AVR: Attention based Salient Visual Relationship Detection

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Abstract

Visual relationship detection aims to locate objects in images and recognize the relationships between objects. Traditional methods treat all observed relationships in an image equally, which causes a relatively poor performance in the detection tasks on complex images with abundant visual objects and various relationships. To address this problem, we propose an attention based model, namely AVR, to achieve salient visual relationships based on both local and global context of the relationships. Specifically, AVR recognizes relationships and measures the attention on the relationships in the local context of an input image by fusing the visual features, semantic and spatial information of the relationships. AVR then applies the attention to assign important relationships with larger salient weights for effective information filtering. Furthermore, AVR is integrated with the priori knowledge in the global context of image datasets to improve the precision of relationship prediction, where the context is modeled as a heterogeneous graph to measure the priori probability of relationships based on the random walk algorithm. Comprehensive experiments are conducted to demonstrate the effectiveness of AVR in several real-world image datasets, and the results show that AVR outperforms state-of-the-art visual relationship detection methods significantly by up to 87.5% in terms of recall.

Introduction

As a critical task of scene understanding, visual relationship detection aims to identify the objects in an image, and recognize the relationship between each pair of objects. The visual relationship can be represented by a triplet <subject, predicate, object> where the predicate is the semantic interaction between the subject and object. The interaction can be spatial relationships (e.g., on, under and behind) or verbs (e.g., eat, walk on and play). The detected visual relationships are useful structured information that can be used by many other high-level applications such as image retrieval (Johnson et al. 2015), image captioning (Yao et al. 2018), and visual question answering (Lu et al. 2018).

It is a great challenge to detect meaningful relationships from natural scene images, which usually contain numerous visual objects and complex relationships between objects. Most of existing algorithms (Lu et al. 2016), (Yu et al. 2017), (Zhuang et al. 2017), (Xu et al. 2017) divide this task into two basic stages: detecting objects, and recognizing the predicate of each pair of detected objects. The detected relationship triplet and the bounding boxes of objects are the final outputs of the algorithms. On the other hand, since the space of all possible relationships is extremely huge and the training dataset hardly cover all possible combinations of objects and predicates. The ability of few-shot and even zero-shot learning is quite necessary to enhance the relationship detection model. Recently, some priori information based methods are proposed to address this problem. Lu et.al. (Lu et al. 2016) propose a language model to predict the priori probability of predicates between objects, and then apply the priori knowledge to finetune the predicate probability predicted from the visual model. (Yu et al. 2017) integrates priori knowledge from the statistics of language text (Wikipedia) so as to optimize the prediction of unseen relationships. On the other hand, the literatures
The rest of this paper is organized as follows: In Section , we present a brief literature review which is related to our work. In Section , we introduce our proposed model AVR for visual relation detection. The experiments are presented in Section . Finally, the conclusion is given in Section .
to the image datasets, the priori knowledge about relationship distribution is also integrated into the Priori Module to refine the accuracy of relationship detection. The details of each module are given as follows.

**Attention based Relationship Prediction**

Like most of the visual relationship detection algorithms (Zhuang et al. 2017), (Yu et al. 2017), (Zhang et al. 2017a), we adopt the object detection algorithm, Faster R-CNN (Ren et al. 2017), to retrieve all objects in the input image. Each detected object $O_j$ is represented as a tuple: $(B_j, V_j, C_j, Pr(C_j|O_j))$. $B_j$ is the bounding box of the object, and is presented as a tuple $(x_j, y_j, w_j, h_j)$, where $(x_j, y_j)$ indicates the left-top position of the object in the image, $w_j$ and $h_j$ are the width and height of the object. While apply $B_j$ to crop the input image, we can achieve the object image, which is denoted as $V_j$. $C_j$ is the most possible class label of the object. $Pr(C_j|O_j)$ means the confidence for the label $C_j$.

