Resource-aware Elastic Swap Random Forest for Evolving Data Streams

Diego Marrón\textsuperscript{1,2,*}, Eduard Ayguadé\textsuperscript{1,2}, José R. Herrero\textsuperscript{2}, Albert Bifet\textsuperscript{3}

\textsuperscript{1} Computer Sciences Department, Barcelona Supercomputing Center, Barcelona, Spain
\textsuperscript{2} Computer Architecture Department, Universitat Politècnica de Catalunya, Barcelona, Spain
\textsuperscript{3} LTCI, Télécom ParisTech, Université Paris-Saclay, 75013 Paris, France
{diego.marron,eduard.ayguade}@bsc.es, josepr@ac.upc.edu, albert.bifet@telecom-paristech.fr

Abstract

Continual learning based on data stream mining deals with ubiquitous sources of Big Data arriving at high-speed and in real-time. Adaptive Random Forest (ARF) is a popular ensemble method used for continual learning due to its simplicity in combining adaptive leveraging bagging with fast random Hoeffding trees. While the default ARF size provides competitive accuracy, it is usually over-provisioned resulting in the use of additional classifiers that only contribute to increasing CPU and memory consumption with marginal impact in the overall accuracy. This paper presents Elastic Swap Random Forest (ESRF), a method for reducing the number of trees in the ARF ensemble while providing similar accuracy. ESRF extends ARF with two orthogonal components: 1) a swap component that splits learners into two sets based on their accuracy (only classifiers with the highest accuracy are used to make predictions); and 2) an elastic component for dynamically increasing or decreasing the number of classifiers in the ensemble. The experimental evaluation of ESRF and comparison with the original ARF shows how the two new components contribute to reducing the number of classifiers up to one third while providing almost the same accuracy, resulting in speed-ups in terms of per-sample execution time close to 3x.

1 Introduction

Nowadays, ubiquitous sources of Big Data are generating an unprecedented amount of dynamic Big Data streams (Volume), at high speed (Velocity), with newer data rapidly superseding older data (Volatility). For example, the Internet of Things is the largest network of sensors and actuators connected by networks to computing systems. This includes sensors across a huge range of settings, for industrial process control, finance, health analytics, home automation and autonomous cars, and often interconnected across domains, monitoring and functioning in people, objects and machines in real-time. Extracting knowledge on-the-fly from these Big Data streams, requires fast incremental algorithms that are able to deal with potentially infinite streams. Also, algorithms should be adaptive, showing the capability of adapting to the evolution of data distributions over time, since changes in them, can cause predictions to become less accurate (Concept Drift).

Ensemble learners are the preferred method for processing evolving data streams due to their better classification performance over single models. Among ensemble learners, ADAPTIVE RANDOM FOREST (ARF) [Gomes et al., 2017] is considered the state-of-the-art ensemble for classifying evolving data streams in the MOA [Bifet et al., 2010] open source infrastructure. ARF requires few hyperparameters to run and adapts to concept drifting by combining adaptive leveraging bagging with fast random Hoeffding decision trees [ Domingos and Hulten, 2000]. Hoeffding trees are used for mining non-evolving data streams doing a single pass over the data; they are based on the theoretical guarantees of the Hoeffding bound to discover how many input samples are needed to decide when to grow the tree.

ARF uses by default 100 random decision trees, a number that is decided independently of the characteristics of the data stream. In this paper, we argue that this number of learners in ARF is not optimal and that we can get similar results using a smaller number of learners. For this, we introduce a new adaptive methodology to automatically decide the number of learners to be used in incremental models.

We present a new ensemble method that extends the originally proposed ARF in two orthogonal directions. On one side, ELASTIC SWAP RANDOM FOREST (ESRF) splits the learners in two groups: a forefront group that contains only the learners used to do predictions, and a second candidate group that contains learners trained in the background and not used to make predictions. At any time, a learner in the forefront group can be replaced by a candidate learner if this swapping operation improves the overall ensemble accuracy. On the other side, ESRF extends ARF by dynamically increasing/decreasing the number of learners in the ensemble, in particular the number of learners in the forefront set.

