



Intern Presentation

Incorporating Weather Data for PUE Prediction in LaRC Data Centers

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01/16/24



CENTER OPERATIONS DIRECTORATE



About Me

- ▶ Machine Learning Engineer Intern here at NASA Langley Research Center (LaRC) for Fall 2023
- ▶ Master's student in Computational Linguistics @ University of Washington (UW)
 - Machine learning (ML) applications for natural language
 - Intersection between Linguistics and Computer Science
 - Branch of linguistics that includes natural language processing (NLP)
- ▶ Previous:
 - Bachelor of Arts in Mathematics & Linguistics @ UW
 - NLP/ML engineer Intern at Customer Relations Management start-up
- ▶ Next:
 - NLP/ML engineer Intern at the AMES Research Center for NASA
 - Graduating Spring 2024

Fig 1. University of Washington. "The purple Block W logo of the University of Washington." 4 Feb, 2018, https://en.wikipedia.org/wiki/File:University_of_Washington_Purple_Block_W_logo.svg. Retrieved 3 Jan. 2024





Agenda

- ▶ **Project Introduction**

- ▶ **Weather Data:**

- Sources
- Automation

- ▶ **Power Usage Effectiveness (PUE) Modeling:**

- Data engineering
- Models
- Model Optimization
- Results



Project Introduction

► My project had two main parts:

1. Collecting LaRC local environmental weather data
 2. Model/estimate PUE using Machine Learning (ML) models
- Incorporate weather data into ML models



Fig. 1: Image from Microsoft Version 2208

PUE

► What is PUE?

- **Power Usage Effectiveness (PUE):** a metric used to measure the efficiency of a data center's energy consumption.
- Ideally, all the energy of a data center would be used to power the computing equipment, rather than for the cooling, heating, lighting, etc.
- Ideal PUE is 1.0

$$PUE = \frac{\text{Total Facility Energy}}{\text{IT Equipment Energy}} = 1 + \frac{\text{Non IT Facility Energy}}{\text{IT Equipment Energy}}$$



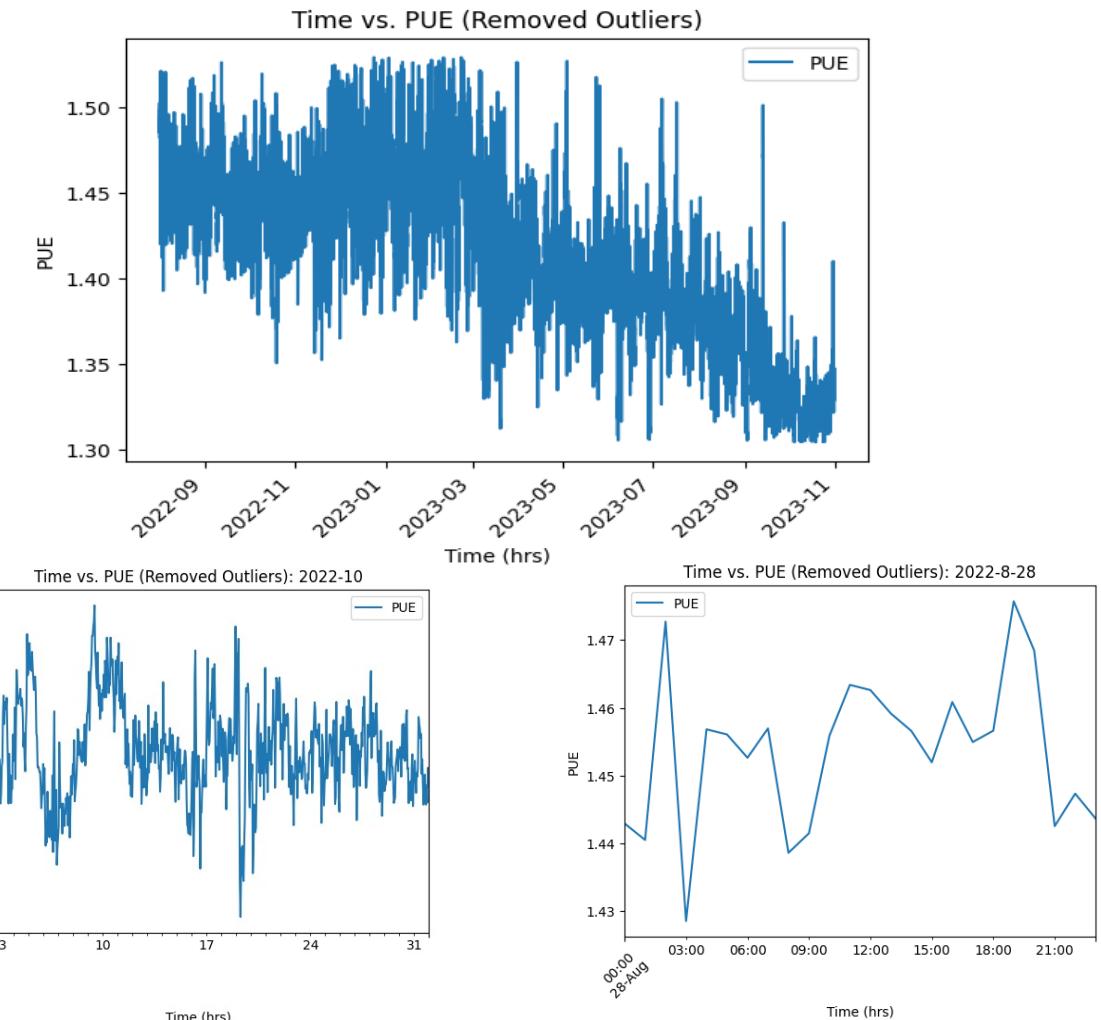
1.

Fig. 1: Image from Microsoft Version 2208



Problem Motivation

- ▶ **Decrease PUE to create efficient data centers**
 - How do we best use pumps, chillers, place thermal tiles, etc.?
- ▶ **PUE fluctuates/varies. A lot!**
 - ▶ PUE is highly dependent on environmental factors
 - ▶ How do we flatten the fluctuations?
- ▶ **Data center consolidation**
 - ▶ Decisions about which data centers to shut down, which to expand, etc.

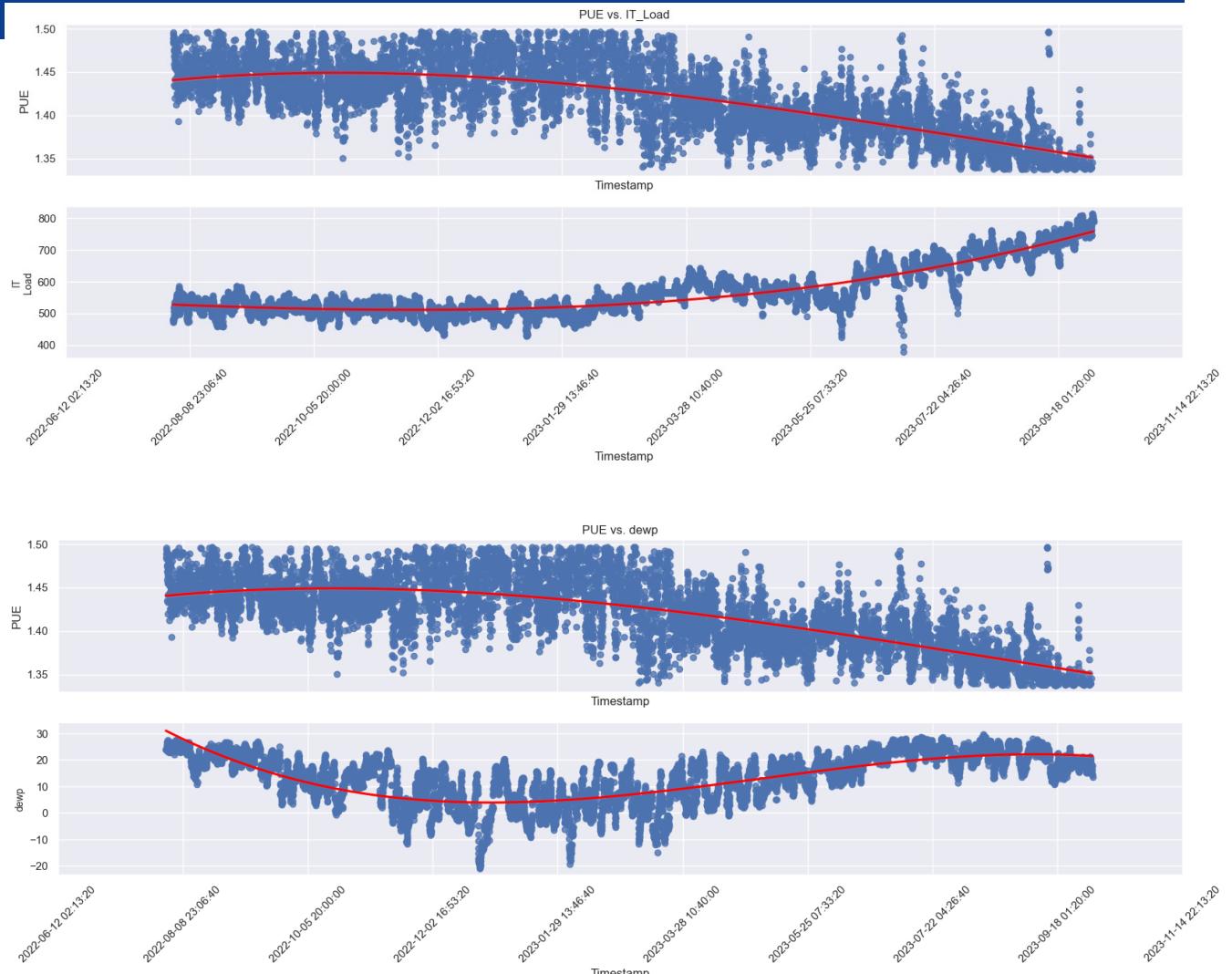




Problem Context

► Why is this a hard problem?

- ▶ PUE data fluctuates and varies greatly over time
- ▶ Limited PUE and data center data
 - ▶ Only have data from 08/01/2022
- ▶ Data center configuration constantly changing
 - ▶ IT Load correlated to PUE
 - ▶ Even thermal tile placement greatly impacts the PUE
- ▶ PUE highly subject to the current environment, e.g., weather





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- ▶ Weather Data Collection:
 - Sources
 - Automation
- ▶ PUE Modeling:
 - Data
 - Model engineering
 - Model Optimization
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Weather Data Sources

- ▶ **Langley Air Force Base (LAFB) (ICAO: KLF)**
 - ▶ Just next door to LaRC!
- ▶ **METeorological Aerodrome Report (METAR)**
 - ▶ Encoded **hourly weather data** pertinent to flying, e.g., temperature, dewpoint, wind speed, pressure, precipitation, etc.
 - ▶ **Automatically** produced weather encodings
- ▶ **Terminal Aerodrome Forecast (TAF)**
 - ▶ Issued about every **6 hours**
 - ▶ Forecast good for the **next 24 to 30** hours for about a **5 mile radius** of LAFB
 - ▶ Created **manually** by a weather forecaster



Fig. 1: Image from Microsoft Version 2208



Aviation Weather Center

- ▶ Aviation Weather Center (AWC) provides weather updates for the purpose of aviation.
- ▶ Data API
 - ▶ The Aviation Weather Center hosts their own data API @ aviationweather.gov/data/api
 - ▶ Pull aviation related weather for **the last 15 days** using **Python code!**
 - ▶ Returns **Json** files!

