

Complex Event Recognition

Alexander Artikis^{1,2}

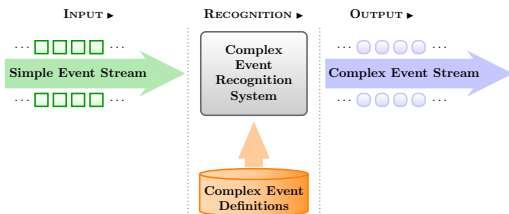
¹NCSR Demokritos, Athens, Greece

²University of Piraeus, Greece

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



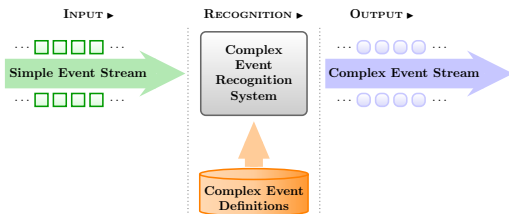
Complex Event Recognition (Event Pattern Matching)^{*,†}



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

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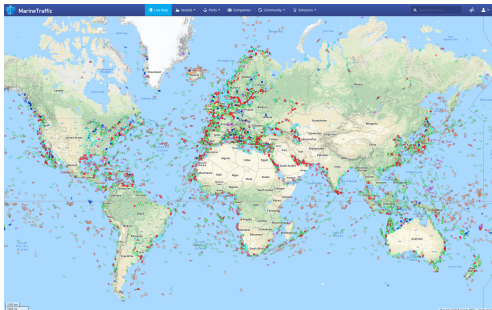


<https://rdcu.be/cNkQE>

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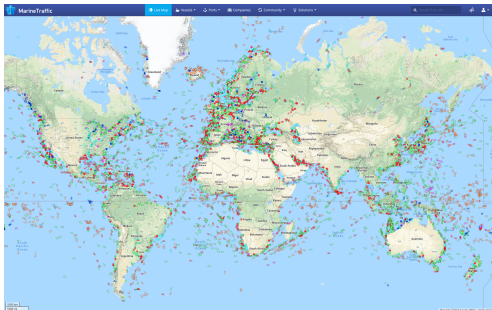
Maritime Situational Awareness*



<http://www.marinetraffic.com>

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

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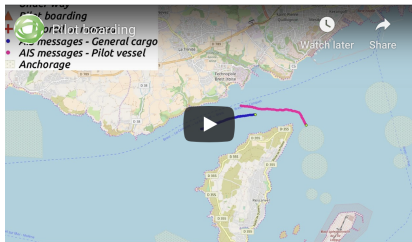
<https://cer.iit.demokritos.gr> (fishing vessel)

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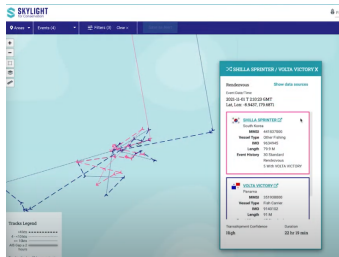
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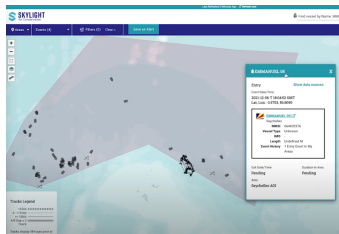
<https://cer.iit.demokritos.gr> (tugging)



<https://cer.iit.demokritos.gr> (pilot boarding)



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



<https://www.skylight.global> (enter area)

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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.

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 - ▶ to avoid the time-consuming, error-prone manual CE definition development.
- ▶ 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.

*Gugola and Margara, Processing Flows of Information: From Data Stream to Complex Event Processing. ACM Computing Surveys, 2012.

Complex Event Recognition vs Database Management Systems*

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- ▶ Users install **standing/continuous queries**:
 - ▶ Queries deployed once and executed continuously until removed.
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- ▶ Latency requirements are very strict.

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We have [Deep Learning](#) and it seems to work. Can we go home?

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[Complex event recognition](#):

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- ▶ **Machine Learning** is necessary. But:
 - ▶ Complex events are rare.
 - ▶ Supervision is scarce.

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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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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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 - ▶ **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.

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

Run-Time Event Calculus (RTEC)*

initiatedAt($F = V, T$) \leftarrow
happensAt($E_{I_{n_1}}, T$),
[conditions]

...

initiatedAt($F = V, T$) \leftarrow
happensAt($E_{I_{n_i}}, T$),
[conditions]

terminatedAt($F = V, T$) \leftarrow
happensAt(E_{T_1}, T),
[conditions]

...

terminatedAt($F = V, T$) \leftarrow
happensAt(E_{T_j}, T),
[conditions]

where

conditions: ${}^{0-K}$ **happensAt**(E_k, T),
 ${}^{0-M}$ **holdsAt**($F_m = V_m, T$),
 ${}^{0-N}$ atemporal-constraint $_n$

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

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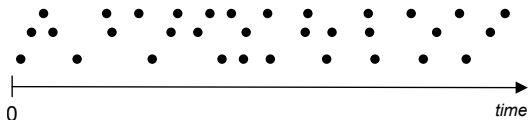
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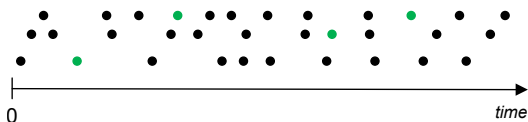
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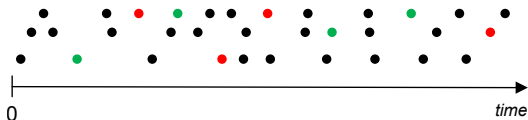
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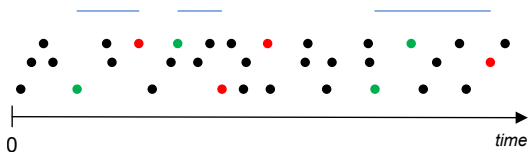
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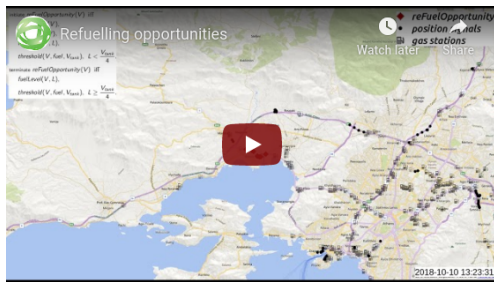
...

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[conditions]

holdsFor($F = V$, I)



Fleet Management*



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

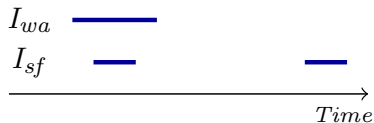
*Tsilionis et al, Online Event Recognition from Moving Vehicles. Theory and Practice of Logic Programming, 2019.

RTEC: Interval-based Reasoning

holdsFor(*anchoredOrMoored*(*Vessel*) = true, *I*) \leftarrow
 holdsFor(*stopped*(*Vessel*) = *farFromPorts*, *I_{sf}*),
 holdsFor(*withinArea*(*Vessel*, *anchorage*) = true, *I_{wa}*),
 intersect_all([*I_{sf}*, *I_{wa}*], *I_{sa}*),
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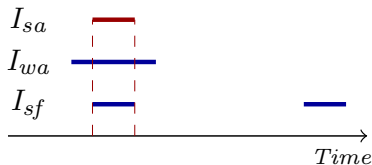
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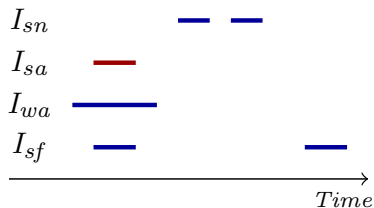
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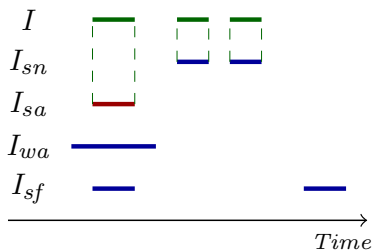
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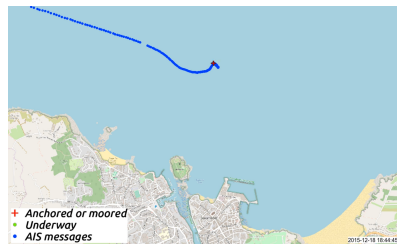
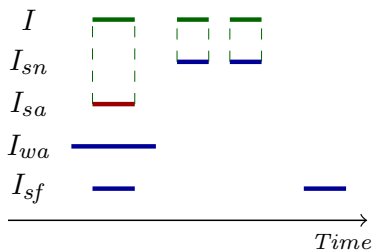
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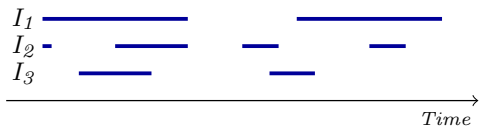
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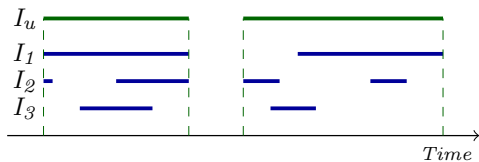
<https://cer.iit.demokritos.gr> (anchored or moored)

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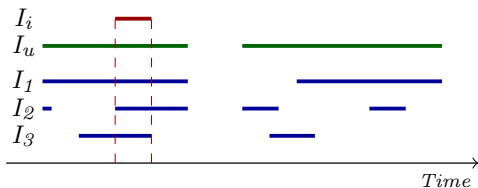
union_all($[I_1, I_2, I_3], I_u$)



