Exploiting Semantics for Scheduling Real-Time Data Collection from Sensors to Maximize Event Detection

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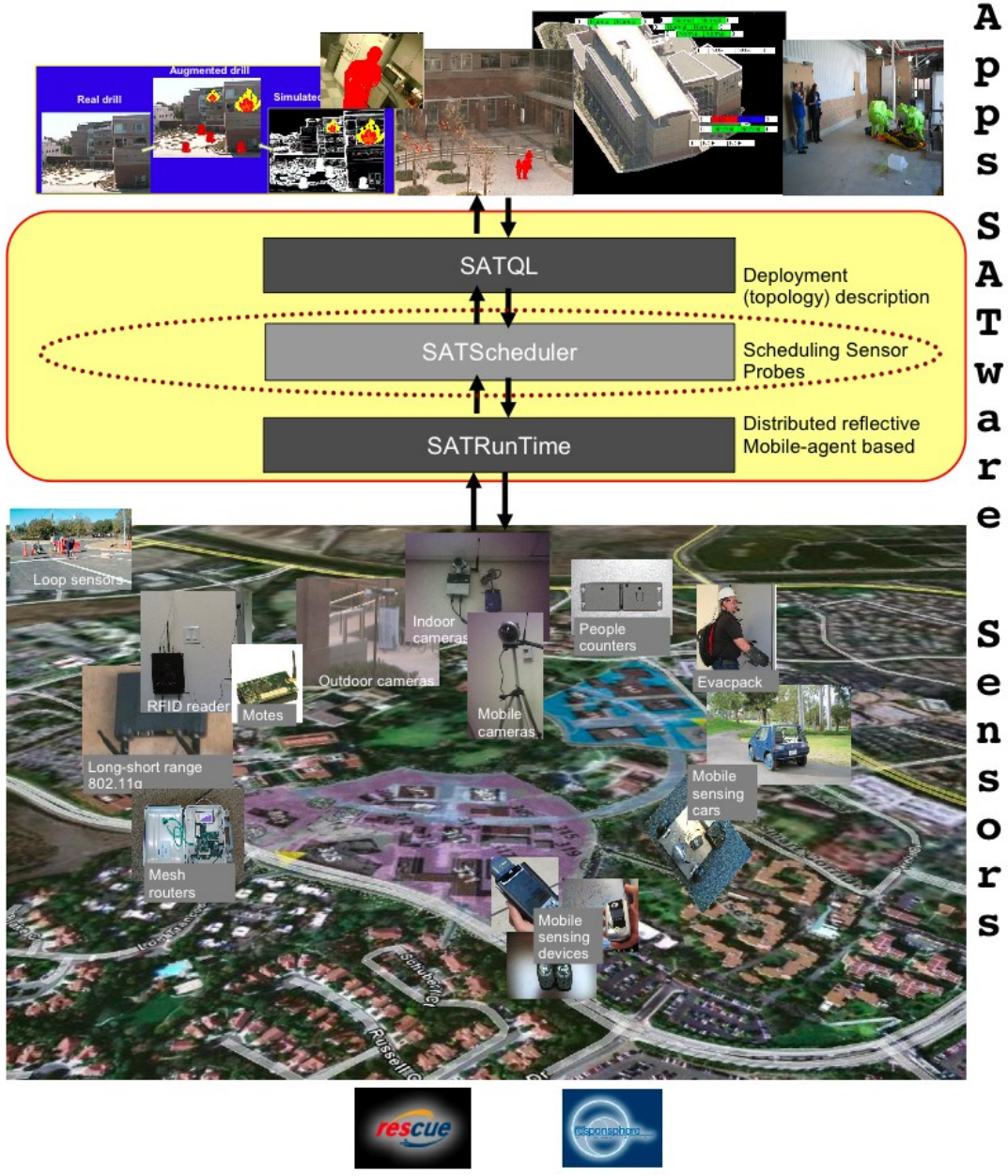
Motivation



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Challenge

- Resource Constraint
  - E.g., Limited network bandwidth, CPU.
- Implication: only a subset of sensors can be probed at a given time.
- Which sensors to probe and when.

