

Phrase Localization and Visual Relationship Detection with Comprehensive Image-Language Cues

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Abstract

This paper presents a framework for localization or grounding of phrases in images using a large collection of linguistic and visual cues. We model the appearance, size, and position of entity bounding boxes, adjectives that contain attribute information, and spatial relationships between pairs of entities connected by verbs or prepositions. Special attention is given to relationships between people and clothing or body part mentions, as they are useful for distinguishing individuals. We automatically learn weights for combining these cues and at test time, perform joint inference over all phrases in a caption. The resulting system produces state of the art performance on phrase localization on the Flickr30k Entities dataset [33] and visual relationship detection on the Stanford VRD dataset [27].¹

1. Introduction

Today's deep features can give reliable signals about a broad range of content in natural images, leading to advances in image-language tasks such as automatic captioning [6, 14, 16, 17, 42] and visual question answering [1, 8, 44]. A basic building block for such tasks is localization or grounding of individual phrases [6, 16, 17, 28, 33, 40, 42]. A number of datasets with phrase grounding information have been released, including Flickr30k Entities [33], ReferIt [18], Google Referring Expressions [29], and Visual Genome [21]. However, grounding remains challenging due to open-ended vocabularies, highly unbalanced training data, prevalence of hard-to-localize entities like clothing and body parts, as well as the subtlety and variety of linguistic cues that can be used for localization.

The goal of this paper is to accurately localize a bounding box for each entity (noun phrase) mentioned in a caption for a particular test image. We propose a joint localization objective for this task using a learned combination of single-phrase and phrase-pair cues. Evaluation is performed on the

Cues	Examples
1) Entities	man, baby, umbrella, woman, jacket
2) Candidate Box Position	—
3) Candidate Box Size	—
4) Common Object Detectors	man → person baby → person woman → person
5) Adjectives	umbrella → red umbrella → blue jacket → red
6) Subject - Verb	(man, carries)
7) Verb - Object	(carries, baby)
8) Verbs	(man, carries, baby)
9) Prepositions	(baby, under, umbrella) (man, next to, woman)
10) Clothing & Body Parts	(woman, in, jacket)

Figure 1: Left: an image and caption, together with ground truth bounding boxes of entities (noun phrases). Right: a list of all the cues used by our system, with corresponding phrases from the sentence.

challenging recent Flickr30K Entities dataset [33], which provides ground truth bounding boxes for each entity in the five captions of the original Flickr30K dataset [43].

Figure 1 introduces the components of our system using an example image and caption. Given a noun phrase extracted from the caption, e.g., *red and blue umbrella*, we obtain single-phrase cue scores for each candidate box based on appearance (modeled with a phrase-region embedding as well as object detectors for common classes), size, position, and attributes (adjectives). If a pair of entities is connected by a verb (*man carries a baby*) or a preposition (*woman in a red jacket*), we also score the pair of corresponding candidate boxes using a spatial model. In addition, actions may modify the appearance of either the subject or the object (e.g., a man carrying a baby has a characteristic appearance, as does a baby being carried). To account for this, we learn subject-verb and verb-object appearance models for the constituent entities. We give special treatment to relationships between people, clothing, and body parts, as these are commonly used for describing individuals, and are also among the hardest entities for existing approaches to localize. To extract as complete a set of relationships as possible, we use natural language processing (NLP) tools to resolve pronoun references within a sentence: e.g., by analyzing the

¹Code: <https://github.com/BryanPlummer/pl-clc>

Method	Single Phrase Cues						Phrase-Pair Spatial Cues		Inference
	Phrase-Region Compatibility	Candidate Position	Candidate Size	Object Detectors	Adjectives	Verbs	Relative Position	Clothing & Body Parts	Joint Localization
Ours	✓	✓	✓	✓*	✓	✓	✓	✓	✓
(a) NonlinearSP [40]	✓	—	—	—	—	—	—	—	—
GroundeR [34]	✓	—	—	—	—	—	—	—	—
MCB [8]	✓	—	—	—	—	—	—	—	—
SCRC [12]	✓	✓	—	—	—	—	—	—	—
SMPL [41]	✓	—	—	—	—	✓*	—	✓	✓
RtP [33]	✓	—	✓	✓*	✓*	—	—	—	—
(b) Scene Graph [15]	—	—	—	✓	✓	—	✓	—	✓
ReferIt [18]	—	✓	✓	✓	✓*	—	✓	—	—
Google RefExp [29]	✓	✓	✓	—	—	—	—	—	—

Table 1: Comparison of cues for phrase-to-region grounding. **(a)** Models applied to phrase localization on Flickr30K Entities. **(b)** Models on related tasks.

* indicates that the cue is used in a limited fashion, i.e. [18, 33] restricted their adjective cues to colors, [41] only modeled possessive pronoun phrase-pair spatial cues ignoring verb and prepositional phrases, [33] and we limit the object detectors to 20 common categories.

sentence *A man puts his hand around a woman*, we can determine that the hand belongs to the man and introduce the respective pairwise term into our objective.

Table 1 compares the cues used in our work to those in other recent papers on phrase localization and related tasks like image retrieval and referring expression understanding. To date, other methods applied to the Flickr30K Entities dataset [8, 12, 34, 40, 41] have used a limited set of single-phrase cues. Information from the rest of the caption, like verbs and prepositions indicating spatial relationships, has been ignored. One exception is Wang *et al.* [41], who tried to relate multiple phrases to each other, but limited their relationships only to those indicated by possessive pronouns, not personal ones. By contrast, we use pronoun cues to the full extent by performing pronominal coreference. Also, ours is the only work in this area incorporating the visual aspect of verbs. Our formulation is most similar to that of [33], but with a larger set of cues, learned combination weights, and a global optimization method for simultaneously localizing all the phrases in a sentence.

In addition to our experiments on phrase localization, we also adapt our method to the recently introduced task of visual relationship detection (VRD) on the Stanford VRD dataset [27]. Given a test image, the goal of VRD is to detect all entities and relationships present and output them in the form (*subject, predicate, object*) with the corresponding bounding boxes. By contrast with phrase localization, where we are given a set of entities and relationships that are in the image, in VRD we do not know *a priori* which objects or relationships might be present. On this task, our model shows significant performance gains over prior work, with especially acute differences in zero-shot detection due to modeling cues with a vision-language embedding. This adaptability to never-before-seen examples is also a notable distinction between our approach and prior methods on related tasks (e.g. [7, 15, 18, 20]), which typically train their models on a set of predefined object categories, providing no support for out-of-vocabulary entities.

Section 2 discusses our global objective function for simultaneously localizing all phrases from the sentence and describes the procedure for learning combination weights. Section 3.1 details how we parse sentences to extract entities, relationships, and other relevant linguistic cues. Sections 3.2 and 3.3 define single-phrase and phrase-pair cost functions between linguistic and visual cues. Section 4 presents an in-depth evaluation of our cues on Flickr30K Entities [33]. Lastly, Section 5 presents the adaptation of our method to the VRD task [27].

2. Phrase localization approach

We follow the task definition used in [8, 12, 33, 34, 40, 41]: At test time, we are given an image and a caption with a set of entities (noun phrases), and we need to localize each entity with a bounding box. Section 2.1 describes our inference formulation, and Section 2.2 describes our procedure for learning the weights of different cues.

2.1. Joint phrase localization

For each image-language cue derived from a single phrase or a pair of phrases (Figure 1), we define a *cue-specific cost function* that measures its compatibility with an image region (small values indicate high compatibility). We will describe the cost functions in detail in Section 3; here, we give our test-time optimization framework for jointly localizing all phrases from a sentence.

Given a single phrase p from a test sentence, we score each region (bounding box) proposal b from the test image based on a linear combination of cue-specific cost functions $\phi_{\{1, \dots, K_S\}}(p, b)$ with learned weights w^S :

$$S(p, b; w^S) = \sum_{s=1}^{K_S} \mathbb{1}_s(p) \phi_s(p, b) w_s^S, \quad (1)$$

where $\mathbb{1}_s(p)$ is an indicator function for the availability of cue s for phrase p (e.g., an adjective cue would be available for the phrase *blue socks*, but would be unavailable for

socks by itself). As will be described in Section 3.2, we use 14 single-phrase cost functions: region-phrase compatibility score, phrase position, phrase size (one for each of the eight phrase types of [33]), object detector score, adjective, subject-verb, and verb-object scores.

For a pair of phrases with some relationship $r = (p, rel, p')$ and candidate regions b and b' , an analogous scoring function is given by a weighted combination of pairwise costs $\psi_{\{1, \dots, K_Q\}}(r, b, b')$:

$$Q(r, b, b'; w^Q) = \sum_{q=1}^{K_Q} \mathbb{1}_q(r) \psi_q(r, b, b') w_q^Q. \quad (2)$$

We use three pairwise cost functions corresponding to spatial classifiers for verb, preposition, and clothing and body parts relationships (Section 3.3).

We train all cue-specific cost functions on the training set and the combination weights on the validation set. At test time, given an image and a list of phrases $\{p_1, \dots, p_N\}$, we first retrieve top M candidate boxes for each phrase p_i using Eq. (1). Our goal is then to select one bounding box b_i out of the M candidates per each phrase p_i such that the following objective is minimized:

$$\min_{b_1, \dots, b_N} \left\{ \sum_{p_i} S(p_i, b_i) + \sum_{r_{ij}=(p_i, rel_{ij}, p_j)} Q(r_{ij}, b_i, b_j) \right\} \quad (3)$$

where phrases p_i and p_j (and respective boxes b_i and b_j) are related by some relationship rel_{ij} . This is a binary quadratic programming formulation inspired by [38]; we relax and solve it using a sequential QP solver in MATLAB. The solution gives a single bounding box hypothesis for each phrase. Performance is evaluated using Recall@1, or proportion of phrases where the selected box has Intersection-over-Union (IOU) ≥ 0.5 with the ground truth.

