It's a Machine Learning world: no future for Complex Event Processing?

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ABSTRACT

In 2010, Complex Event Processing was a groundbreaking approach for data processing for Early Warning Systems and Decision Support Systems in the crisis management domain. Although Machine Learning has eclipsed CEP in the ISCRAM community these last few years, these two approaches do not fulfil the same objectives. With this article, a quantitative analysis is made on papers related to these domains to understand the current trends and identify the next challenges the ISCRAM community should address. Combining CEP with ML can help to overcome the strong assumptions made towards the CEP rules this last decade, such as the availability of experts, structured data, etc. It is then recommended that the ISCRAM community explore the hybridisation of these approaches to improve the responsiveness in real time of EWS and DSS in crisis situations, emphasising the automatic, non-supervised generation of CEP rules.

Keywords

Complex Event Processing, Machine Learning, Early Warning, Decision Making, Trends.

INTRODUCTION

Early Warning Systems (EWS) (UNDRR, 2007) and Decision Support Systems (DSS) rely on data analysis and processing. In the context of EWS, it is crucial to identify, analyse and predict potential hazards and their outcomes. Similarly, in the context of DSS, valuable information must be extracted to support decision-making. Complex Event Processing (CEP) was a top trending event processing approach for data input for EWS and DSS under time-sensitive applications in the last decade, from financial fraud monitoring to crisis management. However, in crisis management, CEP now seems overshadowed, not to say replaced, by Machine Learning (ML) and all the artificial intelligence (AI) related disciplines despite its numerous strengths. For example, the last publications on CEP applications for EWS and DSS in the ISCRAM digital library were published a decade ago (Barthe-Delanoë et al., 2014; Kovordanyi et al., 2014; Pottebaum et al., 2011).

But is this a real trend or just a side effect of all the buzz about AI in the latest research projects and academic publications? Are these approaches exclusive or complementary for real-time data analytics for EWS and DSS in crisis management? Is there a future for CEP in this ML world? The research question is then: What are the current uses of CEP and ML to feed EWS and DSS, from a data analytics perspective?

To answer these questions, this position paper explores the relationship between CEP and ML approaches for data analytics in the context of information systems for crisis management. This paper will study the synergies, complementarities, and potential challenges of integrating ML and CEP for more effective EWS and DSS for crisis management. It will also focus on how the ISCRAM community deals with it now and which challenges they might address in the future.

This paper is structured as follows. First, a brief reminder of the characteristics of each approach is made. The second part will analyse the state-of-the-art in a significant academic publication database. The main takeaways of the analysis will then be addressed to the ISCRAM community in a third part to spark future discussions about efficiency in mining and analysing multiple flows of data in real-time to feed EWS and DSS, before concluding with insights for future research topics for the ISCRAM community.

DATA PROCESSING AND ANALYTICS

DSS and EWS are based on information from the field (real-time data), and historical information (capitalised knowledge). The need to feed these systems with data is facing many constraints: real-time data processing, historical data processing, and management of numerous data sources, sometimes competing, sometimes uncertain, and sometimes temporarily unavailable. The data may also be available in the form of a continuous, ordered flow over time (data stream) or in the form of a cloud of data that is not necessarily ordered. It will also be necessary to aggregate low-level data (e.g. calculating an average temperature over the last 5 minutes of collected data) or to match patterns (e.g. A happening before B and after C within a 10-hour time window). This allows for extracting the necessary information at the right level (regarding the stakeholders' needs) to be actioned for risk assessment, monitoring, forecasting, or any other purpose related to early warning or decision support. Two approaches are mainly used to achieve these data processing and analytics steps in a time-sensitive context: Complex Event Processing (CEP) and Machine Learning (ML).

Complex Event Processing

Event processing is a method of monitoring and analysing (processing) information flows (data) about things that happen (events) to draw a conclusion from them. Complex Event Processing (CEP) is a set of concepts and techniques for processing events in real-time and extracting information from event streams as they arrive (Etzion & Niblett, 2010).

