Department of Computer Science

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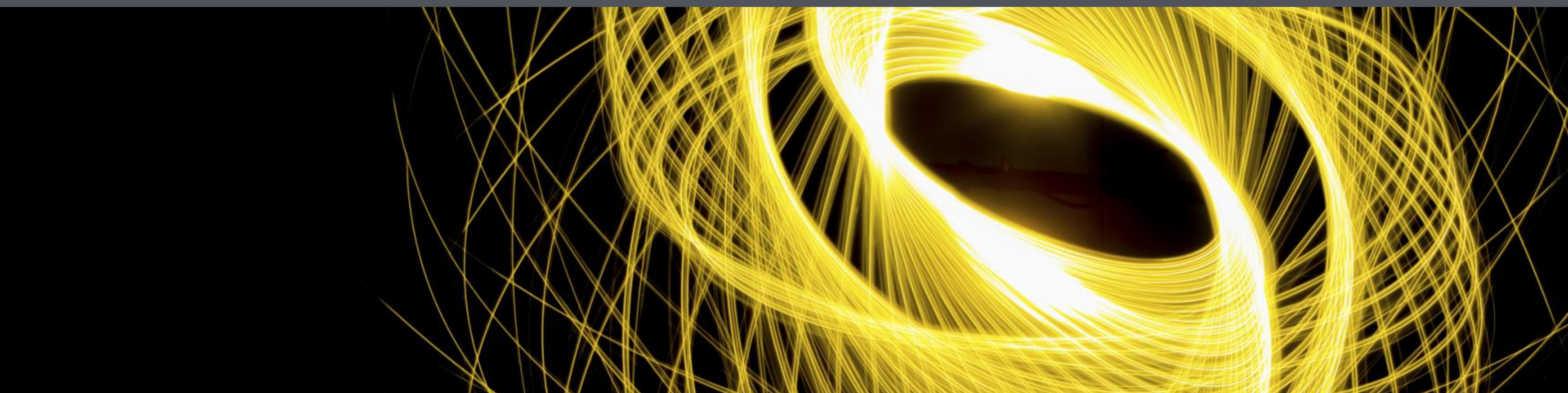
Climate Data Filtration using Deep Learning Methods



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Introduction and Aims

- The effects of a changing climate on multiple meteorological phenomena are being investigated by long General Circulation Model (GCM) simulations
- Each simulation produces large amounts of data which can be inefficient to store and analyse
- The first step to reducing the amount of data is to create a filtration method

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Tropical Cyclones

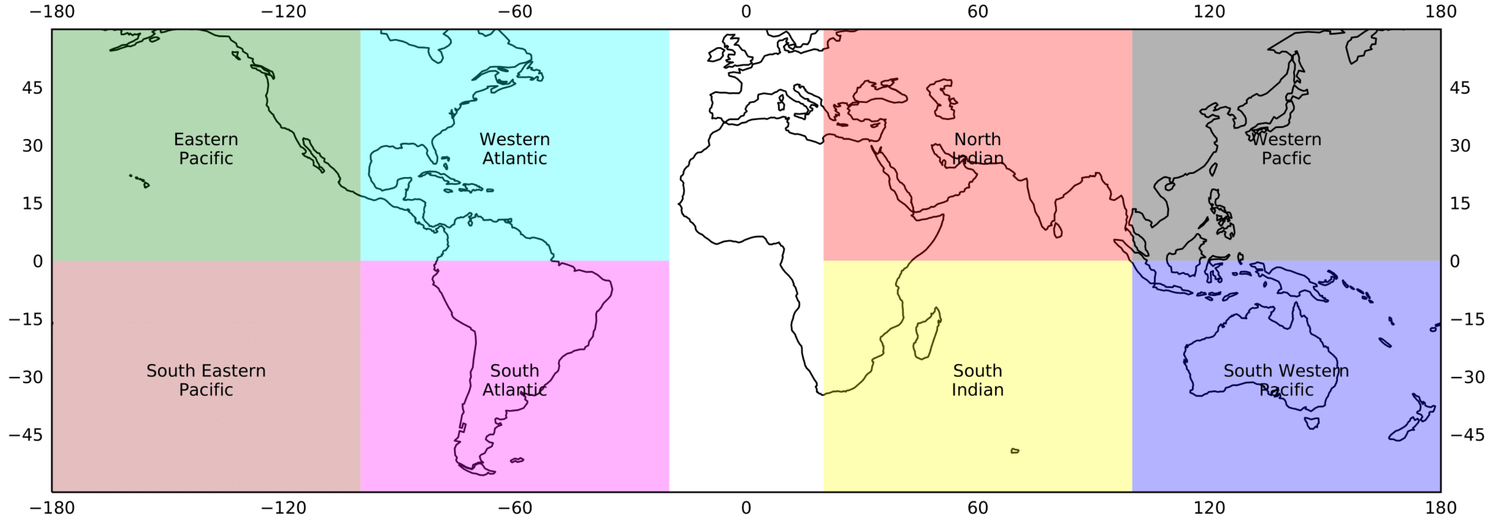
- More commonly known as hurricanes or typhoons
- Tropical Cyclones are events that leave devastating effects
  - In September 2017, Hurricane Irma caused:
    - 47 direct deaths
    - 82 indirect deaths
    - Hundreds of injuries
    - Around $50 billion USD in damage
- They are easy enough to spot by trained meteorologists and associated datasets are easily available

