Emulating The Effects of Climate Change with Deep Learning

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Introduction

Preserving the Earth's ecosystem in the face of our own greenhouse gas and aerosol emissions requires accurate modeling of how the climate will respond to increasing amounts of aerosol particles:

Figure 1 displays the GHG CO_2 inputs for the different scenarios

- **ssp126** - Sustainable Path
- **ssp245** - Middle Path
- **ssp370** - Fragmented Path
- **ssp585** - Fossil Fueled Path

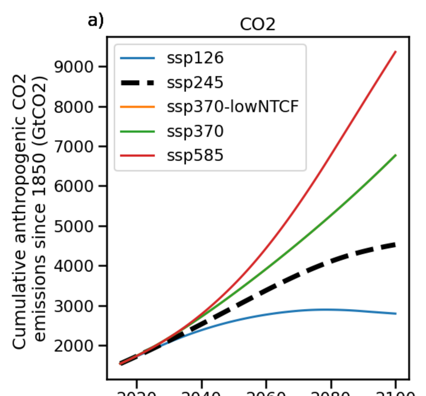


Figure 1. GHG CO_2 scenarios

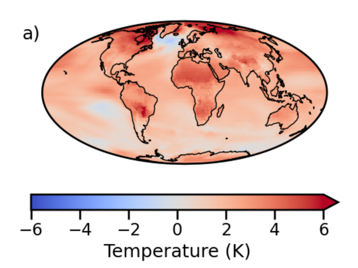


Figure 2. Outputs SSP245

Current Earth System models are based on physical laws and climatological observations and thus are not well-suited for exploring various socioeconomic futures due to their inefficiency. Climate Bench [1], developed by our mentor Duncan Watson-Paris, offers a more effective approach by using Deep Learning to model numerous potential climate futures. Our project seeks to enhance these models by employing advanced Deep Learning techniques, aiming to surpass Climate Bench's benchmarks. *Figure 2* illustrates the mean surface temperature for scenario SSP2-4.5 during the years 2080-2100, serving as the benchmark against which our results will be compared.

Data

The input data for three Deep Learning models is from the Norwegian Earth System Model, which is generated from the NorESM2 model for historical and future emission data. This generated dataset also is a part of the sixth coupled model intercomparison project. The data is multi-dimensional, which includes emission data from different times, longitudes, and latitudes.

Input Variables	Output Variables
CO_2	Temperature
SO_2	Daily Diurnal Temperature Range
CH_4	Precipitation
Black Carbon (BC)	90^{th} Percentile Precipitation

Baseline From Reproduction

Gaussian Process - Gaussian Process was built using 12 Matern32 Kernels, to allow each dimension of the input to be invariant from one another. Trained with a Constant Mean Function and Optimized by minimizing the Loss.

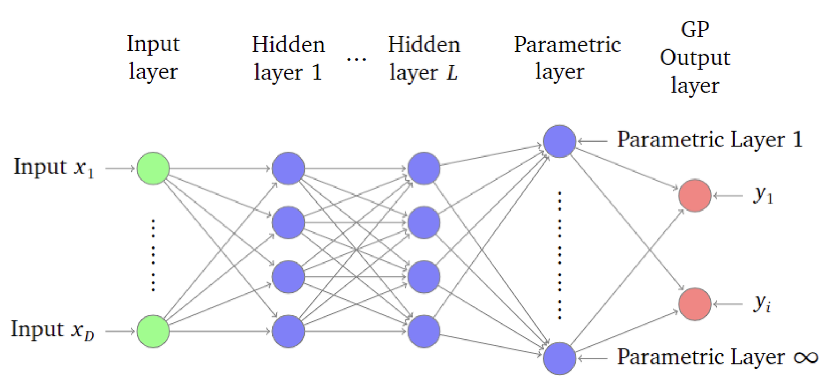
Random Forest - The Random Forest combined the results from multiple decision trees. The "RandomizedSearchCV" technique has been applied for hyperparameters tuning and cross-validation to find the best parameters for the corresponding variables and increase the robustness of the model.

Convoluted Neural Network - Seven layer CNN architecture consisting of 3 Time distributed layers, a LSTM layer with ReLU activation, a Dense layer, a linear activation layer, and a reshape layer. It uses root-mean-squared optimizer and mean-square error as the loss metric.

