

Dual Graph Convolutional Networks with Transformer and Curriculum Learning for Image Captioning

—Supplementary Material—

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ABSTRACT

To demonstrate the effectiveness of our Dual-GCN and Curriculum Learning, and show the limitations of our proposed approach, we provide this supplementary material which mainly contains additional experimental results including (1) the more visualization results compared with state-of-the-arts, (2) more visualization results of our ablation experiments, (3) some visualization results of our similar image selection failure cases and (4) some visualization results of our similar image selection success cases. We also provide the running time information. Note that we don't include all these in the central part of the paper due to the space limit.

KEYWORDS

Graph Convolutional Networks, Transformer, Curriculum Learning, Image Captioning

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1 ADDITIONAL EXPERIMENTAL RESULTS

1.1 More visualization results compared with state-of-the-arts

The more visualization results are provided in Figure 1. We compare our proposed method *Dual-GCN+Transformer+CL* with Up-down [1], AOA-NET [3], GCN-LSTM [4] and M^2 Transformer [2]. Obviously, our proposed method *Dual-GCN+Transformer+CL* obtains better performance in image captioning.

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For the sake of brevity, we temporarily choose the number of nodes as 4 and 5 in the object-level graph and image-level graph, respectively. Note that there might be many nodes selected on the object level, but no more than 36 at most. Similarly, there can be many similar images in the image level selection, but in this experiment, we set it to 8. Figure 1 shows that our *Dual-GCN+Transformer+CL* model can generate more descriptive and accurate sentences, including the supplementary description of visual objects and the generation of non-visual words. This is because GCN_{obj} encodes more detailed information between different objects in an original image, making some objects their interaction behavior not lost.

Similarly, GCN_{img} encodes the information between multiple similar images and uses the global features to guide the text generation. This is because images with high similarity tend to have the same subject-object and background area. This information can enhance the model's understanding of the visual features and strengthen the integration of visual features and text features for text generation.

1.2 More Visualization results of ablation experiments

In our framework, there are four changeable factors. *i.e.*, *Transformer*, *Dual-GCN* including GCN_{obj} and GCN_{img} , and *Curriculum Learning*. Therefore, strictly based on the control variable method, we conduct several ablation experiences. Figure 2 shows more visualization results. From the figure, we can see that our model *Dual-GCN+Transformer+CL* can generate more detailed sentences. For example, in the fourth image, *Dual-GCN+Transformer+CL* generates “**sitting at a counter and talking**”, while the other variants cannot. With any factor changes, either GCN_{img} or *Curriculum Learning*, it may lead to a less reasonable caption generated. All these observations have clearly verified the validity of *Dual-GCN*, *Transformer*, and *Curriculum Learning*.

1.3 More visualization results of high-quality top-K images

To experimentally improve better text generation when the selected multiple similar images are more accurate, we present some visualization results with high-quality contextual images as the top-K ($K = 8$) image as success cases, as shown in Figure 3.