The paper is organised as follows: Section 2 presents the necessary background. Section 3 describes the proposed ESRF ensemble. The experimental evaluation and comparison with ARF is presented in Section 4. Finally, Section 5 concludes the paper and outlines some future work.

\*Contact Author
2 Background and motivation

The Hoeffding Tree (HT) [Domingos and Hulten, 2000] is a very fast incremental decision tree learner for large data streams that assumes that the data distribution is not changing over time. HT grows incrementally based on the theoretical guarantees of the Hoeffding bound; a node is expanded as soon as there is sufficient statistical evidence that an optimal splitting feature exists. The model learned by HT is asymptotically nearly identical to the one built by a non-incremental (batch) learner, if the number of training instances is large enough.

Adaptive Random Forest (ARF) is an adaptive ensemble algorithm for data stream mining that extends the original Random Forest (RF) [Breiman, 2001] to the more challenging data stream setting. RF is an ensemble method that combines bagging with random decision trees. ARF incrementally works by doing a single pass over the data and handles concept drifting [Gama et al., 2014]. A drift detector is associated to each tree in the ensemble. The algorithm uses two thresholds: a first permissive threshold to signal a drift warning; and a second threshold to confirm the drift detection. As soon as a random decision tree signals a drift warning, ARF starts building a background learner for that tree that is not used for doing the ensemble prediction; this background learner can replace the learner if the warning escalates to a drift.

By default, the reference implementation for ARF in the Massive Online Analysis (MOA) framework uses 100 random trees (ARF100). While this configuration provides competitive accuracy we have observed that accuracy can converge for sizes lower than 100 random trees, which is the case for almost all datasets used in this paper as shown in Figure 1. The convergence point is different for each dataset, but once the accuracy converges, adding extra trees only increases computational and memory costs with marginal impact in the accuracy. For example, the RBF_f dataset requires 70 learners in the ensemble to achieve a percentage difference in terms of accuracy (with respect to ARF100) in the second decimal place; however, the COVT dataset achieves the same difference in accuracy with only 30 learners.

In terms of memory, in the worst case scenario ARF allocates twice the number of active learners in the ensemble; however, background learners are simpler since they do not need to keep any drift detection data structure. In terms of execution time, each active and background tree needs to be traversed for each new arriving instance. With the aim of reducing the computational and memory requirements of the ensemble, enabling either high-throughput implementations or their deployment in resource-constrained devices, this paper proposes the Elastic Swap Random Forest algorithm described in the next section.

3 Elastic Swap Random Forest

Elastic Swap Random Forest (ESRF) is a fast streaming random forest based method that adapts its size in an elastic way, to be consistent with the current distribution of the data. ESRF also includes a swap component that maintains two pools of classifiers to decide which ones are actually used for better prediction making. Although the elastic and swap components in ESRF are independent, they are presented together in Algorithm 1.

The swap component in ESRF divides the classifiers into two groups: the foreground (or active) learners and the back-

