# **TIGEr: Text-to-Image Grounding for Image Caption Evaluation** ILLINOIS UCSB Ming Jiang<sup>1</sup>, Qiuyuan Huang<sup>2</sup>, Lei Zhang<sup>2</sup>, Xin Wang<sup>3</sup>, Pengchuan Zhang<sup>2</sup>, Zhe Gan<sup>2</sup>, Jana Diesner<sup>1</sup>, Jianfeng Gao<sup>2</sup>



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### **Motivation and Contribution**



## **TIGE Framework**

#### **Data Encoding**

Region-level & Word-level embedding vectors

#### **Text-to-Image Grounding**

Grounding a caption into each image region.

#### [(Reference vs. Candidate) | Image]

RRS: how similar is the order of image regions based on grounding weights?



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Research

- Metrics based on pure **text-level** comparison **loss image** information and face the challenge of language ambiguity.
- Propose a **novel automatic evaluation metric** called *TIGEr*. - Consider both image content and human-generated
- references. - Measure the consistence with human attention distribution
- among image regions.
- WDS: how similar is the attention distributed by a caption among image regions?

#### TIGEr

• Average value of RRS and WDS

# **TIGEr Workflow**

- Encoding images and texts by a pretrained Bottom-Up Attention and a RNN model.
- Grounding texts and images by a pretrained SCAN model.
- Calculating RRS based on Normalized Discounted Cumulative Gain (NDCG).
- Measuring WDS based on KL Divergence.



### **Metric Performance**

- TIGEr achieved a noticeable improvement in the assessment of caption quality on three benchmark datasets.
- Identifying irrelevant human-written captions in HI is relatively easy for all metrics, while judging the quality of two correct human-annotated captions in HC is more difficult than other comparison groups.
- Given the change of reference sizes, TIGEr achieves a higher judgment accuracy and more stable performance.

	Com	posite	Flickr8k		
	au	ho	au	ho	
BLEU-1	0.280	0.353	0.323	0.404	
BLEU-4	0.205	0.352	0.138	0.387	
ROUGE-L	0.307	0.383	0.323	0.404	
METEOR	0.379	0.469	0.418	0.519	
CIDEr	0.378	0.472	0.439	0.542	
SPICE	0.419	0.514	0.449	0.596	
Ours					
RRS	0.388	0.479	0.418	0.521	
WDS	0.433	0.526	0.464	0.572	
TIGEr	0.454	0.553	0.493	0.606	

Caption-level correlation between metrics and human grading scores in Composite and Flickr 8K dataset by using Kendall tau and Spearman rho. All p-values < 0.01.

	HC	HI	HM	MM	All
BLEU-1	51.20	95.70	91.20	58.20	74.08
BLEU-4	53.00	92.40	86.70	59.40	72.88
ROUGE-L	51.50	94.50	92.50	57.70	74.05
METEOR	56.70	97.60	94.20	63.40	77.98
CIDEr	53.00	98.00	91.50	64.50	76.75
SPICE	52.60	93.90	83.60	48.10	69.55
TIGEr (ours)	56.00	99.80	92.80	74.20	80.70

Accuracy of metrics at matching human judgments on PASCAL-50S with 5 reference captions. The highest accuracy per pair type is shown in bold font. HC: humanhuman correct, HI: human-human incorrect, HM: humanmachine, MM: machine-machine, ALL: all pairs.

Machine-Machine (MM) Pairs

# Analysis

Human: 5

TIGEr: 1

Human: 1

TIGEr: 4

played at night.

- Image region has a higher grounding weight with the corresponding caption than other unrelated regions.
- Text-to-image grounding is more challengeable at action-level compared to object-level.
- Reference captions may not fully cover visual information and TIGEr can measure a caption quality by considering the semantic information of image contents.
- Human interpretation inspired by the image is hard to be judged by an automatic evaluation metric.





### **Related Resource**

REO-Relevance, Extraness, Omission: A Fine-grained Evaluation for Image Captioning. In EMNLP-IJCNLP'19.

- A fine-grained evaluation on description adequacy
- Candidate vs. Image or (Image + References)

**Github Link:** 

https://github.com/SeleenaJM/CapEval

