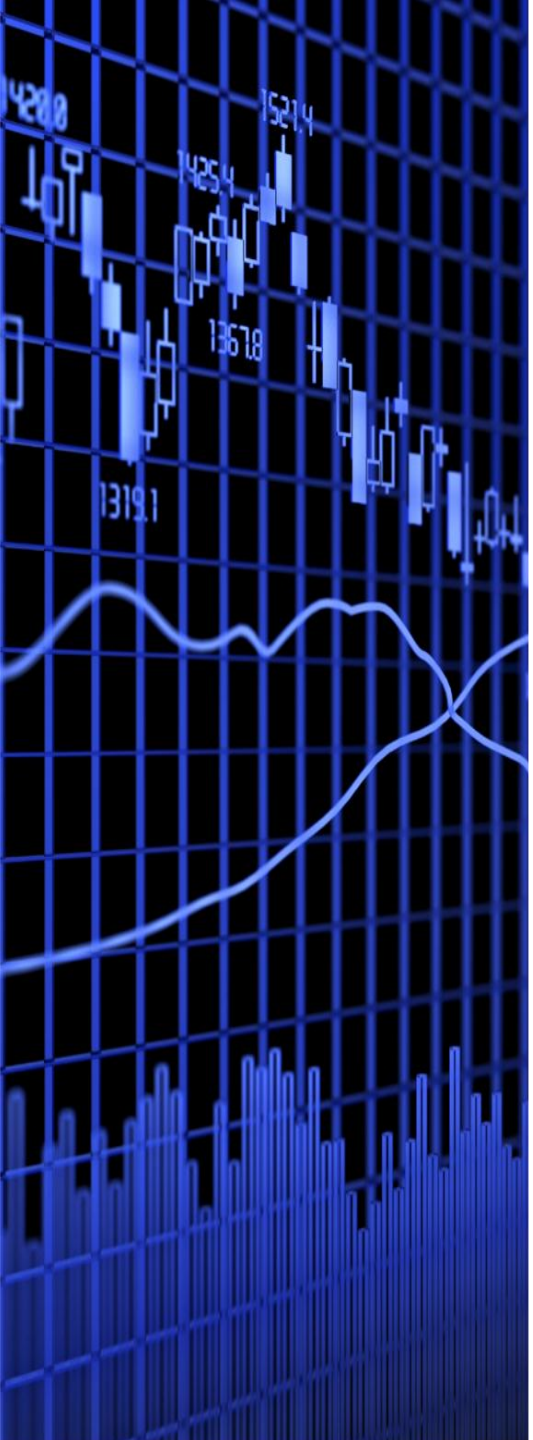

Data Stream Processing and Analytics

Vincent Lemaire

Thank to Alexis Bondu, EDF

Outline

- Introduction on data-streams
- Part 1 : Querying
- Part 2 : Unsupervised Learning
- Part 3 : Supervised Learning
- Conclusion

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Big Data – what does that mean?

Big Data Analytics ?

- Big Data Analytics : Extracting Meaningful and Actionable Information from a Massive Source
- Let’s avoid
  - Triviality, Tautology: a series of self-reinforcing statements that cannot be disproved because they depend on the assumption that they are already correct
  - Thinking that noise is an information
- Let’s try to have
  - Translation: capacity to transfer in concrete terms the discovery (actionable information)
  - TTM: Time To Market, ability to have quickly information on every customers (Who, What, Where, When)

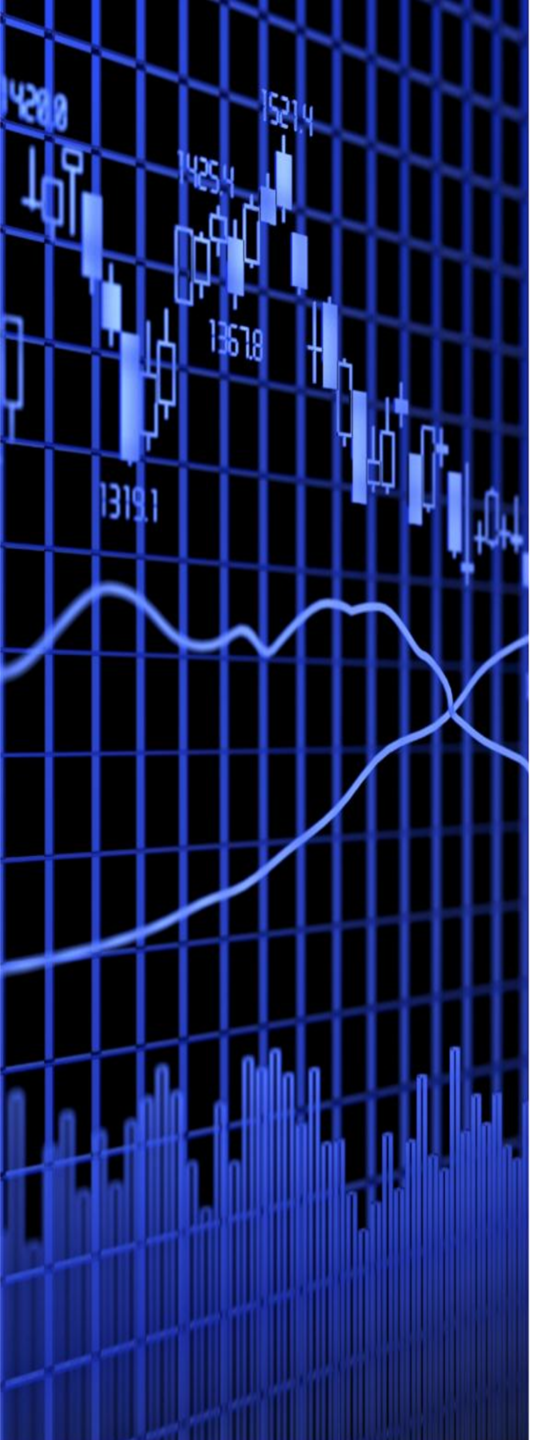
Big Data *vs.* Fast Data

- Big Data :
  - Static data
  - Storage : distributed on several computers
  - Query & Analysis : distributed and parallel processing
  - Specific tools : Very Large Database *(ex : Hadoop)*

More than 10 To

More than 1000 operations / sec

- Fast Data :
  - Data in motion
  - Storage : none *(only buffer in memory)*
  - Query & Analysis : processing on the fly *(and parallel)*
  - Specific Tools : CEP *(Complex Event Processing)*

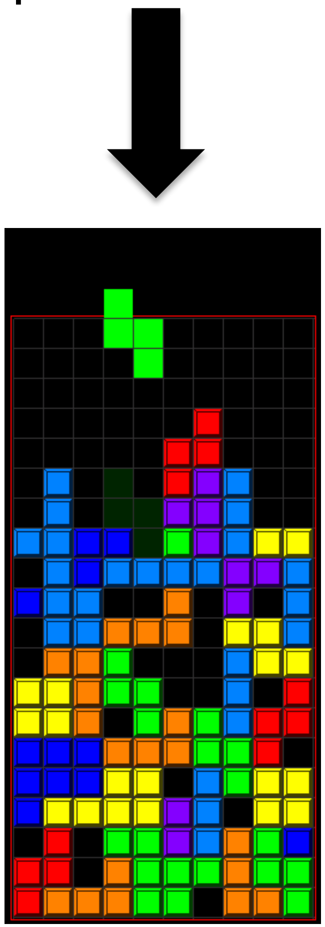


Application Areas

- **Finance:** High frequency trading
  - Find **correlations** between the prices of stocks within the histor data;
  - Evaluate the **stationarity** of these correlations **over the time**;
  - Give more **weight to recent data.**
- **Banking :** Detection of frauds with credit cards
  - Automatiocally **monitor** a **large amount** of transactions;
  - **Detects patterns** of events that indicate a likelihood of fraud;
  - **Stop** the processing and **send an alert** for a human adjudication.
- **Medicine:** Health monitoring
  - Perform **automatic medical analysis** to reduce workload on nurses;
  - Analyze measurements of devices to **detect early signs** of disease.;
  - Help doctors to make a **diagnosis** in real time.
- **Smart Cities & Smart grid :**
  - Optimization of **public transportation**;
  - Management of the **local production** of electricity;
  - Flattening of the **evening peak** of consumption.

