

Complex Event Processing: Languages, Recognition and Forecasting

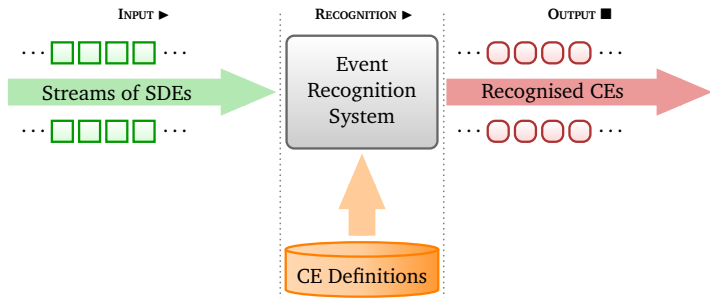
KR 2021 Tutorial

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Complex Event Recognition (Event Pattern Matching)



Human Activity Recognition



Human Activity Recognition



Human Activity Recognition

Input	Output
340 <i>inactive</i> (id_0)	
340 $p(id_0) = (20.88, -11.90)$	
340 <i>appear</i> (id_0)	
340 <i>walking</i> (id_2)	
340 $p(id_2) = (25.88, -19.80)$	
340 <i>active</i> (id_1)	
340 $p(id_1) = (20.88, -11.90)$	
340 <i>walking</i> (id_3)	
340 $p(id_3) = (24.78, -18.77)$	
380 <i>walking</i> (id_3)	
380 $p(id_3) = (27.88, -9.90)$	
380 <i>walking</i> (id_2)	
380 $p(id_2) = (28.27, -9.66)$	

Human Activity Recognition

Input		Output
340	<i>inactive</i> (id_0)	340 <i>left_object</i> (id_1, id_0)
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Credit Card Fraud Recognition



SDE:

- ▶ Credit card transactions from all over the world.

CE:

- ▶ Cloned card — a credit card is being used simultaneously in different countries.
- ▶ New high use — the card is being frequently used in merchants or countries never used before.
- ▶ Potential batch fraud — many transactions from multiple cards in the same point-of-sale terminal in high amounts.

Credit Card Fraud Recognition



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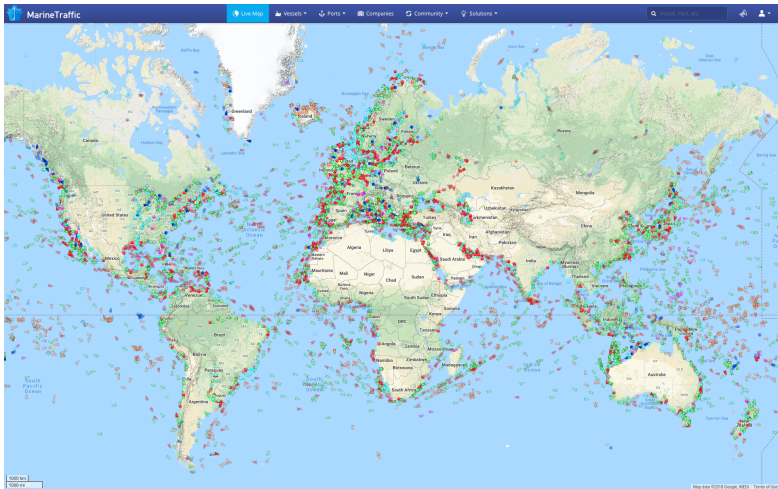
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- ▶ **Fraudulent transactions: 0.1%** of the total number of transactions.
- ▶ Fraud is **constantly evolving**.

