Just-in-Time Classifiers For Recurrent Concepts

Giacomo Boracchi
Politecnico di Milano,
giacomo.boracchi@polim.it
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Universitè Libre de Bruxelles

Joint work with Cesare Alippi and Manuel Roveri

Presentation Outline

- Problem Statement
  - Drift Taxonomy
- Just In Time Classifiers at a Glance
  - Few more details
- Experiments
- Conclusions

PROBLEM FORMULATION

Learning in Nonstationary (Streaming) Environments

CLASSIFICATION OVER DATASTREAMS

The problem: classification over a potentially infinitely long **stream of data**

$$X = \{\boldsymbol{x_0}, \boldsymbol{x_1}, \dots,\}$$

Data-generating process $\mathcal{X}$ generates tuples $(\boldsymbol{x}_t, y_t) \sim \mathcal{X}$

- $\boldsymbol{x}_t$ is the observation at time t (e.g., $\boldsymbol{x}_t \in \mathbb{R}^d$)
- y_t is the associated label which is (often) unknown ($y_t \in \Lambda$)

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Typically, one **assumes**

- Independent and identically distributed (i.i.d.) inputs

$$(\boldsymbol{x_t}, y_t) \sim p(\boldsymbol{x}, y)$$

- a **training set** is provided

$$TR = \{(\boldsymbol{x}_0, y_0), \dots, (\boldsymbol{x}_n, y_n)\}$$

CLASSIFICATION OVER DATASTREAMS

The task: learn a classifier K to predict labels

$$\hat{y}_t = K(\boldsymbol{x}_t)$$

in an **online manner** having a low **classification error**,

$$\widehat{err_K}(T) = \frac{1}{T}\sum_{t=1}^{T} e_t \text{, where } e_t = \begin{cases} 0, & \text{if } \hat{y}_t = y_t \\ 1, & \text{if } \hat{y}_t \neq y_t \end{cases}$$

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Unfortunately, datastreams $\mathcal{X}$ might change during operations. From time t onward

$$(\boldsymbol{x_t}, y_t) \sim p_t(\boldsymbol{x}, y)$$

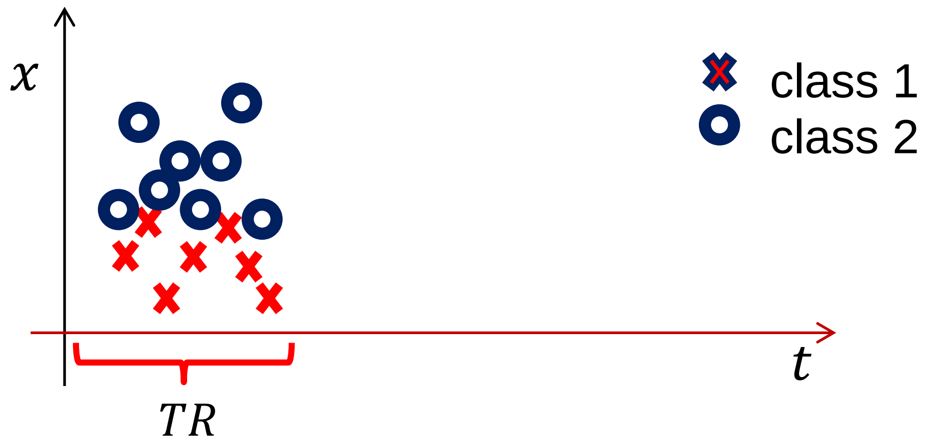
and $\mathcal{X}$ becomes **nonstationary** (undergoes a change) at t if

$$p_t(\boldsymbol{x}, y) \neq p_{\{t+1\}}(\boldsymbol{x}, y)$$

Changes in $\mathcal{X}$ are referred to as **concept drift**

Consider as, an illustrative example, a simple 1-dimensional classification problem, where

- The initial part of the stream is provided for training
- K is simply a threshold



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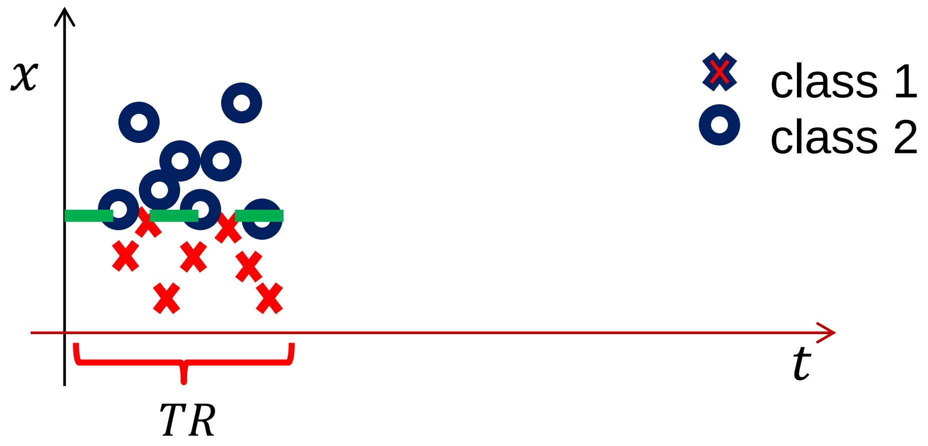

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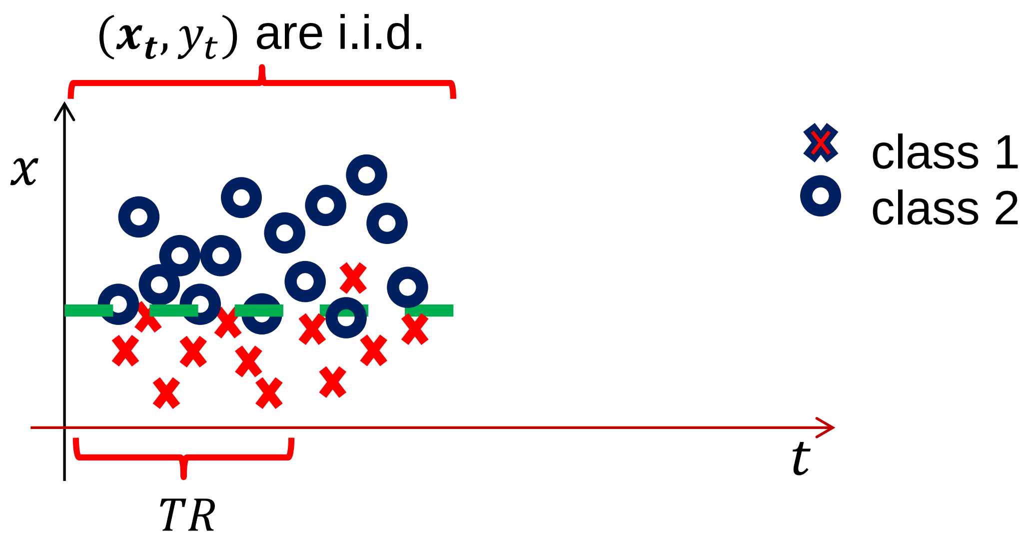

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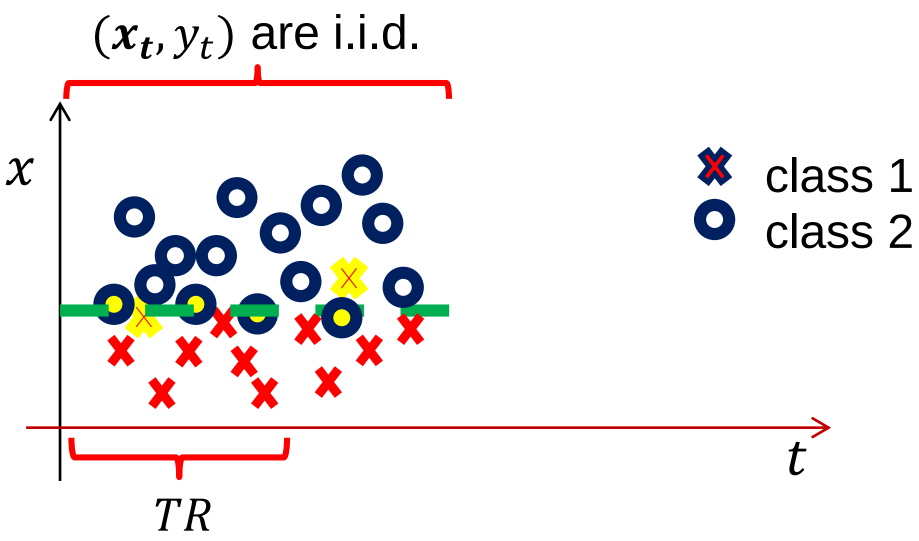
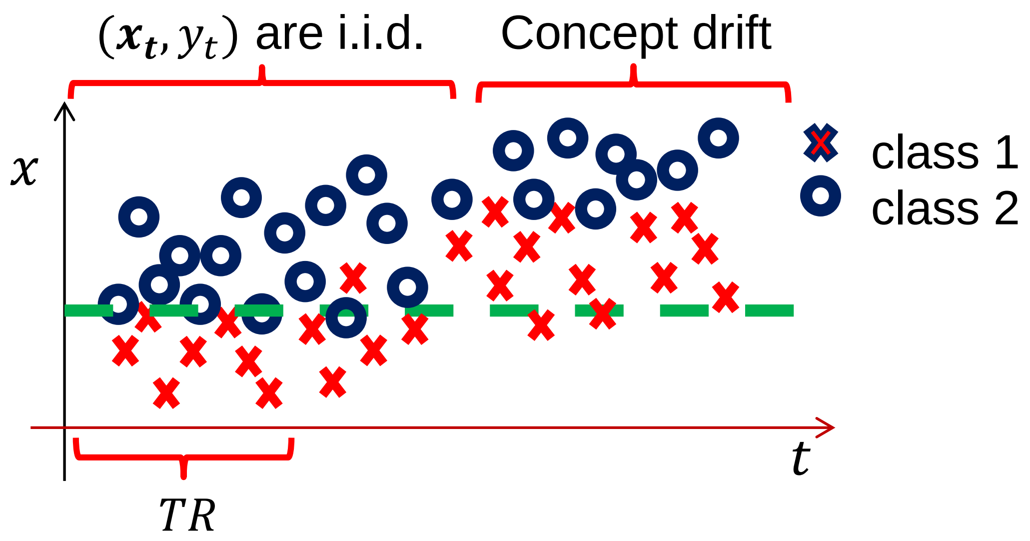
As far as data are i.i.d., the classification error is *controlled*