An example of data stream

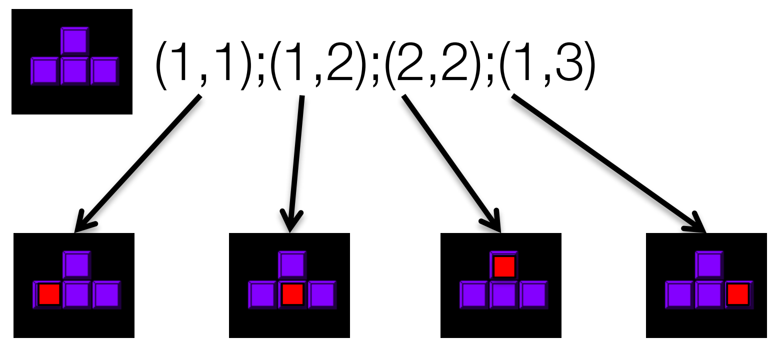
Input data stream



Online processing :

Rotate and combine tuples in a compact way

A tuple :



All tuples can be coded by 4 couples of integers

Specific constrains of stream-processing

What is a tuple ?

- A small **piece of information in motion**
- Composed by several variables
- All tuples share the **same structure** (i.e. the variables)

What is a data stream ?

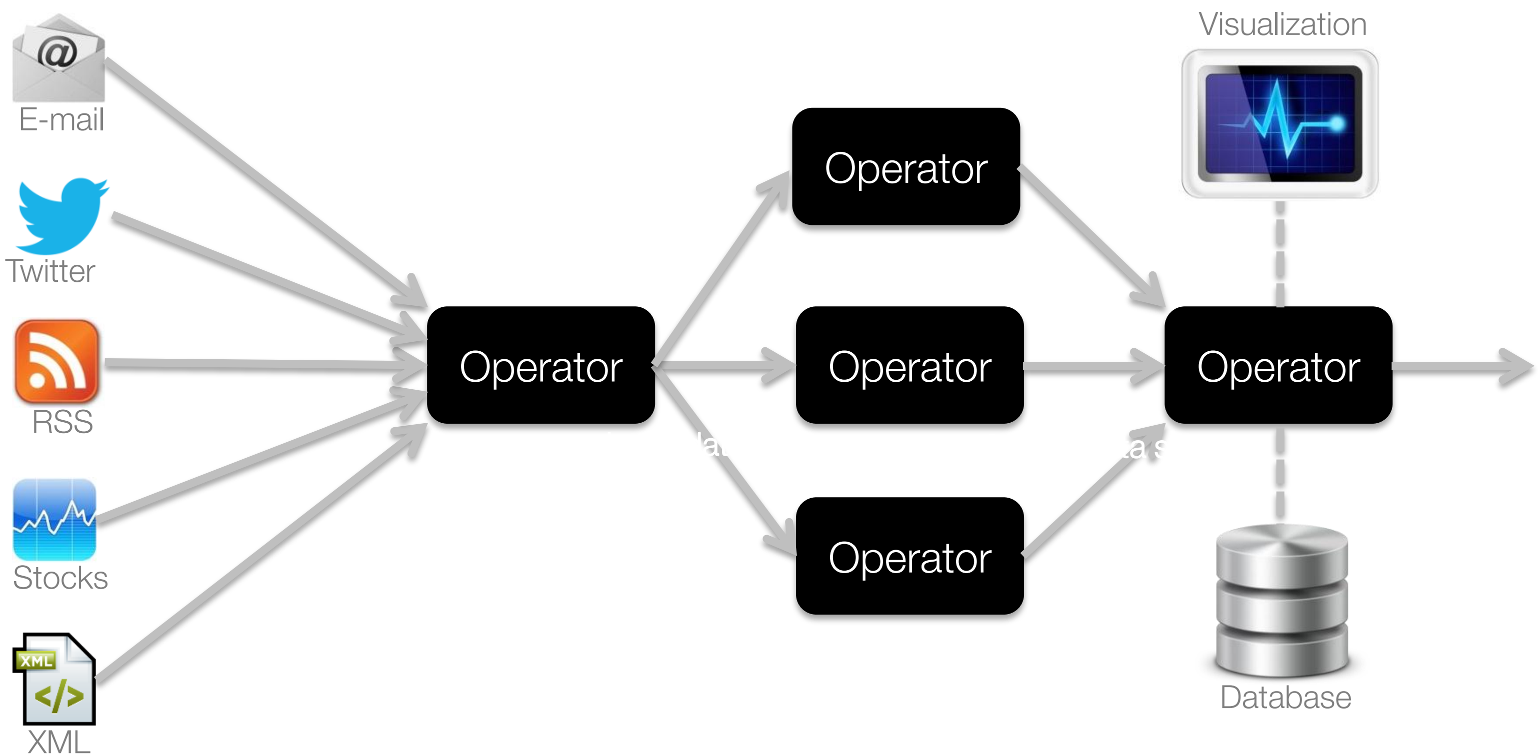
- A data stream **continuously emits** tuples
- The **order** of tuples is not controlled
- The emission **rate** of tuples is not controlled
- Stream processing is an **on-line process**

In the end, **the quality** of the processing is the **adjusting variable**

How to manage the time?

- A timestamp is associated with each tuple :
  - **Explicit timestamp :** defined as a variable within the structure of the data stream
  - **Implicit timestamp :** assigned by the system when tuples are processed
- Two ways of representing the time :
  - **Logical time :** only the order of processed tuples is considered
  - **Physical time :** characterizes the time when the tuple was emitted
- Buffer issues :
  - The tuples are not necessarily received **in the order**
  - **How long** a missing tuple can be waited ?

Complex Events Processing (CEP)



- An operator implements a **query** or a more complex **analysis**
- An operator processes data in motion with a **low latency**
- Several operators run **at the same time**, parallelized on several CPUs and/or Computers
- The graph of operators is **defined before** the processing of data-streams
- Connectors allows to interact with: **external data streams**, **static data** in SGBD, **visualization** tools.

Complex Events Processing (CEP)

Main features:

- High frequency processing
- Parallel computing
- Fault-tolerant
- Robust to imperfect and asynchronous data
- Extensible *(implementation of new operators)*

Notable products:

- StreamBase *(Tibco)*
- InfoSphere Streams *(IBM)*
- STORM *(Open source – Twitter)*
- KINESIS *(Amazon)*
- SQLstream
- Apama

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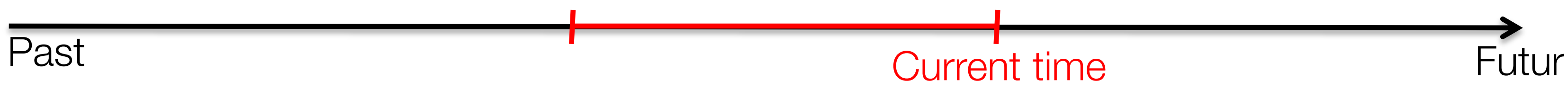
Time-window

- A query is performed on **a finite part** of the past tuples



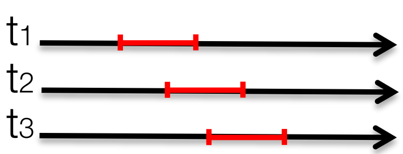
Define a time-window:

