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# The Past and the dubious: Concept Drift

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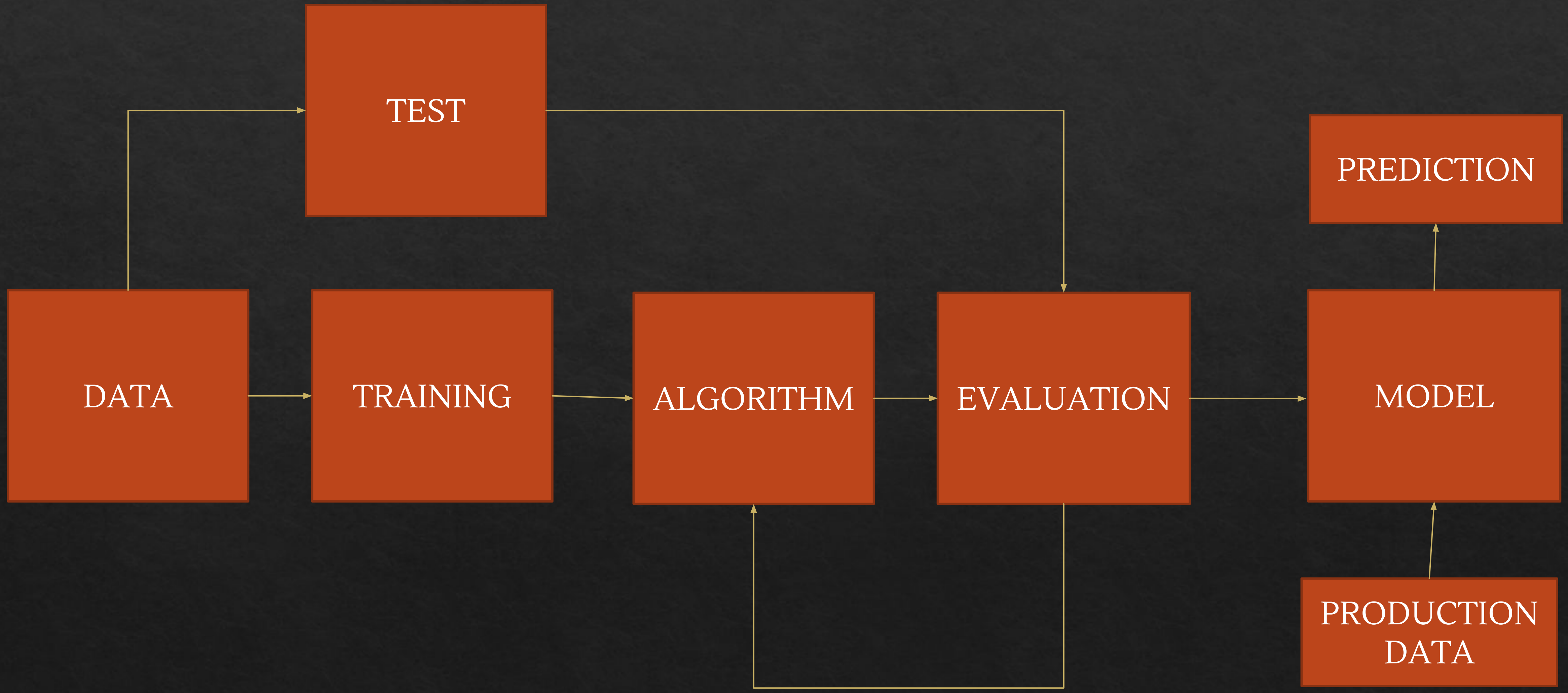
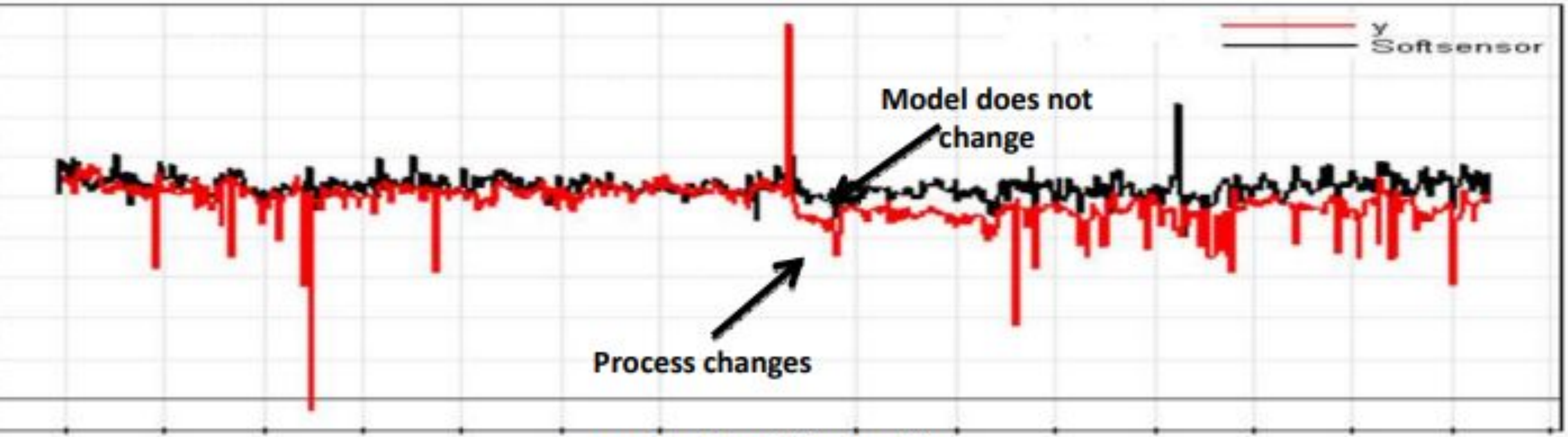
# Typical ML workflow



