Making Sense of Streaming Data

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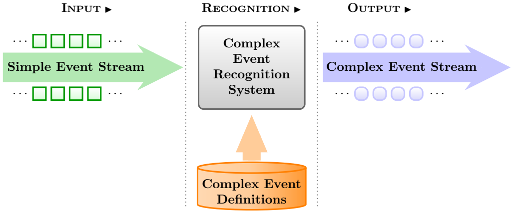
https://cer.iit.demokritos.gr

Complex Event Recognition (Event Pattern Matching)*,†



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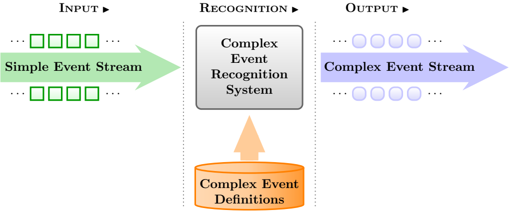

https://rdcu.be/cNkQE

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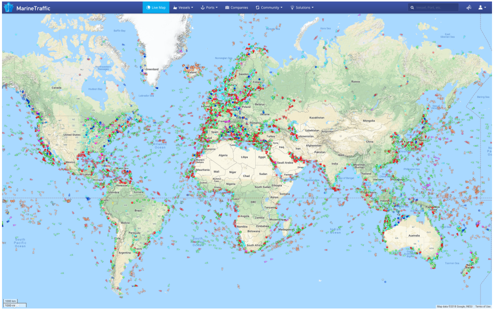
Maritime Situational Awareness*



http://www.marinetraffic.com

*Artikis and Zissis, Guide to Maritime Informatics, Springer, 2021.

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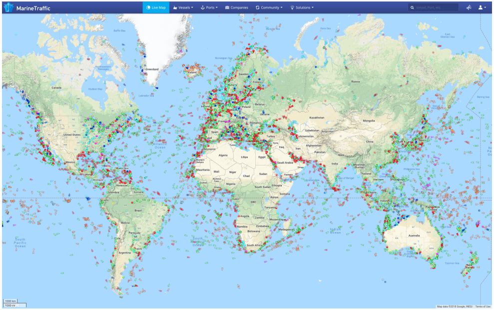

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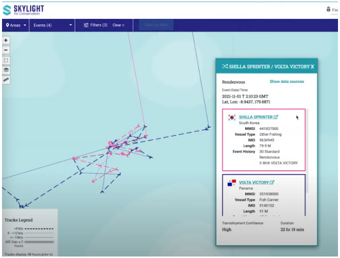
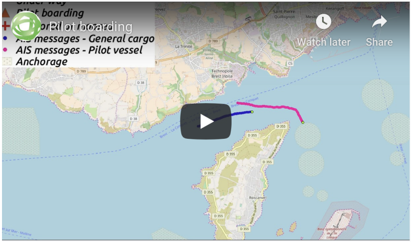


https://www.skylight.global (rendez-vous)



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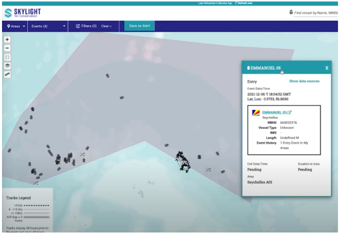

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Data Challenges

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- Lack of Veracity: GPS manipulation, vessels reporting false identity, communication gaps.
- Distribution: Vessels operating across the globe.

Many Other Applications

- Cardiac arrhythmia recognition.
- Financial fraud detection.
- Human activity recognition.
- Intrusion detection in computer networks.
- Traffic congestion recognition and forecasting in smart cities.

Requirements

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- Reasoning under uncertainty
  - to deal with various types of noise.
- Complex event forecasting
  - to support proactive decision-making.

Complex Event Recognition vs Database Management Systems*

Complex event recognition systems:

- Process data without storing them.

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- Latency requirements are very strict.

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Complex Event Recognition vs Deep Learning

We have Deep Learning and it seems to work. Can we go home?

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- Explanation — why did we detect a complex event?
- Machine Learning is necessary. But:
  - Complex events are rare.
  - Supervision is scarce.
- More often than not, background knowledge is available — let's use it!

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A Simple Unifying Event Algebra

$$
\begin{array}{rlll}
ce ::= & se & | & \\
& ce_1 \; ; \; ce_2 & | & \textit{Sequence} \\
& ce_1 \; \vee \; ce_2 & | & \textit{Disjunction} \\
& ce^* & | & \textit{Iteration} \\
& \neg \; ce & | & \textit{Negation} \\
& \sigma_\theta(ce) & | & \textit{Selection} \\
& \pi_m(ce) & | & \textit{Projection} \\
& [ce]_{T_1}^{T_2} & & \textit{Windowing} \text{ (from } T_1 \text{ to } T_2\text{)}
\end{array}
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- *Sequence*: Two events following each other in time.

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- The combination of *Sequence* and *Disjunction* expresses Conjunction (both events occurring).

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- *Iteration*: An event occurring N times in sequence, where $N \geq 0$. This operation is similar to the *Kleene star* operation in regular expressions, the difference being that *Kleene star* is unbounded.

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- *Negation*: Absence of event occurrence.
- *Selection*: Select those events whose attributes satisfy a set of predicates/relations θ, temporal or otherwise.

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- *Projection*: Return an event whose attribute values are a possibly transformed subset of the attribute values of its sub-events.

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- *Projection*: Return an event whose attribute values are a possibly transformed subset of the attribute values of its sub-events.
- *Windowing*: Evaluate the conditions of an event pattern within a specified time window.

Processing Model

Selection strategies filter the set of matched patterns.

- Assume the pattern $\alpha; \beta$ and the stream $(\alpha, 1),\ (\alpha, 2),\ (\beta, 3)$.

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- Assume the pattern $\alpha;\beta$ and the stream $(\alpha, 1),\ (\alpha, 2),\ (\beta, 3)$.
- The multiple selection strategy produces $(\alpha, 1),\ (\beta, 3)$ and $(\alpha, 2),\ (\beta, 3)$.
- The single selection strategy produces either $(\alpha, 1),\ (\beta, 3)$ or $(\alpha, 2),\ (\beta, 3)$.
- The single selection strategy represents a family of strategies, depending on the matches actually chosen among all possible ones.

Instantaneous vs Interval-based Reasoning*,†

Consider:

- the pattern $\beta; (\alpha; \gamma)$
- and the stream $(\alpha, 1), (\beta, 2), (\gamma, 3)$.

Does the stream match the pattern?

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* Paschke, ECA-LP / ECA-RuleML: A Homogeneous Event-Condition-Action Logic Programming Language. RuleML, 2006.

† White et al, What is "Next" in Event Processing?, PODS, 2007.

Deductive Databases*: 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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- 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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Run-Time Event Calculus (RTEC)[*,†]

$$\begin{aligned} &\textbf{initiatedAt}(F = V,\ T) \leftarrow \\ &\qquad \textbf{happensAt}(E_{In_1},\ T), \\ &\qquad [\text{conditions}] \\ &\ldots \\ &\textbf{initiatedAt}(F = V,\ T) \leftarrow \\ &\qquad \textbf{happensAt}(E_{In_i},\ T), \\ &\qquad [\text{conditions}] \end{aligned}$$

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where

$$\text{conditions:} \qquad \begin{aligned} &{}^{0-K}\textbf{happensAt}(E_k,\ T), \\ &{}^{0-M}\textbf{holdsAt}(F_m = V_m,\ T), \\ &{}^{0-N}\text{atemporal-constraint}_n \end{aligned}$$

[*] Artikis et al, An Event Calculus for Event Recognition. IEEE TKDE, 2015.

[†] Mantenoglou et al, Stream Reasoning with Cycles. KR, 2022. https://github.com/aartikis/RTEC

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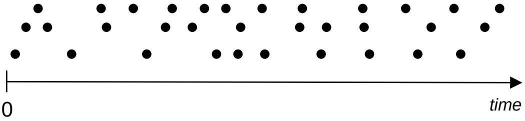

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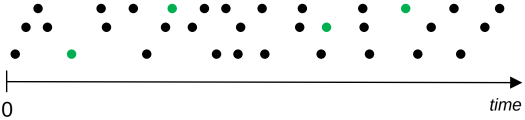

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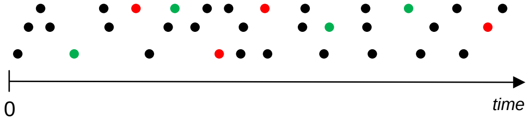

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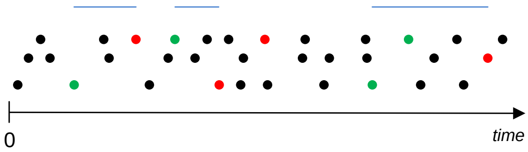
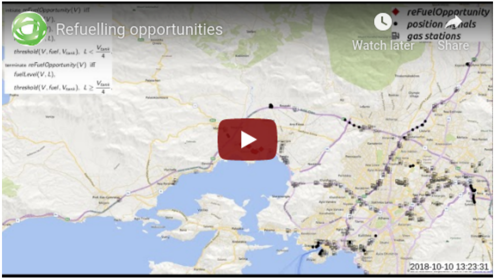
$\textbf{holdsFor}(F = V,\ I)$



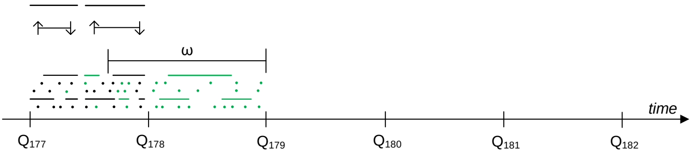
Fleet Management*



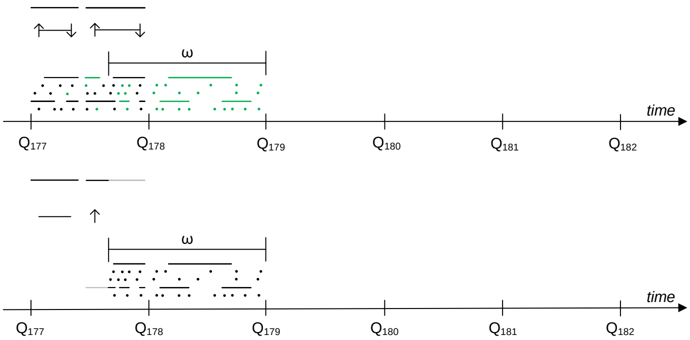
https://cer.iit.demokritos.gr (refuelling opportunities)

*Tsilionis et al, Online Event Recognition from Moving Vehicles. Theory and Practice of Logic Programming, 2019.

