RHEINISCHE

FRIEDRICH-WILHELMS-UNIVERSITT BONN

MASTER THESIS PRESENTATION

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

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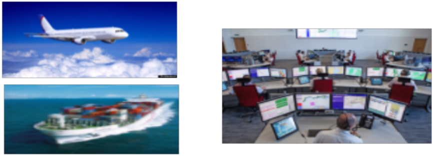
Motivation

A New Era: Big event Data streams

User Activities on Web

Internet of Things (IoT)



Maritime & Aviation surveillance

Motivation

A New Era: Big event Data streams

User Activities on Web

Internet of Things (IoT)

Maritime & Aviation surveillance

- Common goal: recognition and prediction full matches of event patterns (situations of interest) in real-time.

Problem Formulation

- Given a set of k real-time streams of events $S = \{s_1, s_2, ..., s_k\}$.
- Each stream $s_i = \langle e_1, e_3, ..., e_t, ...\rangle$ is a time-ordered infinite sequence of events.
- Each event is defined as a tuple of attributes $e_i = (id, type, \tau, a_1, a_2, \ldots, a_n)$, where $type \in \Sigma$ (i.e., event types), $\tau \in \mathbb{R}$, and $id \in \mathbb{N}$.
- A user-defined pattern $\mathcal{P}$ is given in the form of a regular expression over a set of event types. Σ ($\mathcal{P} := E \mid \mathcal{P}_1; \mathcal{P}_2 \mid \mathcal{P}_1 \vee \mathcal{P}_2 \mid \mathcal{P}_1^*,\ E \in \Sigma$).

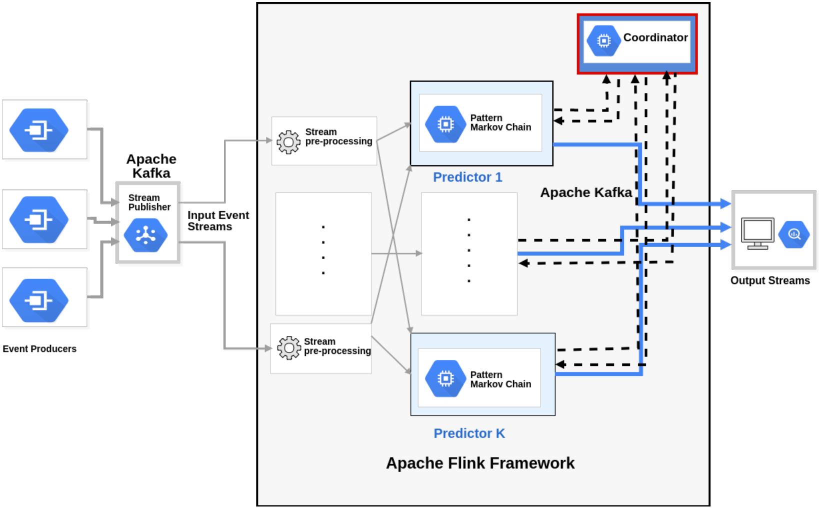
Problem Formulation

- The main objective is to predict the pattern $\mathcal{P}$ completion with certain probability in the future over each stream s_i given the current time event e_t.

Problem Formulation

- The main objective is to predict the pattern $\mathcal{P}$ completion with certain probability in the future over each stream s_i given the current time event e_t.
- (**Pattern Prediction over Multiple Event Streams**)

System Architecture



Scalable Pattern Prediction System [2]

- A scalable and distributed system that provides online pattern prediction over multiple real-time streams of events.
- The proposed system is based on a novel method that combines online probabilistic prediction models based on pattern Markov chain technique [1] with a distributed online learning protocol [6] to learn a global prediction model in a communication-efficient way.
- For large-scale processing support, the system is implemented on top of Apache Flink [3] along with Apache Kafka [5].
- Developed in the context of the datAcron project [1].

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

[2] Source code: `https://goo.gl/BZ2Prk`.

