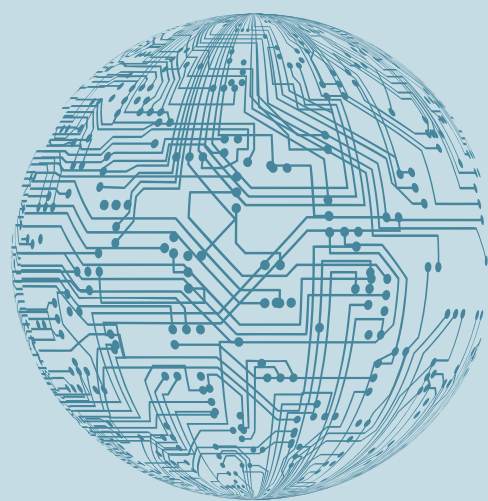


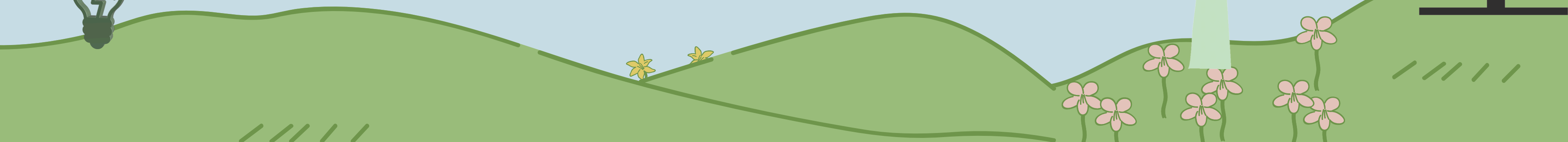
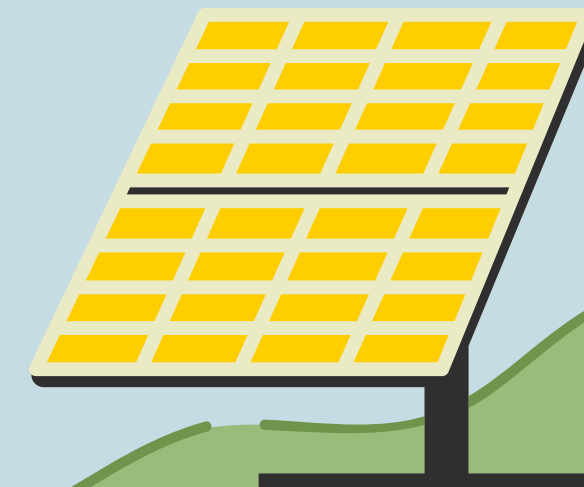
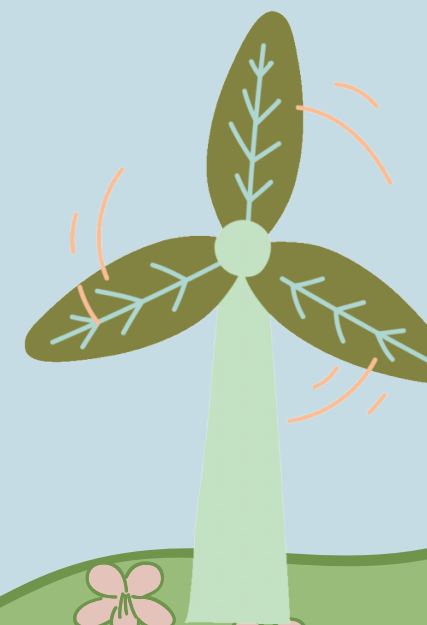
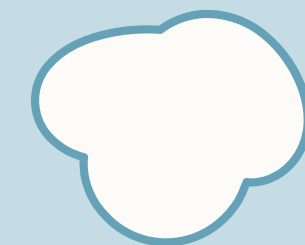
Lightning Talk

