Machine learning for modelling of tipping points in climate variables

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1 Abstract

Due to the increasing threat of climate change, many key tipping points in the climate are now approaching potential irreversible changes. It is therefore paramount that we are able to detect and predict these tipping points. Machine Learning can be a powerful tool in detecting and predicting changes in data, and in this literature review, I have outlined the descriptions and some of the methods that have been used in tipping detection, along with providing an explanation of how those methods have been used. This paper will also propose a project that will develop multiple machine learning models to detect and predict changes in climate variables. The effectiveness of the models will also be evaluated in comparison to one and other as well as to pre-existing predictions of tipping points in climate variables. The aim of the project is to develop a Machine Learning model which could then be used in the global fight against climate change.

I certify that all material in this dissertation which is not my own work has been identified.

2 Introduction

"Climate change is one of the greatest challenges facing humanity" states David Rolnick *et al* and the visible impact of climate change is seen in ecosystems around the world [1]. As such, dealing with climate change is now of the upmost importance for the future of our planet. In order to do this, it is essential to be able predict when changes in climate may happen or be able to identity when we are at the edge of a tipping point in the climate system. Many approaches have been done in order to predict or identify large or irreversible damages to our planet. In this literature review, I will be examining many approaches of detecting tipping points in variables used to describe how the climate will be identified and assessed, and I will concentrate specifically on machine learning approaches, such as Deep Learning, Ordinal Regression, Generative Adversarial Networks, and Reservoir Computing.

2.1 Definition and Identification of Tipping Points

In climate science a Climate Tipping Point (CTP) is a threshold, which when reached leads to large, accelerating, and likely irreversible changes in the climate system [2]. They can come about due to small disturbances causing a larger cascading effect on the system. There are many variables in a climate system which may have a tipping point. These are called climate elements [3]. These range from more immediate ones such as Labrador-Irminger Seas/SPG Convection collapse and the Arctic Winter Sea Ice collapse, to longer term elements such as the Greenland Ice Sheet collapse and the West Antarctic Ice Sheet (collapse) [4].

2.2 Importance of Modelling Tipping Points

There is evidence to suggest that tipping points have been met naturally many times throughout history [5] such as the Pleistocene epoch, which saw many glaciations, and the Little Ice Age from our current Holocene epoch during the years 1300 to 1850 CE [6]. However more recently, human involvement will likely lead us to meeting new tipping point thresholds. Recent research has shown that up to 15 tipping elements are currently active [4]. The most notable tipping point is the internationally agreed Paris Agreement range of $1.5°C$ to $2°C$ increase in average global temperatures [4], which will trigger many tipping elements. According to many scientists six "CTPs become likely (with a further four possible) [...], including collapse of the Greenland and West Antarctic ice sheets, die-off of low-latitude coral reefs, and widespread abrupt permafrost thaw" [4].

This is alarming as currently the world is heading for a $3°C$ to $4°C$ warming, triggering possible further CTPs [4]. Therefore, the need to be able to understand when these tipping points are coming and the specifics of when they will happen is paramount.

3 Machine Learning approaches to detecting tipping points

Machine learning (ML) is a branch of computer/data science which focuses on developing computer systems which emulate human intelligence. ML can adapt without any explicit instructions being given to it. It instead uses algorithms and statistical analysis to analyse and draw patterns from data [7].

3.1 Overview of Machine Learning in Climate Science

Machine learning can be beneficial in climate science as it can be a useful tool in helping us to process our current knowledge in a more significant manner such as improving "the existing (centralized) process of scheduling and dispatch by speeding up power system optimization problems and improving the quality of optimization solutions" [1]. As such there are many use cases for machine learning. These include methods to prevent further human involvement in climate change [1] and methods to predict changes in climate change [1].

