# Visual Madlibs: Fill in the blank Description Generation and Question Answering Supplementary File

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# 1. Results of filtered easy and hard tasks

We show the full tables of accuracies for the filtered easy and hard multiple-choice tasks in Table 1.

# 2. Quantitative analysis of Madlibs responses

In Section 5.1 of our paper, we analyzed the the phrasal structures of our collected Visual Madlibs descriptions for several of our fill-in-the-blank questions. Here, we show the relative frequencies for the top-5 most frequent templates used for all 12 Madlibs questions. In Fig. 1, it is observed that most of the distributions are concentrated on just a few choices, except for the future and past descriptions. One reason is that this question is more open ended, so Turkers are likely to write more lengthy descriptions, i.e., "One or two seconds before this picture was taken, \_\_\_\_". In this setup, annotators have great freedom in expressing their ideas.

We also show an analysis of answer consistency in Fig. 2. Here we compute a histogram of answer similarities for each question, where similarity is measured as the cosine similarity between the mean Word2Vec representations of the 3 collected answers. Most of the similarity histograms have a normal-like distribution with an extra peak around 1, which implies we get some very similar answers for a portion of questions. The exception is the answers for the questions about the past and future, where there is no peak at one for distribution of similarities. This indicates that there are fewer images for past/future predictions where people generate the exact same description, but for some images people do display more consistency than for other images. Also note, the mean for image's emotion is smaller compared with the others, perhaps indicating that this question is relatively more subjective.

Finally, we analyze the word distribution for each question type. In Fig. 3, we show the top 20 most frequently used words for all types of Madlibs questions. It is interesting to find that color words are more often used to describe object's attribute, while the entry-level category words ('woman', 'boy', 'girl', 'child') and the clothes are usually used to describe person's attribute. More than 20% of the images express positive emotions, i.e., 'happy' and 'excited'. Several words related to person are often used to indicate the relative position of object, e.g, 'hand', 'person', 'man', 'woman', etc. Perhaps it is due to the human-centric property of the Visual Madlibs images.

# 3. Additional examples of results

We also show additional examples of the two Visual Madlibs tasks: multiple-choice question answering and focused sentence generation. We first show some correct answers to multiple choice questions in Fig. 4, as well as some wrong answers in Fig. 5. All examples are from the hard version of our multiple-choice question answering task and answers are selected by the nCCA joint-embedding method. This task provides a more straightforward way to measure the quality of the learned joint embedding space in an application scenario.

Then, in Fig. 6, we show some focused sentence generation examples, generated by nCCA and CNN+LSTM. As observed, the nCCA can generate richer but sometimes unrelated sentences, while CNN+LSTM is able to generate relatively shorter but accurate sentences, which helps to achieve higher BLEU-1 and BLEU-2 scores.

