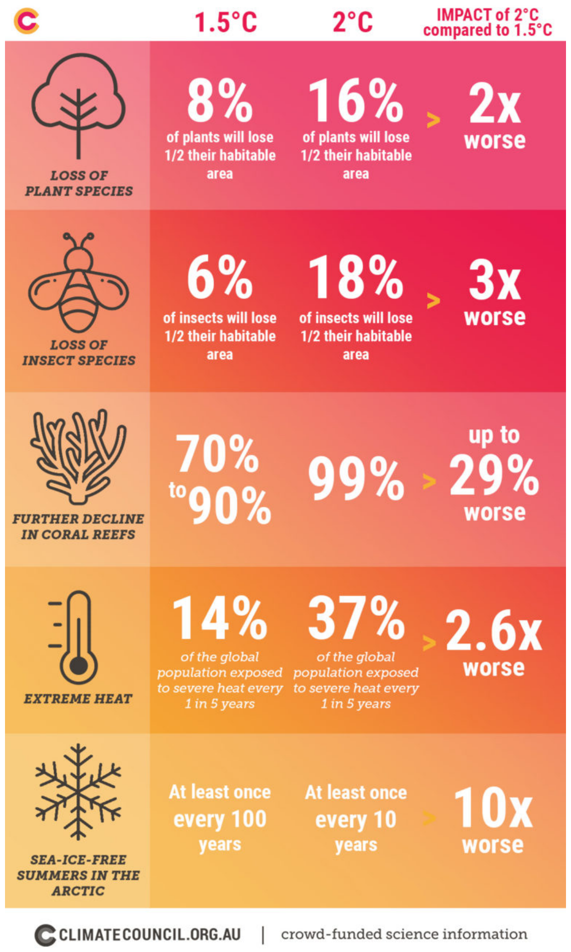
Global Warming

Tigergraph with Machine Learning

Every point-of-a-degree Matters



- At the rate we're going, we've got around 10 years until we hit 1.5C.
- Intergovernmental Panel on Climate Change (IPCC) finds that limiting warming to 1.5C requires global emissions to be slashed by 45 per cent by 2030, compared to 2010 levels
- It's exceedingly unlikely that we will manage to limit warming to below 1.5C without overshoot
- We can expect an average of about 56 centimeters of sea level rise this century at 2C — but up to 96cm in the worst-case scenario
- That extra 0.5C, according to the IPCC, is expected to impact an extra 10.4 million people

Why we need this solution ?

- Global warming is very critical challenge , we humans are the ones who burn fossil fuels and chop down forests, causing average temperatures to rise worldwide.

- That global warming trend is increasingly disrupting our climate — the average weather over many years.

- Created 2 stage approach to combine Tigergraph with machine learning to help track , understand relationship and highlight any anomalies in this overall trend

- Though as part of this challenge started with 4 datasets with monthly granularity but idea is to use this approach for real time per minute , hourly or daily datasets

- Forecasted values from Machine Learning model can be use to understand any anomalies in **Carbon Emission , Temperature Anomaly , Ocean Heat and Arctic sea ice extent** by comparing against actual captured values as its very critical to understand if we heading in right direction or not

How tigergrpah with machine learning can help?

- **Stage-1 :** Started with 4 different time series data sets related to global warming to understand the impact of Carbon Emission on **Temperature Anomaly , Ocean Heat and Arctic sea ice extent**

  - **CO2 :** Global Carbon Emission
  - **Temperature Anomaly :** Change in global surface temperature relative to 1951-1980 average temperature
  - **Ocean Heat** : Ocean heat content change since 1992
  - **Arctic sea ice extent** : Annual Arctic sea ice minimum since 1979, based on satellite observations

- Currently using monthly datapoints but same graph an be extended to use hourly or daily datapoints as well

How tigergrpah with machine learning can help?