Tropical Cyclones

- TCs mostly start their life as a cluster of shallow storms over warm oceans between the latitudes of 60ºS and 60ºN
- If the right meteorological conditions are present, this cluster of storms starts developing by growing taller and becoming more vigorous.
- After forming, the cluster of storms develop an area of low pressure.
- The usual meteorological variables used for detection are wind speed at 10 metres above sea level, mean sea level pressure and vorticity, which is a measure of spin, at various heights in the atmosphere

Data

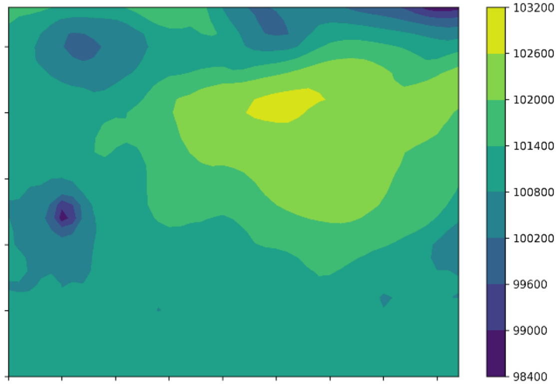
- ERA-Interim reanalyses dataset; each timestep split into 8 regions
- Fields used: 10m wind speed; MSLP; Vorticity at 850hPa, 700hPa, 600hPa at a resolution of 2.8º
- Labels obtained from the IBTrACS database

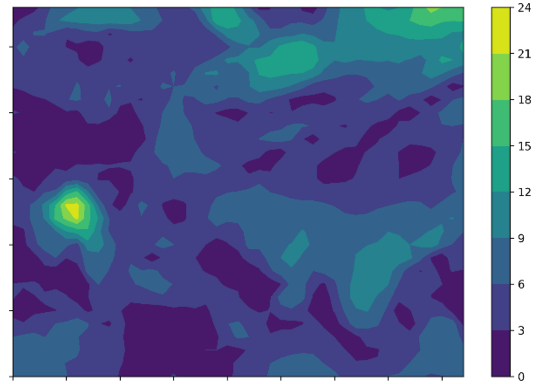


Data

- Two versions of model:
  - Western Pacific and Western Atlantic (WAWP) model:
    - Training Set: January 1979 – June 2017 (112728 cases)
    - Testing Set: July 2017 – August 2019 (6088 cases)
  - Global model:
    - Training Set: January 1979 – June 2017 (450912 cases)
    - Testing Set: July 2017 – August 2019 (24352 cases)

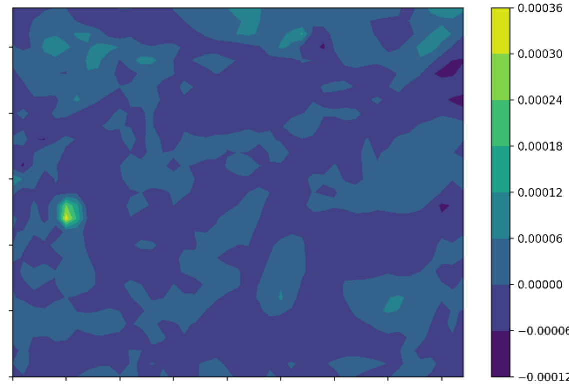
MSLP





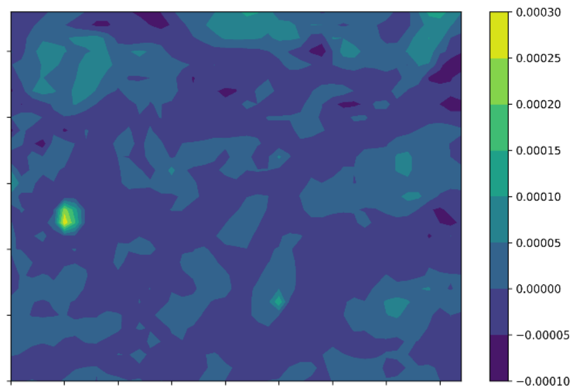
10m wind speed

Vorticity at 850 hPa



Vorticity at 700 hPa

Vorticity at 600 hPa



Deep Learning Model

- The model presented was optimized to the use case of classifying whether an input of weather data has a TC present
- Given the large class imbalance, AUC-PR was used as the performance measure
- The optimizations tested included using:
  - different weight initialization and activation functions
  - early stopping to avoid overfitting
  - various methods of data augmentation
  - a tuned architecture and tuned values for the batch size and the dropout rate

