Learning Human-Object Interactions by Graph Parsing Neural Networks

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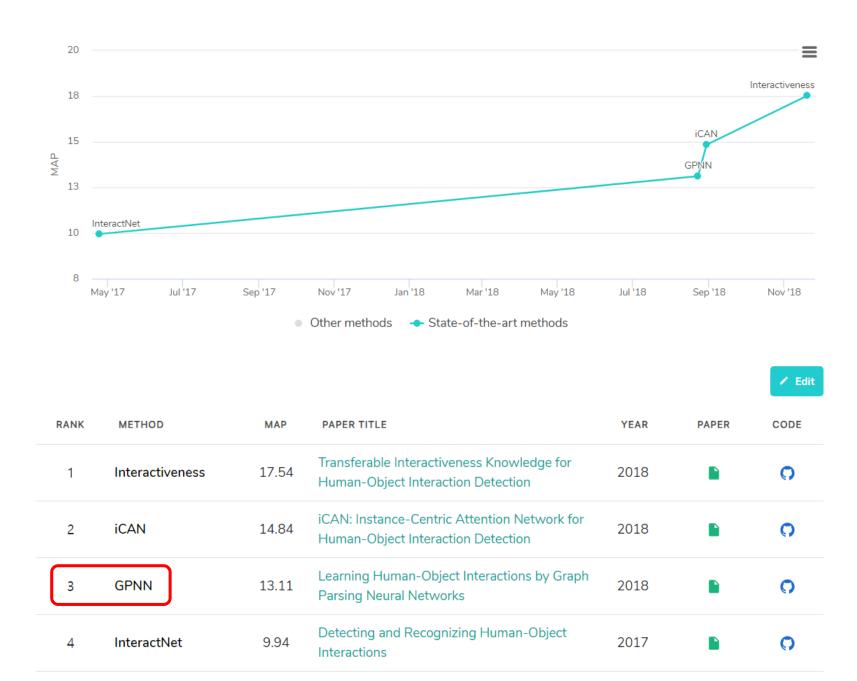
1 University of California, Los Angeles 2 International Center for AI and Robot Autonomy (CARA) 3 Beijing Institute of Technology 4 Peking University 5 Inception Institute of Artificial Intelligence

ECCV 2018

인공지능 연구실 석사과정 구자봉



Human-Object Interaction Detection on HICO-DET





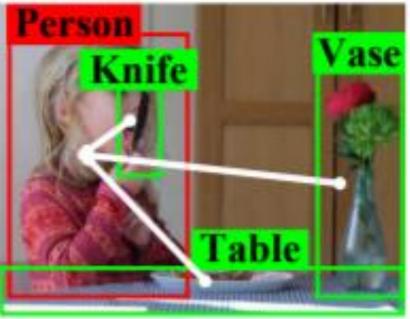
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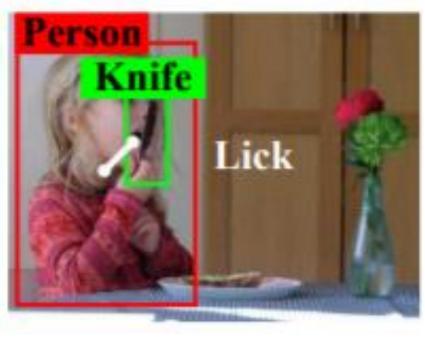
- 1. INTRODUCTION
- 2. RELATED WORKS
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- 4. EXPERIMENTS
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1. INTRODUCTION