2.2. Learning scoring function weights

We learn the weights w^S and w^Q in Eqs. (1) and (2) by directly optimizing recall on the validation set. We start by finding the unary weights w^S that maximize the number of correctly localized phrases:

$$w^S = \arg \max_w \sum_{i=1}^N \mathbb{1}_{IOU \geq 0.5}(b_i^*, \hat{b}(p_i; w)), \quad (4)$$

where N is the number of phrases in the training set, $\mathbb{1}_{IOU \geq 0.5}$ is an indicator function returning 1 if the two boxes have IOU ≥ 0.5 , b_i^* is the ground truth bounding box for phrase p_i , $\hat{b}(p; w)$ returns the most likely box candidate for phrase p under the current weights, or, more formally, given a set of candidate boxes \mathcal{B} ,

$$\hat{b}(p; w) = \min_{b \in \mathcal{B}} S(p, b; w). \quad (5)$$

We optimize Eq. (4) using a derivative-free direct search method [22] (MATLAB’s fminsearch). We randomly initialize the weights, keep the best weights after 20 runs based on validation set performance (takes just a few minutes to learn weights for all single phrase cues in our experiments).

Next, we fix w^S and learn the weights w^Q over phrase-pair cues in the validation set. To this end, we formulate an objective analogous to Eq. (4) for maximizing the number of correctly localized region pairs. Similar to Eq. (5), we define the function $\hat{\rho}(r; w)$ to return the best pair of boxes for the relationship $r = (p, rel, p')$:

$$\hat{\rho}(r; w) = \min_{b, b' \in \mathcal{B}} S(p, b; w^S) + S(p', b'; w^S) + Q(r, b, b'; w). \quad (6)$$

Then our pairwise objective function is

$$w^Q = \arg \max_w \sum_{k=1}^M \mathbb{1}_{PairIOU \geq 0.5}(\rho_k^*, \hat{\rho}(r_k; w)), \quad (7)$$

where M is the number of phrase pairs with a relationship, $\mathbb{1}_{PairIOU \geq 0.5}$ returns the number of correctly localized boxes (0, 1, or 2), and ρ_k^* is the ground truth box pair for the relationship $r_k = (p_k, rel_k, p'_k)$.

Note that we also attempted to learn the weights w^S and w^Q using standard approaches such as rank-SVM [13], but found our proposed direct search formulation to work better. In phrase localization, due to its Recall@1 evaluation criterion, only the correctness of one best-scoring candidate region for each phrase matters, unlike in typical detection scenarios, where one would like all positive examples to have better scores than all negative examples. The VRD task of Section 5 is a more conventional detection task, so there we found rank-SVM to be more appropriate.

3. Cues for phrase-region grounding

Section 3.1 describes how we extract linguistic cues from sentences. Sections 3.2 and 3.3 give our definitions of the two types of cost functions used in Eqs. (1) and (2): single phrase cues (SPC) measure the compatibility of a given phrase with a candidate bounding box, and phrase pair cues (PPC) ensure that pairs of related phrases are localized in a spatially coherent manner.

3.1. Extracting linguistic cues from captions

The Flickr30k Entities dataset provides annotations for Noun Phrase (NP) chunks corresponding to entities, but linguistic cues corresponding to adjectives, verbs, and prepositions must be extracted from the captions using NLP tools. Once these cues are extracted, they will be translated into visually relevant constraints for grounding. In particular, we will learn specialized detectors for adjectives, subject-verb, and verb-object relationships (Section 3.2). Also, because pairs of entities connected by a verb or preposition

have constrained layout, we will train classifiers to score pairs of boxes based on spatial information (Section 3.3).

Adjectives are part of NP chunks so identifying them is trivial. To extract other cues, such as verbs and prepositions that may indicate actions and spatial relationships, we obtain a constituent parse tree for each sentence using the Stanford parser [37]. Then, for possible relational phrases (prepositional and verb phrases), we use the method of Fidler *et al.* [7], where we start at the relational phrase and then traverse up the tree and to the left until we reach a noun phrase node, which will correspond to the first entity in an (*entity1, rel, entity2*) tuple. The second entity is given by the first noun phrase node on the right side of the relational phrase in the parse tree. For example, given the sentence *A boy running in a field with a dog*, the extracted NP chunks would be *a boy, a field, a dog*. The relational phrases would be *(a boy, running in, a field)* and *(a boy, with, a dog)*.

Notice that a single relational phrase can give rise to multiple relationship cues. Thus, from *(a boy, running in, a field)*, we extract the verb relation (*boy, running, field*) and prepositional relation (*boy, in, field*). An exception to this is a relational phrase where the first entity is a person and the second one is of the clothing or body part type,² e.g., *(a boy, running in, a jacket)*. For this case, we create a single special pairwise relation (*boy, jacket*) that assumes that the second entity is attached to the first one and the exact relationship words do not matter, i.e., *(a boy, running in, a jacket)* and *(a boy, wearing, a jacket)* are considered to be the same. The attachment assumption can fail for phrases like *(a boy, looking at, a jacket)*, but such cases are rare.

Finally, since pronouns in Flickr30k Entities are not annotated, we attempt to perform pronominal coreference (i.e., creating a link between a pronoun and the phrase it refers to) in order to extract a more complete set of cues. As an example, given the sentence *Ducks feed themselves*, initially we can only extract the subject-verb cue (*ducks, feed*), but we don't know who or what they are feeding. Pronominal coreference resolution tells us that the ducks are themselves eating and not, say, feeding ducklings. We use a simple rule-based method similar to knowledge-poor methods [11, 31]. Given lists of pronouns by type,³ our rules attach each pronoun with at most one non-pronominal mention that occurs earlier in the sentence (an antecedent). We assume that subject and object pronouns often refer to the main subject (e.g. *[A dog] laying on the ground looks up at the dog standing over [him]*), reflexive and reciprocal pronouns refer to the nearest antecedent (e.g. *[A tennis player] readies [herself]*), and indefinite pronouns do not refer to a previously described entity. It must be noted that

²Each NP chunk from the Flickr30K dataset is classified into one of eight phrase types based on the dictionaries of [33].

³Relevant pronoun types are subject, object, reflexive, reciprocal, relative, and indefinite.

compared with verb and prepositional relationships, relatively few additional cues are extracted using this procedure (432 pronoun relationships in the test set and 13,163 in the train set, while the counts for the other relationships are on the order of 10K and 300K).

3.2. Single Phrase Cues (SPCs)

Region-phrase compatibility: This is the most basic cue relating phrases to image regions based on appearance. It is applied to every test phrase (i.e., its indicator function in Eq. (1) is always 1). Given phrase p and region b , the cost $\phi_{CCA}(p, b)$ is given by the cosine distance between p and b in a joint embedding space learned using normalized Canonical Correlation Analysis (CCA) [10]. We use the same procedure as [33]. Regions are represented by the fc7 activations of a Fast-RCNN model [9] fine-tuned using the union of the PASCAL 2007 and 2012 trainval sets [5]. After removing stopwords, phrases are represented by the HGLMM fisher vector encoding [19] of word2vec [30].

Candidate position: The location of a bounding box in an image has been shown to be predictive of the kinds of phrases it may refer to [4, 12, 18, 23]. We learn location models for each of the eight broad phrase types specified in [33]: people, clothing, body parts, vehicles, animals, scenes, and a catch-all “other.” We represent a bounding box by its centroid normalized by the image size, the percentage of the image covered by the box, and its aspect ratio, resulting in a 4-dim. feature vector. We then train a support vector machine (SVM) with a radial basis function (RBF) kernel using LIBSVM [2]. We randomly sample EdgeBox [46] proposals with $IOU < 0.5$ with the ground truth boxes for negative examples. Our scoring function is

$$\phi_{pos}(p, b) = -\log(\text{SVM}_{type(p)}(b)),$$

where $\text{SVM}_{type(p)}$ returns the probability that box b is of the phrase type $type(p)$ (we use Platt scaling [32] to convert the SVM output to a probability).

Candidate size: People have a bias towards describing larger, more salient objects, leading prior work to consider the size of a candidate box in their models [7, 18, 33]. We follow the procedure of [33], so that given a box b with dimensions normalized by the image size, we have

$$\phi_{size_{type(p)}}(p, b) = 1 - b_{width} \times b_{height}.$$

Unlike phrase position, this cost function does not use a trained SVM per phrase type. Instead, each phrase type is its own feature and the corresponding indicator function returns 1 if that phrase belongs to the associated type.

Detectors: CCA embeddings are limited in their ability to localize objects because they must account for a wide range of phrases and because they do not use negative examples

during training. To compensate for this, we use Fast R-CNN [9] to learn three networks for common object categories, attributes, and actions. Once a detector is trained, its score for a region proposal b is

$$\phi_{det}(p, b) = -\log(\text{softmax}_{det}(p, b)),$$

where $\text{softmax}_{det}(p, b)$ returns the output of the softmax layer for the object class corresponding to p . We manually create dictionaries to map phrases to detector categories (e.g., man, woman, *etc.* map to ‘person’), and the indicator function for each detector returns 1 only if one of the words in the phrase exists in its dictionary. If multiple detectors for a single cue type are appropriate for a phrase (e.g., *a black and white shirt* would have two adjective detectors fire, one for each color), the scores are averaged. Below, we describe the three detector networks used in our model. Complete dictionaries can be found in Appendix B.

Objects: We use the dictionary of [33] to map nouns to the 20 PASCAL object categories [5] and fine-tune the network on the union of the PASCAL VOC 2007 and 2012 trainval sets. At test time, when we run a detector for a phrase that maps to one of these object categories, we also use bounding box regression to refine the original region proposals. Regression is not used for the other networks below.

