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Pattern Mining Based Automated Query Generation for Complex Event Processing

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DECLARATION

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ABSTRACT

Automating the query generation for Complex Event Processing (CEP) has marked its own importance in allowing users to obtain useful insights from data. Existing techniques are both computationally expensive and require extensive domain-specific human interaction. In addressing these issues, we propose a technique that combines both parallel coordinates and shapelets. First, if the provided data is not labeled (i.e., the time instances are not categorized into specific events), we label the data by clustering the dataset into a set of clusters based similarity between time instances. This produces a labeled dataset in which each time instance is labeled with the respective event it belongs to. Next, each time instance of the labeled multivariate dataset is represented as a line on a set of parallel coordinates. Then a shapelet-learner algorithm is applied to those lines to extract the relevant shapelets. Afterwards, the identified shapelets are ranked based on their information gain. Next, the shapelets with similar information gain are grouped together by a shapelet-merger algorithm. The best group to represent each event is then identified based on the event distribution of the dataset. Finally, the best group is used to automatically generate the query to detect the complex events. The proposed technique can be applied to both multivariate and multivariate time-series data, and it is computationally and memory efficient. It enables users to focus only on the shapelets with relevant information gains. We demonstrate the utility of the proposed technique using a set of real-world datasets.

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LIST OF ABBREVIATIONS

API	Application Programming Interface
ARFF	Attribute Relation File Format
CEP	Complex Event Processing
CORI	Collection Retrieval Inference
CSV	Comma Separated Values
CSS	Cascading Style Sheets
DBSCAN	Density Based Spatial Clustering of Applications with Noise
FHSAR	For Hiding Service Association Rules
HMM	Hidden Markov Model
HTML	Hyper Text Markup Language
HTTP	Hyper Text Transfer Protocol
IoT	Internet of Things
JSON	JavaScript Object Notation
JSP	Java Server Pages
MVC	Model View Controller
SPEEDD	Scalable Proactive Event-Driven Decision-making
OPTICS	Ordering points to identify the clustering structure
XSLT	Extensible Stylesheet Language Transformations
XML	Extensible Markup Language

Chapter 1

INTRODUCTION

1.1 Background

Automating query generation in large, multivariate datasets are useful in many application domains. For example, Complex Event Processing (CEP) combines data from multiple, streaming sources to identify meaningful events or patterns in real time. While the detection of relevant events and patterns may give insight about opportunities and threats related to the data being monitored (e.g., a set of sensor readings and credit card transactions), significant domain knowledge is required to write effective CEP queries. Manual analysis of data streams is not only tedious and error prone, but also important events are likely to be missed due to the limited domain knowledge of the query writer. A promising alternative is to automate the CEP query generation by automatically extracting/mining interesting patterns from the past data [1], [2], [3].

1.2 Motivation

Suppose there is multi-story building and multiple rooms in each floor. Each room has smoke and temperature sensors. Suppose the owner wants to detect fire in the building. A CEP engine can be used to detect fire and generate an alarm once the smoke sensor is triggered and temperature is above a set threshold. However, it is nontrivial to decide on a suitable temperature threshold, even if the building has experienced fire in the past. Hence, significant domain knowledge/expertise is required to define such a query. Even if defined, it may not be the most appropriate for the particular building.

Instead, it would be more useful to have a method which will generate these queries automatically. One alternative is to look at the past data from all the sensors and identify the typical behaviour. Anything that is different from this behaviour can be flagged. In case if the data also have sensor readings during a past fire, those could be flagged as outliers. Hence, it is possible to derive basic queries by looking at the data alone. However, it is also important to separate out potential sensor errors/failures and actual fires. If some domain expertise is available those queries could be further refined based on user hints to improve detection rate and accuracy. This idea of automated CEP query generation can be applied to many domains such as stock market, online retail, and Internet of Things (IoT).

However, developing an automated query generation system that works across many domains is not straightforward. Several related work has attempted to address this problem with limited success. For example, AutoCEP [3] is one such approaches that proposed a shapelet-based technique to automate CEP query generation for univariate time series. This itself is a major limitation as the practical presence of univariate time series is limited in CEP. Moreover, AutoCEP generates queries for each and every instance of the detected event, requiring the CEP engine to concurrently process multiple queries. This unnecessarily increases the computational and memory requirements of the CEP engine and consequently degrades its performance. iCEP framework [2] was developed to generate CEP queries automatically using a machine learning model. One of the main drawbacks of iCEP framework is the need of multiple historical datasets. As iCEP framework is based on a machine learning technique, accuracy of the generated queries and event processing based on those queries dependent on the comprehensiveness of the provided historical datasets. Ultra-fast shapelets [4] is proposed for multivariate time-series classification, where it trains a random forest to identify the shapelets with respect to the total dataset. While this technique is effective in classification, it cannot be used to generate CEP queries, as the generated random forest does not support backtracking and obtaining relevant information to determine what data lead to the classification of the event.

1.3 Problem Statement

Given a sample dataset, we address the problem of auto generating relevant queries for Complex Event Processors without having the exact domain knowledge. The specific problem that this project aims to address can be stated as follows:

How to generate CEP queries for multivariate time series datasets that may or may not be annotated without requiring expert domain knowledge?

In proposing the solution we assume that each instance in the obtained dataset is either annotated according to the respective event or can be annotated with bit of effort. Our goal is to construct a filter query per event, which contains the most relevant attributes, their range of values, and the event detection time frame. Target is to develop a CEP filter query similar to the following:

SELECT {∗} **WHERE** {*attr1* ≥ a and *attr2* < b} **WITHIN** {$t_1 \leq \text{time} \leq t_2$}

1.4 Objectives

Objectives of this research are to:

1. Develop a mechanism to convert datasets given in different formats to a common format so that the later processing becomes simple
2. Use the data and pattern mining techniques to identify common patterns and outliers in data
3. Implement a mechanism to obtain user hints and user given rules for generating a query
4. Visualize the identified pattern results back to the user to obtain furthermore insights and feedback
5. Automate the query generation for CEP

1.5 Research Contribution

We propose a technique that represents a given multivariate dataset as a set of parallel coordinates, and then extract shapelets out of those coordinates to auto generate CEP queries [5]. Even a time series can be mapped to a set of parallel coordinates, by representing each time instance as a separate line. Extracted shapelets are sorted according to the information gains and then divided into a set of groups. Among all the groups, best group for each event is then identified. Then the most important shapelets in the identified groups are used to generate one CEP query per group. This enables one to generate CEP queries for commonalities, anomalies, as well as time-series breakpoints in a given multivariate time-series dataset without having any domain knowledge. Users can focus on groups with high or low information gain depending on the application. Moreover, shapelets identify the most relevant attributes in a dataset for a particular event, enabling us to write more efficient CEP queries and only one query per event (unless the same event is triggered by unrelated attribute combinations). Using a set of real-world datasets, we demonstrate that the proposed technique can be applied effectively to auto generate CEP queries for common and abnormal events while identifying the relevant features and event occurrence timeframe. Moreover, the proposed technique has a relatively low computational and memory requirements compared to prior work. Furthermore, to annotate datasets that are not pre-annotated, we propose an unsupervised clustering technique that cluster a numerical dataset without knowing the behaviour of a dataset or in other words, without the interaction of a domain expert. The technique proposed by us initially calculates the euclidean distances between time instances and the obtained distance matrix will be clustered using OPTICS algorithm providing an annotation for each time instance with respect to its belongingness to a particular event.

1.6 Outline

The remainder of the report is organized as follows. Chapter 2 provides a detailed analysis of related work in CEP, query generation, query optimization, event detection, visualization techniques, pattern mining techniques, and clustering techniques. High-level design and detailed design of each module are presented in Chapter 3. Chapter 4 presents the implementation of the tool and performance analysis. Finally, we summarize the work and discuss future work in Chapter 5.

Chapter 2

LITERATURE REVIEW

Section 2.1 describes Complex Event Processing and its usage in real world applications. Next we discuss some related works which we have gone through. Section 2.2 describes related work under query generation. Query optimization, visualization tools, pattern mining techniques and unsupervised techniques are presented in Section 2.3, Section 2.4, Section 2.5, and section 2.6 respectively.

2.1 Complex Event Processing

Complex Event Processing (CEP) refers to event processing that combines data from multiple sources to detect events or patterns that suggest much more complicated circumstances. Modern day CEP is used across many domains and applications with the utmost objective of identifying meaningful events such as opportunities and threats and in order to react to them as quickly as possible [6]. As an example CEP is effectively and widely used in fraud detection where suppose a debit card has been stolen and when it is entered to an automatic teller machine the pattern of entering pin number, number of frequent withdrawals, etc., are analyzed and performed CEP to detect fraudulent activities. This high importance that CEP possesses in today’s context has demanded it to produce highly accurate results. To produce highly accurate results simply the event processor should be accompanied with accurate query generation mechanism.

Esper [16] and WSO2 CEP [14] are two of the leading CEP engines. Complex Event Processor helps identify the most meaningful events and patterns from multiple data sources, analyze their impacts, and act on them in real time. Most importantly, CEP engine can be deployed in standalone or distributed modes. CEP engines can be plugged into existing architectures, for e.g., WSO2 and Esper CEP engines can be embeddable in existing Java-based architectures such as Java Application Servers or Enterprise Service Bus.

2.2 Query Generation in CEP

In CEP systems, query processing takes place according to user-defined rules, which specify the relationship between observed events and phenomena of interest. While preparing queries to detect complex events, several questions such as the following need to be answered:

- Which events are relevant to detect the phenomena of interest and which are not?
- Which values should they carry?
- Do they need to appear in a specific, temporal order?
- How the query can be optimized so that the computing and memory requirements are reduced?

Writing rules with such details may be challenging, even for domain experts. Furthermore, the accuracy of the written queries will depend on the domain expertise that the user possesses. If the query generation process can be automated, we could enable wider use of CEP without domain expertise while simplifying the process and increasing the accuracy.

Several related work try to automate the process to figure out answers to the above mentioned questions. However, they rely on strict assumptions such as dataset is a univariate time-series and end user will be a domain expert [3], [7], [8]. Furthermore, most of the implementations have been domain dependent. Majority of the proposed approaches focused on shortcomings of the manual rule specification, and have concentrated on optimizing the query processing by focusing on a specific CEP engine, which has its own rule definition language and query processing algorithms [1], [2]. Next, we discuss several selected related works on automated CEP query generation and optimization.

2.2.1 autoCEP Framework

Mousheimish et al. [3] proposed autoCEP where initially it learns from histories, then the rules are extracted, and finally deployed into CEP engines in an automatic manner with minimum human intervention. autoCEP is a two-phase framework that relies on data mining techniques, more specifically early classification on time series. The framework learns historical trends and patterns at the first phase, and then algorithmically transforms them into CEP rules at the second one. This seems to be the first application of time series pattern mining techniques in the CEP domain.

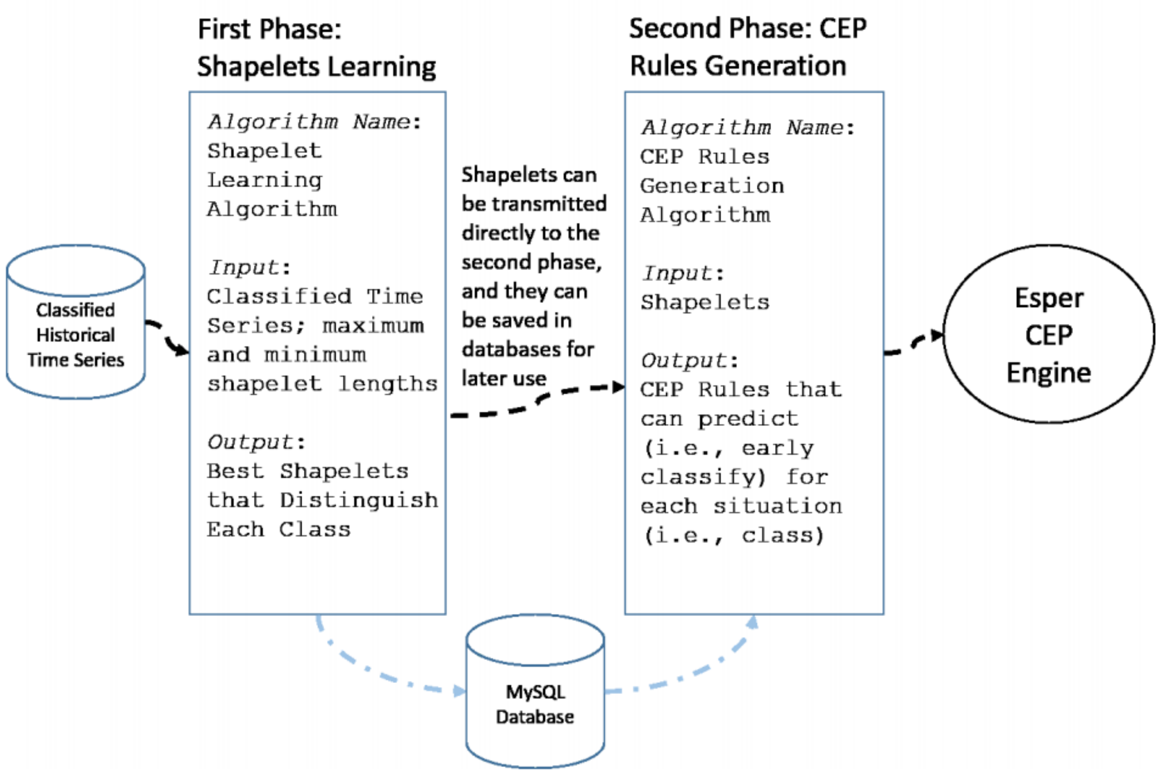

First Phase: Shapelets Learning
Algorithm Name: Shapelet Learning Algorithm
Input: Classified Time Series; maximum and minimum shapelet lengths
Output: Best Shapelets that Distinguish Each Class
Second Phase: CEP Rules Generation
Algorithm Name: CEP Rules Generation Algorithm
Input: Shapelets
Output: CEP Rules that can predict (i.e., early classify) for each situation (i.e., class)
Classified Historical Time Series
Shapelets can be transmitted directly to the second phase, and they can be saved in databases for later use
Esper CEP Engine
MySQL Database

Figure 2.1: High-level architecture of autoCEP [2].

Figure 2.1 illustrates the autoCEP architecture. autoCEP works with univariate time series data which is already labeled for events. Then in the first phase Shapelets [21], [23] are learned, which is a technique to extract similarities in the time series. By scanning through the whole historical time series similar shaped time series subsequences (shapelets) are obtained. Shapelet is defined as a function of three variables defined as $v = (s,\partial,c)$, where s is a numeric time series, ∂ is the distance threshold for run-time classification and c the class of the Shapelet. By this definition unclassified instances are labeled with a class if the similarity between them is less or equal to [3]. There are maximum and minimum lengths to shapelets where a domain expert can specify them to have a better learning process. Then one can obtain the useful shapelets that characterize each class and they are saved in a database (e.g., MySQL). Within the second phase of the implementation, rule generation using the shapelets will take place which is done in a defined procedure. Prototype of the generating rule is as follows:

within[window] {relevant events} *where*[conditions]

In this prototype *within*, *{}*, and *where* are the three main keywords for a generated rule using a shapelet. Window and Conditions can be taken from the derived shapelets saved in the MySQL database [3].

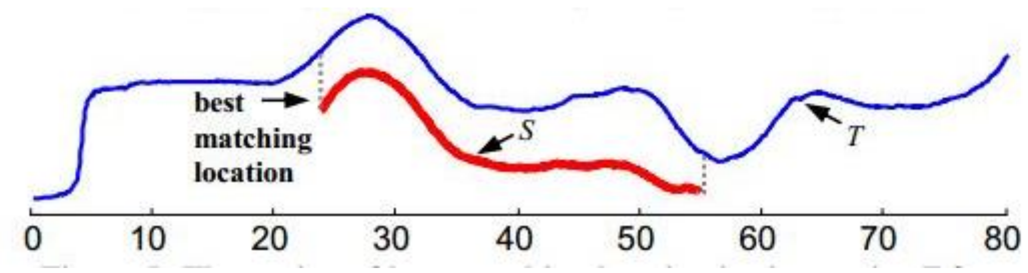


Figure 2.2: Illustration of best matching location [21].

Figure 2.2 shows the comparison of two shapelets. Shapelets are compared by calculating the best distance between two shapelets. The best distance accounts for the distance between *S* and its best matching location somewhere in T [21]. Shapelets can be only used to analyze univariate time series. To overcome this limitation Ultra Fast shapelets [4] are proposed. A method for using shapelets for multivariate time series is proposed and Ultra-Fast Shapelets is proven to be successful under some strict assumptions in comparison to state-of-the-art multivariate time series classifiers on 15 multivariate time series datasets from various domains. Finally, time series derivatives that have proven to be useful for other time series classifiers are investigated for the shapelet-based classifiers. Considering the above, one of the main limitations of ultra-fast shapelets is the inability to generate a query for complex event processing. The generated random forest does not support backtracking and obtaining any relevant information to proceed in building up a query to obtain complex events. Furthermore, ultra-shapelet implementation also fails to identify data columns dynamically into the shapelets.

2.2.2 iCEP Framework

iCEP [2] is a framework that has been developed using machine learning techniques to determine the hidden causality between the events received from the external environment and the situation to detect without the assistance of domain experts. iCEP analyzes historical traces of events and effective use of supervised learning techniques to derive relevant CEP rules. It is a highly modular system, with different components considering different aspects of the rules. Depending on their knowledge of the domain, users can decide which modules to deploy and can provide hints to guide the learning process and increase its precision [1], [2]. Figure 2.3 illustrates the high-level architecture of iCEP which consists of seven different modules as follows:

1. Events and Attributes (Ev) Learner: finds which event types and attributes are relevant for the rule.
2. Window (Win) Learner: finds the minimal time interval that includes all relevant events.
3. Constraints (Constr) Learner: finds the constraints that select relevant events based on the values of their attributes.
4. Aggregates (Agg) Learner: finds the presence and values of aggregate constraints.
5. Parameters (Param) Learner: nds the parameters that bind the value of attributes in different events.
6. Sequences (Seq) Learner: finds the ordering relations that hold among primitive events.
7. Negations (Neg) Learner: finds negation constraints.

