Neuro-Symbolic Complex Event Recognition: Part I

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https://cer.iit.demokritos.gr

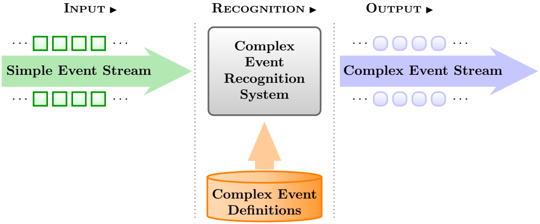
About the Tutorial

Structure:

- Part I: Symbolic AI for complex event recognition.
- Part II: Integration of symbolic with sub-symbolic AI for complex event recognition.

Slides, code, data & opportunities for collaboration:
https://cer.iit.demokritos.gr

Complex Event Recognition (Event Pattern Matching)*,†



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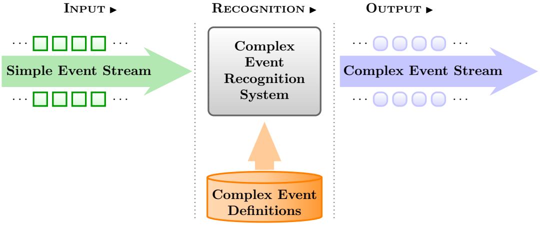

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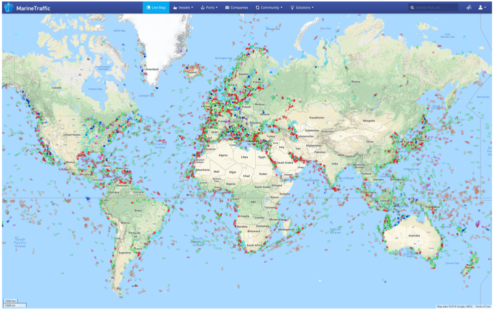
Maritime Situational Awareness*



http://www.marinetraffic.com

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

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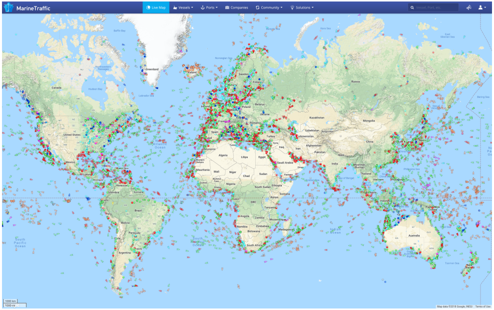

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https://cer.iit.demokritos.gr (fishing vessel)

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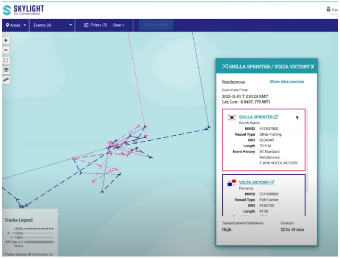
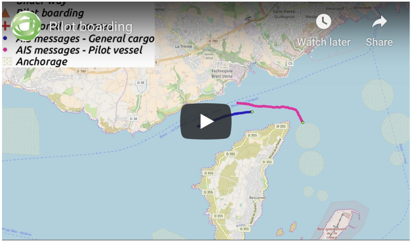
Maritime Situational Awareness*

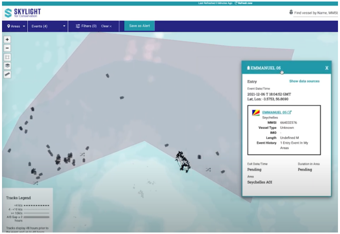
https://cer.iit.demokritos.gr (tugging)



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



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



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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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- Users install standing/continuous queries:
  - Queries deployed once and executed continuously until removed.
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- No assumption can be made on data arrival order.
- Users install standing/continuous queries:
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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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Complex event recognition:

- Formal semantics* for trustworthy models.
- 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!

---

* Grez et al, A Formal Framework for Complex Event Recognition. ACM Transactions on Database Systems, 2021.