Event Forecasting with Pattern Markov Chains [1]

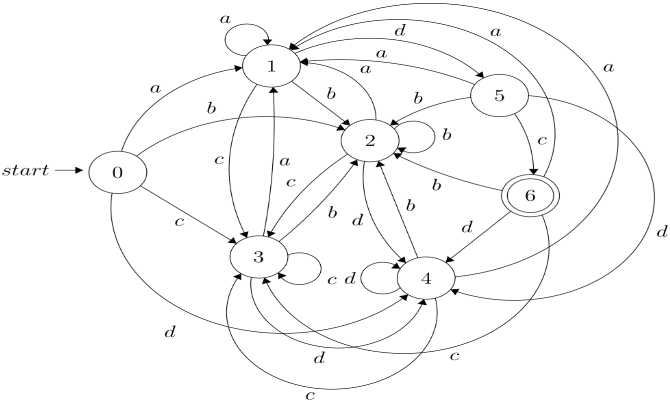
overview

- The model handles a single input stream s_i of events.
- The event stream s_i is assumed to be generated by m-order Markov source.
- The event pattern $\mathcal{P}$ is defined in the form of regular expressions over a finite set of event types Σ.
- A probabilistic model provides online forecasting reports when the $\mathcal{P}$ is expected to be completed in future.

Event Forecasting with Pattern Markov Chains

How does it work?

- The pattern $\mathcal{P} = a; d; c$ is converted to deterministic finite automaton (DFA) with $\Sigma = \{a, b, c, d\}$.



$$Q = \{0, 1, 2, 3, 4, 5, 6\} \text{ for } m = 1$$

Event Forecasting with Pattern Markov Chains

How does it work?

- The *DFA* is used to construct a Markov chain, which is called a Pattern Markov Chain ($PMC_m^{\mathcal{P}}$).
- The states of *DFA* is directly mapped to states of a transition probability matrix $\mathbf{\Pi}$ $|Q| \times |Q|$ of the $PMC_m^{\mathcal{P}}$.
- $$\mathbf{\Pi} = \begin{Bmatrix} 0 \\ 1 \\ . \\ . \\ 6 \end{Bmatrix} \begin{pmatrix} p_{0,0} & . & . & . & p_{0,6} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ 0 & . & . & . & p_{6,6} \end{pmatrix}$$
- The maximum-likelihood estimator is used to compute the transition probabilities $p_{i,j}$ of the matrix $\mathbf{\Pi}$

$$\hat{p}_{i,j} = \frac{n_{i,j}}{\sum_{k \in Q} n_{i,k}} = \frac{n_{i,j}}{n_i} \tag{1}$$

.

Event Forecasting with Pattern Markov Chains

Constructing the Pattern Prediction Model

- The probability distribution of the waiting-time (i.e., time required until the pattern is completed from state q) $P(W_{\mathcal{P}}(q) = n)$, is calculated based on the Markov chain transition matrix.

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

where

$$\boldsymbol{\Pi} = \begin{pmatrix} \boldsymbol{N} & \boldsymbol{C} \\ \boldsymbol{0} & \boldsymbol{I} \end{pmatrix} \tag{2}$$

- The prediction intervals $I = (start, end)$ (i.e., the completion interval of the pattern $\mathcal{P}$ from the current state q) are built using the waiting-time distribution

$$P(I) = \sum_{n \in I} W_{\mathcal{P}}(q) = n), \text{ and } \quad P(I) \geq \theta_p \quad (end - start) \leq \theta_s$$

