Benchmarking Concept Drift Adoption Strategies for High Speed Data Stream Mining

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Abstract —: **Data streams are significantly influenced by the notion change that is termed as concept drift. The act of knowledge discovery from the data streams under notion adaption is a significant act to achieve the conventional learning of the streaming data. The concept drift for conventional learning of streaming data can be done under set of notions that can be either static or dynamic. Due to the large scope of concept drift that spanned to different domain contexts of data streaming, the existing models are partially or fully not generalized and compatible to different streaming and notion change context. In this context, this paper presents the review of these models that includes nomenclature of mining streaming data and notion evolution in concept drift adoption strategies.**

Keywords: concept drift, defensing concept drift, conventional learning, supervised and unsupervised concept drift adoption, data stream mining and concept evolution

1. Introduction

The current era of advanced computational strategies and automation is creating digital data with magnified speed in volume. This statement can be boosted by the report of a survey statistics [1]. This survey quoted that the world of automation and digitization generated around 3 zeta-bytes of data in 2012. The real-time applications such as spam filtering, network traffic monitoring, credit card fraud detection and stock market trend analysis generates data continuously. That further streams from divergent end points of the distributed systems. The features such as Infinite length, variable transmission speed, and changeable data distribution of this streaming data delivers significant challenges in data processing. The knowledge discovery and information retrieval from such streaming data is not compatible to the strategies those generally using in static data volumes. This is due to the fact that the notion changes in static data can be noticed prior to the process of knowledge discovery and information retrieval. In contrast to this, the prior knowledge of possible notions and concept drift [2] [3] is not available in streaming data. Henceforth, developing and generalizing the strategies to predict or notice the notion changes in streaming data, which is termed as concept drift adoption strategies is a significant and considerable research issue. A typical example of the notion change or concept drift is change of followers with different profiles that influenced by the change of tweets in a trend. Such changes in the underlying data distribution cause the models built on old data to be inconsistent with the new concept's data, which will lead to the model being outdated. Over a few years, the research interests are focusing on devising scalable and robust concept drift adoption strategies and significant count of them emerged as benchmark strategies. Due to the large scope of concept drift that spanned to different domain contexts of data streaming, these existing models are partially or fully not generalized and compatible to different streaming and notion change context. Hence it is obvious to predict wide research scope in concept drift adoption strategies. In this context to observe the limits and strengths of the existing strategies available in recent literature. In this paper, we offer the review of these models that includes nomenclature of mining streaming data and notion evolution in concept drift adoption strategies. The rest of the document organized as follows. The section 2 is exploring the nomenclature of the mining data streams and impact of concept drift, section 3 contains the contemporary affirmation of the benchmarking models devised in recent literature. Further the section 4 explores the conclusion of the article and possible research directions.

2. NOMENCLATURE OF THE MINING DATA STREAMS AND THE IMPACT OF CONCEPT DRIFT

2.1 Mining Data streams

The process of mining data streams should be continuous, should meet the speed of the records streaming and also should also able to notice the concept change in streaming records.

2.2 *Concept Drifting:*

Data streams are significantly influenced by the notion change that referred as concept drift. A significant reference to claim the notion change in streaming data is "change in viewer's interest against to the streaming data of news sites". The temporal longevity of the streaming data is certainly influenced by the change of notion that influence the learning strategies applied on data streams. Hence in regard to achieve the conventional learning over data streams, these notion changes should be noticed.

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2.3 Concept Drift Adoption:

The strategic approach involved to achieve conventional learning against notion change over data streams is said to be the Concept Drift adoption.

2.3.1 Notion changeover frequency

It is the average of time taken for all observed concept drift adoption during the process of learning over streaming data. This is also referred as "speed of the concept drift" and that is of two types. One is regular concept drift, which reflects the event of concept drift in regular periods and that may let to predict the time interval of the next concept drift, which is often recursive (concept drift that transformed the data to previous state). The other one is impulsive concept drift that reflects the concept drift suddenly and at uneven time intervals.

