

## An Experiment of Wet and Dry Day Prediction and Qualitative Precipitation Forecast using Data Mining Technique for Port Blair Station

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Article Info Volume 83 Page Number: 1778 - 1783 Publication Issue: May - June 2020

#### Article History

**1. Introduction** 

Article Received: 11August 2019 Revised: 18November 2019 Accepted: 23January 2020 Publication: 10 May2020

### Abstract:

Short range rainfall forecast is usually given based on the synoptic situation. However point rainfall forecast is still a challenging task for the forecasters. With the recent developments of internet several new techniques have evolved in various fields. Data mining presents various rule based techniques and classifier methods for data analysis and extracting knowledge from different fields. The same is tried to forecast the rainfall in a day during various months of North East monsoon at Port Blair, a place of tourist importance station which is an island in Andaman group in Bay of Bengal. The tool is also tested for the qualitative forecast of rain and experimental results are summarized here.

Keywords: Association rule mining, classifier approach, rainfall forecast, qualitative forecast.

Rainfall is predicted from the charts identifying the synoptic system and then capacity to cause rain over a location. However in practice it is found that the forecast is valid over a region as a whole and point rainfall prediction is still a serious task for operational forecasters [3]. For India cyclone and monsoons are systems with understandable rainfall pattern [4]. However for islands with larger continents far awav identification of synoptic system is a difficult to predict the precipitation patterns as there would not be any observations over the surrounding oceans. Radar and satellite data of recent decades help to certain extent in assessing the rain potential of clouds for local forecast. However it is more conversion to rely on local data for a successful forecast as any effect of synoptic system has to implicitly evident in local weather. Such a method is tried for forecast of dry and wet weather for Port Blair which is an island station of Andaman in Bay of Bengal.

Data mining method is preferred in this direction as this is an era of data analytics and

pattern evaluation. The potential of data mining techniques for weather forecast has been reported in recent times [5, 6, 7, 8]. Hence association rules are extracted for precipitation patterns and classified with occurrence of wet spell and dry season during the period of North East Monsoon (NME) and South West Monsoon (SWM) of island station.

### 2. Material and Methods

### 2.1 Data Preparation

Port Blair (Latitude 11°40' N / Longitude 92°44' E) is a beautiful island located in the east coast of South Andaman. The weather patterns of this island is maintained by India meteorological department since 1961. Weather forecasters are considered various atmospheric parameters such as, temperature (TMP), dew point (DEWP), speed of wind (WDSP), visibility (VISIB) precipitation (rainfall) and weather prediction. A data set consists of five atmospheric variables including TMP, DEWP, WDSP, VISIB is collected from National Climatic Data Center



which is world most active weather data center located in United States of America. This scheme concentrates over the month of North East Monsoon (October to December) and South West Monsoon (June to September).

The raw set of seasonal information is converted into nominal values (LOW, MEDIUM and HIGH) by applying unsupervised attribute of discretization algorithm. After the data preprocessing, a total of 2635 instances were obtained for analyzing weather forecast. The discretization approach provides various best fit ranges for the five atmospheric variables which can be used for the investigation of rainy day Table 1.

| Table 1.                                  |         |       |        |       |  |  |  |
|---|---------|-------|--------|-------|--|--|--|
| Nominal values for atmospheric parameters |         |       |        |       |  |  |  |
| oromat                                    | Decemin | Linit | Momino | Domas |  |  |  |

| Paramet | Descrip   | Unit    | Nomina  | Range          |
|---------|-----------|---------|---------|----------------|
|         | -         | Unit    |         | Kalige         |
| er      | tion      |         | 1       |                |
|         |           |         | Variabl |                |
|         |           |         | e       |                |
| TEMP    | Temper    | Celsius | LOW     | < 25.2         |
|         | ature     |         |         | (77.36F)       |
|         |           |         | MEDIU   | 25.2-27.7      |
|         |           |         | М       | (77.36F – 82F) |
|         |           |         | HIGH    | >27.7 (82F)    |
| DEWP    | Dew       | Celsius | LOW     | <19 (66.2F)    |
|         | Point     |         |         |                |
|         |           |         | MEDIU   | 19-22.5 (66.2F |
|         |           |         | М       | – 72.6F)       |
|         |           |         | HIGH    | >22.5(72.6F)   |
| WDSP    | Wind      | Knots   | LOW     | <10.13         |
|         | Speed     |         |         |                |
|         |           |         | MEDIU   | 10.13 - 20.26  |
|         |           |         | М       |                |
|         |           |         | HIGH    | > 20.26        |
| VISIB   | Visibilit | Miles   | LOW     | <4.6           |
|         | у         |         |         |                |
|         | -         |         | MEDIU   | 4.6-8.5        |
|         |           |         | М       |                |
|         |           |         | HIGH    | > 8.5          |
| PRCP    | Rainfall  | Millime | YES     | >0             |
|         |           | ter     |         |                |
|         |           |         | NO      | =0             |