# Static model




*source: Evonik Industries*

Handling Concept Drift: Importance, Challenges & Solutions A. Bifet, J. Gama, M. Pechenizkiy,

# Types of drift in Machine Learning

## Concept Drift

- Statistical properties of Target variable change
- Hidden Context :A dependency not given explicitly in the form of input features.

## Data Drift

- Statistical properties of the input data change
- Seasonality, trend etc
- No impact to previously labeled data

## Upstream/pipeline changes

- Operational changes in data pipeline
- Change in encoding, null value handling etc

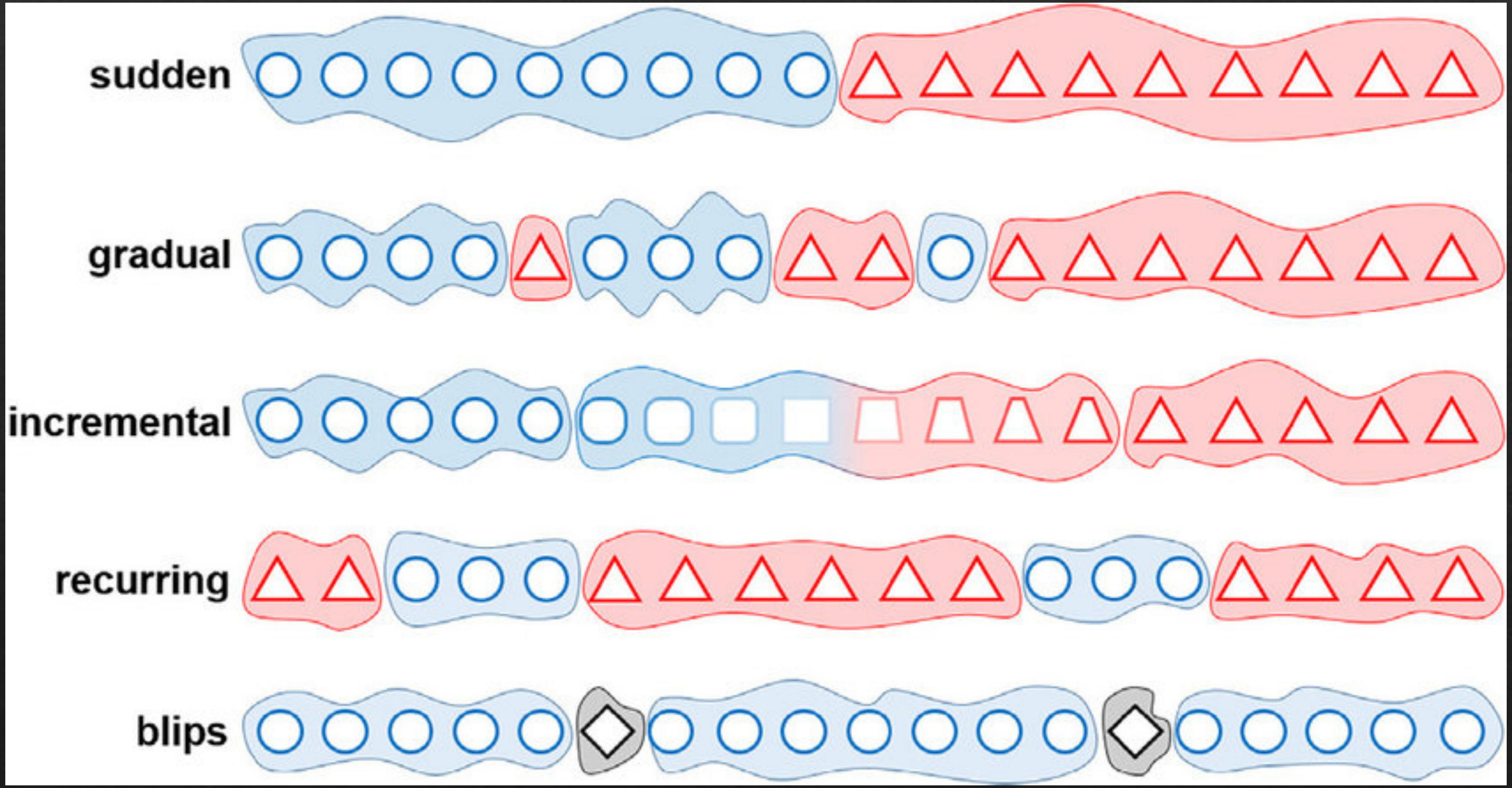
# The Past and the Dubious : Concept Drift

- Renders the model built on data, inconsistent with new data
- Differing decision boundary for the same input data over time

Examples

- Weather Prediction based on historical events
- Buying behavior based on customer preferences
- Fraud prediction based on payments

# Types of concept drift




Abrupt Change in Class Distribution

Class Distribution modified at a slower rate

Drifts reoccur with time. Can be cyclic

Online Ensemble Learning with Abstaining Classifiers for Drifting and Noisy Data Streams - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Four-types-of-concept-drift-according-to-severity-and-speed-of-changes-and-noisy-blips_fig2_321627304 [accessed 3 Dec, 2019]

