A precipitation forecasting model using machine learning on big data in clouds environment

MAHBOOB ALAM and MOHD. AMJAD  
Department of Computer Engineering  
Jamia Millia Islamia University, New Delhi – 110 025, India  
(Received 17 July 2020, Accepted 23 August 2021)  
e mail : mahboobru@gmail.com

Abstract. Numerical weather prediction (NWP) has long been a difficult task for meteorologists. Atmospheric dynamics is extremely complicated to model, and chaos theory teaches us that the mathematical equations used to predict the weather are sensitive to initial conditions; that is, slightly perturbed initial conditions could yield very different forecasts. Over the years, meteorologists have developed a number of different mathematical models for atmospheric dynamics, each making slightly different assumptions and simplifications, and hence each yielding different forecasts. It has been noted that each model has its strengths and weaknesses forecasting in different situations, and hence to improve performance, scientists now use an ensemble forecast consisting of different models and running those models with different initial conditions. This ensemble method uses statistical post-processing; usually linear regression. Recently, machine learning techniques have started to be applied to NWP. Studies of neural networks, logistic regression, and genetic algorithms have shown improvements over standard linear regression for precipitation prediction. Gagne et al proposed using multiple machine learning techniques to improve precipitation forecasting. They used Breiman’s random forest technique, which had previously been applied to other areas of meteorology. Performance was verified using Next Generation Weather Radar (NEXRAD) data. Instead of using an ensemble forecast, it discusses the usage of techniques pertaining to machine learning to improve the precipitation forecast.  

This paper is to present an approach for mapping of precipitation data. The project attempts to arrive at a machine learning method which is optimal and data driven for predicting precipitation levels that aids farmers thereby aiming to provide benefits to the agricultural domain.

Key words – Rainfall, Pollution, Datasets, Analysis, Big data.
1. Introduction

Precise rainfall forecasts has always been one of the most significant concerns in hydrological research since prior warning of extreme weather conditions can help to avoid accidents and damage from natural disasters with beforehand and accurate forecasts. Creating a forecasting system for precise rainfall forecasting is among the biggest challenges in front of researchers in various fields like weather data mining, environmental machine learning, operational hydrology and statistical forecasting. A major and commonly occurring challenge in these problems is to figure out the way to predict the future trends by studying the trends of past (Baldauf et al., 2020).

The parameters needed to forecast rainfall are very convoluted and intricate for short-term periods. Physical processes involved in rainfall usually comprises of several sub-processes. At times, using the same global model for accurately modeling the rainfall isn’t possible. The concept of modular modeling tackles this problem and combining of several separate models has recently gained much attention in rain forecasting.

Firstly the various sub-processes are defined in the modular approach, and thereafter the separate models (which are also known as the local or expert models) are set up for each of them. Quite a few modular models have been proposed till date, which depend on hard or soft segmentation of training data. Soft segmentation is nothing but the overlapping of datasets the weighted average of each local model is utilized to find the overall forecast output (Bi et al., 2015; Cano et al., 2003).

Numerical weather prediction (NWP) has long been a difficult task for meteorologists. Atmospheric dynamics is extremely complicated to model, and chaos theory teaches us that the mathematical equations used to predict the weather are sensitive to initial conditions; that is, slightly perturbed initial conditions could yield very different forecasts.

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2. Literature review

2.1. Scope of work

Farmers, across the nation, are majorly reliant on timely precipitation for harvest and associated profits. Uncertainty clouding this phenomenon, due to the slow onset of vices like the climatic changes and global temperature surge lead to the collaboration of traditional farming methodologies and predictions of precipitation. India being an agrarian country with around 70% of its people depending upon agriculture, accounted for about 12% of suicides by its farmers. Numerous conflicting reasons have been accorded but primarily targeting the failure in monsoon predictions. This adopted the concept of integrating the machine learning in assisting them for cultivation of their harvest and securing their lives (Bhatt et al., 2015; Katal et al., 2013).

2.2. Possible Machine learning models

2.2.1. Naive Bayes Clustering

In ML, the naive bays classifier is a group of probability based classifiers that work by putting to use the Baye’s theorem with robust (naive) assumptions of lack of interdependence among features. Knife bays have been researched upon thoroughly since the 1950s. It was introduced in the early 1960s with different name in the text retrieving fraternity, and is still a widely used (foundational) technique for textual classification, the issue of identifying documents that belong to the same category or another (say, promotional, career related or politics) with frequency of words used as features. By using correct pre-processing, this is a promising method in this field with more sophisticated ways including support vector machines. Besides, this has applications in automated medical diagnosis too (Abaker et al., 2015; Das et al., 2007).

