

# MACHINE LEARNING FOR DATA STREAMS

## DECISION TREES

Note: A number between parenthesis corresponds to a certain survey:

### 1. Mining High-Speed Data Streams (2000)\_VFDT\_NOT READ YET: **No aparece en el survey (6)**

- (1) Pages 3,4

- This method essentially subsamples the data in order to achieve scalability in the construction of the decision tree. The idea is to show that the **entire decision tree constructed would be the same as the one built on sub-sampled data with high probability**.
- The idea is to determine a random sample of sufficient size so that the tree constructed on the sample is the same as that constructed on the entire data set. The **Hoeffding bound** is used to show that the decision tree on the sub-sampled tree would make the same split as on the full stream with high probability. This approach can be used with a variety of criteria such as the gini-index, or information gain.
- The number of examples required to produce the same split as the original data (with high probability) is determined. The Hoeffding bound is used to determine the number of relevant examples, so that this probabilistic guarantee may be achieved. If all splits in the decision tree are the same, then the same decision tree will be created.
- The Hoeffding tree can also be **applied to data streams**, by building the tree incrementally, as more examples stream in, from the higher levels to the lower levels. At any given node, one needs to wait until **enough tuples are available in order to make decisions about lower levels**. The memory requirements are modest, because only the counts of the different discrete values of the attributes (over different classes) need to be maintained in order to make Split decisions.
- The **VFDT algorithm** is also based on the Hoeffding tree algorithm, though it makes a number of modifications. Specifically, it is **more aggressive about making choices in the tie breaking** of different attributes for splits. It also allows the deactivation of less promising leaf nodes. It is generally more memory efficient, because of these optimizations.
- **The original VFDT method is not designed for cases where the stream is evolving over time.**

- <http://www.otnira.com/2013/03/28/hoeffding-tree-for-streaming-classification/>
  - Hoeffding bound gives certain level of confidence on the best attribute to split the tree, hence we can build the model based on certain number of instances that we have seen.
  - Hoeffding-tree, which is a new decision-tree learning method for streaming that solves these following challenges:
    - Uncertainty in learning time. Learning in Hoeffding tree is **constant time per example** (instance) and this means Hoeffding tree is suitable for mining data streaming.
    - The resulting trees are nearly identical with trees built by conventional batch learner, given enough example to train the and build the Hoeffding trees
  - To achieve the streaming classification characteristics, the authors introduce Hoeffding bound to decide **how many examples of instances needed to achieve certain level of confidence** (i.e. the chosen instance attribute using the bound is the close to the attribute chosen when infinite examples are presented into the classifier).
  - What makes Hoeffding bound attractive is its ability to give the same results **regardless the probability distribution generating the observations**. However, the number of observations needed to reach certain values of  $\delta$  and  $\epsilon$  are different across probability distributions.
  - With probability  $1-\delta$ , one attribute is superior compared to others when observed difference of information gain is greater than  $\epsilon$ .
  - The authors implemented the Hoeffding tree algorithm into Very Fast Decision Tree learner (VFDT) which includes some enhancements for practical use, such as node-limiting strategy, introduction of as tie breaking parameter, grace period of bound calculation, poor attributes removal, fast initialization by using conventional RAM-based learner and ability to rescan previously-seen examples when data rate is slow.

## 2. Mining Time-Changing Data Streams (2001)\_CVFDT\_NOT READ YET: No aparece en los surveys (5), (6) y (7)

- (1) Pages 4,5
  - The original VFDT method is not designed for cases where the stream is evolving over time. The work in [47] extends this method to the case of concept-drifting data streams. This method is referred to as **CVFDT**. CVFDT incorporates two main ideas in order to address the additional challenges of drift:
    - A sliding window of training items is used to limit the impact of historical behavior.
    - Alternate subtrees at each internal node  $i$  are constructed.

- Because of the sliding window approach, the main issue here is the update of the attribute frequency statistics at the nodes, as the sliding window moves forward. For the incoming items, their statistics are added to the attribute frequencies in the current window, and the statistics of the expiring items at the other end of the window are decreased. Therefore, **when these statistics are updated, some nodes may no longer meet the Hoeffding bound, and somehow need to be replaced.**

RESUMEN PAPER “Learning Decision Trees from Data Streams with Concept Drift (2016)”: CVFDT is able to adapt to concept-drift in streams, first growing alternate subtrees at each node of the decision tree, and then replacing the current subtree with the alternate whenever the latter becomes more accurate. This is achieved by maintaining sufficient statistics on a time-window moving over the data stream.

