Lifelong Learning Meets Industrial Processes: An Enabling Adaptive Process Modeling Framework with Delayed Process Output Measurement

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Motivation

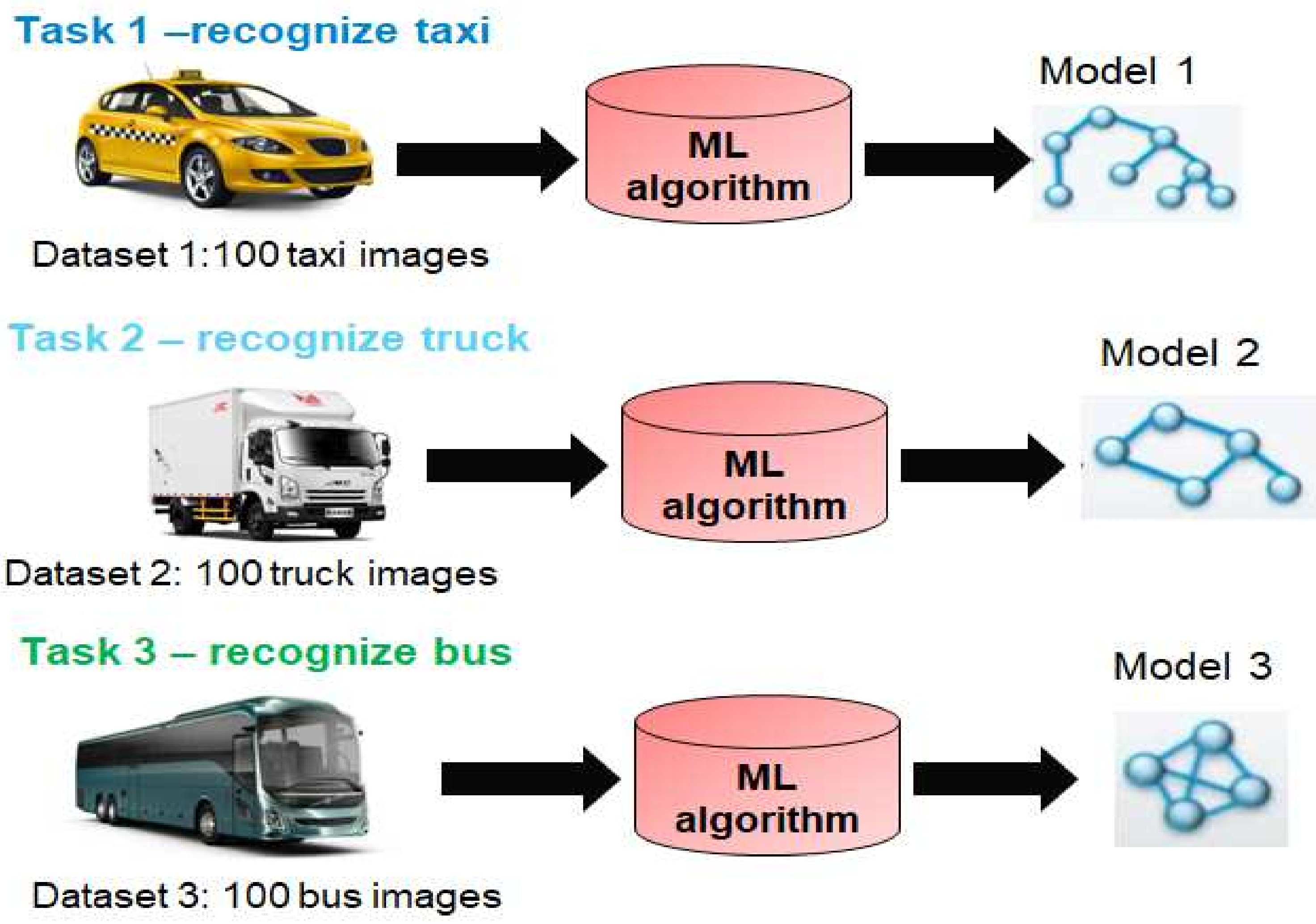
- Many industrial processes operate **continuously** **batch by batch**
  - **Predicting** plant output is needed for monitoring, decision making and control
  - Predictor model is constructed from historical plant operational data

- During plant operation, underlying process characteristics **change**
  - Predictor model must **adapt**, which requires actual process output as desired target

- **Process output measurement** for these batch-by-batch streaming processes is typically seriously **delayed**
  - Without **timely** process output **measurement**, adapting predictor model is **impossible**

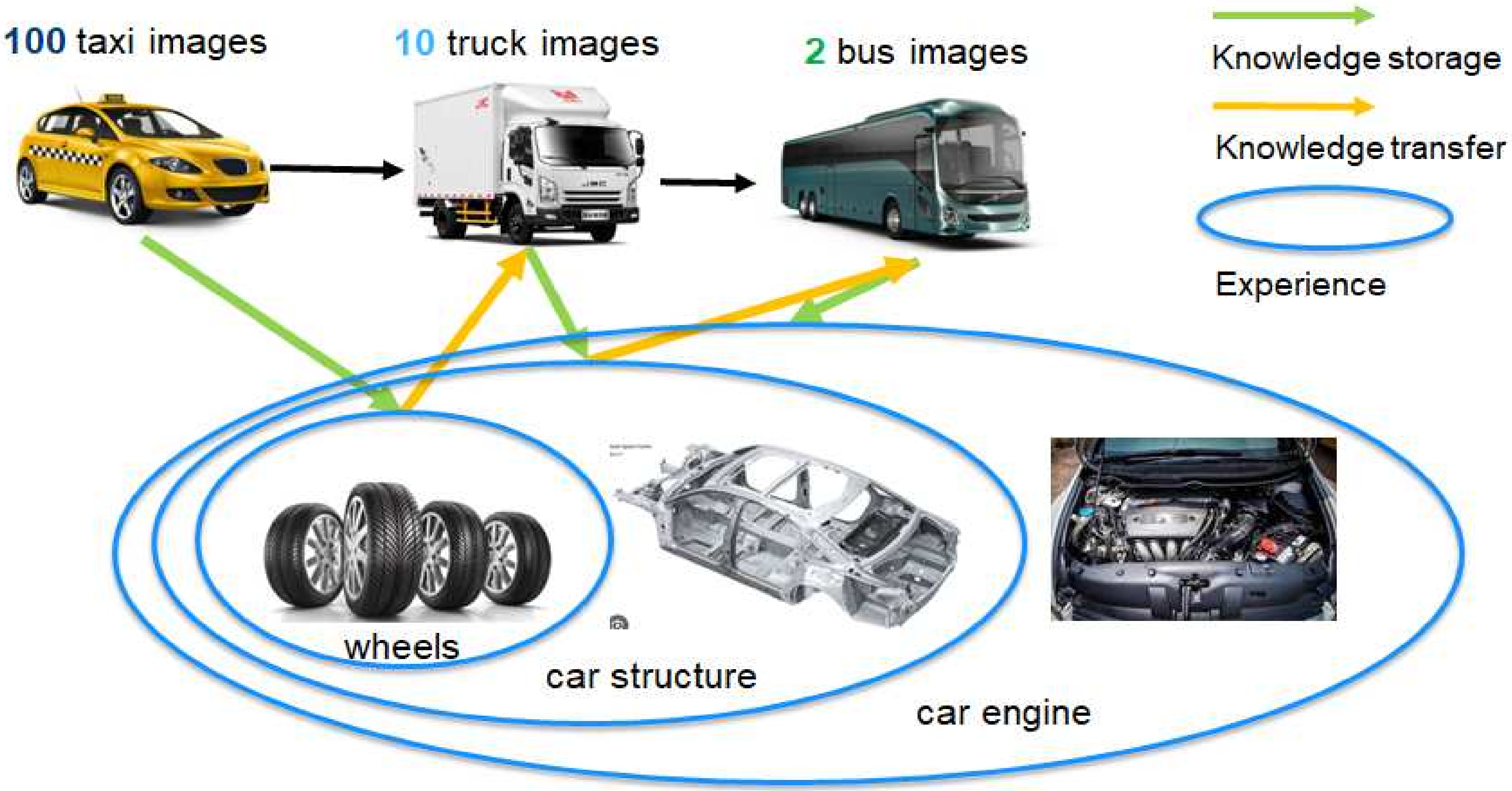
- 'Old' predictor is used **without** adaptation $\Rightarrow$ **degrade** prediction accuracy
  - **How to tackle this problem?**

