UNIVERSITÄT BONN

Fraunhofer IAIS

# Rheinische Friedrich-Wilhelms-Universität Bonn

## Mathematisch-naturwissenschaftliche Fakultät

## Master Thesis

# Distributed Online Learning for Large-scale Pattern Prediction over Real-time Event Streams

*Author:*
Ehab Qadah

*First Examiner:*
PD. Dr. Michael Mock

*Second Examiner:*
Prof. Dr. Stefan Wrobel

Submitted: 26.02.2018

# Declaration of Authorship

I hereby confirm that the work presented here is original and the result of my own investigations. I assure that this work has not been presented in any other form for the fulfillment of any other degree or qualification. Formulations and ideas taken from other sources are cited as such.

***Ehab Qadah***

# Abstract

In many application domains, such as maritime surveillance, financial services, network monitoring, and sensor networks, massive amounts of streaming data (Big Data streams) are being generated in real-time. The record of these streams can be encoded as events. However, in order to benefit from the live streaming events, there is a need for systems that enable the real-time stream processing and analytics tasks at large-scale.

For instance, predicting full matches of complex patterns from the massive streaming events is an important utility for the decision making process. Such a utility allows to react proactively to the new situations and improve the effectiveness of the operational tasks.

In this thesis, we present the design, implementation, and evaluation of a scalable online prediction system for user-defined patterns over multiple massive streams of events. For efficiency and scalability, the system is implemented on top of Apache Flink, a popular engine for distributed and large-scale stream processing. The proposed system is based on a novel approach of combining probabilistic events pattern prediction models on multiple predictor nodes with a distributed online learning protocol, to continuously synchronize the parameters of the prediction models among the predictors in a communication-efficient way.

The key idea of our approach that to enable the collaborative learning and information exchange between the predictors (i.e., sharing a global prediction model), thus the learning convergence is accelerated with less data for each predictor. The patterns are defined in the form of regular expressions over the event types in the stream. The underlying model provides online predictions about when a pattern is expected to be completed within an event stream. We describe the distributed architecture of the proposed system, its implementation in Flink. Furthermore, We provide a theoretical analysis that focuses on giving a probabilistic guarantee on the proposed method efficiency. Experimental results on synthetic and real-world event streams show the effectiveness of our proposed approach.

To my family

# Contents

# List of Figures

# 1 INTRODUCTION

## 1.1 Motivation

In recent years, technological advances have led to a growing availability of massive amounts of continuous streaming data (i.e., data streams observing events) in many application domains such as social networks [43, 32], Internet of Things (IoT) [34], user activities on the web [8, 33] and maritime monitoring [40, 26]. These data streams provide the opportunity to implement reactive components within these domains. For instance, the ability to detect and predict the full matches of a pattern of interest (e.g., a certain sequence of events), defined by a domain expert, is typically important for operational decision making tasks in the respective domains.

An event stream is an unbounded collection of time-ordered data observations in the form of a tuple of attributes that is composed of a value from finite event types along with other categorical and numerical attributes [1, 44, 50]. As an illustrative example, consider the movement event streams in the context of maritime surveillance, the event stream of a moving vessel consists of spatio-temporal and kinematic information along with the vessel's identification and its trajectory related events, based on the automatic identification system (AIS) [38] messages that are continuously sent by the vessel. Therefore, leveraging event patterns prediction over real-time streams of moving vessels is useful to alert maritime operation managers about suspicious activities (e.g., fast sailing vessels near ports, or illegal fishing) before they happen.

However, processing the real-time streaming data poses new challenges, since the data streams are large and distributed in nature and continuously arrive at a high rate [7, 17]. To deal with these data streams in a fast and efficient manner, a distributed stream processing framework [19, 20, 21] is usually used to implement the streaming processing and analytic applications.

## 1.2 Thesis Overview

In this thesis, we present the design, implementation, and evaluation of a scalable and distributed system that provides obline pattern prediction over multiple real-time streams of events. The proposed approach is based on a novel method that combines a distributed online learning protocol [14, 24] with an event forecasting method based on Markov chains [4]. Our system introduces a new synchronization operator withing the distributed online learning protocol, which enables us to synchronize the the parameters of distributed pattern prediction models, where we first provide the theoretical aspects of this operation.

Furthermore, We implemented our system on top of the Big Data framework for stream processing Apache Flink [20], and the distributed streaming platform Apache Kafka [18]. We evaluate our proposed system over synthetic event streams, and real-world data streams of moving vessels, which are provided in the context of the datAcron project[1].

In summary, the main contributions of this thesis are the following:

- An architecture design of a distributed system for event patterns prediction over massive event streams, alongside the implementation details on the top of Apach Flink and Apache Kafka.

- We introduce a new model synchronization operation within a distributed online learning protocol, additionally, we provide a theoretical analysis of the proposed synchronization operation, in which we derive an efficiency probabilistic guarantee.

- Experimental evaluation of the performance for the proposed methods in real- world event streams and synthetic event streams.

## 1.3 Publication

Parts of this thesis have been published in [42]:

Ehab Qadah, Michael Mock, Elias Alevizos, and Georg Fuchs. A Distributed Online Learning Approach for Pattern Prediction over Movement Event Streams with Apache Flink. In *EDBT/ICDT Workshops*, 2018.

[1] `http://www.datacron-project.eu/`

## 1.4 Outline

The rest of this thesis is structured as follows. Chapter 2 provides a review of the related work and used frameworks. In Chapter 3, we describe the problem of events pattern prediction, and our approach along with its practical and theoretical aspects. Chapter 4 presents how the proposed system was built, its architecture, and the implementation details in Flink and Kafka. Chapter 5 presents the experimental setup and results of our system over event streams of moving vessels and synthetic event streams. We further discuss the results of our method and some potential future directions in Chapter 6. Finally, Chapter 7 gives the overall conclusions of this thesis.

# 2 RELATED WORK AND BACKGROUND

In this chapter, we survey some of the related research in the areas of pattern prediction over event streams task, and techniques of distributed online learning over data streams. we also give a brief overview of the Big Data technologies that we used to implement our proposed system.

## 2.1 Related work

### 2.1.1 Pattern Prediction Over Event Streams

Several approaches have been proposed to formalize the task of event patterns prediction over time-evolving data streams. One common way to formalize this task is to assume that the stream is a time-series of numerical values, and the goal is to predict at each time point $t$ the future observation at some future points $t+1$, $t+2$, etc., (or even the output of some function of future values) [35].

Another way to formalize the prediction task is to view streams as sequences of events, i.e., tuples with multiple, possibly categorical, attributes, such as *id*, *event type*, *timestamp* etc., and the goal is to predict future events or patterns of events. In this thesis, we focus on the latter definition of forecasting (event patterns prediction).

A significant body of work has been established in the field of temporal pattern mining that is related to the task of event patterns detection, where events are defined as 2-tuples of the form (*EventType*, *Timestamp*). The goal is to extract patterns of events in the form either of association rules [2] or frequent episode rules [31]. These methods have been extended in order to be able to learn rules for predicting event patterns. For instance, in [46], an association rule mining technique is introduced, by first extract sets of event types that frequently lead to a target event (i.e., a rare event) within a time window of fixed size. And then use them to build a rule-based prediction model. Moreover, Weiss and Hirsh [47] proposed another rule-based method to predict rare events in a stream, using a genetic algorithm to find all predictive patterns to form prediction rules.

On the other hand, Laxman et al. [27] have proposed a probabilistic model for calculating the probability of the immediately next event in the stream. Which is achieved by combining each frequent episode that presents a partially-ordered set of event types [30], with a Hidden Markov Model (HMM). In addition, Fahed et al. [15] proposed episode rules mining algorithm to predict distant events. By generating a set of episode rules in the form $P \rightarrow Q$ where $P$ and $Q$ are two episodes, while these rules have a minimal antecedent (in number of events) and temporally distant consequent.

In [50] a mining method is presented that find the frequent sequential patterns in an event stream, which are used to generate prediction rules. The event stream is processed into batches, where in each batch the events are consumed to find the prefix matches from the discovered frequent patterns, to predict future events using different strategies of prediction scoring.

Event pattern prediction has also attracted some attention from the field of complex event processing (CEP), where the CEP system consumes a stream of low-level events, and the target is to detect patterns of events (composite events), defined using pattern-based languages that provide logic, sequence, and iteration operators such as SQl-like languages [13]. One such early approach is presented in [36], which is based on converting the complex event patterns to automata, and subsequently, Markov chains are used in order to estimate when a pattern is expected to be fully matched.

Moreover, Alevizos et al. [4] have recently presented a similar approach, where again automata and Markov chains are employed in order to provide (future) time intervals during which a match is expected with a probability above a confidence threshold. In this thesis, we leverage this method as the base prediction model for each input event stream (see Section 3.1.2).

### 2.1.2 Distributed Online Learning

In recent years, there have been many research efforts on the problem of distributed online learning over multiple data streams [45, 48, 11, 49, 14, 24]. In contrast to the centralized learning approach in which all records of the streams are processed at a central single machine, the data streams are processed in a distributed fashion on $k$ local learners. Each of which learner processes a single stream and use a local learning algorithm to provide a real-time prediction based service like Classification [11]. However, this setting requires to exchange the parameters of underlaying learning algorithm among the learners to construct a strong global model, in order to preserve the predictive performance as similar as the centralized setting [24]. Different communication schemes between the distributed learners have been proposed in the literature.

For instance, Dekel et al. [14] proposed a distributed online mini-batch prediction approach over multiple data streams. Their approach is based on a static synchronization method. The distributed learners/predictors periodically communicate their local models with a central coordinator unit after consuming a fixed number of input samples/events (i.e., batch size $b$), in order to create a global model parameters and share them between all learners. This work has been extended in [24] by introducing a dynamic synchronization scheme that reduces the required communication to the exchange of information between learners. The protocol relays on a dynamic synchronization operator that controls when the local learners communicate their models, which is based on only synchronizing the local models of the learners if they diverge from a reference model.

This protocol was introduced for linear models, and has been extended to handle kernelized online learning models [25]. In this work, we consider the event patterns prediction models over multiple event streams as learning algorithms, and we introduce to employ the communication-efficient distributed online learning protocol [24] to synchronize their parameters as illustrated in Section 3.2.2.