- Fixed window : *"June 2000"*
- Sliding window : *"last week"*
- Landmark window : *"since 1 January 2000"*

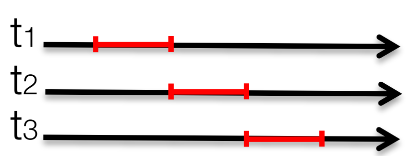
Update interval:

- A result is produced at each update
- The type of window **depends on the update interval**

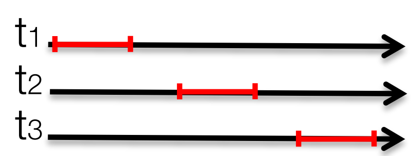
Sliding window



Jumping window



Tumbling window

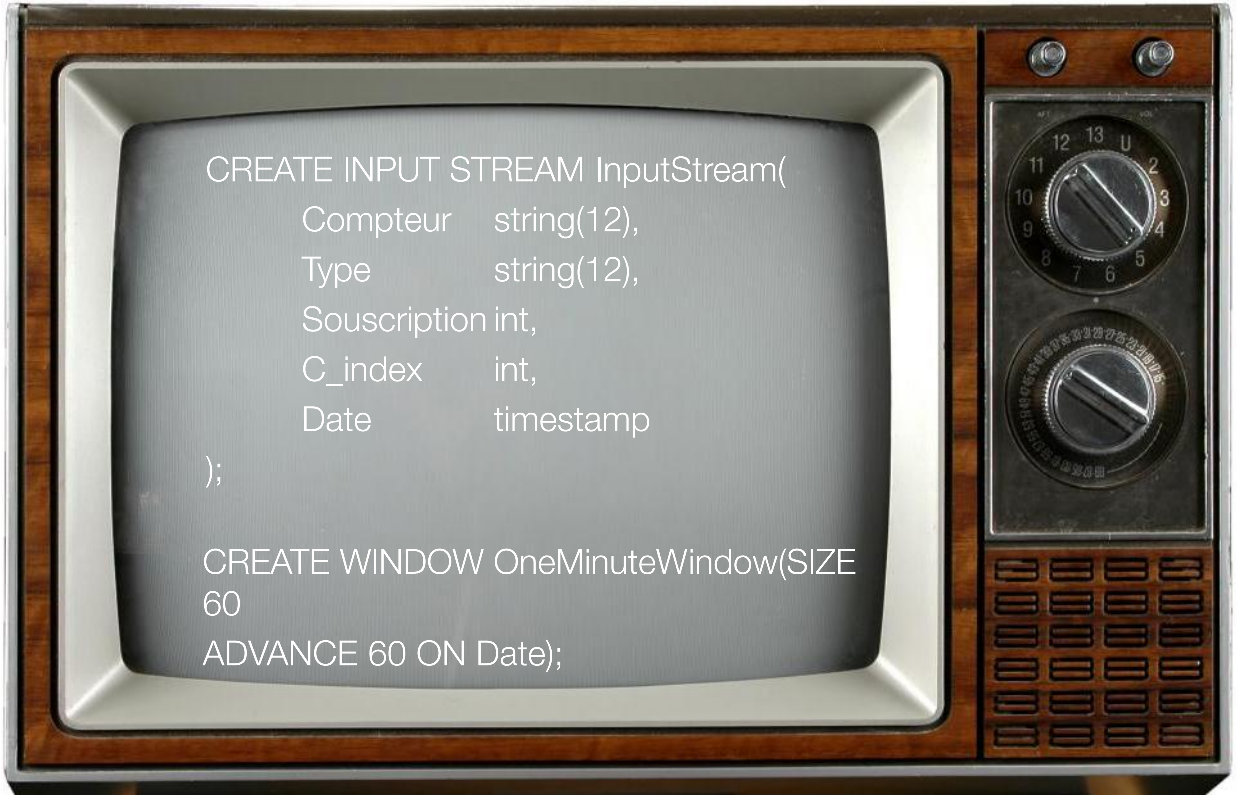


SQL-like language

- Most of the CEP provide a SQL-like language
- Few CEP provide a user-friendly interface
- Each software publisher propose its own language *(**not standardized**)*
- Main features :
  - Define the **structure** of the **connection** of the data streams
  - Define **time-windows** on data streams
  - **Extend** the SQL language *(able to run SQL queries on relational data bases)*
  - **Run queries** on data streams within time-windows
- Additional functions :
  - **Statistics** *(min, max, mean, standard deviation … etc)*
  - **Math** (trigonometry, logarithm, exponential … etc)
  - **String** (regular expression, trim, substring … etc)
  - **Date** (getDayType, getSecond, now … etc)