Classic Machine Learning



- **Isolated learning**: Do not retain knowledge learned in the past and use it in future, requring large number of training data to learn effectively

How Human Learns



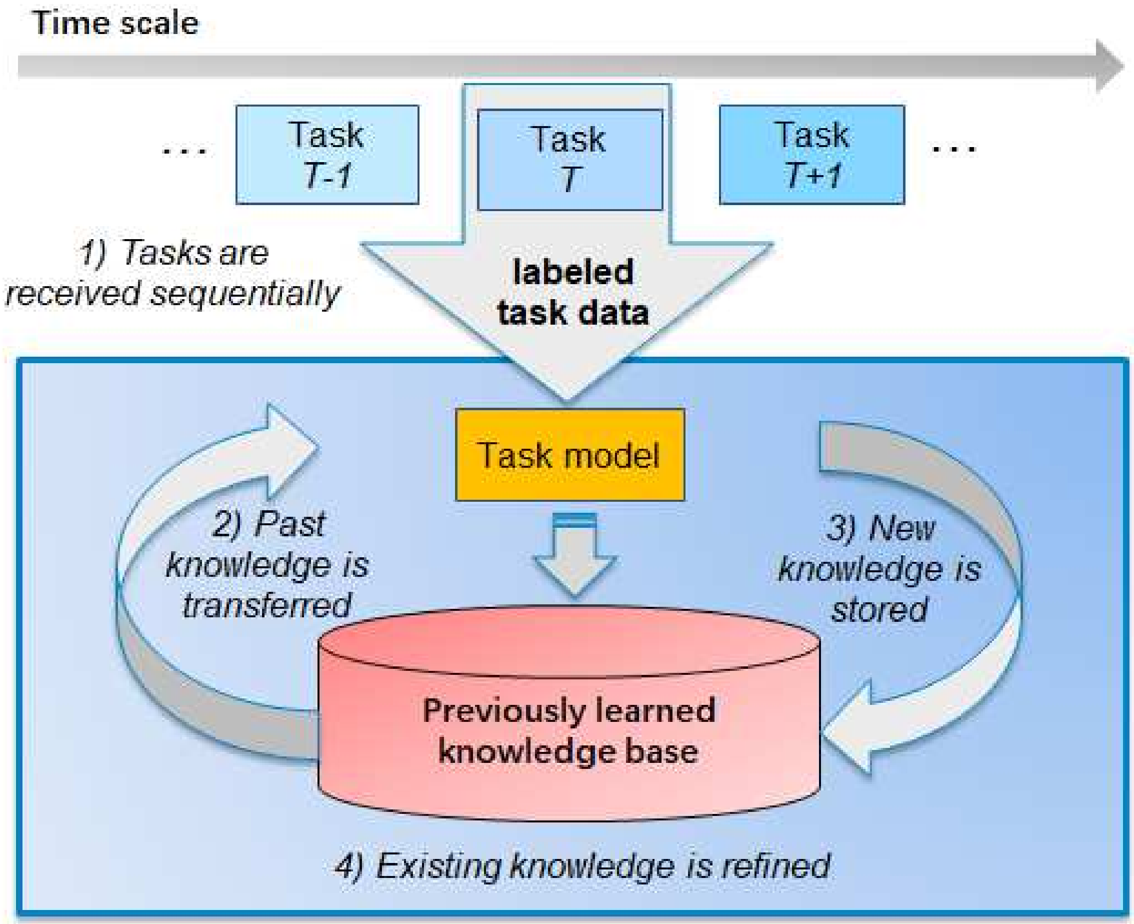
- **Human learning**: Learn continually with experience
  - Maintain **knowledge base** (brain), use past knowledge (**knowledge transfer**) to aid new task, and **store new knowledge** learned for future
  - Quickly learn new tasks with small dataset

Lifelong Maching Learning

- **Lifelong** maching **learning** **imitates** **human learning**
- Efficient lifelong learning algorithm

ELLA:

- Learning tasks consecutively
  - Maintain **knowledge base** for past learned tasks
  - **Transfer knowledge** from previous tasks to learn new task
  - **Store new knowledge learned** in new task to knowledge base
- To build a **task model** required labeled training data (**both inputs and desired outputs**)



ELLA

Efficient Lifelong Learning Algorithm

- ELLA fits a **parametric** model for each task

$$f^{(t)}\left(\boldsymbol{x};\boldsymbol{\theta}^{(t)}\right) = \boldsymbol{x}^{\mathrm{T}}\boldsymbol{\theta}^{(t)} \quad \boldsymbol{\theta}^{(t)} \in \mathbb{R}^d$$

Base model: **linear**, **ELLA**: actually **nonlinear**

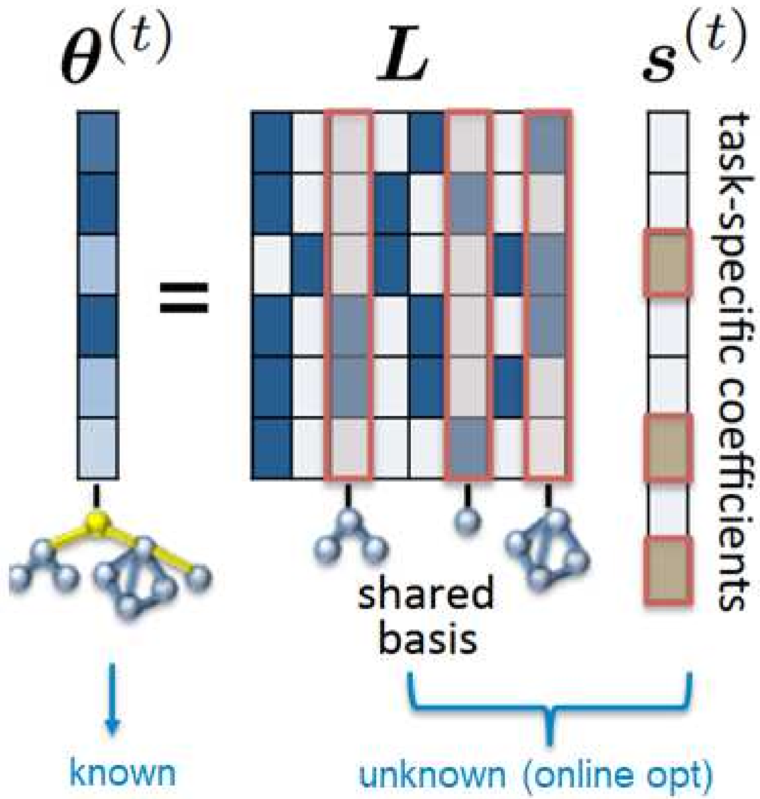
- $\boldsymbol{\theta}^{(t)}$: linear combinations of **knowledge base** $\boldsymbol{L}$ via **sparse encoding** $\boldsymbol{s}^{(t)} \in \mathbb{R}^k$

$$\boldsymbol{\theta}^{(t)} = \boldsymbol{L}\,\boldsymbol{s}^{(t)} \quad \boldsymbol{L} \in \mathbb{R}^{d\times k}$$