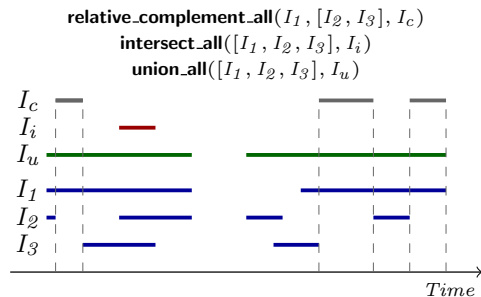
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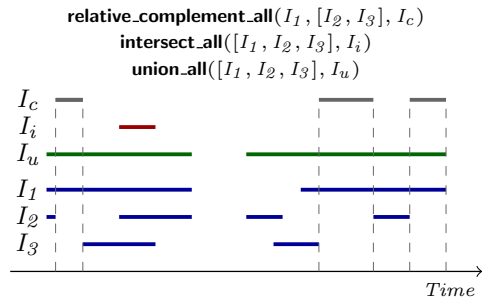
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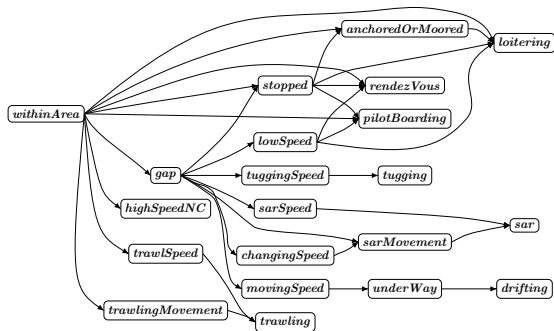
RTEC: Interval-based Reasoning & Allen Relations*



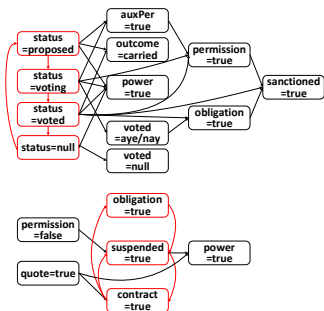
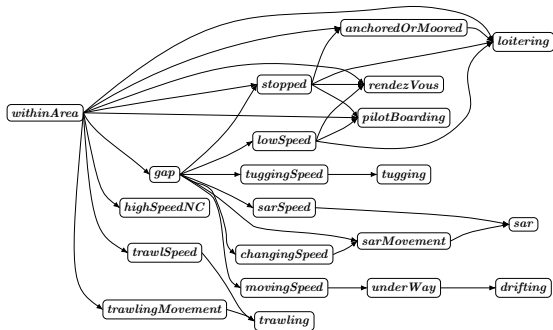
Relation	Illustration
$\text{before}(i^s, i^t)$	
$\text{meets}(i^s, i^t)$	
$\text{starts}(i^s, i^t)$	
$\text{finishes}(i^s, i^t)$	
$\text{during}(i^s, i^t)$	
$\text{overlaps}(i^s, i^t)$	
$\text{equal}(i^s, i^t)$	

* Mantenoglou et al, Complex Event Recognition with Allen Relations. Knowledge Representation and Reasoning (KR), 2023.

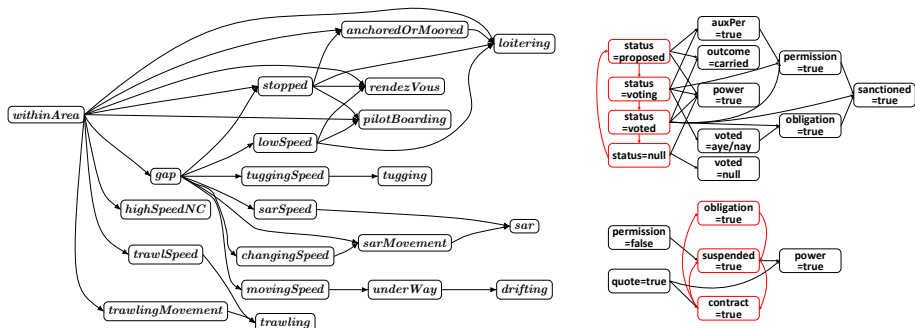
Semantics



Semantics



Semantics

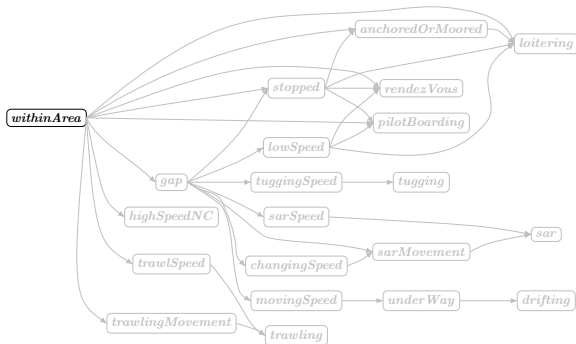


Proposition

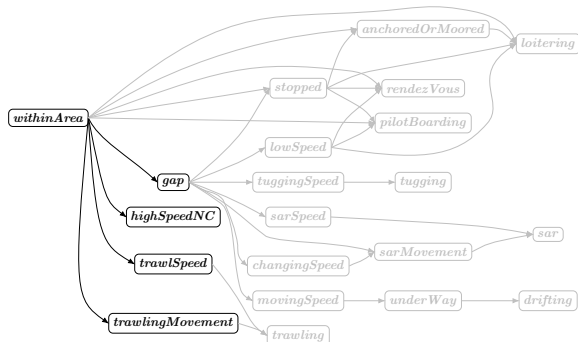
An event description in RTEC is a locally stratified logic program*.

* Mantenoglou et al, Stream Reasoning with Cycles. Knowledge Representation and Reasoning (KR), 2022.

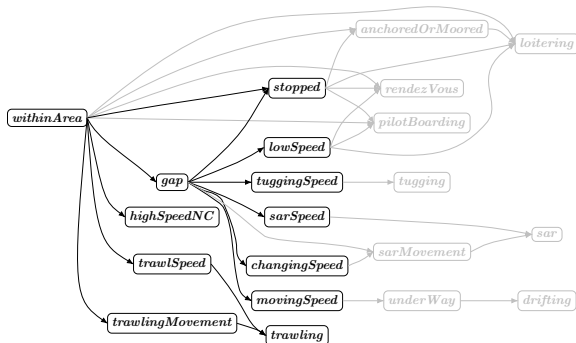
Stratification & Reasoning



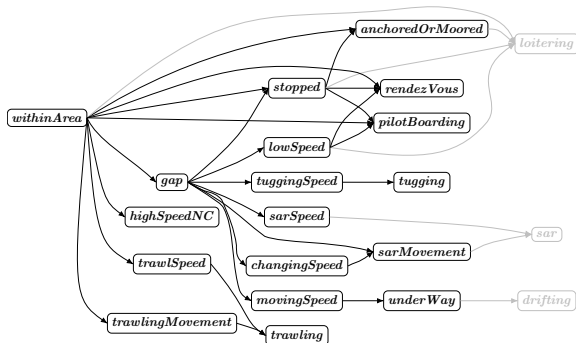
Stratification & Reasoning



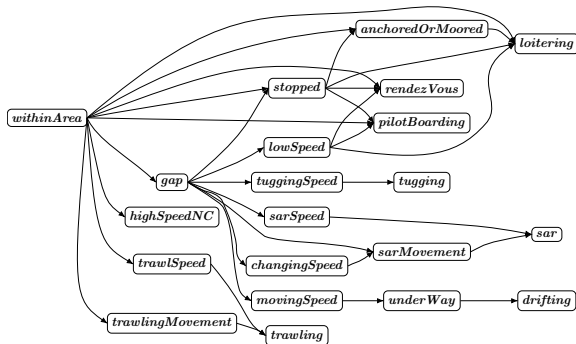
Stratification & Reasoning



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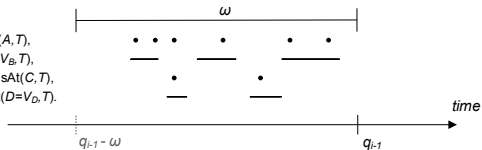


Windowing

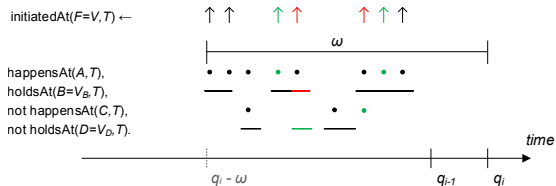
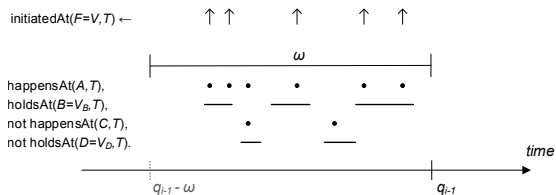
initiatedAt($F=V, T$) ←

↑ ↑ ↑ ↑ ↑

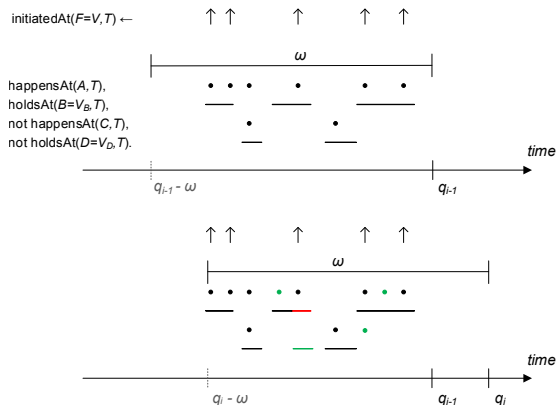
happensAt(A, T),
holdsAt($B=V_B, T$),
not happensAt(C, T),
not holdsAt($D=V_D, T$).



