Using RNNs for Prediction of Forest Fires

AI for Climate

Group Scorched Earth:
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1 Introduction

Forest Fires are a major concern in the context of Climate Change: As an effect of man-made climate change the increasing frequency and scale of Forest Fires is a threat to human lives, infrastructure and wildlife. At the same time they also build a very relevant positive feedback loop by causing further CO_2 emissions.

Probability and scale of Forest Fires are locally dependent on climate and weather conditions as well as the given landcover - e.g. woodland, grassland, etc. We use available data on past Forest Fires and their given climatic and landcover circumstances to learn a model predicting the probability and scale of Forest Fires. With the available climate predictions from CMIP6 we then use this model to predict the probability and scales for future forest fires around the globe.

To build a meaningful model for Forest Fire dynamics we need our model to grasp timeseries data. We successfully built our model around an LSTM[1] structure, which is proven to perform exceptionally well on such timeseries tasks.

2 Data

To get a better feeling for the data we are using, we plotted different attributes compared to the underlying changes through the years. Firstly we were interested whether or not the temperature cycle of a year changed through the years. No significant changes can be seen. However the maximum temperatures did change: 2001 the highest observed temperature was 288.3279 Kelvin while the maximum of 2019 was 288.7818 Kelvin. The next step for us was to see which tiles were available therefore we constructed a graph of the vertical positions against the horizontal ones to get a rough map. The last step was to point out the basis of the man made climate change being that there is a change in overall temperature and rainfall to begin with. The data we were given shows that there is. For that we observed both the average temperature changes but also the increase maximum temperatures which lead to extreme events and forest fires.

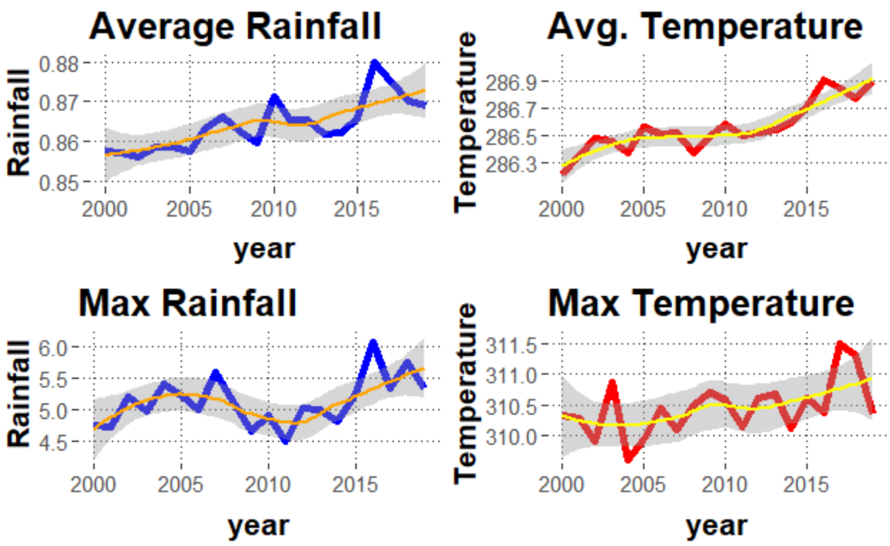

Figure 1: Canges in temperature and rainfall in the used dataset.

For our final models, learning both probability and scale dynamics of forest fires, we need to employ time-series data. We limit our data to MODIS raster tiles, which have meaningful amounts of data for Forest Fires between 2001 and 2017. MODIS raster tiles rasterize the earth surface in a sinusoidal projection in a 18x36 grid (˜1000km edges at the equator). This ensures most tiles with actual landmass are indeed meaningful.

For each tile we create a timeseries, which is made up from climate data and landcover data. Climate data between 2001 and 2017 is available from the ERA5 datasets. For future extrapolation we employ the CMIP6 ssp370 MPI models, which are considered to be an average pathway. In both cases the climate data consists from temperature 2m above ground and precipitation. Temperature is averaged per week, precipitation is summed up for each week. Additionally we make use of landcover data from MODIS MCD12Q1. For each tile this data estimates the area covered in 17 different landcover types, such as e.g. woodland, scrubland and more. Additionally we add some information about the total landmass of the respective tile (to normalize for tiles which are partially covered by sea). We build our dataset on a weekly basis to cover Forest Fire dynamics on a reasonable scale and make good use of the available data. Since vegetation data is only available on a yearly basis, while climate data is available on a weekly basis, we repeat the vegetation input for each week of the year.

