CLIMATEHACK.AI

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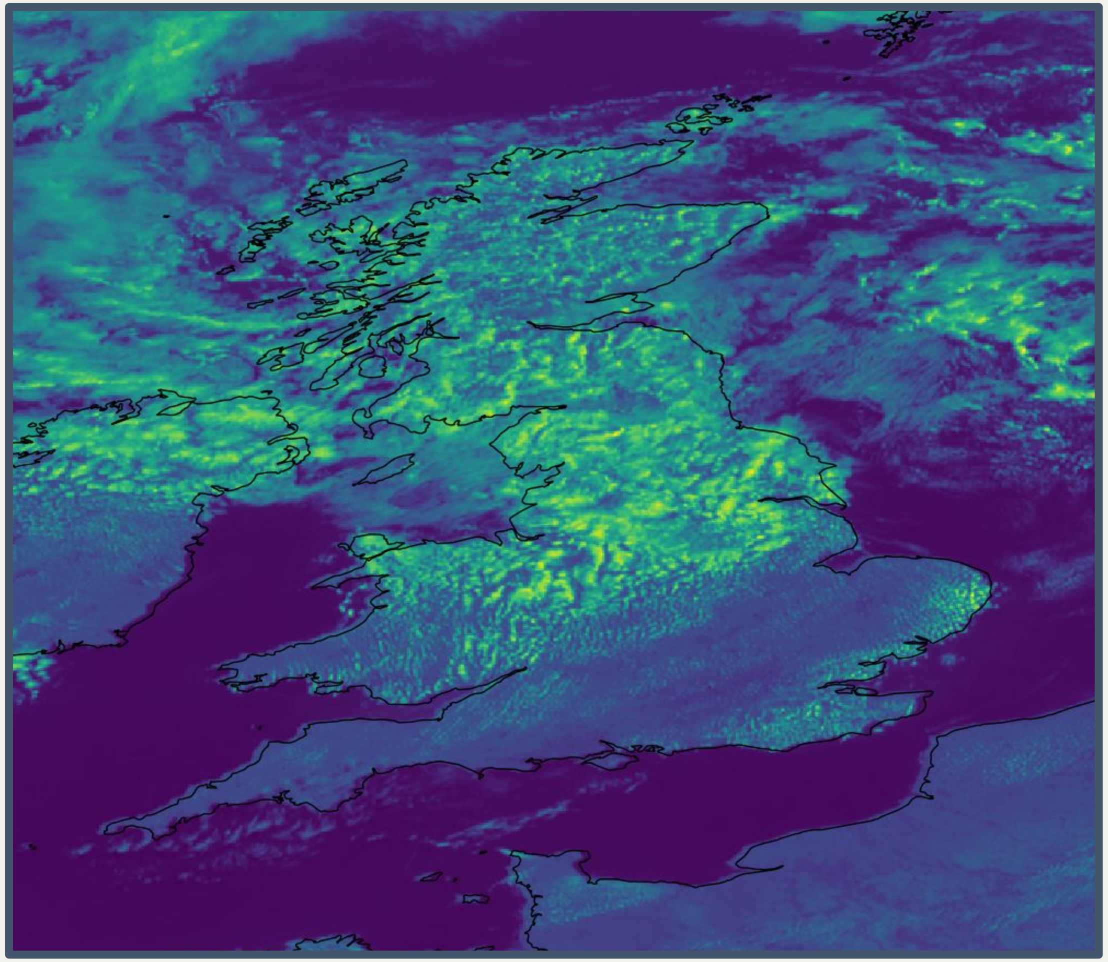
THE CHALLENGE

“Develop a model for site-level PV forecasting over the next four hours that is both accurate and performant”

DATASET

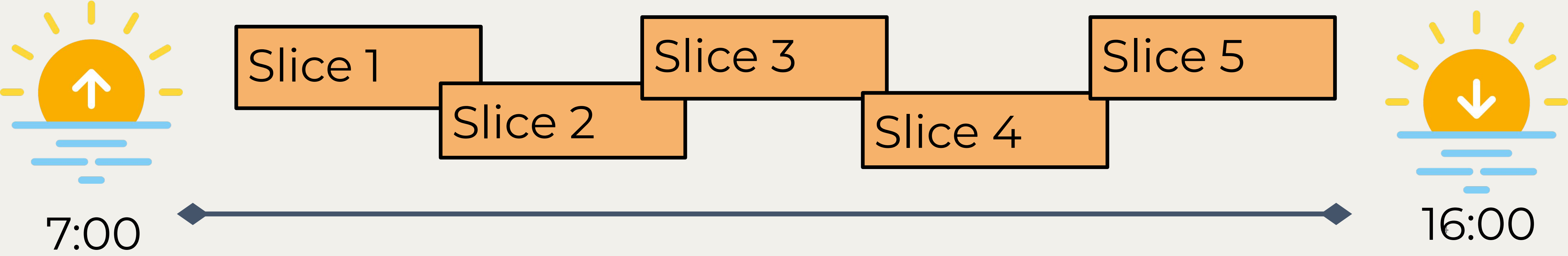


Useful Features

- Past PV
- Weather
  - Diffusive short wave radiation (aswdifd_s)
  - Direct short wave radiation (aswdir_s)
  - Cloud cover % (clch, clcm, clct
  - Relative humidity % (relhum_2m)
- Time
  - Only evaluated between sunrise and sunset

Data Generation

Take 5 4-hour time slices throughout each day, for every date of the year, for every site location

