NTT Code for Good

Topic: Disaster Relief & Response
Kerala Rainfall Prediction

Ashish Singh (NTT Data)
Sumit Sahoo (NTT Data)
Kotha Tejas (IIIT Bangalore)
Tanmay Jain (IIIT Bangalore)

Introduction

- India is the land of agriculture and being a peninsular country, it is highly susceptible to heavy rainfalls in the south.
- Monsoons play an important role in the livelihood of majority of the population thus having a greater impact on life, society and economy.
- The differential heating and cooling of land and water causes humid air to flow into the Indian landmass. Other factors like the El Nino, La Nina, North Atlantic Sea Surface Temperature, etc. influence the monsoons in India.
- These factors generally cause cyclones and typhoons in the Indian peninsula, leading to excessive rainfall in-turn causing floods.

- One such catastrophe was the floods in Kerala in August 2018. It caused havoc in the entire state, there was a huge loss of life and state property. People from all over the country came forward to help and life was finally restored in Kerala, but the loss was inevitable.

- Disasters like these have less chances of causing this intense damage if we are warned early on. Such situations call for a safety measure that can warn us before the disaster even happens.

Solution

Predicting rainfall in states like Kerala for any given month based on the data of past 115 years of rainfall across India.

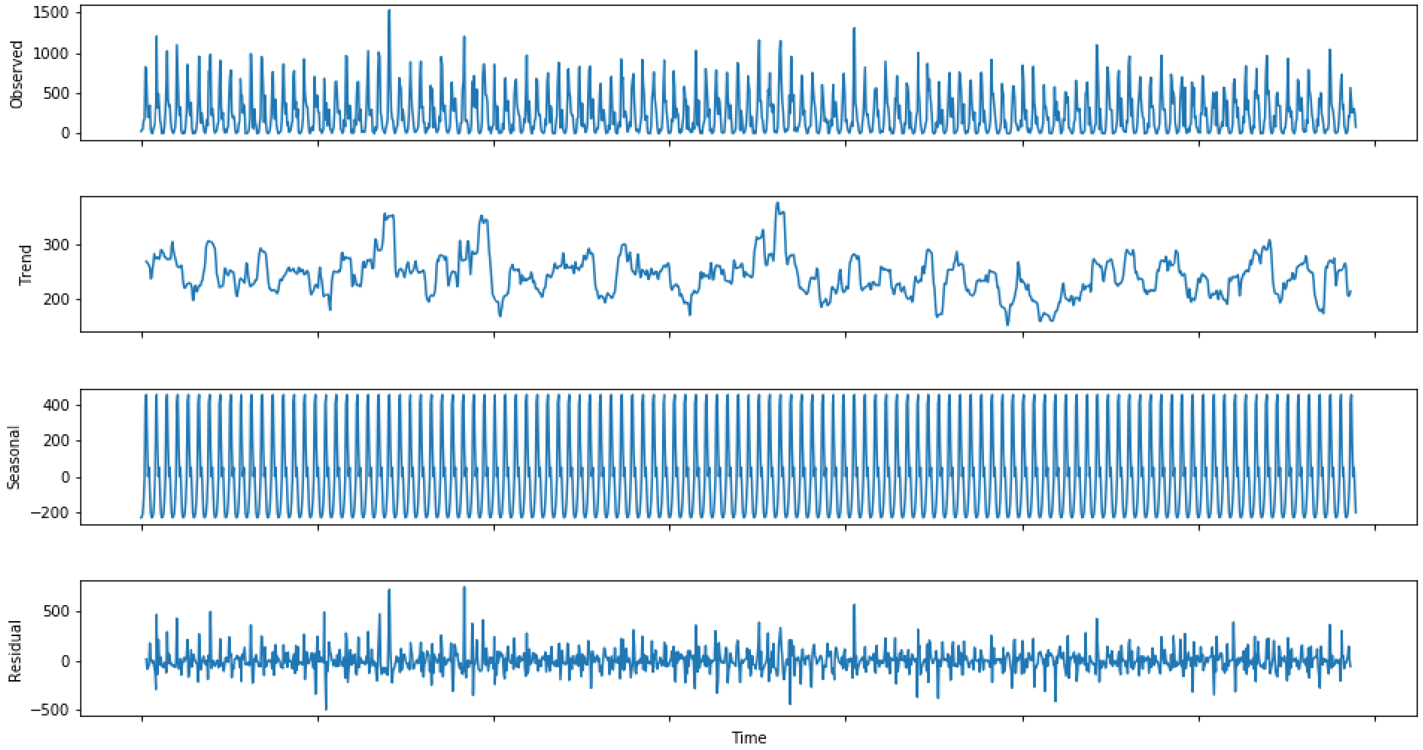
Dataset: https://data.gov.in/resources/sub-divisional-monthly-rainfall-1901-2017