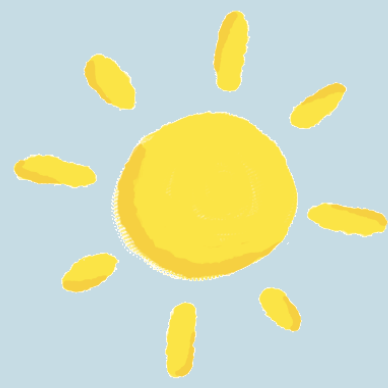


Why your Forecasting Transformer Model is not working

How to fix it in Python

PyTorch Conference 2026

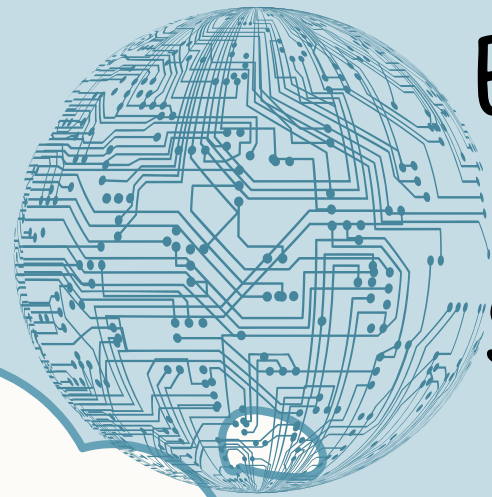
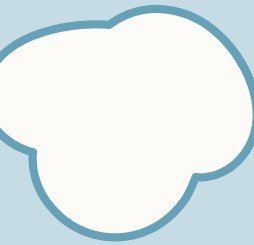




Introduction

Rosheen Naeem

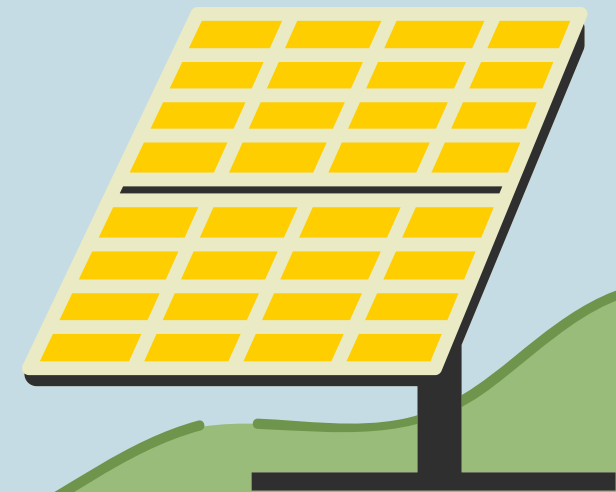
Software Engineer at Miro

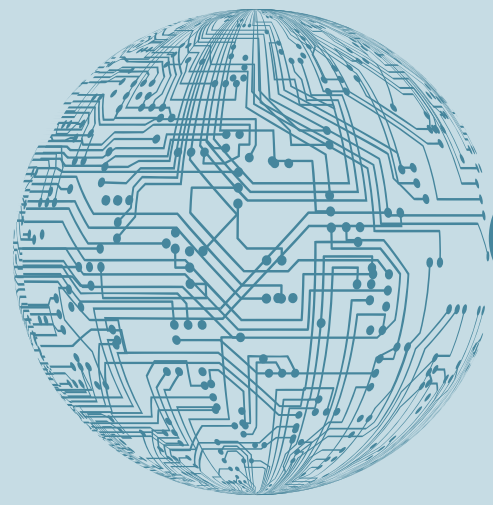


Erasmus Mundus Master's
in
Software Engineering for
Green Deal (SE4GD)