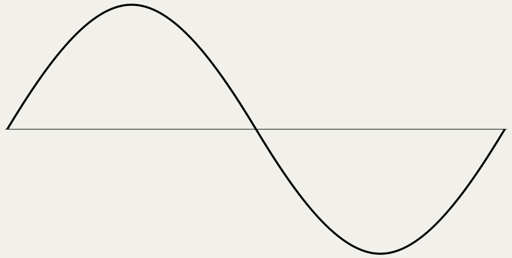


Example

DATA PREPROCESSING

For Time Variables:

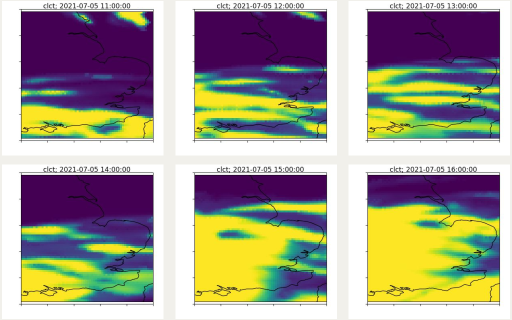
Months / hours →



Sinusoidal Encoding

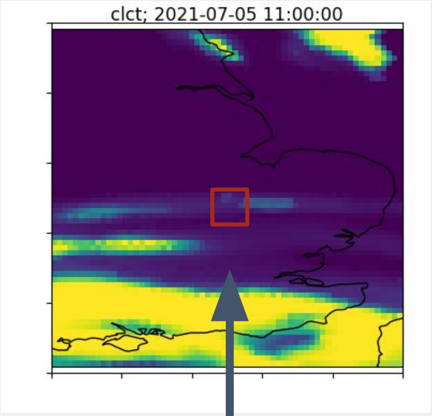
For All Weather Variables:

E.g. Cloud Cover Total (clct) →



$$\frac{\text{[maps]} - \mu_w}{\sigma_w}$$

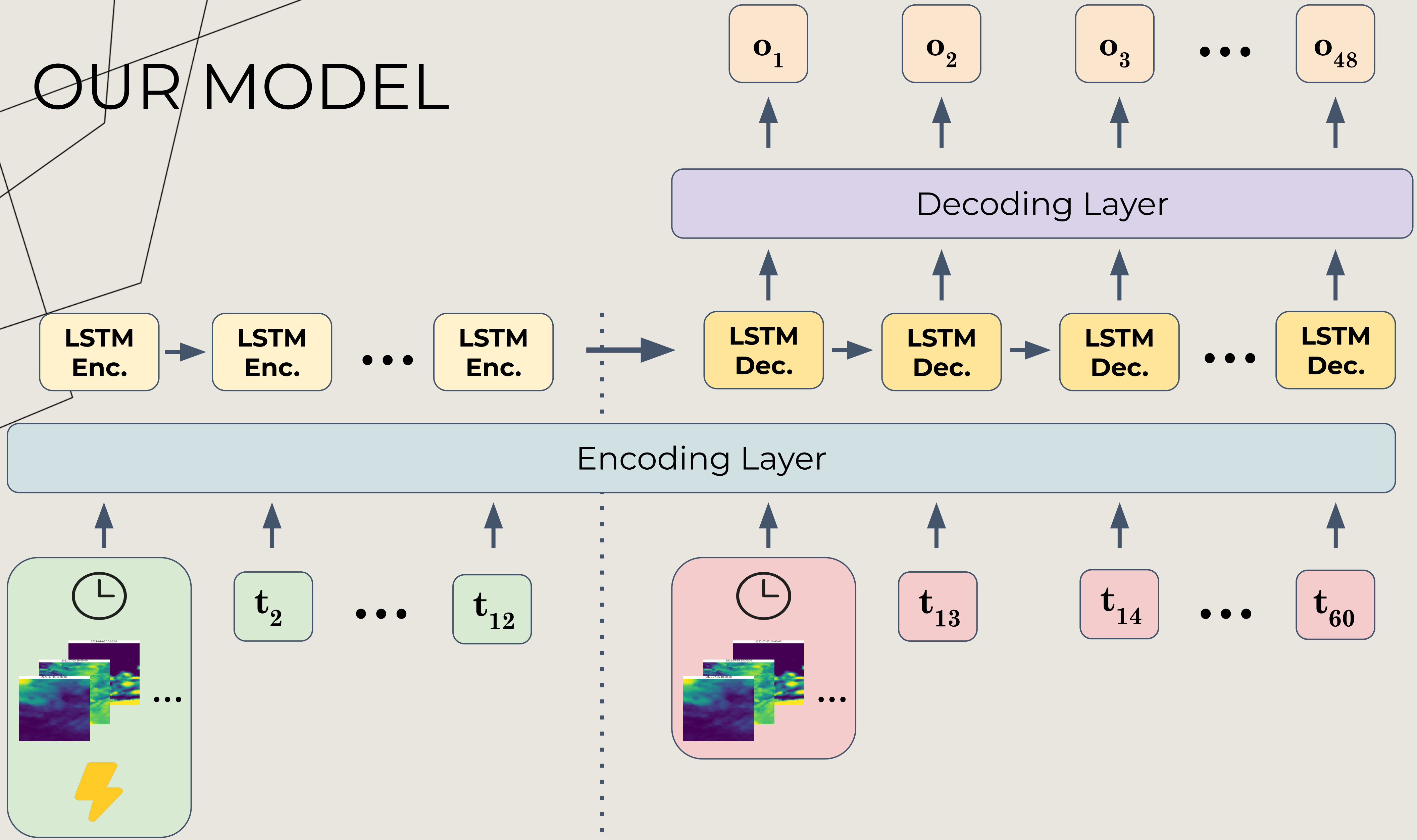
→



Centre 2 x 2

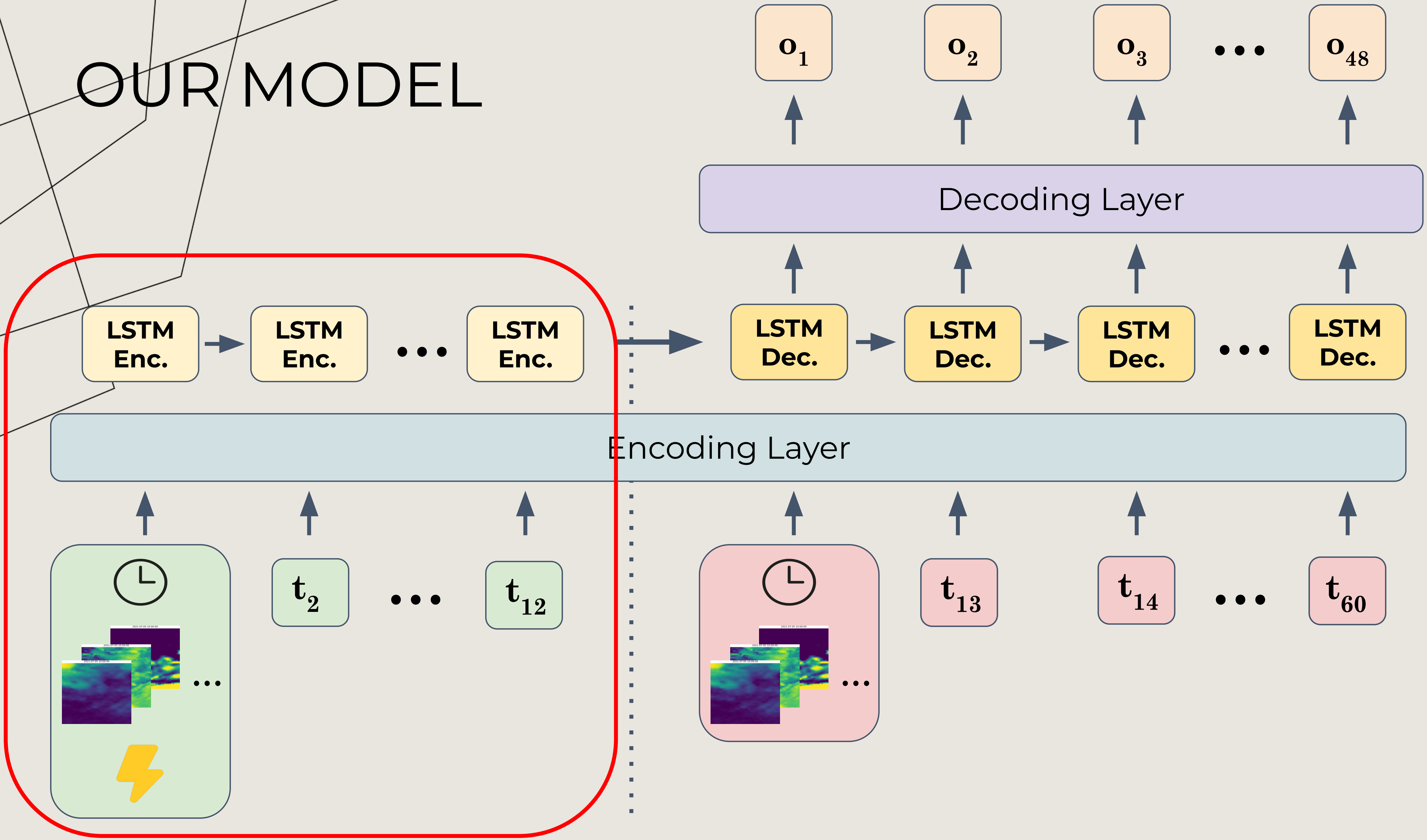
μ_w, σ_w calculated over all selected data points in dataset

OUR MODEL



o1
o2
o3
• • •
o48
Decoding Layer
LSTM Enc.
LSTM Enc.
• • •
LSTM Enc.
LSTM Dec.
LSTM Dec.
LSTM Dec.
• • •
LSTM Dec.
Encoding Layer
t2
• • •
t12
t13
t14
• • •
t60