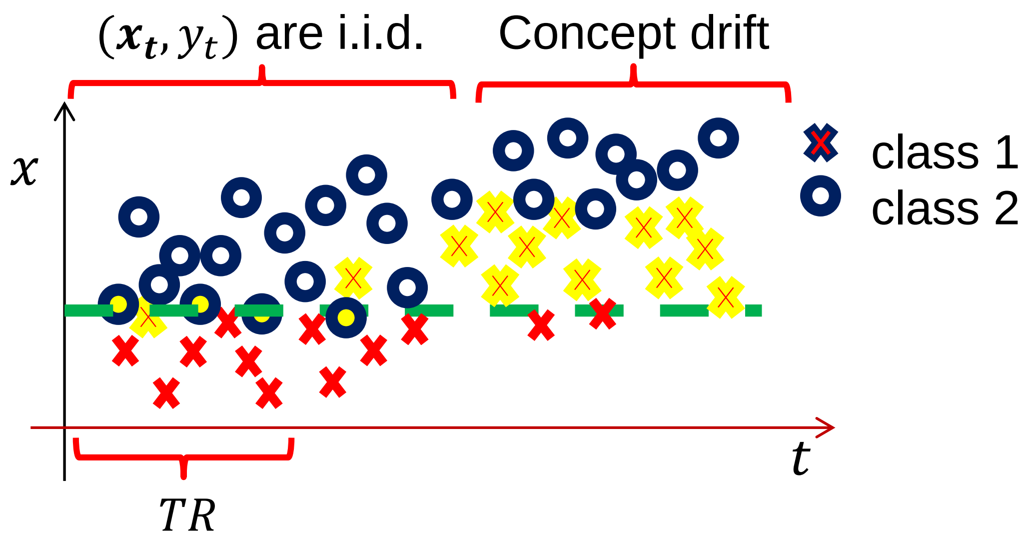
CLASSIFICATION OVER DATASTREAMS

Unfortunately, when concept drift occurs, and pdf p of $\mathcal{X}$ changes,

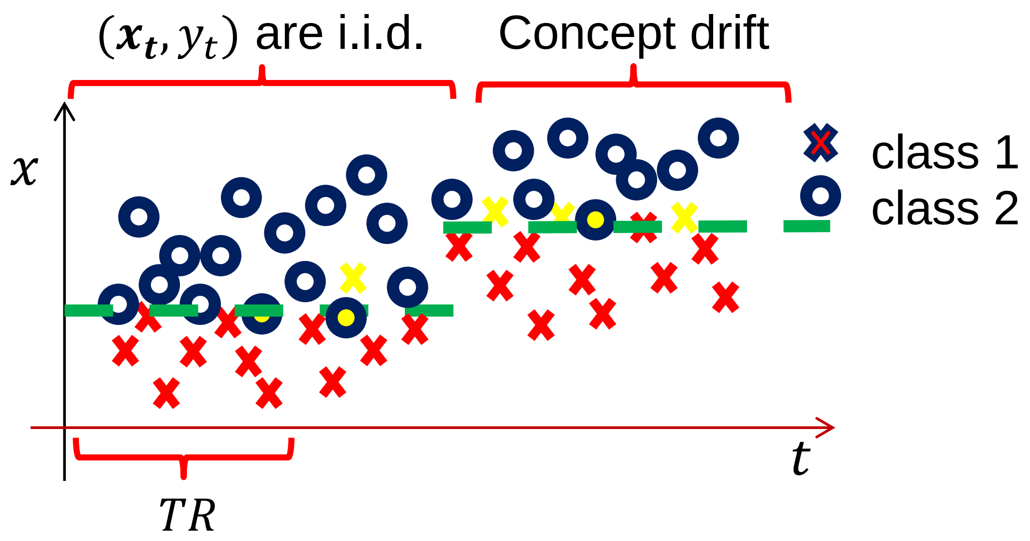


CLASSIFICATION OVER DATASTREAMS

Unfortunately, when concept drift occurs, and pdf p of $\mathcal{X}$ changes, things can be terribly worst.



Adaptation is needed to **preserve** classifier performance



SUPERVISED SAMPLES

We assume that **few supervised samples** are provided during **operations**.

Supervised samples enable the classifier to:

- **React to concept drift** to preserve its performance.
- **Increase its accuracy** in stationary conditions.

The classifier have to be **updated**, thus K becomes K_t

ADAPTATION STRATEGIES

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Consider two straightforward adaptation strategies

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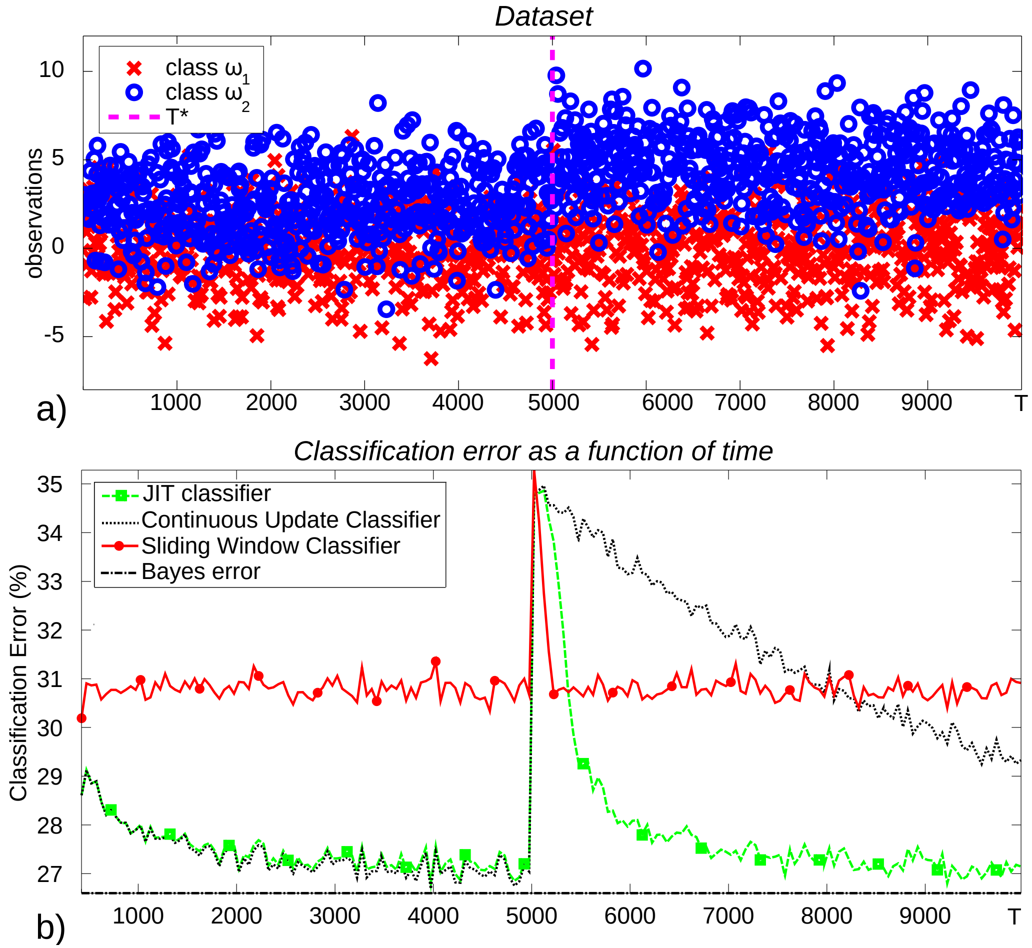

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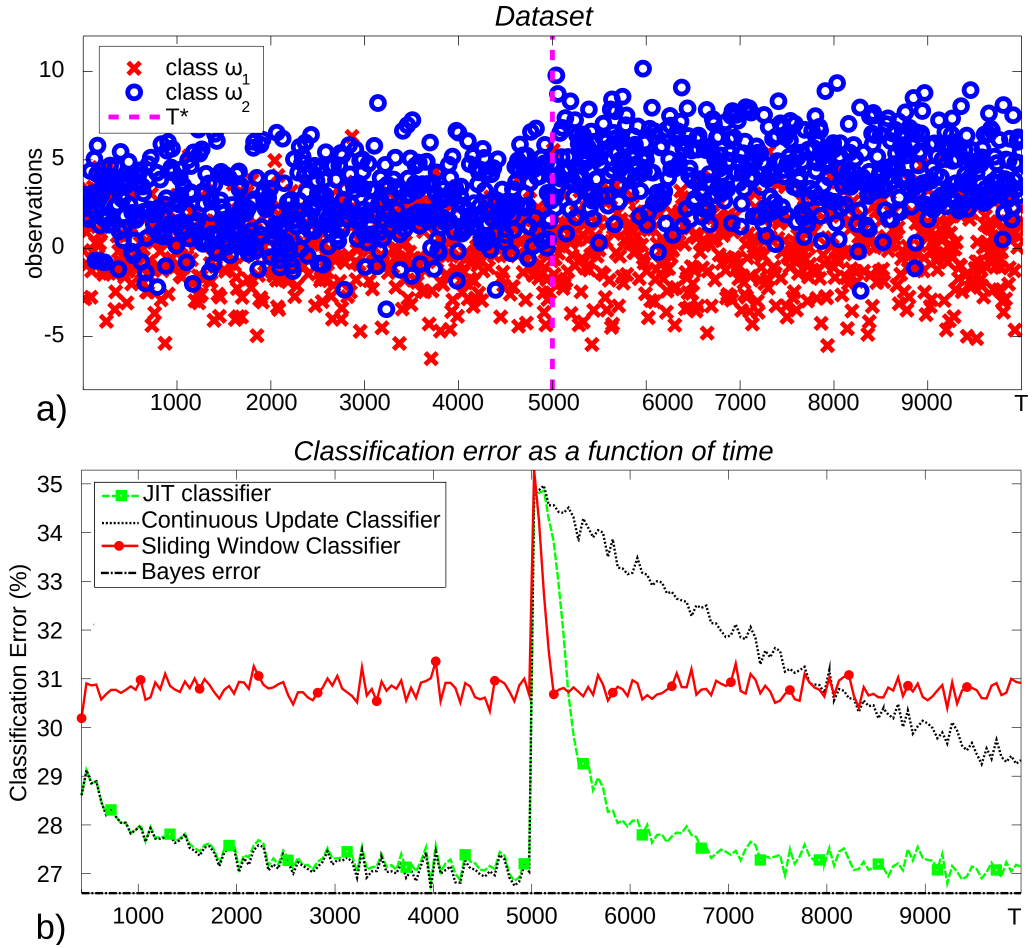


Just including "fresh" training samples is not enough

Adaptation Strategies

Two main solutions in the literature:

- **Active**: the classifier K_t is combined with statistical tools **to detect concept drift and pilot the adaptation**
- **Passive**: the classifier K_t undergoes **continuous adaptation** determining every time which supervised information to preserve

Which is best depends on the expected change rate and memory/computational availability

DRIFT TAXONOMY

DRIFT TAXONOMY

- Drift taxonomy according to two characteristics:
- What is changing?

$$p_t(\boldsymbol{x}, y) = p_t(y|\boldsymbol{x})\, p_t(\boldsymbol{x})$$

- Drift might affect $p_t(y|\boldsymbol{x})$ and/or $p_t(\boldsymbol{x})$
  - Real
  - Virtual
- How does it changes over time?
  - Abrupt
  - Gradual
  - Recurring
  - .....