Raking the Benefit from a Probe

Certain frames are more important than others from application perspective, which is determined by a Benefit Function (BF).

- Application 1: Real-Time building occupancy. BF = frame without presence ranked lower than all others.
- Application 2: Real-Time person location monitoring. BF = frontal image ranked higher.
- Application 3: Alert potential stolen items BF = person with back-bag ranked higher.

(a) No Presence

(b) Carrying a Bag

(c) Facial

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Architecture

Two possible architectures:

- Push: Perform processing at sensor and send frame to server.
- Pull: Based on global system view, select where to probe.
- We follow the pull model for the following reasons:
  1. BF functions in general are complicated.
  2. Push is not adequate for a real-time application.

The Problem Statement

- Let $S_1, .., S_n$ be n sensors.
- Let **benefit function (BF)** be an application-dependant function based on which probes can be ranked.
- Let **cost function (CF)** be the cost of a probe plan

Specify a probe schedule that maximizes application benefit (BF) without exceeding a cost (CF) limit.

The Problem Statement

Assumptions

(d) BF=0,CF=1

(e) BF=1,CF=1

(f) BF=1,CF=1

(g) BF=1,CF=1

- While the framework is more general, in the paper we make two simplifications:
  - **(BF)=1** if frame contains motion, 0 otherwise.
  - **(CF)=1** if sensor probed, 0 otherwise.
- Under assumptions: specify a probe schedule that maximizes $BF(plan)$ while $CF(plan) \leq k$

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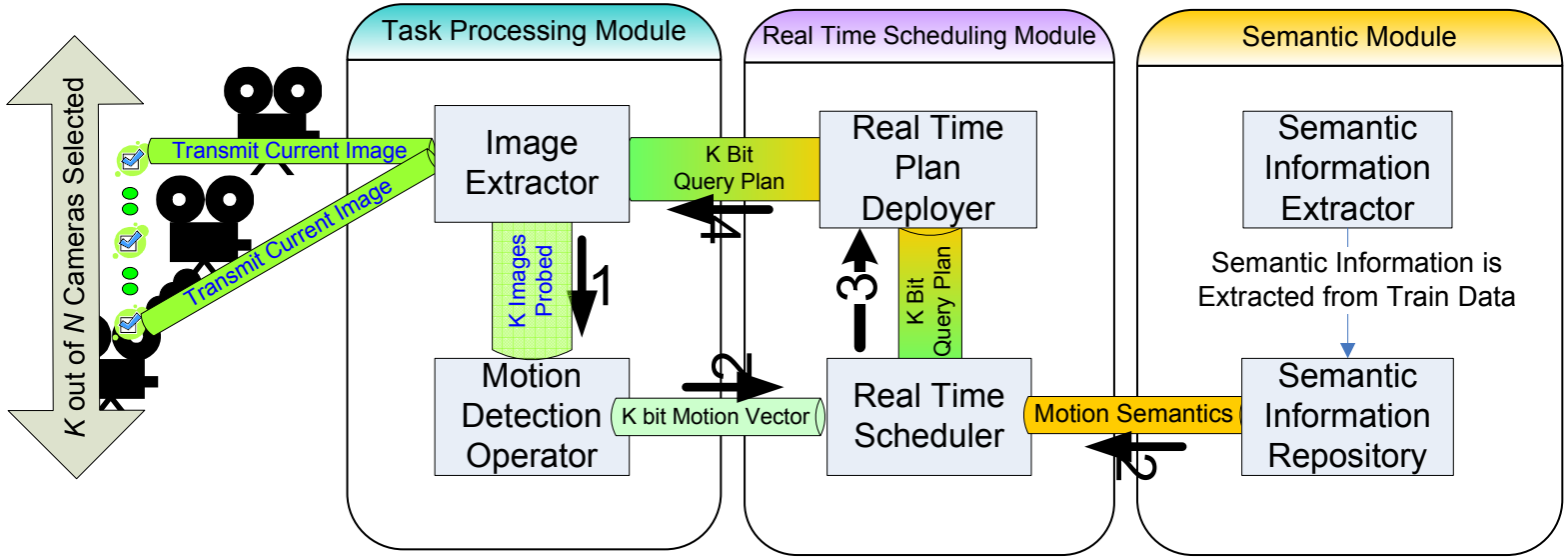
Framework