Windowing

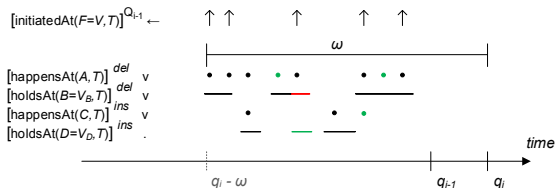
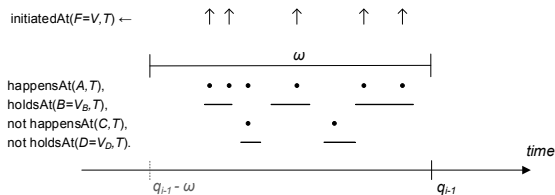


Incremental Reasoning: Deletion Phase*



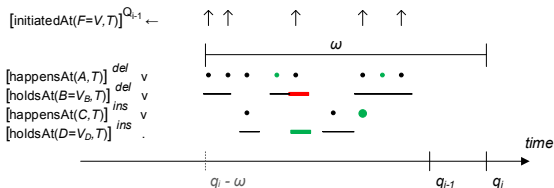
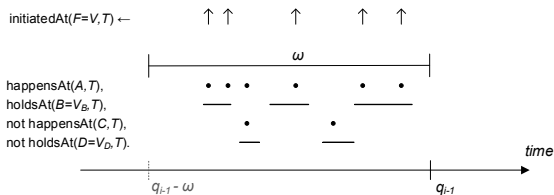
*Tsilionis et al, Incremental Event Calculus for Run-Time Reasoning. Journal of AI Research (JAIR), 2022.

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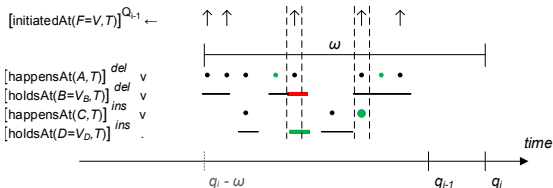
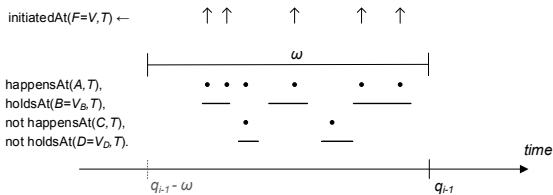
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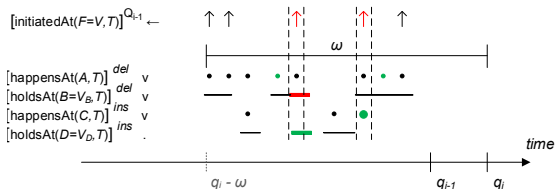
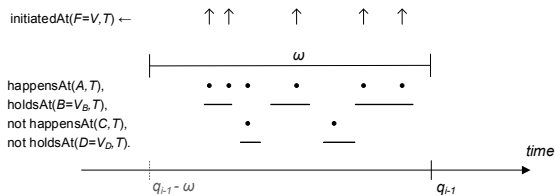
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RTEC: Correctness and Complexity

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.

RTEC: Correctness and Complexity

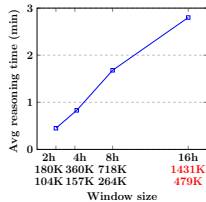
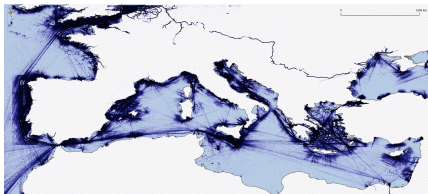
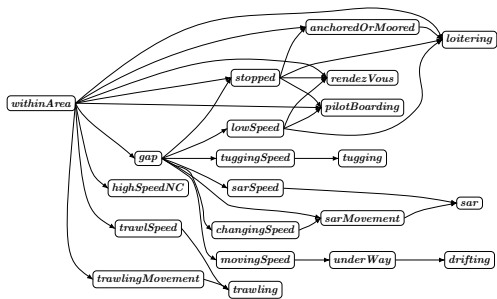
Correctness

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.

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 → avoid unintended semantics.

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Summary

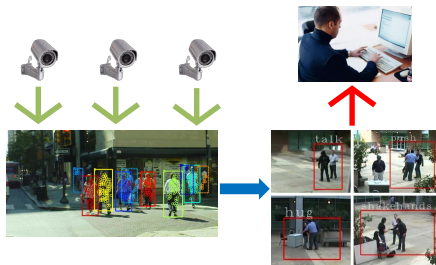
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- ▶ Caching → real-time performance.
- ▶ Various implementation routes*.
- ▶ Direct routes to machine learning → automated complex event definition construction[†].
- ▶ Direct routes to probabilistic reasoning → handle the lack of veracity of data streams.

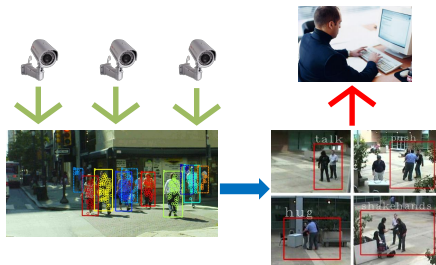
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Human Activity Recognition

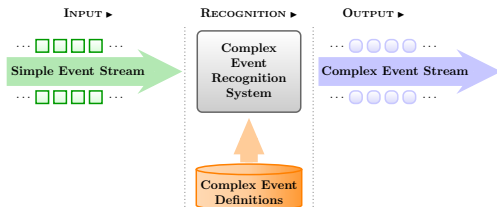


Human Activity Recognition

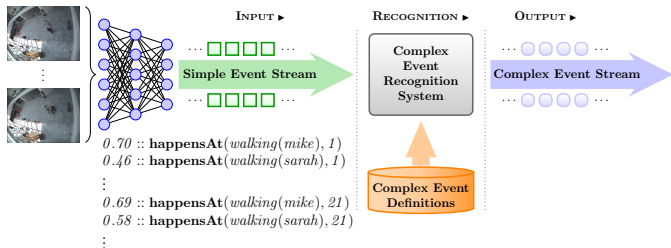


<https://cer.iit.demokritos.gr> (activity recognition)

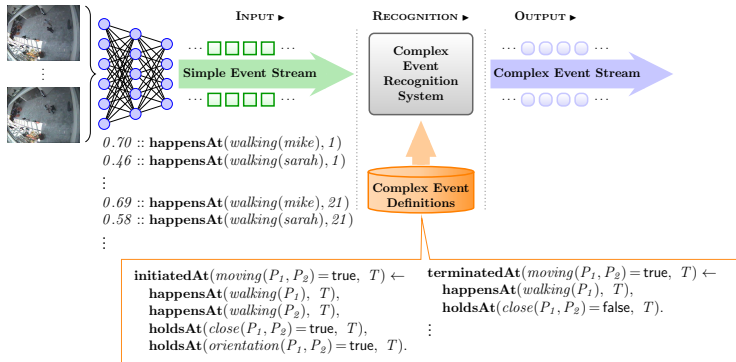
Complex Event Recognition under Uncertainty



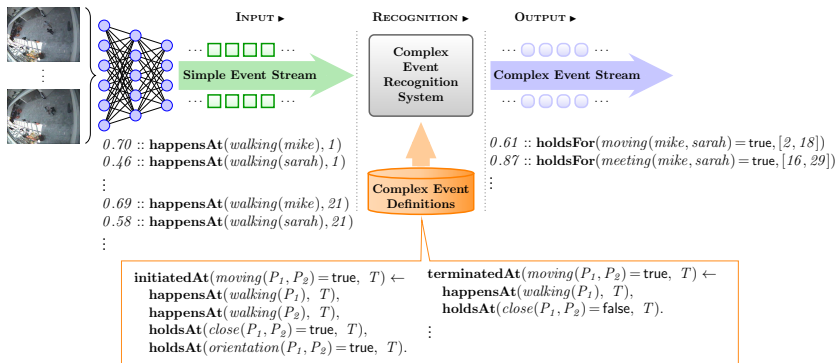
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Complex Event Recognition under Uncertainty

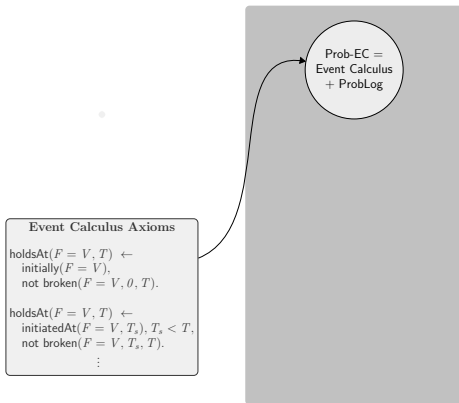


Online Probabilistic Interval-Based Event Calculus

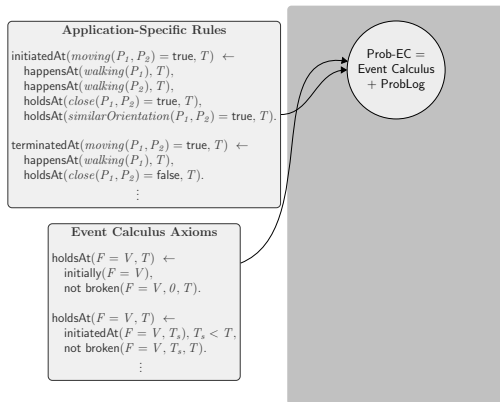


Prob-EC =
Event Calculus
+ ProbLog

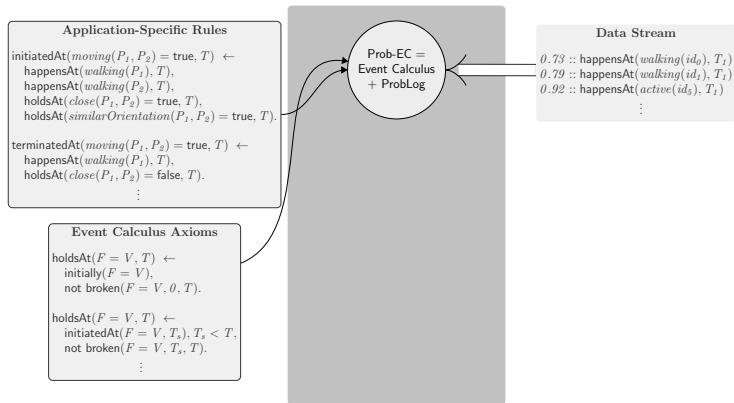
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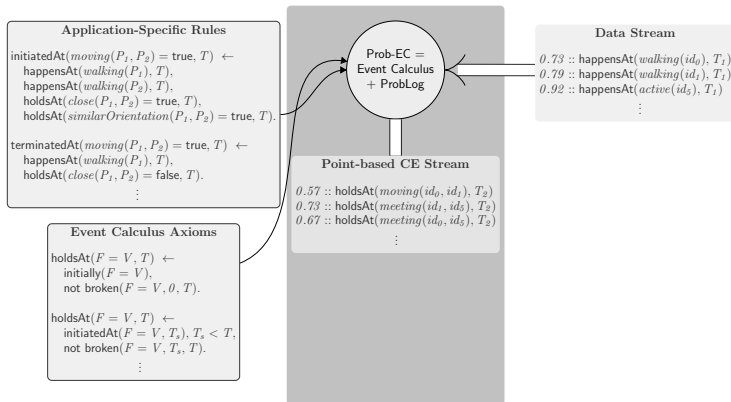
Online Probabilistic Interval-Based Event Calculus