## **2.2 Association Rule mining for weather forecast**

The problem of mining association rules was first nominated and elaborated by Agrawal et al. [1] for discovering interesting patterns using association rules for business intelligence. Recently the rainfall patterns are discovered using association rule mining approach for specific stations where the coastal and inland of Tamil Nadu State of South India in a case study [9]. When the association rule is involved on meteorological data, with each record showing various atmospheric observations including wind direction, wind speed, temperature, relative humidity, rainfall, and mean sea level pressure. These climate parameters were taken at a certain period for certain region, then association rules for occurrence of wet and dry day prediction can be found.

An enhanced predictive Apriori algorithm has been used for the association rule approach with filtered dataset. This algorithm finds the support threshold value for the best 'n' rules concerning a support-based corrected confidence value.

### 3. Results and Discussion

### 3.1 Association rule for weather data

Predictive mining performs inference on the present data in order to make a prediction. Here a weather forecasting has been implemented using classification and association mining with various weather parameters such as temperature, dew point, visibility, wind speed and precipitation. The rule is defined by the expression  $A \Rightarrow B$ . It holds the transaction set D with support s, where s is the percentage of transactions in D that contain A  $\cup B$  (i.e., the union of sets A and B, or say, both A and B). This measurement is taken for finding the probability between P (A  $\cup B$ ).

This term Conditional Probability (CP) for P (B|A) is stated by the following metrics.

Support (S) of  $(A \Rightarrow B) = P(A \cup B)$ 

Confidence(C) of  $(A \Rightarrow B) =$  Support\_Count (SC) of  $(A \cup B)$  / Support\_Count (SC) of (A)

In the past the Association Rule (AR) mining techniques are implemented for the rainfall prediction for 24 hours prior by the authors Meganathan et al., 2011. The predictive Apriori mechanism generates the efficient association patterns as AR. Some of the proficient AR which are utilized to accomplish prediction from the given training dataset are the model generates AR for the incidence and non-incidence of rainfall on wet and dry days for 24 hours prior [Table 2] and 48 hours prior [Table 3]. The motivating practices are also rendered using the AR mining process for



the measurement of the rainfall prediction with class marker 'high' for the precipitation value greater than 2.56 cm (1 inch) and class marker as 'normal' for the precipitation value less than or equal to 2.56cm (1 inch) for 24 hours prior [Table 4] and 48 hours prior [Table 5].

## **Table 2**: Weather patterns for 24 hours aheadrainfall prediction during NEM months.

 $AR(A \Rightarrow B)$ 

[TEMP=(medium or high) ^DEWP=(low or medium or high) ^ WDSP=low ^VISIB=(low or medium)] ==> PRCP=no [TEMP=low ^ DEWP=high ^ WDSP=medium ^

VISIB=low] ==> PRCP=yes

| <b>Table 3:</b> Weather patterns for 48 hours ahead |  |
|---|--|
| rainfall prediction during NEM months.              |  |

| $\mathbf{AR} \ (A \Longrightarrow B)$   |
|---|
| TEMP=medium or high ^ DEWP= low or medium or<br>high ^ VISIB= medium or high ^ WDSP= low or<br>medium ==> PRCP=no |
| TEMP=low or high ^ DEWP=high ^ VISIB=low or<br>medium ^ WDSP=low or medium ==> PRCP=yes                           |

# **Table 4**: Weather practices for rainfallapproximation at 24 hours prior during NEMmonths.

| $\mathbf{AR} \ (A \Longrightarrow B)$   |
|---|
| TEMP=high ^ DEWP= high or medium ^ VISIB=low<br>or medium ^ WDSP=low or medium ==> PRCP=low |
| TEMP= high ^ DEWP = high or medium ^ VISIB=low<br>WDSP='high 4 ==> PRCP=high                |