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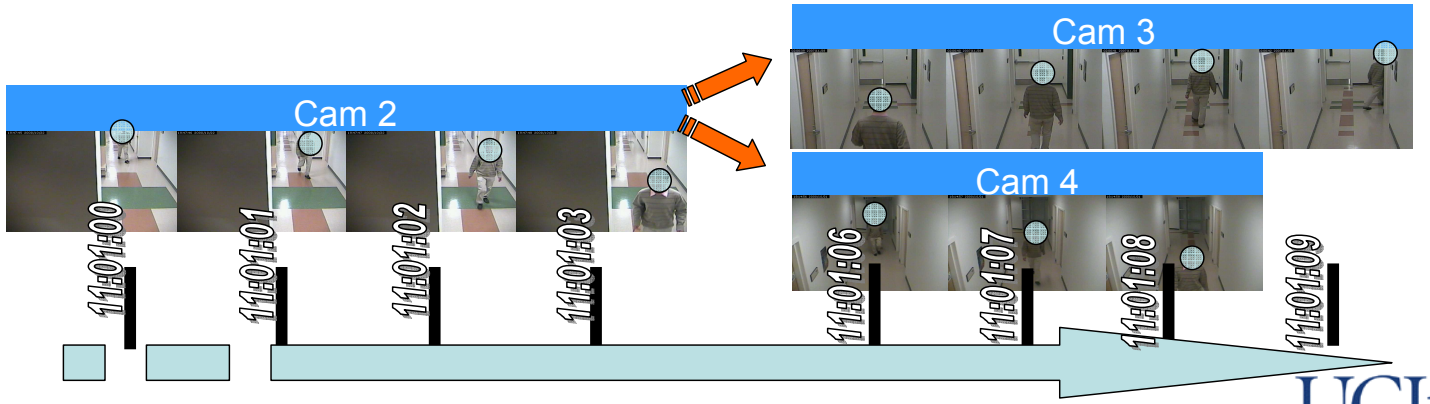
The approach we adopt is to exploit semantics

- 1. **Apriori** probability of where motion is more likely to initiate.

- 2. **Self correlation** of camera stream over time.

- 3. **Cross Correlations** over time between cameras.



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Key Contributions and Challenges

- 1. A Probabilistic semantic model for unscripted human activity.
- 2. Predicting system state based on constrained, partial current state.
- 3. A fast and light weight real-time scheduler.
  - A delayed probe will miss the action.

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Deterministic Alternatives

1. **RR** A based line algorithm, Round Robin.
2. **RR + Stay** Perform RR, Stay as long as motion is detected.
3. **RR + Stay + Go to Nearest Neighbor** Perform RR, Stay as long as motion is detected when it ends, wait (60 time units) to probe motion at nearest neighbor.

1. Not trivial to do better than RR+Stay, following a deterministic algorithm.

Evaluation Setup

- We evaluated our algorithms on a network of 11 cameras distributed on two floors in the CS building at UC Irvine.
- The Data we collected was over a period of two weeks (the first and second weeks of the Spring quarter).
- All cameras were located in hallways.
- We then used the first week to train for optimal collection of the other week.