- Objective function:

$$\min_{\boldsymbol{L},\boldsymbol{S}} \frac{1}{T}\sum_{t=1}^{T}\left(\underbrace{J\left(\boldsymbol{\theta}^{(t)}\right)}_{\text{model fits to each task}} + \mu \underbrace{\|\boldsymbol{s}^{(t)}\|_1}_{\text{sparsity of coding coefficient}}\right) + \lambda \underbrace{\|\boldsymbol{L}\|_F^2}_{\text{regularize base complexity}}$$

$\boldsymbol{S} = \left[\boldsymbol{s}^{(1)}\cdots\boldsymbol{s}^{(T)}\right]$, T: tasks seen so far



- Online optimization: tasks arrive consecutively, update 'recursively' task by task

ELLA (continue)

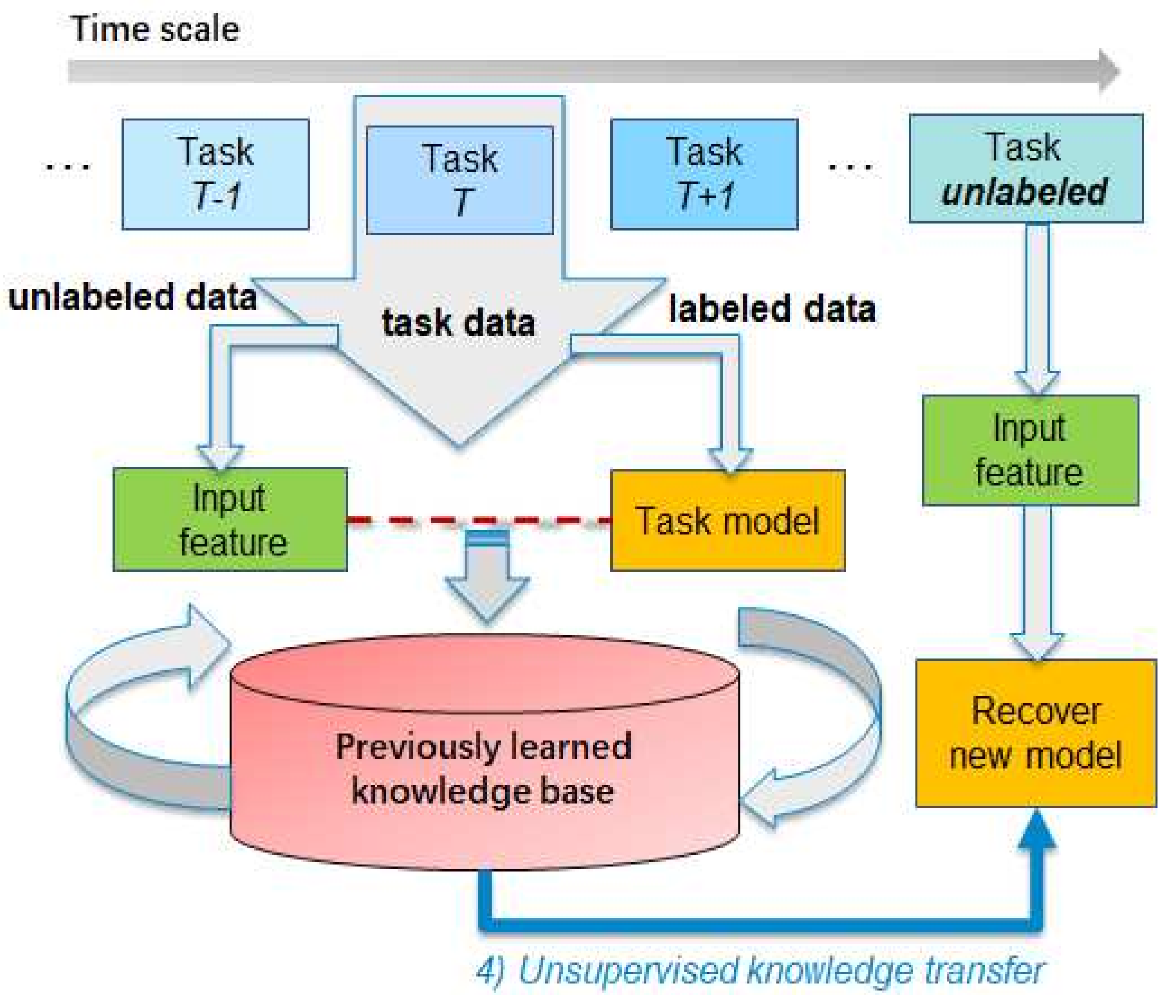
ELLA: given new task (batch) t

1. Train single-task model $\widehat{\boldsymbol{\theta}}^{(t)}$ for task t
   - Estimate $\widehat{\boldsymbol{\theta}}^{(t)}$ requires **labeled training data** (both input and desired output)
2. With $\widehat{\boldsymbol{\theta}}^{(t)}$, **solve sparse coding** coefficient $\boldsymbol{s}^{(t)}$ in current knowledge base or dictionary $\boldsymbol{L}$ via LASSO
   - **Knowledge transfer** from past tasks
3. **Update dictionary** $\boldsymbol{L}$ with $\widehat{\boldsymbol{\theta}}^{(t)}$, $\boldsymbol{s}^{(t)}$ and old $\boldsymbol{L}$ via efficient ELLA unpdate rules
   - **Store knowledge** learned for task t
4. **Current task model** is given by $\boldsymbol{\theta}^{(t)} = \boldsymbol{L}\boldsymbol{s}^{(t)}$

- **Build task model $\boldsymbol{\theta}^{(t)}$ requires labeled training data**
- **Not for streaming batch-by-batch industrial processes with delayed output measurement**

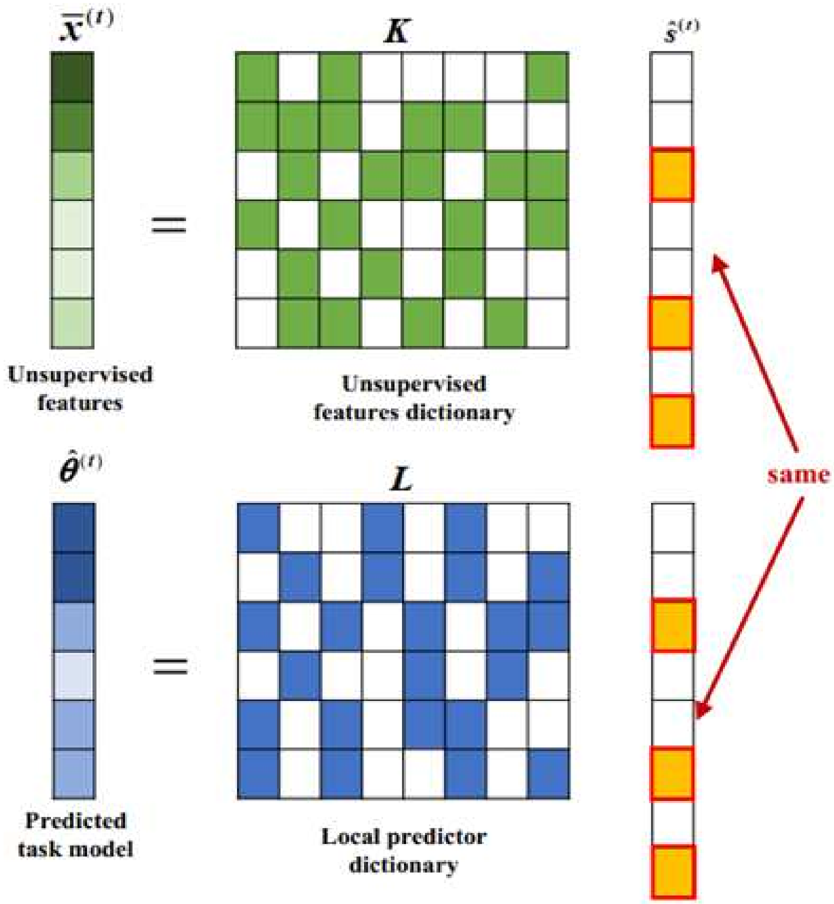
Unsupervised Transfer Aided Lifelong Learning