Google Summer of Code



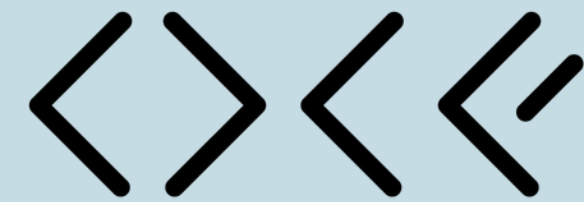


Open climate Fix

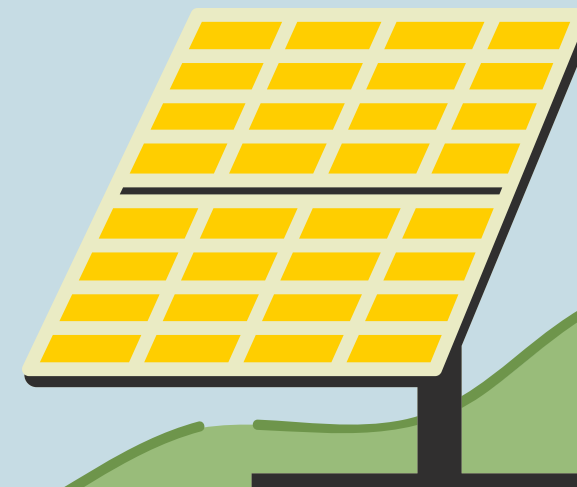
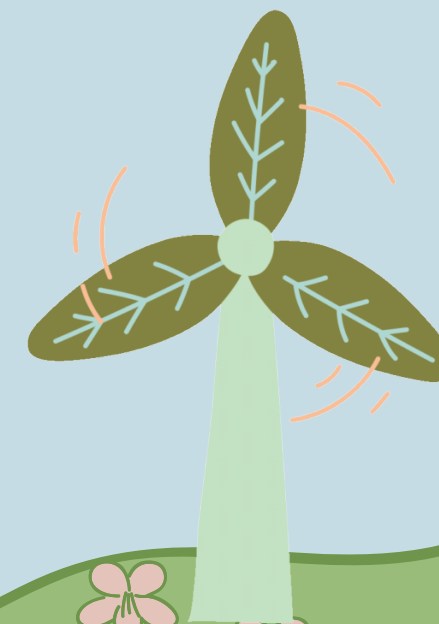
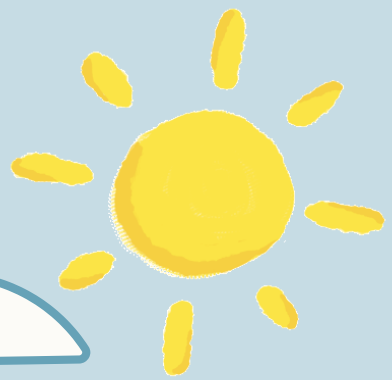
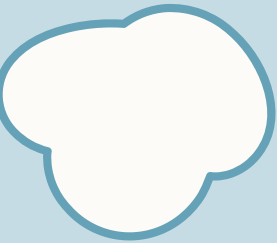
Sustainability by IT

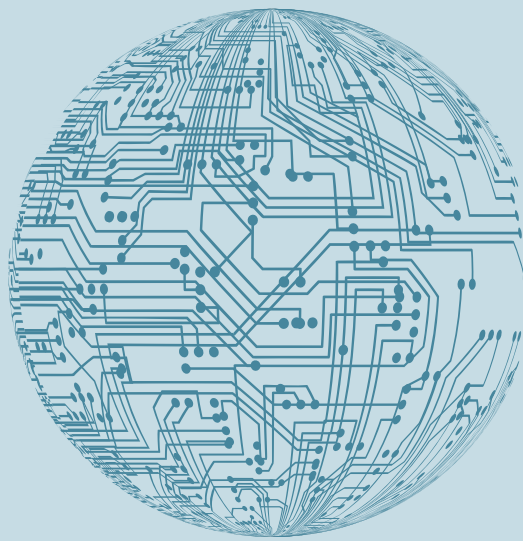
Renewable energy is unpredictable in terms of power generation

- Solar Forecasting
- Cloudcasting
- Wind Forecasting
- Mapping Solar Power
- Unlocking Energy Data



**OPEN
CLIMATE
FIX**





Why Solar Forecasting is important

We can't control the weather, but we can predict it



Variable by nature

PV output can swing dramatically within minutes due to cloud cover — not controllable, only predictable.