Online Probabilistic Interval-Based Event Calculus



Online Probabilistic Interval-Based Event Calculus



Instantaneous Recognition

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

0.70 :: **happensAt**($walking(mike), 1$).
0.46 :: **happensAt**($walking(sarah), 1$).

Instantaneous Recognition

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($orientation(P_1, P_2) = true, T$).

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

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

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

$P(\mathbf{initiatedAt}(moving(mike, sarah) = true, 1)) =$
 $P(\mathbf{happensAt}(walking(mike), 1)) \times$
 $P(\mathbf{happensAt}(walking(sarah), 1)) \times$
 $P(\mathbf{holdsAt}(close(mike, sarah) = true, 1)) \times$
 $P(\mathbf{holdsAt}(orientation(mike, sarah) = true, 1))$
 $= 0.7 \times 0.46 \times 1 \times 1 = 0.322$

Instantaneous Recognition

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($orientation(P_1, P_2) = true, T$).
terminatedAt($moving(P_1, P_2) = true, T$) \leftarrow
 happensAt($walking(P_1), T$),
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0.70 :: **happensAt**($walking(mike), 1$).
0.46 :: **happensAt**($walking(sarah), 1$).

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

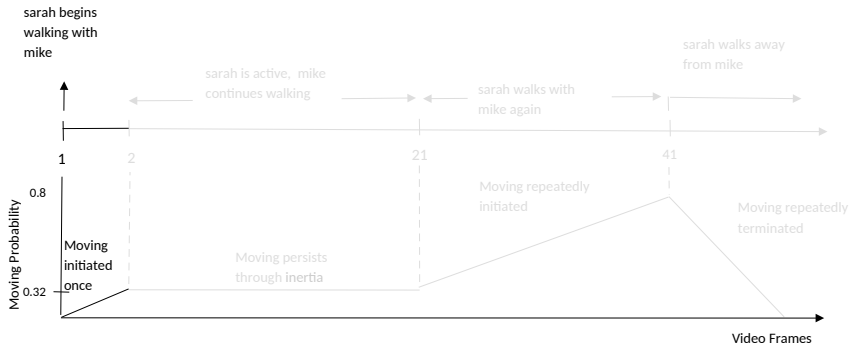
Instantaneous Recognition

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

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

$P(\mathbf{holdsAt}(moving(mike, sarah) = true, 2)) =$
 $P(\mathbf{initiatedAt}(moving(mike, sarah) = true, 1) \vee$
 $(\mathbf{holdsAt}(moving(mike, sarah) = true, 1) \wedge$
 $\neg \mathbf{terminatedAt}(moving(mike, sarah) = true, 1)))$
 $= 0.322 + 0 \times 1 - 0.322 \times 0 \times 1 = 0.322$

Instantaneous Recognition



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

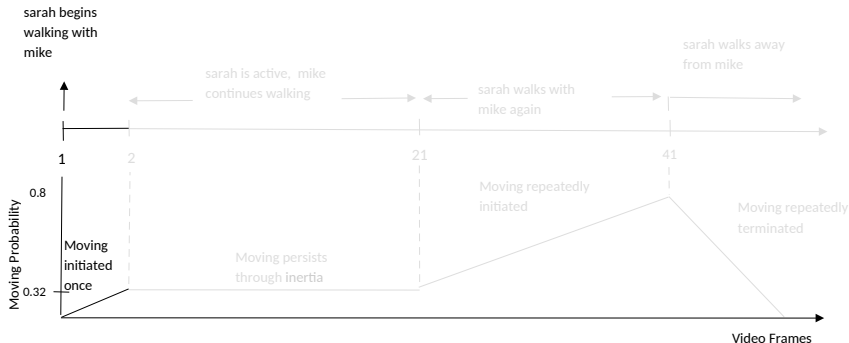
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

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

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

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

Instantaneous Recognition

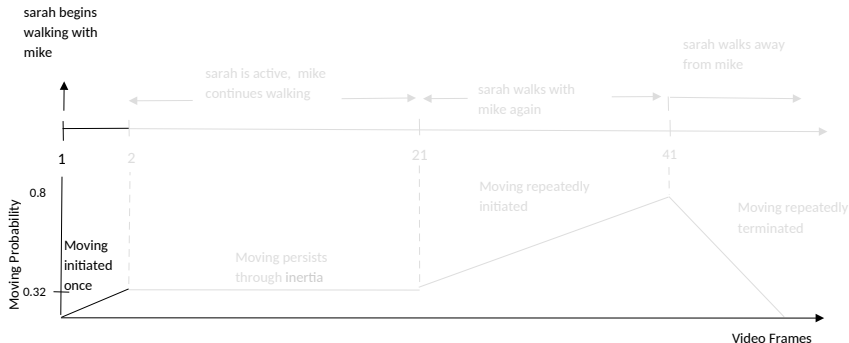


initiatedAt($moving(P_1, P_2) = true, T$) \leftarrow
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happensAt($walking(P_2), T$),
holdsAt($close(P_1, P_2) = true, T$),
holdsAt($orientation(P_1, P_2) = true, T$).

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

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

Instantaneous Recognition



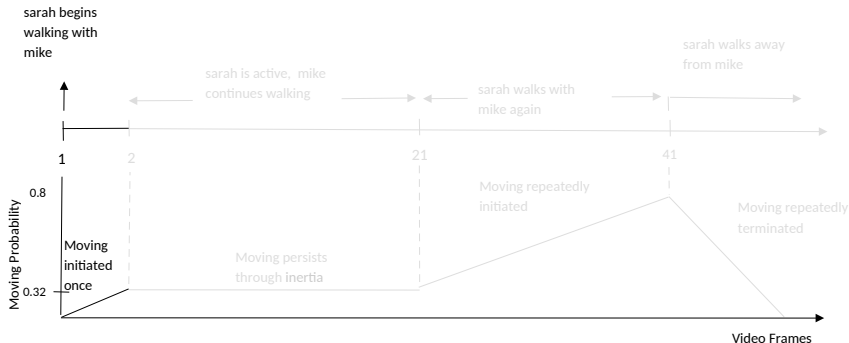
$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{happensAt}(\text{walking}(P_2), T),$
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$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1),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

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

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

Instantaneous Recognition

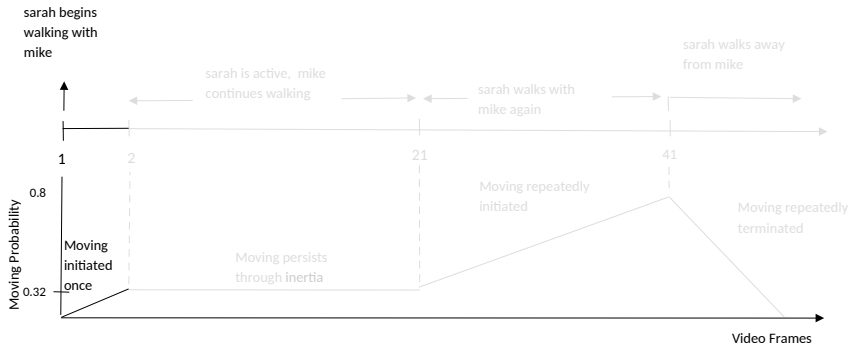


initiatedAt($moving(P_1, P_2) = true, T$) \leftarrow
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happensAt($walking(P_2), T$),
holdsAt($close(P_1, P_2) = true, T$),
holdsAt($orientation(P_1, P_2) = true, T$).