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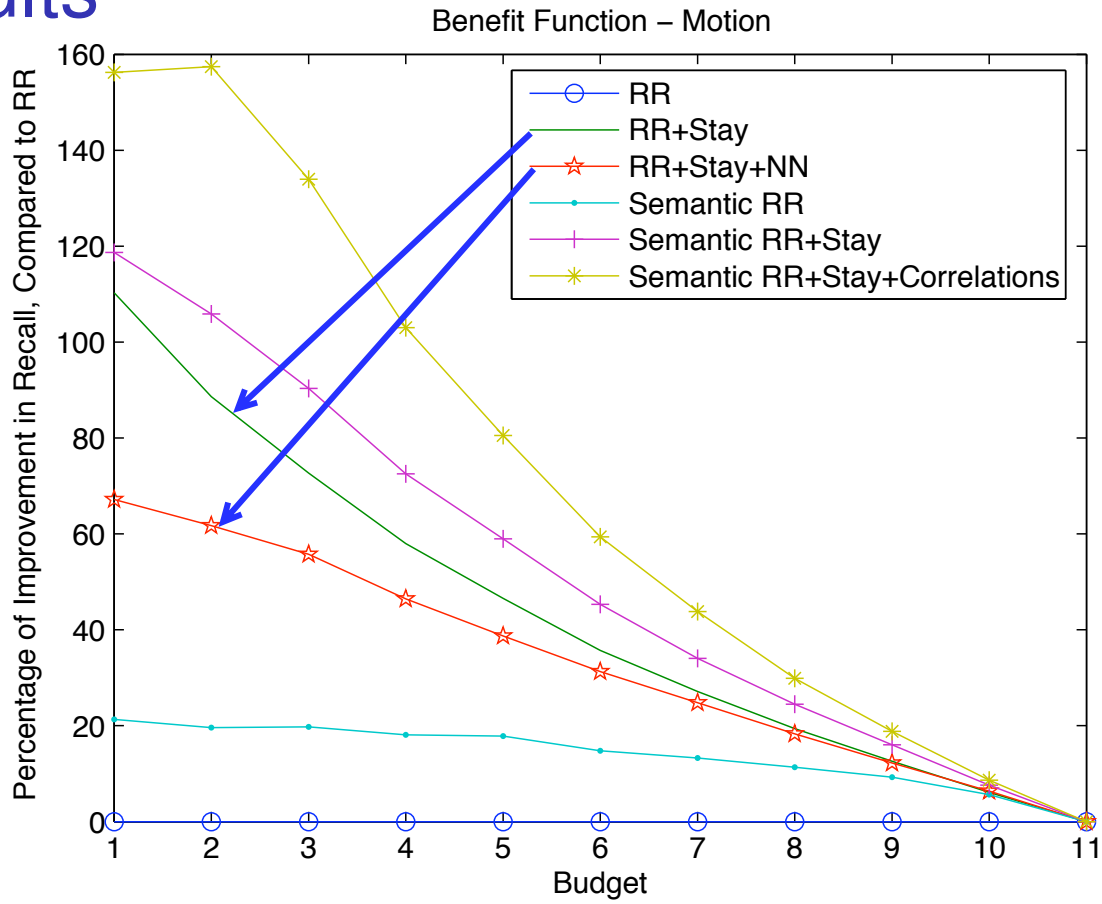
Some Results



- "RR+Stay+NN" performed *much worse* than "RR+Stay". – an ad-hoc approach will prove to perform much worse than a simple alternative("RR+Stay").
- The probabilistic approach "Semantic RR" proved to work better then RR but worse than all other semantic alternatives.

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Semantic RR

- Offline: from train data,compute for each sensor:

$$\frac{cases\ with\ motion}{cases\ with\ or\ without\ motion}$$

- Online: Regardless of the actual probes, choose k nodes based on probability distribution.