After obtaining a list of detected objects $\{O_j\}$, the combination of any pair of objects can constitute a latent relationship in an image. The key of scene understanding is to achieve the most salient visual relationships from these candidates, which represent the most important semantic in the image.

**Bayesian Network based Relationship Inference**

Inspired by the human information processing procedure, we propose an attention based relationship prediction model, which considers visual relationship distribution as an inference procedure in a Bayesian network as Fig. 3. Specifically, given an input image $I$, two objects are detected and selected as the subject $O_s$ and object $O_o$ of the visual relationship. $C_s$ and $C_o$ are the class labels of the selected subject and object respectively. The predicate of the visual relationship $P$ is inferred based on the subject $O_s$, the object $O_o$ and their class labels ($C_s$, $C_o$). According to the Bayesian chain rule, the inference probability of a relationship conditioned on the observed image $I$ can be formulated as follows:

$$
Pr(P|C_s, C_o, O_s, O_o) = Pr(O_s, O_o|I) \cdot Pr(C_s|O_s) \cdot Pr(C_o|O_o) \cdot Pr(P|C_s, C_o, O_s, O_o)
$$

(1)

Here $Pr(O_s, O_o|I)$ indicates the probability of attention on the object pair $(O_s, O_o)$, which is selected from the image $I$.

$C_s$ is the most possible class label of $O_s$, the probability of which is $Pr(C_s|O_s)$. Similarly, $C_o$ is the most possible class label of $O_o$, the probability of which is $Pr(C_o|O_o)$. Both of $Pr(C_s|O_s)$ and $Pr(C_o|O_o)$ are given by the object detection module. $Pr(P|C_s, C_o, O_s, O_o)$ means the probability of the predicate, which is predicted based on the detected subject and object. The detail of calculating the predicate probability $Pr(P|C_s, C_o, O_s, O_o)$ and the attention probability $Pr(O_s, O_o|I)$ will be introduced in the following sections.

**Predicate Prediction Module**

In order to achieve the predicate prediction result $Pr(P|C_s, C_o, O_s, O_o)$, we construct the multi-modal fusion model which integrates the visual features, spatial information and semantic feature of detected objects as shown in Fig. 4(a). Given any pair of detected objects $O_s : (B_s, V_s, C_s, Pr(C_s|O_s))$ and $O_o : (B_o, V_o, C_o, Pr(C_o|O_o))$, the bounding box containing these two objects is defined as the predicate bounding box $B_p$, which is the smallest rectangle containing both of $B_s$ and $B_o$. The image within the bounding box $B_p$ is called the predicate image $I_p$. Similar to Faster R-CNN (Ren et al. 2017), by applying the bounding boxes on the feature maps output by the CNN model, we can achieve the feature maps of $O_s$, $O_o$ and $I_p$. Subsequently, the ROI pooling operation is applied to transform these feature maps into the ones same size. Then the feature maps of $O_s$, $O_o$, and $I_p$ are passed to a two fully connected layers to obtain the subject/object feature $V_s / V_o$. Meanwhile, the feature maps of $O_s$, $O_o$ and $I_p$ are stacked and processed by the following three convolutional layers and two fully connected layers to achieve the predicate feature vector $V_p$. Finally, $V_p$ is concatenated with $V_s$ and $V_o$ together and fed into the two fully connected layers to get the final visual feature $F_{v(s,o)}$, which contains the visual information of the subject, object and their local context.

Besides the visual feature, the spatial feature is also integrated into the prediction model as shown in Fig. 4(a). Particularly, given the bounding box of the subject $B_s = (x_s, y_s, w_s, h_s)$, its normalized bounding box is $[x_s/W, y_s/H, (x_s + w_s)/W, (y_s + h_s)/H, A_s/A_I]$, where $W$ and $H$ are the width and height of the image, $A_s$ is the area of the subject, and $A_I$ is the area of the input im-
feature vector is concatenated with the normalized bounding boxes of the subject and object to form the complete spatial feature $F_{b(s,o)}$.

