Detecting rare visual relations using analogies

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Abstract

We seek to detect visual relations in images of the form of triplets $t = (\text{subject, predicate, object})$, such as ‘person riding dog’, where training examples of the individual entities are available but their combinations are rare or unseen at training. This is an important set-up due to the combinatorial nature of visual relations: collecting sufficient training data for all possible triplets would be very hard. The contributions of this work are three-fold. First, we learn a representation of visual relations that combines (i) individual embeddings for subject, object and predicate together with (ii) a visual phrase embedding that represents the relation triplet. Second, we learn how to transfer visual phrase embeddings from existing training triplets to unseen test triplets using analogies between relations that involve similar objects. Third, we demonstrate the benefits of our approach on two challenging datasets involving rare and unseen relations: on HICO-DET, our model achieves significant improvement over a strong baseline, and we confirm this improvement on retrieval of unseen triplets on the UnRel rare relation dataset.

1. Introduction

Understanding interactions between objects is one of the fundamental problems in visual recognition. To retrieve images given a complex language query such as “a woman sitting on top of a pile of books” we need to recognize individual entities “woman” and “a pile of books” in the scene, as well as understand what it means to “sit on top of something”. In this work we aim to recognize and localize rare or unseen interactions in images, as shown in Figure 1, where the individual entities (“person”, “dog”, “ride”) are available at training, but not in this specific combination. Such ability is important in practice given the combinatorial nature of visual relations where we are unlikely to obtain sufficient training data for all possible relation triplets.

Existing methods [5, 17, 20] to detect visual relations in the form of triplets $t = (\text{subject, predicate, object})$ typically learn generic detectors for each of the entities, i.e. a separate detector is learnt for subject (e.g. “person”), object (e.g. “horse”) and predicate (e.g. “ride”). The outputs of the individual detectors are then aggregated at test time. This compositional approach can detect unseen triplets, where subject, predicate and object are observed separately but not in the specific combination. However, it often fails in practice [35, 23], due to the large variability in appearance of the visual interaction that often heavily depends on the objects involved; it is indeed difficult for a single “ride” detector to capture visually different relations such as “person ride horse” and “person ride bus”.

An alternative approach [30] is to treat the whole triplet as a single entity, called a visual phrase, and learn a separate detector for each of the visual phrases. For instance, separate detectors would be learnt for relations “person ride horse” and “person ride surfboard”. While this approach better handles the large variability of visual relations, it requires...
training data for each triplet, which is hard to obtain as visual relations are combinatorial in their nature and many relations are rare in the real world.

In this work we address these two key limitations. First, what is the right representation of visual relations to handle the large variability in their appearance, which depends on the entities involved? Second, how can we handle the scarcity of training data for rare and unseen visual relation triplets?

To address the first challenge, we develop a hybrid model that combines the compositional and visual phrase representations. More precisely, we learn a compositional representation for subject, object and predicate by learning separate visual-language embedding spaces where each of these entities is mapped close to the language embedding of its associated annotation.

In addition, we also learn a relation triplet embedding space where visual phrase representations are mapped close to the language embedding of their corresponding triplet annotations. At test time, we aggregate outputs of both compositional and visual phrase models. To address the second challenge, we learn how to transfer visual phrase embeddings from existing training triplets to unseen test triplets using analogies between relations that involve similar objects. For instance, as illustrated in Figure 1, we recognize the unseen triplet “person ride dog” by using the visual phrase embedding for triplet “person ride horse” after a transformation that depends on the object embedding “dog” and “horse”. Because we transfer training data only from triplets that are visually similar, we expect transferred visual phrase detectors to better represent the target relations compared to a generic detector for a relation “ride” that may involve also examples of “person ride train” and “person ride surfboard”.

Contributions. Our contributions are three fold. First, we take advantage of both the compositional and visual phrase representations by learning complementary visual-language embeddings for subject, object, predicate and the visual phrase. Second, we develop a model for transfer by analogy to out-of-vocabulary relations and to benefit from powerful pre-learnt language models.

Visual-semantic embeddings. Visual-semantic embeddings have been successfully used for image captioning and retrieval [13, 12]. With the introduction of datasets annotated at the region level [16, 25], similar models have been applied to align image regions to fragments of sentences in a joint embedding space [33]. In contrast, learning embeddings for visual relations still remains largely an open research problem with recent work exploring, for example, relation representations using deformations between subject and object embeddings [35]. Our work is, in particular, related to models [36] learning separate visual-semantic spaces for subject, object and predicate. However, in contrast to [36], we additionally learn a visual phrase embedding space to better deal with appearance variation of visual relations, and develop a model for analogy reasoning to infer embeddings of unseen triplets.

Rare relations and transfer learning. Learning visual phrase embeddings suffers from the problem of limited training data for rare relations. This has been addressed by learning factorized object and predicate representations [9] or by composing classifiers for relations from simpler concepts [22, 14]. In contrast, our approach transfers visual relation representations from seen examples to unseen ones in a similar spirit to how previous work dealt with inferring classifiers for rare objects [2]. The idea of sharing knowledge from seen to unseen triplets to compensate for the scarcity of training data has been also addressed in [27] by imposing constraints on embeddings of actions. Different from this work, we formulate the transfer as an analogy between relation triplets. To achieve that, we build on the computational model of analogies developed in [28] but extend it to representations of visual relations.
Our model consists of two parts: (a) learning embedding spaces for subject, object, predicate and visual phrase by optimizing the joint loss $L = L_s + L_o + L_p + L_{vp}$ combining the input visual $x$ and language $q$ representations; (b) inferring the visual phrase embedding of a new unseen triplet (e.g. “person ride cow”) from seen triplets (e.g. “person ride horse”, “person pet cow”): the visual phrase embeddings $w_{vp}$ of seen triplets are transformed by the analogy transformation $\Gamma$ into target visual phrase embeddings $\tilde{w}_{vp}$ and aggregated using weights $G$ according to their degree of similarity. The outcome is an embedding $\hat{w}_{vp}$ of the unseen triplet. The analogy transformation $\Gamma$ is trained to transform source relations (e.g. “person ride horse”) to analogous target relations (e.g. “person ride elephant”) in the visual phrase embedding space.

3. Model

In this section we describe our model for recognizing and localizing visual relations in images. As illustrated in Figure 2, our model consists of two parts. First, we learn different visual-language embedding spaces for the subject $(s)$, the object $(o)$, the predicate $(p)$ and the visual phrase $(vp)$, as shown in Figure 2(a). We explain how to train these embeddings in Section 3.1. Second, we transfer visual phrase embeddings of seen triplets to unseen ones with analogy transformations, as shown in Figure 2(b). In Section 3.2 we explain how to train the analogy transformations and form visual phrase embeddings of new unseen triplets at test time.