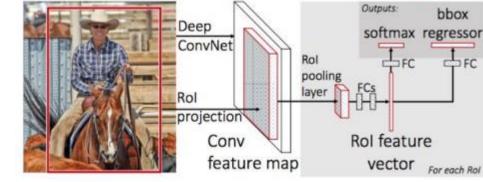


https://seongkyun.github.io/papers/2019/01/06/Object_detection/

2. RELATED WORKS

R-CNN

Object Detection







2. RELATED WORKS

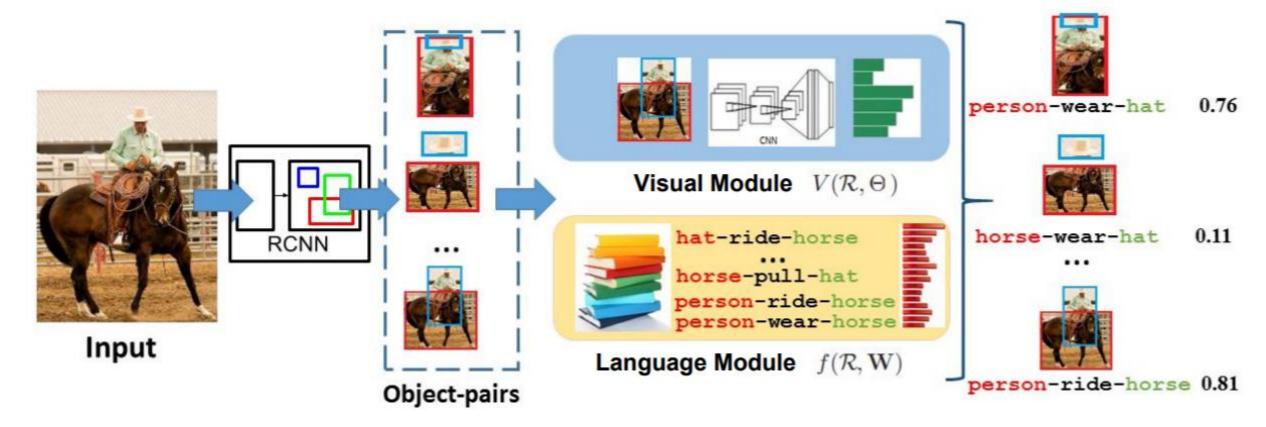
Object Detection

System	Time	07 data	07 + 12 data
R-CNN	~ 50s	66.0	-
Fast R-CNN	~ 2s	66.9	70.0
Faster R-CNN	~ 198ms	69.9	73.2