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

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

Instantaneous Recognition



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

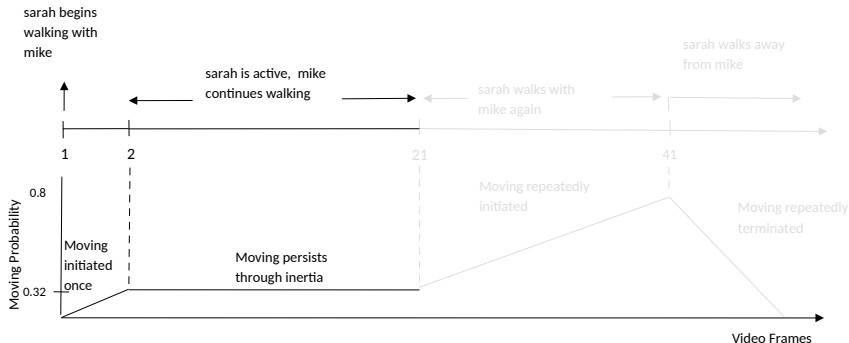
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.45 :: \text{happensAt}(\text{walking}(\text{mike}), 20).$

$0.14 :: \text{happensAt}(\text{active}(\text{sarah}), 20).$

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

Instantaneous Recognition



$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{happensAt}(\text{walking}(P_2), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$
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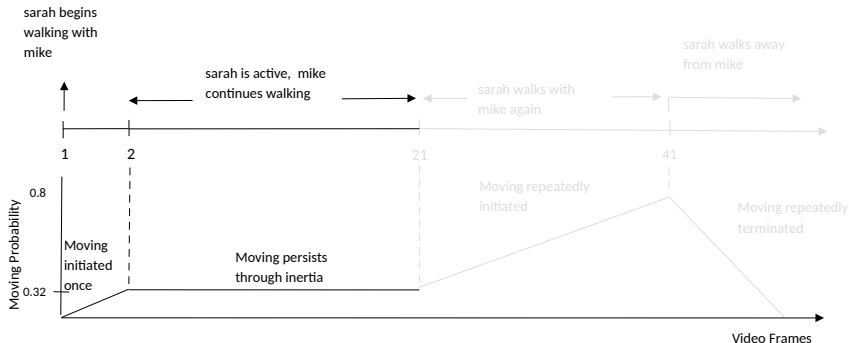
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
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$0.45 :: \text{happensAt}(\text{walking}(\text{mike}), 20).$

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

Instantaneous Recognition

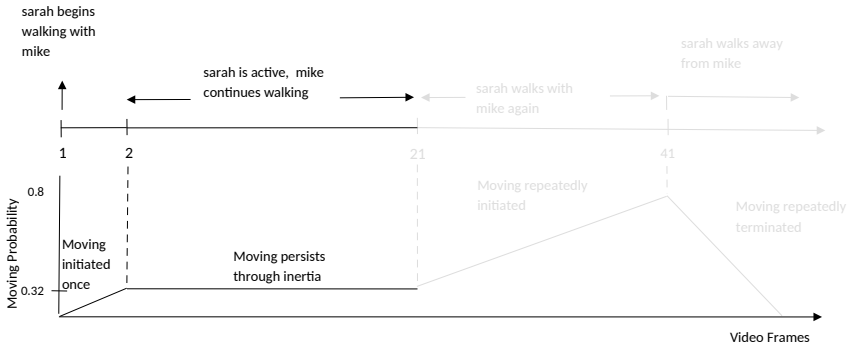


$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{happensAt}(\text{walking}(P_2), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$
 $\text{holdsAt}(\text{orientation}(P_1, P_2) = \text{true}, T).$

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

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

Instantaneous Recognition



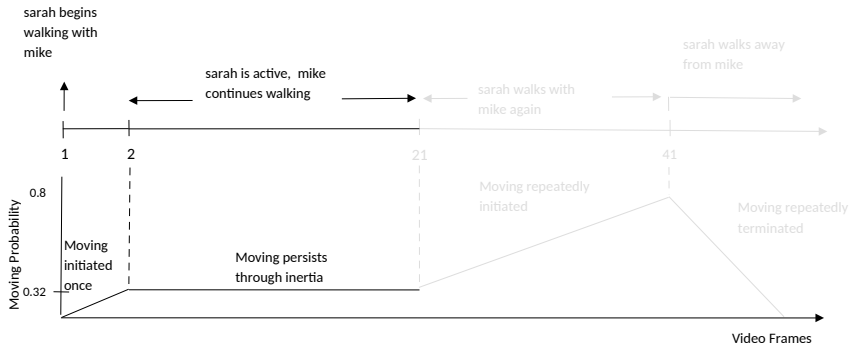
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 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$
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$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
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$0.39 :: \text{happensAt}(\text{walking}(\text{mike}), 21).$
 $0.28 :: \text{happensAt}(\text{walking}(\text{sarah}), 21). \dots$

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

Instantaneous Recognition



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

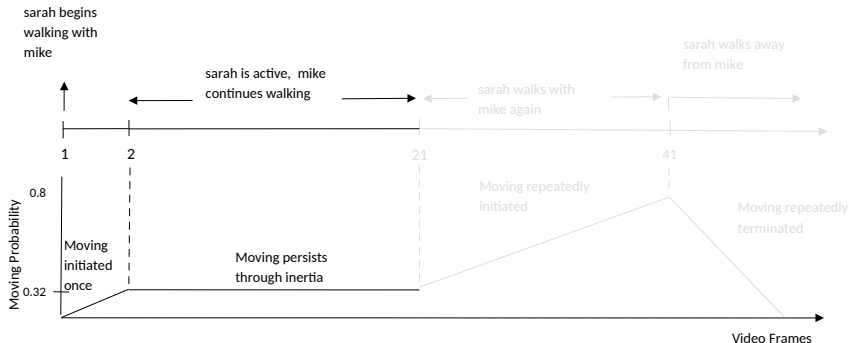
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

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

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

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

Instantaneous Recognition

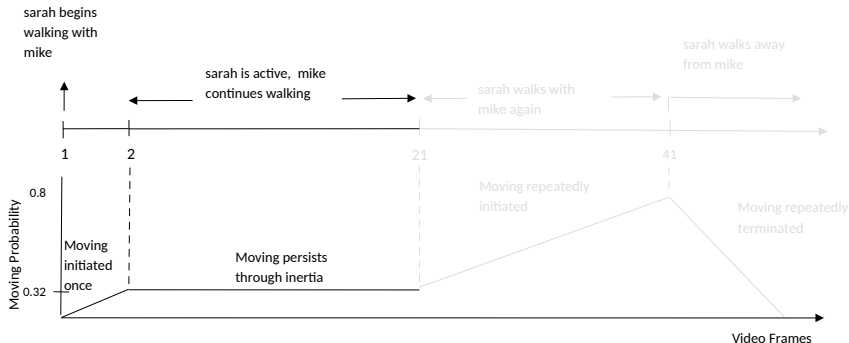


initiatedAt($moving(P_1, P_2) = true, T$) \leftarrow
happensAt($walking(P_1), T$),
happensAt($walking(P_2), T$),
holdsAt($close(P_1, P_2) = true, T$),
holdsAt($orientation(P_1, P_2) = true, T$).

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

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

Instantaneous Recognition



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

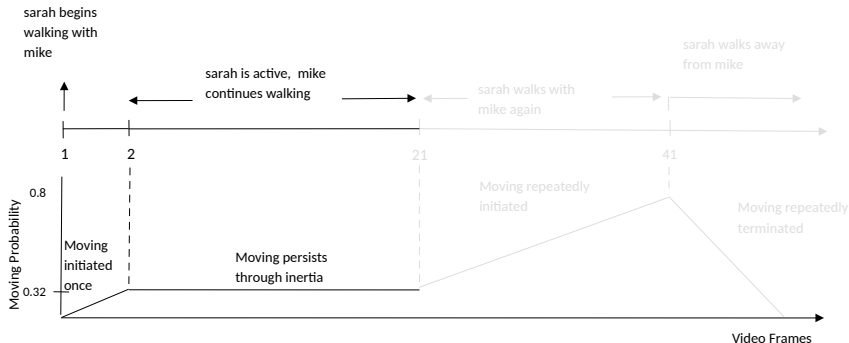
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.28 :: \text{happensAt}(\text{walking}(\text{mike}), 40).$

$0.18 :: \text{happensAt}(\text{walking}(\text{sarah}), 40).$

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

Instantaneous Recognition



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

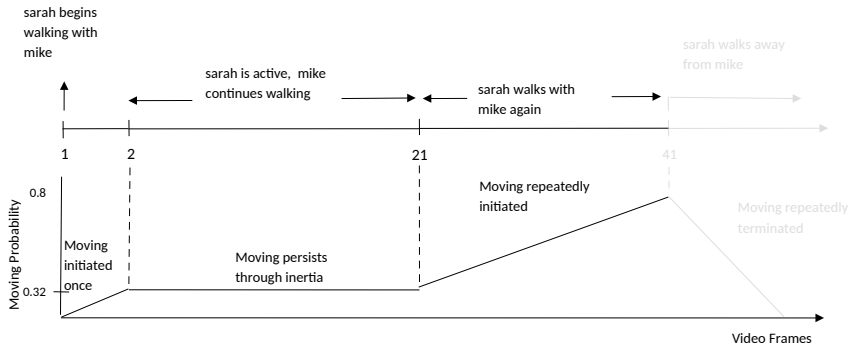
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.28 :: \text{happensAt}(\text{walking}(\text{mike}), 40).$

$0.18 :: \text{happensAt}(\text{walking}(\text{sarah}), 40).$

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

Instantaneous Recognition



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

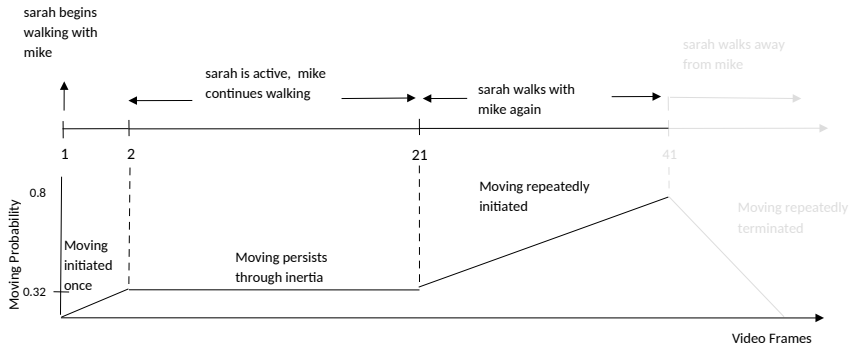
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$0.28 :: \text{happensAt}(\text{walking}(\text{mike}), 40).$