Notation for relation triplets. The training dataset consists of $N$ candidate pairs of bounding boxes, each formed by a subject candidate bounding box proposal and object candidate bounding box proposal. Let $V_s$, $V_o$ and $V_p$ be the vocabulary of subjects, objects and predicates, respectively. We call $V_{vp} = V_s \times V_p \times V_o$ the vocabulary of triplets. A triplet $t$ is of the form $t = (s, p, o)$, e.g. $t = (\text{person}, \text{ride}, \text{horse})$. Each pair of candidate subject and object bounding boxes, $i \in [1 : N]$, is labeled by a vector $(y^i_t)_{t \in V_{vp}}$ where $y^i_t = 1$ if the $i^{th}$ pair of boxes could be described by relation triplet $t$, otherwise $y^i_t = 0$. The labels for subject, object and predicate naturally derive from the triplet label.

3.1. Learning representations of visual relations

We represent visual relations in joint visual-semantic embedding spaces at different levels of granularity: (i) at the unigram level, where we use separate subject, object and predicate embeddings, and (ii) at the trigram level using an analogical visual phrase embedding of the whole triplet. Combining the different types of embeddings results in a more powerful representation of visual relations as will be shown in section 4.

In detail, as shown in Figure 2(a), the input to visual embedding functions (left) is a candidate pair of objects $i$ encoded by its visual representation $x_i \in \mathbb{R}^{d_v}$. This representation is built from (i) pre-computed appearance features obtained from a CNN trained for object detection and (ii) a representation of the relative spatial configuration of the object candidates. The language embeddings (right in Figure 2(a)) take as input a triplet $t$ encoded by its language representation $q_t \in \mathbb{R}^{d_q}$. This representation is built from (i) pre-computed appearance features obtained from a CNN trained for object detection and (ii) a representation of the relative spatial configuration of the object candidates. The language embeddings (right in Figure 2(a)) take as input a triplet $t$ encoded by its language representation $q_t \in \mathbb{R}^{d_q}$ obtained from pre-trained word embeddings. We provide more details about these representations in 4.2. Next we give details of the embedding functions.

Embedding functions. Our network projects the visual features $x_i$ and language features $q_t$ into separate spaces for the subject $(s)$, the object $(o)$, the predicate $(p)$ and the visual phrase $(vp)$. For each input type $b \in \{s, o, p, vp\}$, we embed the visual features and language features into a common space of dimensionality $d$ using projection functions

$$v^b_i = f^{vb}_v(x_i),$$
$$w^b_t = f^{wb}_w(q_t),$$
where \( v^s_t \) and \( w^s_t \) are the output visual and language representations, and the projection functions \( f^b_v : \mathbb{R}^{d_v} \to \mathbb{R}^d \) and \( f^b_w : \mathbb{R}^{d_v} \to \mathbb{R}^d \) are 2-layer perceptrons, with ReLU non-linearities and Dropout, inspired by [33]. Additionally, we L2 normalize the output language features while the output visual features are not normalized, which we found to work well in practice.

**Training loss.** We train parameters of the embedding functions \((f^b_v, f^b_w)\) for each type of input \(b\) (i.e., subject, object, predicate and visual phrase) by maximizing log-likelihood

\[
\mathcal{L}_b = \frac{1}{N} \sum_{i=1}^{N} \sum_{t \in V_b} \mathbb{I}_{y^t_i=1} \log \left( 1 + e^{-w^b_{y^t_i} v^t_i} \right) + \frac{1}{N} \sum_{i=1}^{N} \sum_{t \in V_b} \mathbb{I}_{y^t_i=0} \log \left( 1 + e^{w^b_{y^t_i} v^t_i} \right),
\]

where the first attraction term pushes closer visual representation \( v^b_t \) to its correct language representation \( w^b_t \) and the second repulsive term pushes apart visual-language pairs that do not match. As illustrated in Figure 2, we have one such loss for each input type and optimize the joint loss that sums the individual loss functions \( \mathcal{L}_{joint} = \mathcal{L}_s + \mathcal{L}_o + \mathcal{L}_p + \mathcal{L}_{vp} \).

A similar loss function has been used in [21] to learn word representations, while visual-semantic embedding models [13, 33] typically use triplet ranking losses. Both loss functions work well, but we found embeddings trained with log-loss (3) easier to combine across different input types as their outputs are better calibrated.

**Inference.** At test time, we have a language query in the form of triplet \( t \) that we embed as \((w^s_t)_b\), using Eq. (1). Similarly, pairs \( i \) of candidate object boxes in the test images are embedded as \((v^b_t)_b\). Then we compute a similarity score \( S_{t,i} \) between the triplet query \( t \) and the candidate object pair \( i \) by aggregating predictions over the different embedding types \( b \in \{s,p,o,vp\} \) as

\[
S_{t,i} = \prod_{b \in \{s,p,o,vp\}} \frac{1}{1 + e^{-w^b_{t} v^b_{i}}}. \tag{4}
\]

**Interpretation of embedding spaces.** The choice of learning different embedding spaces for subject, object, predicate and visual phrase is motivated by the observation that each type of embedding captures different information about the observed visual entity. In Figure 3 we illustrate the advantage of learning separate predicate \((p)\) and visual-phrase \((vp)\) embedding spaces. In the \(p\) space, visual entities corresponding to “person ride horse” and “person ride car” are mapped to the same point, as they share the same predicate “ride”. In contrast, in the \(vp\) space, the same visual entities are mapped to two distinct points. This property of the \(vp\) space is desirable to handle both language polysemy (i.e., “ride” has different visual appearance depending on the objects involved and thus should not be mapped into a single point) and synonyms (i.e., “person jump horse” and “person ride horse” projections should be close even if they do not share the same predicate).

### 3.2. Transferring embeddings to unseen triplets by analogy transformations

We propose to explicitly transfer knowledge from seen triplets at training to new unseen triplets at test time by analogy reasoning. The underlying intuition is that if we have seen examples of “person ride horse”, it might be possible to use this knowledge to recognize the relation “person ride cow”, as “horse” and “cow” have similar visual appearance. As illustrated in Figure 2(b), this is implemented as an analogy transformation in the visual phrase embedding space, where a representation of the source triplet (e.g., “person ride horse”) is transformed to form a representation of target triplet (e.g., “person ride cow”). There are two main steps in this process. First, we need to learn how to perform the analogy transformation of one visual phrase embedding (e.g., “person ride horse”) to another (e.g., “person ride cow”). Second, we need to identify which visual phrases are suitable for such transfer by analogy. For example, to form a representation of a new relation “person ride cow” we want to transform the representation of “person ride horse” but not “person ride bus”.

