Navigating Complex Machine Learning Challenges in Streaming Data

ECML Tutorial 2024

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https://heymarco.github.io/ecml24-streamingchallenges/

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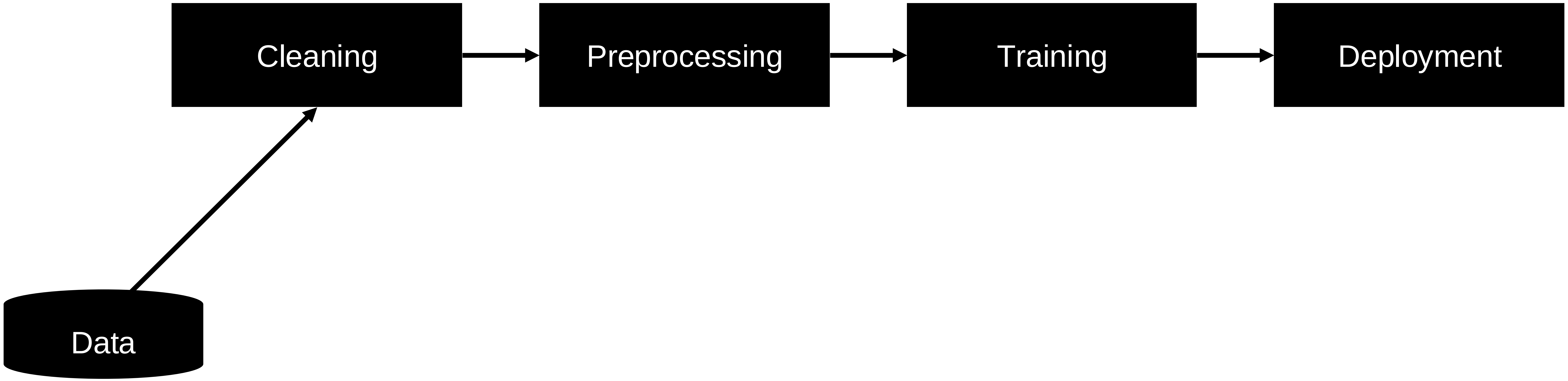
Pipelines

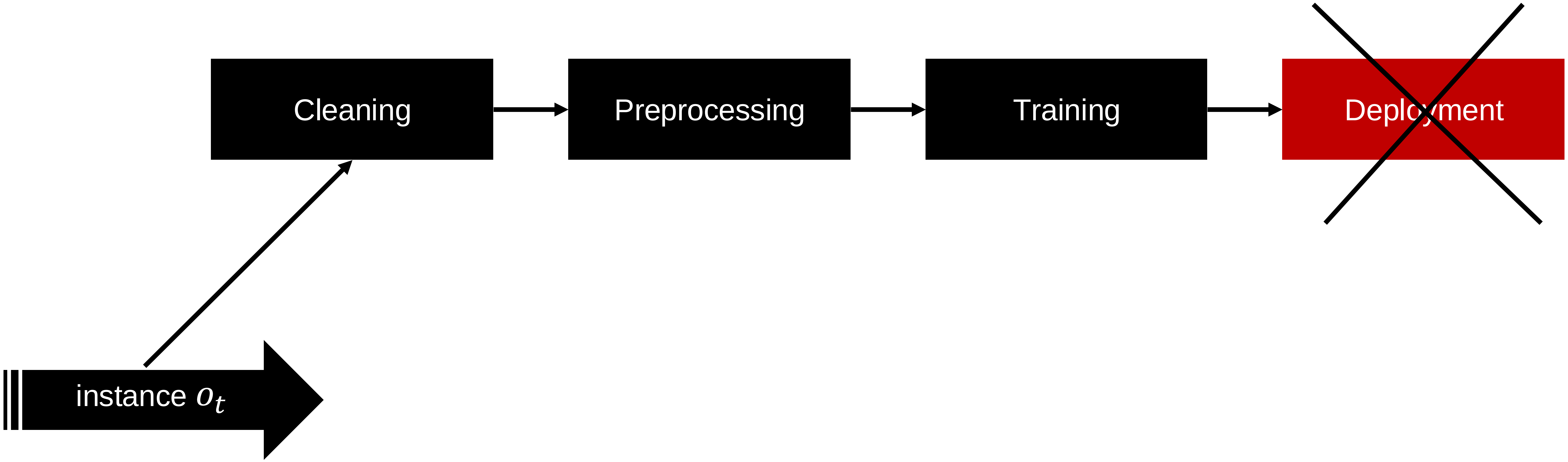
Traditional ML Pipelines

- Traditional ML Pipelines consist of well-defined, separate steps
- After training, model is deployed to make predictions