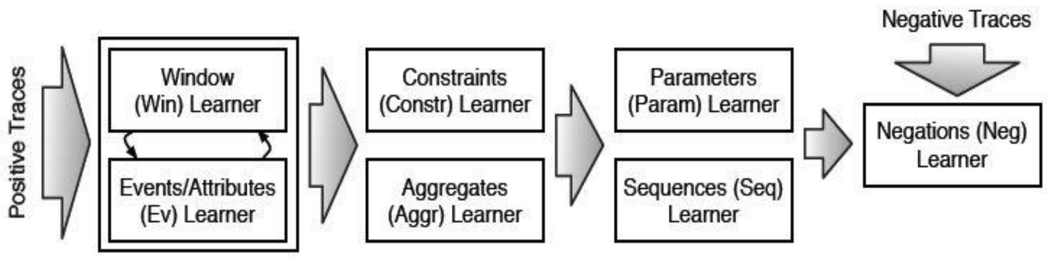

Negative Traces
Positive Traces
Window (Win) Learner
Events/Attributes (Ev) Learner
Constraints (Constr) Learner
Aggregates (Aggr) Learner
Parameters (Param) Learner
Sequences (Seq) Learner
Negations (Neg) Learner

Figure 2.3: iCEP architecture [2].

iCEP relies on applying supervised learning techniques to a given labeled dataset and produces a set of rules (queries) that allows to detect complex events, which are triggered from the primitive events. iCEP would be a learning model containing various algorithms in the machine learning paradigm which would learn from the data provided and infer rules (queries).

Figure 2.4: Executing the win learner [2].

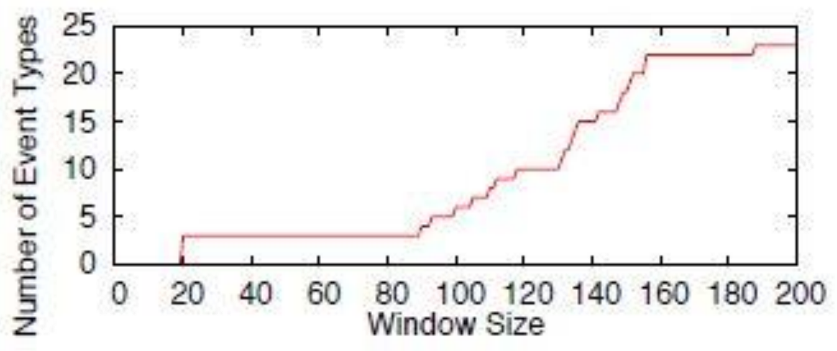
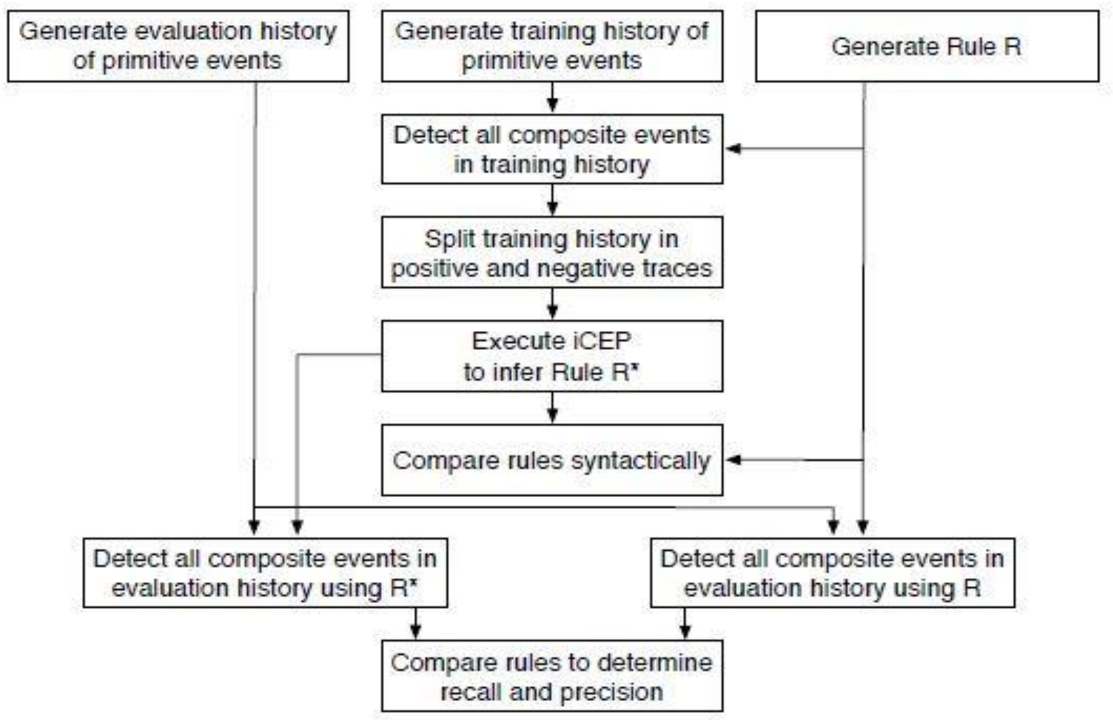


Figure 2.4 illustrates the iCEP implementation in the absence of external hints from domain experts. When iCEP does not have any clue regarding the possible events, attributes or the window size, iCEP address this dependency by using an iterative approach, which solves the two learning problems at once. In particular, iCEP implementation progressively increase the window size (*Ws*) and, for each considered size *Ws*, we execute the Ev Learner assuming such a window *Ws* as the correct one. In doing so, it is noticed that initially the size of events detected monotonically increases with *Ws* (as more events enter the window, more event types are detected as relevant), but this behaviour has an end. At a certain point this growth stops and the size of S

stabilizes in a plateau. In practice, this happens when *Ws* reaches the value of the window to learn.

Following diagrammatic representation visualizes the evaluation of the iCEP framework.



Generate evaluation history of primitive events
Generate training history of primitive events
Generate Rule R
Detect all composite events in training history
Split training history in positive and negative traces
Execute iCEP to infer Rule R*
Compare rules syntactically
Detect all composite events in evaluation history using R*
Detect all composite events in evaluation history using R
Compare rules to determine recall and precision

Figure 2.5: Evaluation architecture - iCEP [2].

As shown in Figure 2.5, there are two evaluation goals which has been evaluated with respect to iCEP.

1) Quantitatively determining the ability of an automatically generated rule to correctly identify composite events;
2) Evaluating how valuable are the indications provided by iCEP.

In terms of evaluating the accuracy of the iCEP framework, a rule known as R will be defined which would perfectly represent the domain of interest, and rule R is used to detect all composite events in the training history. Afterwards, the training history (including primitive and composite events) is split to generate an (almost equal) number of positive and negative traces of events. These traces will be the input to iCEP, which uses them to infer a rule R∗. To quantitatively measure the performance of iCEP following goal (a) above, we generate a new evaluation history of primitive events, and using both R and R∗ to detect composite events over it. This allows us to measure and recall our algorithm, which is the fraction of composite events captured by R that have been also captured by R∗ and the precision, which is the fraction of composite events captured by R∗ that actually occurred, i.e., that were also captured by R. In terms of evaluating subjectively how capable iCEP at determining "correct" rules along the lines of goal (b) above. To do so, we compare rules R and R∗ syntactically, to determine in which aspects they differ [1].

2.2.3 CEP2U and CER Frameworks

CEP2U [12] focuses on the following two possible sources of uncertainty:

- Uncertainty in events: The uncertainty deriving from an incorrect observation of the phenomena under analysis. This means to admit that the notifications entering the CEP engine can be characterized by a certain degree of uncertainty.
- Uncertainty in rules: The uncertainty deriving from incomplete or erroneous assumptions about the environment in which the system operates. This means to admit that the CEP engine has only a partial knowledge about the system under observation, and consequently the CEP rules cannot consider all the factors that may cause the composite events they are in charge of detecting.

CEP2U models uncertainty in events using the theory of probability, while it exploits Bayesian Networks (BNs) to model uncertainty in rules. In particular, it extends the model of events to include probabilistic data into event notifications, while it automatically builds a BN for each TESLA rule deployed in the system. Domain experts are expected to extend such BNs to capture a priori knowledge about those aspects of the environment that cannot be directly observed by sources.

Furthermore, in dealing with uncertainty regarding CEP, many of the CER engines employ finite automata, either Deterministic (DFA) or Nondeterministic (NFA), as well as logic based approaches are preferred [12].

2.2.4 User oriented rule management for event-based applications

Event-pattern rules are the foundation of CEP applications. A research has proposed a rule-management framework [7] for event-based systems. They have only proposed this solution for the Business domain. When it comes to CEP for Business logics, business users depend on technical experts to generate the relevant rules and apply them on the CEP engine. Figure 2.6 shows the different between the existing systems and the proposed solution. As shown in (b) a Technical Expert will prepare a business logic and when Business User needs the help of the system that person does not have to go through the Technical Expert again and again. While this reduces the workload, it works well only in the business domain. Because there are many more use cases other than the business domain, applicability of the proposed system is limited.

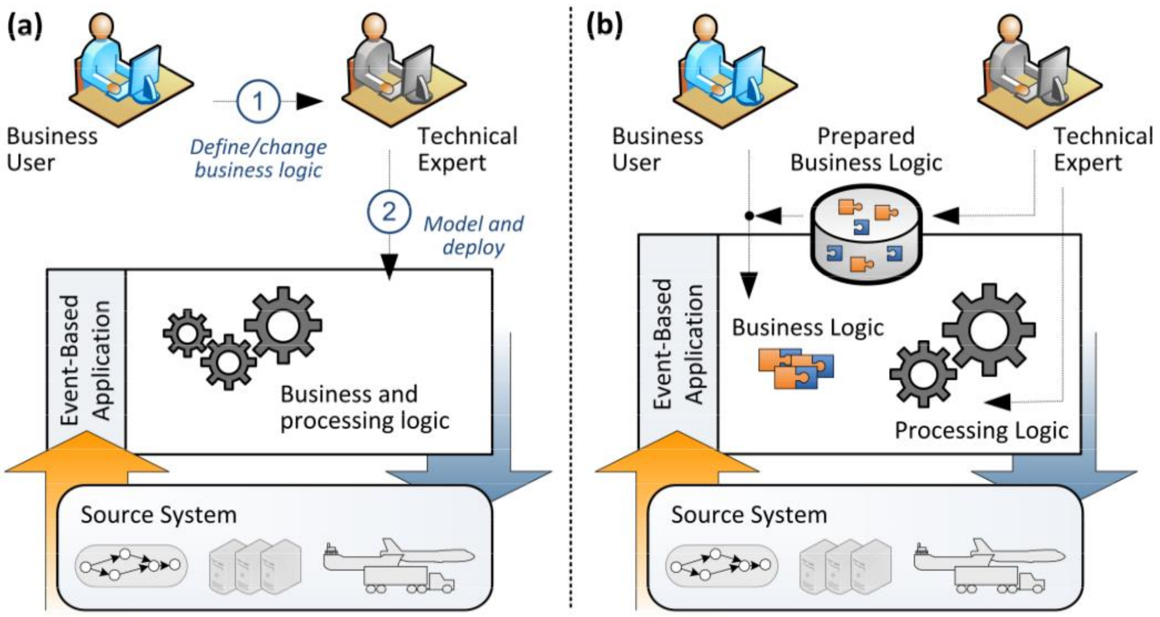


Figure 2.6: Rule-management workflows in existing systems (a) vs the proposed approach (b) [7].

2.3 Query Optimization

2.3.1 Prediction correction paradigm

In many active systems, rules may change over time due to the dynamic nature of the domain. Such changes complicate the specification task even further, as the expert must constantly update the rules. This problem was covered in several researches and one research was about updating the rules over time. In [9] authors focus on two main repetitive stages as Rule/Parameter prediction and correction.

The prediction correction paradigm is illustrated in Figure 2.7. The system utilizes any knowledge regarding how the rule parameters change over time, together with the events materialized by the inference algorithm to "predict" (or update) rule parameter values. The latter stage uses expert feedback regarding the actual occurrence of predicted events and the recently materialized events to update rule parameters for the next prediction stage.

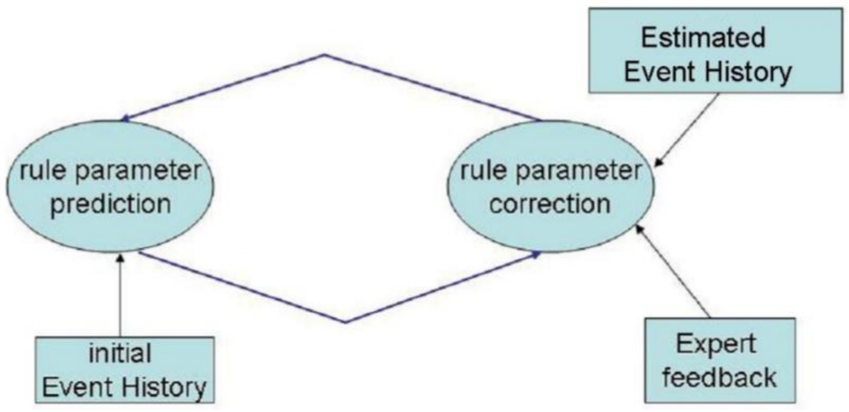


Figure 2.7: Prediction correction paradigm architecture [9].

Key contributions of this work include the following:

- Description of a framework for automating the task of specifying CEP rules, combining knowledge possessed by domain experts with intelligent techniques for specification of rule parameters (details that are hard for experts to provide).

- Description of a simple yet powerful model for rule parameter determination and tuning, taking into account any pre-existing knowledge regarding the updates of parameters over time, with indirect expert feedback.
- Provision of an algorithm based on Discrete Kalman Filters [13] to determine and tune the parameter values.

2.3.2 Iterative event pattern recommendation

Not only CEP rules, CEP patterns may also change over time due to the dynamic nature of the domain. So domain experts must update the patterns constantly. To overcome this, some have come up with a solution which consists of Recommendation Based Pattern Generation [10]. This research paper targets a specific domain which is Ambient Assisted Living domain. This domain serves as an integration as well as the evaluation platform. In order to speed up the pattern generation phase and help the telecare solution and care providers, they believe that some kind of pattern recommendation based on user input and existing patterns could be helpful. Authors made the following contributions:

- An approach for supporting the domain expert in designing new patterns and identifying missing ones
- Implementation of the approach for an use case example
- Evaluation results showing the importance of pattern recommendation during the pattern generation process

2.3.3 Distributed architecture for event-based systems

When it comes to CEP, optimization is a major requirement and there has been so many researches to optimize event-based systems. A research has been done targeting distributed systems and some architectures to improve optimization [15] have been suggested. According to them the following architectures can be used:

- Event-Driven Service Oriented Architecture

  The event-driven SOA is an extension of the SOA re with event processing capabilities. Services are entities that encapsulate business functionalities, offered via described interfaces that are published, discovered and used by clients. Events introduce a different interaction model in which event channels allow consumers to subscribe for specific events, and receive them when such events are published by producers. This mechanism is adopted in open standards (e.g., CORBA), and in products or platforms (such as .NET, WebSphere Business Events, Oracle CEP application server, and others) with the aim of simplifying the design of complex interactions and supporting interoperability.

- Grid Architecture

  Event processing is useful in Data Grids, which allow users to access and process large amounts of diverse data (files, databases, video streams, sensor streams, and so forth) stored in distributed repositories. Data Grids include services and infrastructure made available to user applications for executing different operations such as data discovery, access, transfer, analysis, visualization, transformation, and others.

- Peer-to-peer(P2P) Architecture

  P2P systems are capable of adapting to failures and dynamic populations of nodes while maintaining acceptable performance. P2P systems are used to support application services for communication and collaboration, distributed computation, content distribution, etc., and middleware services like routing and location, anonymity, and privacy.

- Agent Architecture

  Software agents react in response to other agents and to environment changes, and can act independently (are autonomic). In addition, agents initiate actions that affect the environment (are pro-active), are flexible (able to learn) and cooperate with other agents in multi-agent systems.

2.3.4 Processing of uncertain events in a rule-based systems

There is a growing need for systems that react automatically to events. While some events are generated externally and deliver data across distributed systems, others need to be derived by the system itself based on available information. A research has presented a mechanism to construct the probability space that captures the semantics and defines the probabilities of possible worlds using an abstraction based on a

Bayesian network [19]. Solution is to generate the composite events by the system itself. This solution faces the following two major challenges:

- Calculate event probabilities while taking into account various types of uncertainty is not trivial.
- Timely response to events under a heavy load of incoming events from various sources.

Authors have come up with a new sampling algorithm for efficient approximation of new event derivation, enabling a quick computation of probabilities of set of rules, rather than a Bayesian network. They have used the domain of Syndromic Surveillance System (Bioterrorist attack) to validate their solution and have contributed to the CEP domain by

- Describing a simple yet powerful generic model for representing the derivation of new events under uncertainty
- Extending the notion of selectability, which exists also in the context of deterministic event derivation to handle efficiently the derivation of uncertain events. Selectability filters events that are irrelevant to derivation by some rules.
- Proposing an algorithms for calculating selectability enable significant computational improvements by ensuring that rules are not applied to events which are irrelevant to new event derivation.
- Developing a Bayesian network representation to derive new events given the arrival of an uncertain event and to compute its probability
- Developing a sampling algorithm for efficient approximation of new event derivation enabling a quick computation of probabilities of a set of events by sampling over the set of rules, rather than from a Bayesian network
- Demonstrating the scalability and accuracy of the sampling algorithm.

2.4 Visualization tools

2.4.1 SPEEDD Framework

Scalable Proactive Event-Driven Decision-making (SPEEDD) Framework [17] focuses on proactive event driven computing which support autonomous or semi-autonomous decision-making, including a body of tools. This is used to exploit the forecast models and state predictions as a basis for decision-making. The visualization component (dashboard) supports the human interpretation of decisions made in runtime. It facilitates decision making process for business users by providing easily comprehensible visualization of detected or forecasted situations along with output of the automatic decision making component.

2.4.2 Visualization Charts

In order to implement visualization of our research application, we searched about several APIs and libraries such as Google charts, ChartJS and Data-Driven Documents (D3) library. ChartJS provides useful charts to draw graphs, but in our scenario we need to find a chart which can be customize for the user on the web browser. In this case, Google Charts API was not a good solution since it does not support in build customizable charts.

D3 Library is a JavaScript Library which provides dynamic and interactive visualizations in web browsers, and it is more customizable than Google charts [30]. In D3 graphs, user can select column values by drawing a rectangle. This helps to get the range of column values, but it mostly rely on users input, which is not so good for our scenario. If user select a wrong region of values, the accuracy of the final output query will be changed. This can leads to many false positive or false negatives.

ChartJS is the most suitable API for our implementation because it is easy to implement and customize. ChartJS also provide interactive visualization like above mentioned libraries.

2.5 Pattern Mining Techniques

2.5.1 Event sequence generation

Using an Event Cloud, we can generate Event sequences using data mining techniques. PrefixSpan [22] shown in Figure 2.8 is a well suited algorithm as it generates a tree structure and by traversing through it we can generate the event sequences which can be assumed as a composite or a complex event. Furthermore, sequence prediction is another area where events are predicted by generating the sequences of events so that it could predict the next event in the sequence. These type of researches have been carried out earlier but our aim is not only this but also to consider red box of our design as many researches have not been done in that scope. Figure 2.8 shows the tree corresponding to PrefixSpan algorithm.