			F	iltered Qu	estions from	n <b>Easy Ta</b> s	ĸ			
	#Q	n-gram	CCA	nCCA	nCCA (place)	nCCA (bbox)	nCCA (all)	CNN+LSTM (madlibs)	CNN+LSTM(r) (madlibs)	Human
1. scene	5997	24.6%	77.4%	88.8%	87.4%	-	<b>89.7</b> %	76.1%	79.4%	96.4%
2. emotion	2663	27.5%	48.3%	58.8%	<b>59.7</b> %	-	51.0%	39.4%	49.0%	75.5%
3. past	4703	26.0%	62.8%	78.9%	73.9%	-	81.7%	50.5%	47.1%	96.8%
4. future	4495	28.7%	62.2%	79.4%	73.3%	-	81.5%	51.2%	51.4%	97.1%
5. interesting	4940	26.4%	67.6%	77.5%	72.9%	-	<b>79.8</b> %	56.1%	50.5%	96.8%
6. obj attr	6681	32.2%	45.1%	48.9%	45.8%	56.6%	52.4%	48.3%	60.8%	93.3%
<ol><li>obj aff</li></ol>	7043	31.0%	60.8%	74.3%	70.8%	73.5%	77.9%	_	90.8%	95.8%
<ol><li>obj pos</li></ol>	6906	27.0%	54.1%	67.3%	65.6%	60.3%	71.0%	54.9%	71.5%	94.9%
9. per attr	5753	27.3%	42.1%	50.5%	46.6%	56.6%	46.2%	37.2%	49.2%	92.2%
10. per act	6384	27.3%	70.6%	81.2%	77.4%	76.3%	83.3%	65.1%	69.5%	97.9%
11. per loc	6193	24.7%	72.0%	85.1%	85.2%	76.1%	85.3%	62.1%	73.6%	96.8%
12. pair rel	7206	29.5%	55.4%	64.4%	62.8%	65.6%	68.6%	_	74.0%	95.1%
			Fi	iltered Qu	estions fror					
	#Q n-gr	n grom		nCCA	nCCA	nCCA	nCCA	CNN+LSTM	CNN+LSTM(r)	Human
		n-grain			(place)	(bbox)	(all)	(madlibs)	(madlibs)	
1. scene	4940	20.9%	70.4%	77.6%	<b>77.8</b> %	-	76.3%	69.4%	69.7%	89.5%
2. emotion	2052	27.7%	43.1%	49.0%	49.5%	-	43.8%	38.5%	43.0%	72.2%
3. past	3976	24.3%	51.0%	57.4%	53.8%	-	<b>59.4</b> %	42.8%	41.3%	86.6%
4. future	3820	25.7%	51.4%	59.2%	54.2%	-	58.3%	42.1%	41.7%	87.6%
5. interesting	4159	26.9%	56.1%	59.5%	55.1%	-	61.3%	47.8%	40.3%	89.5%
<ol><li>obj attr</li></ol>	5436	30.3%	45.3%	47.2%	44.7%	54.6%	42.8%	45.1%	46.3%	86.2%
<ol><li>obj aff</li></ol>	4581	28.0%	61.2%	71.0%	67.6%	70.5%	57.6%	_	<b>79.0</b> %	73.7%
8. obj pos	5721	29.1%	53.0%	60.2%	57.7%	54.6%	57.7%	48.8%	54.3%	84.5%
9. per attr	4893	25.7%	36.5%	42.4%	38.8%	52.1%	34.4%	36.1%	46.4%	88.2%
10. per act	5813	27.7%	62.0%	68.3%	65.3%	67.9%	<b>69.6</b> %	59.1%	55.3%	92.7%
11. per loc	5096	23.6%	63.1%	69.9%	71.7%	62.6%	70.0%	52.9%	60.6%	88.2%
12. pair rel	5981	28.5%	52.3%	57.6%	55.4%	60.0%	56.5%	-	57.4%	88.5%

Table 1: Accuracies computed for different approaches on the filtered multiple-choice questions of easy and hard task. CCA, nCCA, and CNN+LSTM are trained on the whole image representation for each type of question. nCCA(place) uses Places-CNN feature. nCCA(box) is trained and evaluated on ground-truth bounding-boxes from COCO segmentations. nCCA(all) trains a single embedding using all question types. CNN+LSTM(r) ranks the perplexity of {prompt+choice}.

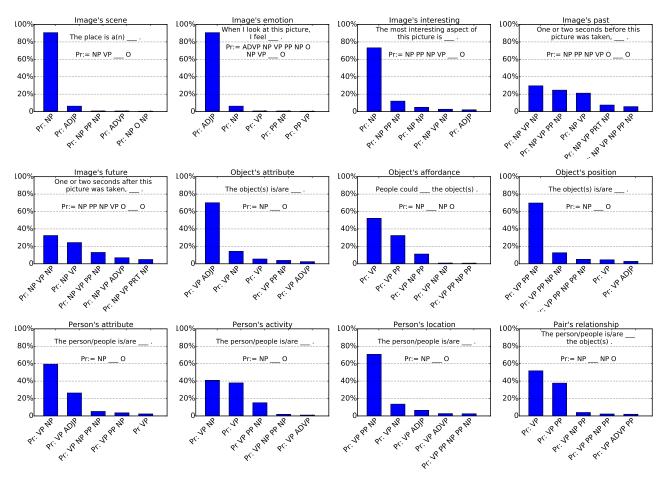


Figure 1: Top-5 most frequent phrase templates for 12 types of Madlibs questions.