OUR MODEL



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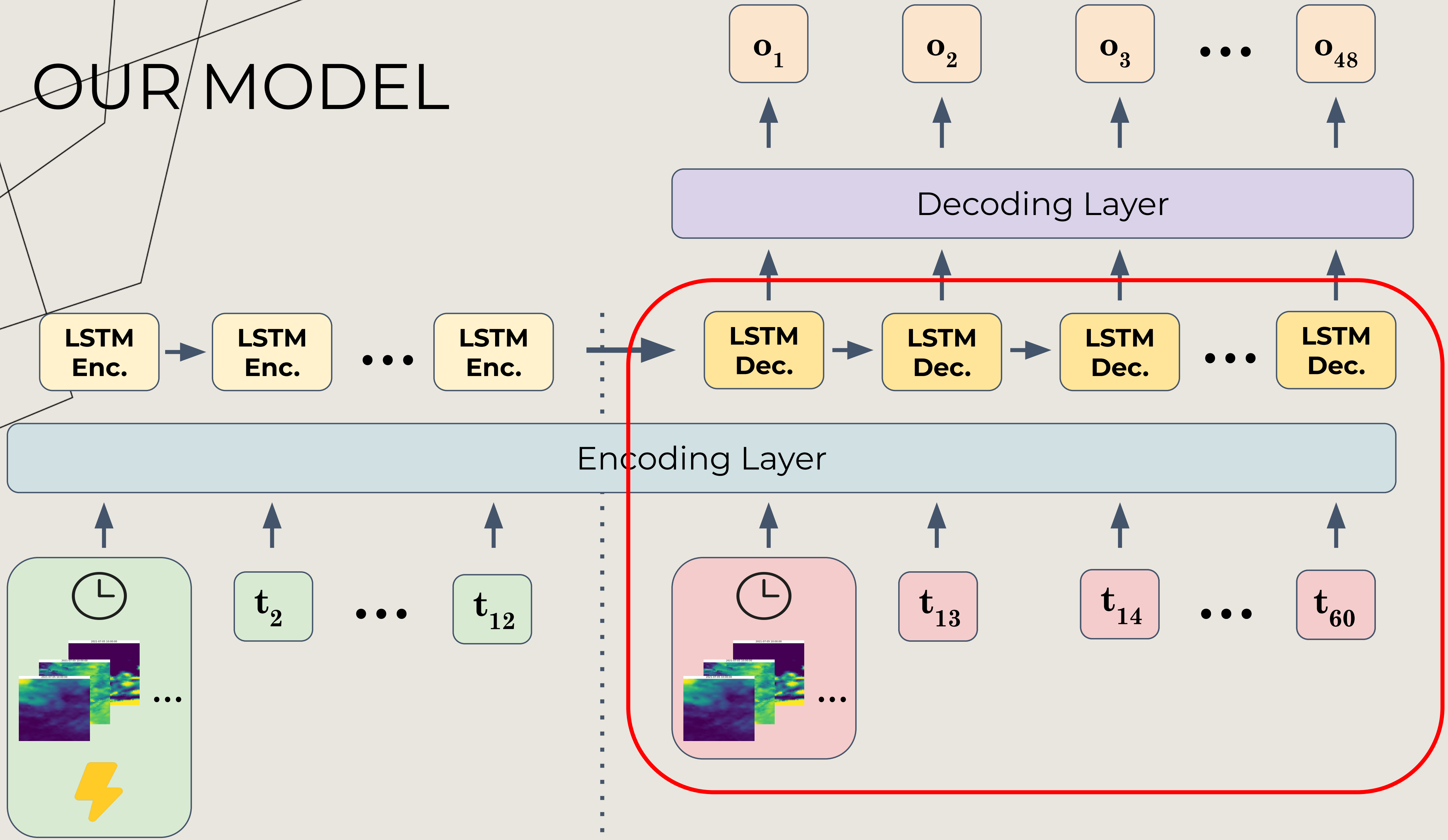

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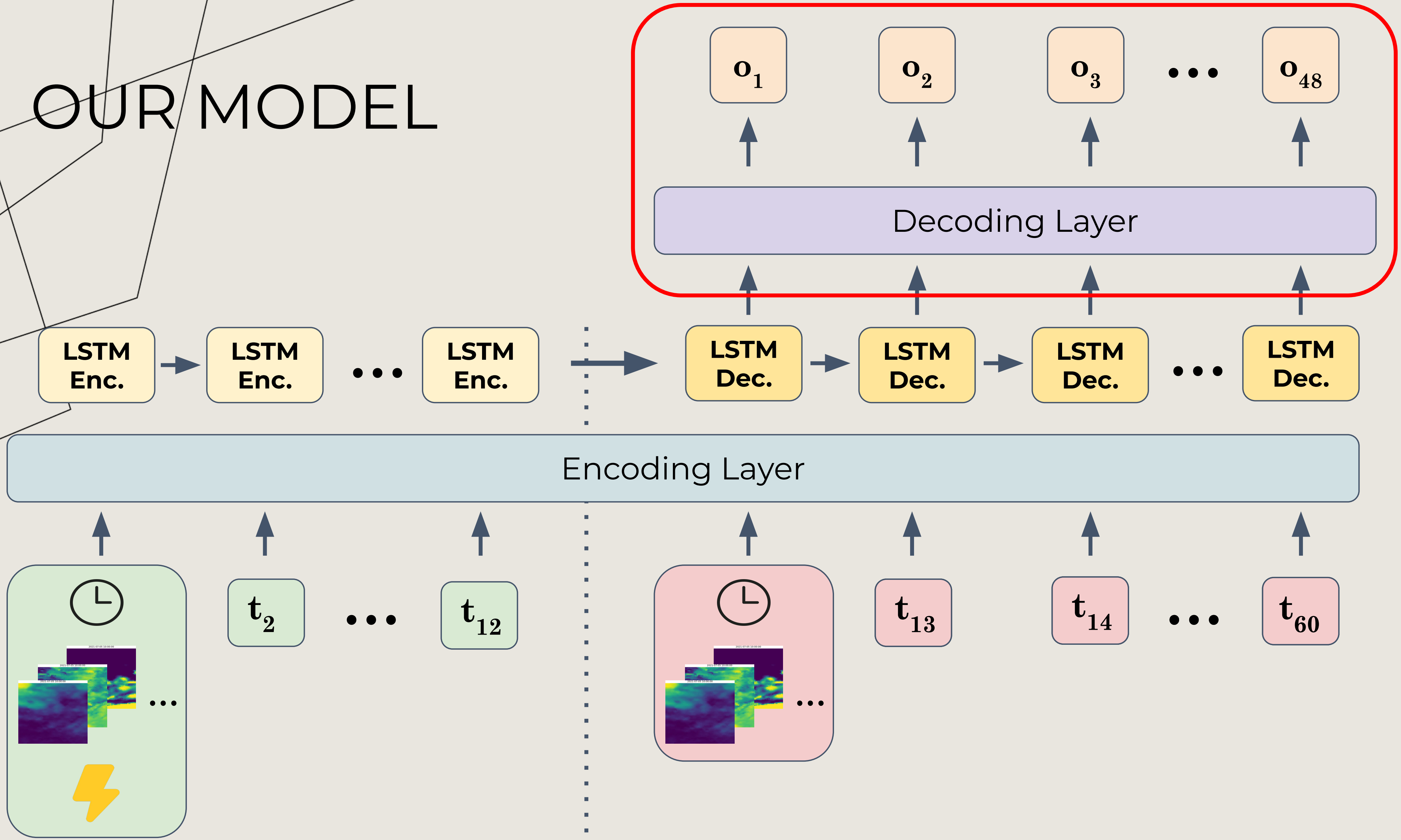