Naive Bayes is an elementary method to create classifiers: The models assigning classes labels for problem instances are depicted as feature value vectors, where a finite set is used to draw the class labels. This is not a standalone algorithm to train such a classifier, rather it is a group of algorithms working on one general principle: The value of one specific feature is assumed by the naïve classifier to exceed that of another feature, provided the class variable is free (Garcia et al., 2012; Alam et al., 2017).

What Naive Bayes classifiers do is that, every single of these characteristics is considered to be contributing independently towards the possibility, the given fruit is a pineapple, irrespective of any probable similarities among
features like shade, gradient, degree of sphericity and radius features. However with certain selected kinds of probability models, Naive Baye’s classifiers also offer the capabilities to be trained effectively in a learning environment which is under supervision. In some real-life applications, estimation of parameters for the Naive Bayes model employs the technique of highest probability; i.e., one could use the naïve Bayes models without having to accept the Bayesian probability or making use of any other Bayesian methods.

In short, the inexperienced Naive is a probabilistic model which is conditional: the problem example is classified, a vector is then used to represent it, which denotes say “m” features (variables that aren’t dependent on each other) (Kittler et al., 1998; F. G. et al., 2010). It specifies the probabilities.

\[ p(C_i|x_1,...,x_n) \]

For every possible outcome of K or Ck squares

The challenge that the above mentioned formula poses is that when the “N” which is the feature count, is large or if an attribute can take multiple values then it is not possible to base such models on probability tables. Hence we make improvements to the model so that it becomes more streamlined. Using the Bayes theorem, we can decompose the conditional probability.

\[ p(C_i|x) = \frac{p(C_i)p(x|C_i)}{p(x)} \]

2.2.2. Support vector machine

In ML, vector machines support (SVMs supports vectored networks too) monitoring learning models with connected learning algorithms that use data frost regression and classification analysis.

With respect to one single or a couple of classes the SVM training algorithm generates such models that provide novel test cases for 1 class or another, which makes it binary linear classifier that isn’t a probabilistic one. However methods such as plot scaling use SVM exits to do probabilistic classification. An SVM model is nothing but a collection of instances like points present in space, mapped such that instances of individual classes are segmented by an explicit difference which is as detailed as possible. The novel instances are then mapped to the same place and it is estimated which category they belong to. Besides demonstrating linear classifications, SVMs can effectively use non-linear classifiers, called kernel moves, to map their inputs in multi-dimensional feature locations (Coulouris et al., 2011; Dean et al., 2010).

Whenever data is not labeled, supervised learning ceases to be a possibility, and the requirement of an untrained learning method arises, which attempts to detect the natural clustering in datum along with the new data which these newly created clusters maps to. The Support Vector Clustering Algorithm, devised by Vladimir Vapnik and Hava Siegelmann, implements support vectors stats, generated by Supported Vector Machines algorithm, for categorizing unlisted datum along with being the most extensively utilised in the industrial uses. Is one of the cluster algorithms to be performed?

Classifying a machine is a usual job in ML. Suppose that a data point in consideration falls under 1 of every 2 classified categories, while our objective is to find out the class to which a new data point will belong to. Whereas in SVMs, a data point is considered as a vector with m-dimensions (array of m numerals), also what needs to be known is if those points can be separated in an m^-1 dimension hyper plane. It is known as Linear Classifier. A number of hyper planes are there for data classification. The most preferred hyper plane is the one which depicts maximum margins or separations among the 2 classified groups. Therefore we attempt to pick the hyper plane in a manner to maximize the distance from the most proximate point. This sort of a hyper plane is called the maximum-margin hyper plane. Also, the linear classifier defining this plane is referred to as the maximum classifier; equivalent, indicating optimal stability (Boyd et al., 2011; Mahmoud et al., 2020).

We can see in Fig. 1 that H1 doesn’t separate class; however it is done by H2, but just with a little origin. H3 separates them with the most margins.