![Figure 1: ARF accuracy evolution with ensemble size.](image-url)
ground (or candidate) learners. The Forefront Set (FS) contains those classifiers with higher accuracy that are used for predicting; the Candidates Set (CS) contains those classifiers that are trained but not used for prediction since they accuracy is low compared to those on the FS. For each arriving instance \( X \), the prediction is done just using the learners in FS (lines 14–16). During training (lines 1–6), as done in ARF, all classifiers are trained simulating bagging by weighting the instance according to a Poisson \((\lambda = 6)\). After that (lines 4–5), ESRF swaps the worst classifier in FS (i.e. the one with the lowest accuracy \( f_{\min} \)) with the best in CS (i.e. the one with the highest accuracy \( c_{\max} \)) when the later becomes more accurate. With the swap component the number of learners required in the ensemble is \(|FS| + |CS|\); all the learners in these two sets are trained for each arriving instance. The elastic component in ESRF dynamically determines the size of the FS. This elastic component is not tied to ESRF and it could be implemented in any ensemble method such as the original ARF. For each arriving instance, the algorithm checks if FS needs to be resized (line 2), adding or removing \( r \) new learners. In case of growing, the new \( r \) learners could be taken from the CS set; however, and in order to add more diversity in the ensemble, the elastic component introduces a third set of learners, the Grown Set (GS) with \( r \) learners, which also needs to be trained on each arriving instance and is reset on every resizing operation. Algorithm 2 details how the elastic component in ESRF works. For each arriving instance, ESRF simulates having three ensembles of random trees (lines 2–4):

- the default one (i.e., the current ensemble with \(|FS|\) learners in FS);
- the shrunk ensemble containing only the \(|FS| - r\) learners with higher accuracies in FS;
- and the grown ensemble containing the learners in FS plus the \( r \) extra learners in the Grow set GS (i.e. in total \(|FS| + r\) learners).

Line 5 decides whether resizing is needed, based on the performance of each of these three ensembles. ESRF may decide to keep the current configuration for the ensemble or to apply a resize operation if either the shrunk or grown ensemble improve the default ensemble performance. In this case, the \( r \) learners in GS are added to FS in case growing is decided (lines 6–9) or the \( r \) classifiers in FS with lowest accuracy are removed in case shrinking is decided (lines 10–13). Observe that the proposed elastic component does not use the candidates set CS, although this is an alternative option that is not considered due to the limit in the number of pages.

The performance for an ensemble is computed using the exponential weighted moving average (EWMA) of its accuracy. EWMA gives larger weight to recent data, and a smaller weight to the older one. The weighting factor decreases exponentially but never reaches zero. It is calculated using this formula:

\[
\text{EWMA}_i = \text{EWMA}_{i-1} + \alpha \cdot (S_i - \text{EWMA}_{i-1})
\]

where \( S_i \) is the current value being added, \( \alpha \) is the weighting factor defined as \( \alpha = \exp(1/W) \), where \( W \) is a fixed time window. In ESRF, \( W = 2000 \) and \( S_i \in \{0,1\} \), 1 for a label predicted correctly and 0 otherwise. EWMA allows ESRF to keep track of each ensemble accuracy without being influenced too much by past prediction results.

The necessary logics to decide whether the ensemble should be resized or not are detailed in function CHECKIFRESIZE in Algorithm 2. First, it updates each ensemble EWMA (lines 16–18); then compares the EWMA estimation of the default ensemble with the other two ensembles to compute the differences \( \Delta_{\text{shrink}} \) and \( \Delta_{\text{grow}} \) (line 19–20). If \( \Delta_{\text{grow}} \) is larger than \( \Delta_{\text{shrink}} \), then a grow operation is triggered (lines 21–23). The shrink operation is decided in lines 24–26 and works similarly. In case \( \Delta_{\text{grow}} = \Delta_{\text{shrink}} \), ESRF favours growing against shrinking by comparing \( \Delta_{\text{grow}} \) first.

As mentioned above, only classifiers in FS are used to make the ensemble prediction (lines 14–16 in Algorithm 1). ESRF implements the same weighting voting policy for instances as in ARF: each classifier has an associated weight that is computed as the number of correctly classified in-

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Algorithm 2 Check resize and update size for ESRF

Require:
\( r \): Resize factor
FS: Set of forefront learners
FS_{\min}: Set of \( r \) learners from FS with lower accuracy
GS: Set of \( r \) random trees
SRK: Shrunken ensemble \( FS \setminus FS_{\min} \)
GRN: Grown ensemble \( FS \cup GS \)
\( T_g \): Grow threshold
\( T_s \): Shrink threshold