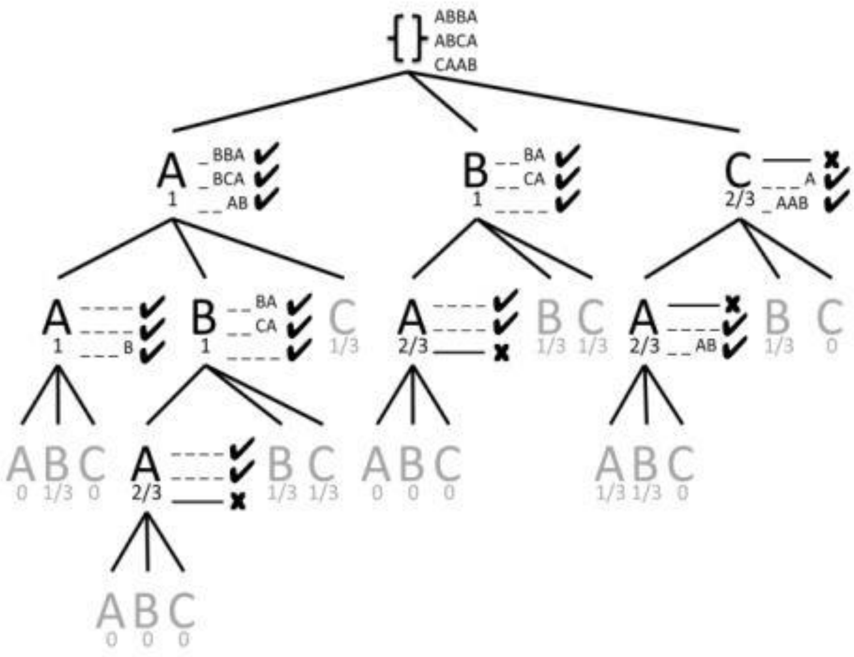


Figure 2.8: Prefixspan algorithm [22].

2.5.2 Hidden Markov Model and Noise Hidden Markov Model

Hidden Markov models (HMM) [11] can automatically infer complex event patterns, but if there is a lot of noise, general HMM are insufficient to detect patterns. Noise Hidden Markov Model which is an extension of hidden Markov models that particularly addresses the problem of only sparsely occurring, significant events that are interspersed with a lot of noise.

Hidden Markov Model (HMM) is a statistical model which is modeled using the Markov model with visible (observed) states and hidden states. An HMM can be represented as the simplest dynamic Bayesian network. It can addresses the following three main problems [11]:

- Evaluation Problem - If we are given a sequence of visible states V, What is the probability that the given V will be generated by given model H.
- Decoding Problem - What is the best state sequence for given model H.
- Learning Problem - How to calculate optimal model parameters for H that maximize total production probability p(O|H)

In this context, Noise HMM has been used to learn event detection rules. Figure 2.9 illustrates the method to detect the ABC pattern, but there are so many unwanted paths the system can follow, which means that from the initialization point system it can follow other paths instead of following ABC paths. These events that are not in the target event are known as Noise events.

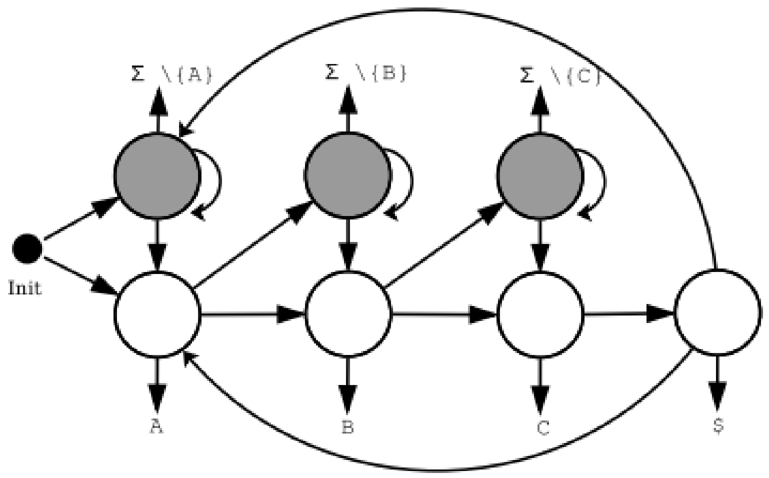


Figure 2.9: Hidden Markov Model for pattern ABC [11].

Noise HMM is similar to the conventional HMM. Since noise events do not show any impact on target function, the probabilities to noise events from target events will be sets to zero and the existing HMM algorithms have been changed to adapt for noise

HMM as in Figure 2.10. This method optimizes the event detection, but the method limits only for given target event. If we do not know the exact target event that we want to achieve, this is not the solution.

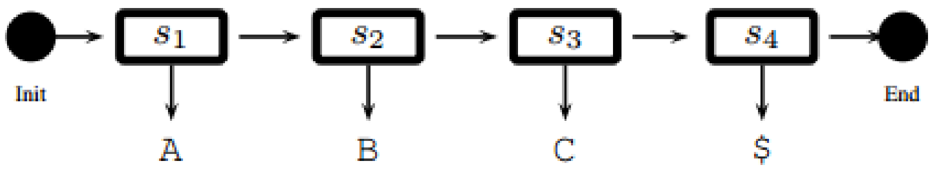


Figure 2.10: Noise Hidden Markov Model [11].

2.5.3 Predictive complex event processing

Predictive analytics can be used with CEP to prevent events (such as credit card fraud) proactively. There is a proposed conceptual framework obtained by merging the two domains [20] which is demonstrated in a proof–of–concept experiment. For the prediction, predictive analytics applies several statistical and data mining techniques, for example clustering, classification, regression and so on. By applying these techniques, predictive analytics builds predictive models which represents certain circumstances between available features or predictors related to the event. Predictive analytics face problems such as how to define predictors and how to calculate them, how to define the event, and so on. Predictive analytics deals with every kind of prediction, while CEP deals with detecting complex events occurring in real time.

2.6 Unsupervised Clustering Techniques

2.6.1 DBSCAN Algorithm

The DBSCAN algorithm [32] performs cluster identification in large spatial datasets by looking at the local density of database elements, using only one input parameter. The DBSCAN can also determine what information should be classified as noise or outliers. In spite of this, its working process is quick and scales very well with the size of the database which happens almost linearly.

In simple terms to find a cluster, DBSCAN starts with an arbitrary point *p* and retrieves all points density-reachable from *p* with respect to the provided maximum radius

(*Eps/ε*) and minimum number of points (*MinPts*). If *p* is a core point, this procedure yields a cluster with respect to *ε*and MinPts. If *p* is a border point then no points are density-reachable from *p* and DBSCAN visits the next point of the database.

2.6.2 OPTICS Algorithm

OPTICS algorithm [31] is an extended version of DBSCAN in which it works very similar to DBSCAN algorithm for an infinite number of distance parameters maximum radius (ε_i) which are smaller than a *generating distance* ε (i.e. $0 \leq \varepsilon_i \leq \varepsilon$). The only difference is that it does not assign cluster memberships. Instead, it stores the order in which the objects are processed and the parameterized information would be used by the algorithm to assign cluster memberships. Following defines and explanations of basic definitions with respect to the OPTICS algorithm.

Definition 1: Directly density-reachable

Object *p* is directly density-reachable from object *q* wrt. ε and *MinPts* in a set of objects *D* if

1. $p \in N_\varepsilon(q)$ ($N_\varepsilon(q)$ is the subset of *D* contained in the ε-neighborhood of *q*.)
2. Card($N_\varepsilon(q)$) ≥ *MinPts* (Card(*N*) denotes the cardinality of the set *N*)

The condition Card($N_\varepsilon(q)$) ≥ *MinPts* is called the *core object condition*. If this condition holds for an object *p*, then we call *p* a *core object*. Only from core objects, other objects can be directly density-reachable.

Definition 2: Density-reachable

An object *p* is density-reachable from an object *q* wrt. ε and *MinPts* in the set of objects *D* if there is a chain of objects $p_1, ..., p_n$, $p_1 = q$, $p_n = p$ such that $p_i \in D$ and p_{i+1} is directly density-reachable from p_i wrt. ε and *MinPts*.

Density-reachability is the transitive hull of direct density reachability. This relation is not symmetric in general. Only core objects can be mutually density-reachable.

Definition 3: Density-connected

Object *p* is density-connected to object *q* wrt. ε and *MinPts* in the set of objects *D* if there is an object $o \in D$ such that both *p* and *q* are density-reachable from *o* wrt. ε and *MinPts* in *D*.

Definition 4: Cluster and noise

Let *D* be a set of objects. A cluster *C* wrt. ε and *MinPts* in *D* is a non-empty subset of *D* satisfying the following conditions:

- Maximality: $\forall p,q \in D$: if $p \in C$ and *q* is density-reachable from *p* wrt. ε and *MinPts*, then also $q \in C$.
- Connectivity: $\forall p,q \in C$: *p* is density-connected to *q* wrt. ε and *MinPts* in *D*.

Every object not contained in any cluster is noise.

Definition 5: Core-distance of an object *p*

Let *p* be an object from a database *D*, let ε be a distance value, let $N_\varepsilon(p)$ be the ε-neighborhood of *p*, let *MinPts* be a natural number and let MinPts-distance(*p*) be the distance from *p* to its *MinPts*' neighbor. Then, the core-distance of *p* is defined as,

$$\text{Core-distance}_{\varepsilon,\text{MinPts}}(p) = \begin{cases} \boldsymbol{undefined}\ if\ Card\ (N\varepsilon(p)) < MinPts \\ \boldsymbol{MinPts}-distance\ (p)\ if\ \ Card\ (N\varepsilon(p))\ \geq MinPts \end{cases}$$

Definition 6: Reachability-distance object *p* w.r.t. object *o*

Let *p* and *o* be objects from a database *D*, let $N_\varepsilon(o)$ be the ε-neighborhood of *o*, and let *MinPts* be a natural number. Then, the reachability-distance of *p* with respect to *o* is defined as

$$\text{reachability-distance}_{\varepsilon,\text{MinPts}(p,o)} = \begin{cases} Undefined\ if\ |\ N\varepsilon\ (o)| < MinPts \\ max\ core-distance\ (o),distance\ (\ o,p\ )\ ,otherwise \end{cases}$$

2.6.3 Single Linkage Clustering

This is an agglomerative clustering technique where we start from a single item and merge them according to a mechanism [24]. Given a set of N items to be clustered, and a N*N distance (or similarity) matrix, the basic process of hierarchical clustering could be explained as below:

- Start by assigning each item to a cluster, so that if you have N items, you now have N clusters, each containing just one item. Let the distances (similarities) between the clusters the same as the distances (similarities) between the items they contain.
- Find the closest (most similar) pair of clusters and merge them into a single cluster, so that now you have one cluster less.
- Compute distances (similarities) between the new cluster and each of the old clusters.
- Repeat steps 2 and 3 until all items are clustered into a single cluster of size N. (*)

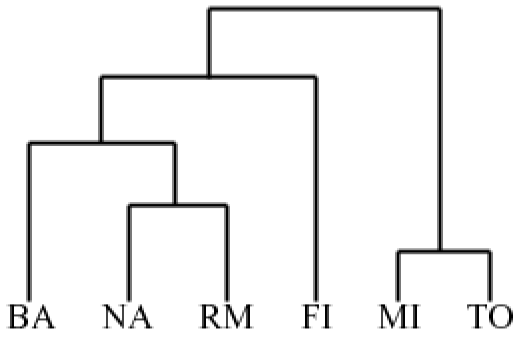


Figure 2.11: Hierarchically clustered city names using Single Linkage Clustering [24].

In terms of the complexity the algorithm is not scaling well. time complexity of at least *O(n^2)*, where n is the number of total objects and space complexity also *O(n^2)* as we form a matrix to cluster data. This happens to be a major limitation of almost all the hierarchical clustering techniques compared to density based clustering techniques [33].

Chapter 3

METHODOLOGY

In terms of auto generating relevant queries for CEP, we propose a technique based on shapelets, parallel coordinates, and information gain. Section 3.1 introduces shapelets, parallel coordinates, and problem formulation. High-level design of the proposed solution is presented in Section 3.2. Detailed design is presented in Section 3.3.

3.1 Preliminaries

We first define relevant terms and then define shapelets and parallel coordinates as applicable to the domain of CEP query generation. The research problem is then formulated.

3.1.1 Definitions

Time-Series - A time-series $T = t_1, ..., t_m$ is an ordered set of m real-valued variables.

Multivariate Time-Series — A multivariate time-series $T = t_1, ..., t_m$ is a sequence of m vectors, where $t_i = (t_{i,1}, ..., t_{i,s}) \in \Re^s$ with s attributes/variables.

Sub-sequence (S_p^t) — Given a time-series T, a subsequence S_p^t of T is a sampling of length $l \leq m$ of contiguous positions from T starting at time p, i.e., $S_p^t = t_p, t_{p+1}..., t_{p+l-1}$, for $1 \leq p \leq m - l + 1$.

Set of All Sub-sequences (ST_l) — Set of all possible subsequences S_p^t that can be extracted by sliding a window of length l across T is $ST_l = \{\text{all } S_p^t \text{ of } T, \text{ for } 1 \leq p \leq m-l+1\}$.

Sub-sequence Distance — Given T and S_p^t SubsequenceDist(T,S_p^t) is the minimum distance between p contiguous positions obtained by sliding S_p^t across T. We use Euclidean distance as the distance function.

Entropy — Consider a time series dataset **D** consisting of two classes, A and B. Let proportions of objects belonging to class A and B be $p(A)$ and $p(B)$, respectively. Then the entropy of **D** is:

$$I(\mathbf{D}) = -p(A)log(p(A)) - p(B)log(p(B)) \quad (1)$$

Information Gain (Gain) — Given a certain split strategy *sp* which divides **D** into two subsets $\mathbf{D}_1$ and $\mathbf{D}_2$, let the entropy before and after splitting be $I(\mathbf{D})$ and $\hat{I}(\mathbf{D})$, respectively. Then the information gain for split *sp* is:

$$\text{Gain}(sp) = I(\mathbf{D}) - \hat{I}(\mathbf{D})$$

$$\text{Gain}(sp) = I(\mathbf{D}) - \left(p(\mathbf{D}_1)\, I(\mathbf{D}_1) + p(\mathbf{D}_2)\, I(\mathbf{D}_2) \right) \quad (2)$$

Optimal Split Point (OSP) — Consider a time-series dataset **D** with two classes *A* and *B*. For a given S_p^t, we choose some distance threshold d_{th} and split **D** into $\mathbf{D}_1$ and $\mathbf{D}_2$, s.t. for every time series object $T_{1,i}$ in $\mathbf{D}_1$, SubsequenceDist($T_{1,i}$, S_p^t) $\leq d_{th}$ and for every $T_{2,i}$ in $\mathbf{D}_2$, SubsequenceDist($T_{2,i}$, S_p^t) $\geq d_{th}$. An Optimal Split Point (OSP) is a distance threshold that Gain(S_p^t, $d_{OSP\ (D,St\ p)}$) $\geq$ Gain(S_p^t ,d_{th}) for any other distance threshold *d-th*.

3.1.2 Shapelets

Shapelets can be defined as time-series subsequences as seen in Figure 3.1. Shapelets can be of varying lengths, and many sub-sequences can be extracted by sliding a window of given length *l*. In shapelet-based classification, the objective is to identify a shapelet that is in some sense maximally representative of a class.

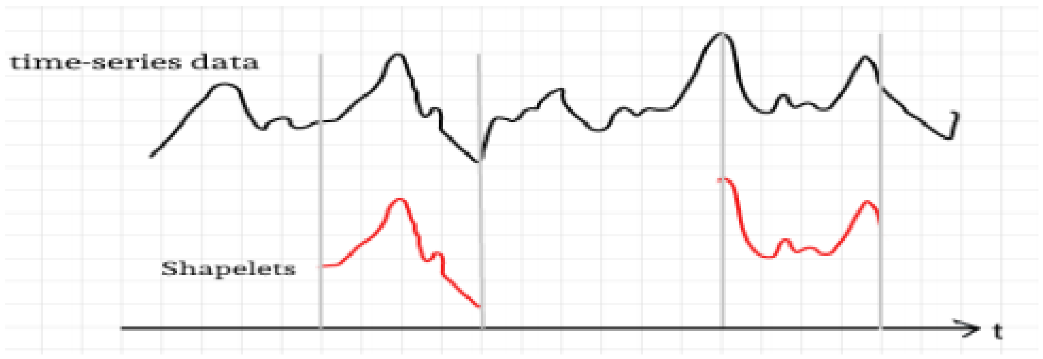


Figure 3.1: Time Series Shapelets.[5]

3.1.3 Parallel Coordinates

Parallel coordinates are widely used to visualize multivariate data [18]. Figure 3.2 illustrates the parallel coordinates representation of the room occupancy dataset obtained from the UCI Machine Learning repository [25], which consists of six attributes. The dataset with *n* dimensions (i.e., attributes) is mapped to a set of points on *n* parallel lines, where each line represents an instance of data. These points are then connected using a line. A separate line is drawn for each instance of data (i.e., each row). For example, in Figure 3.2 part of the dataset selected based on the “Light” attribute is shown in black, and rest of the dataset is visualized in grey. When scaling these coordinate systems, it is recommended to use normalized data to prevent bias to certain dimensions.

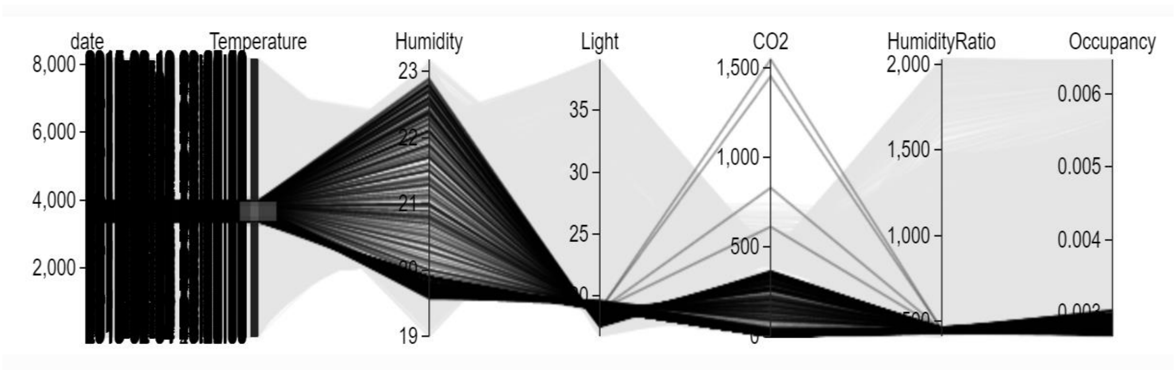


Figure 3.2: Parallel coordinates - Occupancy Detection Dataset.