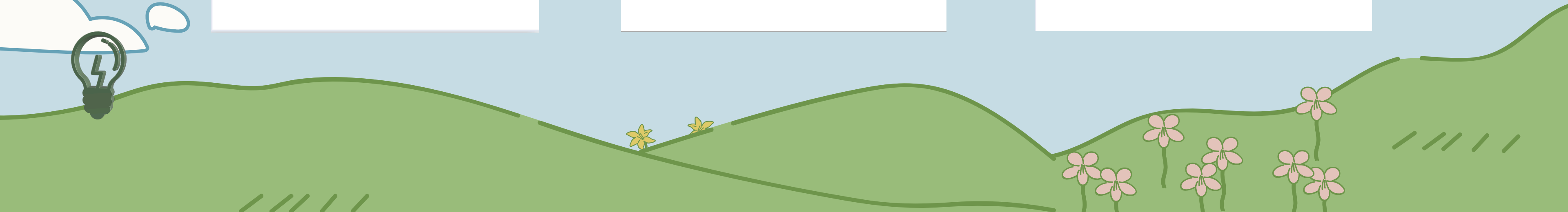
Grid stability

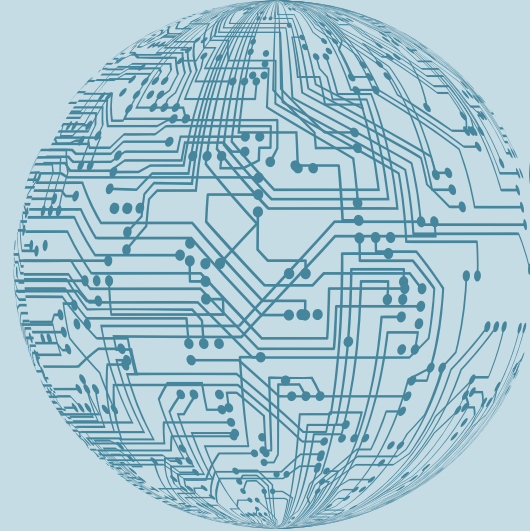
Grid operators need forecasts to balance supply and demand in real time — bad forecasts mean fossil fuel backup.



Smart homes & trading

Accurate forecasts enable energy trading decisions and smart-home optimisation for solar households.





Open Quartz Solar Forecast project

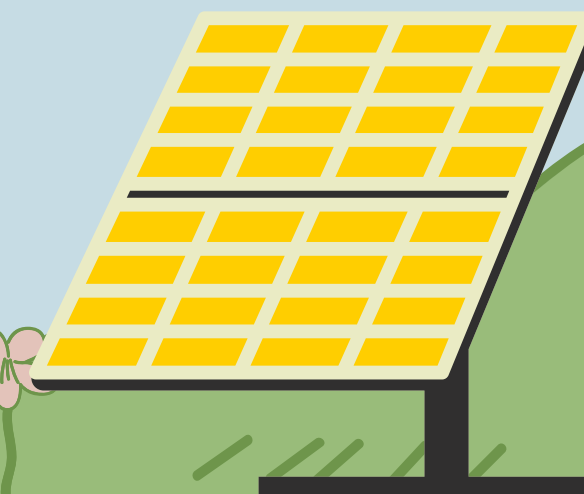
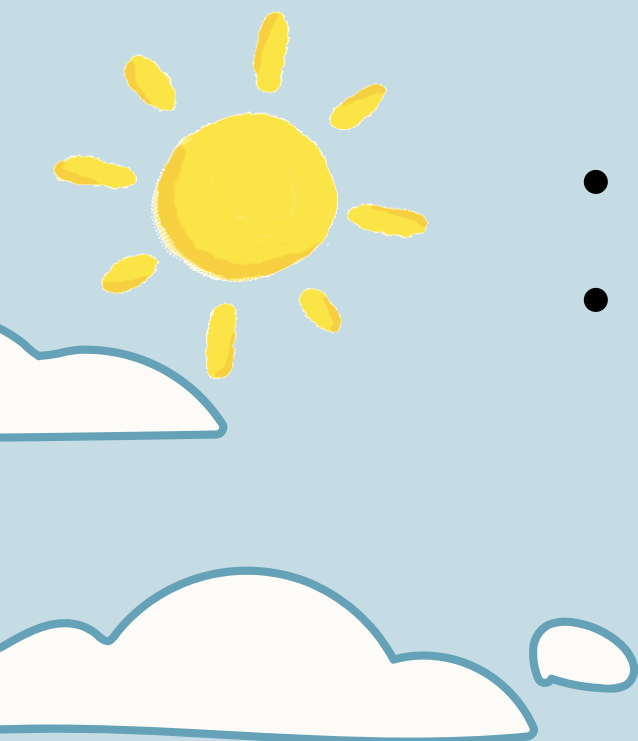
Case study