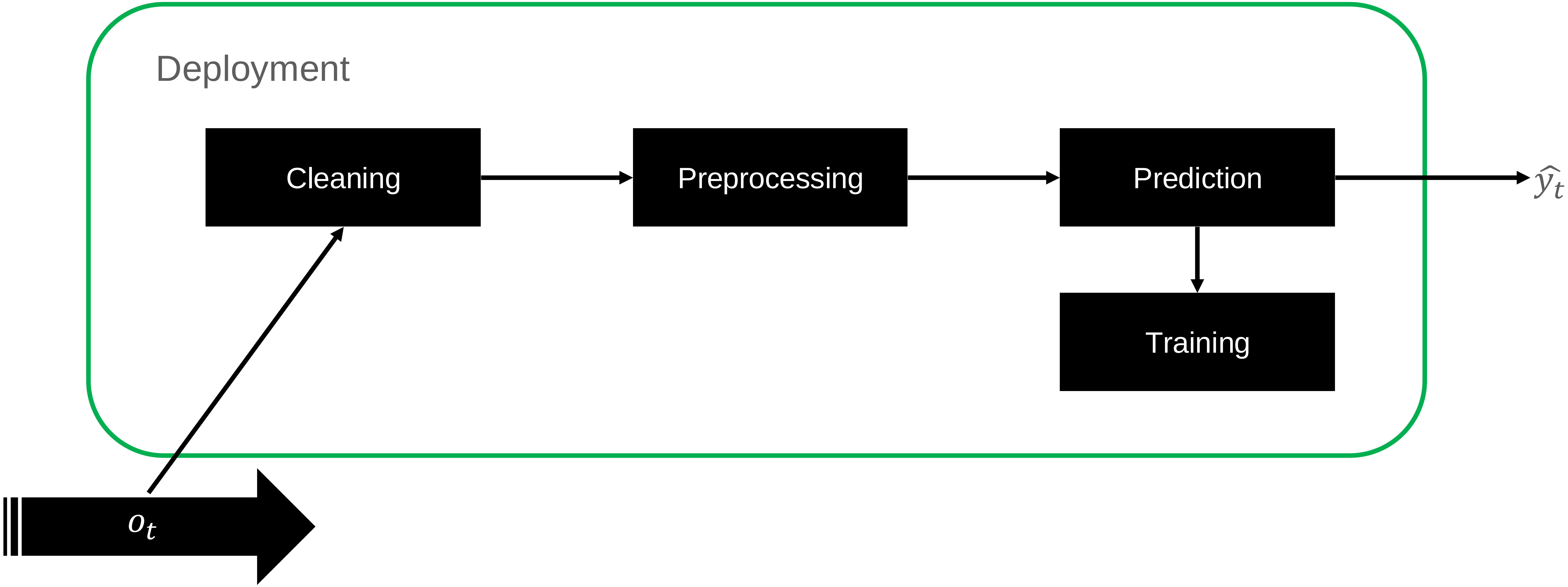
ML Pipelines for Data Streams

- Traditional ML Pipelines consist of well-defined, separate steps
- After training, model is deployed to make predictions
- In data streams, there is no separate deployment phase



ML Pipelines for Data Streams

- In data streams, there is no separate deployment phase
- Rather, one would deploy a pipeline as a trainable model that can predict at any time