3.2 Why Use Machine Learning To Model Tipping Points

The issue with current models to predict CTP is that an uncertainty is created as the models must use idealized representations and parameterizations to simplify the model. Depending on how each process is simplified CTPs can occur at different levels of global warming. The method to counteract this is to run more complicated, higher performance climate models such as the UKESM1 and HadGEM-GC3.1, which use complex equations in order to replicate features of earth including atmosphere, land, oceans, and ice in order to simulate the entire planet [8], [9]. Whilst these can be effective, they potentially may not be the most efficient use of resources because of their large scale and years of development time [8]. Due to this ML can be to increase efficiency as ML developer is not trying to replicate the many small details in the physical world.

3.3 Machine Learning Approaches for Modelling Tipping Points

As ML is already being used in climate science there exists many existing cases of ML being used to model tipping points.

3.3.1 Deep Learning

A study in 2021 used a Deep Learning (DL) algorithm to try and predict tipping points [10]. It required the use of a training library and the training data for it was randomly generated.

A DL network is an Artificial Neural Network (ANN) with more than one hidden layer. The basic structure of an ANN is a three-layer model, an input layer, a hidden layer, and a output layer. Each layer consists of nodes. The nodes in the hidden and output layer are a set of inputs, these sets of inputs are the outputs of the previous layer.

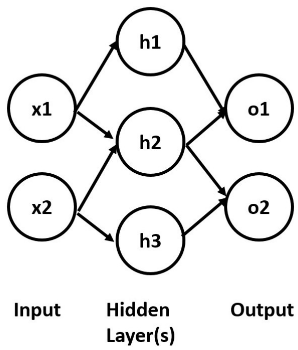

Figure 1: Basic Design of a Neural Network

Each neuron in the network has an activation function. This function determines whether the neuron will activate given the weighted input. The weights are the functions which transform the outputs of the current layer to the input of the next layers. If you were to add another hidden layer to Figure 1 then you would have a Deep ANN (DANN). The use of DANNs is called DL.

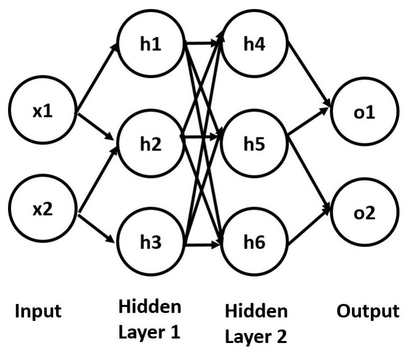

Figure 2: Basic Design of a Deep Neural Network

T.M. Burry *et al* [10] uses a Convolutional Neural Network—Long Short-Term Memory Network (CNN-LSTM) architecture. This uses two different types of ANNs, the CNN layer processes consecutive segments of the time series, capturing distinctive features within these segments. Subsequently, the LSTM layer analyses the CNN's output, deciphering the extracted features. The LSTM layer employs self-referential loops to establish memory, allowing it to identify recurring features across various timestamps in an extensive time series. Consequently, this methodology demonstrates proficiency in recognizing patterns and predicting sequences [10].

Through this they were able to successfully model tipping points using DL. This shows that ML for modelling tipping points can be an effective method.

3.3.2 Ordinal Regression

Another study in 2014 used Ordinal Regression (OR) to detect CTP [11]. This was done by creating three different systems, one of which was a Genetic algorithm (GA) and the other two were time series forecasting models. The GA was used to detect warning signals in abrupt climate change.

OR, sometimes called ranking learning [12], is a progression algorithm used in predicting an ordinal Variable [13]. An ordinal variable is a variable with a natural order to it but the distance between the variables is unknown [13]. OR is used so in order to predict whether a number of independent variables can predict an ordinal dependent variable [14], which researchers such as P. Gutiérrez *et al* took advantage of [11].

3.3.3 How Does Ordinal Regression Work?

OR can be performed by utilising a Generalized Linear Model (GLM).

GLM is a model which generalises linear regression, it is done by having the linear model be related to the response variable using a function, called the link function, which maps a non-linear relationship to a linear relationship so that the linear regression model can fit, and GLM allows the magnitude of the variance of each varible to be a function of its predicted value.

