

Online Ensemble based Reinforcement learning architecture to detect novel class and recurring classes on emerging data streams

K.Amrita Priya¹, Dr.R.Priya²

Research Scholar¹, Associate Professor & Head of Department²

Department of Computer Science, Sree Narayana Guru College, Bharathiar University
Coimbatore

Abstract

The extensive growth of digital technologies has led to new challenges regarding computational complexity on mining streaming data. The data classification is not trivial due to the high volume of data and limited time available for the classification. It is particularly difficult in dealing with data streams, where each instance of data is typically processed once on its arrival (i.e. online) while the underlying data distribution often changes due to the changing environment. In this paper, we propose a novel online ensemble based reinforcement learning for effective data stream classification in the context of changing environment leading to concept drifts (i.e. evolution of data streams). Proposed reinforcement learning uses three strategies to flexibly adapt to different types of concept drifts when performing data stream classification. Proposed architecture initially extract the a set of random feature combinations to form the pool of features on data streams using feature extraction technique such as kernel principle component analysis and Increment Non – Linear discriminant analysis . Pools of feature are classified using ensemble of Reinforcement learning such as Monte Carlo, Genetic algorithm and Q learning. Reinforcement mechanism is proposed to increase the weights of the base classifiers that perform better on the minority class and decrease the weights of the classifiers that perform worse. A resampling buffer is used for storing the instances of the minority class to balance the imbalanced distribution over time. On those classifiers, base classifier has been constructed weighting boosting technique. Extensive result on performance analysis proves that proposed model outperforms existing state of art approaches against various real datasets. The results demonstrated that the proposed framework can provide the best accuracy and computation time on average when comparing with existing models.

Keywords: Online Ensemble Learning, Reinforcement Learning, Concept drift, Class Imbalance, Data Stream Classification

1. Introduction

Due to enormous growth of data due to digital technologies such as online social networks, Internet of things networks has led to major challenges in mining the data with high velocity and large volume[1]. Large number of researches has been carried out using machine learning and ensemble learning model and it is active today with deep learning model to handle those complexities. Despite of those advantages, it is cumbersome task to classify the data on basis of novel class and recurrent classes. In addition, data with concept and feature drift on distribution of data greatly poses some challenges with generation of incremental, recurrent, gradual and abrupt classes[2]. Owing to their flexibility and versatility, ensemble-based learning methods such as chunk based ensemble and online ensemble are among the most popular techniques for data stream mining allowing to effectively dealing with various drifts in non-stationary data streams.

Ensemble learning is machine learning or deep learning approach[3], where instead of training a single classifier, a pool of classifiers are trained to improve the classification accuracy by merging different classifiers in the system. While changing the weights of separate classifiers in an ensemble according to their performance in the given context on the feature vector allows achieving a better overall performance. However the majority of the state-of-the-art ensemble methods for data stream classification are focused on either a specific type of concept drifts[4].

In this paper, a novel online ensemble based reinforcement learning for effective data stream classification in the context of changing environment leading to concept drifts (i.e. evolution of data streams) has been proposed. The model uses ensemble of reinforcement learning such as Monte Carlo, Genetic algorithm and Q learning with strategies to flexibly adapt to different types of concept drifts on pool of features extracted using feature extraction technique. Finally base classifier is achieved using weighting boosting technique.

The rest of the paper is organized as follows, Section 2 describes the related work on the classification of emerging data streams with multiple drift and Section 3 represents the proposed approach to detect the novel classes and recurring classes using strategies of reinforcement learning. Experimental results on proposed and existing approaches have been computed and validated against various performance measures on real time benchmark dataset in section 4. Finally section 5 concludes the work with direction to future work

2. Related works

In this section, various literatures related to ensemble learning techniques has been reviewed to identify novel class and recurring class in the various drift on emerging data streams. The literature has been examined with examples and impacts.

