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Online Learning for Energy Consumption Forecasting in Heavy-Duty Electric Vehicles

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Introduction

- Design tailor-made online learning strategies
  - Forecasting energy consumption
  - Auxiliary systems in heavy-duty bettery electric vehicles
  - EV range prediction, route/charging planning
- Batch learning is not ideal, variabilities in training and testing population
  - Dynamic environment, transportation tasks, component wear etc.
- Can online learning further improves forecasting performances?
  - Trip Sequences collected from HD-BEVs operation
  - Expore and test online learning strategies and parameters
  - Real-time, on edge device
    - Performance and resource trade-offs

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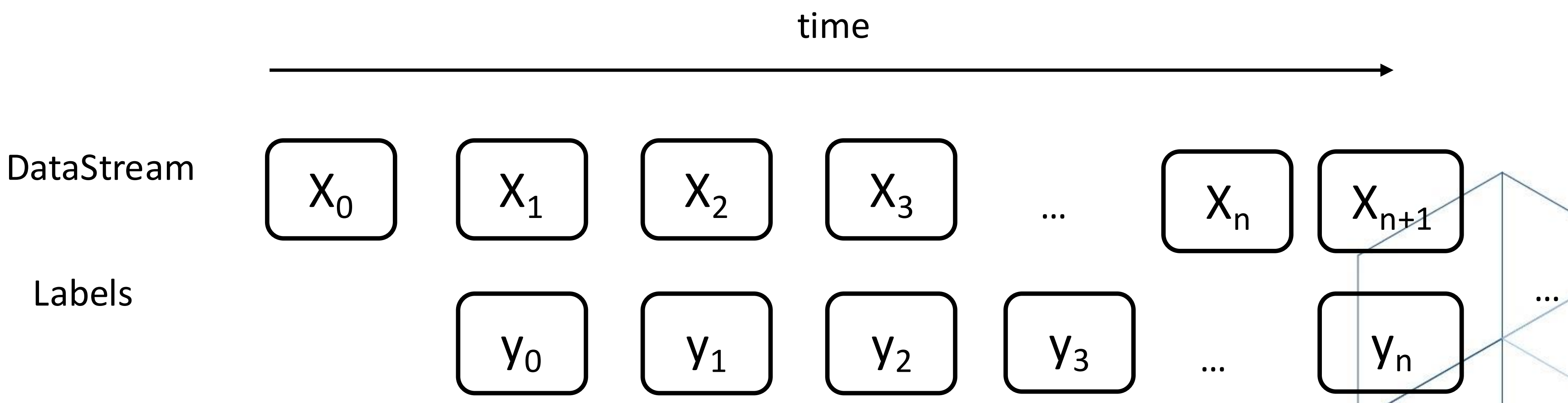
Online Learning

- Delayed labels
    - Prediction Horizon



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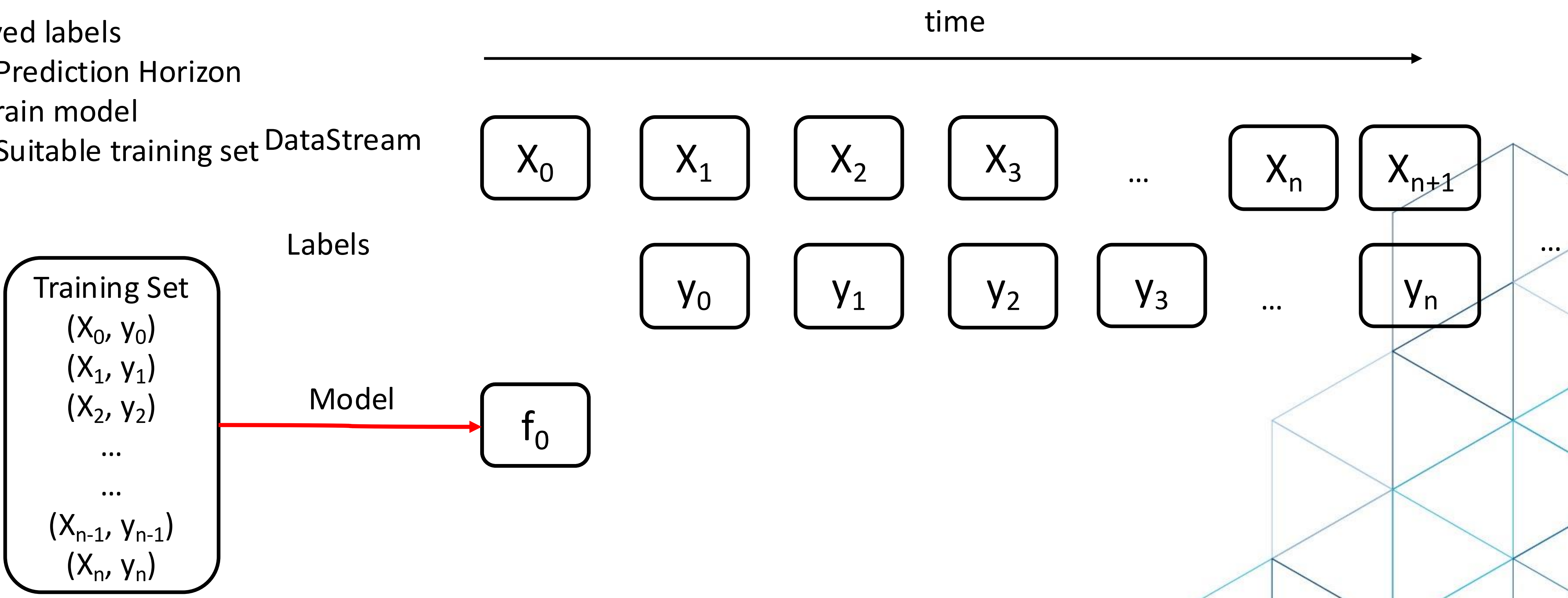
Online Learning

- Delayed labels
  - Prediction Horizon
- Pre-train model
  - Suitable training set



