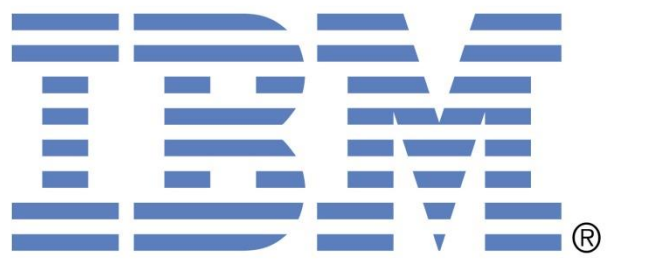# Relative Attributes For Large-scale Abandoned Object Detection (AOD)
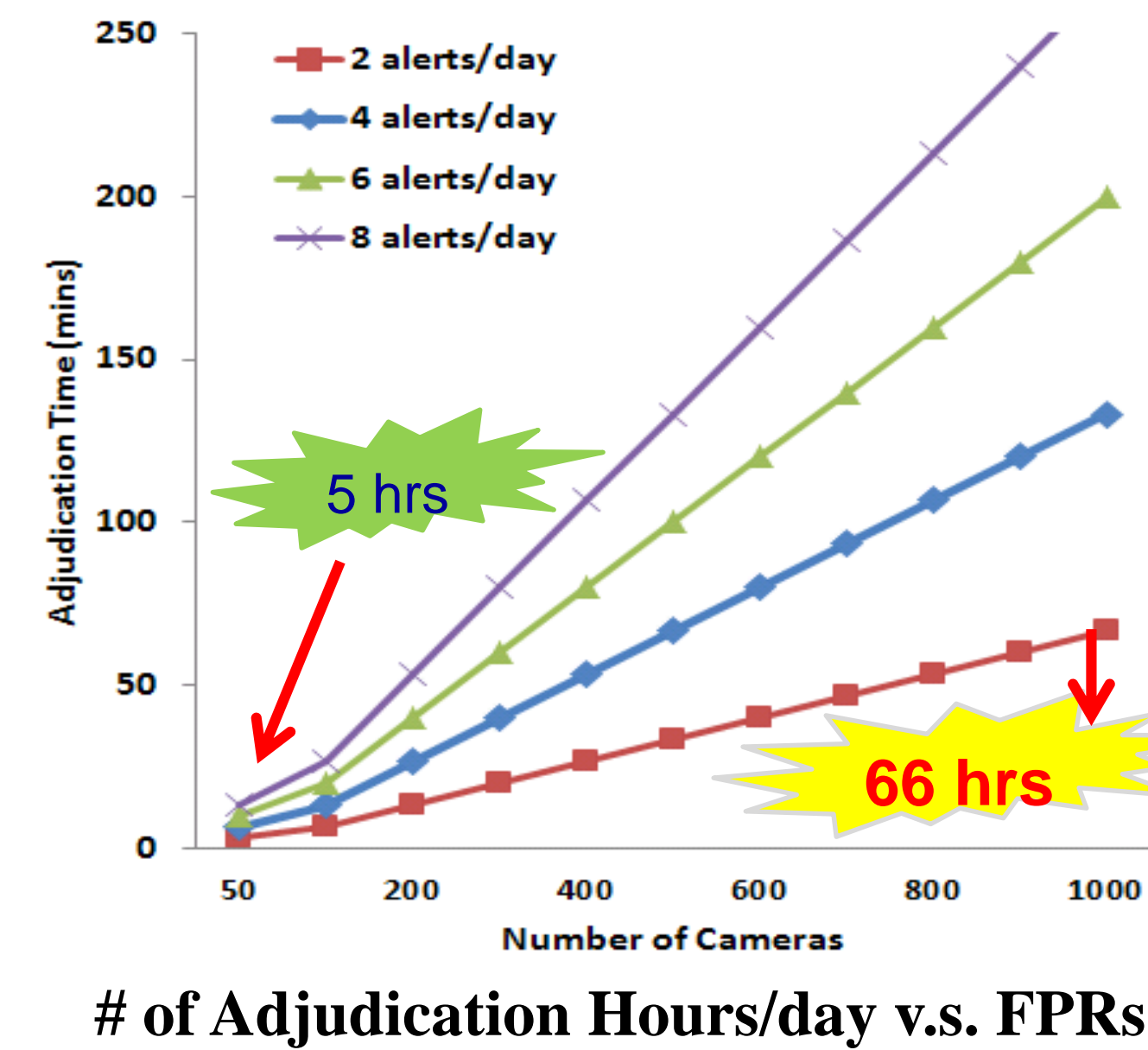
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1 Challenges of Large-scale AOD Deployment