Adjectives: Adjectives found in phrases, especially color, provide valuable attribute information for localization [7, 15, 18, 33]. The Flickr30K Entities baseline approach [33] used a network trained for 11 colors. As a generalization of that, we create a list of adjectives that occur at least 100 times in the training set of Flickr30k. After grouping together similar words and filtering out non-visual terms (e.g., *adventurous*), we are left with a dictionary of 83 adjectives. As in [33], we consider color terms describing people (*black man*, *white girl*) to be separate categories.

Subject-Verb and Verb-Object: Verbs can modify the appearance of both the subject and the object in a relation. For example, knowing that a person is riding a horse can give us better appearance models for finding both the person and the horse [35, 36]. As we did with adjectives, we collect verbs that occur at least 100 times in the training set, group together similar words, and filter out those that don’t have a clear visual aspect, resulting in a dictionary of 58 verbs. Since a person running looks different than a dog running, we subdivide our verb categories by phrase type of the subject (resp. object) if that phrase type occurs with the verb at least 30 times in the train set. For example, if there are enough animal-running occurrences, we create a new category with instances of all animals running. For the remaining phrases, we train a catch-all detector over all the phrases related to that verb. Following [35], we train separate detectors for subject-verb and verb-object relationships, resulting in dictionary sizes of 191 (resp. 225). We also attempted to

learn subject-verb-object detectors as in [35, 36], but did not see a further improvement.

3.3. Phrase-Pair Cues (PPCs)

So far, we have discussed cues pertaining to a single phrase, but relationships between pairs of phrases can also provide cues about their relative position. We denote such relationships as tuples $(p_{left}, rel, p_{right})$ with $left$, $right$ indicating on which side of the relationship the phrases occur. As discussed in Section 3.1, we consider three distinct types of relationships: verbs (*man, riding, horse*), prepositions (*man, on, horse*), and clothing and body parts (*man, wearing, hat*). For each of the three relationship types, we group phrases referring to people but treat all other phrases as distinct, and then gather all relationships that occur at least 30 times in the training set. Then we learn a spatial relationship model as follows. Given a pair of boxes with coordinates $b = (x, y, w, h)$ and $b' = (x', y', w', h')$, we compute a four-dim. feature

$$[(x - x')/w, (y - y')/h, w'/w, h'/h], \quad (8)$$

and concatenate it with combined SPC scores $S(p_{left}, b)$, $S(p_{right}, b')$ from Eq. (1). To obtain negative examples, we randomly sample from other box pairings with $\text{IOU} < 0.5$ with the ground truth regions from that image. We train an RBF SVM classifier with Platt scaling [32] to obtain a probability output. This is similar to the method of [15], but rather than learning a Gaussian Mixture Model using only positive data, we learn a more discriminative model. Below are details on the three types of relationship classifiers. Complete dictionaries can be found in Appendix C.

Verbs: Starting with our dictionary of 58 verb detectors and following the above procedure of identifying all relationships that occur at least 30 times in the training set, we end up with 260 $(p_{left}, rel_{verb}, p_{right})$ SVM classifiers.

Prepositions: We first gather a list of prepositions that occur at least 100 times in the training set, combine similar words, and filter out words that do not indicate a clear spatial relationship. This yields eight prepositions (*in, on, under, behind, across, between, onto, and near*) and 216 $(p_{left}, rel_{prep}, p_{right})$ relationships.

Clothing and body part attachment: We collect $(p_{left}, rel_{c\&bp}, p_{right})$ relationships where the left phrase is always a person and the right phrase is from the clothing or body part type and learn 207 such classifiers. As discussed in Section 3.1, this relationship type takes precedence over any verb or preposition relationships that may also hold between the same phrases.

Method	Accuracy
(a) Single-phrase cues	
CCA	43.09
CCA+Det	45.29
CCA+Det+Size	51.45
CCA+Det+Size+Adj	52.63
CCA+Det+Size+Adj+Verbs	54.51
CCA+Det+Size+Adj+Verbs+Pos (SPC)	55.49
(b) Phrase pair cues	
SPC+Verbs	55.53
SPC+Verbs+Preps	55.62
SPC+Verbs+Preps+C&BP (SPC+PPC)	55.85
(c) State of the art	
SMPL [41]	42.08
NonlinearSP [40]	43.89
GroundeR [34]	47.81
MCB [8]	48.69
RtP [33]	50.89

Table 2: Phrase-region grounding performance on the Flickr30k Entities dataset. (a) Performance of our single-phrase cues (Sec. 3.2). (b) Further improvements by adding our pairwise cues (Sec. 3.3). (c) Accuracies of competing state-of-the-art methods. This comparison excludes concurrent work that was published after our initial submission [3].

4. Experiments on Flickr30k Entities

4.1. Implementation details

We utilize the provided train/test/val split of 29,873 training, 1,000 validation, and 1,000 testing images [33]. Following [33], our region proposals are given by the top 200 EdgeBox [46] proposals per image. At test time, given a sentence and an image, we first use Eq. (1) to find the top 30 candidate regions for each phrase after performing non-maximum suppression using a 0.8 IOU threshold. Restricted to these candidates, we optimize Eq. (2) to find a globally consistent mapping of phrases to regions.

Consistent with [33], we only evaluate localization for phrases with a ground truth bounding box. If multiple bounding boxes are associated with a phrase (e.g., four individual boxes for *four men*), we represent the phrase as the union of its boxes. For each image and phrase in the test set, the predicted box must have at least 0.5 IOU with its ground truth box to be deemed successfully localized. As only a single candidate is selected for each phrase, we report the proportion of correctly localized phrases (i.e. Recall@1).

4.2. Results

Table 2 reports our overall localization accuracy for combinations of cues and compares our performance to the state of the art. Object detectors, reported on the second line of Table 2(a), show a 2% overall gain over the CCA baseline. This includes the gain from the detector score as well as the bounding box regressor trained with the detector in the Fast R-CNN framework [9]. Adding adjective, verb, and size cues improves accuracy by a further 9%. Our last cue in Table 2(a), position, provides an additional 1% improvement.

We can see from Table 2(b) that the spatial cues give only a small overall boost in accuracy on the test set, but that

is due to the relatively small number of phrases to which they apply. In Table 4 we will show that the localization improvement on the affected phrases is much larger.

Table 2(c) compares our performance to the state of the art. The method most similar to ours is our earlier model [33], which we call RtP here. RtP relies on a subset of our single-phrase cues (region-phrase CCA, size, object detectors, and color adjectives), and localizes each phrase separately. The closest version of our current model to RtP is CCA+Det+Size+Adj, which replaces the 11 colors of [33] with our more general model for 83 adjectives, and obtains almost 2% better performance. Our full model is 5% better than RtP. It is also worth noting that a rank-SVM model [13] for learning cue combination weights gave us 8% worse performance than the direct search scheme of Section 2.2.

Table 3 breaks down the comparison by phrase type. Our model has the highest accuracy on most phrase types, with scenes being the most notable exception, for which GroundeR [34] does better. However, GroundeR uses Selective Search proposals [39], which have an upper bound performance that is 7% higher on scene phrases despite using half as many proposals. Although body parts have the lowest localization accuracy at 25.24%, this represents an 8% improvement in accuracy over prior methods. However, only around 62% of body part phrases have a box with high enough IOU with the ground truth, showing a major area of weakness of category-independent proposal methods. Indeed, if we were to augment our EdgeBox region proposals with ground truth boxes, we would get an overall improvement in accuracy of about 9% for the full system.

Since many of the cues apply to a small subset of the phrases, Table 4 details the performance of cues over only the phrases they affect. As a baseline, we compare against the combination of cues available for all phrases: region-phrase CCA, position, and size. To have a consistent set of regions, the baseline also uses improved boxes from bounding box regressors trained along with the object detectors. As a result, the object detectors provide less than 2% gain over the baseline for the phrases on which they are used, suggesting that the regression provides the majority of the gain from CCA to CCA+Det in Table 2. This also confirms that there is significant room for improvement in selecting candidate regions. By contrast, adjective, subject-verb, and verb-object detectors show significant gains, improving over the baseline by 6-7%.

The right side of Table 4 shows the improvement on phrases due to phrase pair cues. Here, we separate the phrases that occur on the left side of the relationship, which corresponds to the subject, from the phrases on the right side. Our results show that the subject, is generally easier to localize. On the other hand, clothing and body parts show up mainly on the right side of relationships and they

	People	Clothing	Body Parts	Animals	Vehicles	Instruments	Scene	Other
#Test	5,656	2,306	523	518	400	162	1,619	3,374
SMPL [41]	57.89	34.61	15.87	55.98	52.25	23.46	34.22	26.23
GroundeR [34]	61.00	38.12	10.33	62.55	68.75	36.42	58.18	29.08
RtP [33]	64.73	46.88	17.21	65.83	68.75	37.65	51.39	31.77
SPC+PPC (ours)	71.69	50.95	25.24	76.25	66.50	35.80	51.51	35.98
Upper Bound	97.72	83.13	61.57	91.89	94.00	82.10	84.37	81.06

Table 3: Comparison of phrase localization performance over phrase types. Upper Bound refers to the proportion of phrases of each type for which there exists a region proposal having at least 0.5 IOU with the ground truth.

Method	Single Phrase Cues (SPC)				Phrase-Pair Cues (PPC)					
	Object Detectors	Adjectives	Subject-Verb	Verb-Object	Verbs		Prepositions		Clothing & Body Parts	
					Left	Right	Left	Right	Left	Right
Baseline	74.25	57.71	69.68	40.70	78.32	51.05	68.97	55.01	81.01	50.72
+Cue	75.78	64.35	75.53	47.62	78.94	51.33	69.74	56.14	82.86	52.23
#Test	4,059	3,809	3,094	2,398	867	858	780	778	1,464	1,591
#Train	114,748	110,415	94,353	71,336	26,254	25,898	23,973	23,903	42,084	45,496

Table 4: Breakdown of performance for individual cues restricted only to test phrases to which they apply. For SPC, Baseline is given by CCA+Position+Size. For PPC, Baseline is the full SPC model. For all comparisons, we use the improved boxes from bounding box regression on top of object detector output. PPC evaluation is split by which side of the relationship the phrases occur on. The bottom two rows show the numbers of affected phrases in the test and training sets. For reference, there are 14.5k visual phrases in the test set and 427k visual phrases in the train set.

tend to be small. It is also less likely that such phrases will have good candidate boxes – recall from Table 3 that body parts have a performance upper bound of only 62%. Although they affect relatively few test phrases, all three of our relationship classifiers show consistent gains over the SPC model. This is encouraging given that many of the relationships that are used on the validation set to learn our model parameters do not occur in the test set (and vice versa).

