Introduction and Abstract

Sean Klein, Kevin Russell, Ataish Nehra Northeastern Data Science Capstone
Supervised by: Dr. Fatema Nafa

1 Abstract.

Climate Change has had a great impact on the globe's environment. One of these effects has been the increase of natural disasters. For preventative measures, there is an important problem of predicting and tracking the number of natural disasters in relation to the worsening of climate change indicators.

To address this issue, modern neural network architectures were trained on the International Monetary Fund's Climate Change Indicator Datasets[1] to predict the number of natural disasters that occur in 30 different countries over a 28 year time-span. The models chosen were the Recurrent Neural Network, Long Short Term Memory, LSTM with Attention[2], and the Forward-Forward Continuous Algorithm.

All architectures were able to estimate the number of natural disasters, 4 years ahead, using climate change data. Results show that commonly known indicators, CO concentrations; surface temperature; end etc, that exhibit climate change does have an impact on the frequency of natural disasters. Additionally, results show how climate change indicators are highly relevant when trying to understand the modern day landscape of the environmental science.

2 Introduction.

2.1 Field:

In the modern field of Data Science, there has been a craze of creating architectures for the purpose of Natural Language, Artificial Intelligence, and Generative Models. This has created a gap of progress for the more classical problems of the field. Our project explores the construction of State of the Art, SOTA, architectures to generalize on a more standardized dataset. Our architecture explores existing methodology as well as extend from a method researched by one of the greatest researchers, Geoffrey Hinton, who developed the Forward-Forward algorithm. [3].

2.2 The Problem:

The goal of our project is to find the correlation between climate change and frequency of natural disasters to better understand the severity of climate change and the impacts of our environment. We hope to achieve this goal by leveraging Artificial Intelligence with advanced Neural Networks to predict the frequency of natural disasters. If frequency can be predicted, humans can have a better understanding of key indicators and how our environment can be changed drastically with devastating natural disasters.

The project aims to address the challenge of predicting natural disasters, with a focus on storms and other catastrophic events, as a time-series and regression problem using machine learning techniques, specifically neural networks. The primary problem being tackled is the unpredictability and often sudden occurrence of natural disasters, which can lead to significant human and environmental losses. By leveraging neural network architectures such as TCNN (Temporal Convolutional Neural Network), RNN (Recurrent Neural Network), LSTNN (Long Short-Term Neural Network), and Attention NN, the project aims to develop models capable of analyzing climate change data over time.

2.3 Objective.

The main goal of the project was creating and training advanced neural networks on a comprehensive dataset, climate change, that could accurately predict natural disaster trends for several different countries using four different neural network models.

2.4 Approach.

The approach for the project can be formulated into three distinct steps:

Data Preprocessing: First step of the project was to combine the 6 datasets by construction rows that were grouped by country year, and the columns held the values from the 6 different datasets. Further pre-processing was needed for the LSTM and Attention LSTM models, the dataset needed to be modified to incorporate time sequential ordering. The data was train/test split of 80/20 respectively.

Model Construction: For the models, each project member chose a neural network to work on independently. Ataish Nehra built the LSTM model, Sean Klein built the Attention model, and Kevin Russell built the Forward Forward model. After the initial constructions for the models, the team members came together to share results and help each other improve and align the models for the final analysis of the project.

Results and Comparison: For proper comparison, it is important that all models were keeping track of the same metrics; MSE, MAE, and graphical representations of the prediction vs actual natural disaster numbers were used. The results from the project showed that LSTM performed the best, followed by Attention LSTM and RNN, and lastly the experimental Forward Forward model was able to achieve as good as the initial results as the other models.

2.5 Contributions.

In this project, our contributions include the development of advanced LSTM models that deviate from the standard architecture by integrating an extended temporal sequence of seven years, contrasting with typical LSTM applications as discussed in the review by Yu. (2019)[4]. This approach captures long-term dependencies in climate data more effectively than the conventional short-term scope. Moreover, drawing inspiration from the greenhouse climate prediction models of Liu. (2022)[5], our models are adapted to a broader and more dynamic dataset, enabling a more accurate and globally relevant prediction of natural disasters. These adaptations embody a significant advancement over standard LSTM networks, offering a comprehensive, nuanced understanding of complex environmental patterns essential for predicting natural disasters.

The contribution this project has on Attention LSTM model was that this was an exploration into how well the attention model would work on a smaller and unique time-series dataset. It has been shown in other research[6] that models with added attention mechanisms can excel on analyzing time-series problems, the issue with this one is that its a dataset that is actually composed of 30 smaller time-series instead of one large one. This project displays that attention models can handle such data.

The Forward-Forward Continuous model extends Geoffrey Hinton's Forward-Forward algorithm [3] to predict continuous values. This extension is an attribute that does not exist currently, as far as we know, in the Artificial Intelligence community, and could pave way towards more generative content. Additionally, the model predictions may provide better insights to the understanding the correlation between climate change and natural disaster frequency.

2.6 Structure.

For the report, Section 2 will be an in depth exploration of the dataset, how it was constructed, and difficulties faced by it. Section 3 is a discussion of neural networks, then more specifically the ones that were chosen to be worked on. Section 4 is a practical breakdown of the methodology and experimentation performed on the models. Then section 5 will focus on the findings of the project. This section will hold all findings, figures, graphs, and a comparison of the models. After discussing the findings of the project, section 6 will extend on what we have found to a more broad discussion on the relevance of this research. Lastly will be section 7, discussing our references and comparing our work to other projects in the related field.

References

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