

# Can Computers Understand What is Happening?

## Probabilistic Complex Event Recognition

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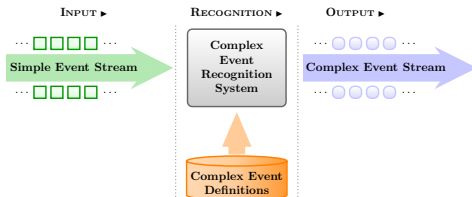
<sup>2</sup>University of Piraeus, Greece

<sup>3</sup>NKUA, Greece

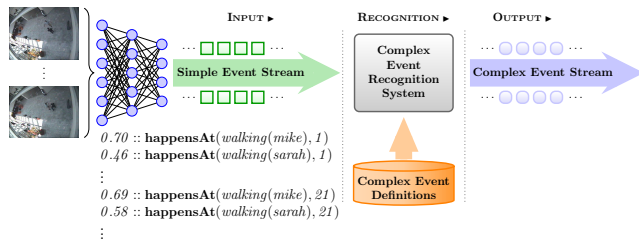
<https://cer.iit.demokritos.gr>



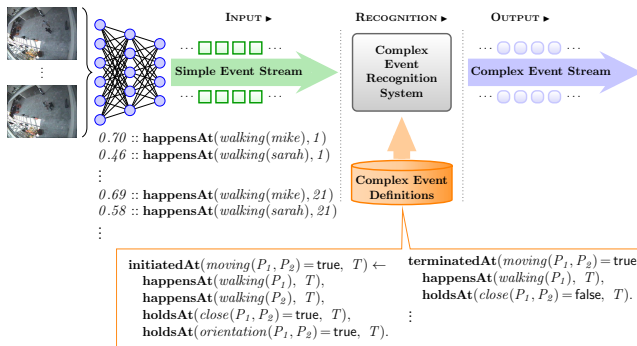
# Complex Event Recognition under Uncertainty



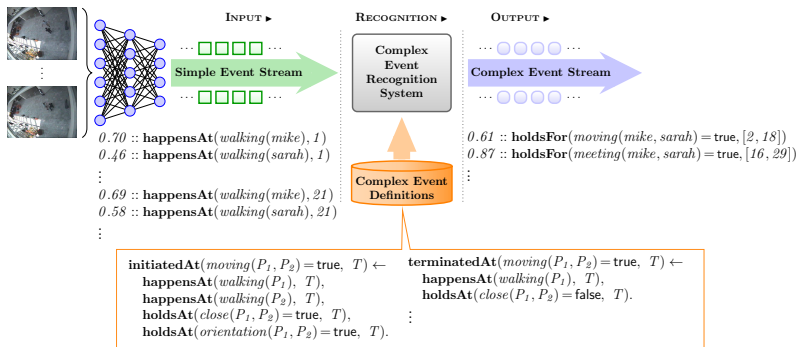
# Complex Event Recognition under Uncertainty



# Complex Event Recognition under Uncertainty



# Complex Event Recognition under Uncertainty



# Human Activity Recognition



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

# 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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\* Kowalski and Sergot, A Logic-based Calculus of Events. New Generation Computing, 1986.

# 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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\* Kowalski and Sergot, A Logic-based Calculus of Events. New Generation Computing, 1986.

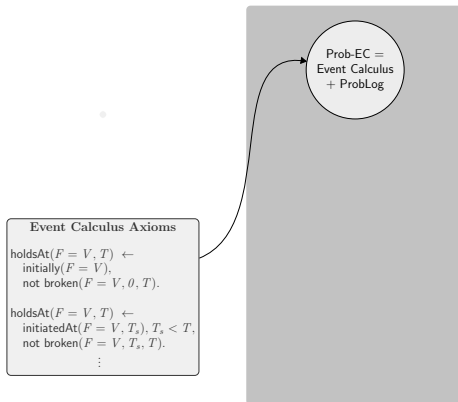


# Online Probabilistic Interval-Based Event Calculus

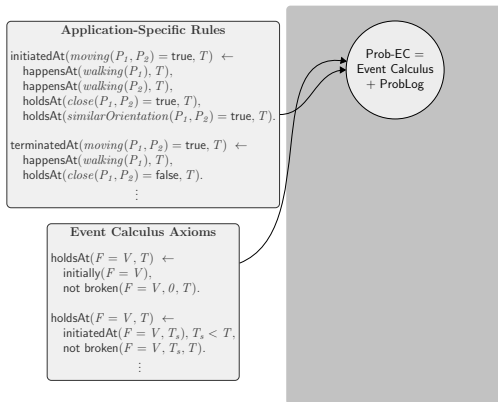


Prob-EC =  
Event Calculus  
+ ProbLog

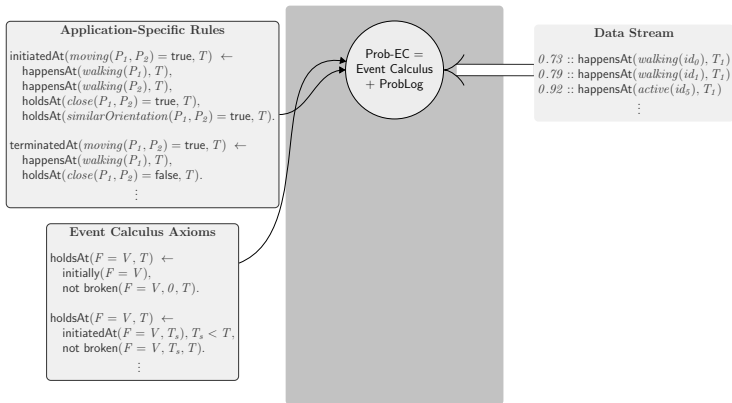
# Online Probabilistic Interval-Based Event Calculus