Methods - Deep Kernel Learning

For one of the models that we implemented, it was a Deep Kernel Learning Regressor. This is a hybrid model that combines both the infinite expressiveness of a Neural Network and the probabilistic modeling of a Gaussian Process. This is done by using the learning capabilities of Neural Networks, to learn a feature representation of the data which will act as the kernel for the Gaussian Process.

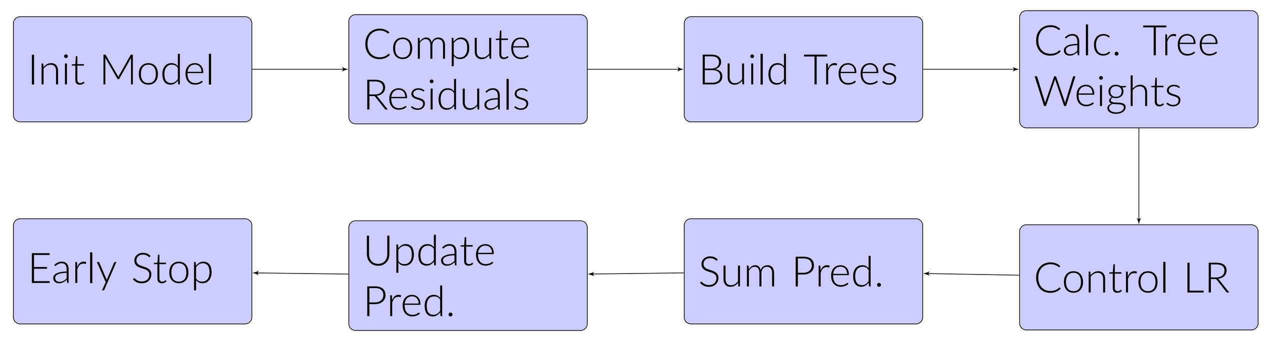
1. Data enters through the input layer
2. Hidden Layers learn the representation of the data
3. Get parametrized in the parametric Layer
4. Goes into a GP that predicts the outcome



Deep Kernel Learning Structure

Methods - XGBoost

The XGBoost stands for "Extreme Gradient Boosting". It not only integrates the predictions from multiple decision trees like Random Forest but also combines multiple machine learning algorithms to boost the decision trees. For example, gradient descent, regularization, and shrinkage are applied to reduce overfitting. Here are the steps for optimization:



Methods - Physics Informed Neural Network (PINN)

Physics informed neural networks are a still emerging field in scientific machine learning. It takes the neural networks' ability to learn weights for parameters and combines it with physical equations to further improve the robustness and accuracy of the resulting model.

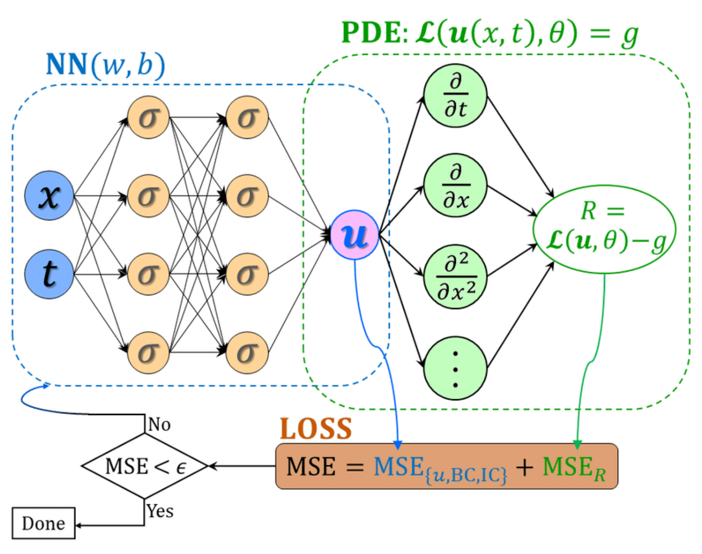


Figure 3. Creating the PINN

By including the physical ordinary differential equations relating the aerosol emission to temperature in the loss function, the resulting network is bounded during the training by physical constraints.

