

Online Reasoning under Uncertainty with the Event Calculus

Alexander Artikis^{2,1} Periklis Mantenoglou^{3,1}

¹NCSR Demokritos, Greece

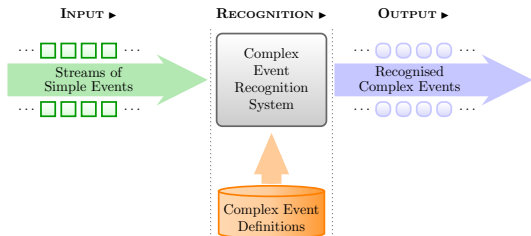
²University of Piraeus, Greece

³National & Kapodistrian University of Athens, Greece

<http://cer.iit.demokritos.gr/>

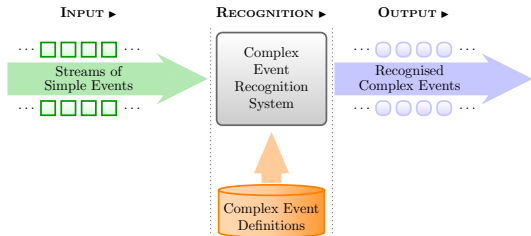


Complex Event Recognition (Event Pattern Matching)



Gitrakos et al, Complex event recognition in the Big Data era: a survey, VLDB Journal, 2020.

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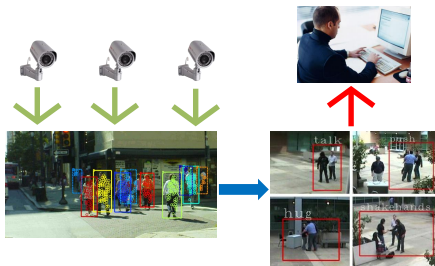
Gitrakos et al, *Complex event recognition in the Big Data era: a survey*, VLDB Journal, 2020.

<https://rdcu.be/cNkQE>

Human Activity Recognition



Human Activity Recognition



<https://cer.iit.demokritos.gr> (activity recognition)

Requirements

- Expressive representation
 - to capture complex relationships between the events that stream into the system.

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 - to support real-time decision-making in large-scale, (geographically) distributed applications.

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 - to deal with various types of noise.

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 - to support proactive decision-making.

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Event Calculus

- A **logic programming language** for representing and reasoning about events and their effects.
- Key components:
 - **event** (typically instantaneous).
 - **fluent**: a property that may have different values at different points in time.

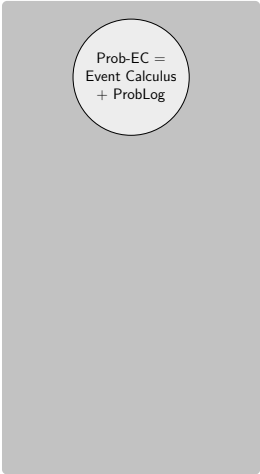
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Event Calculus

- A **logic programming language** for representing and reasoning about events and their effects.
- Key components:
 - **event** (typically instantaneous).
 - **fluent**: a property that may have different values at different points in time.
- Built-in representation of **inertia**:
 - $F = V$ holds at a particular time-point if $F = V$ has been *initiated* by an event at some earlier time-point, and not *terminated* by another event in the meantime.

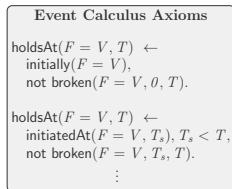
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Online Probabilistic Event Calculus