2.1. Concept Specific Learning model for classification of Dynamic Evolving Data Streams

In this technique, concept specific learning model for data classification of dynamic evolving data streams on estimation of the recurring classes on distributed data streams has been analysed. The classifier are built for evolving data streams in the ensemble manner with decision boundary for each class as class membership and it is frequently updated using incremental learning principles[12]. Error driven representativeness has been considered as it categories accurately the noisy features in the data streams on using dynamic heuristics or probability measures on uncertain data against class membership.

2.2. A deep fast learning framework towards exploring Imbalanced data

In this technique, data stream will be processed to extract the feature using ensemble feature extraction technique such as Incremental Kernel Principle Component Analysis[5], Incremental linear Discriminant analysis and Incremental Linear Principle Component Analysis[6]. Feature subset extracted undergoes ensemble classification through chunk based ensemble classifier and online ensemble classifier. This classifier form uses recurrent neural network, deep belief network, convolution neural network and autoencoder. Base classifier and class imbalance has been handled using weighted average and under sampling methods on replacing the older model with newly trained model. It is also capable of handling multiclass drift.

3. Proposed model

In this section, a new framework named as Reinforcement learning framework which is to detect the adaptation of the class evolution with strategies and buffering. The approach details each component of the framework to detect the novel class and recurring class of emerging data streams with various drift

3.1. Non linear Feature extraction

In this section, non linear feature extraction has been employed to extract the feature on the emerging data streams. Data streams has been segmented into parts and each parts has been processed on the following techniques to generate the feature subset in form of the feature vector which consist of the pool of features instances

3.1.1. Non Linear Discriminant Analysis

Non Linear Discriminant Analysis is to obtain the feature set on the emerging data streams. Feature extraction uses fisher criterion function to transform the data into feature vector. Fisher criterion function uses scatter matrix to compute the mean vector for the emerging data. Non Linear discriminant features minimize the vector scatters. Further weights of the vector are maximized on Eigen vectors.

$$\text{Mean Vector of the data streams} = D_v = \frac{1}{n} \sum_{x \in C} x, D_i$$

Scatter Matrix for Mean Vector is given as $S_w = \sum_{i=1}^c S_i \frac{D_i}{n}$

The non linear mapping of the projection data has been carried out to generate the feature instance on the data streams into feature set.

3.1.2. Non Linear Kernel Principle Component Analysis

Non Linear Kernel Principle Component Analysis is employed on the part of the dataset on various time stamps[7]. It is employ the kernel function to extract the feature vector on the projection of the data. Kernel function generates the kernel matrix. Further extraction of the principal components containing Eigen values on the Eigen vector uses covariance and correlation measures to generate feature space on the projection.

$$K = \{K(x_i, x_j)\},$$

$$\text{Where } K(x_i, x_j) = \phi^T(x_i) \phi(x_j)$$

Normalization of the kernel matrix is given by $Ka = \lambda a$

Principle component of feature describes the greatest amount of variance on the eigen value of eigen vector. The variance computation of the features is given by

$$\text{var}(x) = \frac{\sum_{i=1}^n a(x_i - x)(x_i - x)}{n-1}$$

On basis of variance computation, feature vector has been generated and it is aggregated using sliding window method on the various feature space. Especially it integrates the initial part of data streams generated feature set.

3.2. Ensemble based Reinforcement Learning

Ensemble based Reinforcement learning is a novel ensemble learning framework for data stream classification to the feature set. Feature set is processed using reinforcement learning with two layer which is base layer and optimization layer[8]. Figure 1 represents the proposed architecture towards data stream classification on any size of the ensemble and avoid the buffer replacement of the system. In base layer of the learning, several classifiers are generated to selected feature set for classification to establish an ensemble. Voting mechanism has been carried out with weighted average of the classifier models.