The objective of CEP is to identify significant events (such as opportunities or threats) in real-time situations and respond to them as quickly as possible. These significant events are complex because they cannot be detected or observed directly; they must be identified by deduction, analysis and correlation of observed elementary events (Luckham, 2011). For example, the combination of events embedding the temperature measure of sensors located in various areas of a building can lead to emitting an early fire alert event, indicating an incipient fire as the temperatures are slowly increasing with no abrupt temperature changes. The low latency of real-time data processing (under 10 µs in the state-of-the-art CEP engines) combined with the ability to face high volumes of data makes CEP a top technology for the Internet of Things community (Lima et al., 2022; Shah et al., 2022).

On the technical side (see Figure 1), the CEP system relies on manually pre-defined business rules (implemented as event patterns, event filters, event aggregators, causality rules, timing rules, etc.) continuously executed by the CEP engine over the incoming data streams of events that feed the event cloud. If a rule is verified, then the resulting complex event is generated. The event streams are collected through subscriptions to various heterogeneous event sources: sensors, log files, social networks, reports, etc. The generated complex events can also be collected and processed to deduce other complex events.

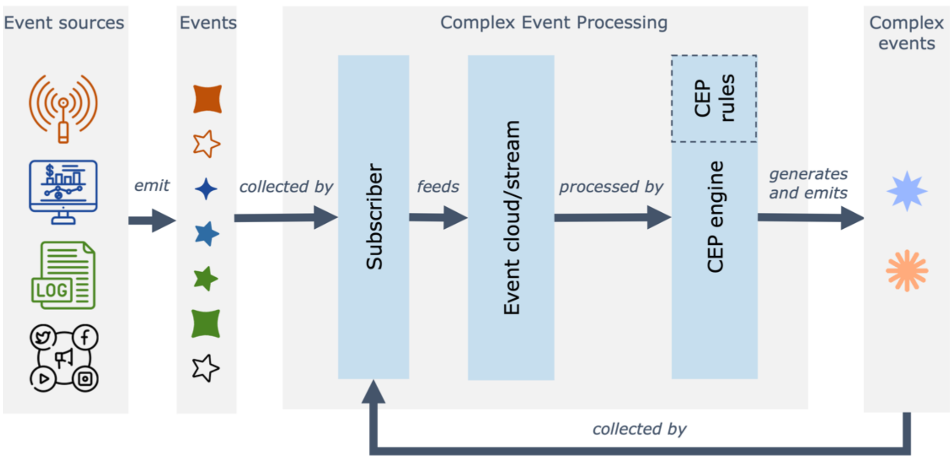

Figure 1. Principles of Complex Event Processing

It must be noted that the time dimension is natively part of the CEP system, allowing it to handle time frames (fixed or sliding) and the non-occurrence of an event. Moreover, CEP is not yet another expert system. CEP is not about decision-making as a standalone solution but about creating knowledge about a system in real-time (Fülöp et al., 2012). The generated complex events are consumed by EWS and DSS applications to feed their knowledge base, Common Operational Picture, and any component relying on situational awareness in a crisis management context, as shown by (Barthe-Delanoë et al., 2014; Kovordanyi et al., 2014; Pottebaum et al., 2011).

Machine Learning

Machine Learning (ML) was defined by (Samuel, 1959) and later by (Mitchell, 1997) as the field of study that enables computers to learn and improve from experience without being explicitly programmed. ML is a branch of Artificial Intelligence (AI) that aims to find the underlying relationships (i.e., models) between data. ML algorithms can analyse large volumes of data to identify patterns and trends that may raise potential opportunities and threats: detecting anomalies in a financial system, predicting failures in aircraft maintenance, identifying structural threats in a building, etc.

Technically, ML algorithms are trained, tested, and evaluated on historical data, split into a training set, a test set, and an evaluation set (see Figure 2). The outcome is a model called a predictor, which is then fed with new data and produces a prediction. The nature of the prediction depends on the type of the trained ML algorithm. It can be a discrete value, a series, a classification, a clustering, a probability, an association, etc.

