Supplementing Missing Visions via Dialog for Scene Graph Generations

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Abstract

Investigation into Incom-Motivation: plete Visual Input.

- Focus: Scene Graph Generation (SGG) with varying levels of missing visual data.
- Issue: Performance drops due to insufficient visual input.

Proposed Solution: Supplementary Interactive Dialog (SI-Dial).

Proposed Method



- Model-agnostic framework for natural language dialog interactions.
- Enhances current AI systems with QA capabilities in natural language.

Experimentation and Results.

- Task setup with missing visual input to test feasibility.
- Effectiveness of dialog module as a supplementary information source.
- Promising performance improvement over multiple baselines in extensive experiments.

SI-Dial for Missing Visions

Input and Output Process. Update representations with dialog interactions.

 $Input: O' = \{V', E'\} \Rightarrow Output: O = \{V, E\},\$

Figure 1: The overall architecture of our proposed *SI-Dial* framework. We first obtain the preliminary objects from the object detector based on the incomplete visual input, and propose to conduct an interactive dialog process. Note that the dashed lines denote the operations only after the dialog is completed) for the final scene graph generation.

xperiments										
		Predicate Classification		Scene Graph Classification			Scene Graph Detection			
Vision Input	Model	mR@20	mR@50	mR@100	mR@20	mR@50	mR@100	mR@20	mR@50	mR@100
	IMP^{\dagger}	-	9.8	10.5	_	5.8	6.0	_	3.8	4.8
Original VG	$FREQ.^{\dagger}$	8.3	13.0	16.0	5.1	7.2	8.5	4.5	6.1	7.1
	$MOTIF^{\dagger}$	11.5	14.6	15.8	6.5	8.0	8.5	4.1	5.5	6.8
	$VCTREE^{\dagger}$	11.7	14.9	16.1	6.2	7.5	7.9	4.2	5.7	6.9
	MOTIF	11.23	14.36	15.71	6.20	7.51	7.90	4.13	5.48	6.82
	VCTREE	11.48	14.61	15.88	5.97	7.46	7.85	4.24	5.66	6.93
Object Blur	MOTIF+Random QA	11.52	14.78	16.08	5.82	7.34	7.86	4.64	6.18	7.24
Object Diur	VCTREE+Random QA	11.55	14.83	16.17	5.51	7.03	7.48	4.71	6.23	7.43
	MOTIF+SI-Dial	13.31	16.74	18.09	6.96	8.51	9.00	5.77	7.76	9.12
	VCTREE+SI-Dial	13.40	16.88	18.26	6.67	8.12	8.59	5.88	7.92	9.28
	MOTIF	11.69	14.31	15.64	6.24	7.56	7.90	3.88	5.21	6.37
	VCTREE	11.72	14.38	15.78	6.03	7.39	7.83	3.82	5.18	6.33
Imaga Blur	MOTIF+Random QA	11.57	13.93	15.14	6.75	8.21	8.69	4.10	5.39	6.26
mage Diur	VCTREE+Random QA	11.70	14.26	15.53	6.68	8.03	8.55	4.07	5.34	6.25
	MOTIF+SI-Dial	12.90	16.26	17.91	8.41	10.33	11.00	5.05	6.96	$\boldsymbol{8.23}$
	VCTREE+SI-Dial	13.62	17.18	18.49	7.93	10.02	10.86	5.24	7.08	8.11
	MOTIF	11.61	14.28	15.57	4.45	5.41	5.68	2.80	3.89	4.76
	VCTREE	11.68	14.32	15.59	4.40	5.38	5.69	2.80	3.87	4.68
Semantic Masked	MOTIF+Random QA	12.00	15.32	16.67	5.83	7.14	7.65	2.79	3.86	4.68
	VCTREE+Random QA	12.28	15.69	17.04	5.66	7.01	7.28	2.92	4.01	4.85
	MOTIF+SI-Dial	12.79	16.26	17.58	6.44	7.85	8.33	3.03	4.21	4.92
	VCTREE+SI-Dial	12.73	16.35	17.63	6.21	7.68	8.05	3.15	4.28	5.00

Question Encoder is used to extract the question embedding for all thee question candidates.

 $x_j = QE(q_{cand.,j}), \ j \in \{1, 2, ..., N_{cand.}\}, \quad (2)$

Question Decoder selects the question that has the highest similarity score with the generated question embedding.

$$q_i = \operatorname{argmin}_k Sim.(QD(O', x_{his,i-1}), x_j), \quad (3)$$

History Encoder is for interactively encoding the QA pairs from the dialog. The output x_{his,N_R} from the history encoder is used as the supplementary information for the missing visual input.

> $x_{his,i} = HE(x_{his,i-1}, x_{qa_i}),$ (4)

Vision Update Module. Preliminary objects O' obtained from the incomplete visions is updated by incorporating the dialog information.

Table 1: Quantitative evaluations for the SGG with missing visions. The results are reported on mean Recall.

Results



References

- Rowan Zellers, Mark Yatskar, Sam Thomson, and Yejin Choi. Neural motifs: Scene graph parsing with global context. In CVPR, 2018.
- [2] Kaihua Tang, Hanwang Zhang, Baoyuan Wu, Wenhan Luo, and Wei Liu. Learning to compose dynamic tree structures for visual contexts. In CVPR, 2019.
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2. What is the woman holding? Kite. 3. How many people? Two. 4. What color is the table? Brown. 5. What is on the table? Food.





(a) Original images

(b) Images with missing visions

(c) Dialog interactions

(d) Baselines

(e) SI-Dial

woman

wearing

Figure 2: Qualitative results for the SGG with missing visions. Displayed in sequence from top to bottom are scenarios with Object Blur, Image Blur, and Semantic Masked.