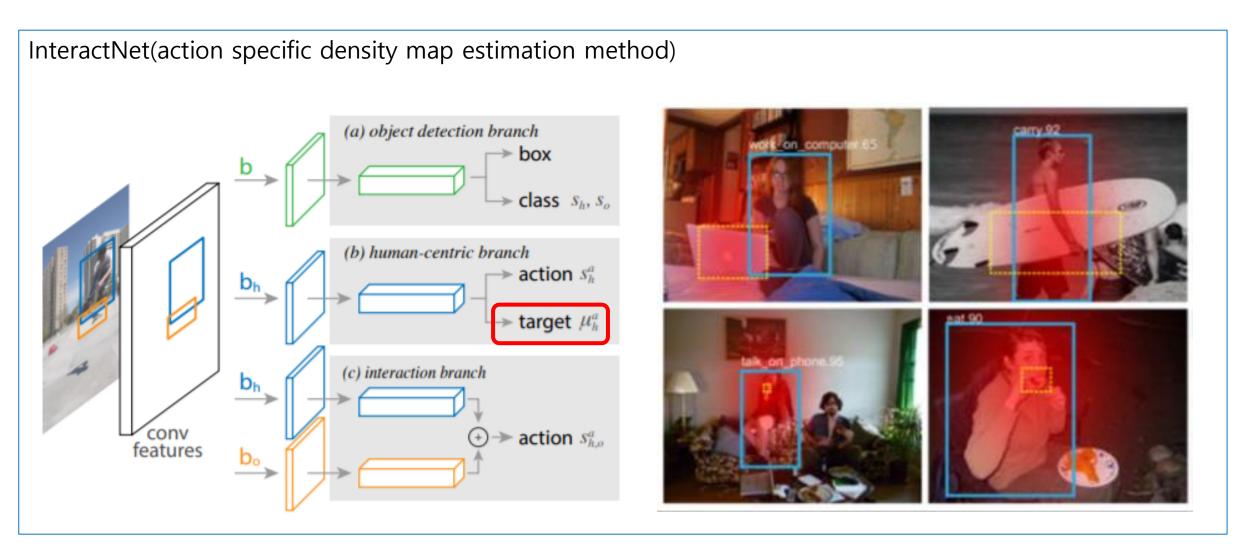


2. RELATED WORKS

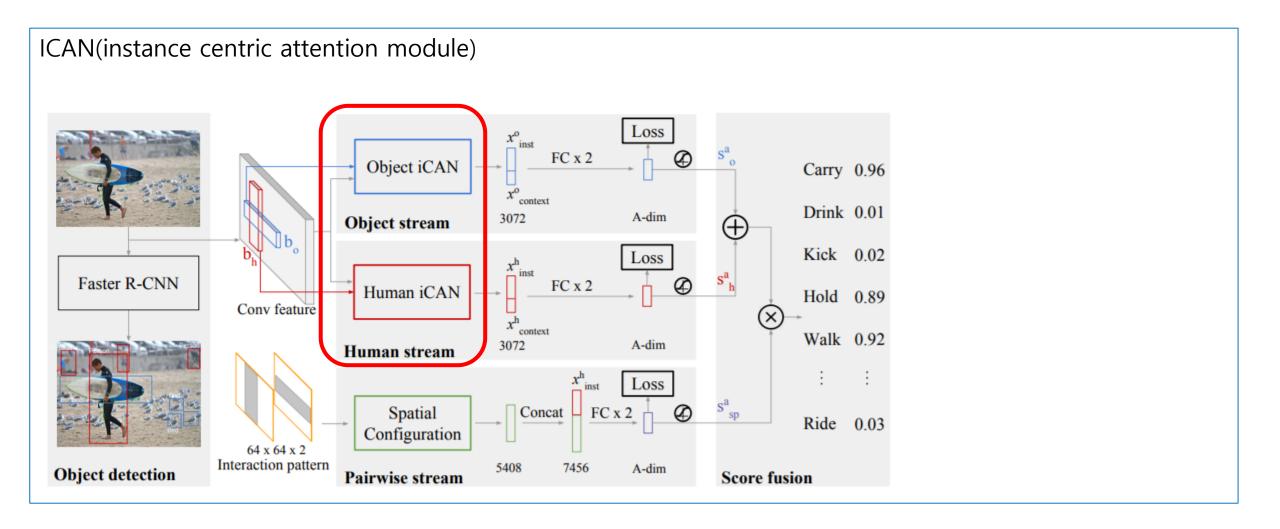
Visual Relationship Detection



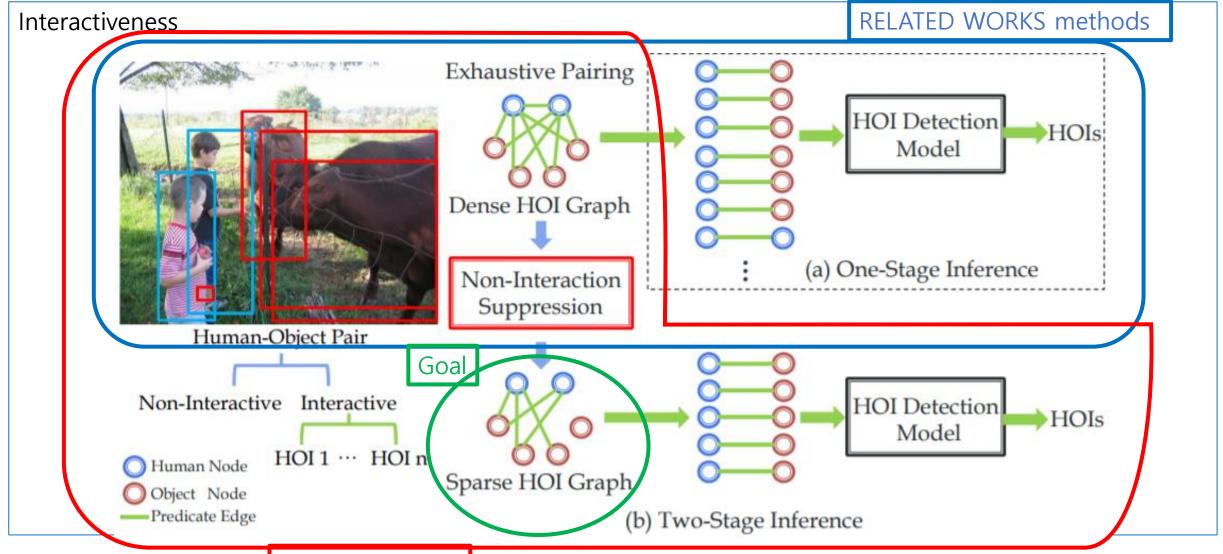




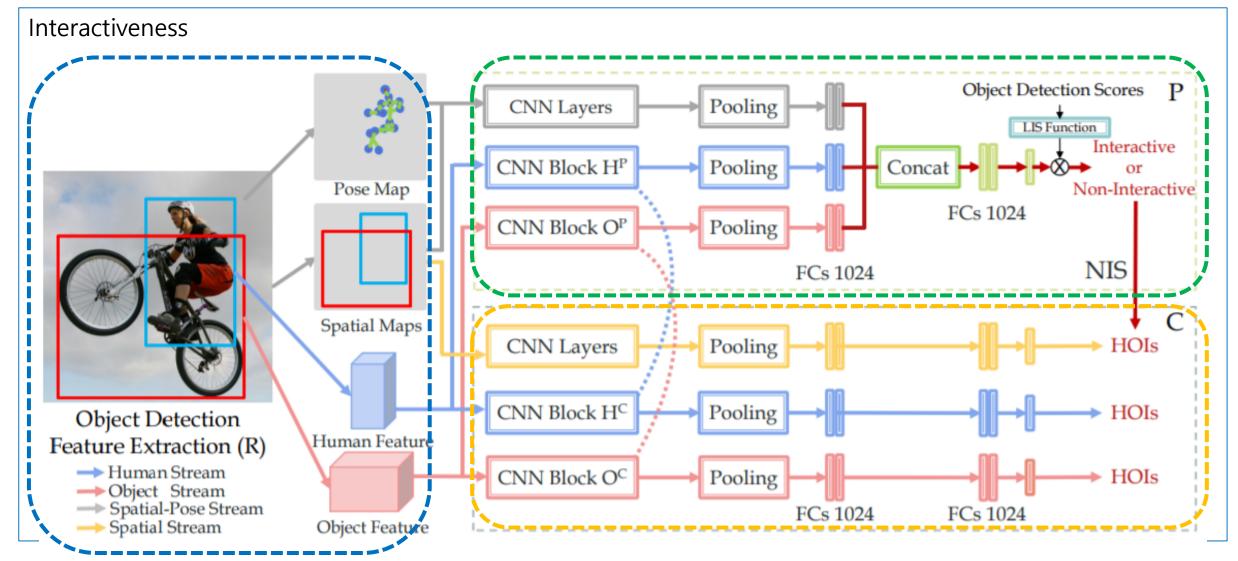