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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- A logic programming language for representing and reasoning about events and their effects.
- Key components:
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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)*

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

$$\begin{array}{l}\textbf{terminatedAt}(F=V,\ T) \leftarrow \\ \quad \textbf{happensAt}(E_{T_1},\ T), \\ \quad [\text{conditions}] \\ \ldots \\ \textbf{terminatedAt}(F=V,\ T) \leftarrow \\ \quad \textbf{happensAt}(E_{T_j},\ T), \\ \quad [\text{conditions}]\end{array}$$

where

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

*Artikis et al, An Event Calculus for Event Recognition. IEEE TKDE, 2015.
https://github.com/aartikis/RTEC

Run-Time Event Calculus (RTEC)

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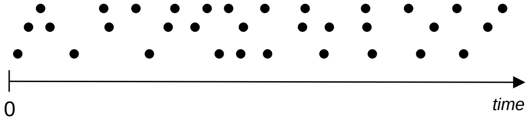

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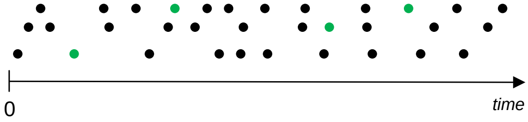

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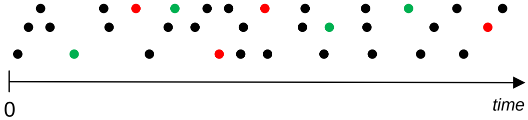

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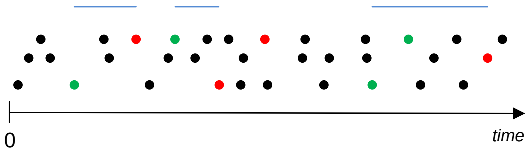
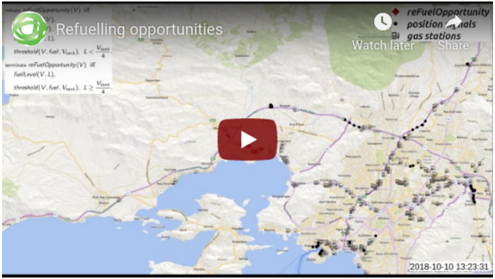
$\textbf{holdsFor}(F = V,\ I)$



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.

RTEC: Interval-based Reasoning

$$
\begin{aligned}
&\textbf{holdsFor}(\mathit{anchoredOrMoored}(\mathit{Vessel}) = \mathrm{true},\ I) \leftarrow \\
&\quad \textbf{holdsFor}(\mathit{stopped}(\mathit{Vessel}) = \mathit{farFromPorts},\ I_{sf}), \\
&\quad \textbf{holdsFor}(\mathit{withinArea}(\mathit{Vessel}, \mathit{anchorage}) = \mathit{true},\ I_{wa}), \\
&\quad \textbf{intersect\_all}([I_{sf}, I_{wa}],\ I_{sa}), \\
&\quad \textbf{holdsFor}(\mathit{stopped}(\mathit{Vessel}) = \mathit{nearPorts},\ I_{sn}), \\
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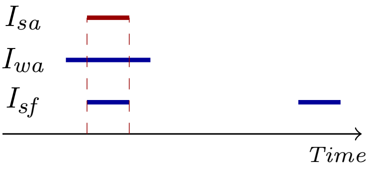

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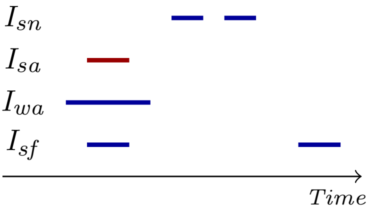

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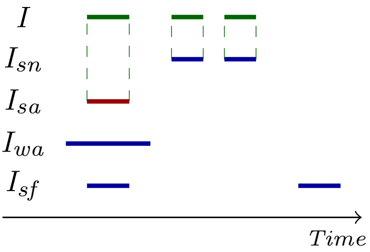

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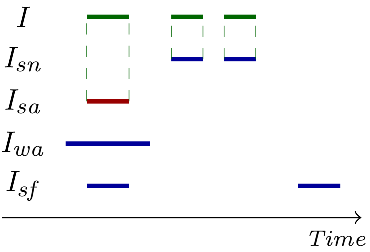

