Using HDDT to avoid instances propagation in unbalanced and evolving data streams

Andrea Dal Pozzolo, Reid Johnson,
Olivier Caelen, Serge Waterschoot,
Nitesh V Chawla and Gianluca Bontempi

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INTRODUCTION

- In many applications (e.g. Fraud detection), we have a stream of observations that we want to classify in real time.
- When one class is rare, the classification problem is said to be unbalanced.
- In this paper we focus unbalanced data stream with two classes, positive (minority) and negative (majority).
- In unbalanced data streams, state-of-the-art techniques use instance propagation and standard decision trees (e.g. C4.5 [13]).
- However, it is not always possible to either revisit or store old instances of a data stream.

Introduction II

- We use Hellinger Distance Decision Tree [7] (HDDT) to deal with skewed distributions in data streams.
- We consider data streams where the instances are received over time in streams of batches.
- HDDT allows us to remove instance propagations between batches, benefits:
  - improved predictive accuracy
  - speed
  - single-pass through the data.
- An ensemble of HDDTs is used to combat concept drift and increase the accuracy of single classifiers.
- We test our framework on several streaming datasets with unbalanced classes and concept drift.

Hellinger Distance Decision Trees

- HDDT [6] use Hellinger Distance as splitting criteria in decision trees for unbalanced problems.
- All numerical features are partitioned into p bins (only categorical variables).
- The Hellinger Distance between the positive and negative class is computed for each feature and then the feature with the maximum distance is used to split the tree.

$$d_H(f_+, f_-) = \sqrt{\sum_{j=1}^{p} \left(\sqrt{\frac{|f_{+j}|}{|f_+|}} - \sqrt{\frac{|f_{-j}|}{|f_-|}} \right)^2} \tag{1}$$

where f_+ denote the positive instances and f_- the negatives of feature f. Note that the class **priors do not appear** explicitly in equation 1.

CONCEPT DRIFT

- The concept to learn can change due to non-stationary distributions.
- In the presence of concept drift, we cannot longer assume that the training and testing batches come from the same distribution.
- Concept drift [11] can occur due to a change in:
  - $P(c)$, class priors.
  - $P(x|c)$, distribution of the classes.
  - $P(c|x)$, posterior distributions of class membership.

Concept drift II

In general we don't know where the changes in distributions come from, but we can measure the distances between two batches to estimate the similarities of the distributions.

- If the batch used for training a model is not similar to the testing batch, we can assume that the model is obsolete.
- In our work we use batch distances to assign low weights to obsolete models.

HELLINGER DISTANCE BETWEEN BATCHES

Let B^t be the batch at time t used for training and B^{t+1} the subsequent testing batch. We compute the distance between B^t and B^{t+1} for a given feature f using Hellinger distance as proposed by Lichtenwalter and Chawla [12]:

$$HD(B^t, B^{t+1}, f) = \sqrt{\sum_{v \in f} \left(\sqrt{\frac{|B^t_{f=v}|}{|B^t|}} - \sqrt{\frac{|B^{t+1}_{f=v}|}{|B^{t+1}|}} \right)^2} \qquad (2)$$

where $|B^t_{f=v}|$ is the number of instances of feature f taking value v in the batch at time t, while $|B^t|$ is the total number of instances in the same batch.

INFORMATION GAIN

- Equation 2 does not account for differences in feature relevance.
- Lichtenwalter and Chawla [12] suggest to use the information gain to weight the distances.

For a given feature f of a batch B, the Information Gain (IG) is defined as the decrease in entropy E of a class c:

$$IG(B,f) = E(B_c) - E(B_c|B_f) \tag{3}$$

where B_c defines the class of the observations in batch B and B_f the observations of feature f.

HELLINGER DISTANCE AND INFORMATION GAIN

We can make the assumption that feature relevance remains stable over time and define a new distance function that combines *IG* and *HD* as:

$$HDIG(B^t, B^{t+1}, f) = HD(B^t, B^{t+1}, f) * (1 + IG(B^t, f)) \tag{4}$$

$HDIG(B^t, B^{t+1}, f)$ provides a relevance-weighted distance for each single feature. The final distance between two batches is then computed taking the average over all the features.

$$D_{HDIG}(B^t, B^{t+1}) = \frac{\sum_{f \in B^t} HDIG(B^t, B^{t+1}, f)}{|f \in B^t|} \tag{5}$$

MODELS WEIGHTS

In evolving data streams it is important to retain models learnt in the past and learn new models as soon as new data comes available.