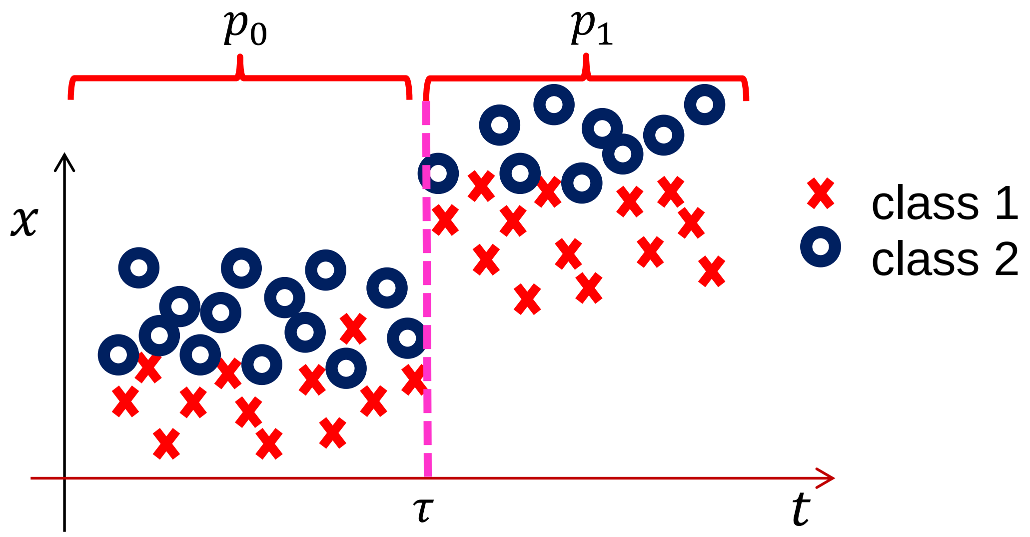
Drift taxonomy: What is changing?

Real Drift

$$p_{\tau+1}(y|\boldsymbol{x}) \neq p_{\tau}(y|\boldsymbol{x})$$

affects $p_t(y|\boldsymbol{x})$ while $p_t(\boldsymbol{x})$ – the distribution of unlabeled data – *might* change or not.

$$p_{\tau+1}(\boldsymbol{x}) \neq p_{\tau}(\boldsymbol{x})$$



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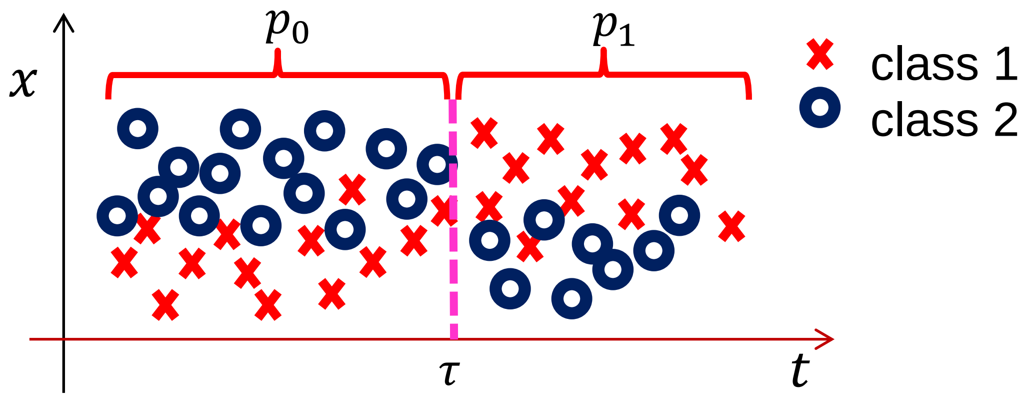
$$p_{\tau+1}(\boldsymbol{x}) = p_{\tau}(\boldsymbol{x})$$

E.g. changes in the "class function", classes swap



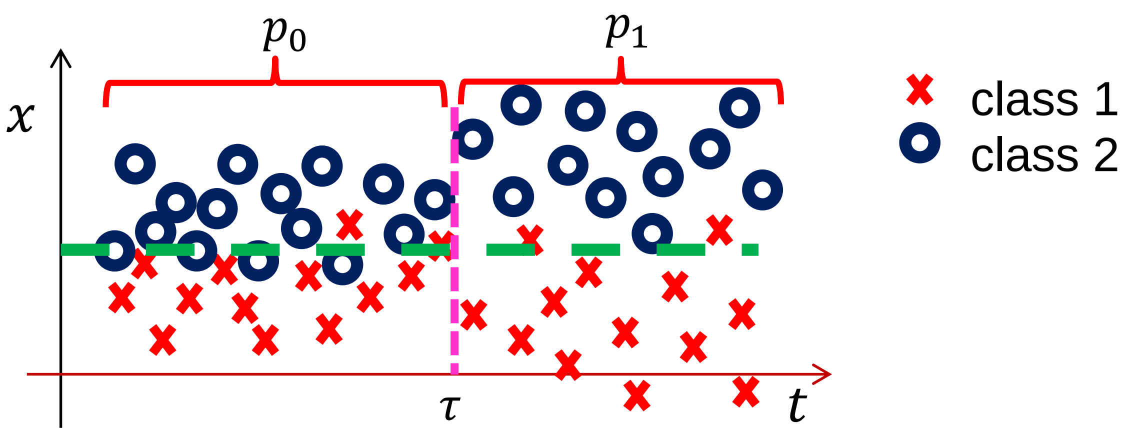
Drift taxonomy: What is changing?

Virtual Drift

$$p_{\tau+1}(y|\boldsymbol{x}) = p_\tau(y|\boldsymbol{x}) \text{ while } p_{\tau+1}(\boldsymbol{x}) \neq p_\tau(\boldsymbol{x})$$

affects only $p_t(\boldsymbol{x})$ and leaves the class posterior probability unchanged.

These are not relevant from a predictive perspective, classifier accuracy is not affected

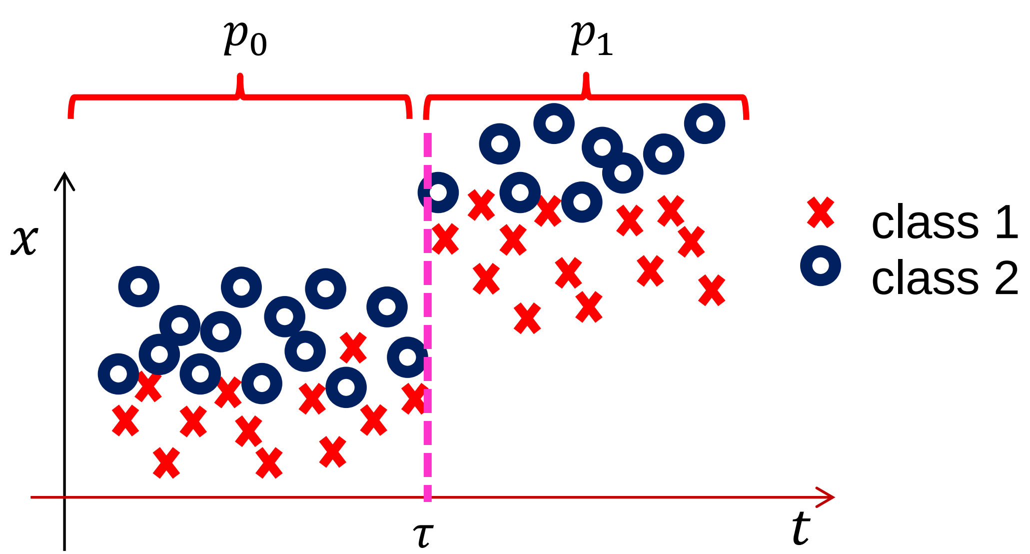


Drift taxonomy: time evolution

Abrupt

$$p_t(\boldsymbol{x}, y) = \begin{cases} p_0(\boldsymbol{x}, y) & t < \tau \\ p_1(\boldsymbol{x}, y) & t \geq \tau \end{cases}$$

Permanent shift in the state of $\mathcal{X}$, e.g. a faulty sensor, or a system turned to an active state

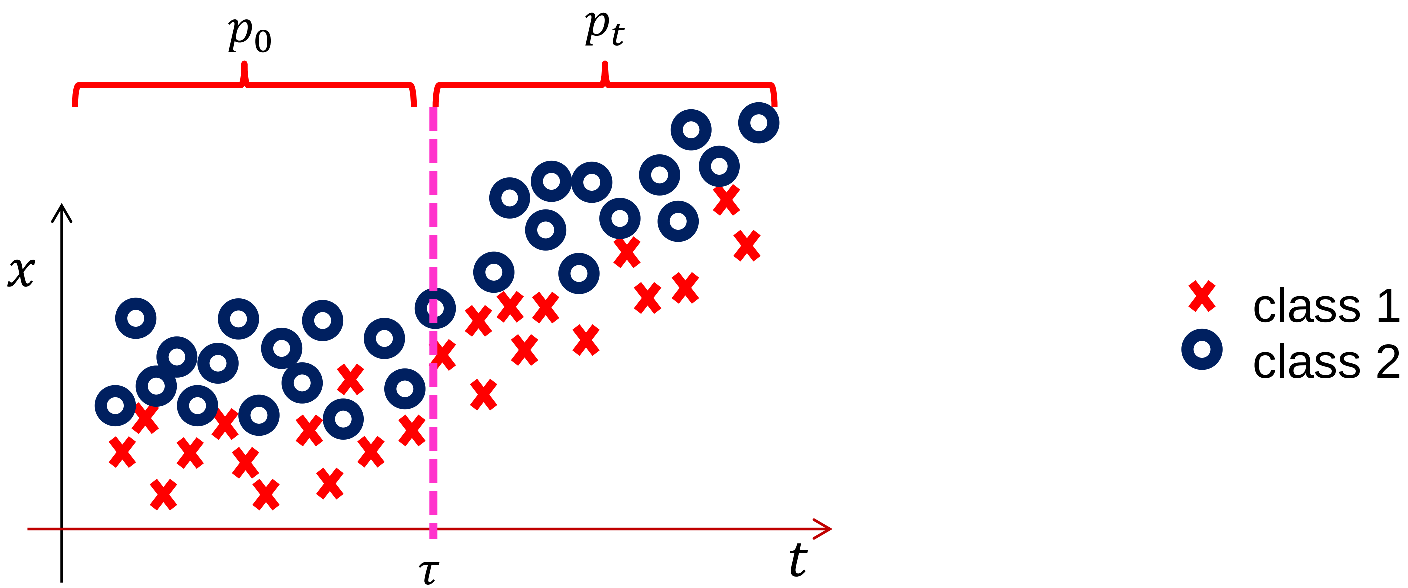


Drift taxonomy: time evolution

Gradual

$$p_t(\boldsymbol{x}, y) = \begin{cases} p_0(\boldsymbol{x}, y) & t < \tau \\ p_t(\boldsymbol{x}, y) & t \geq \tau \end{cases}$$