ML Pipelines for Data Streams

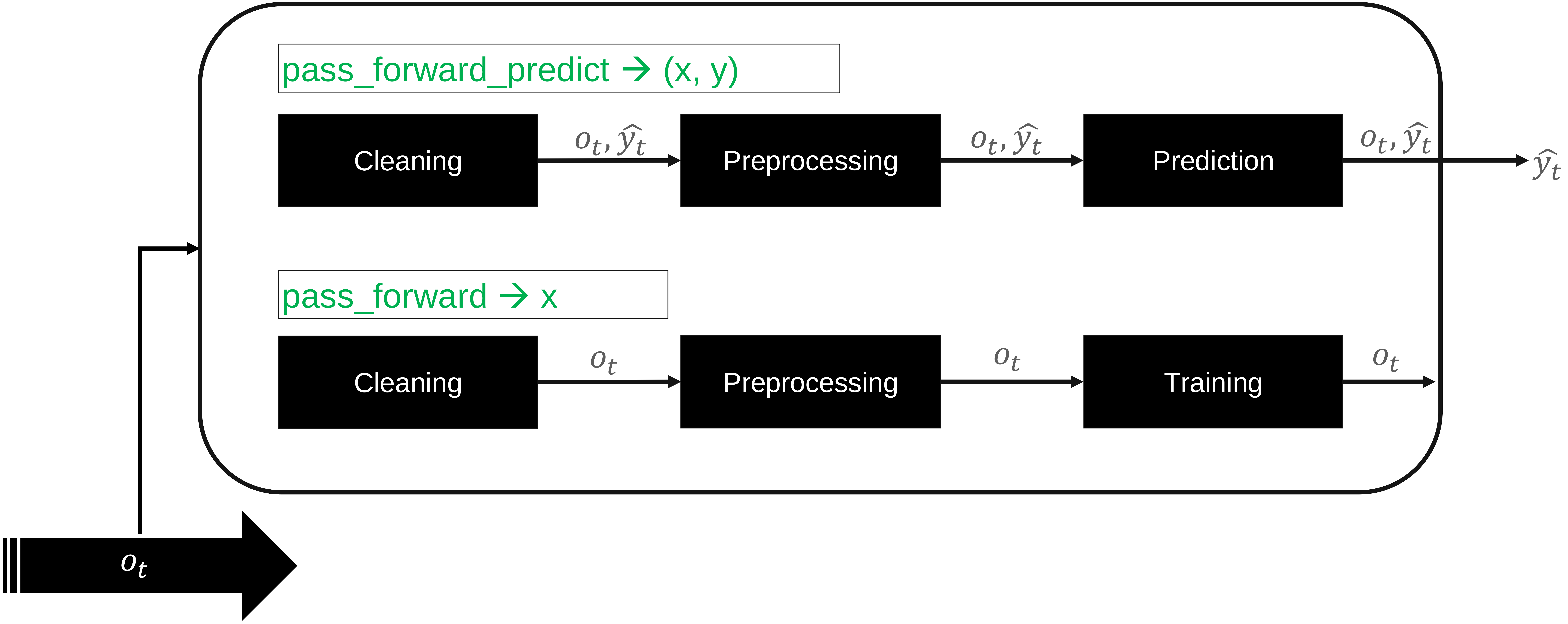
Test-then-train evaluation

For each new instance o_t:

- Clean and preprocess of o_t
- Predict label $\hat{y}_t$ // in the case of classification
- …
- Train model

Pipelines in CapyMOA

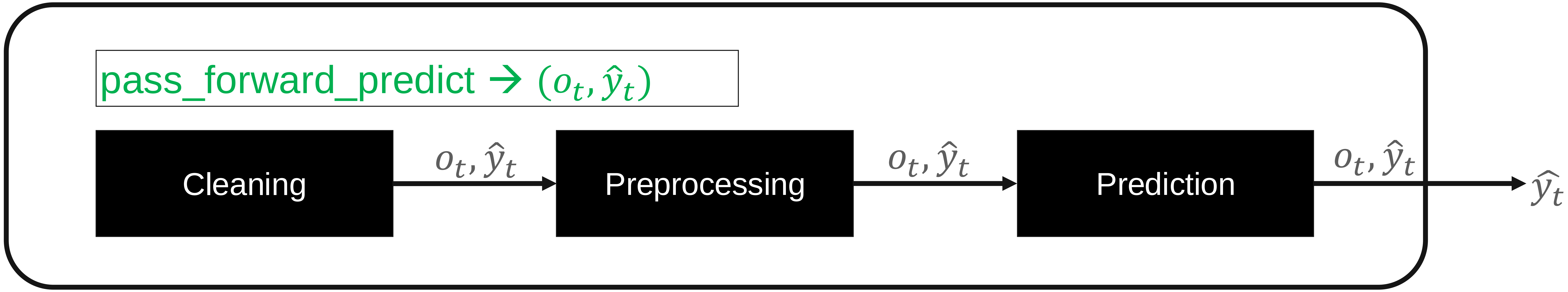
- We separate the pipeline into two basic procedures
- Ensures flexibility and interoperability within CapyMOA ecosystem