**Table 5**: Weather practices for 48 hours aheadrainfall estimation during NEM months.

| $\mathbf{AR} \ (A \Longrightarrow B)$ |
|---------------------------------------|
| TEMP=high DEWP=low or medium or high  |

WDSP=low or medium VISIB=low ==> PRCP=low 21 acc:(0.91196)

TEMP=medium or high DEWP=medium or high WDSP=high VISIB=low => PRCP=high 3

### 3.2 Validation

The justification for the rainfall related data is carried out to detect the reliability of the generated results and to confirm its suitability in live environment for the prediction of dry and wet days. Validation has been done through K\* methodology [2]. For the prediction of rainfall occurrence and nonoccurrence during the monsoon days, the machine learning (ML) technique K\* attains an accuracy of 68% and 65% for NEM months and 75% and 73% for SWM months using cross-validation method [Table 6] and 69% and 65% for NEM months and 77% and 73% for SWM months using percentage split method [Table 8] for 24 and 48 hours prior respectively. The obtained confusion matrix (CM) for the above methods are presented in [Table 7] and [Table 9]. The substantiation outcomes are and [Table 11] using stated in [Table 10] supplied test set method for the rainfall occurrence prediction and assessment of the rainfall [Table 12] with threshold value greater than 2.56cm (1 inch) for high precipitation and less than or equal to 2.56cm (1 inch) for low precipitation and these results are reasonably accurate. The results shows that the rainfall prediction as well as rainfall estimation is more suitable in SWM months rather than NEW months in this island station. However the accuracy brings a good classification results for both NEM and SWM when the accuracy threshold is greater than 66%. It is higher than the existing synoptic method as well as numerical prediction methods.

| Stratified cross-                   |                   | N   | EM                | SWM |                   |     |              |     |
|-------------------------------------|-------------------|-----|-------------------|-----|-------------------|-----|--------------|-----|
| validation                          | 24 Hours (24 Hrs) |     | 48 Hours (48 Hrs) |     | 24 Hours (24 Hrs) |     | 48 Hours (48 |     |
| validation                          | Prior             |     | Prior             |     | Prior             |     | Hrs) Prior   |     |
| Correctly Classified<br>Instances   | 1804              | 68% | 1703              | 65% | 2515              | 75% | 1902         | 73% |
| Incorrectly Classified<br>Instances | 831               | 32% | 932               | 35% | 821               | 25% | 720          | 27% |

Table 6: Correctness of classification over the rainfall data by 10-fold cross validation



### Table 7: CM of 10-fold cross validation for rainfall occurrence prediction during NEM.

|      | 24 hours p | prior           | 48 hours prior |       |                 |  |
|------|------------|-----------------|----------------|-------|-----------------|--|
| a=no | b=yes      | < classified as | a=no           | b=yes | < classified as |  |
| 982  | 506        | a = no          | 918            | 570   | a = no          |  |
| 325  | 822        | b = yes         | 362            | 785   | b = yes         |  |

### Table 8: Classification accuracy using percentage split validation for rainfall prediction.

|                                  | NEM   |          |       |          | SWM   |          |       |          |  |
|----------------------------------|-------|----------|-------|----------|-------|----------|-------|----------|--|
| Stratified group validation      | 24    | Hours    | 48    | Hours    | 24 H  | Iours    | 48 H  | Iours    |  |
| Stratified cross-validation      |       | (24 Hrs) |       | (48 Hrs) |       | (24 Hrs) |       | (48 Hrs) |  |
|                                  | Prior |          | Prior |          | Prior |          | Prior |          |  |
| Correctly Classified Instances   | 621   | 69 %     | 581   | 65 %     | 873   | 77%      | 641   | 72%      |  |
| Incorrectly Classified Instances | 275   | 31 %     | 315   | 35 %     | 261   | 23%      | 250   | 28%      |  |

### **Table 9**: Confusion matrix of percentage split validation for rainfall prediction during NEM.

| 24 hours ahead |       |                 | 48 hours ahead |       |                 |  |
|----------------|-------|-----------------|----------------|-------|-----------------|--|
| a=no           | b=yes | < classified as | a=no           | b=yes | < classified as |  |
| 327            | 157   | a = no          | 293            | 191   | a = no          |  |
| 118            | 294   | b = yes         | 124            | 288   | b = yes         |  |

