

Towards Cautious Collective Inference for Object Verification.

José Oramas M., Luc De Raedt, Tinne Tuytelaars

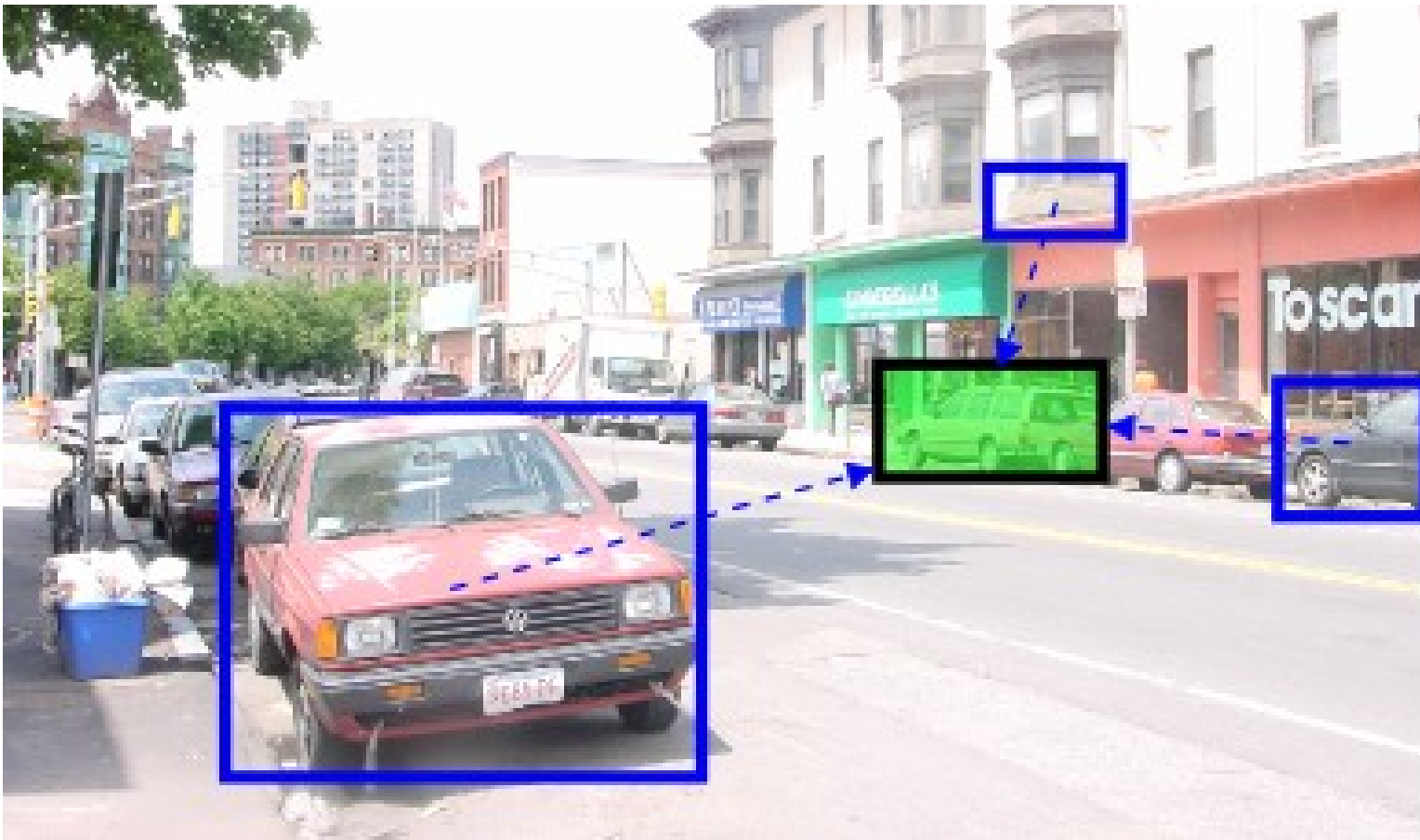
KU Leuven

March 24th 2014