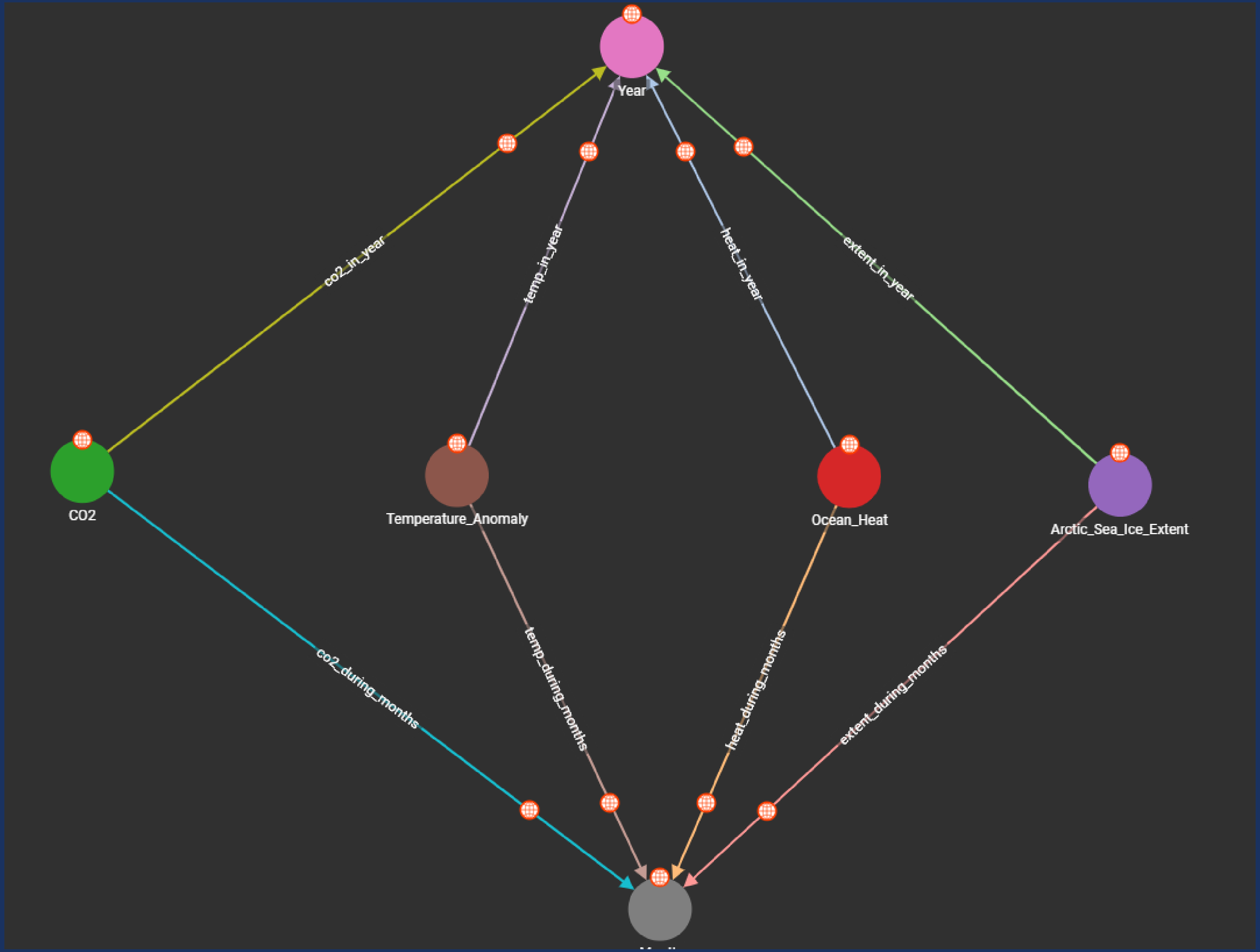
- **Stage-2 :** Used tigergrpah as data source to Regression model post understanding relationship between different datapoints mentioned in stage-1
  - Model-1: Timeseries forecast to predict Carbon Emission based on historical datapoints
  - Model-2:
    - Built Regression model with Carbon Emission as independent variable and **Temperature Anomaly** , **Ocean Heat and Arctic sea ice extent** as dependent variables
    - Used Model-1 forecasted Carbon Emission to forecast future **Temperature Anomaly** , **Ocean Heat and Arctic sea ice extent**

- Output values from Model-2 can be use to understand any anomalies by comparing against actual captured values . Critical to understand if we heading in right direction or not

- This model currently using monthly datapoints but this same model can be used for hourly or daily data samples as well.