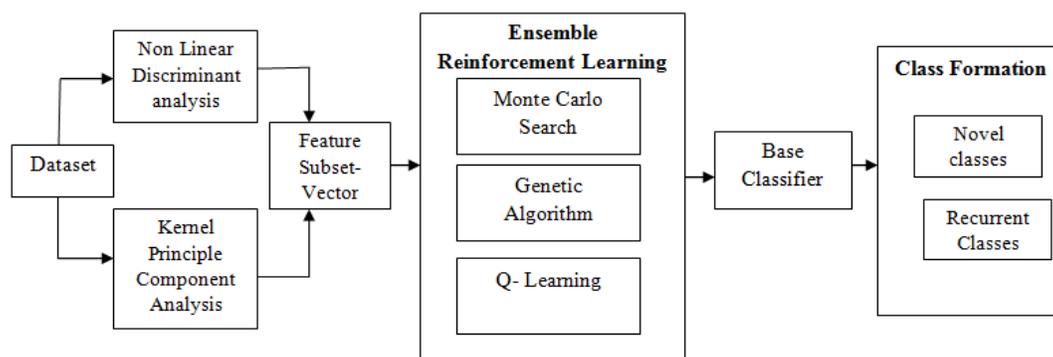


Figure 1: Architecture of proposed Framework

Each classifier projected in ensemble follows the important strategies. Strategies used to update the ensemble model to form base classifier to most recent established feature set. It is used to growing needs to classifier to categorize the feature instances towards achieving better accuracy. Finally these strategies are compatible with streaming data on optimization of the various feature instances on the drift.

3.2.1. Monte Carlo

It is a heuristic search algorithm used for classification of the feature extracted along the strategies constructed. Feature vector are represented in form of search tree based on random sampling[9]. Feature classification is carried in the aspect of roll outs. Each roll out weights the remaining nodes in the tree which consist of feature value to easily categorize it to classes either generating new classes and on existing classes. Monte Carlo tree based classification consist of four steps which is as follows

- **Selection**

It is to select the labels for set of features using centre value of the feature. The label is the identity of the current feature instance and set of features is any features in the feature vector which has potential to be initial feature without any simulation initiated. It is considered as ways of biasing the feature that lets the class tree expansion towards the most promising features.

- **Expansion**

Unless feature for particular class ends decisively, create one feature vector for the label and select one feature from it. Feature vector for the class is valid till class formation by objective function to the feature vector.

- **Simulation**

Simulation is to complete one complete class formation with feature on biasing . This called as rollout. A rollout may be a simple as choosing uniform random moves of feature formation until the class is decided.

- **Back Propagation**

The result of the class formation has been updated periodically from the initialization of the feature to formation of the class to the feature vector. The resultant feature vector formation to classes with labels such as novel classes, recurrent classes and evolution classes is determined.

3.2.2. Genetic Algorithm

Genetic algorithm is used as optimization technique to generate the class for feature vector available from the data streams[10]. It is used to select the best heuristics technique for feature Selection to the class formation .Heuristics is represented as Chromosomes. The genetic algorithm uses following function. Table 1 represents the key terms used in the genetic algorithm for the formation classes to the feature vector.

Table 1: Notation Used in Genetic Algorithm

SI.No	Key Term	Description
1	Individual	Any possible Solution
2	Population	Group of possible Solutions to the Feature
3	Search Space	Group of possible Solution to the Feature
4	Chromosome	Class of the Instance
5	Genome	collection of the Chromosome for an Instance

Genetic process

1. Initialization

- Initially many individual solutions are randomly generated to form an initial population. The population size depends on the no of classes, but typically contains several hundreds or thousands of possible features
- Solution is represented in the Array of features
- Chromosomes composed of feature instances

2. Selection Process

- It is based on roulette-wheel principle:
- Feature selected based on the Fitness value
- Feature are given a probability of being selected that is directly proportionate to their fitness

- Fitness Representation based on the Feature Instance and label, which can be used to index and rank the features and classes
- Single class– Two feature instance are taken and then it reproduce the offspring and it is mutated randomly
- Population varies in each iteration

3. Reproduction

- It is carried out through crossover (single point Cross Over) and mutation to generate a new population based on the same characteristics of initial population
- Single class – Two Individual feature instances are taken and then it reproduce the offspring and it is mutated randomly
- It produces more Chromosomes which heuristics used to execute classes in the feature instance.