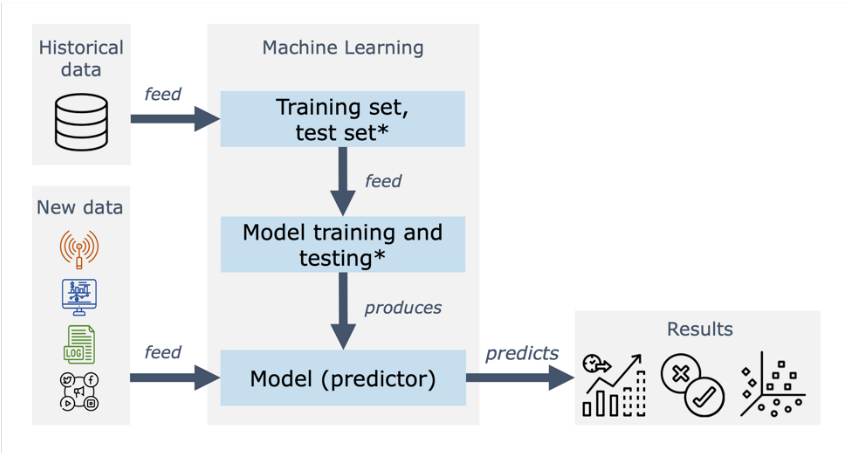

Figure 2. Principles of Machine Learning
(*evaluation step is often included with the test step)

ML can handle complex data better than classical data analytics approaches: datasets with many features and individuals; unstructured data (text, images, etc.); non-linear relationships among features. It can also make predictions, e.g. financial crisis prediction (Jaquart et al., 2021) and identification of disaster news using Natural Language Processing techniques (Chasseray et al., 2021; Domala et al., 2020).

Application to DSS and EWS

In EWS and DSS applications for crisis management, it is necessary to ensure the following requirements regarding the data analytics part: real-time detection of events and patterns of events, forecasting and prediction of the situation, low latency for timely decision-making, and scalability to handle large volumes of data.

Given the above characteristics of each of the CEP and ML approaches, a synthesis of their advantages and limitations is provided in Table 1.

Table 1. Advantages and limitations of CEP and ML for EWS and DSS (crisis management context)

Characteristics	CEP	ML
Real-time detection of events	Yes (real-time flow of data)	No
Real-time detection of patterns	Yes (use of predefined rules)	No
Forecasting and prediction	No	Yes (training on historical data)
Low latency	Yes (<10 µs)	Model dependent
Scalability	Yes (Big Data context)	Yes (Big Data context)

CEP is natively designed to detect events in real-time and complex patterns in huge data streams with low latency, making this approach suitable for time-sensitive applications. On the other hand, ML algorithms can uncover hidden patterns in historical data and make predictions about future events. They can also natively handle large volumes of data.

CEP, ML: WHERE ARE WE?

Overview of the Publication Trends

The first step of the inquiry about the position of CEP and ML in the literature is exploratory data analysis on the publications retrieved through six SCOPUS[1] queries, as shown in Table 2. These queries look for the presence of the CEP and ML approaches with a focus set on crisis management (queries *R1* and *R2*, respectively), on the DSS and EWS (queries *R3* and *R4*, respectively), and finally, on DSS and EWS for crisis management (queries *R5* and *R6*, respectively). The subject areas of all the queries were limited to the relevant ones, given the technical topic and the application domain (*dom*): computer science, engineering, mathematics, decision sciences, social sciences, business, management and accounting, energy, economics and finance.

Table 2. Set of SCOPUS queries

Req.	CEP	Req.	ML
R1	TITLE-ABS-KEY("event process*" AND ("cris* manag*" OR "emer* manag*"))	R2	TITLE-ABS-KEY ("machine learn*" AND ("cris* manag*" OR "emer* manag*"))
R3	TITLE-ABS-KEY("event process*" AND ("decision support*" OR "early warning*") AND system*)	R4	TITLE-ABS-KEY ("machine learn*" AND ("decision support*" OR "early warning*") AND system*)
R5	TITLE-ABS-KEY("event process*" AND ("decision support*" OR "early warning*") AND system* AND ("cris* manag*" OR "emer* manag*"))	R6	TITLE-ABS-KEY("machine learn*" AND ("decision support*" OR "early warning*") AND system* AND ("cris* manag*" OR "emer* manag*"))
dom	AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "MATH") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "ENER") OR LIMIT-TO (SUBJAREA , "ECON"))		

From the raw results of these six queries[2] (before the screening of each paper), it can be observed (Table 3) that the literature is more extensive regarding ML than CEP, which is explained by the variety of techniques and tools that can be found under the umbrella of ML compared to CEP.