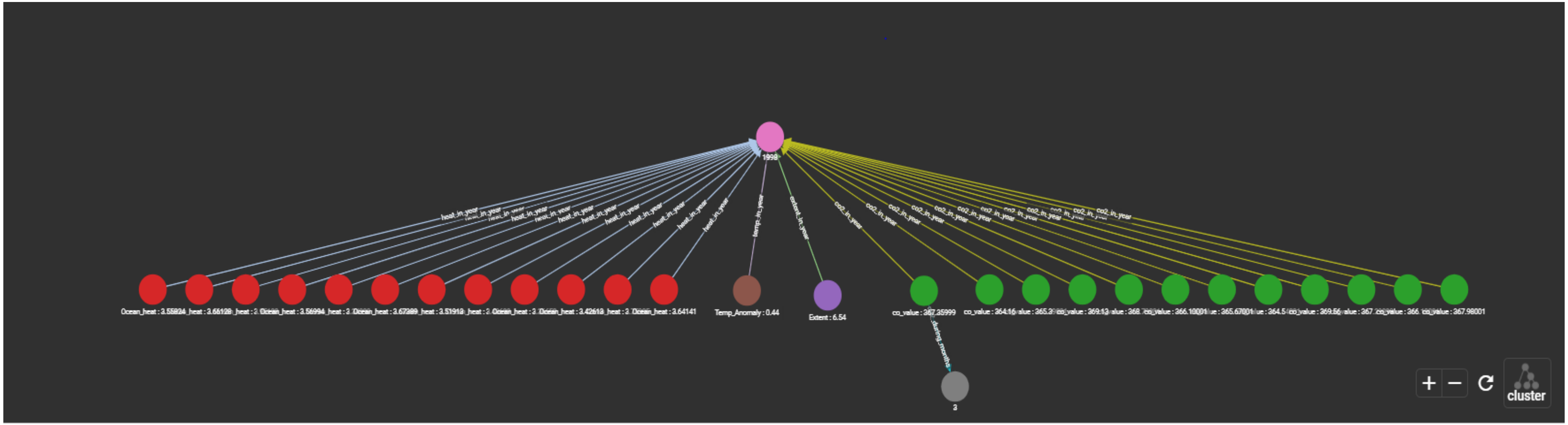
Platform , tools and languages

- **Tigergraph Cloud Based Graph Database :** An easy-to-use, cloud-based graph database built for agile teams.
- **Google Collaboratory** : Colab allows anybody to write and execute arbitrary python code through the browser
- **PyCharm / Python** : To build Machine learning model
- **Scikit-learn :** Regression model python library
- **Data:** All data is collected from NASA Global Climate Change https://climate.nasa.gov/

