nRPN: Hard Example Learning for Region Proposal Networks

{MyeongAh Cho, Tae-young Chung, Hyeongmin Lee and Sangyoun Lee}

Image and Video Pattern Recognition Laboratory, Yonsei University

Introduction

The region proposal task is generating a set of candidate regions that contain an object. In an image, there are too small number of hard negative examples compared to the vast number of easy negatives, so the region proposal networks struggle to train hard negatives.

In this paper, we propose **Negative Region Proposal Network(nRPN)** to improve Region Proposal Network(RPN).

In this paper, our main contributions are,

- nRPN learns hard negative examples from false positives of RPN and provides hard negative examples to RPN. By training RPN and nRPN together, we can easily get hard negatives from nRPN which is only used for training.
- Also we propose Overlap Loss which makes more effective for learning both the size of large and small objects.

Overlap Loss

Since small objects tends to have a lower IoU with anchor than large objects, RPN was not well trained on the small objects. However, this overlap loss can help to learn more balanced with object size.

$$p'_i = \begin{cases} \dfrac{p_i}{IoU} & if\ p^*_i = 0 \\ 1 - p_i & if\ p^*_i = 0 \end{cases}$$

$$L_{ov}(p_i, p^*_i) = -p^*_i log p'_i - (1 - p^*_i) log(1 - p'_i)$$

$$L = \frac{1}{N_{cls}} \sum_i L_{ov}(p_i, p^*_i) + \lambda \frac{1}{N_{reg}} \sum_i L_{reg}(t_i, t)$$