Table 3. Raw results of the SCOPUS queries

Req.	CEP	Req.	ML
R1	31 documents	R2	329 documents
R3	114 documents	R4	6,984 documents
R5	10 documents	R6	24 documents

The gathered results are then plotted (Figure 3) to observe the overall distribution of publications by year for each 2-uple of queries: R1 vs R2, R3 vs R4, and R5 vs R6. It must be noted that since 2024 is at its beginning (to date of this review), the 2024 figures cannot be interpreted as for the previous years. Also, some publications from late 2023 are not yet referenced. A few duplicates were found between queries results (Table 4).

In Figure 3, a first observation is that the distribution of CEP-related publications peaks in the early 2010s, then decreases and reaches an asymptote (between 1 or 2 publications per year in the 2020s). On the other end, the ML-related publications tend to increase over time since mid-2010s with an exponential growth in the 2020s. It appears that the naïve impression of CEP being overshadowed by ML in the academic literature is correct from a quantitative point of view, especially in the case of ML/CEP for DSS and EWS applications, without connection to a specific business domain. However, if the focus is set on DSS and EWS restricted to crisis management applications, the number of publications drops significantly and the ratio between CEP and ML publications per year is far less pronounced (average ratio of 1 per 6).

[1] The focus is set on the SCOPUS database since it references a wider range of publishers (contrary to ScienceDirect or IEEE Xplore), including the ISCRAM digital library.

[2] Data files are available upon request.

The 10 duplicate results between R1 and R3, R1 and R5, and R3 and R5 queries (focus on the CEP approach) are the same 10 documents resulting from the R5 query (CEP × DSS/EWS × crisis management). Half of these 10 documents are authored by the ISCRAM community (in ISCRAM conferences, journals, etc.). They represent 32% of the R1 and 8.7% of the R3 results. The 24 duplicates found between R2 and R4, R2 and R6, and R4 and R6 (focus on the ML approach) are the same documents as the 24 results of the R6 query (ML × DSS/EWS × crisis management). They represent almost 7.3% of the R2 and 0.34% of the R4 results. A few of these 24 publications were authored by the ISCRAM community, not necessarily within the ISCRAM conferences series. R3 and R4 share 7 results, while there is no overlap in R1 with R2 and R5 with R6.