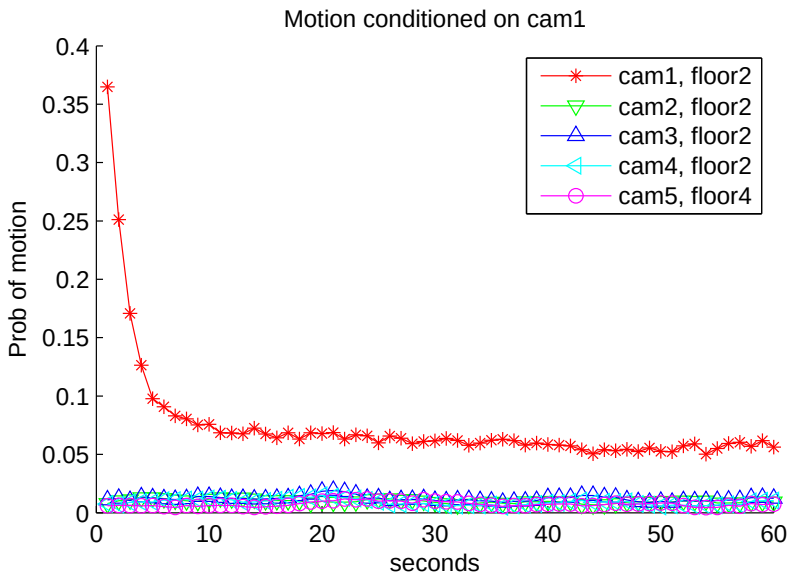
Semantic RR+Stay

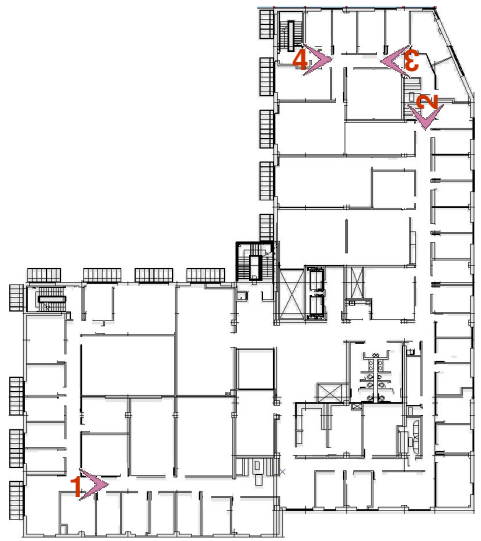
We assume a *Hidden Markov Model* (HMM) of sensor states and observations.

- Offline: from train data, compute for each sensor:

$$P(s_t|s_{t-1})$$

- Online: Based on the actual probes, dynamically compute probabilities for the next time unit and choose k nodes based on probability distribution.





