Making Sense of Streaming Data

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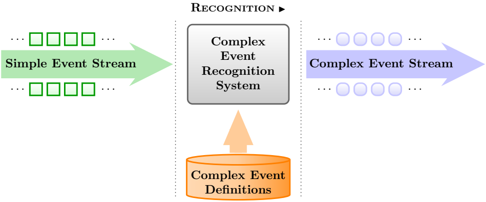
Slides, Papers, Code & Data

Making Sense of Streaming Data

Complex Event Recognition lab

Complex Event Recognition

Complex Event Recognition (CER)*,†



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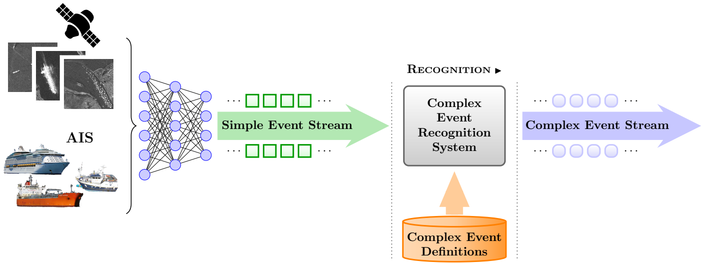

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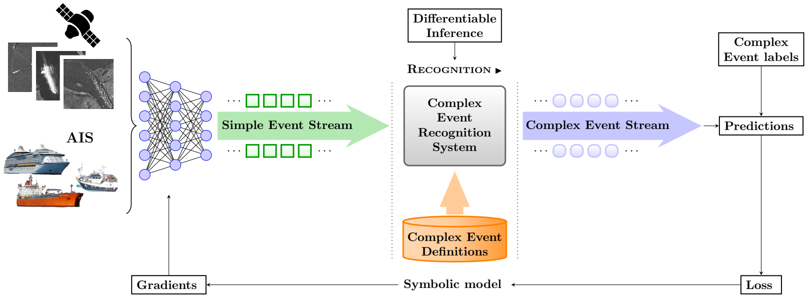

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CER for Maritime Situational Awareness*

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

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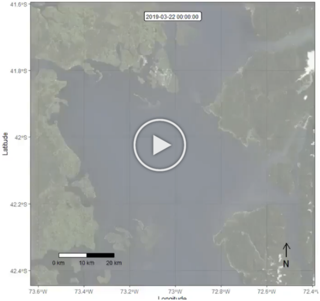

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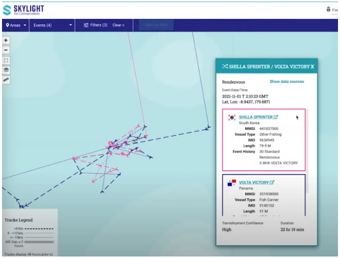
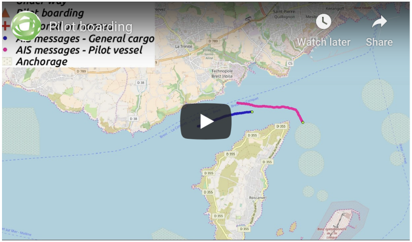


https://www.skylight.global (rendez-vous)



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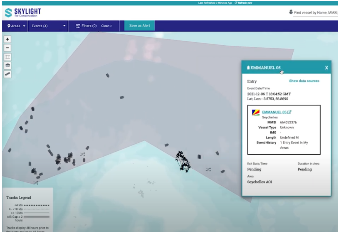

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Data Challenges

- Velocity, Volume: Millions of position signals/day at European scale.

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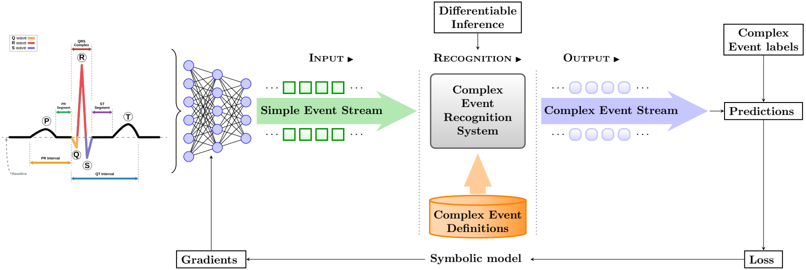
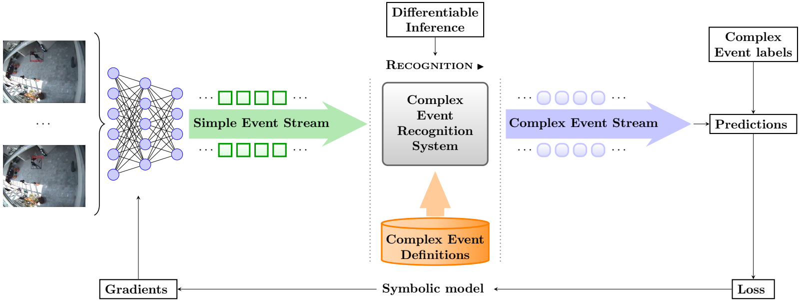
- Distribution: Vessels operating across the globe.

Patient Monitoring



Activity Recognition



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

Course Structure

- Introduction to Complex Event Recognition (CER).
  - We have Deep Learning and Large Language Models — can we go home now?

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Complex Event Recognition & Related Research

CER vs DataBase Management Systems*

Complex event recognition (CER) systems:

- Process data without storing them.

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- Latency requirements are very strict.

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- More often than not, background knowledge is available — let's use it!

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- Prone to hallucinations.
- Limited reasoning capabilities*.

---

*Ishay and Lee, LLM+AL: Bridging Large Language Models and Action Languages for Complex Reasoning About Actions. AAAI 2025.

Models of Complex Event Recognition

A Simple Unifying Event Algebra

$$
\begin{array}{rll}
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} & \quad \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 $N \geq 0$.

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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.
- *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?

* 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.

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