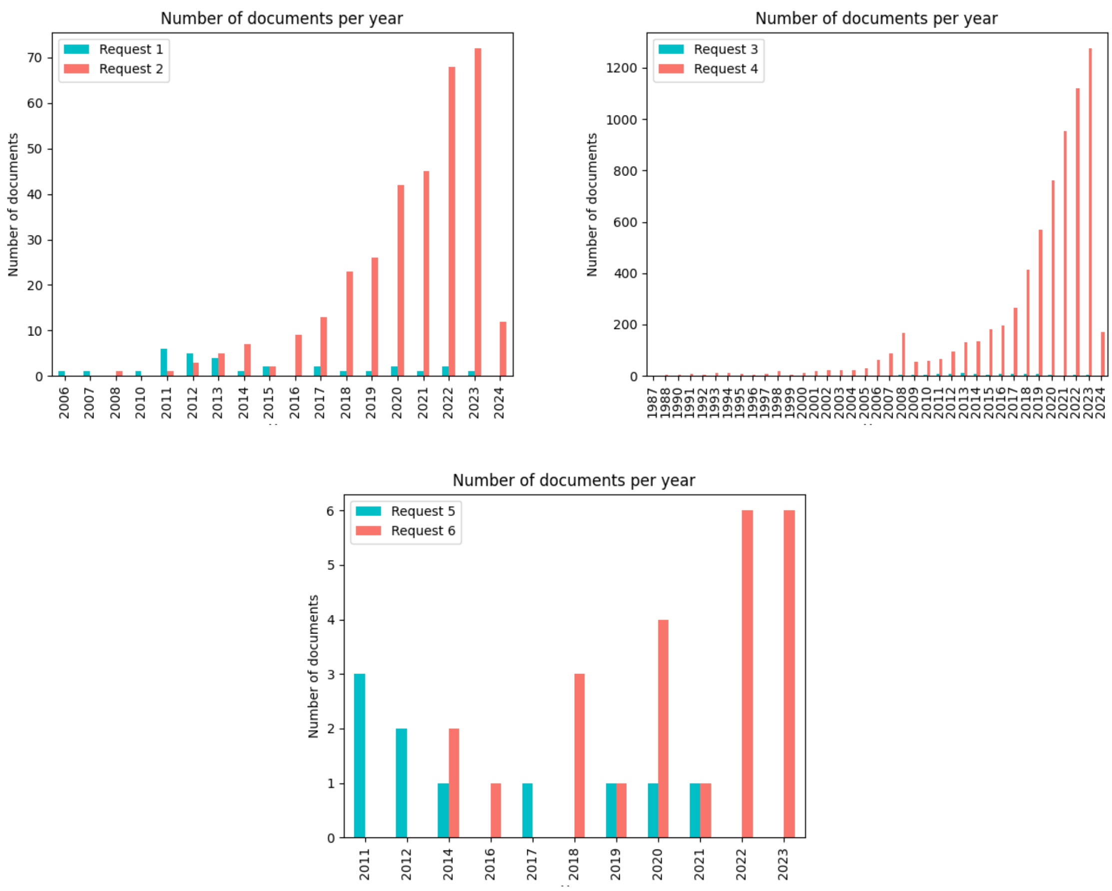

Figure 3. Distribution of the publications per year (R1 to R6 raw results)

Table 4. Duplicates between two queries raw results

Req.	R1	R2	R3	R4	R5
R2	0	-	-	-	-
R3	10	-	-	-	-
R4	-	24	7	-	-
R5	10	-	10	-	-
R6	-	24	-	24	0

The main outcomes of this quick quantitative exploratory data analysis are the following:

- ML is exponentially trending in DSS and EWS studies, exponentially overshadowing CEP for a decade.
- Within the crisis management application domain, the global ratio between CEP and ML publications is of 1 per 9 (R1 vs R2) up to 1 per 2.5 (R5 vs R6).

Deep Dive into the Research Topics

The previous findings show us that it will be more efficient to explore the topics of the publications retrieved by the R5 query and the R6 query to understand the use of CEP or ML for EWS and DSS in crisis management, as well as the seven results common to the R3 and R4 queries to understand the simultaneous presence of CEP and ML in these papers.

This section deep dives into the content of the retrieved documents. First, the relevance is checked by reading the title, abstract, introduction, and conclusion: publications outside the scope of this paper (data analytics to ultimately feed an EWS or a DSS) are not included in the analysis. Then, they are fully read to analyse the research proposal and results and, if applicable, the TRL (Technology Readiness Level) and the assumptions. These will help to understand the current trends found in the previous section, but also the gaps and the maturity level of the proposed solutions.

The results of the R5 query (Barthe-Delanoë et al., 2014; Braun et al., 2012; Fertier et al., 2020, 2021; Itria et al., 2017; Kovordanyi et al., 2012; Kraus et al., 2011; Mijović et al., 2011, 2019; Vranes et al., 2011) all show that the focus of these research works was on proving and demonstrating the integration of CEP components with other information system components (DSS, EWS, simulation tools, COP) within a crisis management context. Several information system architectures based on a hybrid ED-SOA (Event-Driven Service-Oriented Architecture) are also proposed to ensure the low coupling of these components. The proofs-of-concept and demonstrators presented in these publications are TRL 4 up to 6 by the end of the 2010s.