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Online Learning

- Delayed labels
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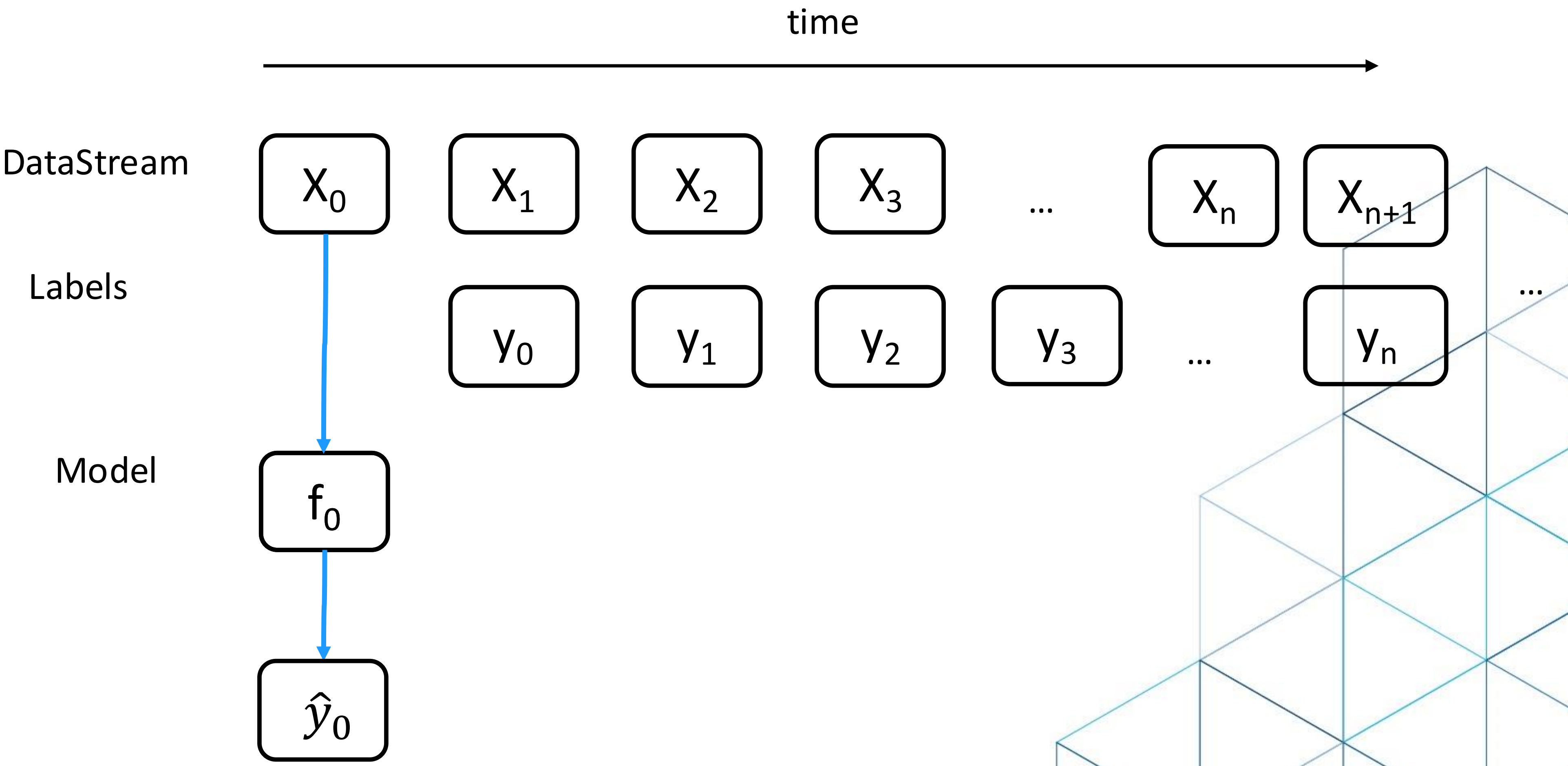
- Online Learning
  - Initialize Predictor
  - Forecast given the streaming sample
    - $\hat{y}_t = f(X_t)$



Online Learning

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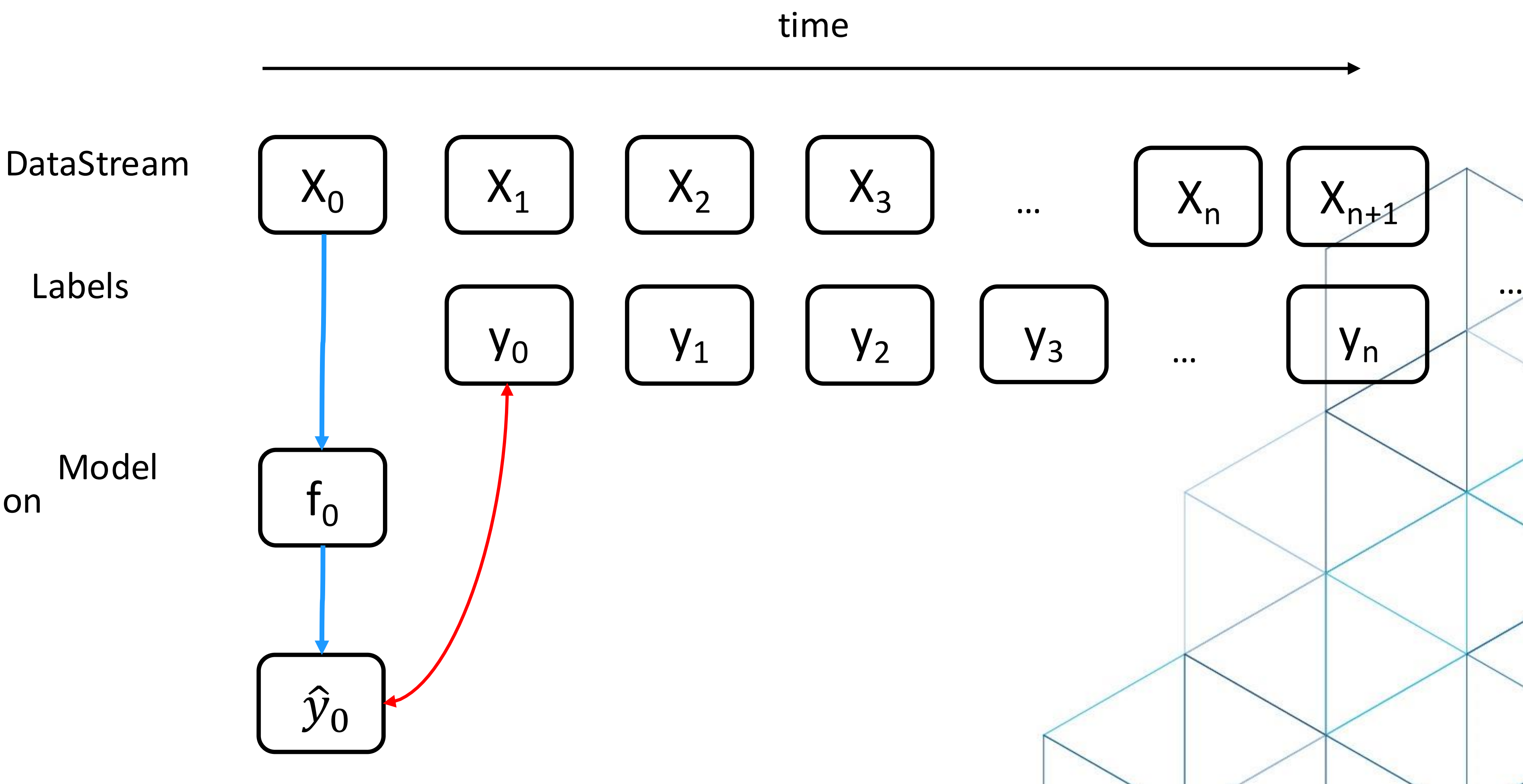
  - Forecast given the streaming sample
    - $\hat{y}_t = f(X_t)$
  - $t \leftarrow t + 1$
  - Prequential evaluation
    - $L(y_{t-1}, \hat{y}_{t-1})$