• *Technical*: all-activity, all-weather, various types of objects and cameras views, …

• *Business*: low-false alarm rates, computational scalability

# of Adjudication Hours/day v.s. FPRs

2 Our Contributions

• Prioritize alerts by ranking (*higher operational ROC point; facilitating tuning and adjudication*)

• Novel representation of AO alerts by high-level relative attributes (*intuitive, compact and efficient*)

• Scalable practical system (*3 times faster than real-time on a VM of 2.93 GHz CPU and 4G RAM*)

3 Overview of Our System
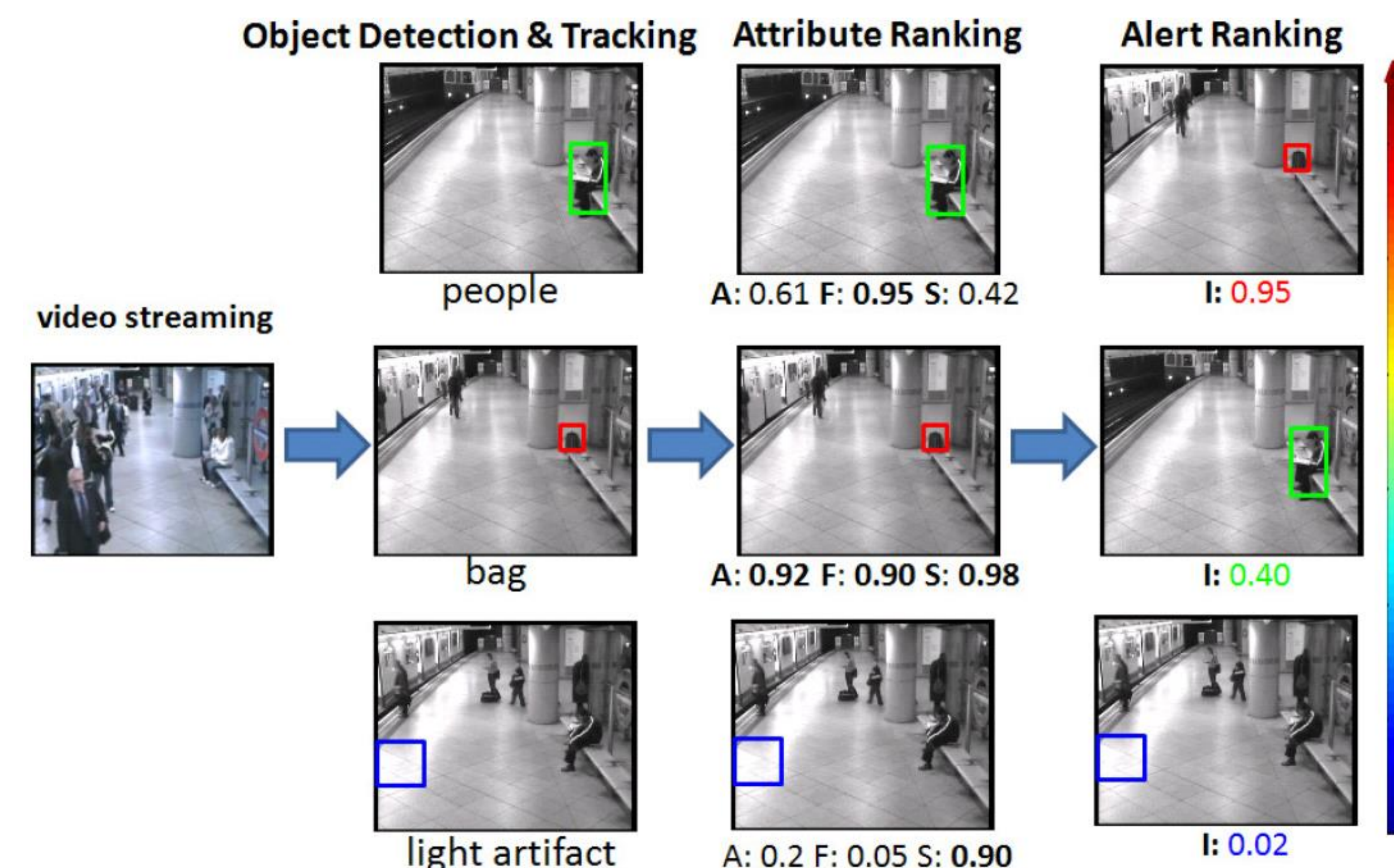
[1] *Modeling of temporarily static objects for robust AOD in urban surveillance*. In AVSS 2011
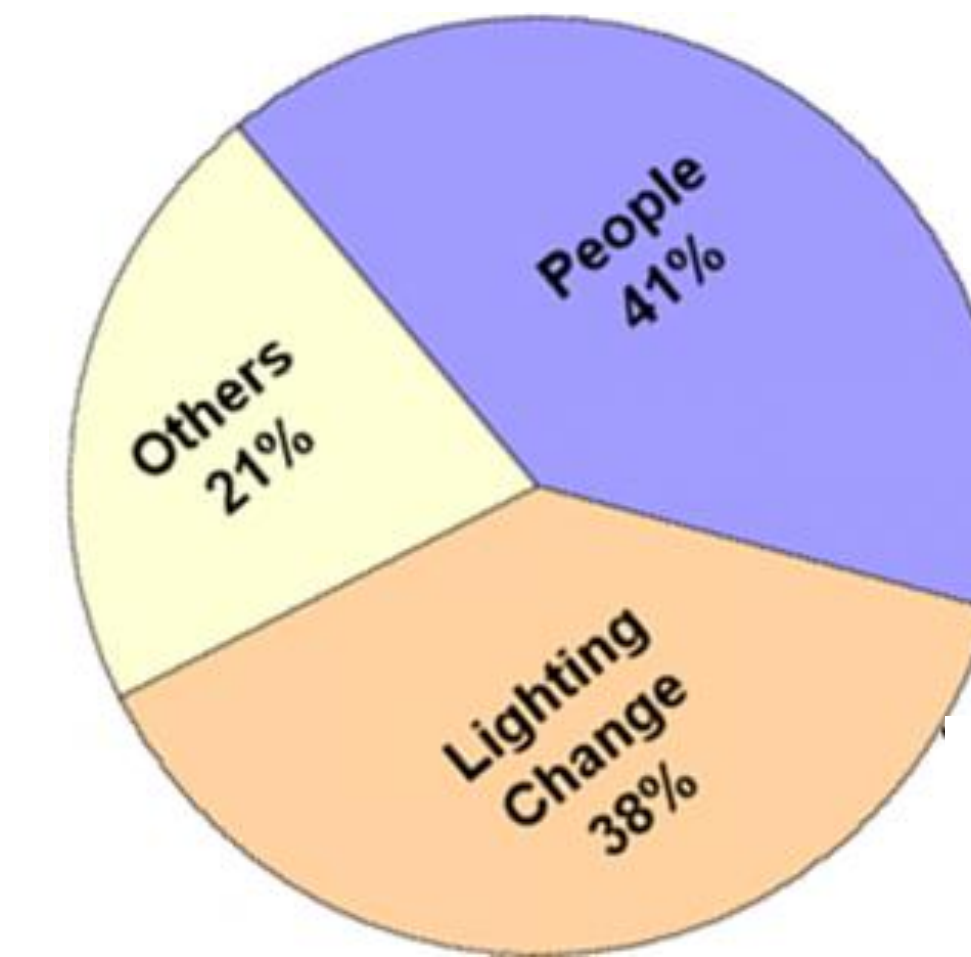
4 Relative Attributes of Abandoned Object Alerts