- We develop UTaLL: **unsupervised transfer** aided **lifelong learning**
- Improve performance by knowledge sharing in two spaces:
  - **Task model space** (as in ELLA)
  - New **input feature space**
- Learn new tasks without labeled data by unsupervised transfer



Liu, Wang, Yang, Chen, Harris, "Unsupervised transfer aided lifelong regression for learning without target output," *IEEE Trans. Knowledge and Data Engineering* **(under second review)**

UTaLL Idea



- **Coupled dictionaries** relate **task model** parameters and **input features**

$$\text{task model } \boldsymbol{\theta}^{(t)} = \boldsymbol{L}\boldsymbol{s}^{(t)}$$

$$\text{input feature } \overline{\boldsymbol{x}}^{(t)} = \boldsymbol{K}\boldsymbol{s}^{(t)}$$

  - $\overline{\boldsymbol{x}}^{(t)}$: averaging inputs of batch t
  - **Input feature** also reflects **underlying plant characteristics**
  - $\boldsymbol{K}$: **knowledge base** for input feature space
- ELLA objective function

$$\min_{\boldsymbol{L},\boldsymbol{S}} \frac{1}{T}\sum_{t=1}^{T}\left(J\left(\boldsymbol{\theta}^{(t)}\right) + \mu\|\boldsymbol{s}^{(t)}\|_1\right) + \lambda\|\boldsymbol{L}\|_F^2$$

- UTaLL objective function

$$\min_{\boldsymbol{L},\boldsymbol{K},\boldsymbol{S}} \frac{1}{T}\sum_{t=1}^{T}\left(\underbrace{J\left(\boldsymbol{\theta}^{(t)}\right)}_{\text{model fit}} + \rho\underbrace{\|\overline{\boldsymbol{x}}^{(t)} - \boldsymbol{K}\boldsymbol{s}^{(t)}\|_2^2}_{\text{input feature fit}} + \mu\underbrace{\|\boldsymbol{s}^{(t)}\|_1}_{\text{sparsity}}\right) + \lambda\underbrace{\left(\|\boldsymbol{L}\|_F^2 + \|\boldsymbol{K}\|_F^2\right)}_{\text{complexity}}$$

- For **labeled task**, learning steps are same as ELLA

Unsupervised Knowledge Transfer

Given new task t with **input data only**

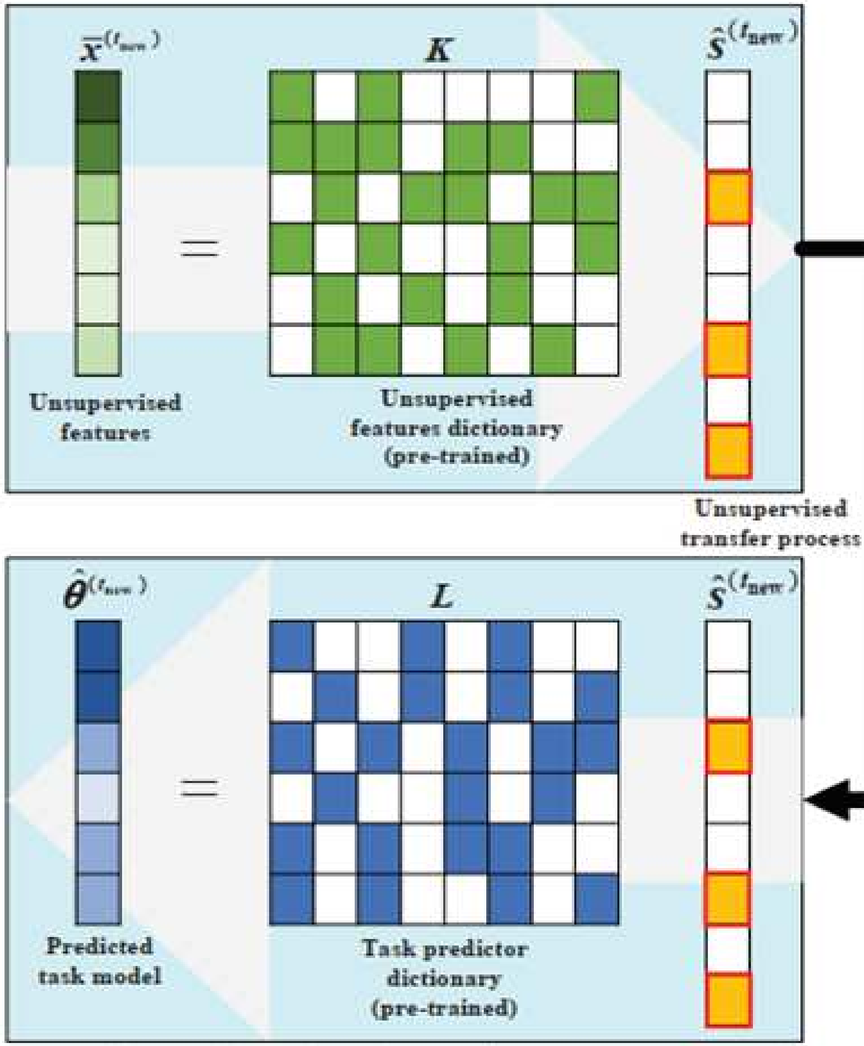
1. Use input feature $\overline{\boldsymbol{x}}$ and dictionary $\boldsymbol{K}$ to **recover sparse code** $\boldsymbol{s}$

$$\boldsymbol{s}^{(t)} = \arg\min_{\boldsymbol{s}} \left\| \overline{\boldsymbol{x}}^{(t)} - \boldsymbol{K}\boldsymbol{s} \right\|_2^2 + \mu \|\boldsymbol{s}\|_1$$

2. Use recovered $\boldsymbol{s}^{(t)}$ and dictionary $\boldsymbol{L}$ to **recover model** parameters $\boldsymbol{\theta}$

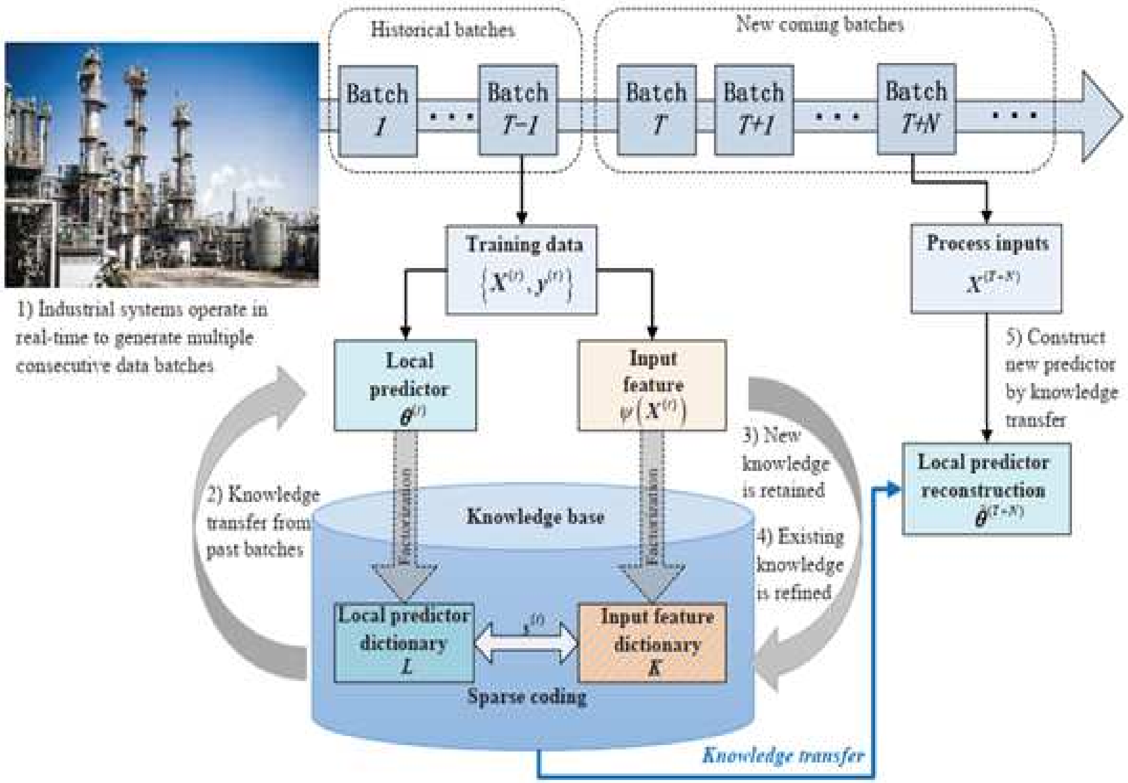
$$\widetilde{\boldsymbol{\theta}}^{(t)} = \boldsymbol{L}\boldsymbol{s}^{(t)}$$