Pre-quential evaluation

Online Learning

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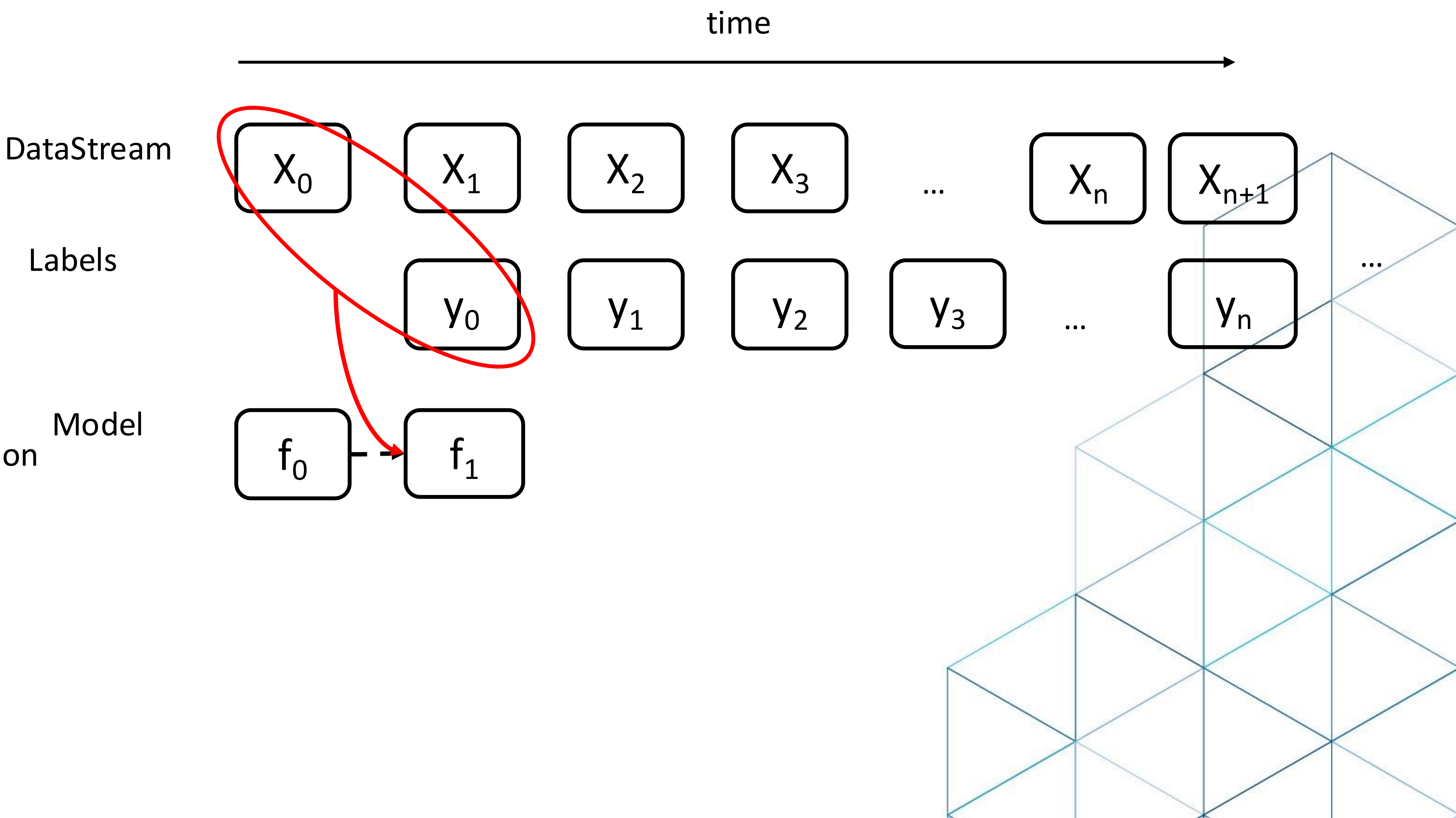
  - Update the model with $\{X_{t-1}, y_{t-1}\}$



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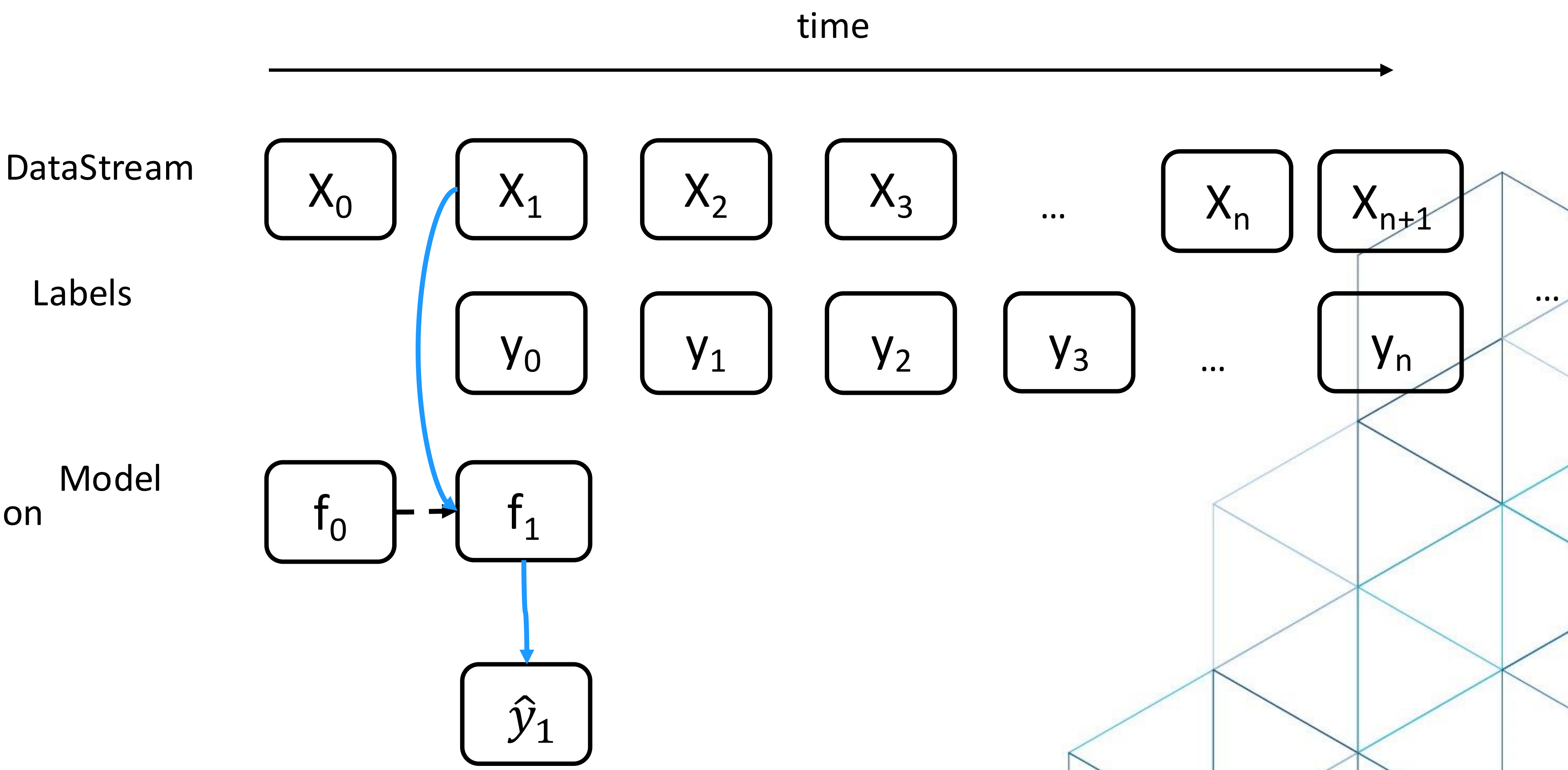

