

A Appendix

A.1 VQA *test-dev* Results

Table 1: The effects of various options for VQA *test-dev*. Here, the model of Figure 3a is used, since these experiments are preliminarily conducted. *VGG-19* features and 1k target answers are used. *s* stands for the usage of Skip-Thought Vectors [6] to initialize the question embedding model of GRU, *b* stands for the usage of Bayesian Dropout [3], and *c* stands for the usage of postprocessing using image captioning model [5].

	Open-Ended				Multiple-Choice			
	All	Y/N	Num.	Other	All	Y/N	Num.	Other
<i>baseline</i>	58.97	81.11	37.63	44.90	63.53	81.13	38.91	54.06
<i>s</i>	59.38	80.65	38.30	45.98	63.71	80.68	39.73	54.65
<i>s,b</i>	59.74	81.75	38.13	45.84	64.15	81.77	39.54	54.67
<i>s,b,c</i>	59.91	81.75	38.13	46.19	64.18	81.77	39.51	54.72

Table 2: The results for VQA *test-dev*. The precision of some accuracies [11, 2, 10] are one less than others, so, zero-filled to match others.

	Open-Ended				Multiple-Choice			
	All	Y/N	Num.	Other	All	Y/N	Num.	Other
Question [1]	48.09	75.66	36.70	27.14	53.68	75.71	37.05	38.64
Image [1]	28.13	64.01	00.42	03.77	30.53	69.87	00.45	03.76
Q+I [1]	52.64	75.55	33.67	37.37	58.97	75.59	34.35	50.33
LSTM Q [1]	48.76	78.20	35.68	26.59	54.75	78.22	36.82	38.78
LSTM Q+I [1]	53.74	78.94	35.24	36.42	57.17	78.95	35.80	43.41
Deep Q+I [7]	58.02	80.87	36.46	43.40	62.86	80.88	37.78	53.14
DPPnet [8]	57.22	80.71	37.24	41.69	62.48	80.79	38.94	52.16
D-NMN [2]	57.90	80.50	37.40	43.10	-	-	-	-
SAN [11]	58.70	79.30	36.60	46.10	-	-	-	-
ACK [9]	59.17	81.01	38.42	45.23	-	-	-	-
FDA [4]	59.24	81.14	36.16	45.77	64.01	81.50	39.00	54.72
DMN+ [10]	60.30	80.50	36.80	48.30	-	-	-	-
<i>Vgg</i> , 1k	60.53	82.53	38.34	46.78	64.79	82.55	39.93	55.23
<i>Vgg</i> , 2k	60.77	82.10	39.11	47.46	65.27	82.12	40.84	56.39
<i>Vgg</i> , 3k	60.68	82.40	38.69	47.10	65.09	82.42	40.13	55.93
<i>Res</i> , 1k	61.45	82.36	38.40	48.81	65.62	82.39	39.65	57.15
<i>Res</i> , 2k	61.68	82.28	38.82	49.25	66.15	82.30	40.45	58.16
<i>Res</i> , 3k	61.47	82.28	39.09	48.76	66.33	82.41	39.57	58.40

Table 3: The effects of shortcut connections of MRN for VQA *test-dev*. *ResNet-152* features and 2k target answers are used. *MN* stands for Multimodal Networks without residual learning, which does not have any shortcut connections. *Dim.* stands for common embedding vector’s dimension. The number of parameters for word embedding (9.3M) and question embedding (21.8M) is subtracted from the total number of parameters in this table.

	L	Dim.	#params	Open-Ended			
				All	Y/N	Num.	Other
MN	1	4604	33.9M	60.33	82.50	36.04	46.89
MN	2	2350	33.9M	60.90	81.96	37.16	48.28
MN	3	1559	33.9M	59.87	80.55	37.53	47.25
MRN	1	3355	33.9M	60.09	81.78	37.09	46.78
MRN	2	1766	33.9M	61.05	81.81	38.43	48.43
MRN	3	1200	33.9M	61.68	82.28	38.82	49.25
MRN	4	851	33.9M	61.02	82.06	39.02	48.04