There is not a stationary state of $\mathcal{X}$ after the change

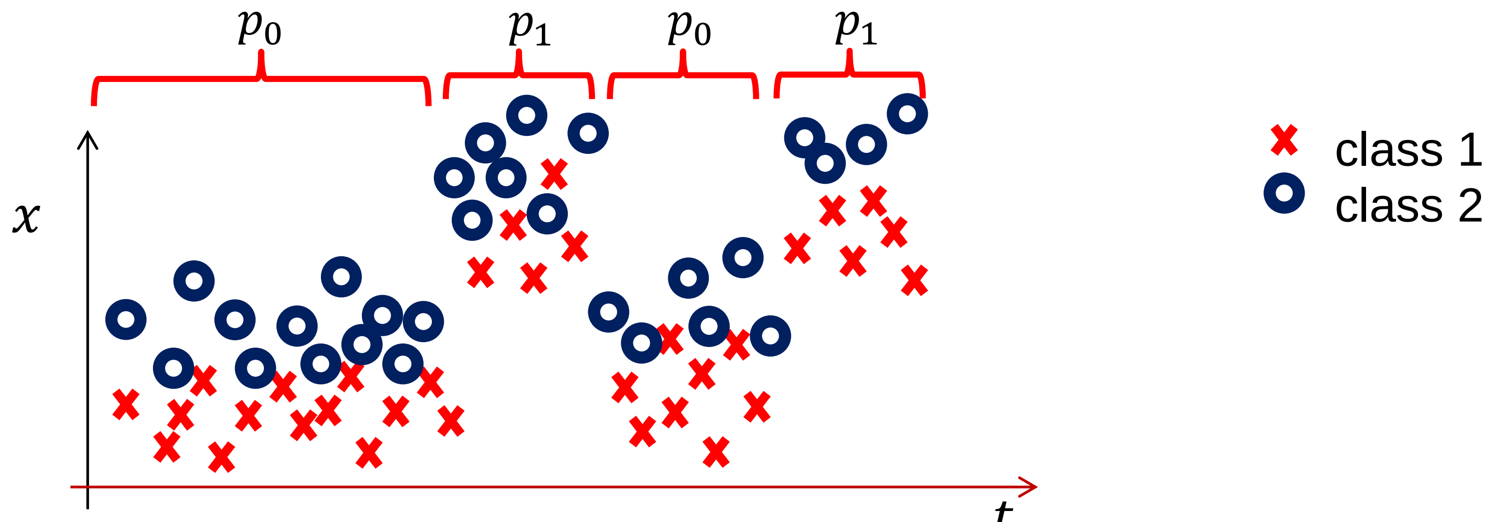


Drift taxonomy: time evolution

Recurring

$$p_t(\boldsymbol{x}, y) = \begin{cases} p_0(\boldsymbol{x}, y) & t < \tau \\ p_1(\boldsymbol{x}, y) & t \geq \tau \\ \quad\ldots & \\ \quad p_1(\boldsymbol{x}, y) & \end{cases}$$

After τ, another concept drift might bring back $\mathcal{X}$ in p_0



What we address here

We present a framework to design adaptive classifiers able to operate on concept drifts that are

- abrupt
- possibly recurrent
- real
- virtual

JUST-IN-TIME CLASSIFIERS

A methodology for designing adaptive classifiers

JIT Classifiers: the Algorithm

1- Build concept $\boxed{C_0 = (Z_0, F_0, D_0)}$ from the training sequence;

2- $Z_{\text{rec}} = \emptyset$ and $i = 0$;

3- **while** *(x_t is available)* **do**

4- $\quad \mathcal{U}(C_i, \{x_t\}) \rightarrow C_i$;

5- $\quad$ **if** *(y_t is available)* **then**

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7- $\quad$ **if** *($\mathcal{D}(C_i) = 1$)* **then**

8- $\quad\quad i = i + 1$;

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14- $\quad\quad \widehat{y}_t = K(Z_i \cup Z_{\text{rec}}, x_t)$.

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Concept Representations

$$C = (Z, F, D)$$

- Z : set of supervised samples
- F : set of features for assessing concept equivalence
- D : set of features for detecting concept drift

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Operators for Concepts

- $\mathcal{D}$ concept-drift detection
- Υ concept split
- $\mathcal{E}$ equivalence operators
- $\mathcal{U}$ concept update

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JIT classifiers can be built upon specific classifier (like svm, decision trees, naive Bayes, knn, etc..)

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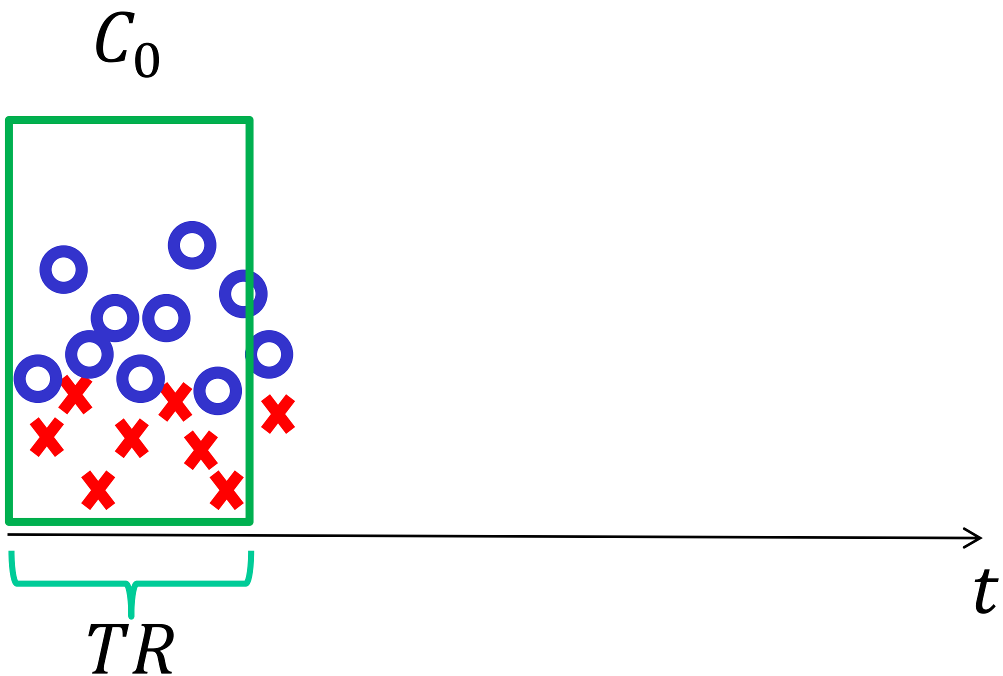
Use the initial training sequence to build the concept representation C_0

JIT Classifier: Concept Representations

Build C_0, a **practical representation** of the **current concept**

- Characterize both $p(\boldsymbol{x})$ and $p(y|\boldsymbol{x})$ in stationary conditions



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During operations, each input sample is analyzed to

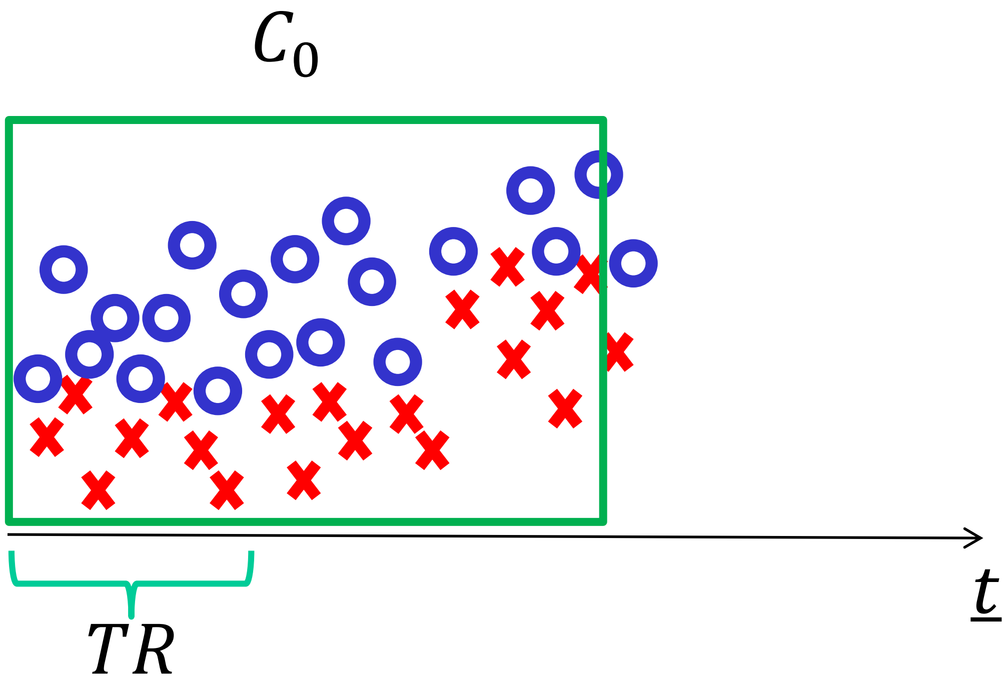
- Extract features that are appended to F_i
- Append supervised information in Z_i

thus updating the current concept representation

JIT Classifiers: Concepts Update

The concept representation C_0 is **always updated** during operation,

- Including supervised samples in Z_0 (to describe $p(y|\boldsymbol{x})$)
- Computing feature F_0 (to describe $p(\boldsymbol{x})$)



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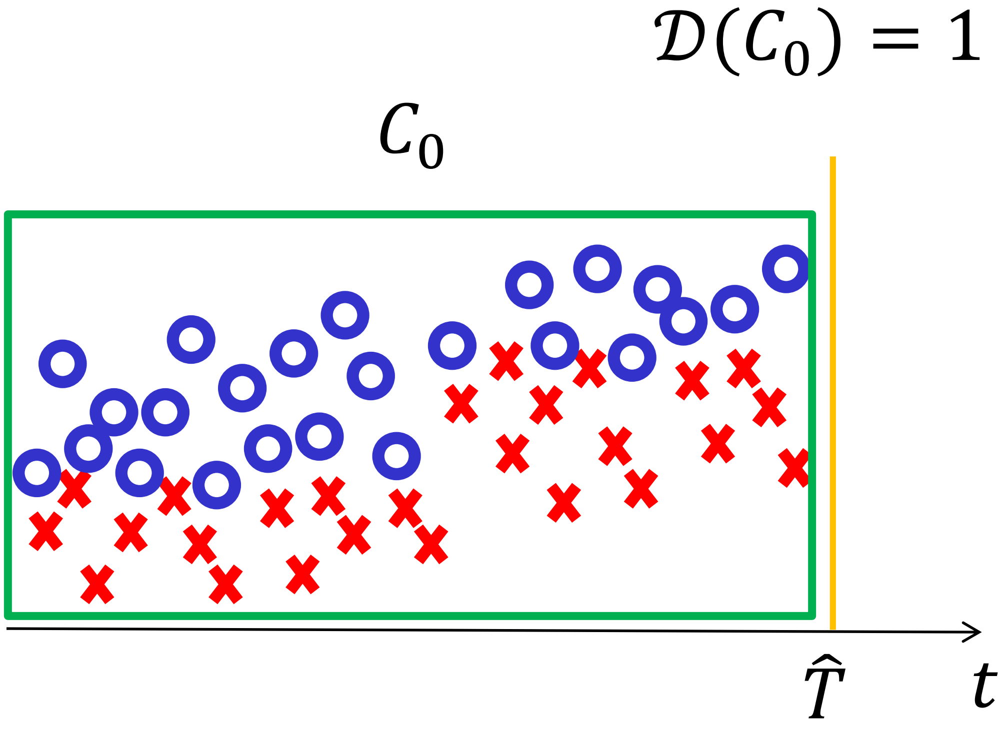
The current concept representation is analyzed by $\mathcal{D}$ to determine whether concept drift has occurred