The screenshot shows the Aviation Weather Center's Data API page. At the top, there is a navigation bar with the AWC logo, the text "Aviation Weather Center", and dropdown menus for "Weather", "Products", "Tools", and "Connect". On the far right of the navigation bar are icons for envelope, user profile, and help. Below the navigation bar, the page title is "Data API". A descriptive paragraph explains that the service facilitates machine-to-machine access to aviation weather information, allowing users to learn about available data, configure specific queries, and try them out. It notes that the weather database currently allows access to the previous 15 days of data. A note at the bottom asks users to keep requests limited in scope and frequency, suggesting the use of cache files. The main content area is titled "Data Decoded weather and navigational information". It lists four API endpoints: 1. GET /api/data/metar METARS 2. GET /api/data/taf TAFs 3. GET /api/data/pirep Pilot Reports 4. GET /api/data/airsigmet Domestic AIRMETs/SIGMETs. Each endpoint is shown in a blue button-like box with a downward arrow icon to its right.



Automated Weather Data Collection

► Gcloud Scheduler

- ▶ Creates the Gcloud pub/sub topic once every hour

► Gcloud pub/sub topics

- ▶ Triggers the Gcloud function

► Gcloud functions

- ▶ To run python script which pulls weather data Json file from aviationweather.gov data API

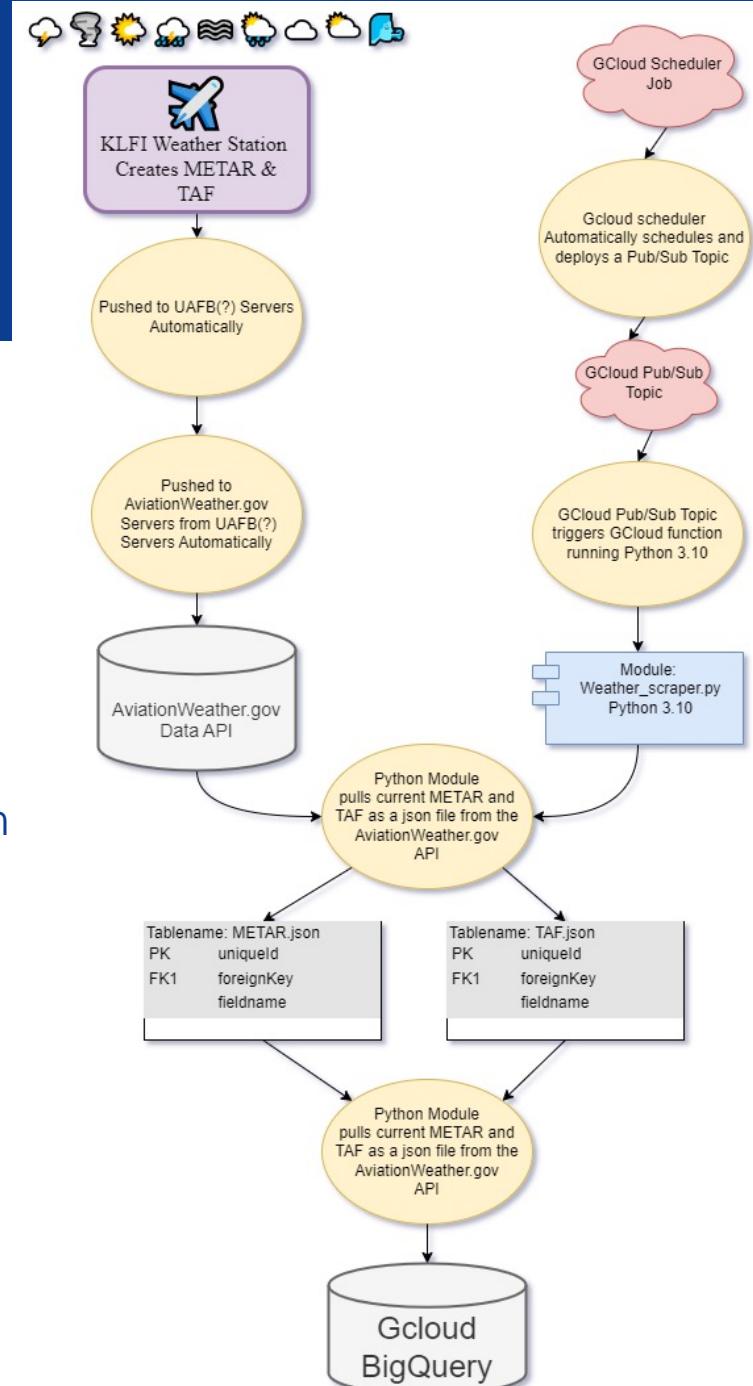
► Gcloud Source Repositories

- ▶ For versioning and version control

► Gcloud BigQuery

- ▶ To store the weather data

► TODO: Deployment!





Agenda

- ▶ Project Introduction

- ▶ Weather Data Collection:

- Sources
 - Automation

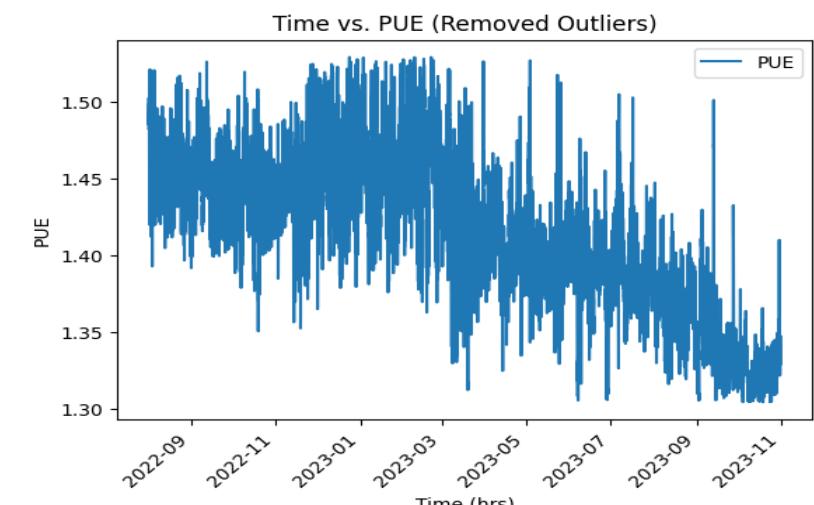
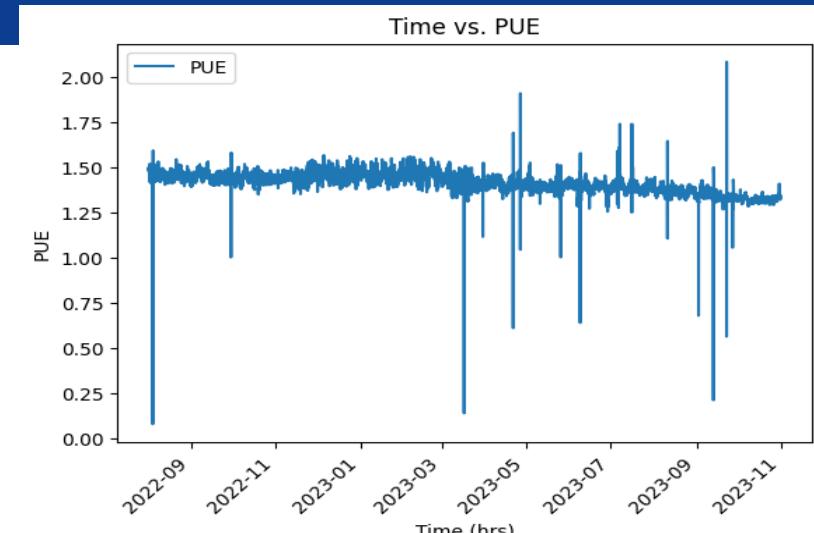
- ▶ PUE Modeling:

- Data Engineering
 - Model engineering
 - Model Optimization
 - Results



Data Center Energy Consumption Data

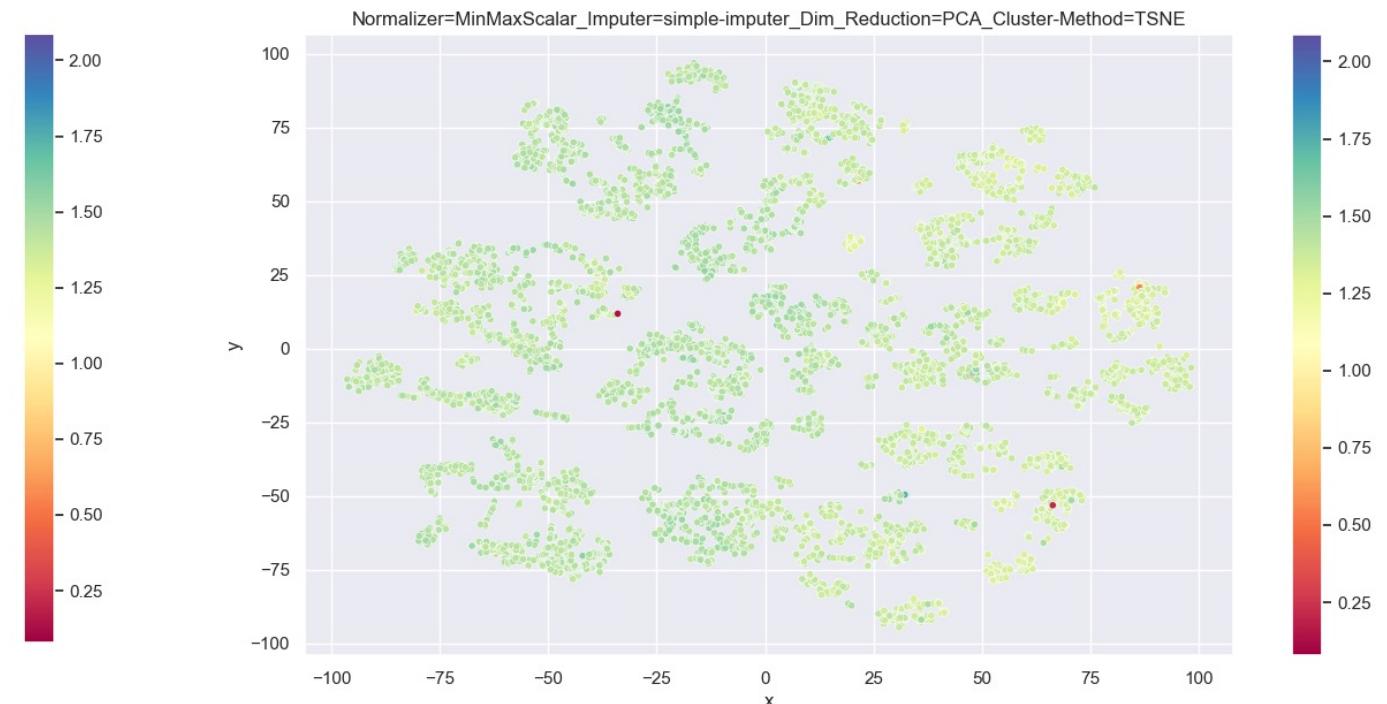
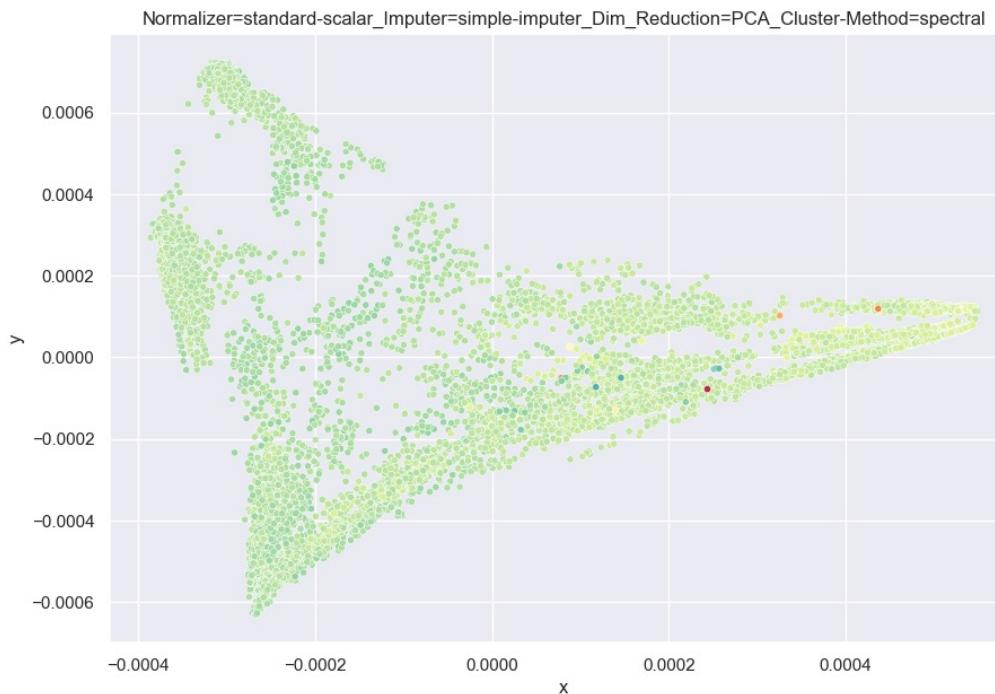
- ▶ Just over 1 year of data center energy consumption data
 - ▶ From 08/01/2022 – 10/31/2023
- ▶ Data includes energy consumption and data center configuration
 - ▶ water pumps, chillers, cooling fans, heaters, etc.
 - ▶ Most importantly, includes the PUE!
- ▶ Sample hourly readings of PUE and data center conditions.
- ▶ Joined with the hourly weather METAR data!
- ▶ Data corresponding to PUE outliers in the bottom 2% and top 2% were removed





Data Visualization

- ▶ Can we make sense of the joint dataset?
 - Dimensionality Reduction & Data visualization techniques...



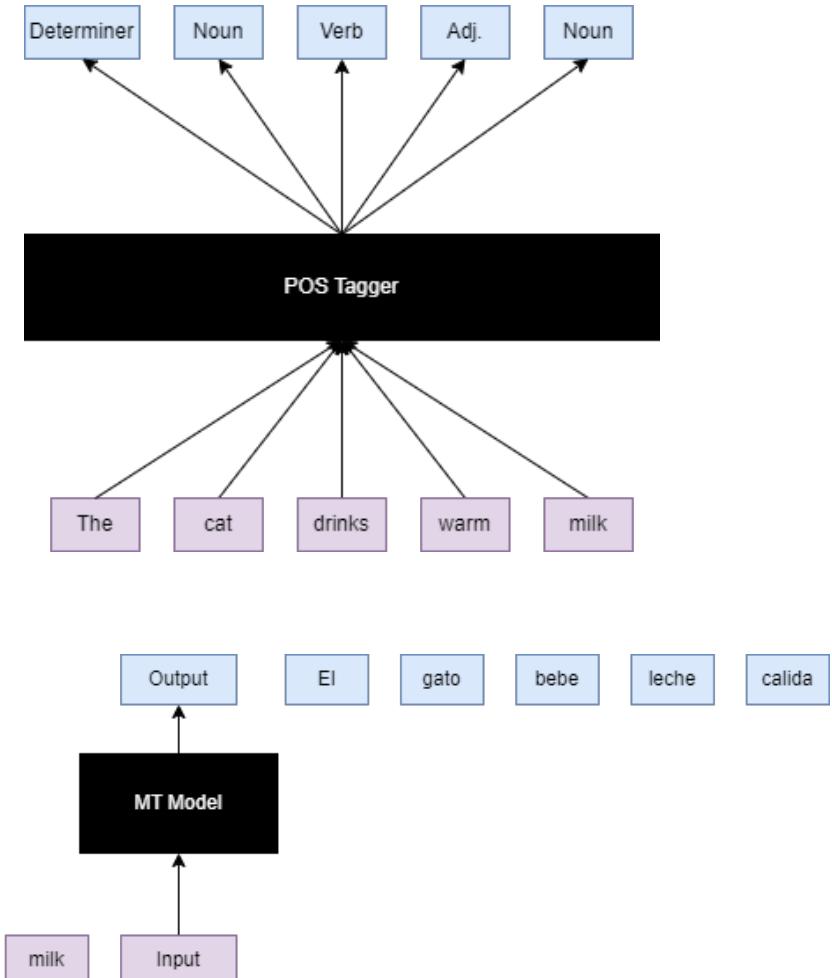
Feature Engineering

- ▶ This data does NOT contain information about changes to the data center, e.g.
 - ▶ IT Load
 - ▶ Replacement of old inefficient hardware
 - ▶ Reconfigured thermal tiles
- ▶ **Problem: How do we get a model to expect such changes in infrastructure, or usage patterns and continue to be able to accurately predict the PUE?**



Approach

- ▶ Problem: Given n timesteps worth of data, can we predict the next n timesteps of PUE?
- ▶ As a computational linguist...
 - I thought of this as a **supervised** problem, we already have the PUE!
 - I thought of this problem as a **machine translation (MT)** problem, or **part-of-speech (POS)** tagging problem
 - One time stamp of data (both data center consumption & weather data) is analogous to a **word embedding**
 - Word embedding: A vector representation of an individual word capturing semantic information about that individual word.
 - The sequence of next n timesteps of PUE is analogous to the translated sentence, or the sequence of part-of-speech tags!





RNNs

- ▶ Recurrent Neural Networks (RNN) work with sequential data
- ▶ Two types of RNNs: Vanilla RNN vs. Long Short-Term Memory (LSTM)

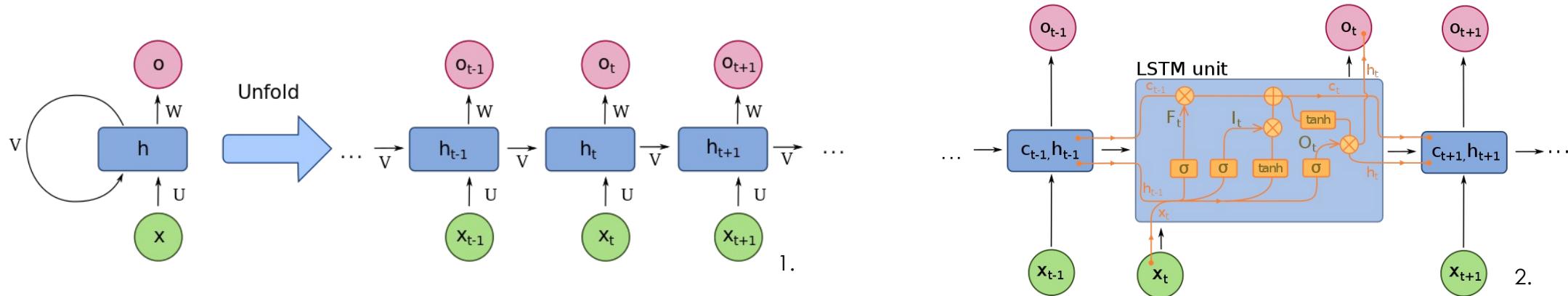


Fig 1. fde洛che, CC BY-SA 4.0 <<https://creativecommons.org/licenses/by-sa/4.0/>>, via Wikimedia Commons, https://upload.wikimedia.org/wikipedia/commons/b/b5/Recurrent_neural_network_unfold.svg

Fig 2. fde洛che, CC BY-SA 4.0 <<https://creativecommons.org/licenses/by-sa/4.0/>>, via Wikimedia Commons, https://upload.wikimedia.org/wikipedia/commons/6/63/Long_Short-Term_Memory.svg



Models

► Vanilla Recurrent Neural Network (RNN)

- ▶ One weight matrix
- ▶ Con: Vanishing/Exploding Gradient Problem
- ▶ Con: Only able to rely on the previous timestamp

Vanishing Gradient:

$$w' = w - \alpha \nabla L(w)$$

$$\nabla L(w) = 0$$

► Sequence to Sequence Long Short-Term Memory (Seq2Seq LSTM)

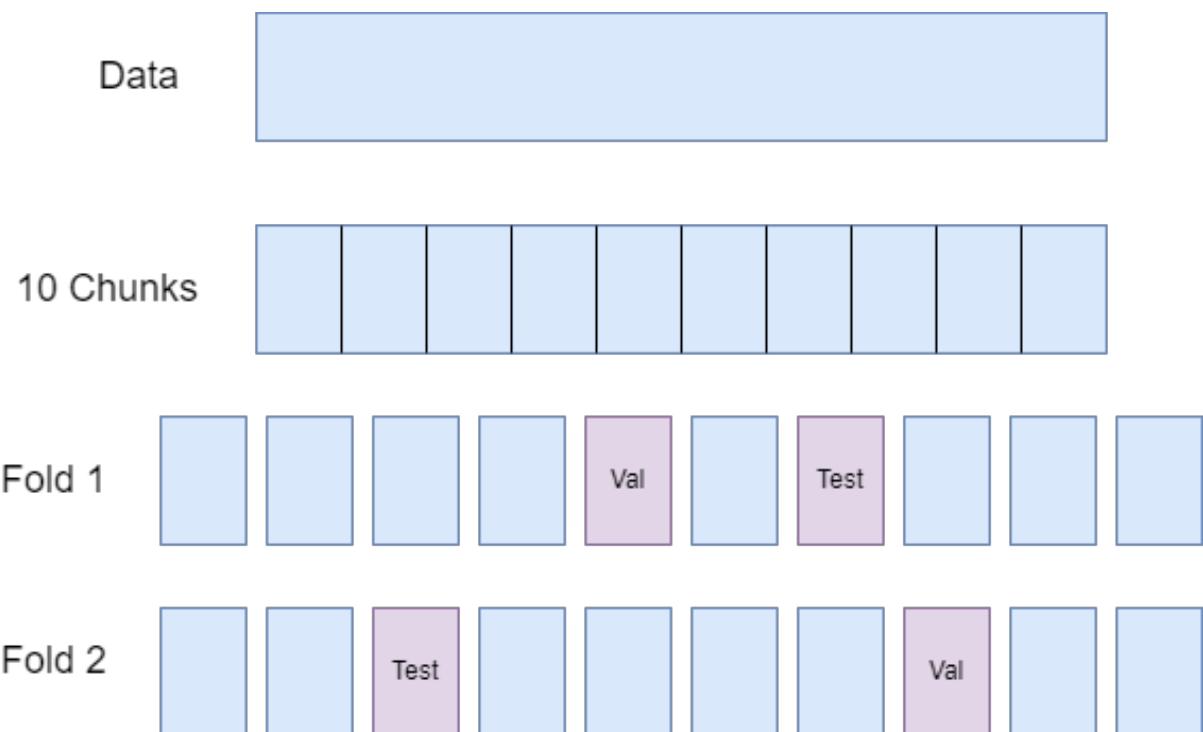
- ▶ Seq2Seq architecture contains an encoder and a decoder (two weight matrices instead of one)
- ▶ LSTM: Solves Vanishing/Exploding Gradient Problem
- ▶ LSTM: Memory cell retains information from much earlier timestamps