**Transfer by analogy.** To transform the visual phrase embedding \( w^s_{t} \) of a source triplet \( t = (s,r,o) \) to the visual phrase embedding \( w^s_{t'} \) of a target triplet \( t' = (s',r',o) \) we learn a transformation \( \Gamma \) such that:

\[
w^s_{t'} = w^s_{t} + \Gamma(t,t'). \tag{5}
\]

Here, \( \Gamma \) could be interpreted as a correction term that indicates how to transform \( w^s_{t} \) to \( w^s_{t'} \) in the joint visual-semantic space \( vp \) to compute a target relation triplet \( t' \) that is analogous to source triplet \( t \). This relates to neural word representations such as [21] where word embeddings of similar concepts can be linked by arithmetic operations such as “king” − “man” + “woman” = “queen”. Here, we would like to perform operations such as “person ride horse” − “horse” + “cow” = “person ride cow”.

**Form of \( \Gamma \).** To relate the visual phrase embeddings of \( t \) and \( t' \) through \( \Gamma \) we take advantage of the decomposition of the triplet into subject, predicate and object. In detail, we use visual embeddings of subject \( s \), predicate \( p \) and object \( o \) to learn how to perform the transformations in the visual phrase \( vp \) space. Using this structure, we redefine the analogy
transformation given by Eq. (5) as

$$
\mathbf{w}_{t'}^{vp} = \mathbf{w}_t^{vp} + \Gamma \begin{bmatrix}
\mathbf{w}_s^p - \mathbf{w}_t^p \\
\mathbf{w}_p^p - \mathbf{w}_t^p \\
\mathbf{w}_o^p - \mathbf{w}_t^p
\end{bmatrix},
$$

(6)

where \(\mathbf{w}_s^p, \mathbf{w}_p^p, \mathbf{w}_o^p\) are the subject, predicate and object embeddings, respectively, and \(t\) and \(t'\) denote again the source and target triplets. For example, the analogy transformation of \(t = (\text{person}, \text{ride}, \text{horse})\) to \(t' = (\text{person}, \text{ride}, \text{camel})\) using Eq. (6) would result in

$$
\mathbf{w}_{t'}^{vp} = \mathbf{w}_t^{vp} + \Gamma \begin{bmatrix}
0 \\
0 \\
\mathbf{w}_{\text{camel}}^p - \mathbf{w}_{\text{horse}}^p
\end{bmatrix},
$$

(7)

Intuitively, we would like \(\Gamma\) to encode how the change of objects, observable through the embeddings of source and target objects, \(\mathbf{w}_s^p, \mathbf{w}_o^p\), influences the source and target visual phrase embeddings \(\mathbf{w}_s^{vp}, \mathbf{w}_o^{vp}\). While different choices for \(\Gamma\) are certainly possible, we opt for a simple linear transform

$$
\Gamma_A(t, t') = A \begin{bmatrix}
\mathbf{w}_s^p - \mathbf{w}_t^p \\
\mathbf{w}_p^p - \mathbf{w}_t^p \\
\mathbf{w}_o^p - \mathbf{w}_t^p
\end{bmatrix},
$$

(8)

where \(A \in \mathbb{R}^{d \times 3d}\) and \(d\) is the dimensionality of the output visual phrase embedding and \(3d\) is the dimensionality of the concatenation of the three input embeddings. Please note that non-linear forms of \(\Gamma\), such as multi-layer perceptrons, are also possible, but our preliminary experiments found that they do not provide much power over the simpler linear form used here. Please also note that here we have shown an example of a transformation resulting from a change of object, but our formulation, given by Eq. (6), allows for changes of subject or predicate in a similar manner.

**Learning \(\Gamma\).** We learn parameters \(A\) of \(\Gamma\) by minimizing the following regression loss

$$
\mathcal{L}_{\text{transfer}}(A) = \sum_{t=1}^N \sum_{t' \in V_{vp}} \mathbb{1}_{w_{t'}^{vp} = \tilde{w}_t^{vp}(A)} \sum_{t \in \mathcal{N}_t} \| \mathbf{w}_t^{vp} - \tilde{\mathbf{w}}_t^{vp}(A) \|_2^2,
$$

(9)

where \(\mathbf{w}_t^{vp}\) is the visual phrase embedding of a target training triplet \(t'\), and \(\tilde{\mathbf{w}}_t^{vp}(A) = \mathbf{w}_t^{vp} + \Gamma_A(t, t')\) the transformed visual phrase embedding of a source triplet suited for analogy transformation, which we define as the triplets that differ by only 1 word (either the subject, the object or the predicate).

**Which triplets to transfer from?** At test time, we compute the visual phrase embedding of an unseen triplet \(u\) by aggregating embeddings of similar seen triplets \(t \in \mathcal{N}_u\) transformed using the analogy transformation:

$$
\tilde{\mathbf{w}}_u^{vp} = \sum_{t \in \mathcal{N}_u} G(t, u) \tilde{\mathbf{w}}_t^{vp},
$$

(10)

where \(\mathbf{w}_u^{vp}\) and \(\mathbf{w}_u^{vp}\) measures similarity between embedded representations \(\mathbf{w}_u\) and scalars \(\alpha_b\) are hyperparameters that reweight the relative contribution of subject, object and predicate similarities. As we constrain \(\sum_b \alpha_b = 1\) the output of \(G(t, u) \in [0, 1]\). In practice, we retain only the top \(k = 4\) most similar triplets for aggregation in Eq. (10). The hyperparameters \(\alpha_s\), \(\alpha_o\), \(\alpha_p\), and \(k\) are optimized on the validation set.

**4. Experiments**

In this section we evaluate the performance of our model for visual relation retrieval on two challenging datasets for rare relations: HICO-DET [3] and UnRel [23]. Specifically,
we numerically assess the two components of our model: (i) learning the visual phrase embedding together with the
unigram embeddings and (ii) transferring embeddings to unseen triplets by analogy transformations.

4.1. Datasets and evaluation set-ups

HICO-DET. The HICO-DET [4, 3] dataset contains images of human-object interactions with box-level annotations. The interactions are varied: the vocabulary of objects matches the 80 COCO [19] categories and there are 117 different predicates. The number of all possible triplets is $1 \times 117 \times 80$ but the dataset contains positive examples for only 600 triplets. All triplets are seen at least once in training. The authors separate a set of 138 rare triplets, which are the triplets that appear fewer than 10 times at training. To conduct further analysis of our model, we also select a set of 25 triplets that we treat as unseen, exclude them completely from the training data in certain experiments, and try to retrieve them at test time using our model. These triplets are randomly selected among the set of non-rare triplets in order to have enough test instances on which to reliably evaluate.