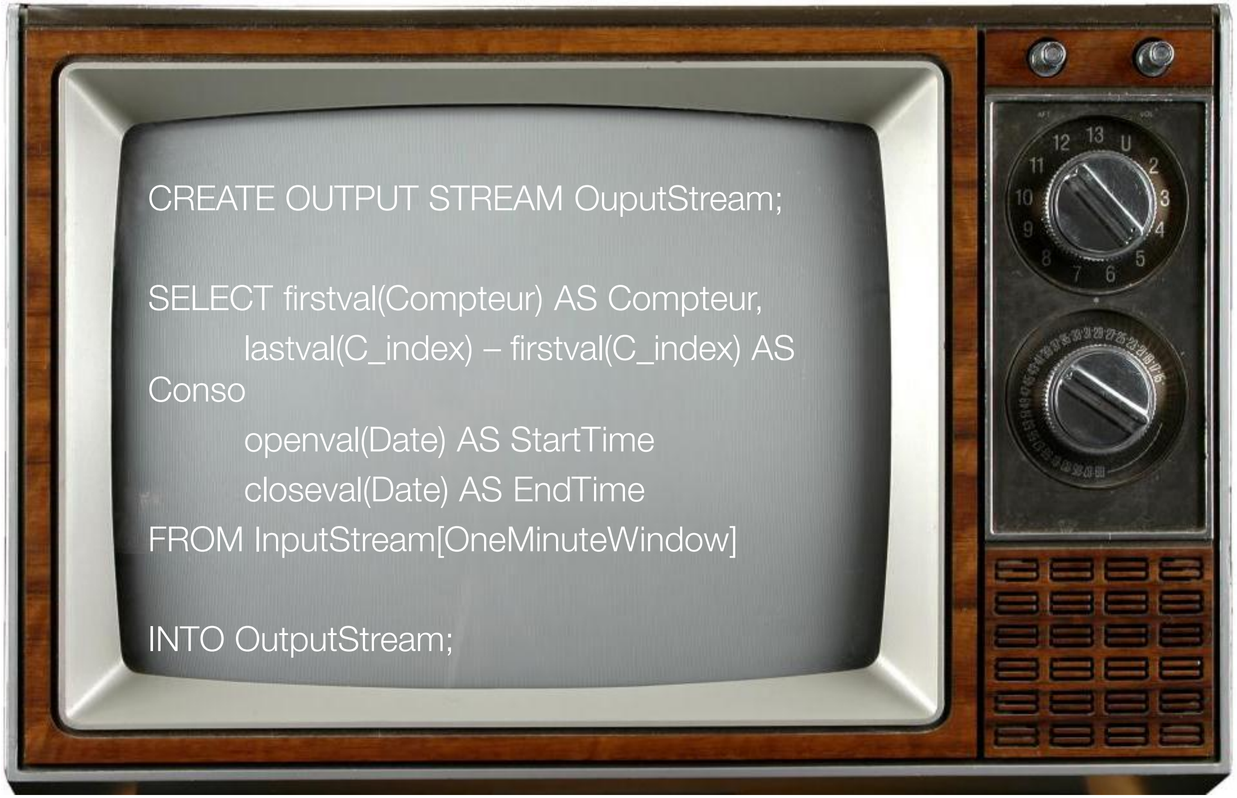
SQL-like language

A simple example with StreamBase : Geek zone



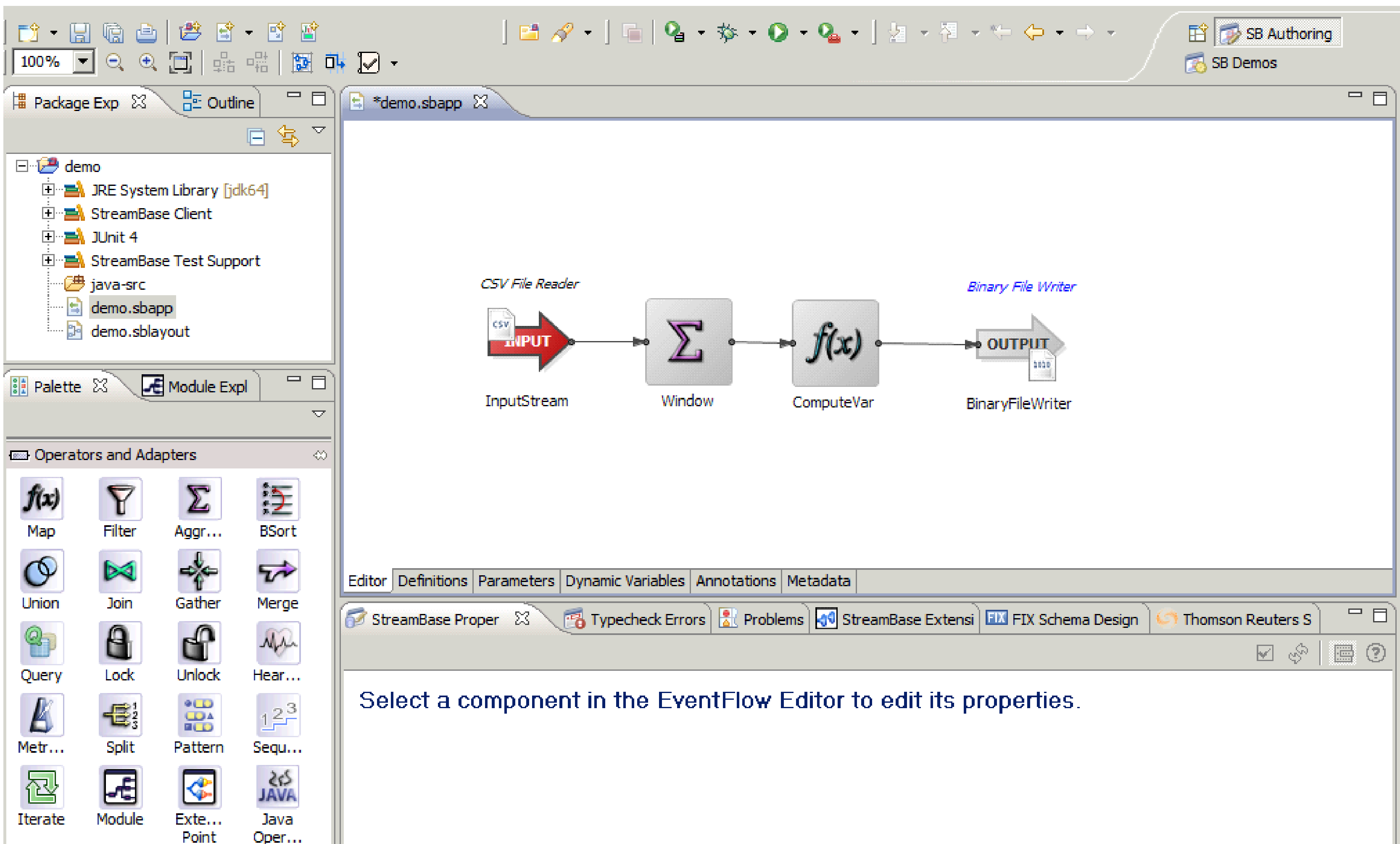
SQL-like language

A simple example with StreamBase : Geek zone



SQL-like language

A simple example with StreamBase : User-friendly interface



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Online *vs.* Batch mode

What is unsupervised learning ?

- Mining data in order to find new knowledge
- No idea about the expected result

Batch mode :

- An entire **dataset is available**
- The examples can be processed **several times**
- **Weak constrain** on the computing time
- The **distribution** of data does **not change** over time

Online processing :

- Tuples are **emitted one by one**
- Tuples **are processed on the fly** due to their high rate
- **Real-time** computing *(low latency)*
- The **distribution** of tuples **changes** over time *(drift)*

Summarizing data streams

Why we need to summarize data streams ?

- The **number** of tuples in **infinite** …
- Their **emission rate** is potentially **very high** …
- The **hardware** resources are **limited** (CPU, RAM & I/O)

What is a summary ?

- A **compact representation** of the past tuples
- With a controlled **memory space** , **accuracy** and **latency**
- Which allows to **query** *(or analyze)* the history of the stream, in an **approximated way**

➡ The objective is to **maximize the accuracy** of the queries, given **technical constrains** (stream rate, CPU, RAM & I/O)

Two types of summary

Specific summaries : dedicated to a single query *(or few)*

- **Flajolet-Martin Sketch :** approximates the number of unique objects in a stream;
- **Bloom Filter :** efficiently tests if an element is a member of a predefine set;
- **Count-Sketch :** efficiently finds the *k* most frequent elements of a set;
- **Count-Min Sketch :** enumerates the number of elements with a particular value, or within an interval of values.

Generic summaries : allow a large range of queries on any past period

- **StreamSamp :** based on successive windowing and sampling;
- **CluStream :** based on micro-clustering;
- **DenStream :** based on evolving micro-clustering;

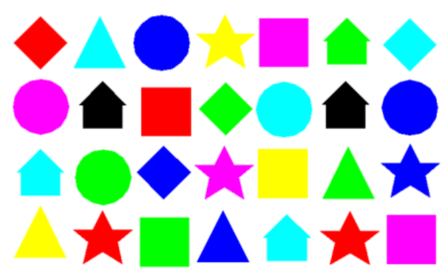
Detailed in this talk

Flajolet-Martin Sketch [1]

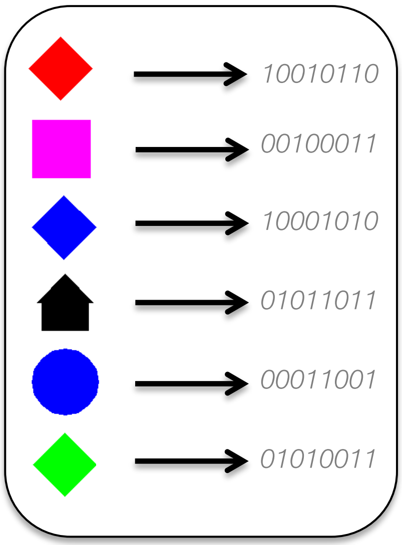
approximates the number of unique objects in a stream

Problem statement:

- **S** is a collection of **N** elements : S = $\{s_1, s_2 \ldots. s_N\}$
- Two elements of S **may be identical**
- S includes only **F** distinct elements
- The objective is to efficiently **estimate F** in terms of:
  - Time complexity
  - Space complexity
  - Probabilistic guarantee