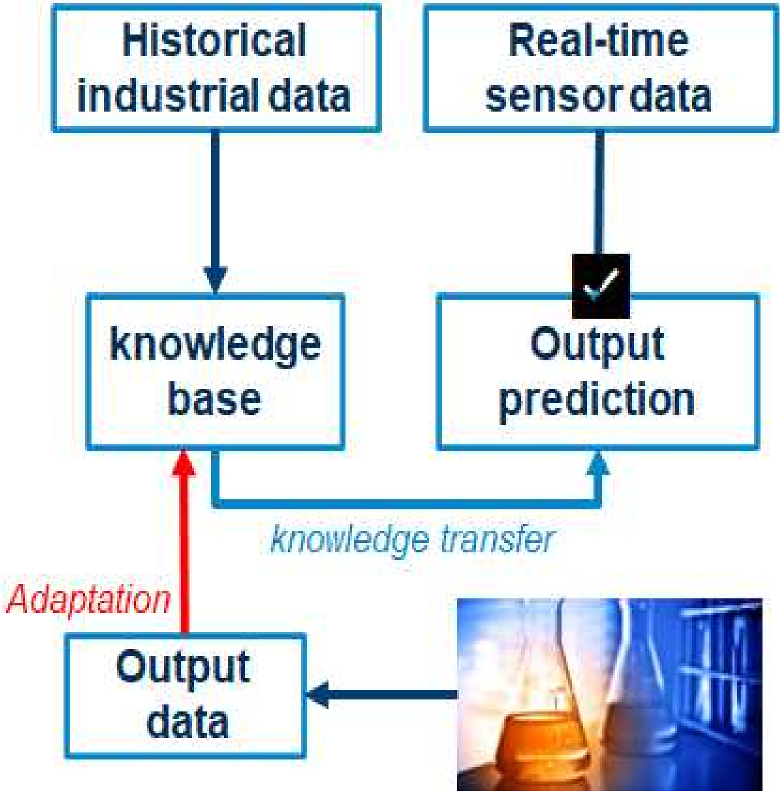
yielding **task model** for new task t



This UTaLL can be apply to online prediction and adaptation of streaming batch-by-batch industrial processes with delayed output measurement

UTaLL Meets Industrial Processes





- Use historical labeled data to build task model dictionary $\boldsymbol{L}$ and input feature dictionary $\boldsymbol{K}$
- During online operation of plant, when a new batch of input data only arrives
  - Use unsupervised knowledge transfer to recover predictor for predicting process output
  - Later if process output measurements arrive, update $\boldsymbol{L}$ and $\boldsymbol{K}$

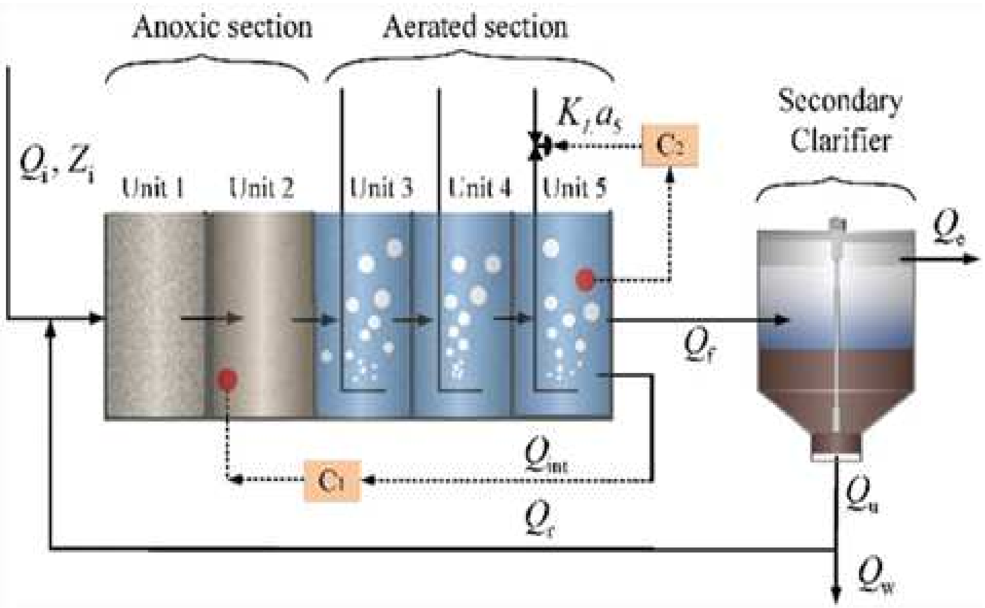
Liu, Chen, Yang, Zhu, Mercangoz, Harris, "Lifelong learning meets dynamic processes: An emerging streaming process prediction framework with delayed quality measurement," *IEEE Trans. Control Systems Technology* **(early access)**

Comparison Schemes

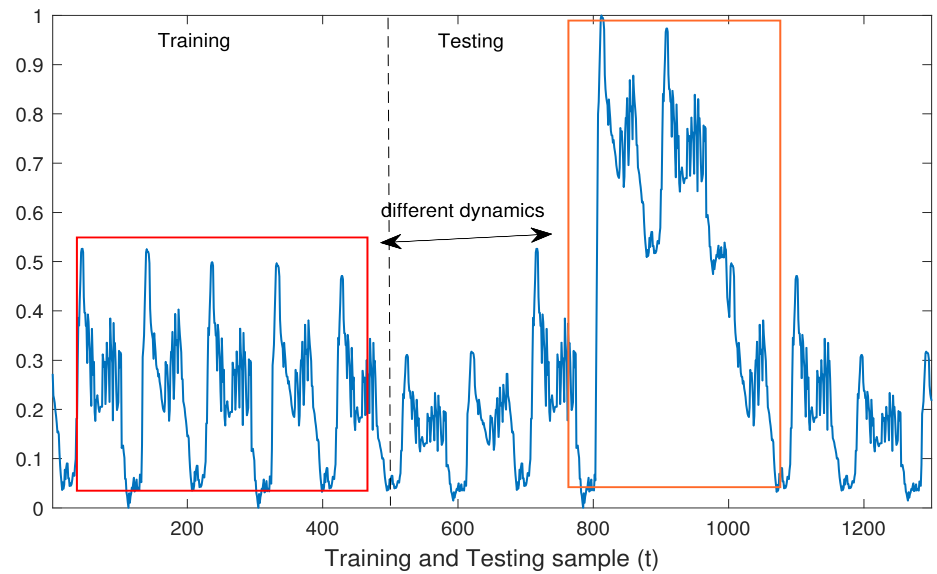
- **LS**, **BAL** (Bayesian augmented Lagrangian), **PLS**: **Nonadaptive**
  - Trained models are fixed during online operation
- **CLR** (clustering-based locally linear regression), **CLR-ensemble**: **Nonadaptive**
  - Trained local model set fixed during online operation
- **RLS-batch**: Model from previous batch is used to predict new batch. After true process output data for this new batch are acquired, it updates model over the batch
- Proposed UTaLL
  - **Pro-nonadaptive**: During online operation, trained KB is fixed, and model is recovered by unsupervised transfer to predict new batch data
  - **Pro-adaptive**: after unsupervised transfer based prediction of new batch data, KB is adapted
- **RLS-idealized**: after predicting output for a given input sample, output measurement is available to adapt model with input-output sample pair
  - **Cannot be used in online modeling and prediction for streaming processes with delayed output measurement**
- **Pro-idealized**: UTaLL continuously operates in training mode
  - **Cannot be used in online modeling and prediction for streaming processes with delayed output measurement**