Credit Card Fraud Recognition



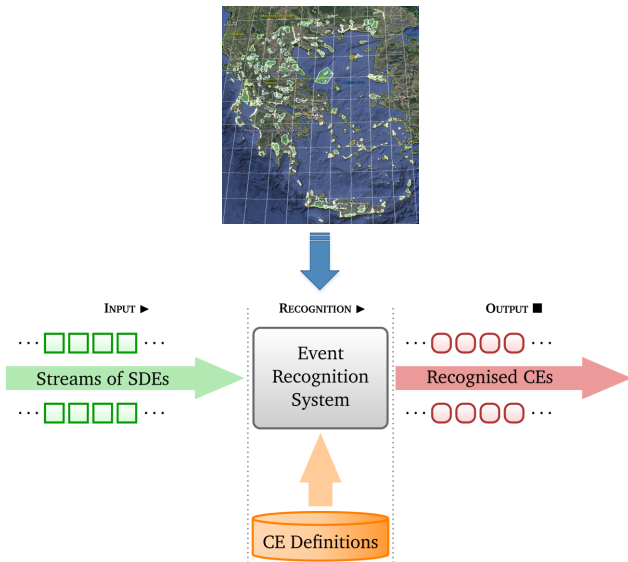
- ▶ Fraud must be detected within **25 milliseconds**.
- ▶ **Fraudulent transactions: 0.1%** of the total number of transactions.
- ▶ Fraud is **constantly evolving**.
- ▶ Erroneous transactions, missing fields.

Maritime Situational Awareness

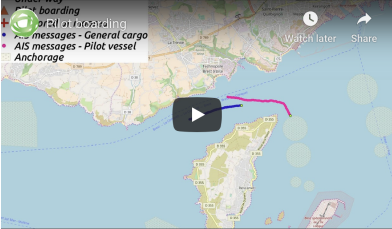
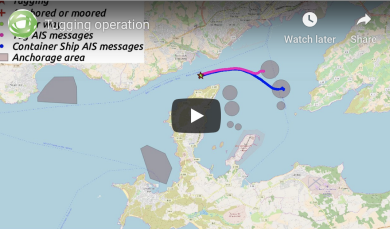


Source: <http://www.marinetraffic.com>

Maritime Situational Awareness



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

Many Other (Big Data) Applications

- ▶ Cardiac arrhythmia recognition.
- ▶ Identification of opportunities for refueling in fleet management.
- ▶ Identification of shipment irregularities inventory management.
- ▶ Intrusion detection in computer networks.
- ▶ Traffic congestion recognition and forecasting in smart cities.

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- ▶ Reasoning under uncertainty
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- ▶ Complex event forecasting
 - ▶ to support proactive decision-making.

Tutorial Structure

- ▶ Part I: Introduction
- ▶ Part II: Logic-based complex event recognition
- ▶ Part III: Automata-based complex event recognition
- ▶ Part IV: Complex event forecasting
- ▶ Part V: Topics not covered

CER vs DBMSs

Traditional Database Management Systems (DBMS)s:

- ▶ Store data before processing.
- ▶ Data updates are relatively infrequent.
- ▶ Typically sort data.
- ▶ Process data only when explicitly asked by the user.

CER vs DBMSs

Complex event recognition (CER) systems:

- ▶ Process data without storing them.
- ▶ Data are continuously updated.
 - ▶ Data stream into the system in high velocity.
 - ▶ Data streams are large (usually unbounded).
- ▶ No assumption can be made on data arrival order.
- ▶ Users install **standing/continuous queries**:
 - ▶ Queries deployed once and execute continuously until removed.
 - ▶ Online reasoning.
- ▶ Latency requirements are very strict.

Models of CER Systems

- ▶ Data model.
- ▶ Time model.
- ▶ Pattern language model.
- ▶ Processing model.
- ▶ Deployment model.

Pattern Language Model

- ▶ CER refers to matching patterns among the incoming streams of Simple, Derived Events (SDE)s.
- ▶ Thus, we need a language for expressing such patterns.
- ▶ We present a simple event algebra with common operators.
- ▶ Some systems extend this algebra with additional operators.

A Simple Unifying Event Algebra

$ce ::= sde$		
$ce_1 ; ce_2$		<i>Sequence</i>
$ce_1 \vee ce_2$		<i>Disjunction</i>
ce^*		<i>Iteration</i>
$\neg ce$		<i>Negation</i>
$\sigma_\theta(ce)$		<i>Selection</i>
$\pi_m(ce)$		<i>Projection</i>
$[ce]_{T_1}^{T_2}$		<i>Windowing</i> (from T_1 to T_2)

- ▶ *Sequence*: Two events following each other in time.