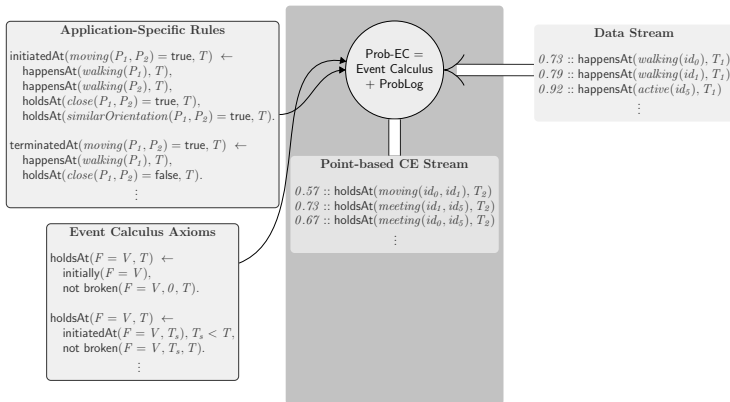
# Online Probabilistic Interval-Based Event Calculus



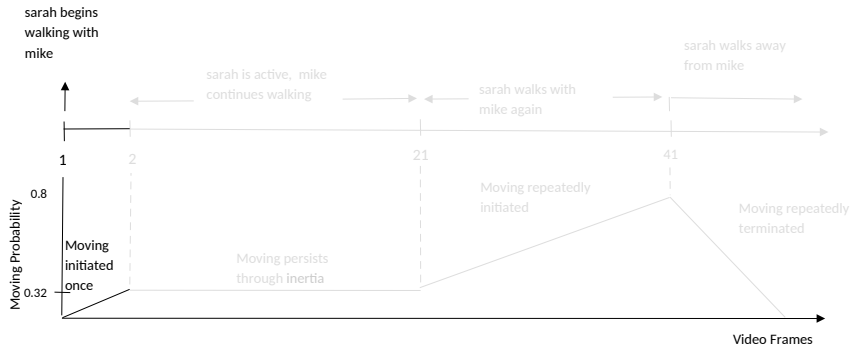
# Online Probabilistic Interval-Based Event Calculus



# Online Probabilistic Interval-Based Event Calculus



# Instantaneous Recognition

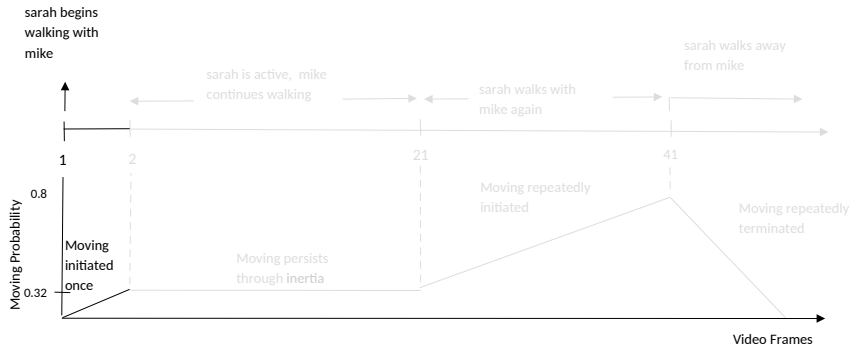


**initiatedAt**( $moving(P_1, P_2) = \text{true}, T$ )  $\leftarrow$   
**happensAt**( $walking(P_1), T$ ),  
**happensAt**( $walking(P_2), T$ ),  
**holdsAt**( $close(P_1, P_2) = \text{true}, T$ ),  
**holdsAt**( $orientation(P_1, P_2) = \text{true}, T$ ).

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

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

# Instantaneous Recognition



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

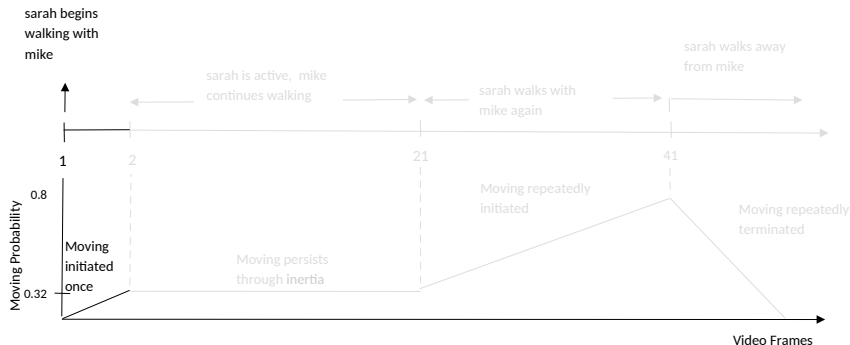
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