Out of the 24 results of query R6, 10 publications are excluded due to language constraints (despite automated translation efforts), being out of the scope of the study (e.g. wildlife activities) or having too few details about the processed data and/or the end use. The remaining 14 publications can be classified as follows, based on their authors' envisioned use:

- ML for DSS: emergency care triage (Rostam Niakan Kalhori, 2022), building structural assessment (Rahman et al., 2020), resources reallocation (Khouj et al., 2014, 2018), nuclear emergency management (Ionescu & Scheuermann, 2016), earthquake damage assessment (Ahadzadeh & Malek, 2021), contingency plans design (Kunikowski et al., 2020).
- ML for EWS: financial crisis (Zhao et al., 2023), citizen complaints (Zhang et al., 2023), flood forecast (Burrichter et al., 2023), building structural assessment (Kim et al., 2022).

These works all have a low TRL (evaluated at 3): the limitations and discussion sections show that the proofs-of-concept are still in their early stages. This can be explained by the recent technological hardware advances that made the wide use of ML algorithms possible. However, they all face the data input issue, either regarding the available volume, the available quality, or the available diversity of the data sources. Most of the authors underline the need for training, testing, and validating on (i) real data rather than on generated data and (ii) various datasets to overcome the overfitting bias.

Among the seven publications in common between the R3 query and R4 query results, one was recently retracted, and only two use both CEP and ML approaches. The works of (Bertoncelli et al., 2023; Sadanandan et al., 2022) aim to detect patterns in real-time data, using pre-defined CEP rules and historical data to learn data patterns with ML algorithms. Both CEP and ML are used concurrently rather than by hybridisation.

PAST AND CURRENT ISSUES

Integrating CEP in Information Systems Is A Mature Research Topic

It is interesting to note that despite a clear difference in the goal of each approach towards data processing and analytics, research on CEP has been almost abandoned in the information systems for crisis management domain since the late 2010s.

Given the findings in the previous section, it seems that this is mainly due to the maturity level of the research results (Barthe-Delanoë et al., 2014; Braun et al., 2012; Fertier et al., 2020, 2021; Itria et al., 2017; Kovordanyi et al., 2012; Kraus et al., 2011; Mijović et al., 2011, 2019; Vranes et al., 2011). The common topic of these papers was proving the benefits of integrating a CEP engine to feed an EWS or a DSS in a crisis management context with quite a high TRL. It means that they were ready for the next stage of development, which is production rather than research and proof.

However, while CEP has now been adopted as a powerful approach to analyze large volume of streaming data in real-time while operating with limited computational resources, a strong assumption was made in the publications related to information systems for crisis management. It was assumed that the knowledge necessary to create and implement the CEP rules was available so that it was ready to use. The questions of sharing explicit knowledge, making tacit knowledge explicit, the availability of experts for knowledge gathering and CEP rules assessment, the volume of knowledge to deal with, etc., to create these CEP rules have not yet been addressed by the ISCRAM community.

Automatic Creation of CEP Rules

The SCOPUS query R7 (Table 5) looks for publications about the automatic generation of CEP rules without limit of time or application domain: 48 documents were retrieved, authored by the Computer Science community, who seized this question (Alakari et al., 2020; Margara et al., 2014; Mehdiyev et al., 2015) mainly in the context of physical/cyber intrusion detection, air quality monitoring, traffic monitoring.

Table 5. Set of SCOPUS queries and results

Req.	Content	Results
R7	TITLE-ABS-KEY("event process*" AND autom* W/5 rule*)	48 documents
R8	TITLE-ABS-KEY "event process*" AND "of thing*" AND autom* W/5 rule*)	14 documents

Among these 48 documents, 25% are related to the Internet of Things (IoT) and Web of Things (WoT) research areas (query R8). The distribution of the publications over time (Figure 4) shows that the question of the automatic creation of CEP rules is still an open issue and has been seized by the IoT and WoT communities in the last decade. This question has been on the roadmap of these research communities (Mehdiyev et al., 2015), among the first to adopt CEP in their software architectures.