In OR a GLM is used to fit both a coefficient vector and a set of thresholds to a dataset. To define OR mathematically: suppose there is a set of data, represented by length p vectors x_1 to x_n, that are the independent variables, with the dependent variables being y_1 to y_n, that are ordinal variables, with a scale $1, ..., K$ and $y_i \leq y_{i+1}$. There is a coefficient vector w of length p and a set of thresholds $\theta_1 < ... < \theta_{K-1}$, that divide the real number line into K amount of disjointed segments, which correspond to the K response levels. The model then be defined as

$$P(y \leq i|x) = \sigma(\theta_i - w \cdot x) \tag{1}$$

Where σ is the inverse link function. Which as the name implies does the opposite of a link function and maps linear values to non-linear values [15]. There are several choices that can be used for σ such as the logistic function, the probit function, and the exponential function [16] each which will give their respective models, as such the choice of function will depend on the problem at hand.

3.3.4 Generative Adversarial Network

A third study in 2023 uses A Generative Adversarial Network (GAN) to assist climate researchers by giving the researchers a direction, which will help reduce the number of models being made in order to make the process of modelling CTP more computationally sound [9]. They were able to conclude that their ML model could be useful in assisting climate researchers with CTP predictions. They concluded that their model "could be used for the original objective, as a way to guide the domain scientist" [9]. Overall, these case studies show that ML can be effective tool in modelling CTP.

3.3.5 How Do Generative Adversarial Networks Work?

A GAN is composed of parts. The first of which is the generator. This generator is responsible for creating data that whilst plausible isn't true, this data is then used as negative instances for the second

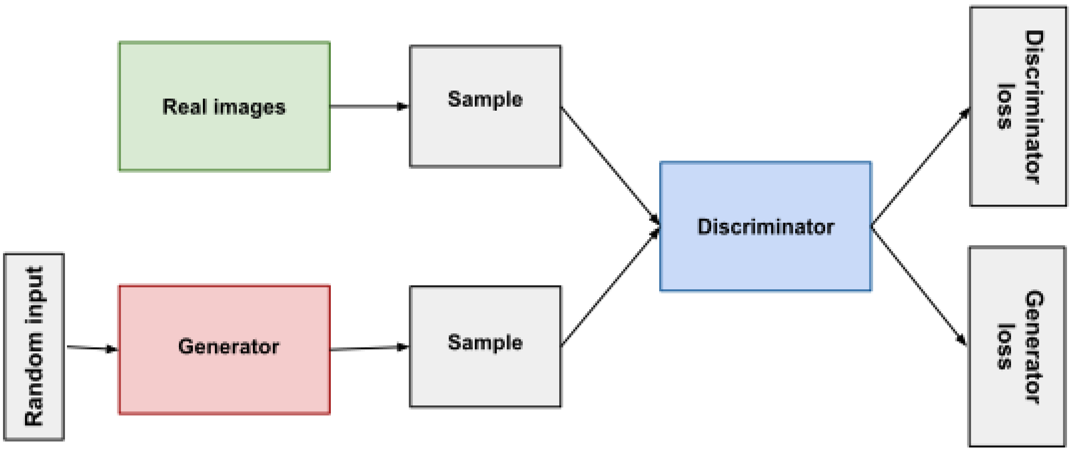

Figure 3: A diagram of a GAN system [17]

part of the GAN, the discriminator. This discriminator is responsible for identifying the fake data created from the generator from actual real data. The discriminator is also responsible for punishing the generator when it produces a result that is too implausible.

The training begins with the generator producing data which is obviously fake. Ideally the discriminator then quickly learns to identify the fakes. As the training processes the generator will get better at producing fake data. This will result in the success rate of the discriminator decreasing. Once the discriminators success rate reaches zero, or a near zero negligible value, the training will be complete and generator will then be effective in replicating real data.[17].