Figure 2 provides a qualitative comparison of our output with the RtP model [33]. In the first example, the prediction for the dog is improved due to the subject-verb classifier for *dog jumping*. For the second example, pronominal coreference resolution (Section 3.1) links *each other* to *two men*, telling us that not only is a man hitting something, but also that another man is being hit. In the third example, the RtP model is not able to locate the woman’s blue stripes in her hair despite having a model for *blue*. Our adjective detectors take into account *stripes* as well as *blue*, allowing us to correctly localize the phrase, even though we still fail to localize the hair. Since the blue stripes and hair should co-locate, a method for obtaining co-referent entities would further improve performance on such cases. In the last example, the RtP model makes the same incorrect prediction for the two men. However, our spatial relationship between the first man and his gray sweater helps us correctly localize him. We also improve our prediction for the shopping cart.

5. Visual Relationship Detection

In this section, we adapt our framework to the recently introduced Visual Relationship Detection (VRD) benchmark of Lu *et al.* [27]. Given a test image without any text annotations, the task of VRD is to detect all entities and relationships present and output them in the form (*subject*,

predicate, object) with the corresponding bounding boxes. A relationship detection is judged to be correct if it exists in the image and both the subject and object boxes have $\text{IOU} \geq 0.5$ with their respective ground truth. In contrast to phrase grounding, where we are given a set of entities and relationships that are assumed to be in the image, here we do not know *a priori* which objects or relationships might be present. On the other hand, the VRD dataset is easier than Flickr30K Entities in that it has a limited vocabulary of 100 object classes and 70 predicates annotated in 4000 training and 1000 test images.

Given the small fixed class vocabulary, it would seem advantageous to train 100 object detectors on this dataset, as was done by Lu *et al.* [27]. However, the training set is relatively small, the class distribution is unbalanced, and there is no validation set. Thus, we found that training detectors and then relationship models on the same images causes overfitting because the detector scores on the training images are overconfident. We obtain better results by training all appearance models using CCA, which also takes into account semantic similarity between category names and is trivially extendable to previously unseen categories. Here, we use fc7 features from a Fast RCNN model trained on MSCOCO [26] due to the larger range of categories than PASCAL, and word2vec for object and predicate class names. We train the following CCA models:

1. CCA(entity box, entity class name): this is the equivalent to region-phrase CCA in Section 3.2 and is used to score both candidate subject and object boxes.
2. CCA(subject box, [subject class name, predicate class name]): analogous to subject-verb classifiers of Section 3.2. The 300-dimensional word2vec features of subject and predicate class names are concatenated.
3. CCA(object box, [predicate class name, object class

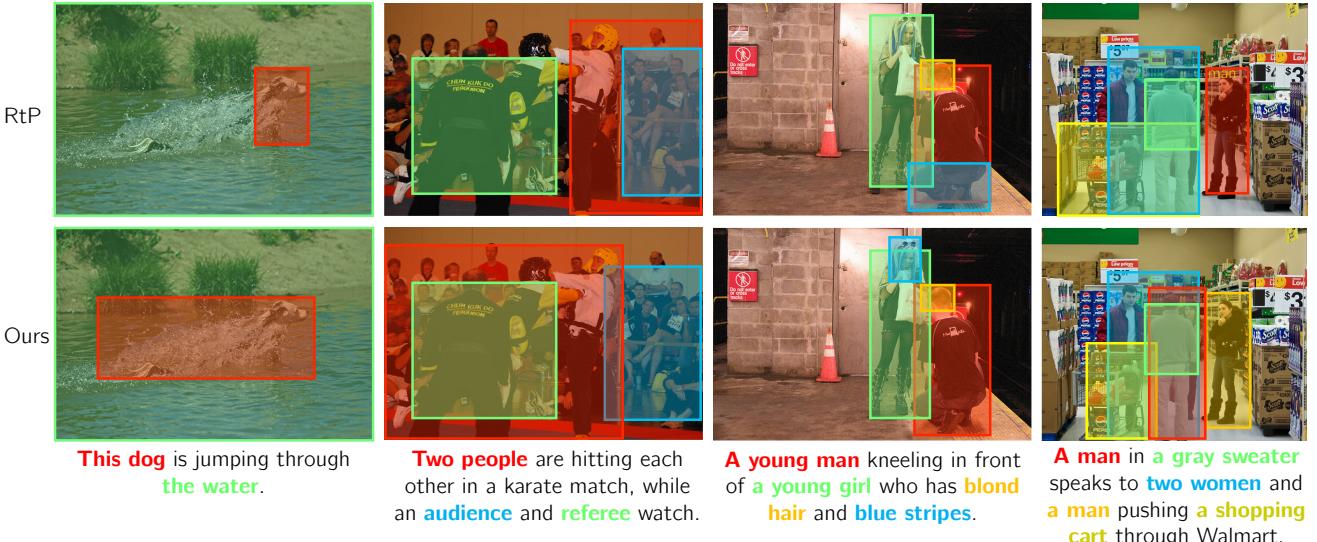


Figure 2: Example results on Flickr30k Entities comparing our SPC+PPC model’s output with the RtP model [33]. See text for discussion.

- name]): analogous to verb-object classifiers of Section 3.2.
4. CCA(union box, predicate class name): this model measures the compatibility between the bounding box of both subject and object and the predicate name.
 5. CCA(union box, [subject class name, predicate class name, object class name]).

Note that models 4 and 5 had no analogue in our phrase localization system. On that task, entities were known to be in the image and relationships simply provided constraints, while here we need to predict which relationships exist. To make predictions for predicates and relationships (which is the goal of models 4 and 5), it helps to see both the subject and object regions. Union box features were also less useful for phrase localization due to the larger vocabularies and relative scarcity of relationships in that task.

Each candidate relationship gets six CCA scores (model 1 above is applied both to the subject and the object). In addition, we compute size and position scores as in Section 3.2 for subject and object, and a score for a pairwise spatial SVM trained to predict the predicate based on the four-dimensional feature of Eq. (8). This yields an 11-dim. feature vector. By contrast with phrase localization, our features for VRD are dense (always available for every relationship).

In Section 2.2 we found feature weights by maximizing our recall metric. Here we have a more conventional detection task, so we obtain better performance by training a linear rank-SVM model [13] to enforce that correctly detected relationships are ranked higher than negative detections (where either box has < 0.5 IOU with the ground truth). We use the test set object detections (just the boxes, not the scores) provided by [27] to directly compare performance with the same candidate regions. During testing,

we produce a score for every ordered pair of detected boxes and all possible predicates, and retain the top 10 predicted relationships per pair of (subject, object) boxes.

Consistent with [27], Table 5 reports recall, $R@\{100, 50\}$, or the portion of correctly localized relationships in the top 100 (resp. 50) ranked relationships in the image. The right side shows performance for relationships that have not been encountered in the training set. Our method clearly outperforms that of Lu *et al.* [27], which uses separate visual, language, and relationship likelihood cues. We also outperform Zhang *et al.* [45], which combines object detectors, visual appearance, and object position in a single neural network. We observe that cues based on object class and relative subject-object position provide a noticeable boost in performance. Further, due to using CCA with multi-modal embeddings, we generalize better to unseen relationships. Qualitative examples and associated discussion can be found in Appendix A.

6. Conclusion

This paper introduced a framework incorporating a comprehensive collection of image- and language-based cues for visual grounding and demonstrated significant gains over the state of the art on two tasks: phrase localization on Flickr30k Entities and relationship detection on the VRD dataset. For the latter task, we got particularly pronounced gains for the zero-shot learning scenario. In future work, we would like to train a single network for combining multiple cues. Doing this in a unified end-to-end fashion is challenging, since one needs to find the right balance between parameter sharing and specialization or fine-tuning required by individual cues. To this end, our work provides a strong baseline and can help to inform future approaches.

Method	Phrase Det.		Rel. Det.		Zero-shot Phrase Det.		Zero-shot Rel. Det.	
	R@100	R@50	R@100	R@50	R@100	R@50	R@100	R@50
(a)	Visual Only Model [27]	2.61	2.24	1.85	1.58	1.12	0.95	0.78
	Visual + Language + Likelihood Model [27]	17.03	16.17	14.70	13.86	3.75	3.36	3.52
	VTTransE [45]	22.42	19.42	15.20	14.07	3.51	2.65	2.14
(b)	CCA	15.36	11.38	13.69	10.08	12.40	7.78	11.12
	CCA + Size	15.85	11.72	14.05	10.36	12.92	8.04	11.46
	CCA + Size + Position	20.70	16.89	18.37	15.08	15.23	10.86	13.43

Table 5: Relationship detection recall at different thresholds (R@{100,50}). CCA refers to the combination of six CCA models (see text). Position refers to the combination of individual box position and pairwise spatial classifiers. This comparison excludes concurrent work that was published after our initial submission [24, 25].

Acknowledgments. This work was partially supported by NSF grants 1053856, 1205627, 1405883, 1302438, and 1563727, Xerox UAC, the Sloan Foundation, and a Google Research Award.