This would help the authorities to take measures for safety, supplies and reallocation of victims, saving thousands of lives living along the coast.

Approach and Architecture

- Weather patterns tend to repeat annually because of the rotation of Earth. After retrieving all of Kerala's data and doing transformations our data looks like this:
- We did a small analysis to see the trend and seasonality of the data, the results are:

	Time	Rain
0	1901-1	28.7
1	1901-2	44.7
2	1901-3	51.6
3	1901-4	160.0



It's interesting to realize that the data is seasonal which means the pattern almost replicates in every 12 months

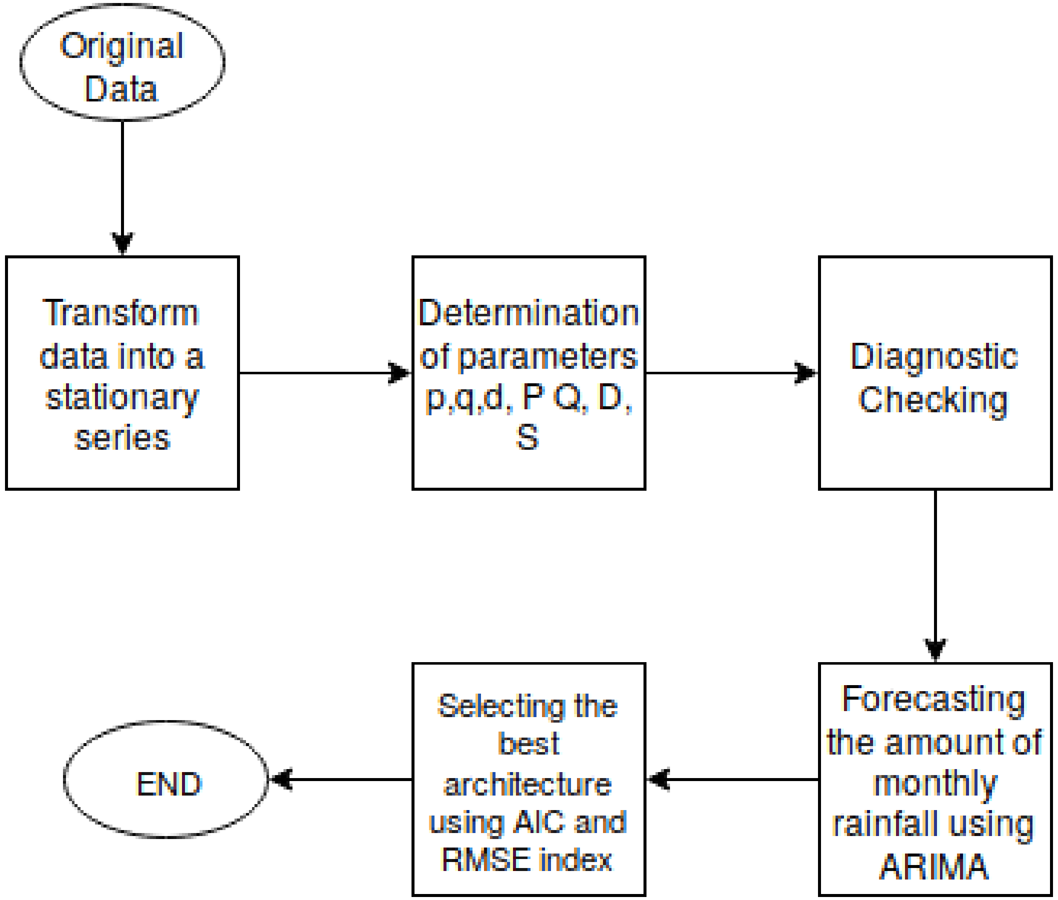
Seasonal ARIMA

The parameters for ARIMA model are referred to as the order of the model and denoted by a 3-tuple (p,d,q), where:

- p: Trend autoregression order.
- d: Trend difference order.
- q: Trend moving average order.

Similarly, in the SARIMA model, we use a set of 2 parameters, one the usual order like the ARIMA model, and another called the seasonal_order for the model. The seasonal_order is a 4-tuple parameter represented as (P,D,Q,S), where:

- P: Seasonal autoregressive order.
- D: Seasonal difference order.
- Q: Seasonal moving average order.
- S: The number of time steps for a single seasonal period.



Results

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                                 Statespace Model Results
==========================================================================================
Dep. Variable:                                Rain   No. Observations:                 1380
Model:             SARIMAX(8, 0, 0)x(10, 1, 1, 12)   Log Likelihood               -8489.599
Date:                             Thu, 14 Mar 2019   AIC                          17019.198
Time:                                     09:21:05   BIC                          17123.620
Sample:                                 01-01-1901   HQIC                         17058.278
                                      - 12-01-2015
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0170      0.022      0.779      0.436      -0.026       0.060