UnRel. UnRel [23] is an evaluation dataset containing visual relations for 76 unusual triplet queries. In contrast to HICO-DET, the interactions do not necessarily involve a human, and the predicate is not necessarily an action (it can be a spatial relation, or comparative). The vocabulary of objects and predicates matches those of Visual Relation Detection Dataset [20]. UnRel is only an evaluation dataset, so similar to [23] we use the training set of Visual Relationship Dataset as training data.

Evaluation measure. On both datasets, we evaluate our model in a retrieval setup. For each triplet query in the vocabulary, we rank the candidate test pairs of object bounding boxes using our model and compute the performance in terms of Average Precision. Overall, we report mean Average Precision (mAP) over the set of triplet queries computed with the evaluation code released by [3] on HICO-DET and [23] on UnRel.

4.2. Implementation details

Candidate pairs. For both datasets, we use pre-extracted candidate pairs of objects from an object detector trained for the vocabulary of objects specific to the dataset. On HICO-DET, we train the object detector on the COCO training data using Detectron [6]. To be comparable to [7], we use a Faster-R-CNN [29] with ResNet-50 Feature Pyramid Network [18]. We post-process the candidate detections by removing candidates whose confidence scores are below 0.05 and apply an additional per-class score thresholding to maintain a fixed precision of 0.3 for each object category. On UnRel, we use the same candidate pairs as [23] to have directly comparable results.

Visual representation. Following [23], we first encode a candidate pair of boxes $(o_s, o_o)$ by the appearance of the subject $a(o_s)$, the appearance of the object $a(o_o)$, and their mutual spatial configuration $r(o_s, o_o)$. For both datasets, the appearance features of the subject and object boxes are extracted from the last fully-connected layer of the object detector. The spatial configuration $r(o_s, o_o)$ is a 8-dimensional feature that concatenates the subject and object box coordinates renormalized with respect to the union box, i.e., we concatenate $[z_{mag}-T, z_{mag}+T, y_{mag}-T, y_{mag}+T]$ for subject and object boxes where $T$ and $A$ are the origin and area of the union box respectively. The visual representation of a candidate pair is:

$$x_i = \begin{bmatrix} MLP_a(a(o_s)) \\ MLP_o(a(o_o)) \\ MLP_r(r(o_s, o_o)) \end{bmatrix}$$

where $MLP_a$, $MLP_o$ contain one layer that projects the appearance features into a vector of dimension 300 and $MLP_r$
is a 2-layer perceptron projecting the spatial features into a vector of dimension 400, making the final dimension of \( x \) equal to 1000. For the subject (resp. object) embeddings, we only consider the appearance of the subject (resp. object) without the spatial configuration.

**Language representation.** For a triplet \( t = (s, p, o) \), we compute the word embeddings \( e_s \) (resp. \( e_p, e_o \)) for subject (resp. predicate, object) with a Word2vec [21] model trained on GoogleNews. The representation of a triplet is taken as the concatenation of the word embeddings \( q_t = [e_s; e_p; e_o] \in \mathbb{R}^{900} \).

**Embedding functions.** The embedding projection functions are composed of two fully connected layers, with a ReLU non-linearity. For the visual projection functions, we use Dropout. The dimensionality of the joint visual-language spaces is set to \( d = 1024 \) for HICO-DET and \( d = 256 \) for UnRel as it is a smaller dataset.

**Batch sampling.** In practice, our model is trained on minibatches containing 64 candidate pairs of objects. 25% of the candidate pairs are positive, i.e. the candidate subject and object are interacting. The rest are negative, randomly sampled among candidate pairs involving the same subject and object category (but not interacting). For training, we use candidates from both groundtruth and object detector outputs. At test time, we only use candidate pairs from the object detector.

**Optimizer.** We learn the parameters of the projection functions by optimizing \( L_{\text{joint}} \) for 10 epochs with Adam optimizer [15] using a learning rate 0.001. For the experiments on zero-shot learning, we fix the parameters of the projection functions learnt after 10 epochs (on a split excluding the zero-shot triplets) and only learn the parameters of the transfer function \( \Gamma \) by optimizing \( L_{\text{transfer}} \) for 5 epochs.

### 4.3. Results on the HICO-DET dataset

**Evaluation on unseen triplets in HICO-DET.** Results on the unseen HICO-DET triplets are shown in Table 2 and confirm benefits of the visual phrase representation \((s+o+p+vp)\) over the compositional baseline \((s+o+p)\). This is an interesting result as the test triplets have not been seen at training, thus, their visual phrase representation in the \( vp \) space is only constrained via sharing the individual subject, object and predicate with other triplets. Furthermore, forming visual phrase embeddings of the unseen test triplets by analogy transformations of similar seen triplets, as described in 3.2, provides a relative gain of over 10% over the

|                  | full   | rare  | non-rare |
|------------------|--------|-------|----------|
| recall           | 57.47  | 58.27 | 57.2     |
| Chao [3]         | 7.71   | 5.37  | 8.54     |
| Gupta [8]        | 9.09   | 7.02  | 9.71     |
| Gkioxari [7]     | 9.94   | 7.16  | 10.77    |
| GPNN [26]        | 13.11  | 9.34  | 14.23    |
| \(s+o+vp)\)      | 18.0   | 13.45 | 19.52    |
| \(s+o+p+vp\)     | 19.4   | 15.4  | 20.75    |
| \(s+o+p+vp\) transfer | 19.19 | 15.03 | 20.59    |

Table 1: Results on HICO-DET dataset in default setting (mAP).

|                  | zero-shot | supervised |
|------------------|-----------|------------|
| recall           | 63.24     | 63.24      |
| \(s+o\)         | 20.34     | 23.0       |
| \(s+o+p\)       | 25.11     | 32.43      |
| \(s+o+p+vp\)    | 26.25     | 33.59      |
| \(s+o+p+vp\) transfer | 27.93 | 33.35      |

Table 2: mAP on the set of 25 zero-shot test triplets of HICO-DET. The first column (zero-shot) is trained on the trainval set excluding the positives for the zero-shot triplets, the second column (supervised) is trained with all training instances.
Figure 5: Top retrieved positives (Q) to retrieve is formed with the embedding of source triplets (S) by analogy.

