A Distributed Online Learning Approach for Large-scale Pattern Prediction (WP3)

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Outline

- datAcron Architecture
- Proposed Approach
  - Event Forecasting with Pattern Markov Chains
  - Communication-Efficient Distributed Online Prediction by Dynamic Model Synchronization
- Evaluation

datAcron Architecture

Problem Setting

- 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 an evolving time-ordered sequence of events.
- Each event is defined as a tuple of attributes $e_t = (type, \tau, id, a_1, a_2 ...., a_n)$ where $type \in \Sigma$ (i.e., event types).
- A user-defined pattern (i.e., complex event of interest) P expressed as sequence of event types.
- Goal: the main objective is to predict the pattern P completion with certain probability in the future over each stream s_i given the current time event e_t.

Maritime Surveillance

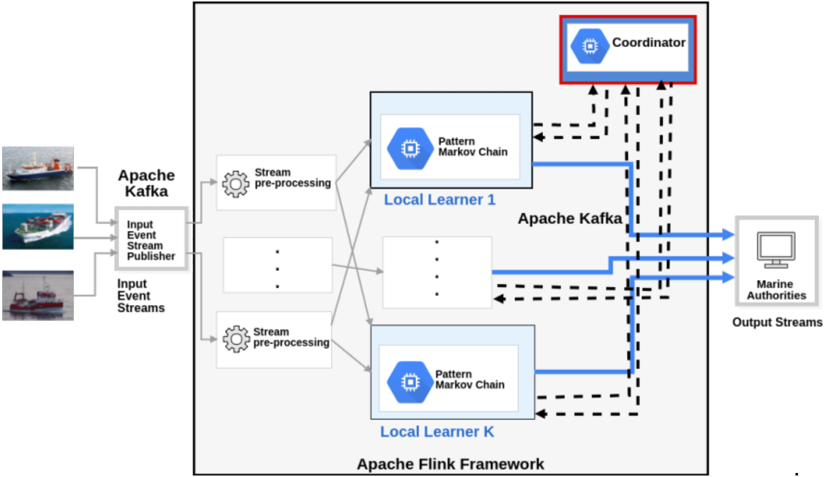
- Event tuple (i.e., critical points) derived from raw Automatic Identification System (AIS) messages of moving vessels e.g.,


```
{
"timestamp":1443651492000,
"id":"228133000",
"annotation":"change_in_heading",
"latitude":48.117775,
"longitude":-4.4205885,
"distance":323.406,
"heading":264.27
"speed":18.48,
}
```


- Example patterns such as
  $P_1 = \mathit{change\_heading} \cdot \mathit{gap\_start} \cdot \mathit{gap\_end} \cdot \mathit{change\_heading}$
  or $P_2 = \mathit{Sailing}$

A Distributed Online Learning Approach for Large-scale Pattern Prediction [1]

Distributed Architecture (Qadah, E., Mock, M., Alevizos, E. & Fuchs, G. (n.d.))



[1] Source Code: https://goo.gl/xwX1Mk

Event Forecasting with Pattern Markov Chains

(Alevizos et al. 2017)

- The system consumes a single input stream s_i of events.
- The event stream s_i is assumed to be generated by m-order Markov source.
- The complex event (i.e., pattern) 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 event pattern P is expected to be completed in future.

Event Forecasting with Pattern Markov Chains

How does it work?

- The deterministic finite automa (*DFA*) is used to construct a Markov chain, which is called a Pattern Markov Chain (PMC).
- The states of *DFA* is directly mapped to states of transition probability matrix $\boldsymbol{M}$ $|Q| \times |Q|$ of the *PMC*.
- $$\boldsymbol{M} = \left\{\begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{matrix}\right\} \begin{pmatrix} p_{0,0} & . & . & . & p_{0,4} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ 0 & . & . & . & p_{4,4} \end{pmatrix}$$
- The maximum-likelihood estimator is used to compute the transition probabilities (i.e., learning) $p_{i,j}$ of the matrix $\boldsymbol{M}$

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

.

Communication-Efficient Distributed Online Prediction by Dynamic Model Synchronization

(Kamp et al. 2014)

- 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) (Dekel et al. 2012).
- A dynamic synchronization scheme based on monitoring the local models variance from a global reference model ($\|f_i - r\|^2 \leq \triangle$).

Communication-Efficient Distributed Online Prediction by Dynamic Model Synchronization

Algorithm 1: Communication-efficient Distributed Online Learning Protocol (Kamp et al. 2014)

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

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

A Distributed Online Learning Approach for Large-scale Pattern Prediction

Synchronization Operation

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

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

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- We measure the divergence of local models from the reference model $\|f_k - f_r\|^2$ by calculating the sum of square difference between the transition probabilities $\mathbf{\Pi}_i$ and $\mathbf{\Pi}_r$:

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

Evaluation of Proposed Approach

Performance Measures

- $Precision = \frac{\#\ of\ correct\ predictions}{\#\ of\ total\ predictions}$ is the fraction of the produced predictions that are correct (i.e., a full match occurred within the prediction interval).

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Performance Measures

- $Precision = \frac{\#\ of\ correct\ predictions}{\#\ of\ total\ predictions}$ is the fraction of the produced predictions that are correct (i.e., a full match occurred within the prediction interval).
- $Spread = end(I) - start(I)$ is the width of the prediction interval I.
- *Cumulative communication*: number of messages, which are required to perform the distributed online learning modes to synchronize the prediction models.