Windowing

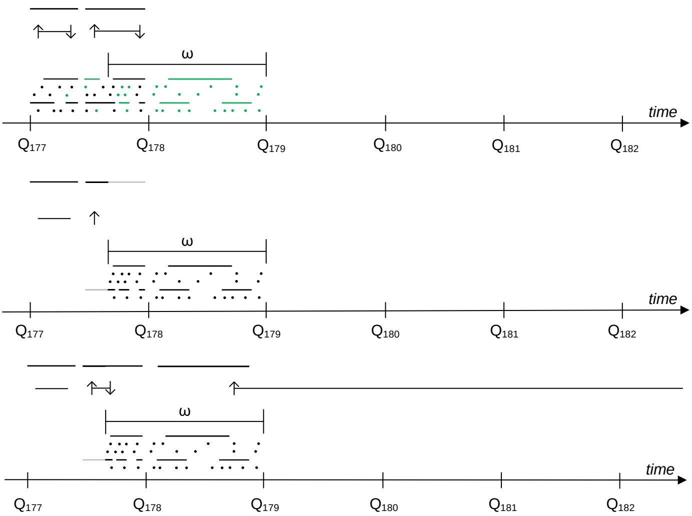


Windowing



ω
time
Q177
Q178
Q179
Q180
Q181
Q182
ω
time
Q177
Q178
Q179
Q180
Q181
Q182

Windowing



ω
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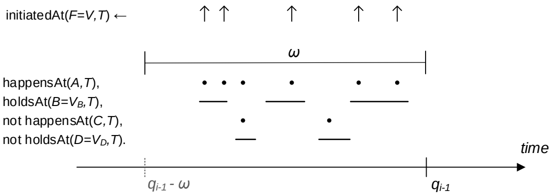
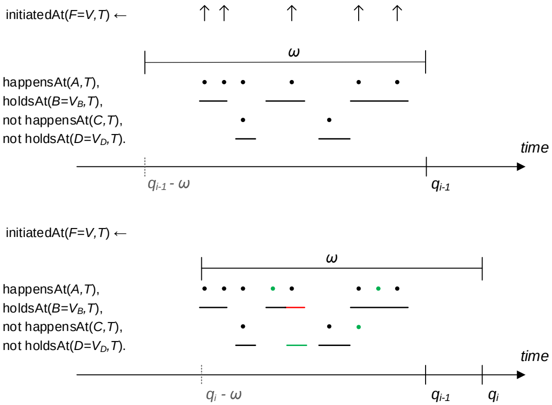
Windowing


initiatedAt(F=V,T) ←
ω
happensAt(A,T),
holdsAt(B=V_B,T),
not happensAt(C,T),
not holdsAt(D=V_D,T).
time
q_i-1 - ω
q_i-1

Windowing



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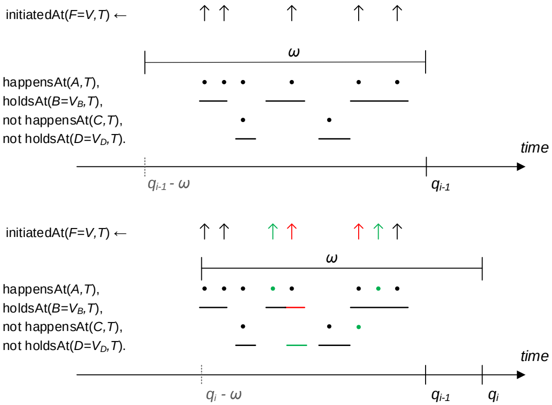
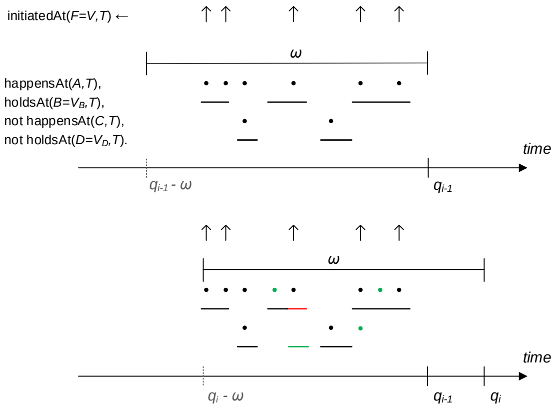
time
q_i - ω
q_{i-1}
q_i

Windowing

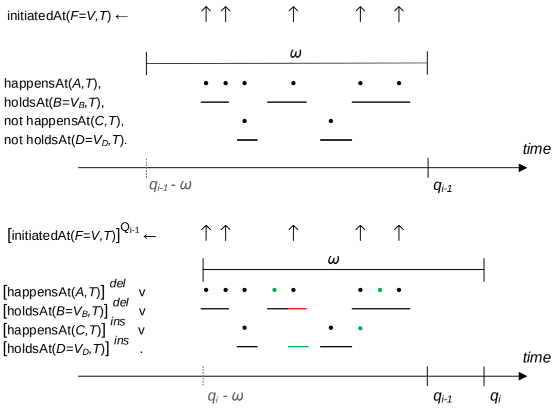

initiatedAt(F=V,T) ←
ω
happensAt(A,T),
holdsAt(B=V_B,T),
not happensAt(C,T),
not holdsAt(D=V_D,T).
time
q_{i-1} - ω
q_{i-1}
initiatedAt(F=V,T) ←
ω
happensAt(A,T),
holdsAt(B=V_B,T),
not happensAt(C,T),
not holdsAt(D=V_D,T).
time
q_i - ω
q_{i-1}
q_i

Incremental Reasoning: Deletion Phase*



*Tsilionis et al, Incremental Event Calculus for Run-Time Reasoning. Journal of AI Research (JAIR), 2022.

Incremental Reasoning: Deletion Phase*



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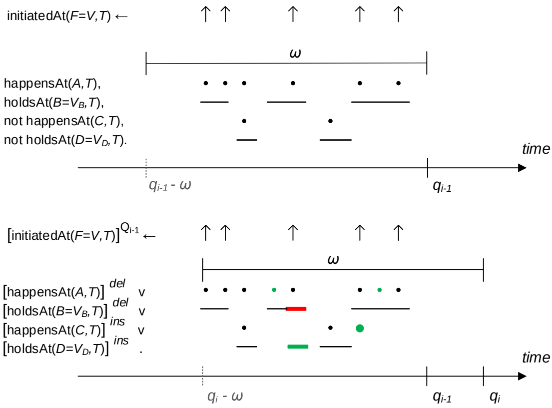
Incremental Reasoning: Deletion Phase*



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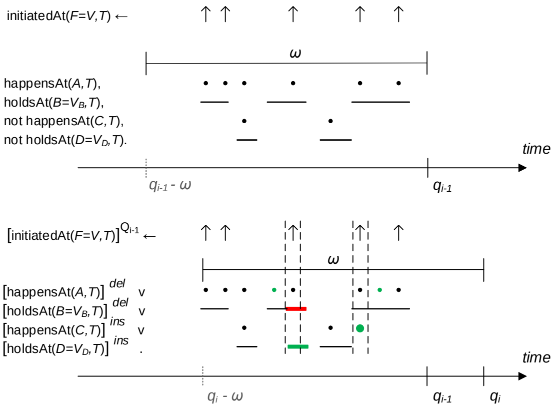

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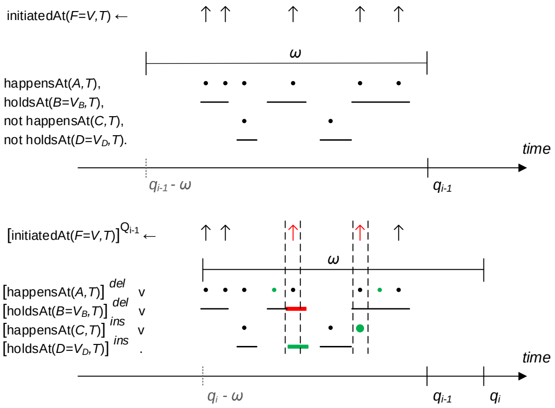

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*Tsilionis et al, Incremental Event Calculus for Run-Time Reasoning. Journal of AI Research (JAIR), 2022.

RTEC: Correctness and Complexity

Correctness

RTEC computes all maximal intervals of a fluent, and no other interval, provided that interval delays/retractions, if any, are tolerated by the window size.

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Correctness

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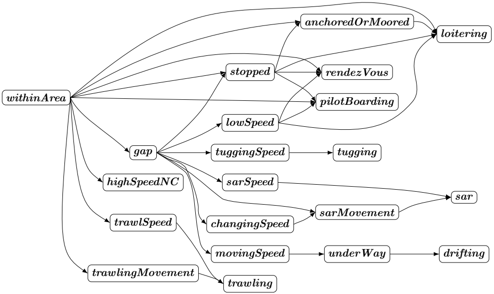
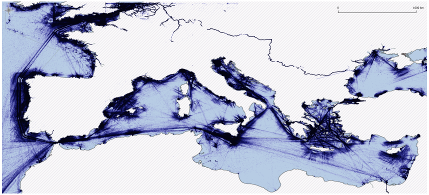
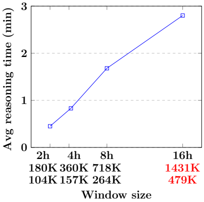
Complexity

The time to compute the maximal intervals of a fluent is linear to the window size.

Performance: Indicative Results







Summary

Run-Time Event Calculus (RTEC):

- Interval-based reasoning* $\rightarrow$ avoid unintended semantics.

*Mantenoglou et al, Complex Event Recognition with Allen Relations. KR, 2023.

Summary

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†Mantenoglou et al, Temporal Specification Optimisation for the Event Calculus. AAAI, 2025.

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- Expressive language $\rightarrow$ *n*-ary constraints.
- Incremental reasoning $\rightarrow$ handle out-of-order streams.
- Caching, temporal specification optimisation† $\rightarrow$ real-time performance.
- Direct routes to probabilistic reasoning $\rightarrow$ handle the lack of veracity of data streams.

---

* Mantenoglou et al, Complex Event Recognition with Allen Relations. KR, 2023.