► Both

- ▶ Recurrent Neural Network architectures
- ▶ Input: timeseries sequence of N timestamps of data
- ▶ Output: corresponding predicted sequence of PUE
- ▶ Loss: Used Mean Squared Error

Hyper-parameter Tuning: Validation

- ▶ Testing different hyper-parameter combinations
 - ▶ K-Fold Cross Validation (K = 5)
 - ▶ Split the data into 10 even chunks
 - ▶ Choose one chunk as the **test** set
 - ▶ Choose a different chunk as the **validation** set
 - ▶ Remaining 8 chunks concatenated as **train** set
 - ▶ For each fold:
 - ▶ Trained on train set
 - ▶ Inferred on the validation and test set
 - ▶ Loss scores between folds were aggregated (mean) to account for run variability



Hyper-parameter Tuning: Random Search

► Why Random Search

- ▶ Hyper-parameter search space is very large
- ▶ Using K-Fold Cross Validation (multiplied # of combinations by K)
- ▶ Only used CPU

► Random search randomly picks a subset of hyperparameter combinations

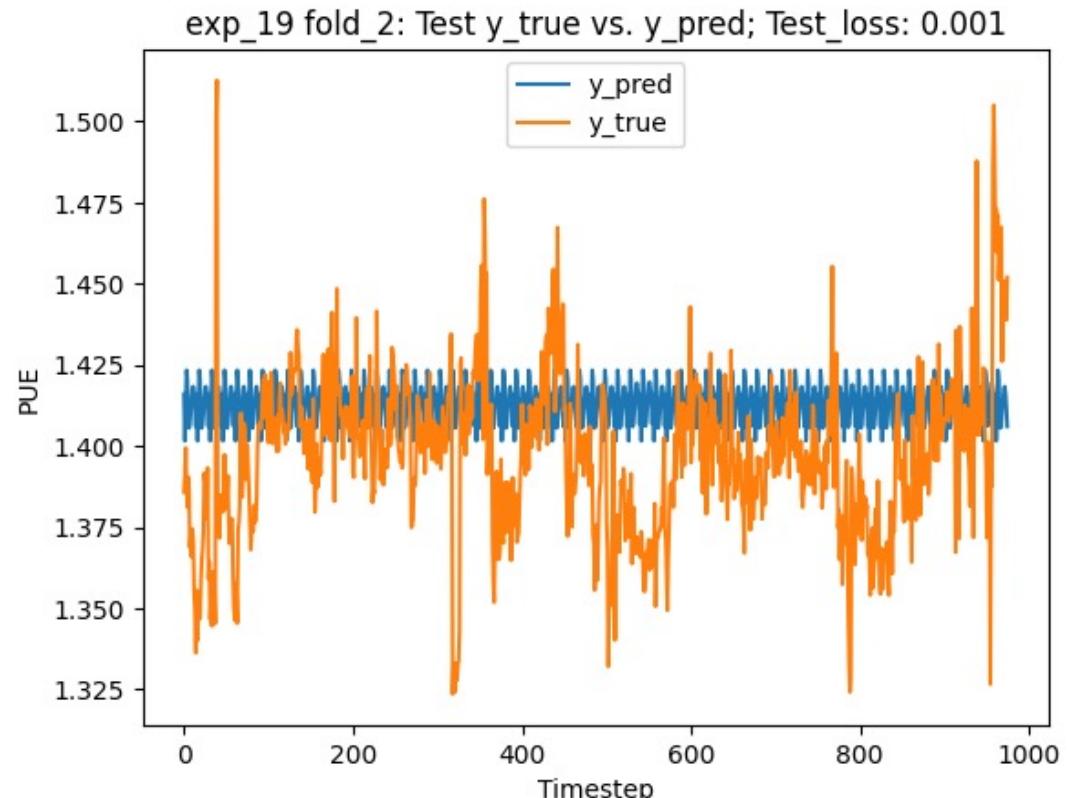
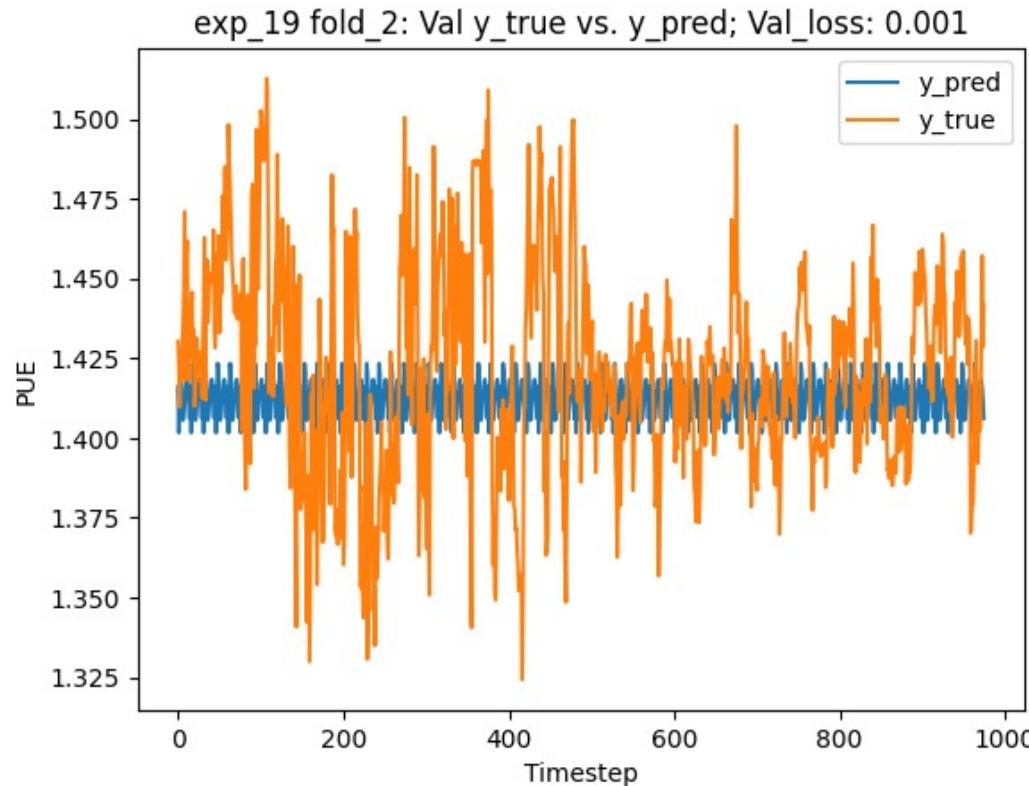
- ▶ Vanilla RNN: tried 20 different models
- ▶ Seq2Seq LSTM: tried 88 different models



Results

► Sometimes good loss scores do not mean good results

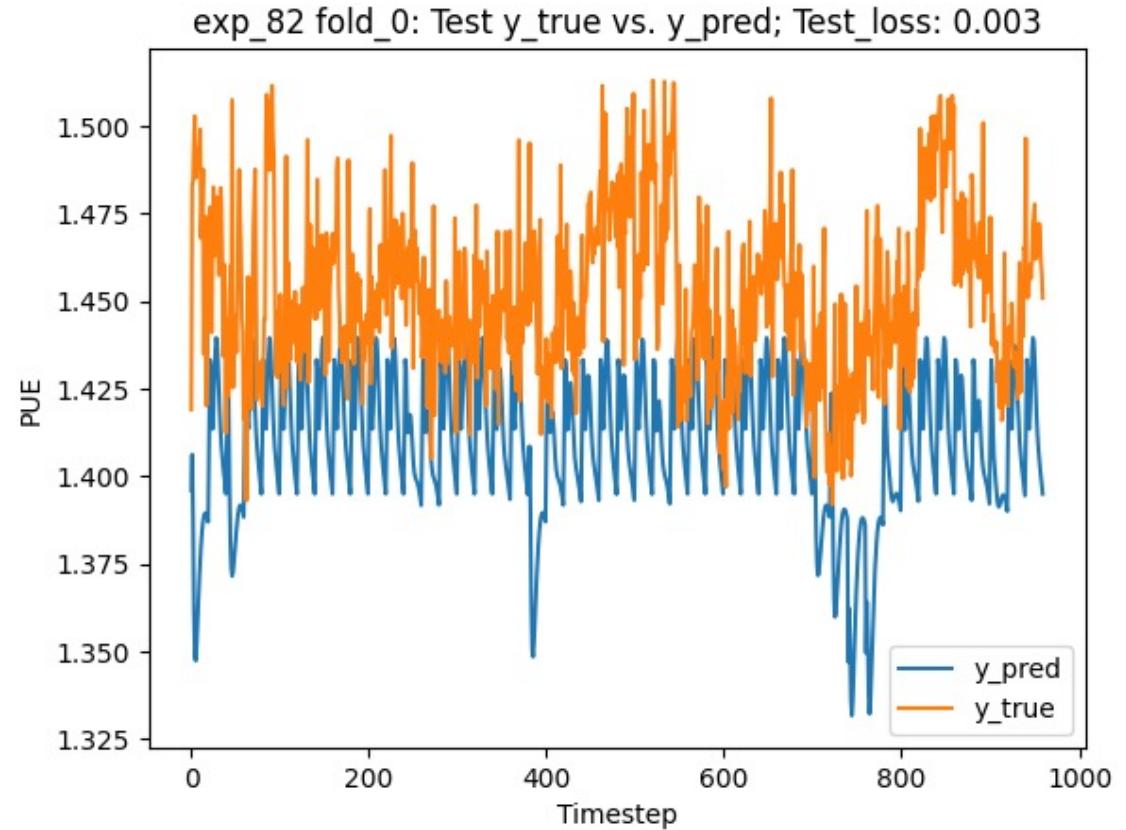
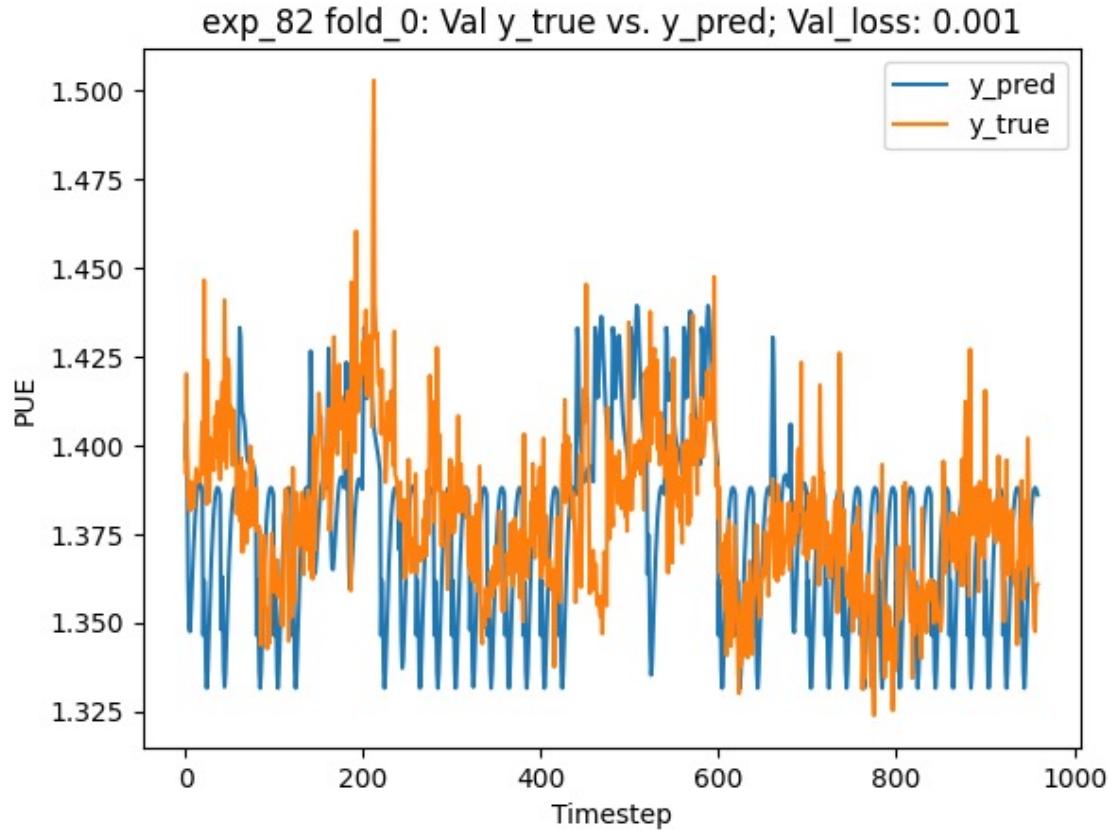
- Model would perform well when only predicting the mean PUE score over the whole val or test set