Deep Learning Model: Optimisations

Step	Choice	K-Fold CV AUC-PR
Choice of Data	Filtered Data; 5 fields	0.5309
Early Stopping	Patience = 10	0.6788
Normalisation	Standardisation	0.7404
Resolution	Sixteenth	0.7842
Dataset Balancing	Undersampling with Replacement	0.7839
Loss and Optimiser	BCE	0.7890
Learning Rate Momentum	LR = 0.01; Mom = 0.8	0.7891
Data Augmentation	Roll in x-dir; Random rotation; Flip Left-Right	0.7988
Data Augmentation Rate	0.6	0.8018
Dropout Position and Rate	All model; Rate = 0.1	0.8104
L2 Norm Position and Rate	Classifier; Rate = 0.005	0.8128
Batch Size	8	0.8135

Deep Learning Model: Optimisations

Step	WAWP Model	Global Model
Choice of Data	0.5830	0.4928
Early Stopping	0.7111	0.5915
Normalisation	0.7469	0.6790
Resolution	0.7908	0.6794
Dataset Balancing	0.7721	0.6856
Loss and Optimiser	0.7849	0.6733
Learning Rate Momentum	0.7980	0.6646
Data Augmentation	0.8038	0.6901
Data Augmentation Rate	0.8035	0.6759
Dropout Position and Rate	0.8091	0.6832
L2 Norm Position and Rate	0.8128	0.6955
Batch Size	0.8176	0.6756

Deep Learning Model: Architecture

Name	Layers	Specifications
Conv Block 1	Conv2D Dropout MaxPooling2D	Glorot Uniform; ReLU; 2x2@8 kernels; Dropout = 0.1
Conv Block 2	Conv2D Dropout MaxPooling2D	Glorot Uniform; ReLU; 2x2@16 kernels; Dropout = 0.1
Conv Block 3	Conv2D Dropout MaxPooling2D	Glorot Uniform; ReLU; 2x2@32 kernels; Dropout = 0.1
Conv Block 4	Conv2D Dropout MaxPooling2D	Glorot Uniform; ReLU; 2x2@64 kernels; Dropout = 0.1
Conv Block 5	Conv2D Dropout MaxPooling2D	Glorot Uniform; ReLU; 2x2@128 kernels; Dropout = 0.1

Deep Learning Model: Architecture

Name	Layers	Specifications
Flatten	Flatten	
Dense Block 1	Dense Dropout	Glorot Uniform; ReLU; 128 nodes; L2 Norm factor = 0.005; DR = 0.1
Dense Block 2	Dense Dropout	Glorot Uniform; ReLU; 64 nodes; L2 Norm factor = 0.005; DR = 0.1
Dense Block 3	Dense Dropout	Glorot Uniform; ReLU; 32 nodes; L2 Norm factor = 0.005; DR = 0.1
Dense Block 4	Dense Dropout	Glorot Uniform; Sigmoid; 1 node; L2 Norm factor = 0.005; DR = 0.1

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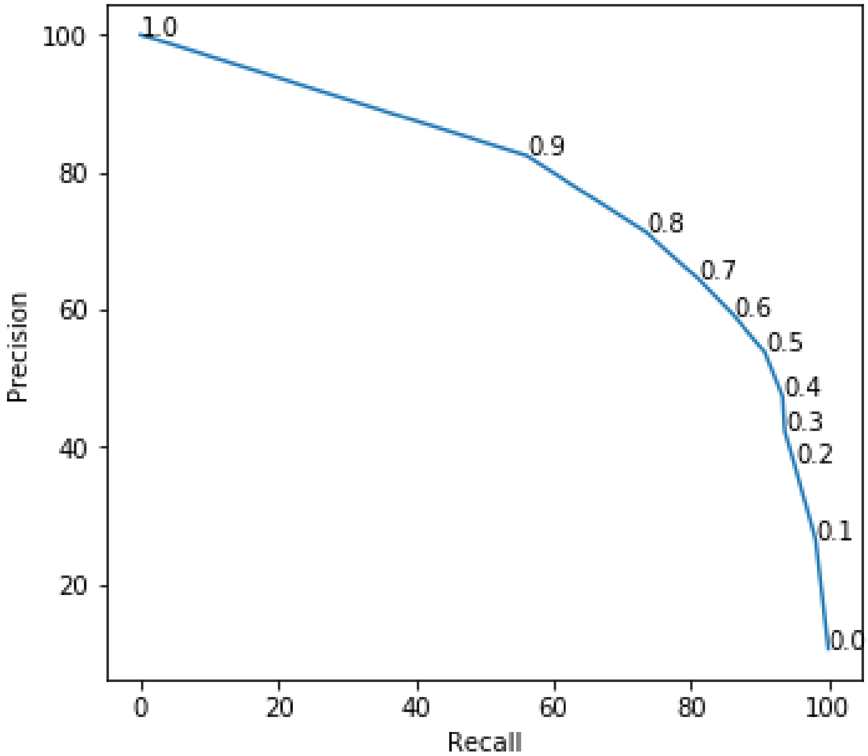
Results