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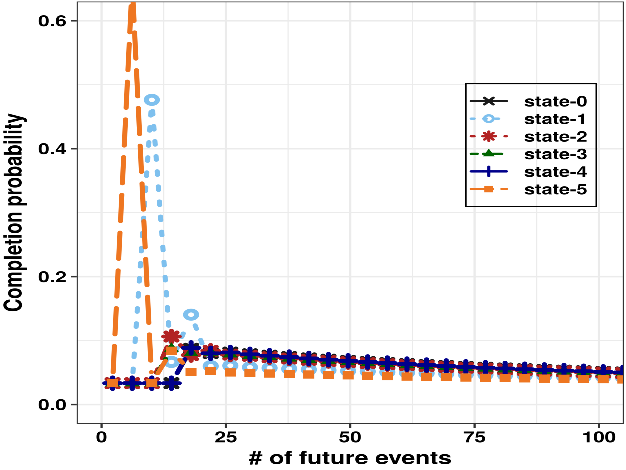
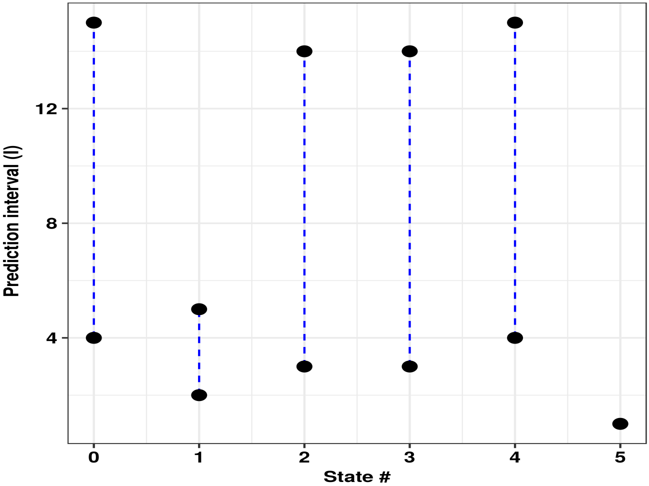
Event Forecasting with Pattern Markov Chains

Waiting-time distribution for $\mathcal{P} = a; d; c$, $\Sigma = \{a, b, c, d\}$, $m = 1$.



Event Forecasting with Pattern Markov Chains

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



Event Forecasting with Pattern Markov Chains

What is wrong?

- The overhead learning time of the Markov transition matrix for each input stream isolated from the others, how can we accelerate it?
- The low performance of the model for an input event stream with less data.
- How can we enable the communication between the local models and leverage an aggregated global shared model in a distributed and communication efficient fashion while maintaining provable and strong guarantees in service quality?

Distributed Online Learning for Pattern Prediction

Algorithm 1: Communication-efficient Distributed Online Learning [5] .

Predictors:

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 parameters of 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 that have not reported violation for their models $B \leftarrow \{w_l : w_l \notin B \text{ and } l \in [k]\}$;

receive models from nodes in B;

compute a new global model $\hat{w}$;

send $\hat{w}$ to all the predictors in B and set $w_1 \ldots w_m = \hat{w}$;

if $|B| = k$ **then**

set a new reference model $w_r \leftarrow \hat{w}$;

Communication-Efficient Distributed Online Prediction by Dynamic Model Synchronization [6]

- A protocol for distributed online prediction over multiple input data streams in a communication efficient manner.
- It allows to combine local models into a global model using a *synchronization operation*.
- The distributed learners exchange their local model with a central coordinator node periodically after observing a fixed number of data points (i.e., mini-batches) [4].
- A dynamic synchronization scheme based on monitoring the local models variance from a global reference model ($\|f_i - r\|^2 \leq \triangle$).

Distributed Online Learning for Pattern Prediction

- The *synchronization Operation* for the global transition probability matrix $\hat{\Pi}$:

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

Where $n_{k,i,j}$ the number of transitions from state i to state j on node k.

Distributed Online Learning for Pattern Prediction

- The divergence of the local models from the reference model $\|w_i - w_r\|^2$ is calculated by the sum of square difference between the local transition probability matrix Π_i and the reference transition matrix Π_r:

$$\|w_i - w_r\|^2 = |\Pi_i - \Pi_r\|^2 = \sum_{l,j} (\pi i, l, j - \pi r, l, j)^2$$

Distributed Online Learning for Pattern Prediction

Probabilistic Learning Guarantee

- The maximum-likelihood learner has been proven to converge to a normal distribution around the real $p_{i,j}$ [2].
- For k distributed $PMC_m^{\mathcal{P}}$ predictors:

$$\Pr\left(|\hat{\pi}_{i,j} - p_{i,j}| \geq c\right) \leq \frac{1}{k} \Pr\left(|\hat{p}_{i,j} - p_{i,j}| \geq c\right)$$

Where $\hat{\pi}_{i,j}$ is the global estimation and $\hat{p}_{i,j}$ is an estimation by an isolated predictor.