## 2.2 Technological Background

In the last years, many systems for large-scale and distributed stream processing have been proposed, including Spark Streaming [19], Apache Storm [21] and Apache Flink [20]. These frameworks can ingest and process real-time data streams, published from different distributed message queuing platforms, such as Apache Kafka [18] or Amazon Kinesis [6]. In this work, we implemented the proposed system in Apache Flink. Flink provides the distributed stream processing components of the distributed event pattern predictors. It works alongside Apache Kafka, which is used for streaming the input event streams and as a messaging platform to enable the distributed online learning functionalities.

### 2.2.1 Apache Flink

Apache Flink is an open source project that provides a large-scale, distributed, and stateful stream processing platform [12]. Flink is one of the most recent and pioneering Big Data processing frameworks. It provides processing models for both streaming and batch data, where the batch processing model is treated as a special case of the streaming one (i.e., finite stream). Flink's software stack includes the *DataStream* and *DataSet* APIs for processing infinite and finite data, respectively.

These two core APIs are built on top of Flink's core dataflow engine and provide operations on data streams or sets such as mapping, filtering, grouping, etc.

The two main data abstractions of Flink are *DataStream* and *DataSet*, they represent read-only collections of data elements. The list of elements is bounded (i.e., finite) in *DataSet*, while it is unbounded (i.e., infinite) in the case of *DataStream*. Flink's core is a distributed streaming dataflow engine. Each Flink program is represented by a data-flow graph (i.e., directed acyclic graph - DAG) that gets executed by Flink's dataflow engine [12]. The data flow graphs are composed of stateful operators and intermediate data stream partitions. The execution of each operator is handled by multiple parallel instances whose number is determined by the *parallelism* level. Each parallel operator instance is executed in an independent task slot on a machine within a cluster of computers [20].

### 2.2.2 Apache Kafka

Apache Kafka is a scalable, fault-tolerant, and distributed streaming framework/messaging system [18]. It allows to publish and subscribe to arbitrary data streams, which are managed in different categories (i.e., *topics*) and partitioned in the Kafka cluster. The Kafka Producer API provides the ability to publish a stream of messages to a topic. These messages can then be consumed by applications, using the Consumer API that allows them to read the published data stream in the Kafka cluster. In addition, the streams of messages are distributed and load balanced between the multiple receivers within the same consumer group for the sake of scalability.

# 3 Problem and proposed Approach

## 3.1 Pattern Prediction Over an Event Stream

This chapter introduces the problem that we address in this thesis, including the formal definition of the pattern prediction over a single event stream and multiple streams. First, we introduce the base model for pattern prediction, and our proposed approach to leverage the distributed online protocol to enable knowledge sharing between prediction models over multiple event streams. Furthermore, we provide an analysis of the theoretical efficiency of distributing the pattern prediction models. We follow the general notation and terminology of [1, 44, 29, 3, 50, 24] to formalize the problem we tackle and our solution approach.

### 3.1.1 Problem Formulation

We first define the input event and the stream of events as follows:

**Definition 1.** *Each event is defined as a tuple of attributes* $e_i = (id, type, \tau, a_1, a_2....., a_n)$, *where type is the event type attribute that takes a value from a set of finite event types/symbols* $\Sigma$, $\tau$ *represents the time when the event tuple was created, the* $a_1, a_2, ..., a_n$ *are spatial or other contextual features (e.g., speed); these features are varying from one application domain to another. The attribute id is a unique identifier that connects the event tuple to an associated domain object.*

**Definition 2.** *A stream* $s = \langle e_1, e_3, ..., e_t, ...\rangle$ *is a time-ordered sequence of events.*

A user-defined pattern $\mathcal{P}$ is given in the form of a regular expression over a set of event types $\Sigma$ (i.e., alphabet). Let a word over $\Sigma$ be a sequence of event types, and the set of words over $\Sigma$ be a language $L$. Then $L(\mathcal{P})$ is the regular language defined by the regular expression $(\mathcal{P})$ [22, 37, 4], where a regular expression is an empty word or an event type $\in \Sigma$, or defined using the following operators over regular expressions:

- *sequence* that represents a concatenation of two regular expressions languages
- *disjunction* i.e., union, which is the language that its words belong to one of the languages of the two regular expressions

- *iteration* operation to define the set of all possible concatenation over a regular expression

More formally, a pattern is given through the following grammar:

**Definition 3.** $\mathcal{P} := E \mid \mathcal{P}_1;\mathcal{P}_2 \mid \mathcal{P}_1 \vee \mathcal{P}_2 \mid \mathcal{P}_1^*$, *where* $E \in \Sigma$ *is a constant event type.* ; *stands for sequence,* $\vee$ *for disjunction and* $*$ *for Kleene* $- *$. *The pattern* $\mathcal{P} := E$ *is matched by reading an event* $e_i$ *iff* $e_i.type = E$. *The other cases are matched as in standard automata theory.*

The problem setting can be summarized as follows: given a stream $s$ of low-level events and a pattern $\mathcal{P}$, the goal is to estimate at each new event arrival the number of future events that we will need to wait for until the pattern is completed (full match).

## 3.1.2 Base Model

In this thesis, we use the Event Forecasting with Pattern Markov Chains method [4] as the base to construct a pattern prediction model over an event stream. In next, we describe the details of this approach. We first provide an overview of the Patten Markov Chain framework [37]. We then describe how this framework is used to build a pattern prediction model [4].

### Construction of Pattern Markov Chains (PMCs)

Alevizos et al. [4] proposed to employ the Pattern Markov Chain (PMC) [37] to build an online prediction associated with a pattern over an event stream. The algorithm of constructing a PMC associated with a pattern $\mathcal{P}$ over a stream of events $s$ consists of the following steps:

- Build a deterministic finite automata (DFA) that accepts the regular expression $\Sigma^*;\mathcal{P}$. We define the the DFA as following:

  **Definition 4** ([22])**.** $(\Sigma, Q, s, F, \delta)$ *is a deterministic finite automaton (DFA) where* $\Sigma$ *a finite alphabet of event types, and* $Q$ *is a finite set of states,* $s \in Q$ *a start state and* $F \subset Q$ *represents all final states.* $\delta : Q \times \Sigma \rightarrow Q$ *is a transition function from a state to another state given an input event type, which is defined as recursive function* $\delta(q, e_1e_2 \dots e_d) = \delta(\delta(q, e_1e_2 ... e_{d-1}), e_d)$. *If* $\delta(s, w) \in F$ *of a word* $w = e_1e_2 \dots e_d \in \Sigma^*$, *then the word* $w$ *is said to be accepted by the DFA. In addition,* $\delta(q)^{-m}$ *is the set of words of size* $m$ *defined as* $\{w \in \Sigma^m \mid \exists q \in Q,\ \delta(p, w) = q\}$

First, the regular expression $\Sigma^*; \mathcal{P}$ is converted to non-deterministic finite automata (NFA), then an equivalent DFA of the constructed NFA is computed using the subset construction [22, 4]. And the events stream $s$ is considered as the input word of the DFA.
Furthermore, if $\forall q \in Q$ of a DFA the all $\delta(q)^{-m}$ are sets of cardinality 1, then the DFA is called *m-unambiguous*. Nuel [37] proposed a procedure to transform any DFA to an *m-unambiguous* DFA, which is achieved by incrementally duplicate all states have m-ambiguity (i.e., $|\delta(q)^{-m}| > 1$). Figure 3.1 shows an associated DFA of a sequential pattern $\mathcal{P} = a; d; c$ over an alphabet $\Sigma = \{a, b, c, d\}$.

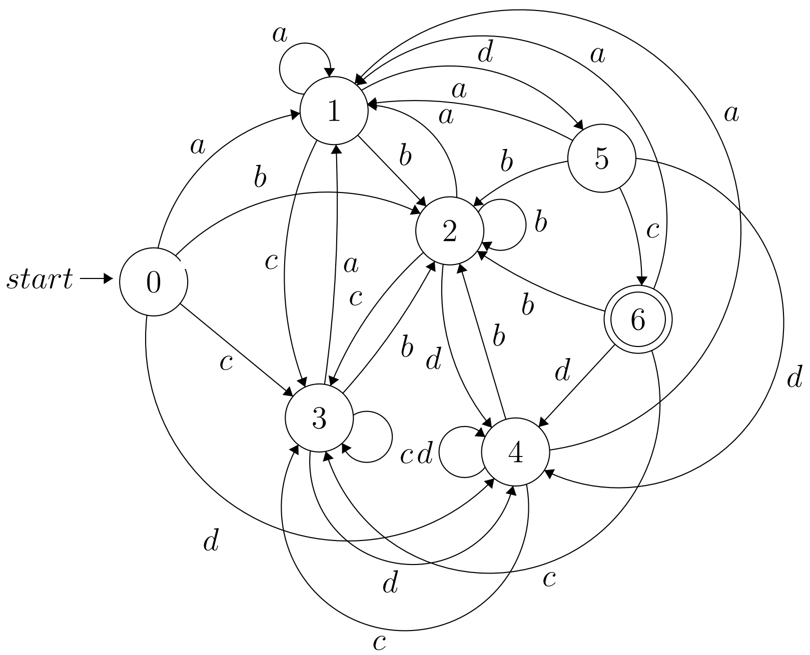



**Figure 3.1:** $DFA_{\Sigma^*;\mathcal{P}}$ for $\mathcal{P} = a; d; c$ with $\Sigma = \{a, b, c, d\}$, and order $m = 1$.

- Assume that the input events stream $s = \langle e_1, e_3, ..., e_t, ...\rangle$ is a $m$-order Markov sequence, where $m \geq 1$. Given a constructed *m-unambiguous* DFA for the pattern $\mathcal{P}$, Nuel [37] showed that the sequence of states of the DFA that generated by consuming the input events stream $s$ is a first-order Markov chain, which is represented by $\langle q_0, q_1, ..., q_t, ...\rangle$, where $q_0 = s$ and $q_t = \delta(q_{t-1}, e_t)$. We denote by $PMC_m^{\mathcal{P}}$ the derived Markov chain associated with a pattern $\mathcal{P}$ that is called a Pattern Markov Chain (PMC) of order $m$ [37]. In other words, we perform a direct mapping of the states of the DFA to states of a Markov chain and the transitions of the DFA to transitions of the Markov chain.Thus, the terms *m-unambiguous* DFA of a pattern and

the corresponding $PMC_m^{\mathcal{P}}$ we will be used interchangeably.
Furthermore, the $PMC_m^{\mathcal{P}}$ is characterized by $|Q| \times |Q|$ transition probability matrix $\Pi$ where $Q$ is again the set of states of the *m-unambiguous* DFA. Figure 3.1 depicts the PMC of order 1 for the generated DFA of Figure **??**.