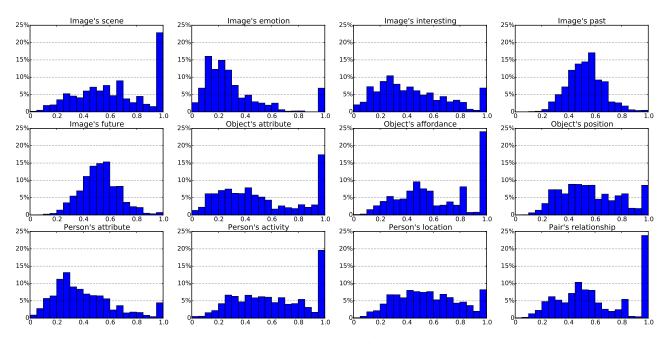


Figure 2: Histograms of similarity of answers for 12 types of Madlibs questions.

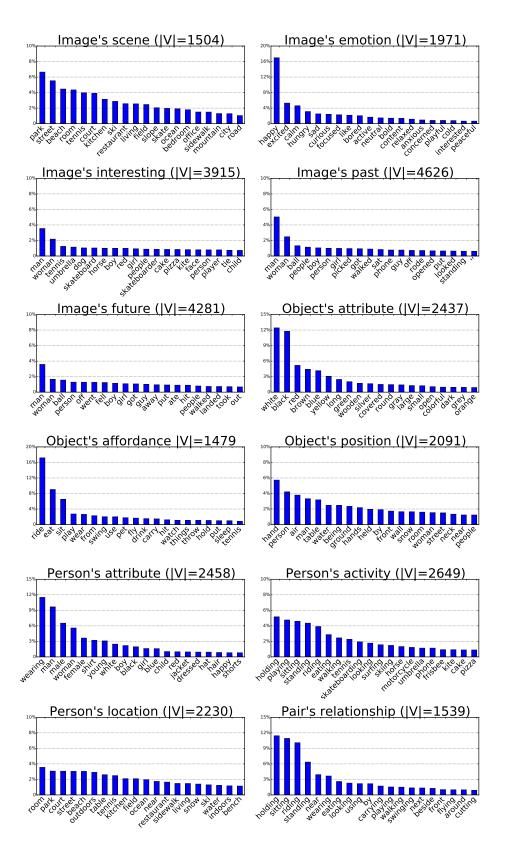
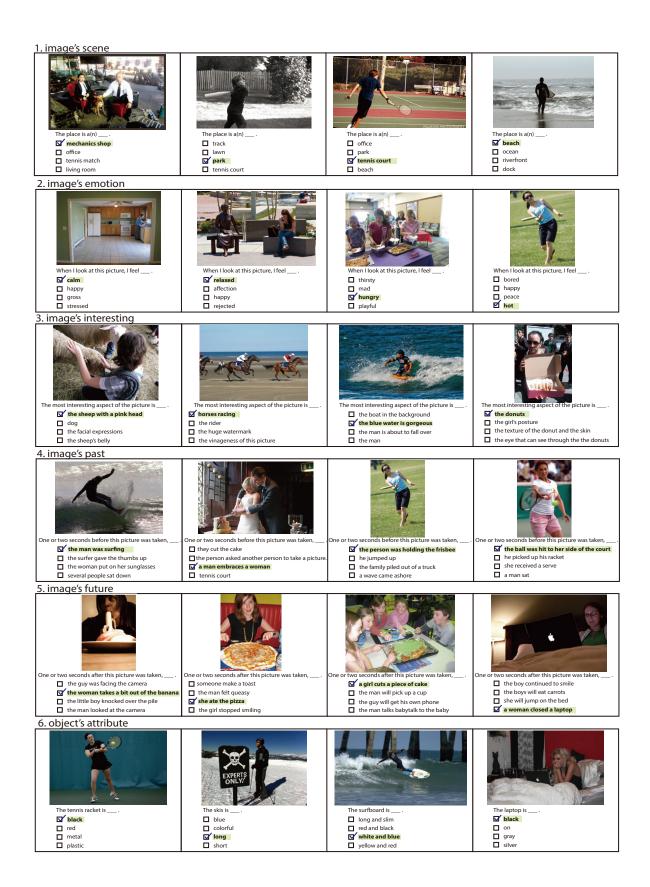


Figure 3: Top 20 words used in the answers for all 12 types of questions. |V| denotes the vocabulary size. Note y-axis range differs across question types, depending on the highest bin of each.