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A. Visualization of detected relationships (VRD Dataset)

Below are some example detections on the VRD test set. Figure 3 shows some of the highly confident and correctly localized detections. We detect different types of relationships - spatial (*post*, *behind*, *car*), (*sky*, *above*, *laptop*), (*laptop*, *on*, *table*), clothing (*person*, *wear*, *hat*), (*person*, *has*, *shorts*), and actions (*person*, *ride*, *skateboard*).

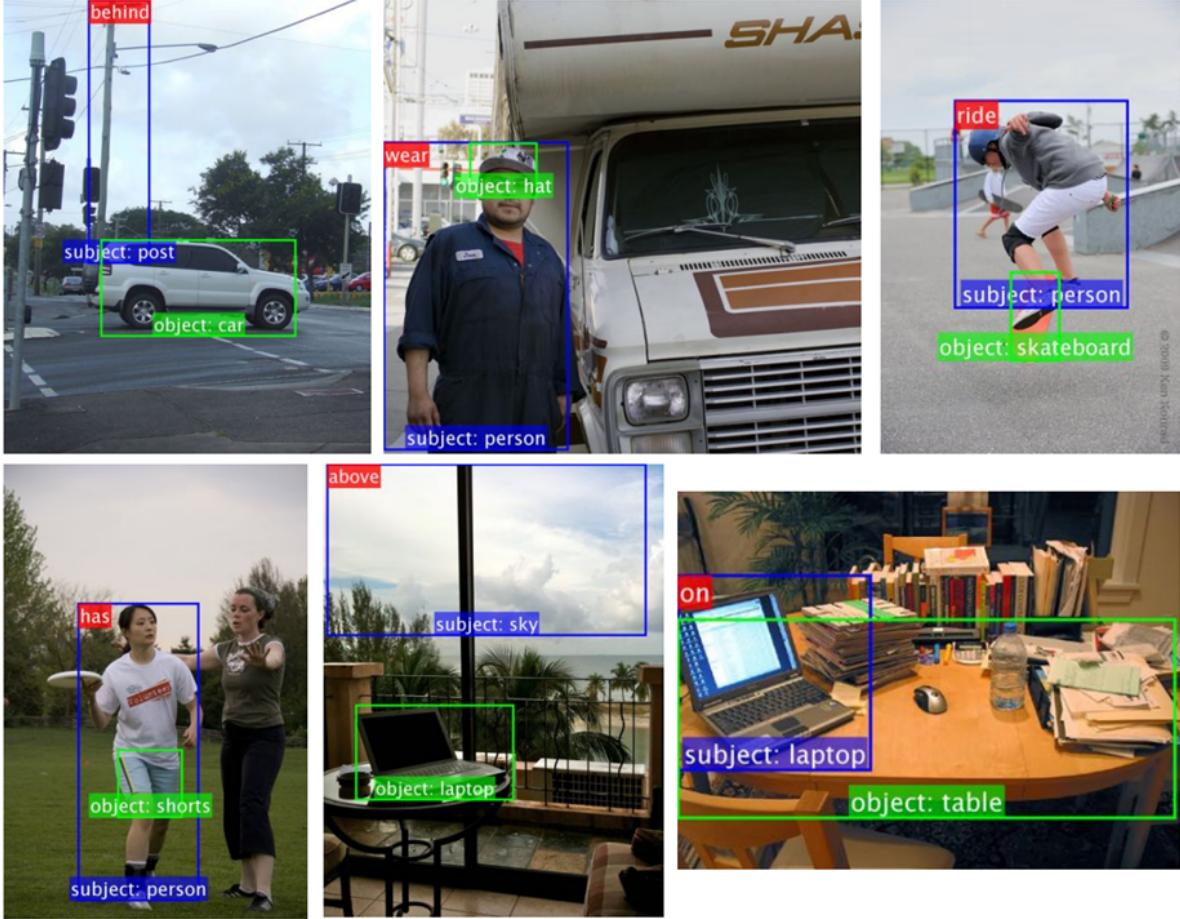


Figure 3: Highly confident and correctly localized relationships on the VRD dataset.

Figure 4 shows detections which were marked as negatives by the evaluation code as these relationships were not annotated in the corresponding images. However, note that these predictions are logically correct. The *mouse* is indeed *next to* the *laptop* (leftmost, first row), and the *laptop* is *under* the *sky* (middle, first row). Further, in the leftmost, second row image of Figure 3, the relationship (*person*, *has*, *shorts*) was marked as present, whereas the middle, second row image in Figure 4 has (*person*, *has*, *hat*) marked as absent, which indicates a lapse in annotation.

Figure 5 shows examples of wrongly detected relationships. Some of these relationships are logically implausible such as (*hat*, *hold*, *surfboard*) (leftmost, first row), while others such as (*jeans*, *on*, *table*) (middle, first row), while plausible, aren't contextually true in the image. Other failure modes include incorrect detections such as the *sky* in the (rightmost, first row) image and the *phone* in the (leftmost, second row) image.

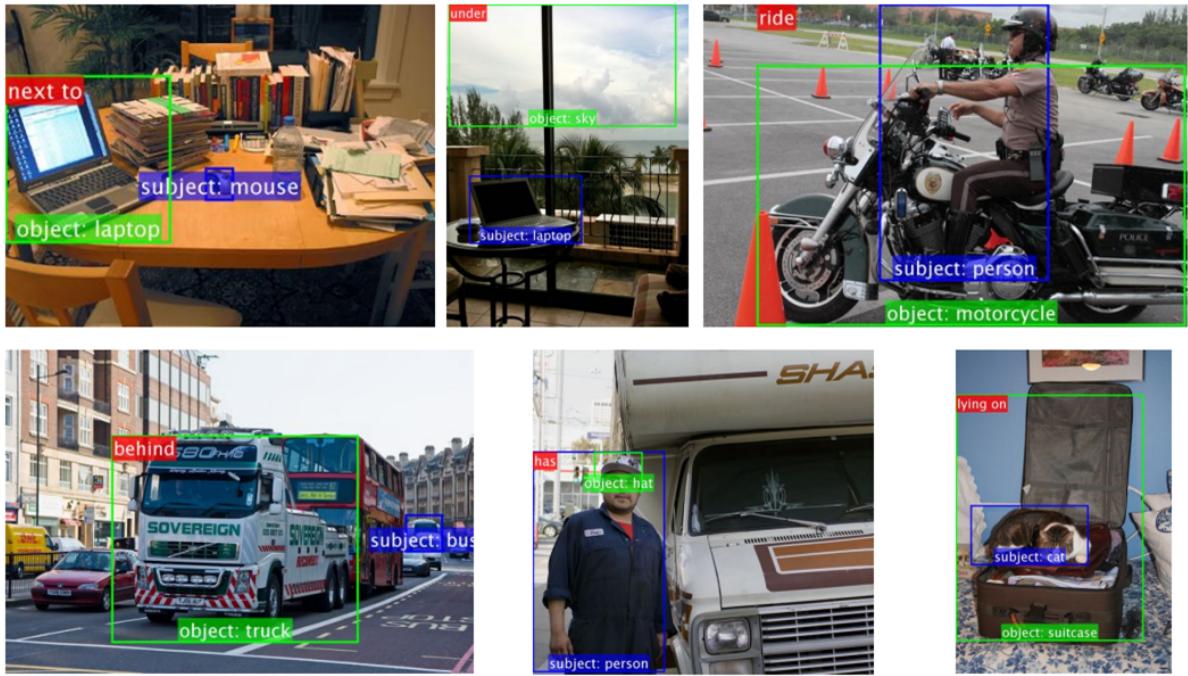


Figure 4: Plausible and logically correct detected relationships, penalized as negatives due to lack of annotations in the VRD dataset.

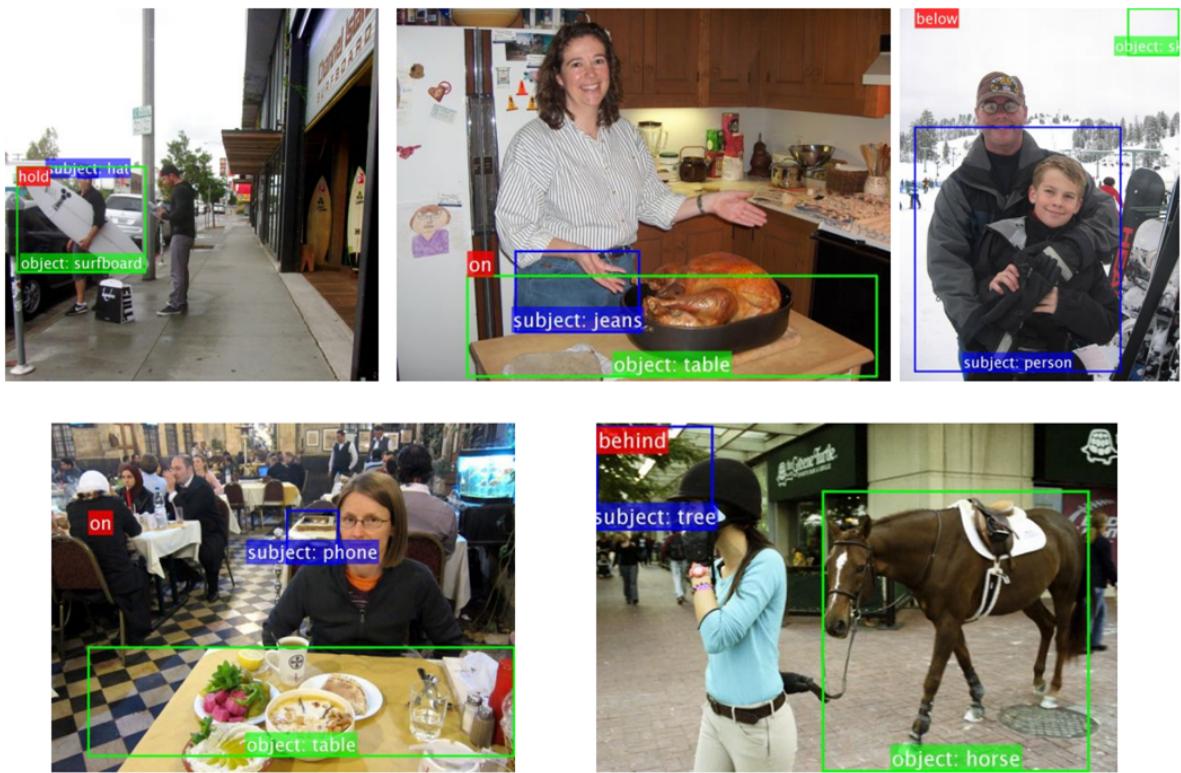


Figure 5: Falsely detected relationships on the VRD dataset. Mistakes are either due to incorrect localization of objects, prediction of implausible relationships, contextually incorrect relationships, or a combination of mistakes.