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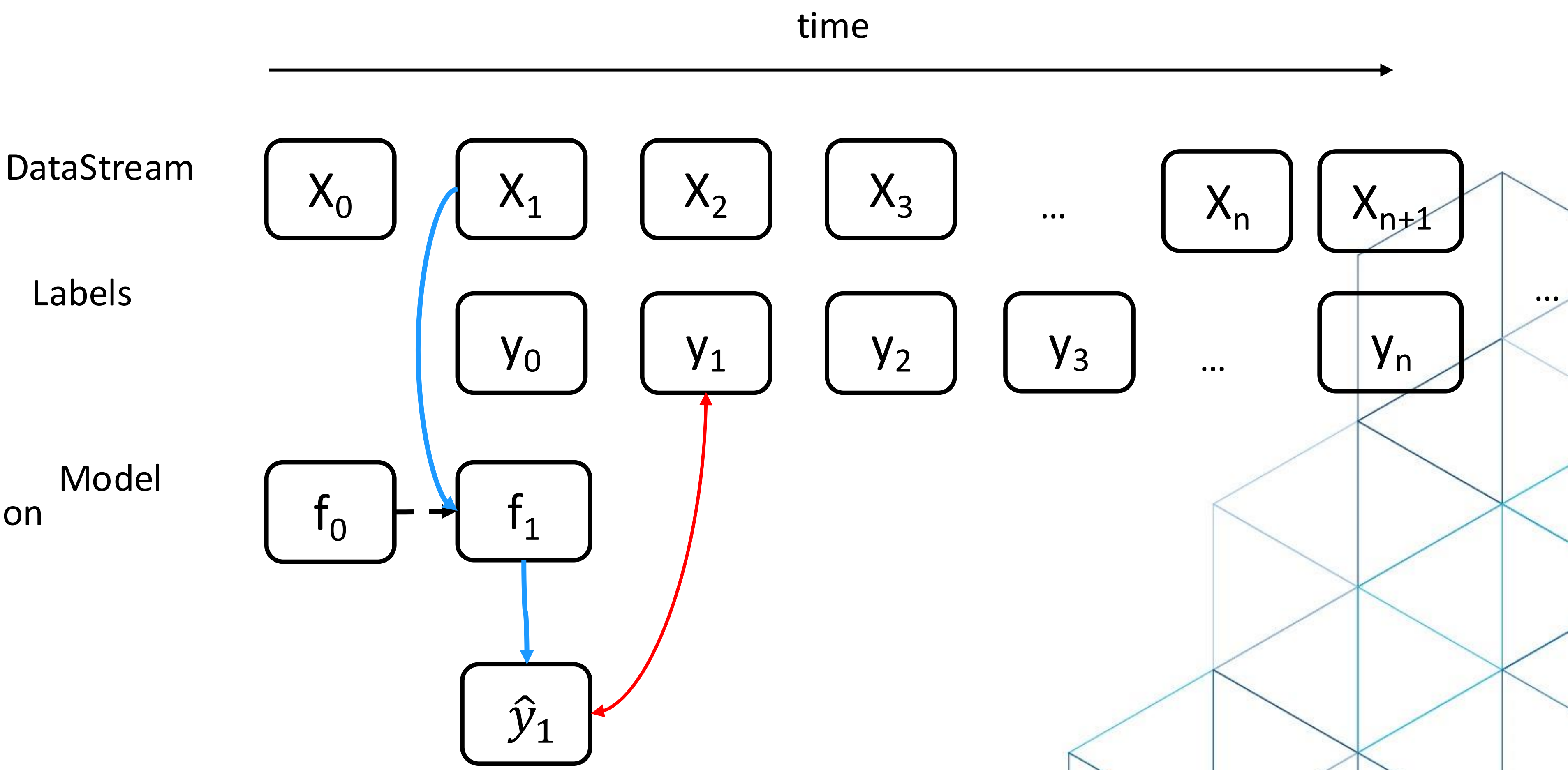