Furthermore, the class labels $C_s$ and $C_o$ are also utilized to support precise prediction. The word embedding technique (Mikolov et al. 2013) is utilized to represent these labels as embedding vectors, which are concatenated and input into the fully connected layers to obtain the semantic feature $F_{c(s,o)}$. At last, the visual feature $F_{v(s,o)}$, the spatial feature $F_{b(s,o)}$, and the semantic feature $F_{c(s,o)}$ are fused in the softmax layer to achieve the final prediction probability as follows:

$$ Pr(P|C_s, C_o, O_s, O_o) = \text{softmax}(W_v F_{v(s,o)} + W_c F_{c(s,o)} + W_b F_{b(s,o)} + b) $$

(2)

where $W_v$, $W_c$, $W_b$ and $b$ are the parameters in the model.

While training the model, the following cross entropy loss function is adopted to measure the precision of prediction:

$$ Loss_P = \sum_{(s,o)} -y_i \log(P_r(P_i|C_s, C_o, O_s, O_o)) $$

(3)

Here $y_i$ is the indicator of ground truth predicate label. $y_i$ is equal to 1 if the $i$th predicate is the ground truth label of the $O_s$ and $O_o$, otherwise $y_i$ is equal to 0.

**Attention Module**  As mentioned in Eq. (1), the attention module aims to measure the probability of focusing on a pair of objects in an image: $Pr(O_s, O_o|I)$, which indicates the attention on the selected objects. Inspired by the human attention mechanism, we measure the attention based on the visual, spatial, and semantic information of the objects as shown in Fig. 4(b).

Specifically, while considering the visual clues, we combine the visual feature of the objects $F_{v(s,o)}$ and the convolutional feature $F_a$ of the whole image in the following manner:

$$ F'_{v(s,o)} = R(W_3 R(W_1 F_{v(s,o)} + W_2 F_a + b_1) + b_2) $$

(4)

where $W_i$ and $b_i$ ($i \in Z^+$) are all tunable parameters in the neural network. $R(.)$ is the nonlinear activation function ReLU. Furthermore, as shown in Fig. 4(b), the spatial feature $F_{b(s,o)}$ and the semantic feature $F_{c(s,o)}$ are integrated with the visual feature $F_{v(s,o)}$ to achieve the attention score as:

$$ e_{(s,o)} = R(W_4 F'_{v(s,o)} + W_5 F_{b(s,o)} + W_6 F'_{c(s,o)} + b_3) $$

(5)

where $F'_{c(s,o)}$ is a nonlinear transformation of the semantic feature $F_{c(s,o)}$:

$$ F'_{c(s,o)} = R(W_7 F_{c(s,o)} + b_4) $$

(6)

Finally, the softmax function is applied to achieve the normalized attention:

$$ Pr(O_s, O_o|I) = \frac{\exp(e_{(s,o)})}{\sum_{i,j=1} \exp(e_{(i,j)})} $$

(7)

When training the attention module, we regard it as a binary classification problem to predict whether a relationship is important or not from the human perspective. The cross entropy loss for each input image is defined for training as follows.

$$ Loss_A = \sum_{(s,o)} (-L_{(s,o)} \log(\sigma(e_{s,o}))- (1-L_{(s,o)}) \log(1-\sigma(e_{s,o}))) $$

(8)

Here $L_{(s,o)}$ indicates the attention label of the objects pair $O_s$ and $O_o$. Since there are not annotated importance of relationships on datasets, we simply regard the annotated relationships are important than those unannotated. Thus, if $O_s$ and $O_o$ are the subject and object of a annotated relationship on dataset, $L_{(s,o)}$ is 1. Otherwise, $L_{(s,o)}$ is 0. $\sigma$ is the sigmoid function transforming the attention score into the scope $[0,1]$. This attention loss is combined with the predicate loss of Eq.(3) in the following form to optimize the whole model by minimizing the loss.

$$ Loss = Loss_A + Loss_P $$

(9)
Priori Knowledge Graph based Enhancement

We also integrate the priori knowledge in the global context of the whole dataset to further improve the precision of relationship detection. Specifically, we model the priori knowledge as a heterogeneous graph (shown in Fig. 5), where all possible predicates and object pairs are denoted as nodes.