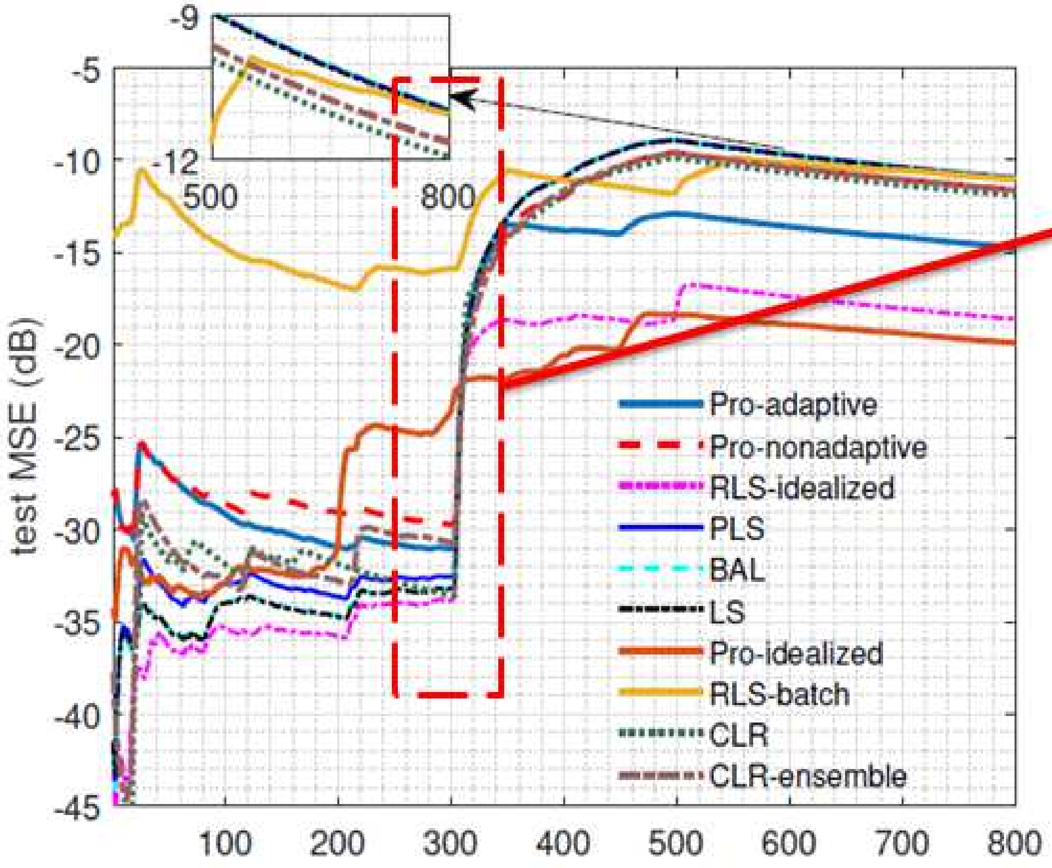
Wastewater Treatment Plant

Input/output	Description
x_1	Readily biodegradable substrate
x_2	Particulate inert organic matter
x_3	Slowly biodegradable substrate
x_4	Active heterotrophic biomass
x_5	$NH_4^+ + NH_3$ nitrogen
y	Flow rate

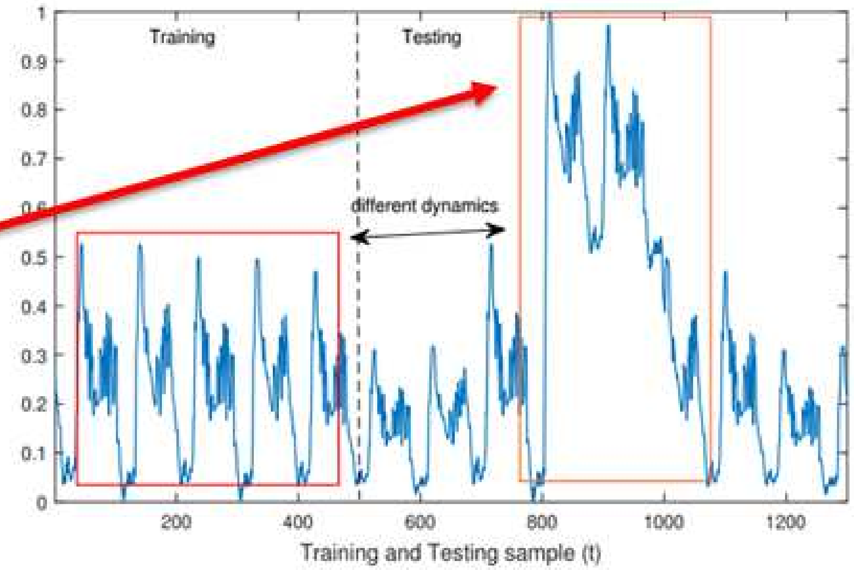


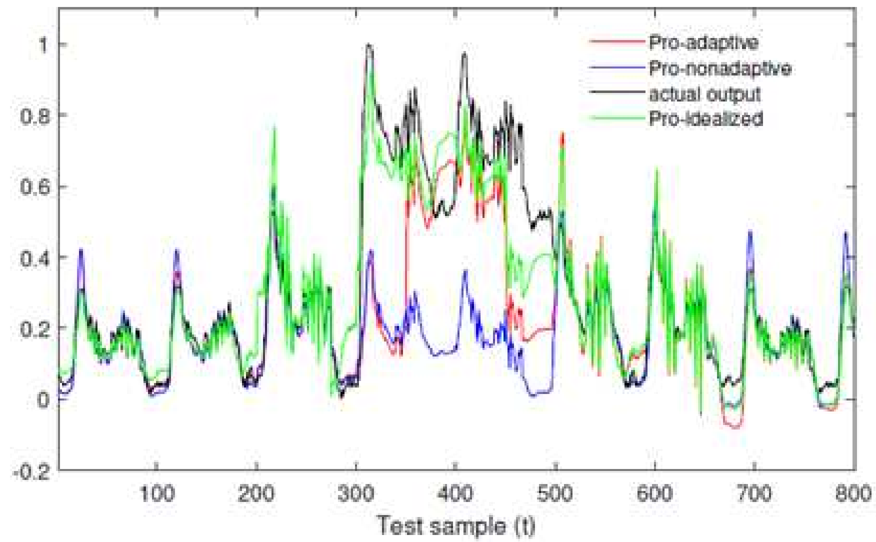
- 1300 samples are collected
- 40% training, 60% online testing
- Delayed output measurement time: 50
- Highly **time-varying** data: combination of **dry** weather and long **rainy** period