2.4 The taxonomy of concept drift adoption strategies

The process of learning over streaming data under the influence of concept drift is done in two levels. The initial level of the learning process is tracing the significant notion change as concept drift and further in second level, adapting the learning process towards the convention of new state of the streaming data. The Concept drift adoption towards conventional learning of the data streams can be categorized as follows:

2.4.1 Adaptive learners

The simplest way to adapt the concept drift is through Adaptive learners. These Adaptive learners reflecting a learning process over data streams that mutes current learning considerations against a concept drift and alters them towards the notion changes, which are contradicting with state of data prior to concept drift observed. The Adaptive learners adapts the concept drift, either by dynamically expanding or restricting the scope of the observable streaming data. The process adapted by Adaptive learners is supervised or semi supervised learning strategy, which is indicating that the full or partial prior knowledge of notion changes is a must constraint.

2.4.2 Adaptive Training set based Learners

This category of concept drift adoption is of unsupervised learning strategy. Since the learning is done either on set of records as a window collected under similar notion or set of records considered by the similar instance weights. Further, the present training set is in use with classifier will be muted and updates learning set according to the new notion of the window or new instances with similar weights.

2.4.3 Ensemble Learners

The use of multiple learners' together is common practice and often noticed in data engineering community, which is due to the pragmatic efficiency reflected by these Ensemble Learners. Applying multiple learners collectively on same data often leads the classifier to deliver predictions with magnified accuracy. The constraint of these ensemble or Ensemble Learners' strategy is to be the significant diversification in learning process of the different classifiers is must, otherwise this strategy influenced by the defused performance due to overfitting. These Ensemble Learners strategy is de facto standard for data streams with unappropriated notion changes also can termed as data with imbalanced classes.

2.5 Notion Progression in data streams with concept drift proneness

Notion progression during the process of evolving new classes is a considerable and significant issue of leaning over data streams with concept drift proneness such as network traffic stream that used to learn towards the intrusion detection. The notion progression can be noticeable, if we consider each type of attack as a class label in network traffic streams, then notion progression occurs when a completely new kind of attack occurs in the traffic. The other life hack is the case of data streams related to twitter, where trends are considerable as class labels and if a new trend is initiated then the notion progression may be noticeable if the tweets under this new trend is different from the previously observed tweets. The issue of notion progression is addressed as a significant issue of learning over data streams with concept drift proneness is very much limited.

3. CONTEMPORARY AFFIRMATION OF BENCHMARKING CONCEPT DRIFT ADOPTION STRATEGIES IN RECENT LITERATURE

3.*1 Decision Trees*

One of the model of type Adaptive learners is decision trees, in particular C4.5 [4]. The model Very Fast Decision Tree (VFDT) [5], is said to be the first in decision tree category. The decision trees in streaming data is formed by the VFDT, which is primarily using Hoeffding bounds [6], [7] to decide the minimum number of arriving examples to give certain level of confidence in splitting the node . Further, many revisions to this model were applied in the context of magnifying speed and accuracy of concept drift adoption.

3.2 K-Nearest Neighbors

Another heavily studied learning algorithm that has been adapted for concept drift is the kNearest Neighbors (kNN) algorithm. Alippi and Roveri [8][9] demonstrate how to modify the kNN algorithm for use in the streaming case. First, they demonstrate how to appropriately choose k in a data stream which does not exhibit concept drift based on theoretical results from Fukunga [10].

With this framework, they describe how to update the kNN classifier when no concept drift is detected (add new instances to the knowledge base), and when concept drift is detected (remove obsolete examples from the knowledge base).

3.3 Single Classifier

A single classifier based model is proposed in [15]. The approach of the devised model is based on single best supervised learning algorithm that performs test instance classification on runtime. The evaluation test is initially partitioned to subsets, which is based on the values represented by the instance attributes. The selection of the classifier is done through learning accuracy observed. This strategy of supervised learning is labeled as Attribute-oriented Dynamic Classifier that miles ahead to most of the Ensemble Learners. The big constraint of the model is that its accuracy inversely proportionate to frequency of concept drift. If concept drift frequency is high then learning accuracy, scalability and robustness of the model is low.

