#### Being Negative but Constructively: Lessons Learnt from Creating Better Visual Question Answering Datasets



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Fei Sha



## Vision and language

Computer Vision

Visual Captioning



Natural Language Image Retrieval

Visual Question Answering (Visual QA) Natural Language Processing



(learning signal)

(test environment)

## Vision and language

Computer Vision

Visual Captioning





Natural Language Image Retrieval

Visual Question Answering (Visual QA) Natural Language Processing



#### How to design good datasets?

# Outline

- Introduction on Visual QA
- Issues on existing datasets

# Machines can do well while ignoring either visual or language information!

#### • Our contributions:

➢ Diagnosis of the issues

Automatic procedures to remedy existing datasets

Comprehensive evaluation on five existing datasets

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# Visual question answering (Visual QA)



#### comprehend and reason with both visual and language information

## Evaluation



Scicetion decuracy as i

• Goal:

# comprehend and reason with both visual and language information

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#### How Visual QA datasets are created?



#### • Generate decoys:

- Human generation according to (Q, T) [Visual7W]
- Random or high-frequency (target) answers [VQA]

## Detailed analysis on Visual7W

• Model: MLP with (I, Q, C) as the input [following Jabri et al., 2016]

Given an IQA triplet, where  $A = \{C_1, ..., C_K\}$  $M(I, Q, C_1)$   $\vdots$   $M(I, Q, C_k)$  argmax :MLP  $M(\mathbf{I}, \mathbf{Q}, \mathbf{C}_{\mathbf{K}})$ Score

	a b c d	Question What vehicle is pict A bicycle. A bus. A cab. A train.	tured?
Information	Machines	Humans	
Random	25.0%	25.0%	]

65.7%

88.4%

[Example from Visual7W, Zhu et. al. ]

I + Q + A



[Example from Visual7W, Zhu et. al. ]

		<b>C</b> W	<b>Luestion</b> /hat vehicle is pict	ured
2		a. b. c. d.	A bicycle. A bus. A cab. A train.	
Information	Machines	5	Humans	
Random	25.0%		25.0%	
I + Q + A	65.7%		88.4%	
<b>Q + A</b>	58.2%		36.4%	

[Example from Visual7W, Zhu et. al. ]

	a. b c. d	<b>?</b> . A bicycle. . A bus. . A cab. . A train.	
Information	Machines	Humans	
Random	25.0%	25.0%	

65.7%

62.4%

88.4%

73.5%

[Example from Visual7W, Zhu et. al. ]

I + Q + A

I+A

Information		a. A bicycle. b. A bus. c. A cab. d. A train.	
Information	Machines	Humans	
Random	25.0%	25.0%	

#### Machines can do well while ignoring information!

[Example from Visual7W, Zhu et. al. ]

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## **Diagnosis: Shortcuts in decoys**

(1) Decoys are less frequently used as targets

A frequency based baseline

 $\mathcal{S}core(\mathbf{C}) = \frac{\# \text{ of } \mathbf{C} \text{ as } \mathbf{T}}{\# \text{ of } \mathbf{C} \text{ as } \mathbf{T} + \# \text{ of } \mathbf{C} \text{ as } \mathbf{D}}$  $Prediction = \operatorname{argmax} \mathcal{S}core(C)$  $C \in A$ 

48% accuracy

# Diagnosis: Shortcuts in decoys

(2) Decoys might not be visually grounded in images



machines can perform attribute/object detection

#### (3) Decoys might not be grounded in questions

[Example from Visual7W, Zhu et. al. ]

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## Principles for decoys

• Neutrality:

Equal likely used as the target

• IoU (Image-only-Unresolvable):

Plausible to the image

• QoU (Question-only-Unresolvable):

Plausible to the question

### Automatic procedures

- Assumptions:
  - $\succ$ A dataset with (I, Q, T) triplets is given.
  - $\succ$ An image is associated with multiple (Q, T).
- For a (I, Q, T) triplet:

#### IoU-decoys: from T' of triplets with the same I



Q: What vehicle is pictured?



Q': When is the picture taken? T': **Daytime.** 

### Automatic procedures

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#### IoU-decoys: from T' of triplets with the same I

#### **QoU-decoys:** from T' of triplets with similar Q'



Q: What vehicle is pictured?



