Constructing a Visual Relationship Authenticity Dataset

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Abstract
A visual relationship denotes a relationship between two objects in an image, which can be represented as a triplet of (subject; predicate; object). Visual relationship detection is crucial for scene understanding in images. Existing visual relationship detection datasets only contain true relationships that correctly describe the content in an image. However, distinguishing false visual relationships from true ones is also crucial for image understanding and grounded natural language processing. In this paper, we construct a visual relationship authenticity dataset, where both true and false relationships among all objects appeared in the captions in the Flickr30k entities image caption dataset are annotated. The dataset is available at https://github.com/codecreator2053/VR_ClassifiedDataset.

We hope that this dataset can promote the study on both vision and language understanding.

Keywords: visual relationship, authenticity

1. Introduction

A visual relationship is any relationship describing the interaction between two objects in an image (Sadeghi and Farhadi, 2011) [Sadeghi and Farhadi, 2011]. Scene Graph (Johnson et al., 2015) [Johnson et al., 2015], Visual Relationship Detection (VRD) (Lu et al., 2016) [Lu et al., 2016] and Visual Genome (VG) (Krishna et al., 2016) [Krishna et al., 2016]. There are various visual relationships between the objects in an image. For example, in Figure 1 the relationship between “two bikers” and “a bench” is “are sitting on” or “are sitting and talking on.” Similarly, the relationship between “two bikers” and “bike gear” is “in” or “dressed in.” Detecting such visual relationships can make the understanding of the entire image possible.

Four datasets have been published for visual relationship detection between objects in an image, i.e., Visual Phrases (Sadeghi and Farhadi, 2011) [Sadeghi and Farhadi, 2011], Scene Graph (Johnson et al., 2015) [Johnson et al., 2015], Visual Relationship Detection (VRD) (Lu et al., 2016) [Lu et al., 2016] and Visual Genome (VG) (Krishna et al., 2016) [Krishna et al., 2016]. In these existing datasets, visual relationships are represented as triplets of (subject; predicate; object). Subject and object are two different objects in an image, and predicate can be either a preposition that describes the positional relationship such “under” or “in front of,” or verbal relationship such as “hold” or “ride.”

A problem with the Visual Phrases dataset is that the number of types of visual relationships is limited (i.e., only 13 relationship types). The Scene Graph, VRD, and VG datasets have adequate numbers of types of visual relationships, but the annotations are limited to true visual relationships. We define a visual relationship as true if it correctly describes the content in an image; otherwise, the relationship is false. For example, in Figure 1 “two bikers in bike gear” is a true visual relationship, while “bike gear are sitting on a bench” is a false one. However, distinguishing false visual relationships from true ones is also crucial for image understanding as well as for some grounded natural language processing (NLP) tasks. For example, in visually grounded paraphrase identification (Chu et al., 2018) [Chu et al., 2018], false visual relationships should be excluded from valid paraphrase candidates. Moreover, the correct detection of true and false visual relationships between objects represented by noun phrases, can improve dependency parsing of the noun phrases.

In this paper, we construct an authenticity dataset for visual relationships. We annotate the true and false visual relationships among all objects/entities appeared in the captions of the Flickr30k entities image caption dataset (Plummer et al., 2015) [Plummer et al., 2015]. Our annotation has been done in two stages: Firstly, we list all visual relationships to be annotated in an image and use dependency parsing to detect the true relationships; Secondly, we annotate the relationships that could not be detected by dependency parsing via crowd-sourcing. As a result, we successfully construct a visual relationship dataset with both true and false relationships, which covers relationships among all objects that appeared in the captions of the Flickr30k dataset. This dataset can not only promote the study on image understanding but also contribute to NLP.

2. Related Work

2.1. Visual Relationship Datasets

The Visual Phrases dataset (Sadeghi and Farhadi, 2011) contains 17 phrases and 8 objects on the Pascal VOC2008 dataset (Everingham et al., 2010) [Everingham et al., 2010]. The Scene Graph dataset consists of not only visual relationships but also the attributes of objects (Johnson et al., 2015) [Johnson et al., 2015]. Their dataset is mainly constructed for image retrieval, which contains...
1. Two bikers in bike gear are sitting on a bench.
2. Two people rest on a park bench next to their bikes.
3. Women in bike helmets take a break from long ride.
4. Two bikers are sitting and talking on a bench in front of their bikes.
5. A bike riding couple dressed in bike gear and helmets take a minute to sit on a bench to talk and park their bikes.

