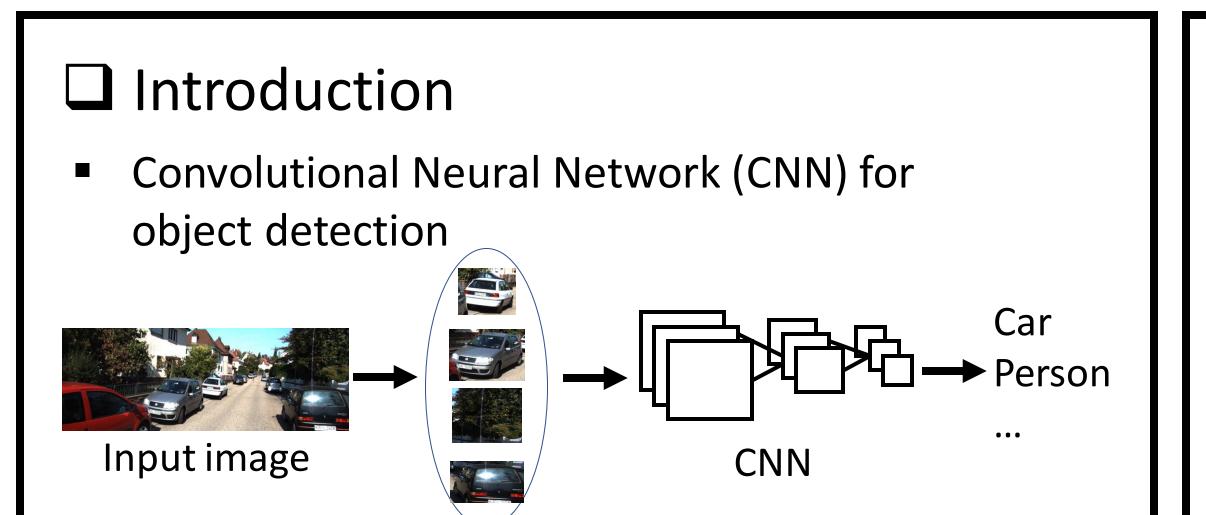
Subcategory-aware Convolutional Neural Networks for Object Proposals and Detection

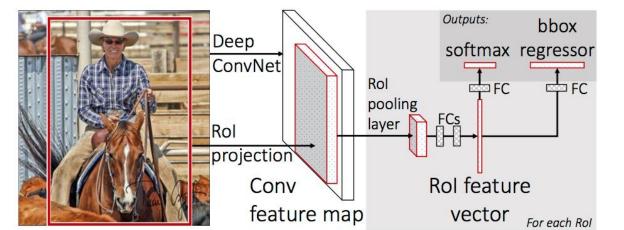
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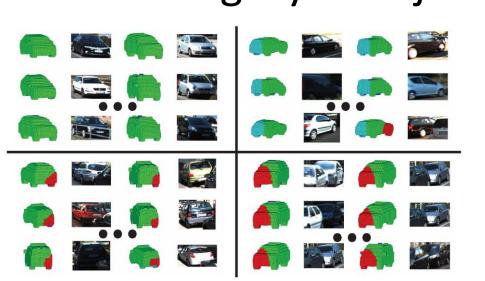
Region proposals

- How to handle large scale change, occlusion and truncation?
- How to estimate detailed properties of objects (3D pose, 3D shape, 3D location)?
- We use subcategory information to help object proposal and detection in this work.
- ☐ Related Work
- CNN-based object detection