4. Termination

- Termination point of the iteration depends the no. of generation -population of the individuals also depends on the fitness level.
- Fitness value is used to termination condition that is the no. of individuals (Feature generated as per the Class) generated by selection process and Cross over process

3.2.3. Q learning

Q learning is a model free reinforcement learning to learn the feature vector to classify the classes without considering the environment such as novel classes, recurrent classes and others[11]. The model is capable of handling feature mapping to the classes without requiring adaptation of the objective function for class generation. It is heuristics based model to determine feature instance to the class. Q learning finds the optimal solutions to the class on basis of action selection policy for given markov decision process. Class prediction function for feature vector is given by

$$Q(s_t, a_t) = E\{r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \gamma^3 r_{t+4} + \dots\}$$

Where State of the feature is S_t

E is the expected feature and r is a reward function

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha[r + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

Prediction function is delay scalar feedback and it determines the shortest path on basis of state action pair on NN to approximate.

3.3.Base Classifier

Base classifier on ensemble learning using reinforcement learning will be constructed using weighted aggregation of majority[13]. In this base learner maintains the weight vector which combines linearly with local class prediction vector composed of the feature instance using reinforcement learning on q learning or genetic algorithm. Weighted majority scheme determines the base learner to particular type of instance classification. Class determination is as follows

$$Q(s, a) = Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

Algorithm 1: Ensemble Reinforcement learning

Input: Data Instance in streams or chunks Data instance (x_t, y_t) at time t , Class Set C_t , Feature subset F_t

Output: Class formation – New or Existing class

Process Initialize $Q(s, a)$ arbitrarily

Repeat (for each episode):

 Initialize s

 Repeat (for each step of feature instance F_t):

 Choose a from s using policy derived from Q for function

$$Q(s, a) = Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

$s \leftarrow s'$;

 Until s is terminal

Assign the Class Label C_E to the feature instance F_t

4. Experimental Results

In section, the experimental results of the proposed ensemble based reinforcement learning model and it has been evaluated against the existing approaches on emerging data streams. The performance evaluation has been computed on real time benchmark dataset in terms of precision and recall measures on k fold validation. The evaluation of the ensemble classification has been done with through Dotnet environment is as follows

4.1 Dataset

The dataset employed for evaluation of the proposed ensemble based reinforcement learning model against the novel class and recurring classes is described as follows

4.1.1. Forest Cover type dataset

Forest cover dataset contains 581,000 instances, 7 classes, and 54 numeric attributes which is extracted from the UCI repository has been used for analysis of performance using ensemble based reinforcement learning[14]. It randomly generates 10 different sequences of each dataset, and report the average result.

4.2. Evaluation

The proposed ensemble reinforcement learning Framework for data stream classification is evaluated against the following measures

- **Precision**

The precision is a measure of positive predictive value of feature class. It is also considered as ratio of retrieved instance to resultant instance of the feature vector towards classification [15]. The performance outcome is represented in the figure 2

$$\text{Precision} = P = \frac{\text{Relevant retrieved result set}}{\text{Overall Retrived Result set}}$$

