Prediction of Climate Change using SVM and Naïve Bayes Machine Learning Algorithms

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Article History: Received: 11 January 2021; Accepted: 27 February 2021; Published online: 5 April 2021

Abstract: Various reasons are there in failures of Intergovernmental Panel on Climate Change (IPCC) simulation model for prediction of climate change. For the better understanding of IPCC model’s failures by researchers, an improvement is qualitative and quantitative analysis is required and to be implemented. We come across a continuous crashes in simulation of Parallel Ocean Program (POP2) component of the Community Climate System Model (CCSM4), while measuring the impact of ocean model parameter uncertainties on weather simulations, during the period of uncertainty quantification (UQ) ensemble. This manuscript analyse the different machine learning algorithms, such as, Random forest, Linear Regression, k-means and naïve-bayes algorithms. From machine learning, a quality classifier called support vector machine (SVM) classification is used to predict and quantify the failures probability as a function of the values of POP2 parameters. Apart from quantification and prediction, this method performs a better understanding in simulation crashes in other complex geo-scientific models.

Keywords: Support Vector Machine, Naïve Bayes’ algorithm, Community Climate System Model.

1. Introduction

Recent global 3D climate models are working excellently in unfurl of complex scientific problems using latest software’s. To solve the equations of state of machines, energy, atmospheric momentum, land, reservoirs of earth system, oceans, we need a thousand of details and billion lines of codes. With a quantity of interest, to prompt the cycles of sulphur, ozone gases [1] and other extent related to climates require a numerous algorithms on chemical, biological, geologic, and anthropogenic processes.

Machine learning deals with study of algorithms which improves consequently through experience. Several number of algorithms [2-4] has been plotted for several functions on Artificial Intelligence. This introduction section analyses the various machine learning algorithms. These algorithms operate on different dimensions of magnitude in time, space, solid, liquid, gas and different component phases, which contain fine particles having multiple complexity[5].

In linear regression, which seeks to identify and forecast the low and high temperatures as a linear functional combinations of the features [12]. Since straight relapse can’t be utilized with characterization information, this calculation didn’t utilize the climate order of every day [15-16]. Climatologically conditions need to be predicted to save the life of people which is a challenging problem. Machine learning techniques may be applied to forecast the extreme weather events. The author [16] addresses the use of ML algorithms to filter and visualize the extreme weather event. In the proposed system, AFM method is used to filter the events and based on the results the class labels are assigned.

The extreme and non-extreme weather events are visualized using DBSCAN and K-means clustering algorithm. The past extreme events like BOB (06), Thane and Vardahare validated and the results are verified by the parameters like homogeneity and completeness. This paper addresses the use of ML algorithms to filter and visualize the extreme weather event [8]. In the proposed system, AFM technique is used to filter the events and based on the results the class labels are assigned. The extreme and non-extreme weather events are visualized using DBSCAN and K-means clustering algorithm [17-18].

2. Naïve Bayes Algorithm

The below equation shows the Bayes theorem,

\[ P(B \mid A)P(A) \]
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\[ P(A |B) = \frac{P(B)}{P(A)} \quad \text{---- Eq.(1)} \]

Probability of happening A calculated using Bayes Theorem. Here, B is the Evidence and A is the Hypothesis. where A and B are events

- To find probability of occasion A, given the occasion B is valid. Occasion B is named as proof.
- \( P(A) \) is the priori of A
- \( P(A|B) \) is deduced probability of B

3. Support Vector Machine (SVM)

SVM classification [9] classification problem can also be controlled using analogous methods, such as decision trees, and random forests. The learning algorithms associated with supervised learning model for regression and classification used for analysis are implemented using support vector networks or support vector machines (SVM) in machine learning.

A SVM classifier [14] builds a model to predict classes with new examples. A Binary SVM Classifier is obtained; if there are only 2 classes are available. An apparent gap separates these data points. A hyper plane dividing 2 classes will predict straight forward. The outcome of drawing of hyper-plane is called as a maximum-margin hyper plane.