3.3.6 How was The Generative Adversarial Network Used?

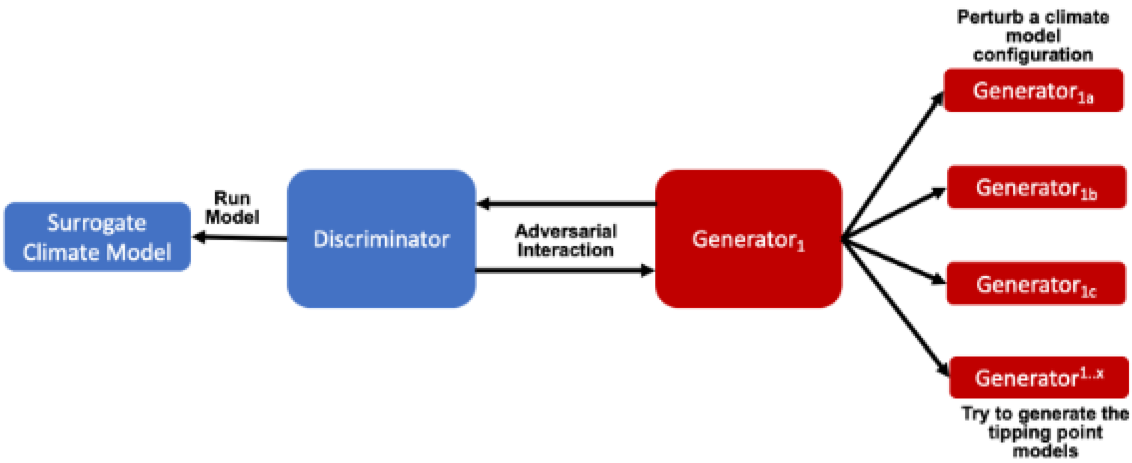

Figure 4: The Climate Tipping Point GAN (TIP-GAN) [9]

As seen in Figure 4 the GAN J. Sleeman *et al* [9] used included set of generators, instead of the usual one, and a surrogate climate model, along with the discriminator. The surrogate model works as the source of knowledge for the generators to base their generations on. The researchers chose to use multiple generators in order to explore the different modalities of the distribution and to improve the stability of the GAN. This is because each generator whilst training often explores a different modality of the distribution. J. Sleeman *et al* [9] took advantage of this fact with each generator exploiting a different modality of the tipping point parameter space.

3.4 Reservoir Computing

There is another case of data scientist using ML to detect tipping points; however, their work was focused on medical applications instead of climate. They also used a different method to these other cases called Reservoir Computing(RC) [18].

3.4.1 Why Use Reservoir Computing?

RC is more resource efficient form ML which is effective with Complex Dynamical Systems(CDS) [18], which are systems composed of dynamical systems, which them selves are systems whose state evolves with time [19].

3.4.2 How Does Reservoir Computing Work?

A RC is a type of Recurrent Neural Network(RNN). It maps input signals to to a fixed non-linear system of a higher dimension, this system is called the reservoir. This reservoir is a black box, meaning its operations aren't visible to the user, and more simple mechanism is trained to read the state of the reservoir. With this is it can be mapped to a desired output.

