Associating People Dropping off and Picking up Objects

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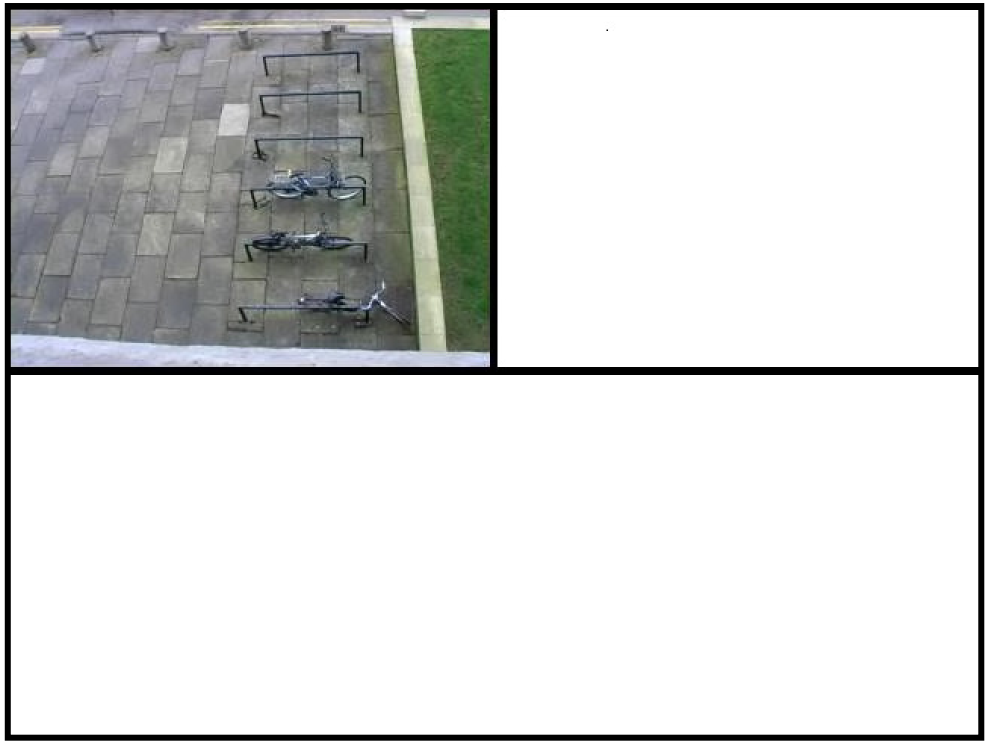
BMVC07

