# 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 $\mathrm{CNN}+\mathrm{LSTM}$. 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.

Filtered Questions from Easy Task

|  | \#Q | n-gram | CCA | nCCA | nCCA <br> (place) | nCCA <br> (bbox) | nCCA <br> (all) | CNN+LSTM <br> (madlibs) | CNN+LSTM(r) <br> (madlibs) | Human |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1. scene | 5997 | $24.6 \%$ | $77.4 \%$ | $88.8 \%$ | $87.4 \%$ | - | $\mathbf{8 9 . 7 \%}$ | $76.1 \%$ | $79.4 \%$ | $96.4 \%$ |
| 2. emotion | 2663 | $27.5 \%$ | $48.3 \%$ | $58.8 \%$ | $\mathbf{5 9 . 7 \%}$ | - | $51.0 \%$ | $39.4 \%$ | $49.0 \%$ | $75.5 \%$ |
| 3. past | 4703 | $26.0 \%$ | $62.8 \%$ | $78.9 \%$ | $73.9 \%$ | - | $\mathbf{8 1 . 7 \%}$ | $50.5 \%$ | $47.1 \%$ | $96.8 \%$ |
| 4. future | 4495 | $28.7 \%$ | $62.2 \%$ | $79.4 \%$ | $73.3 \%$ | - | $\mathbf{8 1 . 5 \%}$ | $51.2 \%$ | $51.4 \%$ | $97.1 \%$ |
| 5. interesting | 4940 | $26.4 \%$ | $67.6 \%$ | $77.5 \%$ | $72.9 \%$ | - | $\mathbf{7 9 . 8} \%$ | $56.1 \%$ | $50.5 \%$ | $96.8 \%$ |
| 6. obj attr | 6681 | $32.2 \%$ | $45.1 \%$ | $48.9 \%$ | $45.8 \%$ | $56.6 \%$ | $52.4 \%$ | $48.3 \%$ | $\mathbf{6 0 . 8 \%}$ | $93.3 \%$ |
| 7. obj aff | 7043 | $31.0 \%$ | $60.8 \%$ | $74.3 \%$ | $70.8 \%$ | $73.5 \%$ | $77.9 \%$ | - | $\mathbf{9 0 . 8 \%}$ | $95.8 \%$ |
| 8. obj pos | 6906 | $27.0 \%$ | $54.1 \%$ | $67.3 \%$ | $65.6 \%$ | $60.3 \%$ | $\mathbf{7 1 . 0} \%$ | $54.9 \%$ | $71.5 \%$ | $94.9 \%$ |
| 9. per attr | 5753 | $27.3 \%$ | $42.1 \%$ | $50.5 \%$ | $46.6 \%$ | $\mathbf{5 6 . 6 \%}$ | $46.2 \%$ | $37.2 \%$ | $49.2 \%$ | $92.2 \%$ |
| 10. per act | 6384 | $27.3 \%$ | $70.6 \%$ | $81.2 \%$ | $77.4 \%$ | $76.3 \%$ | $\mathbf{8 3 . 3} \%$ | $65.1 \%$ | $69.5 \%$ | $97.9 \%$ |
| 11. per loc | 6193 | $24.7 \%$ | $72.0 \%$ | $85.1 \%$ | $85.2 \%$ | $76.1 \%$ | $\mathbf{8 5 . 3} \%$ | $62.1 \%$ | $73.6 \%$ | $96.8 \%$ |
| 12. pair rel | 7206 | $29.5 \%$ | $55.4 \%$ | $64.4 \%$ | $62.8 \%$ | $65.6 \%$ | $68.6 \%$ | - | $\mathbf{7 4 . 0 \%}$ | $95.1 \%$ |


