering in the EQA

The task: given the last five (5) images in the end of the navigation, answer the question: *What colour is the fireplace?*



- Dataset: Matterport3D-EQA (Wijmans et al., 2019)
  - Images: Matterport 3D scenes
  - 3 types of questions: Colour Room, Colour, Location





CLASP centre for linguistic theory and studies in probability

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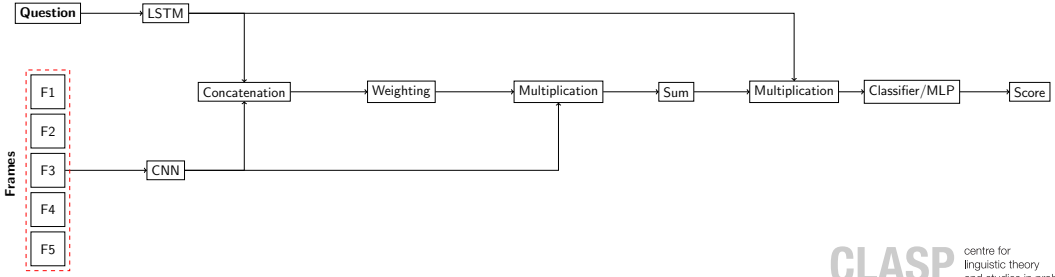
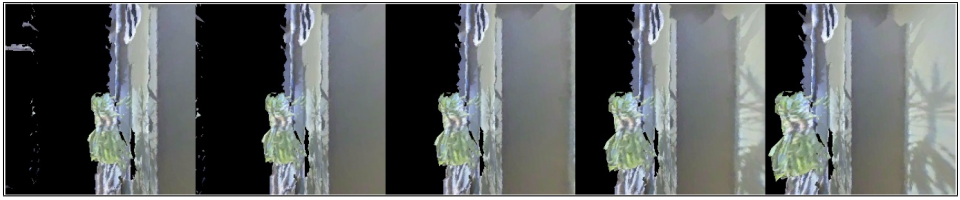
The model:



EQA is hard because

- The quality of rendered scenes is often poor.

Q: What colour is the plant in the kitchen?
Ground truth answer: Green.
Predicted answer: Olive green.



EQA is hard because

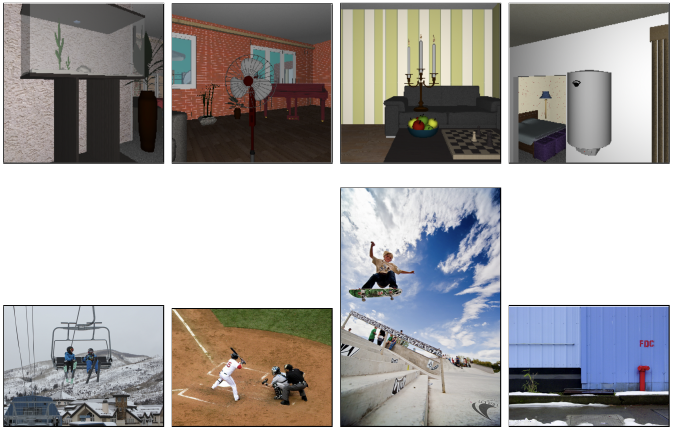
- The QA dataset is generated automatically.
  - Many answers are limited and fixed, e.g. there are only 24 colour answers.

KELLY'S 22 COLOURS OF MAXIMUM CONTRAST

Colour serial or selection number	Colour sample matched visual to ISCC-NBS centroid colour	General colour name	ISCC-NBS centroid number	ISCC-NBS colour name (abbreviation)	Munsell notation of ISCC-NBS centroid colour
1		white	263	white	2.5PB 9.5/0.2
2		black	267	black	N 0.8
3		yellow	82	v.Y	3.3Y 8.0/14.3
4		purple	218	s.P	6.5P 4.3/9.2
5		orange	48	v.O	4.1YR 6.5/15.0
6		light blue	180	v.l.B	2.7PB 7.9/6.0
7		red	11	v.R	5.0R 3.9/15.4
8		buff	90	gy.Y	4.4Y 7.2/3.8
9		grey	265	med.Gy	3.3GY 5.4/0.1
10		green	139	v.G	3.2G 4.9/11.1
11		purplish pink	247	s.pPk	5.6RP 6.8/9.0
12		blue	178	s.B	2.9PB 4.5/10.4
13		yellowish pink	26	s.yPk	8.4R 7.0/9.5
14		violet	207	s.V	0.2P 3.7/10.1
15		orange yellow	66	v.OY	8.6YR 7.3/15.2
16		purplish red	255	s.pR	7.3RP 4.4/11.4
17		greenish yellow	97	v.gY	9.1Y 8.2/12.0
18		reddish brown	40	s.rBr	0.3YR 3.1/9.9
19		yellow green	115	v.YG	5.4GY 6.8/11.2
20		yellowish brown	75	deep yBr	8.8YR 3.1/5.0
21		reddish orange	34	v.rO	9.8R 5.4/14.5
22		olive green	126	d.OlG	8.0GY 2.2/3.6

EQA is hard because

- All questions are about house environments which are more similar to each other in terms of structure and present objects than photographs used for VQA.