3.1.4 Problem Formulation

In contrast to relational database systems that issue dynamic queries on stored and indexed data, CEP filters incoming streams of data through pre-written queries to detect events of interest. Hence, relevant queries need to be provided to the CEP engine apriori. We address the problem of needing domain knowledge to write a meaningful CEP queries through automation. Though a couple of related work attempt to automate CEP query generation, they support only univariate time series data [3].

We propose a solution which can be used to generate CEP queries for multivariate time series without requiring expert domain knowledge. In proposing the solution we assume that each instance in the obtained dataset is annotated according to the respective event. Our goal is to construct a filter query per event, which contains the most relevant attributes, their range of values, and the event detection time frame. An example CEP filter query may look like the following:

$$\textbf{SELECT}\ \{*\}\ \textbf{WHERE}\ \{attr1 \geq \text{a and } attr2 < \text{b}\}\ \textbf{WITHIN}\ \{t_1 \leq \text{time} \leq t_2\}$$

3.2 High-Level Design

Figure 3.3 illustrates the proposed architecture which consists of four main components. The provided dataset first enters the data processor module. The data processor is effectively used to transform an unlabeled dataset to a labeled dataset. If the dataset is already labeled, meaning each time instance is accompanied with a specific event it belongs to, then the data processor will effectively not do any special task, rather it will simply pass the dataset to the shapelet generator module. If the provided dataset is unlabeled, then we calculate Euclidian distances among the time instances and obtain a distance matrix. This matrix is then processed through the OPTICS algorithm [31] to label each time instance corresponding to a particular event. Labelled dataset is then moved to the query generator module, which maps the dataset into a set of parallel coordinates. Shapelets are then extracted from the parallel coordinate representation. After generating the shapelets, it runs through a filtration process to identify the most important shapelets with respect to each event. The extracted important shapelets are then used to generate the CEP queries. If the user happens to be a domain expert, prior to building the query, the visualization module is been used to visualize the most important shapelets to the user and obtain his/her insights and improve and customize the auto generated CEP query. Next, we discuss each of the components in detail.

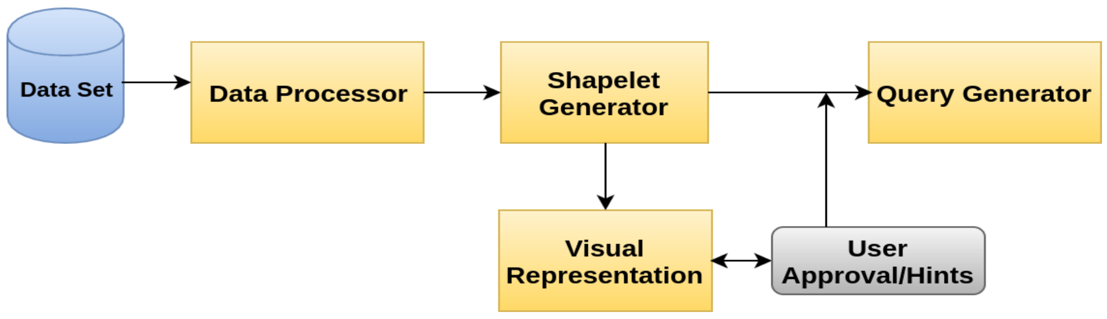


Figure 3.3: Proposed system architecture.

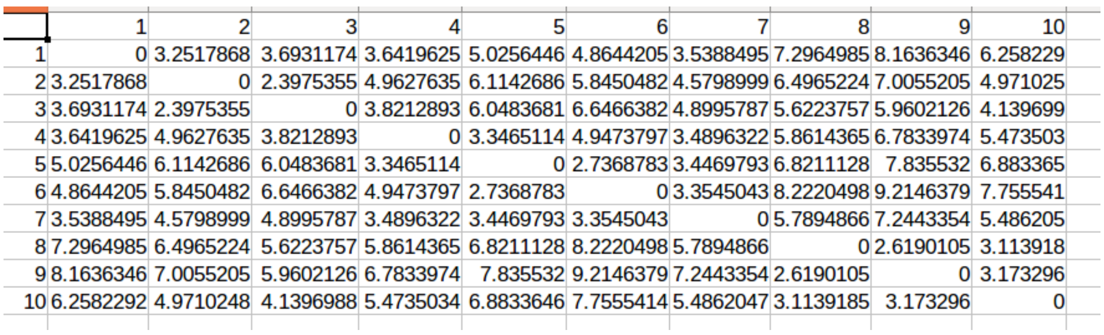
3.2.1 Data Processor

First, the system identifies the dataset and convert that dataset into a generic format before any further proceedings. The input dataset could be provided in any format (e.g., .txt, .xml, and .csv). Data Processor module converts the data to a generic format before any further processing. This enables us to provide a solution that is applicable for datasets from multiple domains, as well as supports both time-series datasets and none time-series datasets.

We assume that each instance in the given dataset corresponds to an occurrence of a specific event, i.e., each data instance is classified/labeled with the corresponding event. The module then counts the number of events of each type, and their proportions with respect to the total number of events in the entire dataset.

If the given dataset is not pre-annotated we propose a clustering-based technique to annotate the dataset. Annotating each data point with the corresponding event is important to calculate the information gain with respect to each shapelet, which is required to filter out the generated shapelets to identify the most important shapelets.

The data processor then clusters the dataset, if the dataset provided is not already labelled. Algorithm 3.1 initially calculates Euclidian distances between each pair of time instances. The resulting distance matrix is then clustered using OPTICS algorithm [31] resulting an annotation for each time instance. In doing so, the dataset in common data format needs to be clustered in a manner in which each time instance is classified with respect to an identified event. The output of the clustering technique would modify the dataset by appending another column with numerical values to denote the cluster number which indicate the event type that each column belongs to. This information then will be effectively used in the information gain calculation step inside the query generator module.



	1	2	3	4	5	6	7	8	9	10
1	0	3.2517868	3.6931174	3.6419625	5.0256446	4.8644205	3.5388495	7.2964985	8.1636346	6.258229
2	3.2517868	0	2.3975355	4.9627635	6.1142686	5.8450482	4.5798999	6.4965224	7.0055205	4.971025
3	3.6931174	2.3975355	0	3.8212893	6.0483681	6.6466382	4.8995787	5.6223757	5.9602126	4.139699
4	3.6419625	4.9627635	3.8212893	0	3.3465114	4.9473797	3.4896322	5.8614365	6.7833974	5.473503
5	5.0256446	6.1142686	6.0483681	3.3465114	0	2.7368783	3.4469793	6.8211128	7.835532	6.883365
6	4.8644205	5.8450482	6.6466382	4.9473797	2.7368783	0	3.3545043	8.2220498	9.2146379	7.755541
7	3.5388495	4.5798999	4.8995787	3.4896322	3.4469793	3.3545043	0	5.7894866	7.2443354	5.486205
8	7.2964985	6.4965224	5.6223757	5.8614365	6.8211128	8.2220498	5.7894866	0	2.6190105	3.113918
9	8.1636346	7.0055205	5.9602126	6.7833974	7.835532	9.2146379	7.2443354	2.6190105	0	3.173296
10	6.2582292	4.9710248	4.1396988	5.4735034	6.8833646	7.7555414	5.4862047	3.1139185	3.173296	0

Figure 3.4: Distance matrix.

The implemented clustering technique is domain independent and is based on the numerical values within the dataset. We initially extract the numerical values out of the obtained dataset and then normalize those values. We then calculate the Euclidean distances among the data points of each time instance. The calculation happens as such a particular time instance would be selected and would be compared against all the other time instances one at a time providing Euclidean distances for each obtained time instance pair which will produce a distance matrix which is similar to Figure 3.4. Then the obtained distance matrix will be fed into the OPTICS algorithm, which clusters each row separately. The reason to use this technique is, in terms of detecting events, we look for different pattern instances within the obtained time instances throughout the dataset. Calculation of the distance of corresponding data points with respect to each time instances is one of the best methods to compare and identify the differences in patterns among the time instances.

The most important factor is our clustering implementation is compatible to work without any user input apart from providing the dataset meaning any unannotated dataset could even be processed via our implementation.

The reason to have a distance matrix is because shapelets are distinguished according to the distances of each rows. Thus, having a distance matrix to distinguish the dataset is more appropriate. Now each row is clustered with OPTICS algorithm, as it is an unsupervised, density-based clustering technique which is more suitable for our approach as shapelets are extracted according to their similarity of distances and densities.

Then in the next iteration the base time instance will become the next time instance in the dataset and the above process will continue as explained. At the end of each iteration the obtained Euclidean distances per each time instance with respect to selected base time instance, will be clustered using the OPTICS algorithm. The output of the OPTICS algorithms clustering process would provide each time instance the cluster that it belongs to which would update in a results array in which increments a counter with respect to the relevant cluster and this will repeatedly happen with the base time instance changing iteratively. After scanning through the entire dataset we obtain the results array and scan through it and assign each time instance to the cluster which has the highest count in terms of it belongingness. This value will be appended to the dataset in which each time instance would have its corresponding event type.

Line 2 of the pseudo code representation of the clustering algorithm (Algorithm 3.1) normalize the data and assign it to *normData* array. Then the for loop starting from line 5 starts to scan through each element in *normData* and for each of the element of this array we calculate Euclidean distance with all the other elements. The number of times line 8 is executed equals to the array size. This allows us to obtain a distance matrix. Afterwards, each of the rows in this distance matrix is processed through the OPTICS algorithm to cluster which contains one-dimensional clustering of the obtained distances. This is implemented in line 11 and 12. At the end, algorithm analyses the row-wise cluster distribution and assigns each row for the respective cluster which it happens to fall to most. The rest of the code is implemented such that *result* array (line 4) is updated by giving the annotation.

In terms of clustering the obtained Euclidean distances, we went through the implementations of popular unsupervised density based clustering techniques namely DBSCAN [32], OPTICS, and Single-Linkage Clustering [33] which is a hierarchical clustering technique. One of the main drawbacks in DBSCAN is we have to decide parameters globally. Deciding parameters globally is utmost important in which without it the hierarchical nature of densities could not be measured and in order to do decide parameters globally we need to have an idea of the data distribution within the dataset. Since from the beginning we intended to make the total implementation domain and user independent obtaining information on the data distribution within the dataset becomes infeasible and makes it even harder using DBSCAN. The reason because DBSCAN cannot always be used to cluster data with different densities. So if need to cluster data we need to know the densities of data so that we can give a suitable ε as a parameter.

For instance, within the DBSCAN implementation if a selected radius ‘r1’ is gives a cluster named C and another radius ‘r2’ which is greater than ‘r1’ gives a separate cluster named B, this would make C as a subset of B which limits the precision of the derived clusters. This happens with inappropriate global parameter setting. This issue of global parameter setting is overcome with OPTICS algorithm by iteratively developing clusters starting from a small neighbourhood radius.

Furthermore, hierarchical clustering techniques also do provide satisfactory results but with the limitation of high time and memory complexity compared to density based methods. So to go line with our objective of finding time instances of similar patterns which are dense around another time instance, hence it is required to cluster the obtained Euclidean distance values considering the density and in doing so we did use OPTICS algorithm which happens to be an extension of DBSCAN with overcoming DBSCAN algorithm’s limitations.

In terms of user interaction with our system, in which the user happens to be a domain expert that user could provide us with the additional information such as the number of events within the dataset and proportionate event distribution to increase the accuracy levels of the implementation. Conducting parameter tuning in the OPTICS algorithm also allows a user to increase the accuracy levels of the clustering implementation.

Algorithm 1 Cluster Data

```
procedure ClusterData(Data, $\epsilon$, $m$, $NumberofEvents$)
    $normData \leftarrow Normalize(\text{Data})$
    $distList \leftarrow list()$
    $results \leftarrow array(\text{Data}.rows, NumberofEvents)$
    for $row$ in $normData$ do
        $distListRow \leftarrow list()$
        for $row1$ in $normData$ do
            $distance \leftarrow Euclidean(row, row1)$
            $distListRow.append(distance)$
        end for
        $distList.append(distListRow)$
        $opticsInstance \leftarrow$ OPTICS($distListRow, \epsilon, m$)
        $opticsInstance.process()$
        $clusters \leftarrow opticsInstance.getClusters()$
        $noises \leftarrow opticsInstance.getNoise()$
        $numClust \leftarrow 1$
        for c in clusters do
            for value in c do
                if $NumberofEvents$ is 0 then
                    $temp \leftarrow numClust - 1$
                    $results[value][temp] \leftarrow results[value][temp] + 1$
                else
                    if $numClust \leq (NumberofEvents)$ then
                        $temp \leftarrow numClust - 1$
                        $results[value][temp] \leftarrow results[value][temp] + 1$
                    else
                        $temp \leftarrow NumberofEvents - 1$
                        $results[value][temp] \leftarrow results[value][temp] + 1$
                    end if
                end if
            end for$numClust + +$
        end for
    end for$return \leftarrow results$
end procedure
```

Algorithm 3.1: Algorithm to cluster data using OPTICS.

3.2.2 Shapelet Generator

This is the core module of the system which uses pattern mining. This module identifies the most appropriate shapelets to represent each event. First, the multivariate time series dataset is mapped to a set of parallel coordinates. Figure 3.5 is an exemplary representation of a multivariate time series with six attributes and five, time instances converted to parallel coordinates. Then all the shapelets are extracted from the parallel coordinates while varying the length l of the sliding window. Though the shape of the extracted shapelets depend on the order of the attributes, the final outcome of the solution is independent of the order. Length of an identified shapelet is bounded by number of attributes m in the time series (i.e., $1 \leq l \leq m$). Therefore, our technique produces a much lower number of shapelets compared to prior work, where m can be as large as the length of the time series. Moreover, it is not required to apply heuristics or expert knowledge to determine the optimum minimum and maximum length of shapelets. Therefore, our Shapelet Learner Algorithm is both computationally and memory efficient. Once all shapelets are extracted, the next step is to identify a subset of the shapelets that are representative of patterns in the parallel coordinates. For this, we use information gain to quantify the extent to which a selected shapelet is similar to a given line on parallel coordinates. For example, Figure 3.6 shows two shapelets, one with attributes 1 and 2 (shapelet S_1) and another with attributes 1, 2, and 3 (shapelet S_2). We slide both S_1 and S_2 across the line/row with $t = 5000$ and find the minimum distance between the shapelet and line. For example, S_1 has a relatively lower distance between the attributes 1-2 and 3-4, whereas S_2 has a relatively lower distance between attributes 1-3 and 4-6. This is estimated using the *SubsequenceDist*() function defined in Section 3.1.1. The same process is applied to all other time instances and shapelets. This results in a matrix of minimum distance values for each (shapelet, time instance) pair. We then find the Optimal Splitting Point (OSP) [21] for each row of minimum distance values, to find the maximum information gain for each shapelet. The shapelets are then ranked based on the descending order of its information gain. We then use Shapelet Merger Algorithm to group shapelets within the ranked list with respect to their information gain. Because the shapelets with similar information gains produce similar insights, groups created using Shapelet Merger Algorithm allows us to cluster the similar informative shapelets together. Finally, Important Shapelet Extraction Algorithm is used to identify the most suitable shapelets to represent each event type.

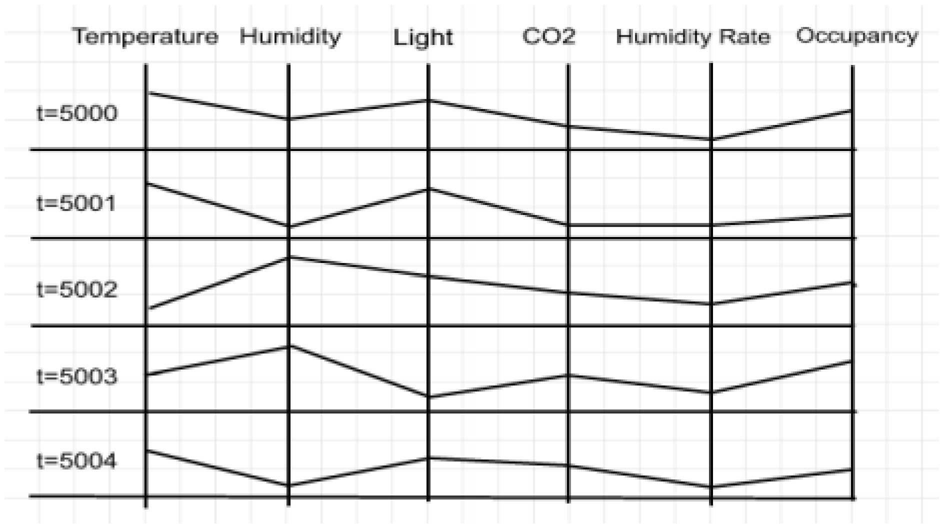


Figure 3.5: Multivariate time series mapped as parallel coordinates.

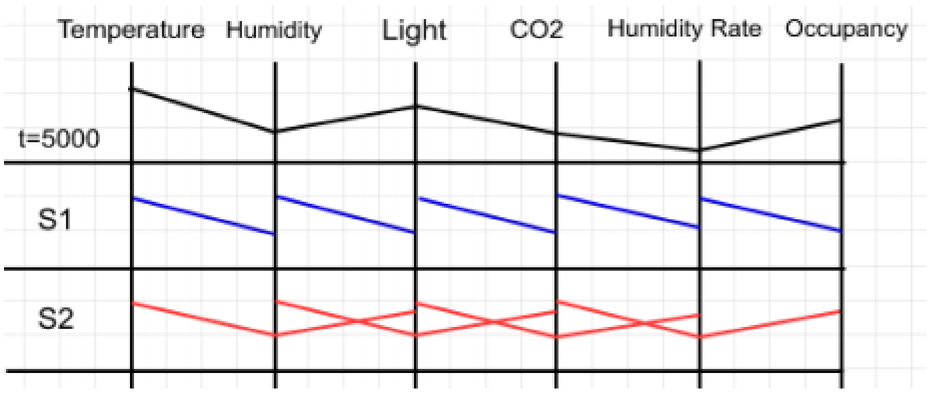


Figure 3.6: Shapelets slide across the time series.

3.2.3 Visual Representation

This module visualizes generated shapelets, optionally enabling users to select what shapelets to choose for query writing. While the system can auto generate queries without any user suggestions, this module facilitates and accepts user approval allowing the user to select the shapelets that user is interested in. User may also select a subset of the attributes and their range of values that he/she expects to use in the generated queries. Such user intervention reduces false positives and improves the performance of the CEP engine, as not every identified event may be of practical importance.