nRPN

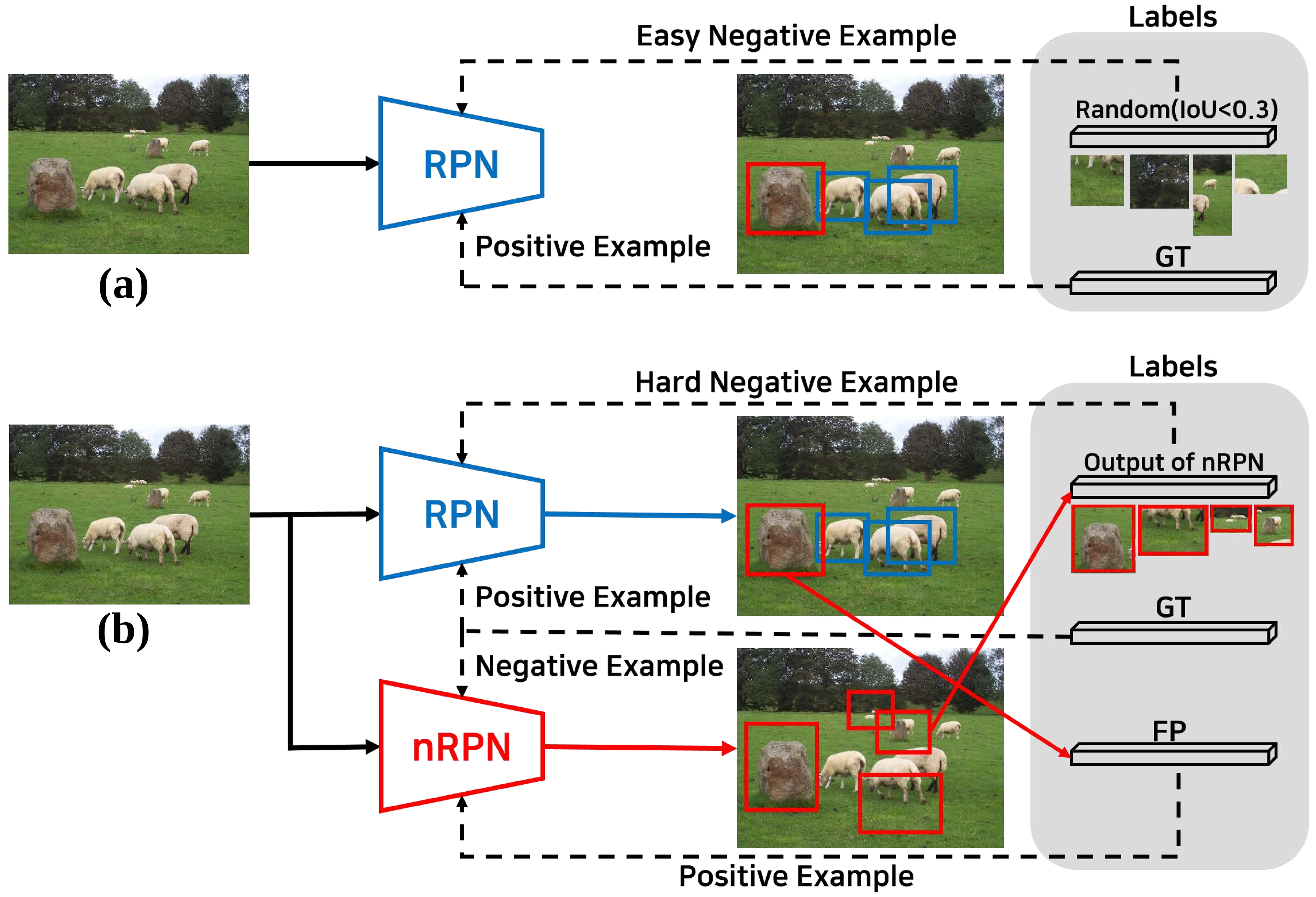

Fig 1. Framework of (a) original RPN and (b) RPN with nRPN

Unlike detectors which false positives are very small, RPN has large number of false positives. Therefore, it's easy to get false positives for nRPN. Also, since nRPN predicts the hard negative examples, RPN can easily trained with hard negatives.

- The nRPN aims to propose hard negative examples that the RPN might incorrect. nRPN trains with the false positives from RPN, in the meanwhile, RPN trains with the hard negative examples which are proposed by the nRPN.
- Both RPN and nRPN train at the same time, they provide positive or negative examples to each other and gradually generates more difficult examples.

Experiments

Recall(%)		RPN 0.5	RPN 0.7	RPN 0.9	RPN+nRPN 0.5	RPN+nRPN 0.7	RPN+nRPN 0.9	RPN+nRPN+L_{ov} 0.5	RPN+nRPN+L_{ov} 0.7	RPN+nRPN+L_{ov} 0.9
50	S	48.7	21.0	0.4	55.2	**28.4**	**0.7**	**56.4**	27.7	0.4
	M	66.7	39.6	1.1	68.9	43.6	1.7	**73.2**	**46.6**	**2.0**
	L	91.6	68.6	3.4	93.5	**68.0**	**3.0**	**93.5**	67.4	**3.0**
	all	81.7	57.1	2.5	83.9	58.4	2.5	**85.3**	**58.9**	**2.6**
100	S	54.7	23.8	0.4	60.1	**31.2**	0.7	**61.4**	30.0	**0.7**
	M	77.8	48.4	0.3	80.0	52.5	2.1	**83.0**	**55.7**	**2.3**
	L	95.6	76.2	3.9	**97.1**	**76.8**	3.3	96.9	75.2	**3.5**
	all	88.0	64.9	2.9	89.9	**66.9**	2.8	**90.8**	**66.9**	**3.0**
300	S	65.6	27.5	0.5	68.4	**35.1**	0.9	**69.1**	33.0	**0.9**
	M	89.1	59.7	1.7	91.2	65.3	2.6	**92.9**	**67.5**	**2.7**
	L	98.7	84.1	4.2	**99.3**	**85.7**	3.9	99.2	84.3	**4.0**
	all	94.1	73.7	3.2	95.2	**76.8**	3.3	**95.7**	76.5	**3.4**

Table 1. Results of ablation studies on the PASCAL VOC 2007 dataset.