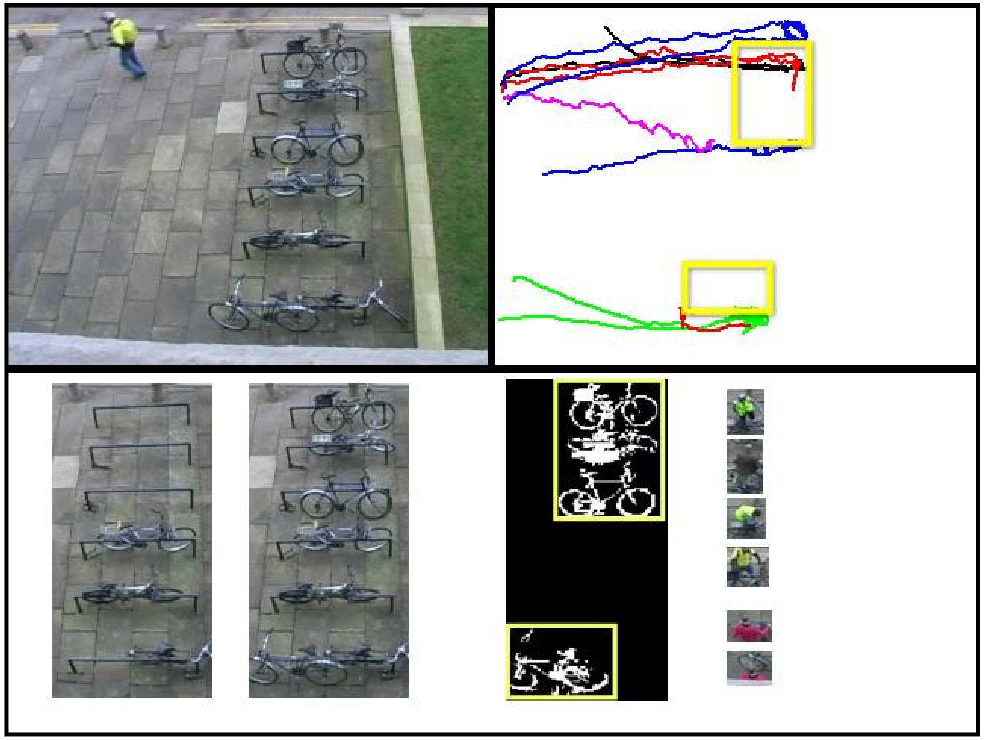
The Task

Tracking people and detecting objects



The video is a sequence of periods of activity

Tracking people and detecting objects



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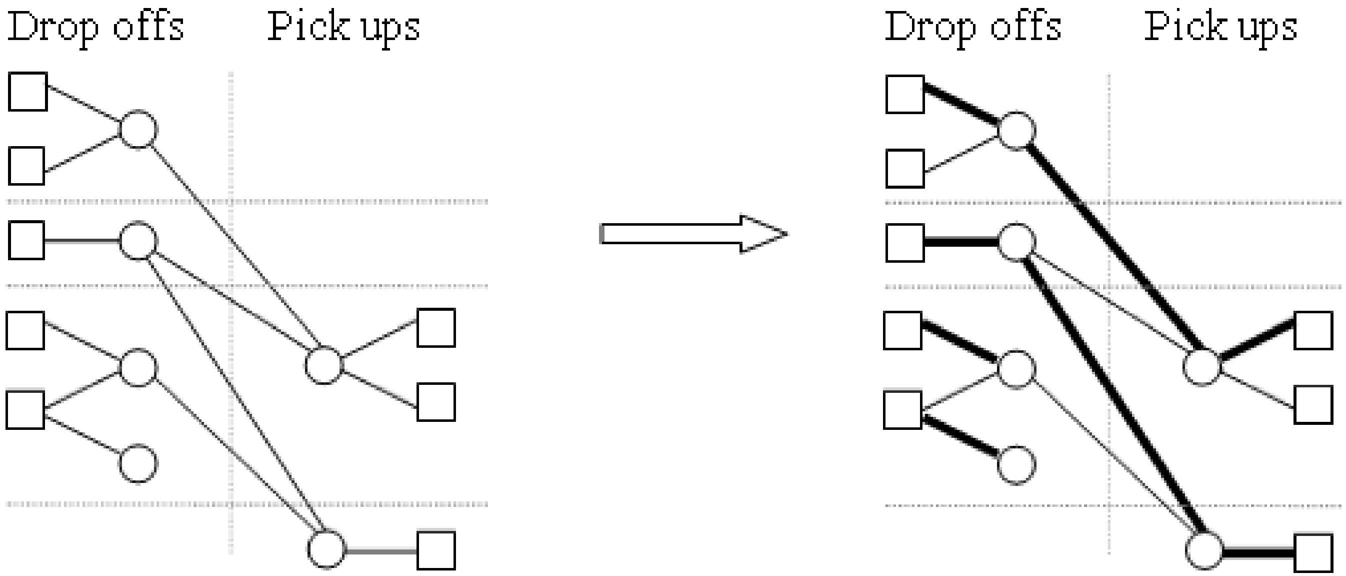
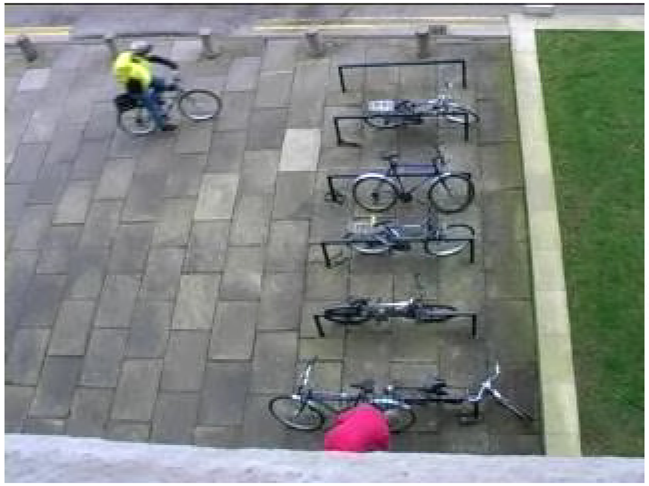
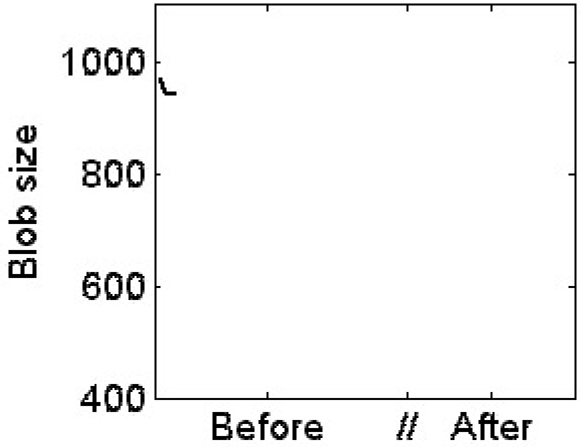
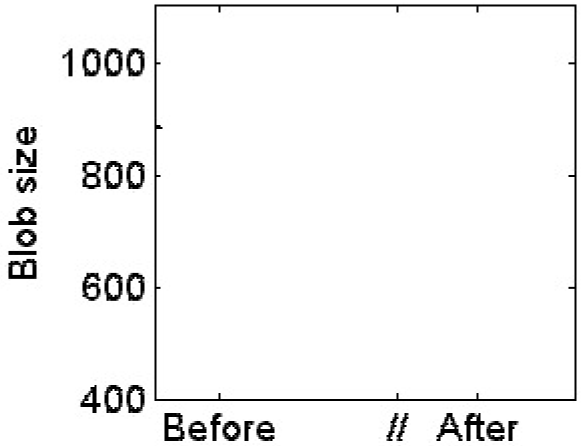
Associating drops with picks