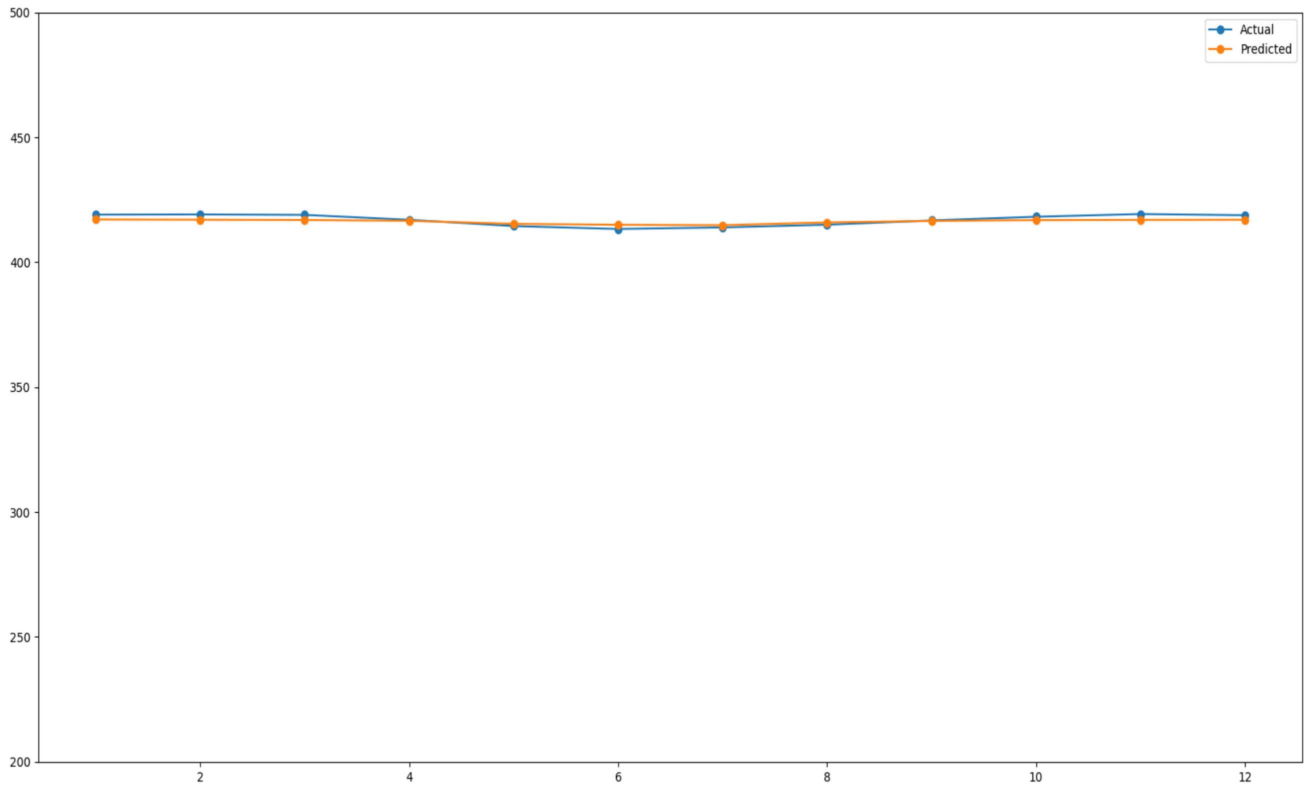


TIGERGRAPH DESIGN SCHEMA

Example: Year 2018 monthly data-points for CO2 ,Ocean Heat , Temp Anomaly and Ice Extent



Machine Learning (Carbon Emission Time series Forecast)