$0.18 :: \text{happensAt}(\text{walking}(\text{sarah}), 40).$

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

Instantaneous Recognition

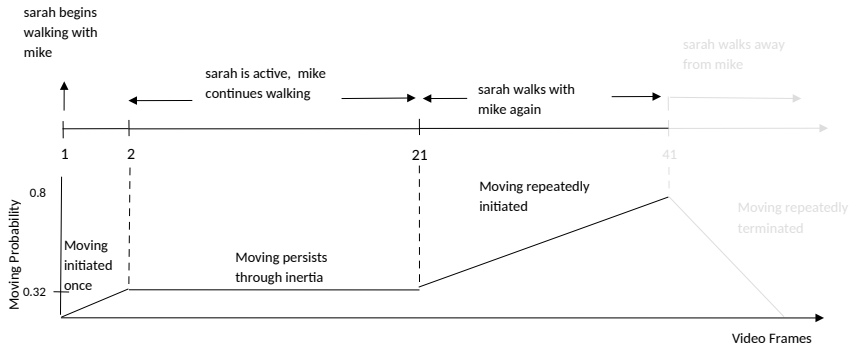


$\text{initiatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{happensAt}(\text{walking}(P_2), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{true}, T),$
 $\text{holdsAt}(\text{orientation}(P_1, P_2) = \text{true}, T).$

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

$0.18 :: \text{happensAt}(\text{walking}(\text{mike}), 41).$
 $0.79 :: \text{happensAt}(\text{inactive}(\text{sarah}), 41). \dots$

Instantaneous Recognition



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

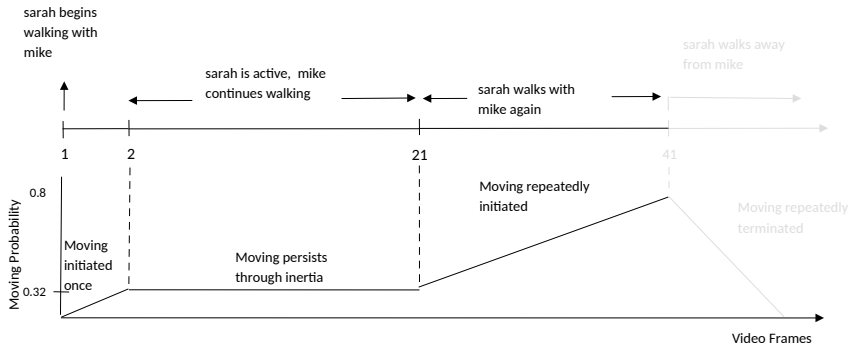
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

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

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

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

Instantaneous Recognition



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

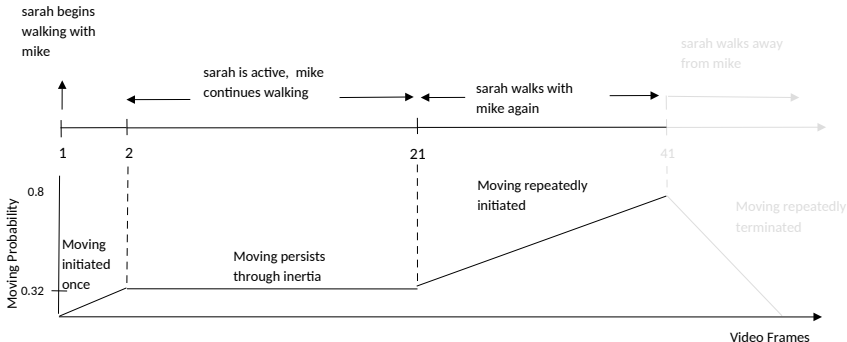
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

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

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

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

Instantaneous Recognition

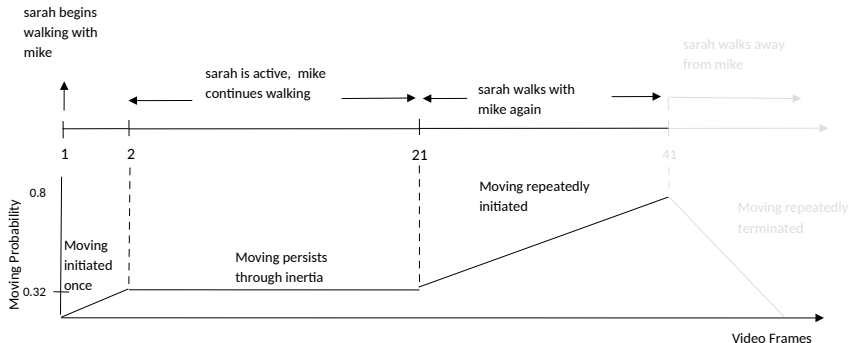


initiatedAt($moving(P_1, P_2) = true, T$) \leftarrow
happensAt($walking(P_1), T$),
happensAt($walking(P_2), T$),
holdsAt($close(P_1, P_2) = true, T$),
holdsAt($orientation(P_1, P_2) = true, T$).

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

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

Instantaneous Recognition



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

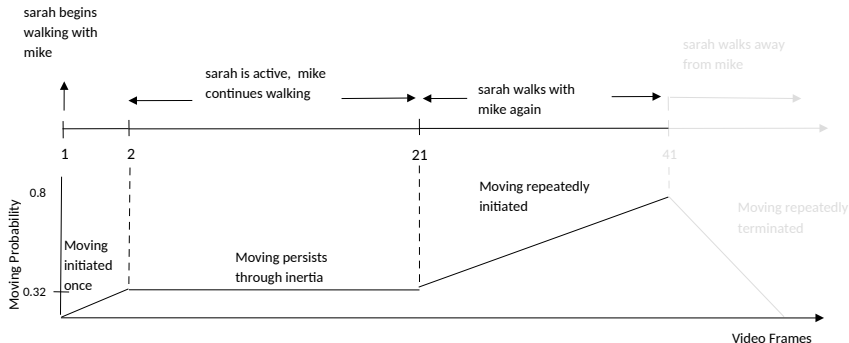
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$1.00 :: \text{happensAt}(\text{walking}(\text{mike}), 49).$

$0.96 :: \text{happensAt}(\text{inactive}(\text{sarah}), 49).$

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

Instantaneous Recognition



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

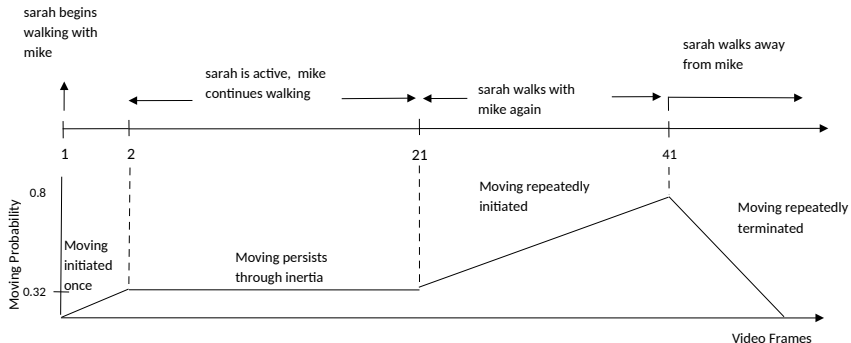
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$1.00 :: \text{happensAt}(\text{walking}(\text{mike}), 49).$

$0.96 :: \text{happensAt}(\text{inactive}(\text{sarah}), 49).$

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

Instantaneous Recognition



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

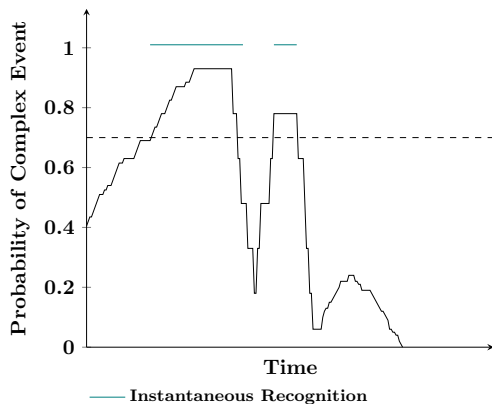
$\text{terminatedAt}(\text{moving}(P_1, P_2) = \text{true}, T) \leftarrow$
 $\text{happensAt}(\text{walking}(P_1), T),$
 $\text{holdsAt}(\text{close}(P_1, P_2) = \text{false}, T).$

$1.00 :: \text{happensAt}(\text{walking}(\text{mike}), 49).$

$0.96 :: \text{happensAt}(\text{inactive}(\text{sarah}), 49).$

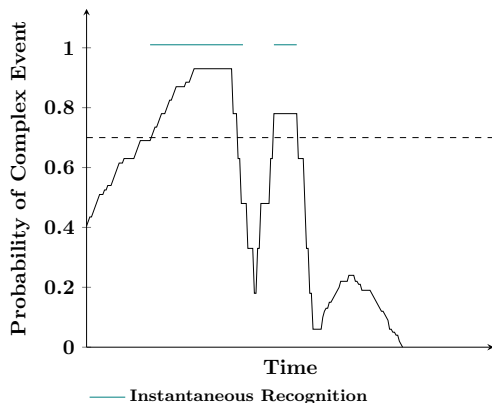
$$\begin{aligned}
 &P(\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 50)) = \\
 &P(\text{initiatedAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 49) \vee \\
 &\quad (\text{holdsAt}(\text{moving}(\text{mike}, \text{sarah}) = \text{true}, 49) \wedge \\
 &\quad \neg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

Instantaneous Recognition*



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

Instantaneous Recognition*

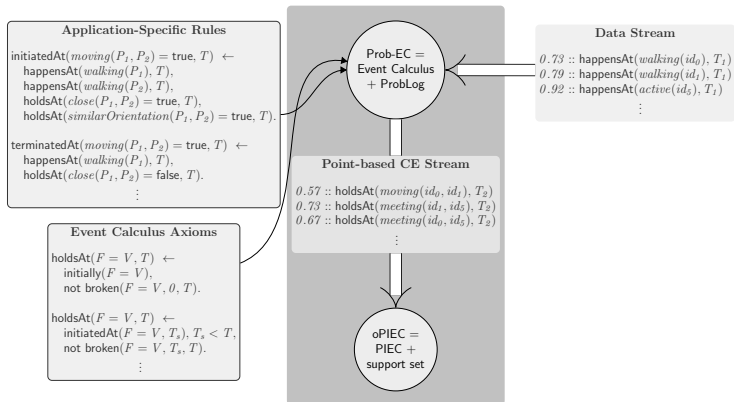


Higher accuracy than crisp reasoning in the presence of:

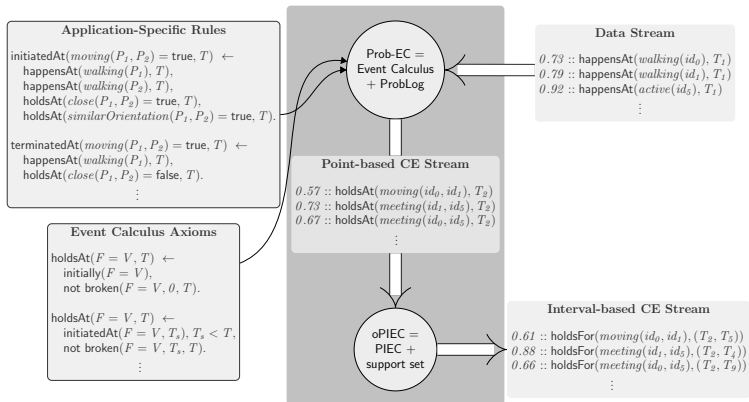
- several initiations and terminations;
- few probabilistic conjuncts.

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

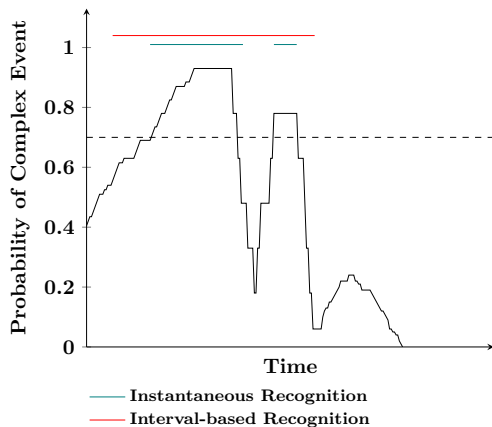
Online Probabilistic Interval-Based Event Calculus



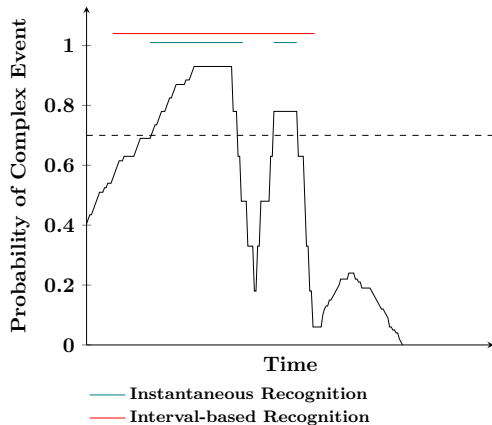
Online Probabilistic Interval-Based Event Calculus



Instantaneous vs Interval-based Recognition

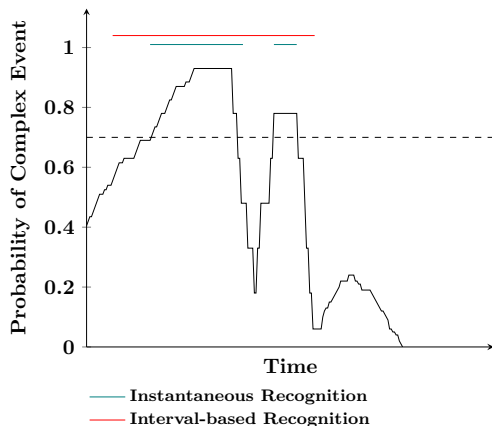


Instantaneous vs Interval-based Recognition



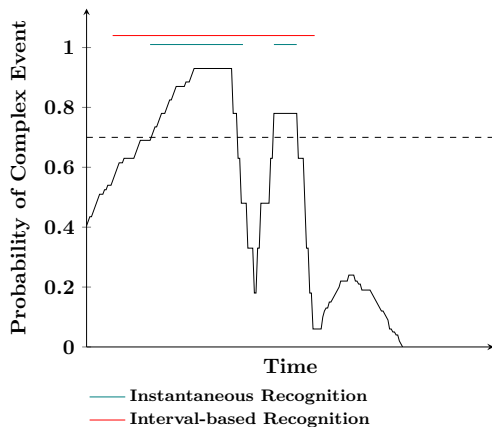
- **Interval Probability:** average probability of the time-points it contains.

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

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

Interval-based Recognition

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

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

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>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

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

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>										

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

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

Interval-based Recognition

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

Interval-based Recognition

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

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

Interval-based Recognition

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

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

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

Interval-based Recognition

Time	\uparrow 1	2	3	4	5	\downarrow 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

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


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

Interval-based Recognition

Time		↑					↓			
	1	2	3	4	5	6	7	8	9	10
<i>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



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*

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

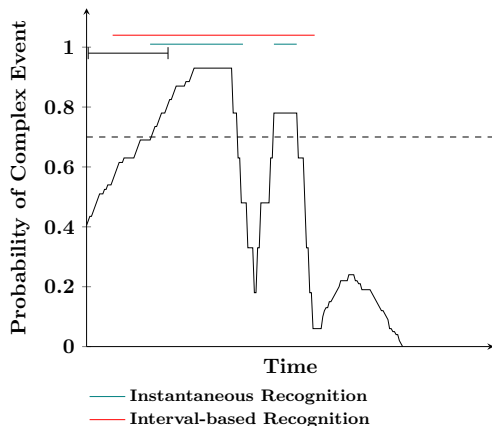
An interval is computed iff it is a probabilistic maximal interval.

Complexity

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

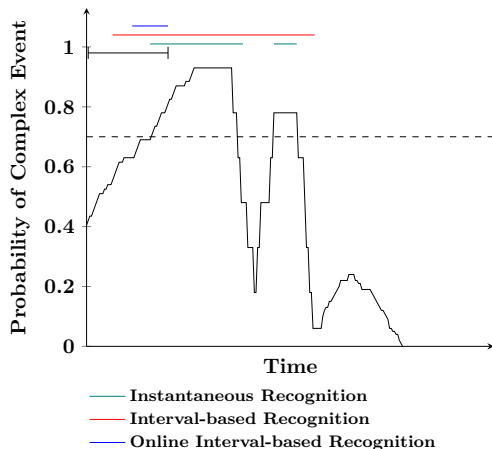
* Artikis et al, A Probabilistic Interval-based Event Calculus for Activity Recognition. Annals of Mathematics and Artificial Intelligence, 2021.

Online Interval-based Recognition



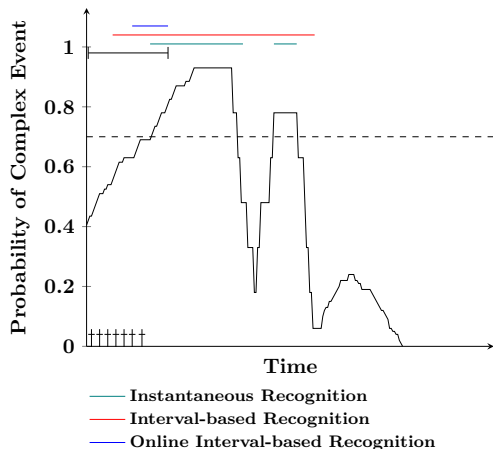
- Windowing.

Online Interval-based Recognition



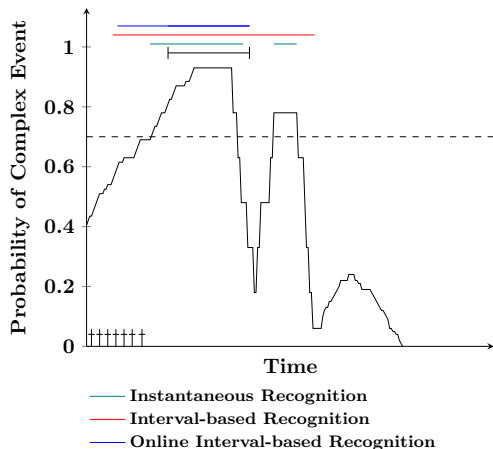
- Windowing.
- Probabilistic maximal interval computation.

Online Interval-based Recognition



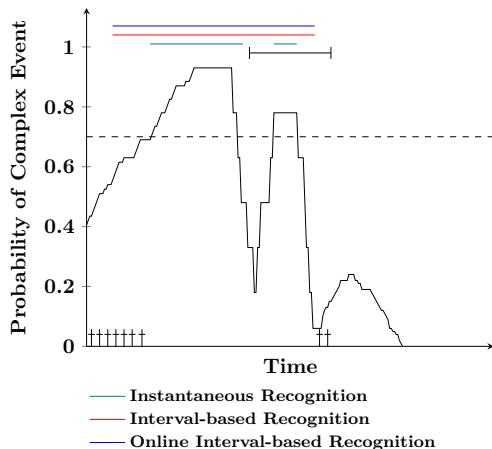
- Windowing.
- Probabilistic maximal interval computation.
- Caching **potential starting points**.
 - Discard time-point t iff there is a $t' < t$ that can be the starting point of a probabilistic maximal interval including t .