#### 7. object's affordance

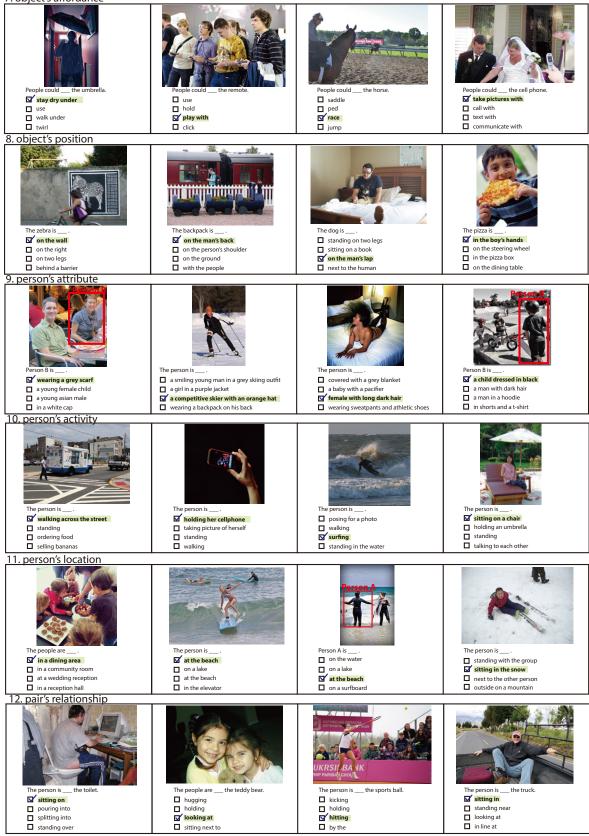


Figure 4: Examples of correct answers made by nCCA for 12 types of multiple-choice question-answering.

1. image's scene



# 7. object's affordance

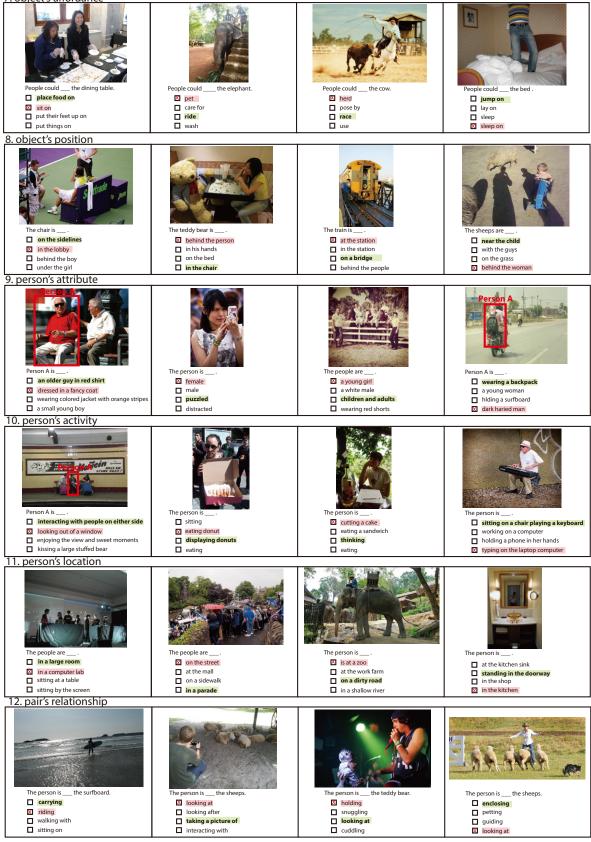


Figure 5: Examples of wrong answers made by nCCA for 12 types of multiple-choice question-answering.

# 1. image's scene



### 2. image's emotion



#### 3. image's interesting



# 4. image's past



# 5. image's future



#### 6. object's attribute



# 1. image's scene



#### 2. image's emotion



#### 3. image's interesting



#### 4. image's past



 he jumped on the skateboard.
 she sliced pizza.
 the ball was kicked.
 they sliced the pizza.

 CNN+LSTM: One or two seconds before this picture was
 SNN+LSTM: One or two seconds before this picture was
 CNN+LSTM: One or two seconds before this picture was
 CNN+LSTM: One or two seconds before this picture was

 taken, the woman vase eating.
 taken, the woman vase eating.
 taken, the woman picked up the pizza.

# 5. image's future



the man boarded the bus. taken, the man will move forward. The man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the ford. The man will and the man will and the bus the ford. The man will and the bus the man will and the ford. The man will and the man will and the ford. The man will and the ford.

#### 6. object's attribute



Figure 6: Examples of focused sentence generation achieved by nCCA and CNN+LSTM.