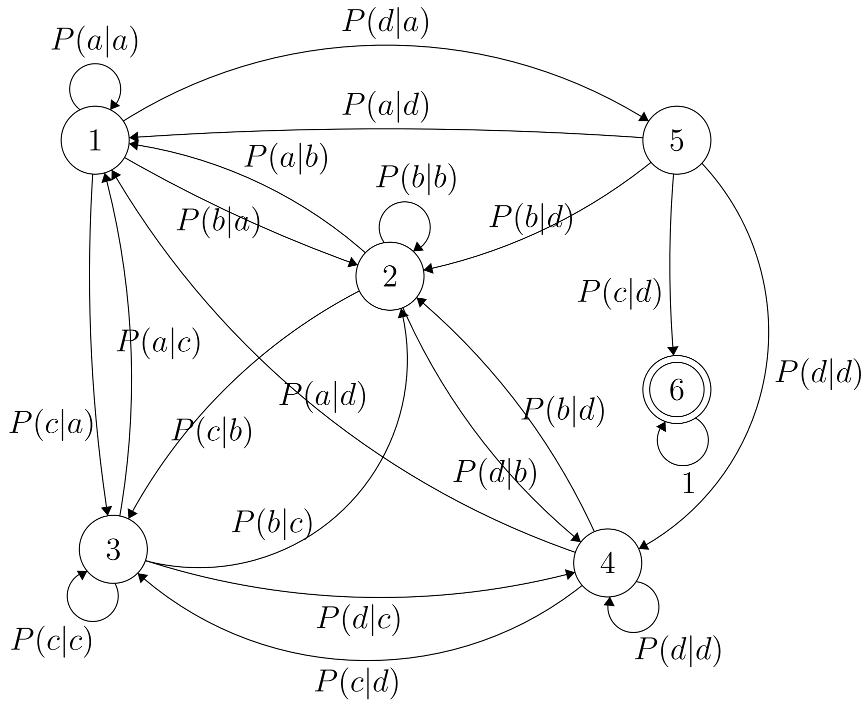



**Figure 3.2:** $PMC_{\mathcal{P}}^{1}$ for $\mathcal{P} = a; d; c$ with $\Sigma = \{a, b, c, d\}$, and order $m = 1$.

### Constructing Pattern Prediction Model

Alevizos et al. [4] proposed to use the constructed $PMC_m^{\mathcal{P}}$ to build a probabilistic prediction model that describes the DFA's run-time behavior. The method is based on calculating the *waiting-time* distributions. Given a specific state of the $PMC_m^{\mathcal{P}}$ , a *waiting-time* distribution provides the probability of reaching a set of absorbing states in $n$ transition from current state. So by mapping the final states of the DFA to absorbing states of the $PMC_m^{\mathcal{P}}$ by adding self-loops with probabilities equal to 1.0. Therefore, we can calculate the probability of reaching a final state in $n$ transitions, which means predicting a full match of the defined pattern $\mathcal{P}$.

We denote by $W_{\mathcal{P}}(q)$ the waiting-time random variable that represents the number of transitions from a current state $q$ of DFA to reach a final state [4], where it also represents the expected number of future events from the current time event to a full match of the pattern $\mathcal{P}$, which is given by

$$W_{\mathcal{P}}(q) = inf\{n : q_0, q_1, ..., q_n, q_0 = q, q \in Q \backslash F, q_n \in F\}$$

However, the *waiting-time* distribution of the $W_{\mathcal{P}}(q)$ random variable can be computed based on the transition probability matrix $\Pi$ of the $PMC_m^{\mathcal{P}}$ , where it has $h$ non-final states and $d$ final states (absorbing states) [4], then distribution is calculated by the following equation

$$P(W_{\mathcal{P}}(q) = n) = \boldsymbol{\xi_q} \boldsymbol{N}^{n-1} (\boldsymbol{I} - \boldsymbol{N}) \mathbf{1}$$

where $\boldsymbol{N}$ is $h \times h$ matrix that obtained by re-arranging the transition matrix $\Pi$ to include transitions between the non-final states of the DFA, $\boldsymbol{I}$ is an identity matrix of size $d \times d$, and $\mathbf{1}$ is $h \times 1$ vector of ones. The $\boldsymbol{\xi_q}$ is $1 \times h$ row of elements that contains zeros except 1.0 in the cell corresponding to $q$.

Finally, the model provides the prediction reports in the form of intervals i.e., $I = (start, end)$. Which means that the DFA is expected to reach a final state after future transitions ( number of events $n$) between *start* and *end* with probability $P(I)$ at least some constant threshold $\theta_p$ that defined by the user, given by: given by:

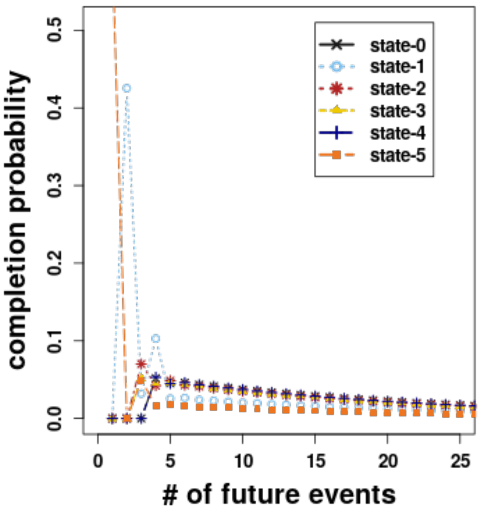
$$P(I) = \sum_{n \in I} P(W_{\mathcal{P}}(q) = n) \ where \ P(I) \geq \theta_p$$

where $P(I)$ equals the sum of probabilities of all number of future events $n$ that fall within $I$ ($start \leq n \leq end$). Furthermore, the length of the intervals ($spread(I) = end - start$) can be restricted to not be greater than a maximum spread threshold $\theta_s$.

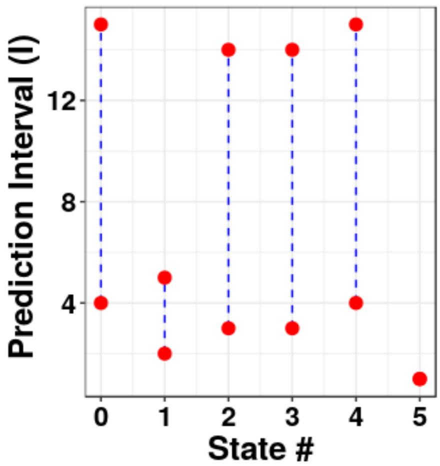
$$spread(I) \leq \theta_s$$

These intervals are estimated by a single-pass algorithm that scans a waiting-time distribution and finds the smallest (in terms of length) interval that exceeds the $\theta_p$ and has a spread not greater that $\theta_s$. Figure 3.3 shows an example of how the predictions intervals are produced, where Figure 3.3a shows the *waiting-time* distributions for all non-final states of the DFA presented in Figure 3.1, and the generated intervals are depicted in Figure 3.3b.

The proposed method assumes that the transition probability matrix $\Pi$ is available to build the prediction intervals. However, this is not true in the real-world applications. Therefore, it is essential to learn the values of the $PMC_m^{\mathcal{P}}$ 's transition probability matrix in order apply this method. One common way, is to use the maximum-likelihood estimator to learn the transition probabilities as illustrated in Section 3.3.1.




**(a)** Waiting-time distribution.




**(b)** Prediction intervals.

**Figure 3.3:** Example of computed prediction intervals for $\mathcal{P} = a; d; c$, $\Sigma = \{a, b, c, d\}$, $m = 1$, $\theta_p = 0.5$ *and* $\theta_s = 20$.

This model is performing the learning over an event stream $s$ that might requires a large amount of time until convergence to a sufficiently good model. Where in the case of multiple event streams, a unique model associated with each stream is needed. Accordingly, we present in this work, a technique to share information among $PMC_m^{\mathcal{P}}$ predictors over multiple input event streams (i.e., distributed learning of the transition probability matrix).

## 3.2 Pattern Prediction over Multiple Event Streams

### 3.2.1 Problem Formulation Extension

In this section, we extend the problem of pattern prediction over an event stream to consider the setting where there are multiple input event streams: Let $O = \{o_1, ..., o_k\}$ be a set of $K$ objects/entities (e.g., moving objects), each of which is generating an event stream $s_i$, hence, we have a set of real-time input event streams $S = \{s_1, ..., s_k\}$.

Let $\mathcal{P}$ be a user-defined pattern given in the form of regular expression, which is monitored in every stream $s_i \in S$. Then, we have a system consists of $K$ distributed predictor (learner) nodes $n_1, n_2..., n_k$, each of which receives an input event stream $s_i \in S$ associated with an object $o_i \in O$.

The goal is to provide online predictions about the completion of the pattern $\mathcal{P}$ within each stream $s_i$. Toward this goal, each node maintains a local prediction model $f_i$ associated the user-defined pattern $\mathcal{P}$. Then for each new arriving event tuple $e_t \in s_i$, the $f_i$ model provides an online prediction interval about the future full match of the pattern $\mathcal{P}$.

In summary, we have multiple running instances of an online prediction algorithm on distributed nodes for multiple input event streams. For example, massive streams of events that describe trajectories of moving vessels in the context of maritime surveillance, where there is one predictor node for each vessel's event stream.

### 3.2.2 The Proposed Approach

We design and develop a scalable and distributed pattern prediction system over a massive input event streams. As the base prediction model, we use the PMC forecasting method [4], where there is a $PMC_m^{\mathcal{P}}$ model associated with each input event stream $s_i$. Thus, the prediction model $f_i$ on a predictor node is represented by $PMC_m^{\mathcal{P}}$ and its associated DFA.

We propose to enable the information exchange among the distributed predictors of the input event streams, by adapting a distributed online prediction protocol [24] to synchronize the parameters of prediction models, which are represented by the transitions probabilities matrix of the $PMC_m^{\mathcal{P}}$ predictors. This protocol provides a communication-efficient dynamic synchronization scheme based on a periodic static scheme. In next, we describe the details of adapting this protocol with pattern prediction models.