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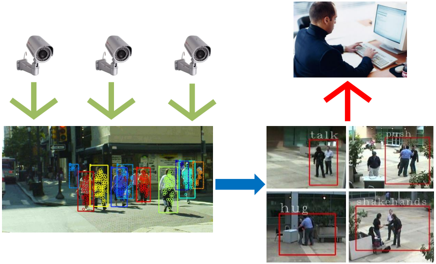
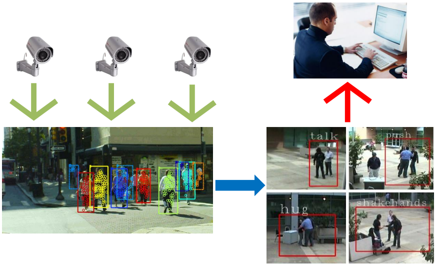
Human Activity Recognition

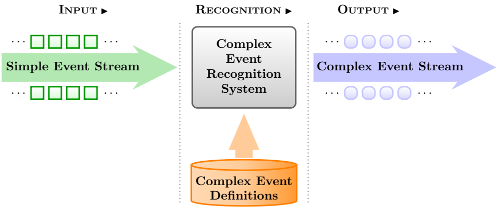


Human Activity Recognition

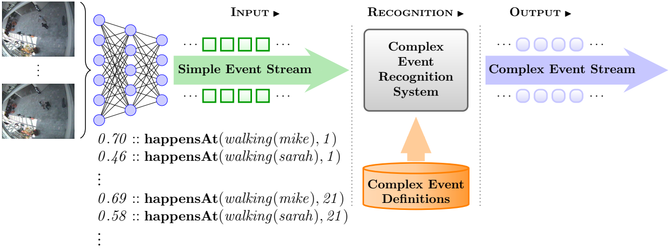


https://cer.iit.demokritos.gr (activity recognition)

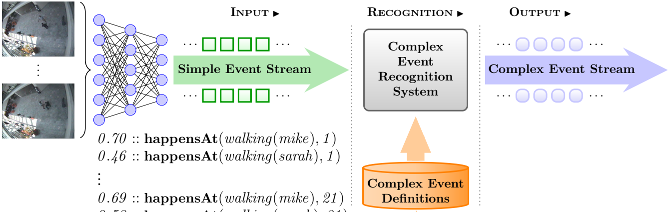
Complex Event Recognition under Uncertainty



Complex Event Recognition under Uncertainty



Complex Event Recognition under Uncertainty

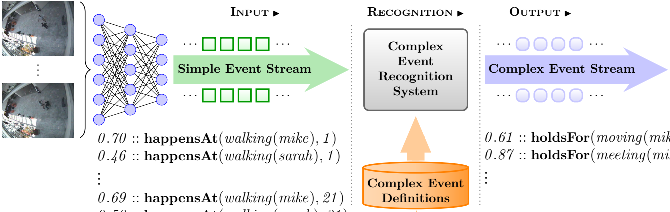


0.70 :: **happensAt**(*walking*(*mike*), 1)
0.46 :: **happensAt**(*walking*(*sarah*), 1)
⋮
0.69 :: **happensAt**(*walking*(*mike*), 21)
0.58 :: **happensAt**(*walking*(*sarah*), 21)
⋮

initiatedAt(*moving*(P_1, P_2) = true, T) ←
  happensAt(*walking*(P_1), T),
  happensAt(*walking*(P_2), T),
  holdsAt(*close*(P_1, P_2) = true, T),
  holdsAt(*orientation*(P_1, P_2) = true, T).

terminatedAt(*moving*(P_1, P_2) = true, T) ←
  happensAt(*walking*(P_1), T),
  holdsAt(*close*(P_1, P_2) = false, T).
⋮

Complex Event Recognition under Uncertainty



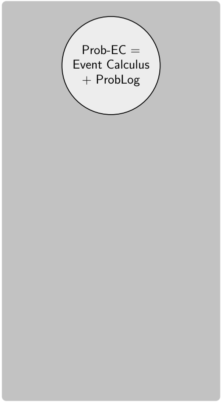
0.70 :: **happensAt**$(walking(mike), 1)$
0.46 :: **happensAt**$(walking(sarah), 1)$
$\vdots$
0.69 :: **happensAt**$(walking(mike), 21)$
0.58 :: **happensAt**$(walking(sarah), 21)$
$\vdots$

0.61 :: **holdsFor**$(moving(mike, sarah) = \mathsf{true}, [2, 18])$
0.87 :: **holdsFor**$(meeting(mike, sarah) = \mathsf{true}, [16, 29])$
$\vdots$

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

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

Online Probabilistic Interval-Based Event Calculus



Online Probabilistic Interval-Based Event Calculus

Prob-EC = Event Calculus + ProbLog

Event Calculus Axioms

holdsAt$(F = V, T) \leftarrow$
  initially$(F = V)$,
  not broken$(F = V, 0, T)$.

holdsAt$(F = V, T) \leftarrow$
  initiatedAt$(F = V, T_s), T_s < T$,
  not broken$(F = V, T_s, T)$.

$\vdots$

Online Probabilistic Interval-Based Event Calculus

Application-Specific Rules

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

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

$\vdots$

Event Calculus Axioms

holdsAt($F = V$, T) $\leftarrow$
  initially($F = V$),
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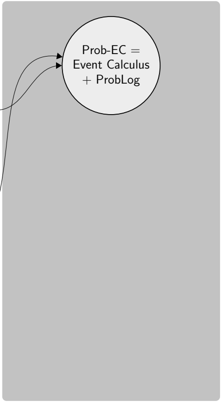
holdsAt($F = V$, T) $\leftarrow$
  initiatedAt($F = V$, T_s), $T_s < T$,
  not broken($F = V$, T_s, T).

$\vdots$



Online Probabilistic Interval-Based Event Calculus

Application-Specific Rules

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

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

$\vdots$

Event Calculus Axioms

$\mathsf{holdsAt}(F = V, T) \leftarrow$
$\quad \mathsf{initially}(F = V),$
$\quad \mathsf{not\ broken}(F = V, 0, T).$

$\mathsf{holdsAt}(F = V, T) \leftarrow$
$\quad \mathsf{initiatedAt}(F = V, T_s), T_s < T,$
$\quad \mathsf{not\ broken}(F = V, T_s, T).$

$\vdots$

Prob-EC =
Event Calculus
+ ProbLog

Data Stream

$0.73 :: \mathsf{happensAt}(walking(id_0), T_1)$
$0.79 :: \mathsf{happensAt}(walking(id_1), T_1)$
$0.92 :: \mathsf{happensAt}(active(id_5), T_1)$
$\vdots$

Online Probabilistic Interval-Based Event Calculus

Application-Specific Rules

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

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

$\vdots$

Event Calculus Axioms

holdsAt($F = V$, T) $\leftarrow$
initially($F = V$),
not broken($F = V$, 0, T).

holdsAt($F = V$, T) $\leftarrow$
initiatedAt($F = V$, T_s), $T_s < T$,
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$\vdots$

Prob-EC =
Event Calculus
+ ProbLog

Data Stream

0.73 :: happensAt($walking(id_0)$, T_1)
0.79 :: happensAt($walking(id_1)$, T_1)
0.92 :: happensAt($active(id_5)$, T_1)
$\vdots$

Point-based CE Stream

0.57 :: holdsAt($moving(id_0, id_1)$, T_2)
0.73 :: holdsAt($meeting(id_1, id_5)$, T_2)
0.67 :: holdsAt($meeting(id_0, id_5)$, T_2)
$\vdots$

Instantaneous Recognition

$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$\begin{aligned}
&\mathit{0.70} :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ \mathit{1}). \\
&\mathit{0.46} :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ \mathit{1}).
\end{aligned}$$

Instantaneous Recognition

$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\mathit{0.70} :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ \mathit{1}). \\
&\mathit{0.46} :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ \mathit{1}).
\end{aligned}
$$

$$
\begin{aligned}
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, \mathit{1})) = \\
&\quad P(\textbf{happensAt}(\mathit{walking}(\mathit{mike}), \mathit{1})) \times \\
&\quad P(\textbf{happensAt}(\mathit{walking}(\mathit{sarah}), \mathit{1})) \times \\
&\quad P(\textbf{holdsAt}(\mathit{close}(\mathit{mike}, \mathit{sarah}) = \text{true}, \mathit{1})) \times \\
&\quad P(\textbf{holdsAt}(\mathit{orientation}(\mathit{mike}, \mathit{sarah}) = \text{true}, \mathit{1})) \\
&\quad = \mathit{0.7} \times \mathit{0.46} \times \mathit{1} \times \mathit{1} = \mathit{0.322}
\end{aligned}
$$

Instantaneous Recognition

$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$\begin{aligned}
&0.70 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 1). \\
&0.46 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 1).
\end{aligned}$$

$$\begin{aligned}
&P(\textbf{holdsAt}(CE = \text{true}, t)) = \\
&\quad P(\textbf{initiatedAt}(CE = \text{true}, t-1) \vee \\
&\qquad (\textbf{holdsAt}(CE = \text{true}, t-1) \wedge \\
&\qquad \neg\ \textbf{terminatedAt}(CE = \text{true}, t-1)))
\end{aligned}$$

Instantaneous Recognition

$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
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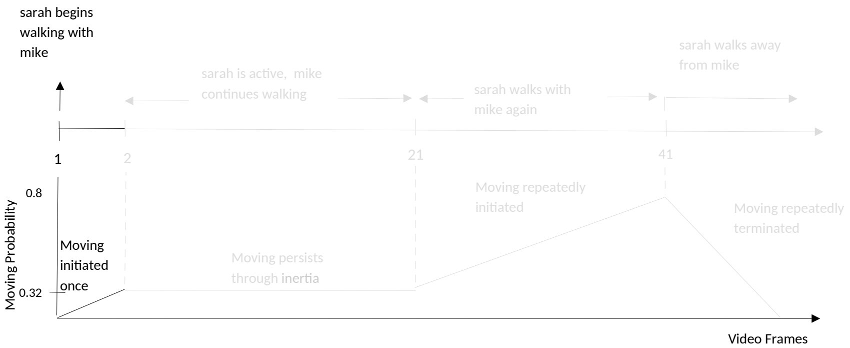
&0.46 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 1).
\end{aligned}
$$

$$
\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 2)) = \\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 1) \vee \\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 1) \wedge \\
&\quad \neg\textbf{terminatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, \\
&= 0.322 + 0 \times 1 - 0.322 \times 0 \times 1 = 0.322
\end{aligned}
$$