3.4 Rule Mining Tree

A novel tree based model to assess the concept drift is proposed in [16], which is referred as Concept Drift Rule Mining Tree (CDR-Tree). The objective of the proposed model is to define the inference of concept drift as a form of set of hierarchically ordered rules. The contributions of this model are unique and first of their kind. The approach, initially pairs the old and new instances of divergent time points in order to form the CDR-Tree. The node's split point is determined by the process of information gain. The concept drift under high frequency leads to CDR-Tree more complexed, hence the accuracy will be compromised. Though the devised model recommended the discretization strategy to minimize the complexity, it's influence is nominal to retain accuracy and if the concept drift is influenced by recursive concepts then tree construction is gloomy.

3.5 Ensemble Learner

The model devised here in [17] is in the context of single learner based classification limits observed on text stream under considerable concept drift. In order to overcome the limits of single learner based classifier, the model in [17] ensembles set of learners as a stack and classifies the concept drift influenced data. This process is referred as stacking approach. This model also lost its control on memory usage if the concept drift frequency is high, which insists more stacks. Process complexity also magnifies, if data is with considerable noise. This stacking approach is one of the good strategy to handle the concept drift with recursive concepts.

The approach that contributed in [18] is adapting the pair of learners as Ensemble Learner. One of these learners is online learner and the other learner works as reactive leaner to fulfill the objective of concept drift identification. The online learner performs classification by using its entire training knowledge, but the reactive learner performs according to the knowledge gained through the training process applied on recent window. This Ensemble Learner of two classifiers is outperforms if mining process encountered any unknown class labels. The significant constraint of this collective leaner approach is that, it cannot perform well against concept drift due to noise in streaming data. This is due to neither of the classifier is unable to track out the noise.

In order to overcome the limits observed in [18], a Ensemble Learner strategy based ensemble classifier framework is proposed in [19]. Here, the major makeover of the paired learner model devised in [18] is the usage of weighted ensemble (WE) [31] as online learner and the averaging probability ensemble (AE) [32] under the "Learnable Assumption" [32] as reactive learner. The weighted ensemble classifier of the proposal trains on maximum data chunks and the averaging ensemble classifier trained on the most recent data chunk. The context of the concept drift and concept drift with recursive concept remains puzzle for this model.

Ensemble Learner based ensemble classifier is devised in [20]. This ensemble classifier was introduced a novel E-Tree Indexing structure to handle the time complexity of mining process in high speed DataStream. In order to achieve this, the ensemble models initially molded as spatial databases to enable the spatial indexing techniques. The concept drift prediction and handling is not clearly elevated in this model. This model is lagging at assessment of temporal validity of the class label and concept drift.

A novel Ensemble Learner based ensemble classifier that labeled as Rot-SiLA is devised in [26]. This ensemble classifier is the combination of Rotation Forest algorithm [30] and SiLA [29]. This model classifies based on similarity than distance. The experimental results are concluding the optimality of the devised model. The model is initially dividing the extracted feature set into subsets, which is based on PCA, the accuracy of the said model dependent of the accuracy of variance matrix formation for Principal component analysis.

3.6 Weighted Features

The data stream classification method introduced in [21] is the combination of weighted majority and adaptive sliding window approaches. This model is devised under the aim of handling noisy and concept drifting data streams with magnified accuracy in supervised learning. The weighted majority model adapted here in this model is capable to adjust the weights of the features reflecting the present concept and according to these weights, predicts the drift in the present concept. The thresholds involved to slide the window in sliding window concept is critical to achieve accuracy in supervised learning. This indicates that the prior knowledge of concept labels only magnifies the accuracy in classification.

3.7 Time Classification

Handling latency and concept drift is the prime criteria of the model devised in [22]. In order to achieve this the devised model is equipped with set of algorithms CDTC version 1 and CDTC version 2 that are based on time of classification protocol to handle the latency. The model explored here is a novel and the best of my knowledge, it would be the first attempt to assessing the concept drift under temporal validity.