o_1
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o_{48}
Decoding Layer
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t_{60}

Model Training

Loss Function: **MAE**

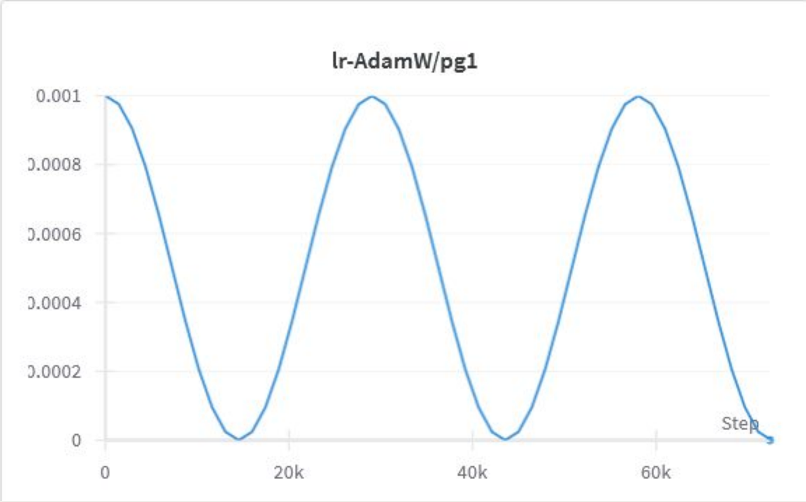
Optimizer: **Adam**

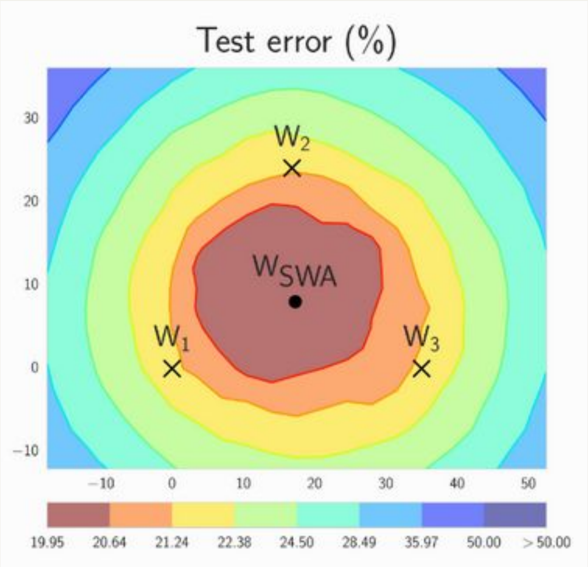
Training Tricks:

- *Cyclic learning rate scheduling*
- *Stochastic Weight Averaging*

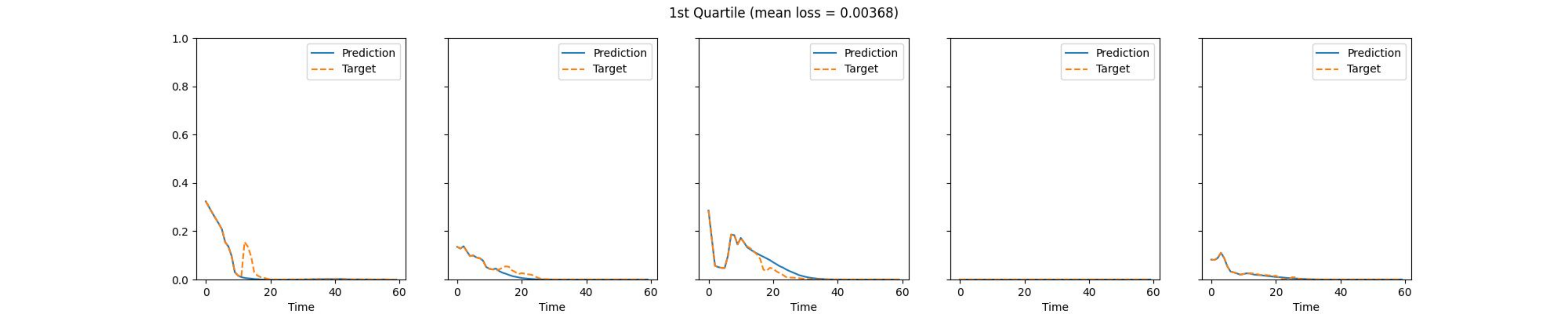
Epochs: 12 ⇒ Training Time: ~7 hours

Hardware: Trained on the Cloud – AWS/Vast.ai

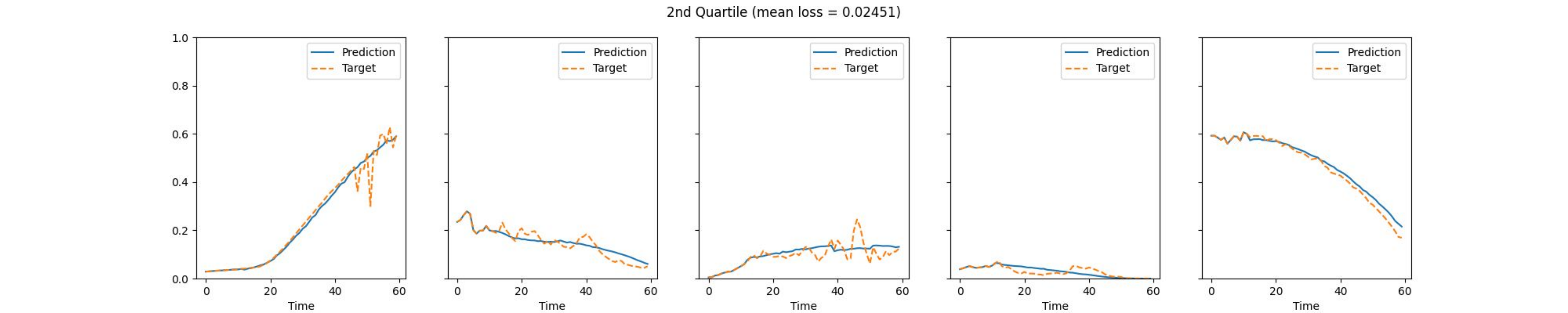




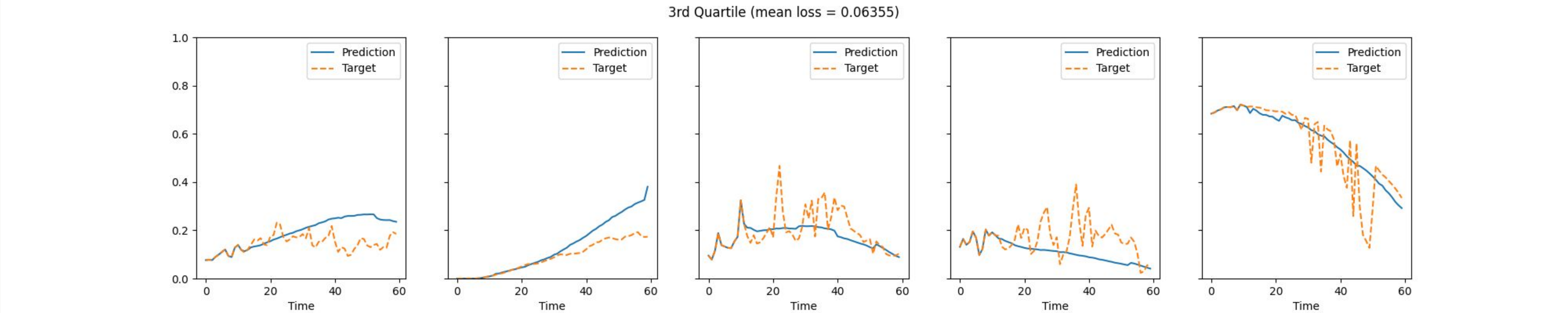
Model Performance: 1st Quartile



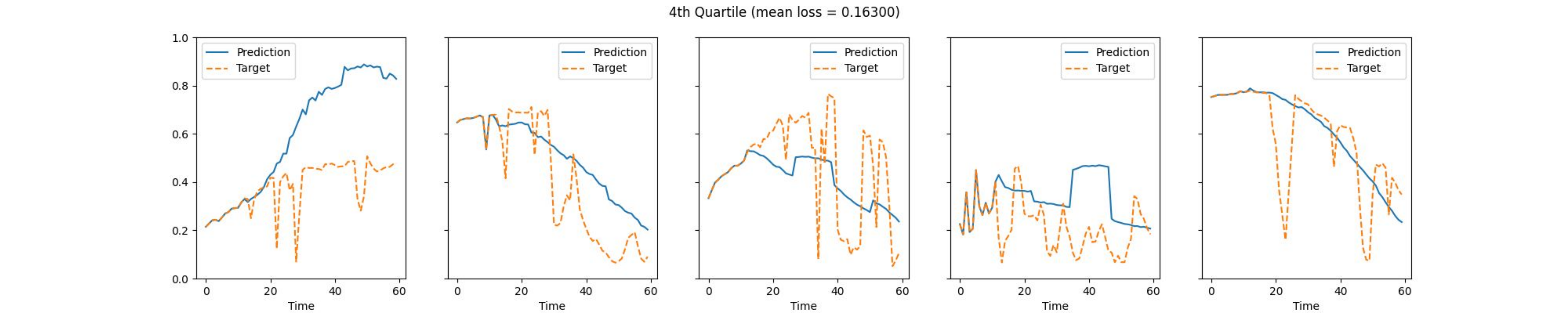
Model Performance: 2nd Quartile



Model Performance: 3rd Quartile



Model Performance: 4th Quartile