B. List of detector classes from Flickr30k Entities

B.1. Adjectives

1) white	2) people-white	3) female	4) empty	5) new	6) black	7) people-black
8) grassy	9) wet	10) colored	11) red	12) people-red	13) sunny	14) smiling
15) professional	16) brown	17) people-blond	18) snowy	19) african	20) indoor	21) gray
22) people-blue	23) male	24) indian	25) oriental	26) blond	27) people-green	28) crowded
29) bald	30) cold	31) blue	32) people-yellow	33) shirtless	34) american	35) hot
36) green	37) young	38) dirt	39) dark-haired	40) dark-skinned	41) orange	42) younger
43) paved	44) teenage	45) cloudy	46) pink	47) older	48) rocky	49) urban
50) military	51) purple	52) asian	53) hard	54) light	55) hooded	56) yellow
57) dark	58) beautiful	59) sandy	60) adult	61) golden	62) elderly	63) bright
64) chinese	65) little	66) tan	67) old	68) concrete	69) outdoors	70) long
71) colorful	72) wooden	73) full	74) plastic	75) tall	76) striped	77) middle-aged
78) multicolored	79) bearded	80) huge	81) short	82) high	83) top	

B.2. Subject-Verb

1) animals-catching	2) animals-climbing	3) animals-digging	4) animals-fighting	5) animals-flying
6) animals-holding	7) animals-jumping	8) animals-playing	9) animals-running	10) animals-sitting
11) animals-sleeping	12) animals-splashing	13) animals-standing	14) animals-swimming	15) animals-walking
16) bodyparts-holding	17) bodyparts-sitting	18) bodyparts-walking	19) clothing-climbing	20) clothing-dancing
21) clothing-eating	22) clothing-holding	23) clothing-jumping	24) clothing-performing	25) clothing-playing
26) clothing-posing	27) clothing-reading	28) clothing-riding	29) clothing-running	30) clothing-singing
31) clothing-sitting	32) clothing-sleeping	33) clothing-smiling	34) clothing-standing	35) clothing-talking
36) clothing-walking	37) clothing-working	38) instruments-singing	39) other-cooking	40) other-drinking
41) other-eating	42) other-flying	43) other-holding	44) other-jumping	45) other-performing
46) other-playing	47) other-pointing	48) other-posing	49) other-reading	50) other-riding
51) other-running	52) other-singing	53) other-sitting	54) other-sleeping	55) other-smiling
56) other-standing	57) other-talking	58) other-throwing	59) other-walking	60) other-working
61) other-writing	62) people-blowing	63) people-catching	64) people-cleaning	65) people-climbing
66) people-cooking	67) people-cutting	68) people-dancing	69) people-digging	70) people-drawing
71) people-drinking	72) people-driving	73) people-eating	74) people-falling	75) people-fighting
76) people-fishing	77) people-flying	78) people-hiking	79) people-hit	80) people-holding
81) people-hugging	82) people-juggling	83) people-jumping	84) people-kicking	85) people-kissing
86) people-kneeling	87) people-laughing	88) people-painting	89) people-performing	90) people-playing
91) people-pointing	92) people-posing	93) people-pushng	94) people-reaching	95) people-reading
96) people-riding	97) people-running	98) people-serving	99) people-shopping	100) people-singing
101) people-sitting	102) people-skiing	103) people-sleeping	104) people-sliding	105) people-smiling
106) people-smoking	107) people-splashing	108) people-standing	109) people-surfing	110) people-sweeping
111) people-swimming	112) people-swinging	113) people-talking	114) people-throwing	115) people-touches
116) people-walking	117) people-waving	118) people-working	119) people-writing	120) scene-eating
121) scene-holding	122) scene-playing	123) scene-reading	124) scene-running	125) scene-sitting
126) scene-standing	127) scene-talking	128) scene-walking	129) vehicles-driving	130) vehicles-holding
131) vehicles-running	132) vehicles-sitting	133) vehicles-throwing	134) sitting	135) holding
136) playing	137) standing	138) walking	139) running	140) riding
141) jumping	142) working	143) talking	144) performing	145) eating
146) posing	147) climbing	148) hiking	149) reading	150) dancing
151) smiling	152) singing	153) sleeping	154) pushing	155) swimming
156) throwing	157) painting	158) driving	159) cooking	160) cutting
161) cleaning	162) serving	163) swinging	164) laughing	165) kicking
166) hit	167) fighting	168) juggling	169) flying	170) kissing
171) pointing	172) blowing	173) sliding	174) drinking	175) fishing
176) writing	177) skiing	178) catching	179) kneeling	180) hugging
181) digging	182) smoking	183) shopping	184) surfing	185) waving
186) sweeping	187) falling	188) reaching	189) drawing	190) splashing
191) touches				

B.3. Verb-Object

1)	other-blowing	2)	other-catching	3)	scene-catching	4)	other-cleaning
5)	scene-cleaning	6)	bodyparts-climbing	7)	other-climbing	8)	scene-climbing
9)	bodyparts-cooking	10)	other-cooking	11)	bodyparts-cutting	12)	other-cutting
13)	clothing-dancing	14)	other-dancing	15)	people-dancing	16)	scene-dancing
17)	other-digging	18)	scene-digging	19)	other-drawing	20)	other-drinking
21)	scene-drinking	22)	other-driving	23)	scene-driving	24)	vehicles-driving
25)	other-eating	26)	people-eating	27)	scene-eating	28)	other-falling
29)	scene-falling	30)	other-fighting	31)	scene-fishing	32)	other-flying
33)	scene-flying	34)	scene-hiking	35)	other-hit	36)	people-hit
37)	animals-holding	38)	bodyparts-holding	39)	clothing-holding	40)	instruments-holding
41)	other-holding	42)	people-holding	43)	scene-holding	44)	vehicles-holding
45)	people-hugging	46)	other-juggling	47)	animals-jumping	48)	bodyparts-jumping
49)	other-jumping	50)	people-jumping	51)	scene-jumping	52)	vehicles-jumping
53)	other-kicking	54)	people-kicking	55)	people-kissing	56)	scene-kissing
57)	other-kneeling	58)	scene-kneeling	59)	other-laughing	60)	people-laughing
61)	other-painting	62)	scene-painting	63)	instruments-performing	64)	other-performing
65)	people-performing	66)	scene-performing	67)	animals-playing	68)	clothing-playing
69)	instruments-playing	70)	other-playing	71)	people-playing	72)	scene-playing
73)	vehicles-playing	74)	bodyparts-pointing	75)	other-pointing	76)	people-pointing
77)	scene-pointing	78)	bodyparts-posing	79)	clothing-posing	80)	other-posing
81)	people-posing	82)	scene-posing	83)	otherpushing	84)	peoplepushing
85)	vehiclespushing	86)	other-reaching	87)	scene-reaching	88)	other-reading
89)	people-reading	90)	animals-riding	91)	other-riding	92)	people-riding
93)	scene-riding	94)	vehicles-riding	95)	animals-running	96)	bodyparts-running
97)	clothing-running	98)	other-running	99)	people-running	100)	scene-running
101)	vehicles-running	102)	other-serving	103)	people-serving	104)	other-shopping
105)	instruments-singing	106)	other-singing	107)	people-singing	108)	animals-sitting
109)	bodyparts-sitting	110)	clothing-sitting	111)	instruments-sitting	112)	other-sitting
113)	people-sitting	114)	scene-sitting	115)	vehicles-sitting	116)	scene-skiing
117)	bodyparts-sleeping	118)	other-sleeping	119)	people-sleeping	120)	scene-sleeping
121)	other-sliding	122)	scene-sliding	123)	bodyparts-smiling	124)	clothing-smiling
125)	other-smiling	126)	people-smiling	127)	scene-smiling	128)	other-smoking
129)	scene-splashing	130)	animals-standing	131)	bodyparts-standing	132)	clothing-standing
133)	other-standing	134)	people-standing	135)	scene-standing	136)	vehicles-standing
137)	scene-surfing	138)	other-sweeping	139)	scene-sweeping	140)	other-swimming
141)	scene-swimming	142)	other-swinging	143)	clothing-talking	144)	other-talking
145)	people-talking	146)	scene-talking	147)	other-throwing	148)	people-throwing
149)	scene-throwing	150)	bodyparts-touches	151)	other-touches	152)	animals-walking
153)	bodyparts-walking	154)	clothing-walking	155)	other-walking	156)	people-walking
157)	scene-walking	158)	vehicles-walking	159)	bodyparts-waving	160)	other-waving
161)	people-waving	162)	clothing-working	163)	other-working	164)	people-working
165)	scene-working	166)	vehicles-working	167)	other-writing	168)	sitting
169)	holding	170)	playing	171)	standing	172)	walking
173)	running	174)	riding	175)	jumping	176)	working
177)	talking	178)	performing	179)	eating	180)	posing
181)	climbing	182)	hiking	183)	reading	184)	dancing
185)	smiling	186)	singing	187)	sleeping	188)	pushing
189)	swimming	190)	throwing	191)	painting	192)	driving
193)	cooking	194)	cutting	195)	cleaning	196)	serving
197)	swinging	198)	laughing	199)	kicking	200)	hit
201)	fighting	202)	juggling	203)	flying	204)	kissing
205)	pointing	206)	blowing	207)	sliding	208)	drinking
209)	fishing	210)	writing	211)	skiing	212)	catching
213)	kneeling	214)	hugging	215)	digging	216)	smoking
217)	shopping	218)	surfing	219)	waving	220)	sweeping
221)	falling	222)	reaching	223)	drawing	224)	splashing
225)	touches						