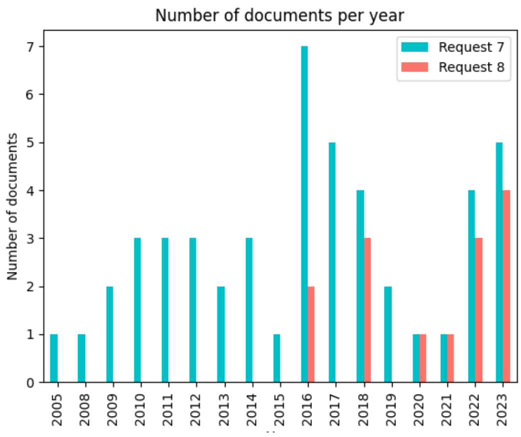

Figure 4. Distribution of the publications per year (R7 and R8)

Most of the papers propose using ML algorithms to generate CEP rules automatically: Deep Learning algorithms (Liu et al., 2022; Simsek et al., 2021; Simsek & Özdemir, 2018), classification algorithms (Kumar et al., 2023; Petersen et al., 2018; Sun et al., 2020), Principal Component Analysis (PCA) (Roldán-Gómez et al., 2023), time series shapelet (Li et al., 2019; Mousheimish et al., 2017). Only a few papers use approaches such as optimisation: evolutionary algorithms (Lv et al., 2022) or swarm algorithms (Bruns et al., 2023). All these research works focus on numerical and categorical data, mostly in a supervised training context.

CEP and ML are, in fact, complementary, given their features (see Table 1). CEP natively offers the processing of event flows in real time and enables patterns to be detected in real time, with limited computational resources. ML, on the other hand, makes it possible to exploit historical data to generate the CEP rules automatically (or as much as possible).

However, the results of the IoT and WoT communities may not be directly transposable to the field of crisis management (civil, humanitarian, agricultural, etc.). To prepare or to respond to a crisis, data are collected from various sources and in various types: numerical measures from sensors, text and images from social media (Coche et al., 2020; Power et al., 2022; Salemi et al., 2023) and from reports and press articles (Chasseray et al., 2021), speech (Cámbara et al., 2023), etc.

In other words, there is a significant challenge in processing structured and unstructured data when the CEP-ML solutions referenced above use datasets with numerical features (mostly) and categorical features.

Another key challenge is the learning part itself: most of the cited works use supervised algorithms, meaning their training datasets are labelled. In the context of crisis management, where the context is dynamic and the data sources volatile, the task of labelling datasets to train ML algorithms is unrealistic. It is then necessary to explore ways to perform CEP and ML hybridisation that rely on unsupervised learning algorithms.

CONCLUSION AND RECOMMENDATIONS

In this position paper, a short quantitative analysis was conducted on the papers related to CEP and ML for processing and analysing data to feed DSS and EWS. The naïve thought of CEP being overshadowed by the trending ML in the ISCRAM community is due to the maturity of the past research topics. However, the major issue of the automatic CEP rule creation was not addressed in the crisis management area. It is still an open issue, now seized by the Internet and Web of Things communities. They propose to use ML to deduce CEP rules, mainly using labelled datasets.

It is then recommended that the information systems for the crisis management community (particularly the ISCRAM community) focus on the potential of CEP in conjunction with ML. A hybrid approach may be the key to overcoming the challenges associated with automatic rule generation by exploiting the advantages of ML to process historical data and extract the necessary knowledge, whether explicit or tacit, whether from experts' interviews or written documents, images, etc.

It is crucial to address the assumptions related to the availability of knowledge and the resources required in the proposed solutions and to keep in mind the specific challenges faced by the crisis management domain compared to other application domains: the variety and the reliability of data sources; the availability of data sources and knowledge resources; structured, semi-structured and unstructured data; labelled and unlabeled data (to name a few).

A potential agenda for future research could lie in these four threads:

- Exploring methods to generate CEP rules from unsupervised ML algorithms automatically, trained on non-structured data;
- Optimizing CEP rules to balance accuracy, completeness, and efficiency considering the complexity and volatility of data sources;
- Adjusting CEP rules dynamically based on feedback from practitioners and end-users;
- Considering the ethical and societal implications of using ML-generated CEP rules such as privacy, transparency, bias, and fairness awareness (to name a few).

By investing in CEP-ML hybrid approaches adapted to the crisis management domain characteristics, DSS and EWS could significantly improve responsiveness and accuracy in crisis situations.

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