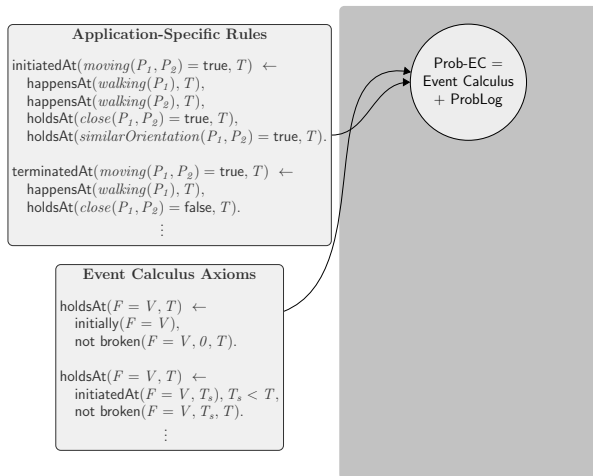
Prob-EC =
Event Calculus
+ ProbLog

Online Probabilistic Event Calculus

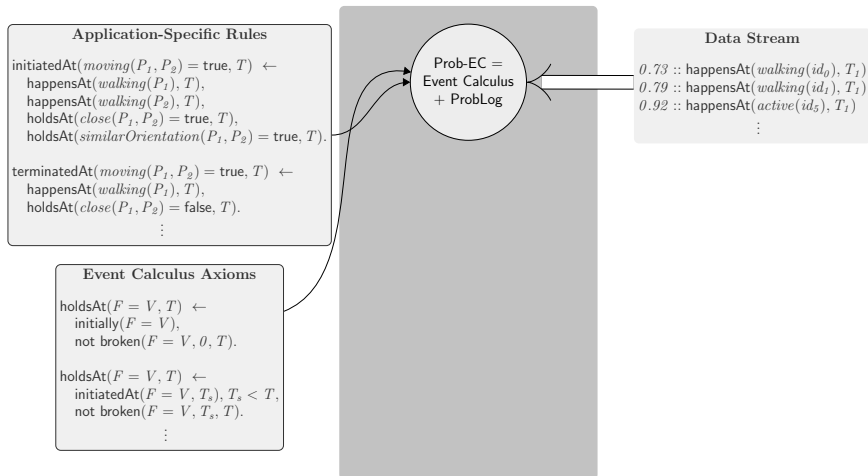


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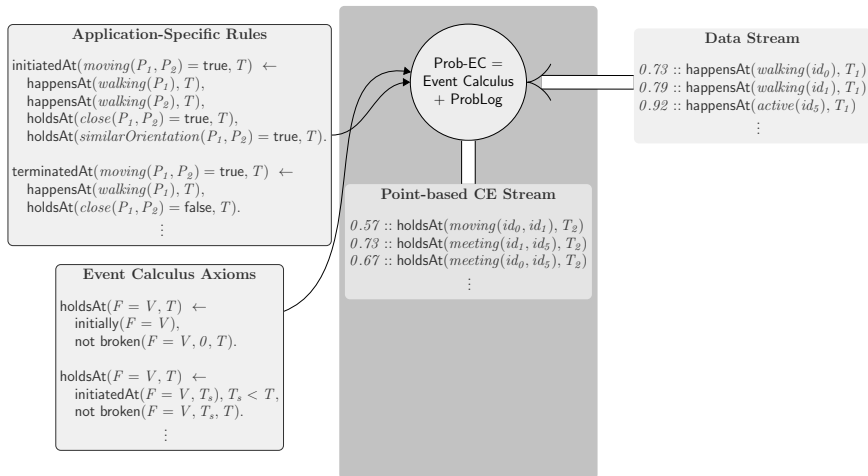
Online Probabilistic Event Calculus