a) Staged drops b) Staged drops c) Natural drops

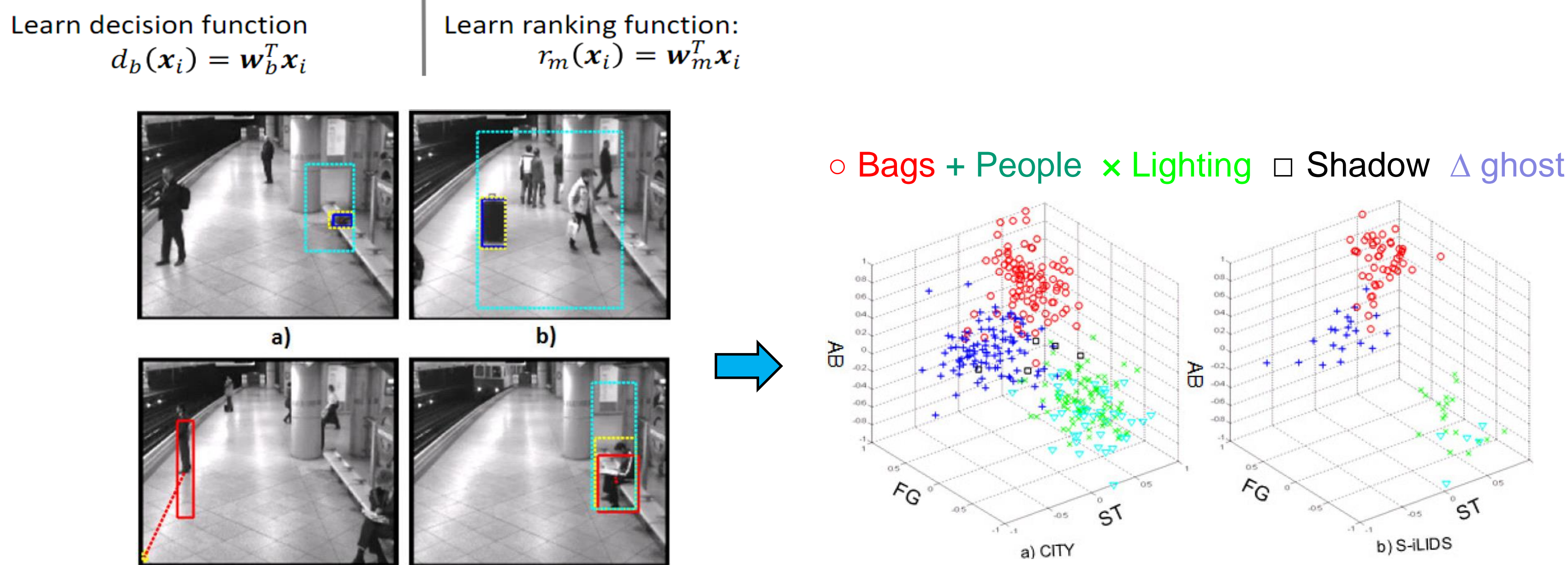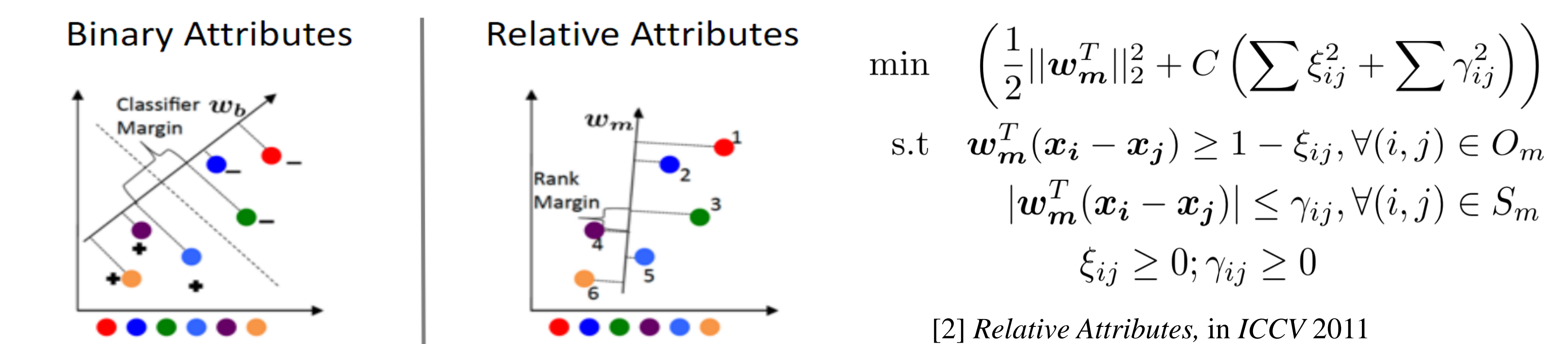d) Sitting people e) Occluded people f) Light artifacts