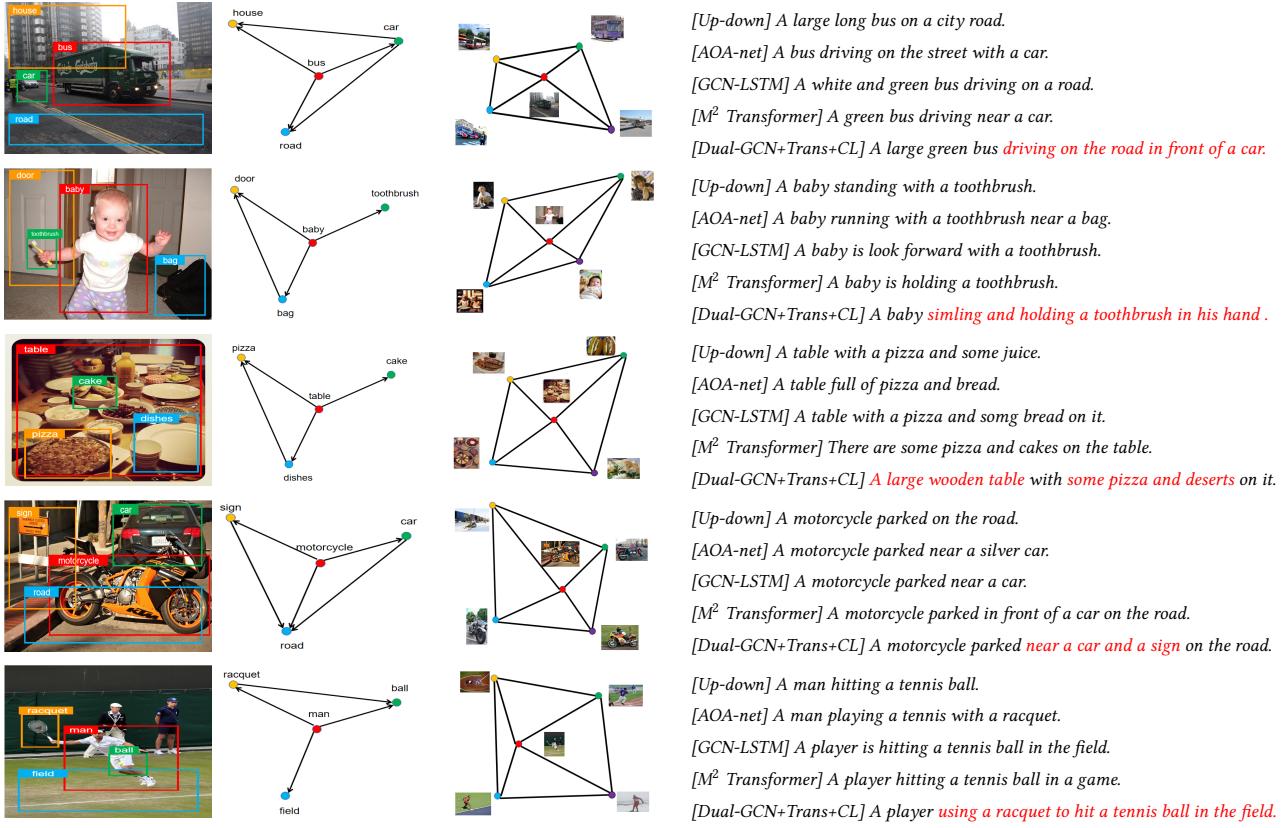


Figure 1: Visualization results compared with four state-of-the-arts. Note that we only plot top-4 images for simplicity.

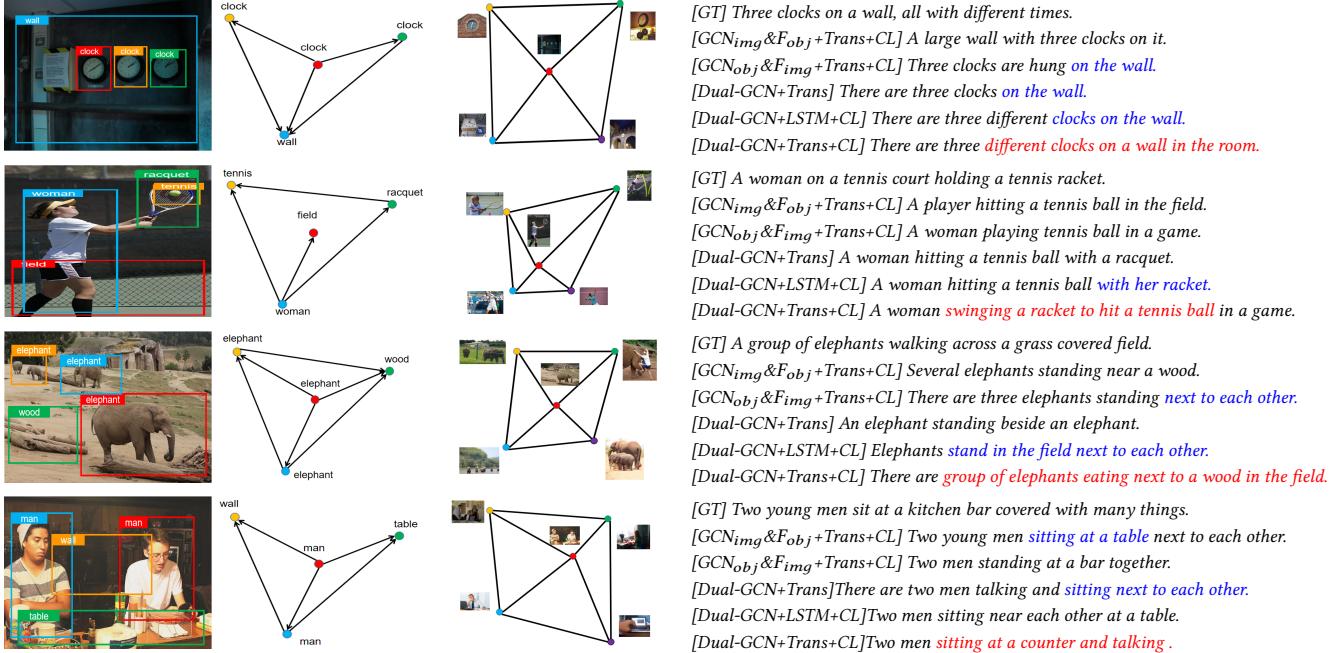


Figure 2: Visualization results of ablation experiments. Note that we only plot top-4 images for simplicity.



[GT] A bowl filled with lots of oranges on a counter.
[Output] There is a bowl filled with some oranges.



[GT] A man riding skis down a snow covered ski slope.
[Output] A man is skiing and coming down in front of the slope.

Figure 3: The result of similar image selection success.

1.4 More visualization results of low-quality top- K images

Although images with high similarity can provide certain visual information, distinguishing similar images accurately remains a complex problem. In our proposed method, there might be errors in the selection of a similar image sometimes. Figure 4 shows some visual examples of selection failure. We can find that sometimes the model selects visually irrelevant images for guidance. In this case, it leads to inaccuracy and even some errors in text generation. Apparently, this suggests that there still exist space and potential for our proposed method to improve.

2 ADDITIONAL ANALYSIS

2.1 Running time

At the testing stage, we take our model to generate captions of 100 images. It totally took about one minute. The average time to generate caption for a single image is 0.6 second.

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[GT] *A man riding a surfboard in the ocean.*

[Output] *A man riding a surfboard **on a boat**.*



[GT] *A public bus parked at a bus stop .*

[Output] *A red bus **sitting next to a train**.*

Figure 4: The result of similar image selection failure.