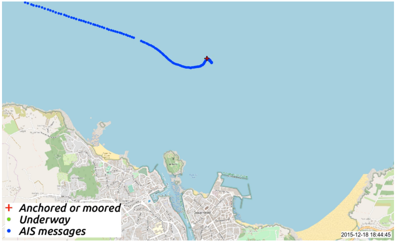

https://cer.iit.demokritos.gr (anchored or moored)

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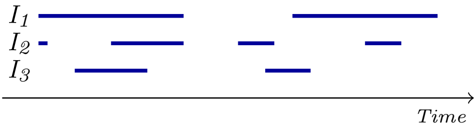
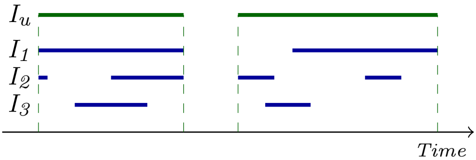


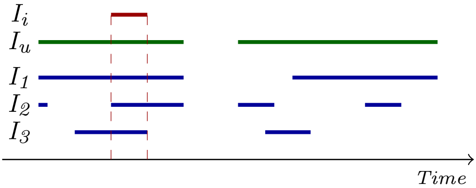
RTEC: Interval-based Reasoning

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



RTEC: Interval-based Reasoning

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

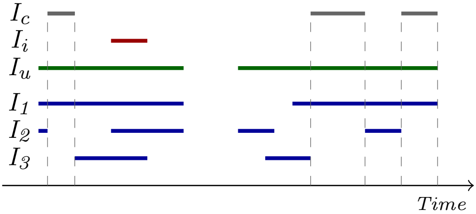


RTEC: Interval-based Reasoning

relative_complement_all$(I_1, [I_2, I_3], I_c)$

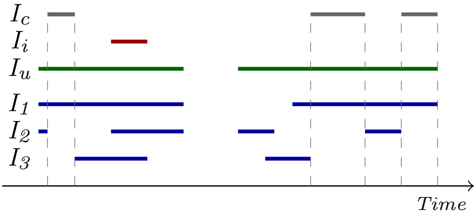
intersect_all$([I_1, I_2, I_3], I_i)$

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



RTEC: Interval-based Reasoning & Allen Relations*

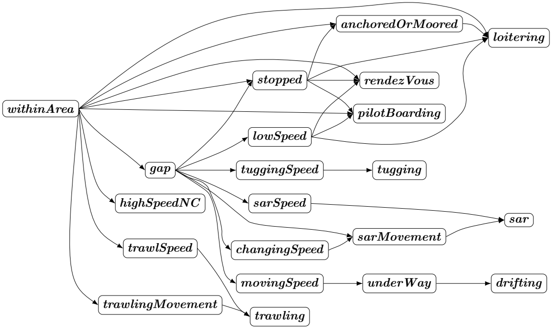
relative_complement_all$(I_1, [I_2, I_3], I_c)$
intersect_all$([I_1, I_2, I_3], I_i)$
union_all$([I_1, I_2, I_3], I_u)$



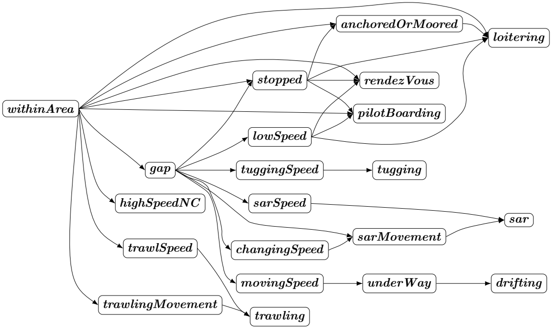
Relation	Illustration
before(i^s, i^t)	i^s i^t
meets(i^s, i^t)	i^s i^t
starts(i^s, i^t)	i^s i^t
finishes(i^s, i^t)	i^s i^t
during(i^s, i^t)	i^s i^t
overlaps(i^s, i^t)	i^s i^t
equal(i^s, i^t)	i^s i^t