| all   | action | spatial |
|-------|--------|---------|
| DenseCap [10] | 6.2    | -       |
| Lu [20]     | 12.0   | -       |
| Peyre [23] full | 14.1   | 17.0   | 10.8 |
| p           | 17.3   | 19.7   | **14.5** |
| vp          | 13.0   | 16.7   | 8.6    |
| p+vp        | 17.4   | 20.1   | 14.2   |
| p+vp transfer | **17.4** | **20.2** | 14.1   |

Table 3: Retrieval on UnRel (mAP) in the evaluation setup “union” of [23] with IoU=0.3

**Qualitative results.** In Figure 4 we show qualitative results for retrieval of unseen triplets with our full model (s+o+p+vp+transfer). For a query triplet (Q), such as “person pet cat” we show the top 3 retrieved candidate pairs (green), and the top 1 false positive (red). Also, for each target triplet, we show the source triplets (S) used in the transfer by analogy (Eq. 10). We note that the source triplets appear relevant to the query. For example, for “person pet cat”, our model automatically selects “person pet dog”, “person feed dog” and “person scratch cat”, that are visually similar both in terms of object and predicate. Interestingly, the top false positives correspond to a correct interaction involving a visually similar object (“cat” confused with “dog” and “donut” with “sandwich”). We provide more examples in the Section A of the appendix.

**4.4. Results on the UnRel dataset**

In Table 3 we show numerical results for retrieval on the UnRel dataset. For space reasons, we only report here results on the evaluation set-up “union” of [23] with IoU=0.3. The full set of results is in Section B of the appendix. Similar to [23], we also do not use subject and object scores as we found them uninformative on this dataset containing hard to detect objects. Because UnRel triplets are extremely diverse, we further split the analysis into the triplets involving an action (e.g. “ride”), and those involving a spatial relation (e.g. “above”). First, we observe that our results improve over all other methods, improving the current state-of-the-art [23] on this data. Second, as on HICO-DET, we observe benefits of the proposed visual phrase representation (p+vp) compared to the compositional baseline (p). The gain is obtained on the action triplets for which it seems to be crucial to have a finer appearance (vp) representation compared to the spatial relations. In contrast to HICO-DET, the transfer by analogy (p+vp transfer) brings modest improvement over the visual phrase representation (p+vp). To analyze this effect, we looked more closely at the triplet queries on UnRel and analyzed candidate source triplets for transfer. We believe that this may be attributed to the fact that the UnRel dataset contains very unusual relations for which the transfer by analogy is still difficult. Examples are shown in Figure 5. For instance, for “person hold car”, source triplets automatically selected by our method (e.g. “person hold box”, “person hold plate”) are reasonable, but it is still unclear how a “car” should be actually hold. Similarly, transferring from “person wear shoes” to “dog wear shoes” is complicated as the appearance of both subject (“person” to “dog”) and object (“shoes” for two legs to “shoes” for four legs) change at the same time. This makes UnRel a very challenging dataset for transfer by analogy. A possible solution could be using additional training data with unusual source triplets closer to UnRel triplet queries. We provide additional qualitative results and analysis in Section B of the appendix.

**5. Conclusion**

We have developed a new approach for visual relation detection that combines compositional and visual phrase representations. Furthermore, we have proposed a model for transfer by analogy able to compute visual-phrase embeddings of never seen before relations. Finally, we have demonstrated benefits of our approach outperforming current the state-of-the-art on HICO-DET and UnRel datasets.
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Appendix

In this appendix, we provide additional quantitative and qualitative results using our model described in Section 3 of the main paper. First, in Section A we give detailed numerical results for retrieval of unseen triplets on the HICO-DET dataset including additional qualitative results. Similarly, in Section B we provide a detailed evaluation and additional qualitative results for the UnRel dataset. Then, in Section C, we provide additional intuition for transfer by analogy, described in 3.2 of the main paper, by analyzing (i) the influence of the source triplets used for the transfer and (ii) the analogy transformation $\Gamma$. Finally, in Section D, we qualitatively analyze the joint embedding spaces learnt by our model described in Section 3.1 by showing t-sne [32] visualization and retrieval results for unseen queries with out-of-vocabulary predicates.

A. Additional results on HICO-DET dataset

**Additional qualitative results.** In Figure 6 we show additional examples of retrieved detections for unseen triplets that supplement Figure 4 of the main paper. These qualitative examples confirm that our model for transfer by analogy (Section 3.2 of the main paper) automatically selects relevant source triplets (S) given an unseen triplet query (Q). For instance, for the query triplet “person throw frisbee” (first row), our model selects (1) a source triplet that involves the same action, with a different, but similar, object “person throw sports ball” and (2) two other source triplets with the same object, and different, but related, actions “person catch frisbee”, “person block frisbee”. Similar conclusions hold for the other examples displayed. The top false positives show the two main failure modes: (1) the interacting object has a wrong category (e.g. the door of a bus is mistaken with a “surfboard” in row 2, a “cow” is mistaken for a “dog” in row 4, or a “dog” is confused with “sheep” in row 6), (2) the interaction is confused with another similar interaction (e.g. “inspect” is confused with “wash” in row 3 or “pick up” is confused with “hold” in last row).

**Additional numerical results.** In Table 4, we provide the performance (AP) per triplet for the set of zero-shot triplets excluded from HICO-DET with the different variants of our model. Confirming the mAP results, we see that for more than half of the triplets adding the visual phrase representation (s+o+p+vp) is helping over the compositional representation only (s+o+p) and that the best improvement is obtained by transferring the visual phrase embedding of seen triplets to the zero-shot ones (s+o+p+vp transfer). We can try to interpret the numerical results per triplet by confronting them to the qualitative results in Figure 6. First, for the zero-shot triplets on which our method of transfer by analogy (s+o+p+vp transfer) works well, we remark that there exist good source triplets to be sampled, i.e. at training, the model learns on visual phrases that are not too far from these zero-shot triplets. This is the case of “person hug dog” which is transferred from similar triplets such as “person hug cat” or “person kiss dog”; or “person lie on bed” which is transferred from “person lie on couch”. On the contrary, some zero-shot triplets such as “person hold surfboard” do not benefit more for transfer maybe because their visual phrase embedding already benefit from synonyms such as “person carry surfboard” seen at training that do not require analogy transformation. Then, for the zero-shot triplets which benefit neither from the visual phrase representation nor from transfer, we propose two interpretations: (1) either there is not much intra-class variability of appearance among the class (e.g. “person herd cow”, “person sit on bench”) and thus the visual phrase representation does not add much on top of the generic representation (2) either the visual phrases candidates for transfer are not well learnt themselves (e.g. for “person inspect bicycle”, the source triplets “person inspect motorcycle”, “person inspect backpack”, “person wash bicycle” are not rare relations, but are still not well learnt as they do not have a huge number of training data).