# What can we do / must be done

- **Monitor the distribution of the incoming data :** Small distribution changes may require an update to the model on more recent data, while large deviations may require a full re-training of the model
- **Regular model refresh necessary :** Use SME to review model outputs periodically, and to determine new labels/ data points that can be used to update the model
- **Assume** that concept drift would occur, and periodically update
- **Adapt to concept drift**, with limited resources (time and memory)

https://www.dataversity.net/handling-concept-drift-in-interventional-machine-l

# Handling Concept Drift

Three Basic approaches

- **Instance Selection**
- Instance Weighting
- Ensemble learning

Consists in generalizing from a window that moves over recently arrived instances and uses the learnt concepts for prediction only in the immediate future.

The window size can be fixed or heuristically determined (Adaptive)

*The Problem of Concept Drift: Definitions and Related Work - Alexev Tsymbalo paper.*

# Concept drift with Python - learning from evolving data streams

**Drift Detection: skmultiflow.drift_detection**

The skmultiflow.drift_detection module includes methods for Concept Drift Detection.

| | |
|---|---|
| drift_detection.ADWIN | Adaptive Windowing method for concept drift detection. |
| drift_detection.DDM | Drift Detection Method. |
| drift_detection.EDDM | Early Drift Detection Method. |
| drift_detection.PageHinkley | Page-Hinkley method for concept drift detection. |