Empirical evaluation

Evaluation Metrics

- $Precision = \frac{\#\ of\ correct\ predictions}{\#\ of\ total\ predictions}$. The fraction of the predictions that are correct.
- $Spread = end(I) - start(I)$. The width of the prediction interval I, which represents the number of events between the start and the end of I.
- $PS-\text{score} = \alpha * precision + (1-\alpha) * (1 - \frac{spread}{max\ spread})$. In analogy with the $F - score$ we introduce this new score to assess the performance of the system in terms of both the *precision* and the *spread* combined.
- $Distance = start(I) - now$. The distance between the start of the prediction interval I and the time of prediction is produced (now).

Empirical evaluation

Evaluation Metrics

- *Cumulative communication*. The number of messages, which are required to perform the distributed online learning modes to synchronize the prediction models.
- *Throughput*. The number of events processed per unit time (second).

Empirical evaluation

Synchronization Schemes

Our proposed system can operate in three different modes of synchronization schemes:

- continuous full synchronization for each incoming event (hypothetical).
- static scheme based on synchronizing the prediction models periodically every b of input events in each stream.
- 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 Δ (recommended).

Empirical evaluation

Over Real-word Event Streams

- Event streams describe critical points (i.e., synopses) of moving vessels trajectories, which are derived from raw AIS messages as described in [7].
- $4,684,444$ critical points in Brest, France: October 2015 to March 2016 ($\approx$ 5000 vessels).
- $\mathcal{P}_1 = \textit{Sailing}$ with $m = 2$ over $\Sigma_1 = \{\textit{VerySlow, Slow, Moving, Sailing, Stopping}\}$.

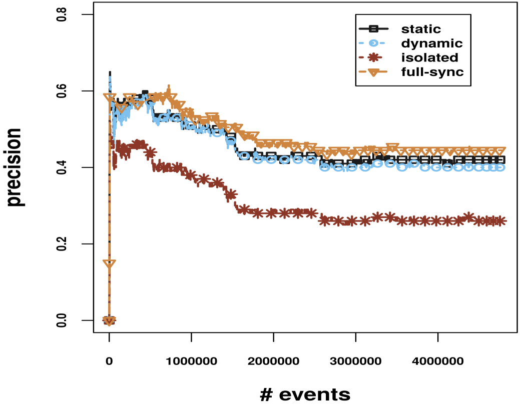
Empirical evaluation

Over Real-word Event Streams

- $\mathcal{P}_2 =$*changeInHeading; gapStart; gapEnd; changeInHeading* with $m = 1$ over $\Sigma_2 = \{$*stopStart, stopEnd, changeInSpeedStart, changeInSpeedEnd, slowMotionStart, slowMotionEnd, gapStart, gapEnd, changeInHeading*$\}$.
- All experiments are performed with setting the batch size of 100 ($b = 100$), the variance threshold of 2 ($\Delta = 2$), 80% as PMC prediction threshold ($\theta_p = 80\%$), and 200 for the maximum spread ($\theta_s = 200$)

Results on Real-word Event Streams

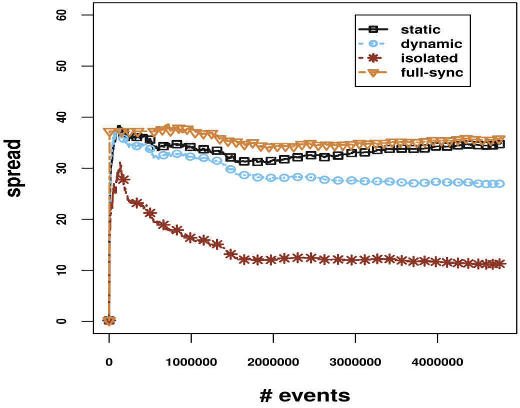
Precision scores with respect to the number of input events over time for $\mathcal{P}_1$.