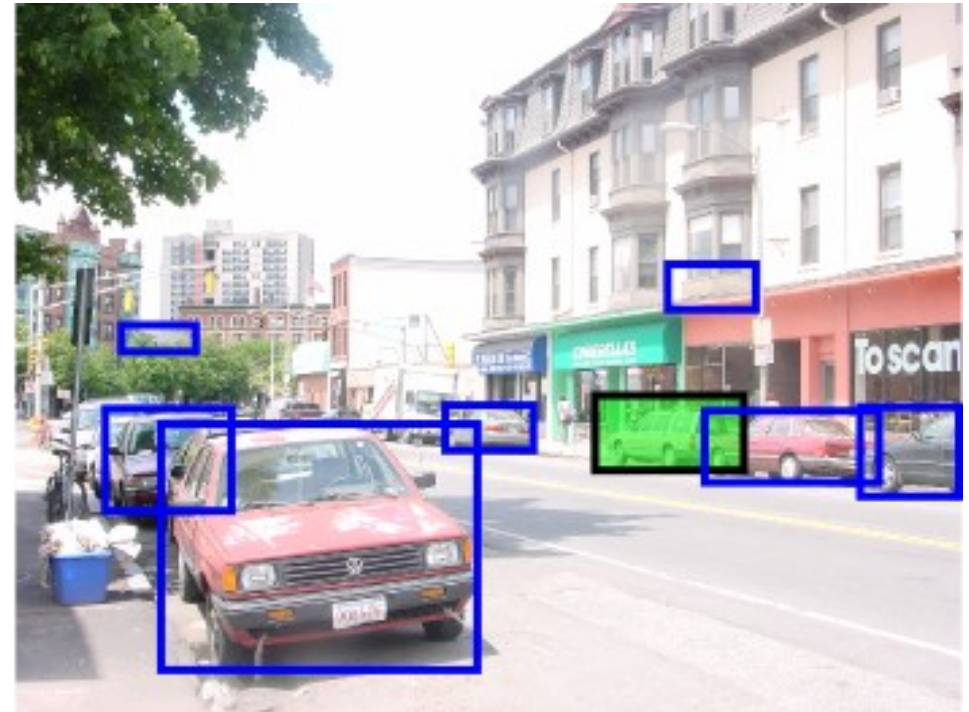
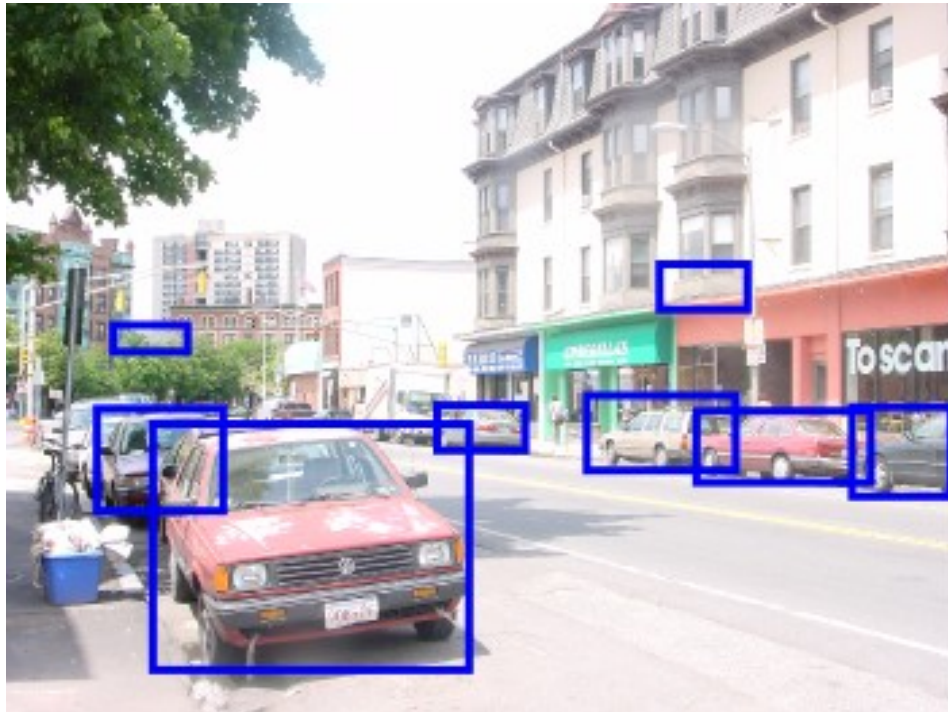


Object Verification

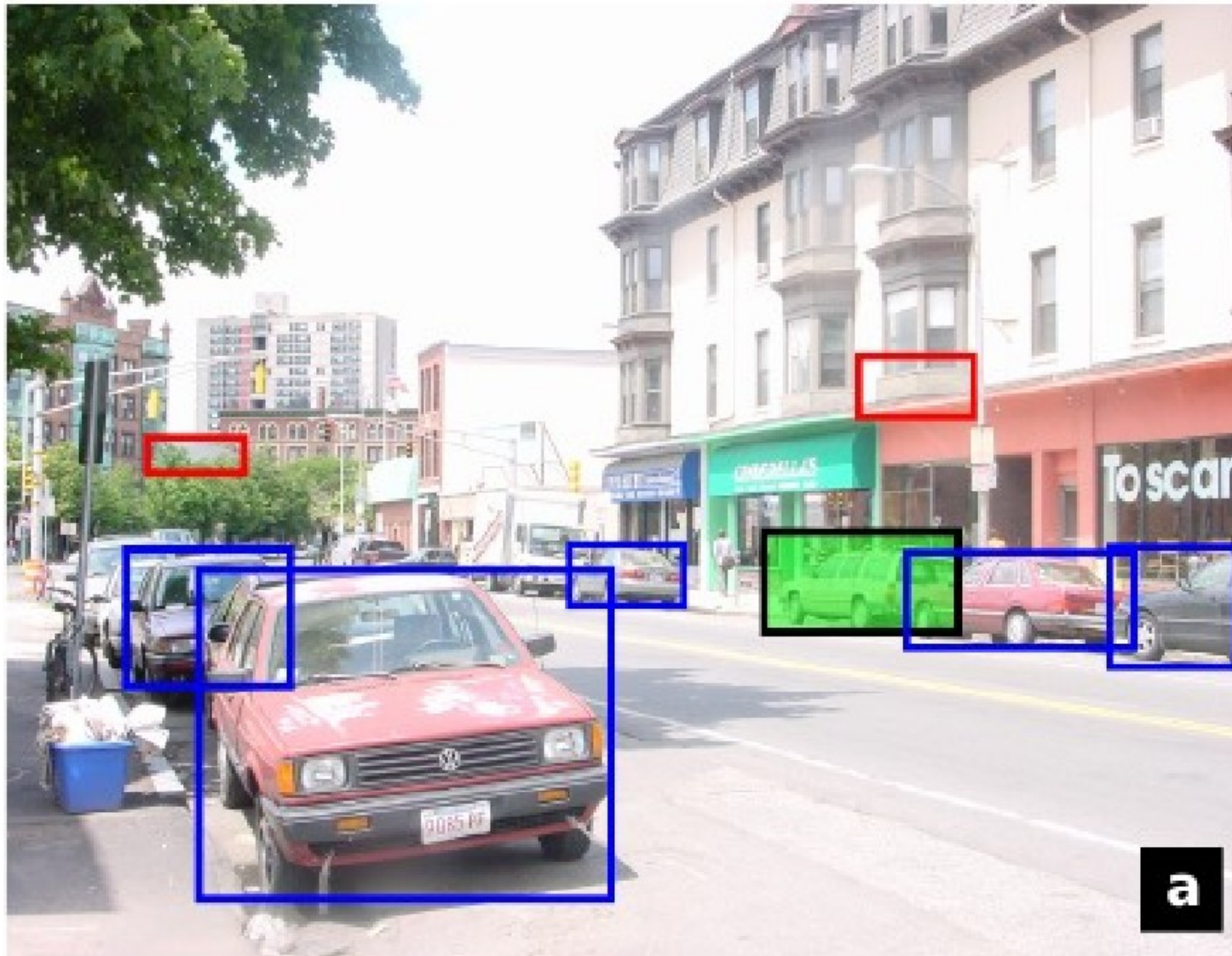
(Context-based Object Detection)