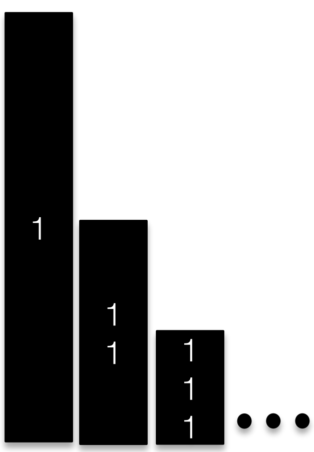


Flajolet-Martin Sketch [1]



Hash function : *h(.)*

- Associates an element s_i with a **random binary value**
- *h(.)* is a **deterministic** function
- *w* is the length of binary values *(number of bits)*
- *w* is an integer such that $2^w \geq N \geq F$
- Random values are **uniformly drawn** within $\left[0, 2^w - 1\right]$



Intuition :

Given a large set of random binary values,

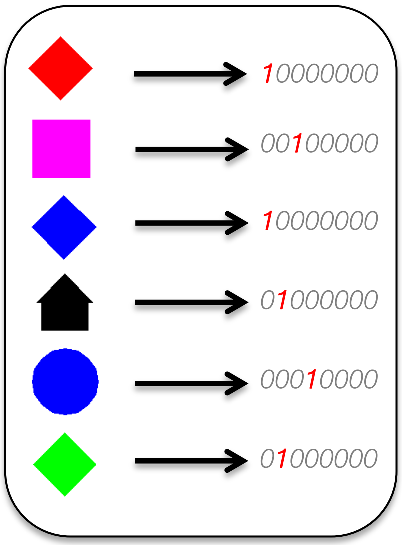
$\frac{1}{2}$ of them begin with "1"

$\frac{1}{4}$ of them begin with "11"

$\frac{1}{8}$ of them begin with "111"

$\frac{1}{2^k}$ of them begin with k "1"

Flajolet-Martin Sketch [1]



$B = 11110000$

$R = 5$

Location of the first "1" within *h(.)*

t(.) is the function which keeps only the first "1" *(counting from left)*, other bits are set to "0"

Example : $h(s_i) = 01001111011010$ $\quad t(h(s_i)) = 01000000000000$

Fusion of binary words :

B is the fusion of all the binary words ***t(h(s***$_i$***))***
by using the OR operator denoted by $\oplus$

$$B = \bigoplus_{i=1}^{N} t(h(s_i)) \qquad R = \left[\underset{N}{MAX}\, t(h(s_i)) \right] + 1$$

R is the rank of the first "0" *(counting from left)* within B.
That is a **random variable related with F !**

Flajolet-Martin Sketch [1]

<u>A single-pass algorithm :</u>

Input data stream

FM Sketch

$R = 0$

$B = 000000000000000$

$h(a) = 0100111011010$

$t(h(a)) = 0100000000000$

Flajolet-Martin Sketch [1]

<u>A single-pass algorithm :</u>

FM Sketch

$R = 2$

$B = 01000000000000$

Input data stream

$h(a) = 01001111011010$ $\quad t(h(a)) = 01000000000000$

$h(b) = 10001010011011$ $\quad t(h(b)) = 10000000000000$

Flajolet-Martin Sketch [1]

A single-pass algorithm :

FM Sketch

$R = 2$

$B = 11000000000000$

Input data stream

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(b) = 10001010011011$ $t(h(b)) = 10000000000000$

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

Flajolet-Martin Sketch [1]

<u>A single-pass algorithm :</u>

FM Sketch

$R = 2$

$B = 11000000000000$

Input data stream

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(b) = 10001010011011$ $t(h(b)) = 10000000000000$

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(c) = 00010110010110$ $t(h(c)) = 00010000000000$

Flajolet-Martin Sketch [1]

A single-pass algorithm :

FM Sketch

$R = 4$

$B = 11010000000000$

Input data stream

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(b) = 10001010011011$ $t(h(b)) = 10000000000000$

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(c) = 00010110010110$ $t(h(c)) = 00010000000000$

$h(b) = 10001010011011$ $t(h(b)) = 10000000000000$

Flajolet-Martin Sketch [1]

<u>A single-pass algorithm :</u>

FM Sketch

$R = 4$

$B = 11010000000000$

Input data stream

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(b) = 10001010011011$ $t(h(b)) = 10000000000000$

$h(a) = 01001111011010$ $t(h(a)) = 01000000000000$

$h(c) = 00010110010110$ $t(h(c)) = 00010000000000$

$h(b) = 10001010011011$ $t(h(b)) = 10000000000000$

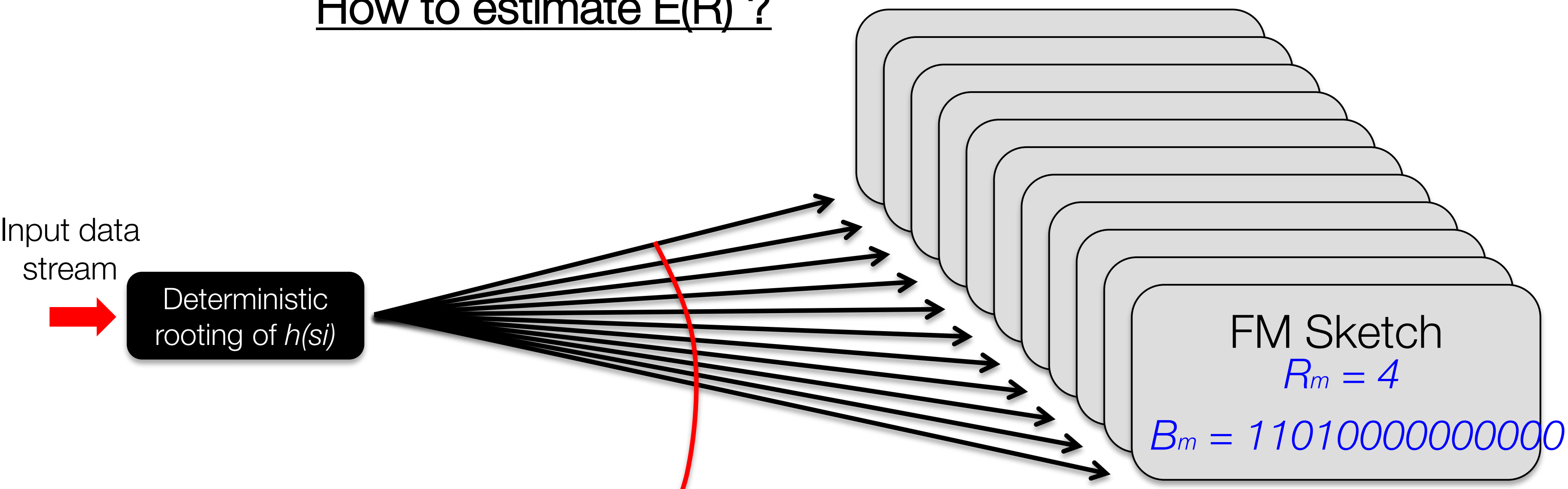
- This single-pass algorithm is adapted to **data streams**
- **Few pieces of information** need to be **stored** in the RAM
- R is a random variable such that :

$$E(R) \approx \log_2 \varphi F$$

Flajolet-Martin Sketch [1]

Collection of *m* Sketch

<u>How to estimate E(R) ?</u>



- The first bits of $h(s_i)$ are used to affect each element to a sketch

  if $m = 16$, the 4 first bits of *h(si)* represent the ID of the corresponding Sketch

