

# Batch construction and multitask learning in visual relationship recognition

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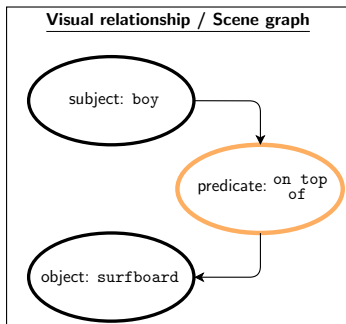
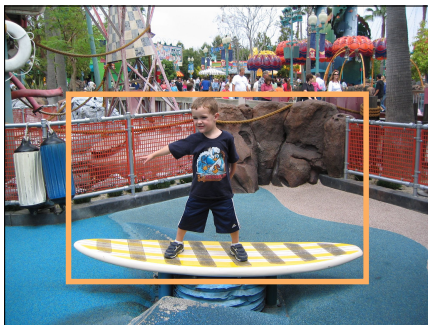
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## Visual relationship recognition

**Task:** produce a (subject, predicate, object) triplet given an image.

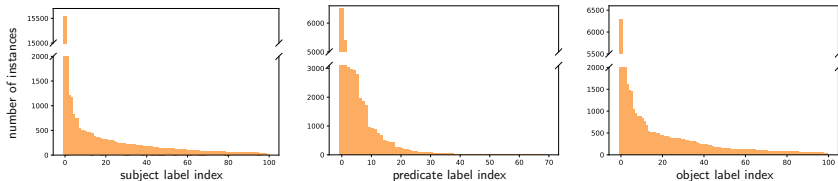
**Example:**



## Challenges

**Combinatorial:** with 100 subject, 70 predicate, and 100 object labels we have 700,000 possible relationships.

**Data distribution:** is typically long-tailed, making it difficult to learn rare relationships.



## Our approach

Treat VRR as a classification problem.

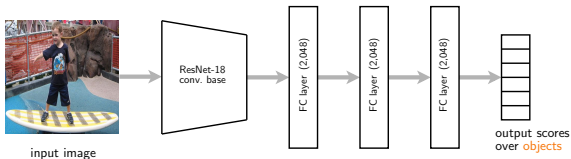
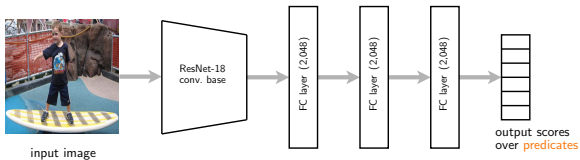
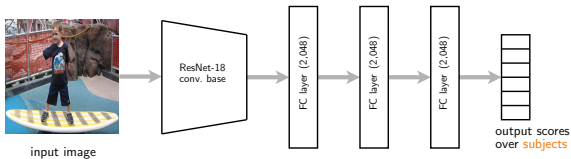
**Input:** image, cropped around a pair of objects.

**Output:** (subject, predicate, object) triplet.

Three tasks: predict the subject, predict the predicate and predict the object. Avoid predicting over 700,000 classes.

Obtain normalised scores over classes in each task. Combine scores through multiplication.

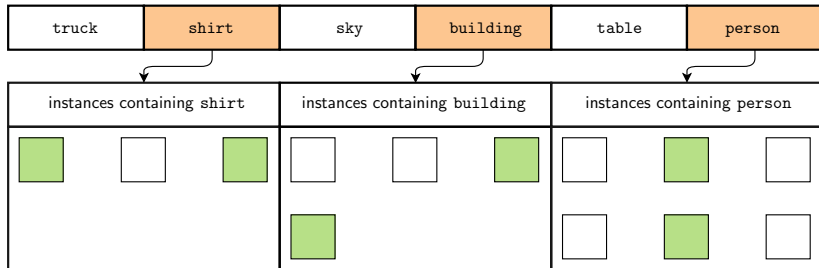
# Single task learning with standard batching



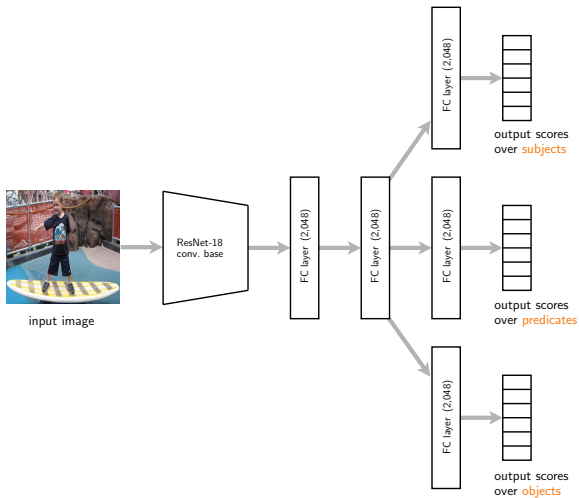
## Class-selective batch construction

Select  $n$  classes from a vocabulary of  $N$  classes, uniformly at random.

Sample  $m$  instances from each selected class, uniformly at random.








# Multitask learning



## VRD dataset (Lu et al. ECCV 2016)

5,000 images, 37,987 visual relationships but only 15,448 unique relationships.

100 labels for both subject and objects, 70 predicate labels in five categories.