Online MSE comparison

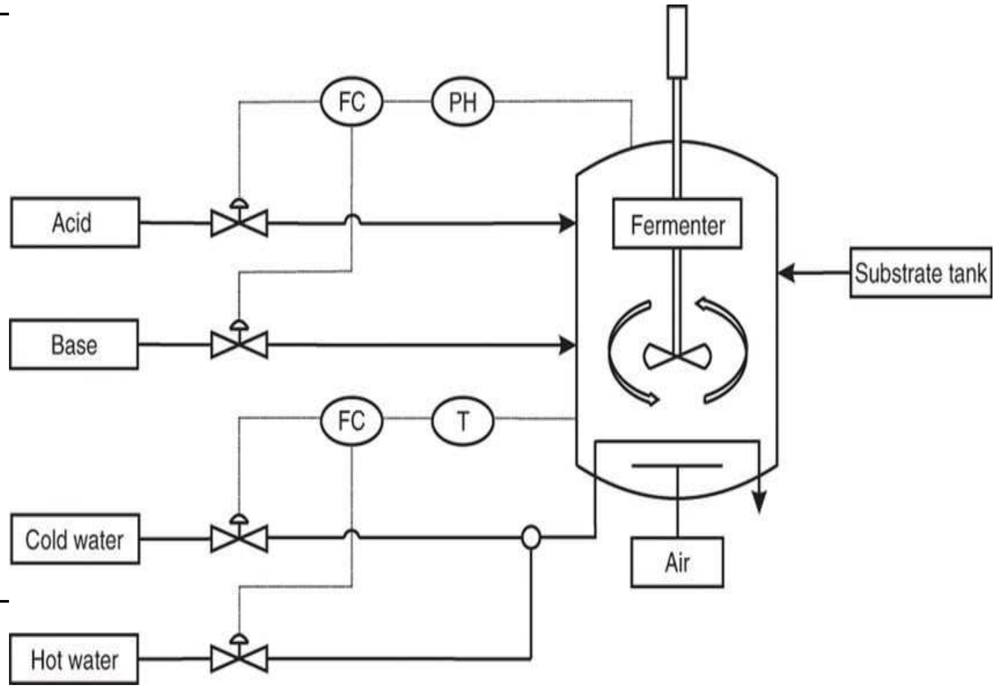




Model prediction by lifelong learner

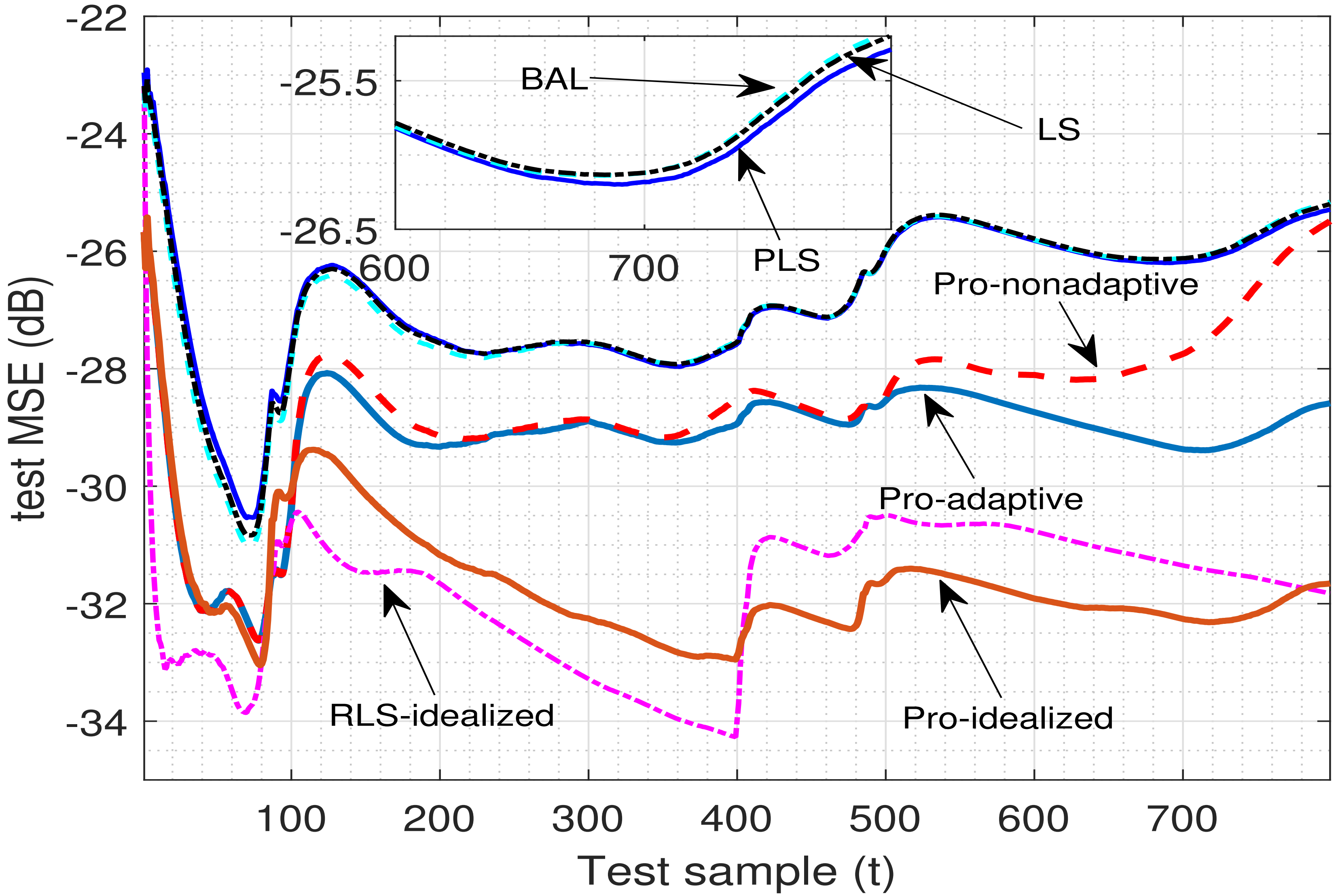
Penicillin Fermentation Process

Input/Output	Description
x_1	Aeration rate
x_2	Agitator power
x_3	Substrate feed rate
x_4	Substrate feed temperature
x_5	Dissolved oxygen concentration
x_6	Culture volume
x_7	Carbon dioxide concentration
x_8	pH
x_9	Fermentor temperature
x_{10}	Generated heat
y_1	Penicillin concentration
y_2	Substrate concentration