The edge connecting any predicate $P_t$ and any object pair $(C_s, C_o)$ indicates the relationship $<C_s, P_t, C_o>$, which is labeled in the datasets. The weight of the edge indicates the frequency that the relationship appears in the dataset.

However, the graph is usually very sparse because of the long-tailed relationship distribution. Thus, we augment the graph by adding the edges between object pairs node to measure their similarity, where the weight of each edge is assigned with the similarity of the embedding vectors of objects.

Based on this augmented heterogeneous graph, we infer the dependency of predicates and object pairs by performing random walk from predicates to object pairs. In this way, the priori probability $Pr(C_s, P_t, C_o)$ can be measured by the probability of that the random walker starting from $P_t$ reaches the object pair $(C_s, C_o)$.

Specifically, the adjacency matrix between predicates and object pairs are denoted as $D_0$ with size $K \times N^2$, where $N$ is the number of object categories and $K$ is the number of predicate categories. Furthermore, the adjacency matrix between object pairs is an $N^2 \times N^2$ matrix $M$. Both $D_0$ and $M$ is normalized by rows. The transition probability matrix of the $t$-step random walk from predicates to object pairs is:

$$D_{t+1} = D_t M$$

where $t$ indicates the $t$-th iteration of the random walk. Following the research on random walk based dependency inference (Shen et al. 2018), we add a balance parameter $\lambda$ to prevent the updated $D_{t+1}$ deviates too far from initial $D_0$.

$$D_{t+1} = \lambda D_t M + (1 - \lambda) D_0$$

When $t$ tends to infinity, the final priori probability is

$$Pr(C_s, P_t, C_o) = D_\infty = (1 - \lambda)(I - \lambda M)^{-1} D_0$$

(12)

By combining Eq. (1) and Eq. (12), we can achieve the final decision of a relationship $<C_s, P, C_o>$ in the image $I$:

$$f(C_s, P, C_o, I) = Pr(P, C_s, C_o, O_s, O_o | I) \cdot Pr(C_s, P, C_o)$$

(13)

which combines both of posterior probability and priori knowledge in the datasets for precise prediction.

Table 1: The statistics of datasets.

| Dataset       | Nobj | Npred | Training Set | Test Set |
|---------------|------|-------|--------------|----------|
| VRD          | 100  | 70    | 3780         | 954      |
| VG-VtransE   | 200  | 100   | 73794        | 25858    |
| VG-MSDN      | 150  | 50    | 46164        | 10000    |

Experiments

Datasets: In the experiments, the VRD (Lu et al. 2016) and VG (Krishna et al. 2017) datasets are used to verify the effectiveness of the proposed AVR model. Specifically, VG (Krishna et al. 2017) is a large image dataset with over 2 million annotated relationships. It is pre-processed in different ways in previous literatures (Zhang et al. 2017a), (Li et al. 2017b), (Yin et al. 2018). For fair comparison, we use two commonly used versions of VG, i.e., VG-VtransE (Zhang et al. 2017a) and VG-MSDN (Li et al. 2017b). The details of the datasets are showed in Table 1. Here Nobj denotes the number of object categories and Npred denotes the number of predicate categories. Nimg denotes the number of images, while Nrel represents the average number of annotated relationships in an image.