3.4.3 How Was Reservoir Computing Used?

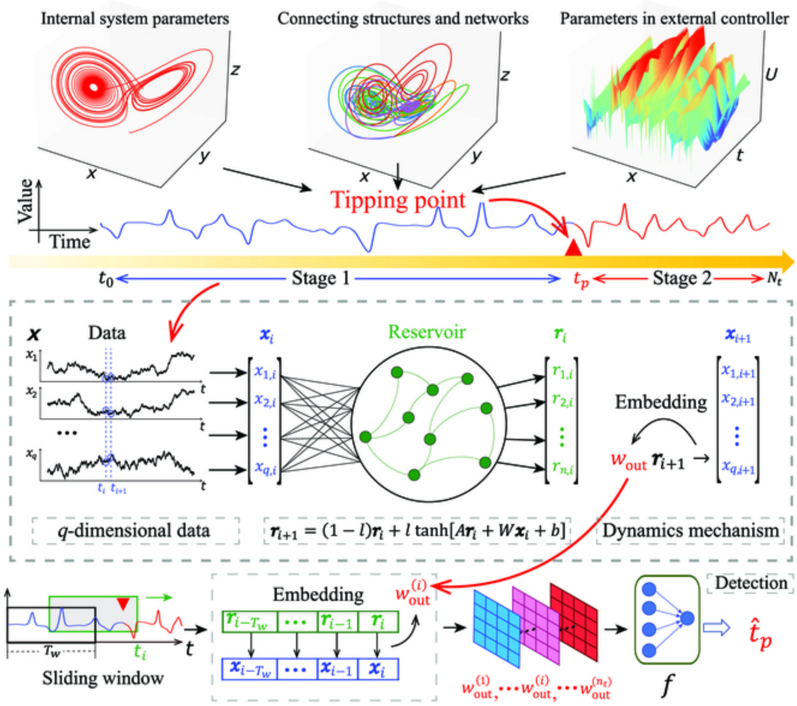

Figure 5: A sketch on applying the RC-TPD framework containing the RC and the sliding windows to locate the tipping point[18]

In [18] their RC consists of three layers, an input layer, a hidden layer(reservoir) and an output layer. The in put data X of q dimensions is embedded in a higher n dimensional space to obtain the state sequence r_t. Where $X = \{x_1, x_2, ..., x_t, ...\}$, any time instance $t = i$, and the leakage parameter $= l$, the dynamical evolution of the RC is represented by

$$r_{i+1} = (1 - l) \times r_i + l \times tanh(Ar_i + Wx_i + b) \tag{2}$$

In equation 1, b is the bias value, W is a matrix of $n \times q$ dimensions, A is the adjacency matrix for the reservoir network. Matrices W and A are randomly generated and then fixed during the evolution of the system. Due to this the reservoir is mapped back to is q-dimensional data through a matrix W_{out} as:

$$\hat{x}_{i+1} = W_{out} r_{i+1} \tag{3}$$

where $\hat{X} = \{\hat{x}_1, \hat{x}_2, ..., \hat{x}_t, ...\}$.

For an RC to be good you want to minimise the loss function so that the RC will be trained to find the optimal W_{out} in order to minimize the difference between $\hat{X}$ and X. The loss function can be represented as,

$$L = \Sigma_{i=0}^{T} (W_{out} r_i - x_i)^2 + \beta \times ||W_{out}||, \tag{4}$$

where $\beta > 0$ is the regularization penalty term coefficient, T is the data length, and $||W_{out}||$ is the matrix norm of W_{out}.

With this the RC has now encoded the dynamic information of the system to the weights of the read out layer(W_{out}). W_{out} changes corresponding to the stability of the system. Therefore, [18] was able to establish a function f mapping W_{out} to the tipping point of the system. They did this mapping by applying ML techniques. They go on to mention that many ML techniques can be used such as CNN, Logistic Regression, and the Random Forrest. However, in [18] they had chosen to use the Ridge Regression this was likely due to its ability to in the estimation of coefficients in multiple regression models where independent variables are highly correlated [20]. Though [18] had chosen to use the Ridge Regression other, ML techniques are worth experimenting with.

3.4.4 How Effective Was Reservoir Computing In Modelling Tipping Points?

The model used in [18] was able to effectively detect tipping points in its training data with minimal margins of error. Their framework remained effective when it was applied to real world data. The research of X. Li et al of its the tipping point detection, credited the effectiveness of their model to the good qualities of RC [18].

4 Project Specification

The objective of this project is to apply and evaluate the effectiveness of ML approaches to detecting CTP. Multiple ML models will be tested to see which one will yield the most accurate results.