A.2 More Examples

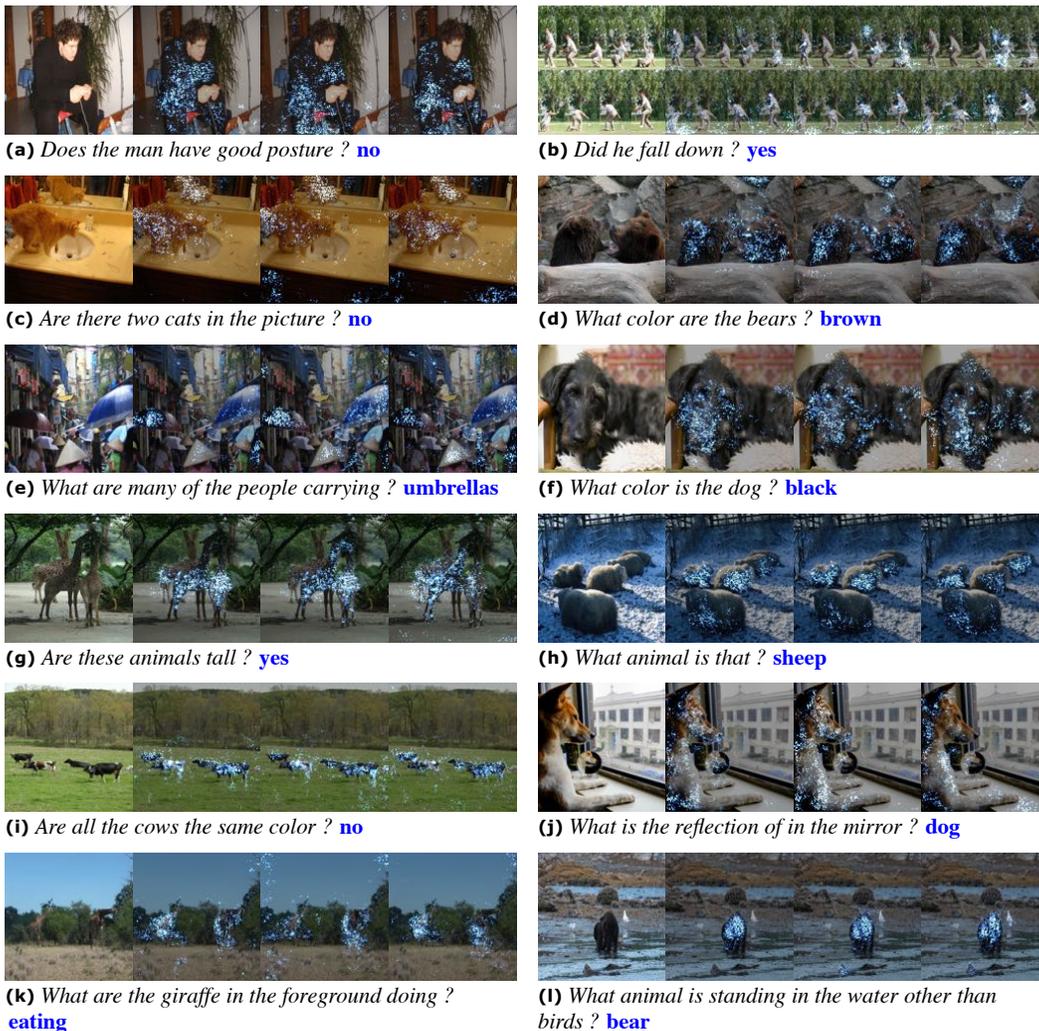


Figure 1: More examples of Figure 4 in Section 5.2.

A.3 Comparative Analysis



(a1) *What is the animal on the left ?* giraffe



(a2) *Can you see trees ?* yes



(b1) *What is the lady riding ?* motorcycle



(b2) *Is she riding the motorcycle on the street ?* no

Figure 2: Comparative examples on the same image. (a1) and (a2) depict a giraffe (left) and a man pointing at the giraffe. MRN consistently highlights on the giraffe in (a1). However, the other question “*Can you see trees?*” makes MRN less attentive to the giraffe, while a tree in the right of background is more focused in (a2). Similarly, the attention effect of (b2) is widely dispersed on background than (b1) in the middle of sequences, may be to recognize the site. However, the subtlety in comparative study is insufficient to objectively assess the results.