Methods of distributed learning outperform the isolated method.

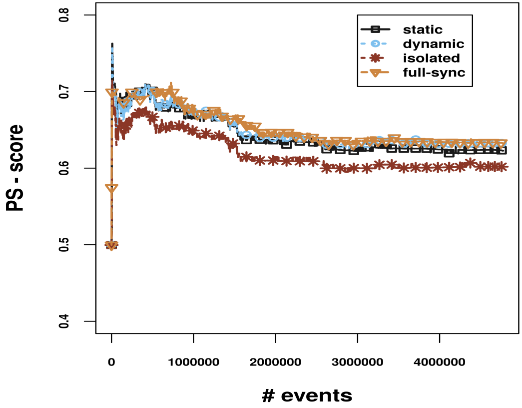
Results on Real-word Event Streams

Average spread for $\mathcal{P}_1$.



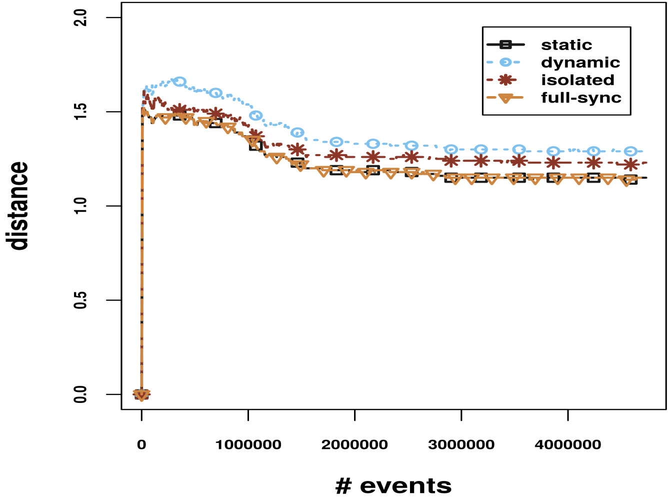
Results on Real-word Event Streams

PS-score for $\mathcal{P}_1$ with $\alpha = .5$.



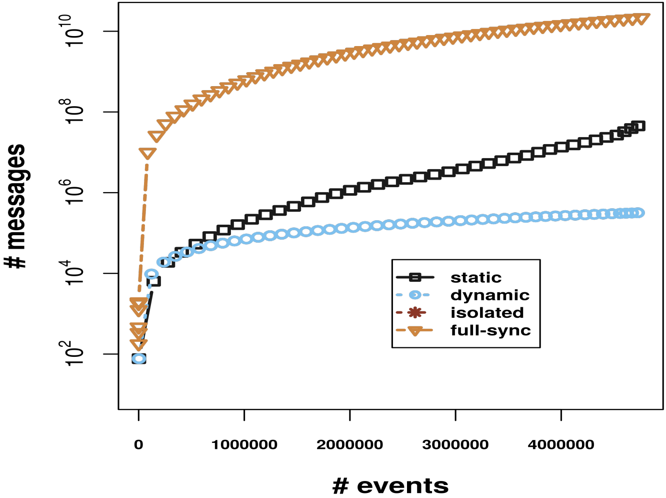
Results on Real-word Event Streams

Distance for $\mathcal{P}_1$.



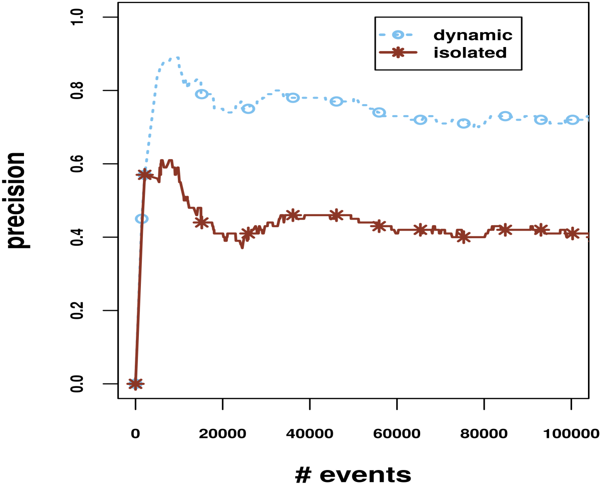
Results on Real-word Event Streams

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



Results on Real-word Event Streams

Precision scores of $\mathcal{P}_2$ for vessels of *pleasure craft* type.