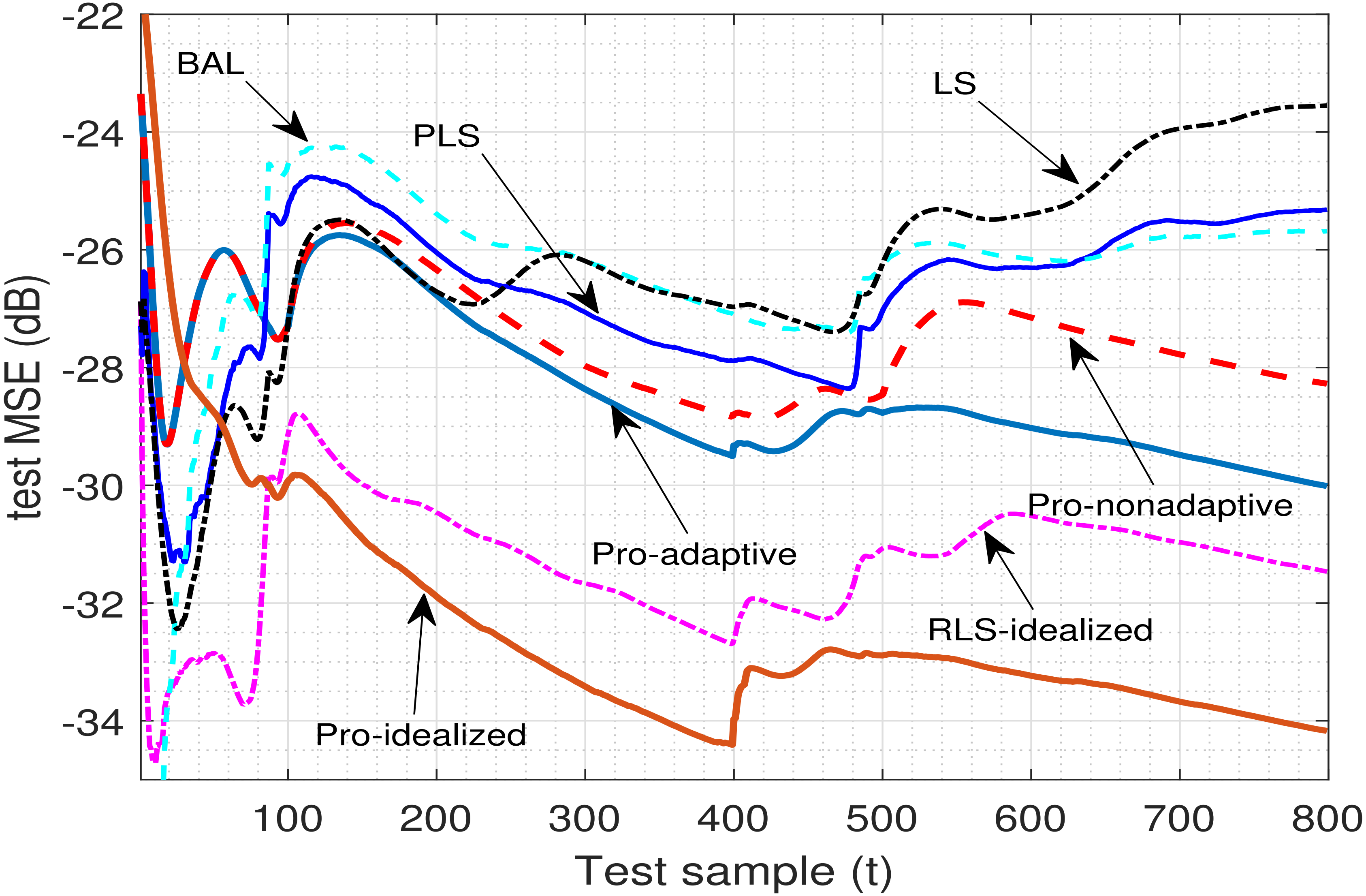
- 1600 samples are collected
- 50% training, 50% online testing
- Delayed output measurement time: 100
- **Multi-mode time-varying nonlinear** characteristics

Predicting Penicillin Concentration



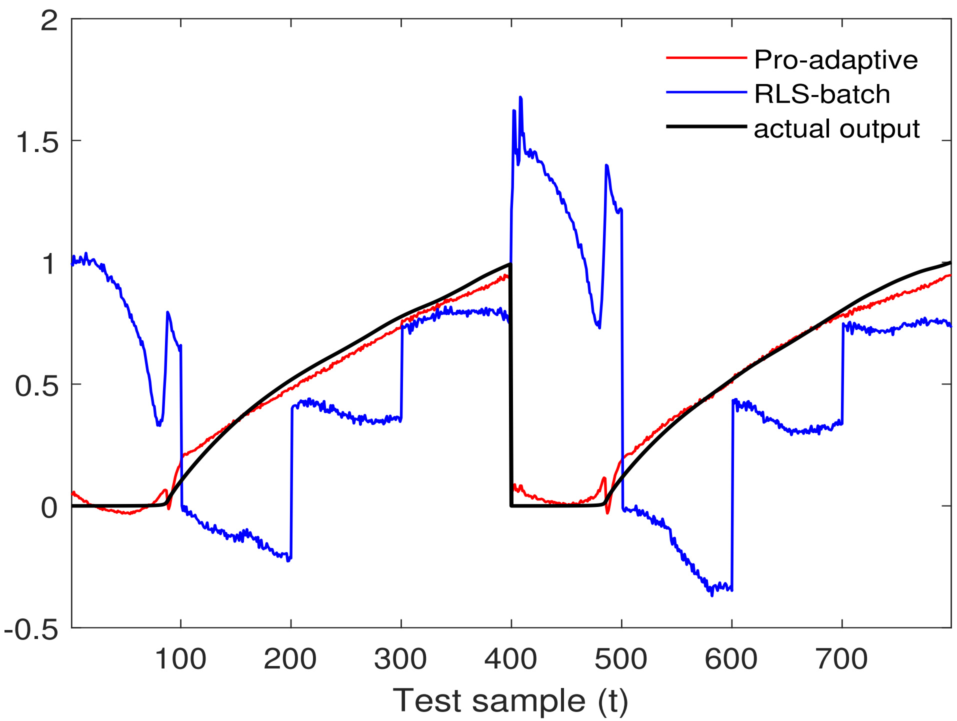
Prediction performance of RLS-batch is extremely poor, off the scale

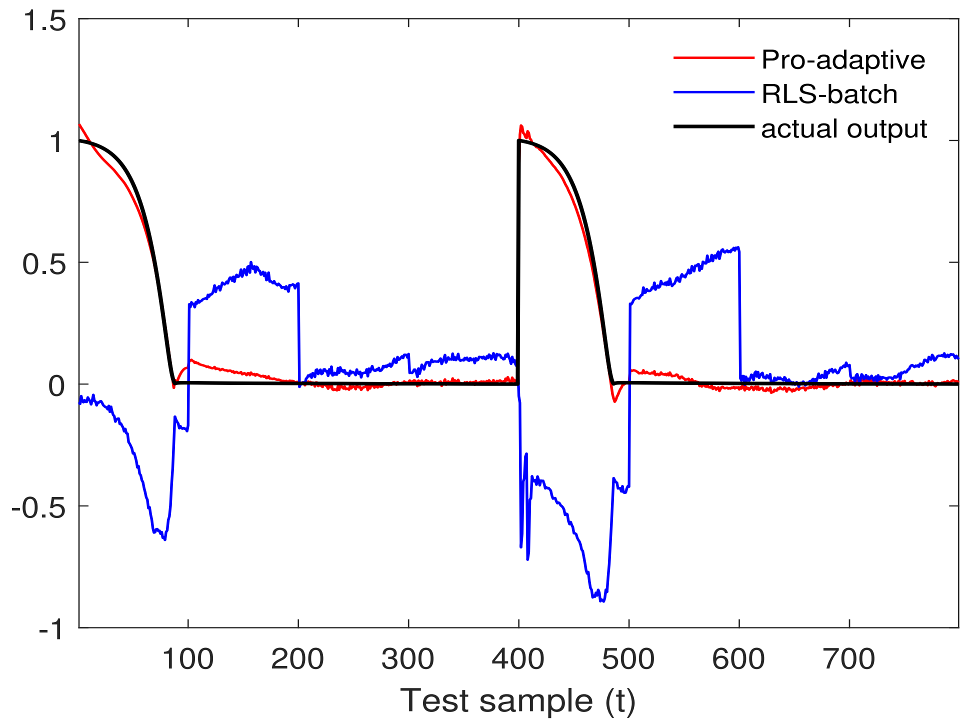
Predicting Substrate Concentration



Prediction performance of RLS-batch is extremely poor, off the scale

Why RLS-batch So Poor





- RLS has short memory, allowing it to forget past data and concentrate on current data
- After batch adaptation, model forgets most of past knowledge and captures characteristics of current batch
- This model is then used to predict next batch
- For highly time-varying nonlinear process, characteristics of next new batch can be very different from those captured in model

Conclusions

- Many industrial processes operate **continuously** **batch by batch**
  - **Predicting** plant output from plant input is essential during online operation
  - Online **adapting model** is vital to track plant time-varying characteristics
  - Process output measurements of these streaming batch-by-batch processes are seriously **delayed**, making it **challenging** for online adapting model

- **Lifelong** machine **learning** imitates **human learning** and has many advantages
  - Require **input-output data** to construct predictor, and cannot be applied to streaming batch-by-batch processes with delayed output measurement

- We have developed novel **unsupervised transfer aided lifelong learning**, capable of construct predictor from **input data only**
  - **Ideal for online prediction and model adaptation of streaming batch-by-batch processes with delayed output measurement**