ar.L2         -0.0098      0.024     -0.417      0.677      -0.056       0.036
ar.L3         -0.0344      0.034     -1.024      0.306      -0.100       0.031
ar.L4          0.0117      0.037      0.312      0.755      -0.062       0.085
ar.L5          0.0190      0.049      0.388      0.698      -0.077       0.115
ar.L6         -0.0005      0.060     -0.008      0.993      -0.119       0.118
ar.L7          0.0203      0.052      0.390      0.697      -0.082       0.123
ar.L8          0.0275      0.039      0.698      0.485      -0.050       0.105
ar.S.L12       0.0541      0.020      2.667      0.008       0.014       0.094
ar.S.L24       0.0312      0.020      1.538      0.124      -0.009       0.071
ar.S.L36       0.0008      0.021      0.039      0.969      -0.041       0.043
ar.S.L48      -0.0213      0.021     -1.011      0.312      -0.063       0.020
ar.S.L60      -0.0517      0.023     -2.249      0.024      -0.097      -0.007
ar.S.L72      -0.0639      0.020     -3.252      0.001      -0.102      -0.025
ar.S.L84      -0.0027      0.021     -0.124      0.901      -0.045       0.039
ar.S.L96      -0.0436      0.019     -2.244      0.025      -0.082      -0.006
ar.S.L108      0.0194      0.022      0.890      0.374      -0.023       0.062
ar.S.L120     -0.0121      0.021     -0.573      0.567      -0.054       0.029
ma.S.L12      -0.9700      0.009   -108.028      0.000      -0.988      -0.952
sigma2      1.401e+04    302.875     46.260      0.000    1.34e+04    1.46e+04
===================================================================================
Ljung-Box (Q):                       24.41   Jarque-Bera (JB):              1910.65
Prob(Q):                              0.98   Prob(JB):                         0.00
Heteroskedasticity (H):               0.70   Skew:                             0.72
Prob(H) (two-sided):                  0.00   Kurtosis:                         8.61
===================================================================================
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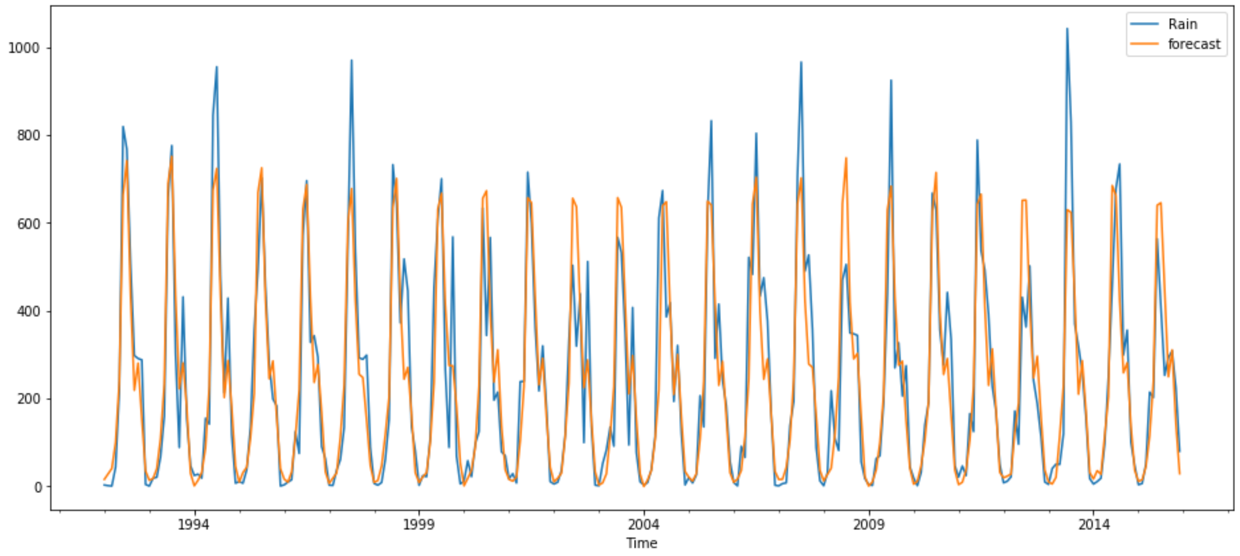
After Grid Search, we got the best results for SARIMAX(8,0,0)x(10,1,1,12).