Results II

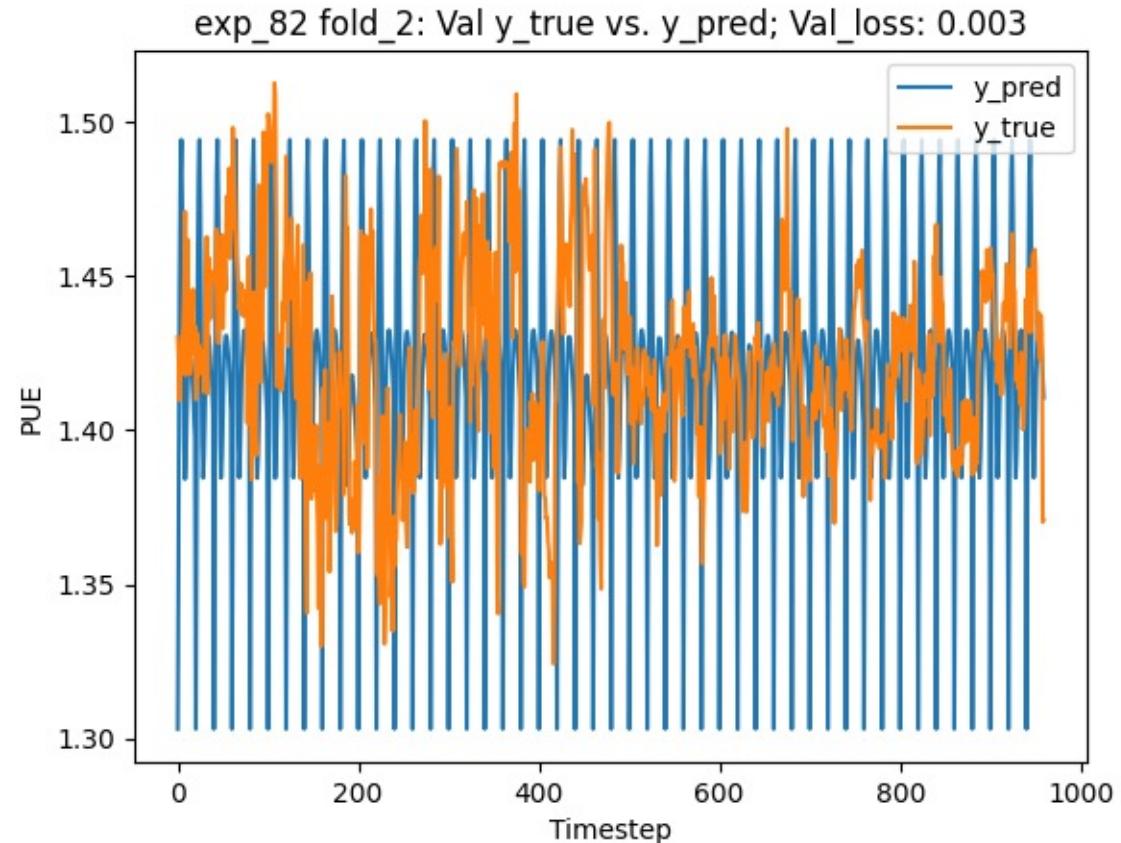
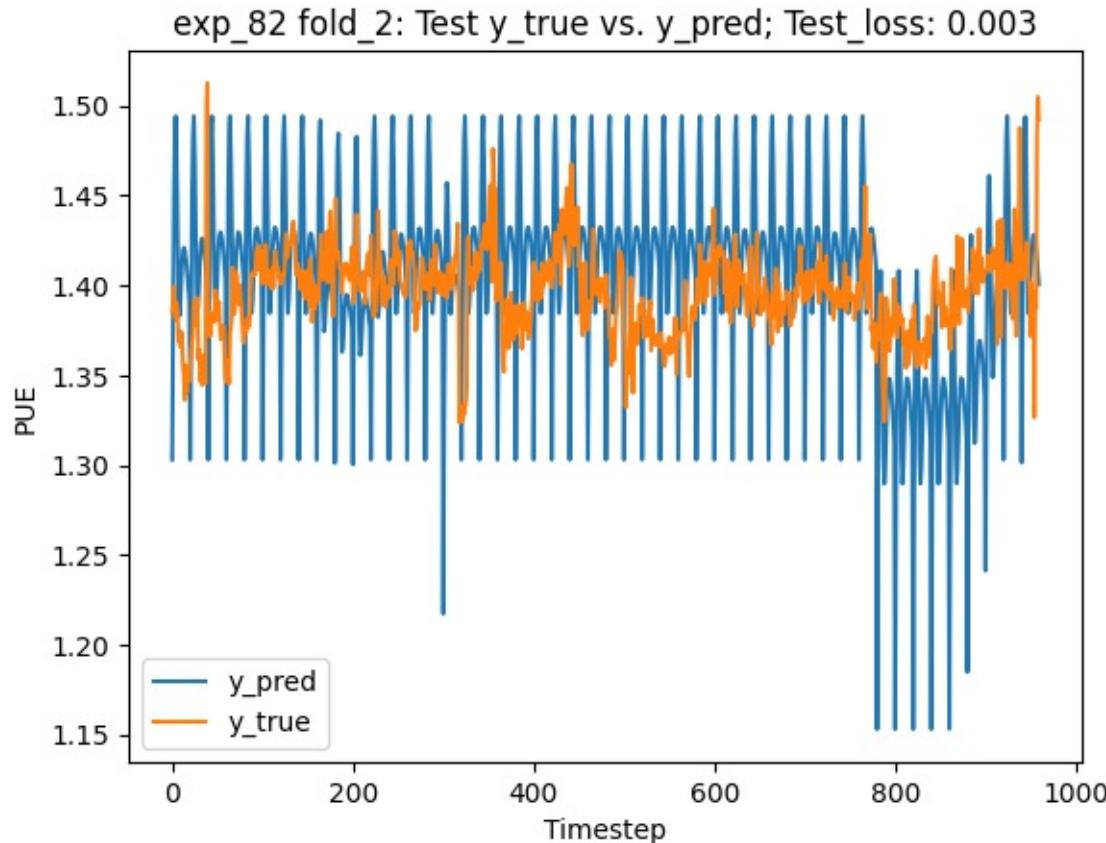
- Sometimes results varied very widely between folds