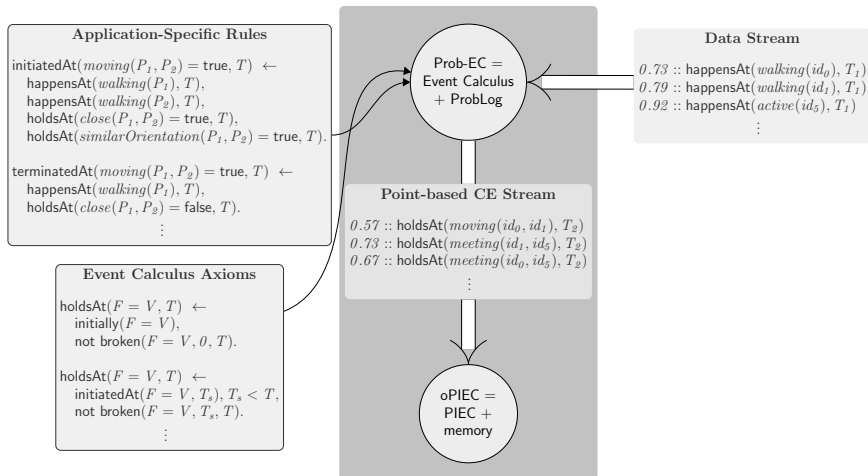
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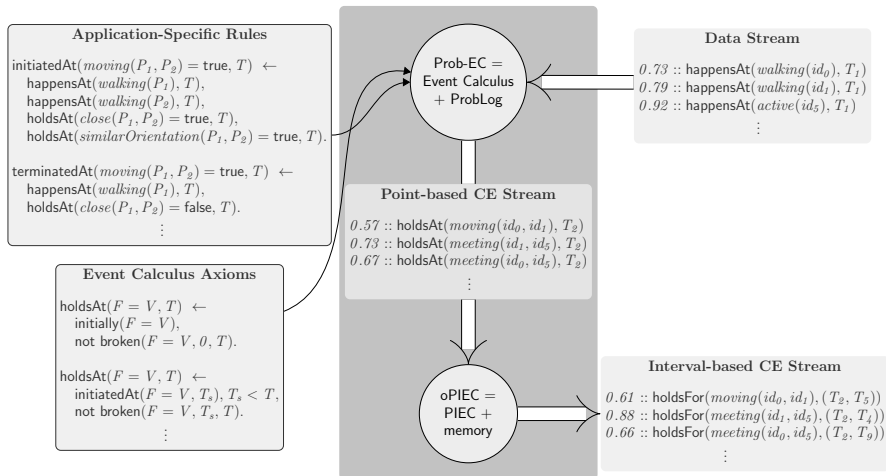
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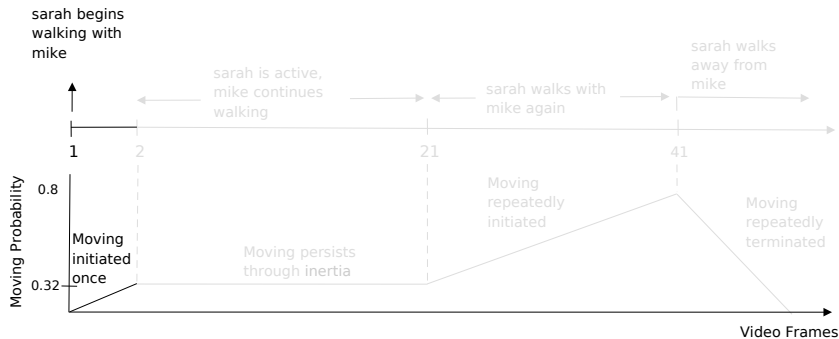
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Online Probabilistic Event Calculus



Instantaneous Recognition

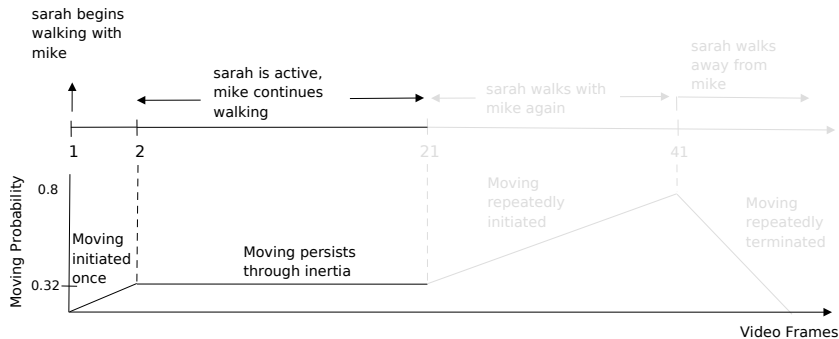


initiatedAt($moving(P_1, P_2) = \text{true}, T$) $\leftarrow$
happensAt($walking(P_1), T$),
happensAt($walking(P_2), T$),
holdsAt($close(P_1, P_2) = \text{true}, T$),
holdsAt($similarOrientation(P_1, P_2) = \text{true}, T$).

$0.70 :: \text{happensAt}(walking(mike), 1).$
 $0.46 :: \text{happensAt}(walking(sarah), 1).$

terminatedAt($moving(P_1, P_2) = \text{true}, T$) $\leftarrow$
happensAt($walking(P_1), T$),
holdsAt($close(P_1, P_2) = \text{false}, T$).