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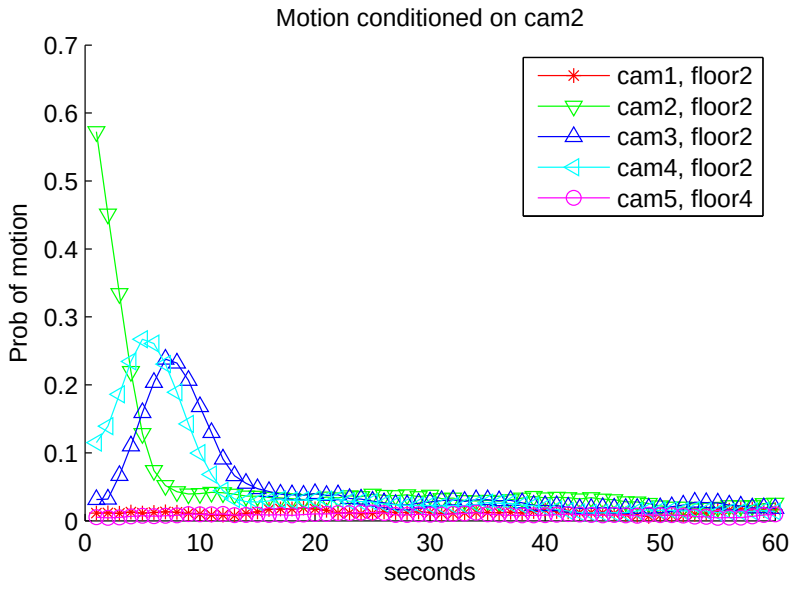
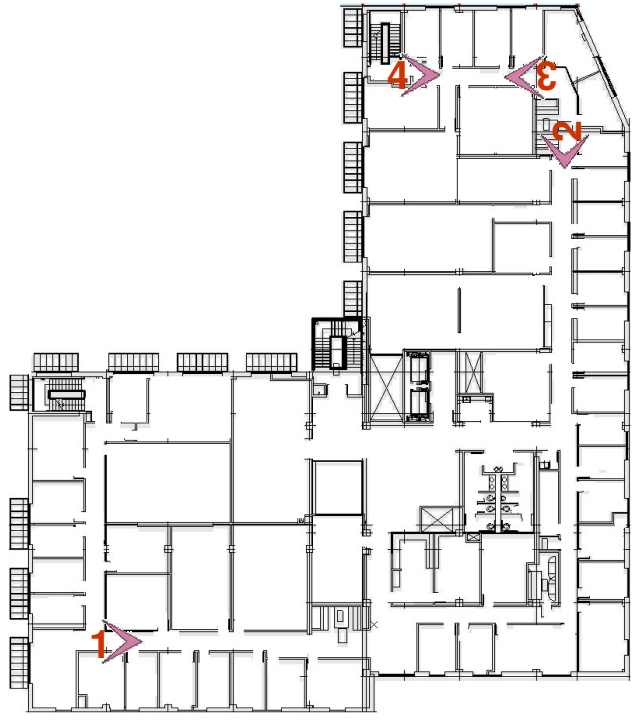
Semantic RR+Stay+Correlations(t=1)

We would like to capture interactions between N cameras:





$$P(s_t^i | s_{t-1}^{1:N}) \quad (1)$$

- Superscripts denote cameras, subscripts - time.

Exponential Blowup:

- The conditional probability table has 2^N entries.

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Semantic RR+Stay+Correlations(t=1)

Making it Scale

We assume that people move independently throughout our camera network.

- We want to intuitively "add" such probabilities across i to compute $P(s_t^j)$.
- The transition model now simplifies to:

$$P(s_t^i | s_{t-1}^{1:N}) = 1 - \prod_{j=1}^{N} (1 - \alpha_{ij} s_{t-1}^j) \tag{2}$$

1. α_{ij} - the probability that a person seen at camera i moves to camera j in the next timestep.
2. The above model is usually refereed to as a *noisy-OR* model.

The above model has $O(N^2)$ parameters - scales.

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Semantic RR+Stay+Correlations(t=M)

- Again, a native implementation of $P(s^i_{t+1}|s^{1:N}_{(t-M):t})$ - exponential.

With similar reasoning, the transition model simplifies to:

$$P(s^i_t|s^{1:N}_{(t-M):(t-1)}) = 1 - \prod_{o=1}^{M}\prod_{j=1}^{N}(1 - \alpha^o_{ij}s^j_{t-o}) \tag{3}$$

where α^o_{ij} - the probability that a person in camera i moves to camera j, o timesteps later.

The above model has $O(M * N^2)$ parameters - scales.

Semantic RR+Stay+Correlations(t=M)

The M^{th}-Order model states that if there is no motion activity in any camera in the past M-seconds, there can be no motion in any camera currently.