- We learn a new model as soon as a new batch is available and store all the models.
- The learnt models are then combined into an ensemble where the weights are inversely proportional to the batches' distances.
- The lower the distance between two batches the more similar is the concept between them.

Lichtenwalter and Chawla [12] suggest to use the following transformation:

$$weights_t = \frac{1}{D_{HDIG}(B^t, B^{t+1})^b} \tag{6}$$

where b represents the ensemble size.

Experimental setup

- We compare HDDT with C4.5 [13] decision tree which is the standard for unbalanced data streams [10, 9, 12, 8].
- We considered instance propagation methods that assume no sub-concepts within the minority class:
  - SE (Gao's [8] propagation of rare class instances and undersampling at 40%)
  - BD (Lichtenwalter's Boundary Definition [12]: propagating rare-class instances and instances in the negative class that the current model misclassifies.)
  - UNDER (Undersampling: no propagation between batches, undersampling at 40%)
  - BL (Baseline: no propagation, no sampling)
- For each of the previous sampling strategies we tested:
  - HDIG: D_{HDIG} weighted ensemble.
  - No ensemble: single classifier.

DATASETS

We used different types of datasets.

- UCI datasets [1] to first study the unbalanced problem without worrying about concept drift.
- Artificial datasets from MOA [2] framework with drifting features to test the behavior of the algorithms under concept drift.
- A credit card dataset (online payment transactions between the 5^{th} of September and the 25^{th} of September 2013).

Name	Source	Instances	Features	Imbalance Ratio
Adult	UCI	48,842	14	3.2:1
can	UCI	443,872	9	52.1:1
compustat	UCI	13,657	20	27.5:1
covtype	UCI	38,500	10	13.0:1
football	UCI	4,288	13	1.7:1
ozone-8h	UCI	2,534	72	14.8:1
wrds	UCI	99,200	41	1.0:1
text	UCI	11,162	11465	14.7:1
DriftedLED	MOA	1,000,000	25	9.0:1
DriftedRBF	MOA	1,000,000	11	1.02:1
DriftedWave	MOA	1,000,000	41	2.02:1
Creditcard	FRAUD	3,143,423	36	658.8:1

Results UCI datasets

HDDT is better than C4.5 and ensembles have higher accuracy.

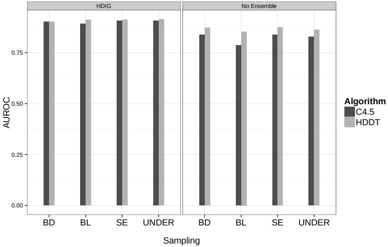

Figure : Batch average results in terms of **AUROC** (higher is better) using different sampling strategies and batch-ensemble weighting methods with C4.5 and HDDT over all **UCI datasets**.

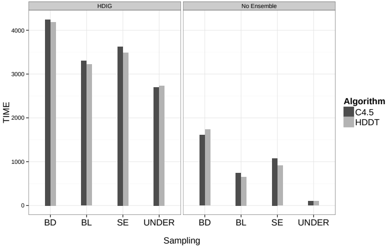

Figure : Batch average results in terms of computational **TIME** (lower is better) using different sampling strategies and batch-ensemble weighting methods with C4.5 and HDDT over all **UCI datasets**.

Results MOA datasets

HDIG-based ensembles return better results than a single classifiers and HDDT again gives better accuracy than C4.5.

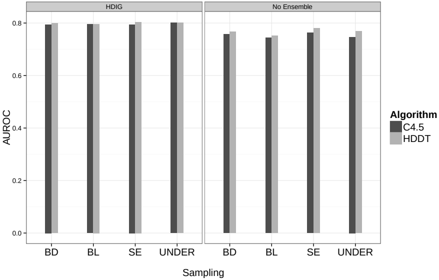

Figure : Batch average results in terms of computational **AUROC** (higher is better) using different sampling strategies and batch-ensemble weighting methods with C4.5 and HDDT over all drifting **MOA datasets**.

Results Credit card dataset

Figure 5 shows the sum of the ranks for each strategy over all the chunks. For each chunk, we assign the highest rank to the most accurate strategy and then sum the ranks over all chunks.

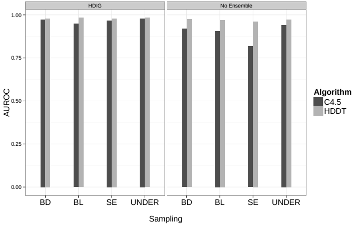

Figure : Batch average results in terms of **AUROC** (higher is better) using different sampling strategies and batch-ensemble weighting methods with C4.5 and HDDT over **Credit card dataset**.