Algorithm 1 presents the distributed online prediction protocol by dynamic model synchronization on both the predictor nodes and the coordinator. We refer to the PMC's transition matrix $\mathbf{\Pi}_i$ on predictor node $n_i$ by $w_i$. That is, when a predictor $n_i : i \in [k]$ observes an event $e_j$ it revises its internal model state (i.e., $f_i$) and provides a prediction report. Then it checks the local conditions (batch size $b$ and local model divergence from a reference model $w_r$) to decide whether there is a need to synchronize its local model with the coordinator [or not]. $w_r$ is maintained in the predictor node as a copy of the last computed aggregated model $\hat{w}$ from the previous full synchronization step, which is shared between all local predictors/learners. By monitoring the local condition $\|w_i - w_r\|^2 > \Delta$ on all local predictors, we have a guarantee that if none of the local conditions is violated, the divergence (i.e., variance of local models $\delta(w) = \frac{1}{k}\sum_{j=1}^{k} \|w_i - \hat{w}\|^2$) does not exceed the threshold $\Delta$ [24].

On the other hand, the coordinator receives the prediction models from the predictor nodes that requested for model synchronization (violation). Then it tries to keep incrementally querying other nodes for their local prediction models until reaching out all nodes, or the variance of the aggregated model $\hat{w}$ that is computed from the already received models less or equal than the divergence threshold $\Delta$. Finally, the aggregated model $\hat{w}$ is sent back to the predictor nodes that sent their models after the violation or have been queried by the coordinator.

**Algorithm 1:** Communication-efficient Distributed Online Learning [24].

**Predictor** node $n_i$: at observing event $e_j$
  update the parameters of the local prediction model $w_i$ and provide a prediction interval $I$ ;
  **if** $j \mod b = 0$ *and* $\|w_i - w_r\|^2 > \Delta$ **then**
    send $w_i$ to the Coordinator (violation) ;

**Coordinator**:
  receive local models with violation $B = \{w_i\}_{i=1}^{m}$ ;
  **while** $|B| \neq k$ *and* $\frac{1}{|B|} \sum_{w_i \in \Pi} \|w_i - \hat{w}\|^2 > \Delta$ **do**
    add other nodes have not reported violation for their models $B \leftarrow \{w_l : f_l \notin B \text{ and } l \in [k]\}$ ;
    receive models from nodes in $B$;
  compute a new global model $\hat{w}$ ;
  send $\hat{w}$ to all the predictors in $B$ and set $f_1 \ldots f_m = \hat{w}$;
  **if** $|B| = k$ **then**
    set a new reference model $w_r \leftarrow \hat{w}$ ;

We use this protocol for the pattern prediction model, which is internally based on the $PMC_m^{\mathcal{P}}$ . This allows the distributed $PMC_m^{\mathcal{P}}$ predictors for multiple event streams to synchronize their models (i.e., the transition probability matrix of each predictor) within the system in a communication-efficient manner.

We propose a *synchronization operation* for the parameters of the models ($w_i = \mathbf{\Pi}_i : i \in [k]$) of the $k$ distributed PMC predictors. The operation is based on distributing the maximum-likelihood estimation [5] for the transition probabilities of the underlying $PMC_m^{\mathcal{P}}$ models described by:

$$\hat{\pi}_{i,j} = \frac{\sum_{k \in K} n_{k,i,j}}{\sum_{k \in K} \sum_{l \in L} n_{k,i,l}} \tag{3.1}$$

Moreover, we measure the divergence of the local models from the reference model $\|w_k - w_r\|^2$ by calculating the sum of square difference between the transition probabilities $\mathbf{\Pi}_i$ and $\mathbf{\Pi}_r$:

$$\|w_k - w_r\|^2 = \sum_{i,j} (\hat{\pi}_k i, j - \hat{\pi}_r i, j)^2$$

## 3.3 Analysis of Proposed Approach

Generally, our approach relies on enabling the collaborative learning among the distributed predictors. Each predictor node receives a stream of events related to a distinct moving object, and the central coordinator is responsible of synchronizing their prediction models using the *synchronization operation*. Moreover, the predictors they only need to share the parameters of their models.

In addition, our approach relies on enabling the collaborative learning between the prediction models of the input event streams. By doing so, we assume that the underlying event streams belong to the same distribution and share the same behavior (e.g., mobility patterns). We claim this assumption is reasonable in many application domains: for example, in the context of maritime surveillance, vessels travel through standard routes, defined by the International Maritime Organization (IMO). Additionally, vessels have similar mobility patterns in specific areas such as moving with low speed and multiple turns near the ports [39, 28]. That allows our system to construct a coherent global prediction model dynamically for all input event streams based on merging their local prediction models.

### 3.3.1 Theoretical Analysis

In this section, we present preliminaries of Markov chain and the maximum likehood estimator of the transition probabilities, and we describe the theoretical properties of our proposed synchronization operator and its relation with the maximum likelihood estimator.

#### Preliminaries

In this section, we first present some definitions related to Markov chain theory, where the theoretical definitions presented are based on the work described in [9, 10, 5, 23].

**Definition 5.** *Let $\{s_0, s_1, \dots s_n\}$ be a sequence of random variables as **Markov chain**, where $s_i$ belongs to a finite state space $\mathbf{S} = \{\mathbf{1}, \dots \mathbf{m}\}$ and represents the observed state of the chain at time $i$. Let the transition probabilities of the Markov chain $p_{ij}(t+1)$ such that $i, j \in S$ and $t = 0, \dots, n$, where $p_{ij}(t+1)$ is the probability of the state $j$ at time $t+1$, given state $i$ at time $t$, where the sequence $\{s_0, s_1, \dots s_n\}$ satisfies the **Markov property***

$$P(s_{t+1} = j | s_t = i, s_{t-1} = i_{t-1}, \dots, s_0 = i_0) = P(s_{t+1} = j | s_t = i) \quad \forall i, j, i_{t-1}, i_0 \in S \tag{3.2}$$

*Thus, the probability of moving to a future state only depends on the current state (first-order Markov chain). While for higher order $m$ Markov chains the conditional probabilities can be modeled to be dependent on the last $m$ states.*

*When the conditional probabilities $P(s_{t+1} = j | s_t = i)$ are independent of the time $t$, the Markov chain is called **homogeneous** such that $p_{ij} := P(s_{t+1} = j | s_t = i)$.*

The transition probabilities of the Markov chain are represented by a $m \times m$ matrix that called **transition probability matrix $\mathbf{\Pi}$** with $p_{ij}$ elements

$$\mathbf{\Pi} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdot & \cdot & \cdot & p_{1,m} \\ p_{2,1} & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_{m,1} & p_{m,1} & \cdot & \cdot & \cdot & p_{m,m} \end{pmatrix} \tag{3.3}$$

where $0 \leq p_{i,j} \leq 1$ and the rows sum up to one

$$\sum_{j=1}^{m} p_{i,j} = 1 \qquad i = 1, 2 \dots m \tag{3.4}$$

**Learning the Transition Probability Matrix**. As mentioned in Section 3.1.2, we rely on the transition probability matrix of $PMC_m^{\mathcal{P}}$ to build the predictions table. However, in practice the underlying transition probability matrix is unknown, and desirable to estimate or learn it form the observed sequence $\{s_0, s_1, \dots s_n\}$. The maximum likelihood estimator (MLE) is a common method to estimate the transition probability matrix [5].

**Definition 6.** *Let* $\mathbf{\Pi}$ *is the transition probability matrix of a single Markov chain with a set of states* $S$*,* $\pi_{i,j}$ *the transition probability from state* $i$ *to state* $j$*,* $n_{i,j}$ *the number of observed transitions from state* $i$ *to state* $j$*, then the maximum likelihood estimator finds* $\hat{\mathbf{\Pi}}$ *as an estimate for* $\mathbf{\Pi}$*, where its elements* $\hat{p}_{i,j}$ *are*

$$\hat{p}_{i,j} = \frac{n_{i,j}}{\sum_{l \in S} n_{i,l}} = \frac{n_{i,j}}{n_i} \tag{3.5}$$

The maximum likelihood estimates of transition probabilities of a single sequence $\{s_0, s_1, \ldots s_n\}$ are obtained based on the observed transitions between the states of the chain. That is, the maximum likelihood estimates are basically the count of transitions from $i$ to $j$ divided by the total count of the chain being in state $i$.

Anderson and Goodman [5] have shown that

$$\begin{aligned} \sqrt{n}\ (\hat{p}_{i,j} - p_{i,j}) \xrightarrow{d} \mathcal{N}(\mu,\, \sigma^2_{mle_n}) \\ as\ n \to \infty \end{aligned} \tag{3.6}$$

Thus, the random variable $\sqrt{n}\ (\hat{p}_{i,j} - p_{i,j})$ has asymptotically normal distribution with mean $\mu = 0$. Therefore, the MLE is an asymptotically normal. While the variance $\sigma^2_{mle_n}$ is given by

$$\begin{aligned} \sigma^2_{mle_n} = \mathrm{Var}(\sqrt{n}\ (\hat{p}_{i,j} - p_{i,j})) = \frac{p_{i,j}\ (1 - p_{i,j})}{\phi_i} \\ \text{s.t. } \phi_i = \sum_{l=1}^{m} \sum_{t=1}^{n} \eta_l\ p^{t-1}_{l,j} \end{aligned} \tag{3.7}$$

Where $p^{t-1}_{l,j}$ is the probability of state $j$ at time $t-1$ given that the state $l$ at time 0 [5]. We are interested in the variances of $(\hat{p}_{i,j} - p_{i,j})$ that represents the error in estimating $p_{i,j}$ by MLE, which is given by:

$$\mathrm{Var}(\hat{p}_{i,j} - p_{i,j}) = \frac{\sigma^2_{mle_n}}{n} \tag{3.8}$$

It is clearly seen that variances are dropping as the sample size $n$ grows large. In next, we will show that our proposed approach of synchronizing the maximum likelihood estimators over $k$ chains is preserving a similar asymptotic behavior.