Discriminating drops from picks - people







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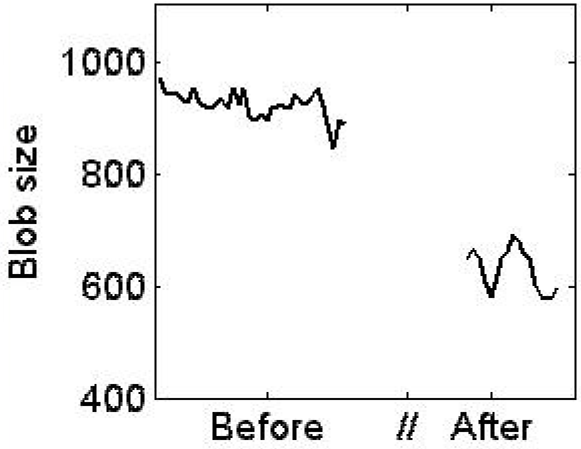
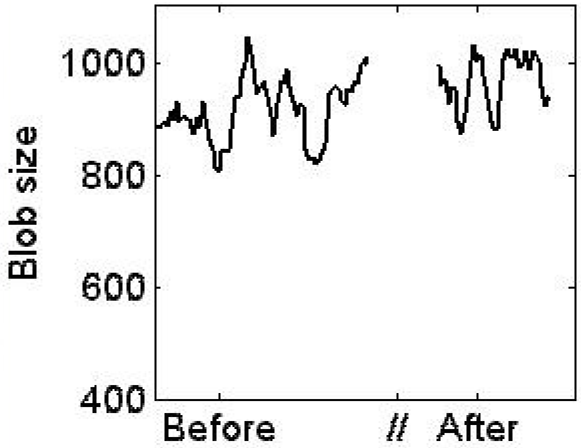
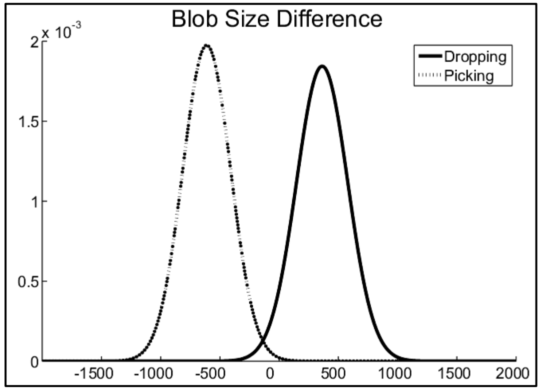
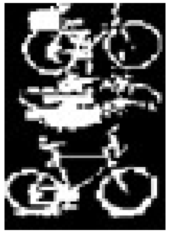