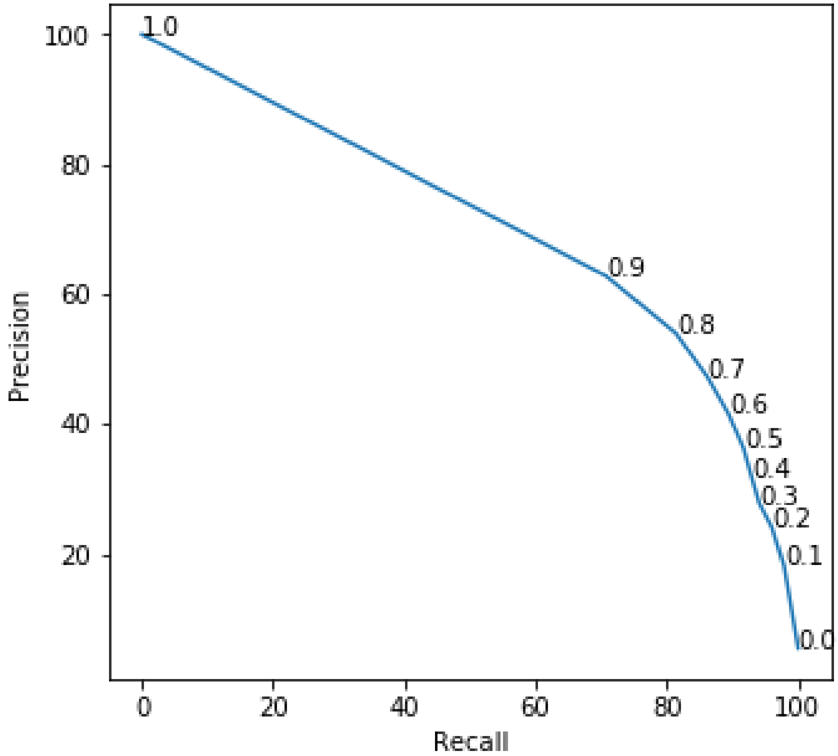
- An accuracy of 90.65% was obtained when testing on data from July 2017 until August 2019
- 1231 out of 1342 (91.73%) positive cases were correctly classified

		Identified	
		TC Present	TC Not Present
Ground Truth	TC Present	1231	111
	TC Not Present	2166	20844

Results



WAWP
(AUC-PR = 0.7884)



Global
(AUC-PR = 0.7173)

Results: TC Category

- The cases which had a TC present were split by the maximum category of TC, as given by IBTrACS according to the Saffir-Simpson scale, present in the case
- The metric of recall, was used to check how well each category was classified
- Recall can be defined as the percentage of positive cases correctly classified

