# Appendix for Paper 4531

## 1 Statistical Significance Tests

In this experiment, we also perform the statistical significance tests. The experimental results are summarized in Table A.1, which show that our model achieves statistically significantly better results than the compared baseline methods on MSCOCO dataset (t-test, p-value $< 0.05$).

| Methods | **BLEU-1** | **BLEU-2** | **BLEU-3** | **BLEU-4** | **METEOR** | **ROUGE** | **CIDEr** |
|---|---|---|---|---|---|---|---|
| Soft-Attention | 70.7 | 49.2 | 34.4 | 24.3 | 23.9 | - | - |
| Hard-Attention | 71.8 | 50.4 | 35.7 | 25.0 | 23.0 | - | - |
| VAE | 72.0 | 52.0 | 37.0 | 28.0 | 24.0 | - | 90.0 |
| Google NICv2 | - | - | - | 32.1 | 25.7 | - | 99.8 |
| Attributes-CNN | 74.0 | 56.0 | 42.0 | 31.0 | 26.0 | - | 94.0 |
| $\mathrm{CNN}_{\mathcal{L}}$+RNN | 72.3 | 55.3 | 41.3 | 30.6 | 26.0 | - | 94.0 |
| PG-SPIDEr-TAG | 75.4 | 59.1 | 44.5 | 33.2 | 25.7 | 55.0 | 101.3 |
| Adaptive | 74.2 | 58.0 | 43.9 | 33.2 | 26.6 | 54.9 | 108.5 |
| SCST:Att2in | 76.9 | 60.2 | 45.1 | 33.3 | 26.3 | 55.3 | 111.4 |
| SCST:Att2all | 77.4 | 60.9 | 46.0 | 34.1 | 26.7 | 55.7 | 114.0 |
| TopDown | 79.8 | 63.4 | 48.4 | 36.3 | 27.7 | 56.9 | 120.1 |
| StackCap | 78.4 | 62.5 | 47.9 | 36.1 | 27.4 | 56.9 | 120.4 |
| TextAtt+ResNet | 74.9 | 58.1 | 43.7 | 32.6 | 25.7 | - | 102.4 |
| CNN+Att | 71.1 | 53.8 | 39.4 | 28.7 | 24.4 | 52.2 | 91.2 |
| GroupCap | 74.4 | 58.1 | 44.3 | 33.8 | 26.2 | - | - |
| NBT | 75.5 | - | - | 34.7 | 27.1 | - | 107.2 |
| ICKC (ours) | **80.9*** | **64.6*** | **49.5*** | **37.8*** | **28.6*** | **58.1*** | **121.3** |

Table A.1: Comparisons of ICKC and baseline methods on MSCOCO Karpathy test split. Scores with * mean that improvement of our model is statistically significant over the baseline methods (t-test, p-value $< 0.05$).

## 2 Error Analysis

To examine the limitations of the proposed model, we additionally carry out an analysis of the errors made by ICKC model. Specifically, we randomly choose 100 images from test set whose captions generated by our model have low evaluation scores. We reveal several reasons of the low evaluation scores, which can be divided into two primary categories. **First**, ICKC fails to identify the difference between visually similar images, thus generates general captions that are not tailored to the given images. For example, as shown in Table A.2, the proposed ICKC model generates the same caption for two different images. This may be because that we employ guidance captions in both encoding and decoding. One possible solution is to employ the generative adversarial network (GAN) framework in ICKC and use the discriminative model in GAN to distinguish the correct and incorrect image-caption pairs. **Second**, ICKC fails to detect some objects in the images that have no high-quality guidance captions. As shown in Table A.3, ICKC cannot correctly identify the "umbrella" object in image, thus generates object-irrelevant captions. It suggests that certain object detection strategy needs to be devised in the future so as to generate better captions for specific images.

## 3 Ablation Study of External Knowledge in Encoding and Decoding

For the purpose of analyzing the effectiveness of external knowledge in encoding and decoding phases, we report the ablation test of our model by replacing the knowledge embeddings with Glove (Pennington et al., 2014) embeddings in encoding and decoding respectively, denoted as w/o KB in encoder and w/o KB in decoder. The ablation results are demonstrated in Table A.4. We can observe that the commonsense knowledge has larger impact in encoding phase than in decoding phase. The reason may be that the commonsense knowledge help the encoder to learn better image features, which is the basis of the decoder.

| | | |
|---|---|---|
| |  |  |
| ground truth | "a elephant drinks from a stream with several other elephants walking in background" | "a group of elephants bathing and playing in the water' |
| ICKC | "a herd of elephants walking in a watering hole" | "a herd of elephants walking in the water" |

Table A.2: Two images with ground-truth captions and generated captions by ICKC.