4.1 Project Aims

The aim of this project is to develop ML models which will be able to identify the tipping points in climate data. Furthermore, the models should be able to potentially predict future tipping points in the climate system. The models that will be developed are a Deep Learning Neural Network, an Ordinal Regression model, and a Generative Adversarial Network, as they have proven to be effective at modelling tipping point. To expand upon this, a reservoir computer will be developed for further experimentation. An explanation on how these models work has been mentioned above. Below is a list of aims for the project:

1. Develop Deep Learning Network
2. Develop Ordinal Regression model
3. Develop Generative Adversarial Network
4. Develop Reservoir Computer
5. Analyse and compare models
6. Write the report for the project

4.2 Success Criteria

The project will be considered a success if a conclusion can be drawn on the effectiveness of ML models. This will be reached if any of ML models are able in the first instance to identify tipping points in the climate data. How well they do this can be assessed as a successful if the tipping points they identify, align with those that we suppose or know to have already been reached [21]. Secondly, for the ML models to be considered a successful, they will have to be able to make a reliable prediction of future CTP. These predictions will be compared to pre-existing climate predictions such as the IPCC Sixth Assessment Report [22]. The models closer to the pre-existing estimates would be considered better than those that aren't. The models will be compared to each other in order to find which of them is most effective and in comparing different models, a more decisive conclusion can be reached.

4.3 Data Set

The data set being used comes from kaggle [23] who uses findings from Berkley Earth [24], who have been measuring global temperatures since 1750CE. Berkley Earth is a trusted institute for climate research and the scale of its global coverage ensures that data the data provided will be of reliable and of high quality.

