

# Using Machine Learning to Improve Numerical Weather Prediction



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Project Diary

*Chemical, Physical, and Mathematical Sciences*

Stand 3300 - BTYSTE 2021

# Weekly Events

## Week of the 28th of September, 2020

During the course of the week, the proposal for this project was submitted for consideration in the BT Young Scientist and Technology Exhibition. Extensive project management and time management was also conducted during the course of the week to avoid any possible conflict with preparation for the Leaving Certificate Examination concerning timetabling and scheduling.

## Week of the 19th of October, 2020

The most significant event which occurred during the course of the week was receiving confirmation that the project was accepted for display at the virtual BT Young Scientist and Technology Exhibition this year. Significant progress was made in developing the new neural network architecture during the duration of the week herein. It was determined that a generator needed to be developed to compensate for the significant size of the dataset.

## Week of the 30th of November, 2020

During the course of the week, the required dataset was downloaded in its entirety from the European Centre for Medium Range Weather Forecasting's Copernius Climate Data Store. The size of the dataset was approximately 400 GB, with four parameters being downloaded. These parameters were air temperature at 850 hectopascals, geopotential at 500 hectopascals, total precipitation, and air temperature at 2 metres above the surface of the Earth. The resolution of the dataset was approximately 25 kilometres ( $0.25^\circ$ ), which corresponds to a total of 1,038,240 grid points ( $721 \times 1440$ )

## Week of the 7th of December, 2020

During the course of the week, the new neural network architecture was finalised. It was determined that the ConvLSTM layer was the most approachable for this particular problem. The spatiotemporal sequence forecasting problem under consideration

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of this project is different from the one-step time series forecasting problem because the prediction target of the problem is a sequence which contains both spatial and temporal structures. Although a LSTM layer has proven powerful for handling temporal correlation, it contains too much redundancy for spatial data. To address this problem, this project will use a ConvLSTM layer which has convolutional structures in both the input-to-state and state-to-state transitions.

## **Week of the 14th of December, 2020**

During the course of the week, significant memory issues were encountered; both concerning system memory and graphical processing unit memory. After several tragically unsuccessful attempts at solving the underlying issue myself, I conveyed my deep concerns and reservations to my science teacher. She put me in contact with a machine learning researcher she knew, Tadhg Fitzgerald. A solution was ultimately reached by the end of the week. This involved segmenting and preprocessing the dataset into individual sample NumPy files due to their greater compatibility with the TensorFlow ecosystem. This, however, dramatically increased the size of the aforementioned dataset into several terabytes. In the future, a more suitable option must be investigated as with a larger dataset, spanning a longer time frame, would eventually encompass tens or hundreds of terabytes. The video to be viewed by the public over the course of the virtual exhibition in January was recorded, and I assisted other exhibitors from my school to plan and record their project videos.

## **Week of the 21st of December, 2020**

Over the course of the week, the training process finally commenced. Issues emerged concerning the amount of time required to conduct the training. It was uncovered that the graphical processing unit was not set up and functioning correctly with TensorFlow. After extensive troubleshooting, this problem was rectified. This, however, resulted in another issue emerging concerning the graphical processing unit memory. These issues were ultimately solved by reducing the batch size during the training process.

## **Week of the 28th of December, 2020**

During the course of the week, the finishing touches to the project were added. This included, but, was not limited to: audial and visual editing in relation to the 3 minutes to be viewed by the public over the course of the virtual exhibition in January, completing any required benchmarking for the project, visualising the results of the benchmarks, creating the slides which will act as the visual display during the course of the judging process, and a plethora of benign and repetitive tasks which must be completed by the deadline of midnight on the 30th of December, 2020.

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