Empirical evaluation

Experimental Setup

- Synopses over raw AIS messages in Brest, France: 1 October 2015 to 31 March 2016 (ais_brest_synopses.json).
- $4,684,444$ derived critical points.
- $\approx$ 5000 vessels.

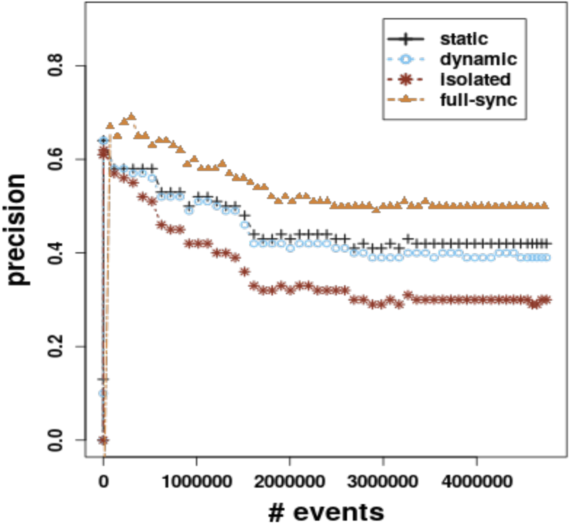
Empirical evaluation

Experimental Setup

- Synopses over raw AIS messages in Brest, France: 1 October 2015 to 31 March 2016 (ais_brest_synopses.json).
- $4,684,444$ derived critical points.
- ≈ 5000 vessels.
- Used patterns are: $\mathcal{P}_1 =$ *Sailing* & $\mathcal{P}_2 =$*changeInHeading; gapStart; gapEnd; changeInHeading*.

Empirical evaluation

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



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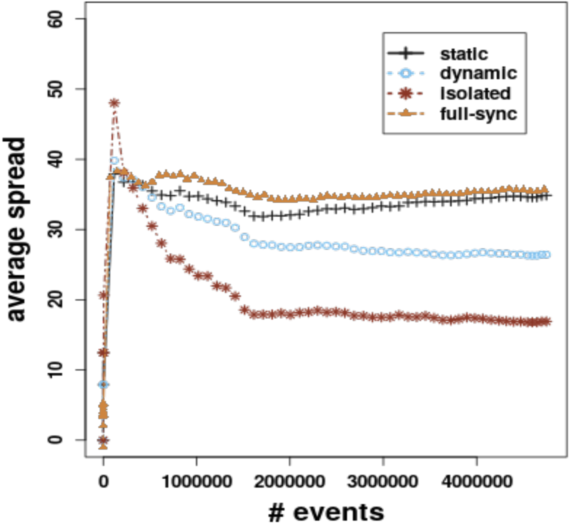
Precision scores with respect to the number of input events over time for $\mathcal{P}_1$

Empirical evaluation

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

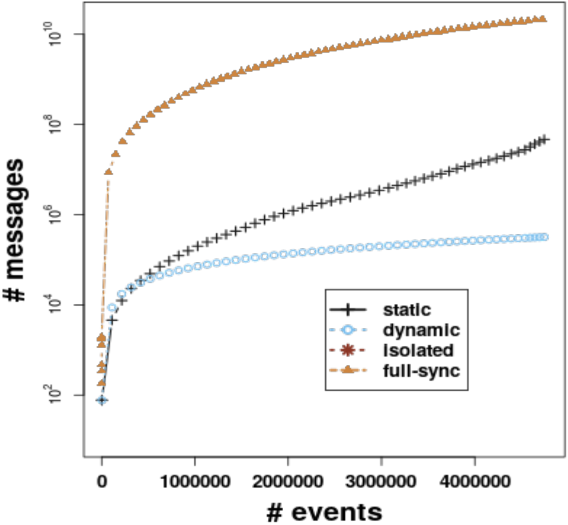


Empirical evaluation

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

Empirical evaluation

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

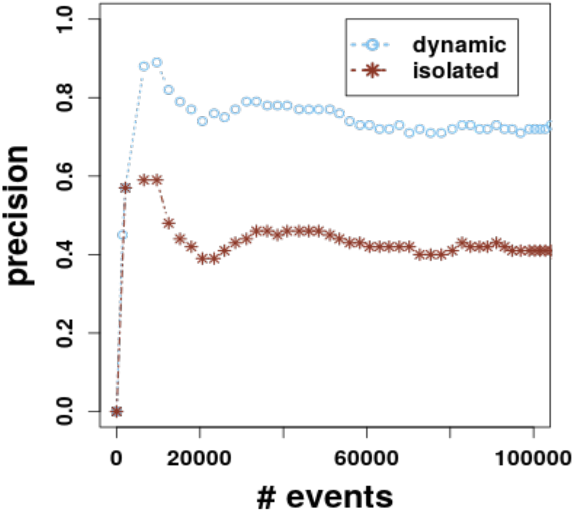


Empirical evaluation

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

Empirical evaluation

Precision scores of $\mathcal{P}_2$ for *PLEASURE CRAFT* vessels



Empirical evaluation

Precision scores of $\mathcal{P}_2$ for *PLEASURE CRAFT* vessels

Bibliography

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