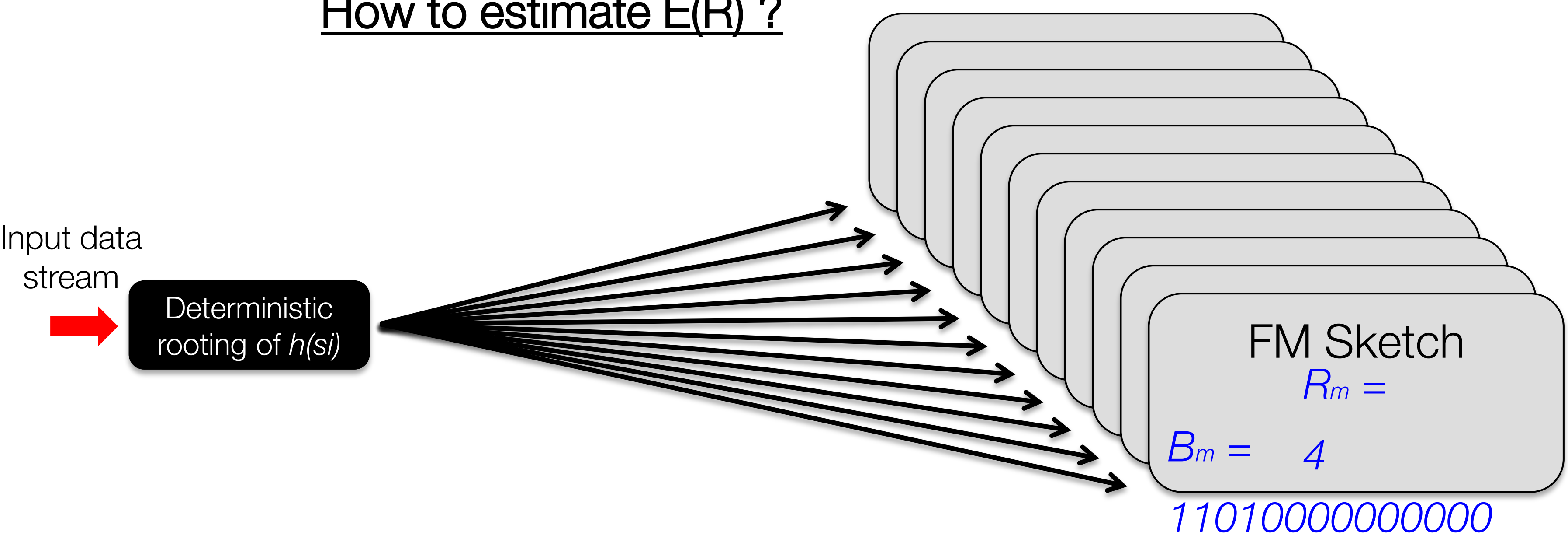
  $h(s_1)$ = <u>0011</u>001000101 -> 0011 = 3 -> s1 is affected to the *3th* sketch

- Each Sketch counts approximately **F/m** distinct elements

Flajolet-Martin Sketch [1]

<u>How to estimate E(R) ?</u>

Collection of *m* Sketch



$$\frac{F}{m} \approx \frac{2^{E(R)}}{\varphi} \xrightarrow[\text{Stochastic average}]{} F \approx \frac{m}{\varphi} 2^{\frac{1}{m}\sum_{i=1}^{m} R_m}$$

Two types of summary

Specific summaries : dedicated to a single query *(or few)*

- Flajolet-Martin Sketch : approximates the number of unique objects in a stream;
- Bloom Filter : efficiently tests if an element is a member of a predefine set;
- Count-Sketch : efficiently finds the *k* most frequent elements of a set;
- Count-Min Sketch : enumerates the number of elements with a particular value, or within an interval of values.

Generic summaries : allow a large range of queries on any past period

- StreamSamp : based on successive windowing and sampling;
- CluStream : based on micro-clustering;
- DenStream : based on evolving micro-clustering;

Detailed in this talk

Sampling based summaries

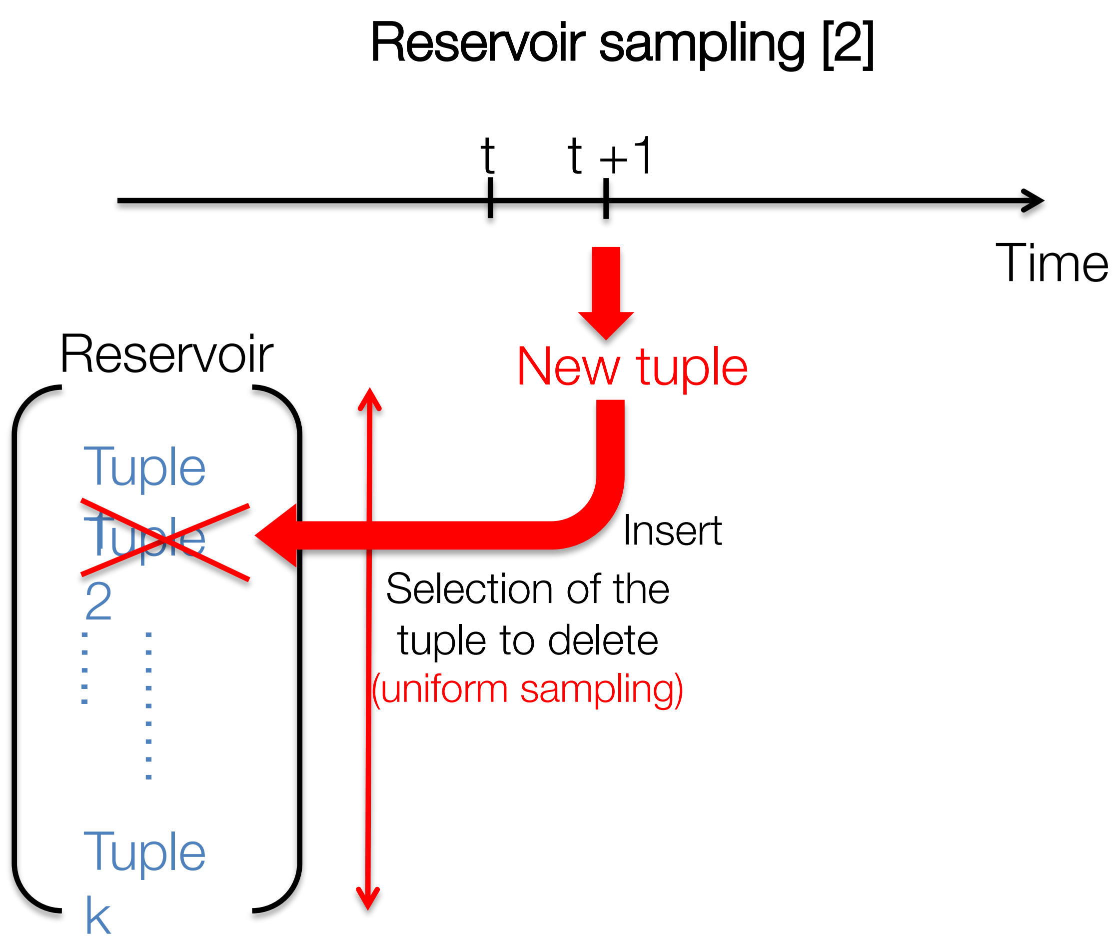
Objectives of a generic summary :

- Summarizes the **entire history** of the data stream
- Requires a **bounded memory space**
- Allows **a large range of queries**, including **supervised** and **unsupervised** analysis

Summarize by sampling the tuples :