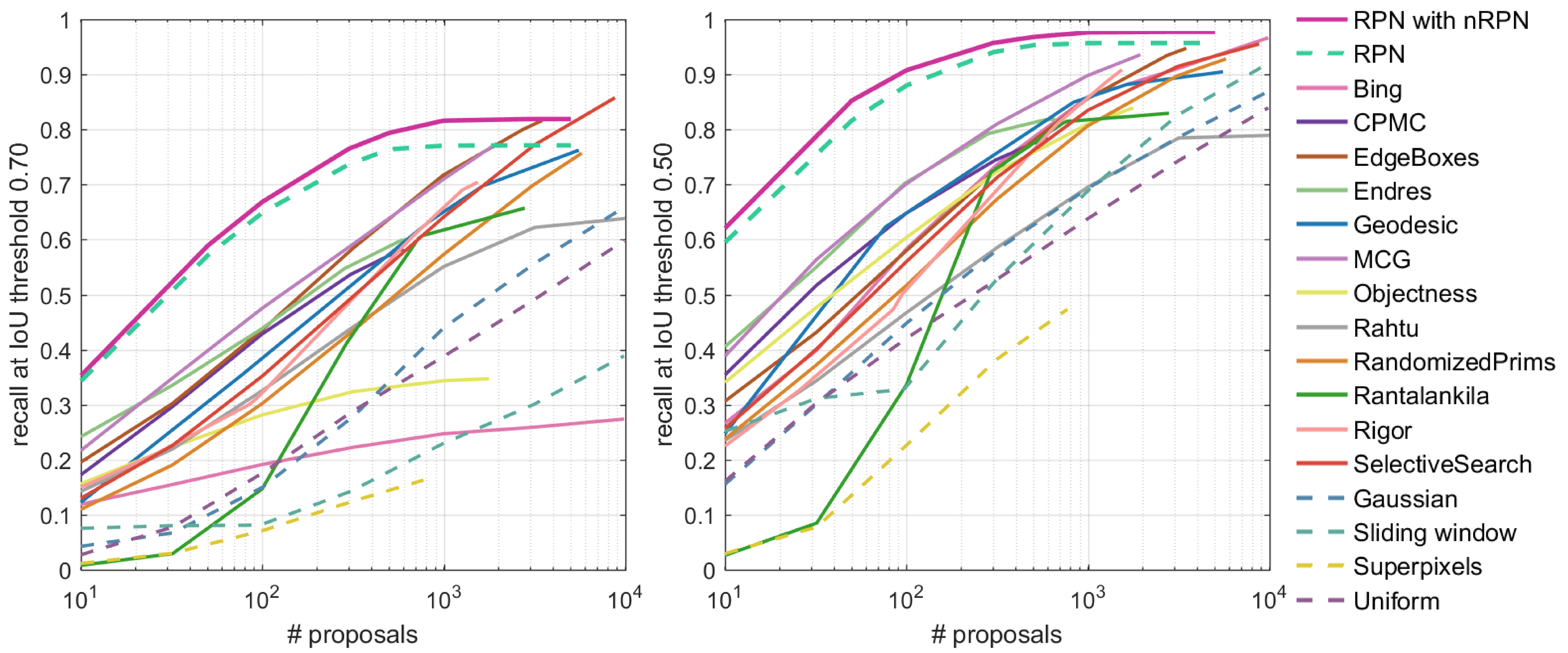

Fig 2. Recall rates of the proposed model and other region proposal models on PASCAL VOC 2007 testset.

Results

(a) RPN (b) RPN with nRPN

Future Works

Our future works will be applying proposed hard example training method to other different tasks such as object tracking or re-identification where hard negative examples plays an important role.

Contact Information

Email maycho0305@yonsei.ac.kr

Laboratory mvp.yonsei.ac.kr