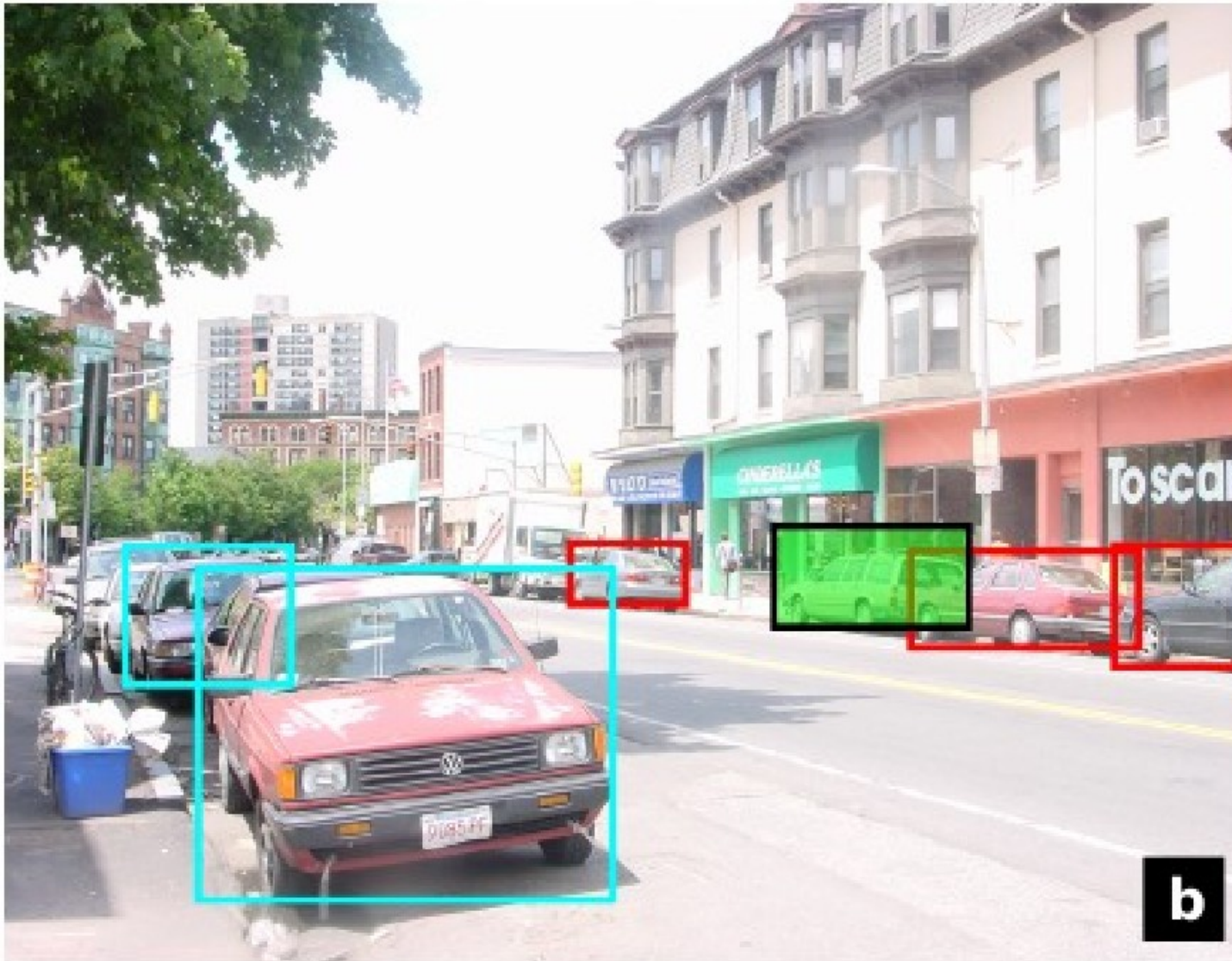
A traditional pipeline



(Q) How to properly use relations between objects?