#### 3.3.1.1 Properties of the Synchronization Operator

The proposed synchronization operator is basically aggregating the maximum likelihood estimates over $k$ observed sequences (i.e., sequences of the DFA states based on the consumed event streams), the operator estimates the maximum likelihood of the probabilities for a set of $k$ sequences, which are arranged in serial order as one large chain with length $N = kn$ where we assume that all $k$ sequences have $n$ observations. For the sake of simplicity, we assume that the synchronization phase happens on batch size equals $n$ (i.e., $b = n$) the, then it follows that

$$\hat{\pi}_{i,j} = \frac{\sum_{k \in K} n_{k,i,j}}{\sum_{k \in K} \sum_{l \in L} n_{k,i,l}} = \hat{p}_{i,j}(N) \qquad \text{where } N = kn. \tag{3.9}$$

Thus, this operation it allows to observe more samples, which is naturally producing a better estimates of the transition probabilities. In addition, our proposed synchronization operation of the $k$ transition matrices has the same proprieties as the maximum likelihood estimator over a serial sequence of all $k$ sequences, but with skipping $k-1$ transitions between each two consecutive sequences, which is in practice a small number that can be neglected comparing to the total transitions count $kn$. As result, the probabilities estimates of our estimator (i.e.,global) based on the proposed operation within the distributed online learning protocol have the same properties as maximum likelihood estimates, in particular, the the random variable $\sqrt{N}\ (\hat{\pi}_{i,j} - p_{i,j})$ has asymptotically normal distribution with mean $\mu = 0$ following Equation 3.6 we have

$$\sqrt{N}\ (\hat{\pi}_{i,j} - p_{i,j}) \xrightarrow{d} \mathcal{N}(0,\, \sigma^2_{mle_N}) \qquad as\ N \to \infty \qquad where\ N = nk. \tag{3.10}$$

So,

$$\mathrm{Var}(\hat{\pi}_{i,j} - p_{i,j}) = \frac{\sigma^2_{mle_N}}{N} = \frac{\sigma^2_{mle_n}}{kn} \tag{3.11}$$

That is, since $N > n$ combining $k$ sequences, the variances of our method estimates $\mathrm{Var}(\hat{\pi}_{i,j} - p_{i,j})$ are smaller than the estimates of MLE over an isolated sequence $\mathrm{Var}(\hat{p}_{i,j} - p_{i,j})$. Thus, it follows from the Chebyshev's inequality [16] that we have for the random variable $\hat{p}_{i,j} - p_{i,j}$, for any constant $c > 0$

$$\Pr\left(|(\hat{p}_{i,j} - p_{i,j}) - \mu| \geq c\right) \leq \frac{\mathrm{Var}(\hat{p}_{i,j} - p_{i,j})}{c^2}$$

where the mean $\mu = 0$ is zero and the $\mathrm{Var}(\hat{p}_{i,j} - p_{i,j})$ equals $\frac{\sigma^2_{mle_n}}{n}$, and therefore

$$\Pr\left(|\hat{p}_{i,j} - p_{i,j}| \geq c\right) \leq \frac{\sigma^2_{mle_n}}{c^2 n}$$

$\hat{p}_{i,j} - p_{i,j}$ represents the deviation/error between the estimates of MLE over a single (i.e., isolated) sequence and the true probabilities. On the other hand, we can obtain, in the same way, the probability bound of deviations for our synchronization operator estimates as follows:

$$\Pr\left(|\hat{\pi}_{i,j} - p_{i,j}| \geq c\right) \leq \frac{\sigma^2_{mle_n}}{c^2 nk}$$

Using Equation 3.11 we obtained the value $\mathrm{Var}(\hat{\pi}_{i,j} - p_{i,j})$. Since $k \geq 1$ we have that the variance of $(\hat{\pi}_{i,j} - p_{i,j})$ is less than or equal to the variance of $\hat{p}_{i,j} - p_{i,j}$

$$\frac{\sigma^2_{mle_n}}{c^2 nk} \leq \frac{\sigma^2_{mle_n}}{c^2 n}$$

This is equivalent to,for any constant $c > 0$ and $k \geq 1$ we have

$$\Pr\left(|\hat{\pi}_{i,j} - p_{i,j}| \geq c\right) \leq \Pr\left(|\hat{p}_{i,j} - p_{i,j}| \geq c\right)$$

To summarize, our approach is based aggregating the MLE estimates over $k$ sequences, which speeds up the convergence to reach the true transition probabilities as result of the smaller variances.

#### 3.3.1.2 Computing the Transition Matrix of the Underlaying Markov Chain

In order to empirically study the asymptotic behavior of our proposed synchronization operator, we need to compute the transition probability matrix of the underlying Markov chain that the events belong to, and we introduce to calculate it based on the transition matrix ($\Pi$) of $PMC_m^{\mathcal{P}}$ that describes the Markov chain of the pattern.

Nuel [37] showed in **Theorem 3** the relation between the elements of $\Pi$ and the conditional probabilities of the $m-$order Markov chain $X = \{X_1, X_2, \dots X_n\}$ described by

$$\Pi(p,q) = \begin{cases} P(X_{m+1} = b | X_1 \dots X_m = \delta^{-m}(p)) & \text{if } \delta(p,q) = b \\ 0 & \text{if } p \notin \delta(p, X) \end{cases}$$

Using this theorem, we can compute the transition probabilities of the Markov chain $X$. For example, the transition probability matrix of the DFA of the pattern $\mathcal{P} = a; d; c$ over $\Sigma = \{a, b, c, d\}$ can be represented by:

$$\mathbf{\Pi} = \begin{Bmatrix} 0 \\ 1 \\ 2 \\ 3 \end{Bmatrix} \begin{pmatrix} P(b) + P(c) & P(a) & 0 & 0 \\ P(b) & P(a) & P(c) & 0 \\ P(b) & P(a) & 0 & P(c) \\ 0 & 0 & 0 & 1.0 \end{pmatrix}$$

# 4 System Overview

## 4.1 System Architecture

Our system consumes as an input[1] an aggregated stream of events coming from a large number of moving objects, which is continuously collected and fed into the system. It allows users to register a pattern $\mathcal{P}$ to be monitored over each event stream of a moving object. The output stream consists of original input events and predictions of full matches of $\mathcal{P}$, displayed to the end users. Figure 4.1 presents the overview of our system architecture and its main components.

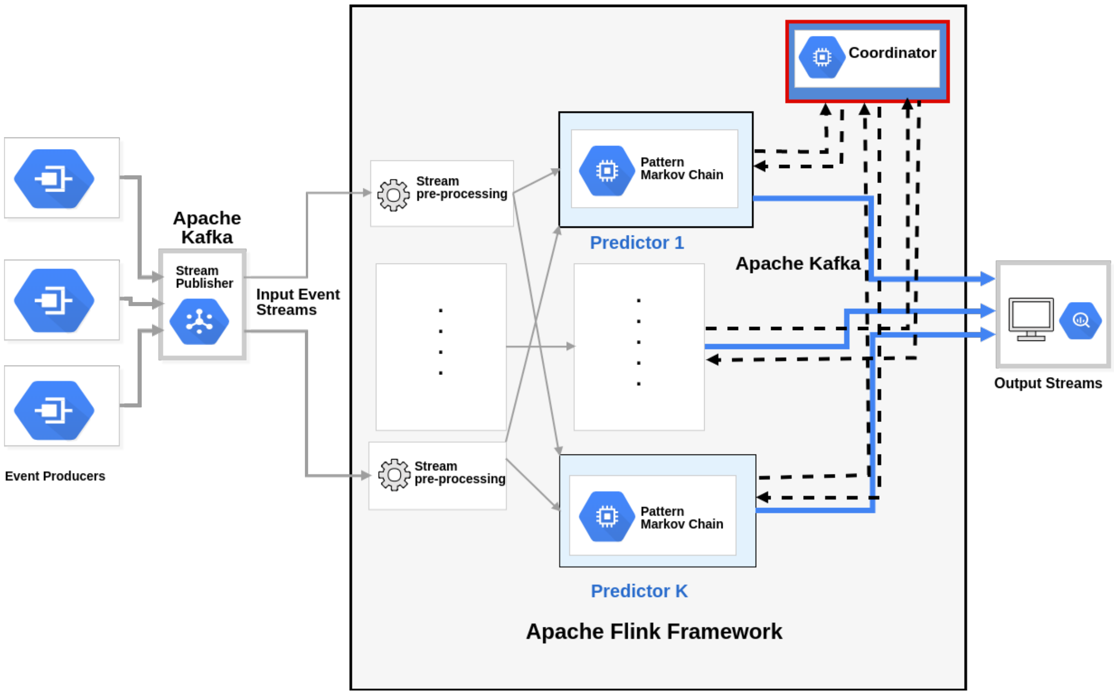



**Figure 4.1:** System architecture overview.

The system is composed of three processing units:

[1]In practice, the aggregated input events stream is composed of multiple event streams (partitions) from a set of moving objects.

1. pre-processing operators that receive the input event stream and perform filtering and ordering operations, before partitioning the input event stream to multiple event streams based on the associated moving object

2. predictor nodes (learners), which are responsible for maintaining a prediction model for the input event streams. Each prediction node is configured to handle an event stream from the same moving object, in order to provide online predictions for a predefined pattern $\mathcal{P}$

3. a coordinator node that communicates through Kafka stream channels with the predictors to realize the distributed online learning protocol. It builds a global prediction model, based on the received local models, and then shares it among the predictors.

Our distributed system consists of multiple pre-processing operators, prediction nodes, and a central coordinator node. All units run concurrently and are arranged as a data processing pipeline, depicted in Figure 4.1. We leverage Apache Kafka as a messaging platform to ingest the input event streams and to publish the resulting streams. Also, it is used as the communication channel between the predictor nodes and the coordinator. Apache Flink is employed to execute the system's distributed processing units over the input event streams: the pre-processing operators, the prediction units, and the coordinator node. Our system architecture can be modeled as a logical network of processing nodes, organized in the form of a DAG, inspired by the Flink runtime dataflow programs [12].

## 4.2 Implementation Details

In this section, we describe in detail the implementation of our system. It has been implemented on top of Apache Flink and Apache Kafka frameworks. Each of the three sub-modules, described in Section 4.1, have been implemented as Flink operations over the input events stream.

**Pre-processing and Prediction Operators.** Listing 4.1 shows how the main workflow of the system is implemented as Flink data flow program.