Distribution of FPs

Alerts	ST	FG	AB
B^+	High	High	High
P^-	Low	High	Medium
L^-	High	Low	Low
S^-	High	Medium	Low
G^-	High	Low	Low
Relative	$B^+ > P^-$	$B^+, P^- > S^-$	$B^+ > P^-$
Order	$L^-, S^-, G^- > P^-$	$S^- > L^-, G^-$	$P^- > S^-, L^-, G^-$

True alerts: high staticness (**ST),** high foregroundness (**FG**) and high abandonment (**AB**).

B⁺: bags; **P⁻**: people; **L⁻**: light artifacts; **S⁻**: shadows; **G⁻**: ghosts

5 Relative Attribute Learning

Binary Attributes   Relative Attributes

Learn decision function
$d_b(x_i) = w_b^T x_i$

Learn ranking function:
$r_m(x_i) = w_m^T x_i$

$$\min \left(\frac{1}{2}||w_m^T||_2^2 + C\left(\sum \xi_{ij}^2 + \sum \gamma_{ij}^2\right) \right)$$

$$s.t \quad w_m^T(x_i - x_j) \geq 1 - \xi_{ij}, \forall (i,j) \in O_m$$

$$|w_m^T(x_i - x_j)| \leq \gamma_{ij}, \forall (i,j) \in S_m$$

$$\xi_{ij} \geq 0; \gamma_{ij} \geq 0$$

[2] *Relative Attributes*, in ICCV 2011

○ Bags + People × Lighting □ Shadow △ ghost

a) CITY   b) S-iLIDS

Spatio-temporal Low-level feature extraction (mini-tracker)

6 Alert Ranking

• Use learnt relative attributes as input to a ranker to sort alerts by relevance (*bags > people > others*)

• Treat relevance as one single attribute and apply the technique of [2] again for alert ranking

7 Experiments

Data	#camera	duration (hrs)	#drops	Bag (B^+)	People (P^-)	Light (L^-)	Shadow (S^-)	Ghost (G^-)	Total
PETS2006	1	0.15	6	5	0	1	0	0	6
AVSS-AB	1	0.01	3	3	1	3	0	0	7
i-LIDS	2	3.8	60	48	21	19	0	5	93
CITY	30	70.5	255	196	203	187	9	83	678
NATS	2	96	19	19	139	238	9	107	512

Evaluation on Public Datasets

Methods	*PETS2006* P	*PETS2006* R	*AVSS-AB* P	*AVSS-AB* R
[24]	0.05	1.0	0.01	1.0
[10]	0.6	1.0	0.1	1.0
[15]	0.5	1.0	0.03	1.0
[13]	0.75	1.0	0.33	1.0
[21]	0.37	1.0	0.05	1.0
FSM-AOD [9]	0.83	0.83	0.5	1.0
LL-SVM	1.0	0.26	1.0	0.40
HL-SVM	1.0	0.42	1.0	0.90
HL-RANK	0.95	0.80	0.97	1.0