|                        | s+o+p | s+o+p+vp | s+o+p+vp (transfer) |
|------------------------|-------|----------|---------------------|
| person - hold - elephant | 19.65 | 28.08    | 25.79               |
| person - pet - cat      | 33.38 | 33.42    | 34.77               |
| person - watch - giraffe| 34.34 | 38.62    | 38.99               |
| person - herd - cow     | 8.93  | 8.73     | 8.45                |
| person - ride - horse   | 57.4  | 60.4     | 63.7                |
| person - walk - sheep   | 3.71  | 5.7      | 5.52                |
| person - hug - dog      | 25.49 | 23.8     | 30.95               |
| person - eat - banana   | 15.09 | 16.14    | 22.05               |
| person - hold - carrot  | 16.63 | 19.28    | 18.88               |
| person - carry - hot dog| 18.95 | 17.47    | 20.5                |
| person - eat - donut    | 42.24 | 45.94    | 47.94               |
| person - pick up - cake | 21.03 | 24.46    | 21.54               |
| person - carry - skateboard| 15.17 | 20.67   | 22.6                |
| person - carry - surfboard| 33.5  | 42.81    | 42.73               |
| person - jump - snowboard| 45.01 | 43.23    | 49.22               |
| person - ride - skis    | 22.31 | 18.53    | 23.97               |
| person - straddle - motorcycle| 41.48 | 41.19   | 46.98               |
| person - inspect - bicycle| 23.73 | 12.94   | 20.18               |
| person - lie on - bed   | 40.73 | 39.27    | 42.97               |
| person - hold - wine glass | 29.63 | 33.75   | 33.93               |
| person - carry - bottle | 6.53  | 7.52     | 5.07                |
| person - hold - knife   | 10.3  | 10.88    | 10.35               |
| person - throw - frisbee| 8.29  | 9.27     | 9.32                |
| person - sit on - bench | 38.37 | 37.23    | 37.39               |
| person - wear - backpack| 16.05 | 16.98   | 14.51               |

Table 4: AP for the unseen triplets excluded from the HICO-DET training set.
Then, we show that the combination with the visual phrase
In Figure 7 we show additional
More qualitative results.
In Table 5 we provide the full
Detailed numerical results.
B. Additional results on UnRel dataset

Detailed numerical results. In Table 5 we provide the full set of results for retrieval on the UnRel dataset for all the evaluation measures used in [23]. In detail, Union counts the detection as positive if the union box of candidate subject and object boxes intersects the union box of the groundtruth subject and object box, subject counts the detection as positive if the candidate subject box matches the groundtruth subject box, and subject-object counts as positive the candidates for which both candidate subject and object boxes intersect the groundtruth subject and object boxes. Results in Table 5 follow the same pattern as reported in the main paper. First, our model improves over the state-of-the-art [23]. Then, we show that the combination with the visual phrase representation (p+vp) improves on the action triplets over the compositional representation (p). Finally, on the action triplets we also show a slight improvement by using the transfer (p+vp+transfer). The per triplet results are given in Table 7.

More qualitative results. In Figure 7 we show additional qualitative results of our model (p+vp+transfer) for retrieval of unusual triplets on the UnRel dataset. Like in the main paper, we indicate the source triplets (S) automatically sampled by our analogy model that are used to form the visual phrase embedding of the target query (Q). The top true positive retrievals are shown in green, the top false positive retrieval is shown in red.

The automatically sampled source triplets all appear relevant. Our method samples source triplets involving (1) a different subject (“dog ride bike” is transferred from “person ride bike”, “building has wheel” is transferred from “bike has wheel”), (2) different object (“person stand on horse” is transferred from “person stand on sand”), or (3) different predicate (“person ride train” is transferred from “person drive train”).

An important difficulty with transfer by analogy on UnRel is the absence of close enough source triplets. For instance, it is hard to form a good embedding for “car in tree” from the source triplets “car in street”, “car in road”, “car by tree” as these source triplets have very different visual appearance. The same holds for a triplet such as “elephant sleep on person” which is difficult to retrieve if one has never seen what an elephant sleeping looks like.

Another difficulty comes from the VRD training dataset which already involves a few unusual triplets such as “person ride luggage”, “dog ride motorcycle” with only 1 training instance. This makes the visual phrase of such source triplets badly learnt and might affect the transfer by analogy.

Finally, a major failure mode is due to incorrect object detection. For instance, a “bus” is confused with a “building”, an “elephant” carrying an umbrella is confused with a “person”. This phenomenon occurs more dramatically on the UnRel dataset than in other image datasets such as MS COCO as UnRel was explicitly collected to include common objects in unusual contexts. For instance, the last row in Figure 7, that corresponds to “elephant wear pants” query, has only a single returned true positive as the object detector for “pants” fails to detect pants with four legs.

C. How does transfer by analogy work?

Here, we give additional intuition for our transfer by analogy approach. We begin with an ablation study demon-

|                      | all | action | spatial | all | action | spatial | all | action | spatial |
|----------------------|-----|--------|---------|-----|--------|---------|-----|--------|---------|
| DenseCap [10]        | 6.2 | -      | -       | 6.8 | -      | -       | -   | -      | -       |
| Lu [20]              | 12.0| -      | -       | 10.0| -      | -       | 7.2 | -      | -       |
| Peyre [23] full      | 14.1| 17.0   | 10.8    | 12.1| 14.1   | 9.8     | 9.9 | 11.3   | 8.3     |
| p                    | 17.3| 19.7   | 14.5    | 15.2| 17.0   | 13.1    | 12.8| 14.1   | 11.3    |
| vp                   | 13.0| 16.7   | 8.6     | 11.5| 15.1   | 7.3     | 9.4 | 12.3   | 6.0     |
| p+vp                 | 17.4| 20.1   | 14.2    | 15.7| 18.0   | 12.9    | 13.2| 15.2   | 10.9    |
| p+vp+transfer        | 17.4| 20.2   | 14.1    | 15.7| 18.1   | 12.8    | 13.2| 15.3   | 10.8    |

Table 5: Complete results for retrieval on the UnRel dataset (mAP) with IoU=0.3.

Table 6: Ablation study on unseen triplets of HICO-DET (test set) for our final model (s+o+p+vp transfer). For a target triplet $t' = (s', p', o')$, we sample candidate source triplets using different strategies: change of object only $t = (s', p', o)$, change of predicate only $t = (s', p, o')$ or change of both $t = (s', p, o)$. Also, we report results with and without regression $\Gamma$. These results show that we can have improvement by transferring from both types of source triplets. Also the analogy transformation $\Gamma$ is specifically important when transferring from triplets that involve a different object (first and last column).
strating the influence of different components of our model, and then provide a qualitative study of the effect of choosing different source triplets for the analogy transformation.