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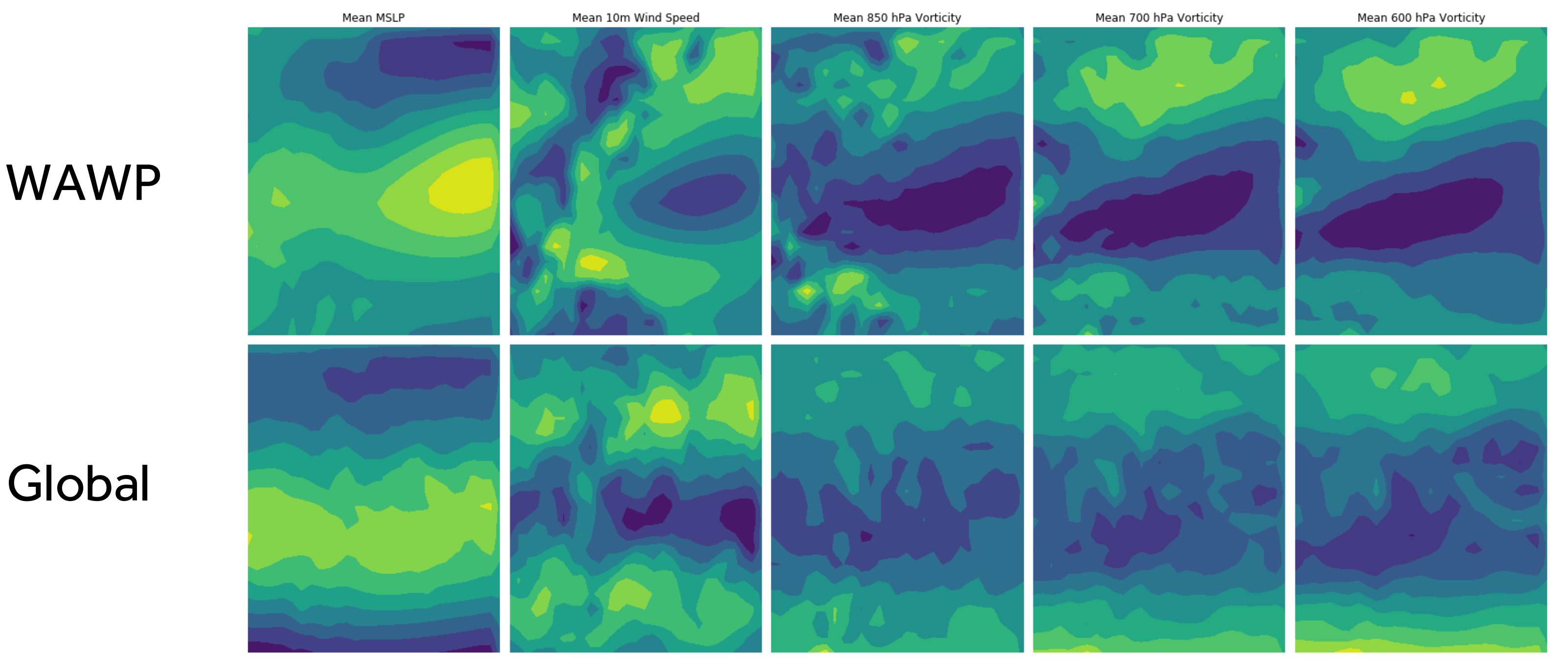
Results: TC Category

Category	WAWP Model	Global Model
1	85.66%	88.02%
2	89.24%	91.53%
3	94.25%	94.19%
4	97.00%	94.64%
5	100.00%	100.00%

- This upward trend of recall with maximum category shows that TCs of higher categories are being identified better they have features which are more easily identifiable

Results: Regions

Model	Training Region	Testing Region	AUC-PR
WAWP	WAWP	WAWP	0.7884
WAWP	WAWP	Global	0.6491
Global	Global	Global	0.7173