3.2.4 Query Generator

Given the chosen shapelets this module auto generates CEP queries based on the input provided by the shapelet generator module and incorporating any user provided hints. Here we generate one query per each event with the relevant query parameters generated by the system, or set of attributes and ranges approved by the user. The module identifies the most relevant attributes and their value ranges to be used in constructing the query along with the optimal time periods within which each event occurs. Optimal time periods are identified by analyzing the event distribution of the actual dataset and choosing the longest event detection time period with respect to each occurrence of an event. Using these data, the module generates filter queries for each and every event of the given dataset.

3.3 Detailed Architecture

Few and recent efforts that touched about Shapelets are discussed in [3], [21], [23]. We introduce a new approach to define Shapelets using parallel coordinates as an Object with four attributes $\hat{\boldsymbol{s}} = (\boldsymbol{g}, \boldsymbol{i}, \boldsymbol{a}, \boldsymbol{c})$, where **g** is the information gain which represents how much similar the data set for the shapelet, **i** is the series id which represents the row id of the data set, **a** is the starting column id and **c** is the content of data. Based on the above explanation our implementation with shapelets would be divided into two phases

- Extract all possible shapelets from a given data set.
- Identify important shapelets from the generated shapelets.

Before extracting shapelets from the given dataset, the dataset will be transformed into a parallel coordinates system. Figure 3.5 displays a visual representation of the obtained parallel coordinates which would be used to extract shapelets.

Our method builds upon two main phases which are shown in Figure 3.7.

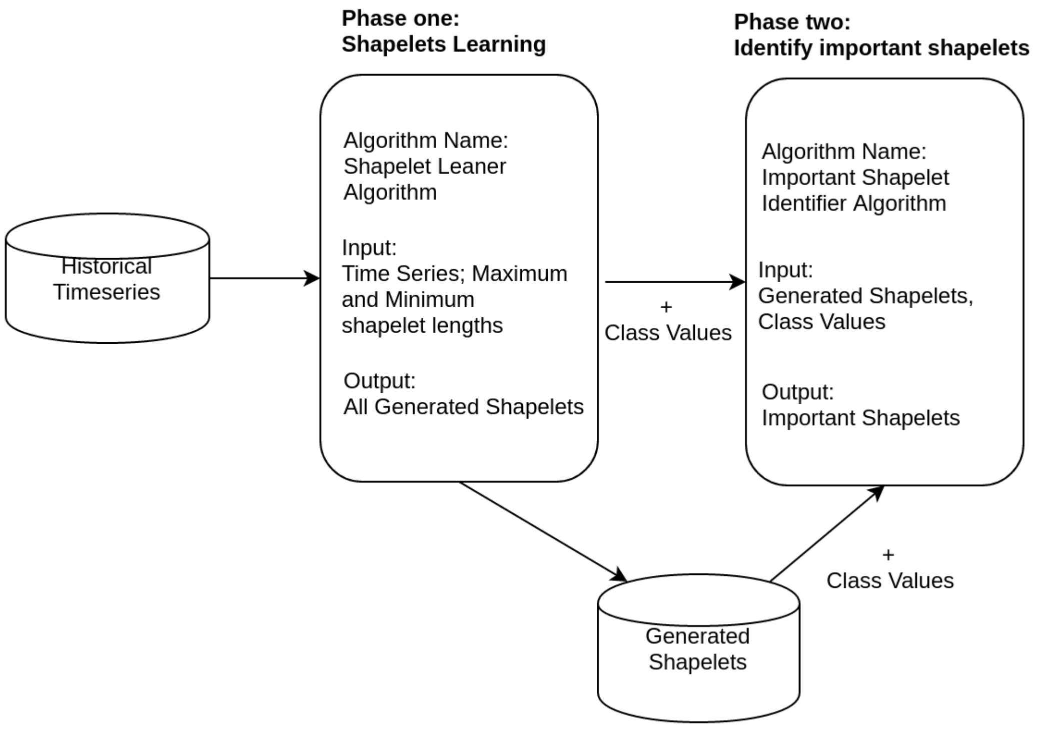

Phase one:
Shapelets Learning
Phase two:
Identify important shapelets
Historical Timeseries
Algorithm Name: Shapelet Leaner Algorithm
Input: Time Series; Maximum and Minimum shapelet lengths
Output: All Generated Shapelets
+ Class Values
Algorithm Name: Important Shapelet Identifier Algorithm
Input: Generated Shapelets, Class Values
Output: Important Shapelets
+ Class Values
Generated Shapelets

Figure 3.7: Architecture - Shapelet generator module.

3.3.1 Phase one: Shapelet Learner

The Shapelet Learner extracts all the shapelets from the obtained parallel coordinates. We set the default minimum length (*lmin*) of a shapelet as two, while the maximum (*lmax*) is set to the number of attributes m (i.e., $2 \leq l \leq m$). However, a user may override these values. Afterwards, Algorithm 2 of the Shapelet Generator module extracts all possible shapelets while varying the shapelet length. First, the shapelet list is initialized to store the extracted shapelets (line 2). Then shapelets are extracted by going through each row *r* in the Dataset **D**. The outer loop increments the length of a shapelet *l* up to *lmax*, while the inner loop increments start to scans through each *r*. The inner-most loop (line 13-16) extracts all attributes between *lmin* to *l* for a given starting point. Then we convert each shapelets content to standard normal using *zNorm*() function to prevent any biases to specific attributes. Moreover, in line 19 we also store the raw values of shapelets, as they are later required while generating queries. We also calculate and save the information gain of each shapelets using *infoGain()* function (line 20). First, the *SubsequenceDist*() function is used to find the minimum distance between the row and the shapelet by sliding the shapelet across the row, one attribute at a time (see Figure 3.6). By repeating the function, the minimum distance per each row is found and saved in an array. Then by sequentially splitting the array we calculate the information gain using Eq. 2. Finally, for each shapelet we get the maximum information gain and the corresponding split point, which would be the Optimum Splitting Point of the array. In line 21, each shapelet and its metadata are then added to the shapelets list, which is later returned by the algorithm.

Algorithm 2 Shapelet Learner Algorithm

```
 1: procedure ShapeletLearner($D, l_{\min}, l_{\max}$) ▷ Time series dataset D and
    shapelet length
 2:     $shapelets \leftarrow \{\}$
 3:     for each row $r$ in D do
 4:         $wholeCandidate \leftarrow r$
 5:         $l \leftarrow l_{\min}$
 6:         while $l \leftarrow l_{\max}$ do
 7:             $l++$
 8:             $start \leftarrow 0$
 9:             while $start \leftarrow r.length$ do
10:                 $start++$
11:                 $candidate \leftarrow \{\}$
12:                 $m \leftarrow start$
13:                 while $m<start + length$ do
14:                     $m++$
15:                     $candidate[m - start] \leftarrow wholeCandidate[m]$
16:                 end while
17:                 $finalCandidate \leftarrow newShapelet$
18:                 $finalCandidate$.setContent(zNorm($candidate$))
19:                 $finalCandidate$.setRawContent($candidate$)
20:                 $finalCandidate$.setInfoGain(infoGain($candidate$))
21:                 $shapelets$.add($finalCandidate$)
22:             end while
23:         end while
24:     end for
25:     return $shapelets$                 ▷ generated shapelets will be returned
26: end procedure
```

Algorithm 3.2: Shapelet learner algorithm.

All possible shapelets will be extracted from a given dataset. In addition to the Algorithm 3.2 the dataset will be standardized in to a normal distribution and based on that shapelets will be extracted. Extracted shapelets can be saved into a database or simply use as the input for the second phase.

3.3.2 Phase two Shapelet Extraction

All the extracted shapelets are first sorted according to their information gain. Then these shapelets are divided into a set of groups and then merged using Algorithm 3.3. Algorithm takes the set of shapelets *S* and number of shapelets per group (*groupsize*) as the input. *groupsize* is selected based on the cluster pruning technique in which we set the number of groups to the square root of the total number of identified shapelets. If desired, the user may also define the *groupsize*. Then in line 12 to 15 the grouped shapelets are updated by adding their series ID (i.e., row number), starting positions (i.e., starting attribute index), and class value (i.e., event type). Finally, the algorithm return all the merged shapelets (line 25).

Algorithm 3 Shapelet Merger Algorithm

```
 1: procedure SHAPELETMERGER($S, size$)        ▷ Shapelet Array S sorted
    according to information gains and size of the group
 2:     $mergedShapelets \leftarrow \{\}$
 3:     $count \leftarrow S.\textbf{size}()/size$
 4:     $values \leftarrow \{\{\}\}$
 5:     $currentRow \leftarrow \{\}$
 6:     while S.hasNext() do
 7:         $currentShapelet \leftarrow S.\textbf{next}()$
 8:         if count>0 then
 9:             $currentRow \leftarrow currentShapelet.\textbf{getRawContent}()$
10:             $rawSize \leftarrow currentRow.\textbf{size}() - 1$
11:             $classVal \leftarrow currentRow.\textbf{get}(rawSize)$
12:             $currentRow.\textbf{remove}(rawSize)$
13:             $currentRow.\textbf{add}(rawSize, currentShapelet.\textbf{getSeriesId}())$
14:             $currentRow.\textbf{add}(rawSize{+}1, currentShapelet.\textbf{getStartPos}())$
15:             $currentRow.\textbf{add}(rawSize + 2, classVal)$
16:             $index \leftarrow S.\textbf{size}()/size - count$
17:             $values.\textbf{add}(index, currentRow)$
18:             $count - -$
19:         else
20:             $count \leftarrow \textbf{S.size}()/size$
21:             $mergedShapelet.\textbf{add}(newShapelet(values))$
22:             $values \leftarrow \{\{\}\}$
23:         end if
24:     end while
25:     return $mergedShapelets$        ▷ generated shapelets will be returned
26: end procedure
```

Algorithm 3.3: Shapelet merger algorithm.

Important Shapelet Finder algorithm (Algorithm 3.4) takes in three parameters, namely merged shapelets, classified/labelled dataset and class values (i.e., event types). Line 2 and 3 initialize two lists named *shapeletArr* and *classValueProb*, which would respectively contain important shapelets and probabilities for class values within the total dataset. Then for each class value, a set data structure is created named *shapeletBucket*. *findProb*() function calculates the probability of the relevant class values within the dataset, and then put that to *shapeletBucket* (line 8 to 10). As the next step, (in line 12 to 17) each merged shapelet is included into a relevant *shapeletBucket*, based on the most probable class values for each group of shapelets. This is achieved using *maxProbClassVal*() function. Next, Algorithm 3.4 finds the absolute differences between the probabilities of actual events of the dataset and groups of shapelets. This is calculated using the *getMinDifShape*() function (line 28). Because the chosen group of shapelets per each event comprises of the minimum difference with respect to the actual event distribution in the dataset, it enables us to choose the most representative groups of shapelets per each event. Finally, the extracted group of shapelets are added to the *shapeletArr* (line 29).

Algorithm 4 Important Shapelets

```
1: procedure GETIMPORTANTSHAPELETES($S, D, classValues$)    ▷ Shapelet array S, Time Series Dataset D and array of class values
2:     $shapeletArr \leftarrow$ list()
3:     $classValProbs \leftarrow$ list()
4:     $shapeletBucket \leftarrow$ map()
5:     $clasNprob \leftarrow$ map()
6:     $shapeDiff \leftarrow$ map()
7:     for $i \leftarrow 0$ to $classValues$.size() do
8:         $var \leftarrow ShapeletBucket(classValues$.get(i)$)$
9:         $classValProbs$.add(findProb($D, classValues$.get(i)))
10:        $shapeletBucket$.put($classValues$.get(i), $var$)
11:    end for
12:    for all $s \in$ S do
13:        for all $val \in$ MaxProbClassVal(s).keys() do
14:            $clasNprob$.put($val$,MaxProbClassVal(s).get($val$));
15:            $shapeletBucket$.get($val$).put($s$);
16:        end for
17:    end for
18:    $count \leftarrow 0$
19:    for all $c \in classValues$ do
20:        $varMap \leftarrow$ map()
21:        $aVal \leftarrow classValProbs$.get($count$)
22:        $count \leftarrow count + 1$;
23:        for all $s \in$ shapeletBucket.get($c$).getShapeletSet() do
24:            $val \leftarrow clasNprob$.get($c$)
25:            $varMap$.put($s$, $val - aVal$)
26:            $shapeDiff$.put($c$,$varMap$)
27:            $newMap \leftarrow shapeDiff$.get($c$)
28:            $newShape \leftarrow$ GetMinDifShape($newMap$)
29:            $shapeletsArr$.add($newShape$);
30:        end for
31:    end for
32:    return $shapeletsArr$    ▷ Important shapelets array will be returned
33: end procedure
```

Algorithm 3.4: Shapelet finder algorithm.

3.3.3 Query Generation

Returned *shapeletArr* from Algorithm 3.4 is the input for Query generator Algorithm (see Algorithm 5). This algorithm is developed to generate CEP queries from the extracted shapelets. If user wants to customize the generated shapelets, then user can decide that in the hint approval phase. In Algorithm 3.5, generated important shapelets may grouped into more than one group. If so, the system should be able to identify the relevant groups and relevant information in generating the query. To identify that, Algorithm 3.5 stores starting positions of the shapelets in a hash map and then uses the created hash map to calculate the most suitable group of shapelets. Between lines 2 to 6 the algorithm stores those starting positions in a hash map. After that it identifies the most common starting positions of the provided shapelets. That process happens from line 7 to 15. Most common starting positions will be saved in a variable called *startPos.* To come up with a meaningful query we need two values with respect to a given column. Those two required values with respect to a column is its *upperbound* and the *lowerbound*. In this algorithm two lists will be created and those required values will be saved in those two lists. Initializing of those two lists is done in line 16 and 17. Between lines 18 to 41, system identifies those values from the provided *shapeletArr.* Previously defined *startPos* variable is used for this process. After completing this process, as collected information we have the following,

1. Starting column number (*startPos)*
2. Upper Bound values of the relevant columns (*upperBound*)
3. Lower Bound values of the relevant columns (*lowerBound*)

Using the above information we can write any type of a CEP query. Note that, when implementing this, CEP query specification should also be there in this algorithm. After specifying the CEP query in this algorithm, we can return the generated query from this algorithm

Algorithm 5 Query Generator

```
 1: procedure GENERATEQUERY($shapelets$)        ▷ 2 dimensional array of generated shapelets
 2:     $countMap \leftarrow$ hashMap()
 3:     for all $s$ in $shapelets$ do
 4:         $countTemp \leftarrow$ getStartPos($s$)
 5:         $countMap.set(countTemp, countMap.get(countTemp) + 1)$
 6:     end for
 7:     $maxCount \leftarrow 0$
 8:     $startPos \leftarrow 0$
 9:     for all $entry$ in $countMap$ do
10:         $temp \leftarrow entry.getValue()$
11:         if (temp>maxCount) then
12:             $startPos \leftarrow entry.getKey()$
13:             $maxCount \leftarrow temp$
14:         end if
15:     end for
16:     $upperBound \leftarrow$ list()
17:     $lowerBound \leftarrow$ list()
18:     for all $s$ in $shapelets$ do
19:         $index \leftarrow 0$
20:         for each $val$ in $s$ do
21:             try
22:                 $tempUp \leftarrow upperBound.get(j)$
23:             catch (IndexOutOfBoundsException exception)
24:                 $upperbound.add(j, MaxVal)$
25:                 $tempUp \leftarrow upperBound.get(j)$
26:             end try
27:             try
28:                 $tempLow \leftarrow lowerBound.get(j)$
29:             catch (IndexOutOfBoundsException exception)
30:                 $lowerBound.add(j, MaxVal)$
31:                 $tempLow \leftarrow lowerBound.get(j)$
32:             end try
33:             if (val>tempUp) then
34:                 $upperBound.set(j, val)$
35:             end if
36:             if (val<tempLow) then
37:                 $lowerBound.set(j, val)$
38:             end if
39:             $j \leftarrow j + 1$
40:         end for
41:     end for
42:         ▷ startPos variable, upperBound array and lowerBound array can be used to generate any type of CEP query
43: end procedure
```

Algorithm 3.5: Query generator algorithm.

Chapter 4

IMPLEMENTATION AND PERFORMANCE EVALUATION

We implemented a web application to visualize the project output to the user. This web application demonstrate the full life cycle of automated query generation. Section 4.1 describes the development framework. The features of the web application are presented in Section 4.2. Section 4.3 illustrates the data visualization of the application and performance evaluation is presented in Section 4.4.

4.1 Web Application with spring

SPRING Framework has been used for this development and the resulted shapelets will be appeared to the user as set of graphs [27]. Then user can customize the generated results and proceed to create a query for the respective events.

The reasons of selecting spring framework for our development are as follows:

1. Spring provides a very clean division between controllers, JavaBean models, and views. Here the complete application has been divided into three main components.
    a. Model - Model is where the application's data objects are stored. The model does not know anything about views and controllers. When a model changes, typically it will notify its observers that a change has occurred.
    b. View - View is what is presented to the users and how users interact with the app. The view is made with HTML, CSS, JavaScript and often templates.
    c. Controller - The controller is the decision maker and the glue between the model and view. The controller updates the view when the model changes. It also adds event listeners to the view and updates the model when the user manipulates the view.
2. Spring MVC is truly view-agnostic. You do not get pushed to use JSP if you do not want to; you can use Velocity, XLST or other view technologies. If you want to use a custom view mechanism

3. Spring comes with various design patterns in its core principles
4. Provides dependency injection.

4.2 Features of Web Application

This web application provides following set of APIs:

1. Uploading a dataset

   API can be used to upload datasets to the system. Any supported dataset (CSV of ARFF can be uploaded using this API. If there is an annotated dataset user can specify it to proceed directly to the Shapelet Generator module, otherwise dataset can be annotated by Data Processor module with user request. A HTTP POST request should be sent to the API with the Multipart File attached.
2. Get uploaded datasets

   All the uploaded files will be saved in the system for reuse. A HTTP GET request should be sent to the API and it will send back a JSON file containing all the details of the uploaded datasets.
3. Start generating shapelets

   A HTTP GET request should be sent to the API with Email and Dataset name attached as parameters. Here Spring Asynchronous task will be initiated. Since this process may take some time to complete, an email will be sent to the provided email address with a url once the process completed. Websockets are used to notify the frontend once the generating shapelets is completed. In summary there are two ways to notify the user once the processing is completed.

      a. Email notification [28].
      b. Notification on frontend [29].
4. Get generated shapelets by simply sending a HTTP GET request to this API with dataset name attached as a parameter, generated shapelets files can be retrieved. A simple JSON file will be returned.
5. Generate queries - This API can be used to generate the queries for most important shapelets generated by the system. Dataset name has to be sent as a parameter and a JSON file containing all the queries will be returned.