Online Interval-based Recognition



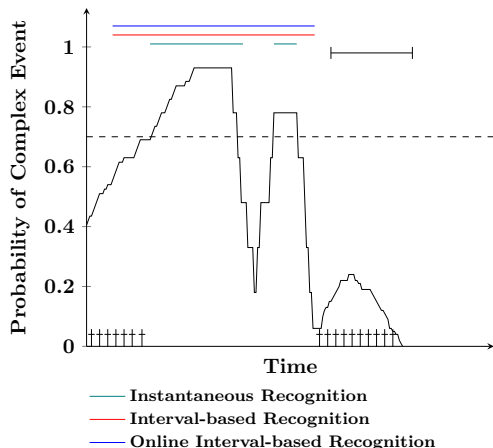
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Online Interval-based Recognition



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- 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: Properties

Memory Minimality

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

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

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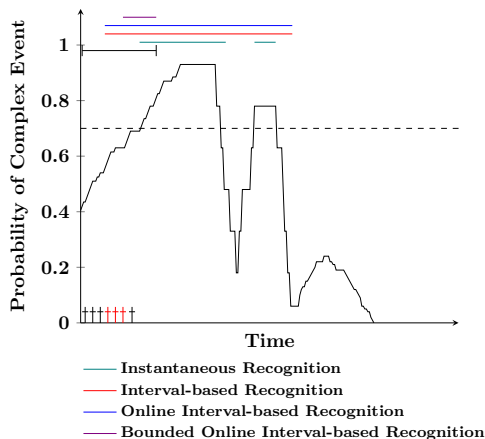
Interval Computation Correctness

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

Complexity

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

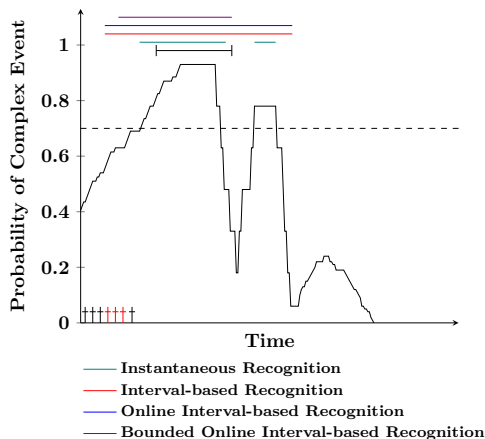
Bounded Online Interval-based Recognition*



- 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>

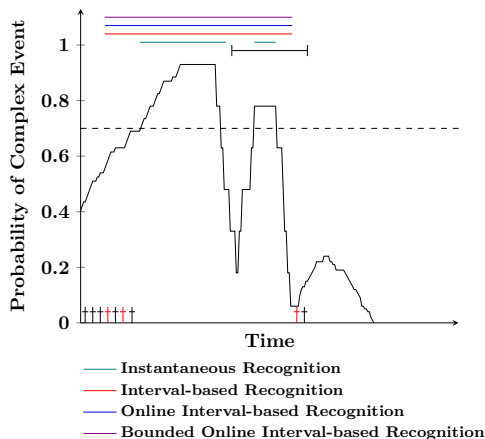
Bounded Online Interval-based Recognition*



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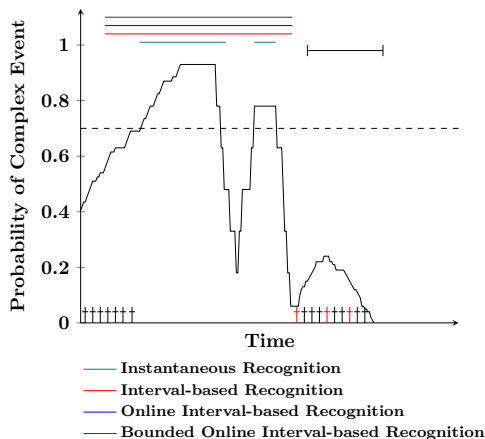
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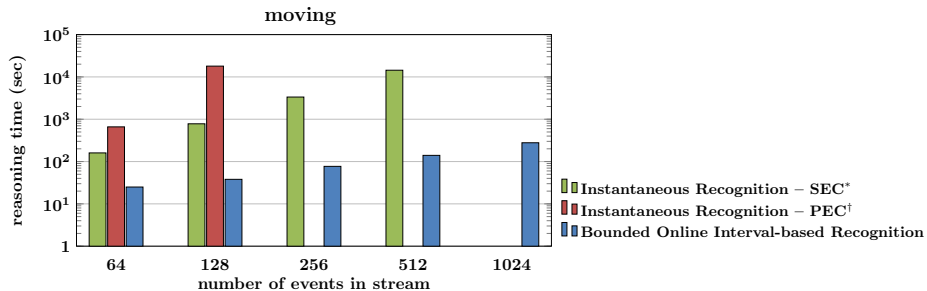
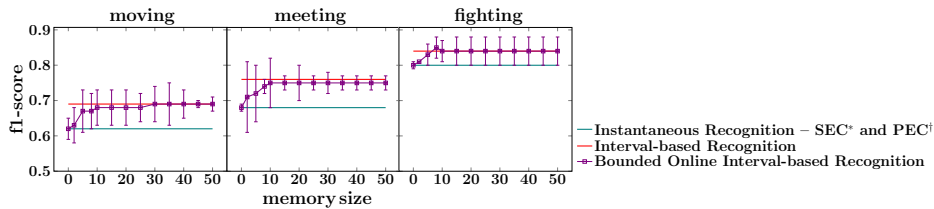
Bounded Online Interval-based Recognition*



- 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:

- Probabilistic reasoning → robust complex event recognition.

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- Optimal stream compression → correct complex event recognition.

Summary

Complex event recognition over noisy streams:

- Probabilistic reasoning → robust complex event recognition.
- Interval-based reasoning → improved predictive accuracy.
- Optimal stream compression → run-time performance.
- Optimal stream compression → correct complex event recognition.
- Direct routes to neuro-symbolic learning → end-to-end optimisation of simple and complex event recognition.

Topics not covered

- ▶ Formal models of CER
 - ▶ Other approaches on formal complex event recognition^{*,†}.

* Bucchi et al, CORE: a COmplex event Recognition Engine. VLDB Endowment, 2022.

<https://github.com/CORE-cer/CORE>

† Alevizos et al, Complex Event Recognition with Symbolic Register Transducers. VLDB, 2024.

<https://github.com/EIAlev/Wayeb>

Topics not covered

- ▶ Formal models of CER
 - ▶ Other approaches on formal complex event recognition^{*,†}.
 - ▶ 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/EIAlev/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[§],[¶].

^{*}Bucchi et al, CORE: a COMplex event Recognition Engine. VLDB Endowment, 2022.

<https://github.com/CORE-cer/CORE>

[†]Alevizos et al, Complex Event Recognition with Symbolic Register Transducers. VLDB, 2024.

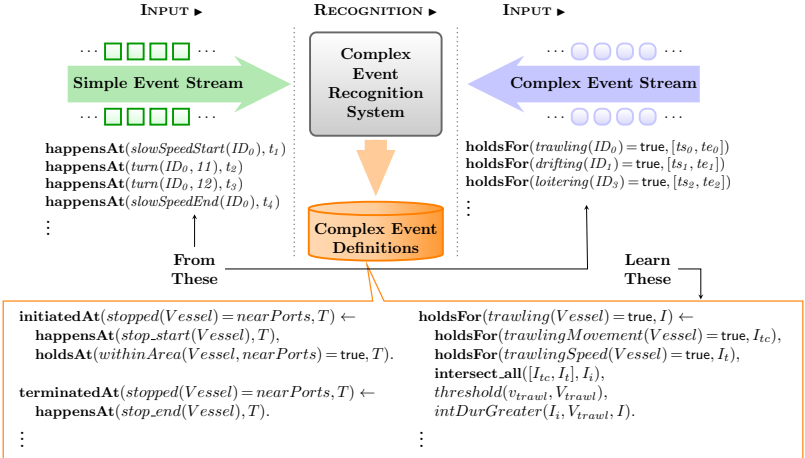
<https://github.com/EIAlev/Wayeb>

[‡]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.

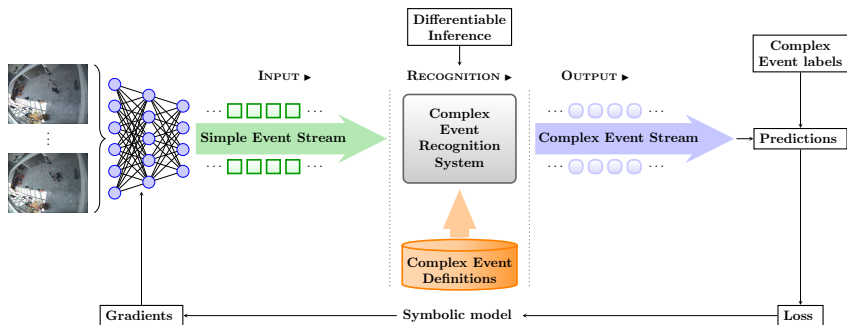
Machine Learning for Complex Event Recognition*,†



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

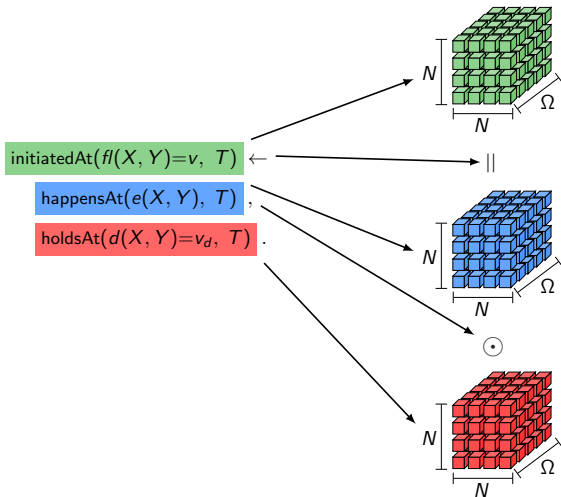
†Michelioudakis et al, Online semi-supervised learning of composite event rules by combining structure and mass-based predicate similarity. Machine Learning, 2024.

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*



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

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](#)