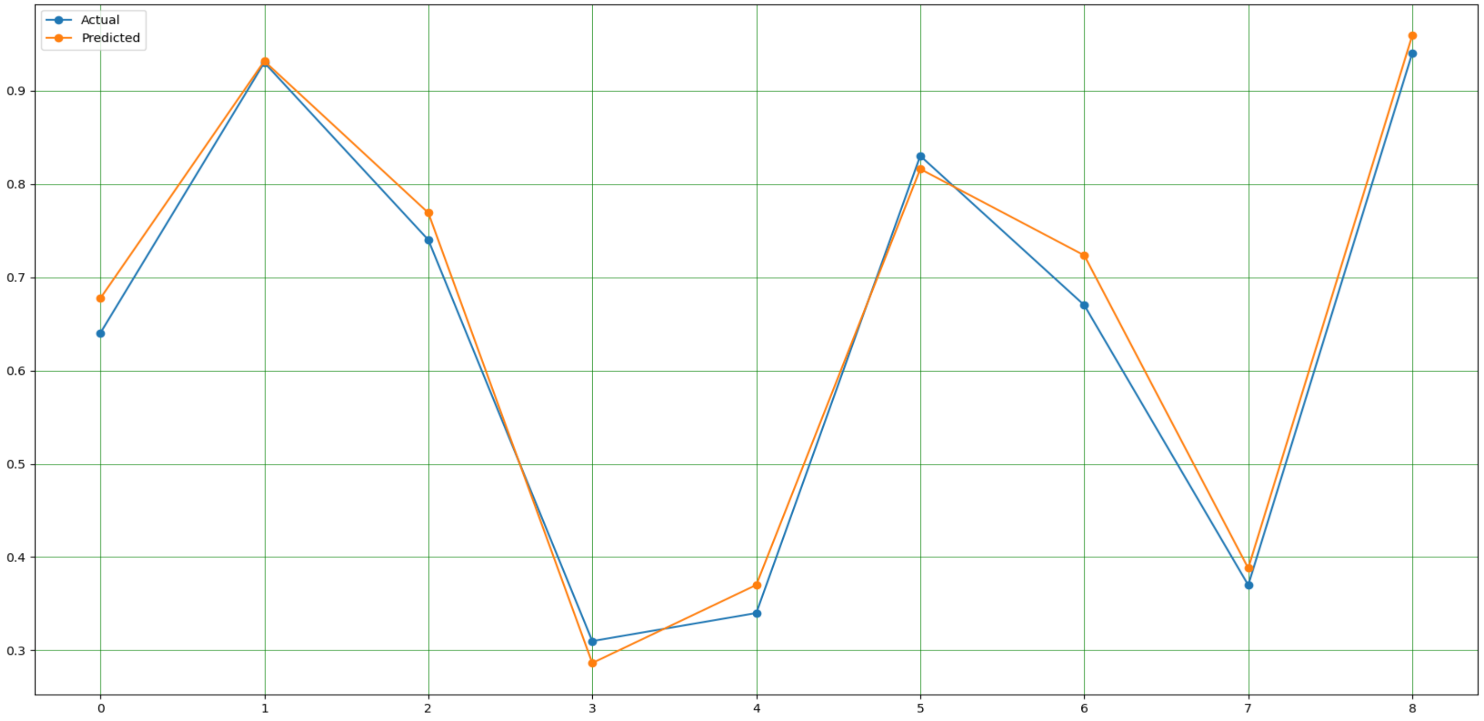


- **Root Mean Squared Error:** 1.5406

- RMSE of 1.5406 with CO_2 values in range of 410-420

- Validation set proves the forecasting of Carbon Emission time series data

Machine Learning (Temperature Anomaly Forecast)