### 3. Efficient Decision Tree Construction on Streaming Data (2003)\_NOT READ

**YET: No aparece en los surveys (2), (3), (4), (5), (6) y (7)**

○ (1) Page 4

- One of the major challenges of the VFDT family of methods is that it is naturally suited to categorical data. This is a natural derivative of the fact that decision tree splits implicitly assume categorical data. Furthermore, discretization of numerical to categorical data is often done offline in order to ensure good distribution of records into the discretized intervals. Of course, it is always possible to test all possible split points, while dealing with numerical data, but the number of possible split points may be very large, when the data is numerical. The bounds used for ensuring that the split is the same for the sampled and the original data may also not apply in this case. The technique in [48] uses **numerical interval pruning in order to reduce the number of possible split points**, and thereby make the approach more effective.
- Furthermore, the work uses the properties of the gain function on the entropy in order to achieve the **same bound as the VFDT method** with the use of a smaller number of samples.

### 4. Accurate Decision Trees for Mining High-speed Data Streams (2003)\_VDTc\_NOT READ YET

RESUMEN DEL PAPER “Learning Decision Trees from Data Streams with Concept Drift (2016)”: Another extension of VFDT is VFDTc, which is able to deal with numerical attributes, i.e. not only categorical ones [12]. The algorithm in each leaf stores counters for numerical values. Additionally, to improve performance authors proposed to add a local model in the leaves (i.e. a naïve Bayes).

### 5. Adaptive Learning from Evolving Data Streams (2009)\_HWT\_HAT\_NOT READ YET.

RESUMEN Y COMPARACIÓN DEL PAPER “Learning Decision Trees from Data Streams with Concept Drift (2016)”: Since development of the Hoeffding bounds, a number of modifications have been proposed. Bifet and Gavalda proposed the Hoeffding Window Tree (HWT) and the Hoeffding Adaptive Tree (HAT). HWT differs from CVFDT since it creates subtrees without waiting for a fixed number of instances (faster reaction for drift) and updates a subtree as soon as there is a benefit from building the new one., instead of using fixed-size sliding window to detect changes, HAT employs an adaptive window at each internal node.

**6. Fast Perceptron Decision Tree Learning from Evolving Data Streams (2010)\_NOT READ YET: No aparece en los surveys (2), (4), (5), (6) y (7)**

- (1) Page 5
  - Bifet et al [19] proposed a method, that shares similarities with the work in [40]. However, the work in [19] replaces the naive Bayes with perceptron classifiers. The idea is to gain greater efficiency, while maintaining competitive accuracy.

**7. Decision Trees for Mining Data Streams Based on the McDiarmid's Bound (2013)\_NOT READ YET:**

RESUMEN DEL PAPER “Learning Decision Trees from Data Streams with Concept Drift (2016)”: There are also other bounds – like the McDiarmid. In [21] authors proved that the Hoeffding’s inequality is not suitable for solving the underlying problem.

**8. Learning Decision Trees from Data Streams with Concept Drift (2016)\_CEVOT: No aparece en los surveys (1), (2), (3), (4), (5), (6) y (7)**

- The proposed algorithm, named **Concept-adapting Evolutionary Algorithm For Decision Tree** does not require any knowledge of the environment such as numbers and rates of drifts. The novelty of the approach is **combining tree learner and evolutionary algorithm**, where the decision tree is learned incrementally and all information is stored in an internal structure of the trees’ population. The proposed algorithm is experimentally compared with state-of-the-art stream methods on several real live and synthetic datasets.
- There is lack of adaptive approaches for evolutionary tree learning.
- Proposed algorithm is extension of our batch (offline) algorithm EVO-Tree
- CEVOT learns from the sliding windows without making any assumption about the nature or type of a drift nor on presence or lack of new concept classes. The novelty of the approach is **combining tree learner and**

**evolutionary algorithm, where the decision tree is learned incrementally and all information (knowledge) is stored in the internal structure of the population of trees.**