Discriminating drops from picks - objects



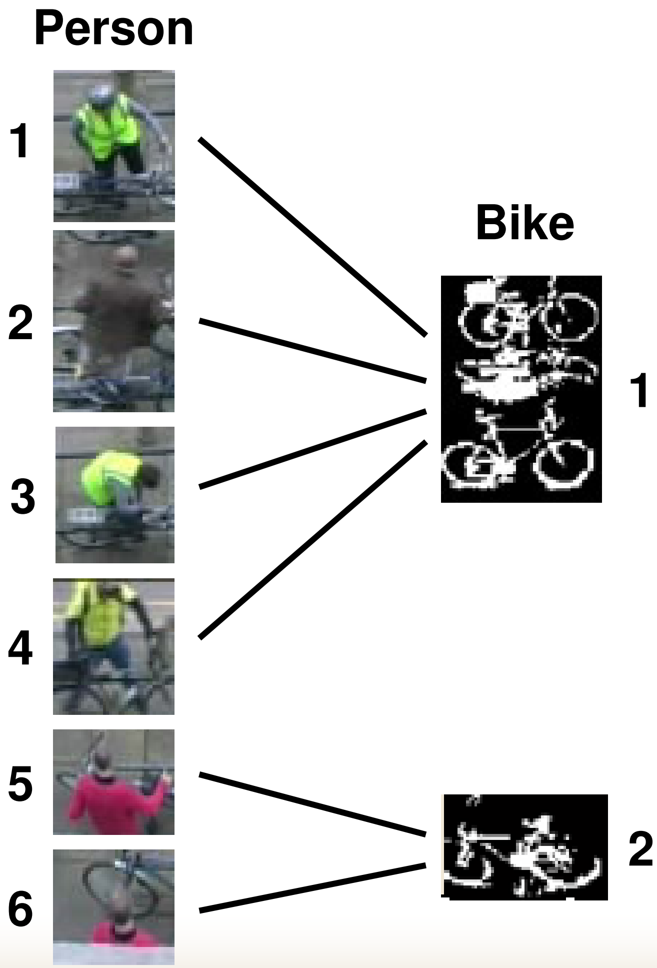
Masked edges

'before' reference image

'after' reference image

Possible assignments for a period of activity

$$d(p_i, o_j) = \begin{cases} 1 - \max\left(\frac{Box(p_i) \cap Box(o_j)}{min(Box(p_i), Box(o_j))}\right) & \text{if } (interval(p_i) \subset interval(o_j)) \\ \infty & otherwise \end{cases}$$



<u>Assignments set 1:</u>
drop(Person1, Bike1)
none(Person2)
drop(Person3, Bike1)
drop(Person4, Bike1)
none(Person5)
drop(Person6, Bike2)

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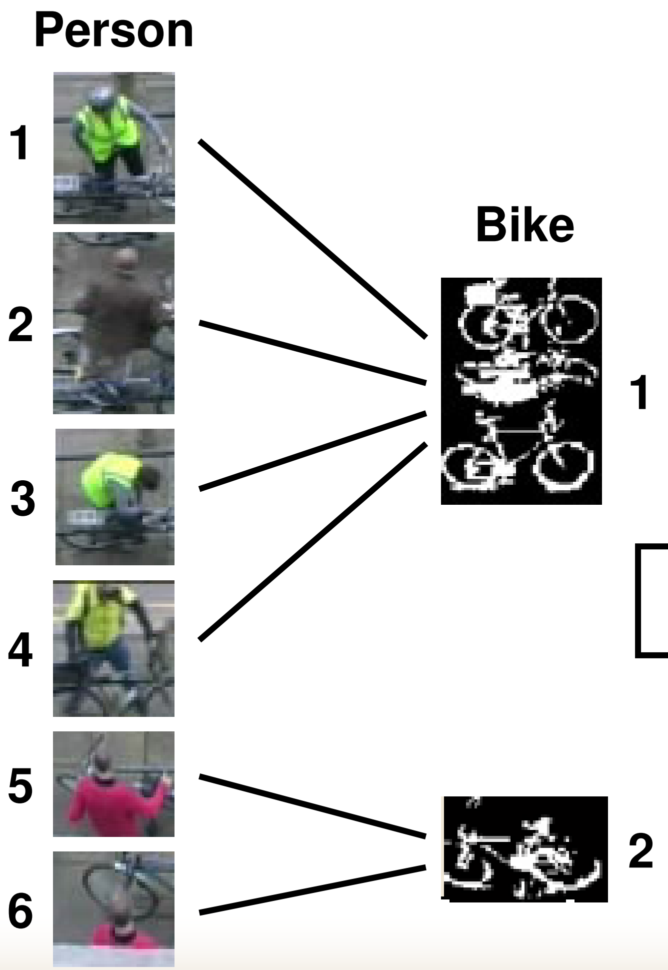

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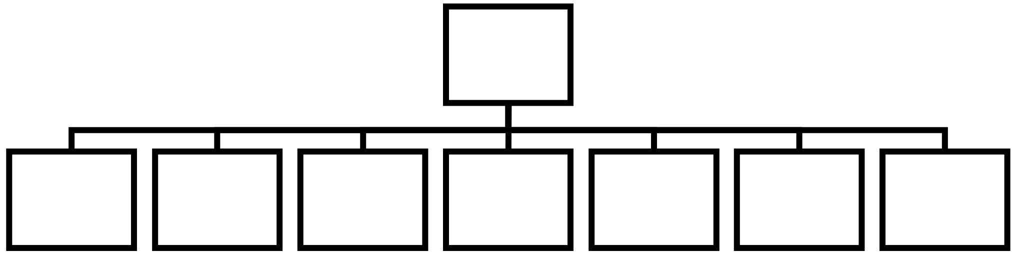
Tree of hypotheses: sequences of assignments

Period of activity

1

2



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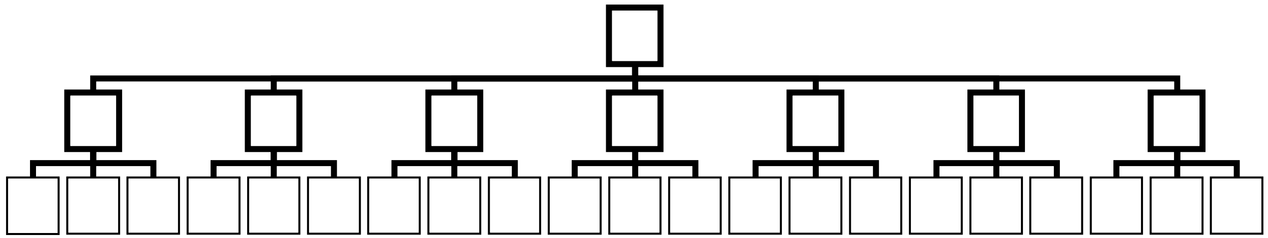