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

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

$$\begin{aligned}
 P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 1)) &= \\
 &P(\text{happensAt}(\text{walking}(\text{mike}), 1)) \times \\
 &P(\text{happensAt}(\text{walking}(\text{sarah}), 1)) \times \\
 &P(\text{holdsAt}(\text{close}(\text{mike}, \text{sarah}) = \text{true}, 1)) \times \\
 &P(\text{holdsAt}(\text{orientation}(\text{mike}, \text{sarah}) = \text{true}, 1)) \\
 &= 0.7 \times 0.46 \times 1 \times 1 = 0.32
 \end{aligned}$$

# Instantaneous Recognition



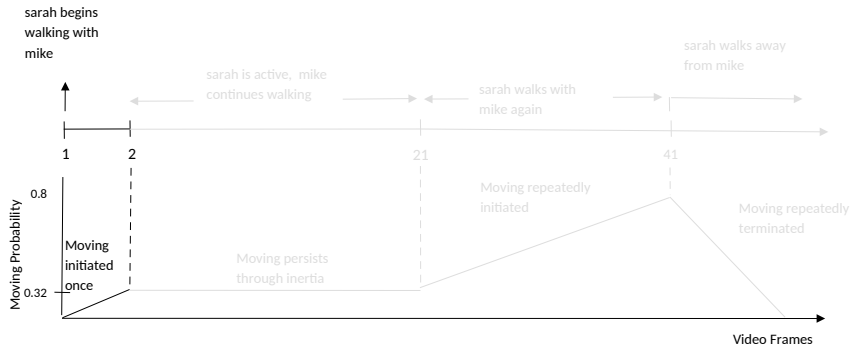
$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{happensAt}(\text{walking}(P_2), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$   
 $\text{holdsAt}(\text{orientation}(P_1, P_2) = \text{true}, T).$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

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

$P(\text{holdsAt}(CE = \text{true}, t)) =$   
 $P(\text{initiatedAt}(CE = \text{true}, t-1) \vee$   
 $(\text{holdsAt}(CE = \text{true}, t-1) \wedge$   
 $\neg \text{terminatedAt}(CE = \text{true}, t-1)))$



# Instantaneous Recognition

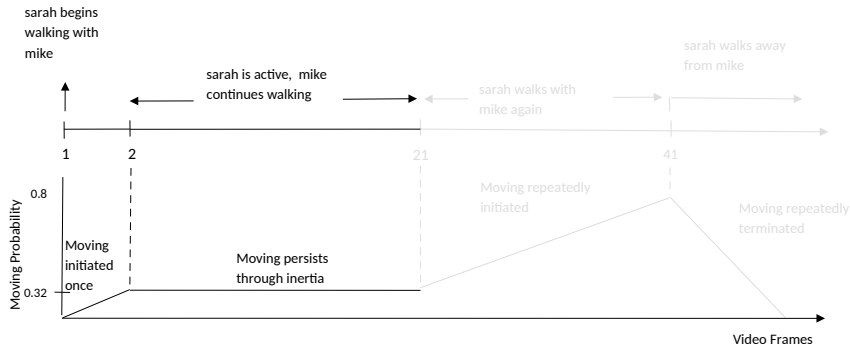


$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{happensAt}(\text{walking}(P_2), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$   
 $\text{holdsAt}(\text{orientation}(P_1, P_2) = \text{true}, T).$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

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

$P(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 2)) =$   
 $P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 1) \vee$   
 $(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 1) \wedge$   
 $\neg \text{terminatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 1)))$   
 $= 0.32 + 0 \times 1 - 0.32 \times 0 \times 1 = 0.32$

# Instantaneous Recognition



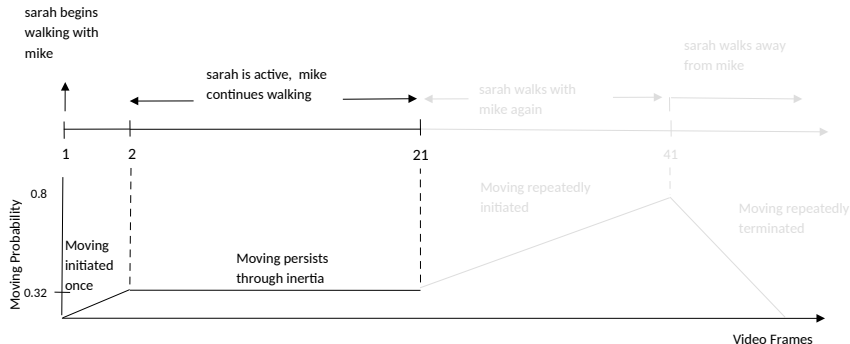
$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{happensAt}(\text{walking}(P_2), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$   
 $\text{holdsAt}(\text{orientation}(P_1, P_2) = \text{true}, T).$

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

$0.73 :: \text{happensAt}(\text{walking}(\text{mike}), 2).$   
 $0.55 :: \text{happensAt}(\text{active}(\text{sarah}), 2). \dots$