Instantaneous Recognition



$$
\begin{aligned}
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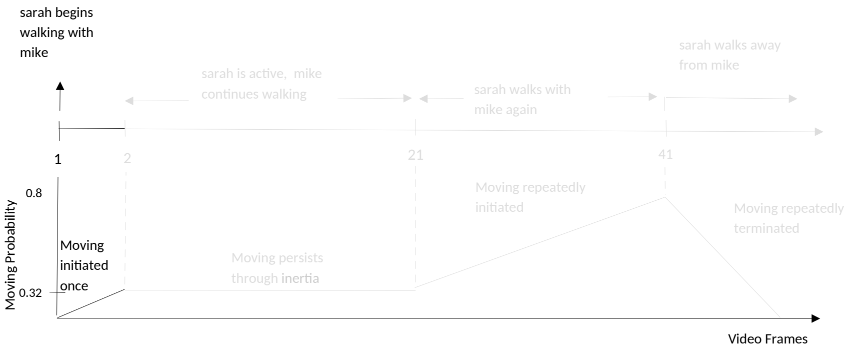
&\quad \textbf{happensAt}(\textit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\textit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\textit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\textit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\textit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\textit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&0.70 :: \textbf{happensAt}(\textit{walking}(\textit{mike}),\ 1). \\
&0.46 :: \textbf{happensAt}(\textit{walking}(\textit{sarah}),\ 1).
\end{aligned}
$$

$$
\begin{aligned}
&P(\textbf{holdsAt}(\textit{moving}(\textit{mike}, \textit{sarah}) = \text{true}, 2)) = \\
&P(\textbf{initiatedAt}(\textit{moving}(\textit{mike}, \textit{sarah}) = \text{true}, 1) \vee \\
&\quad (\textbf{holdsAt}(\textit{moving}(\textit{mike}, \textit{sarah}) = \text{true}, 1) \wedge \\
&\quad \neg\textbf{terminatedAt}(\textit{moving}(\textit{mike}, \textit{sarah}) = \text{true}, \\
&= 0.322 + 0 \times 1 - 0.322 \times 0 \times 1 = 0.322
\end{aligned}
$$

Instantaneous Recognition

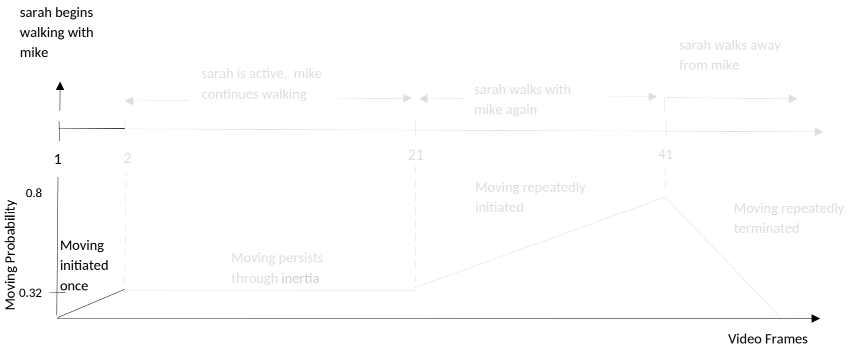


$\mathbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow$
$\quad \mathbf{happensAt}(\mathit{walking}(P_1),\ T),$
$\quad \mathbf{happensAt}(\mathit{walking}(P_2),\ T),$
$\quad \mathbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T),$
$\quad \mathbf{holdsAt}(\mathit{orientation}(P_1,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

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

$0.73 :: \mathbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 2).$
$0.55 :: \mathbf{happensAt}(\mathit{active}(\mathit{sarah}),\ 2).\ \cdots$

Instantaneous Recognition



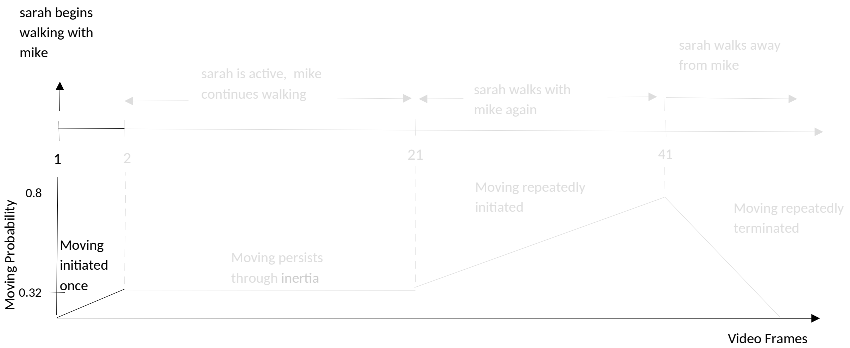
$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&0.73 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 2). \\
&0.55 :: \textbf{happensAt}(\mathit{active}(\mathit{sarah}),\ 2).\ \cdots
\end{aligned}
$$

$$
\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 3)) = \\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 2) \vee \\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 2) \wedge \\
&\quad \neg\textbf{terminatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 2)) \\
&= 0 + 0.322 \times 1 - 0 \times 0.322 \times 1 = 0.322
\end{aligned}
$$

Instantaneous Recognition

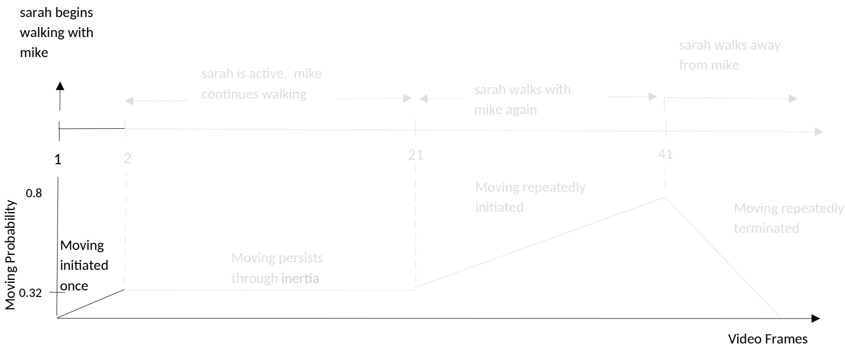


$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\mathit{0.45} :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ \mathit{20}). \\
&\mathit{0.14} :: \textbf{happensAt}(\mathit{active}(\mathit{sarah}),\ \mathit{20}).
\end{aligned}
$$

Instantaneous Recognition



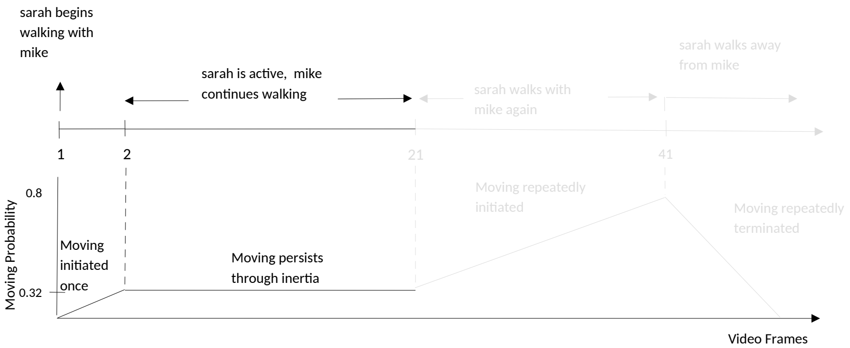
$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$0.45 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 20).$$
$$0.14 :: \textbf{happensAt}(\mathit{active}(\mathit{sarah}),\ 20).$$

$$\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21)) = \\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 20) \vee \\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 20) \wedge \\
&\quad \neg\textbf{terminatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 20) \\
&= 0 + 0.322 \times 1 - 0 \times 0.322 \times 1 = 0.322
\end{aligned}$$

Instantaneous Recognition



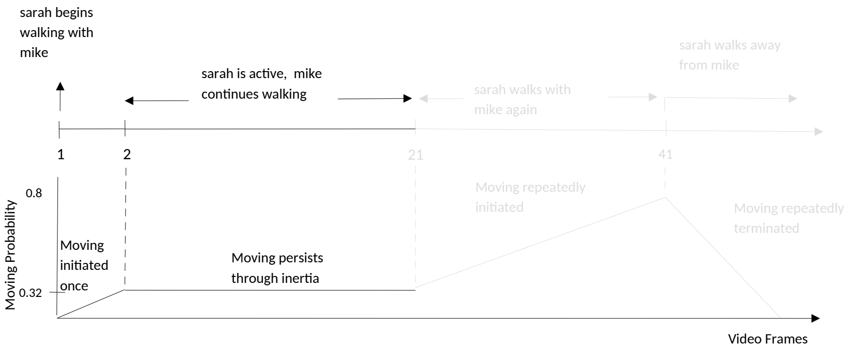
$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow\\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T),\\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T),\\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow\\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$\begin{aligned}
&0.45 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 20).\\
&0.14 :: \textbf{happensAt}(\mathit{active}(\mathit{sarah}),\ 20).
\end{aligned}$$

$$\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21)) =\\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 20) \vee\\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 20) \wedge\\
&\quad \neg\textbf{terminatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 20)\\
&= 0 + 0.322 \times 1 - 0 \times 0.322 \times 1 = 0.322
\end{aligned}$$

Instantaneous Recognition

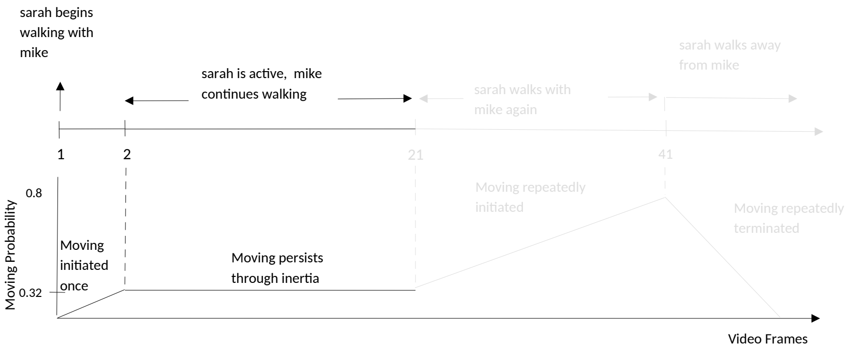


$$\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow$$
$$\textbf{happensAt}(\mathit{walking}(P_1),\ T),$$
$$\textbf{happensAt}(\mathit{walking}(P_2),\ T),$$
$$\textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T),$$
$$\textbf{holdsAt}(\mathit{orientation}(P_1, P_2) =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