Parameters Setting: We use Faster R-CNN (Ren et al. 2017) to localize all objects in an image and VGG16 is selected as the backbone network to extract visual features, because it is commonly used by recent literatures (Yin et al. 2018), (Li et al. 2018). The parameters of VGG16 are initialized by the parameters pre-trained in the Faster R-CNN on the training set, and kept unchanged during training the predicate prediction model. The optimization method we used is the SGD with momentum 0.9. In addition, the embedding vectors of the caption words used to obtain the semantic feature $F_{(s,o)}$ are the pre-trained vectors of Glove (Pennington, Socher, and Manning 2014), the dimension of which is 50. In the priori module of Section , the parameter $\lambda$ of random walk is set to 0.5 for VRD and 0.3 for both VG-VtransE and VG-MSDN.

Visual Relationship Detection Tasks: Generally, there are three kinds of popularly used tasks for visual relationship detection (Lu et al. 2016), which are listed as follows:

1. **Predicate Detection:** This task aims to determine the predicate of a given objects pair in an image, where the bounding boxes and class labels of the objects are provided.

2. **Phrase Detection:** Given an image, this task aims to output a set of relationship triplets $<\text{subject}, \text{predicate}, \text{object}>$ in the image and localize each relationship with one bounding box. A detected relationship $<\text{subject}, \text{predicate}, \text{object}>$ is considered as a correct match if and only if its bounding box has at least 0.5 overlap with one of the bounding boxes of ground truth relationships.

3. **Relationship Detection:** This task aims to output the relationship triplets $<\text{subject}, \text{predicate}, \text{object}>$ of a given image, and localize the bounding boxes of the subject and object of each relationship. If the bounding boxes of the subject and object have at last 0.5 overlap with the ground truth bounding boxes respectively, it is considered as a hit.

Metrics: Following (Lu et al. 2016), (Yin et al. 2018),
the metric Rec@N used here is the recall rate of top N predicted relationships, which are sorted by the probabilities of relationships output by the models. If multiple relationships with the same subject and object are detected by the model, only top K relationships are selected in each group for testing. For example, if K is 1, only the predicate with maximum probability is selected for each pair of detected subject and object.

### Analysis of the Components in AVR

To analyze the effectiveness of different components of the AVR model, several variation models with different components are implemented and tested for comparison. The experimental results are illustrated on Table 2 and Table 3.

**Table 2: Evaluation of different variation models in the Predicate Detection task on VRD dataset.**

| Method | K=1   | K=70  |
|--------|-------|-------|
|        | Rec@50 | Rec@50 | Rec@100 | Rec@100 | Rec@100 | Rec@100 |
| F₀     | 38.07  | 38.07  | 80.82   | 90.01   |
| F_c    | 48.77  | 48.77  | 86.68   | 93.79   |
| F_v    | 51.75  | 51.75  | 89.94   | 95.92   |
| F_v+F_b| 52.36  | 52.36  | 90.35   | 95.99   |
| Baseline(F_v+F_b+F_c) | 54.54  | 54.54  | 91.47   | 96.65   |
| Priori_{ids} | 51.59  | 51.59  | 82.51   | 87.65   |
| Priori_{rw} | 51.87  | 51.87  | 88.71   | 94.30   |
| Baseline+Priori_{ids} | 53.99  | 53.99  | 82.46   | 87.46   |
| Baseline+Priori_{rw} | 55.61  | 55.61  | 90.73   | 95.72   |

The Baseline model with the priori knowledge Priori_{rw} performs better than the Baseline for all tasks. Particularly, the attention module Att can further improve the performance significantly by up to 10%~18% for K=1 and 22%~32% for K=70. This confirms that the attention mechanism can effectively distinguish the importance of relationships in an image and pick out the salient relationships for better scene understanding.