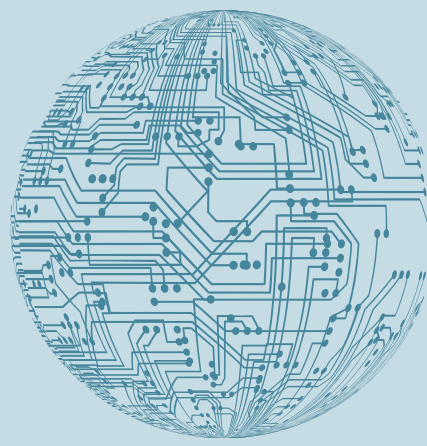
The project

- Open-source PV regular ML forecasting model
- Uses public data
- Originally a single-model architecture

What i built

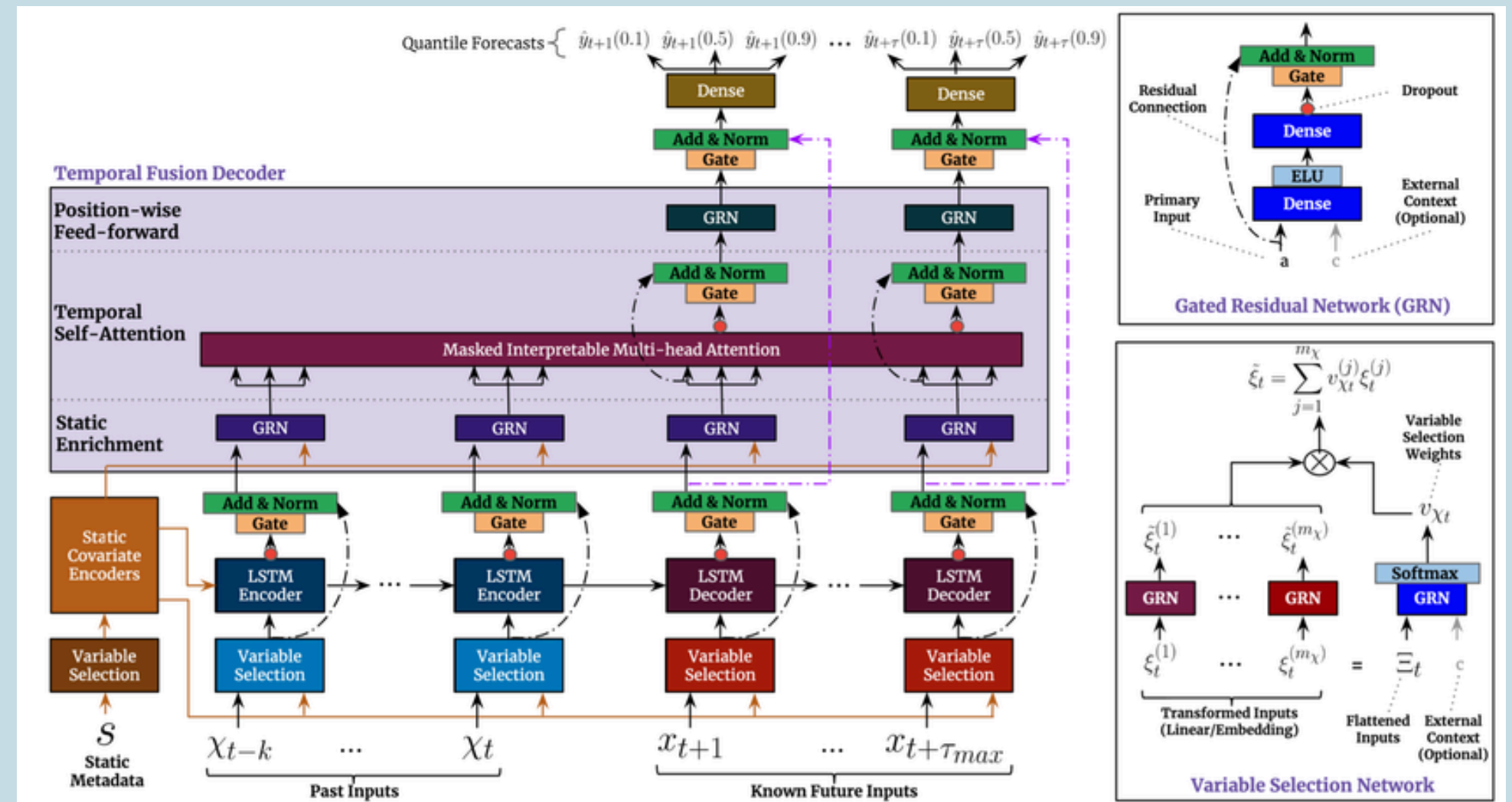
- Added a multi-horizon, multi-source forecasting model
- Fused 3 data sources into one pipeline
- 36-hour continuous multi-horizon forecasts