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

$$\mathit{0.39} :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ \mathit{21}).$$
$$\mathit{0.28} :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ \mathit{21}).\ \cdots$$

Instantaneous Recognition



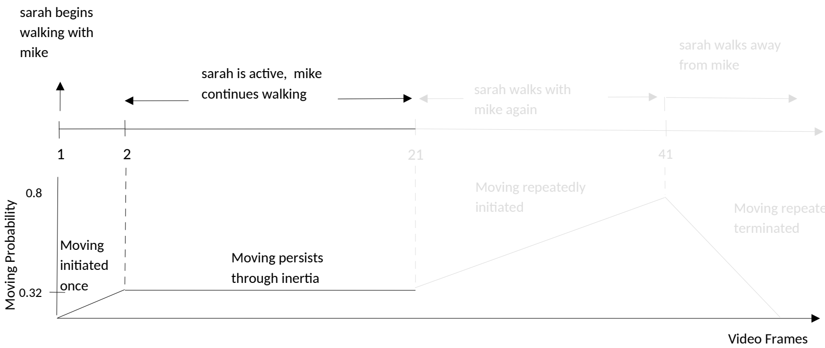
$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$\begin{aligned}
&0.39 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 21). \\
&0.28 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 21).\ \cdots
\end{aligned}$$

$$\begin{aligned}
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21)) = \\
&\quad P(\textbf{happensAt}(\mathit{walking}(\mathit{mike}), 21)) \times \\
&\quad P(\textbf{happensAt}(\mathit{walking}(\mathit{sarah}), 21)) \times \\
&\quad P(\textbf{holdsAt}(\mathit{close}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21)) \times \\
&\quad P(\textbf{holdsAt}(\mathit{orientation}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21)) \\
&\quad = 0.39 \times 0.28 \times 1 \times 1 = 0.11
\end{aligned}$$

Instantaneous Recognition



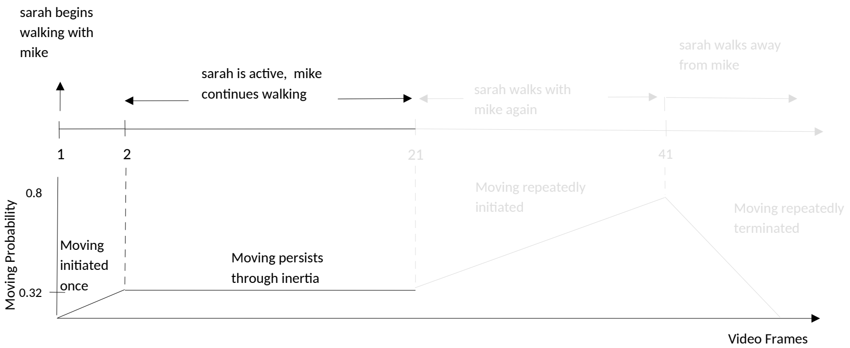
$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&0.39 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 21). \\
&0.28 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 21).\ \cdots
\end{aligned}
$$

$$
\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 22)) = \\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21) \vee \\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21) \wedge \\
&\quad \neg\textbf{terminatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 21)) \\
&= 0.11 + 0.322 \times 1 - 0.11 \times 0.322 \times 1 = 0.39
\end{aligned}
$$

Instantaneous Recognition

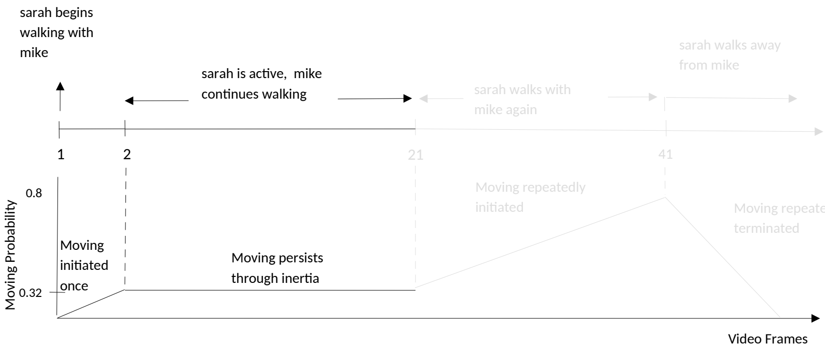


$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\mathit{0.28} :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ \mathit{40}). \\
&\mathit{0.18} :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ \mathit{40}).
\end{aligned}
$$

Instantaneous Recognition



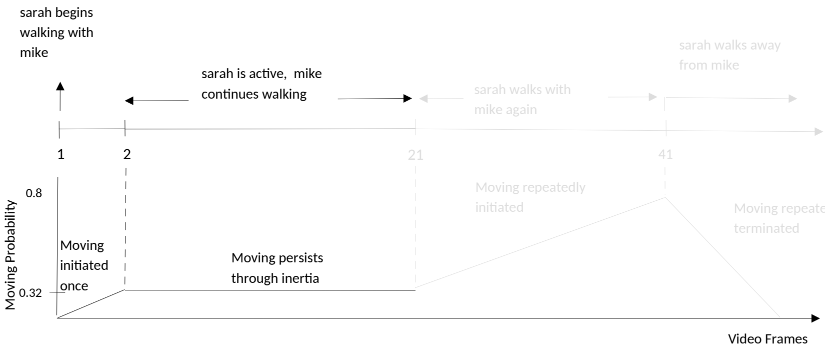
$$\textbf{initiatedAt}(moving(P_1, P_2) = \text{true},\ T) \leftarrow$$
$$\textbf{happensAt}(walking(P_1),\ T),$$
$$\textbf{happensAt}(walking(P_2),\ T),$$
$$\textbf{holdsAt}(close(P_1, P_2) = \text{true},\ T),$$
$$\textbf{holdsAt}(orientation(P_1, P_2) = \text{true},\ T).$$

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

$$0.28 :: \textbf{happensAt}(walking(mike),\ 40).$$
$$0.18 :: \textbf{happensAt}(walking(sarah),\ 40).$$

$$P(\textbf{initiatedAt}(moving(mike, sarah) = \text{true}, 40)) =$$
$$P(\textbf{happensAt}(walking(mike), 40)) \times$$
$$P(\textbf{happensAt}(walking(sarah), 40)) \times$$
$$P(\textbf{holdsAt}(close(mike, sarah) = \text{true}, 40)) \times$$
$$P(\textbf{holdsAt}(orientation(mike, sarah) = \text{true}, 40))$$
$$= 0.28 \times 0.18 \times 1 \times 1 = 0.05$$

Instantaneous Recognition



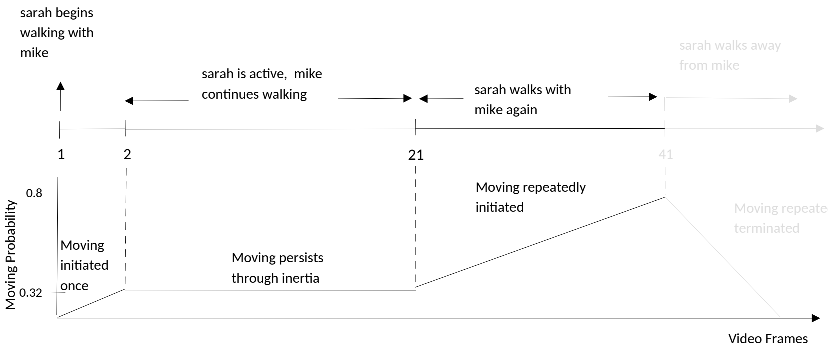
$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1,P_2)=\text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1,P_2)=\text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1,P_2)=\text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1,P_2)=\text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1,P_2)=\text{false},\ T).
\end{aligned}$$

$$0.28 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 40).$$
$$0.18 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 40).$$

$$\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike},\mathit{sarah})=\text{true}, 41)) = \\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike},\mathit{sarah})=\text{true}, 40) \vee \\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike},\mathit{sarah})=\text{true}, 40) \wedge \\
&\quad \neg\textbf{terminatedAt}(\mathit{moving}(\mathit{mike},\mathit{sarah})=\text{true}, 40)) \\
&= 0.05 + 0.79 \times 1 - 0.05 \times 0.79 \times 1 = 0.80
\end{aligned}$$

Instantaneous Recognition



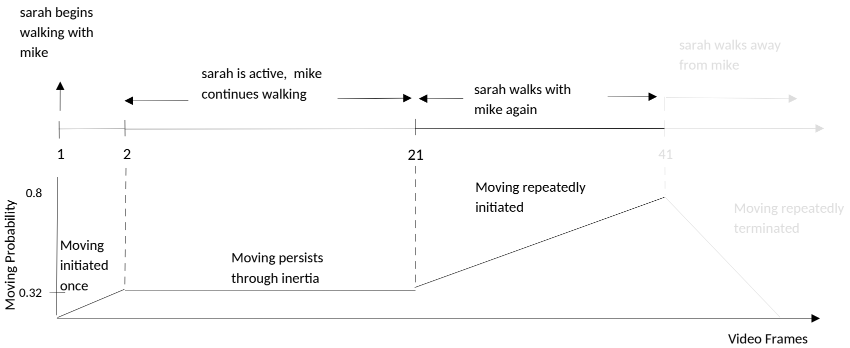
$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$0.28 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 40).$$
$$0.18 :: \textbf{happensAt}(\mathit{walking}(\mathit{sarah}),\ 40).$$

$$\begin{aligned}
&P(\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 41)) = \\
&P(\textbf{initiatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 40) \vee \\
&\quad (\textbf{holdsAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 40) \wedge \\
&\quad \neg \textbf{terminatedAt}(\mathit{moving}(\mathit{mike}, \mathit{sarah}) = \text{true}, 40)) \\
&= 0.05 + 0.79 \times 1 - 0.05 \times 0.79 \times 1 = 0.80
\end{aligned}$$