Results II

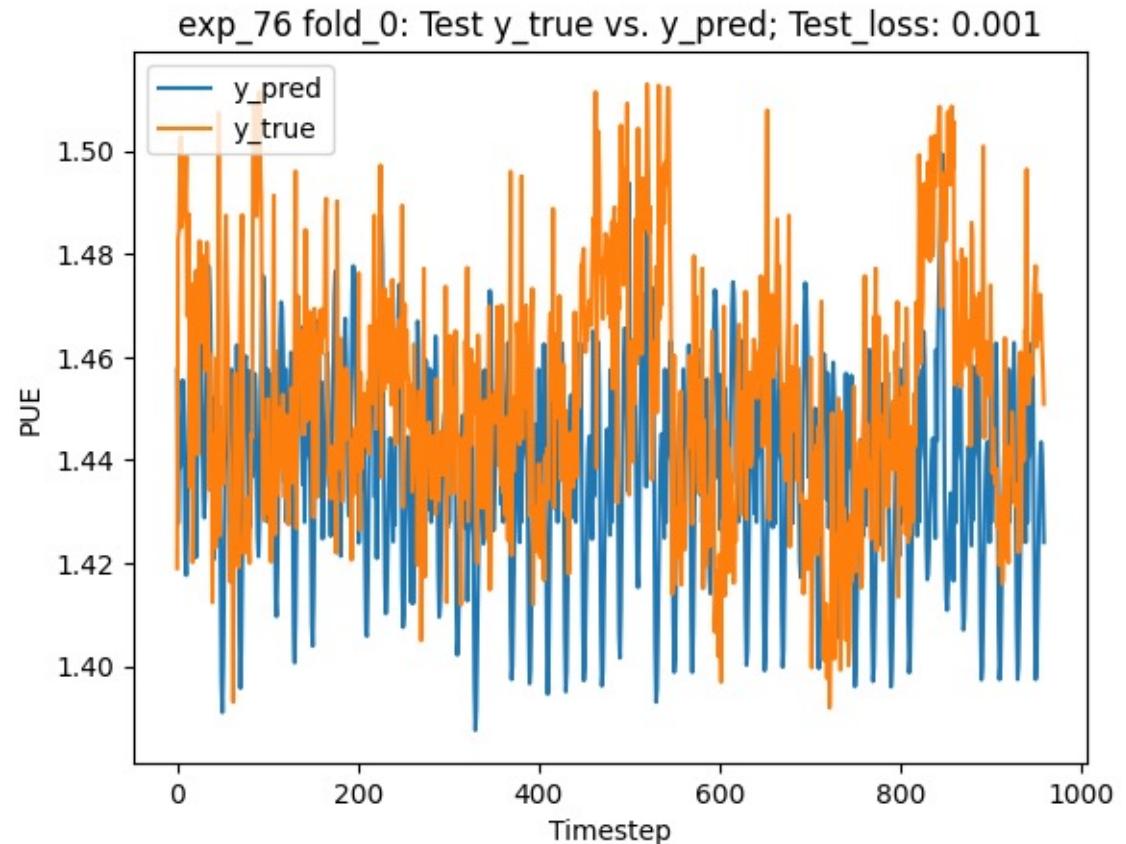
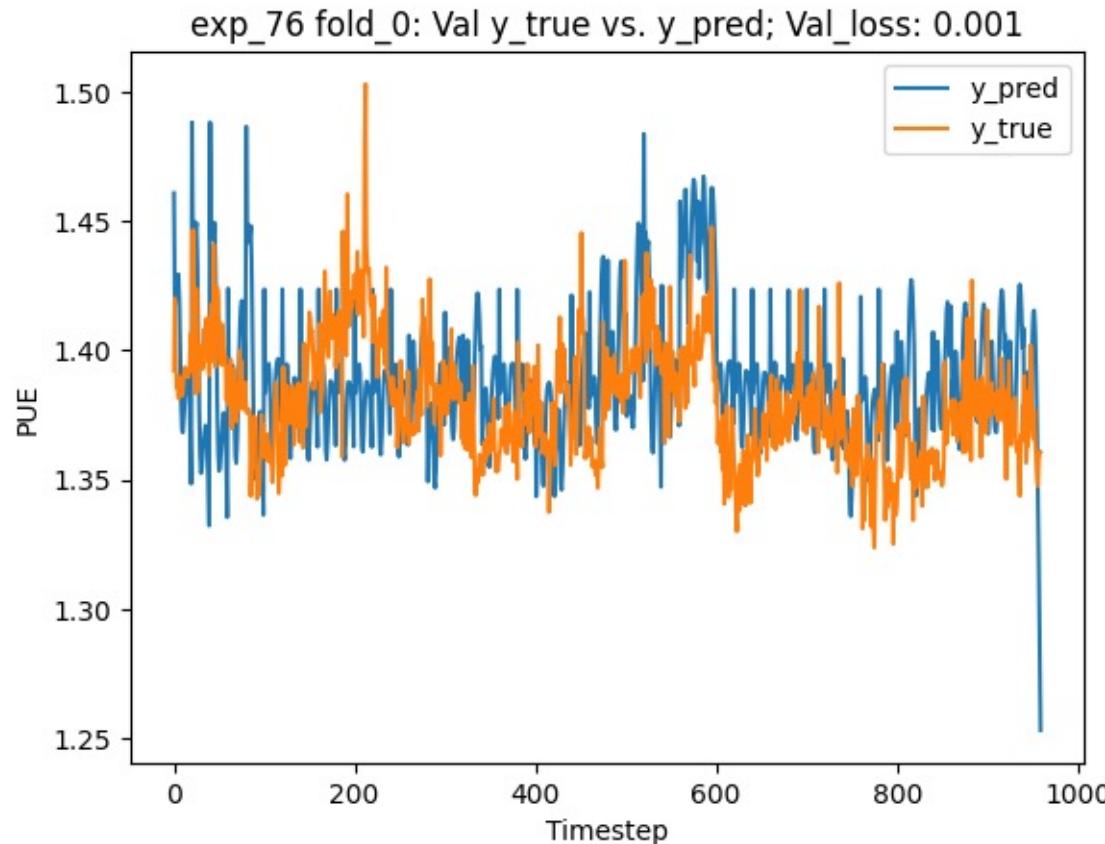
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Results III

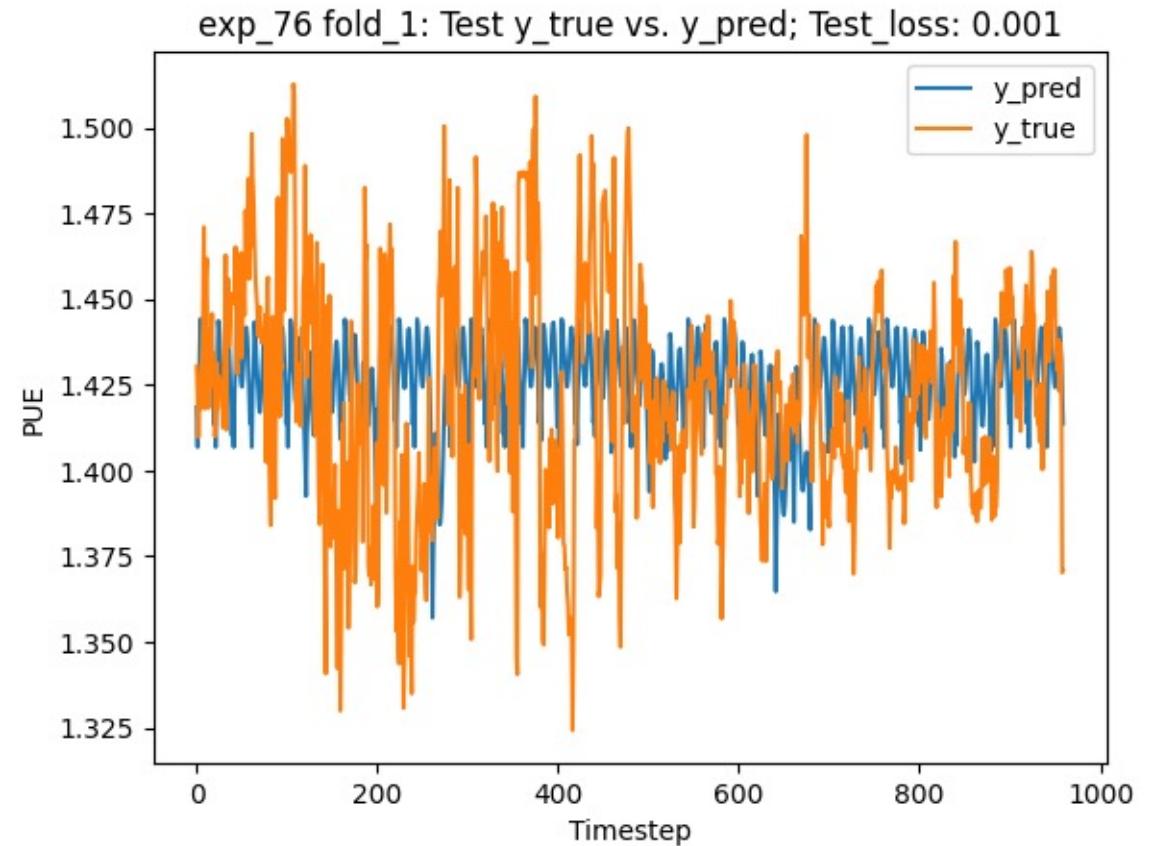
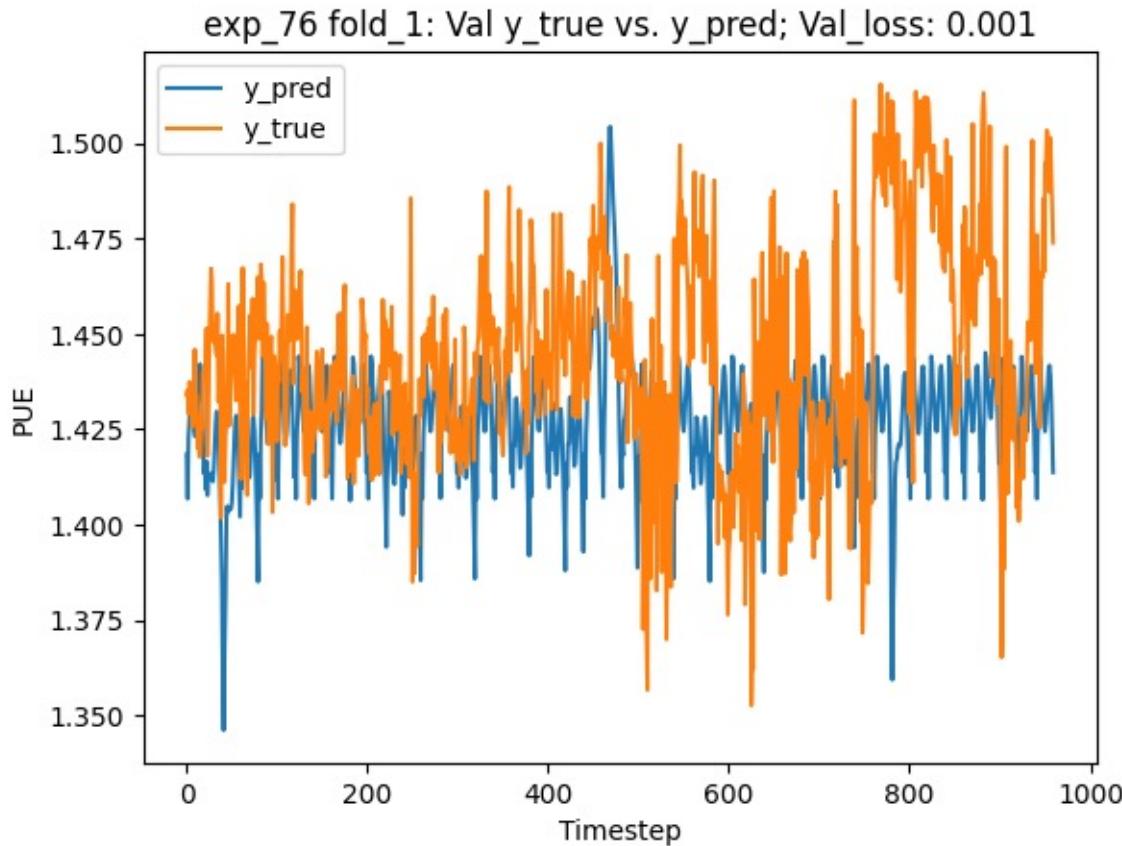
- Sometimes results look pretty good