In a more formal sense, an SVM generates a high-plane or collection of hyper planes in a very high or
infinite-dimensional space that can be used to do other tasks like classification, regression, or outlier detection. Obviously, an honest distinction is obtained by the hyperplane having the biggest distance to the closest training-data point of any category (also known the functional margin), because the normally large margin is that the normalization error for that class.

The essential problem is defined in finite dimensional space, what usually happens is that sets to distinguish aren't different in a linear sense there in space. As a consequence of this, it had been suggested that the initial finite-dimensional space should be mapped to an awfully high-dimensional space, possibly leading to the distance in this space easier to stay the computational load reasonable, the mapping utilized by Support Vector Machine criterions meant to make sure that the scalar-product are calculated with ease in terms of variables within the original space. Allowing the kernel function \( k(x, y) \) to be resolved the matter by defining as. Hyper planes in high-dimensional space are described as clusters of points whose real number is constant along the vector in space. The vectors that define the hyper plane will be chosen for linear combinations with the parameters \( a_i \) of images of the feature vectors \( x_i \) occurring within the data base. The purpose \( x \) within the feature space to be mapped to the hyper plane, is calculated by the relation (Iqbal et al., 2020; Galar et al., 2012).

One thing to be observed here is that as \( k(x, y) \) gets smaller as it moves farther from \( x \),

\[
\sum a_i k(x_i, x) = \text{constant}
\]

Then every term that measures the degree of proximity of the test point \( x \) to the corresponding data base point \( x_i \). Thus, the summation of the kernels given above can provide us with the relative inflation of each test point, with the origin of the data points discriminating one or the other. Note that consequently the point set \( x \) mapped with any hyperplane can be rather complex as a result, which allows for more complicated differentiation among sets which aren’t convex.

3. System methodology

In this paper, we gave the brief description about the system design and methodology of our research work. The chapter includes the complete and detailed system design and the complete system architecture. The system design includes how the flow of data will take place from one activity to the activity. The system architecture will explain the way, the user will interact with the system through the user interface [8][9]. The user will then give its review about the product through the interface and the featured based structured summary of that particular
product will be dynamically updated. The chapter also includes diagrams depicting the flow of data and the use case schematic drawing of our research work. It also includes the various algorithms that we will use in the implementation of the research (Tsai et al., 2016, Mayer et al., 2014; Kaur et al., 2017).

3.1. Data Flow Diagram

We have two level flow diagrams Fig. 2 and Fig. 3 (level-0 and level-1) in which we can see how the process will work.

3.2. Algorithm

Algorithm

Model Selection Using Genetic Algorithm

1. Generic algorithms are employed to select models and hyper parameters optimization.

2. Multiple copies of dataset will be created and different models are applied as input to the genetic algorithms initial population.

3. With each generation on the basis of fitness function GA will select an optimum machine learning model with optimum hyper parameters.

4. The output of genetic algorithms will be a model from the pool of algorithms like Naive Bayes Classifier, nearest neighbours, DCCA, Transferred Data Clustering, etc.

We can also select the best Parameters for each machine learning model through genetic Algorithms.

3.2.1. Proposed model

The layout structure is used to analysis huge datasets and the effects will assist to identify styles in area of evaluation. We can describe layout architecture in four layers as shown in Fig. 4, We are going to describe layers as given below (Englei et al., 2020; Fan et al., 2012, Lopez et al., 2015).

First Layer: The information layer deal with information procurement forms; it gets information from various sources which are dealt with by administrative and open structures.

Second Layer: The cloud layer stores big datasets on the cloud. In this layer all big datasets stores on cloud then work on distributed, parallel processing.

Third Layer: The facts layer elements and use large datasets of monetary and economic statistics, this accretion paintings on dispensed, parallel processing.

Fourth Layer: The consumer layer is the interface for person to get entry to massive datasets and manages the query for analysis and reviews.

The ETL (extract, transform and load) server is a mediator layer placed between the second layer and third layer, get records from the information crawler and harvester detail, adjustments it in a brand new shape. The ETL regularize data, transforms it based totally on a predefined shape and rejects not needed or incompatible information.

The ETL layer inserts facts inside the parallel allotted DBMS that implements the Hadoop and MapReduce framework. The goal of the layer is to regularize statistics and convey it to a not unusual layout, asked through the parallel DBMS.