$P(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 3)) =$   
 $P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 2) \vee$   
 $\quad (\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 2) \wedge$   
 $\quad \neg \text{terminatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 2)))$   
 $= 0 + 0.32 \times 1 - 0 \times 0.32 \times 1 = 0.32$

# Instantaneous Recognition



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

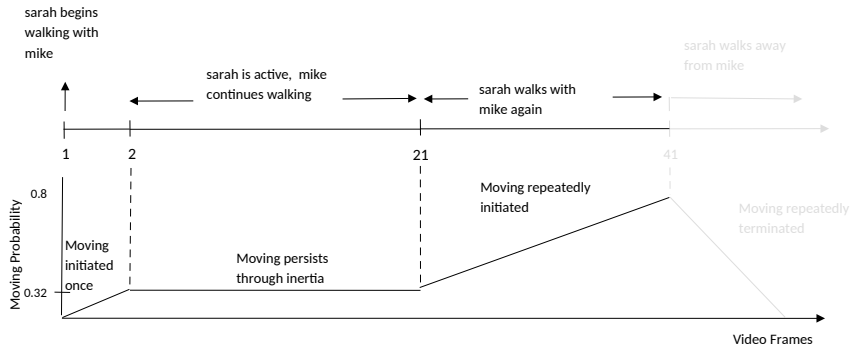
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.73 :: \text{happensAt}(\text{walking}(\text{mike}), 2).$

$0.55 :: \text{happensAt}(\text{active}(\text{sarah}), 2). \dots$

$$\begin{aligned}
 &P(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 21)) = \\
 &P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 20) \vee \\
 &\quad (\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 20) \wedge \\
 &\quad \neg \text{terminatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 20))) \\
 &= 0 + 0.32 \times 1 - 0 \times 0.32 \times 1 = 0.32
 \end{aligned}$$

# Instantaneous Recognition



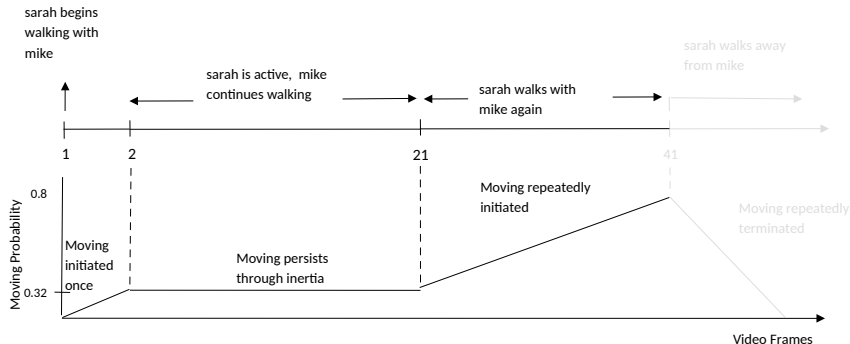
$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{happensAt}(\text{walking}(P_2), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$   
 $\text{holdsAt}(\text{orientation}(P_1, P_2) = \text{true}, T).$

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

$0.39 :: \text{happensAt}(\text{walking}(\text{mike}), 21).$   
 $0.28 :: \text{happensAt}(\text{walking}(\text{sarah}), 21). \dots$

$P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 21)) =$   
 $P(\text{happensAt}(\text{walking}(\text{mike}), 21)) \times$   
 $P(\text{happensAt}(\text{walking}(\text{sarah}), 21)) \times$   
 $P(\text{holdsAt}(\text{close}(\text{mike}, \text{sarah}) = \text{true}, 21)) \times$   
 $P(\text{holdsAt}(\text{orientation}(\text{mike}, \text{sarah}) = \text{true}, 21))$   
 $= 0.39 \times 0.28 \times 1 \times 1 = 0.11$

# Instantaneous Recognition



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

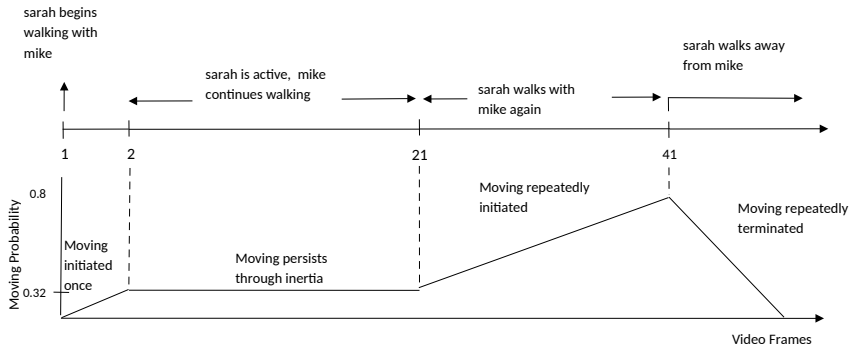
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.39 :: \text{happensAt}(\text{walking}(\text{mike}), 21).$

$0.28 :: \text{happensAt}(\text{walking}(\text{sarah}), 21). \dots$

$P(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 22)) =$   
 $P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 21) \vee$   
 $(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 21) \wedge$   
 $\neg \text{terminatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 21)))$   
 $= 0.11 + 0.32 \times 1 - 0.11 \times 0.32 \times 1 = 0.39$