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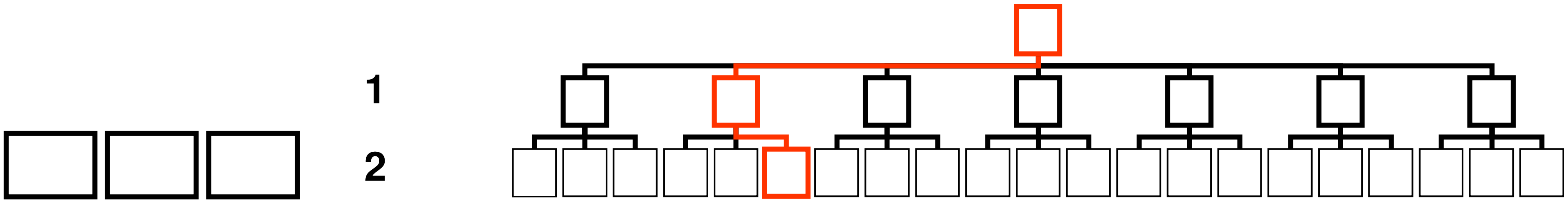

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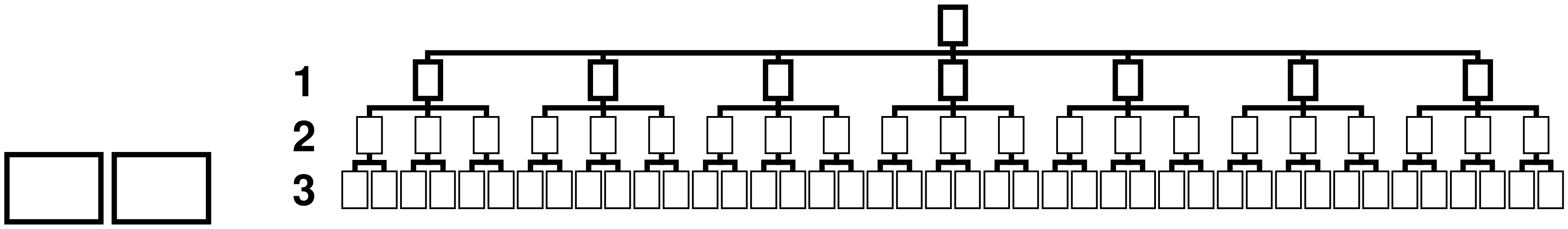

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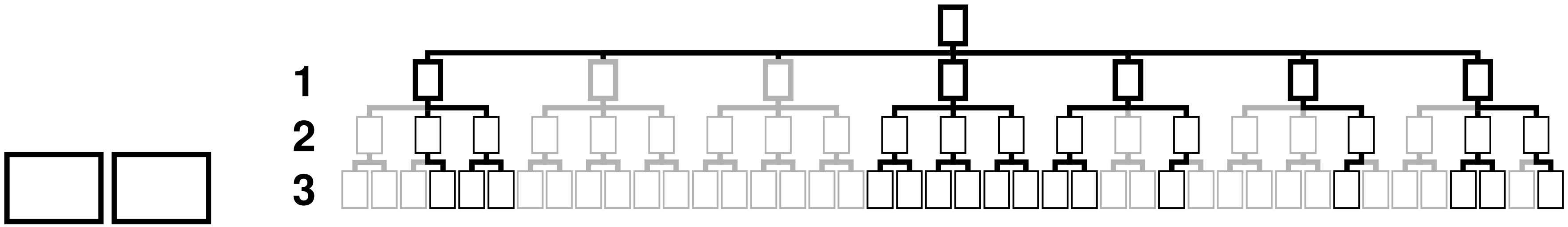