EQA requires fine-grained visual understanding

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- House environments are visually similar and consist of many instances of the same object classes (e.g., sofas, plants) that often share the same attributes (e.g., sofas are brown, plants are green).

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- House environments are visually similar and consist of many instances of the same object classes (e.g., sofas, plants) that often share the same attributes (e.g., sofas are brown, plants are green).

- However, previous research has shown that EQA models often struggle to learn from vision, learning mostly from language alone (Anand et al., 2018; Thomason et al., 2019).
- Given that the models do not exploit vision as much as they should, **we are going to examine what is it exactly that makes them learn so little from vision.**

Experiment I: is vision really needed?

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We train three kinds of models to predict the most probable answer $a^\star$:

Given both question and images, predict the answer; Vis-L:

$$a^\star = \underset{a \in \mathcal{A}}{\operatorname{argmax}} \, \mathrm{P}(a | \mathbf{Q}, \mathbf{I}_{T-N}, \ldots, \mathbf{I}_T). \quad (1)$$

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Given question and black images, predict the answer; Blind-L:

$$\mathbf{I}_t = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{bmatrix}, \quad \mathbf{I}_t \in \mathbb{R}^{3 \times 256 \times 256}. \tag{2}$$

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Given question, predict the answer; Ø-L:

$$a^\star = \underset{a \in \mathcal{A}}{\operatorname{argmax}} \, \mathrm{P}(a|\mathbf{Q}). \tag{3}$$

Experiment I: vision improves accuracy for a wrong reason

Metric	Vis-L	Blind-L	Ø-L
↓ Overall Mean Rank (MR)	4.352	4.454	3.685
MR, Color Room Questions	3.611	3.157	3.247
MR, Color Questions	2.693	2.261	2.304
MR, Location Questions	10.137	13.667	7.611
↑ Overall Accuracy (A)	**0.38**	0.323	0.362
A, Color Room Questions	**0.374**	0.348	0.337
A, Color Questions	**0.528**	0.478	0.522
A, Location Questions	0.222	0	0.278
Kappa Score	**-0.005**	0.014	0.024

Experiment I: vision is not used for every question type

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Experiment I: model's approximations are better without vision

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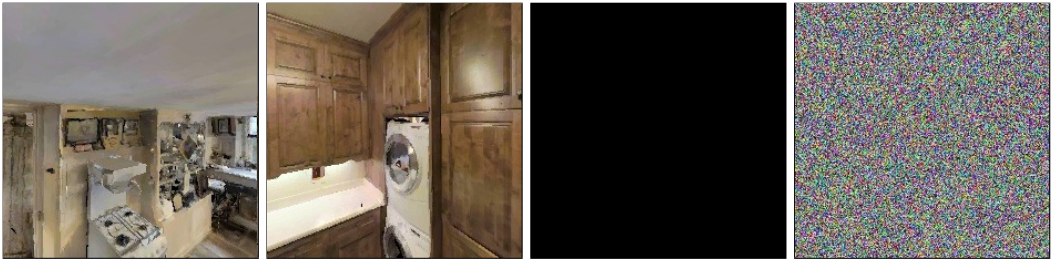
Experiment II: "how much" vision is required?



- We take the original model (**Vis-L**) that sees both question and original images and evaluate it on different types of vision.
- From left to right (given the question "What colour is the stove in the kitchen?"):
  - **Original**, structure, content and context are present
  - **Eval-Shuffled**, structure and content are present, but context is incorrect
  - **Eval-Blind**, no content and context, but structure
  - **Eval-Random**, most disturbed representation

Experiment II: Vis-L confused by novel input

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Metric	Vis-L	Eval-Shuffled	Eval-Blind	Eval-Random
↓ Overall Mean Rank (MR)	4.352	5.145	5.508	6.899
MR, Color Room Questions	3.611	4.157	4.562	5.512
MR, Color Questions	2.693	3.035	3.087	3.319
MR, Location Questions	10.137	12.722	13.278	18.33
↑ Overall Accuracy (A)	0.38	0.266	0.246	0.211
A, Color Room Questions	0.374	0.264	0.258	0.258
A, Color Questions	0.528	0.307	0.217	0.194
A, Location Questions	0.222	0.222	0.222	0
Kappa Score	-0.005	0.013	0.004	-0.005

What did we learn about question answering in EQA?

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- The model can extract general patterns from images (but these patterns have to be present there). However, it cannot utilise images fully and acquire deeper understanding of what is in the image.
- We have identified multiple dataset and model biases through our experiments which suggest directions for future research:
  - Improve model's vision my implementing cognitive attention (Kruijff-Korbayová et al., 2015; Dobnik and Kelleher, 2016)
  - Split question answering into several subtasks
  - Using pre-trained multi-modal transformer such as LXMERT (Tan and Bansal, 2019) could tell us whether these models are able to overcome problems related to dataset construction and image selection for the task.

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Thank you!

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Kappa

$$\kappa = (p_0 - p_e)/(1 - p_e) \tag{4}$$

where p_0 is the observed agreement, in this case accuracy, and p_e is the expected agreement, calculated by:

$$p_e = \sum_{k \in K} P(k|classifier) \cdot P(k|ground\_truth) \tag{5}$$