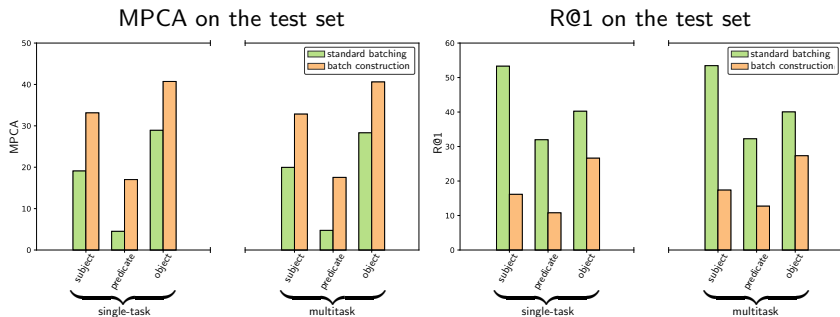
				
action verb	spatial	preposition	comparative	non-action verb
person kick ball	person on top of ramp	motorcycle with wheel	elephant taller than person	person wear shirt



## Metrics

- MPCA:** mean per-class accuracy; used to measure performance on rare classes in the individual tasks.
- R@k:** recall-at- $k$ ; percentage of times the correct label occurs in the top  $k$  predictions (if ordered by output scores).
- Tail R@k:** R@k measured on visual relationship classes that have fewer than 1,000 samples for subject, predicate, and object labels.

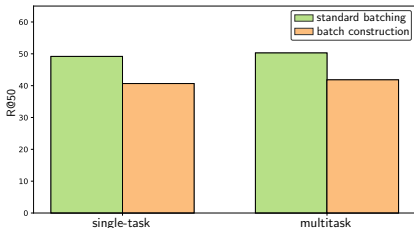
## Quantitative results: individual tasks



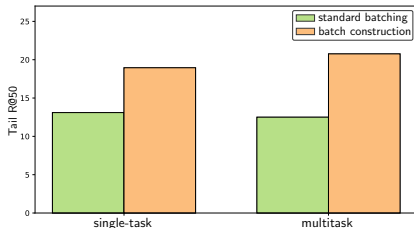
Batch construction is performed with respect to label on x-axis (same as the task being predicted).

## Quantitative results: visual relationship recognition

R@50 on the test set







Tail R@50 on the test set



Batch construction is performed with respect to the object labels since it performed better overall.

# Qualitative results

Models	person, on, horse 	giraffe, taller than, giraffe 	person, on, skateboard 	person, feed, elephant 
ST-SB	person, on, horse 12.0 person, ride, horse 7.0 person, wear, horse 5.3 person, has, horse 5.2 person, on, person 3.1	giraffe, taller than, giraffe 25.1 giraffe, in front of, giraffe 20.8 giraffe, next to, giraffe 9.5 giraffe, above, giraffe 7.6 giraffe, behind, giraffe 7.2	person, wear, person 11.8 person, wear, shirt 10.5 person, wear, skateboard 10.0 person, wear, shoes 5.4 person, wear, pants 4.4	person, above, street 4.3 person, on, street 4.1 person, under, street 3.0 sky, above, street 1.7 sky, on, street 1.6
ST-BC-O	person, on, horse 18.7 person, has, horse 11.8 person, wear, horse 7.7 person, in front of, horse 4.3 person, next to, person 3.7	giraffe, in front of, giraffe 98.6 giraffe, taller than, giraffe 0.4 giraffe, behind, giraffe 0.4 giraffe, next to, giraffe 0.1 giraffe, beside, giraffe 0.1	person, wear, skateboard 25.6 person, on, skateboard 10.0 person, has, skateboard 9.6 person, ride, skateboard 5.2 person, wear, shoes 3.5	person, under, elephant 16.4 person, in front of, elephant 16.0 person, above, elephant 10.0 person, near, elephant 4.7 person, behind, elephant 4.1
MT-SB	person, wear, horse 9.3 person, on, horse 6.8 person, wear, person 3.4 person, behind, horse 3.1 person, has, horse 2.6	giraffe, taller than, giraffe 45.4 giraffe, in front of, giraffe 18.9 giraffe, next to, giraffe 8.6 giraffe, behind, giraffe 7.3 giraffe, under, giraffe 2.6	person, wear, shirt 15.5 person, wear, person 9.6 person, wear, skateboard 6.9 person, wear, shoes 6.1 person, wear, pants 4.1	person, on, street 4.7 person, under, street 3.9 person, above, street 3.4 person, on, person 2.4 person, under, person 1.9
MT-BC-O	person, on, horse 13.2 person, above, horse 12.0 person, behind, horse 6.3 person, ride, horse 5.3 person, has, horse 4.8	giraffe, in front of, giraffe 92.5 giraffe, taller than, giraffe 6.0 giraffe, behind, giraffe 0.9 giraffe, next to, giraffe 0.3 giraffe, beside, giraffe 0.07	person, wear, skateboard 20.0 person, wear, shoes 14.0 person, wear, helmet 12.0 person, has, skateboard 3.8 person, wear, pants 3.7	person, in front of, elephant 7.4 person, near, elephant 6.9 person, under, elephant 5.1 person, on, elephant 3.4 person, above, elephant 2.4

ST-SB	single-task, standard batching	MT-SB	multitask, standard batching
ST-BC-O	single-task, batch construction from object labels	MT-SB-O	multitask, batch construction from object labels

## Conclusion

Class-selective batch construction improves performance on the tail of the distribution, at the cost of performance on the small number of dominating classes.

Multitask learning neither improves nor impedes performance. Reduced capacity can be beneficial.

Predicates are difficult to model. Limitation of pretrained models?

Misclassifications are often semantically similar to groundtruth. We could use a language model to incorporate semantics.