Pipelines in CapyMOA

pass_forward_predict → $(o_t, \hat{y}_t)$

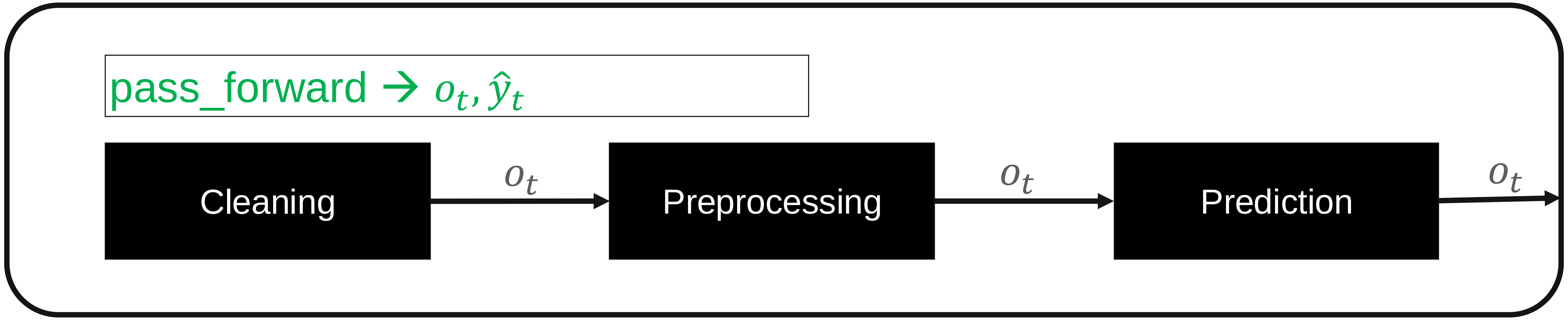
- Each element in the pipeline takes as input $(o_t, \hat{y}_t)$ and ouputs $(o_t, \hat{y}_t)$
- What happens within each pipeline element depends on its type
- For example: preprocessing → transforms o_t, prediction → classifier predicts $\hat{y}_t$



Pipelines in CapyMOA

pass_forward → o_t

- Each element in the pipeline takes as input o_t and outputs o_t
- What happens within each pipeline element depends on its type
- For example: preprocessing → transforms o_t, classifier → trains on o_t