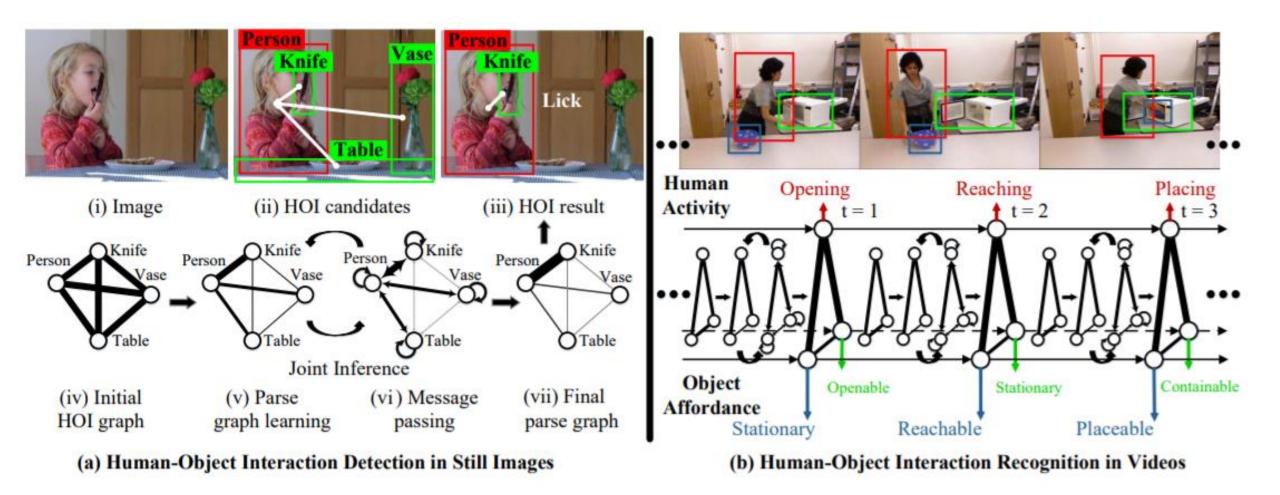




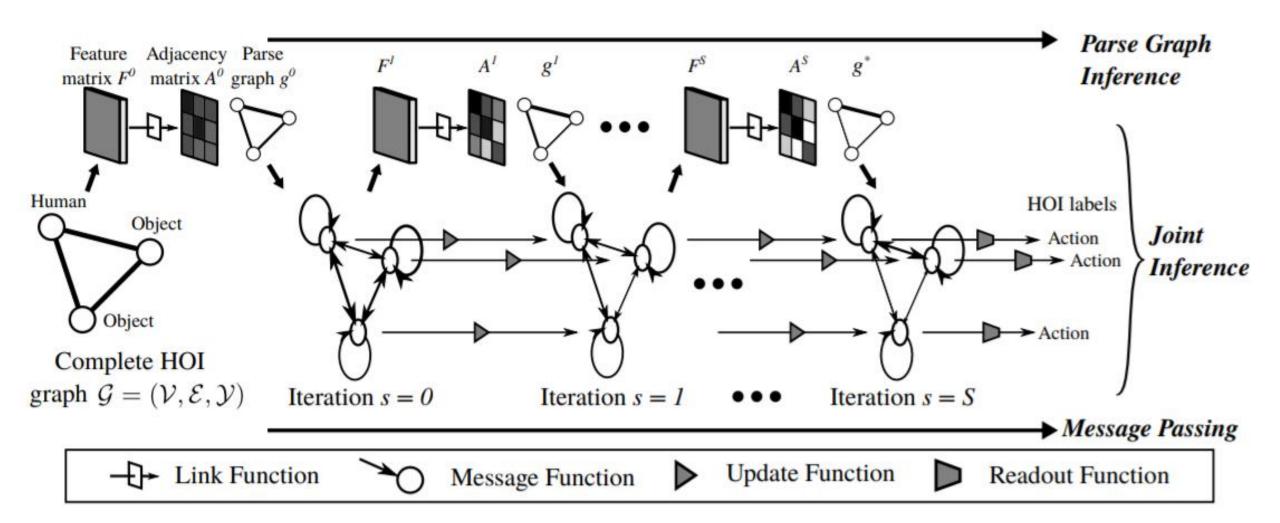




3. PROPOSED MODEL







$$\Gamma = \{ \Gamma^{\mathcal{V}}, \Gamma^{\mathcal{E}} \} \quad p(\mathcal{V}_g, \mathcal{E}_g | \Gamma, \mathcal{G}) \qquad g^* = \underset{g}{\operatorname{argmax}} \quad p(g | \Gamma, \mathcal{G}) = \underset{g}{\operatorname{argmax}} \quad p(\mathcal{V}_g, \mathcal{E}_g, \mathcal{Y}_g | \Gamma, \mathcal{G})$$