Advantages & Limitations

Advantages

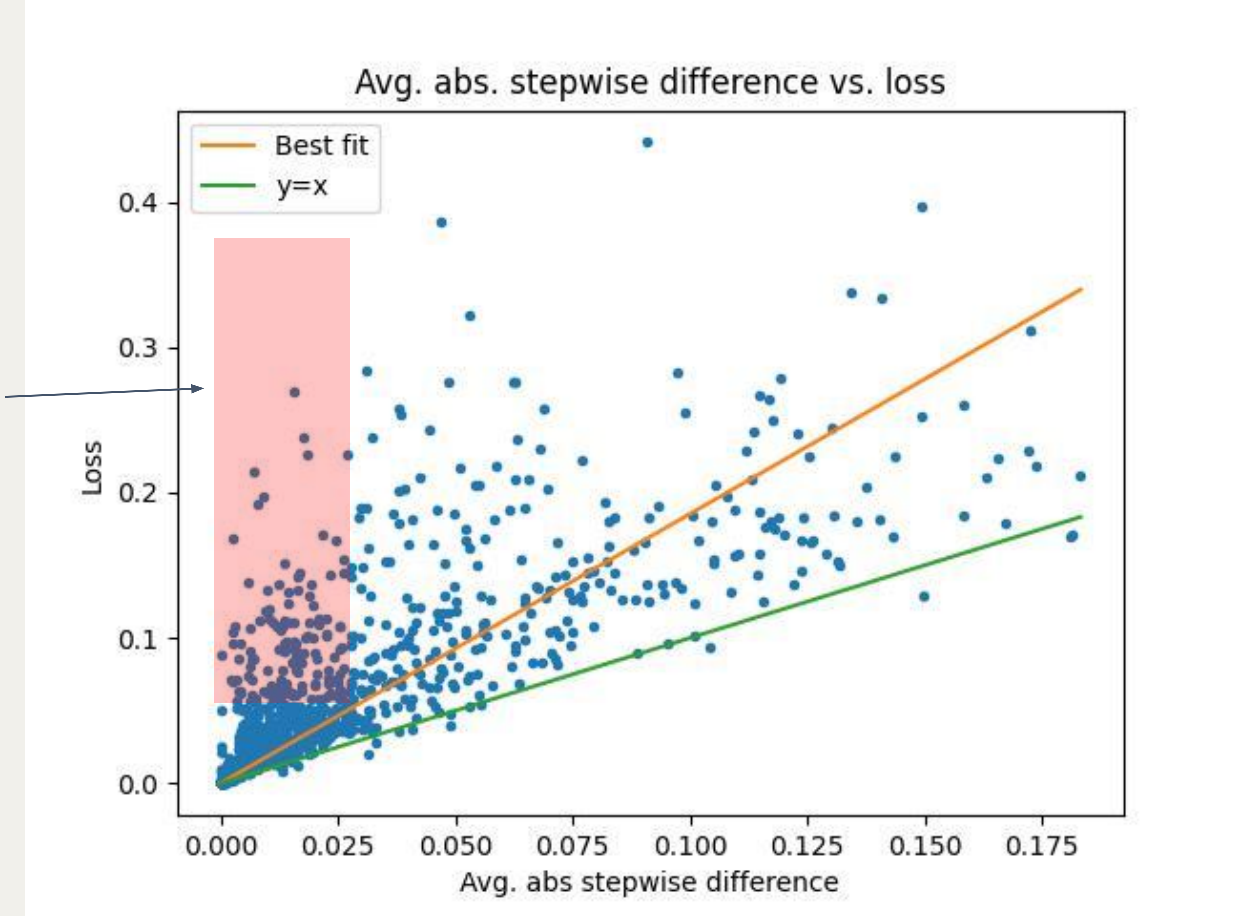
1. **Lightweight/Highly Deployable**
   a. Faster inference
   b. Lower Training Time
   c. Compact
2. Simplicity

Limitations

1. Only uses weather features, which has low time resolution
2. Is poorer at predicting volatile targets

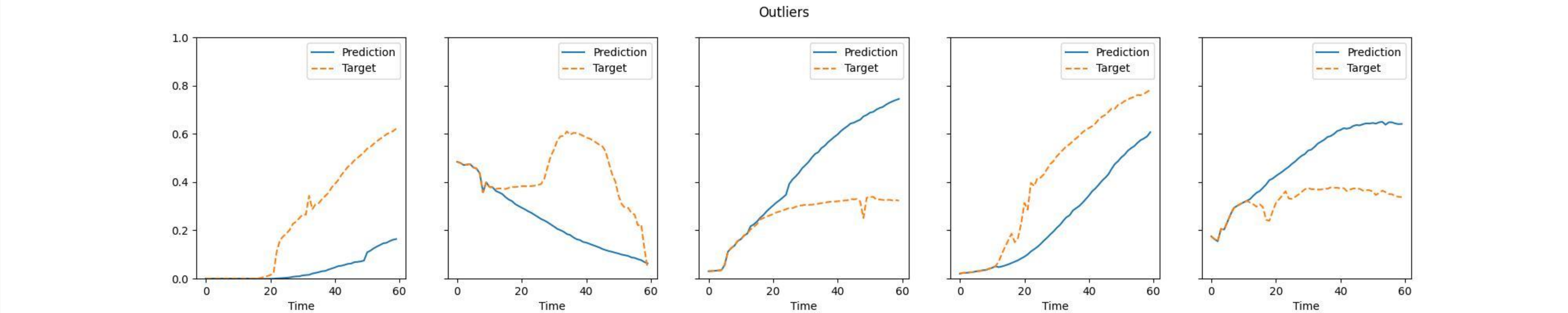
Advantages & Limitations

Region with unexpectedly poor performance



"Volatility"