| Filtered Questions from Hard Task |  |  |  |  |  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | \#Q | n-gram | CCA | nCCA | nCCA <br> (place) | nCCA <br> (bbox) | nCCA <br> (all) | CNN+LSTM <br> (madlibs) | CNN+LSTM(r) <br> (madlibs) | Human |
| 1. scene | 4940 | $20.9 \%$ | $70.4 \%$ | $77.6 \%$ | $\mathbf{7 7 . 8} \%$ | - | $76.3 \%$ | $69.4 \%$ | $69.7 \%$ | $89.5 \%$ |
| 2. emotion | 2052 | $27.7 \%$ | $43.1 \%$ | $49.0 \%$ | $\mathbf{4 9 . 5 \%}$ | - | $43.8 \%$ | $38.5 \%$ | $43.0 \%$ | $72.2 \%$ |
| 3. past | 3976 | $24.3 \%$ | $51.0 \%$ | $57.4 \%$ | $53.8 \%$ | - | $\mathbf{5 9 . 4 \%}$ | $42.8 \%$ | $41.3 \%$ | $86.6 \%$ |
| 4. future | 3820 | $25.7 \%$ | $51.4 \%$ | $\mathbf{5 9 . 2} \%$ | $54.2 \%$ | - | $58.3 \%$ | $42.1 \%$ | $41.7 \%$ | $87.6 \%$ |
| 5. interesting | 4159 | $26.9 \%$ | $56.1 \%$ | $59.5 \%$ | $55.1 \%$ | - | $\mathbf{6 1 . 3} \%$ | $47.8 \%$ | $40.3 \%$ | $89.5 \%$ |
| 6. obj attr | 5436 | $30.3 \%$ | $45.3 \%$ | $47.2 \%$ | $44.7 \%$ | $\mathbf{5 4 . 6 \%}$ | $42.8 \%$ | $45.1 \%$ | $46.3 \%$ | $86.2 \%$ |
| 7. obj aff | 4581 | $28.0 \%$ | $61.2 \%$ | $71.0 \%$ | $67.6 \%$ | $70.5 \%$ | $57.6 \%$ | - | $\mathbf{7 9 . 0 \%}$ | $73.7 \%$ |
| 8. obj pos | 5721 | $29.1 \%$ | $53.0 \%$ | $\mathbf{6 0 . 2 \%}$ | $57.7 \%$ | $54.6 \%$ | $57.7 \%$ | $48.8 \%$ | $54.3 \%$ | $84.5 \%$ |
| 9. per attr | 4893 | $25.7 \%$ | $36.5 \%$ | $42.4 \%$ | $38.8 \%$ | $\mathbf{5 2 . 1 \%}$ | $34.4 \%$ | $36.1 \%$ | $46.4 \%$ | $88.2 \%$ |
| 10. per act | 5813 | $27.7 \%$ | $62.0 \%$ | $68.3 \%$ | $65.3 \%$ | $67.9 \%$ | $\mathbf{6 9 . 6} \%$ | $59.1 \%$ | $55.3 \%$ | $92.7 \%$ |
| 11. per loc | 5096 | $23.6 \%$ | $63.1 \%$ | $69.9 \%$ | $\mathbf{7 1 . 7 \%}$ | $62.6 \%$ | $70.0 \%$ | $52.9 \%$ | $60.6 \%$ | $88.2 \%$ |
| 12. pair rel | 5981 | $28.5 \%$ | $52.3 \%$ | $57.6 \%$ | $55.4 \%$ | $\mathbf{6 0 . 0 \%}$ | $56.5 \%$ | - | $57.4 \%$ | $88.5 \%$ |

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 PlacesCNN 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.

2. image's emotion

3. image's interesting



The person is __ the truck.
$\boldsymbol{\square}$ sitting in

- standing near
looking at
in line at

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


3．image＇s interesting

|  |  |  | The most interesting aspect of the picture is $\qquad$ the pose of the person frisbee $\square$ the jumping man peace sign |
| :---: | :---: | :---: | :---: |



5．image＇s future

ne or two seconds after this picture was taken，
［ the two sisters fighted over the bear
区 the child hugged the anmial
$\square$ the girl left for school
the man made a missy fac
6．object＇s attribute


The sandwich is
区 hot
－a reuben
－partially eaten



9．person＇s attribute

$\square$ an older guy in red shirt
dressed in a fancy coat
wearing colored jacket with orange stripes
a small young boy

| Person A is $\qquad$ interacting with people on either side looking out of a window enjoying the view and sweet moments kissing a large stuffed bear |  |  | The person is $\qquad$ ． sitting on a chair playing a keyboard working on a computer holding a phone in her hands typing on the laptop computer |
| :---: | :---: | :---: | :---: |



## 12．pair＇s relationship



The people are $\square$ in a large room $\boxed{\text { in a computer lab }}$ －sitting at a table －sitting by the screen


The person is＿the surfboard．
－carrying
区 riding
walking with
waking with


The person is＿＿the sheeps．
区 looking at
looking after
taking a picture of
interacting with


The person is＿the teddy bear．
区 holding
snuggling
looking at


The person is＿＿the sheeps．
$\square$ enclosing
petting
guiding
guiding

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

1. image's scene

2. image's past

3. image's future

4. object's attribute


5. image's interesting

6. object's attribute


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