4. Confusion Matrix

The below table shows the confusion matrix [10-11],

|        | Actual |
|--------|--------|
| Failure|        |
| TP     |        |
| FP     |        |
| Success|        |
| FN     |        |
| TN     |        |

Table 1. Confusion Matrix

Classification Rate or Accuracy is given by the relation:

\[ \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{---- Eq.(2)} \]

5. Dataset Information

This dataset contains records of propagation crashes experienced during environment model vulnerability evaluation (UQ) troupes. Outfit individuals were built utilizing a Latin hypercube strategy in LLNL’s UQ Pipeline programming structure to test the vulnerabilities of 18 model boundaries inside the (POP2) segment of the (CCSM4). The aim is to utilize classification to forecast simulation result using sensitivity analysis from input parameter values for regulating the seed of simulation crashes.

5.1. Attribute Information

Aim of it is to estimate environment model re-enactment results given scaled estimations of environment model information boundaries.

Section 1: Latin hypercube study ID (study 1 to contemplate 3)
Section 2: reproduction ID (run 1 to run 180)
Sections 3-20: values of 18 environment model boundaries
Section 21: simulation outcome (0 = disappointment, 1 = achievement)

5.2. Features description

Consider an environment dataset that portrays the climate conditions for if the environment crashes. Given climate conditions; each tuple characterizes the conditions as fit ("Yes") or unfit ("No") for environment crashes. The dataset grouped into Feature framework and the Response vector. In above dataset, the class variable name is “Outlook”.

Table 2. Parameters Sampled in the CCSM4 Parallel Ocean Model
6. Results and Discussions

The Figure 1. shows the predictive values of Naïve Bayes’ Classifier for Discrete Predictors. The model makes the contingent Probability for each element independently. We likewise have the a priori probabilities which show the dissemination of our information. From the Figure 1. We understand that the accuracy value using naive Bayes classifier for discrete predictors is 0.9382

The underneath plot is showing that our classifier is giving best precision. The result classify 151 out of 156 “No” cases correctly and 1 out of 5 “Yes” cases correctly. This implies the capacity of Naïve Bayes calculation
to anticipate "No" cases is about 96.5% yet it tumbles down to just 20% of the "Yes" cases bringing about a general precision of 94%.

![Confusion Matrix](image)

Figure 2. Prediction of 'Yes' and 'No' cases

We have to apply the same data set information in Support Vector Machine algorithm.

```r
> confusionMatrix(
+   factor(test_pred),
+   factor(testing$outcome)
+ )
Confusion Matrix and Statistics

Reference
Prediction 0 1
0 9 1
1 4 148

Accuracy : 0.9691
95% CI : (0.9294, 0.9899)
No Information Rate : 0.9198
P-Value [Acc > NIR] : 0.00819

Kappa : 0.7663
Mcnemar's Test P-Value : 0.37109

Sensitivity : 0.69231
Specificity : 0.94329
Pos Pred Value : 0.90000
Neg Pred Value : 0.97368
Prevalence : 0.08025
Detection Rate : 0.05556
Detection Prevalence : 0.06173
Balanced Accuracy : 0.84280

'Positive' Class : 0
```

Figure 3. Result Screenshot for Confusion Matrix

Data slicing is to split the data into train and test set. Using confusion matrix, we can be able to know how accurately the model is working. We can get statistics of our results based on applying the confusion matrix. From the Figure 3., it clearly represent that the accuracy value is 0.9691 and balance accuracy is 0.84280. Our model using SVM shows the accuracy for test set is 97%.

From our results, we conclude that the SVM is the best algorithm for our dataset because the accuracy is more when compared to naïve bayes. Therefore, support vector machine algorithm is suitable for predicting climate crashes. The beneath plot is showing that our classifier is giving best precision on C = 0.25
7. Conclusion

A sequence of code crashes occurred during execution of simulations with the mentioned parameters. Machine learning types are used to define in aggregating failure probabilities of listed parameters. Sensitivity analysis utilized to analyze various parameters and modules to explain the simulation failures. We have presented probabilistic networks and show their relevance for nearby climate forecasting and down scaling. In this paper, the fundamental results shows how such models can be fabricated and how they can use for performing derivation.
Further analysis is as yet required for deciding the pragmatic employable productivity of these models; first tests are being promising. We are right now chipping away at adjusting existing learning calculations for managing this unique issue, where the proof is constantly given in similar subset of factors.

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