3.8 Incremental Classification

The new classification algorithm called improved incremental harmony-based classifier proposed in [23] is able to classify the batch data. The classification strategy adopted here is an incremental approach that continuously updates the core classes. The computational overhead is minimal if the concept drift is not considered. The experiments claimed the robustness of the proposal to perform mining on DataStream with noise. The performance evaluation not discussed the influence of less significant concept drift and the concept drift by recursive concept.

3.9 Naive Bayes classifiers

A supervised learning model that devised in [24] is attempting to quantify the concept drift in the network traffic. The strategy of determining the concept drift is based on the curves reflecting the receiver operating characteristics. The outcomes of the Naive Bayes classifiers is used to define these curves and further used these curves to identify the concept drift of the active class. The adaptive learning strategy that uses fixed window to perform training is critical process of the model. The experimental results are not convincing to claim that the said model is significant towards DataStream with capricious data characteristics and noise.

3.10 Clustering

SRASTREAM framework [25] is a conditionally involved unsupervised learning framework that clusters the data during the concept drift. This framework is the combination of tasks listed as (i) clustering (ii) computing, (iii) evolution detection and (iv) resource monitoring. The model is aimed at improvisation of the clustering speed under the expense of acceptable cluster accuracy. The experimental results claimed the same but there is no evidence to conclude the stability at losing cluster accuracy in order to achieve the clustering speed. In particular the model is most suspicious if concept drifting is with recursive concept.

The model devised in [28] is a Density-based unsupervised learning approach, which is capable to learn from data with capricious characteristics and noise. This approach is the combination of two algorithms labeled as micro-cluster formation algorithm and grid formation algorithm, which is robust and scalable to investigate the concept drifts in data streams and demands no prior knowledge of number of clusters.

SA-Miner algorithm that devised in [27] is a frequent itemset mining model that uses support determined by approximation strategy. The discovery of concept drift is done through the support relationships. The core principle of the SA-Miner is that the support variation observed under the process of support-relationship assessment is proportionate to concept drift. The empirical study explored by authors indicating that the proposed method is significant towards accurate mining of the DataStream with minimal process time and memory usage. The model is not evident to handle the DataStream with concept drift reflected by recursive concepts.

The ARTMAP [11] and fuzzy based ARTMAP [12] are two contributions in order to assess the concept drift of input data stream. The Adaptive Resonance Theory Map (ARTMAP) is an unsupervised learning strategy that forms clusters against all possible patterns in incremental order. Further these clusters are used to perform supervised learning such that the attributes of the each cluster will be assigned to compatible class label. The further contribution found in [12] is utilizing fuzzy principals along with ARTMAP. The fuzzification is done by two versions of Adaptive Resonance Theory labeled as ARTa and ARTb. These two versions are synced through an inter Adaptive Resonance module. The incremental clustering that adapted here in these models is capable to deal the concept drift in effective manner.

The contribution found in [13] is an extension to the models devised in [11] and [12], which enables the frequent update of the fuzzy rules by pruning the inactive obsolete fuzzy rules. The dynamic pruning is done through the pruning strategy devised in [14] that prunes according the attributes called rule confidence, rule usage frequency and rule significance. The model devised in [12] required to maintain the details of all instances towards statistical assessment that leads to computational overhead. The model devised in [13] prunes the instances by their relative confidence, usage frequency and significance. In order to assess the concept drift with recursive concept impact and with high frequency, the rule update process is more computationally complexed and redundant in all of these three models devised in [11][12] and[13].