- To overcome this limitation, we allow for a probability α_i that a person will spontaneously appear at camera i - this is equivalent to a ***leaky* noisy OR.**
- We add in $(1 - \alpha_i)$ as an extra term:

$$P(s_t^i | s_{(t-M):(t-1)}^{1:N}) = 1 - (1 - \alpha_i) * \prod_{o=1}^{M} \prod_{j=1}^{N} (1 - \alpha_{ij}^{o} s_{t-o}^{j}) \qquad (4)$$

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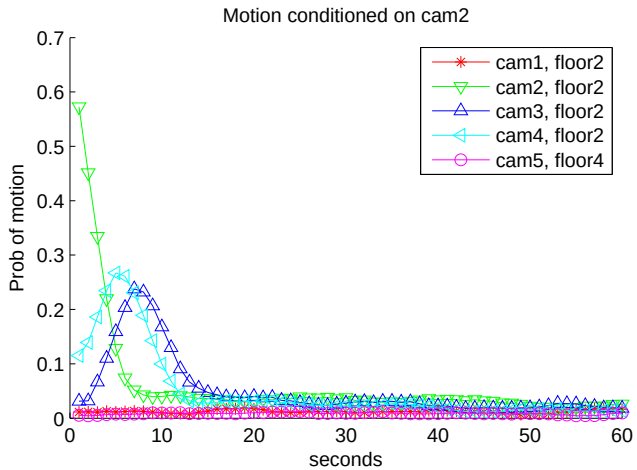
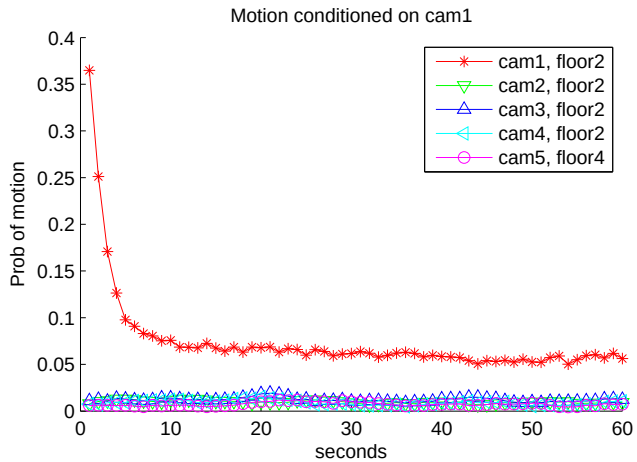
Semantic RR+Stay+Correlations(t=M)

Implementation

Further optimization:

- We observe that most of the α_{ij}^{o} dependencies are weak (far-away cameras do not effect each other).
- We zero out the α_{ij}^{o} values below some threshold.
- In our case, thresholding on 0.05 reduced table from 1815 to 165 entries.





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Semantic RR+Stay+Correlations(t=M)

Implementation

While experimenting we identified two pitfalls:

1. First we choose to probe based on **sampling**, as opposed to probing based on the order of probabilities (high to low).
2. The second relates to the history table, only motion probed should be used for prediction.
   - When predicting based on probability for motion -

plan	C_{10}	C_{10}	C_9	C_{10}	C_{10}	C_9	C_9	C_9
Cam9 Projected Prob.	0.11	0.26	0.33	0.51	0.66	0.65	0.65	0.67
Cam10 Projected Prob.	0.45	0.66	0.69	0.79	0.875	0.88	0.9	0.916
time	1	2	3	4	5	6	7	8
result	+	+	-	+	+	-	-	-

   - When basing decision only on probed motion -

plan	C_10	C_{10}	C_9	C_{10}	C_{10}	C_9	C_9	C_5
Cam9 Projected Prob.	0.11	0.21	0.25	0.34	0.42	0.43	0.41	0.38
Cam10 Projected Prob.	0.45	0.65	0.56	0.71	0.8	0.67	0.63	0.6
time	1	2	3	4	5	6	7	8
result	+	+	-	+	+	-	-	-