K-best – k-min-cost

Tree of hypotheses: sequences of assignments

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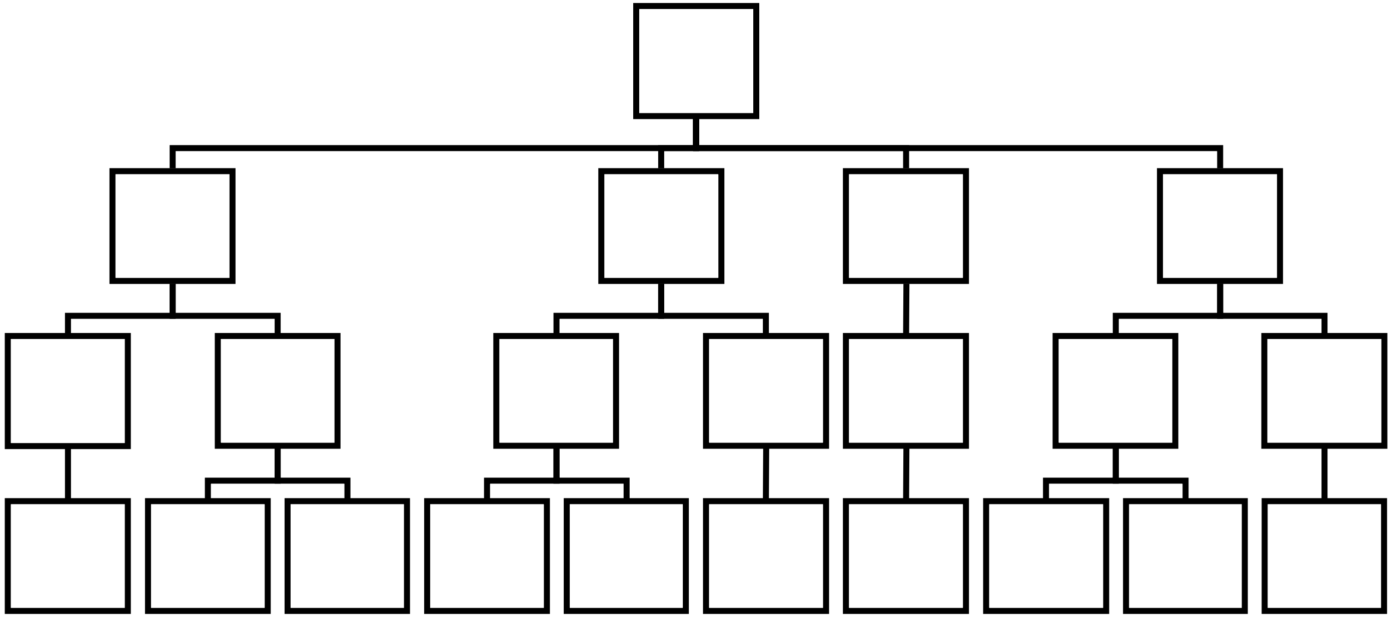
2

3



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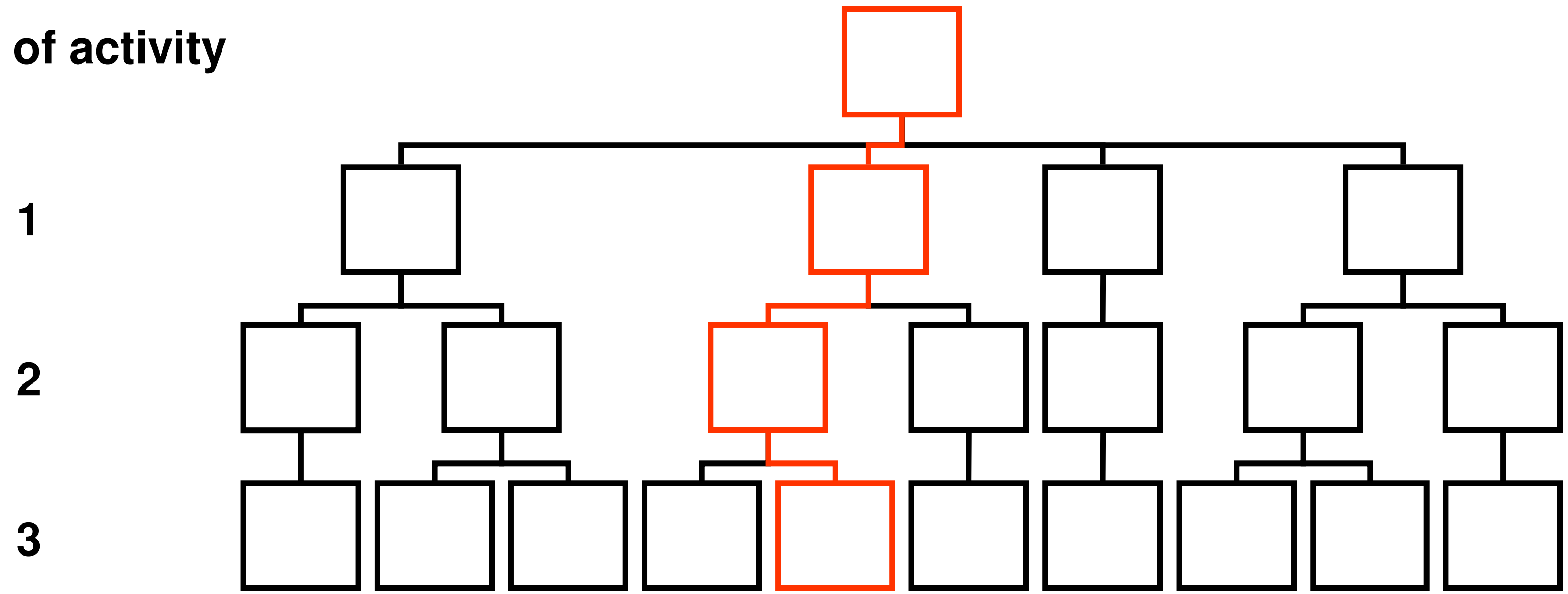