Q': What is the vehicle? T': **A truck.** 

#### Automatic procedures

- Assumptions:
  - $\succ$ A dataset with (I, Q, T) triplets is given.
  - $\succ$ An image is associated with multiple (Q, T).
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IoU-decoys: from T' of triplets with the same I

**QoU-decoys: from T' of triplets with similar Q'** 

#### **Neutrality follows naturally**

## Illustration

				Question: What vehicle Candidate An Orig a. A car. b. A bus. c. A cab. d. A train.	e is pictured? swers: ginal (0.2083) (0.6151) (0.5000) √ (0.7328)	Freq- Baseline: 48%	
Frea-	Image only Unresolva	ble (IoU)	Ques	stion only Unres	olvable (QoU)	Frea-	
Basalina	a. Overcast.	<b>X</b> (0.5455)	a. A bi	cycle.	(0.2813)	Pacalina	
Daseille.	b. Daytime.	(0.4941)	b. A tr	uck.	🗶 (0.5364)	Baseline:	
26%	c. A building.	(0.4829)	c. A bo	at.	(0.4631)	30%	
	d. A train.	(0.5363)	d. A tra	ain.	(0.5079)		

[Numbers are Score(C); accuracy are based on each set of decoys.]

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#### Experimental setup

Five datasets







#### Visual Genome (VG) [IJCV 2017]



What is there in front of the sofa? Ground truth: table

COCOQA 5078 How many leftover donuts is the red bicycle holding? Ground truth: three

COCOQA [NIPS 2015]









How many children are in the bed?







Where is the child sitting? fridge arms



man

Who is wearing glasses?





### **Experimental setup**

• Five datasets: all with images from MSCOCO

Dataset	# Training/Test triplets	Original decoys
Visual7W [CVPR 2016]	69K/42K	3 (4 choose 1)
VQA [ICCV 2015]	248K/121K	17 (18 choose 1)
Visual genome [IJCV 2017]	727K/433K	None
VQA2 [CVPR 2017]	444K/214K	None
COCOQA [NIPS 2015]	79K/39K	None

Create 3 IoU & 3 QoU decoys (6 decoys in total)
Remove Yes/No triplets from VQA, VQA2 (~30%)

## Original vs. New

#### Visual7W

VQA-

(exclude YES/NO)

Method	Original	loU + QoU
MLP-A	52.9	17.7
MLP-IA	62.4	23.6
MLP-QA	58.2	37.8
MLP-IQA	65.7	52.0
Human	88.4	84.1
Random	25.0	14.3

Original	loU + QoU
28.8	23.6
43.0	35.5
45.8	38.2
55.6	53.7
-	85.5
5.6	14.3

## Original vs. New

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MLP-IQA	65.7	52.0	55.6	53.7
Human	88.4	84.1	-	85.5
Random	25.0	14.3	5.6	14.3

#### **Algorithm with answer information only fails!**

## Original vs. New

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VQA-

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MLP-IQA	65.7	52.0	55.6	53.7
Human	88.4	84.1	-	85.5
Random	25.0	14.3	5.6	14.3

#### Algorithm needs all information to perform well!

## New multiple-choice datasets

Method	VG	VQA2-	COCOQA
MLP-A	19.5	21.3	26.6
MLP-IA	25.2	31.0	60.7
MLP-QA	43.9	37.2	51.4
MLP-IQA	58.5	53.8	75.9
Human	82.5	-	-
Random	14.3	14.3	14.3

Similar Results are obtained across all multiple-choice datasets!

#### Qualitative results



#### What is the man wearing?

- A. Black.
- B. Mountains.
- C. The beach.
- D. Board shorts.
- E. He wears white shoes.
- F. A white button down shirt and a black tie.
- G. Wetsuit.



Where do the stairs lead?

- A. A parking lot.
- B. The building.
- C. The windows.
- D. From the canal to the bridge.
- E. Up.
- F. To the building.
- G. To the plane.



What is the color of his

#### wetsuit?

- A. When waves are bigger.
- B. It is not soft and fine.
- C. It is a picture of nature.

D. Green.

- E. Blue.
- F. Red.
- G. It is black.



What is the right man on the right holding?

- A. Brown.
- B. The man on the right.
- C. Four.
- D. A bottle.
- E. A surfboard.
- F. Cellphone.
- G. A bat.

#### Failure cases

#### Who is wearing glasses?



Where are several trees?





## Conclusions

- Design good multiple-choice Visual QA datasets
- Analyze issues in existing datasets

Machines can do well while ignoring either visual or language information!

• Propose automatic procedures to remedy

**IoU-decoys:** from T' of triplets with the same I

#### **QoU-decoys: from T' of triplets with similar Q'**

• Conduct comprehensive experiments to validate

# Q & A

## All curated datasets available at: http://www.teds.usc.edu/website\_vqa/



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