4.4 Project Management

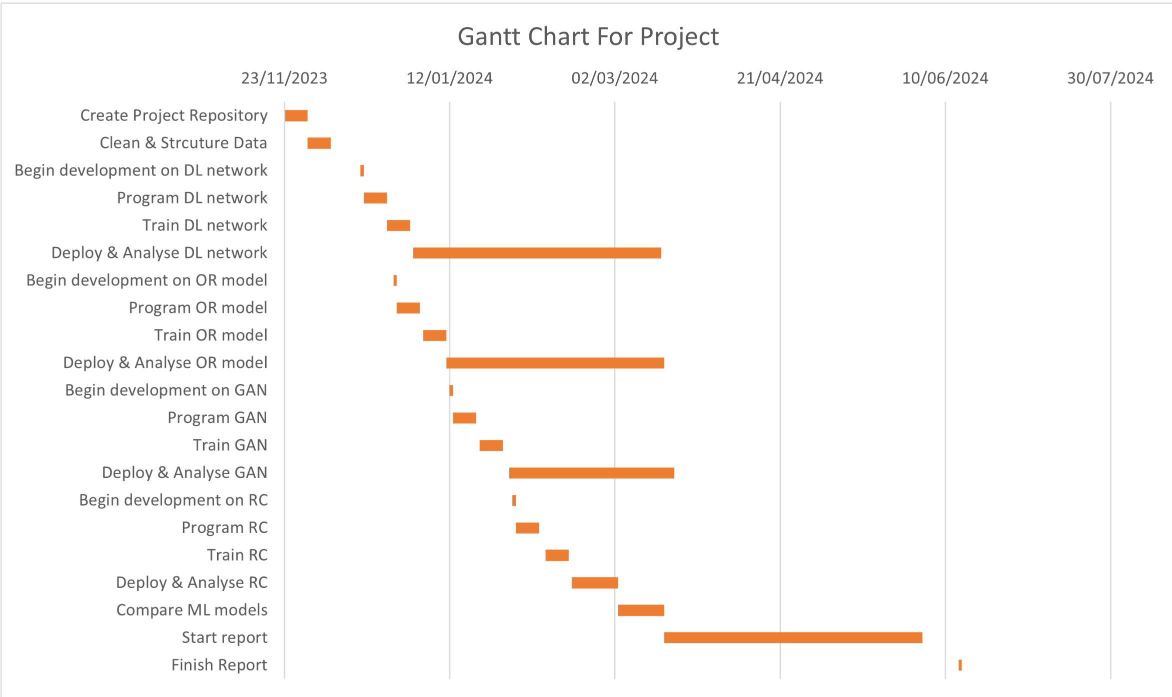

Figure 6: Gantt chart outlying the time frame for the project

Figure 6 shows a Gantt Chart outlying the task to be done in the project and the time frame those tasks are expected to be one in. It is worth considering that these tasks and time frames are not concrete, that is if unforeseen issues arise then the tasks/time frames will be changed accordingly.

4.5 Risks, Legal, and Ethical Issues

In the development of this project, it is important to be aware of the risks involved. Furthermore, it is paramount that those potential risks as well as legal and ethical issues are identified and addressed appropriately.

4.5.1 Risks

The first potential risk identified would be if the dataset being used is not sufficient in training the ML models, so if this issue arises, then another dataset will have to be used. The second risk is a time constraint one as the training time for the ML models may well be too long, resulting in not been able to use the findings and that model consequently not being used, instead the experiment will continue only using the other three being models developed.

4.5.2 Legal Issues

The main legal issue which may arise, would be the use of data without the rights or license to use it [25]. As this needs to be avoided at all costs, appropriate checks would be put into place and permissions requested before use if necessary.

4.5.3 Ethical Issues

There are minimal ethical issues in this project. The most likely ethical issue would be the unwitting use of someone else's intellectual property without seeking out appropriate permissions.

5 Conclusion

To conclude, climate change continues to be a major challenge of the modern world. With many tipping points in the climate approaching it is important now more than ever to be able to understand more about them, and Machine Learning can be used as a way to do this. This literature review has gone over the many Machine Learning techniques (those being Deep Learning, Ordinal Regression, Generative Adversarial Networks, and Reservoir Computing) which have or could potentially be used to model climate tipping points. The details of a further research project which will be conducted has also been specified and evaluated.

References

[1] D. Rolnick, P. L. Donti, L. H. Kaack, K. Kochanski, A. Lacoste, K. Sankaran, A. S. Ross, N. Milojevic-Dupont, N. Jaques, A. Waldman-Brown *et al.*, "Tackling climate change with machine learning," *ACM Computing Surveys (CSUR)*, vol. 55, no. 2, pp. 1–96, 2022.

[2] T. M. Lenton, J. Rockström, O. Gaffney, S. Rahmstorf, K. Richardson, W. Steffen, and H. J. Schellnhuber, "Climate tipping points—too risky to bet against," *Nature*, vol. 575, no. 7784, pp. 592–595, 2019.

[3] T. M. Lenton, H. Held, E. Kriegler, J. W. Hall, W. Lucht, S. Rahmstorf, and H. J. Schellnhuber, "Tipping elements in the earth's climate system," *Proceedings of the national Academy of Sciences*, vol. 105, no. 6, pp. 1786–1793, 2008.

[4] D. I. Armstrong McKay, A. Staal, J. F. Abrams, R. Winkelmann, B. Sakschewski, S. Loriani, I. Fetzer, S. E. Cornell, J. Rockström, and T. M. Lenton, "Exceeding 1.5 c global warming could trigger multiple climate tipping points," *Science*, vol. 377, no. 6611, p. eabn7950, 2022.

[5] V. Brovkin, E. Brook, J. W. Williams, S. Bathiany, T. M. Lenton, M. Barton, R. M. DeConto, J. F. Donges, A. Ganopolski, J. McManus *et al.*, "Past abrupt changes, tipping points and cascading impacts in the earth system," *Nature Geoscience*, vol. 14, no. 8, pp. 550–558, 2021.

[6] S. T. Jackson and . J. P. Rafferty. (2023, October 13) Little ice age. encyclopedia britannica. "Accessed on 21/11/2023". [Online]. Available: "https://www.britannica.com/science/Little-Ice-Age"

[7] I. El Naqa and M. J. Murphy, *What is machine learning?* Springer, 2015.