The system ingests the input events stream from a Kafka cluster that is mapped to a *DataStream* of events, which is then processed by an *EventTuplesMapper* to create tuples of *(id, event)*, where the *id* is associated to the identifier of the moving object. To handle events coming in out of order in a certain margin, the stream of event tuples is processed by a *TimestampAssigner*, it assigns the timestamps for the input events based on the extracted creation time. Afterwards, an ordered stream of event tuples is generated using a process function *EventSorter*.

```
DataStream<Event> eventsStream = env.addSource(kafkaConsumer);
// Create event tuples (id,event) and assign time stamp
DataStream<Tuple2<String,Event>> eventTuplesStream =
inputEventsStream.map(new EventTuplesMapper())
.assignTimestampsAndWatermarks(new EventTimeAssigner());
// Create the ordered keyed stream
 keyedEventsStream = eventsStream.keyBy(0).process(new
     EventSorter()).keyBy(0);
//Initialize the predictor node
LocalPredictorNode predictorNode =new LocalPredictorNode<Event>(P);
// Process the keyedEventsStream by the predictor
DataStream<Event> processedEventsStream =
keyedEventsStream.map(predictorNode);
```

**Listing 4.1:** Flink pipeline for local predictors workflow

The ordered stream is then transformed to a *keyedEventsStream* by partitioning it, based on the ids values, using a *keyBy* operation. A local *predictor* node in a distributed environment is represented by a *map* function over the *keyedEventsStream*. Each parallel instance of the map operator (predictor) always processes all events of the same moving object (i.e., equivalent id), and maintains a bounded prediction model (i.e., $PMC_m^{\mathcal{P}}$ predictor) using the Flink's Keyed State [2]. The output streams of the moving objects from the parallel instances of the predictor map functions are sent to a new Kafka stream (i.e., same topic name). They then can be processed by other components like visualization or users notifier.

Moreover, the implementation of the *predictor* map function includes the communication with *coordinator* using Kafka streams. At the beginning of the execution, it sends a registration request to the coordinator. Also at the run-time, it sends its local prediction model as synchronization request, or as a response for a resolution request from the coordinator. These communication messages are published into different Kafka topics as depicted in Table 4.1.

**Coordinator.** Listing 4.2 presents the workflow of the coordinator node that manages the distributed online learning protocol operations, which is implemented as Flink program. The coordinator receives messages from the local predictors through a Kafka Stream of a topic named *"LocalToCoordinatorTopicId"*. It is implemented as a single *map* function over the messages stream, by setting the

[2] Keyed State in Flink: https://ci.apache.org/projects/flink/flink-docs-release-1.3/dev/stream/state.html#kayed-state

**Table 4.1:** Messages to Kafka topics mapping.

| Message | Kafka Topic |
|---|---|
| *RegisterNode*, *RequestSync*, and *ResolutionAnswer* | LocalToCoordinatorTopicId |
| *CoordinatorSync* and *RequestResolution* | CoordinatorToLocalTopicId |

*parallelism* level of the Flink program to *"1"*. Increasing the parallelism will scale up the number of parallel coordinator instances, for example, in order to handle different groupings of the input event streams. The map operator of the coordinator handles three message types from the predictors:

1. **RegisterNode** that contains a registration request for a new predictor node,
2. **RequestSync** to receive a local model after violation,
3. **ResolutionAnswer** to receive a resolution response from a local predictor node.

In addition, it sends **CoordinatorSync** messages for all predictors after creating a new global prediction model, or **RequestResolution** to a ask the local predictors for their prediction models.

```
 streamExecutionEnvironment.setParallelism(1);
// Read messages from local predictors
DataStream<TopicMessage> messagesStream = readKafkaStream(env,
    "LocalToCoordinatorTopicId");
// Initialize the coordinator node
CompunctionEfficientCoordinator coordinatorNode = new
    CompunctionEfficientCoordinator(configs);
// Ingest the messages stream by the coordinator
DataStream<CoordinatorMessage> coordinatorMessagesStream =
    messageStream.map(coordinatorNode);
// Send the messages from the coordinator to the local predictors
writeKafkaStream(coordinatorMessagesStream,
    CoordinatorToLocalTopicId);
```

**Listing 4.2:** The coordinator Flink program.

# 5 Empirical Evaluation

## 5.1 Evaluation Over Synthetic Event Streams

## 5.2 Evaluation Over Real-word Event Streams

In this section, we evaluate our proposed system by analyzing the predictive performance and communication complexity using real-world event streams provided by the datAcron project in the context of maritime monitoring. The used event streams describe critical points (i.e., synopses) of moving vessels trajectories, which are derived from raw AIS messages as described in [41]. In particular, for our evaluation experiments we used a data set of synopses that contains $4,684,444$ critical points of 5055 vessels sailing in the Atlantic Ocean during the period from 1 October 2015 to 31 March 2016.

We used the synopses data set to generate a simulated stream of event tuples i.e., *(id, timestamp, longitude, latitude, annotation, speed, heading)*, which are processed by the system to attach an extra attribute *type* that represents the event value, where *type* $\in \Sigma$, and $\Sigma = \Sigma_1 =\{$ *VerySlow, Slow, Moving, Sailing, Stopping*$\}$, which is based on a discretization of the speed values. That is, $\Sigma_1$ includes a simple derived event types based on the speed value that can be used over streams of raw AIS or critical points. Or $\Sigma = \Sigma_2 = \{$*stopStart, stopEnd, changeInSpeedStart, changeInSpeedEnd, slowMotionStart, slowMotionEnd, gapStart, gapEnd, changeInHeading*$\}$, which is derived based on the values of the *annotation* attribute that encodes the extracted trajectory movement events [41]. $\Sigma_2$ represents the set of possible mobility changes in the vessel's trajectory [41], each critical point has at least one event. Where in the case of multiple values we generate duplicate points each of which corresponding to one event in the same order of $\Sigma_2$.

In our experiments, we monitor a pattern $\mathcal{P}_1 = Sailing$ with $\Sigma_1$ that detects when the vessel is underway (sailing). Likewise, we test a second pattern $\mathcal{P}_2 =$*changeInHeading; gapStart; gapEnd; changeInHeading* with $\Sigma_2$ that describes a potential illegal fishing activity [4].

### Experimental setup

We ran our experiments on single-node standalone Flink cluster deployed on an Ubuntu Server 17.04 with Intel(R) Core(TM) i7-7700 CPU @ 3.60GHz X 8 processors and 32GB RAM. We used Apache Flink v1.3.2 and Apache Kafka v0.10.2.1 for our tests.

### Evaluation criteria

Our goal is to evaluate our distributed pattern prediction system, which enables the synchronization of prediction models (i.e., PMC models) on the distributed predictor nodes. Our proposed system can operate in three different modes of protocols/schemes of models synchronization:

(i) static scheme based on synchronizing the prediction models periodically every $b$ of input events in each stream,

(ii) continuous, full synchronization for each incoming event (hypothetical),

(iii) dynamic synchronization protocol based on making the predictors communicate their local prediction models periodically but only under condition that the divergence of the local models from a reference model exceeds a variance threshold $\Delta$ (recommended).

We compare our proposed system against the isolated prediction mode, in which models are computed on single streams only, and compare the predictive performance in terms of :

(i) $Precision = \frac{\#\ of\ correct\ predictions}{\#\ of\ total\ predictions}$ is the fraction of the produced predictions that are correct. For each new event in the stream, the predictor provides a prediction interval where the full match of the pattern might occur. Thus, the predictions are temporarily stored until a full match is detected. At that point, all stored prediction intervals are evaluated by considering those intervals where the full match occurred within as correct.

(ii) $Spread = end(I) - start(I)$ is the width of the prediction interval $I$, which represents the number of events between the start and the end of $I$.

Moreover, we study the communication cost by measuring the *cumulative communication* that captures the number of messages, which are required to perform the distributed online learning modes to synchronize the prediction models. Next, we present the experimental results for the patterns $\mathcal{P}_1 = Sailing$ with an order of $m = 2$, and $\mathcal{P}_2 =$ *changeInHeading; gapStart; gapEnd; changeInHeading* with first order $m = 1$. All experiments are performed with setting the batch size to 100 ($b = 100$), the variance threshold of 2 ($\Delta = 2$), 80% as PMC prediction threshold ($\theta_c = 80\%$), and 200 for the maximum spread.

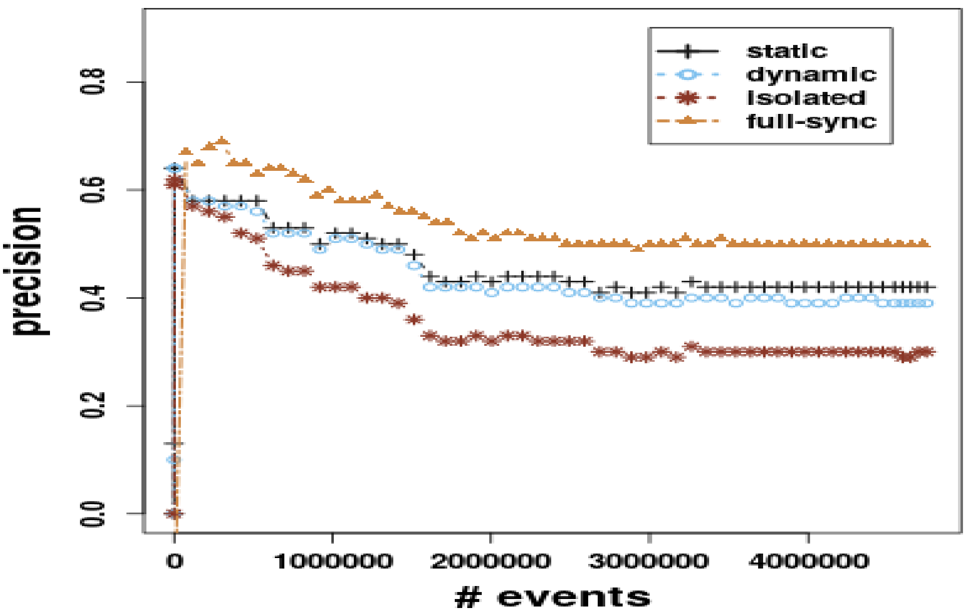



**Figure 5.1:** Precision scores with respect to the number of input events over time for $\mathcal{P}_1$.

### Experimental results

Figure 5.1 depicts the average precision scores of predictions models (one prediction model per vessel) of all synchronization modes for the first pattern $\mathcal{P}_1 = \mathit{Sailing}$, namely, isolated without synchronization, continuous (full-sync), static, and our recommended approach based on the dynamic synchronization scheme. It can be clearly seen that all methods of distributed learning outperform the isolated prediction models. The hypothetical method of full continuous synchronization has the highest precision rates, while the static and dynamic synchronization schemes have close precision scores. Consequently, dynamic synchronization is not much weaker than the static synchronization, but requires much less communication, as explained below.