The summary of the important algorithms is shown in table 1

TABLE 1 SUMMARY OF THE IMPORTANT ALGORITHMS

Drifting Strategies	Benchmark Models	Objective	Observation
Decision Trees	The model Very Fast Decision Tree (VFDT) [5].	To build a decision tree to deal with streaming data which is capable of learning from high speed data stream.	Works focus on streaming data comparing to traditional decision tree in speed, accuracy and memory utilization. However, it still cannot handle concept drift in data streams.
	A Decision Tree-Based Approach to Mining the Rules of Concept Drift [16].	Defines the inference of concept drift as a form of set of hierarchically ordered rules.	The contributions of this model are unique and first of their kind. It's influence is nominal to retain accuracy and if the concept drift is influenced by recursive concepts then tree construction is gloomy.
Single Classifier	Dynamic Classifier Selection for Effective Mining from Noisy Data Streams [15]. AO-DCS (Attribute-Oriented Dynamic Classifier Selection).	It is based on single best supervised learning algorithm classifies on runtime. for effective mining from noisy data streams.	Its accuracy inversely proportionate to frequency of concept drift, if concept drift frequency is high then learning accuracy, scalability and robustness of the model is low.

Ensemble Learner	One-class Classification of Text Streams with Concept Drift [17].	Ensemble Learner approach that attempted to classify the concept drift influenced data using the stacking approach.	This model also lost its control on memory usage if the concept drift frequency is high, which insists more stacks. Process complexity also magnifies, if data is with considerable noise.
	Paired Learners for Concept Drift[18],	This approach is adapting the pair of learners as collective Learner, one of these learners is online learner and the other learner works as reactive leaner to fulfill the objective of concept drift identification.	The significant constraint of this collective leaner approach is that, it cannot perform well against concept drift due to noise in streaming data. This is due to neither of the classifier is unable to track out the noise.
	E-Tree: An Efficient Indexing Structure for Ensemble Models on Data Streams [20].	a novel E-Tree Indexing structure to handle the time complexity of mining process in high speed data stream.	The concept drift prediction and handling is not clearly elevated in this model. This model is lagging at assessment of temporal validity of the class label and concept drift.
Weighted Features	New Evolving Ensemble Classifier for Handling Concept Drifting Data Streams [21]	Combination of weighted majority and adaptive sliding window approaches, which are capable to adjust the weights of the features reflecting the present concept and according to these weights, predicts the drift in the present concept.	Prior knowledge of concept labels only magnifies the accuracy in classification. This algorithm mainly focused on accuracy at the expense of the performance in terms of time and memory.
Time Classification	The use of time stamps in handling latency and concept drift in online learning [22].	Using set of algorithms CDTC version 1 and 2 that are based on time of classification protocol to handle the latency.	The first attempt to assessing the concept drift under temporal validity.
Incremental Classification	A new method of mining data streams using harmony search harmony-based classifier [23].	Able to classify the batch data	The performance evaluation not discussed the influence of less significant concept drift and the concept drift by recursive concept.
Clustering	Concept Drifting based Clustering Framework for Data Streams (SRAStream) [25].	(i) Combination of clustering, computing, evolution detection and resource monitoring, (ii)aimed at improvisation of the clustering speed under the expense of acceptable cluster accuracy	-This algorithm shows no evidence to conclude the stability at losing cluster accuracy in order to achieve the clustering speed. -The model is most suspicious if concept drifting is with recursive concept.
	An approach of support approximation to discover frequent patterns from concept-drifting data streams based on concept learning SA-Miner [27].	Study the presence of concept drift under the problem of mining frequent patterns from transactional data streams.	The model is not evident to handle the DataStream with concept drift reflected by recursive concepts.

4. CONCLUSION

The objective of the paper is taxonomy and contemporary affirmation of the recent literature over mining data streams under the influence of concept drift. The observations of the review is that the current research domain is seriously contributing the novel and optimal concept drift handling strategies for mining data streams. The review was explored on the benchmark contributions found in the literature of past decade. The majority of these models are aimed at factors such as high speed data streams, data streams with noise, mining accuracy and time complexity of the mining strategy. The factors such as context of concept drift, concept drift temporal validity and concept drift with recursive concepts were almost overlooked. Henceforth, it is obvious to conclude that there is a big scope to conduct research towards finding new models to handle the concept drift in mining data streams under the context of factors like concept drift temporal validity, context and influence of recursive concept. Our future research contributions will be the new or extended models in the contest of the review.

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