After generating shapelets, we generate a JSON file including all the details of generated shapelets such as no of events, event type, content values for each content etc. Then this JSON file was used to draw graphs. Since we have to get user involvement on graphs we tried different APIs which supports our requirement. Google Chart, ChartJS are two APIs and D3 is a library which supports dynamic visualizations on web browsers. Out of these we chose ChartJS which is the best solution for our scenario to customize graphs.

4.3 Screenshots of Web Application

4.3.1 Home Page

Homepage enables user to upload data files to the server, here the file type should be .csv or .arff. Even user can upload multiple files to the server for later usages. After getting uploaded files to the server user can start the process in the shapelet generator module by selecting a uploaded dataset and providing an valid email address. This email address will get an email after completing the process in the server.

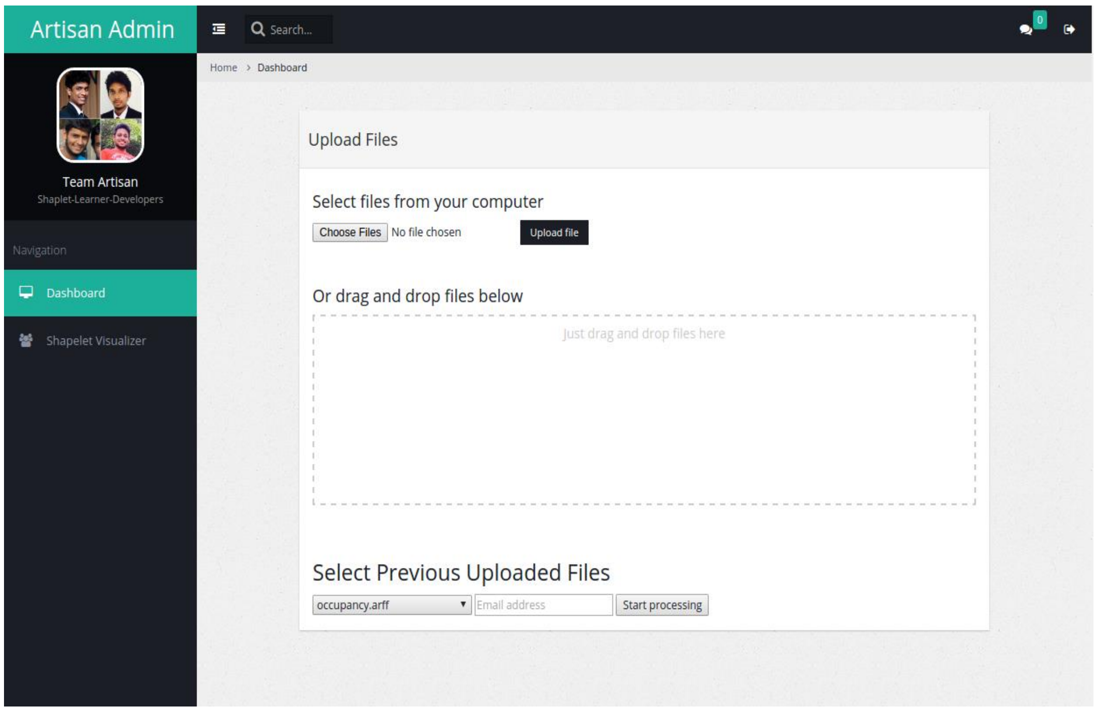


Figure 4.1: Home page of Web application.

4.2.2 Shapelet Visualization

Shapelet Visualization page illustrate the graphical representation of the important shapelets which was generated by shapelet generator module for all events. Figure 4.2 and Figure 4.3 show the visualization of shapelets for Occupancy dataset [25] for relevant two events.

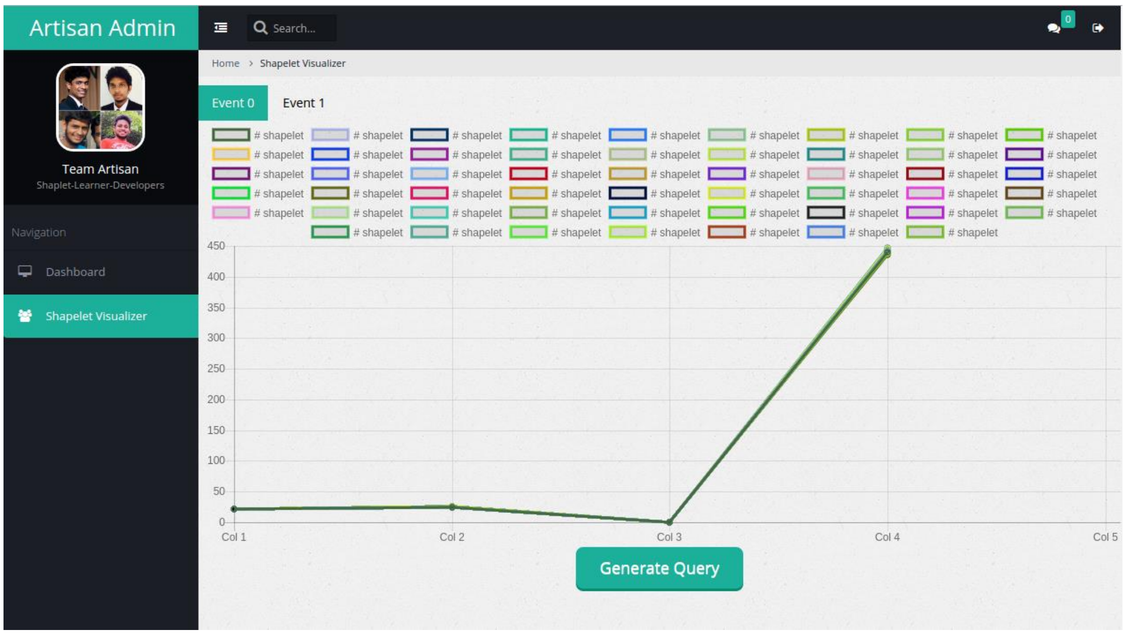


Figure 4.2: Event 0 (Occupied) - Shapelet representation.

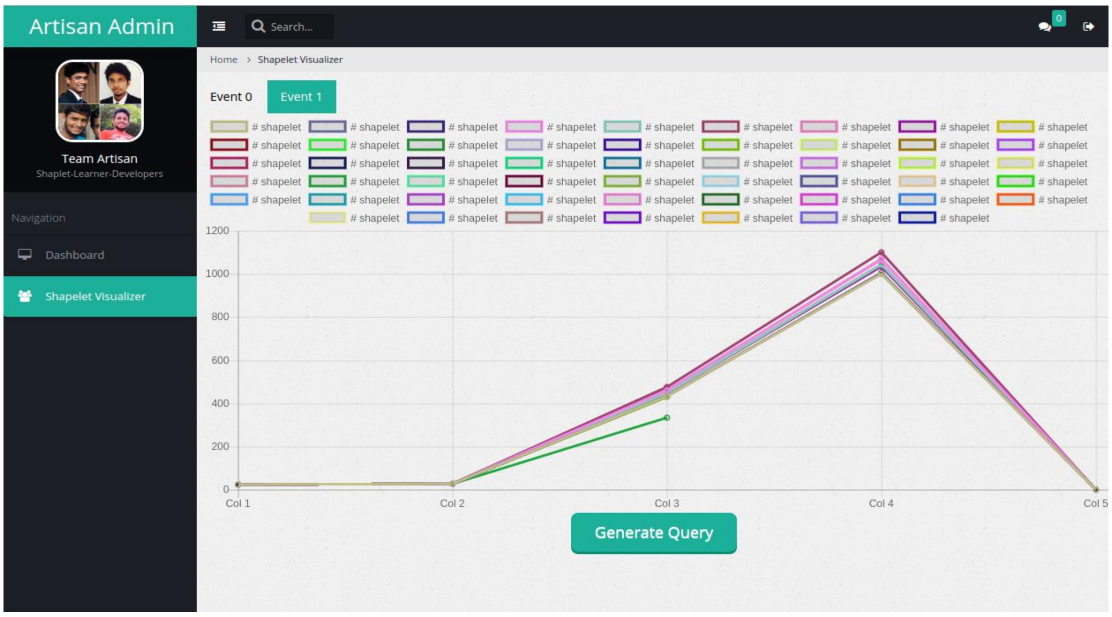


Figure 4.3: Event 1 (Non- Occupied) - Shapelet representation.

4.4 Performance Evaluation

Next we provide an analysis of clustering technique as well as query generation using shapelets and parallel coordinates. In order to test the accuracy of the clustering technique, we evaluated the clustering implementation through two datasets in which the time instances were already clustered into different events.

Table 4.1 refer to clustering results obtained upon the "Occupancy Detection" dataset provided in UCI Machine Learning Repository [25] which is a multivariate time series dataset which has 7 attributes. The dataset contains real world data. The dataset itself consist of 8143 instances out of which it has 6,414 instances which has a state of not occupied (occupancy = 0) and 1729 instances which has a state of occupied (occupancy = 1) resulting approximately 78% of not occupied events and 21% of occupied events.

Table 4.2 refer to clustering results obtained upon the "EEG-Eye State" dataset provided in UCI Machine Learning Repository [26] which is a multivariate time series dataset which has 15 attributes. The dataset contains real world data. The dataset itself consist of 14980 instances which comprises of time instances with respect to eye open and eye closed events.

We processed the total dataset without the column with the event label and obtained the cluster distribution for each time instance and compared it against the original column which had the event label.

Table 4.1: Occupancy dataset clustering results.

Metric	**Value**
maximum radius (ε)	0.19
minimum number of points (m)	2
Total number of time instances considered	1100
Correctly clustered time instances	1018

Incorrectly clustered time instances	82
Accuracy of the clustering technique	92.55% (1018/1100)

Table 4.2: EEG dataset clustering results.

Metric	Value
maximum radius (ε)	0.18
minimum number of points (m)	2
Total number of time instances considered	1000
Correctly clustered time instances	795
Incorrectly clustered time instances	205
Accuracy of the clustering technique	79.5% (795/1000)

In terms of the above used dataset our research has been conducted to solve the problem of generating queries in order to detect the occupied event as well as not occupied event along with a timely representation. "Occupancy Detection" dataset [25] represents accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements.

Figure 4.4 illustrates the extracted shapelets visualization with respect to event 1 of detecting non occupancy events as well as Figure 4.5 displays the extracted shapelets visualization with respect to event 2 of detecting occupancy events.

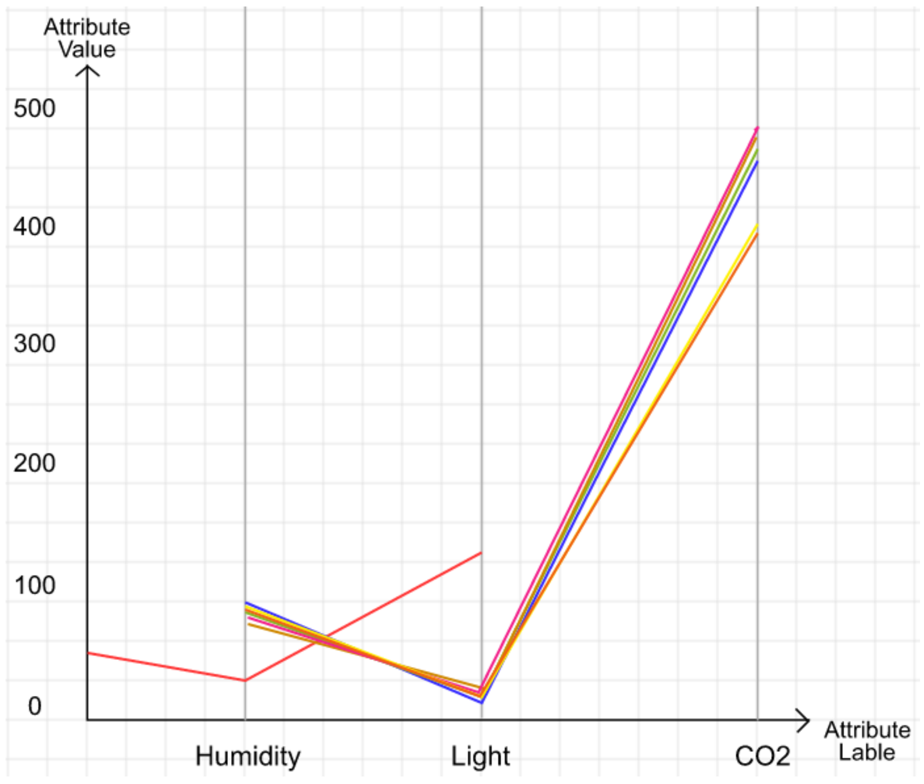


Figure 4.4: Extracted shapelets for Event 1 - Occupancy dataset.

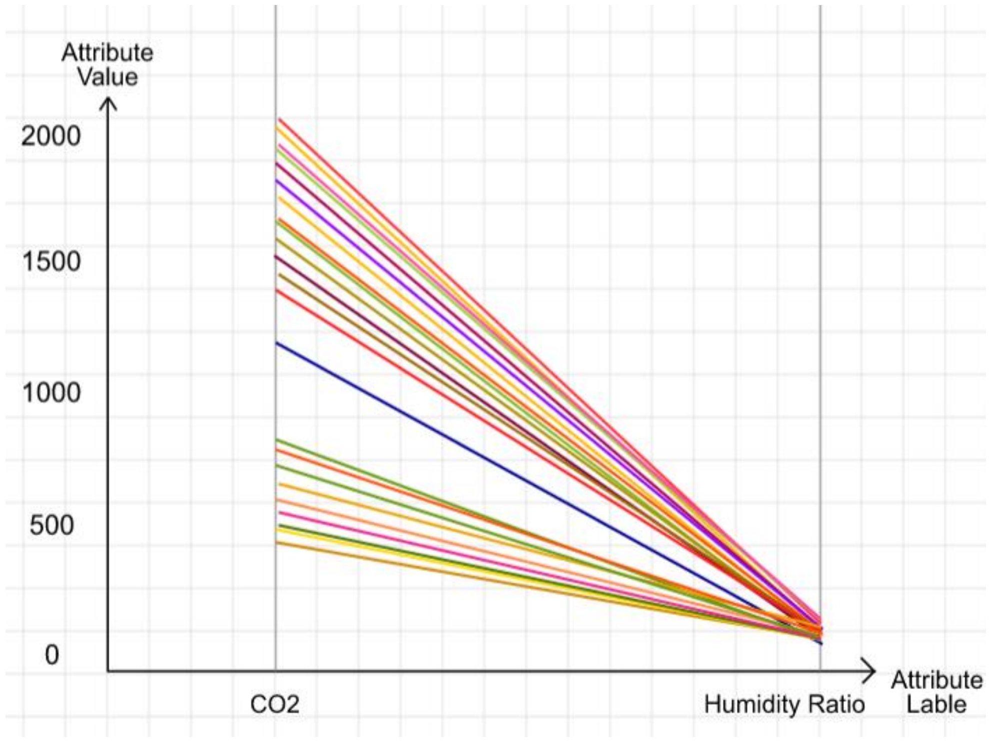


Figure 4.5: Extracted shapelets for Event 2 - Occupancy dataset.

Table 4.3: Occupancy dataset event detection results.

Event	Metric	Value
Not occupied	No of events in dataset	291
	No of events detected using CEP query	286
	Recall	98.28%
	Precision	100.00%
	False positives	0
	False negatives	5 (1.72%)
Occupied	No of events in dataset	196
	No of events detected using CEP query	196
	Recall	100.00%
	Precision	84.48%
	False positives	36 (18.37
	False negatives	0

We also used electroencephalogram (EEG) dataset related to opening and closing of eyes. The eye state was detected via a camera during the EEG measurement and later used to annotate the EEG time series by analyzing the video frames. The eye-open state is indicated using binary 0 while the eye-closed state is indicated using 1. The extracted shapelets for the identified two events is visualized in below figures as well as the recorded results of event detection for the corresponding events in the EEG dataset is listed in the table below.

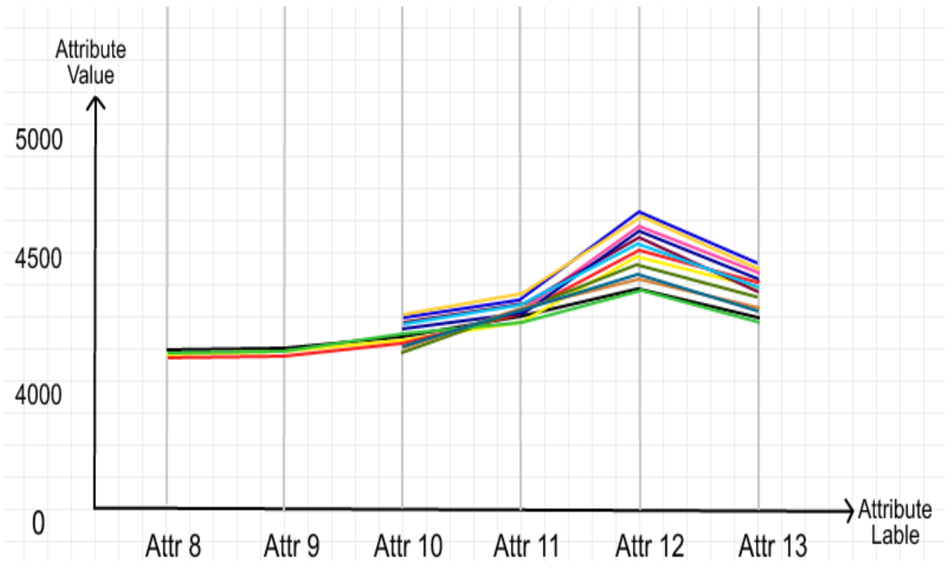


Figure 4.6: Extracted shapelets for Event 1 - EEG dataset.