# Instantaneous Recognition



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

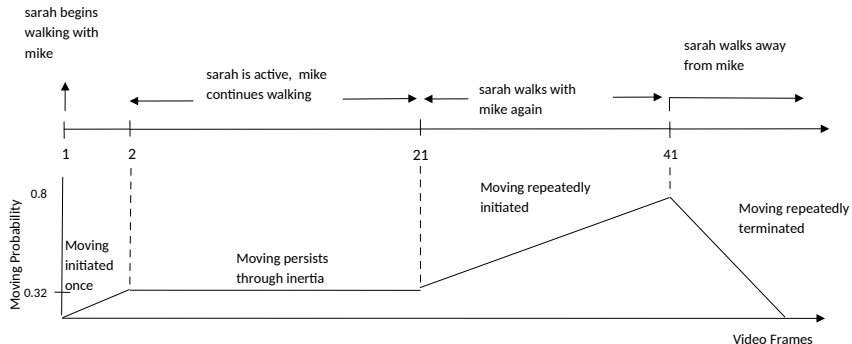
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.18 :: \text{happensAt}(\text{walking}(\text{mike}), 41).$

$0.79 :: \text{happensAt}(\text{inactive}(\text{sarah}), 41). \dots$

$$\begin{aligned}
 P(\text{terminatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 41)) &= \\
 P(\text{happensAt}(\text{walking}(\text{mike}), 41)) \times \\
 P(\text{holdsAt}(\text{close}(\text{mike}, \text{sarah}) = \text{false}, 41)) \\
 &= 0.18 \times 1 = 0.18
 \end{aligned}$$

# Instantaneous Recognition



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

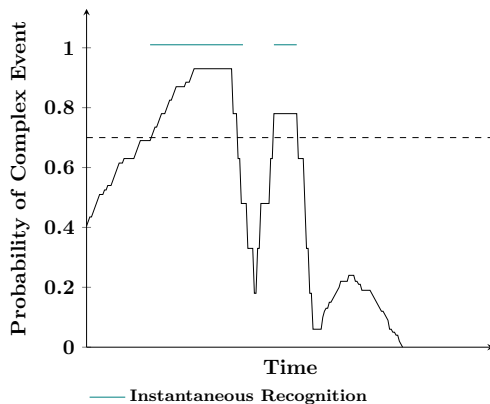
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$   
 $\text{happensAt}(\text{walking}(P_1), T),$   
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.18 :: \text{happensAt}(\text{walking}(\text{mike}), 41).$

$0.79 :: \text{happensAt}(\text{inactive}(\text{sarah}), 41). \dots$

$$\begin{aligned}
 &P(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 42)) = \\
 &P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 41) \vee \\
 &\quad (\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 41) \wedge \\
 &\quad \neg \text{terminatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 41))) \\
 &= 0 + 0.8 \times (1 - 0.18) - 0 \times 0.8 \times (1 - 0.18) = 0.66
 \end{aligned}$$

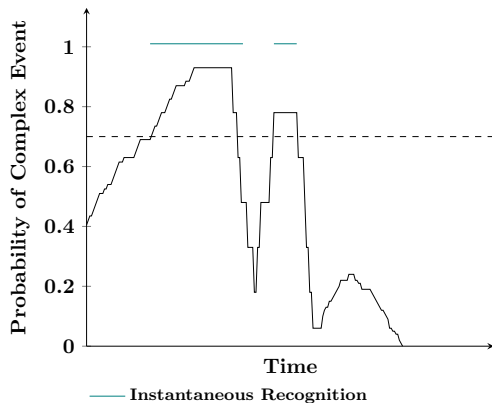
# Instantaneous Recognition\*



\*Skarlatidis et al, A Probabilistic Logic Programming Event Calculus. Theory & Practice of Logic Programming, 2015.



# Instantaneous Recognition\*



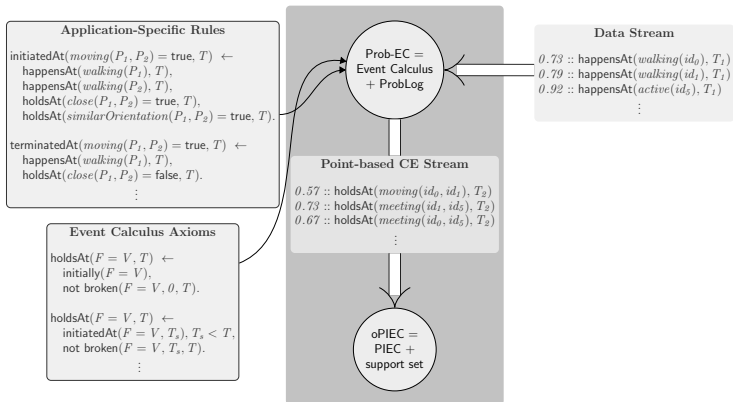
Higher accuracy than crisp reasoning in the presence of:

- several initiations and terminations;
- few probabilistic conjuncts.

