

IMPROVING CONTEXT MODELLING IN MULTIMODAL DIALOGUE GENERATION



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OVERVIEW

Goal: Multimodal dialogue response generation

- Task oriented dialogue system in e-commerce setting
- Based on recently released MultiModal Dialogue (MMD) dataset
- Multimodal HRED with attention for textual response generation
- Improved context modeling by incorporating multiple images

DATASET

 Raw chatlog of an user-agent interaction in the fashion domain (150k chat sessions with 40 dialogue turns per session)

SHOPPER: Hello

AGENT: Hi, please tell me what i can help you with today? SHOPPER: show me few of your top large sized rubber type upper material clogs that is mostly light pink in colored that i would like .

AGENT: Sorry i dont have any in pink but would you like to see some in

AGENT: Of course. Just wait a few seconds while i browse through my



SHOPPER: Please show me something similar to the 1st image but in a different upper material



SHOPPER: I like the 4th result . Show me something like it but in material as in the 1st image from what you had previously shown me in clogs

- Saha et al. 'unroll' multiple images in a single utterance to include only one image per utterance
- Example chatlog and corresponding context for a system response

AGENT: Sorry i dont think i have any 100% acrylic but i can show you in



SHOPPER: Show me something similar to the 4th image but with the material different

AGENT: The similar looking ones are





Our version of the dataset

Text Context: Sorry i don't think i have any 100 % acrylic but i can show you in knit | Show me something similar to the 4th image but with the material different

Image Context: [Img 1, Img 2, Img 3, Img 4, Img 5] | [0, 0, 0, 0, 0]

Target Response: The similar looking ones are

Saha et al. **Text Context:**

Image Context: Img 4 | Img 5

Target Response: The similar looking ones are

EVALUATION AND RESULTS

sorry i dont think i have anything in casual but do you want to see some in different fit Agent



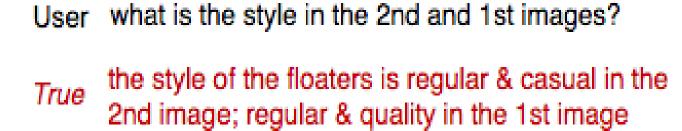
from some different orientations True image from the front, right, back and left

orientations respectively Predicted image from the front , right , back and

left orientations respectively







Predicted the style of the floaters is regular in the 1st and 2nd image



sorry i dont think i have anything in casual but do you want to see some in different fit

Predicted sorry i dont think i have anything in woven but would you like something in other types