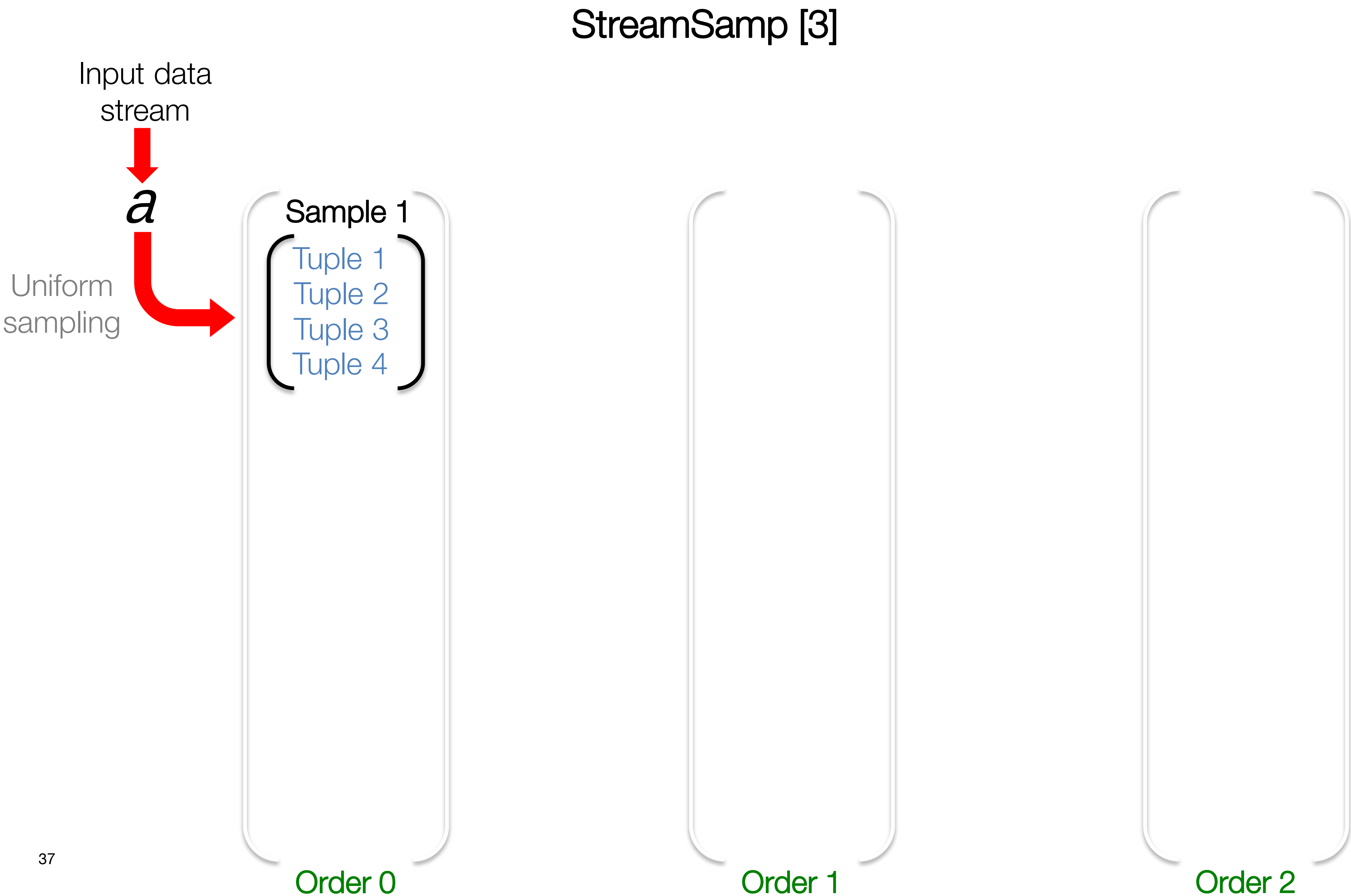
- The sampling technics are adapted to **incremental processing**
- A **limited number** of tuples are stored
- The stored tuples constitute a **representative sample**
- The **recent past** can be favored in terms of **accuracy** *(i.e. sampling rate)*

Sampling based summaries

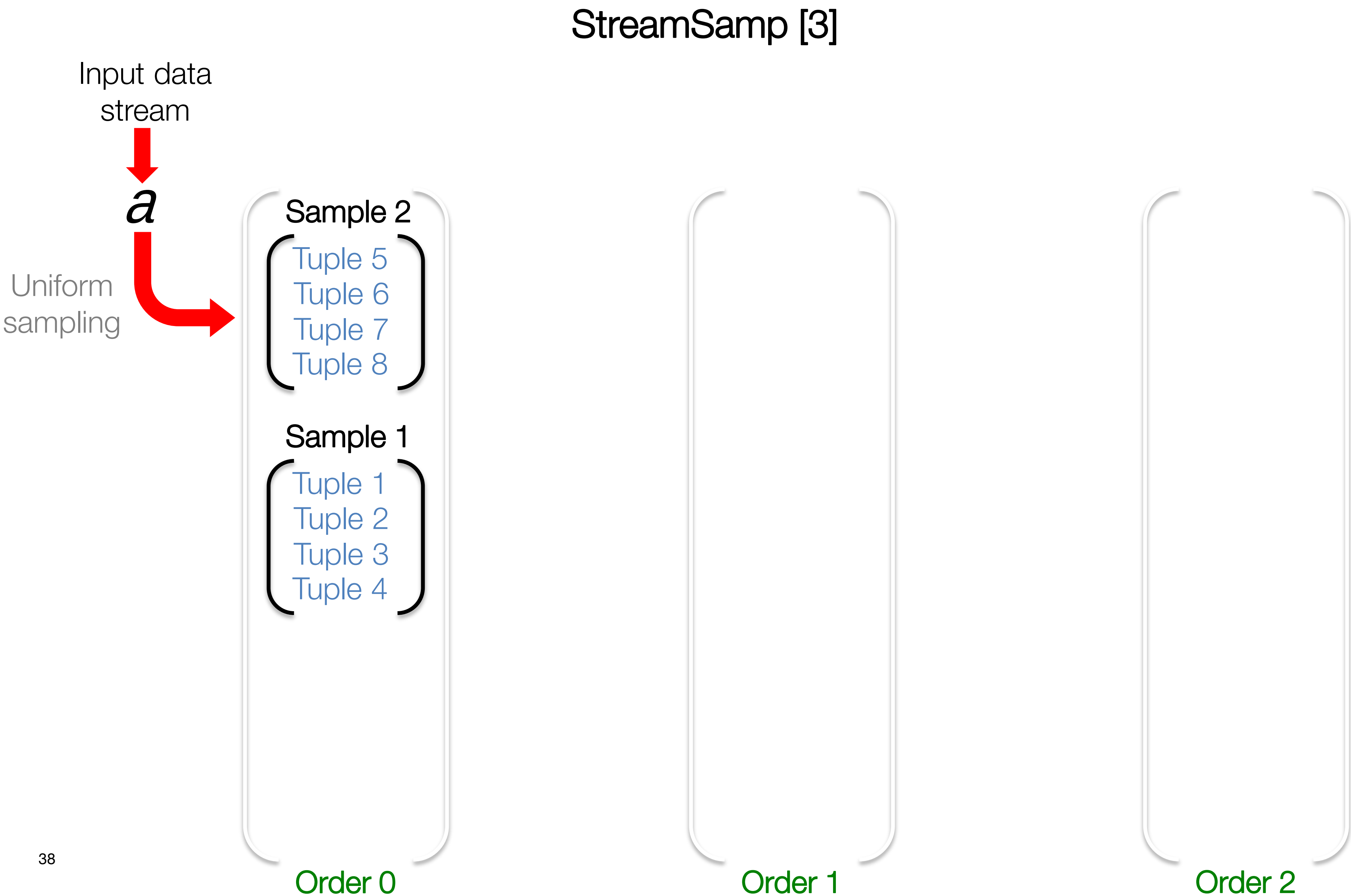


- The reservoir is a **uniform sampling**;
- The sampling **rate decreases** over time;
- The **probability** that tuples are included in the reservoir is : **k / Nb_Emitted_Tuples**

