a representative image from an image collection has been introduced in the album summarization task. To fnd the common occurring visual features as a representation, estimating visual features using clustering methods is a popular technique. In addition, by describing an image collection with keywords or tags, the summarization focuses on fnding shared concepts of an image collection. However, this approach is still restricted to specifc domains. Recently, an image collection captioning task [16] has been introduced to summarize the commonly occurring visual features and relations of an image collection into a caption.

The main discussion of an image collection summarization task is to fnd common visual features and relationships, such as objects, events, or concepts shared in an image collection. Finding shared concepts by integrating external knowledge into the summarization model has become popular in summarizing an image collection [17], [22]. In contrast, integrating external knowledge into a model can lead to complexity in estimating and understanding the exact representations in the summarization process.

Based on the idea of incorporating external knowledge in an image collection summarization task, we hence propose a scene graph summarization model for an image collection that learns from the knowledge graphs. To understand the relationship between images in an image collection in the learning process, we introduce an enhanced relation predictor layer by integrating semantic knowledge into the learning process instead of applying the summarization process directly after obtaining scene graphs from scene graph generation.

2. Related Work

2.1 Image Collection Summarization

Image collection summarization is typically introduced to fnd representative information of an image collection. Many works fnd a representative image of an image collection using a clustering algorithm, such as Self-Organization Map (SOM) [9] or k-Medoids [13] to cluster images. Some recent works [17], [22], [29] aim to generate a short phrase, keywords, and tags of a semantic image collection in a specifc domain. We [16] introduced a graph summarization process

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Fig. 1: Overview of the image collection scene graph summarization model, the proposed method (right) compared with the baseline method (left) with scene graph generation and summarization process. The proposed method takes advantage of knowledge graphs to relax the relation predictor of scene graph generation in generating a summarized scene graph.

by merging all scene graphs into a combined scene graph and then selecting a representative scene graph using graph theory in the process. To summarize an image collection, our approach aims to describe image collection in a scene graph form, focusing on integrating external knowledge into the learning process.

2.2 Scene Graph Generation

Scene graph generation [5] is a popular technique in describing relationships between objects in an image. The relationships of objects are generally represented in triplets which consist of subject, predicate, and object. In recent years, scene graph generation has been widely introduced and implemented on the Visual Genome dataset [10], a popular scene graph generation dataset. In addition, scene graph generation is also adapted to various applications, such as image captioning [12] and image retrieval [18], and has shown to advance their results. Various techniques are introduced in scene graph generation; Neural Motif [26] is built with Faster-RCNN with ResNext-101 [24], then computes and propagates through Bidirectional LSTM for predicting relations. From the long-tail problem of the scene graph dataset, the most recent work [21] aims to introduce a technique to solve the bias of the dataset.

2.3 Knowledge Base

Knowledge base is widely used to enrich models, especially text-generation models [25]. ConceptNet [19] and Wikipedia dataset[*1] are popular knowledge bases that are used in the generation process. ConceptNet is a knowledge graph that represents general knowledge and commonsense information, while Wikipedia is structured knowledge data with detailed information on each topic. In recent years, the knowledge graph has become a popular knowledge base on various generation processes, mainly focusing on capturing commonsense reasoning during the generation. To tackle the long-tail issues of scene graph generation mentioned above, integrating knowledge graphs to improve generation is widely introduced, and the result shows the advantage of using it. Moreover, a knowledge graph is additionally implemented in an image retrieval task which aims to reason on the semantic context and generalize the concepts inside an image [29].

3. Proposed Method

Scene graph generation has become a popular task to describe an image in a scene graph form. Using scene graph generation incorporating external knowledge to nd shared concepts of an image collection has become a trend in recent years. However, identifying the exact shared concepts still relies on the summarization process and external knowledge.