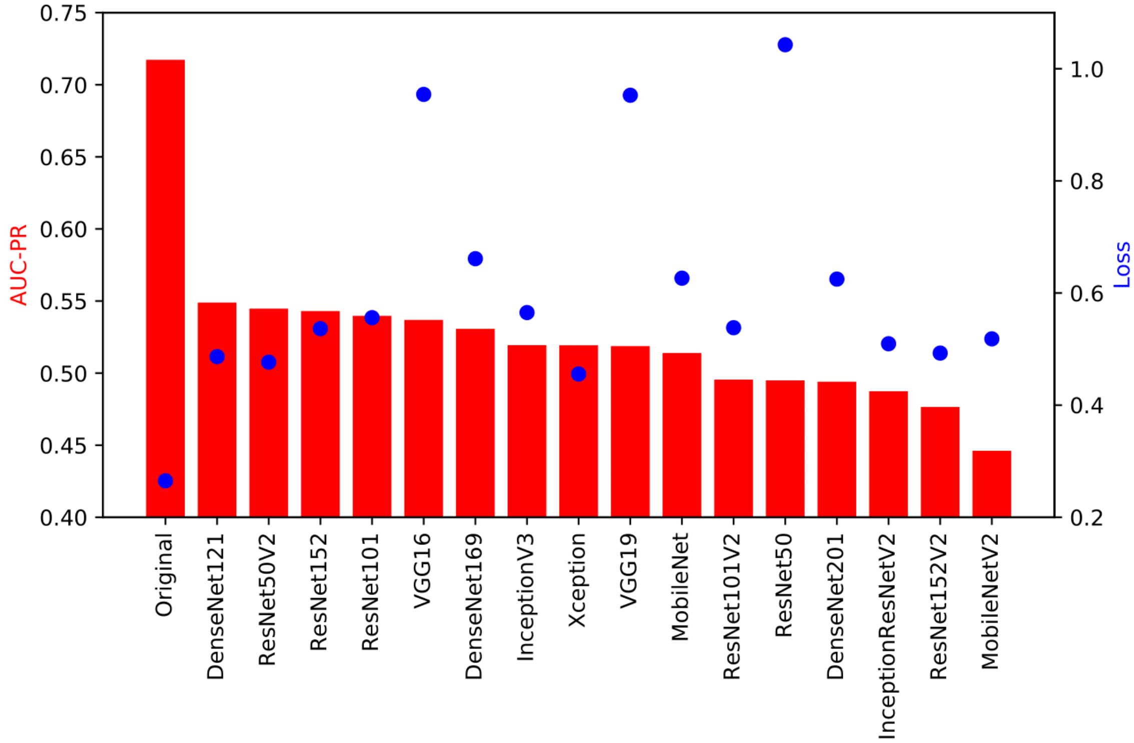


Results: Model Generalization

- The WAWP model performs best on the Western Pacific and Western Atlantic regions, as expected.
  - Western Atlantic obtained a recall of 90.80%
  - Western Pacific obtained a recall of 90.75%
  - Only one other region obtained a recall higher than 80%
- The Global model performed much better on all regions.
  - Only one region obtained a recall less than 80%, and this is due to a limited amount of positive cases in the region

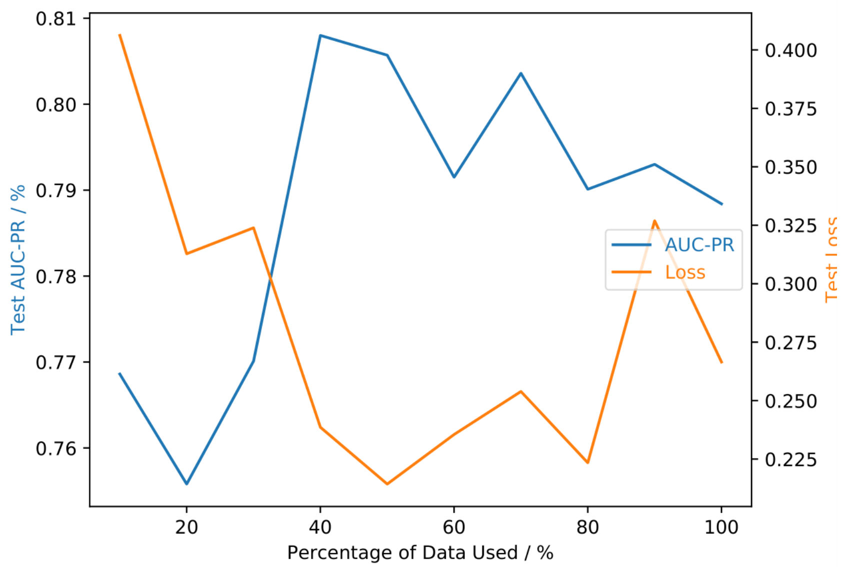
Results: Standard Models

- The model developed was compared with some standard models. It did not obtain the best accuracy, but did get the best loss

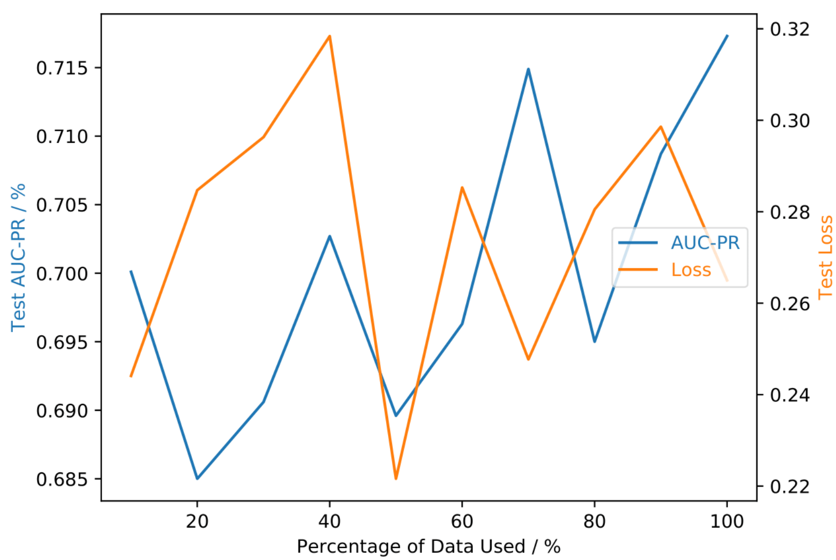


Results: Size of Dataset

- The effect of the size of the training dataset was queried
- The graphs below shows how test accuracy and loss varied with varying sizes of training data.