1: function RESIZEENSEMBLE(x, z)
2: \( y_s \leftarrow \text{PREDICTLABEL}(x, SRK) \)
3: \( y_d \leftarrow \text{PREDICTLABEL}(x, FS) \)
4: \( y_g \leftarrow \text{PREDICTLABEL}(x, GRN) \)
5: Operation \( \leftarrow \text{CHECKIFRESIZE}(z, y_s, y_d, y_g) \)
6: if Operation==GROW then
7: \( FS = FS \cup GS \)
8: \( \text{Start new GS with } r \text{ new trees} \)
9: end if
10: if Operation==SHRINK then
11: \( FS = FS \setminus FS_{\min} \)
12: \( \text{Start new GS with } r \text{ new trees} \)
13: end if
14: end function

15: function CHECKIFRESIZE(z, y_s, y_d, y_g)
16: Update EWMA_{shrink} using \( y_s \) and \( z \)
17: Update EWMA_{default} using \( y_d \) and \( z \)
18: Update EWMA_{grow} using \( y_g \) and \( z \)
19: \( \Delta_{\text{shrink}} = \text{EWMA}_{\text{shrink}} - \text{EWMA}_{\text{default}} \)
20: \( \Delta_{\text{grow}} = \text{EWMA}_{\text{grow}} - \text{EWMA}_{\text{default}} \)
21: if \( \Delta_{\text{grow}} > \Delta_{\text{shrink}} \) and \( \Delta_{\text{grow}} > T_g \) then
22: return GROW;
23: end if
24: if \( \Delta_{\text{shrink}} > \Delta_{\text{grow}} \) and \( \Delta_{\text{shrink}} > T_s \) then
25: return SHRINK
26: end if
27: end function

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stances divided by the total number of instances since last reset (due to concept drift), reflecting the classifier performance on the current concept. To cope with evolving data streams, a drift detection algorithm is used with each learner of the ensemble algorithm described above (not shown in algorithm 1). ESRF resets a tree as soon as it detects concept drifting. This is much simpler than the drift detection algorithm in ARF since there is a single threshold and no background learners are created when drift is detected.

4 Experimental Evaluation

ELASTIC SWAP RANDOM FOREST (ESRF) has been implemented in the MOA (Massive Online Analysis) framework [Bifet et al., 2010], an open source software environment for data stream mining, that implements a large number of data stream learning methods, including ADAPTIVE RANDOM FOREST (ARF). MOA is written in Java, making easier the prototyping and evaluation of novel online learning proposals and their comparison with state-of-the-art algorithms.

Fourteen datasets have been used for the evaluation of ESRF and comparison with ARF. Ten of these datasets are synthetically generated using well known data generators: LED [Breiman et al., 1984], SEA [Street and Kim, 2001], Agrawal [Agrawal et al., 1993], Random Tree Generator (RTG) [ Domingos and Hulten, 2000], Radial Basis Function (RBF) [Hulten et al., 2001] and Hyperplane [Hulten et al., 2001]. The datasets generated with the first three generators simulate both abrupt and gradual drifts. The dataset generated with the RTG generator does not simulate drift. The three datasets generated with RBF and Hyperplane simulate incremental (moderate or fast) drifts. In addition to these synthetic datasets, four real-world datasets that are widely used in the literature to evaluate data stream classification are also used: Airlines (AIRL) [Ikonomovska, 2009], Electricity [Harries, 1999], Forest Covertype [Blackard and Dean, 1999] and Give Me Some Credit (GMSC) [Competition, 2012]. Table 1 presents an overview of these data sets, including number of samples, attributes and labels, as well as drift type.