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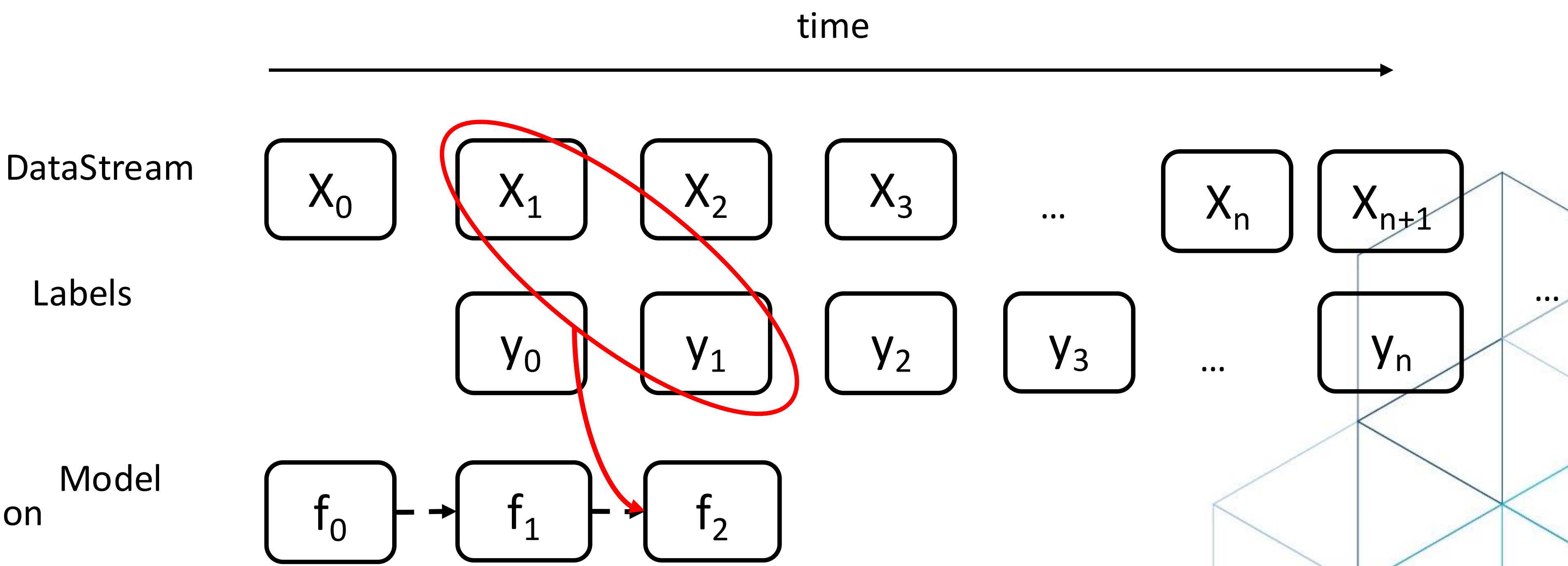

Online Learning Parameters and configurations

- Loss function
- Learning triggers
- Adaptive Learning rate
- Buffer training set
  - augmented data, curriculum learning