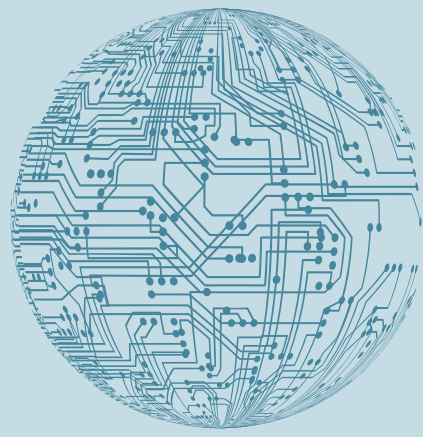




Temporal Fusion Transformer (TFT)

- Combines LSTM encoders + attention layer to model complex time series data
- An attention mechanism to dynamically weigh the importance of different variables
- Handles three feature types: static, time-varying known, and time-varying unknown
- Interpretability





Building the Data Pipeline



UK PV Data

Hugging Face dataset
Hourly generation values
2018 – 2021

Site Metadata

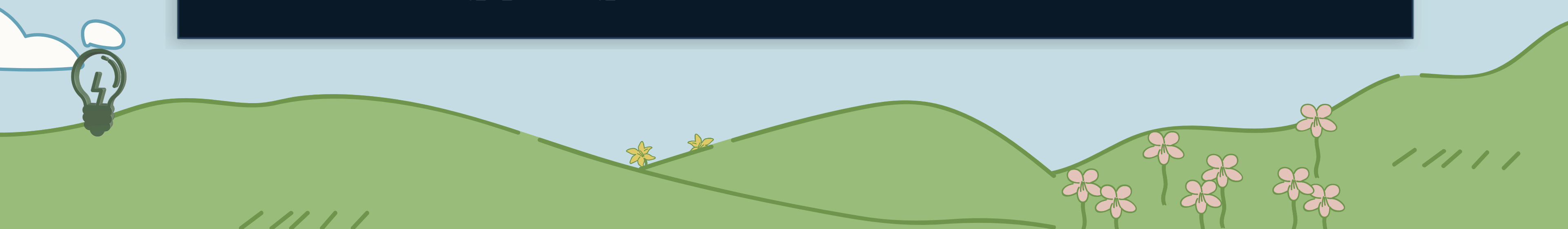
Lat, lon, tilt
Orientation, capacity
Per installation

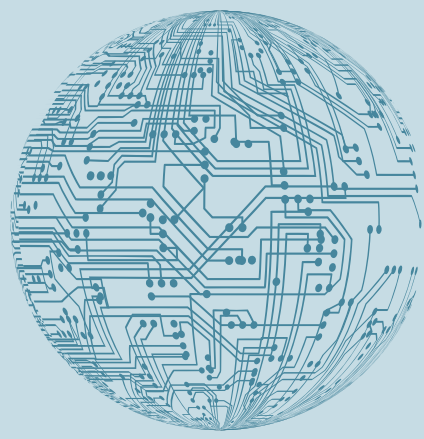
NWP Weather

ECMWF IFS model
14 weather variables
Init time + step

Merged Dataset — 36-hour continuous batches, no nulls

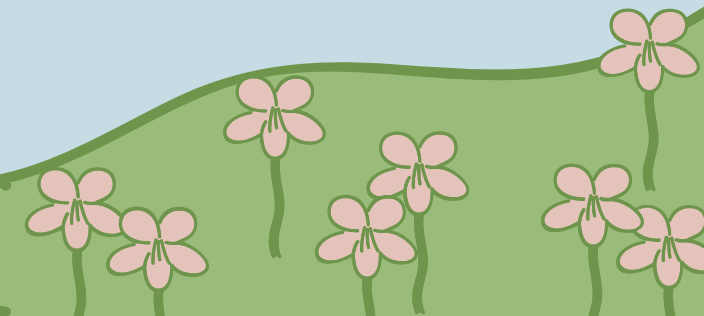
ss_id · pv_datetime · generation · horizon (1→36) · lat/lon/tilt/orientation/capacity · init_time · step · dlwrf · dswrf · duvrs · hcc · lcc · t2m · u10 · v10 · month · day_of_week · day_hour