JIT Classifier: Drift Detection

$\mathcal{D}$ monitoring the datastream by means of **online** and **sequential** change-detection tests (CDTs)

- Changes are detected monitoring $p(y|\boldsymbol{x})$ and $p(\boldsymbol{x})$



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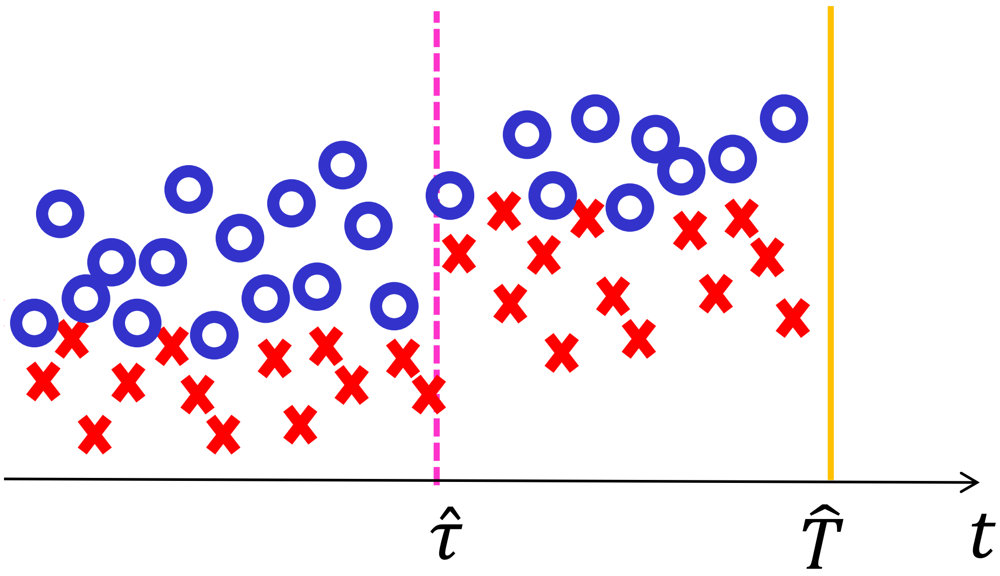
If concept drift is detected, the concept representation is split, to isolate the recent data that refer to the new state of $\mathcal{X}$

A new concept description is built

JIT Classifiers: Concept Splits

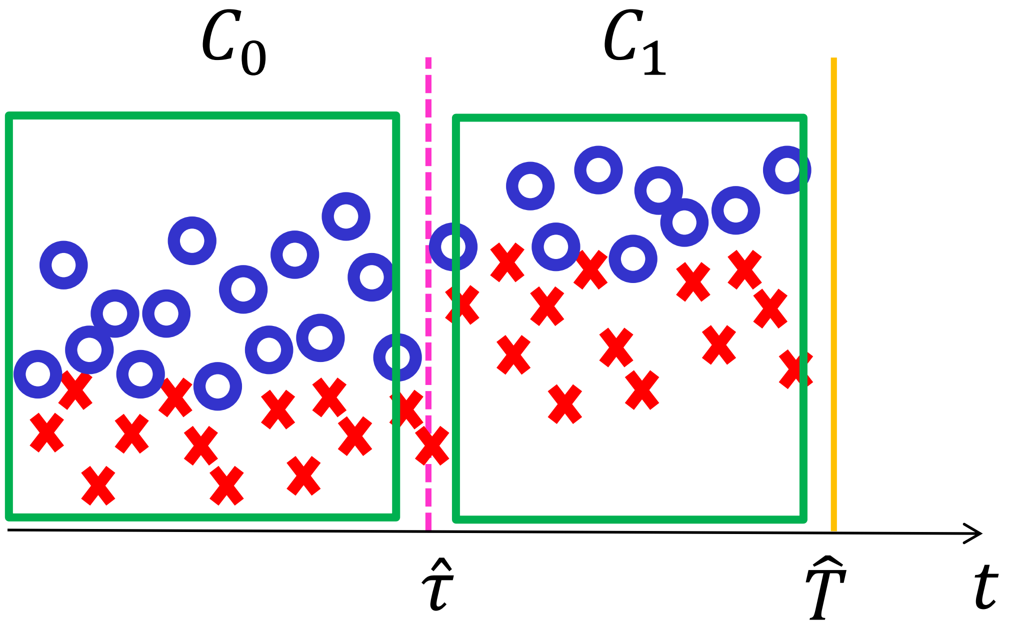
Offline and **retrospective** statistical tools such as hypothesis tests (HT) or change-point methods (CPM) can be used to estimate the change point.



JIT Classifiers: Concept Splits

Two concept descriptions are constructed

$$\Upsilon(C_0) = (C_0, C_1)$$



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Look for concepts that are equivalent to the current one.

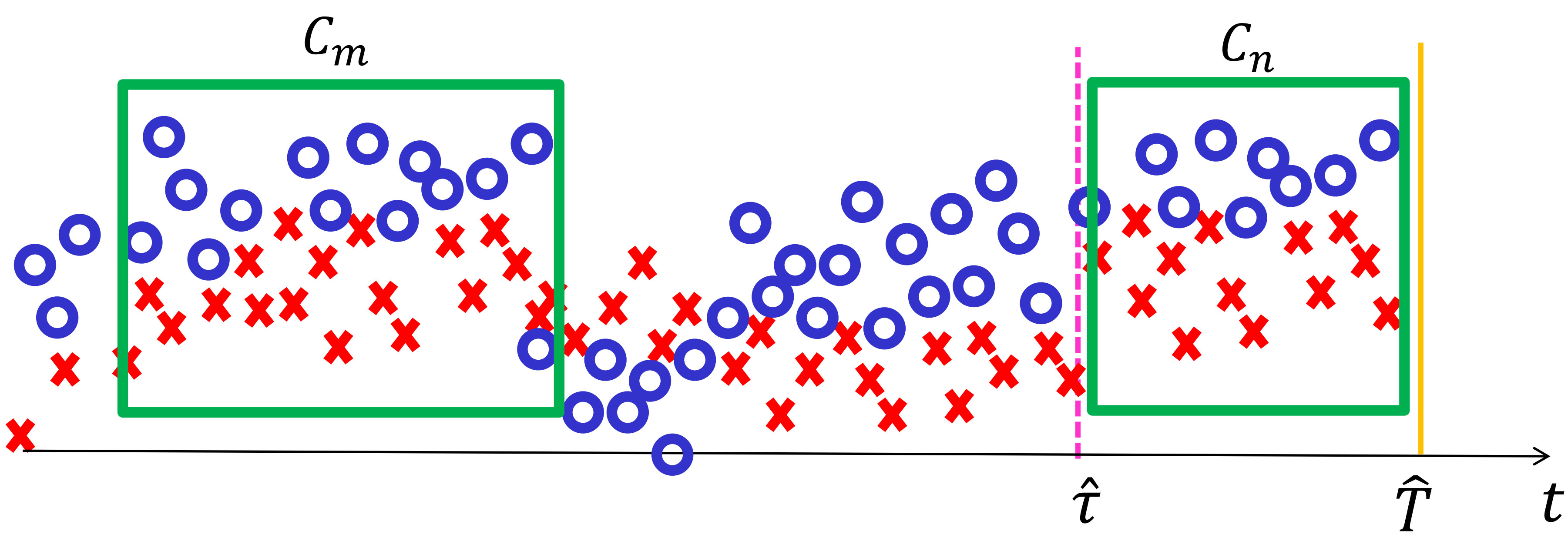
Gather supervised samples from all the representations C_j that refers to the same concept

JIT Classifiers: Comparing Concepts

Concept equivalence is assessed by

- comparing features F to determine whether $p(\boldsymbol{x})$ is the same on C_m and C_n
- comparing classifiers trained on C_m and C_n to determine whether $p(y|\boldsymbol{x})$ is the same

$$\mathcal{E}(C_m, C_n) = 1$$



JIT Classifiers: the Algorithm

1- Build concept $C_0 = \big(Z_0, F_0, D_0\big)$ from the training sequence;
2- $Z_{\text{rec}} = \emptyset$ and $i = 0$;
3- **while** *(x_t is available)* **do**
4- $\quad \mathcal{U}(C_i, \{x_t\}) \to C_i$;
5- $\quad$ **if** *(y_t is available)* **then**
6- $\quad\quad \mathcal{U}(C_i, \{(x_t, y_t)\}) \to C_i$;
$\quad$ **end**
7- $\quad$ **if** *($\mathcal{D}(C_i) = 1$)* **then**
8- $\quad\quad i = i + 1$;
9- $\quad\quad \Upsilon(C_{i-1}) \to (C_k, C_l)$;
10- $\quad\quad C_i = C_l$;
11- $\quad\quad C_{i-1} = C_k$;
12- $\quad\quad Z_{\text{rec}} = \bigcup_{\substack{\mathcal{E}(C_i, C_j)=1 \\ 0 \leq j < i}} Z_j$;
$\quad$ **end**
13- $\quad$ **if** *(y_t is not available)* **then**
14- $\quad\quad \boxed{\widehat{y}_t = K(Z_i \cup Z_{\text{rec}}, x_t).}$
$\quad$ **end**
end

The classifier K is reconfigured using all the available supervised couples

JUST-IN-TIME CLASSIFIERS

Few more details about a specific example

Concept Representations

$$C_i = (Z_i, F_i, D_i)$$

- $Z_i = \{(\boldsymbol{x_0}, y_0), \dots, (\boldsymbol{x_n}, y_n)\}$: **supervised samples** provided during the i^{th} concept
- F_i **features describing** $p(\boldsymbol{x})$ of the i^{th} concept. We take:
  - the sample mean $M(\cdot)$
  - the power-low transform of the sample variance $V(\cdot)$

  extracted from **nonoverlapping sequences**
- D_i **features for detecting** concept drift. These include:
  - the sample mean $M(\cdot)$
  - the power-low transform of the sample variance $V(\cdot)$
  - the average classification error $\widehat{err}$

  extracted from **nonoverlapping sequences**

Update Operator

Update operator

$$\mathcal{U}(C_i, \{(\boldsymbol{x_0}, y_0)\}) = C_i$$

insert the **supervised couple** $(\boldsymbol{x_0}, y_0)$ in Z_i and

$$\mathcal{U}(C_i, \{\boldsymbol{x_0}, \dots, \boldsymbol{x_n}\}) = C_i$$

Takes a sequence of unsupervised data as input, **extracts features** values and **appends** them to F_i