C. List of phrase-pair relationships from Flickr30k Entities

C.1. Verbs

- | | | | | | | | |
|------|------------------------------|------|--------------------------|------|------------------------------|------|----------------------------|
| 1) | dog-catching-frisbee | 2) | dog-holding-stick | 3) | dog-jumping-ball | 4) | dog-jumping-frisbee |
| 5) | dog-jumping-hurdle | 6) | dog-jumping-people | 7) | dog-jumping-water | 8) | dog-playing-ball |
| 9) | dog-running-beach | 10) | dog-running-field | 11) | dog-running-grass | 12) | dog-running-snow |
| 13) | dog-running-water | 14) | dog-swimming-water | 15) | dogs-playing-grass | 16) | dogs-playing-snow |
| 17) | dogs-running-field | 18) | dogs-running-grass | 19) | people-blowing-bubbles | 20) | people-catching-ball |
| 21) | people-catching-wave | 22) | people-cleaning-dishes | 23) | people-climbing-mountain | 24) | people-climbing-rock |
| 25) | people-climbing-rock+wall | 26) | people-climbing-rocks | 27) | people-climbing-tree | 28) | people-climbing-wall |
| 29) | people-cooking-food | 30) | people-cutting-cake | 31) | people-dancing-people | 32) | people-dancing-stage |
| 33) | people-digging-snow | 34) | people-drinking-beer | 35) | people-eating-food | 36) | people-eating-meal |
| 37) | people-eating-table | 38) | people-hit-ball | 39) | people-hit-tennis+ball | 40) | people-holding-ball |
| 41) | people-holding-book | 42) | people-holding-box | 43) | people-holding-camera | 44) | people-holding-cup |
| 45) | people-holding-dog | 46) | people-holding-drink | 47) | people-holding-flag | 48) | people-holding-flags |
| 49) | people-holding-flowers | 50) | people-holding-football | 51) | people-holding-guitar | 52) | people-holding-microphone |
| 53) | people-holding-object | 54) | people-holding-people | 55) | people-holding-rope | 56) | people-holding-shovel |
| 57) | people-holding-sign | 58) | people-holding-signs | 59) | people-holding-something | 60) | people-holding-stick |
| 61) | people-holding-tennis+racket | 62) | people-hugging-people | 63) | people-jumping-ball | 64) | people-jumping-bed |
| 65) | people-jumping-bike | 66) | people-jumping-hurdle | 67) | people-jumping-people | 68) | people-jumping-pool |
| 69) | people-jumping-ramp | 70) | people-jumping-rock | 71) | people-jumping-swimming+pool | 72) | people-jumping-trampoline |
| 73) | people-jumping-water | 74) | people-kicking-ball | 75) | people-kicking-people | 76) | people-kicking-soccer+ball |
| 77) | people-kissing-people | 78) | people-laughing-people | 79) | people-painting-picture | 80) | people-performing-people |
| 81) | people-performing-stage | 82) | people-playing-accordion | 83) | people-playing-bagpipes | 84) | people-playing-ball |
| 85) | people-playing-basketball | 86) | people-playing-beach | 87) | people-playing-board+game | 88) | people-playing-cello |
| 89) | people-playing-dog | 90) | people-playing-drum | 91) | people-playing-drums | 92) | people-playing-flute |
| 93) | people-playing-football | 94) | people-playing-fountain | 95) | people-playing-frisbee | 96) | people-playing-game |
| 97) | people-playing-guitar | 98) | people-playing-guitars | 99) | people-playing-instrument | 100) | people-playing-instruments |
| 101) | people-playing-keyboard | 102) | people-playing-people | 103) | people-playing-piano | 104) | people-playing-pool |
| 105) | people-playing-sand | 106) | people-playing-saxophone | 107) | people-playing-snow | 108) | people-playing-soccer |
| 109) | people-playing-stage | 110) | people-playing-swing | 111) | people-playing-toy | 112) | people-playing-toys |
| 113) | people-playing-trumpet | 114) | people-playing-violin | 115) | people-playing-volleyball | 116) | people-playing-water |
| 117) | people-posing-people | 118) | people-posing-picture | 119) | people-pushng-cart | 120) | people-pushng-people |
| 121) | people-pushng-stroller | 122) | people-reading-book | 123) | people-reading-magazine | 124) | people-reading-newspaper |
| 125) | people-reading-paper | 126) | people-riding-bicycle | 127) | people-riding-bicycles | 128) | people-riding-bike |
| 129) | people-riding-bikes | 130) | people-riding-bull | 131) | people-riding-dirt+bike | 132) | people-riding-horse |
| 133) | people-riding-horses | 134) | people-riding-motorbike | 135) | people-riding-motorcycle | 136) | people-riding-people |
| 137) | people-riding-scooter | 138) | people-riding-skateboard | 139) | people-riding-street | 140) | people-riding-surfboard |
| 141) | people-riding-unicycle | 142) | people-riding-wave | 143) | people-running-ball | 144) | people-running-beach |
| 145) | people-running-field | 146) | people-running-grass | 147) | people-running-people | 148) | people-running-road |
| 149) | people-running-sidewalk | 150) | people-running-street | 151) | people-running-track | 152) | people-running-water |
| 153) | people-serving-food | 154) | people-singing-guitar | 155) | people-singing-microphone | 156) | people-singing-people |
| 157) | people-sitting-beach | 158) | people-sitting-bed | 159) | people-sitting-bench | 160) | people-sitting-benches |
| 161) | people-sitting-bike | 162) | people-sitting-blanket | 163) | people-sitting-boat | 164) | people-sitting-building |
| 165) | people-sitting-chair | 166) | people-sitting-chairs | 167) | people-sitting-couch | 168) | people-sitting-curb |
| 169) | people-sitting-desk | 170) | people-sitting-dock | 171) | people-sitting-floor | 172) | people-sitting-grass |
| 173) | people-sitting-horse | 174) | people-sitting-ledge | 175) | people-sitting-motorcycle | 176) | people-sitting-park+bench |
| 177) | people-sitting-people | 178) | people-sitting-rock | 179) | people-sitting-rocks | 180) | people-sitting-sidewalk |
| 181) | people-sitting-steps | 182) | people-sitting-stool | 183) | people-sitting-street | 184) | people-sitting-swing |
| 185) | people-sitting-table | 186) | people-sitting-tables | 187) | people-sitting-tree | 188) | people-sitting-wall |
| 189) | people-sitting-water | 190) | people-sleeping-bench | 191) | people-sleeping-chair | 192) | people-sleeping-couch |
| 193) | people-sleeping-grass | 194) | people-sleeping-people | 195) | people-sliding-base | 196) | people-sliding-slide |
| 197) | people-smiling-people | 198) | people-smoking-cigarette | 199) | people-standing-beach | 200) | people-standing-boat |
| 201) | people-standing-bridge | 202) | people-standing-building | 203) | people-standing-car | 204) | people-standing-counter |
| 205) | people-standing-door | 206) | people-standing-doorway | 207) | people-standing-fence | 208) | people-standing-field |
| 209) | people-standing-grass | 210) | people-standing-ladder | 211) | people-standing-line | 212) | people-standing-people |
| 213) | people-standing-platform | 214) | people-standing-podium | 215) | people-standing-road | 216) | people-standing-rock |
| 217) | people-standing-rocks | 218) | people-standing-sidewalk | 219) | people-standing-sign | 220) | people-standing-snow |
| 221) | people-standing-stage | 222) | people-standing-street | 223) | people-standing-table | 224) | people-standing-tree |
| 225) | people-standing-wall | 226) | people-standing-water | 227) | people-surfing-wave | 228) | people-swimming-pool |
| 229) | people-swingng-bat | 230) | people-swingng-swing | 231) | people-talking-cellphone | 232) | people-talking-microphone |
| 233) | people-talking-people | 234) | people-talking-phone | 235) | people-throwng-ball | 236) | people-throwng-frisbee |
| 237) | people-throwng-people | 238) | people-walking-beach | 239) | people-walking-bicycle | 240) | people-walking-bike |
| 241) | people-walking-bridge | 242) | people-walking-building | 243) | people-walking-city+street | 244) | people-walking-dog |
| 245) | people-walking-dogs | 246) | people-walking-field | 247) | people-walking-grass | 248) | people-walking-hill |
| 249) | people-walking-path | 250) | people-walking-people | 251) | people-walking-road | 252) | people-walking-sidewalk |
| 253) | people-walking-snow | 254) | people-walking-stairs | 255) | people-walking-street | 256) | people-walking-trail |
| 257) | people-walking-wall | 258) | people-walking-water | 259) | people-working-machine | 260) | people-working-people |