**Ablation study for transfer by analogy.** To evaluate benefits of the different components of our transfer by analogy model, we conduct an ablation study on unseen triplets of the HICO-DET dataset. Results are shown in Table 6. There are two main components we evaluate: (i) the influence of the choice of candidate source triplets and (ii) the influence of the regression function \( \Gamma \). First, we study the effect of restricting the set of source triplets for computing the visual phrase embedding of the unseen triplet. This corresponds to restricting the set of source triplets \( N_s \) in Equation 10 in the main paper. More precisely, for an unseen triplet \( t' = (s', p', o') \) we : (1) restrict the source triplet \( t \) to only differ by the object \( t = (s', p', o) \), (2) restrict the source triplet \( t \) to differ only by predicate \( t = (s', p, o') \), or (3) apply no restriction, i.e. \( t = (s', p, o) \). Please note that the subject is always a “person” on the HICO-DET dataset, thus remains the same.

Second, we evaluate the transfer by analogy without the transformation \( \Gamma \) (first row of Table 6) and with transformation (second row of Table 6). Results of these ablations show that we can already transfer reasonably well from source triplets involving the same object but different predicate (AP of 27.39 compared to 27.93). This could be attributed to the fact that in HICO-DET several predicates often describe similar interactions (e.g. “carry” and “hold” or “pet”, “hug”, “kiss”), and some of these similar predicates appear in the source and some in the target set. Using the transformation \( \Gamma \) provides only a slight improvement for the transfer from a similar predicate when the object is the same. However, the importance of transformation \( \Gamma \) is clear when transferring from triplets that involve a different object. Here using transformation \( \Gamma \) significantly improves the final result (mAP of 22.61 without \( \Gamma \) compared to 28.01 when using \( \Gamma \)). Note that here the model sampling only among source triplets involving the same predicate \( t = (s', p', o) \) with \( \Gamma \) is slightly better than the complete model \( t = (s', p, o) \) with \( \Gamma \) due to the fact that these ablation studies are carried on test set, while the best source triplets sampling strategy is automatically selected to optimize the performance on the validation set.

**Choice of source triplets: qualitative study.** In Figure 8, we illustrate transfer by analogy described in Section 3.2 of the main paper. For this, we show an unseen query triplet (Q), here “person hug dog”, and perform retrieval with visual phrase embeddings obtained using two different source triplets (S). First, “person hug sheep”, differs by change of object (“sheep” to “dog”). Then, “person kiss dog” differs by change of predicate (“kiss” to “hug”). In the first row ‘without \( \Gamma \)’, we show the top detections when using directly the visual phrase embedding of the source triplet. This is equivalent to taking \( \Gamma = 0 \). In the second row ‘with \( \Gamma \)’, we perform the analogy transformation of the visual phrase embedding of the source triplet to account for the change of object or predicate. Our observations qualitatively confirm the numerical results in Table 6: the effect of the transformation by analogy \( \Gamma \) is especially visible on the source triplets that differ by the change of object (more positives among the top 4 detections). Thanks to the analogy transformation, it is possible to transfer the visual phrase embedding of a source triplet to a target triplet involving a different object.

**D. Visualizing joint embedding spaces**

Here, we provide additional insights about the embedding spaces learnt on the HICO-DET dataset using the t-sne visualization [32] of the final learnt joint embedding. Finally, we also show that our model can retrieve queries involving out-of-vocabulary predicates.

**T-sne visualization.** First, we show t-sne visualization [32] of the joint embedding spaces learnt for objects and predicates to better understand which concepts are close in these spaces. For the object embedding, as shown in Figure 9, objects are grouped according to their visual and semantic similarity. The same holds for predicate embeddings shown in Figure 10. Learning good embedding for unigrams is crucial in our model that uses the transfer by analogy, as unigram embeddings directly influence the analogy transformation from the seen visual phrases to the unseen ones.

**Retrieval of unseen predicates.** Finally, our model, without further modification, enables retrieval of unseen queries involving unseen predicates, that is predicates that have not been observed during the training stage. This is possible thanks to the use of pre-trained word embeddings for the individual terms of the triplet. This pre-trained word embedding contains already some semantic information about the predicates. For a few manually chosen unseen queries, we show in Figure 11 the top detections returned by our model \((s+o+p+vp \text{ transfer})\) trained on HICO-DET. We obtain relevant retrieval results for unseen queries that are close to some of the training triplets (e.g. “person cuddle bird”, “person cuddle elephant”). When the meaning of the triplet is more ambiguous (e.g. “person educate dog”), the detections are not as easily interpretable.
|                                | p   | p+vp | p+vp (transfer) | recall |
|--------------------------------|-----|------|-----------------|--------|
| building - has - wheel         | 17.8| 21.3 | 23.7            | 67.4   |
| cat - ride - skateboard        | 60.6| 62.6 | 63.0            | 69.2   |
| cat - wear - tie               | 53.7| 55.6 | 55.6            | 55.6   |
| dog - drive - car              | 7.1 | 3.6  | 3.6             | 7.1    |
| dog - pull - horse             | 4.0 | 4.0  | 4.0             | 50.0   |
| dog - pull - person            | 7.2 | 9.9  | 10.2            | 73.8   |
| dog - rest on - person         | 5.3 | 3.8  | 3.6             | 64.7   |
| dog - ride - bike              | 59.0| 58.4 | 58.1            | 72.2   |
| dog - ride - dog               | 2.9 | 3.6  | 3.7             | 50.0   |
| dog - ride - horse             | 17.7| 23.1 | 21.2            | 47.1   |
| dog - ride - motorcycle        | 22.8| 24.9 | 24.9            | 31.3   |
| dog - ride - person            | 26.2| 31.4 | 31.6            | 85.0   |
| dog - wear - hat               | 0.5 | 0.7  | 0.8             | 6.7    |
| dog - wear - helmet            | 23.8| 28.6 | 28.6            | 42.9   |
| dog - wear - pants             | 6.7 | 6.4  | 6.4             | 36.4   |
| dog - wear - shirt             | 7.6 | 2.1  | 1.9             | 20.0   |
| dog - wear - shoes             | 4.2 | 2.3  | 2.0             | 38.9   |
| dog - wear - sunglasses        | 11.4| 11.4 | 11.4            | 11.4   |
| dog - wear - tie               | 41.9| 45.9 | 47.4            | 61.5   |
| elephant - cover - car         | 33.3| 29.3 | 28.8            | 60.0   |
| elephant - ride - bike         | 43.8| 43.8 | 43.8            | 50.0   |
| elephant - sleep on - person   | 7.0 | 7.1  | 7.6             | 75.0   |
| elephant - wear - glasses      | 0.0 | 0.0  | 0.0             | 0.0    |
| elephant - wear - hat          | 5.0 | 13.1 | 13.3            | 30.0   |
| elephant - wear - pants        | 19.1| 19.6 | 19.4            | 66.7   |
| person - carry - bed           | 2.8 | 3.3  | 3.4             | 25.0   |
| person - carry - chair         | 3.3 | 3.6  | 3.7             | 23.5   |
| person - hold - car            | 24.1| 24.5 | 26.2            | 60.5   |
| person - hold - plane          | 0.3 | 0.9  | 0.9             | 2.7    |
| person - hold - shoes          | 0.6 | 1.1  | 1.1             | 14.3   |
| person - pull - boat           | 25.6| 25.3 | 24.4            | 66.7   |
| person - ride - dog            | 42.4| 30.2 | 29.1            | 80.0   |
| person - ride - giraffe        | 24.9| 22.2 | 21.1            | 31.6   |
| person - ride - suitcase       | 23.1| 28.4 | 28.2            | 54.6   |
| person - ride - train          | 18.8| 17.7 | 17.5            | 25.0   |
| person - stand on - bench      | 15.2| 17.2 | 16.6            | 40.0   |
| person - stand on - car        | 9.9 | 13.3 | 13.4            | 57.9   |
| person - stand on - horse      | 27.8| 34.5 | 35.4            | 88.2   |
| person - wear - cone           | 0.0 | 0.0  | 0.0             | 0.0    |
| truck - carry - elephant       | 56.1| 44.9 | 45.4            | 58.3   |
| umbrella - cover - dog         | 42.4| 46.4 | 46.4            | 52.9   |