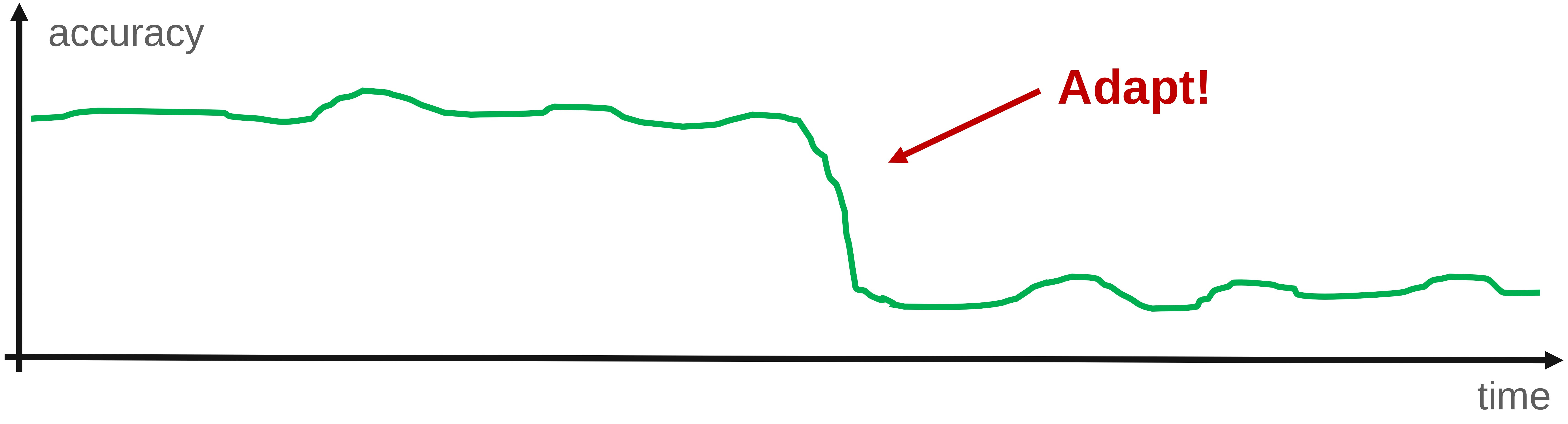
Pipelines

Adaptation to Concept Drift

Adaptation to Concept Drift

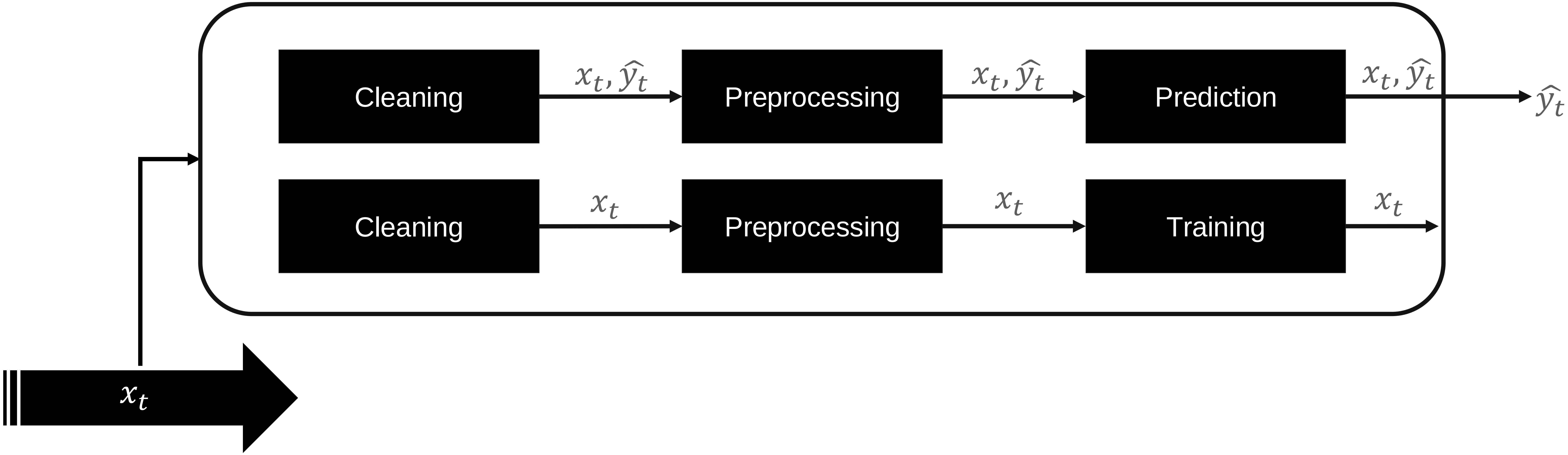
Data stream pipelines should offer ways to **adapt to concept drift**
- For example, one might want to reset a classifier after a change

This opens up several **design choices**, e.g.:
- Where in the pipeline to place drift detector? Multiple ones?
- How to facilitate drift adaptation?
- How to prepare input to drift detector? (can we maintain flexibility?)



Adaptation to Concept Drift

Where in the pipeline to place drift detector?



Adaptation to Concept Drift

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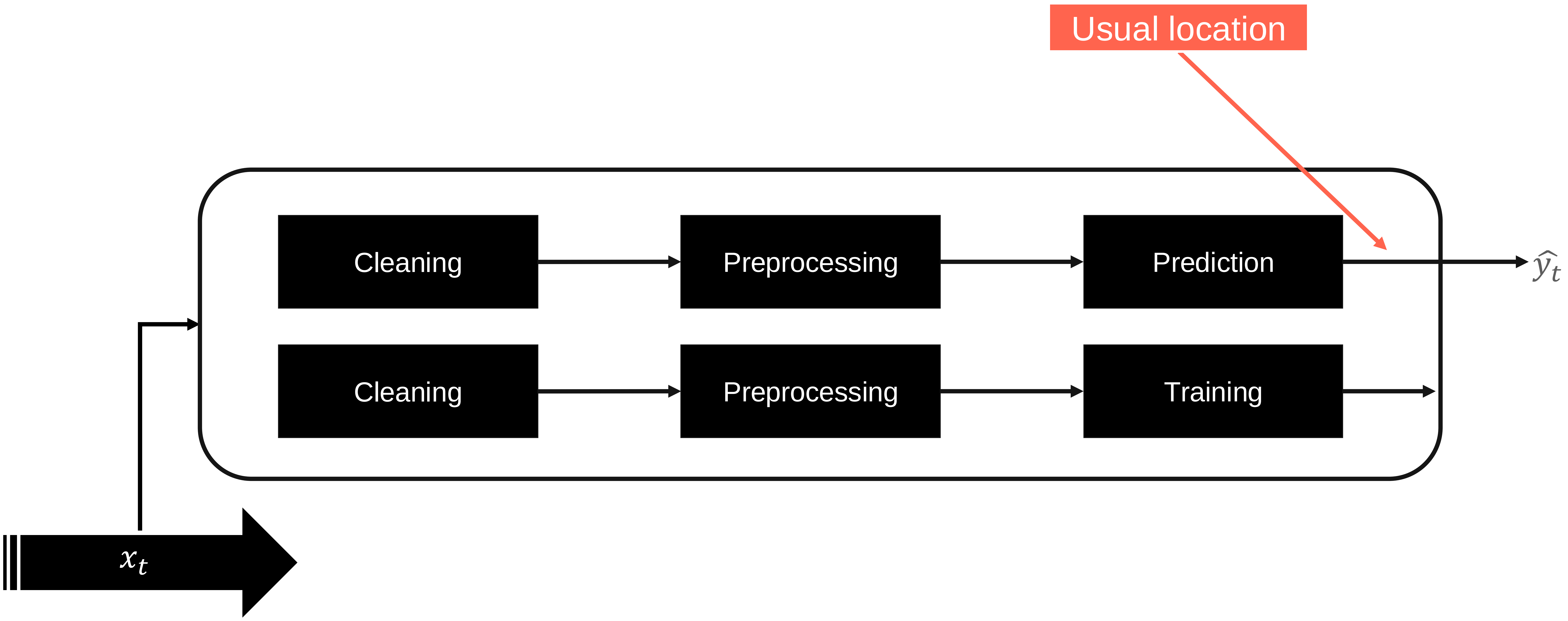