# ADWIN (**AD**aptive **WIN**dowing)

- ADWIN efficiently keeps a variable-length window of recent items
- Window has the maximal length statistically consistent with the hypothesis *there has been no change in the average value inside the window*
- This window is further divided into two sub-windows (W0, W1) used to determine if a change has happened.
- ADWIN compares the average between W0 and W1 to confirm that they correspond to the same distribution.
- Concept drift is detected if the distribution equality no longer holds
- Upon detecting a drift, W0 is replaced by W1 and a new W1 is initialized.
- ADWIN uses a confidence value $\delta = \in (0, 1)$ to determine if the two sub-windows correspond to the same distribution

*JACOB MONTIEL LOPEZ - Fast and Slow Machine Learning These de doctorat de l'Universit ` e Paris-Saclay ´ prepar ´ ee´ a T`*

In [1]:

```
>>> # Imports
>>> import numpy as np
>>> from skmultiflow.drift_detection.adwin import ADWIN
>>> adwin = ADWIN()
>>> # Simulating a data stream as a normal distribution of 1's and 0's
>>> data_stream = np.random.randint(2, size=2000)
>>> # Changing the data concept from index 999 to 2000
>>> for i in range(999, 2000):
        data_stream[i] = np.random.randint(4, high=80)
        #print(data_stream[i])
>>> # Adding stream elements to ADWIN and verifying if drift occurred
>>> for i in range(2000):
        adwin.add_element(data_stream[i])
        print(data_stream[i])
        if adwin.detected_change():
            print('Change detected in data: ' + str(data_stream[i]) + ' - at index: ' + st
```

```
53
15
34
67
68
69
Change detected in data: 69 - at index: 1055
36
30
```

# EDDM (Early Drift Detection Method)

- Method to detect changes in the distribution of the training examples which monitors the online error-rate
- Learning takes place in a sequence of trials
- When a new training example is available, it is classified using the current model.
- Warning level and Drift level are defined
- A new context is declared, if in a sequence of examples, the error increases reaching the warning level at example Kw, and the drift level at example Kd.
- This is taken as an indication of a change in the distribution of the examples.
- Works well with and gets good results with slow gradual changes

https://www.cs.upc.edu/~abifet/EDD

# EDDM - Early Drift Detection Method

In [2]:

```
>>> # Imports
>>> import numpy as np
>>> from skmultiflow.drift_detection.eddm import EDDM
>>> eddm = EDDM()
>>> # Simulating a data stream as a normal distribution of 1's and 0's
>>> data_stream = np.random.randint(2, size=2000)
>>> # Changing the data concept from index 999 to 1500, simulating an
>>> # increase in error rate
>>> for i in range(999, 1500):
...     data_stream[i] = 0
>>> # Adding stream elements to EDDM and verifying if drift occurred
>>> for i in range(2000):
...     eddm.add_element(data_stream[i])
...     if eddm.detected_warning_zone():
...         print('Warning zone has been detected in data: ' + str(data_stream[i]) + ' - c
...     if eddm.detected_change():
...         print('Change has been detected in data: ' + str(data_stream[i]) + ' - of inde
```

```
Warning zone has been detected in data: 1 - of index: 69
Warning zone has been detected in data: 0 - of index: 70
Warning zone has been detected in data: 0 - of index: 71
Warning zone has been detected in data: 1 - of index: 72
Change has been detected in data: 1 - of index: 73
Change has been detected in data: 1 - of index: 131
```

# Some advanced methods

- Handling concept drift using Instance Weighting
  - Weighting by:
    - Age
    - Relevance to the current concept.

- Handling Concept Drift using Ensemble Learning
  - The Very Fast Decision Tree (VFDT) Algorithm
  - Ensembles of Classifiers
  - Support Vector Machines

# To summarize

- Concept Drift is Real, and is a challenge!
- Most of the algorithms for handling concept drift consider incremental (online) learning environments as opposed to batch learning.
  - Because real life data often needs to be processed in an online manner.
    - Data Streams -> incremental learning
    - Databases -> batch learning
- Acknowledging that models must/will evolve continuously is the key to understand and fix concept drift

# References/Bibliography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