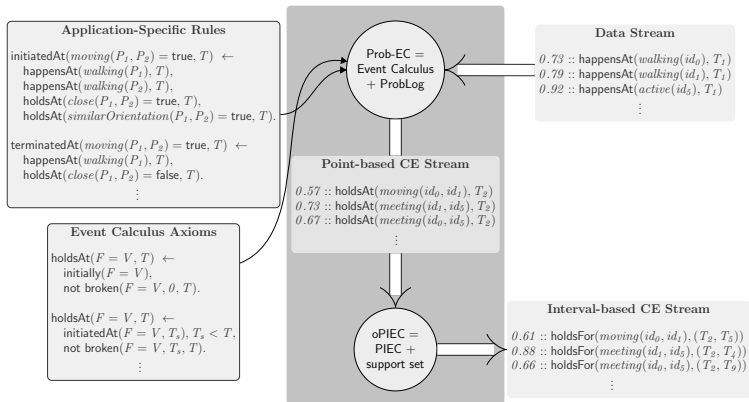
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\*Skarlatidis et al, A Probabilistic Logic Programming Event Calculus. Theory & Practice of Logic Programming, 2015.

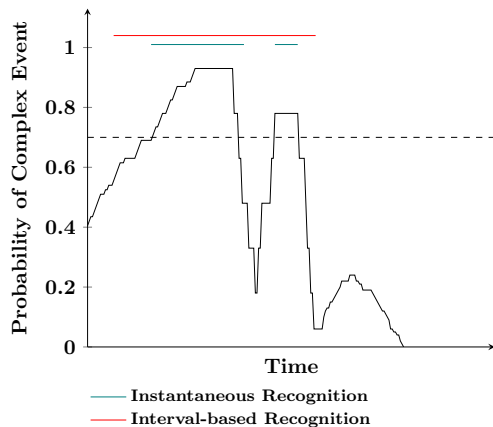
# Online Probabilistic Interval-Based Event Calculus



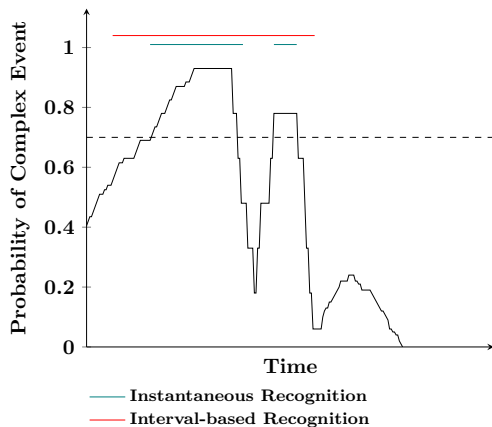
# Online Probabilistic Interval-Based Event Calculus



# Instantaneous vs Interval-based Recognition

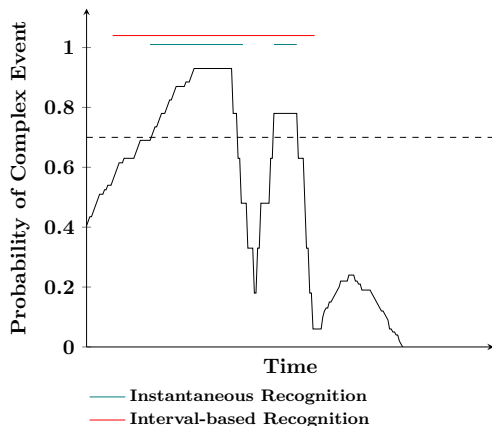


# Instantaneous vs Interval-based Recognition



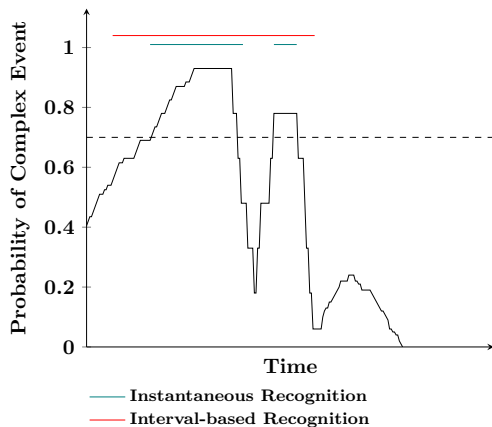
- **Interval Probability:** average probability of the time-points it contains.

# Instantaneous vs Interval-based Recognition



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

# Instantaneous vs Interval-based Recognition



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

# Interval-based Recognition

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



# Interval-based Recognition

Time	1	2	3	4	5	6	7	8	9	10
$ln$	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

$$L[i] = ln[i] - \mathcal{T}$$

# 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>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

$$prefix[i] = \sum_{j=1}^i L[j]$$

# Interval-based Recognition

<b>Time</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<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

$$dp[10] = \max_{10 \leq j \leq 10} (prefix[j])$$

# 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>									-0.9	-0.9

$$dp[9] = \max_{9 \leq j \leq 10} (prefix[j])$$

# 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>								-0.9	-0.9	-0.9

$$dp[8] = \max_{8 \leq j \leq 10} (prefix[j])$$

# 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>							-0.9	-0.9	-0.9	-0.9

$$dp[7] = \max_{7 \leq j \leq 10} (prefix[j])$$

# 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>						-0.4	-0.9	-0.9	-0.9	-0.9

$$dp[6] = \max_{6 \leq j \leq 10} (prefix[j])$$



# 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

$$dp[i] = \max_{i \leq j \leq 10} (prefix[j])$$

# 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

	$\uparrow\downarrow$									
<b>Time</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<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

	$\uparrow\downarrow$									
<b>Time</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<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

	$\uparrow$				$\downarrow$					
<b>Time</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<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>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

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


# 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>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



<b>Time</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<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\*

## Interval Computation Correctness

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

---

\* Artikis et al, A Probabilistic Interval-based Event Calculus for Activity Recognition. Annals of Mathematics and Artificial Intelligence, 2021.