Instantaneous Recognition

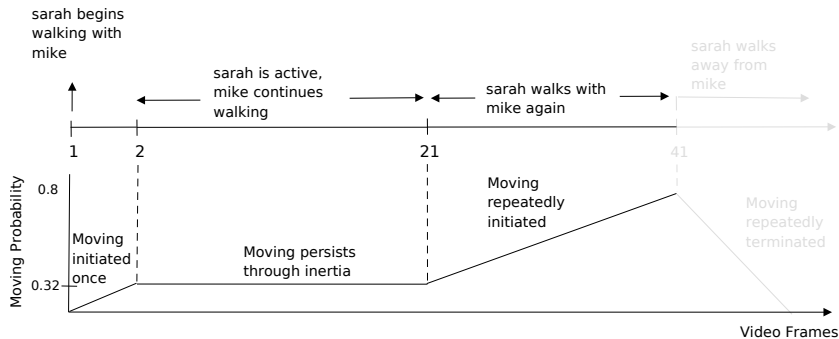


initiatedAt($moving(P_1, P_2) = true, T$) $\leftarrow$
 $happensAt(walking(P_1), T),$
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$0.70 :: happensAt(walking(mike), 1).$
 $0.46 :: happensAt(walking(sarah), 1).$
 $0.73 :: happensAt(walking(mike), 2).$
 $0.55 :: happensAt(active(sarah), 2). \dots$

Instantaneous Recognition

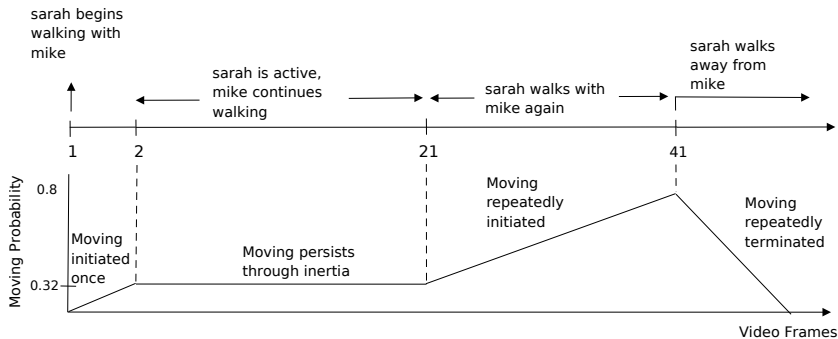


initiatedAt($moving(P_1, P_2) = \text{true}, T$) $\leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{happensAt}(\text{walking}(P_2), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$
 $\text{holdsAt}(\text{similarOrientation}(P_1, P_2) = \text{true}, T).$

terminatedAt($moving(P_1, P_2) = \text{true}, T$) $\leftarrow$
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$0.70 :: \text{happensAt}(\text{walking}(\text{mike}), 1).$
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 $0.73 :: \text{happensAt}(\text{walking}(\text{mike}), 2).$
 $0.55 :: \text{happensAt}(\text{active}(\text{sarah}), 2). \dots$
 $0.69 :: \text{happensAt}(\text{walking}(\text{mike}), 21).$
 $0.58 :: \text{happensAt}(\text{walking}(\text{sarah}), 21). \dots$

Instantaneous Recognition

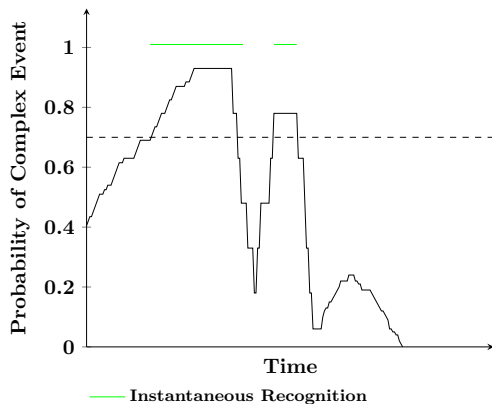


initiatedAt($moving(P_1, P_2) = true, T$) $\leftarrow$
happensAt($walking(P_1), T$),
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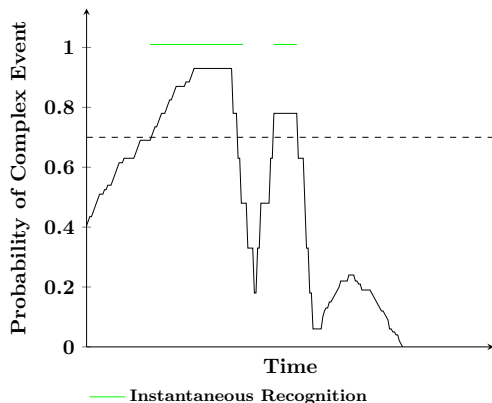
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0.73 :: **happensAt**($walking(mike), 2$).
0.55 :: **happensAt**($active(sarah), 2$). ...
0.69 :: **happensAt**($walking(mike), 21$).
0.58 :: **happensAt**($walking(sarah), 21$). ...
0.82 :: **happensAt**($inactive(mike), 41$).
0.79 :: **happensAt**($walking(sarah), 41$). ...