Figure 5.2 provides the amount of the accumulated communication that is required by the three modes of the distributed online learning, while the isolated approach does not require any communication between the predictors. These results are shown for $\mathcal{P}_1$. As expected, a larger amount of communication is required for the continuous synchronization comparing to the static and dynamic approaches. Also, it can be seen that we can reduce the communication overhead by applying the dynamic synchronization protocol (a reduction by a factor of 100) comparing to the static synchronization scheme, even with a small variance threshold $\Delta = 2$. Furthermore, the dynamic protocol is still preserving a close predictive performance to the static one (see Figure 5.1). Therefore, we will only consider the dynamic synchronization and the isolated approach in the evaluation of the second pattern.

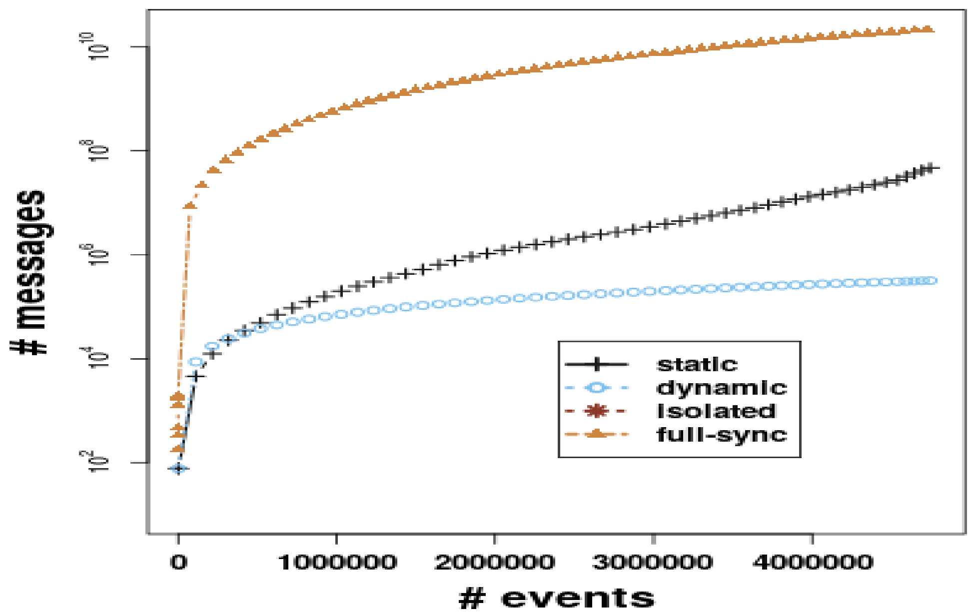



**Figure 5.2:** Cumulative communication with respect to the number of input events over time for $\mathcal{P}_1$.

In Figure 5.1, we also noted that the precision is going down in a first phase and stabilizes then. This seems to be counter-intuitive, as the models should improve when getting more data up to a certain point. For explanation, we have investigated the effect of the distributed synchronization of the prediction models on the average spread value, Figure 5.3 shows the spread results for all approaches. It can be seen that the spread is higher for the distributed learning based methods comparing to the isolated approach. Furthermore, the average spread is decreasing

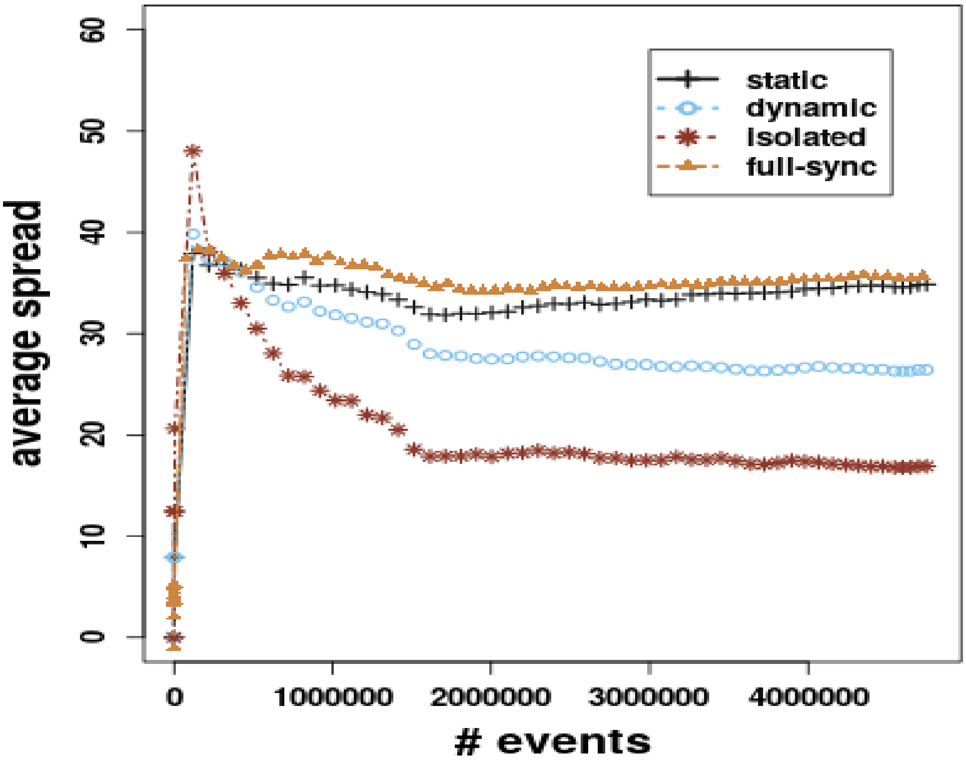



**Figure 5.3:** Average spread value for $\mathcal{P}_1$.

over time until convergence, as result of confidence increase in the models. This may explain the drop in the precision scores from the beginning until reaching the convergence. We will investigate further in the interrelation between precision and spread in future work.

For the second, more complex pattern ($\mathcal{P}_2$), we have found that the precision was worse for a distributed model generated over all vessels than in the model created for each vessel in isolation. This indicates that there is no global model describing the behavior of all models consistently. However, when looking at specific groups of vessels, we achieved an improvement in terms of precision. As initial experiment, we only enable the synchronization of the prediction models associated with vessels that belong to the same vessel class. Currently, this change is technically performed by an extra filter step that passes only one type of vessels, while multiple runs of the system are required for all vessel types. For example, Figure 5.4 shows the precision scores for vessels of class *PLEASURE CRAFT*. This case might seem to contradict of our assumption that the input event streams belong to the same distribution and share the same behavior, but it actually follows the same

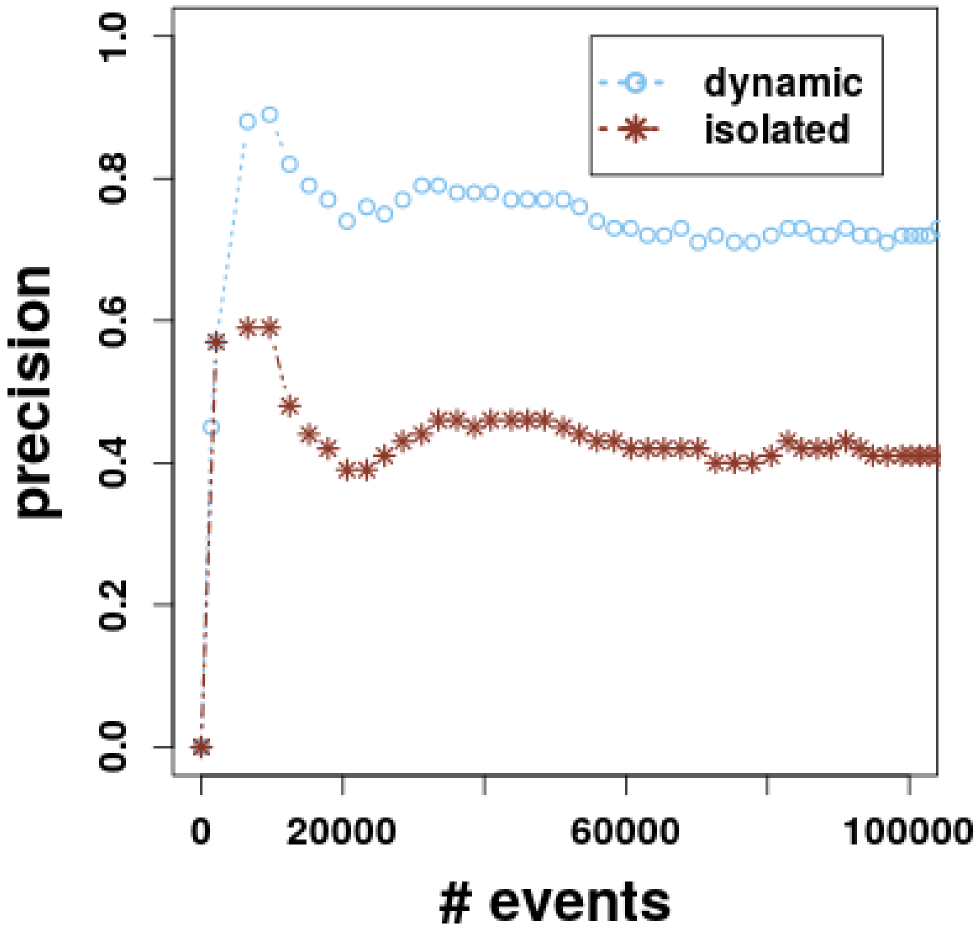



**Figure 5.4:** Precision scores of $\mathcal{P}_2$ for *PLEASURE CRAFT* vessels.

assumption but between the predictors of vessels within the same type group. An interesting observation is that the dynamic synchronization approach still has a higher precision scores than the isolated approach. We will further investigate the effect of groupings and more patterns in future work.

# 6 Discussion

In this chapter, we discuss the results of our system, and some of the aspects of underlying method. Also we give some proposals for future work.

## 6.1 Result

## 6.2 Approach

## 6.3 Future Work

- In some practical applications the input event streams may belong to different distributions, we propose to divide the input event streams into similar groups, in order to combine the corresponding predictions models to construct a representative global model in each group. The aggregation operation refers to the synchronization operation (e.g., joint average of the local models) in the distributed online learning protocol, which is performed by a central coordinator that constructs and distributes a global prediction model for the input event streams based on the local models.
- temporal patterns
- another communication media
- theoretical analysis of dynamic protocol
- another transition probabilities learning technique
- another weighted sync operator

# 7 Conclusion

In this paper, we have presented a system that provides a distributed pattern prediction over multiple large-scale event streams of moving objects (vessels). The system uses the event forecasting with Pattern Markov Chain (PMC) [4] as the base prediction model on each event stream, and it applies the protocol for distributed online prediction [24] to exchange information between the prediction models over multiple input event streams. Our proposed system has been implemented using Apache Flink and Apache Kafka, and empirically tested against large real-world event streams related to trajectories of moving vessels. As future work, we will investigate the effect of grouping the input event streams on the predictive performance of our proposed system. Furthermore, we will study the interrelation between precision and spread scores.

