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

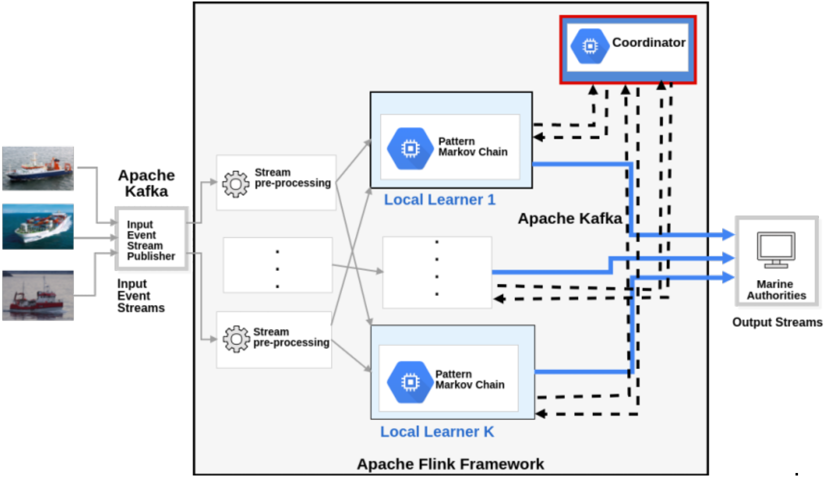
- Event tuple (i.e., critical points) derived from raw Automatic Identification System (AIS) messages of moving vessels e.g.,


```
{
"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*.
- $$\boldsymbol{M} = \begin{Bmatrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{Bmatrix} \begin{pmatrix} p_{0,0} & . & . & . & p_{0,4} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ 0 & . & . & . & p_{4,4} \end{pmatrix}$$
- 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 $f_1 \ldots f_m = \hat{f}$;

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:

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

A Distributed Online Learning Approach for Large-scale Pattern Prediction

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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).

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).
- $Spread = end(I) - start(I)$ is the width of the prediction interval I.

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).
- $Spread = end(I) - start(I)$ 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.
- ≈ 5000 vessels.

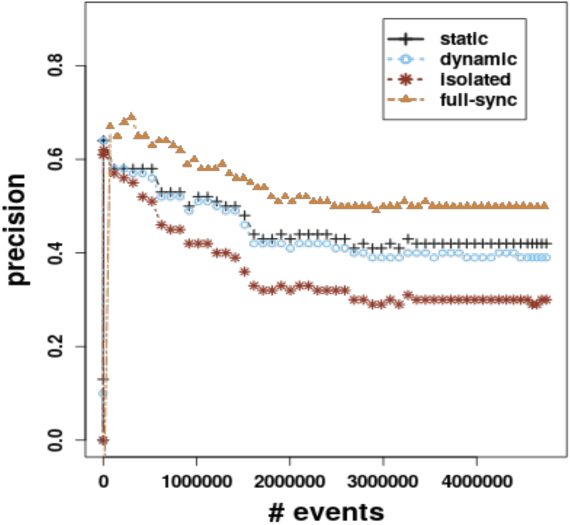
Empirical evaluation

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.
- $\approx$ 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 $\mathcal{P}_1$



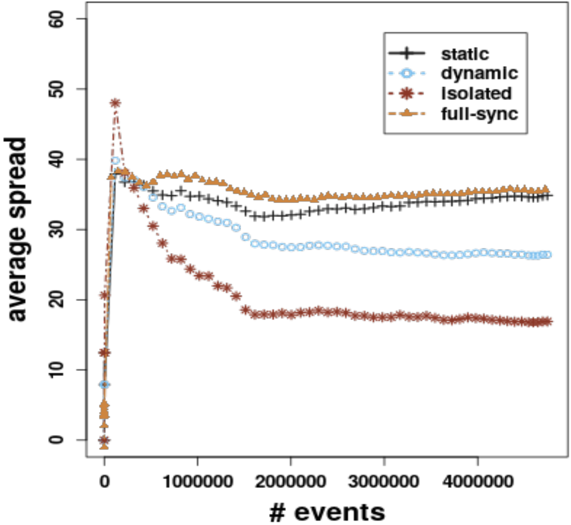
Empirical evaluation

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

- All methods of distributed learning outperform the isolated prediction model
- The hypothetical method of full continuous synchronization has the highest precision rates.
- The static and dynamic synchronization schemes have close precision scores

Empirical evaluation

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



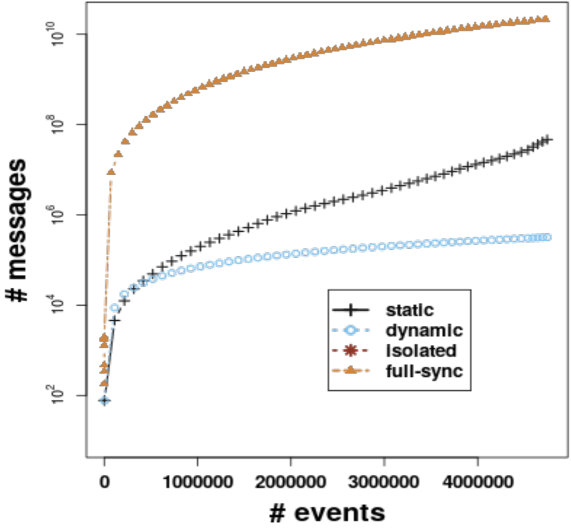
Empirical evaluation

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

- The spread is higher for the distributed learning based methods comparing to the isolated approach
- The average spread is decreasing over time until convergence,which may explains the drop in the precision scores from the beginning until reaching the convergence.

Empirical evaluation

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



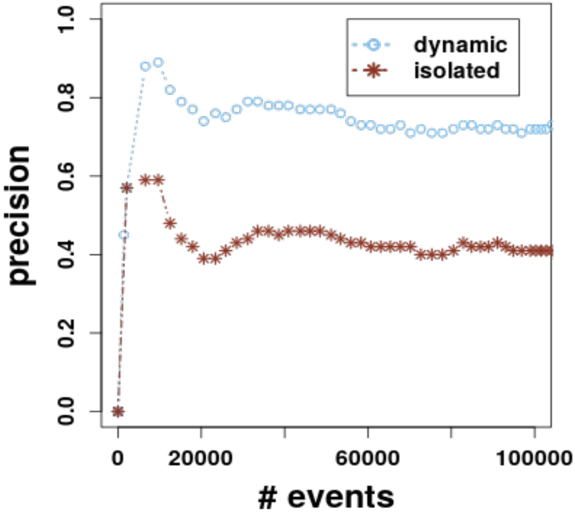
Empirical evaluation

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

- A larger amount of communication is required for the continuous synchronization comparing to the static and dynamic approaches
- 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

Empirical evaluation

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



Empirical evaluation

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

- 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
- So we only enabled the synchronization of the prediction models associated with vessels that belong to the same vessel class e.g., *PLEASURE CRAFT*

Next steps

- Interface definition with Elias for independent updates
- Evaluation on synthetic data
- Analysis of distributed learning effects
- Performance measurements on datAcron cluster
- Prediction intervals with time information

Bibliography

Alevizos, E., Artikis, A. & Paliouras, G. (2017), Event forecasting with pattern markov chains, *in* 'Proceedings of the 11th ACM International Conference on Distributed and Event-based Systems', ACM, pp. 146–157.

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