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

Semantics


anchoredOrMoored
loitering
stopped
rendezVous
withinArea
pilotBoarding
lowSpeed
gap
tuggingSpeed
tugging
highSpeedNC
sarSpeed
sar
sarMovement
trawlSpeed
changingSpeed
movingSpeed
underWay
drifting
trawlingMovement
trawling

Semantics



withinArea
anchoredOrMoored
loitering
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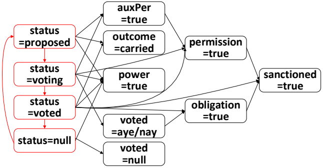
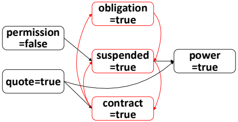
trawlingMovement
trawling

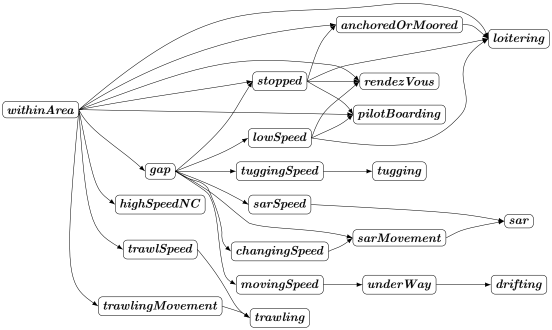


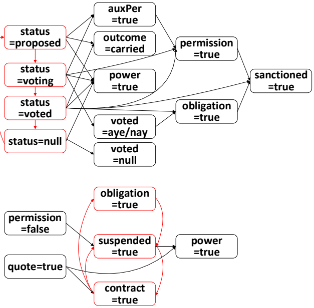
status =proposed
status =voting
status =voted
status=null
auxPer =true
outcome =carried
power =true
voted =aye/nay
voted =null
permission =true
obligation =true
sanctioned =true



permission =false
quote=true
obligation =true
suspended =true
contract =true
power =true

Semantics



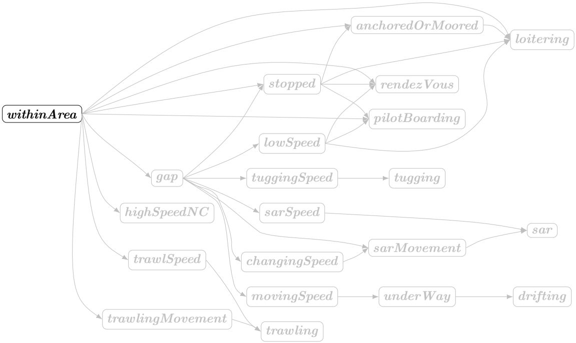


Proposition

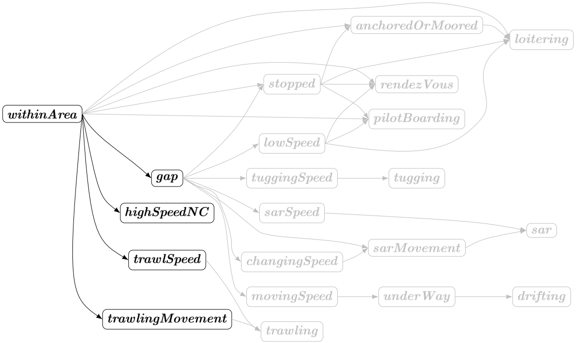
An event description in RTEC is a locally stratified logic program*.