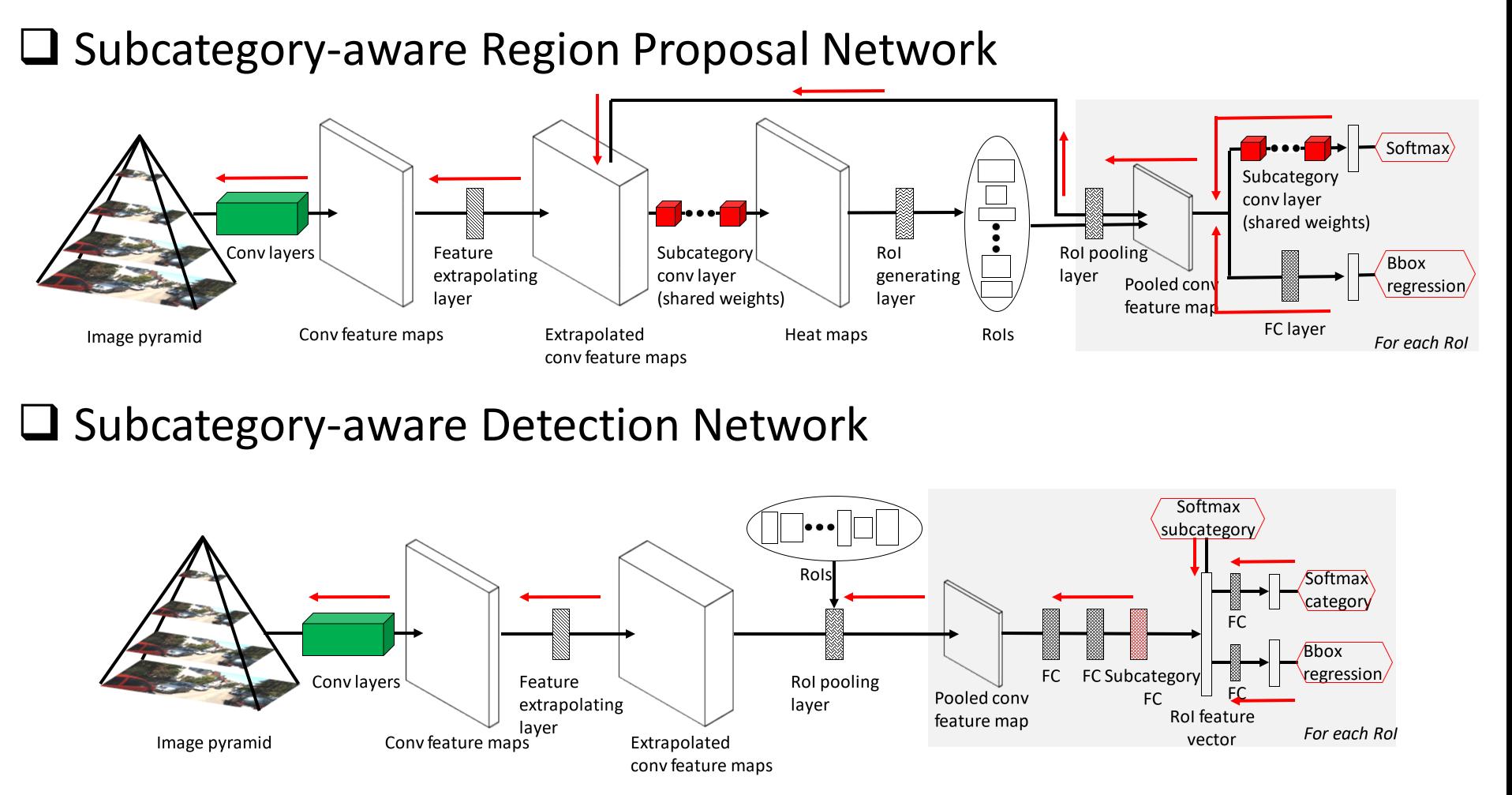


Fast RCNN. R. Girshick., ICCV'15. Faster RCNN. Ren et al., NIPS'15. YOLO. Redmon, et al., CVPR'16. SSD. Liu et al., ECCV'16.

Subcategory in object detection



DPM. Felzenszwalb et al., TPAMI'10. Gu & Ren, ECCV'10.
Ohn-Bar & Trivedi, ITS'15.
3DVP. Xiang et al., CVPR'15.





Experiments

Region proposal performance on KITTI [16]

Method	Easy	Moderate	Hard	Easy	Moderate	Hard	Easy	Moderate	Hard
		Car			Pedestrian			Cyclist	
SelectiveSearch [1]	58.17	42.12	37.62	68.95	57.65	52.57	57.05	49.59	49.44
EdgeBoxes [2]	81.40	61.84	55.68	86.15	71.88	65.39	56.11	46.52	45.72
RPN [3]	98.84	97.37	95.31	98.88	91.69	88.64	96.55	91.80	89.41
SubCNN	99.27	96.28	93.14	99.44	93.46	91.02	99.67	93.03	91.64

Detection and Orientation Estimation on KITTI car

	Object Detection (AP)			Orientation Estimation (AOS)		
Method	Easy	Moderate	Hard	Easy	Moderate	Hard
ACF [4]	55.89	54.74	42.98	N/A	N/A	N/A
DPM [5]	68.02	56.48	44.18	67.27	55.77	43.59
DPM-VOC+VP [6]	74.59	64.71	48.76	72.28	61.84	46.54
OC-DPM [7]	74.94	65.95	53.86	73.50	64.42	52.40
SubCat [8]	84.14	75.46	59.71	83.41	74.42	58.83
Regionlets [9]	84.75	76.45	59.70	N/A	N/A	N/A
AOG [10]	84.80	75.94	60.70	33.79	30.77	24.75
Faster R-CNN [3]	86.71	81.84	71.12	N/A	N/A	N/A
3DVP [11]	87.46	75.77	65.38	86.92	74.59	64.11
3DOP [12]	93.04	88.64	79.10	91.44	86.10	76.52
Mono3D [13]	92.33	88.66	78.96	91.01	86.62	76.84
SDP+RPN [14]	90.14	88.85	78.38	N/A	N/A	N/A
MS-CNN [15]	90.03	89.02	76.11	N/A	N/A	N/A
SubCNN-VGG16	90.74	88.55	77.95	90.49	87.88	77.10
SubCNN-GoogleNet	90.81	89.04	79.27	90.67	88.62	78.68

Detection and Pose Estimation on PASCAL3D+ [17]

Method	DPM [5]	DPM-VOC+VP [6]	Ours w/o extra	Ours Full	
Detection AP	29.6	28.3	58.8	60.7	
Pose 4 views AVP	19.5	24.5	45.2	47.5	
Pose 8 views AVP	18.7	22.2	28.6	31.9	
Pose 16 views AVP	15.6	17.9	22.3	24.5	
Pose 24 views AVP	12.1	14.4	17.9	19.3	

Cabler and D. Cabiela Multivianus and 2d defermental and translated TDAMI 2015	CVPR, 2016.
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