- This method has other advantages:
  - A natural variable-length encoding structure is used, because the optimal size of a tree for a given data set is not known a priori;
  - The initial algorithm allows for random generation of unbalanced trees of different sizes;
  - The fitness function allows for simultaneous optimization of both, the accuracy and the tree size;
  - All crossover and mutation operators are designed in such a way that as a result only correct individuals, i.e. decision trees, are created.
- CEVOT inherits from EVO-Tree an evolutionary computation to process population of trees. The difference is its ability to handle data streams and gather knowledge.
- CEVOT uses **fixed size sliding window** that takes a chunk of data of size  $w$  and retrains the model with the last  $w$  examples. Because nonstationary environment is considered, CEVOT algorithm will evolve with data.
- Algorithm starts by random generation of an initial population. Nonetheless, this action takes place only when the first data chunk is received. For each subsequent chunks, CEVOT starts with population which remained from the previous run – this is a key feature which maintains “memory”. The idea is that the algorithm adapts itself to data. With every incoming chunk, population of trees shall converge to a current state (i.e. concept) and improve their accuracy.
- **The main limitation of the blind approaches is slow reaction to the concept drift in data. CEVOT forgets old concepts at a constant speed, independently of whether changes are happening or not (individuals selection process). To discard old information we implemented a special destructive mutation mechanism. It works as follows. Randomly selected internal nodes are converted to leaves and the sub-trees rooted at those nodes are pruned.**
- Comparison with Hoeffding Adaptive Tree (HAT), Hoeffding Tree (HT), Naïve Bayes (NB), Accuracy Updated Ensemble (AUE) (based on HT), Accuracy Weighted Ensemble (AWE) (based on HT):
  - CEVOT creates the smallest model for prediction (a single tree classifier). This result is achieved through the optimal tree structure encoding and minimizing size of the tree in evolutionary algorithm.

The fastest classifiers were NB, HT and HAT, respectively. Unfortunately, these algorithms also have the lowest prediction performance. This fact can be explained by the simplicity of their models.
  - -Ensemble models received not much worse times than single classifier models (NB, HT, HAT) but AUE predicts much better than AWE. The details are given in Table 4. CEVOT turned out to

be the slowest classifier. Evolutionary computation are very time-consuming processes. The positive aspect is the fact that most of real live datasets processing time was about five second

**9. Extremely Fast Decision Tree (2018)\_HAT\_: No aparece en los surveys (1), (2), (3), (4), (5), (6) y (7)**

- Novel incremental decision tree learning algorithm, Hoeffding Anytime Tree, that is statistically **more efficient than current state-of-the-art, Hoeffding Tree**.
- Hoeffding Anytime Tree produces the asymptotic batch tree in the limit, is naturally resilient to concept drift, and can be used as a higher accuracy replacement for Hoeffding Tree in most scenarios, at a small additional computational cost.
- In practice, if no split attribute exists at a node, rather than splitting only when the top candidate split attribute outperforms the second-best candidate, HATT will split when the information gain due to the top candidate split is non-zero with the required level of confidence. At later stages, HATT will split when the difference in information gain between the current top attribute and the current split attribute is non-zero, assuming this is better than having no split.
- Comparison with VFDT:
  - Our implementation of the Hoeffding Anytime Tree algorithm, the Extremely Fast Decision Tree (EFDT), achieves higher sequential accuracy than the Hoeffding Tree implementation Very Fast Decision Tree (VFDT) on many standard benchmark tasks.
  - HT constructs a tree incrementally, delaying the selection of a split at a node until it is confident it has identified the best split, and never revisiting that decision. In contrast, HATT seeks to select and deploy a split as soon as it is confident the split is useful, and then revisits that decision, replacing the split if it subsequently becomes evident that a better split is available.
  - The HT strategy is more efficient computationally, but HATT is more efficient statistically, learning more rapidly from a stationary distribution and eventually learning the asymptotic batch tree if the distribution from which the data are drawn is stationary. Further, false acceptances are inevitable, and since HT never revisits decisions, increasingly greater divergence from the asymptotic batch learner results as the tree size increases.
  - They observe VFDT taking longer and longer to learn progressively more difficult concepts obtained by increasing the number of classes. EFDT learns all of the concepts very quickly. and keeps adjusting for potential overfitting as fresh examples are observed.
  - In scenarios where information distribution among attributes is skewed, with some attributes containing more information than others, such a policy (building structure that improves on the

current state but making subsequent corrections when further alternatives are found to be even better) can be highly effective because of the limited cost of rebuilding the tree when replacing a higher-level attribute with a highly informative one. However, where information is more uniformly distributed among attributes, Hoeffding Tree will struggle to split and might have to resort to using a tie-breaking threshold that depends on the number of random variables, while HATT will pick an attribute to begin with and switch when necessary, leading to faster learning.