Instantaneous Recognition



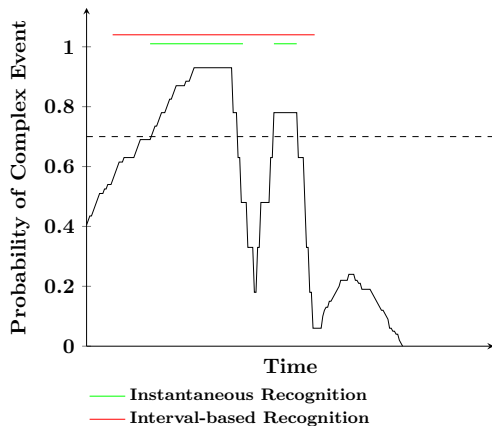
Instantaneous Recognition



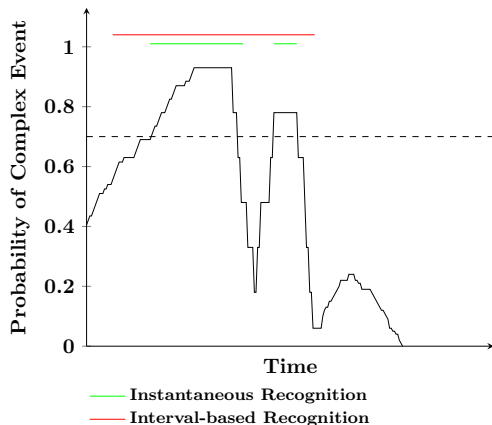
Higher accuracy than crisp reasoning in the presence of:

- several initiations and terminations;
- few probabilistic conjuncts.

Instantaneous vs Interval-based Recognition

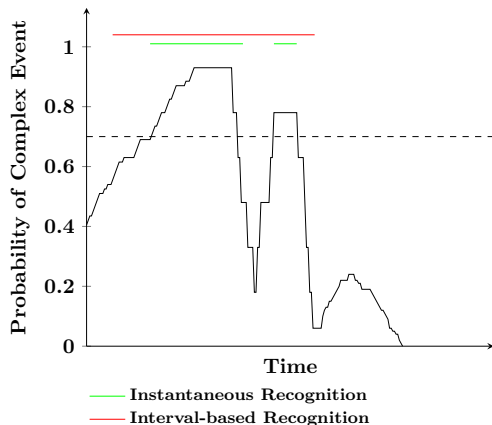


Instantaneous vs Interval-based Recognition



- **Interval Probability:** average probability of the time-points it contains.

Instantaneous vs Interval-based Recognition



- **Interval Probability:** average probability of the time-points it contains.
- **Probabilistic Maximal Interval:**
 - probability above a given threshold;
 - no super-interval with probability above the threshold.

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	<i>0</i>	<i>0.5</i>	<i>0.7</i>	<i>0.9</i>	<i>0.4</i>	<i>0.1</i>	<i>0</i>	<i>0</i>	<i>0.5</i>	<i>1</i>

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
I_n	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
L	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
l_n	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
L	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5

$$\sum_{i=s}^e L[i] \geq 0 \Leftrightarrow P([s, e]) \geq \mathcal{T}$$

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>										-0.9

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Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>									-0.9	-0.9

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Time	1	2	3	4	5	6	7	8	9	10
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<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>								-0.9	-0.9	-0.9

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Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>							-0.9	-0.9	-0.9	-0.9

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>						-0.4	-0.9	-0.9	-0.9	-0.9

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[s, e] = \begin{cases} dp[e] - prefix[s-1] & \text{if } s > 1 \\ dp[e] & \text{if } s = 1 \end{cases}$$

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[s, e] = \begin{cases} dp[e] - prefix[s-1] & \text{if } s > 1 \\ dp[e] & \text{if } s = 1 \end{cases}$$

$$dprange[s, e] \geq 0 \Rightarrow \exists e^* : e^* \geq e, P([s, e^*] \geq \mathcal{T})$$

