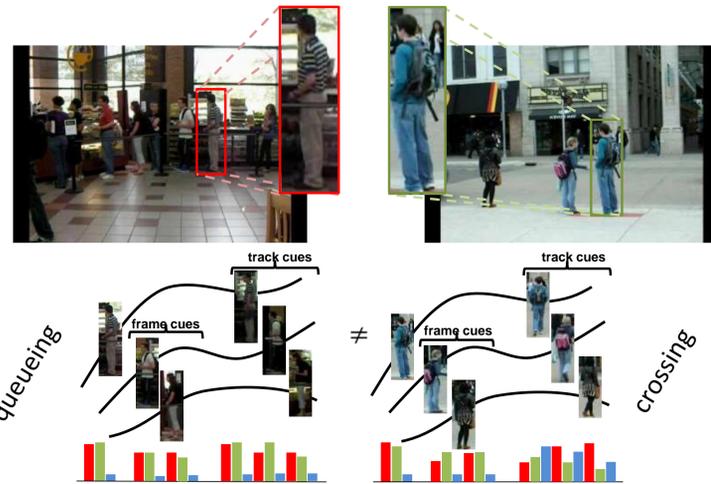




## The Motivation

- Recognizing human activity from pose and motion still subject to error due to appearance aliasing.



- Integrate tracking and scene context into action recognition to overcome this.
- Solve the coupled problem jointly!

## The Approach

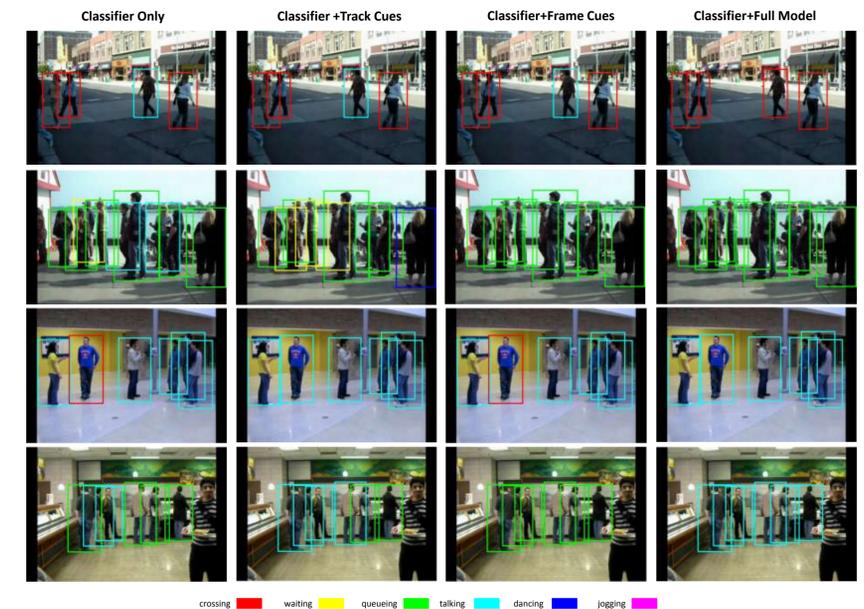
- Our goal is to formulate the problem as a tractable optimization function.
- The function should minimize
  - The action classification costs.
  - The per-track identity association costs.
  - The per-frame scene harmony costs.
- The action classification cost is based on the Action-Context (AC) descriptor [2] using HOG as the underlying representation.
- The identity association cost penalizes appearance and action transition inconsistencies.
  - Appearances are modeled by a distance matrix learned using LMNN [4] between the downsampled detection boxes as raw features.
  - Action transitions are modeled by a transition matrix learned by counting action pairs on the same track.
- The scene harmony cost is modeled by the joint likelihood of scene types and actions.
  - Scene types are approximated by the cluster centroids of K-means on the per-frame action histograms.
  - Scene prior is also estimated from the output of K-means.

## The Results

- We report results on two public multi-person action recognition datasets [1]

Approach / Dataset	5 Activities	6 Activities
Classifier Only	68.8%	81.5%
Classifier + Track Cues	70.9%	83.7%
Classifier + Frame Cues	70.7%	84.8%
Classifier + Full Model	<b>72.0%</b>	<b>85.8%</b>

	crossing	waiting	queueing	walking	talking
crossing	67.2%	5.3%	0.9%	19.3%	2.2%
waiting	2.9%	56.8%	13.1%	10.4%	0.8%
queueing	4.7%	29.4%	81.1%	3.5%	0.5%
walking	24.6%	5.9%	0.8%	61.5%	3.2%
talking	0.5%	2.7%	4.2%	5.4%	93.3%



## The Model

- Inference can be formulated as a linear program relaxation, but it is more advantageous to leverage the underlying structure of our model.
- As a function of (A)ctions, (S)cenec, and (I)dentities, our problem can be broken into two smaller and easier-to-solve subproblems.

$$\min_{A,S,I} F(A,S,I) = \min_{A,S,I} [F_1(A,S) + F_2(A,I)]$$

- Separate the subproblems by duplicating the "complicating" variables.

$$\min_{A_1,A_2,S,I} F_1(A_1,S) + F_2(A_2,I)$$

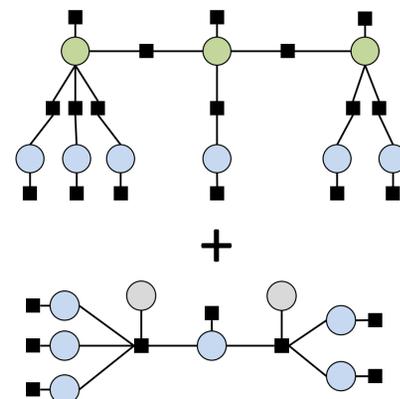
s.t.  $A_1 = A_2$

- Form the Lagrangian to reveal the separable but modified subproblems.

$$L(A_1, A_2, S, I, \nu) = F_1(A_1, S) + F_2(A_2, I) + \nu A_1 - \nu A_2$$

- Optimizing the Lagrangian by an iterative primal-dual approach tightens the bound on the optimal solution of the original problem.

$$\max_{\nu} L(A_1, A_2, S, I, \nu) = \max_{\nu} \left[ \underbrace{\min_{A_1,S} [F_1(A_1, S) + \nu A_1]}_{\text{Belief Propagation}} + \underbrace{\min_{A_2,I} [F_2(A_2, I) - \nu A_2]}_{\text{Minimum Cost Flow}} \right]$$



- A tree-structured pairwise graphical model
- Solves action recognition consistent with scene context
- Max-Product Belief Propagation is exact and efficient

- A minimum cost flow problem based on [3, 5]
- Jointly solves action recognition and tracking
- Constraint matrix is totally unimodular, so a globally optimal integral solution exists

## The References

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