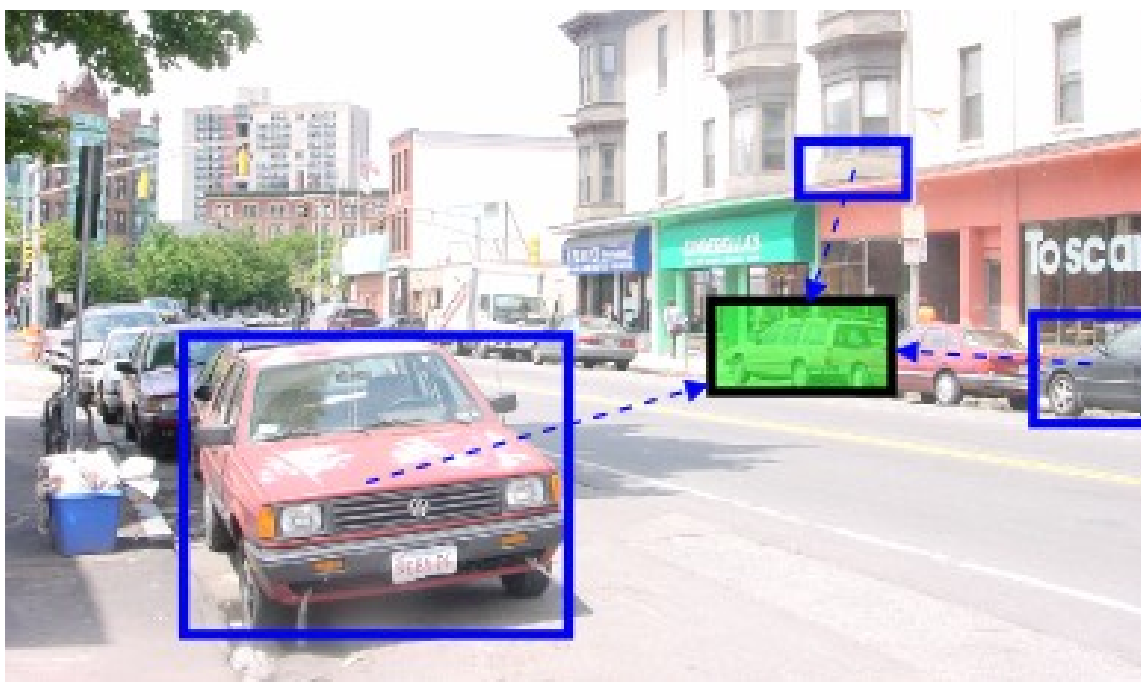


(Q) How to properly use relations between objects?



Defining Pairwise Relations between Objects

Derived from the features of the bounding boxes



Relations :

$$r_{ij}^{(RF1)} = (\Delta x_{ij}, \Delta y_{ij}, \Delta \theta_{ij})$$

$$r_{ij}^{(RF2)} = (rx_{ij}, ry_{ij}, r\rho_{ij}, ra_{ij}) \quad (\text{based on Li et al's, CVPR 2012})$$

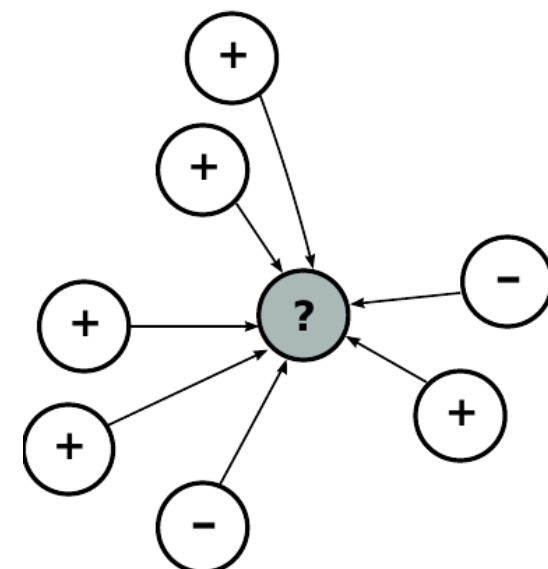
$$r_{ij}^{(RF3)} = (\Delta x_{ij}, \Delta y_{ij}) \quad (\text{based on Perko et al's, CVIU 2010})$$

Aggressive Inference

$$wvRN(o_i|N_i) = \frac{1}{z} \sum_{o_j \in N_i} p(o_i|o_j) \cdot w_{ij} \quad (\text{Mackassy et al., JMLR 2007})$$

$$p(o_i|o_j) = p(o_i|r_{ij}) = \frac{p(r_{ij}|o_i)p(o_i)}{p(r_{ij}|o_i)p(o_i) + p(r_{ij}|\neg o_i)p(\neg o_i)}$$