[8] met office. New flagship climate models - ukesm1 and hadgem3-gc3.1. "Accessed on 21/11/2023". [Online]. Available: https://www.metoffice.gov.uk/research/approach/modelling-systems/new-flagship-climate-models

[9] J. Sleeman, D. Chung, A. Gnanadesikan, J. Brett, Y. Kevrekidis, M. Hughes, T. Haine, M.-A. Pradal, R. Gelderloos, C. Ashcraft *et al.*, "A generative adversarial network for climate tipping point discovery (tip-gan)," *arXiv preprint arXiv:2302.10274*, 2023.

[10] T. M. Bury, R. Sujith, I. Pavithran, M. Scheffer, T. M. Lenton, M. Anand, and C. T. Bauch, "Deep learning for early warning signals of tipping points," *Proceedings of the National Academy of Sciences*, vol. 118, no. 39, p. e2106140118, 2021.

[11] P. Gutiérrez, C. Hervás-Martínez, F. Fernández-Navarro, A. Dicaire, M. Pérez-Ortiz, J. Sánchez-Monedero, P. A. Gutiérrez, and L. Summerer, "Climate tipping points: Detection and analysis of patterns using an ordinal regression approach," 2014.

[12] A. Shashua and A. Levin, "Ranking with large margin principle: Two approaches," *Advances in neural information processing systems*, vol. 15, 2002.

[13] V. E. Johnson and J. H. Albert, *Ordinal data modeling.* Springer Science & Business Media, 2006.

[14] F. E. Harrell, Jr and F. E. Harrell, "Ordinal logistic regression," *Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis*, pp. 311–325, 2015.

[15] M.-H. Chen and D. K. Dey, "Bayesian analysis for correlated ordinal data models," *BIOSTATISTICS-BASEL-*, vol. 5, pp. 133–158, 2000.

[16] P. McCullagh, "Regression models for ordinal data," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 42, no. 2, pp. 109–127, 1980.

[17] Google. Overview of gan structure. "Accessed on 24/11/2023". [Online]. Available: "https://developers.google.com/machine-learning/gan/gan_structure"

[18] X. Li, Q. Zhu, C. Zhao, X. Qian, X. Zhang, X. Duan, and W. Lin, "Tipping point detection using reservoir computing," *Research*, vol. 6, p. 0174, 2023.

[19] A. C. Luo and G. Zaslavsky, "Monograph series on nonlinear science and complexity," *(No Title)*, 2007.

[20] D. E. Hilt and D. W. Seegrist, *Ridge, a computer program for calculating ridge regression estimates*. Department of Agriculture, Forest Service, Northeastern Forest Experiment . . . , 1977.

[21] W. J. Ripple, C. Wolf, T. M. Newsome, J. W. Gregg, T. M. Lenton, I. Palomo, J. A. J. Eikelboom, B. E. Law, S. Huq, P. B. Duffy, and J. Rockström, "World Scientists' Warning of a Climate Emergency 2021," *BioScience*, vol. 71, no. 9, pp. 894–898, 07 2021. [Online]. Available: "https://doi.org/10.1093/biosci/biab079"

[22] IPCC. Ipcc sixth assessment report. "Accessed on 24/11/2023". [Online]. Available: "https://www.ipcc.ch/assessment-report/ar6/"

[23] Climate change: Earth surface temperature data. "Accessed on 24/11/2023". [Online]. Available: "https://www.kaggle.com/datasets/berkeleyearth/climate-change-earth-surface-temperature-data/"

[24] Berkley. (2022) Data overview. "Accessed on 24/11/2023". [Online]. Available: "https://berkeleyearth.org/data/"

[25] U. Goverment. (2023) The rights granted by copyright. "Accessed on 24/11/2023". [Online]. Available: "https://www.gov.uk/guidance/the-rights-granted-by-copyright"