# Interval-based Recognition\*

## Interval Computation Correctness

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

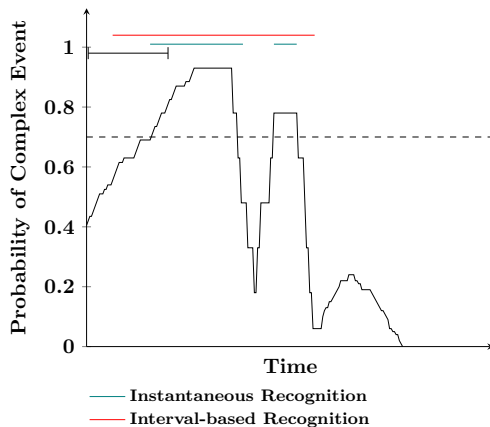
## Complexity

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

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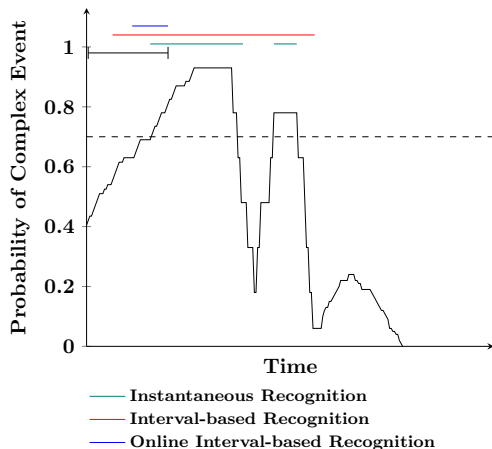
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# Online Interval-based Recognition



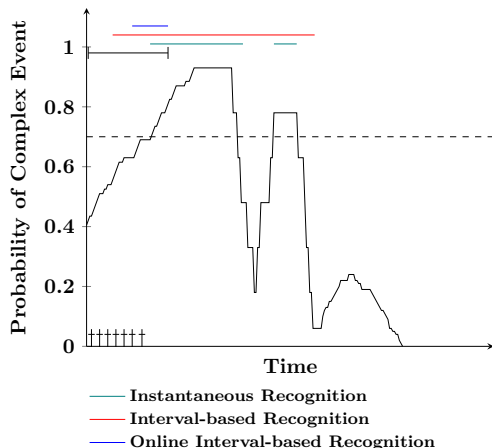
- Windowing.

# Online Interval-based Recognition



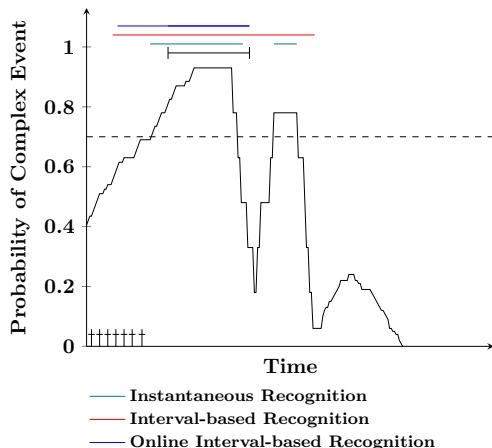
- Windowing.
- Probabilistic maximal interval computation.

# Online Interval-based Recognition



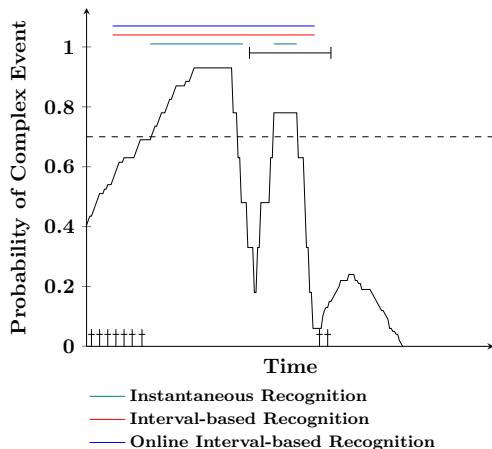
- Windowing.
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- Caching **potential starting points**.
  - Discard time-point  $t$  iff there is a  $t' < t$  that can be the starting point of a probabilistic maximal interval including  $t$ .