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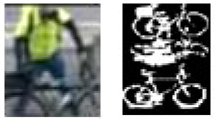

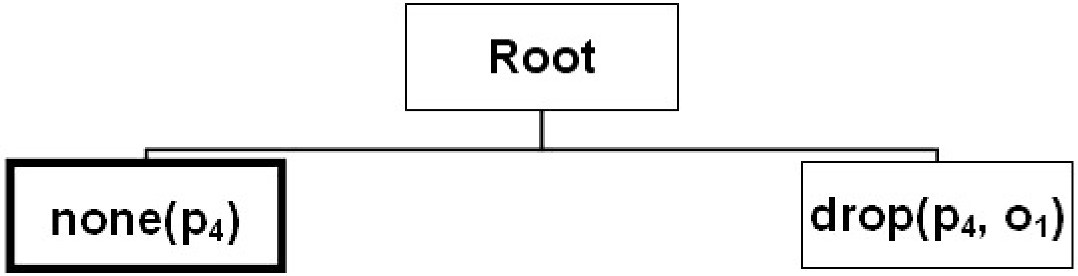

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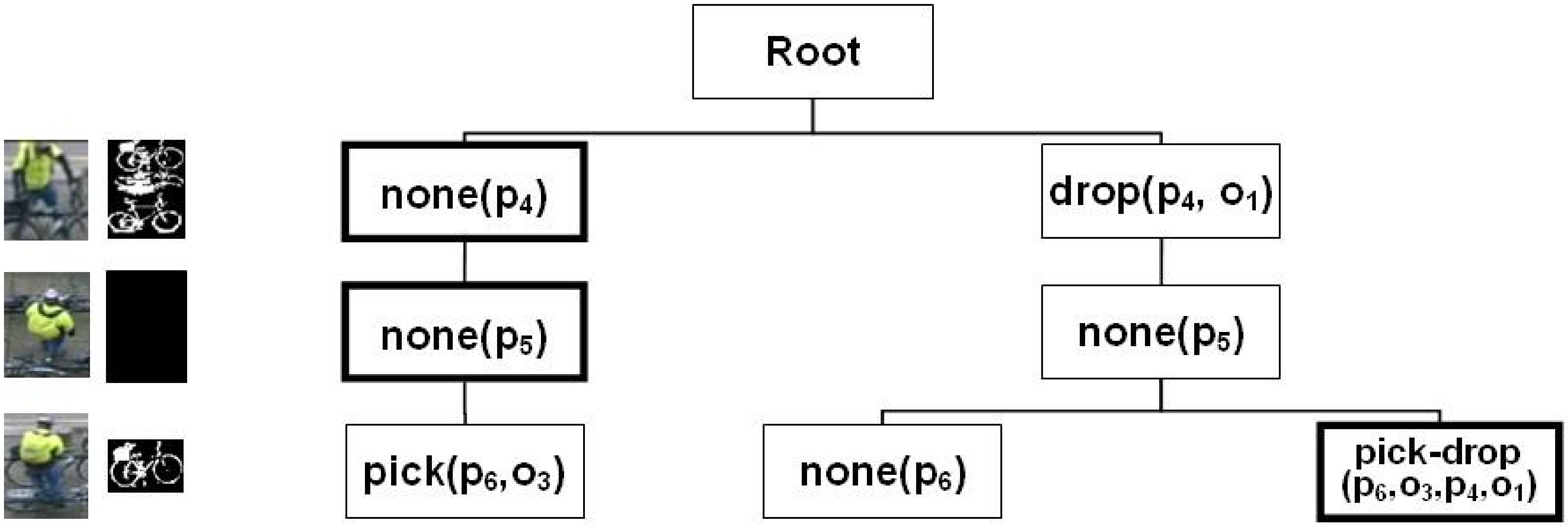