Concept Drift Detection Operator

$$\mathcal{D}(C_i) \in \{0,1\}$$

- Implements **online** change-detection tests (**CDTs**) based on the Intersection of Confidence Intervals (ICI) rule
- The ICI-rule is an adaptation technique used to define adaptive supports for polynomial regression
- **The ICI-rule determines** when feature sequence (D_i) cannot be fit by a zero-order polynomial, thus **when D_i is non stationary**
- ICI-rule requires **Gaussian**-distributed **features** but **no assumptions on the post-change distribution**

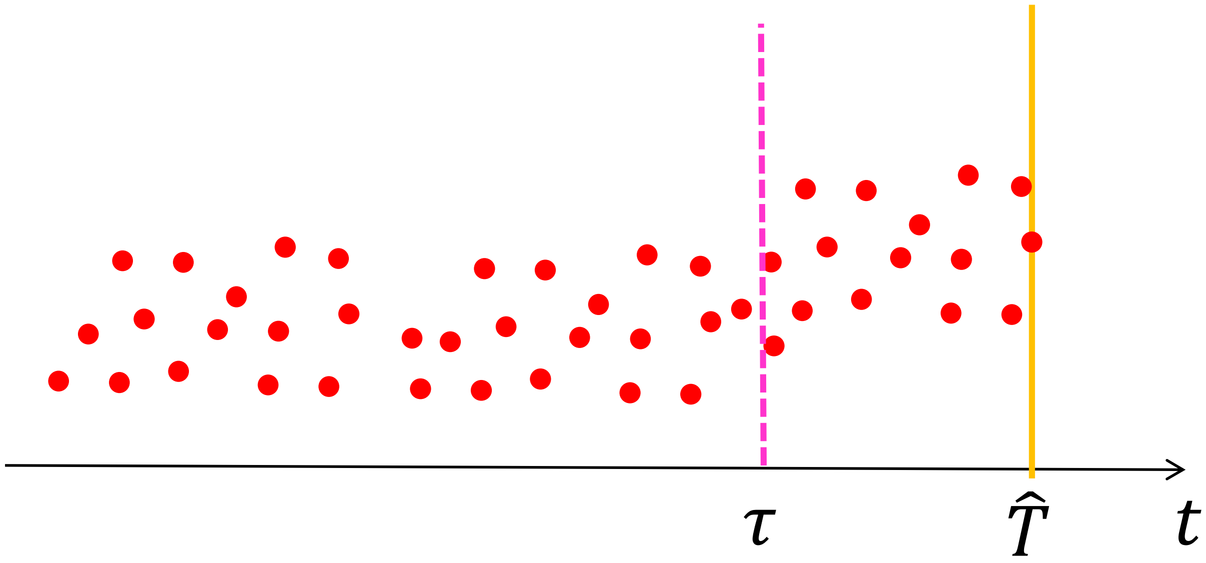
[1] A. Goldenshluger and A. Nemirovski, "On spatial adaptive estimation of nonparametric regression," Math. Meth. Statistics, vol. 6, pp. 135–170,1997.

[2] V. Katkovnik, "A new method for varying adaptive bandwidth selection," IEEE Trans. on Signal Proc, vol. 47, pp. 2567–2571, 1999.

Split Operator

$$\Upsilon(C_0) = (C_0, C_1)$$

- It performs an **offline analysis** on F_i (just the feature detecting the change) to estimate **when concept drift has actually happened**
- Detections $\hat{T}$ are delayed w.r.t. the actual change point τ



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- It performs an **offline analysis** on F_i (just the feature detecting the change) to estimate **when concept drift has actually happened**
- Detections $\hat{T}$ are delayed w.r.t. the actual change point τ
- ICI-based CDTs implement a refinement procedure to stimate τ after having detected a change at $\hat{T}$.
- Change-Point Methods implement the following Hypothesis test on the feature sequence:

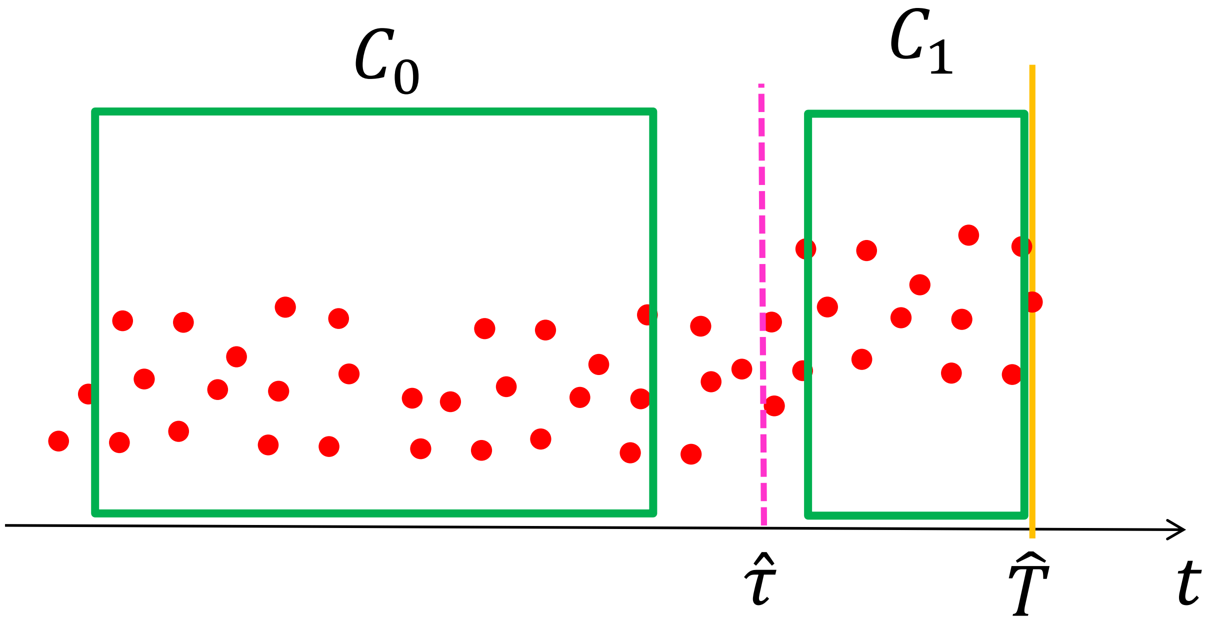
$$\begin{cases} H_0: \text{"}F_i \text{ contains i.i.d. samples"} \\ H_1: \text{"}F_i \text{ contains a change point"} \end{cases}$$

testing all the possible partitions of F_i and determining the most likely to contain a change point

Split Operator

$$\Upsilon(C_0) = (C_0, C_1)$$

- In both cases, it is convenient to exclude data close to the estimated change point $\hat{\tau}$, implementing some heuristic



Equivalence Operator

$$\mathcal{E}(C_0, C_1) \in \{0,1\}$$

- **Determines if** C_0 and C_1 **refer** to the **same concept**
  - Performs an **equivalence testing** problem to determine whether F_0 and F_1 refer to the same $p(\boldsymbol{x})$
  - **Compares classifiers** trained on Z_0 and Z_1 on the same validation set to determine if $p(y|\boldsymbol{x})$ was the same
- Recurrent concepts are identified by performing a **pair-wise comparison** against the previously encountered concepts

EXPERIMENTS

Considered Classifiers

We considered the following adaptive classifiers:

- JIT for recurrent concepts
- JIT without recurrent concepts handling
- W: a **sliding window** classifier
- E: a two-individuals **ensemble** which pairs JIT and W
- U: a classifier trained on **all** the available **data**

that have been tested on KNN, and Naive Bayes Classifiers

Considered Classifiers

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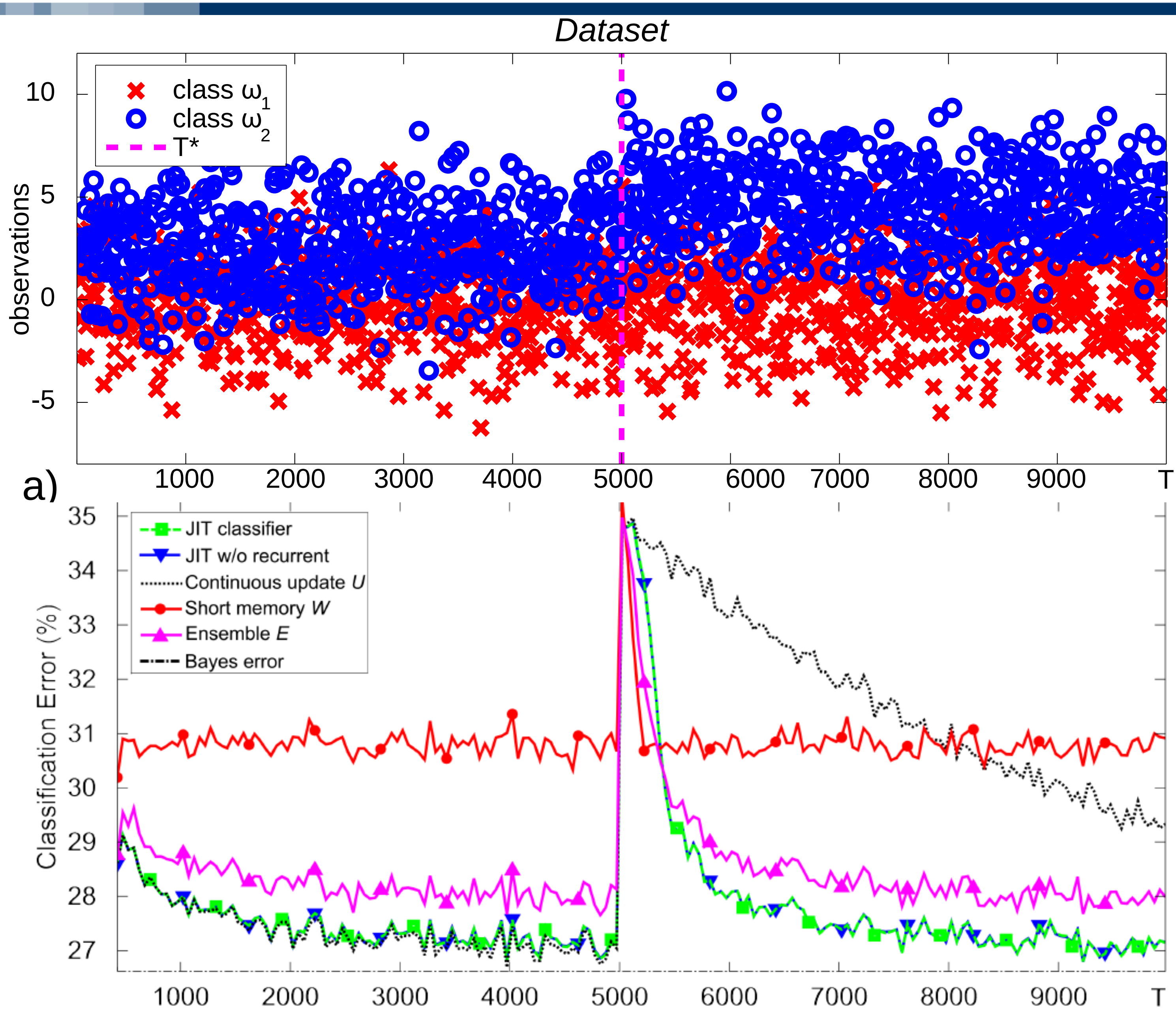
In the ensemble E, the output is defined by **selecting** the most accurate classifier over the last 20 samples (like in paired learners)