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

Stratification & Reasoning



Stratification & Reasoning



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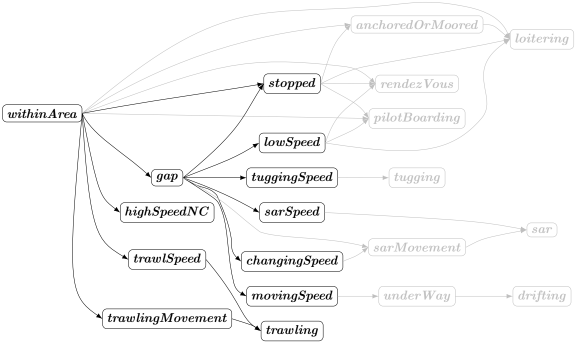
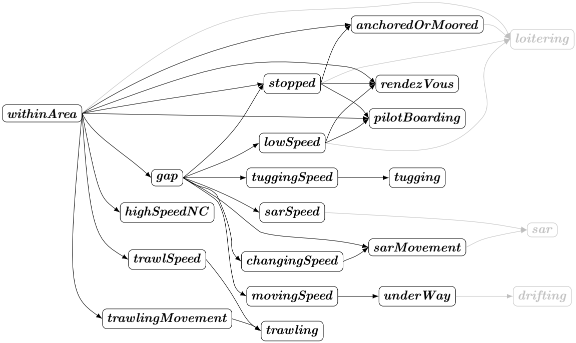
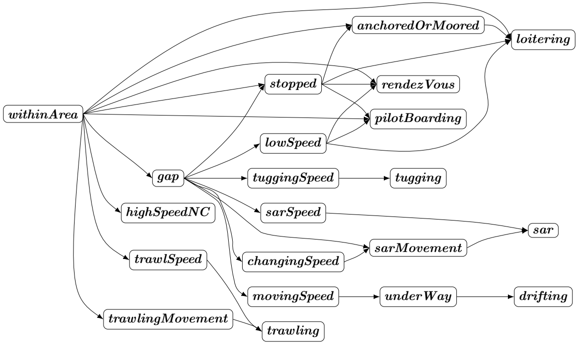


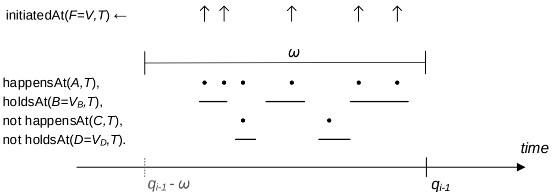
Stratification & Reasoning



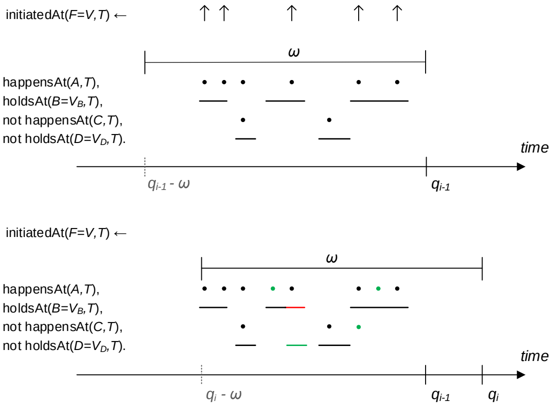
Stratification & Reasoning



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


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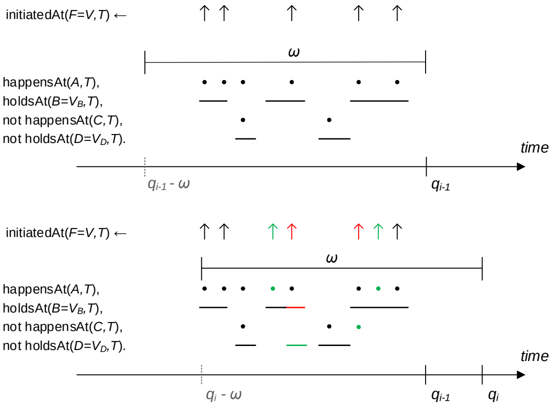
time
q_i - ω
q_{i-1}
q_i

