Good, Better, Best: Textual Distractors Generation for Multiple-Choice Visual Question Answering via Reinforcement Learning

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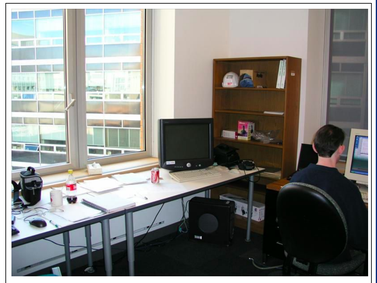
Introduction

- DG-VQA: A novel task called textual Distractors Generation for VQA is proposed, as the demand of automated multiple-choice VQA grows.
- GOBBET: A Reinforcement Learning Framework for DG-VQA is developed, which does not require training samples.
- Experiments: Distractors generated by GOBBET can fool existing VQA models; these distractors can also help build robust VQA models.
- Case Study: The quality of generated distractors is further examined.



Q: What can be seen from the windows?

(a) Input Image and Question

A: **More windows** ✓
A: The passing scenery
A: Snow falling
A: The backyard patio

(b) Original Answer Choices

A: More windows
A: A mirror
A: **Lights** ✗
A: A laptop

(c) Generated Distractors

Problem Definition

I:

Q: How many black cows are there?

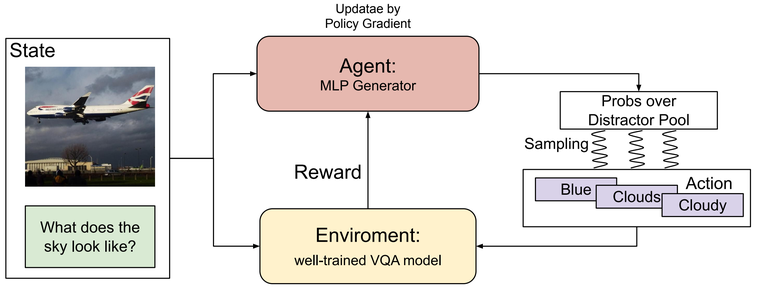
A: 3

D_1: Two

D_2: Four

D_3: One

Methods



GOBBET Framework

- Agent: a distractor generator produces distractors according to the input image, question and answer
- Environment: a pre-trained VQA model serves as alternative knowledge source
- Reward: the performance degradations of pre-trained VQA models
- RL algorithm: a policy gradient-based method to maximize the "expected" rewards

Main Experiment

Table 1 in the paper. ΔAcc denotes the performance degradation.

Model	TellingVQA [49]		RevisitedVQA [19]		MCB [7]	
	Acc	ΔAcc	*Acc*	ΔAcc	*Acc*	ΔAcc
Original distractors	55.6%	-	64.8%	-	62.2%	-
Baselines						
Q-type prior	57.3%	-1.7%	68.7%	-3.9%	85.7%	-23.5%
Adversarial Matching [47]	54.7%	0.9%	71.7%	-6.9%	51.3%	10.9%
LSTM Q+I [1]	41.7%	13.9%	68.9%	-4.1%	85.7%	-23.5%
Proposed Methods						
Reward from RevisitedVQA						
- GOBBET-base	86.5%	-30.9%	0.01%	**64.7%**	26.5%	**35.7%**
- GOBBET-warmup	33.7%	**21.9%**	49.1%	15.8%	37.5%	24.7%

Case Study

Text in boldface denotes the answer option chosen by pre-trained VQA model.

Q:What does the sky look like?

Q:How many black cows are there?

Q:What sport are they playing?

Original Choices		
A: **Stormy** ✓	A: **3** ✓	A: Golf
A: Hazy	A: 9	A: **Baseball** ✗
A: Windy	A: 8	A: Hockey
A: Sunny	A: 7	A: Basketball
Distractors by *Adversarial Matching*		
A: Stormy	A: 3	A: **Golf** ✓
A: **Sky** ✗	A: Zero	A: Volleyball
A: Blue	A: 5	A: Playing soccer
A: Cloudy	A: **0** ✗	A: Soccer
Distractors by GOBBET-warmup		
A: Stormy	A: 3	A: Golf
A: **Cloudy** ✗	A: Two	A: **Baseball** ✗
A: Blue	A: Four	A: Soccer
A: Clouds	A: **One** ✗	A: Tennis

References

[1] Antol, et al. "Vqa: Visual question answering." *ICCV*. 2015.

[7] Fukui, et al. "Multimodal Compact Bilinear Pooling for Visual Question Answering and Visual Grounding." EMNLP. 2016.

[19] Jabri, et al. "Revisiting visual question answering baselines." ECCV, 2016.

[47] Zellers et al. "From recognition to cognition: Visual commonsense reasoning." CVPR. 2019.

[49] Zhu, et al. "Visual7w: Grounded question answering in images." *CVPR*. 2016.