# Online Interval-based Recognition



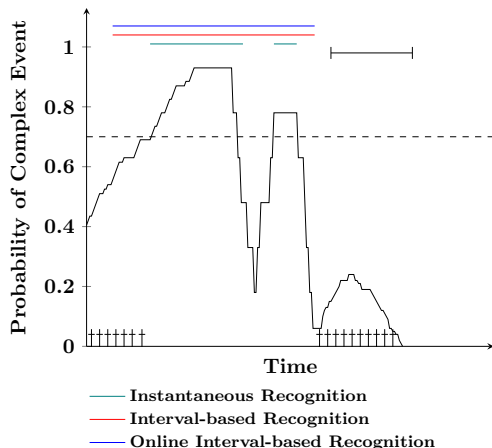
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# Online Interval-based Recognition: Properties

## Memory Minimality

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

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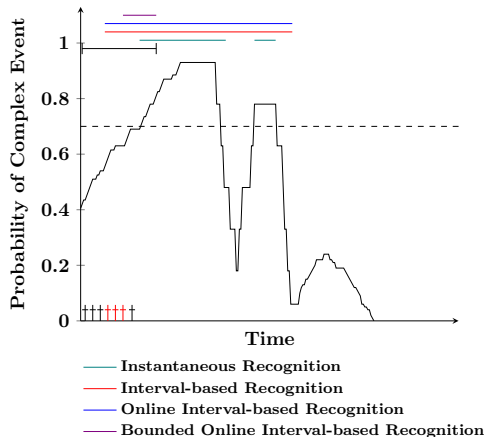
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## Complexity

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

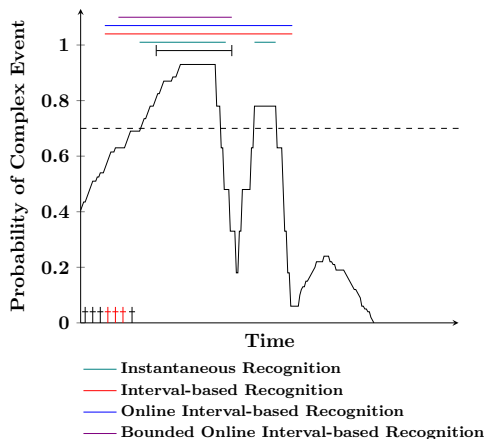
# Bounded Online Interval-based Recognition\*



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

\* Mantenoglou et al, Online Event Recognition over Noisy Data Streams. International Journal of Approximate Reasoning, 2023. <https://github.com/Periklismant/oPIEC>

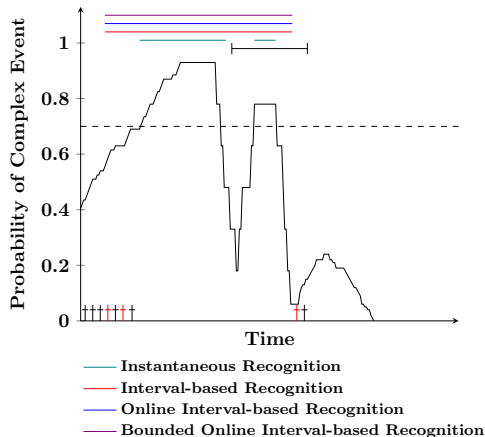
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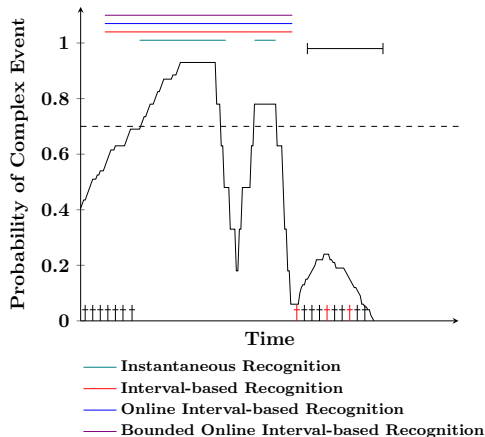
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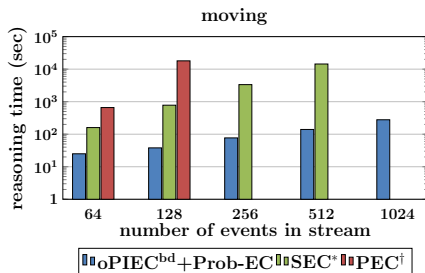
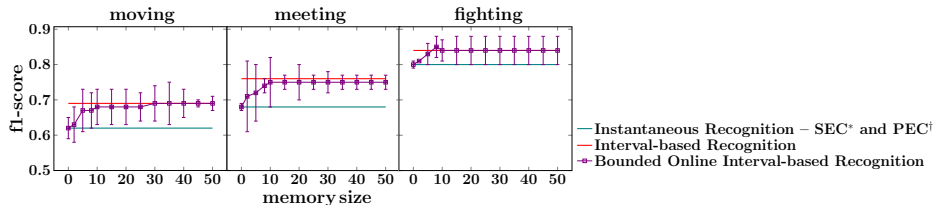
# Bounded Online Interval-based Recognition\*



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

\* Mantenoglou et al, Online Event Recognition over Noisy Data Streams. International Journal of Approximate Reasoning, 2023. <https://github.com/Periklismant/oPIEC>

# Indicative Experimental Results



\* McAreevey et al., The event calculus in probabilistic logic programming with annotated disjunctions. AAMAS, 2017.

† D'Asaro et al., Probabilistic reasoning about epistemic action narratives. Artificial Intelligence, 2021.



# Summary

Complex event recognition over noisy streams:

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Next:

- **Forecast** complex events.