Windowing


initiatedAt(F=V,T) ←
ω
happensAt(A,T),
holdsAt(B=V_B,T),
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q_{i-1}
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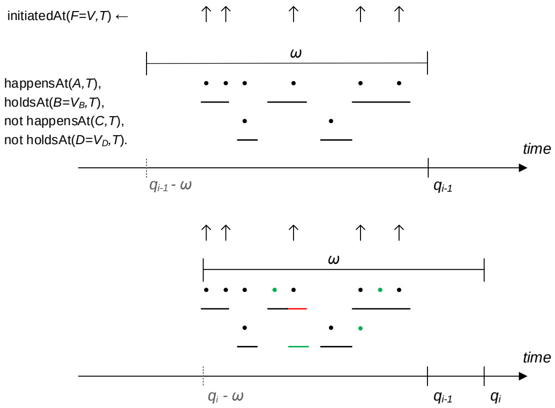
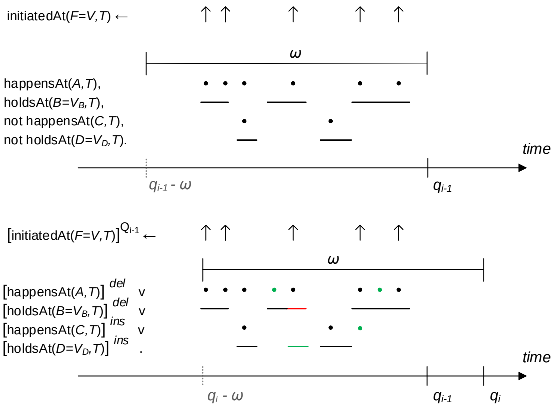
q_i - ω
q_{i-1}
q_i

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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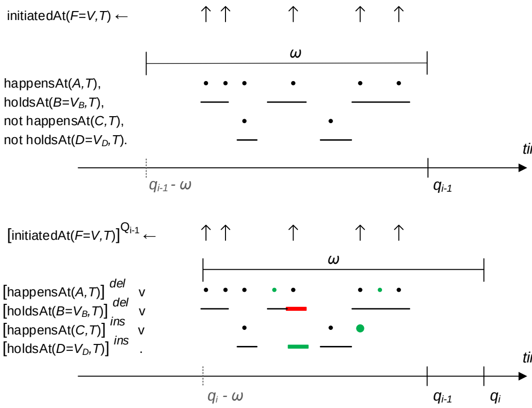

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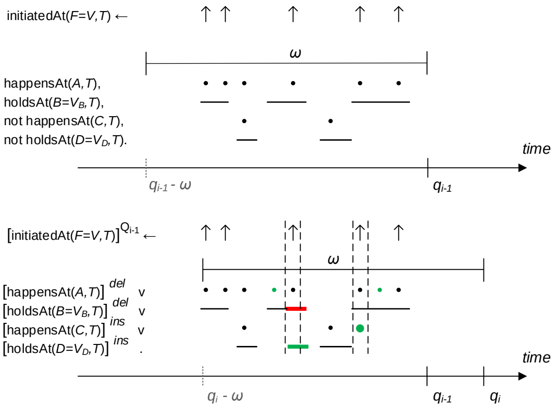

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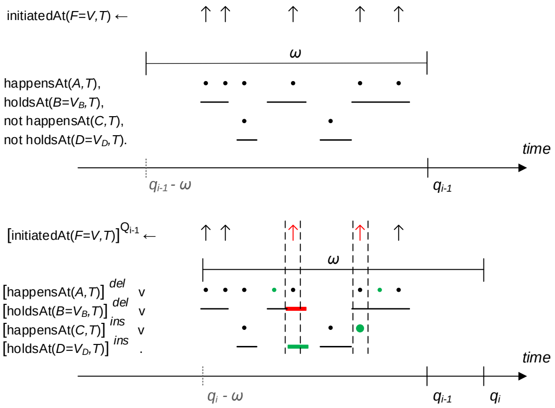

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RTEC: Correctness and Complexity

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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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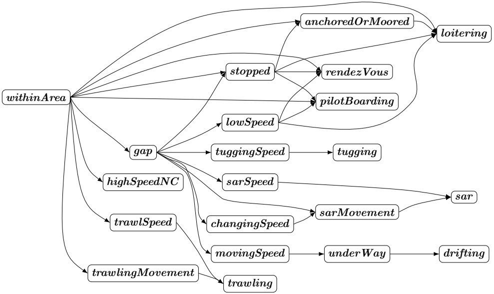
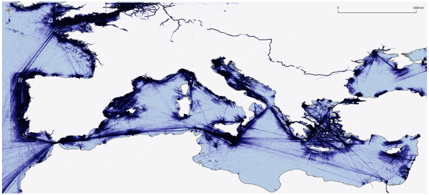
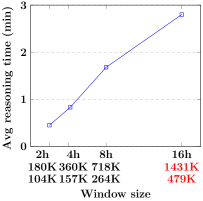
Complexity