Adaptation to Concept Drift

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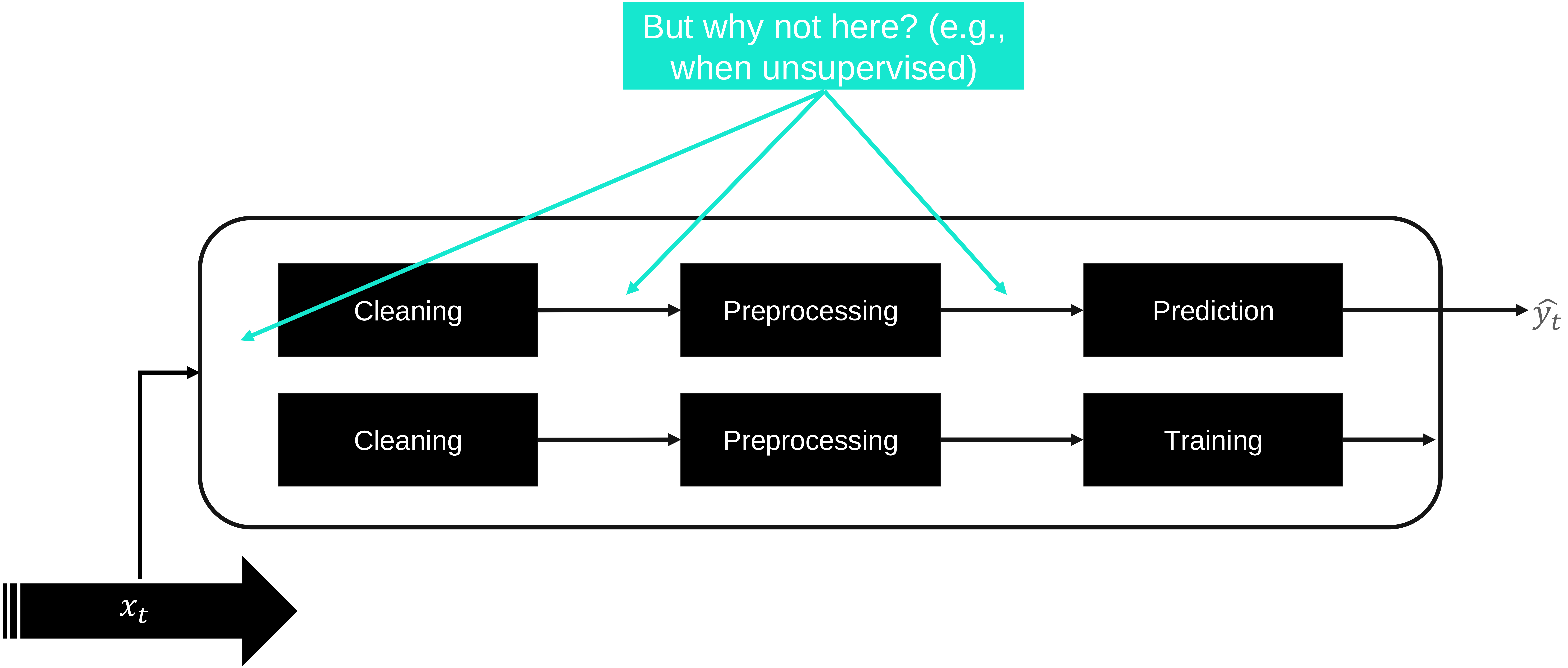
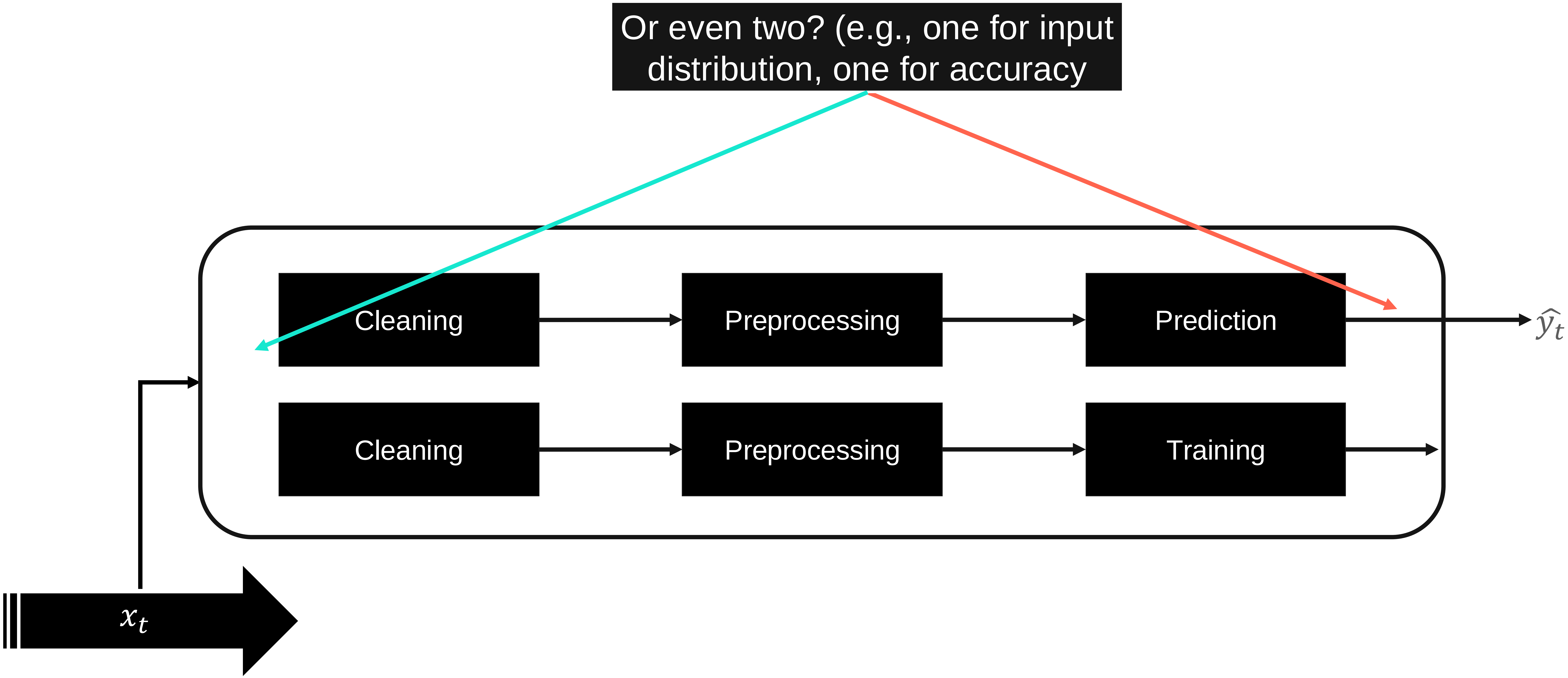