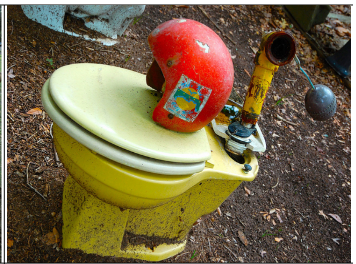
| | | |
|---|---|---|
| |  |  |
| ground truth | "a child holding a flowered umbrella and petting a yak" | "a yellow toilet with a red helmet on top of it" |
| ICKC | "a group of people with a herd of cows" | "a yellow toy sitting on top of a banana" |

Table A.3: Two images with ground-truth captions and generated captions by ICKC.

| | Cross-entropy | | | | | | | CIDEr-optimization | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | B-1 | B-2 | B-3 | B-4 | METEOR | ROUGE | CIDEr | B-1 | B-2 | B-3 | B-4 | METEOR | ROUGE | CIDEr |
| ICKC (ours) | 78.1 | 61.9 | 47.3 | 36.5 | 27.2 | 56.4 | 114.7 | 80.9 | 64.6 | 49.5 | 37.8 | 28.6 | 58.1 | 121.3 |
| w/o Knowledge | 76.2 | 60.5 | 46.4 | 35.3 | 26.7 | 55.9 | 111.4 | 78.7 | 62.5 | 47.9 | 35.6 | 27.5 | 57.3 | 116.5 |
| w/o KB in encoder | 76.9 | 60.9 | 46.8 | 35.7 | 26.8 | 56.1 | 112.9 | 79.6 | 63.4 | 48.7 | 36.5 | 28.1 | 57.8 | 118.5 |
| w/o KB in decoder | 77.3 | 61.2 | 46.9 | 36.1 | 27.1 | 56.3 | 113.6 | 80.2 | 63.8 | 49.0 | 37.2 | 28.3 | 57.9 | 120.3 |

Table A.4: Ablation study of external knowledge in KB on MSCOCO Karpathy test split. Here, B-n is short for BLEU-n.

## 4 Experimental Results on Flickr30k Dataset

We additionally evaluate our model on Flickr30k which is a widely used benchmark in image captioning. In particular, Flickr30k contains 31,000 images, including 29,000 images for training, 1,000 images for validation, and 1,000 images for testing. The experimental results are reported in Table A.5 for Flickr30k. Our model achieves statistically significantly better performance than the state-of-the-art competitors on several evaluation metrics (t-test, p-value $< 0.05$). It is noteworthy that our results can be further improved by tweaking the hyper-parameters.

## References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| Methods | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE | CIDEr |
|---|---|---|---|---|---|---|---|
| Soft-Attention (Xu et al., 2015) | 66.9 | 43.4 | 28.8 | 19.1 | 18.5 | - | - |
| Hard-Attention (Xu et al., 2015) | 66.7 | 43.9 | 29.6 | 19.9 | 18.5 | - | - |
| VAE (Pu et al., 2016) | 72.0 | 53.0 | 38.0 | 25.0 | - | - | - |
| Google NIC (Vinyals et al., 2017) | 63.0 | 41.0 | 27.0 | - | - | - | - |
| ATT-FCN (You et al., 2016) | 64.7 | 46.0 | 32.4 | 23.0 | 18.9 - | - | - |
| Att-CNN+RNN (Wu et al., 2016) | 73.0 | 55.0 | 40.0 | 28.0 | - | - | - |
| SCN-LSTM (Gan et al., 2017) | 73.5 | 53.0 | 37.7 | 25.7 | 21.0 - | - | - |
| SCA-CNN-ResNet (Chen et al., 2017) | 68.2 | 49.6 | 35.9 | 25.8 | 22.4 | 50.9 | 66.5 |
| Adaptive (Lu et al., 2017) | 67.7 | 49.4 | 35.4 | 25.1 | 20.4 | - | 53.1 |
| CNNL+RHN (Gu et al., 2017) | 73.8 | 56.3 | 41.9 | 30.7 | 21.6 | - | 61.8 |
| Self-retrieval-SR-PL (Liu et al., 2018) | 72.9 | 54.5 | 40.1 | 29.3 | 21.8 | 49.9 | 65.0 |
| ICKC (ours) | **74.3** | **57.6*** | **42.5** | **31.3** | **23.4*** | **53.1*** | **67.8*** |

Table A.5: Single-model performance by our proposed method and state-of-the-art methods on Flickr30k dataset. Scores with * mean that improvement of our model is statistically significant over the baseline methods (t-test, p-value $< 0.05$).


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