C.2. Prepositions

1)	ball-in-mouth	2)	bicycle-on-street	3)	boat-in-water	4)	building-in-people
5)	dog-in-ball	6)	dog-in-collar	7)	dog-in-dog	8)	dog-in-field
9)	dog-in-grass	10)	dog-in-snow	11)	dog-in-stick	12)	dog-in-toy
13)	dog-in-water	14)	dog-on-beach	15)	dog-on-grass	16)	dog-on-hind+legs
17)	dog-on-leash	18)	dogs-in-dogs	19)	dogs-in-field	20)	dogs-in-grass
21)	dogs-in-snow	22)	dogs-in-water	23)	dogs-on-grass	24)	guitar-in-people
25)	hands-in-people	26)	object-in-mouth	27)	one-in-shirt	28)	other-in-shirt
29)	people-across-street	30)	people-behind-building	31)	people-behind-counter	32)	people-behind-fence
33)	people-behind-people	34)	people-between-people	35)	people-in-area	36)	people-in-back
37)	people-in-ball	38)	people-in-bed	39)	people-in-bicycle	40)	people-in-bike
41)	people-in-blanket	42)	people-in-boat	43)	people-in-body+water	44)	people-in-building
45)	people-in-camera	46)	people-in-cane	47)	people-in-canoe	48)	people-in-car
49)	people-in-cart	50)	people-in-chair	51)	people-in-chairs	52)	people-in-cigarette
53)	people-in-colors	54)	people-in-dirt	55)	people-in-dog	56)	people-in-dogs
57)	people-in-doorway	58)	people-in-face+paint	59)	people-in-field	60)	people-in-flowers
61)	people-in-football	62)	people-in-fountain	63)	people-in-gear	64)	people-in-grass
65)	people-in-guitar	66)	people-in-highchair	67)	people-in-instruments	68)	people-in-kayak
69)	people-in-kitchen	70)	people-in-lake	71)	people-in-line	72)	people-in-microphone
73)	people-in-mirror	74)	people-in-mud	75)	people-in-number	76)	people-in-ocean
77)	people-in-park	78)	people-in-people	79)	people-in-pool	80)	people-in-river
81)	people-in-room	82)	people-in-sand	83)	people-in-snow	84)	people-in-soccer+ball
85)	people-in-street	86)	people-in-stroller	87)	people-in-swimming+pool	88)	people-in-swing
89)	people-in-towel	90)	people-in-toy	91)	people-in-toys	92)	people-in-tree
93)	people-in-tub	94)	people-in-water	95)	people-in-wheelchair	96)	people-in-yard
97)	people-near-beach	98)	people-near-brick+wall	99)	people-near-building	100)	people-near-car
101)	people-near-fence	102)	people-near-fountain	103)	people-near-lake	104)	people-near-people
105)	people-near-pole	106)	people-near-road	107)	people-near-sidewalk	108)	people-near-street
109)	people-near-table	110)	people-near-tree	111)	people-near-wall	112)	people-near-water
113)	people-near-window	114)	people-on-back	115)	people-on-balcony	116)	people-on-beach
117)	people-on-bed	118)	people-on-bench	119)	people-on-benches	120)	people-on-bicycle
121)	people-on-bicycles	122)	people-on-bike	123)	people-on-bikes	124)	people-on-blanket
125)	people-on-board	126)	people-on-boat	127)	people-on-bridge	128)	people-on-building
129)	people-on-bus	130)	people-on-cellphone	131)	people-on-chair	132)	people-on-chairs
133)	people-on-city+street	134)	people-on-cliff	135)	people-on-computer	136)	people-on-couch
137)	people-on-curb	138)	people-on-deck	139)	people-on-dock	140)	people-on-fence
141)	people-on-field	142)	people-on-floor	143)	people-on-grass	144)	people-on-grill
145)	people-on-hill	146)	people-on-horse	147)	people-on-horses	148)	people-on-ice
149)	people-on-ladder	150)	people-on-lawn	151)	people-on-ledge	152)	people-on-machine
153)	people-on-mat	154)	people-on-motorcycle	155)	people-on-motorcycles	156)	people-on-mountain
157)	people-on-park+bench	158)	people-on-path	159)	people-on-pavement	160)	people-on-people
161)	people-on-phone	162)	people-on-pier	163)	people-on-platform	164)	people-on-porch
165)	people-on-raft	166)	people-on-rail	167)	people-on-railing	168)	people-on-ramp
169)	people-on-road	170)	people-on-rock	171)	people-on-rocks	172)	people-on-roof
173)	people-on-rope	174)	people-on-sand	175)	people-on-scaffold	176)	people-on-scaffolding
177)	people-on-scooter	178)	people-on-shore	179)	people-on-side+road	180)	people-on-sidewalk
181)	people-on-skateboard	182)	people-on-sled	183)	people-on-slide	184)	people-on-snowboard
185)	people-on-soccer+field	186)	people-on-sofa	187)	people-on-stage	188)	people-on-stairs
189)	people-on-step	190)	people-on-steps	191)	people-on-stilts	192)	people-on-stool
193)	people-on-street	194)	people-on-surfboard	195)	people-on-swing	196)	people-on-table
197)	people-on-tire+swing	198)	people-on-track	199)	people-on-trail	200)	people-on-train
201)	people-on-trampoline	202)	people-on-tree	203)	people-on-walkway	204)	people-on-wall
205)	people-on-water	206)	people-on-wave	207)	people-under-tree	208)	shirt-in-people
209)	something-in-mouth	210)	stick-in-mouth	211)	street-in-people	212)	table-in-people
213)	tattoo-on-people	214)	tennis+ball-in-mouth	215)	toy-in-mouth	216)	wall-in-graffiti

C.3. Clothing and Body Part Attachment

1)	people-apron	2)	people-aprons	3)	people-arms	4)	people-attire
5)	people-backpack	6)	people-backpacks	7)	people-bag	8)	people-bags
9)	people-ball+cap	10)	people-bandanna	11)	people-baseball+cap	12)	people-baseball+uniform
13)	people-bathing+suit	14)	people-bathing+suits	15)	people-beanie	16)	people-beard
17)	people-beret	18)	people-bikini	19)	people-bikinis	20)	people-black
21)	people-black+shirt	22)	people-black+white	23)	people-blond-hair	24)	people-blouse
25)	people-blue	26)	people-body	27)	people-boots	28)	people-brown
29)	people-brown+jacket	30)	people-brown+shirt	31)	people-business+attire	32)	people-business+suit
33)	people-camouflage	34)	people-cap	35)	people-checkered+shirt	36)	people-clothes
37)	people-clothing	38)	people-coat	39)	people-coats	40)	people-collared+shirt
41)	people-costume	42)	people-costumes	43)	people-cowboy+hat	44)	people-cowboy+hats
45)	people-curly+hair	46)	people-denim+jacket	47)	people-dreadlocks	48)	people-dress
49)	people-dress+shirt	50)	people-dresses	51)	people-eyes	52)	people-face
53)	people-faces	54)	people-feet	55)	people-finger	56)	people-fingers
57)	people-flip-flops	58)	people-garb	59)	people-glasses	60)	people-gloves
61)	people-goggles	62)	people-gold	63)	people-gray	64)	people-green
65)	people-hair	66)	people-haircut	67)	people-hand	68)	people-hands
69)	people-harness	70)	people-hat	71)	people-hats	72)	people-head
73)	people-headband	74)	people-headphones	75)	people-heads	76)	people-headscarf
77)	people-heels	78)	people-helmet	79)	people-helmets	80)	people-hoodie
81)	people-jacket	82)	people-jackets	83)	people-jean+shorts	84)	people-jeans
85)	people-jersey	86)	people-jerseys	87)	people-jumpsuit	88)	people-khaki+pants
89)	people-kilt	90)	people-knees	91)	people-lab+coat	92)	people-lap
93)	people-leather+jacket	94)	people-leg	95)	people-legs	96)	people-leotard
97)	people-life+jacket	98)	people-life+jackets	99)	people-makeup	100)	people-mask
101)	people-mohawk	102)	people-mouth	103)	people-mustache	104)	people-necklace
105)	people-nose	106)	people-orange	107)	people-orange+dress	108)	people-orange+hat
109)	people-orange+jacket	110)	people-orange+shirt	111)	people-orange+vest	112)	people-orange+vests
113)	people-outfit	114)	people-outfits	115)	people-overalls	116)	people-pajamas
117)	people-pants	118)	people-people	119)	people-pigtails	120)	people-pink
121)	people-pink+coat	122)	people-pink+dress	123)	people-pink+hat	124)	people-pink+jacket
125)	people-pink+outfit	126)	people-pink+pants	127)	people-pink+shirt	128)	people-pink+sweater
129)	people-plaid+shirt	130)	people-polo+shirt	131)	people-ponytail	132)	people-purple
133)	people-purple+shirt	134)	people-purse	135)	people-red	136)	people-red+white
137)	people-red+hair	138)	people-ring	139)	people-robe	140)	people-robes
141)	people-rock+face	142)	people-safety+vest	143)	people-safety+vests	144)	people-sandals
145)	people-scarf	146)	people-scrubs	147)	people-shirt	148)	people-shirts
149)	people-shoe	150)	people-shoes	151)	people-shopping+bag	152)	people-shopping+bags
153)	people-shorts	154)	people-shoulder	155)	people-shoulders	156)	people-skirt
157)	people-skirts	158)	people-sleeveless+shirt	159)	people-smile	160)	people-sneakers
161)	people-snowshoes	162)	people-snowsuit	163)	people-socks	164)	people-straw+hat
165)	people-striped+shirt	166)	people-suit	167)	people-suits	168)	people-sunglasses
169)	people-suspenders	170)	people-sweater	171)	people-sweatshirt	172)	people-swim+trunks
173)	people-swimming+trunks	174)	people-swimsuit	175)	people-swimsuits	176)	people-t-shirt
177)	people-t-shirts	178)	people-tan+jacket	179)	people-tan+pants	180)	people-tan+shirt
181)	people-tank	182)	people-tank+top	183)	people-tattoo	184)	people-tattoos
185)	people-teeth	186)	people-thumbs	187)	people-tie	188)	people-tongue
189)	people-top	190)	people-tops	191)	people-trunks	192)	people-turban
193)	people-tuxedo	194)	people-umbrella	195)	people-umbrellas	196)	people-underwear
197)	people-uniform	198)	people-uniforms	199)	people-vest	200)	people-vests
201)	people-wedding+dress	202)	people-wetsuit	203)	people-white	204)	people-wig
205)	people-winter+clothes	206)	people-winter+clothing	207)	people-yellow		