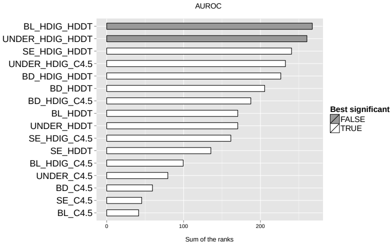

Figure : Sum of ranks in all chunks for the **Credit card dataset** in terms of **AUROC**. In gray are the strategies that are not significantly worse than the best having the highest sum of ranks.

Conclusion

- In unbalanced data streams, state-of-the-art techniques use instance propagation/sampling to deal with skewed batches.
- HDDT without sampling typically leads to better results than C4.5 with sampling.
- The removal of the propagation/sampling step in the learning process has several benefits:
    - It allows a single-pass approach (avoids several passes throughout the batches for instance propagation).
    - It reduces the computational cost (with massive amounts of data it may no longer be possible to store/retrieve old instances).
    - It avoids the problem of finding previous minority instances from the same concept.

Conclusion II

- HDIG ensemble weighting strategy:
  - has better performances than single classifiers.
  - takes into account drifts in the data stream.
- With the credit card dataset HDDT performs very well when combined with BL (no sampling) and UNDER sampling.
- These sampling strategies are the fastest, since no observations are stored from previous chunks.
- Future work will investigate propagation methods such as REA [4], SERA [3] and HUWRS.IP [9] that are able to deal with sub-concepts in the minority class.

THANK YOU FOR YOUR ATTENTION

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HELLINGER DISTANCE

- Quantify the similarity between two probability distributions [14]
- Recently proposed as a splitting criteria in decision trees for unbalanced problems [6, 7].
- In data streams, it has been used to detect classifier performance degradation due to concept drift [5, 12].

Hellinger Distance II

Consider two probability measures P_1, P_2 of discrete distributions in Φ. The Hellinger distance is defined as:

$$d_H(P_1, P_2) = \sqrt{\sum_{\phi \in \Phi} \left(\sqrt{P_1(\phi)} - \sqrt{P_2(\phi)} \right)^2} \tag{7}$$

Hellinger distance has several properties:

- $d_H(P_1, P_2) = d_H(P_1, P_2)$ (symmetric)
- $d_H(P_1, P_2) >= 0$ (non-negative)
- $d_H(P_1, P_2) \in [0, \sqrt{2}]$

d_H is close to zero when the distributions are similar and close to $\sqrt{2}$ for distinct distributions.

Concept drift II

Let us define $X_t = \{x_0, x_1, ..., x_t\}$ as the set of labeled observations available at time t. For a new unlabelled instance x_{t+1} we can train a classifier on X_t and predict $P(c_i|x_{t+1})$. Using Bayes' theorem we can write $P(c_i|x_{t+1})$ as:

$$P(c_i|x_{t+1}) = \frac{P(c_i)P(x_{t+1}|c_i)}{P(x_{t+1})} \tag{8}$$

Since $P(x_{t+1})$ is the same for all classes c_i we can remove $P(x_{t+1})$:

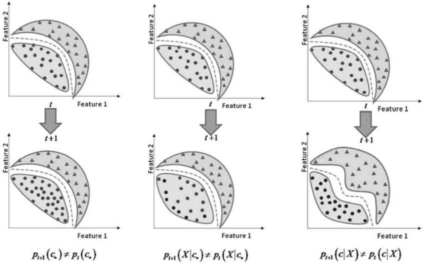
$$P(c_i|x_{t+1}) = P(c_i)P(x_{t+1}|c_i) \tag{9}$$

Kelly [11] argues that concept drift can occur from a change in any of the terms in equation 9, namely:

- $P(c_i)$, class priors.
- $P(x_{t+1}|c_i)$, distribution of the classes.
- $P(c_i|x_{t+1})$, posterior distributions of class membership.

Concept drift III

The change in posterior distributions is the worst type of drift, because it directly affects the performance of a classifier [9].


Feature 2
Feature 1
t
t+1
$P_{t+1}(c_*) \neq P_t(c_*)$
$P_{t+1}(X|c_*) \neq P_t(X|c_*)$
$P_{t+1}(c|X) \neq P_t(c|X)$

(a) Drift type 1. Note that the circle class occurs more frequently after drift.

(b) Drift type 2. Note that the boundary of the circle class instances changes drastically after drift.

(c) Drift type 3. Note that the dashed class boundary between the circle and triangular instances changes drastically after drift.

In general we don’t know where the changes in distributions come from, but we can measure the distances between two batches to estimate the similarities of the distributions.