- Number of iterations

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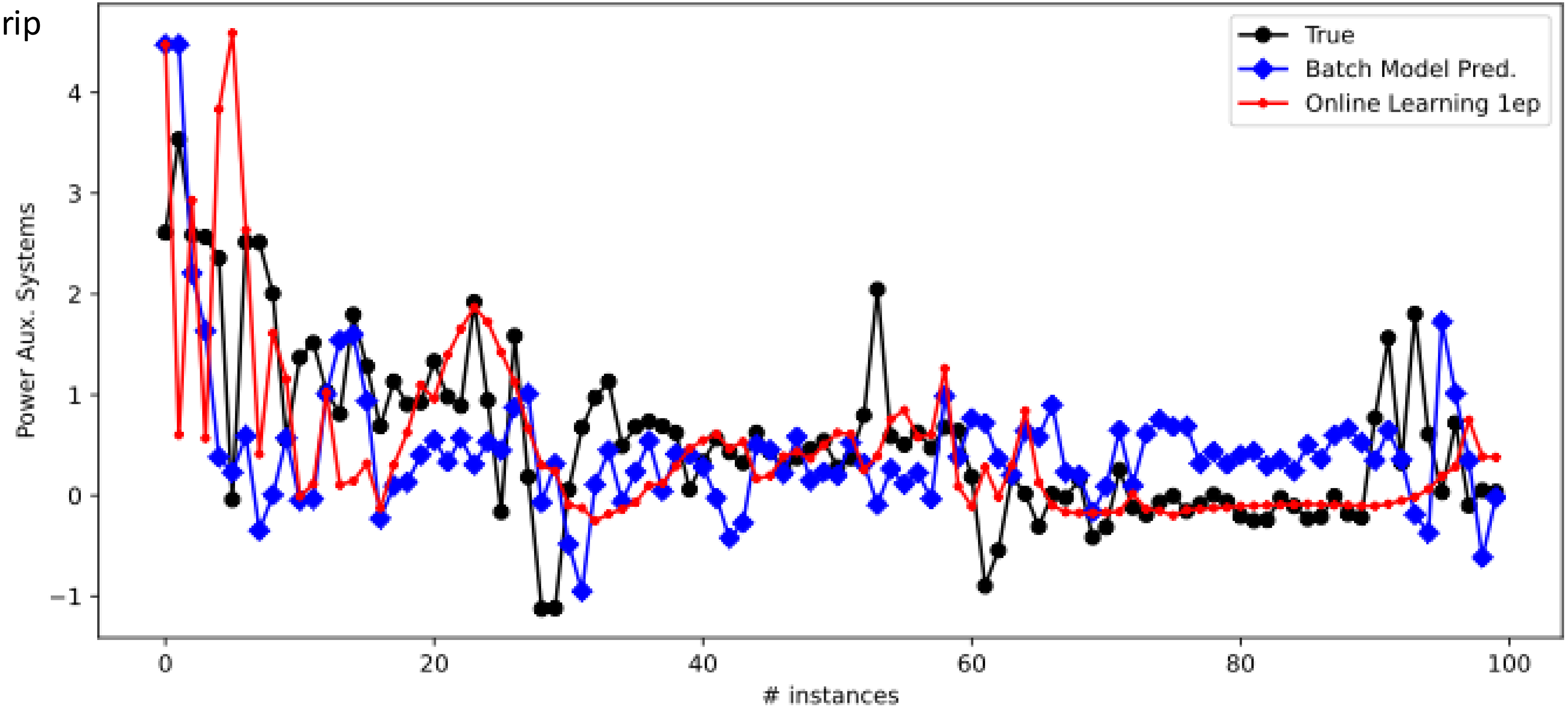
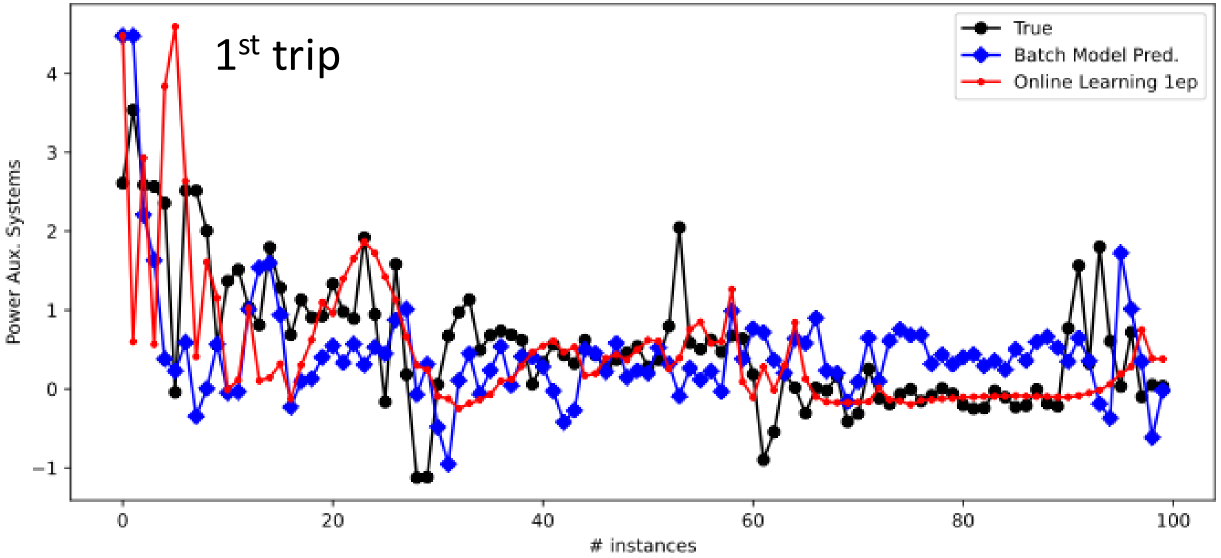
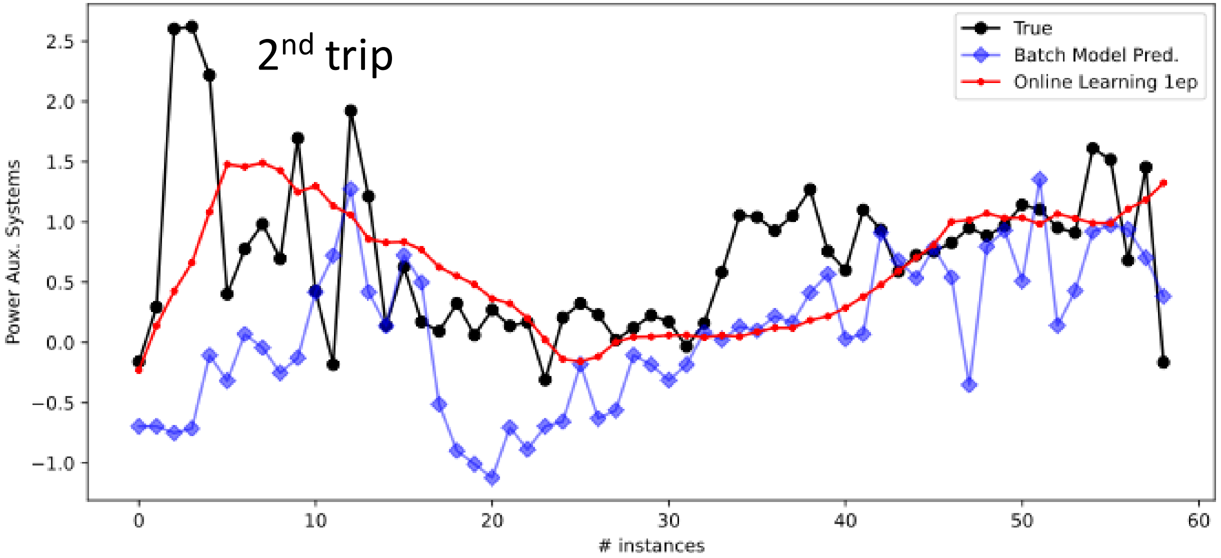
Online learning for Energy Consumption Forecasting