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- ▶ *Sequence*: Two events following each other in time.
- ▶ *Disjunction*: Either of two events occurring, regardless of temporal relations.
- ▶ 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.

Types of Window

- ▶ **Logical (time-based) windows:** bounds are defined as a function of time.
 - ▶ Example: Match a pattern only on the events received in the last 10 minutes.
- ▶ **Physical (count-based) windows:** bounds depend on the number of items included in the window.
 - ▶ Example: Match a pattern only on the last 10 received events.

Types of Window

Orthogonal classification based on the way bounds move:

- ▶ **Fixed windows** do not move!
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- ▶ **Sliding windows** have a fixed size, i.e. both bounds advance with a pre-defined logical or physical **step**.
 - ▶ Process the last 10 received events.
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- ▶ **Sliding windows** have a fixed size, i.e. both bounds advance with a pre-defined logical or physical **step**.
 - ▶ Process the last 10 received events.
 - ▶ Process the events received in the last 10'.
- ▶ **Pane windows**: overlapping sliding windows.
- ▶ **Tumble windows**: non-overlapping sliding windows.

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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- ▶ 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.

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Consumption policies place constraints on the use of events.

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- ▶ The **zero consumption** policy produces $(\alpha, 1), (\beta, 2)$ and $(\alpha, 1), (\beta, 3)$.
 - ▶ ... assuming a multiple selection strategy.
- ▶ The **selected consumption** policy produces $(\alpha, 1), (\beta, 2)$.
 - ▶ $(\alpha, 1)$ is consumed when the pattern is matched (at the arrival of $(\beta, 2)$), and thus no longer available when $(\beta, 3)$ arrives.
 - ▶ Once $(\alpha, 1)$ is consumed, it is not considered in ANY other pattern!

Literature/Sources

Surveys:

- ▶ G. Cugola, A. Margara: Processing flows of information: From data stream to complex event processing. *ACM Comput. Surv.* 44(3): 15:1-15:62, 2012.
- ▶ E. Alevizos et al: Probabilistic Complex Event Recognition: A Survey. *ACM Comput. Surv.* 50(5): 71:1-71:31, 2017.
- ▶ M. Dayarathna, S. Perera: Recent Advancements in Event Processing. *ACM Comput. Surv.* 51(2): 33:1-33:36, 2018.
- ▶ N. Giatrakos et al: Complex Event Recognition in the Big Data Era: A Survey. *The VLDB Journal*, 29, pp. 313–352, 2020.

Books:

- ▶ D. C. Luckham: The power of events—an introduction to complex event processing in distributed enterprise systems. ACM 2005, ISBN 978-0-201-72789-0.
- ▶ O. Etzion, P. Niblett: Event Processing in Action. Manning Publications Company 2010, ISBN 978-1-935182-21-4.

Conferences/Proceedings:

- ▶ International Conference on Distributed and Event-Based Systems (DEBS). [\(2021\)](#), [\(2020\)](#), [\(2019\)](#), ...
- ▶ SIGMOD, VLDB, ICDT, PODS, EDBT, IJCAI, ECAI.

Literature/Sources

Foundations:

- ▶ A. Grez et al: A Formal Framework for Complex Event Processing. ICDT 2019: 5:1-5:18.
- ▶ A. Grez et al: On the Expressiveness of Languages for Complex Event Recognition. ICDT 2020: 15:1-15:17.
- ▶ A. Artikis et al: Dagstuhl Seminar on the Foundations of Composite Event Recognition. SIGMOD Rec. 49(4): 24-27, 2020.

Applications:

- ▶ N. P. Schultz-Møller et al: Distributed complex event processing with query rewriting. DEBS 2009.
- ▶ A. Artikis et al: Heterogeneous Stream Processing and Crowdsourcing for Urban Traffic Management. EDBT 2014: 712-723.
- ▶ M. Pitsikalis et al: Composite Event Recognition for Maritime Monitoring. DEBS 2019, pp. 163-174, 2019.

Public datasets:

- ▶ [DEBS challenges](#).
- ▶ [Maritime situational awareness](#).
- ▶ [Human activity recognition](#).