Instantaneous Recognition

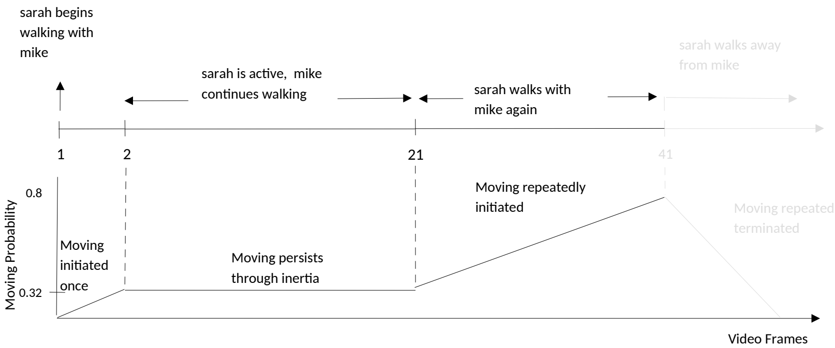


$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \mathrm{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \mathrm{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \mathrm{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \mathrm{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \mathrm{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\mathit{0.18} :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ \mathit{41}). \\
&\mathit{0.79} :: \textbf{happensAt}(\mathit{inactive}(\mathit{sarah}),\ \mathit{41}).\ \cdots
\end{aligned}
$$

Instantaneous Recognition



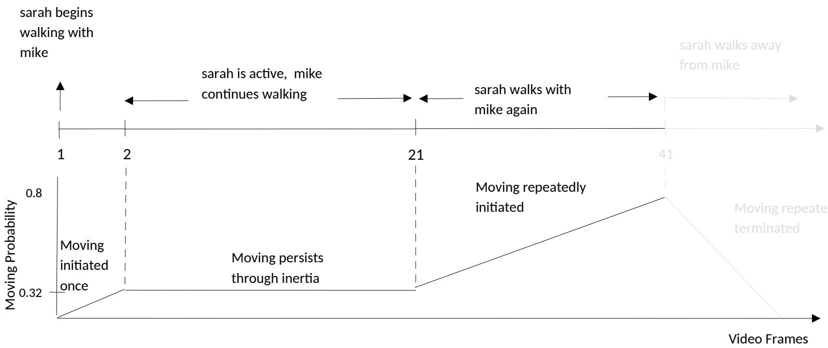
$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

$$\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}$$

$$\begin{aligned}
&0.18 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 41). \\
&0.79 :: \textbf{happensAt}(\mathit{inactive}(\mathit{sarah}),\ 41).\ \cdots
\end{aligned}$$

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

Instantaneous Recognition



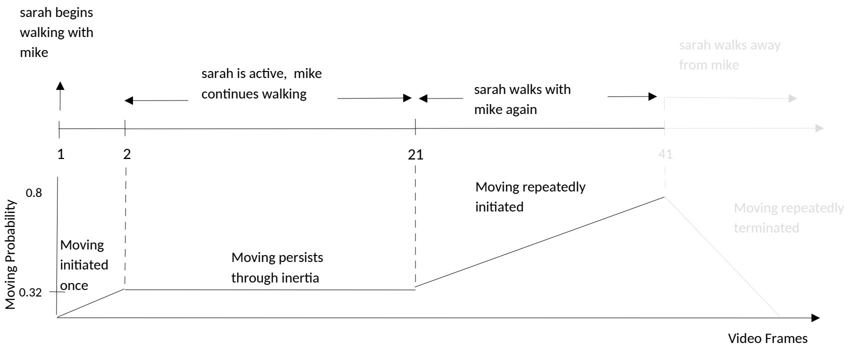
$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \mathrm{true},\ T) \leftarrow\\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T),\\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \mathrm{true},\ T),\\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \mathrm{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \mathrm{true},\ T) \leftarrow\\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \mathrm{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&0.18 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 41).\\
&0.79 :: \textbf{happensAt}(\mathit{inactive}(\mathit{sarah}),\ 41).\ \cdots
\end{aligned}
$$

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

Instantaneous Recognition

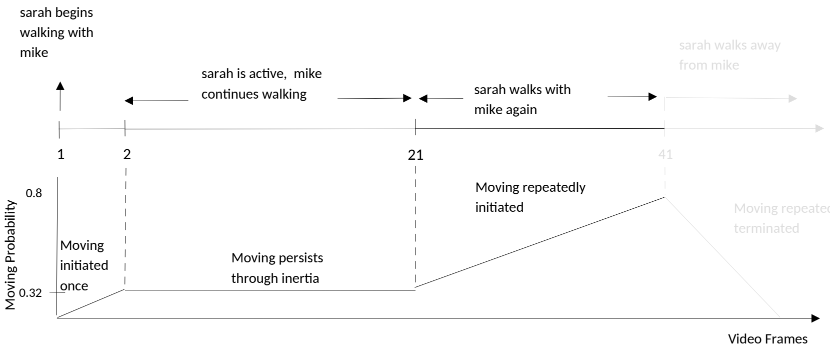


$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1, P_2) = \text{true},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{terminatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T), \\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{false},\ T).
\end{aligned}
$$

$$
\begin{aligned}
&1.00 :: \textbf{happensAt}(\mathit{walking}(\mathit{mike}),\ 49). \\
&0.96 :: \textbf{happensAt}(\mathit{inactive}(\mathit{sarah}),\ 49).
\end{aligned}
$$

Instantaneous Recognition



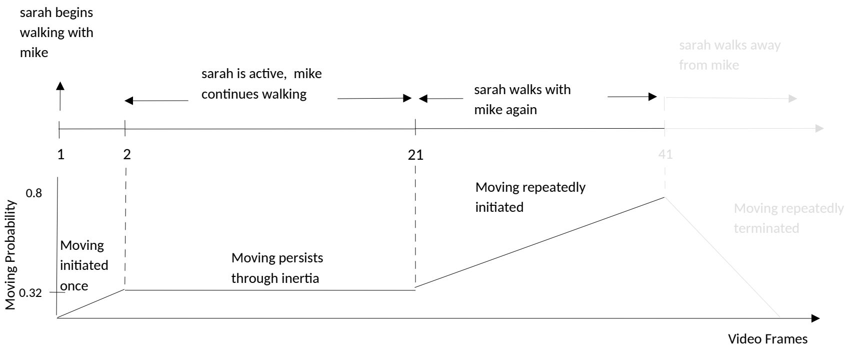
$$\mathbf{initiatedAt}(moving(P_1, P_2) = \text{true},\ T) \leftarrow$$
$$\quad \mathbf{happensAt}(walking(P_1),\ T),$$
$$\quad \mathbf{happensAt}(walking(P_2),\ T),$$
$$\quad \mathbf{holdsAt}(close(P_1, P_2) = \text{true},\ T),$$
$$\quad \mathbf{holdsAt}(orientation(P_1, P_2) = \text{true},\ T).$$

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

$$1.00 :: \mathbf{happensAt}(walking(mike),\ 49).$$
$$0.96 :: \mathbf{happensAt}(inactive(sarah),\ 49).$$

$$P(\mathbf{terminatedAt}(moving(mike, sarah) = \text{true}, 49)) =$$
$$P(\mathbf{happensAt}(walking(mike), 49)) \times$$
$$P(\mathbf{holdsAt}(close(mike, sarah) = \text{false}, 49))$$
$$= 1 \times 1 = 1$$

Instantaneous Recognition



$$\begin{aligned}
&\textbf{initiatedAt}(moving(P_1, P_2) = \text{true},\ T) \leftarrow \\
&\quad \textbf{happensAt}(walking(P_1),\ T), \\
&\quad \textbf{happensAt}(walking(P_2),\ T), \\
&\quad \textbf{holdsAt}(close(P_1, P_2) = \text{true},\ T), \\
&\quad \textbf{holdsAt}(orientation(P_1, P_2) = \text{true},\ T).
\end{aligned}$$

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&\textbf{terminatedAt}(moving(P_1, P_2) = \text{true},\ T) \leftarrow \\
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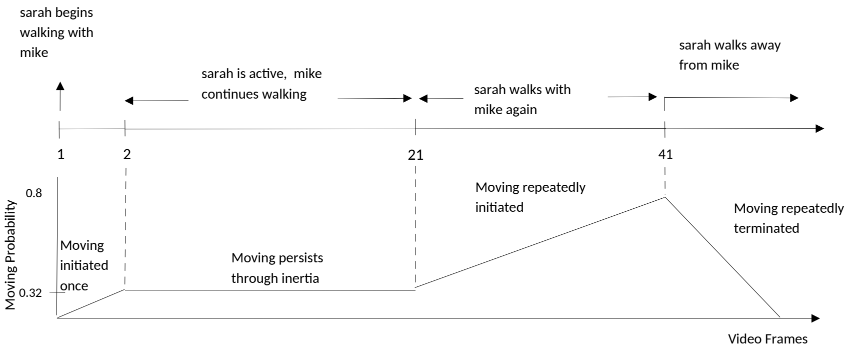
$$\begin{aligned}
&P(\textbf{holdsAt}(moving(mike, sarah) = \text{true}, 50)) = \\
&P(\textbf{initiatedAt}(moving(mike, sarah) = \text{true}, 49) \vee \\
&\quad (\textbf{holdsAt}(moving(mike, sarah) = \text{true}, 49) \wedge \\
&\quad \neg\textbf{terminatedAt}(moving(mike, sarah) = \text{true}, 49)) \\
&= 0 + 0.07 \times 0 - 0 \times 0.07 \times 0 = 0
\end{aligned}$$

Instantaneous Recognition



$$\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \text{true},\ T) \leftarrow\\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T),\\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \text{true},\ T),\\
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\end{aligned}$$

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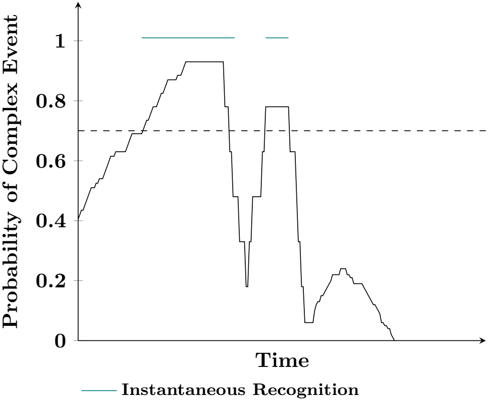
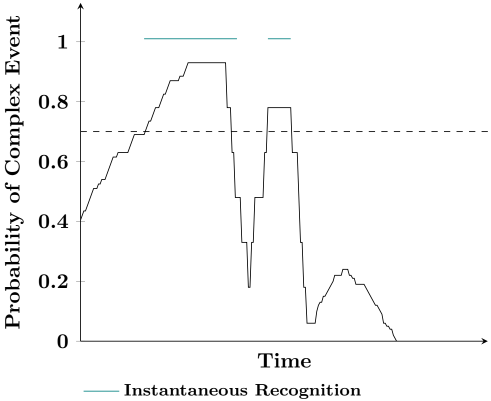
Instantaneous Recognition*



