

Ask, Attend and Answer: Exploring Question-Guided **Spatial Attention for Visual Question Answering**

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GOAL

- Task
 - •Visual Question Answering (VQA)
 - ·Answer a question about a given photograph
- · Applications
 - Assist the visually impaired
 - Automatically query surveillance video

CONTRIBUTIONS

- · Existing Methods
 - · End-to-end deep VQA networks adapted from captioning models: utilize a recurrent LSTM network, which takes the question and CNN image features as input and outputs the answer. [6, 7]
- Problems
 - Do not have any explicit notion of object position
 - Use the whole question encoding to infer the answer, without considering fine-grained information from the auestion
- Contributions
 - Propose Spatial Memory Network VQA (SMem-VQA)
 - Incorporate explicit spatial attention based on memory
 - Use fine-grained word embeddings to collect visual evidence for each word in the question

SCHEMATIC DIAGRAM

Attention is applied in two steps (hops):

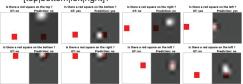
What is the child standing on? skateboard



SYNTHETIC EXPERIMENTS

By visualizing attention, we can figure out how the network learns to answer questions.

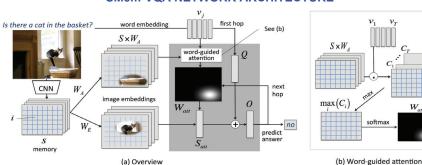
- · Absolute Position Recognition
 - Input image: a red square appears in one of the four regions of a white-background image
 - Question: Is there a red square on the [top|bottom|left|right]?



- Network learned two logic rules
 - Look at the position specified in question (top|bottom|right|left), if it contains a square, then answer "yes"; if not, then answer "no".
 - Look at the region where there is a square, then answer "yes" for the question about that position and "no" for the questions about the other three positions.
- Relative Position Recognition



SMem-VQA NETWORK ARCHITECTURE



hop1:

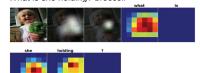
$$\begin{split} C &= V \cdot (S \cdot W_A + b_A)^T \\ W_{att} &= \operatorname{softmax}(\max_{i=1,\cdots,T}(C_i)), \ C_i \in \mathbb{R}^L \\ S_{att} &= W_{att} \cdot (S \cdot W_E + b_E) \\ Q &= W_Q \cdot V + b_Q \\ P &= \operatorname{softmax}(W_P \cdot f(S_{att} + Q) + b_P) \end{split}$$

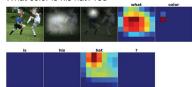
hop2:

$$\begin{split} O_{hop1} &= S_{att} + Q \\ C_{hop2} &= (S \cdot W_E + b_E) \cdot O_{hop1} \\ W_{att2} &= \text{softmax}(C_{hop2}) \\ S_{att2} &= W_{att2} \cdot (S \cdot W_{E_2} + b_{E_2}) \\ P &= \text{softmax}(W_P \cdot f(O_{hop1} + S_{att2}) + b_P) \end{split}$$

Visualization of attention weights Satt, Satt2, and correlation matrix C:

What is she holding? broccoli





EXPERIMENTAL RESULTS

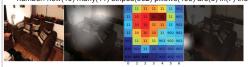
Test-dev and test-standard results on Open-Ended VQA dataset [1] (accuracy). Models with * use extra training data in addition to the VQA dataset.

methods	test-dev			test-standard				
	Overall	yes/no	number	others	Overall	yes/no	number	others
LSTM Q+I [1]	53.74	78.94	35.24	36.42	54.06	-	-	-
ACK* [2]	55.72	79.23	36.13	40.08	55.98	79.05	36.10	40.61
DPPnet* [3]	57.22	80.71	37.24	41.69	57.36	80.28	36.92	42.24
iBOWIMG [4]	55.72	76.55	35.03	42.62	55.89	76.76	34.98	42.62
SMem-VQA 1-Hop	56.56	78.98	35.93	42.09	-	-	-	-
SMem-VQA 2-Hop	57.99	80.87	37.32	43.12	58.24	80.8	37.53	43.48

- 0-1 accuracy result on the reduced DAQUAR dataset [5] is 40.07%.
- Per-answer category attention weight visualization analysis:



number: how(10) manv(11) striped(902) pillows(405) are(5) in(7) the(2) sofa(830)? 4



REFERENCES

[1] Antol, Stanislaw, et al. "Vqa: Visual question answering." Proceedings of the IEEE International Conference on Computer Vision. 2015.

[2] Wu, Qi, et al. "Ask Me Anything: Free-form Visual Question Answering Based on Knowledge from External Sources." arXiv preprint arXiv:1511.06973(2015) [3] Noh, Hyeonwoo, Paul Hongsuck Seo, and Bohyung Han. "Image question answering using convolutional neural network with dynamic parameter prediction." arXiv preprint arXiv:1511.05756 (2015).

[4] Zhou, Bolei, et al. "Simple Baseline for Visual Question Answering." arXiv preprint arXiv:1512.02167 (2015).

[5] Malinowski, Mateusz, and Mario Fritz. "A multi-world approach to question answering about real-world scenes based on uncertain input." Advances in Neural Information Processing Systems. 2014.

[6] Malinowski, Mateusz, Marcus Rohrbach, and Mario Fritz. "Ask your neurons: A neural-based approach to answering questions about images." Proceedings of the IEEE International Conference on Computer Vision. 2015. [7] Ren, Mengye, Ryan Kiros, and Richard Zemel. "Exploring models and data for image question answering." Advances in Neural Information Processing Systems. 2015.