### Table 10: Classification accuracy using supplied test set method for NEM rainy day forecasting

|         | 24 hor               | ur ahead                | 48 hour ahead           |                         |  |  |
|---------|----------------------|-------------------------|-------------------------|-------------------------|--|--|
| Testing | Percentage of        | Percentage of           | Percentage of           | Percentage of           |  |  |
| year    | Instances Classified | Instances Classified at | Instances Classified at | Instances Classified at |  |  |
|         | at acceptable level  | unacceptable level      | acceptable level        | unacceptable level      |  |  |
| 2006    | 63 %                 | 37 %                    | 57 %                    | 43 %                    |  |  |
| 2007    | 74 %                 | 26 %                    | 72 %                    | 28 %                    |  |  |
| 2008    | 71 %                 | 29 %                    | 66 %                    | 34 %                    |  |  |
| 2009    | 60%                  | 40 %                    | 54 %                    | 46 %                    |  |  |
| 2010    | 76 %                 | 24 %                    | 74 %                    | 26 %                    |  |  |

| Testing | 24 Hours (24 Hrs)    |                         | 48 Hours (48 Hrs)    |                         |
|---------|----------------------|-------------------------|----------------------|-------------------------|
| year    | Prior                |                         | Prior                |                         |
|         | Percentage of        | Percentage of           | Percentage of        | Percentage of Instances |
|         | Instances Classified | Instances Classified at | Instances Classified | Classified at           |
|         | at acceptable level  | unacceptable level      | at acceptable level  | unacceptable level      |
| 2006    | 89%                  | 11%                     | 89%                  | 11%                     |
| 2007    | 86%                  | 14%                     | 86%                  | 14%                     |
| 2008    | 86%                  | 14%                     | 86%                  | 14%                     |
| 2009    | 81%                  | 19%                     | 81%                  | 19%                     |
| 2010    | 84%                  | 16%                     | 84%                  | 16%                     |



| Testing | 24 Hours (24 Hrs)    |                         | 48 Hours (48 Hrs)       |                       |  |  |  |
|---------|----------------------|-------------------------|-------------------------|-----------------------|--|--|--|
| year    | Prior                |                         | Prior                   |                       |  |  |  |
|         | Percentage of        | Percentage of           | Percentage of           | Percentage of         |  |  |  |
|         | Instances Classified | Instances Classified at | Instances Classified at | Instances Classified  |  |  |  |
|         | at acceptable level  | unacceptable level      | acceptable level        | at unacceptable level |  |  |  |
| 2006    | 76.6667 %            | 23.3333 %               | 76.6667 %               | 23.3333 %             |  |  |  |
| 2007    | 81.8182 %            | 18.1818 %               | 81.8182 %               | 18.1818 %             |  |  |  |
| 2008    | 74.2857 %            | 25.7143 %               | 74.2857 %               | 25.7143 %             |  |  |  |
| 2009    | 90.6977 %            | 9.3023 %                | 90.6977 %               | 9.3023 %              |  |  |  |
| 2010    | 76.2712 %            | 23.7288 %               | 76.2712 %               | 23.7288 %             |  |  |  |

 Table 12: Classification accuracy using supplied test set (STS) methodology for precipitation assessment with a possible threshold values during NEM.

### 4. Conclusion

The AR mining process and instance based classifier approach (IBCA) are employed to detect the occurrence of rainfall on wet and dry days with class markers. The observed outcomes states the AR mining methodology based that. forecasting system works at a proficient rate and the predictions are reasonably accurate and can be used for predicting the occurrence and non occurrence also. The same could be deployed to estimate the rainfall with 2.56cm (1 inch) threshold value for Port Blair island station of Bay of Bengal. As per the stated outcomes, the methodology is suitable for detecting weather conditions and predicts the rainy days 48 hours prior of its occurrence and estimates the normal and high precipitation during both SWM and NEM periods. Hence the scheme prognosticates to be a valuable solitary for tropical islands.

### Acknowledgements

The authors of the above stated research would like to state their heartfelt thanks to National Climatic Data Center (NCDC), Asheville, North Carolina, U.S.A., for their support to carry out this work at seamless level by their dataset and special thanks to the Indian Meteorological Department scientists Late Dr. T.R.Sivaramakrishnan, S.R.Ramanan and S.Balachandran at Chennai for useful discussions. The authors thank SASTRA University for utilizing the Discrete Mathematics Laboratory funded by Department of Science and Technology – Fund for Improvement of S&T Infrastructure in Universities Higher and Educational Institutions, Government of India (SR/FST/MSI-107/2015).

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