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

Instantaneous Recognition*

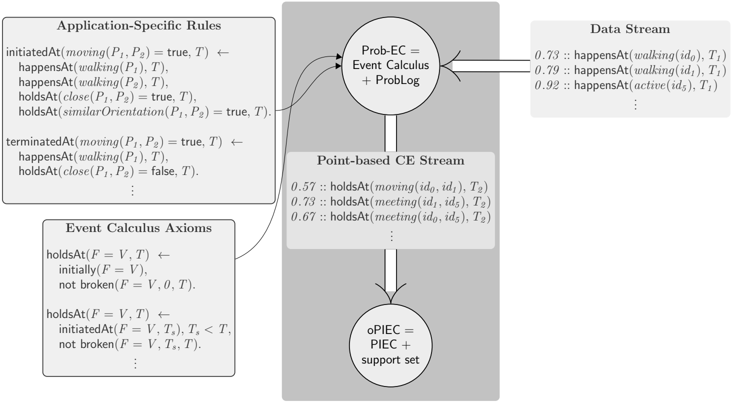


Higher accuracy than crisp reasoning in the presence of:

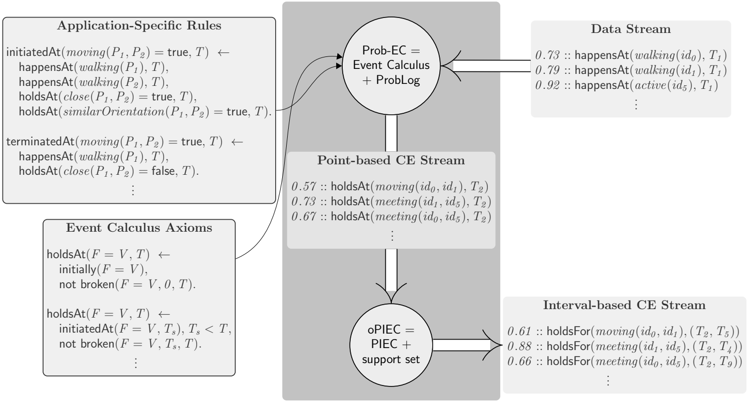
- several initiations and terminations;
- few probabilistic conjuncts.

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

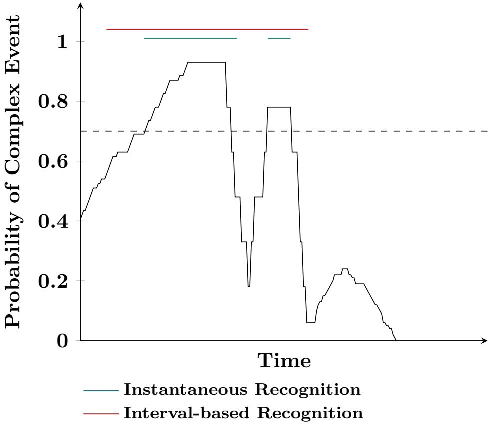
Online Probabilistic Interval-Based Event Calculus



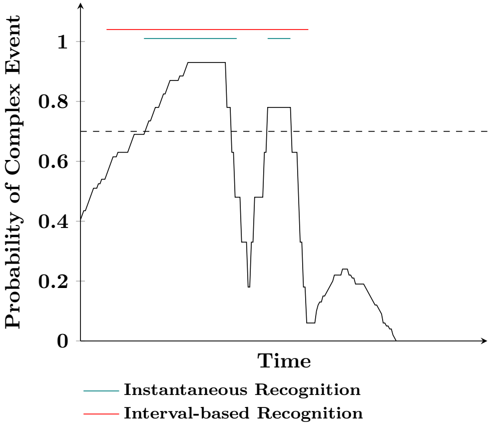
Online Probabilistic Interval-Based Event Calculus



Instantaneous vs Interval-based Recognition

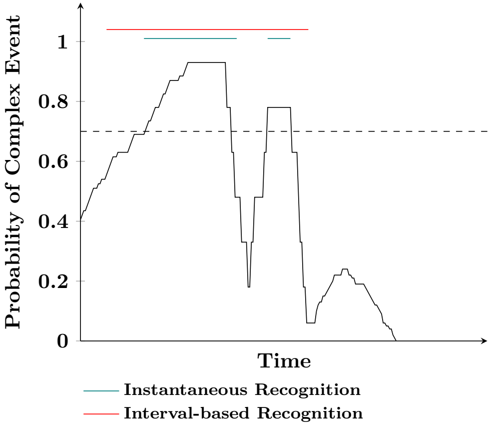


Instantaneous vs Interval-based Recognition



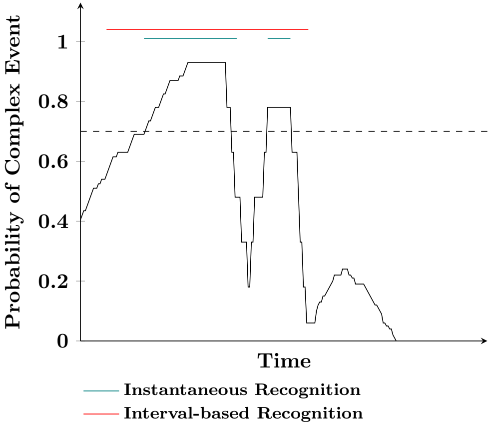
- Interval Probability: average probability of the time-points it contains.

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*

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

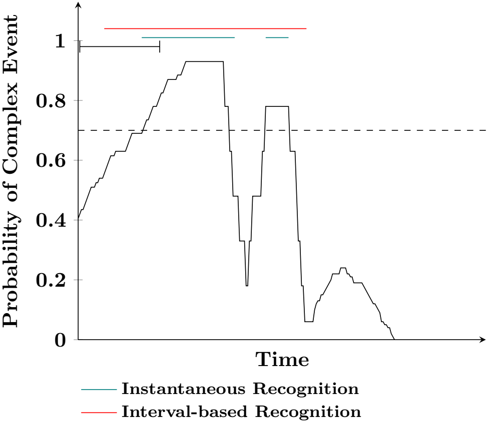
An interval is computed iff it is a probabilistic maximal interval.

Complexity

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

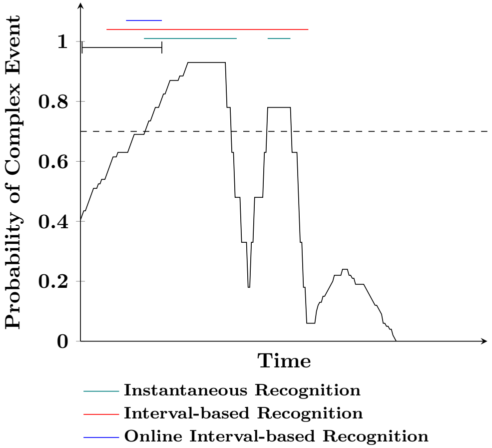
* Artikis et al, A Probabilistic Interval-based Event Calculus for Activity Recognition. Annals of Mathematics and Artificial Intelligence, 2021.

Online Interval-based Recognition



- Windowing.

Online Interval-based Recognition



- Windowing.
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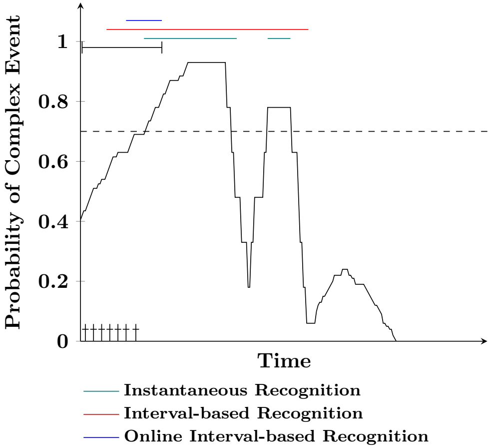
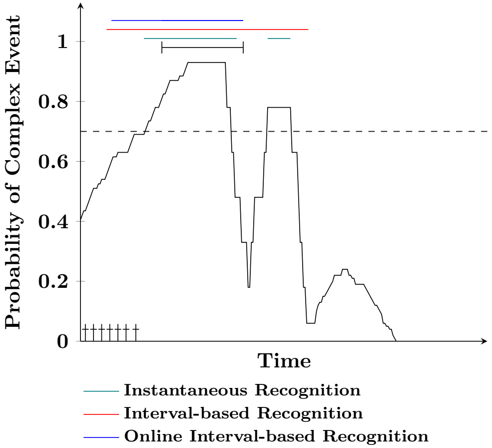
Online Interval-based Recognition



- Windowing.
- Probabilistic maximal interval computation.
- 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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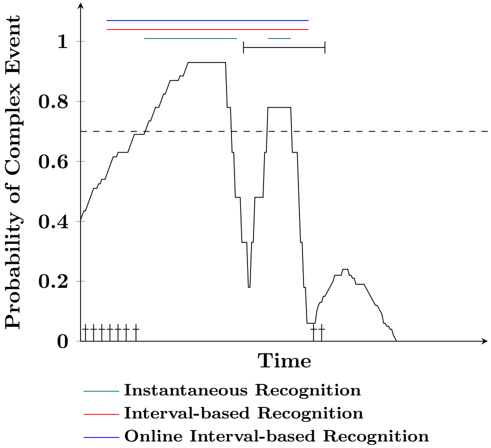

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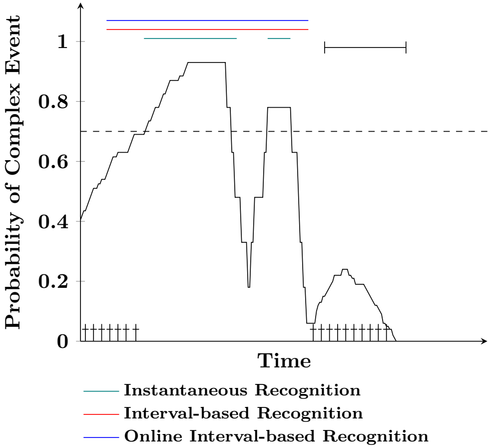

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Online Interval-based Recognition: Properties

Memory Minimality

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

Online Interval-based Recognition: Properties

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

Online Interval-based Recognition: Properties

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

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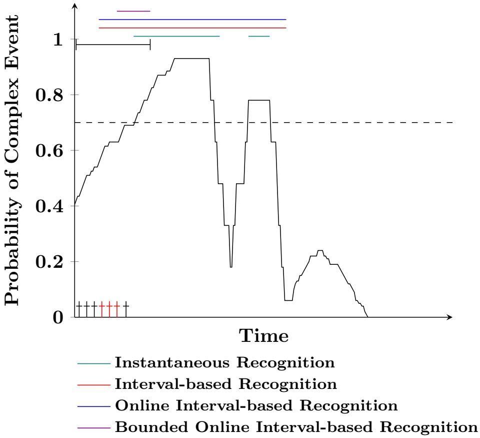
An interval is computed iff it is a probabilistic maximal interval given the data seen so far.