$$= \underset{g}{\operatorname{argmax}} \quad p(\mathcal{Y}_g | \mathcal{V}_g, \mathcal{E}_g, \Gamma) p(\mathcal{V}_g, \mathcal{E}_g | \Gamma, \mathcal{G})$$



$$\Gamma^{\mathcal{V}}$$
 $\Gamma^{\mathcal{E}}$

$$A \in [0,1]^{|\mathcal{V}| \times |\mathcal{V}|}$$

$$A_{vw} = L(\Gamma_v, \Gamma_w, \Gamma_{vw})$$

$$A^s = \sigma(\mathbf{W}^L * F^s)$$

$$h_v^s = U(h_v^{s-1}, m_v^s)$$

$$h_v^s = U(h_v^{s-1}, m_v^s) = GRU(h_v^{s-1}, m_v^s)$$

$$A_{vw}^{s} = L(h_{v}^{s-1}, h_{w}^{s-1}, m_{vw}^{s-1})$$



Message Function

$$m_v^s = \sum_w A_{vw} M(h_v^{s-1}, h_w^{s-1}, \Gamma_{vw})$$

$$M(h_v, h_w, \Gamma_{vw}) = [\mathbf{W}_V^M h_v, \mathbf{W}_V^M h_w, \mathbf{W}_E^M \Gamma_{vw}]$$

Readout Function

$$y_v = R(h_v^S)$$

$$y_v = R(h_v^S) = \varphi(\mathbf{W}^R h_v^S)$$

$$A_{vw}^{s} = L(h_{v}^{s-1}, h_{w}^{s-1}, m_{vw}^{s-1}) \qquad m_{v}^{s} = \sum_{w} A_{vw}^{s} M(h_{v}^{s-1}, h_{w}^{s-1}, \Gamma_{vw})$$

4. EXPERIMENTS

Datasets

V-COCO Images 10,346(2,533, 2,867, 4,946)

People 16,199 HOI 29 (24(object), 5(no object))

HICO-DET Images 47,776 (38,118, 9,658) Objects 80 (airplane, apple...) Verbs 117 (carry, catch...) HOI 600 (airplane – board, direct, exit, fly...)

HOI Remark >= 150k

CAD-120

Environment

라이브러리 : PyTorch

GPU: Nvidia Titan Xp GPU

평가지표: mAP



		실제 정답		
		True	False	
분류	True	True Positive	False Positive	
분류 결과	False	False Negative	True Negative	

$$(Precision) = \frac{TP}{TP + FP}$$
 $(Recall) = \frac{TP}{TP}$

$$(Accuracy) = \frac{TP + TN}{TP + FN + FP + TN}$$

$$(F1\text{-}score) = 2 \times \frac{1}{\frac{1}{Precision} + \frac{1}{Recall}} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

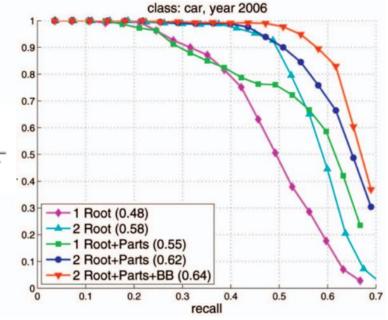


그림 1. precision-recall 그래프의 예

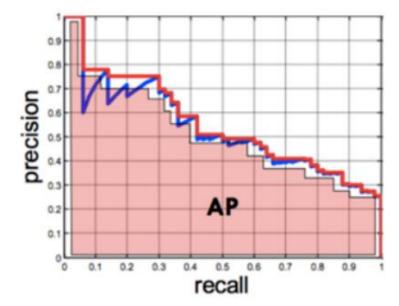


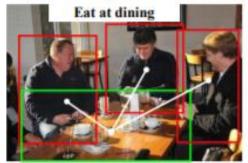
그림 2. average precision

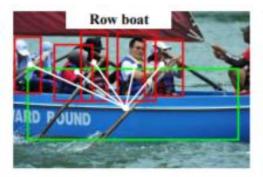
mAP(**mean Average Precision**): 멀티 오브젝트 디텍션 문제에 있어 AP 들의 mean 값