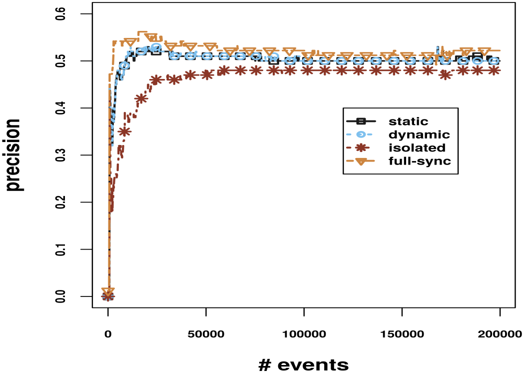
Empirical evaluation

Over Synthetic Event Streams

- We generate 20 streams of size 10,000 events from a simulated 1-order Markov process over $\Sigma = \{a, b, c, d\}$.
- The used pattern $\mathcal{P} = a; d; c$ with $m = 1$.
- We set the batch size to 20 ($b = 20$), the variance threshold to .0001 ($\Delta = .0001$), the $PMC_m^{\mathcal{P}}$ prediction threshold to 50% ($\theta_p = 50\%$), and the maximum spread to 10 ($\theta_s = 10$).

Results on Synthetic Event Streams

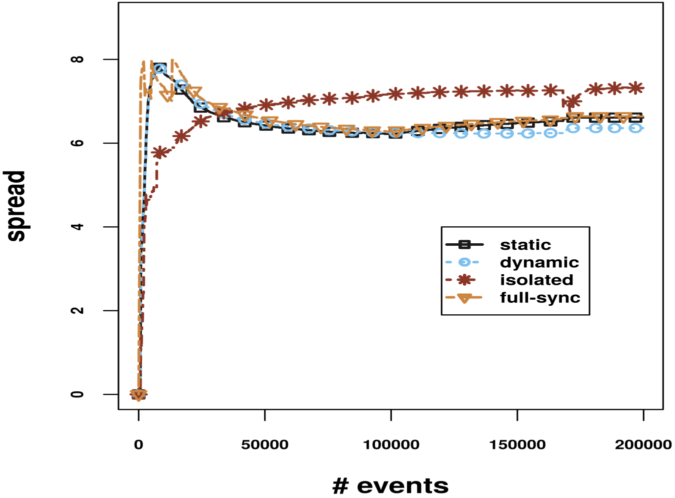
Precision scores with respect to the number of input events over time for $\mathcal{P} = a; d; c$.



Methods of distributed learning converge faster than the isolated method.

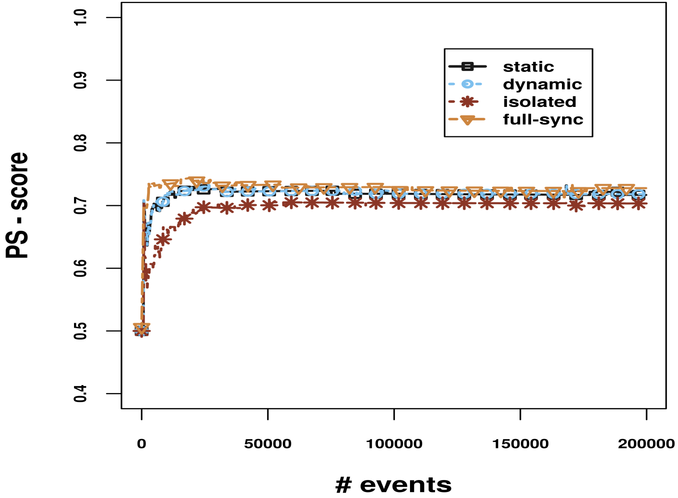
Results on Synthetic Event Streams

Average spread with respect to the number of input events over time for $\mathcal{P} = a; d; c$.