In total this results in a 22 dimensional input for each week. In total our training set has 258 meaningful tiles over 887 weeks, resulting in a training dataset of shape [258x887x22]. For future extrapolation we make use of landcover types as in 2017 as the best approximation, and use CMIP6 ssp370 MPI from 2021 until 2100, resulting in 4175 weeks for extrapolation for each cell.

3 Model & Training

3.1 Training framework

We use Tensorflow in Google Colab for easy access to computational ressources and a scalable Deep Learning framework with good support for building efficient data pipelines. We preprocess our data by normalizing it element wise. We serve the data via an efficient data pipeline with a TF dataset.

3.2 Model

Our Model is a timeseries model based on the successful LSTM architecture. The input is fed into a fully connected feed forward layer of size 64 as an embedding. Subsequently we use two stacked LSTMs with 64 units each as the recurrent network element to process timeseries information. Finally we use a fully connected feed forward layer with 64 hidden units followed by a single output neuron. Our LSTM uses default activations [1], with a bias initialization of 1, which has been proven to have a major impact on convergence time.

We use two identical but seperatedly trained networks, the only difference being the output neuron: It is used with linear (i.e. no) activation for regression of amount of burning area, and sigmoid activation for probability of Forest Fires existing in the tile at each timestep.

3.3 Training

We train our models using Adam Optimizer [2] with Mean Squared Error for regression and binary Crossentropy for predicting probability of a forest fire. We train for 200 epochs, where in each epoch from each tile timeseries we cut 100 random subsequences of length 24 (i.e. 24 weeks) for training from this sequence to use with truncated Backpropagation through time, which is the preferred mode of training for LSTM models. Loss tracking proves that our models converge.

4 Results & Discussion

Evaluation of convergence and loss of our models implies we learned the underlying structure well. We end up with a MSE of ˜0.12 on normalized fire data (i.e. expected variance of 1 in the predicted data). A final mean BCE of smaller than 0.1 also implies good predictive qualities for our model predicting the likelihood of Forest Fires.

To visualize our results we create heatmaps based on the MODIS raster tiles of both the regression and classification model. We created videoclips to analyze these heatmap results over time, which are also available in the submitted folder. The video data supports our good convergence results in multiple ways: From the classification/probability model we can clearly see the effects of seasons alternating on the northern and southern hemisphere. Our regression model clearly shows large forest areas in southern america, african rainforest/central africa and australia as having the largest forest fires even for

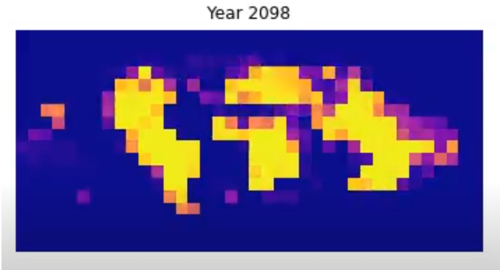

Figure 2: Result via Classification

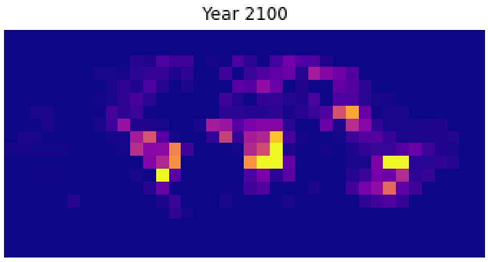

Figure 3: Result via Regression

the future extrapolation. This strongly agrees with the current situation and predictions. We have not yet been able to show a significant increase in the burnt area.

5 Outlook

Given the limited timeframe of the Hackathon we were only able to create a prototype. There are several ways in which we would like to improve our model:

Most obvious to us is the idea of not relying on the landcover data of 2017 for future predictions. Instead we hope to either obtain future landcover predictions to make our Forest Fire predictions even stronger. Alternatively we already created a first prototype to model landcover change with DL, which could be further refined for this purpose.

Our Deep Learning model had to stay somewhat unoptimized given the limited scope of this hackathon. We would like to further increase its performance by scaling it up when we have more time for training on our hands. Furthermore we would like to employ some more sophisticated hyperparameter optimization. Finally we believe more performance could be obtained by replacing the LSTM-based model with an attention based model like a Transformer network.

Even more we would like to spend more time on a detailed quantitivative analysis of our results.

Finally together with Group HurricAIne we developed ideas for an residual CNN-LSTM based climate model, which we would like to use for landcover modelling in the future.

References

[1] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[2] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.