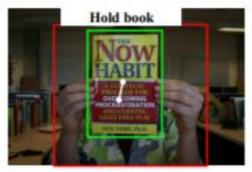
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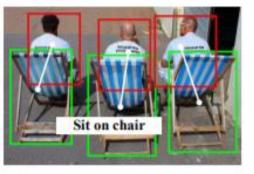






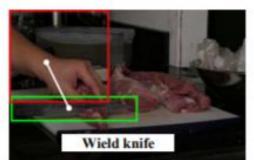


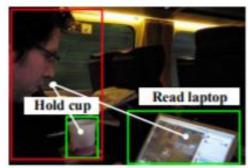










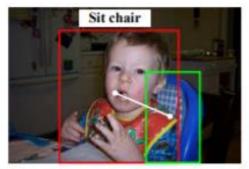


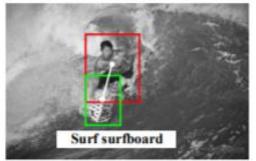
Methods	Full (mAP %) ↑	Rare (mAP %) ↑	Non-rare (mAP %) ↑
Random	1.35×10^{-3}	5.72×10^{-4}	1.62×10^{-3}
Fast-RCNN(union) [13]	1.75	0.58	2.10
Fast-RCNN(score) [13]	2.85	1.55	3.23
HO-RCNN [1]	5.73	3.21	6.48
HO-RCNN+IP [1]	7.30	4.68	8.08
HO-RCNN+IP+S [1]	7.81	5.37	8.54
Gupta et al. [17]	9.09	7.02	9.71
Shen <i>et al.</i> [38]	6.46	4.24	7.12
InteractNet [14]	9.94	7.16	10.77
GPNN	13.11	9.34	14.23
Performance $Gain(\%)$	31.89	30.45	32.13