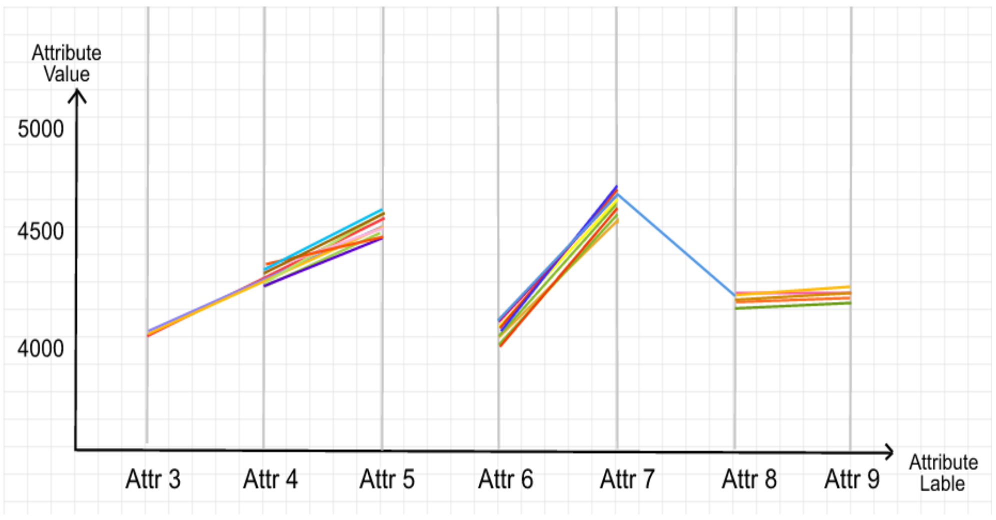


Figure 4.7 : Extracted shapelets for Event 2 - EEG dataset.

Table 4.4: EEG dataset event detection results**.**

Event	**Metric**	**Value**
Eye-open	No of events in dataset	652
	No of events detected using CEP query	635
	Recall	97.39%
	Precision	100.00%
	False positives	0
	False negatives	17(2.67%)
Eye-closed	No of events in dataset	69
	No of events detected using CEP query	68
	Recall	98.55%
	Precision	100.00%
	False positives	0
	False negatives	1(1.45%)

Chapter 5

SUMMARY

5.1 Conclusion

Complex Event Processing (CEP) combines data from multiple sources to detect events or patterns that suggest much more complicated circumstances. Modern day CEP engines are used across many domains and applications with the objective of identifying meaningful events in near real time. For example, CEP is effectively used in the financial domains such as stock markets and credit card fraud detection Accuracy of the output of CEP depends on the queries that are used to process the data. However, it is not straightforward to write CEP queries, as they depend on many attributes of the event being monitored and their correlations. Moreover, significant insight is required to write effective queries; hence the the query generation process is domain and user dependent. Automated CEP query generation is identified as one of the promising alternatives, and several prior work address different aspects of the problem. However, existing techniques are computationally expensive, works only for univariate data, and require extensive domain-specific human interaction.

We looked into this issue of providing a domain and user independent solution for the automated query generation for CEP. We proposed technique to automatically generate CEP queries based on multivariate time series data. The proposed technique first map the multivariate time series to a set of parallel coordinates. Then key patterns that are representative of the events are identified using time series shapelets. We also propose a technique to identify the most relevant shapeless per event, such that only a single CEP query will be generated per event. This enables one to generate CEP queries for commonalities, anomalies, as well as time-series breakpoints in a given multivariate time-series dataset without having any domain knowledge. Users can focus on groups with high or low information gain depending on the application. Furthermore, for datasets that are not pre-annotated, we proposed a technique to label the data by clustering the dataset into a set of clusters based on similarity (measured using Euclidean distance) between time instances. This produces a labeled dataset in which each time instance is labeled with the respective event it belongs to.

The proposed technique is both computationally and memory efficient compared to prior work, as the length of a shapelet is bounded by the number of attributes. Moreover, the performance of the CEP engine is also improved, as only one query will be generated per events. The proposed technique can be applied to both multivariate and multivariate time-series data regardless of the domain, and it is computationally and memory efficient. Using two real datasets, we demonstrate that the resulting queries have good accuracy in detecting relevant events. Our approach remarks its importance due to its nature of user and domain independence, as well as producing high accuracies and precision with respect to the experimental results. Furthermore, the developed tool enables if a domain expert users interacts with our system and use, our approach facilitates to that user also by allowing the user to provide insights in order to optimize and change the query generation process to his or her likeness.

5.2 Future Work

The current implementation does not facilitate constructing CEP queries while capturing interdependencies among attributes in multivariate time series. For example, on a server CPU fan speed is correlated to the CPU utilization. However, as the CPU utilization increases, fan speed does not increase immediately. It will increase the speed only after sometime. Similarly, fan speed does not reduce as soon as CPU utilization goes down. The proposed technique cannot write accurate window-based queries for such instances. Figuring out such interdependencies among the attributes would be useful to generate more accurate and complex queries.

While the proposed clustering-based technique is effective in annotating time series datasets with events, it accuracy need to be further improved. Similarly, between two time series instances cannot capture complex relationships among data points. For example, the CPU utilization and fan speed example could be interpreted as two independent events by our clustering solution. Hence, further work is required in this area. Moreover, due to curse of dimensionality Euclidean distance based similarity measure becomes less effective as the number of attributes increase.

In terms of the web interface the limitation exists in obtaining user insights provided that the user needs to interact with the systems. Here the main issue lies within the difficulty of allowing user to select the ranges of the most important shapelets that are been generated from the system in order to build up the CEP query.

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Appendix A: Accepted paper for IEEE International Conference on Smart Data 2016

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Shapelets and Parallel Coordinates Based Automated Query Generation for Complex Event Processing

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***Abstract*—Automating the query generation for Complex Event Processing (CEP) has marked its own importance in allowing users to obtain useful insights from data. Existing techniques are both computationally expensive and require extensive domainspecific human interaction. In addressing these issues, we propose a technique that combines both parallel coordinates and shapelets. First, each instance of the multivariate data is represented as a line on a set of parallel coordinates. Then a shapelet-learner algorithm is applied to those lines to extract the relevant shapelets. Afterwards, the identified shapelets are ranked based on their information gain. Next, the shapelets with similar information gain are divided into groups by a shapeletmerger algorithm. The best group for each event is then identified based on the event distribution of the dataset. Then the best group is used to generate the query to detect the complex events. The proposed technique can be applied to both multivariate and multivariate time-series data, and it is computationally and memory efficient. It enables users to focus only on the shapelets with relevant information gains. We demonstrate the utility of the proposed technique using a set of real-world datasets.**

Index Terms—Complex Event Processing, Multivariate Time Series, Parallel Coordinates, Shapelets

I. INTRODUCTION

Automating query generation in large, multivariate datasets are useful in many application domains. For example, Complex Event Processing (CEP) [1] combines data from multiple, streaming sources to identify meaningful events or patterns in real time. While the detection of relevant events and patterns may give insight about opportunities and threats related to the data being monitored (e.g., a set of sensor readings and credit card transactions), significant domain knowledge is required to write effective CEP queries. Manual analysis of data streams is not only tedious and error prone, but also important events are likely to be missed due to the limited domain knowledge of the query writer. A promising alternative is to automate the CEP query generation by automatically extracting/mining interesting patterns from the past data [2], [3], [4].

Time-series pattern mining and classification techniques are extensively studied in the literature. Dynamic Time Warping (DTW) [5] is one such technique used to measure the similarity between two time-series based on a distance measure. However, the computational complexity of DTW grows exponentially with large and multiple time-series limiting its usages. Moreover, the accuracy of the results depends on the chosen sliding window, which is nontrivial to estimate [2]. A shapelet [6] is a time series subsequence that is identified as being representative of class membership; hence, useful in time-series classification. AutoCEP [2] proposed a shapeletbased technique to automate the CEP query generation for univariate time series. This itself is a major limitation as the practical presence of univariate time series is limited in CEP. Moreover, AutoCEP generates queries for each and every instance of the detected event, requiring the CEP engine to concurrently process multiple queries. This unnecessarily increases the computational and memory requirements of the CEP engine and consequently degrades its performance. One trivial optimization is to use the assistance of a domain-expert to aggregate the queries and attempt to write one or few queries. Ultra-fast shapelets [7] are proposed for multivariate time-series classification. Ultra-fast shapelets calculate a vectorized representation of respective attributes of the dataset. Then a random forest is trained to identify the shapelets with respect to the total dataset. The leaves of the random forest are considered to be the symbols. The number of occurrences of a symbol in the raw data is counted and these symbol histograms are used for the final classification using random forests. While this technique is effective in classification, it cannot be used to generate CEP queries, as the generated random forest does not support backtracking and obtaining any relevant information as to what data lead to the classification of the event [7]. Rare itemset pattern mining (AprioriRare) [8] is another technique. This technique cannot be used to detect events that occur within a short period of time. Moreover, most related work focus only on domain-specific datasets limiting the usability across diverse datasets and applications [9], [10].

We propose a technique that represents the given multivariate dataset as a set of parallel coordinates, and then extract shapelets out of those coordinates to auto generate CEP queries. Even a time series can be mapped to a set of parallel coordinates, by representing each time instance as a separate line. Extracted shapelets are sorted according to the information gains and then divided into several groups. Out of all the groups, best group for each event is identified. Then the most important shapelets in the identified groups are used to generate one CEP query per group. This enables one to generate CEP queries for commonalities, anomalies, as well as time-series breakpoints in a given multivariate time-series dataset without having any domain knowledge. Users can focus on groups with high or low information gain depending on the application. Moreover, shapelets identify most relevant attributes in a dataset for a particular event, enabling us to write more efficient CEP queries and only one query per event (unless the same event is triggered by unrelated attribute combinations). Using a set of real-world datasets, we demonstrate that the proposed technique can be applied effectively to auto generate CEP queries for common and abnormal events while identifying the relevant features and event occurrence timeframe. Moreover, the proposed technique has a relatively low computational and memory requirements compared to prior work.

Rest of the paper is organized as follows. Section II introduces shapelets, parallel coordinates, and problem formulation. Section III presents the proposed technique and Section IV explains implementation details. Performance analysis is presented in Section V. Concluding remarks and future work are discussed in Section VI.

II. PRELIMINARIES

We first define relevant terms and then define shapelets and parallel coordinates as applicable to the domain of CEP query generation. The research problem is then formulated.

A. Definitions

Time-Series — A time-series T = t1, ..., tm is an ordered set of m real-valued variables.

Multivariate Time-Series — A multivariate time-series T = t1, ..., tm is a sequence of m vectors, where ti = (ti,1, ..., ti,s) Rs with s attributes/variables.

Sub-sequence (St p) — Given a time-series T, a subsequence St p of T is a sampling of length l ≤ m of contiguous positions from T starting at time p, i.e., St p = tp, tp+1..., tp+l−1, for 1 ≤ p ≤ m − l + 1.

Set of All Sub-sequences (STl) — Set of all possible subsequences St p that can be extracted by sliding a window of length l across T is STl = {all St p of T, for 1 ≤ p ≤ m−l+1}.

Sub-sequence Distance — Given T and St p SubsequenceDist(T,St p) is the minimum distance between p contiguous positions obtained by sliding St p across T. We use Euclidean distance as the distance function.

Entropy — Consider a time series dataset D consisting of two classes, A and B. Let proportions of objects belonging to class A and B be p(A) and p(B), respectively. Then the entropy of D is: I(D) = −p(A)log(p(A)) − p(B)log(p(B)) -----(1)

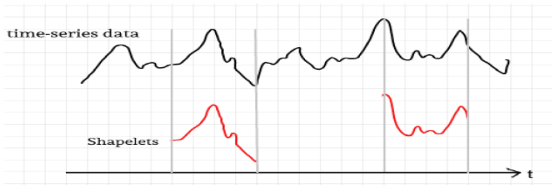

Fig. 1: Time-series shapelets.

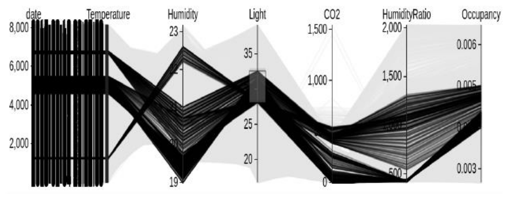

Fig. 2: Parallel coordinates representation of Occupancy Detection dataset [12].

Information Gain (Gain) — Given a certain split strategy sp which divides D into two subsets D1 and D2, let the entropy before and after splitting be I(D) and ˆI(D), respectively. Then the information gain for split sp is: Gain(sp) = I(D) − ˆI(D) Gain(sp) = I(D) − (p(D1)(ID1) + p(D2)I(D2))-- (2)

Optimal Split Point (OSP) — Consider a time-series dataset D with two classes A and B. For a given St p, we choose some distance threshold dth and split D into D1 and D2, s.t. for every time series object T1,i in D1, SubsequenceDist(T1,i, St p) ≤ dth and for every T2,i in D2, SubsequenceDist(T2,i, St p) ≥ dth. An Optimal Split Point (OSP) is a distance threshold that Gain(St p, dOSP (D,St p)) ≥ Gain(St p, d th) for any other distance threshold d th.

B. Shapelets

Shapelets can be defined as time-series sub-sequences as seen in Fig. 1. Shapelets can be of varying lengths, and many sub-sequences can be extracted by sliding a window of given length l. In shapelet-based classification, the objective is to identify a shapelet that is in some sense maximally representative of a class.

C. Parallel Coordinates

Parallel coordinates are widely used to visualize multivariate data [11]. Fig. 2 illustrates the parallel coordinates representation of the room occupancy dataset obtained from the UCI Machine Learning repository [12], which consists of six attributes. The dataset with n dimensions (i.e., attributes) is mapped to a set of points on n parallel lines, where each line represents an instance of data. These points are then connected using a line. A separate line is drawn for each instance of data (i.e., each

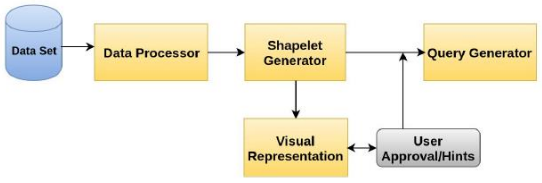

Fig. 3: High-level architecture of the proposed solution.

row). For example, in Fig. 2 part of the dataset selected based on the "Light" attribute is shown in black, and rest of the dataset is visualized in grey. When scaling these coordinate systems, it is recommended to use normalized data to prevent bias to certain dimensions.

D. Problem Statement

In contrast to relational database systems that issue dynamic queries on stored and indexed data, CEP filters incoming streams of data through pre-written queries to detect events 846 847 Fig. 3: High-level architecture of the proposed solution. of interest. Hence, relevant queries need to be provided to the CEP engine apriori. We address the problem of needing domain knowledge to write a meaningful CEP queries through automation. Though a couple of related work attempt to automate CEP query generation, they support only univariate time series data [2].

We propose a solution which can be used to generate CEP queries for multivariate time series without requiring expert domain knowledge. In proposing the solution we assume that each instance in the obtained dataset is annotated according to the respective event. Our goal is to construct a filter query per event, which contains the most relevant attributes, their range of values, and the event detection time frame. An example CEP filter query may look like the following:

SELECT {∗} WHERE {attr1 ≥ a and attr2 < b} WITHIN {t1 ≤ time ≤ t2} --(3)

III. PROPOSED TECHNIQUE

To auto generate queries for Complex Event Processors, we propose the modularized architecture illustrated in Fig. 3. The four main modules perform the following tasks:

Data Processor — Converts the input dataset (e.g., time series data in .txt, .xml, or .csv format) into a generic format used by rest of the modules. We assume that each instance in the given dataset corresponds to an occurrence of a specific event, i.e., each data instance is classified/labeled with the corresponding event. The module then counts the number of events of each type, and their proportions with respect to the total number of events in the entire dataset.

Shapelet Generator — This is the core module of the system which uses pattern mining. This module identifies the most appropriate shapelets to represent each event. First, the multivariate time series dataset is mapped to a set of parallel coordinates. Fig. 4 is an exemplary representation of a multivariate time series with six attributes and five, time instances converted to parallel coordinates. Then all the shapelets are extracted from the parallel coordinates while varying the length l of the sliding window. Though the shape of the extracted shapelets depend on the order of the attributes, the final outcome of the solution is independent of the order. Length of an identified shapelet is bounded by number of attributes m in the time series (i.e., 1 ≤ l ≤ m). Therefore, our technique produces a much lower number of shapelets compared to prior work, where m can be as large as the length of the time series. Moreover, it is not required to apply heuristics or expert knowledge to determine the optimum minimum and maximum length of shapelets. Therefore, our Shapelet Learner Algorithm is both computationally and memory efficient. Once all shapelets are extracted, the next step is to identify a subset of the shapelets that are representative of patterns in the parallel coordinates. For this, we use information gain to quantify the extent to which a selected shapelet is similar to a given line on parallel coordinates. For example, Fig. 5 shows two shapelets, one with attributes 1 and 2 (shapelet S1) and another with attributes 1, 2, and 3 (shapelet S2). We slide both S1 and S2 across the line/row with t = 5000 and find the minimum distance between the shapelet and line. For example, S1 has a relatively lower distance between the attributes 1-2 and 3-4, whereas S2 has a relatively lower distance between attributes 1-3 and 4-6. This is estimated using the SubsequenceDist() function defined in Sec. 2.1. The same process is applied to all other time instances and shapelets. This results in a matrix of minimum distance values for each (shapelet, time instance) pair. We then find the Optimal Splitting Point (OSP) [6] for each row of minimum distance values, to find the maximum information gain for each shapelet. The shapelets are then ranked based on the descending order of its information gain. We then use Shapelet Merger Algorithm to group shapelets within the ranked list with respect to their information gain. Because the shapelets with similar information gains produce similar

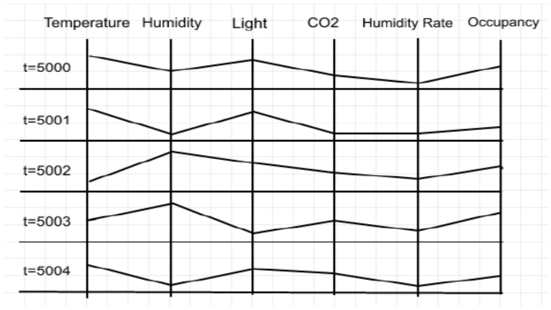

Fig. 4: Multivariate time series mapped as parallel coordinates.

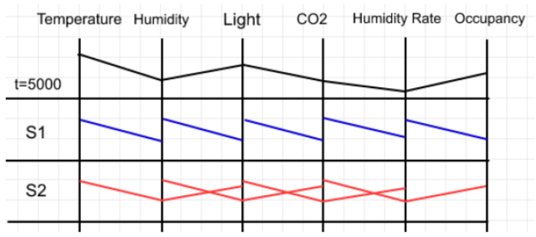

Fig. 5: Shapelets slide accross the time series

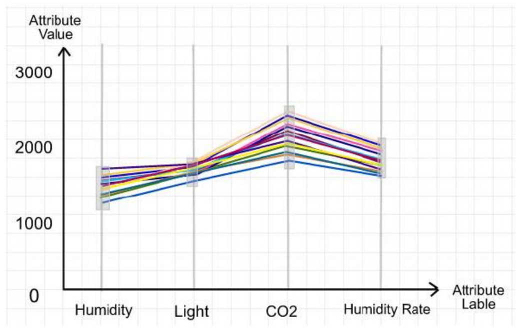

Fig. 6: Shapelets that are representative of event

insights, groups created using Shapelet Merger Algorithm allows us to cluster the similar informative shapelets together. Finally, Important Shapelet Extraction Algorithm is used to identify the most suitable shapelets to represent each event type, which would result in an output similar to Fig. 6.