Figure 1: An example from the Flickr30k dataset. There are 5 captions for each image. Objects/entities in each caption are localized to corresponding image regions in the image (shown in the same color). The underlined phrases denote the predicates among the objects. There can be both true and false visual relationships among the objects. For example, “two bikers in bike gear” is a true visual relationship, while “bike gear are sitting on a bench” is a false one.

109,535 instances of relationships in 5,000 images. The VRD dataset contains 100 object categories and 70 predicates for 5,000 images (Lu et al., 2016). VG is a large-scale dataset containing more than 100k images, annotated with various labels such as objects, attributes, relations, and scene graphs (Krishna et al., 2016). Being different from these existing datasets, our dataset is the only one that annotates the authenticity of visual relationships. A statistical comparison of our dataset and previous ones are shown in Table [1].

2.2. Visual Relationship Detection Models

The most challenging problem in visual relationship detection is the data sparseness of relationships, and many studies have been conducted to address this problem. Lu et al. (2016) proposed a model that handles objects and predicates independently. They then combined them for visual relationship detection. Yu et al. (2017) used linguistic knowledge from both the dataset and Wikipedia to regularize the visual model. Plummer et al. (2017) used various visual features, such as the appearance, size, position, attribute of objects, and spatial relationships between objects. Zhuang et al. (2017) pointed out the importance of language bias and spatial features, and fused them for visual relationship detection. Peyre et al. (2017) proposed a weakly-supervised model learnt from image-level labels. Zhang et al. (2017) simultaneously selected object pairs and classified them for both object and relationship detection. Jae Hwang et al. (2018) first learnt a prior by a multi-relational learning model, and then used a factorization scheme for the prior. Liao et al. (2018) used a recurrent neural network to model the semantic connection among objects. Peyre et al. (2019) transferred visual phrase embeddings from triplets in the training data to unseen test triplets using analogies between relationships containing similar objects. Zhan et al. (2019) used unlabeled relationships to improve the accuracy of visual relationship detection.

3. Dataset Construction

The pipeline for constructing our visual relationship authenticity dataset is shown in Figure [2]. Firstly, we pre-process the captions from the Flickr30k dataset to generate all possible visual relationship candidates. Next, we apply dependency parsing to construct a dependency relationship graph among the entities and the predicates. After that we propose to apply type extraction to detect true relationships among the candidates. The detected ones must belong to both the predefined types in the relationship graph and the visual relationship candidates. Furthermore, the visual relationship candidates that are not detected by type extraction are further annotated via crowdsourcing.

3.1. The Flickr30k Entities Dataset

Our dataset is based on the Flickr30k entities dataset (Plummer et al., 2015). Flickr30 entities is a large-scale dataset with images and captions, in which the entities in the captions are localized to the regions in the images. Following (Plummer et al., 2015), we use 29,769, 1,000, and 1,000 samples as training, validation, and testing splits, respectively. An example of an image and its captions from the Flickr30k entities dataset is shown in Figure [3]. Each image has 5 captions, and the entities in the captions are localized by their corresponding regions in the image. In this example, all entities in the captions have corresponding regions in the image; however, there can be more abstract entities related to events and scenes, such as “break” and “a minute” that do not have corresponding visual concepts.
and thus have no corresponding regions in the image.

3.2. Visual Relationship Candidate Generation

In the Flickr30k entities dataset, entities in captions are annotated by chunking noun phrases in the Flickr30k captions \cite{young2014image}. These entities are further categorized into types such as people, body parts, and clothing etc., using a manually constructed dictionary \cite{plummer2015flickr30k}. As shown in Figure 3, visual relationship candidates are generated by combining two entities in a caption. Specifically, all pairs of entities in a single caption are combined as candidate relationships, where the subjects and objects must be the ones in which they appear in the caption. We define the phrase lying between two entities as predicate. More specifically, the phrase that comes right before the second entity in the caption is treated as the predicate. In Figure 3 three visual relationship candidates are generated.

Some phrases lying between two entities like “,”, “and”, “while” and “space” are not predicates and thus are removed from the group of candidates. Entities in the dataset have type tags describing their characteristics (such as “people” or “clothing”). The entities having the type tag “notvisual” do not qualify as candidates for visual relationships, because they are not visual in the image. The statistics of the generated visual relationship candidates are shown in the first row of Table 2.

3.3. Relationship Detection via Dependency Parsing

If a caption correctly represents image content and has correct dependency relations, we can detect true visual relationships based on the dependency relationship between two entities. In this section, we describe the method for detecting true visual relationships via dependency parsing. Dependency parsing of the captions is done by the Stanford parser \footnote{https://nlp.stanford.edu/software/lex-parser.shtml}. The parsed captions are cross checked with the candidates for visual relationships obtained in Section 3.2, and then true visual relationships are extracted. In detail, the detection of true visual relationships are carried out in the following manner.