LL-SVM: SVM using low-level features

HL-SVM: SVM using relative attributes

HL-Rank: ranking with relative attributes

General Test

Cross-data validation
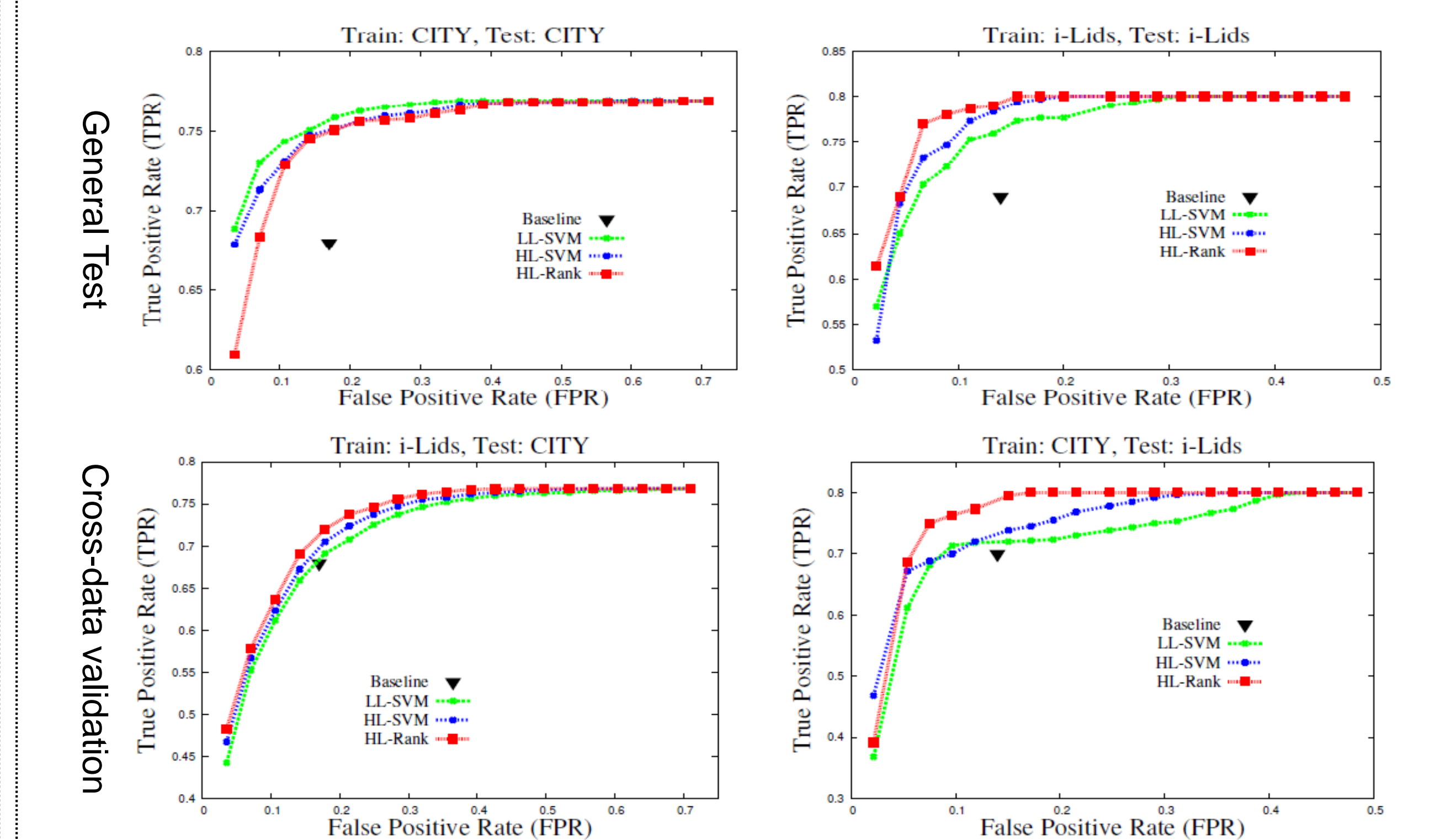
Evaluation on Natural Dataset

Data	MAP LL-SVM	MAP HL-SVM	MAP HL-RANK	NDCG LL-SVM	NDCG HL-SVM	NDCG HL-RANK
Cam #1	0.20	0.16	**0.22**	0.46	0.41	**0.53**
Cam #2	0.15	0.15	**0.18**	0.42	0.47	**0.51**