Results III

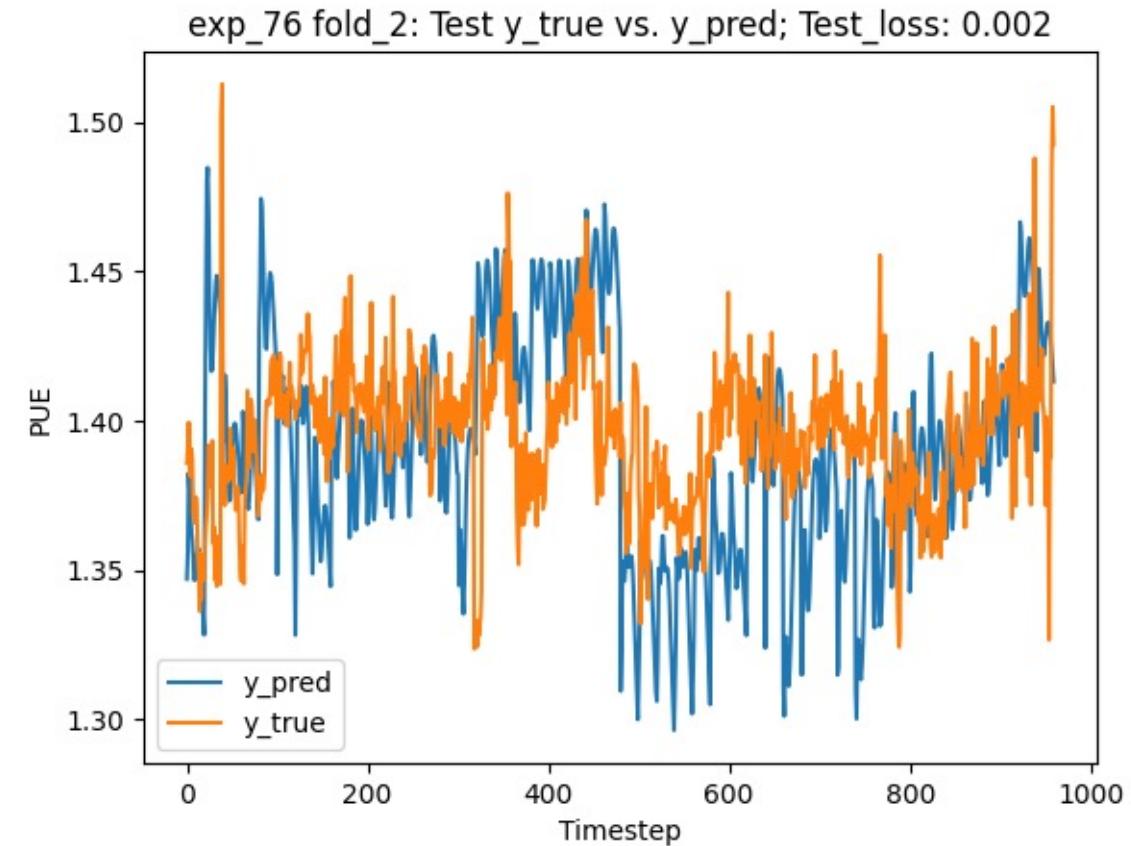
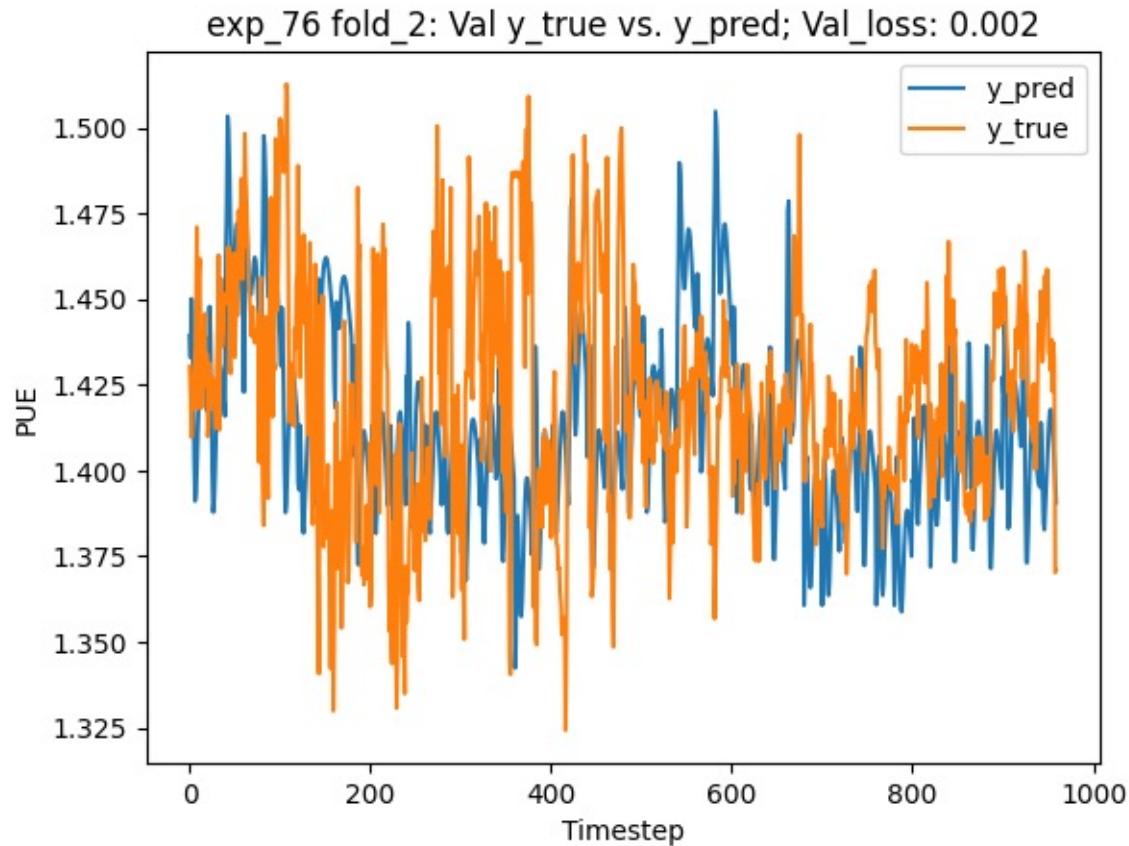
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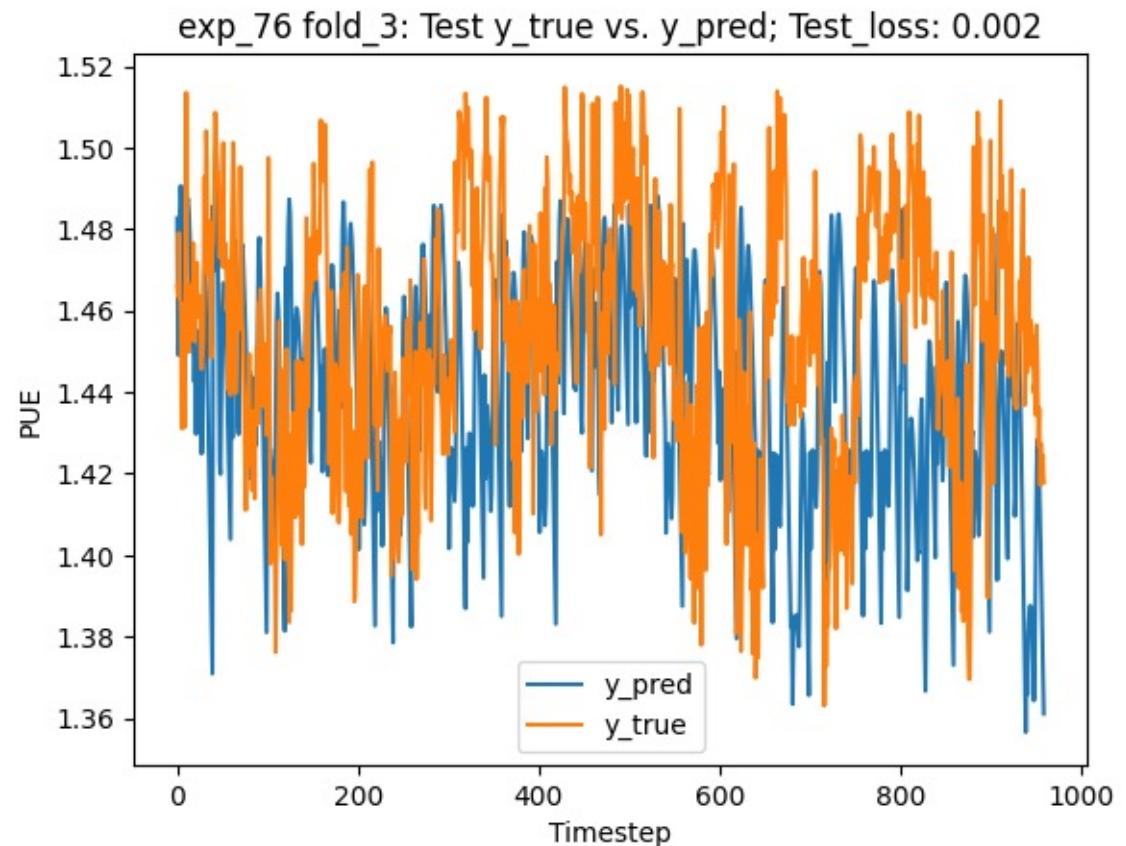
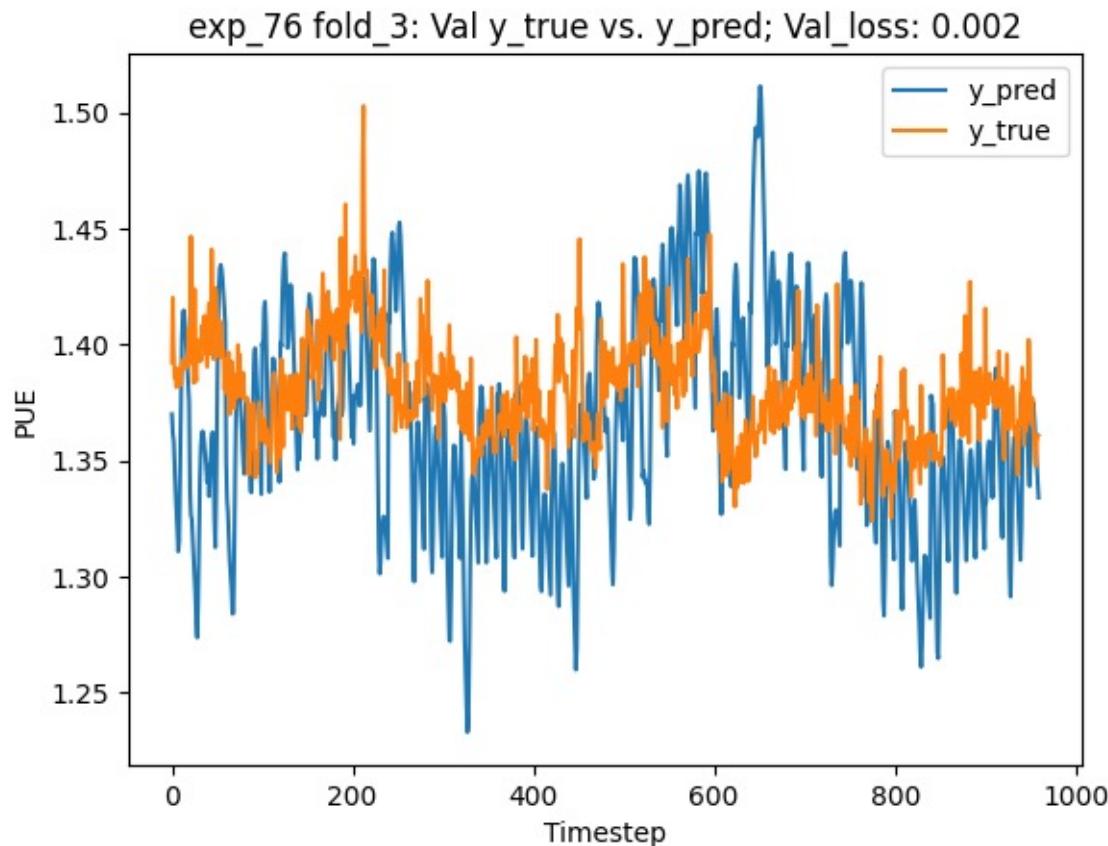
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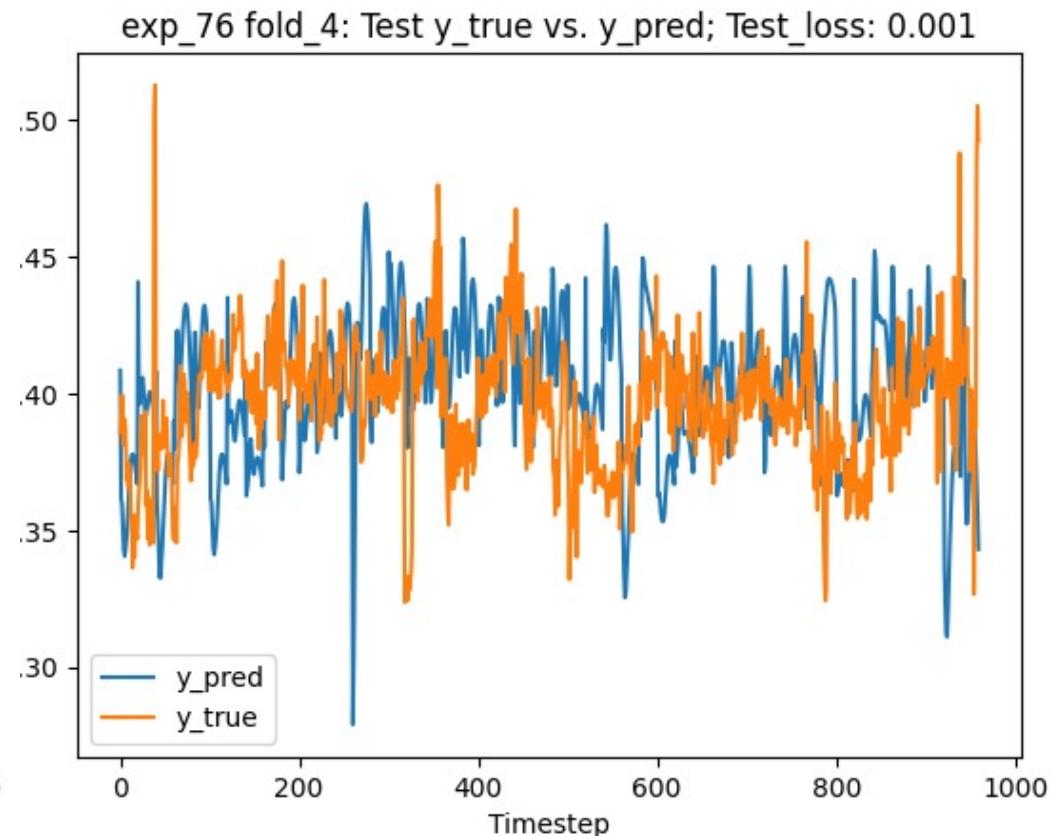
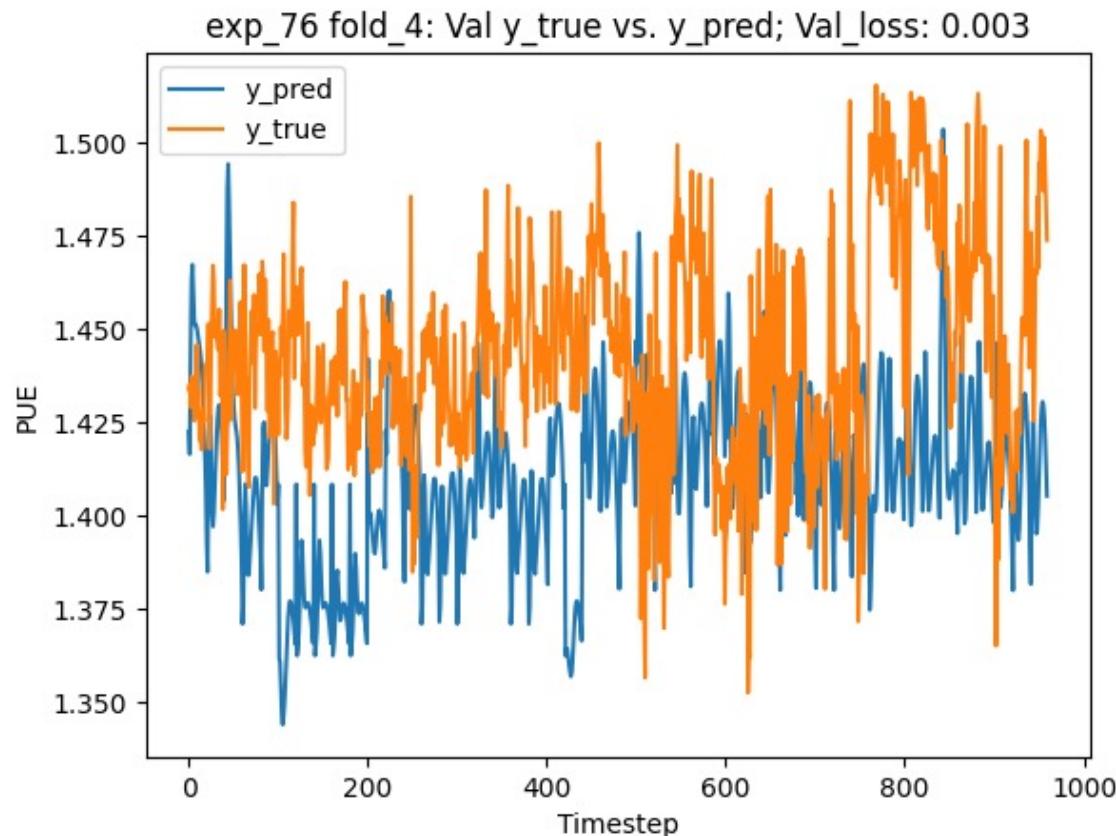
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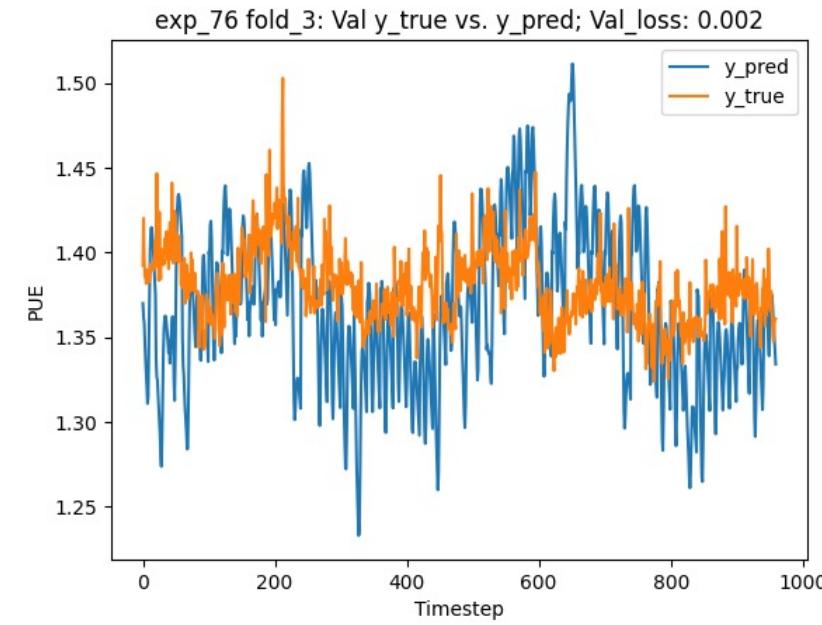
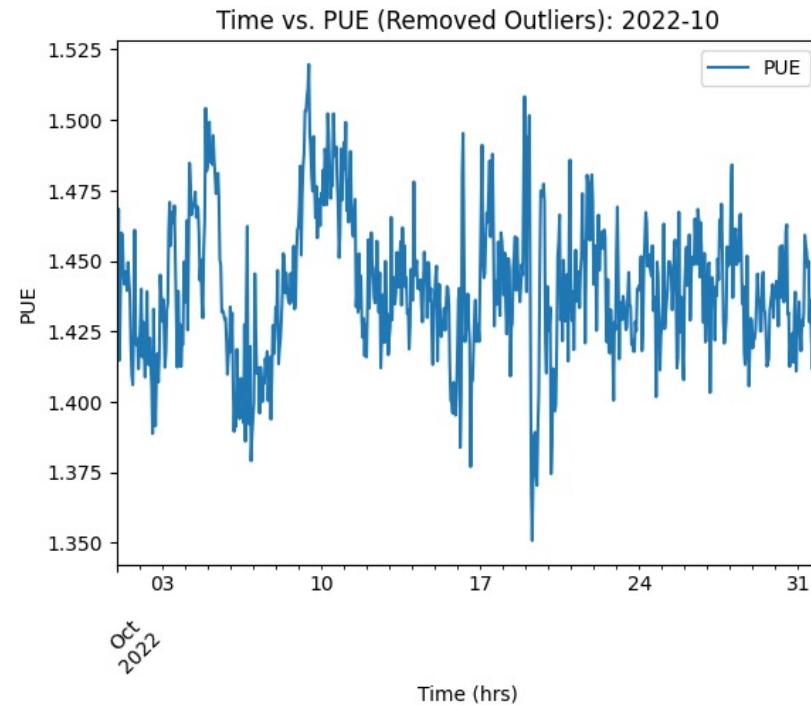
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Results IV

- ▶ You may have noticed the predicted PUE fluctuates quite a bit and is very “spiky”
- ▶ Hypothesis: The PUE data fluctuates quite a bit → model has learned this behavior
- ▶ This could be a problem





Future Work

- ▶ **Do more thorough examination of salient and pertinent weather features**
- ▶ **Other inputs**
 - Is it a work day? Is it evening?
- ▶ **Figure out which hyper-parameters affect the model performance the most**
- ▶ **Try other models such as a transformer model**
- ▶ **Consider new model features to account for data center reconfiguration**
 - e.g., What happens to the PUE if we add a new data server?

Acknowledgements

► Many thanks to...

- Charles Liles, Project Mentor
- Langley Transformation Initiative
- LaRC Center Operations Directorate
- LaRC Integrated Operations Center
- Guardians of Honor
- Mark Pugh, Stephen Fehr, Danny Morris for meeting Charles and I to discuss the data center energy consumption and how to better model PUE
- Mike Mueller and his son Thomas Mueller for getting me a working NASA laptop after everything that happened

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