1. Do dependency parsing on the captions and construct a directional graph, of which nodes are words.

2. Merge nodes in the graph based on the entities and predicates in Flickr30k. The edges connecting the same nodes are ignored.

3. Get the visual relationship if the entities and their predicate belong to predefined types.

4. Extract the visual relationships obtained in Step 3 as true visual relationship if they are also contained in the candidates generated in Section 3.2.

Steps 3 and 4 are named as type extraction. The “predefined types” in Step 3 refer to the dependency relationship of the entity pair and their predicate. As dependency parsing is not error-free, we empirically decide the combination of types. Let $EN_1$ (i.e., subject) and $EN_2$ (i.e., object) be the pair of entities and $RE$ be the predicate between them. As long as $EN_1$, $EN_2$, and $RE$ are linked in the graph, the combinations that make a valid visual relationship are the following 7 types.

- $A$: $RE \rightarrow EN_1, RE \rightarrow EN_2$
- $B$: $EN_1 \rightarrow RE, EN_1 \rightarrow EN_2$
- $C$: $EN_1 \rightarrow PRE, EN_2 \rightarrow RE$
- $D$: $RE \rightarrow EN_1, EN_2 \rightarrow EN_1$
- $E$: $EN_1 \rightarrow RE \rightarrow EN_2$
- $F$: $RE \rightarrow EN_1 \rightarrow EN_2$
- $G$: $EN_1 \rightarrow EN_2 \rightarrow RE$

$A$ and $B$ are cases of having a common parent node, and $C$ and $D$ are cases of having a common child node. Figure 4 shows an example of a graph built by the dependency parsing with entities and predicates being merged into nodes for the caption “[EN#1/people Two bikers] in [EN#2/other bike gear] are sitting on [EN#3/other a bench].” In this example, “Two bikers in bike gear” and “bike gear are sitting on a bench” are extracted as types $A$ and $G$, respectively. Note that the latter candidate is an erroneous extraction due to parsing errors. Likewise, “two bikers are sitting on a bench” is a valid candidate but cannot be extracted because it does not match any of the types. To see which types contribute to extraction, we annotated 186 visual relationship candidates from the validation data by ourselves for the evaluation. The precision/recall/F-score when either one of $A$ to $G$ or some combinations of them are used is shown in Table 2. Note that the $B$, $D$, and $F$ types yielded neither true positives nor true negatives, so their scores could not be calculated. The combinations were decided upon by combining the most precise types. Because of the high precision and recall of 90.5% and 49.7% respectively, we use $A$, $E$ and $G$ for combination of types. The visual relationships within the 186 manually annotated data that can be extracted as type $C$ were also

Table 2: Numbers of visual relationships obtained in different steps of our dataset construction pipeline. “Auth.” denotes authenticity, “Rel.” denotes relationships, and “DP” denotes dependency parsing.

| # Candidates | Auth. | Train | Validation | Test |
|--------------|-------|-------|------------|------|
| # Candidates | N/A   | 249,706 | 8,425 | 8,292 |
| # DP Rel.    | True  | 90,665 | 3,015 | 2,933 |
| # Rel. by AMT| True  | 91,608 | 3,455 | 3,299 |
|              | False | 67,433 | 1,955 | 2,060 |
Two bikers in bike gear are sitting on a bench

Type A: RE1->EN1, RE1->EN2
Type G: EN2->EN3->RE2

Figure 4: A graph with nodes merged according to entities and predicates. Note that the visual relationship of “Two bikers are sitting on a bench” cannot be extracted in this graph.

Table 3: Precision/recall/f-score when either one of types A-G or their combinations are used.

| Type | TP | FP | FN | Precision | Recall | F-score |
|------|----|----|----|-----------|--------|---------|
| A    | 15 | 1  | 138| 93.8      | 9.8    | 17.8    |
| C    | 5  | 1  | 148| 83.3      | 3.3    | 6.3     |
| E    | 41 | 7  | 112| 85.4      | 26.8   | 40.8    |
| G    | 23 | 1  | 130| **95.8**  | 15.0   | 26.0    |
| AG   | 37 | 2  | 116| 94.9      | 24.2   | 38.5    |
| AEG  | 76 | 8  | 77 | 90.5      | **49.7** | **64.1** |
| ACEG | 76 | 8  | 77 | 90.5      | **49.7** | **64.1** |