Interval-based Recognition

	$\uparrow\downarrow$									
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

Interval-based Recognition

	$\uparrow\downarrow$									
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 1] = dp[1] = 0.1 \geq 0$$

Interval-based Recognition

	$\uparrow\uparrow$	$\downarrow\downarrow$								
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

Interval-based Recognition

	$\uparrow$	$\downarrow$								
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 2] = dp[2] = 0.1 \geq 0$$

Interval-based Recognition

	$\uparrow$		$\downarrow$							
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 3] = dp[3] = 0.1 \geq 0$$

Interval-based Recognition

	$\uparrow$			$\downarrow$						
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 4] = dp[4] = 0.1 \geq 0$$

Interval-based Recognition

	$\uparrow$				$\downarrow$					
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 5] = dp[5] = 0 \geq 0$$

Interval-based Recognition

	$\uparrow$					$\downarrow$				
Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 6] = dp[6] = -0.4 < 0$$

Interval-based Recognition

	$\uparrow$					$\downarrow$				
Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[1, 6] = dp[6] = -0.4 < 0$$

Interval-based Recognition

		↑↑				↓↓				
Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[2, 6] = dp[6] - prefix[1] = 0.1 \geq 0$$

Interval-based Recognition

		↑					↓			
Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[2, 7] = dp[7] - prefix[1] = -0.4 < 0$$

Interval-based Recognition



Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

$$dprange[2, 7] = dp[7] - prefix[1] = -0.4 < 0$$

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>In</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

Interval Computation Correctness

An interval is computed iff it is a probabilistic maximal interval.

Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
<i>ln</i>	0	0.5	0.7	0.9	0.4	0.1	0	0	0.5	1
<i>L</i>	-0.5	0	0.2	0.4	-0.1	-0.4	-0.5	-0.5	0	0.5
<i>prefix</i>	-0.5	-0.5	-0.3	0.1	0	-0.4	-0.9	-1.4	-1.4	-0.9
<i>dp</i>	0.1	0.1	0.1	0.1	0	-0.4	-0.9	-0.9	-0.9	-0.9

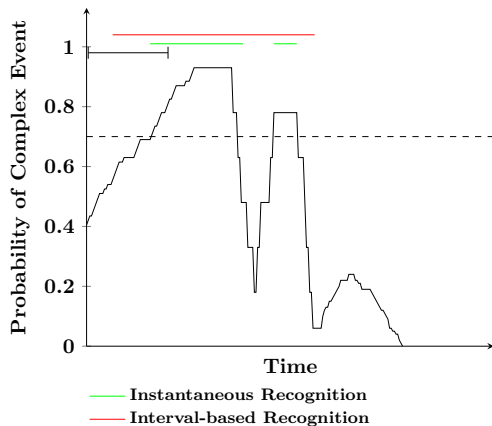
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Complexity

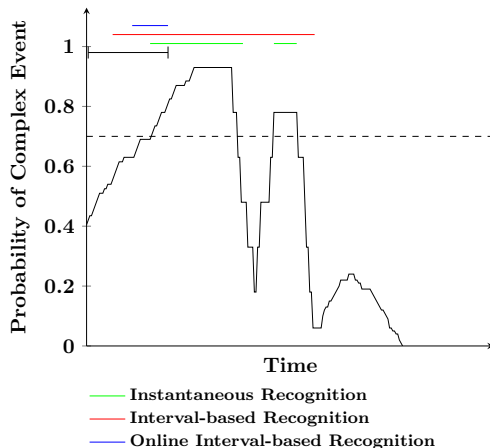
The computation of probabilistic maximal intervals is linear to the dataset size.

Online Interval-based Recognition



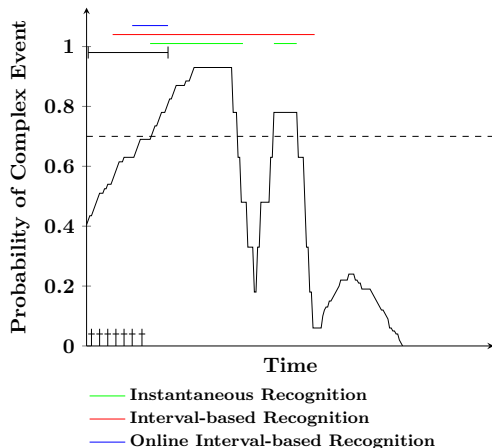
- Windowing.