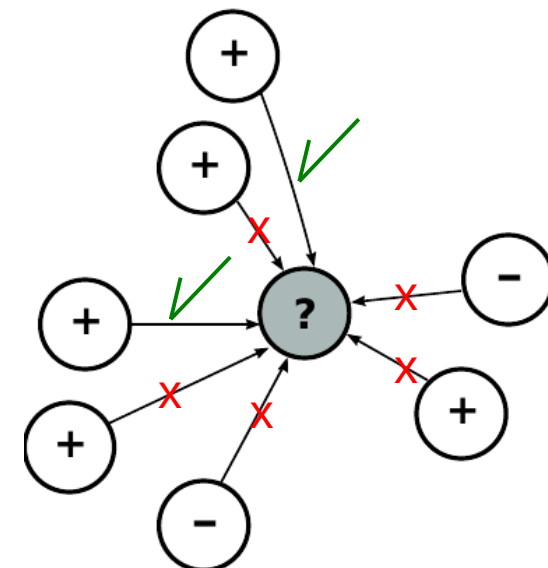
$$w_j = p(o_j|s_j) = \frac{p(s_j|o_j)p(o_j)}{p(s_j|o_j)p(o_j) + p(s_j|\neg o_j)p(\neg o_j)}$$



Cautious Inference

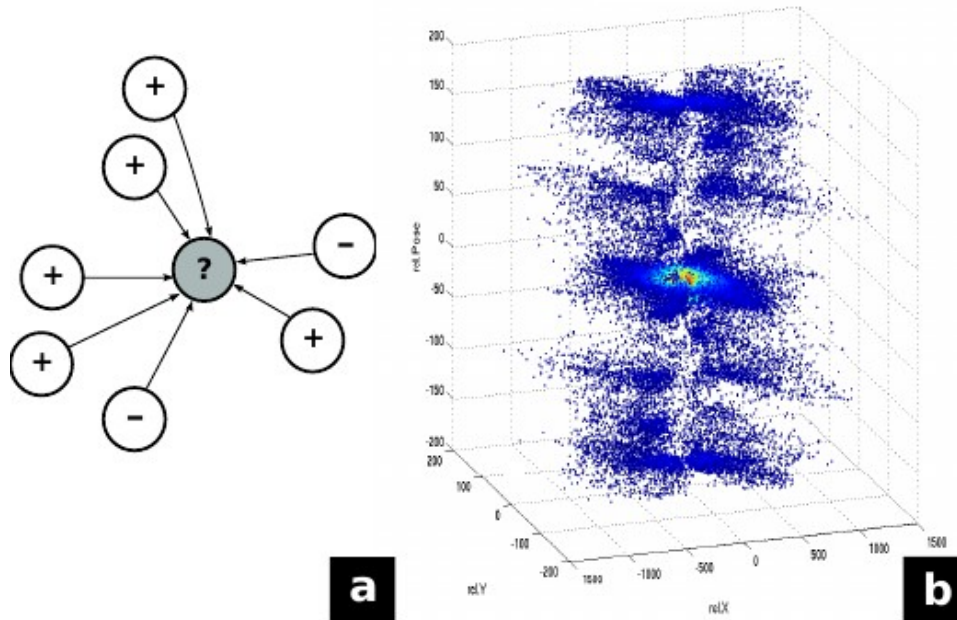
- McDowel et al., JMLR 2009
- Neville et al, SRL ws@AAAI 2000

$$wvRN(o_i^u|N_i) = \frac{1}{z} \sum_{o_j^k \in (N_i \cap O^k)} p(o_i^u|o_j^k) \cdot w_{ij}$$

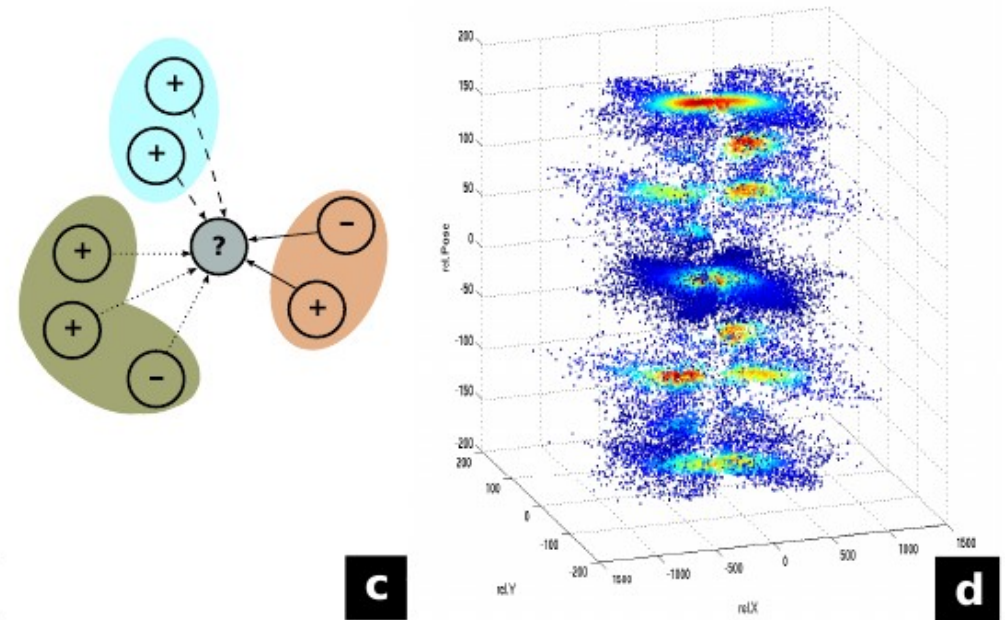


How objects associate to each other ?