i think ill buy the 1st one

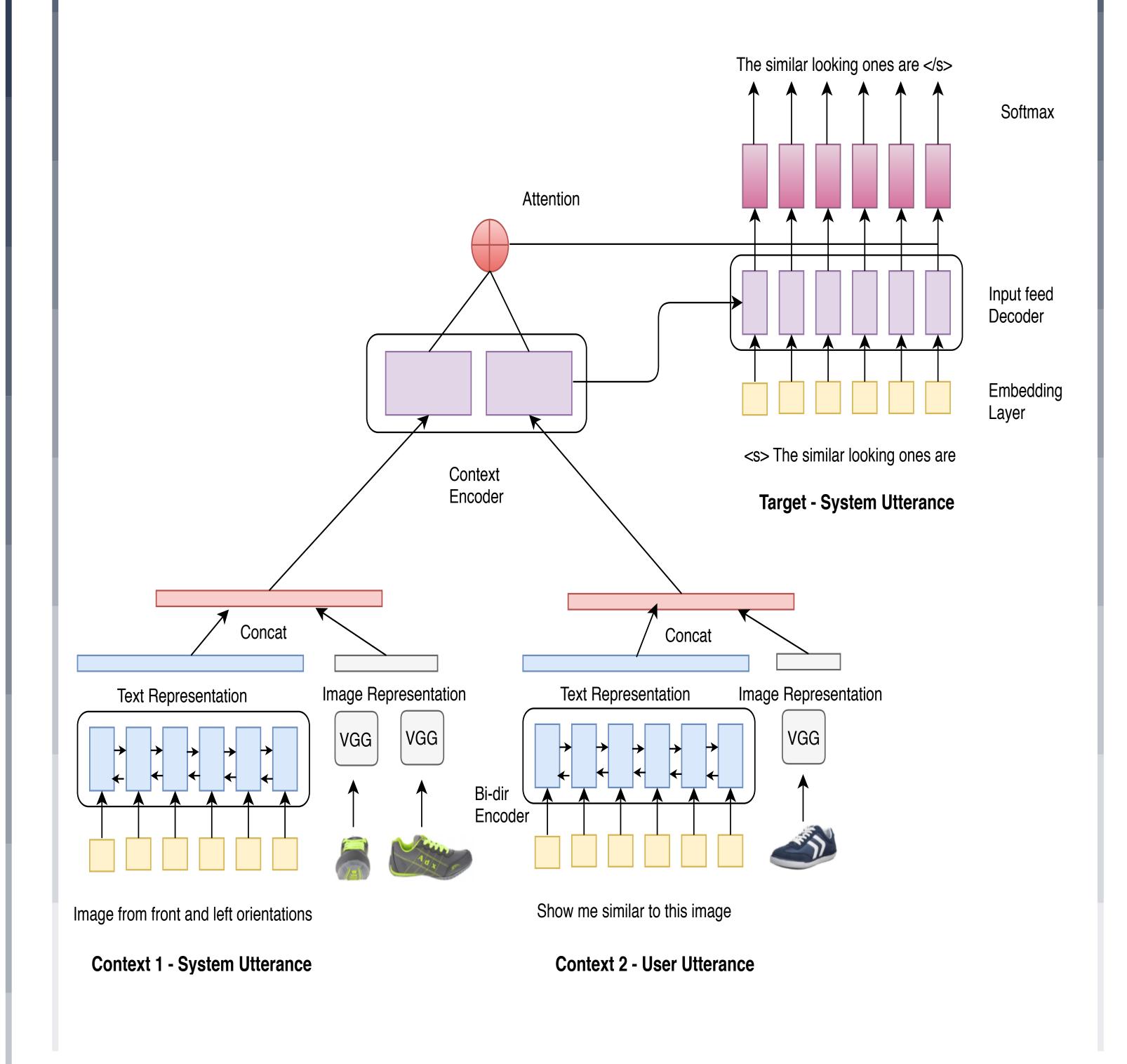
sure. thats a great choice

Predicted absolutely, i think thats a great jeans

(d)

MODEL

- Multimodal extension to Hierarchical Recurrent Encoder Decoder (HREDs) over multiple images
- Model in encoder-decoder paradigm with four modules
 - Text (Utterance) Encoder
 - Image Encoder
 - Context encoder
 - Input Feeding Decoder



EVALUATION AND RESULTS

Model	Cxt	BLEU-4	METEOR	Rouge-L
Saha et al. M-HRED	2	0.3767	0.2847	0.6235
T-HRED	2	0.4292	0.3269	0.6692
M-HRED	2	0.4308	0.3288	0.6700
T-HRED-attn	2	0.4331	0.3298	0.6710
M-HRED-attn	2	0.4345	0.3315	0.6712
T-HRED-attn	5	0.4442	0.3374	0.6797
M-HRED-attn	5	0.4451	0.3371	0.6799

Table 1: Automatic evaluation based on BLEU-4, METEOR & ROUGE-L

CONCLUSION

- Contrary to Saha et al., generated outputs improved by adding attention and increasing context size
- Multimodal HRED (M-HRED-attn) does not improve significantly over text-only HRED (T-HRED-attn)
- Model learns to handle textual correspondence between the questions and answers, mostly *ignoring* the visual context
- Need better visual models to encode the image representations when we have multiple similar-looking images
- Improvement of 7 BLEU points over the baseline approach
- Code available at https://github.com/shubhamagarwa192/mmd