### Comparisons with State-of-the-Art Methods

We also compare AVR with several state-of-the-art methods and show the results on the VRD dataset in Table 4. In the Predicate Detection task, AVR performs better than other methods except CAI+SCA-M (Yin et al. 2018) in the case K=1, but the AVR obtains much better performance in the case K=70 compared with the CAI+SCA-M. Furthermore, in the advanced tasks such as Phrase Detection and Relationship Detection, the AVR is significantly better than state-of-the-art methods by 10%~21% on recall. On the other hand, we also test AVR on the larger VG datasets (VG-VtransE (Zheng et al. 2017a) and VG-MSDN (Li et al. 2017b)), and show the results on Table 5. It can be observed that the Baseline with the priori module can offer better results than the original Baseline on three tasks for all K. Meanwhile, the Baseline combined with Priori_{rw} and attention module (Baseline+Priori_{rw}+Att) has significantly improved performance compared with the other methods. In some difficult cases, e.g., in the Relationship Detection task on the VG-VtransE dataset, the improvement can be up to 87.5% (marked with underline in the table).

Furthermore, to show the performance of the AVR model intuitively, we visualize some test examples with the salient weights of predicted relationships in Fig. 6. We can see that the predicates between objects are predicted accurately than the Baseline model. This may be because the VRD dataset is small-sized, and the priori knowledge extracted from the global context is not accurate enough. Actually, for the larger dataset VG, the Priori_{rw} can effectively improve the precision for all test cases as shown in Table 5.
and the salient weights $\alpha$ can precisely indicate the importance of the relationships in an image. For example, in the first image of Fig. 6, the salient weights of the relationships $<\text{person, on, bench}>$ and $<\text{bag, on, bench}>$ are larger than the weights of $<\text{cup, next to, person}>$ and $<\text{shirt, on, person}>$. This indicates AVR can pay more attention on the salient relationships in the image.

To further visualize the effectiveness of different components of AVR, we show the ranking results of three variation models (i.e., Baseline, Baseline+$\text{Priori}_{rw}$, and Baseline+$\text{Priori}_{rw}+$Att) on a test example in Fig. 7. It can be observed that the model with the attention module can significantly enhance the rankings of the important relationships (e.g., $<\text{person, on, bench}>$) and decrease the rankings of relatively unimportant relationships (e.g., $<\text{cup, next to, bag}>$). Furthermore, the $\text{Priori}_{rw}$ can effectively correct some mistakes about predicates, e.g., the $<\text{cup, on, person}>$ is revised to $<\text{cup, next to, person}>$, which is more precise to describe the relationship.

**Conclusion**

In this paper, we propose an attention based model AVR to solve the problem of salient visual relationship detection. AVR can not only precisely recognize the interaction between objects by fusing visual, spatial and semantic features, but also distinguish the importance of relationships with the attention based mechanism. Besides the multi-view information in the local context of an image, the global context in the whole dataset is also used to improve the accuracy of prediction by performing random walk on the heterogeneous priori knowledge graph. Comprehensive experiments are conducted on the real-world VRD and VG datasets and the results show that AVR outperforms state-of-the-art methods significantly.
Examples of Relationships:
Baseline:
<bag, on, bench>
<shirt, on, person>
<person, wear, shirt>
<person, on, bench>
<bench, under, laptop>
<shirt, on, person>
<cup, next to, bag>
<cup, next to, person>
<bench, under, laptop>

Baseline+PriorRW:
<bag, on, bench>
<shirt, on, person>
<person, wear, shirt>
<person, on, bench>
<bench, under, laptop>
<shirt, on, person>
<cup, next to, bag>
<cup, next to, person>
<bench, under, laptop>

Baseline+PriorRW+Att:
<bag, on, bench>
<shirt, on, person>
<person, wear, shirt>
<person, on, bench>
<bench, under, laptop>
<shirt, on, person>
<cup, next to, bag>
<cup, next to, person>
<bench, under, laptop>

Figure 6: Qualitative examples of detected relationships and the salient weights \( \alpha \) given by the proposed AVR. The objects in colors are localized with the bounding boxes with same colors.

Figure 7: According the confident probabilities of relationships, the several sorting relationships of three different models (i.e., Baseline, Baseline+PriorRW and Baseline+PriorRW+Att) are listed for comparison.

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