Visual Representation — This module visualizes generated shapelets, optionally enabling users to select what shapelets to choose for query writing. While the system can auto generate queries without any user suggestions, this module facilitates and accepts user approval allowing the user to select the shapelets that user is interested in. As seen in Fig. 6 user may also select a subset of the attributes and their range of values that he/she expects to use in the generated queries. Such user intervention reduces false positives and improves the performance of the CEP engine, as not every identified event may be of practical importance.

Query Generator — Given the chosen shapelets this module auto generates CEP queries based on the input provided by the hint generator module and incorporating any user provided hints. Here we generate one query per each event with the relevant query parameters generated by the system, or set of attributes and ranges approved by the user. The module identifies the most relevant attributes and their value ranges to be used in constructing the query along with the optimal time periods within which each event occurs. Optimal time periods are identified by analyzing the event distribution of the actual dataset and choosing the longest event detection time period with respect to each occurrence of an event. Using these data, the module generates filter queries (similar to Eq. 3) for each and every event of the given dataset.

IV. IMPLEMENTATION

In this paper, we introduce a new approach to define shapelets using parallel coordinates as an object with four attributes s = (g, i, a, c). g is the information gain, which measures the similarity between shapelet and time series. i is the time series identifier, which is the row number of the line on parallel coordinates (see Fig. 4). a is the starting column/attribute number. We store the normalized values of the attributes which belong to the particular shapelet in c. We also keep track of the original values c, as those are later required to generate CEP queries.

We first transform the multivariate time series dataset into parallel coordinates as seen in Fig. 2. Our method builds upon two main phases which are illustrated in Fig. 7. Next, implementation of each phase is discussed in detail.

A. Phase one: Shapelet Learner

The Shapelet Learner extracts all the shapelets from the obtained parallel coordinates. We set the default minimum length (lmin) of a shapelet as two, while the maximum (lmax) is set to the number of attributes m (i.e., 2 ≤ l ≤ m). However, a user may override these values. Afterwards, Algorithm 1 of the Shapelet Generator module extracts all possible shapelets while varying the shapelet length. First, the shapelet list is initialized to store the extracted shapelets (line 2). Then shapelets are extracted by going through each row r in the Dataset D. The outer loop increments the length of a shapelet l up to lmax, while the

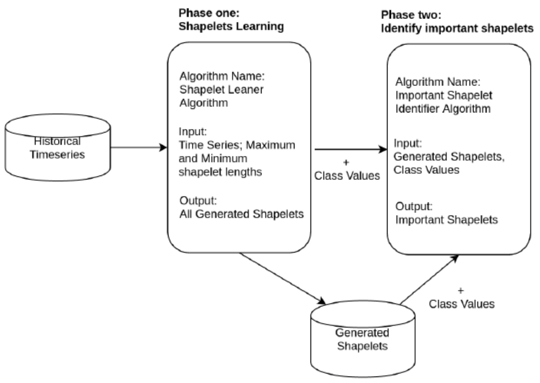
Phase one:
Shapelets Learning
Phase two:
Identify important shapelets
Historical Timeseries
Algorithm Name: Shapelet Leaner Algorithm
Input: Time Series; Maximum and Minimum shapelet lengths
Output: All Generated Shapelets
+ Class Values
Algorithm Name: Important Shapelet Identifier Algorithm
Input: Generated Shapelets, Class Values
Output: Important Shapelets
Generated Shapelets
+ Class Values

Fig. 7: Architecture of the Shapelet Generator module

Algorithm 1 Shapelet Learner Algorithm

```
1: procedure ShapeletLearner($D, l_{\min}, l_{\max}$) ▷ Time series dataset D and shapelet length
2:     $shapelets \leftarrow \{\}$
3:     for each row $r$ in D do
4:         $wholeCandidate \leftarrow r$
5:         $l \leftarrow l_{\min}$
6:         while $l \leftarrow l_{\max}$ do
7:             $l++$
8:             $start \leftarrow 0$
9:             while $start \leftarrow r.length$ do
10:                $start++$
11:                $candidate \leftarrow \{\}$
12:                $m \leftarrow start$
13:                while $m < start + length$ do
14:                    $m++$
15:                    $candidate[m - start] \leftarrow wholeCandidate[m]$
16:                end while
17:                $finalCandidate \leftarrow newShapelet$
18:                $finalCandidate$.setContent(zNorm($candidate$))
19:                $finalCandidate$.setRawContent($candidate$)
20:                $finalCandidate$.setInfoGain(infoGain($candidate$))
21:                $shapelets$.add($finalCandidate$)
22:            end while
23:        end while
24:    end for
25:    return $shapelets$                ▷ generated shapelets will be returned
26: end procedure
```

inner loop increments start to scans through each r. The inner-most loop (line 13-16) extracts all attributes between lmin to l for a given starting point. Then we convert each shapelets content to standard normal using zNorm() function to prevent any biases to specific attributes. Moreover, in line 19 we also store the raw values of shapelets, as they are later required while generating queries.

We also calculate and save the information gain of each shapelets using infoGain() function (line 20). First, the SubsequenceDist() function is used to find the minimum distance between the row and the shapelet by sliding the shapelet across the row, one attribute at a time (see Fig. 5). By repeating the function, the minimum distance per each row is found and saved in an array. Then by sequentially splitting the array we calculate the information gain using Eq. 2. Finally, for each shapelet we get the maximum information gain and the corresponding split

Algorithm 2 Shapelet Merger Algorithm

```
 1: procedure ShapeletMerger(S, size)            ▷ Shapelet Array S sorted
    according to information gains and size of the group
 2:     mergedShapelets ← {}
 3:     count ← S.size()/size
 4:     values ← {{}}
 5:     currentRow ← {}
 6:     while S.hasNext() do
 7:         currentShapelet ← S.next()
 8:         if count>0 then
 9:             currentRow ← currentShapelet.getRawContent()
10:             rawSize ← currentRow.size() − 1
11:             classVal ← currentRow.get(rawSize)
12:             currentRow.remove(rawSize)
13:             currentRow.add(rawSize, currentShapelet.getSeriesId())
14:             currentRow.add(rawSize+1, currentShapelet.getStartPos())
15:             currentRow.add(rawSize + 2, classVal)
16:             index ← S.size()/size − count
17:             values.add(index, currentRow )
18:             count − −
19:         else
20:             count ← S.size()/size
21:             mergedShapelet.add(newShapelet(values))
22:             values ← {{}}
23:         end if
24:     end while
25:     return mergedShapelets          ▷ generated shapelets will be returned
26: end procedure
```

point, which would be the Optimum Splitting Point of the array. In line 21, each shapelet and its metadata are then added to the shapelets list, which is later returned by the algorithm.

B. Phase Two - Shapelet Extraction

All the extracted shapelets are first sorted according to their information gain. Then these shapelets are divided into a set of groups and then merged using Algorithm 2. Algorithm takes the set of shapelets S and number of shapelets per group (groupsize) as the input. groupsize is selected based on the cluster pruning technique in which we set the number of groups to the square root of the total number of identified shapelets. If desired, the user may also define the groupsize. Then in line 12 to 15 the grouped shapelets are updated by adding their series ID (i.e., raw number), starting positions (i.e., starting attribute index), and class value (i.e., event type). Finally, the algorithm return all the merged shapelets (line 25). Important Shapelet Finder algorithm (Algorithm 3) takes in three parameters, namely merged shapelets, classified/labelled dataset. and class values (i.e., event types). Line 2 and 3 initialize two lists named shapeletArr and classValueProb, which would respectively contain important shapelets and probabilities for class values within the total dataset. Then for each class value, a set data structure is created named shapeletBucket. findProb() function calculates the probability of the relevant class values within the dataset, and then put that to shapeletBucket (line 8 to 10). As the next step, (in line 12 to 17) each merged shapelet is included into a relevant shapeletBucket, based on the most

Algorithm 3 Important Shapelets

```
 1: procedure GetImportantShapeletes(S, D, classValues)          ▷ Shapelet
    array S, Time Series Dataset D and array of class values
 2:     shapeletArr ← list()
 3:     classValProbs ← list()
 4:     shapeletBucket ← map()
 5:     clasNprob ← map()
 6:     shapeDiff ← map()
 7:     for i ← 0 to classValues.size() do
 8:         var ← ShapeletBucket(classValues.get(i))
 9:         classValProbs.add(findProb(D, classValues.get(i)))
10:         shapeletBucket.put(classValues.get(i), var)
11:     end for
12:     for all s ϵ S do
13:         for all val ϵ MaxProbClassVal(s).keys() do
14:             clasNprob.put(val,MaxProbClassVal(s).get(val));
15:             shapeletBucket.get(val).put(s);
16:         end for
17:     end for
18:     count ← 0
19:     for all  c ϵ classValues do
20:         varMap ← map()
21:         aVal ← classValProbs.get(count)
22:         count ← count + 1;
23:         for all  s  ϵ   shapeletBucket.get(c).getShapeletSet() do
24:             val ← clasNprob.get(c)
25:             varMap.put(s, val − aVal)
26:             shapeDiff.put(c,varMap)
27:             newMap ← shapeDiff.get(c)
28:             newShape ← GetMinDifShape(newMap)
29:             shapeletsArr.add(newShape);
30:         end for
31:     end for
32:     return shapeletsArr        ▷ Important shapelets array will be returned
33: end procedure
```

probable class values for each group of shapelets. This is achieved using maxProbClassVal() function. Next, Algorithm 3 finds the absolute differences between the probabilities of actual events of the dataset and groups of shapelets. This is calculated using the getMinDifShape() function (line 28). Because the chosen group of shapelets per each event comprises of the minimum difference with respect to the actual event distribution in the dataset, it enables us to choose the most representative groups of shapelets per each event. Finally, the extracted group of shapelets are added to the shapeletArr (line 29).

Regardless of the CEP query language, two blocks are needed to generate a meaningful CEP query for an event (see Eq. 3). First, the time frame (or window) of the rule need to be identified from the extracted shapelets. This is specified using the within construct. Second, the conditions that need to be met on the captured sequence of events is defined using the where construct. Once the relevant parameters and constructs are known, we use the technique proposed in [2] to automatically generate the queries. The conditions are extracted using the selected attributes and their respective range of the important shapelets. If user wants to get a CEP rule to identify multiple events, in addition to above two blocks, filter block should be added as follows:

within[window]{relevent−events}where[conditions]------ (4)

V. PERFORMANCE ANALYSIS

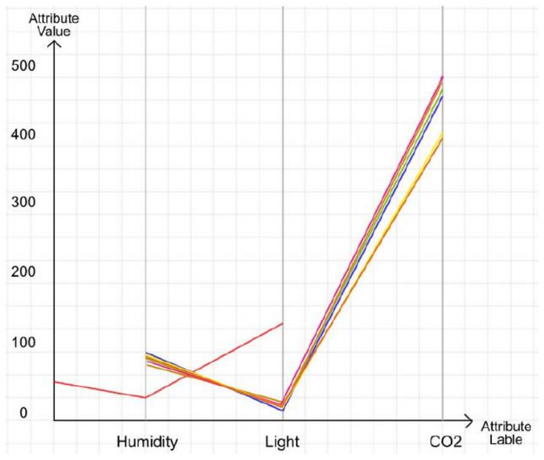

Fig. 8: Shapelets corresponding to not occupied events.

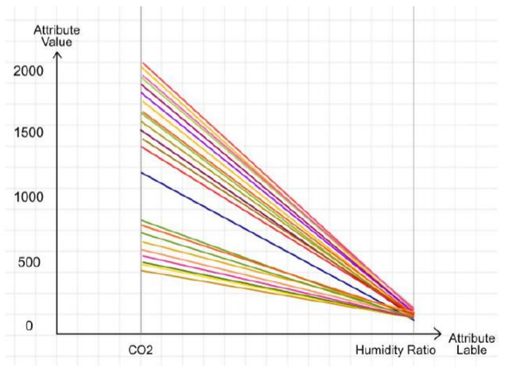

Fig. 9: Shapelets corresponding to occupied events

We use two multivariate time-series datasets from UCI machine learning repository [12], [13] to demonstrate that our technique can automate CEP query generation for different types of domains. We quantify the accuracy of the generated CEP queries using recall, precision, false positives, and false negatives. In addition to that, the computational complexity is analysed theoretically.

A. Occupancy Dataset

Occupancy Detection dataset [12] is a multivariate timeseries dataset of which measure the occupancy factor of an office room with respect to light, temperature, humidity, and CO2 measurements. It consists of 8,143 instances out of which 6,414 (78%) instances are labeled as not occupied (occupancy= 0) while the remaining 1,729 (21%) instances are labeled as occupied (occupancy = 1). Our objective is to auto generate queries to detect both the occupied and not occupied events.

This dataset results in 9,344 shapelets, and then the most appropriate shapelets are filtered out and used for the

TABLE I: Occupancy dataset event detection results

Event	Metric	Value
Not occupied	No of events in dataset	291
	No of events detected using CEP query	286
	Recall	98.28%
	Precision	100.00%
	False positives	0
	False negatives	5 (1.72%)
Occupied	No of events in dataset	196
	No of events detected using CEP query	196
	Recall	100.00%
	Precision	84.48%
	False positives	36 (18.37
	False negatives	0

query generation process. Fig. 8 and Fig. 9 illustrate the most appropriate shapelets to detect not occupied and occupied events. Most appropriate shapelets of Fig. 8 are within attributes 1 and 3 (i.e., humidity and CO2). As seen in Fig. 9 for the occupied event CO2 and humidity ratio attributes are more relevant. The longest time window for not occupied events was between 17:32:00 - 22:23:00 on 2015/02/08. Whereas for the occupied events it was 14:49:00 - 18:40:00 on 2015/02/09. Based on these time gaps we set the event detection time frame. These attributes, their range of values, and the optimal event detection time frames are then used to generate queries.

Table I summarizes the accuracy of detected events based on the auto-generated queries. It can be seen that the generate CEP query is able to detect all the occupied events, it missed a few not occupied events (1.7% of total dataset). However, false positives for occupied events were relatively high (18.4%). Overall recall, precision, false positive, and false negative values are acceptable for both the occupied and not occupied events, indicating the usefulness of auto-generate CEP queries.

B. EEG Eye State Dataset

Next, we used electroencephalogram (EEG) dataset related to opening and closing of eyes [13]. The eye state was detected via a camera during the EEG measurement and later used to annotate the EEG time series by analysing the video frames. The eye-open state is indicated using binary 0 while the eyeclosed state is indicated using 1. Fig. 10 and 11 correspond to the most appropriate shapelets to detect event 0 and 1 respectively. Most appropriate shapelets for an eye-open state are within attributes 8-13 (Fig. 10). As seen on Fig. 10 attributes 4-5, 6-7, and 8-9 are more relevant for an eye-closed event. The longest time window for an eye-open state was between time stamps 128,349s to 204,516s, while for an eyeclosed events it was 14,976s to 128,232s. We generate queries based on these three shapelets and event detection time

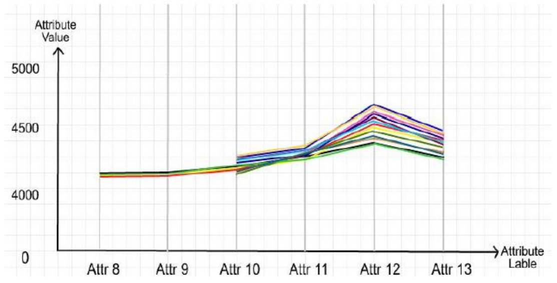

Fig. 10: Shapelets corrosponding to EEG eye-open state.

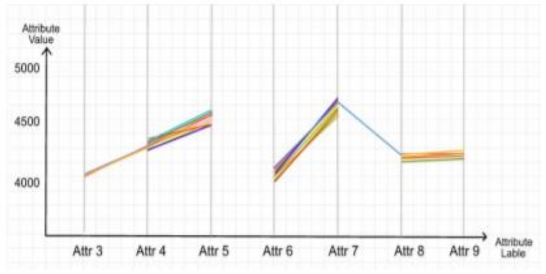

Fig. 11: Shapelets corrosponding to EEG eye-closed state.

frames. As there are three shapelets the where clause in Eq. 3 is of the form (Attr 4's range AND Attr 5's range) OR (Attr 6's range AND Attr 7's range) OR (Attr 8's range AND Attr 9's range).

Table II summarizes the accuracy of detected events based on the auto-generated queries. For this dataset zero false positives are observed for both eye-open and eye-closed events. False negatively are also very low for both events (2.7% and 0.1%, respectively). Both the precision and recall are also close to 100%, indicating that results queries are able to detect relevant events with good accuracy.

Since the solution has been divided into three main algorithms, we have computed the time complexities of those three algorithms separately. Algorithm 1 has a time complexity of O(nm3). Algorithm 2 has a time complexity of O(nm2). Algorithm 3 has a time complexity of O(n3/2m3). Ultra-fast Shapelets [7] has a time complexity of O(pnm2) and AutoCEP [2] has a time complexity of O(n2) where n is the number of instances (time-series), m is the number of attributes and p(< n) is a random number. Even though the listed complexities are as such, Ultra-fast shapelets introduces a shapelet-based clustering technique in which they do not focus on query generation and AutoCEP only focuses on univariate domain makes it harder to compare those two techniques directly with ours as we cover full cycle from shapelet generation to the query generation.

TABLE II: EEG Eye State dataset event detection results.

Event	Metric	Value
Eye-open	No of events in dataset	652
	No of events detected using CEP query	635
	Recall	97.39%
	Precision	100.00%
	False positives	0
	False negatives	17 (2.67%)
Eye-closed	No of events in dataset	69
	No of events detected using CEP query	68
	Recall	98.55%
	Precision	100.00%
	False positives	0
	False negatives	1 (1.45%)

VI. SUMMARY AND FUTURE WORK

We propose a technique to automatically generate CEP queries based on multivariate time series data. The proposed technique first map the multivariate time series to a set of parallel coordinates. Then key patterns that are representative of the events are identified using time series shapelets. We also propose a technique to identify the most relevant shapeless per event, such that only a single CEP query will be generated per event. The proposed technique is computationally efficient compared to prior work, as the length of a shapelet is bounded by the number of attributes whereas in prior work it is bounded by the length of the time-series. Moreover, the performance of the CEP engine is also improved, as only one query will be generated per events. Furthermore, using two real datasets, we demonstrate that the resulting queries have good accuracy in detecting relevant events. In future, we plan to further improve the accuracy and extend the proposed technique work with unlabeled time series datasets.

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