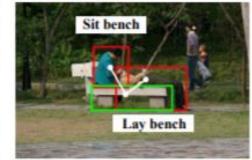


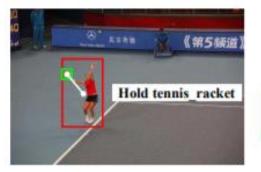


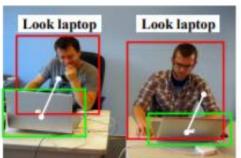


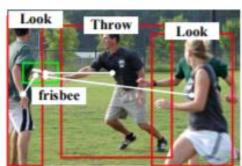


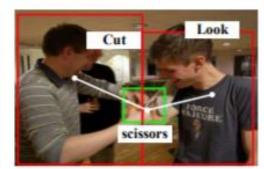


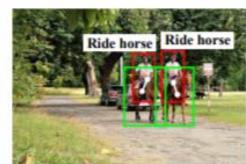






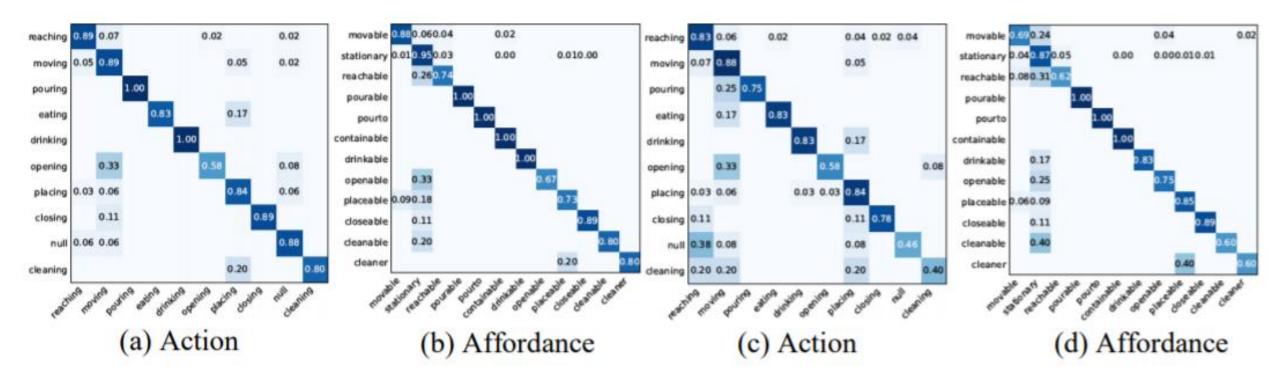




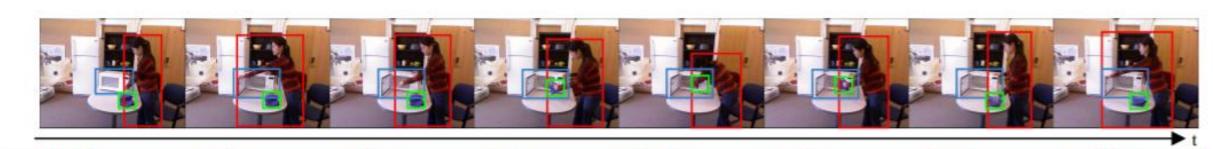


Method	Set 1 (mAP %) ↑	Set 2 (mAP %) ↑	Ave. (mAP %) ↑
Gupta et al. [17]	33.5	26.7	31.8
InteractNet [14]	42.2	33.2	40.0
GPNN	44.5	42.8	44.0
$Performance\ Gain(\%)$	5.5	28.9	10.0





	Detection	(F1-score) ↑	Anticipation (F1-score) ↑		
Method	Sub	Object	Sub	Object	
Method	-activity(%)	Affordance(%)	-activity(%)	Affordance(%)	
ATCRF [22]	80.4	81.5	37.9	36.7	
S-RNN [20]	83.2	88.7	62.3	80.7	
S-RNN (multi-task) [20]	82.4	91.1	65.6	80.9	
GPNN	PNN 88.9		75.6	81.9	
$Performance\ Gain(\%)$	8.1	-	15.2	1.2	



	GT	reaching	opening	reaching	moving	cleaning	moving	placing	reaching
ıman Ac	Detec.	reaching	opening	reaching	moving	cleaning	moving	placing	null
	Antici.		opening	reaching	moving	cleaning	moving	moving	reaching
Ē	GT :	reachable	openable	stationary	stationary	cleanable	stationary	stationary	reachable
Object Affordance		reachable	openable	stationary	stationary	cleanable	stationary	stationary	reachable
	Detec.		openable	stationary	stationary	cleanable	stationary	stationary	reachable
	Antici.	stationary	stationary	reachable	movable	cleaner	movable	placeable	stationary
	GT	stationary	stationary	reachable	movable	cleaner	movable	placeable	stationary
	Detec.	stationary	stationary	reachable	movable	cleaner	stationary	placeable	stationary
	Antici.		Stationary	reachaore	movable	Cicanci	Stationary	piaceaoie	Stationary



5. CONCLUSION

• GPNN (link functions, message functions, update functions and readout functions)

	RANK	METHOD	MAP	RANK	METHOD	MAP		
HICO-DET	1	Interactiveness	17.54	1	Interactiveness	49.0		
	2	2 iCAN 14.84	2	iCAN	44.7	V-COCO		
	3	GPNN	13.11		CDNINI	44.0		
	4	InteractNet	9.94	3	GPNN	44.0		



Q&A