| Dataset | Samples | Attrs | Labels | Generator | Drift |
|---------|---------|-------|--------|-----------|-------|
| AGR_a   | 1,000,000 | 9     | 2      | Agrawal   | A     |
| AGR_g   | 1,000,000 | 9     | 2      | Agrawal   | G     |
| HYPER   | 1,000,000 | 10    | 2      | Hyperplane| LF    |
| LED_a   | 1,000,000 | 24    | 10     | LED Drift | A     |
| LED_g   | 1,000,000 | 24    | 10     | LED Drift | G     |
| RBF_m   | 1,000,000 | 10    | 5      | RBF       | LM    |
| RBF_f   | 1,000,000 | 10    | 5      | RBF       | LF    |
| RTG     | 1,000,000 | 10    | 2      | RTG       | N     |
| SEA_a   | 1,000,000 | 3     | 2      | SEA       | A     |
| SEA_g   | 1,000,000 | 3     | 2      | SEA       | G     |
| AIRL    | 539,383  | 7     | 2      | -         | -     |
| COVT    | 581,012  | 54    | 7      | -         | -     |
| ELEC    | 45,312   | 8     | 2      | -         | -     |
| GMSC    | 150,000  | 11    | 2      | -         | -     |

The hardware platform that has been used to conduct the performance analysis is an Intel(R) Xeon(R) Platinum 8160 CPU running at 2.10GHz (24 cores, 48 threads), 96GB of RAM, SUSE Linux Enterprise Server 12 SP2 (kernel 4.4.120-92.70-default) and openJDK 64bits 1.8.0_161.

We gradually evaluate the impact of the two components in the proposed ESRF. First we evaluate the performance of the swap component and then we evaluate the impact of adding the elastic component, always comparing against the baseline ARF ensemble with 100 learners (ARF100). Two parameters in ESRF are fixed in the evaluation presented in this paper: |CS| = 10 and r = |GS| = 1. Regarding the number of learners in CS, we have observed that it does not have a major impact in terms of accuracy for values larger than 10; in order to make a fair comparison in terms of resources when comparing with ARF, we set the value to 10, which coincides with the average number of background learners that are required by the drift mechanism in ARF for the datasets used in this paper. Regarding the resize factor in the elastic component, we have evaluated values of 1, 2 and 5, but not included the results due to lack of space since it does not have a significant impact in terms of accuracy. The parameters that are evaluated are: |FS| (with a minimum value of 15 and maximum limited to |FS| + |CS| + |GS| = 100) and the two thresholds that decide resizing (T_0 and T_r). The rest of hyperparameters, which are common for both ESRF and ARF100, are set to their default values in MOA.

The evaluation methodology that has been used to conduct all the experiments reported is streaming prequential 10-fold cross-validation [Bifet et al., 2015].

4.1 Swap Random Forest

This subsection individually evaluates the swap component in ESRF in terms of accuracy and ensemble size, using ARF100 as a reference. We will refer to this ESRF ensemble configuration as SWAP RANDOM FOREST (SRF).

Figure 2 shows the accuracy obtained by SRF when using a fixed number of learners in the FS. Comparing to Figure 1 one can appreciate that the accuracy of SRF converges faster than ARF100. With only 35 learners in FS the differences in accuracy are less than 1 percentage point, while ARF100 required 50 learners to be within the same range.

Table 2 details the results for two SRF configurations (SRF F35 and F50) and ARF100. The Δ column always shows the difference with ARF100. When using 35 learners in the front set of SRF, the differences observed in terms of accuracy are marginal in most of the tests, except for the two RBF datasets that are a little bit more noticeable; however, in terms of resources, SRF is only using one third of the trees that are used in ARF100. When using 50 learners, half of the trees compared to ARF100, SRF outperforms ARF100 in 11 of the 14 datasets, being the differences in the other 3 smaller than before. The reduction in size for F50 implies a speedup of 2.03x on average. Looking at the average for all datasets, we conclude that the average difference is very small (0.07 worse for F35 and 0.06 better for F50 wrt ARF100).
In this subsection we evaluate the complete ESRF ensemble, using both the swap and elastic component together. Once we have seen in the previous subsection how the swap component is able to significantly reduce the number of learners required in the ensemble, we want to see if the elastic component is able to dynamically determine the most appropriate size for the ensemble, we want to see if the elastic component is able to significantly reduce the number of learners required in the ensemble. In general, more permissive thresholds make \( T_g \) and \( T_s \) grow faster, which in turn reduces the differences with ARF100; however more restrictive thresholds have the opposite effect. Figure 3 shows an example of this trend for the AIRL dataset, in which moving from more restrictive thresholds (\( T_g = T_s = 0.5 \)) to more permissive ones (\( T_g = T_s = 0.001 \)) improves the difference in accuracy from -0.2 to 0.3. The detailed analysis for all datasets is not included due to the limitation in the number of pages.