Adaptation to Concept Drift

Where in the pipeline to place drift detector?

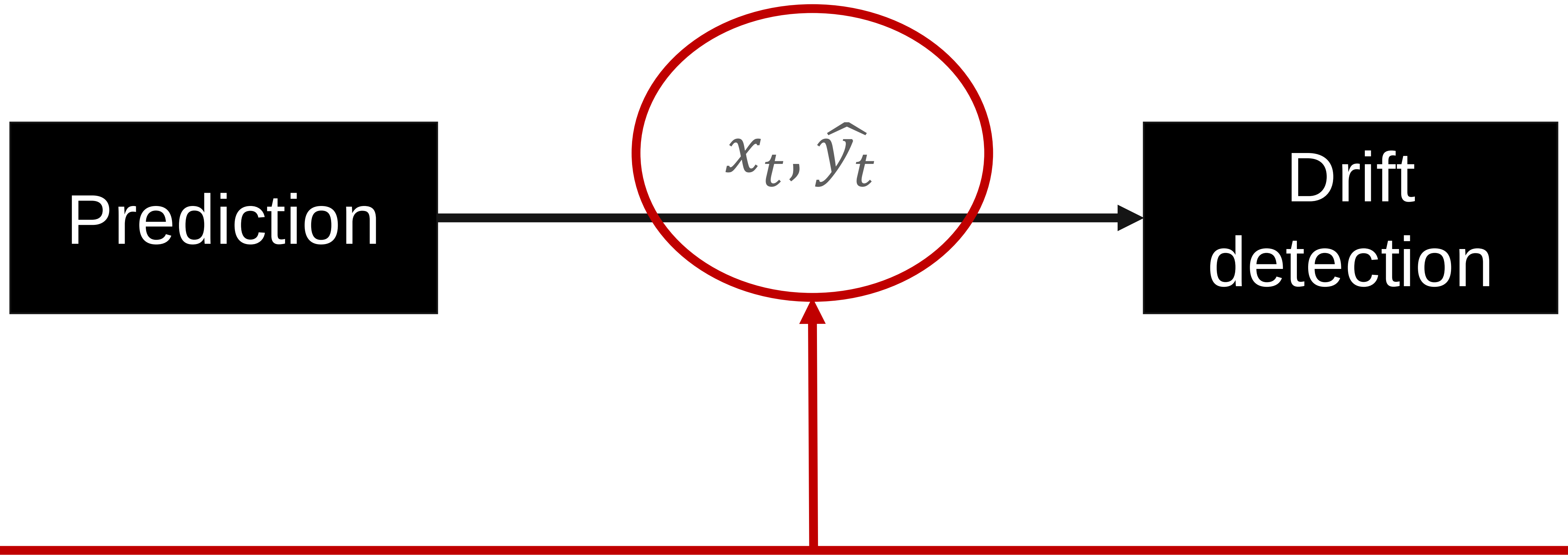


Adaptation to Concept Drift

- **Our pipelines can facilitate all the discussed combinations**
- **We are still working on the drift adaptation feature, so stay tuned!**

Adaptation to Concept Drift

How to prepare input to drift detector? (can we maintain flexibility?)



- As part of a pipeline, input to drift detector pipeline element always $(x_t, \hat{y}_t)$
- What if drift detector monitors accuracy (i.e., if $y_t = \hat{y}_t$)? Or the correlation between certain input features?

→ **We don't know. But we want to provide this flexibility!**

Adaptation to Concept Drift

→ Specify a function that prepares the input for the drift detector

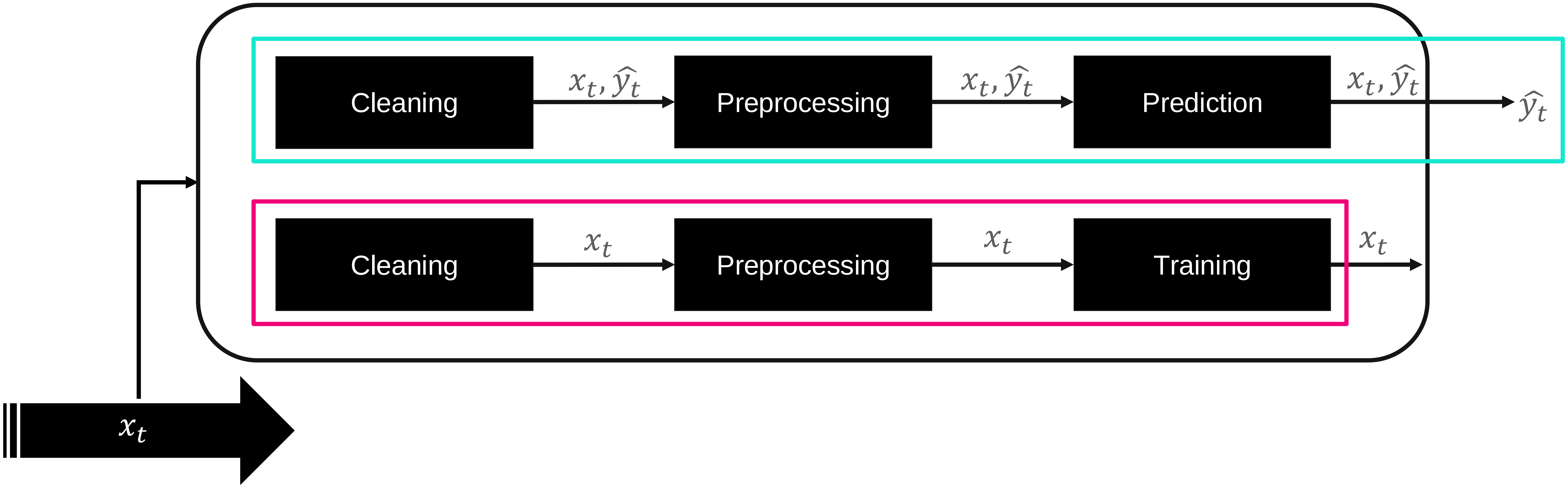
```
def accuracy(instance, y_hat):
    return int(y == y_hat)

detector = Adwin()
drift_pe = DriftDetectorPipelineElement(
                                  detector=detector,
                                  input_func=accuracy)

// Internally, the pipeline element runs:
input = self.input_func(instance, y_hat)
self.detector.update(input)
```

Classifier and Regressor Pipelines

- Besides "abstract" pipelines, we also support classifier and regressor pipelines
- These pipelines implement **predict** and **train** and can thus be used like any other classifier



Practical examples

ECML_2024_pipelines.ipynb