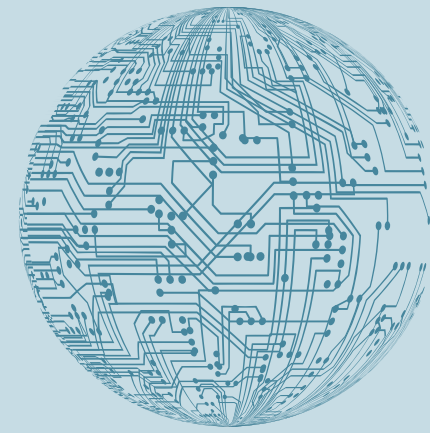




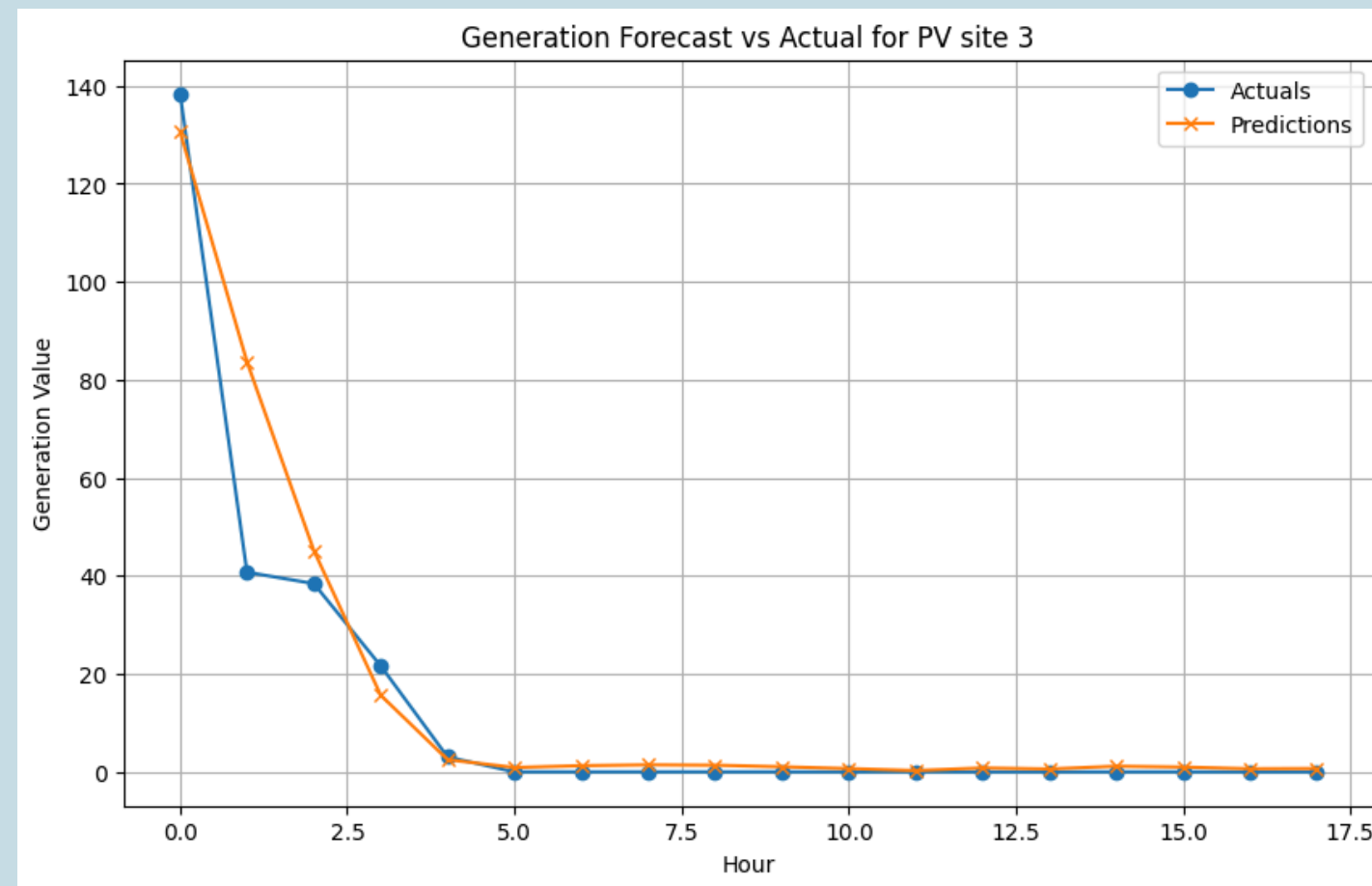
Model Implementation

- The TFT model implementation used PyTorch Forecasting with PyTorch Lightning as the training framework.
- Learning rate was optimised using PyTorch Lightning Tuner's lr_find method
- Early stopping to prevent overfitting
- Gradient clipping set to 0.1





Results



Variable importance (encoder)

dswrf (solar radiation)



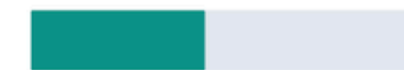
duvrs (UV radiation)



lcc (low cloud cover)



t2m (temperature 2m)

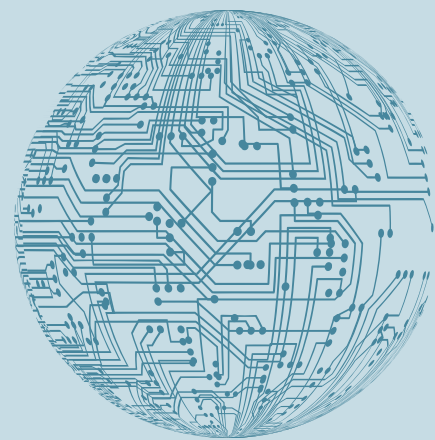


tcc (total cloud cover)



capacity (static)