Class-based Homophily



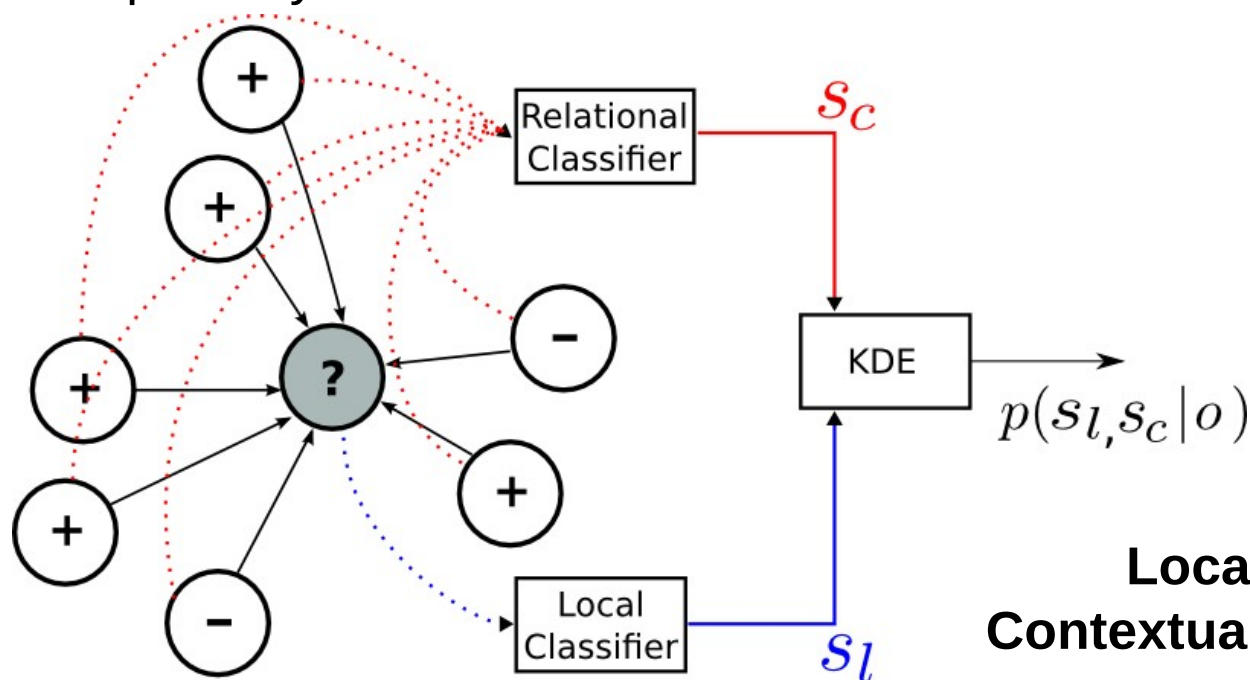
Relationship-based Homophily



$$wvRN(o_i|N_i) = \frac{1}{z} \sum_{o_j \in N_i} p(o_i|o_j) \cdot w_{ij}$$

Combining local and contextual sources of Information

Inspired by the score combination method of Perko et al., CVIU 2010.



Local Support : $s_l = p(\hat{o}_i)$
Contextual Support : $s_c = wvRN(o_i|N_i)$

- Score Combination

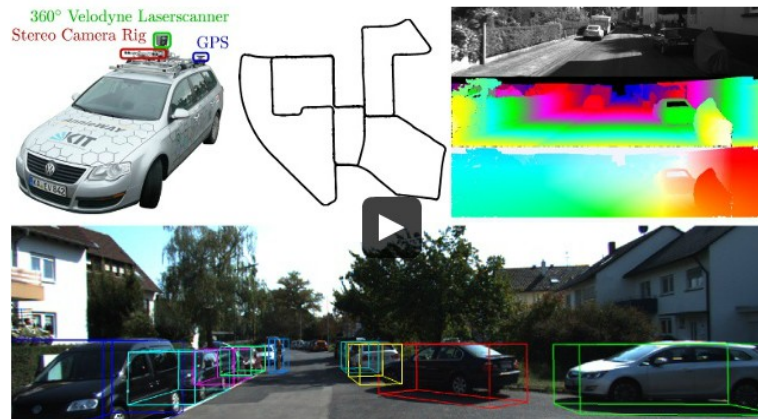
$$p(o|s_l, s_c) = \frac{p(s_l, s_c | o)p(o)}{p(s_l, s_c | o)p(o) + p(s_l, s_c | \neg o)p(\neg o)}$$