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

Performance: Indicative Results







Summary

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- Direct routes to machine learning $\rightarrow$ automated complex event definition construction†.
- Direct routes to probabilistic reasoning $\rightarrow$ handle the lack of veracity of data streams.

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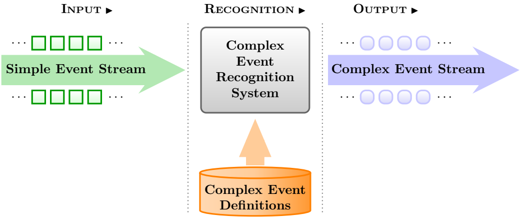
Complex Event Recognition under Uncertainty* and route to Neuro-Symbolic AI†



*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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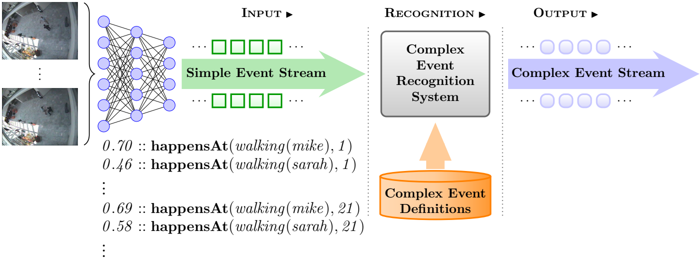

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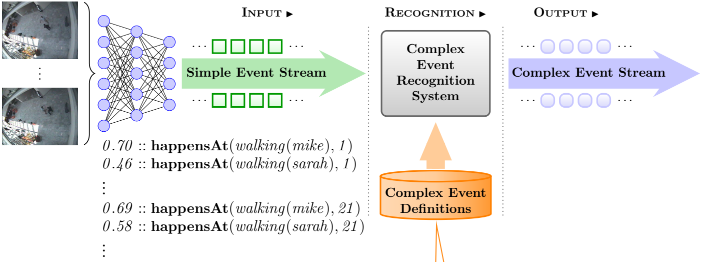

$$
\begin{aligned}
&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \mathsf{true},\ T) \leftarrow\\
&\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\
&\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T),\\
&\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \mathsf{true},\ T),\\
&\quad \textbf{holdsAt}(\mathit{orientation}(P_1,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

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

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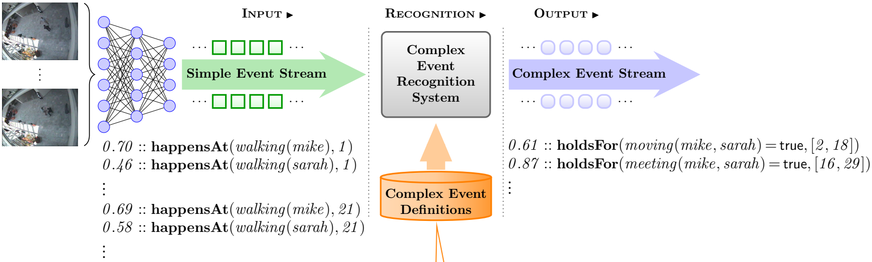

$$\begin{aligned}&\textbf{initiatedAt}(\mathit{moving}(P_1, P_2) = \mathsf{true},\ T) \leftarrow\\ &\quad \textbf{happensAt}(\mathit{walking}(P_1),\ T),\\ &\quad \textbf{happensAt}(\mathit{walking}(P_2),\ T),\\ &\quad \textbf{holdsAt}(\mathit{close}(P_1, P_2) = \mathsf{true},\ T),\\ &\quad \textbf{holdsAt}(\mathit{orientation}(P_1,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

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