3.4. Annotation with AMT

Visual relationships that could not be extracted via dependency parsing are manually annotated via a crowdsourcing service, Amazon Mechanical Turk (AMT). The screenshots of the instruction part and some annotation tasks in AMT are shown in Figures 5 and 6, respectively. Our interface covers a single session for multiple annotation tasks. The first part of our interface provides the instructions for annotation, some annotation examples with correct and incorrect annotation results, and their reasons. It also notifies that there are dummy questions and workers who fail to answer these dummy questions would be rejected. Our dummy questions are the same annotation task but are preliminarily annotated so that we can automatically evaluate the dummy questions.

Below the instruction part, the interface continues to actual annotation tasks. It shows 10 panels (on average) like Figure 6, each of which covers a single image (and thus have multiple annotation tasks for the image). Each image yields 1 to 10 candidate visual relationships to be annotated. We put many panels as a single session, which contains 50 annotation tasks. An annotation task is simply choosing Yes/No on a radio button. A single session comes with 5 dummy questions. A worker who achieves an accuracy higher than 0.8 on the dummy questions is accepted and otherwise are rejected. Figure 6 shows an example, where the second question about the visual relationship “man with a fish” is a dummy question. The reward for a single session was set to $0.2, and we only recruited workers who have the AMT master qualification.

Each session serves as a human intelligence task (HIT) in AMT. The overall flow of our AMT-based annotation is as follows.

1. Issue HITs in AMT.
2. Workers annotate HITs.
3. The accuracy of a single HIT is computed as the accuracy over the dummy questions.
4. If the accuracy is higher than 0.8, we accept the HIT. Otherwise we reject it.
5. The responses from the workers are aggregated and only candidate visual relationships for which the majority (i.e., more than 3 out of 5) of the responses are Yes are labelled as true; otherwise, they are labelled as false.

We carefully annotated 149 candidate visual relationships (from the ones to be annotated by AMT) by ourselves to included in type E. The number of visual relationships obtained by dependency parsing are presented in the second row of Table 2.

Figure 5: The instruction part in our interface.

Figure 6: Example annotation tasks about an image in our interface. Note that the dummy question is highlighted with the red underline for readers’ convenience; the interface does not have the underline.

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Only workers whose HIT is accepted get the reward. Rejected HITs yield no reward and are not included in the dataset.
evaluation the dataset. The accuracy, precision, recall, and f-score is summarized in Table 4. We can see that the AMT workers yield a high F-score of 94.9%. The third and fourth rows in Table 4 show the statistics of true and false visual relationships obtained by AMT. We can see that the number of true relationships obtained by AMT is comparable to that number obtained by dependency parsing, indicating the limitation of dependency parsing in visual relationship detection. In addition, nearly 70k false relationships are annotated by AMT. These visual relationships annotated by AMT can be used to give feedback to and thus improve dependency parsing. However, we leave it as future work.

4. Annotation Error Analysis

Figures 7(a) and 7(b) show two examples of dependency parsing failure to extract true visual relationships. Our dependency parsing extracted “video camera standing next to a woman” as a true visual relationship for Figure 7(a), which actually is a false visual relationship. Similarly, for the image in Figure 7(b), “group of people playing board games” is a true visual relationship but could not be extracted through dependency parsing. False positive visual relationships of dependency parsing could not be corrected because they were not included in candidate visual relationships to be annotated with AMT. We leave this issue as one of our future work.

Figures 7(c) and 7(d) are failure examples in AMT-based annotation. “backstroke in swimming pool” is one of the candidate visual relationships extracted for Figure 7(c), but “backstroke” is not an object and hence not a true visual relationship. However, all workers labeled it as true even though our instruction states that a coreference cannot be an entity, as shown in Figure 8. This implies that our instruction is not sufficiently clear. For Figure 7(d), “museum from antiquity” should be false because it shows an exhibition from antiquity but not a museum of antiquity. Yet, around 80% of the workers labeled the candidate visual relationship as true. The workers might deduce that the exhibition should be in the museum and thus the candidate is true. However, the image itself does not show the museum itself, and so the museum cannot be an entity.

5. Conclusion

In this paper, we constructed a dataset on visual relationships between two objects in images. The dataset was constructed by performing dependency parsing and AMT-based annotation on the Flickr30k entities dataset. Being different from previous studies, our dataset is annotated with both true and false visual relationships, covering all visual relationships in Flickr30k’s captions. Our future work includes to explore a visual relationship detection model on our dataset.

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