Experimental details

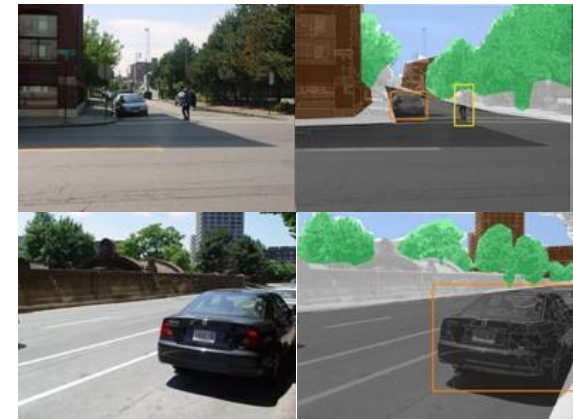
Datasets:

KITTI benchmark (Geiger et al, CVPR 2012)

- Class of Interest : **car**
- Focus on Images with more than 2 objects



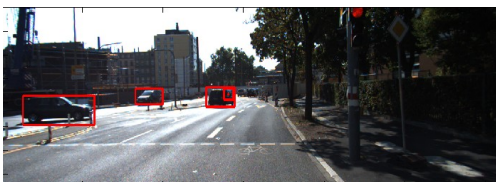
MIT StreetScenes (Bileschi et al)



Object Localization:

Object Detection (2D)

[1] López et al. ,ws@ICCV 2011.



Parameters:

- **Inference Type:** *Aggressive* | *Cautious* .
- **Homophily Type:** *class-based* | *relation-based* .

Only using contextual information

Dataset KITTI benchmark	Relations Representation : RF1				Relations Representation : RF2			
	Class-based Hom.		Relation-based Hom.		Class-based Hom.		Relation-based Hom.	
	Global		Global		Global		Global	
Set all	aggre. 0.29	caut. 0.38	aggre. 0.28	caut. 0.37	aggre. 0.32	caut. 0.40	aggre. 0.41	caut. 0.50

Dataset MIT StreetScenes	Relations Representation : RF3				Relations Representation : RF2			
	Class-based Hom.		Relation-based Hom.		Class-based Hom.		Relation-based Hom.	
	Global		Global		Global		Global	
Set all	aggre. 0.54	caut. 0.63	aggre. 0.51	caut. 0.59	aggre. 0.51	caut. 0.56	aggre. 0.49	caut. 0.55

Combination of Local and Contextual Information

Dataset KITTI benchm [1]		RF1		RF2	
		Class-based Homophily		Relation-based Homophily	
		Global		Global	
Set all	Detector [14] 0.61±0.011	aggre. 0.61±0.009	caut. 0.63±0.007	aggre. 0.65±0.011	caut. 0.68±0.003

Dataset MIT StreetScen [1]		RF3		RF2	
		Class-based Homophily		Class-based Homophily	
		Global		Global	
Set all	Detector [14] 0.69±0.006	aggre. 0.77±0.001	caut. 0.80±0.028	aggre. 0.73±0.011	caut. 0.76±0.014

Collecting Hypotheses using DPM

Dataset KITTI benchmark		RF3		RF2	
		Class-based Homophily		Relation-based Homophily	
		Global		Global	
Set all	Detector [2] 0.65±0.003	aggre. 0.68±0.007	caut. 0.71±0.007	aggre. 0.72±0.009	caut. 0.75±0.003

Dataset MIT StreetScenes		RF3		RF2	
		Class-based Homophily		Class-based Homophily	
		Global		Global	
Set all	Detector [2] 0.62±0.004	aggre. 0.66±0.011	caut. 0.71±0.012	aggre. 0.65±0.026	caut. 0.69±0.014

[1] López et al. ,ws@ICCV 2011.

[2] Felzenszwalb et al. ,TPAMI 2010.

Only using contextual information

Dataset KITTI benchmark	Relations Representation : RF1				Relations Representation : RF2			
	Class-based Hom.		Relation-based Hom.		Class-based Hom.		Relation-based Hom.	
	Global		Global		Global		Global	
Set all	aggre. 0.29	caut. 0.38	aggre. 0.28	caut. 0.37	aggre. 0.32	caut. 0.40	aggre. 0.41	caut. 0.50

Dataset MIT StreetScenes	Relations Representation : RF3				Relations Representation : RF2			
	Class-based Hom.		Relation-based Hom.		Class-based Hom.		Relation-based Hom.	
	Global		Global		Global		Global	
Set all	aggre. 0.54	caut. 0.63	aggre. 0.51	caut. 0.59	aggre. 0.51	caut. 0.56	aggre. 0.49	caut. 0.55

Combination of Local and Contextual Information

Dataset		RF1		RF2	
KITTI benchm[1]		Class-based Homophily		Relation-based Homophily	
		Global		Global	
Set all	Detector [14] 0.61±0.011	aggre. 0.61±0.009	caut. 0.63±0.007	aggre. 0.65±0.011	caut. 0.68±0.003

Dataset		RF3		RF2	
MIT StreetScen[1]		Class-based Homophily		Class-based Homophily	
		Global		Global	
Set all	Detector [14] 0.69±0.006	aggre. 0.77±0.001	caut. 0.80±0.028	aggre. 0.73±0.011	caut. 0.76±0.014

Collecting Hypotheses using DPM

Dataset		RF3		RF2	
KITTI benchmark		Class-based Homophily		Relation-based Homophily	
		Global		Global	
Set all	Detector [2] 0.65±0.003	aggre. 0.68±0.007	caut. 0.71±0.007	aggre. 0.72±0.009	caut. 0.75±0.003

Dataset		RF3		RF2	
MIT StreetScenes		Class-based Homophily		Class-based Homophily	
		Global		Global	
Set all	Detector [2] 0.62±0.004	aggre. 0.66±0.011	caut. 0.71±0.012	aggre. 0.65±0.026	caut. 0.69±0.014

[1] López et al. ,ws@ICCV 2011.