We tested our model on the data from Jan 1992 to Dec 2015, which was a total of 288 data points. We achieved an **RMSE of 105.275 mm** on the Kerala rainfall dataset.



Demo URL: https://frenzytejask98.github.io/

Technologies Used

We used Python as programming language. We used the following packages in order to build our pipeline :

- Matplotlib for plotting
- Plotly for the demo plot
- Pandas
- NumPy
- Jupyter Notebook
- Statsmodel API for SARIMA algorithm

We used an Intel i7 6th generation processor laptop with a RAM of 8GB to perform our analysis. It takes around for 4 minutes to run the pipeline.

Importance:

- The Kerala Floods in August 2018 claimed lives of 483 people and around 14 went missing.
- The total loss in property and crops was estimated to be Rs 8000 crore.
- This could have been prevented up to a large extent.

The idea is to keep in track the rainfall patterns in the months of historically heavy rainfalls and be prepared for emergency evacuation plans. The Government will be well aware for the prone and can plan their budget and actions ahead in the year.

The Indian Meteorological Department can only warn about a cyclone just before a day of the event. This solution will give a heads up to Government agencies to prepare for emergency conditions beforehand.

Challenges faced

- The dataset for Kerala was very skewed as the rainfall pattern in Kerala has been rather unstable.
- The dataset originally had only 115 data points which made it really hard for us to train a good model.
- We first converted the dataset into a 3-month dependency rainfall pattern, i.e., for any given month, we used the past 3 months of rainfall as data to predict the rainfall for the given month. This gave us a decent 1400 data points to work with.
- But as we know, rainfall doesn't follow this kind. Eg: The rain pattern of March, April and May (next to NIL) would tell us nothing about the rain in June (heavy rains).
- Preparing the dataset was a challenge for us as we had to juggle between solving the problem as a Regression problem or as a Time series problem. Both these approaches have different needs in terms of data so, figuring out on how to prepare the dataset was a challenge.

Thank You