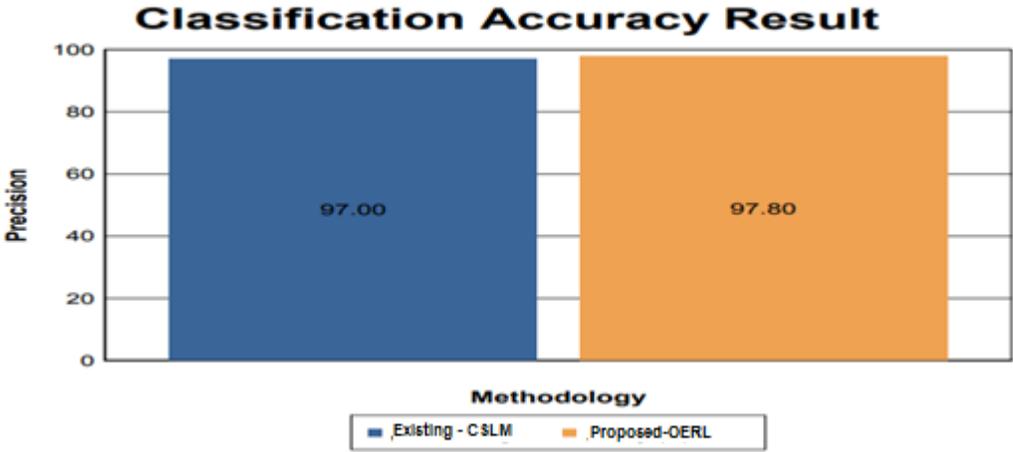


Figure 2: Performance Analysis of Ensemble based reinforcement learning against the Precision

- **Recall**

The Recall is ratio of relevant feature instance extracted in the vector to retrieved feature vector on class of instance. It is considered as exact class as novel class or recurrent class over the feature vector on the classes composing feature instances. Its performance outcome is represented in figure 3 and table 2

$$\text{Recall} = R = \frac{\text{Relevant retrieved result set}}{\text{Relevant Result in database}}$$

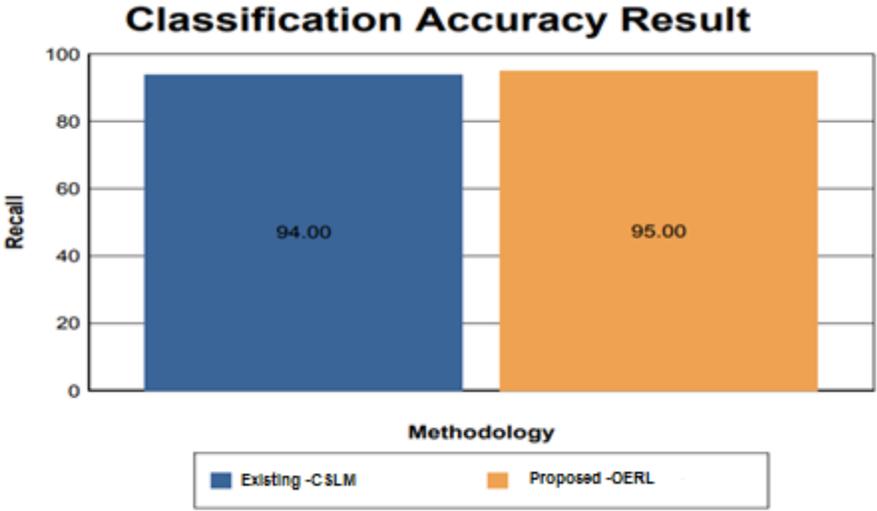


Figure 3: Performance Analysis of the Ensemble based reinforcement learning against the Recall

The evaluation model generates the high possible evaluation results compared with other possibilities approaches in class formation to different class or categories on feature instances of the feature vector.

Table 2: Performance Analysis of the Ensemble learning approaches

Technique	Precision	Recall
Concept specific Learning Model- Existing	97	94
Online Ensemble Based Reinforcement learning - proposed	97.8	95

In order to examine the performance of the different online ensemble learning of proposed reinforcement learning greatly increase the accuracy of the classification on the data streams. Finally it is proved that it achieves better results in terms of the data reliability.

Conclusion

Online Ensemble Based reinforcement learning has been designed and implemented on real time benchmark dataset to cope with different concept drifts in data stream classification. Various strategies has been proposed on the reinforcement model such as q learning , genetic and monte carlo search after feature extraction of data stream using kernel based principle component analysis and non linear discriminant analysis. Base classifier for reinforcement learning has been computed on weighted average on available classifier prediction function. The performance of

the model has been cross validated with k fold validation on performance measure such as precision and recall. The results of the comparison demonstrated the proposed model had the highest average accuracy and best

average rank among all compared methods. In the future, we plan to extend our current work to implement and analyse the following ideas: Propose a novel concept drift detection algorithm by conducting a behavioural analysis of the classification and use a dynamic weighting mechanism to the outcomes of the classifier.

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