WAWP



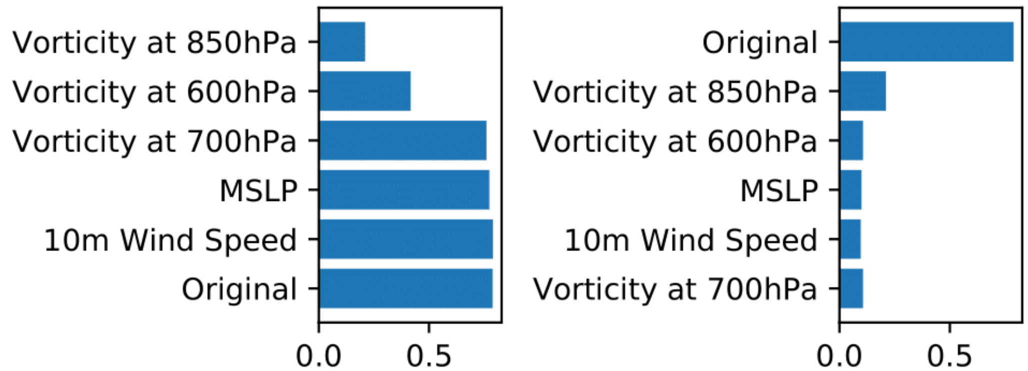
Whole World

Results: Feature Importance

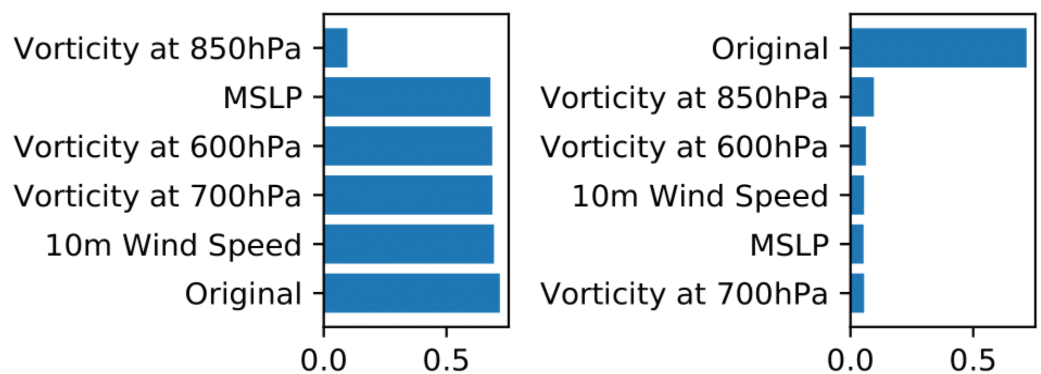
- Breiman Method:
  - Each field is permuted across all testing cases
  - If performance decreases from original, the field is important for the model
  - The larger the decrease, the more important the field
- Lakshamanan Method:
  - Each field is permuted across all testing cases
  - Most important is kept permuted, while the next important is found
  - Keep on going until all fields are permuted