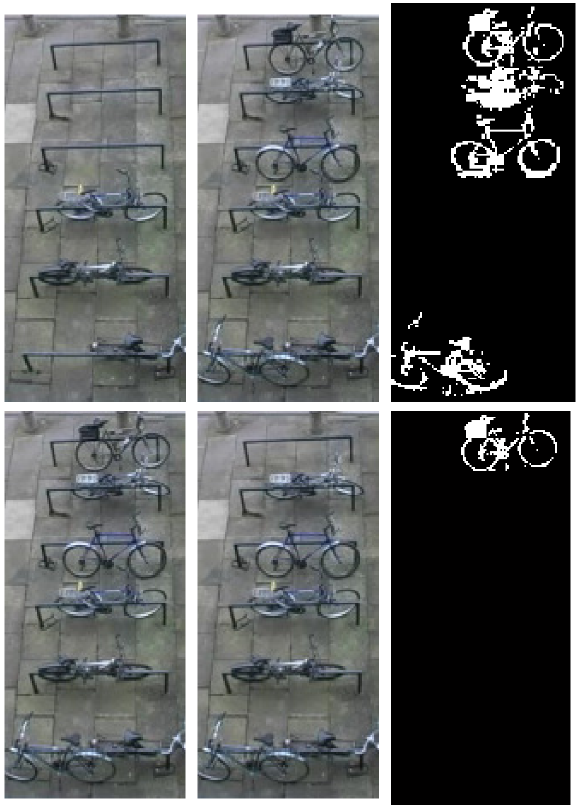
Constrained optimisation

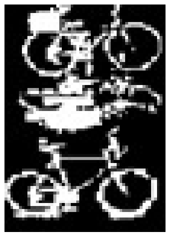
$$f_{pkdp}(p_i,o_j,p_k,o_l) = d(p_i,o_j) + d(o_j,o_l) + d(p_k,o_l \mid o_j)$$
$$f_{dp}(p_i,o_j) = f_{pk}(p_i,o_j) = d(p_i,o_j) + \alpha$$
$$f_{none}(p_i) = \beta$$

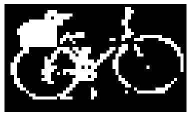
$$f(e) = \sum_{C_{pkdp}} f_{pkdp}(p_i,o_j,p_k,o_l) + \sum_{C_{dp}} f_{dp}(p_i,o_j) + \sum_{C_{pk}} f_{pk}(p_i,o_j) + \sum_{C_{none}} f_{none}(p_i)$$

each person should be involved in exactly one event

Post-segmentation







$$d(o_i, o_j) = \begin{cases} 1 - \dfrac{\sum\limits_{x,y} (o_i(x,y) \wedge o_j(x,y))}{\min(\sum\limits_{x,y} o_i(x,y), \sum\limits_{x,y} o_j(x,y))} & \text{if } o_i \in \text{picked} \wedge o_j \in \text{dropped} \wedge I(o_i) > I(o_j) \\ \infty & \textit{otherwise} \end{cases}$$

$$d(p_k, o_l \mid o_j)$$

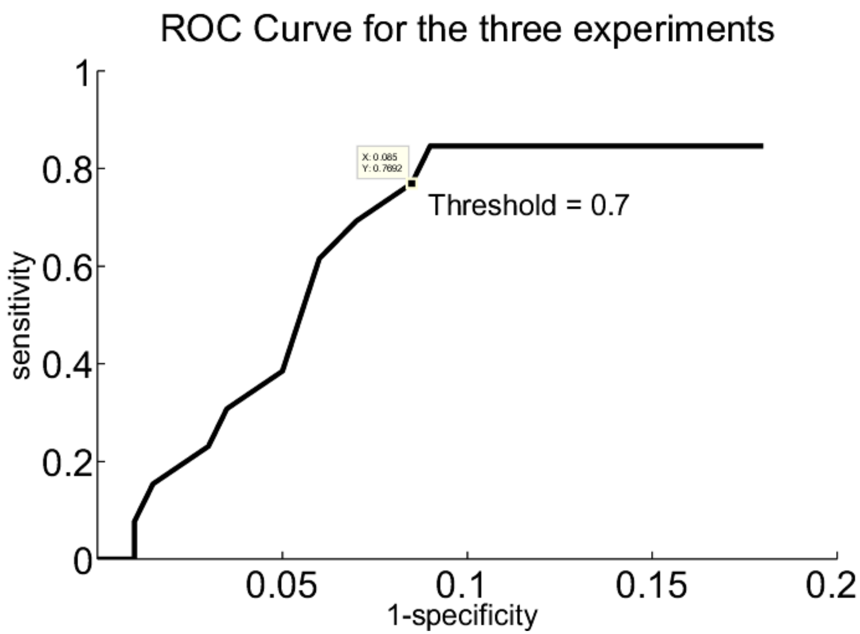
Experiments & Results

- 3 experiments
  - 1 hour (45 events)
  - 50 minutes (22 events)
  - Full day (9 hours and 30mins) (40 events)

	% of correct connections	
Exp #	Unconstrained	Constrained
1	75.86	93.10
2	70.37	92.59
3	83.59	96.09

Application to bicycle theft detection

- 8×8×8 scale-normalized equal-bin-size colour histogram
- Scale-by-max
- Median histogram



	Predicted	
Actual	Thief	Non-Thief
Thief	10	3
Non-Thief	17	183

Summary

- Deal with ambiguity in the visual data through the use of global constraints on what is possible.
- Comparison with unconstrained and partially-constrained solutions (in the paper).
- Ambiguities in the observations are expressed as multiple hypotheses.
- Hypotheses can then be verified or invalidated by future observations.

Thank you for listening

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