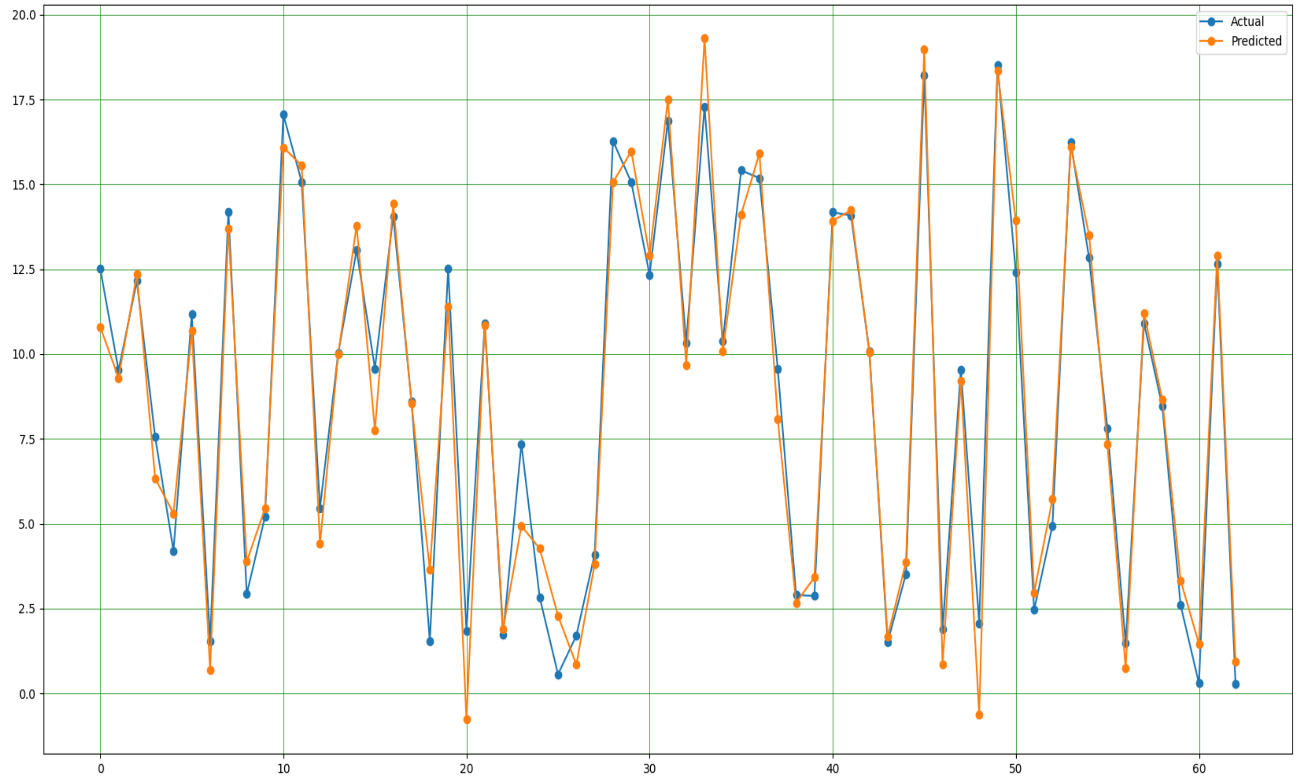
ot Mean Squared Error:
287

iance score: 0.98

value of 0.98 which is very
se to 1 with root mean
ıared error of only 0.0287

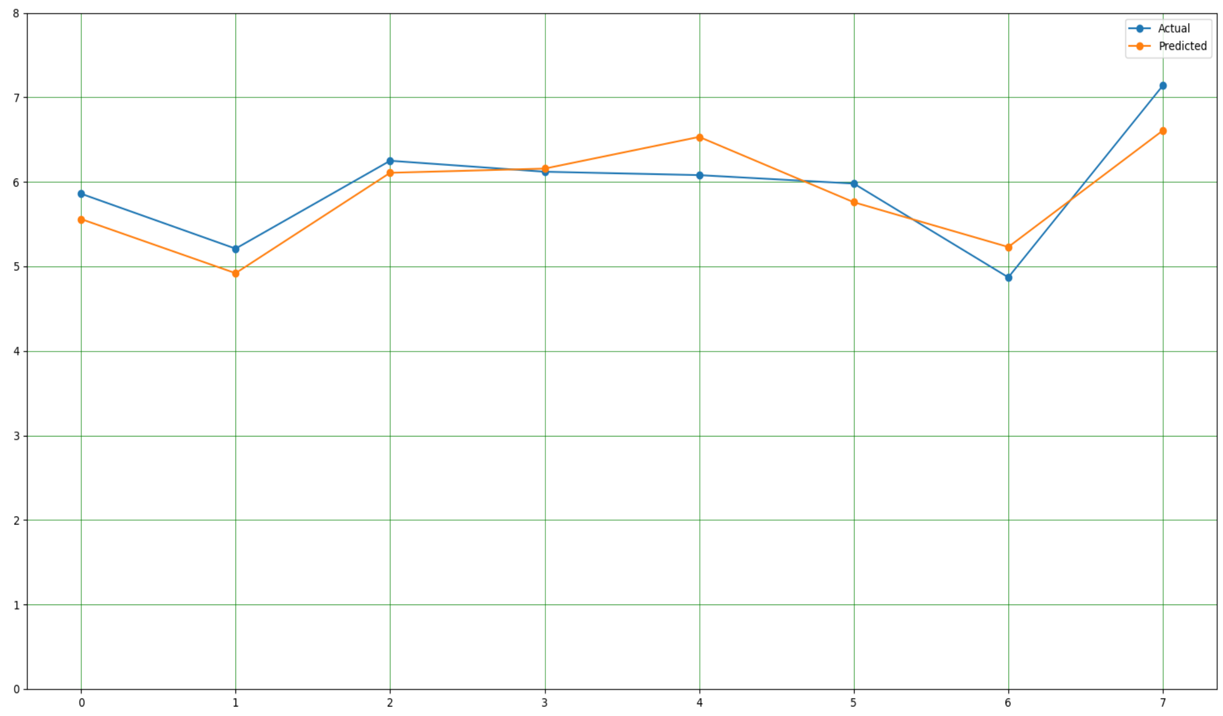
ves strong relationship
ween Carbon Emission and
nperature Anomaly

Machine Learning (Ocean Heat Forecast)



- **Root Mean Squared Error:** 1.03074
- **Variance score**: 0.97
- R2 value of 0.97 which is very close to 1 with root mean squared error of only 0.3281
- Proves strong relationship between Carbon Emission and Ocean Heat

Machine Learning (Arctic Sea Ice Extent Forecast)



- **Root Mean Squared Error:** 0.3281
- **Variance score**: 0.74
- R2 value of 0.74 which is very close to 1 with root mean squared error of only 0.3281
- Proves good relationship between Carbon Emission and Arctic Sea Ice Extent

Demo