With the help of ETL system, gets consolidate, altered and loaded into the parallel DBMS, using a facts model optimized for records retrieval and evaluation. The user will process his task via a the front cease application server, with a purpose to translate them into queries and publish them to the parallel DBMS for dealing out
3.2.2. Design goal

The aim of our layout architecture is to do green and precise of weather forecasting. To obtain this, we are going to system the input records, discern out the selected features and thoroughly analysis. Therefore, the following measures are important for the processing performance of our proposed structure.

(i) Analysis accuracy : This is the main goal of our architecture design.

(ii) Rate of reduction : In this architecture, the act of characteristic engineering influences the accuracy of analysis directly.

(iii) Efficiency in time : carried out in climate forecasting, the architecture must evaluation rapid.

4. Results and analysis

The performance of PCA, SVM, Random forest, Gaussian Naïve Bayes, ANN/MLPC classifier has been evaluated on the basis of precision score as shown in Fig. 5. In information retrieval, precision is a measure of result relevancy and hence, is a useful measure for predicting the success when the classes are highly imbalanced.

The following graph depicts the results based on precision score for various models use on different set of months.

4.1. Result for May-June-July

We can see the results for the set of month May, June and July as given following.

4.1.1. Artificial Neural Network (ANN)

The result of above set of month by using ANN is shown in Fig. 6.

4.1.2. Naïve Bayes

The result of above set of month by using naïve bayes is shown in Fig. 7.

4.1.3. Random forest

The result of above set of month by using random forest is shown in Fig. 8.
Fig. 9. Result after using SVM for May-June-July month

Fig. 10. Result after using PCA for May-June-July month

Fig. 11. Result after using ANN for May-June month

Fig. 12. Result after using Native Bayes for May-June month

Fig. 13. Result after using Random Forest for May-June month


4.1.4. Support Vector Machine (SVM)

The result of above set of month by using SVM is shown in Fig. 9.

4.1.5. Principal Component Analysis (PCA)

The result of above set of month by using PCA is shown in Fig. 10.

It is quite clear that the PCA model did not perform well and had a negative precision score. So, PCA was not used for further observations.

4.2. Result for May-June

We can see the results for the set of month may and june as given following.

4.2.1. ANN

The result of above set of month by using ANN is shown in Fig. 11.

4.2.2. Naïve Bayes

The result of above set of month by using native bayes is shown in Fig. 12.

4.2.3. Random Forest

The result of above set of month by using random forest is shown in Fig. 13.

4.2.4. SVM

The result of above set of month by using SVM is shown in Fig. 14.

4.3. Result for May

We can see the results for the month may as given following.

4.3.1. ANN

We can see the result for the month may by using ANN is shown in Fig. 15.

4.3.2. Naïve Bayes

We can see the result for the month may by using native bayes is shown in Fig. 16.

4.3.3. Random Forest

We can see the result for the month may by using random forest is shown in Fig. 17.

4.3.4. SVM

We can see the result for the month may by using SVM is shown in Fig. 18.

5. Comparison of the results

We can see in following graphs the comparison of the precision score of different methods for the different
set of months. Fig. 19 shows the result by artificial neural network (ANN), Fig. 20 shows the result by naïve bayes, Fig. 21 shows the result by random forest and Fig. 22 shows the result by support vector machine (SVM).

Finding the model that can best describe the data and can best predict the rainfall is very essential. From the results, we can see according to the precision score as shown in Table 1. SVM (Support Vector Machine) classifier performed best among all the classifiers in the given performance metric - Precision score.

### Table 1

| Months      | ANN | Naive Bayes | Random Forest | SVM |
|-------------|-----|-------------|---------------|-----|
| May-June-July | .40 | .49         | .50           | .52 |
| May-June    | .56 | .53         | .53           | .56 |
| May         | .58 | .55         | .52           | .59 |

6. Conclusion

Forecasting of rainfall has long been a difficult task. Since, atmospheric dynamics is extremely complicated to model; several models have been used in this research work, each having its own strengths and weaknesses in forecasting for different months. For reasonable evaluation of the performance of these models - PCA, SVM, Random forest, Gaussian Naïve Bayes, ANN/MLPC classifier, they have been separately used for the purpose of comparison. This chapter summarizes the main results of the project.

Future prospects include the following things:

(i) Research of the climate change and its impact on health Using approaches of distributed and parallel analytics big data using cloud environment.

(ii) The structure optimization of the climate change and its impact on health using approaches of distributed and parallel analytics big data using cloud environment.

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