1st trip



Online learning for Energy Consumption Forecasting





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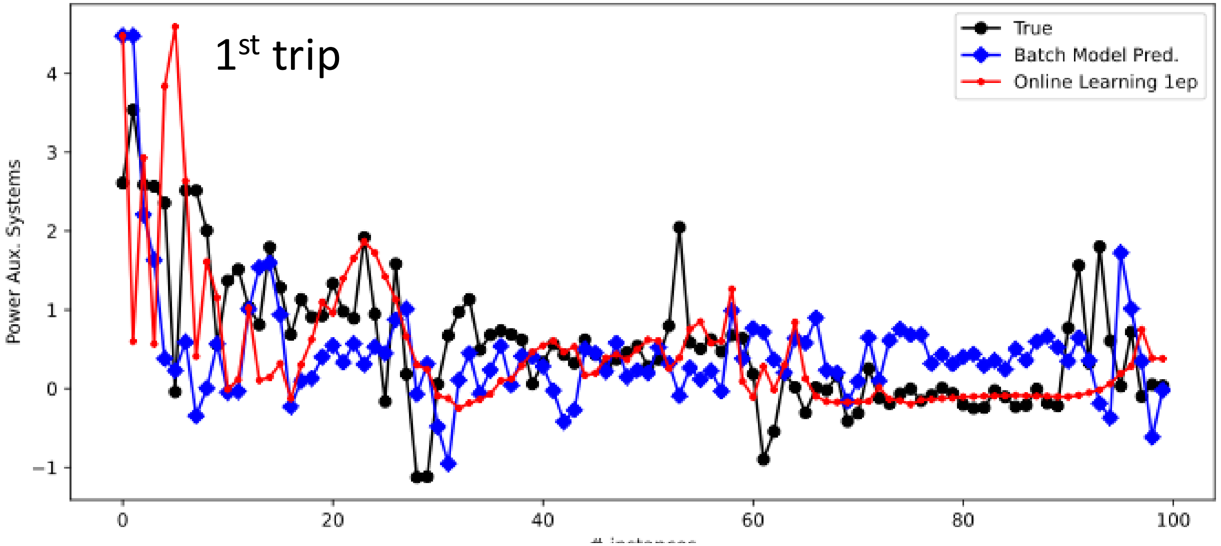
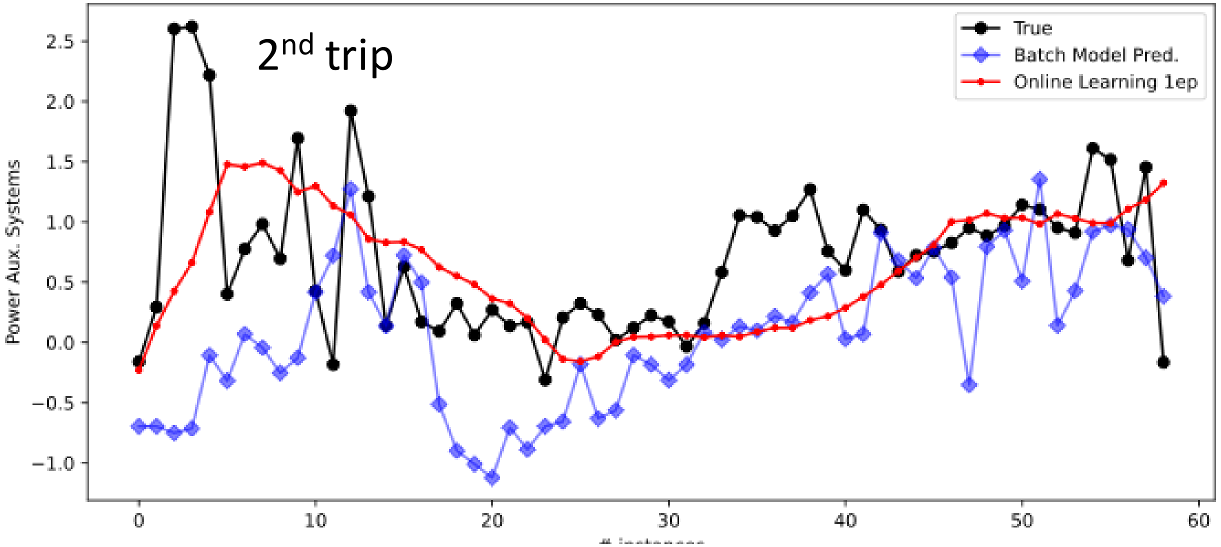
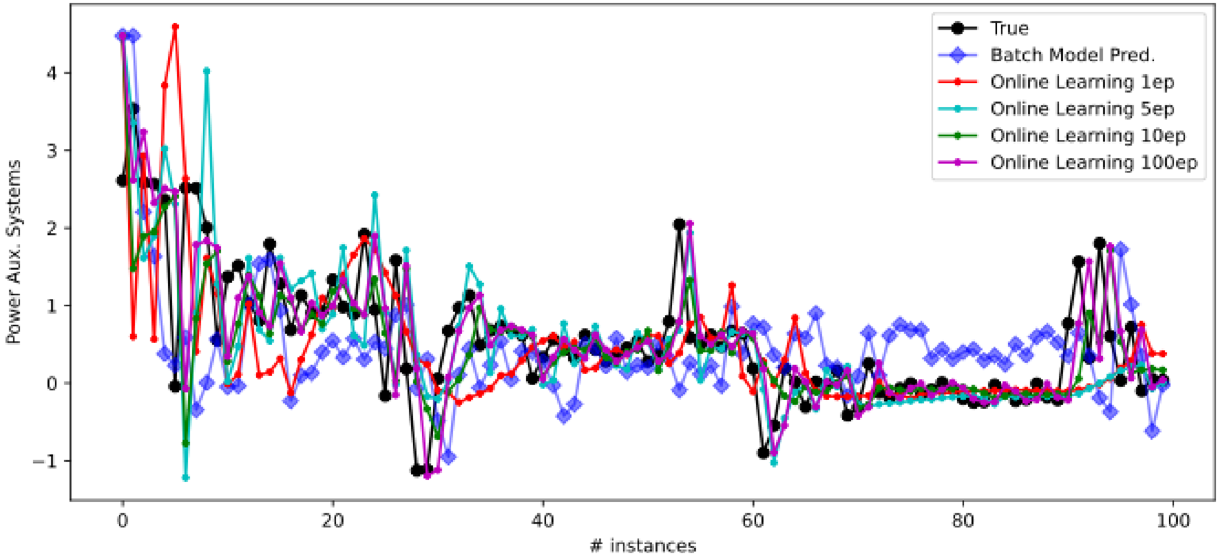
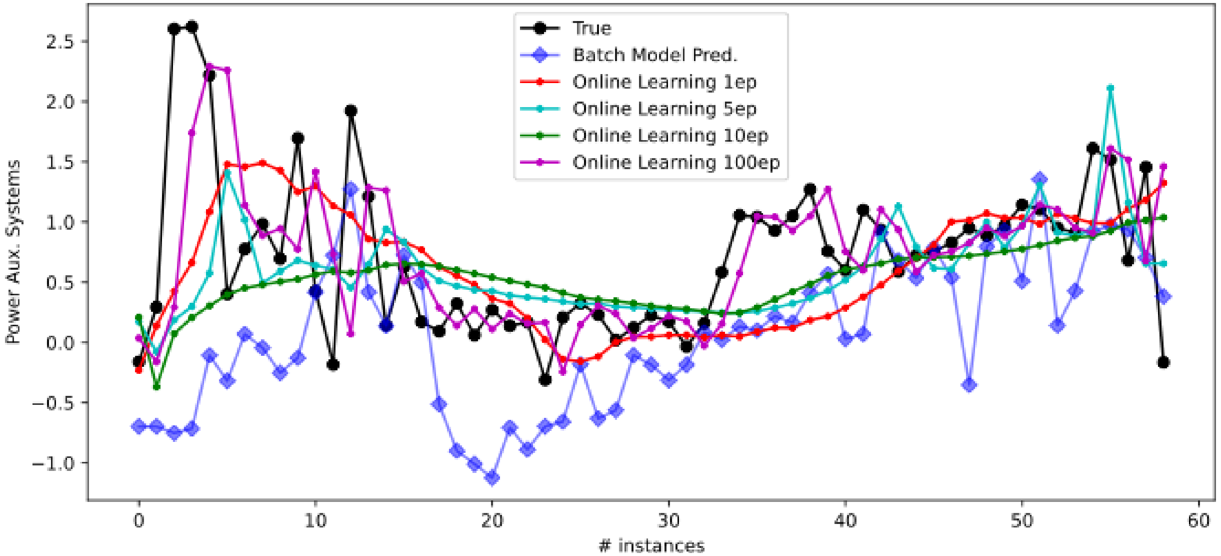
Online learning for Energy Consumption Forecasting