Complexity

The computation of probabistic 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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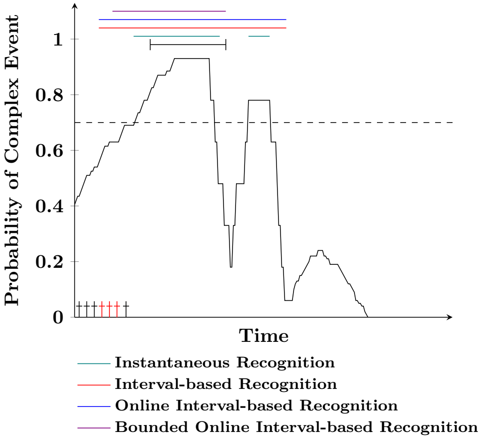

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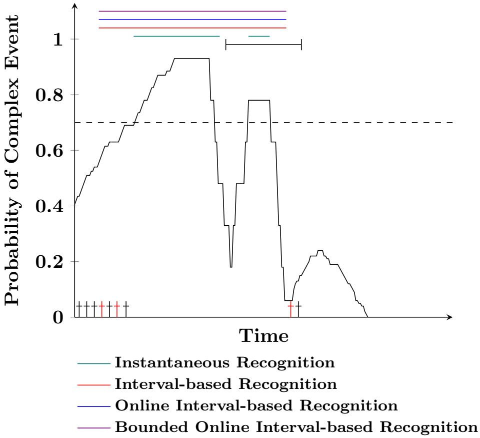

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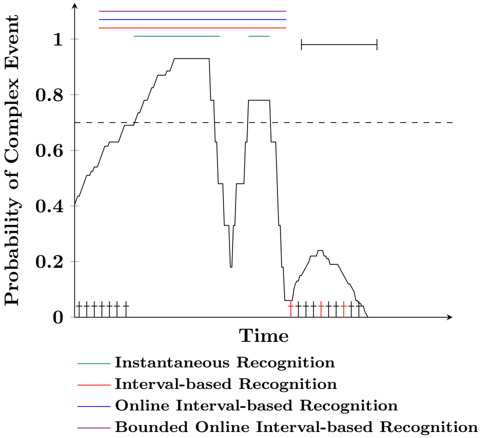

- Complex event duration statistics favor more recent potential starting points.
- Comparable accuracy to batch reasoning.

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

Topics not covered

- Formal models of CER
  - Other approaches on formal complex event recognition[*,†].

[*] Bucchi et al, CORE: a COmplex event Recognition Engine. VLDB, 2022.
https://github.com/CORE-cer/CORE

[†] Alevizos et al, Complex Event Recognition with Symbolic Register Transducers. VLDB, 2024.
https://github.com/ElAlev/Wayeb

Topics not covered

- Formal models of CER
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  - Comparison in terms of expressive power, complexity and performance‡.

---

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†Alevizos et al, Complex Event Recognition with Symbolic Register Transducers. VLDB, 2024. https://github.com/ElAlev/Wayeb

‡Grez et al, A Formal Framework for Complex Event Recognition. ACM TODS, 2021.

Topics not covered

- Formal models of CER
  - Other approaches on formal complex event recognition[*,†].
  - Comparison in terms of expressive power, complexity and performance[‡].
- Probabilistic CER
  - Uncertainty in the complex event definitions[§,¶].

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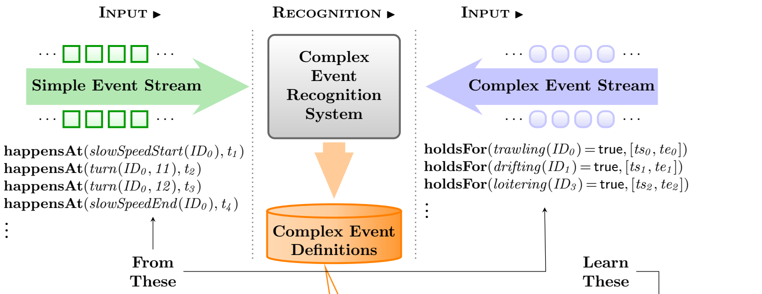
[†] Alevizos et al, Complex Event Recognition with Symbolic Register Transducers. VLDB, 2024. https://github.com/ElAlev/Wayeb

[‡] Grez et al, A Formal Framework for Complex Event Recognition. ACM TODS, 2021.

[§] Skarlatidis et al, Probabilistic Event Calculus for Event Recognition. ACM TOCL, 2015.

[¶] Alevizos et al, Probabilistic Complex Event Recognition: A Survey. ACM Computing Surveys, 2017.

Machine Learning for Complex Event Recognition*,†



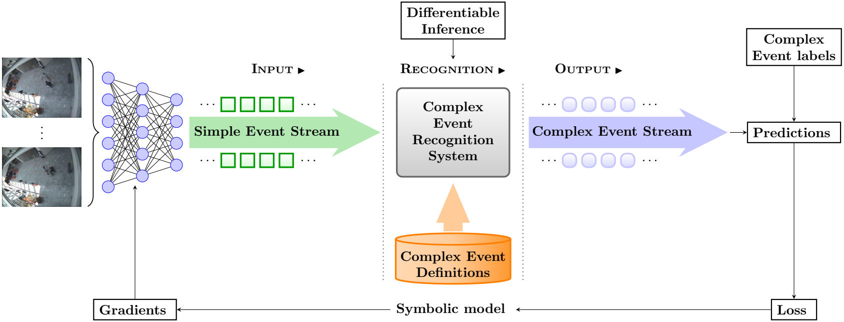
$$
\begin{aligned}
&\textbf{initiatedAt}(stopped(Vessel) = nearPorts, T) \leftarrow\\
&\quad \textbf{happensAt}(stop\_start(Vessel), T),\\
&\quad \textbf{holdsAt}(withinArea(Vessel, nearPorts) = \mathsf{true}, T).\\[1em]
&\textbf{terminatedAt}(stopped(Vessel) = nearPorts, T) \leftarrow\\
&\quad \textbf{happensAt}(stop\_end(Vessel), T).\\
&\vdots
\end{aligned}
$$

$$
\begin{aligned}
&\textbf{holdsFor}(trawling(Vessel) = \mathsf{true}, I) \leftarrow\\
&\quad \textbf{holdsFor}(trawlingMovement(Vessel) = \mathsf{true}, I_{tc}),\\
&\quad \textbf{holdsFor}(trawlingSpeed(Vessel) = \mathsf{true}, I_t),\\
&\quad \textbf{intersect\_all}([I_{tc}, I_t], I_i),\\
&\quad threshold(v_{trawl}, V_{trawl}),\\
&\quad intDurGreater(I_i, V_{trawl}, I).\\
&\vdots
\end{aligned}
$$

*Katzouris et al, Online Learning Probabilistic Event Calculus Theories in Answer Set Programming. Theory and Practice of Logic Programming, 2023.

†Michelioudakis et al, Online semi-supervised learning of composite event rules by combining structure and mass-based predicate similarity. Machine Learning, 2024.

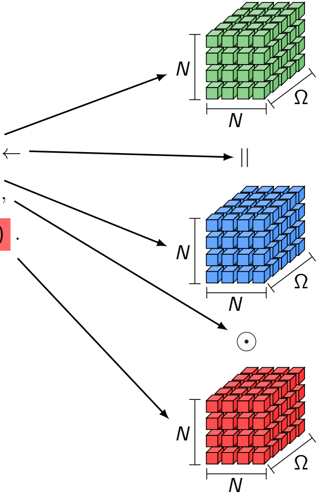
Neuro-Symbolic Complex Event Recognition*



*Marra et al, From statistical relational to neurosymbolic artificial intelligence: A survey. Artificial Intelligence, 2024.

Tensor-Based Complex Event Recognition*

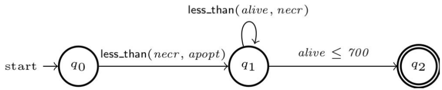
$\text{initiatedAt}(fl(X,Y){=}v,\ T) \leftarrow$
$\text{happensAt}(e(X,Y),\ T)$,
$\text{holdsAt}(d(X,Y){=}v_d,\ T)$.



*Tsilionis et al, A Tensor-Based Formalization of the Event Calculus. IJCAI, 2024.

Complex Event Forecasting*

- Forecast the occurrence of a complex event.
- Symbolic automata for complex event patterns
  - Closure properties.
  - Formal compositional semantics.



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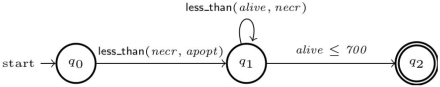

- Prediction suffix trees for long-term dependencies
  - Higher accuracy.
  - Comparable training time and acceptable throughput.

https://cer.iit.demokritos.gr (forecasting)

*Alevizos et al, Complex Event Forecasting with Prediction Suffix Trees. VLDB Journal, 2022.
https://github.com/ElAlev/Wayeb

Tutorial Resources

Resources: http://cer.iit.demokritos.gr

- Slides: http://cer.iit.demokritos.gr/talks
- Code: http://cer.iit.demokritos.gr/software
- Data: http://cer.iit.demokritos.gr/datasets
- Opportunities for (funded) collaboration: job openings and topics for BSc/MSc theses and internships