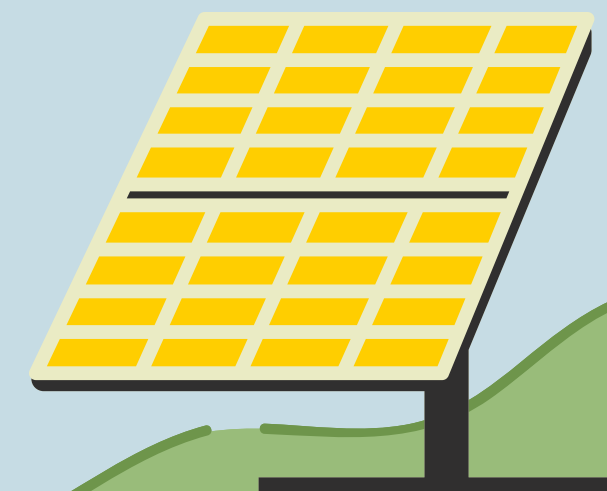


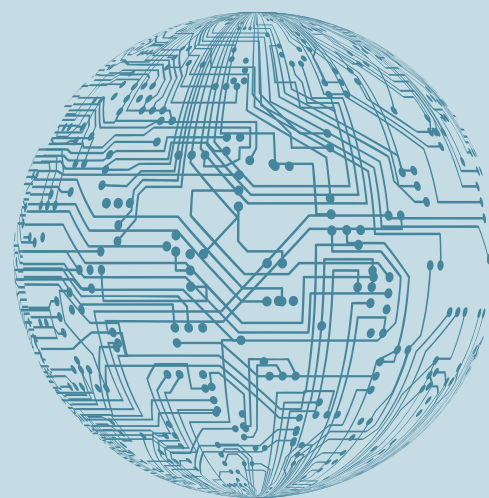


Key Takeaways



1. PyTorch Forecasting abstracts away a lot of TFT's complexity.
2. Data quality over model complexity – continuous windows, zero nulls, correct horizon column
3. Classify every feature – static, time-varying known, time-varying unknown – wrong classification silently kills performance
4. Always run `lr_find` and set `gradient_clip_val=0.1`





Thank you

Project Code:

github.com/openclimatefix/gsoc-open-quartz

Organization:

openclimatefix.org

Open Quartz
Solar Forecast:

github.com/openclimatefix/Open-Source-Quartz-Solar-Forecast