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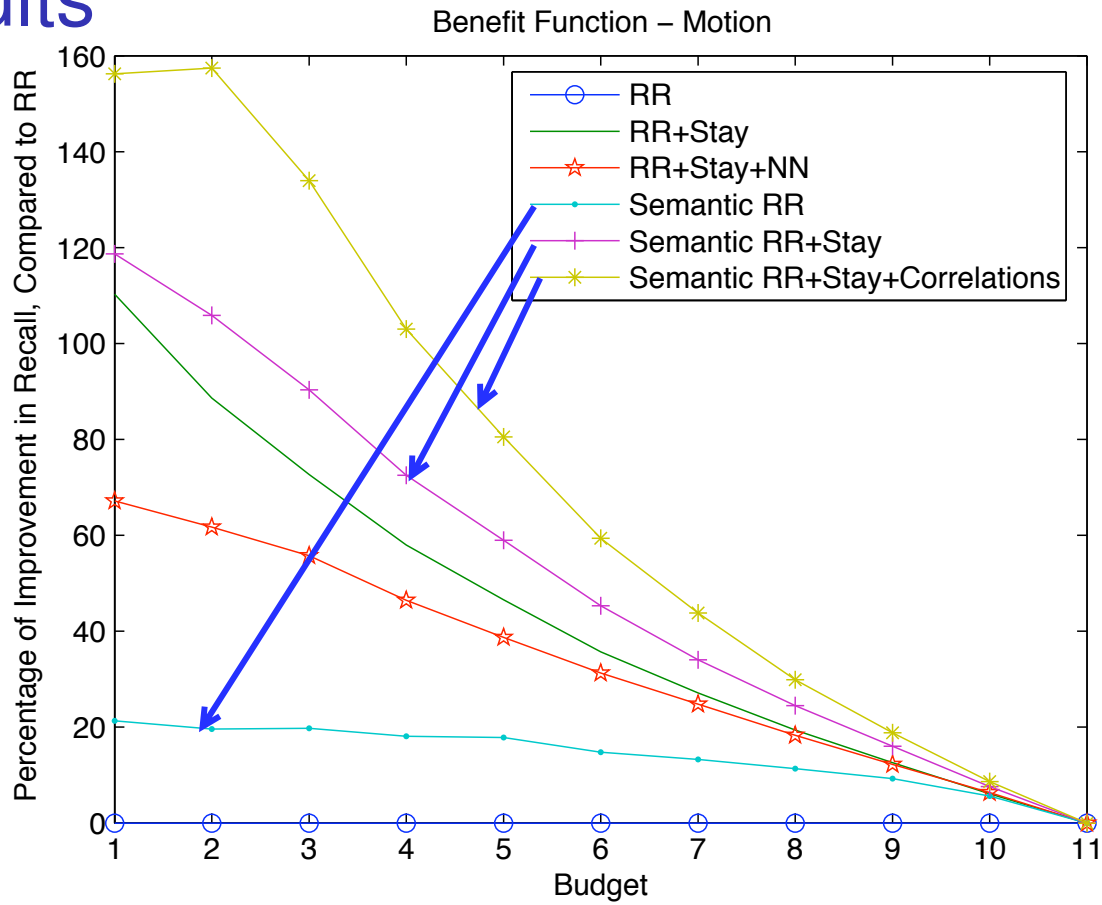
Some Results



- With a budget of 1, our last semantic algorithm achieved over 150%(!) improvement over RR.
- With budget of 50%, the last semantic algorithm achieves about 90% recall (compared to about 50% of RR).
- Demo.

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Summary

- We designed and implemented a fully functional system using available off-the-shelf cameras to learn motion semantics.
- Our semantic based algorithm that takes into account all available semantic information proves that even under significant resource constraints, we can detect a very large number of events.
- The scheduling algorithm is *very* light weight and is suitable for a real-time application.

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Outlook

- Experimenting with other **Benefit Functions**.
  - Instead of 0/1 no motion/motion.
- Take into account different **Cost Functions**.
  - Probe in low/high resolution.
- Updating the Semantic Model while the system is in operation.
  - Relates to a problem addressed by the database communitee: estimating query selectivity based on the actual query results.

Thank You

Thank You!
.. Any questions?

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