Advantages & Limitations



Other Ideas Tried

Curve Fitting

- Fit a quartic curve to data per each month
- *Drawback: Does not account for imagery/site data*

K-Nearest-Neighbors

- Match data that is “similar” in various features (month, time, weather, hrv, etc.)
- *Drawback: Computational time increases linearly with number of dimensions and data-points used; can become very large.*

Sunlight Baseline

- Compute sun angle at time with lat., lon; combine with orientation and tilt to approximate amount of sunlight on solar panel
- *Drawback: Does not account for imagery/site data*

Expectation Maximization

- Used the same LSTM architecture but also predicted uncertainty; tried variety of distributions (normal, laplace, truncated normal/laplace)
- *Drawback: Performance was worse than normal LSTM*

Future Improvements

- Explore if larger model size (e.g. more combinations of variables) leads to better performance
  - Utilize more weather variables
- Explore optimal crop location and size
  - most important region not necessarily centered on site due to location of sun in sky
  - larger crops necessary for higher altitude features due to light diffusion
- Incorporate HRV with weather features (e.g. wind speed) to get better time resolution using optical flow

Future Improvements

- Investigate importance of aerosol and non-HRV data
- Predict difference from sunlight baseline
  - Force model to predict high time resolution variations
  - Handle smooth prediction with basic model
- Improve expectation maximization models so that performance is comparable to simpler model
  - Could be used to generate ensemble (take least uncertain predictions at each time step)

Overall Insights

- Importance of feature engineering & normalization
- Difficulty of determining influential parameters – importance of time ⇒ LSTM

Skills Developed

- Data pre-processing
- Setting up organized training modules and designing efficient training methods
- Implementing and evaluating different DL models in PyTorch

Thank You!

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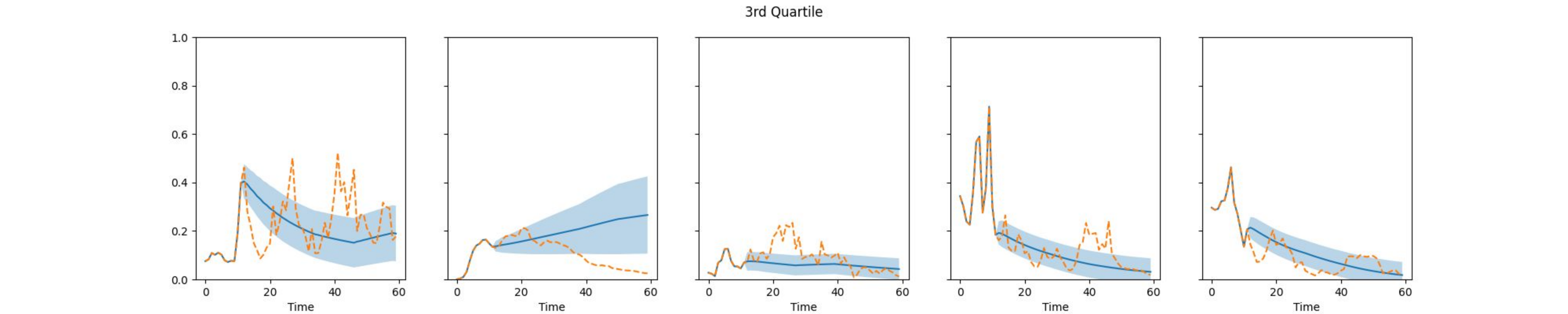
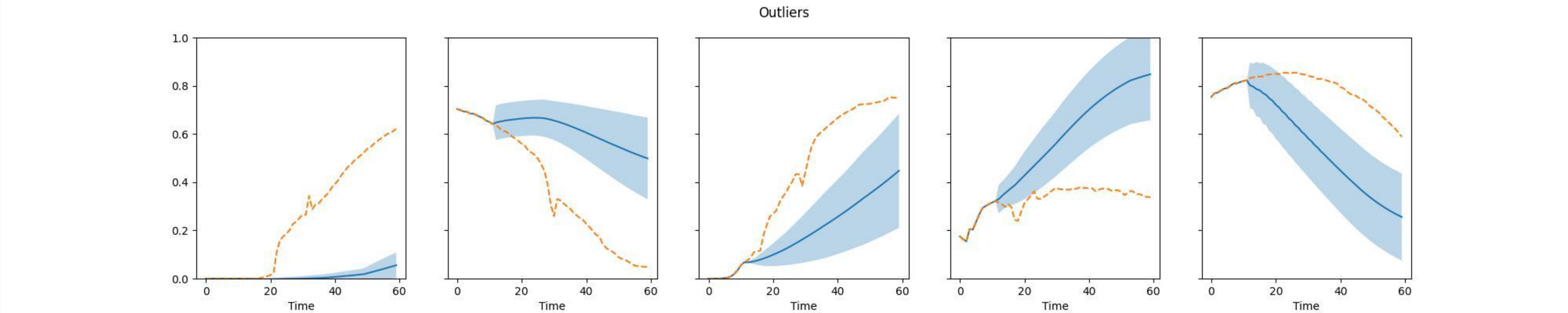

3rd Quartile
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
Time


Outliers
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
Time