Evaluation Metric

We are using the same metric used in ClimateBench[1] to compare with the baselines models.

$$NRMSE_s = \sqrt{\langle(|x_{i,j,t}|_t - |y_{i,j,t,n}|_{n,t})^2\rangle} / |\langle y_{i,j}\rangle|_{t,n} \tag{1}$$

$$NRMSE_g = \sqrt{|(\langle x_{i,j,t}\rangle - \langle |y_{i,j,t,n}|_n\rangle)^2|_t} / |\langle y_{i,j}\rangle|_{t,n} \tag{2}$$

$$NRMSE_t = NRMSE_s + \alpha \times NRMSE_g \tag{3}$$

$NRMSE_s$ is the global mean root-mean-squared error, and $NRMSE_g$ is its global mean equivalent. The equation features a weighting function for the diminishing grid-cell area near the poles. The coefficient $\alpha = 5$, as per the ClimateBench paper, balances the measures. This yields a total $NRMSE_t$ that evaluates both global and spatial accuracy.

Model Comparisons

To compare our results, we are going to put each model head to head against its counterpart comparing the $NRMSE_t$, as the evaluation.

Model	GPs		CNNS		Random Forests	
Variables	Baseline	DKL	Baseline	PINN	Baseline RF	XGBoost
Temperature	0.309	**0.304**	0.317	0.317	2.422	0.911
Temperature range	22.443	16.287	14.563	**13.017**	27.017	24.995
Precipitation	4.222	4.004	**3.153**	3.158	10.217	5.937
90^{th} Precipitation	4.582	4.558	4.380	**4.286**	11.712	6.664

Table 1. Comparison Table

Overall, our models have slight improvement upon the NRMSE scores of ClimateBench.

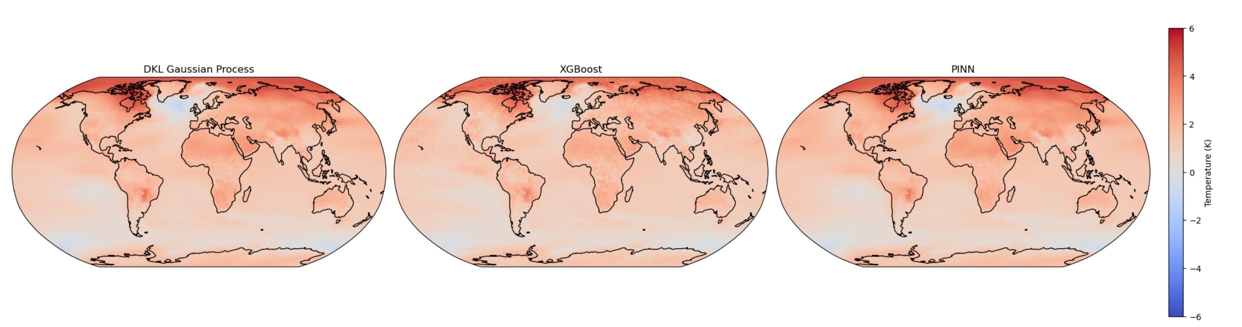


Figure 4. Model Results for Mean Temperature

References

[1] D. Watson-Parris, Y. Rao, D. Olivié, Ø. Seland, P. Nowack, G. Camps-Valls, P. Stier, S. Bouabid, M. Dewey, E. Fons, *et al.*, "Climatebench v1. 0: A benchmark for data-driven climate projections," *Journal of Advances in Modeling Earth Systems*, vol. 14, no. 10, p. e2021MS002954, 2022.

[2] A. G. Wilson, Z. Hu, R. Salakhutdinov, and E. P. Xing, "Deep kernel learning," in *Proceedings of the 19th International Conference on Artificial Intelligence and Statistics* (A. Gretton and C. C. Robert, eds.), vol. 51 of *Proceedings of Machine Learning Research*, (Cadiz, Spain), pp. 370–378, PMLR, 09–11 May 2016.

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[4] N. J. Leach, S. Jenkins, Z. Nicholls, C. J. Smith, J. Lynch, M. Cain, T. Walsh, B. Wu, J. Tsutsui, and M. R. Allen, "Fairv2.0.0: A generalized impulse response model for climate uncertainty and future scenario exploration," Copernicus GmbH, May 2021.