The **ensemble** is meant to **improve reaction promptness** to concept drift. In stationary conditions JIT outperforms E

The Ensemble E



Synthetic Datasets

Checkerboard: sequences are composed of

- 10000 samples uniformly distributed in $[0, 1] \times [0,1]$
- Classification function is a checkerboard of side 0.5
- Concept drift affects classification function by rotating the checkerboard every 2000 samples.
- One sample every 5 is supervised

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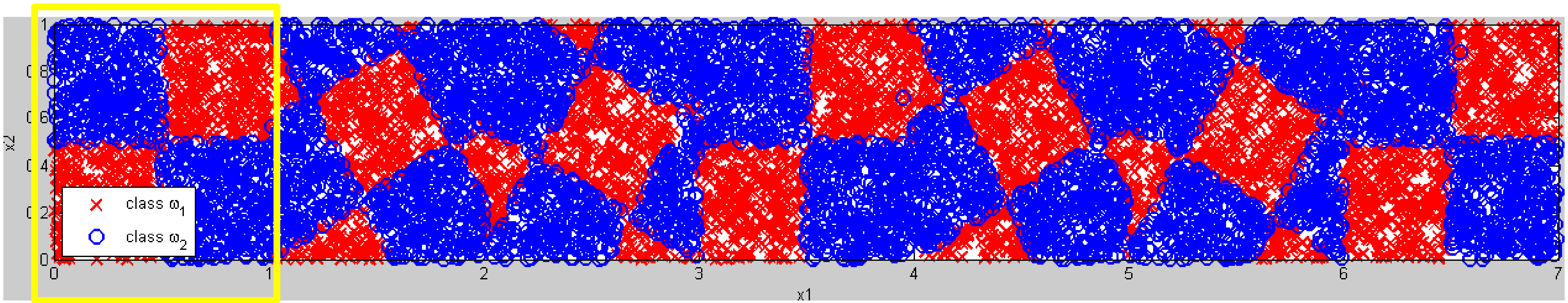

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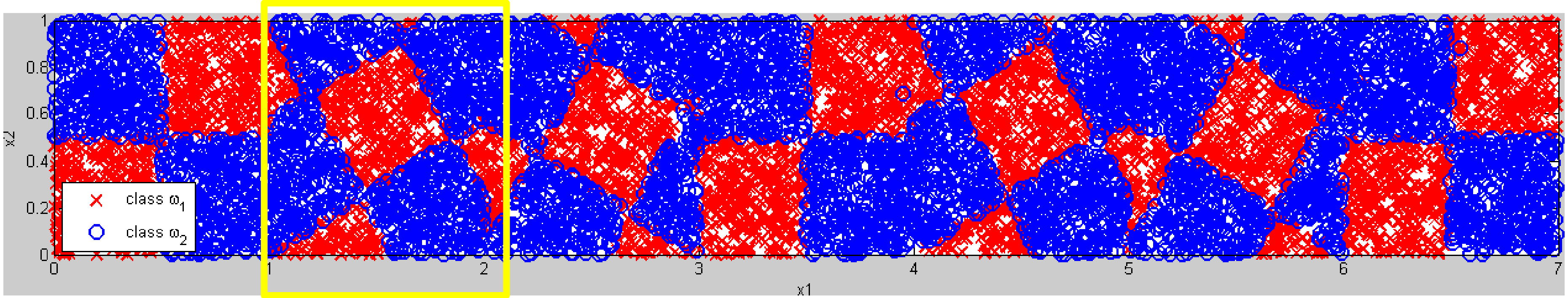

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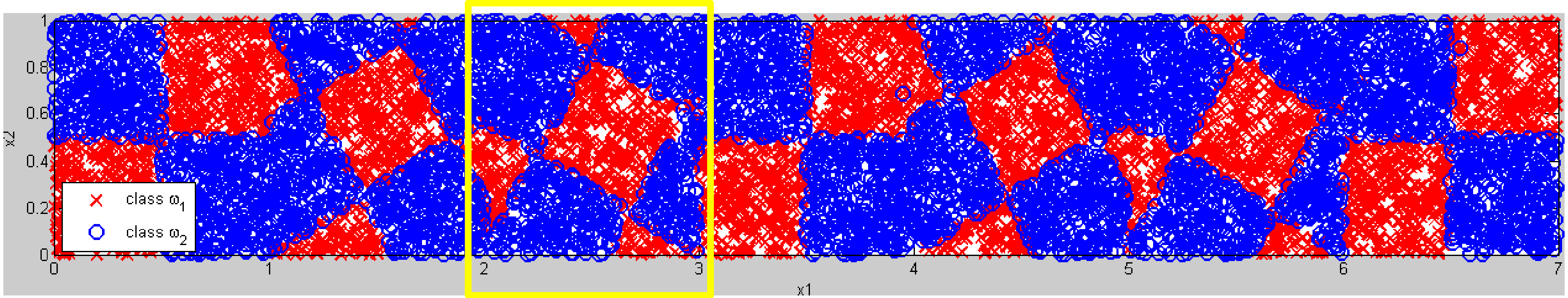

R. Elwell and R. Polikar, "Incremental learning of concept drift in nonstationary environments," Neural Networks, IEEE Transactions on, vol. 22, no. 10, pp. 1517 –1531, oct. 2011

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Sine:

- Similar to CB, class function is a sine
- Tested introducing irrelevant components and class noise

W. N. Street and Y. Kim, "A streaming ensemble algorithm (sea) for large-scale classification," in Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining, ser. KDD '01

Figures of Merit

- Classification error averaged over 2000 runs
- Precision and Recall for the identification of recurrent concept (JIT classifier only)

$$precision = \frac{tp}{tp+fp} \text{ and } recall = \frac{tp}{tp+fn}$$

Experiment	Base classifier	JIT	Ensemble	JIT w/o recurrent	Short Memory (W)	Continuous Update (U)	Precision Recurrent	Recall Recurrent
CHECKERBOARD_1	k-NN	21.45	**17.06**	21.41	21.77	44.58	0.422	0.724
CHECKERBOARD_2	k-NN	19.92	**14.32**	20.37	18.93	24.48	1	0.799
CHECKERBOARD_3	k-NN	18.60	**15.60**	18.83	20.48	25.67	0.977	0.833
MULTIVARIATE GAUSSIAN	k-NN	23.60	**21.74**	23.61	25.00	47.85	1	0.947
	NB	21.52	**19.97**	21.52	21.08	49.03	1	1
SINE_2	k-NN	14.33	**11.09**	15.50	15.59	44.07	1	0.987
SINE_2A	k-NN	19.49	**12.80**	20.55	18.10	44.43	1	0.932
SINE_IRREL_2	k-NN	23.76	**18.37**	24.79	24.19	45.49	1	0.793
SINE_IRREL_2A	k-NN	31.23	**22.05**	31.64	27.33	45.83	1	0.415
EMAIL_LIST	k-NN	42.00	**36.65**	42.00	36.55	37.03	-	0
	SVM	22.34	**17.31**	22.90	22.62	42.83	1	0.250

Figures of Merit

- **Classification error** averaged over 2000 runs
- **Precision** and **Recall** for the identification of recurrent concept (JIT classifier only)

$$precision = \frac{tp}{tp+fp} \text{ and } recall = \frac{tp}{tp+fn}$$

CHECKERBOARD_1 dataset does not contain recurrent concepts. Equivalence operator can correctly associate concepts that have been split by FP of $\mathcal{D}$

Experiment	Base classifier	JIT	Ensemble	JIT w/o recurrent	Short Memory (W)	Continuous Update (U)	Precision Recurrent	Recall Recurrent
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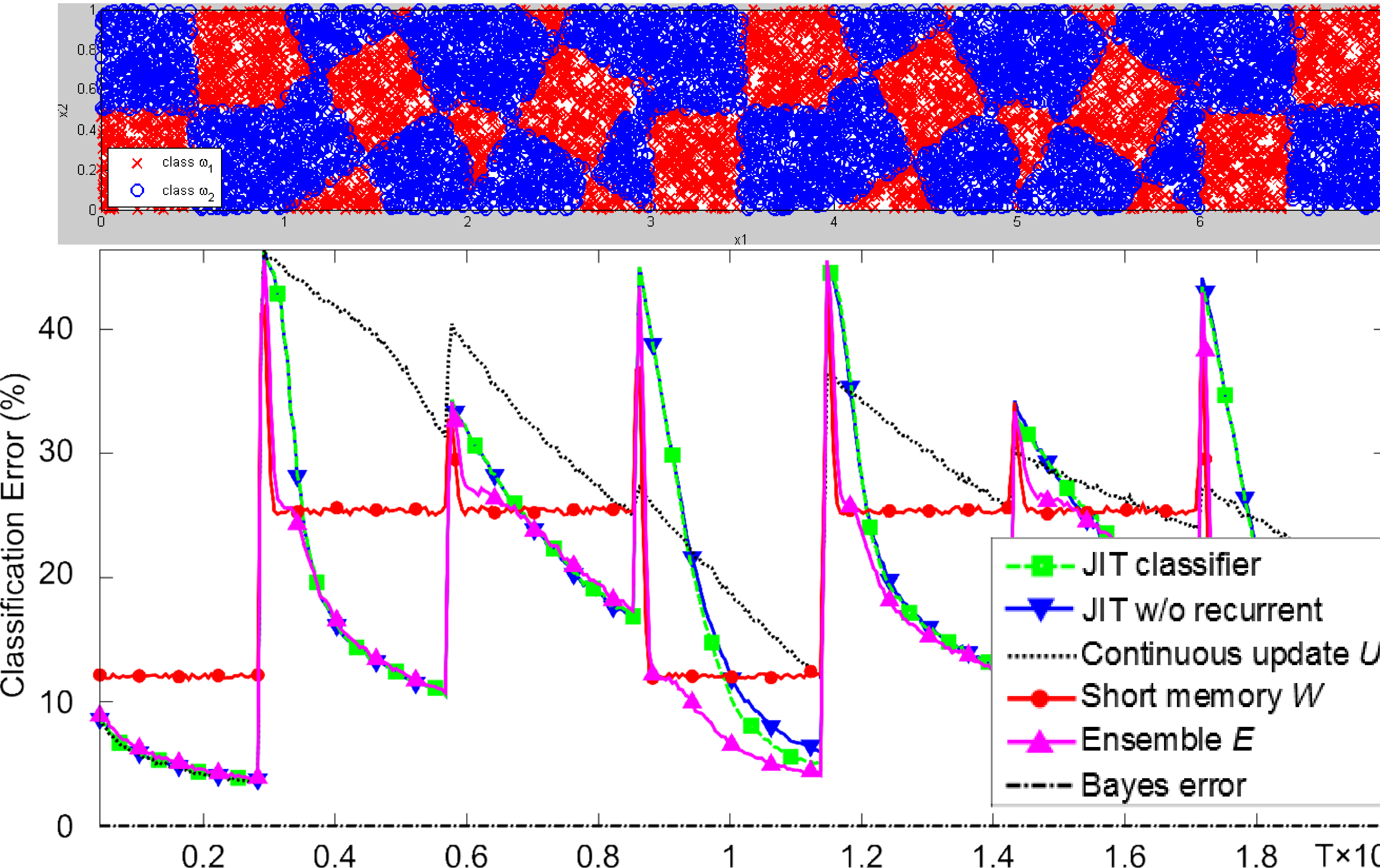
Exploiting Recurrent Concepts