Results: Feature Importance

WAWP



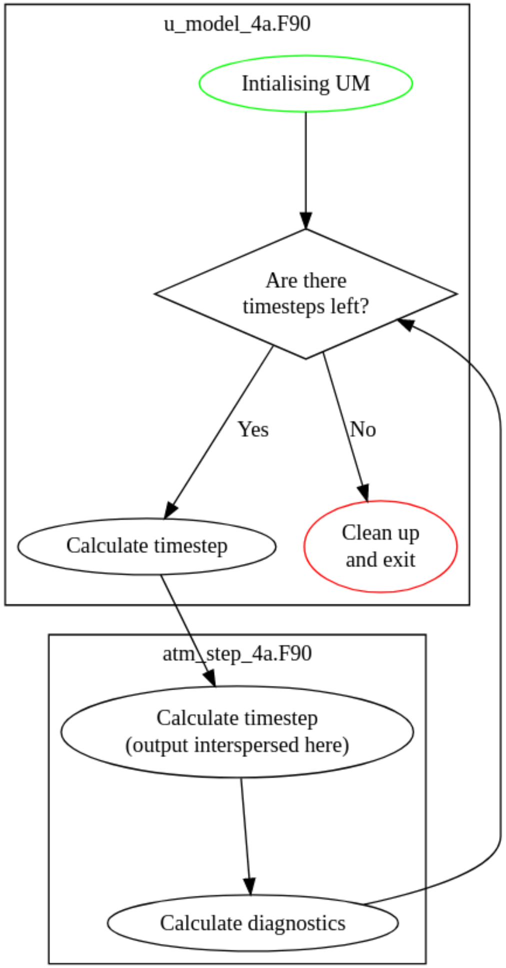
Global



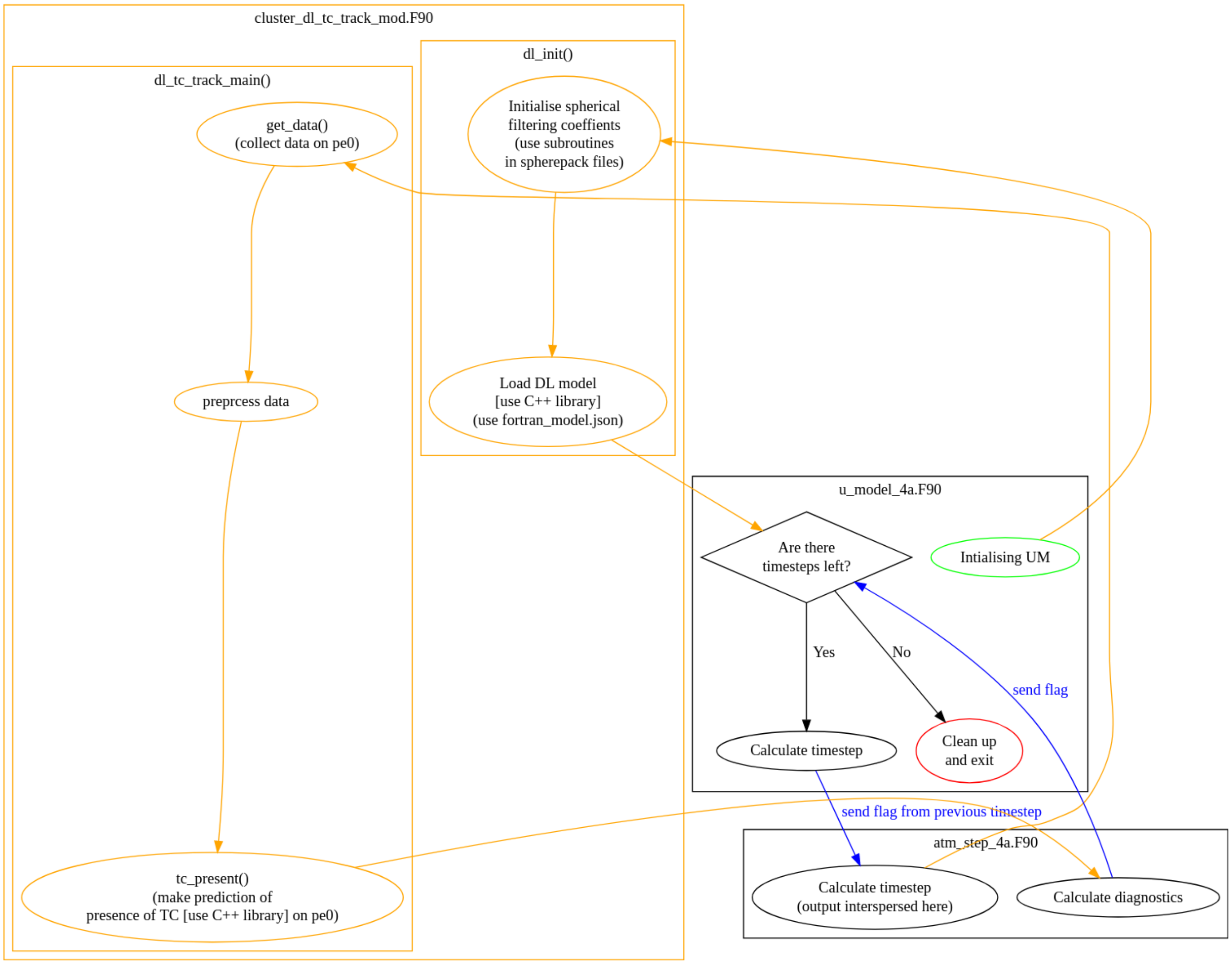
Current Work: Implementation in UM

- Current climate models produce a large amount of data
  - CMIP6 is expected to have 18PB of compressed data
- This data needs to be processed if any science is to be performed, and has to be stored
- Also, IO amounts for a non-trivial amount of execution time
- Therefore, the Deep Learning model is being run during the climate model execution to reduce the amount of data being written to disk
- The time saved in IO can be used to run more versions (ensemble members) of the model

Current Work: Implementation in UM



Current Work: Implementation in UM



Conclusions and Future Work

- A Deep Learning model aimed at detecting the presence or absence of a Tropical Cyclone in weather data has been presented
- It achieved an accuracy of 90.65%, with 91.73% recall, on a test set spanning from July 2017 until August 2019
- The Deep Learning model has been implemented into the UK Met Office's Unified Model (MetUM) for it to act as a data filtration method that can work during the MetUM's execution, rather than after
- Next steps include finding how effective this method is and what performance gains are expected

Acknowledgements

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