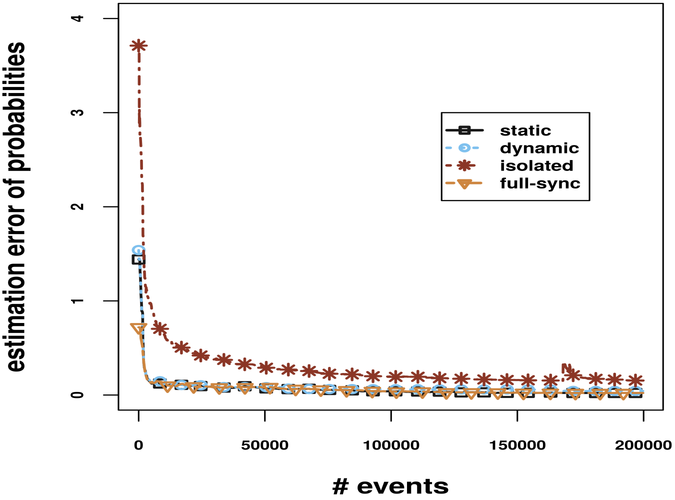
Results on Synthetic Event Streams

PS-score for $\mathcal{P} = a; d; c$ with $\alpha = .5$.



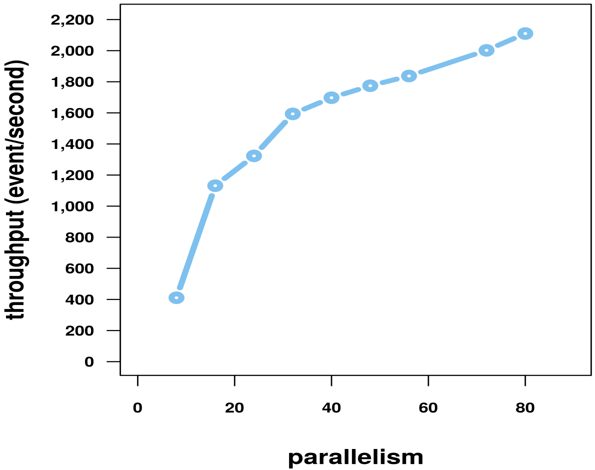
Results on Synthetic Event Streams

The error $\sum_{i,j} |\hat{p}_{i,j} - p_{i,j}|)$ of estimating the transition probabilities for $\mathcal{P} = a; d; c$.



Throughput Results

Throughput of the system on YARN cluster in in terms of number of events processed per second with respect to the parallelism level over $\mathcal{P}_1$ with batch size $b = 100$ and divergence threshold $\Delta = 2$.



Future Work

- In some applications the input event streams may belong to different distributions, we propose to dynamically divide the input event streams into similar groups (clusters).
- Introducing a weighted based synchronization operation. For example, the transition counts could be weighted by the number of the full matches of the monitored pattern in the associated event stream.

Future Work

- Provide real-time predictions intervals by also predicting the time-stamp of the future events using some machine learning techniques.
- The derived probabilistic learning guarantee relies on the static-like synchronization scheme ($\Delta = 0$). Therefore, it would be interesting to study the effects of the dynamic synchronization scheme on the learning guarantee ($\Delta > 0$).

Summary

- We have presented a system that provides a distributed pattern prediction over multiple large-scale event streams.
- The system uses the event forecasting with pattern Markov chain (PMC) [1] as the base prediction model on each event stream, and it applies the protocol for distributed online prediction [6] to exchange the information among the distributed predictors.
- The system has been implemented using Apache Flink and Apache Kafka.
- Experimental results over synthetic event streams and large real-world event streams related to trajectories of moving vessels show the effectiveness of our approach.

Publication

Parts of this thesis have been published in [8]:

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.

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[8] 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.

Questions?

Thank you!