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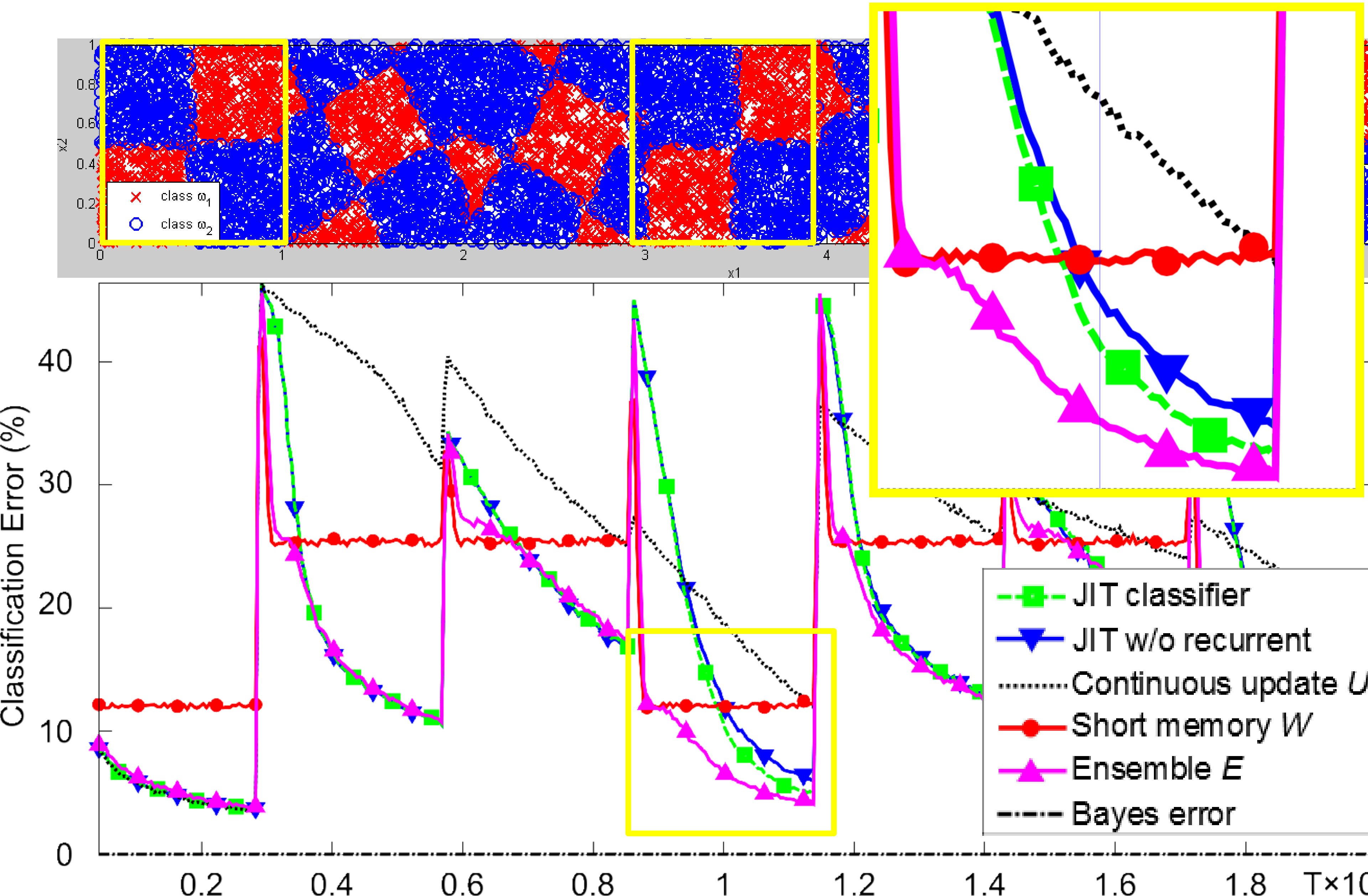
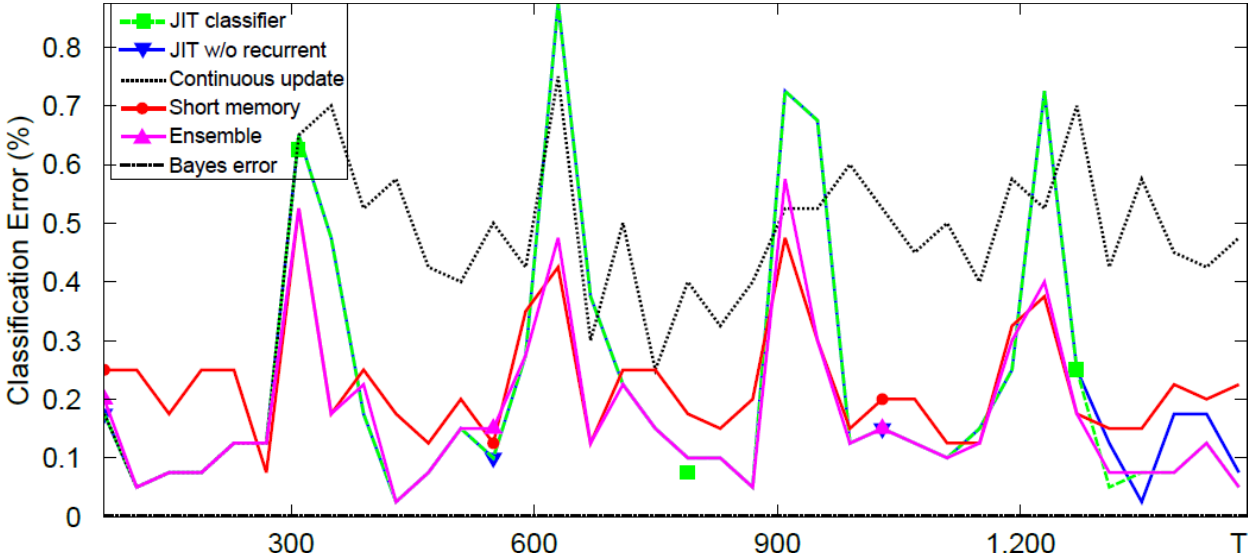


Spam Email Dataset

- Inputs x are email text in the bag-of-words representation (913 Boolean attributes)
- Each email refers to a specific topic. Some topics are considered of interest, the remaining are considered spam
- Concept drift is introduced every 300 emails by swapping spam/ham labels, simulating a change in user interests



I. Katakis, G. Tsoumakas, and I. Vlahavas, "Tracking recurring contexts using ensemble classifiers: an application to email filtering," Knowl. Inf. Syst., vol. 22, no. 3, pp. 371–391, Mar. 2010

CONCLUDING REMARKS

Conclusions

- We proposed a **general methodology** for designing different JIT Classifiers based on different
  - concept representations
  - techniques to detect concept drift, split concept representations and assess concept equivalence
  - base classifiers
- Concept representations have to be *condensed* for the JIT classifiers to be efficient in the real-world
  - Pruning / down sampling Z, F, D
  - Learn models describing data distributions in Z, F, D

  not investigated yet

  Similarly, very old concept representations might be dropped if necessary

Conclusions

- Unfortunately, most of nonparametric techniques for analyzing $p(\boldsymbol{x})$ are meant for scalar data
  - These can be though applied to multivariate data by **monitoring the log-likelihood** of a models learned to describe unsupervised data

Kuncheva L.I., Change detection in streaming multivariate data using likelihood detectors, IEEE Transactions on Knowledge and Data Engineering, 2013, 25(5), 1175-1180 (DOI: 10.1109/TKDE.2011.226).

Conclusions

- Unfortunately, most of nonparametric techniques for analyzing $p(\boldsymbol{x})$ are meant for scalar data
  - These can be though applied to multivariate data by **monitoring the log-likelihood** of a models learned to describe unsupervised data
- Monitoring the **classification error** is straightforward **but**: the error of K_t is nonstationary, since K_t is updated.
  - It is more convenient to monitor the error of a second classifier K_0 that is never updated

Kuncheva L.I., Change detection in streaming multivariate data using likelihood detectors, IEEE Transactions on Knowledge and Data Engineering, 2013, 25(5), 1175-1180 (DOI: 10.1109/TKDE.2011.226).

Conclusions

- Extension to **gradual drifts**
  - «detection / adaptation» paradigm is not optimal since the post-change conditions are nonstationary
  - Need to interpret and compensate drift as in semi-supervised learning methods

Dyer K., Capo R., Polikar R., "COMPOSE: A Semi-Supervised Learning Framework for Initially Labeled Non-Stationary Streaming Data" IEEE Transactions on Neural Networks and Learning Systems, Special issue on Learning in Nonstationary and Dynamic Environments – Systems, vol. 25, no. 1, pp. 12-26, 2014

Thank you, questions?

Preprint and (some) codes available from

home.deib.polimi.it/boracchi/index.html

Just In Time Classifiers for Recurrent Concepts
Cesare Alippi, Giacomo Boracchi and Manuel Roveri,
IEEE Transactions on Neural Networks and Learning Systems, 2013. vol. 24, no.4, pp. 620 -634 *doi:10.1109/TNNLS.2013.2239309*

A just-in-time adaptive classification system based on the intersection of confidence intervals rule,
Cesare Alippi, Giacomo Boracchi, Manuel Roveri
Neural Networks, Elsevier vol. 24 (2011), pp. 791-800 *doi:10.1016/j.neunet.2011.05.012*

Thank you, questions?