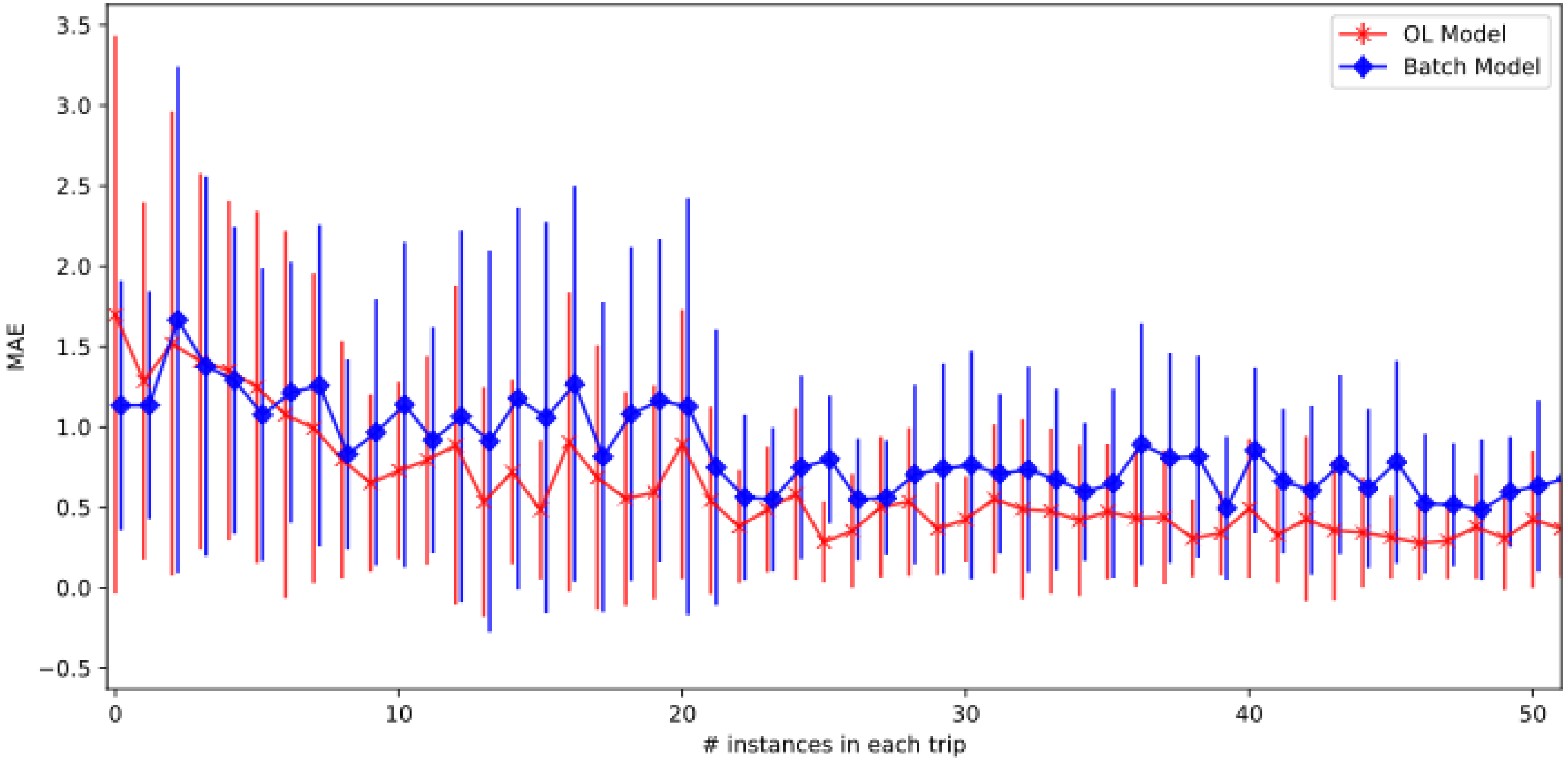


Results

Online Learning Parameters and configurations

- Loss function
- Learning triggers – losses, drift detector
- Adaptive Learning rate
- Buffer training set
    - augmented data, curriculum learning
- Number of iterations

- Leanring trigger based on a pre-determined loss threshold
- More intensive learning in the initial period, and less update when consumption stablizes



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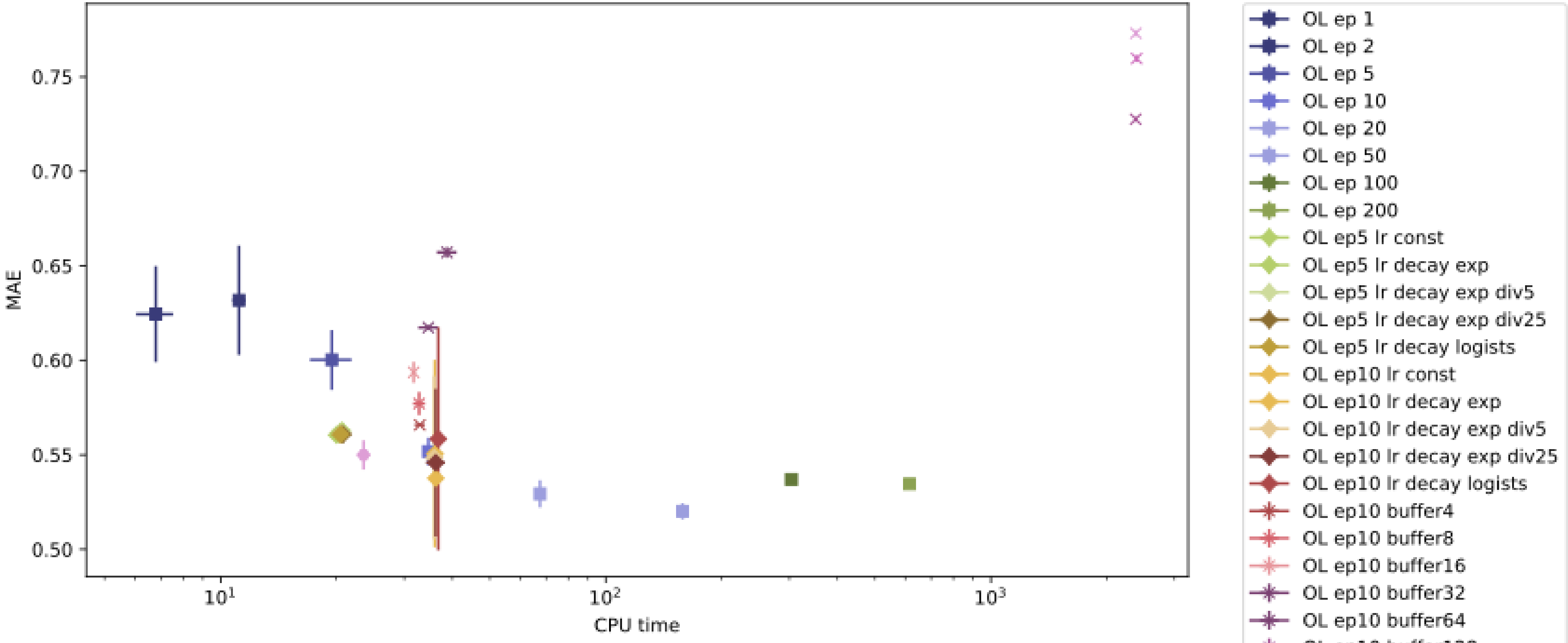
Results



- Online learning P iterations for every N instances, with Q recent samples
- Intense learning for the first 20 instances, P doubled
- Training is activated for K instances with error exceeds a threshold
    - logists decay learning rate function
    - With double amout of iterations

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Thanks! ☺