A.4 Failure Examples

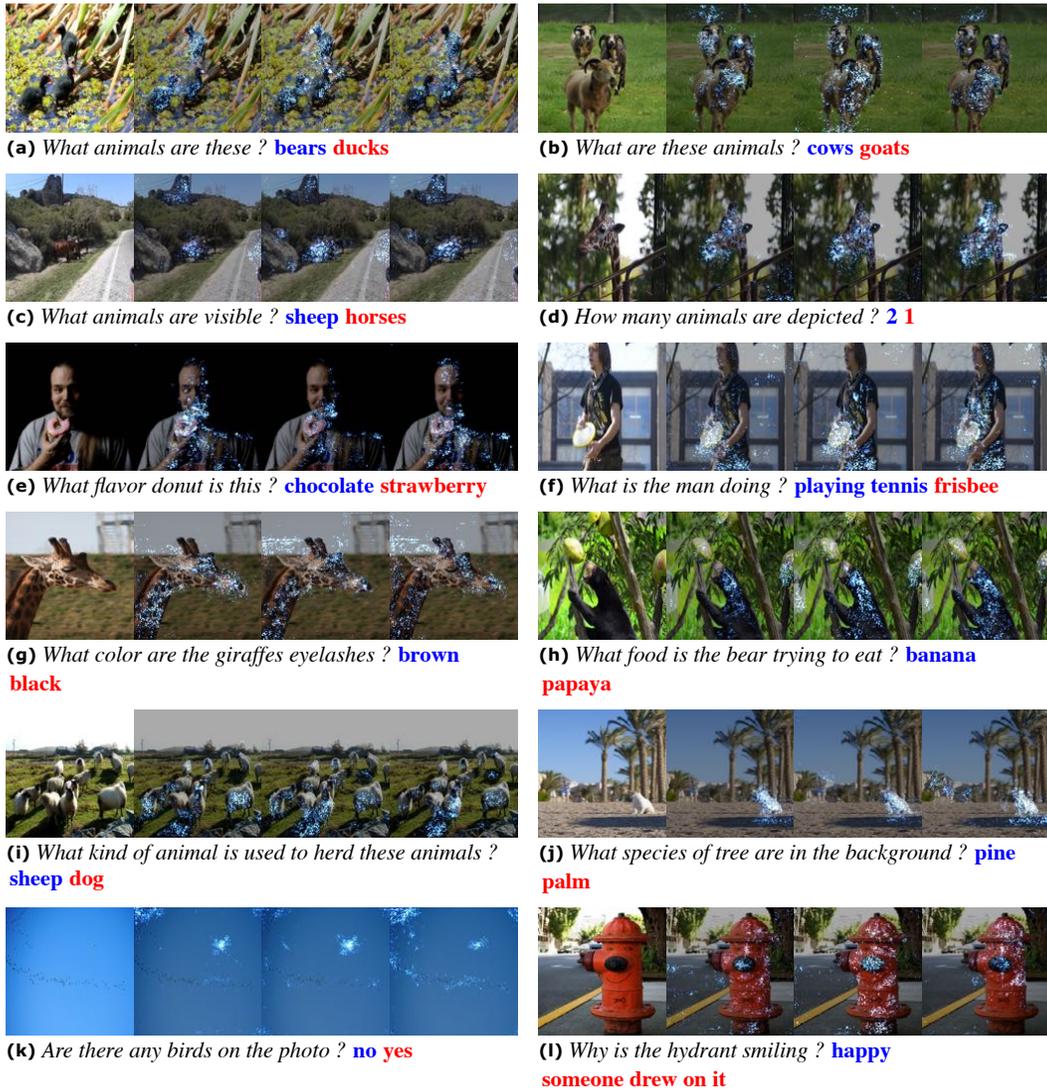


Figure 3: Failure Examples. Each question is followed by model prediction (blue) and answer (red). As mentioned in Section 5, MRN shows the weakness of counting in (d) and (k). Sometimes, the model finds objects regardless of the given question. In (j), even if a word *cat* does not appear in the question, the cat in the image is surely attended. (i) shows the limitation of attentional mechanism, which needs an inference using world knowledge.

References

- [1] Aishwarya Agrawal, Jiasen Lu, Stanislaw Antol, Margaret Mitchell, C. Lawrence Zitnick, Dhruv Batra, and Devi Parikh. VQA: Visual Question Answering. In *International Conference on Computer Vision*, 2015.
- [2] Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. Learning to Compose Neural Networks for Question Answering. *arXiv preprint arXiv:1601.01705*, 2016.
- [3] Yarin Gal. A Theoretically Grounded Application of Dropout in Recurrent Neural Networks. *arXiv preprint arXiv:1512.05287*, 2015.
- [4] Ilija Ilievski, Shuicheng Yan, and Jiashi Feng. A Focused Dynamic Attention Model for Visual Question Answering. *arXiv preprint arXiv:1604.01485*, 2016.
- [5] Andrej Karpathy and Li Fei-Fei. Deep Visual-Semantic Alignments for Generating Image Descriptions. In *28th IEEE Conference on Computer Vision and Pattern Recognition*, 2015.
- [6] Ryan Kiros, Yukun Zhu, Ruslan Salakhutdinov, Richard S. Zemel, Antonio Torralba, Raquel Urtasun, and Sanja Fidler. Skip-Thought Vectors. *arXiv preprint arXiv:1506.06726*, 2015.
- [7] Jiasen Lu, Xiao Lin, Dhruv Batra, and Devi Parikh. Deeper LSTM and normalized CNN Visual Question Answering model. https://github.com/VT-vision-lab/VQA_LSTM_CNN, 2015.
- [8] Hyeonwoo Noh, Paul Hongsuck Seo, and Bohyung Han. Image Question Answering using Convolutional Neural Network with Dynamic Parameter Prediction. *arXiv preprint arXiv:1511.05756*, 2015.
- [9] Qi Wu, Peng Wang, Chunhua Shen, Anthony Dick, and Anton van den Hengel. Ask Me Anything: Free-form Visual Question Answering Based on Knowledge from External Sources. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2016.
- [10] Caiming Xiong, Stephen Merity, and Richard Socher. Dynamic Memory Networks for Visual and Textual Question Answering. *arXiv preprint arXiv:1603.01417*, 2016.
- [11] Zichao Yang, Xiaodong He, Jianfeng Gao, Li Deng, and Alex Smola. Stacked Attention Networks for Image Question Answering. *arXiv preprint arXiv:1511.02274*, 2015.