The two thresholds can also be set to target different target scenarios. For example, on hardware platforms, such as ARM boards typically used in Internet of Things (IoT) applications, it may be desirable to make the ensemble only grow if strictly needed and force it to reduce its size as soon as it can in order to save memory and computation time. This can be achieved by using a shrink threshold (\( T_s \)) lower than the grow threshold (\( T_g \)), for example \( T_g = 0.01 \) and \( T_s = 0.001 \).

Table 3 details results obtained with this configuration. Observe that the average performance of ESRF and ARF100 are very similar (ESRF worse by \(-0.08 \) difference). In 11 out of the 14 datasets, the difference in accuracy is never worse than -0.23, being able to outperform ARF100 by 1 percentage point in the AGR.g dataset. The three datasets presenting more challenges to this configuration are RTG, RBF.f, RBF.m, being the last the worst performing one (-0.81 difference). As shown in the central and right part of this table, the main advantage of this configuration is that the average number of trees used in the ensemble is 22, (4.5 times less trees than ARF100, with the same proportional reduction in memory used); in 10 out of the 14 datasets ESRF never required more than 42 trees. This reduction in the ensemble size implies an average speedup of 3.84x, or in other words, may allow the use of devices up of 3.84x less powerful.

For other scenarios requiring higher accuracy, or in which memory or CPU time are not an issue, ESRF may use more sensitive thresholds in order to grow faster and reach higher accuracy requirements. For example, Table 4 shows the results that are obtained when using \( T_g = T_s = 0.001 \). This configuration allows ESRF to grow larger in those datasets that were more challenging in Table 3, while keeping similar average size for the rest of the datasets. This narrows the differences.
ference in accuracy to be not lower than \(-0.05\) in 12 out of the 14 datasets, and in the worst case \(-0.3\) (RTG). In terms of number of learners and speedup the same table shows a reduction of the execution time by 3.14x and the use of 33 learners on average, always compared to ARF100.

## 5 Conclusions

This paper presents a new ensemble method for evolving data streams: **Elastic Swap Random Forest (ESRF)**. **ESRF** aims at reducing the number of trees required by the reference **Adaptive Random Forest (ARF)** ensemble while providing similar accuracy. **ESRF** extends **ARF** with two orthogonal components: 1) a swap component that splits learners into two sets based on their accuracy (only classifiers with the highest accuracy are used to make predictions); and 2) an elastic component for dynamically increasing or decreasing the number of classifiers in the ensemble. The experimental evaluation of **ESRF** and comparison with the original **ARF** shows how the two new components effectively contribute to reducing the number of classifiers up to one third while providing almost the same accuracy, resulting in speed-ups in terms of per-sample execution time close to 3x. In addition, a sensitivity analysis of the two thresholds determining the elastic nature of the ensemble has been performed, establishing a trade-off in terms of resources (memory and computational requirements) and accuracy (which in all cases is comparable to the accuracy achieved by **ARF100**).

**ESRF** has been implemented in the MOA (Massive Online Analysis) framework, an open source software environment for data stream mining, that implements a large number of data stream learning methods, including **ARF**.

As part of our future work we plan to improve the resize logic, trying to make it more adaptive and correlated with the performance evolution of each tree and the drift detectors.

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