平均值 19.7 20.1 20.2 53.8

Table 7: AP per triplet for UnRel queries involving an action. AP is computed with the union setup and IoU=0.3 similar to Table 3 in the main paper.
Figure 6: Retrieval on HICO-DET dataset. Top retrieved positives (green) and negatives (red) using our model (+s+o+p+vp transfer) for unseen triplet queries. The query is marked as (Q). The source triplets automatically selected by our model are marked as (S). For instance, for the query triplet “person throw frisbee” (first row), our model selects (1) a source triplet that involves the same action, with a different, but similar, object “person throw sports ball” and (2) two other source triplets with the same object, and different, but related, actions “person catch frisbee”, “person block frisbee”. The top false positives show the two main failure modes: (1) the interacting object has a wrong category (e.g. the door of a bus is mistaken with a “surfboard” in row 2, a “cow” is mistaken for a “dog” in row 4, or a “dog” is confused with “sheep” in row 6), (2) the interaction is confused with another similar interaction (e.g. ‘inspect” is confused with “wash” in row 3 or “pick up” is confused with “hold” in last row).
Figure 7: Querying for unusual triplets on the UnRel dataset. Examples of retrieval using our complete model (s+o+p+vp transfer). The query triplet is marked as (Q). The source triplets (S) seen in training are automatically selected by our model described in 3.2 and used to transfer the visual phrase embedding using the analogy transformation. The automatically selected source triplets all appear relevant. Our method selects source triplets involving (1) a different subject (“dog ride bike” is transferred from “person ride bike”, “building has wheel” is transferred from “bike has wheel”), (2) different object (“person stand on horse” is transferred from “person stand on sand”), or (3) different predicate (“person ride train” is transferred from “person drive train”). Note that there is only a single positive in the last row, as detection of objects in unusual situations (here pants on an elephant) remains a difficult problem.
Figure 8: **Influence of the choice of the source triplet.** Top retrieved results for query (Q) “person hug dog” with our model (s+o+vp transfer). Here, we qualitatively illustrate the influence of the source triplet (S) and the analogy transformation $\Gamma$. First, “person hug sheep”, differs by change of object (“sheep” to “dog”). Then, “person kiss dog” differs by change of predicate (“kiss” to “hug”). For each example, in the first row 'without $\Gamma$', we show the top detections when using directly the visual phrase embedding of the source triplet. In the second row ’with $\Gamma$’, we perform the analogy transformation of the visual phrase embedding of the source triplet to account for the change of object or predicate. This visualization confirms quantitative results in Section C showing that the analogy transformation $\Gamma$ is especially beneficial when using source triplets that differ by the change of object.
Figure 9: Object embedding visualized using T-sne [32]. Objects appear to be grouped according to their visual and semantic similarity. For example, we highlight regions corresponding to: (A) sport instruments (e.g. “tennis racket”, “frisbee”), (B) big transportation (e.g. “bus”, “train”), (C) eating instruments (e.g. “fork”, “cup”), (D) food (e.g. “pizza”, apple”), (E) animals (e.g. “giraffe”, “bird”). Learning a good embedding for unigrams (here objects) is crucial in our model that uses the transfer by analogy, as unigram embeddings directly influence the analogy transformation from the seen visual phrases to the unseen ones.
Figure 10: Predicate embedding visualized with T-sne [32]. The predicates are grouped according to their visual and semantic similarity. For example, we highlight regions corresponding to: (A) interactions related to sports (e.g. “throw”, “dribble”), (B) gentle interactions with animal/person (e.g. “hug”, “kiss”), (C) interactions with big transportation (e.g. “board”, “exit”), (D) interactions with (electronic) devices (e.g. “text on”, “read”), (E) interactions with food (e.g. “smell”, “lick”). Learning a good embedding for unigrams (here predicates) is crucial in our model that uses transfer by analogy, as unigram embeddings directly influence the analogy transformation from the seen visual phrases to the unseen ones.
Figure 11: **Retrieval using out-of-vocabulary predicates.** Retrieval of unseen triplet queries (Q) involving out-of-vocabulary predicates using our model (s+o+p+vp transfer) trained on HICO-DET. Because we are using pre-trained language embedding for predicates, it is possible to query images with predicates that have not been in the vocabulary of training predicates (though they were seen when pre-training the language model). These results are only qualitative, as these unseen relations are not annotated in HICO-DET. We obtain relevant retrieval results for unseen queries that are close to some of the training triplets (e.g. “person cuddle bird”, “person cuddle elephant”). When the meaning of the triplet is more ambiguous (e.g. “person educate dog”), the detections are not as easily interpretable.