[2] Felzenszwalb et al. ,TPAMI 2010.

Qualitative Results

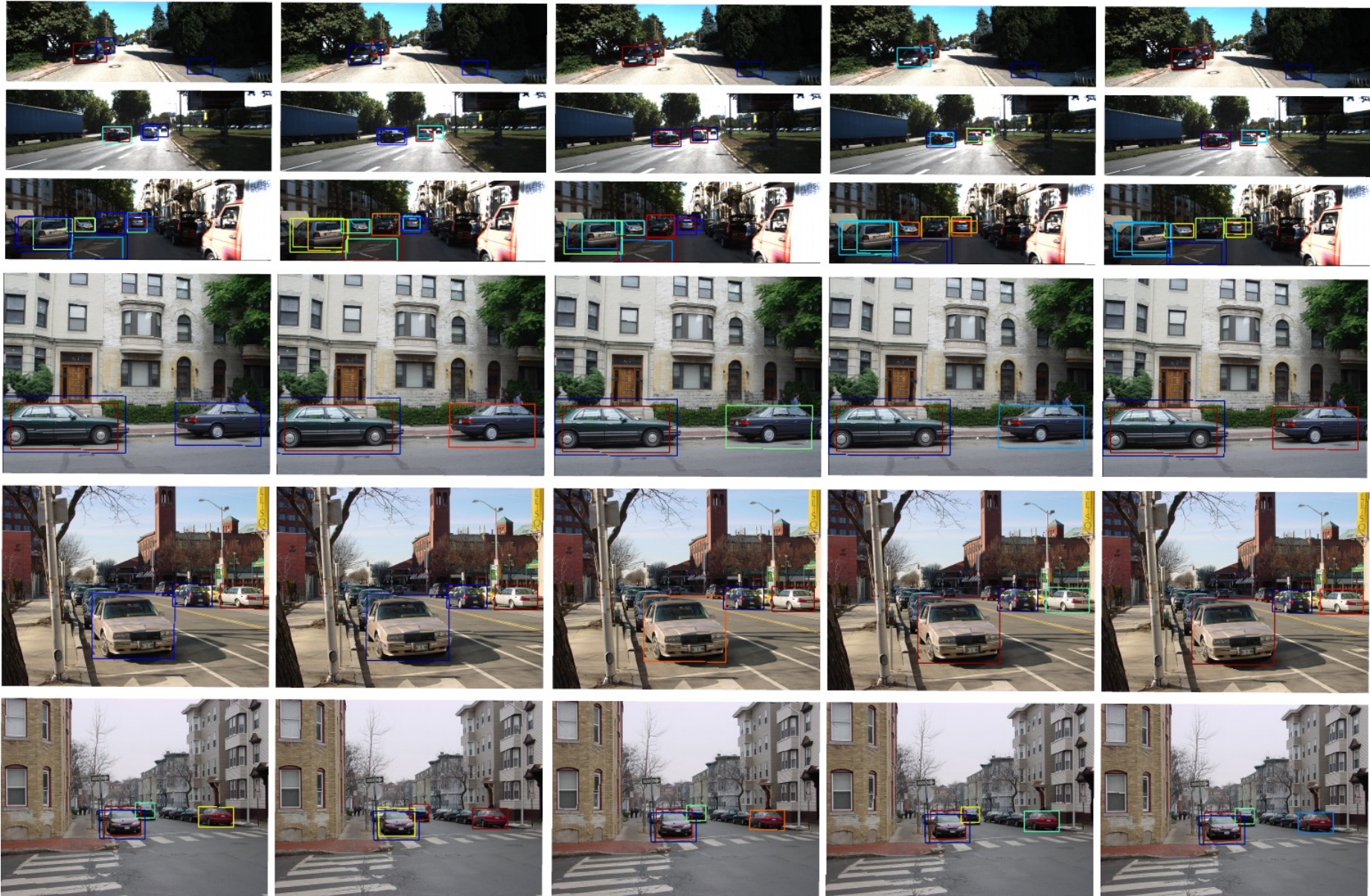
Obj. Detector

Class-based H. | Agressive Inf.

Class-based H. | Cautious Inf.

Relation-based H. | Agressive Inf.

Relation-based H. | Cautious Inf.



Max.



Min.

- **Cautious Inference about object relations outperforms traditional aggressive counterparts.**
- **Relation-based Homophily is good for scenarios where there is no local information about the unknown object.**
(e.g. in an inpainting scenario)
- **Future Work**
 - Better representations for reasoning in 3D space.
 - Investigate methods to recover the underlying structures in the relational space.
 - Investigate the generality of the method in the context of other object categories or alternative applications.

Questions?

Towards Cautious Collective Inference for Object Verification.

José Oramas M., Luc De Raedt, Tinne Tuytelaars

KU Leuven

March 24th 2014