Online Interval-based Recognition



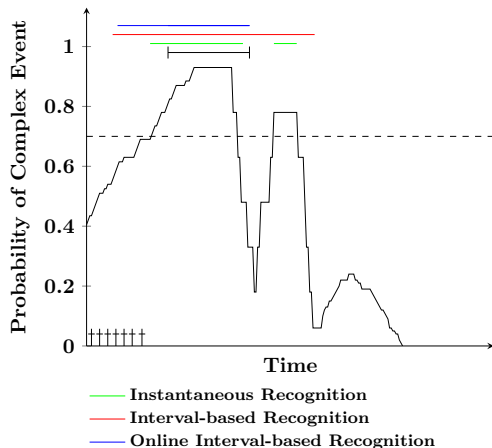
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Online Interval-based Recognition



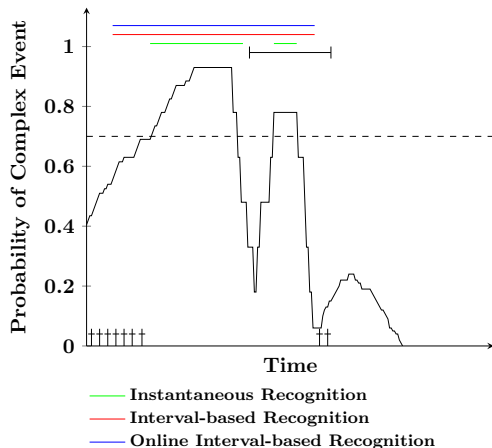
- Windowing.
- Probabilistic maximal interval computation.
- Caching potential starting points.

Online Interval-based Recognition



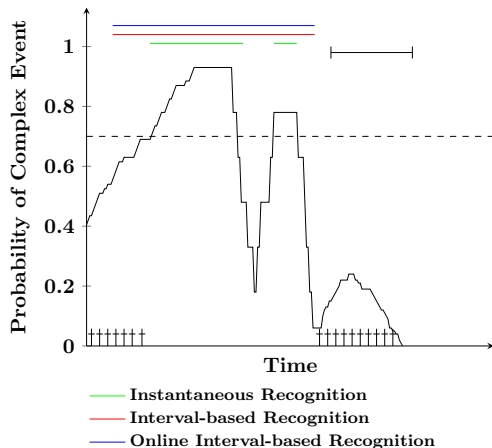
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Online Interval-based Recognition



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Online Interval-based Recognition: Properties

Memory Minimality

A time-point is cached iff it may be the starting point of a future probabilistic maximal interval.

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An interval is computed iff it is a probabilistic maximal interval given the data seen so far.

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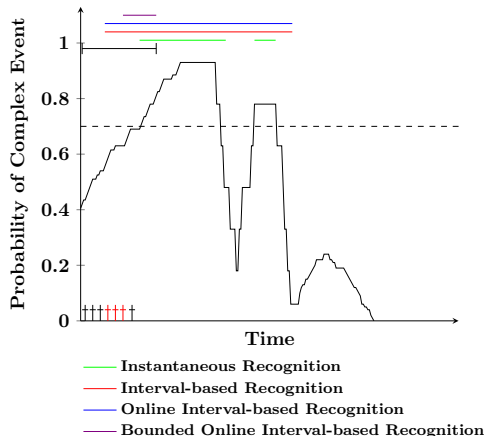
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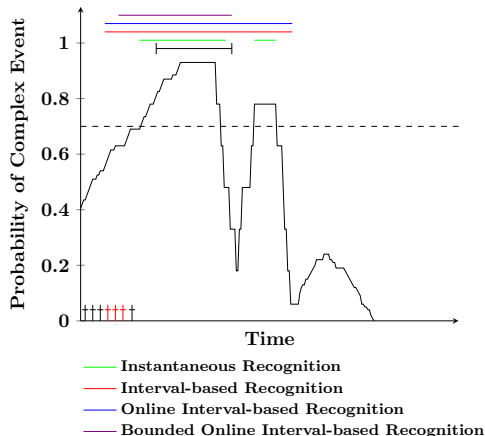
The computation of probabilistic maximal intervals is linear to the window and memory size.