# Bibliography

[1] Jagrati Agrawal, Yanlei Diao, Daniel Gyllstrom, and Neil Immerman. Efficient pattern matching over event streams. In *Proceedings of the 2008 ACM SIGMOD international conference on Management of data*, pages 147–160. ACM, 2008.

[2] Rakesh Agrawal, Tomasz Imieliński, and Arun Swami. Mining Association Rules Between Sets of Items in Large Databases. In *ACM SIGMOD*, 1993.

[3] Elias Alevizos, Anastasios Skarlatidis, Alexander Artikis, and Georgios Paliouras. Complex event recognition under uncertainty: A short survey. *Event Processing, Forecasting and Decision-Making in the Big Data Era (EP-ForDM)*, pages 97–103, 2015.

[4] Elias Alevizos, Alexander Artikis, and George Paliouras. Event forecasting with pattern markov chains. In *Proceedings of the 11th ACM International Conference on Distributed and Event-based Systems*, pages 146–157. ACM, 2017.

[5] Theodore W Anderson and Leo A Goodman. Statistical inference about markov chains. *The Annals of Mathematical Statistics*, pages 89–110, 1957.

[6] Amazon Web Services (AWS). Amazon Kinesis. `https://aws.amazon.com/de/kinesis/`, 2013.

[7] Brian Babcock, Shivnath Babu, Mayur Datar, Rajeev Motwani, and Jennifer Widom. Models and Issues in Data Stream Systems. *Proceedings of the 21st ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems*, pages 1–16, 2002. ISSN 1581135076. doi: 10.1145/543614.543615.

[8] Arindam Banerjee and Joydeep Ghosh. Clickstream clustering using weighted longest common subsequences. In *Proceedings of the web mining workshop at the 1st SIAM conference on data mining*, volume 143, page 144, 2001.

[9] Dimitri P Bertsekas and John N Tsitsiklis. *Introduction to probability*, volume 1. Athena Scientific Belmont, MA, 2002.

[10] P Billingsley. Statistical Methods in Markov Chains. *The Annals of Mathematical Statistics*, 32(1):12–40, 1961. ISSN 00034851. doi: 10.1214/aoms/1177705148. URL `http://www.jstor.org/stable/2238700`.

[11] Luca Canzian, Yu Zhang, and Mihaela van der Schaar. Ensemble of distributed learners for online classification of dynamic data streams. *IEEE Transactions on Signal and Information Processing over Networks*, 1(3):180–194, 2015.

[12] Paris Carbone, Asterios Katsifodimos, Stephan Ewen, Volker Markl, Seif Haridi, and Kostas Tzoumas. Apache flink: Stream and batch processing in a single engine. *Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, 36(4), 2015.

[13] Gianpaolo Cugola and Alessandro Margara. Processing flows of information: From data stream to complex event processing. *ACM Comput. Surv.*, 44(3): 15:1–15:62, June 2012. ISSN 0360-0300. doi: 10.1145/2187671.2187677. URL `http://doi.acm.org/10.1145/2187671.2187677`.

[14] Ofer Dekel, Ran Gilad-Bachrach, Ohad Shamir, and Lin Xiao. Optimal distributed online prediction using mini-batches. *Journal of Machine Learning Research*, 13(Jan):165–202, 2012.

[15] Lina Fahed, Armelle Brun, and Anne Boyer. Efficient Discovery of Episode Rules with a Minimal Antecedent and a Distant Consequent. In *Knowledge Discovery, Knowledge Engineering and Knowledge Management*. Springer, 2014.

[16] William Feller. *An introduction to probability theory and its applications: volume I*, volume 3. John Wiley & Sons New York, 1968.

[17] Ioannis Flouris, Nikos Giatrakos, Antonios Deligiannakis, Minos Garofalakis, Michael Kamp, and Michael Mock. Issues in complex event processing: Status and prospects in the Big Data era. *Journal of Systems and Software*, 127:217–236, 2017. ISSN 01641212. doi: 10.1016/j.jss.2016.06.011.

[18] The Apache Software Foundation. Apache Kafka. `https://kafka.apache.org/`, 2012.

[19] The Apache Software Foundation. Apache Spark Streaming. `http://spark.apache.org/streaming/`, 2013.

[20] The Apache Software Foundation. Apache Flink. `https://flink.apache.org/`, 2014.

[21] The Apache Software Foundation. Apache Storm. `http://storm.apache.org/`, 2014.

[22] John E Hopcroft, Rajeev Motwani, and Jeffrey D Ullman. Automata theory, languages, and computation. *International Edition*, 24, 2006.

[23] Ronald A Howard. *Dynamic probabilistic systems: Markov models*, volume 1. Courier Corporation, 2012.

[24] Michael Kamp, Mario Boley, Daniel Keren, Assaf Schuster, and Izchak Sharfman. Communication-efficient distributed online prediction by dynamic model synchronization. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 623–639. Springer, 2014.

[25] Michael Kamp, Sebastian Bothe, Mario Boley, and Michael Mock. Communication-efficient distributed online learning with kernels. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 805–819. Springer, 2016.

[26] Rikard Laxhammar and Göran Falkman. Conformal prediction for distribution-independent anomaly detection in streaming vessel data. In *Proceedings of the First International Workshop on Novel Data Stream Pattern Mining Techniques*, pages 47–55. ACM, 2010.

[27] Srivatsan Laxman, Vikram Tankasali, and Ryen W. White. Stream Prediction Using a Generative Model Based on Frequent Episodes in Event Sequences. In *ACM SIGKDD*, 2008.

[28] Bo Liu, Erico N de Souza, Stan Matwin, and Marcin Sydow. Knowledge-based clustering of ship trajectories using density-based approach. In *Big Data (Big Data), 2014 IEEE International Conference on*, pages 603–608. IEEE, 2014.

[29] David Luckham. The power of events: An introduction to complex event processing in distributed enterprise systems. In *International Workshop on Rules and Rule Markup Languages for the Semantic Web*, pages 3–3. Springer, 2008.

[30] Heikki Mannila, Hannu Toivonen, and A Inkeri Verkamo. Discovery of frequent episodes in event sequences. *Data mining and knowledge discovery*, 1 (3):259–289, 1997.

[31] Heikki Mannila, Hannu Toivonen, and A. Inkeri Verkamo. Discovery of Frequent Episodes in Event Sequences. *Data Mining and Knowledge Discovery*, 1997.

[32] Michael Mathioudakis and Nick Koudas. Twittermonitor: trend detection over the twitter stream. In *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*, pages 1155–1158. ACM, 2010.

[33] Ahmed Metwally, Divyakant Agrawal, and Amr El Abbadi. Duplicate detection in click streams. In *Proceedings of the 14th international conference on World Wide Web*, pages 12–21. ACM, 2005.

[34] Daniele Miorandi, Sabrina Sicari, Francesco De Pellegrini, and Imrich Chlamtac. Internet of things: Vision, applications and research challenges. *Ad Hoc Networks*, 10(7):1497–1516, 2012.

[35] Douglas C Montgomery, Cheryl L Jennings, and Murat Kulahci. *Introduction to time series analysis and forecasting*. Wiley, 2015.

[36] Vinod Muthusamy, Haifeng Liu, and Hans-Arno Jacobsen. Predictive Publish/Subscribe Matching. In *DEBS*. ACM, 2010.

[37] Grégory Nuel. Pattern Markov Chains: Optimal Markov Chain Embedding through Deterministic Finite Automata. *Journal of Applied Probability*, 2008.

[38] International Maritime Organization. Automatic identification systems. `http://www.imo.org/OurWork/Safety/Navigation/Pages/AIS.aspx`, 2001.

[39] Giuliana Pallotta, Michele Vespe, and Karna Bryan. Vessel pattern knowledge discovery from ais data: A framework for anomaly detection and route prediction. *Entropy*, 15(6):2218–2245, 2013.

[40] Kostas Patroumpas, Alexander Artikis, Nikos Katzouris, Marios Vodas, Yannis Theodoridis, and Nikos Pelekis. Event recognition for maritime surveillance. In *EDBT*, pages 629–640, 2015.

[41] Kostas Patroumpas, Elias Alevizos, Alexander Artikis, Marios Vodas, Nikos Pelekis, and Yannis Theodoridis. Online event recognition from moving vessel trajectories. *GeoInformatica*, 21(2):389–427, 2017.

[42] Ehab Qadah, Michael Mock, Elias Alevizos, and Georg Fuchs. A Distributed Online Learning Approach for Pattern Prediction over Movement Event Streams with Apache Flink. In *EDBT/ICDT Workshops*, 2018.

[43] Timo Reuter and Philipp Cimiano. Event-based classification of social media streams. In *Proceedings of the 2nd ACM International Conference on Multimedia Retrieval*, page 22. ACM, 2012.

[44] Nicholas Poul Schultz-Møller, Matteo Migliavacca, and Peter Pietzuch. Distributed complex event processing with query rewriting. In *Proceedings of the Third ACM International Conference on Distributed Event-Based Systems*, page 4. ACM, 2009.

[45] Cem Tekin, Simpson Zhang, and Mihaela van der Schaar. Distributed online learning in social recommender systems. *IEEE Journal of Selected Topics in Signal Processing*, 8(4):638–652, 2014.

[46] R. Vilalta and Sheng Ma. Predicting rare events in temporal domains. In *ICDM*, 2002.

[47] Gary M Weiss and Haym Hirsh. Learning to predict rare events in event sequences. In *KDD*, pages 359–363, 1998.

[48] Feng Yan, Shreyas Sundaram, SVN Vishwanathan, and Yuan Qi. Distributed autonomous online learning: Regrets and intrinsic privacy-preserving properties. *IEEE Transactions on Knowledge and Data Engineering*, 25(11):2483–2493, 2013.

[49] Yu Zhang, Daby Sow, Deepak Turaga, and Mihaela van der Schaar. A fast online learning algorithm for distributed mining of bigdata. *ACM SIGMETRICS Performance Evaluation Review*, 41(4):90–93, 2014.

[50] Cheng Zhou, Boris Cule, and Bart Goethals. A pattern based predictor for event streams. *Expert Systems with Applications*, 2015.