Following the idea of building a scene graph summarization model by integrating commonsense knowledge into the relation predictor instead of summarizing all scene graphs

[*1] https://www.tensor ow.org/datasets/catalog/wikipedia/ (Accessed May 26, 2023)

Table 1: Evaluation on an image of the VG200 compared to other baselines

MODEL	SGDets			SGCls			PredCls		
	R@20	R@50	R@100	R@20	R@50	R@100	R@20	R@50	R@100
VCTree [20]	0.2453	0.3193	0.3621	0.3401	0.3748	0.385	0.5902	0.6542	0.6718
Neural Motif [26]	0.2548	0.3278	0.3716	0.3687	0.4018	0.4102	0.5846	0.6518	0.6701
Proposed	0.2277	0.2864	0.3262	0.3594	0.3863	0.3943	0.4335	0.4974	0.5167

from the MS-COCO dataset. To experiment on a scene graph image collection summarization task, we built a testing set of an image collection by extending from the MS-COCO testing dataset using VSE++ [2], which is an image retrieval task by estimating the similarity of image contexts and image captions. Following the Karpathy split [7] on the MS-COCO dataset, our initial testing set was selected from 5,000 images of the MS-COCO testing set. Then, we retrieved 5 images to build each collection, making our testing set contain 5,000 collections with 6 images each.

4.2 Training Strategy

With the limitation in scene graph summarization datasets, we frst trained the scene graph generation on a single image of the Visual Genome dataset. After training, we extended the model to a multiple-image inference process. In the training phase, we trained the model with the training split of VG200 with 0.12 of the initial learning rate. We used Adam [8] for optimization and cross-entropy loss as the loss function. We observed *SGDet* recall to select the best checkpoint for an image collection scene graph summarization task.

4.3 Evaluation

The evaluation of the proposed method consists of two phases. As we modify the relation prediction of the scene graph generation model, we frst evaluated the proposed method on VG200 compared with the baseline to ensure that the proposed method still sustains good results on a single image scene graph generation. We observed *Scene Graph Classification Recall (SGCls Recall)*, *Predicate Classification Recall (PredCls Recall)*, and *Scene Graph Detection Recall (SGDet Recall)* on a single image. We lastly evaluated the proposed method with an image collection.

4.4 Results

We will frst see the result of the proposed method on image scene graph generation on VG200, which shows the proposed method with no bias. Based on the evaluation in scene graph generation with *SGCls, PredCls, and SGDet* as shown in Table 1, the proposed method still sustains an image scene graph generation task. The results show that enhancing the relation predictor still keeps good results on a single image scene graph generation. Due to focusing on SGDet Recall to select the best checkpoint, this experiment shows that the proposed method achieves results not much lower than the baseline.

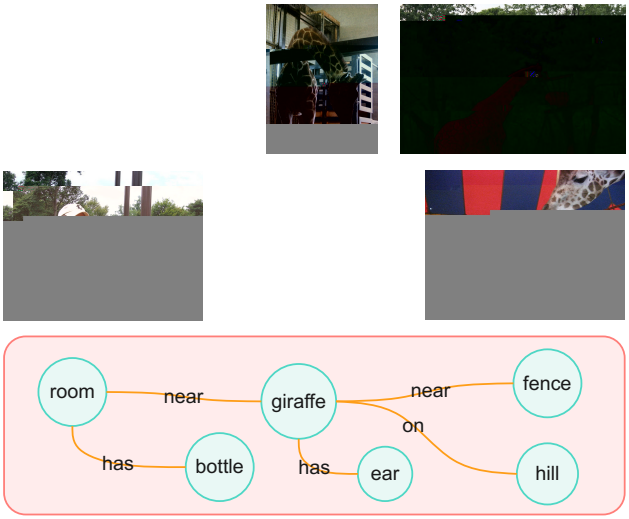

Fig. 2: Example of the proposed method showing the summarization of an image collection into a scene graph.

Next, we will see the output of an image collection scene graph summarization. An example is shown in Fig. 2. It demonstrates that the proposed method can generate a summarized scene graph containing the main object \girafe" and image locations from most images.

5. Conclusion

We introduced a novel scene graph summarization model incorporating external knowledge following the idea that aims to relax the relation predictor in the training process for an image collection. A preliminary experiment demonstrated promising results of the proposed method. In addition, the result further showed a good result on an image collection of the MS-COCO dataset. In the future, we plan to introduce a new evaluation method on scene graph summarization that focuses on the context coverage of a summarized scene graph on a single scene graph and implement the proposed method on an annotated MS-COCO panoptic scene graph summarization dataset [14].

Acknowledgments

This work was supported in part by the Ministry of Education, Culture, Sports, Science and Technology (MEXT), Japan, through Grant-in-Aid for Scientifc Research under Grant JP21H03519. The computation was carried out using the General Projects on the supercomputer \Flow" at Information Technology Center, Nagoya University.

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