Bounded Online Interval-based Recognition



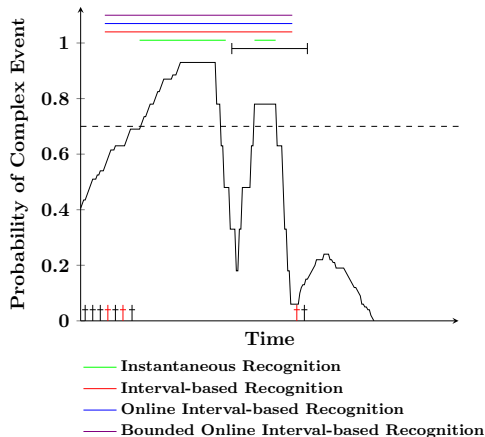
- Complex event duration statistics favor more recent potential starting points.

Bounded Online Interval-based Recognition



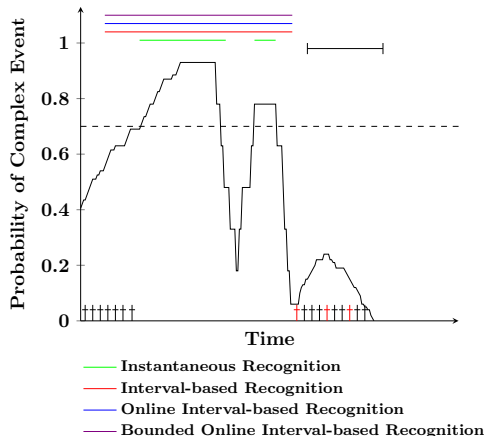
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Bounded Online Interval-based Recognition



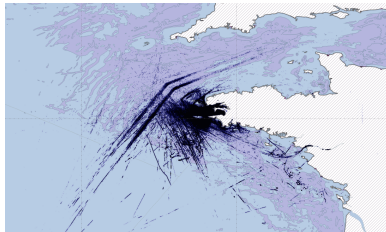
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Bounded Online Interval-based Recognition



- Complex event duration statistics favor more recent potential starting points.
- Comparable accuracy to batch reasoning.

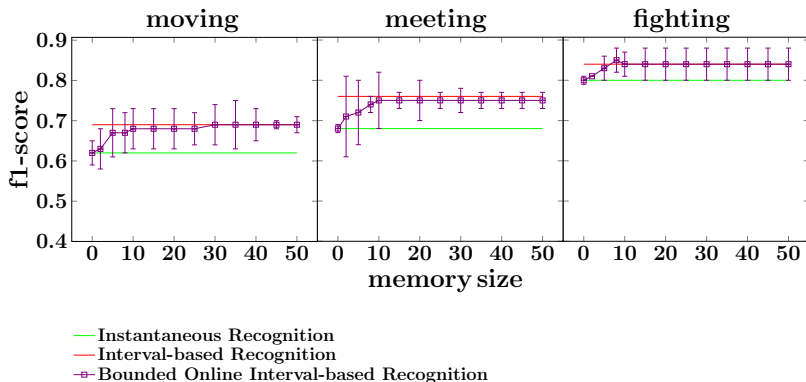
Experimental Setup



- Human Activity Recognition:
 - Input: manually annotated simple activities on individual video frames.
 - Output: maximal intervals of complex activities.
- Maritime Situational Awareness:
 - Input: vessel position signals from the area of Brest, France.
 - Output: maximal intervals of complex vessel activities.
- <https://github.com/Periklismant/oPIEC>

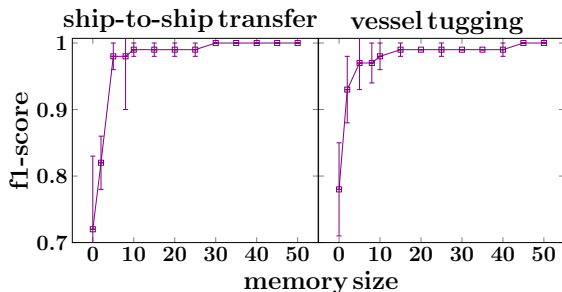
Experimental Results: Human Activity Recognition

Comparison against ground truth



Experimental Results: Maritime Situational Awareness

Performance of bounded online recognition against batch recognition



Summary & Topics not Covered

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- Optimal history compression for correct interval computation.
- Reproducible evaluation on benchmark, real data.

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