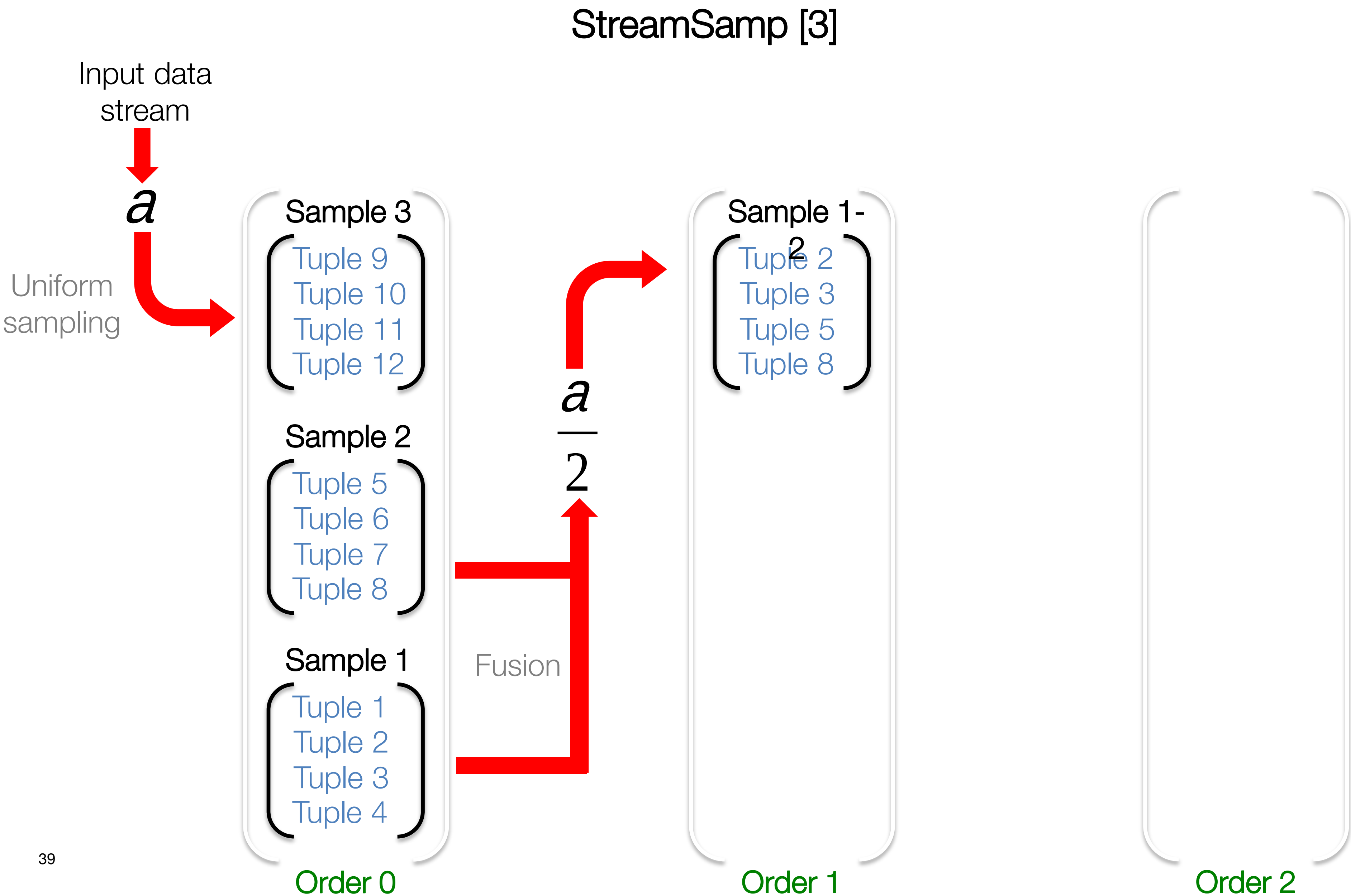
Sampling based summaries



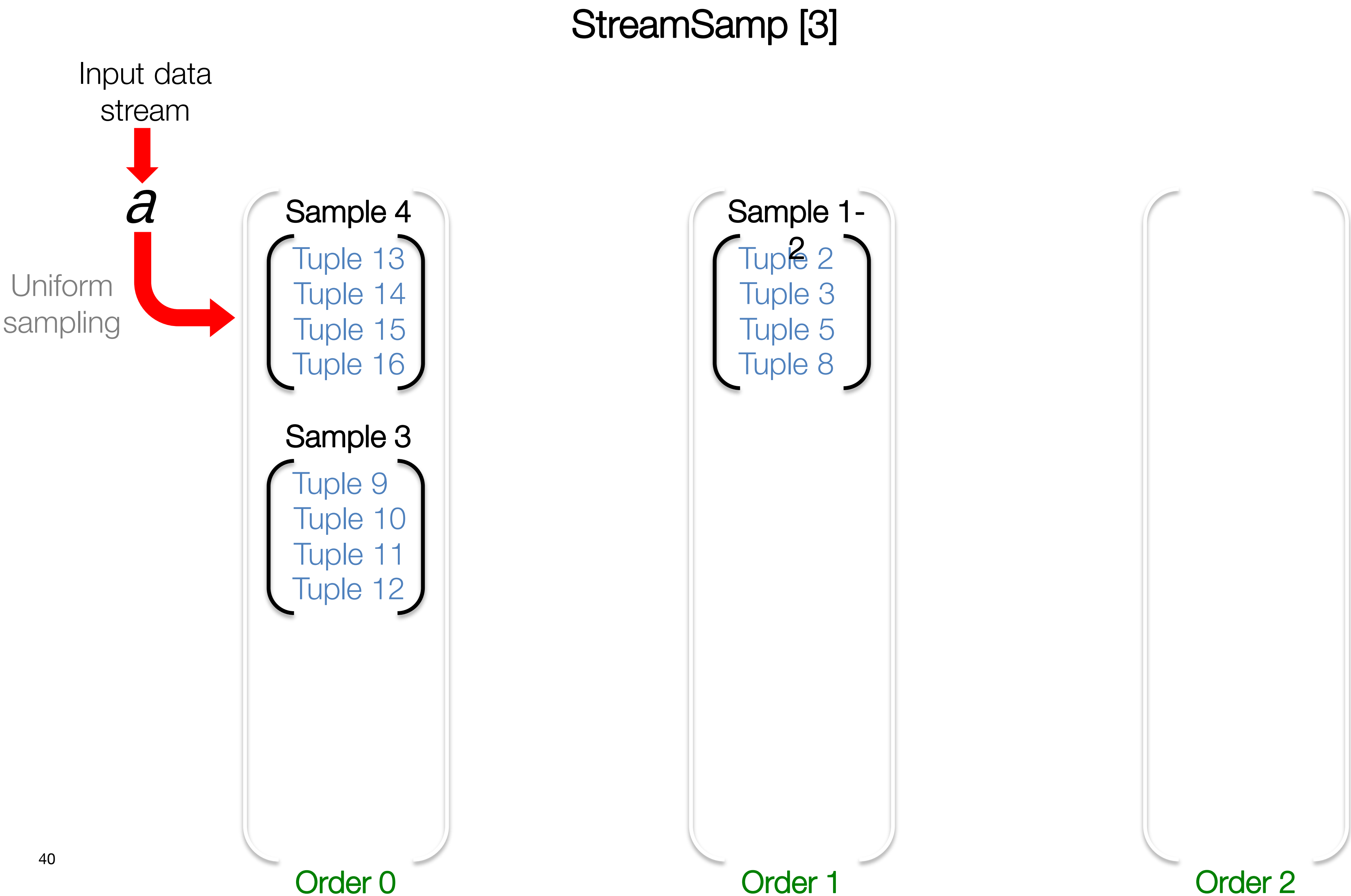
Sampling based summaries



Sampling based summaries



Sampling based summaries



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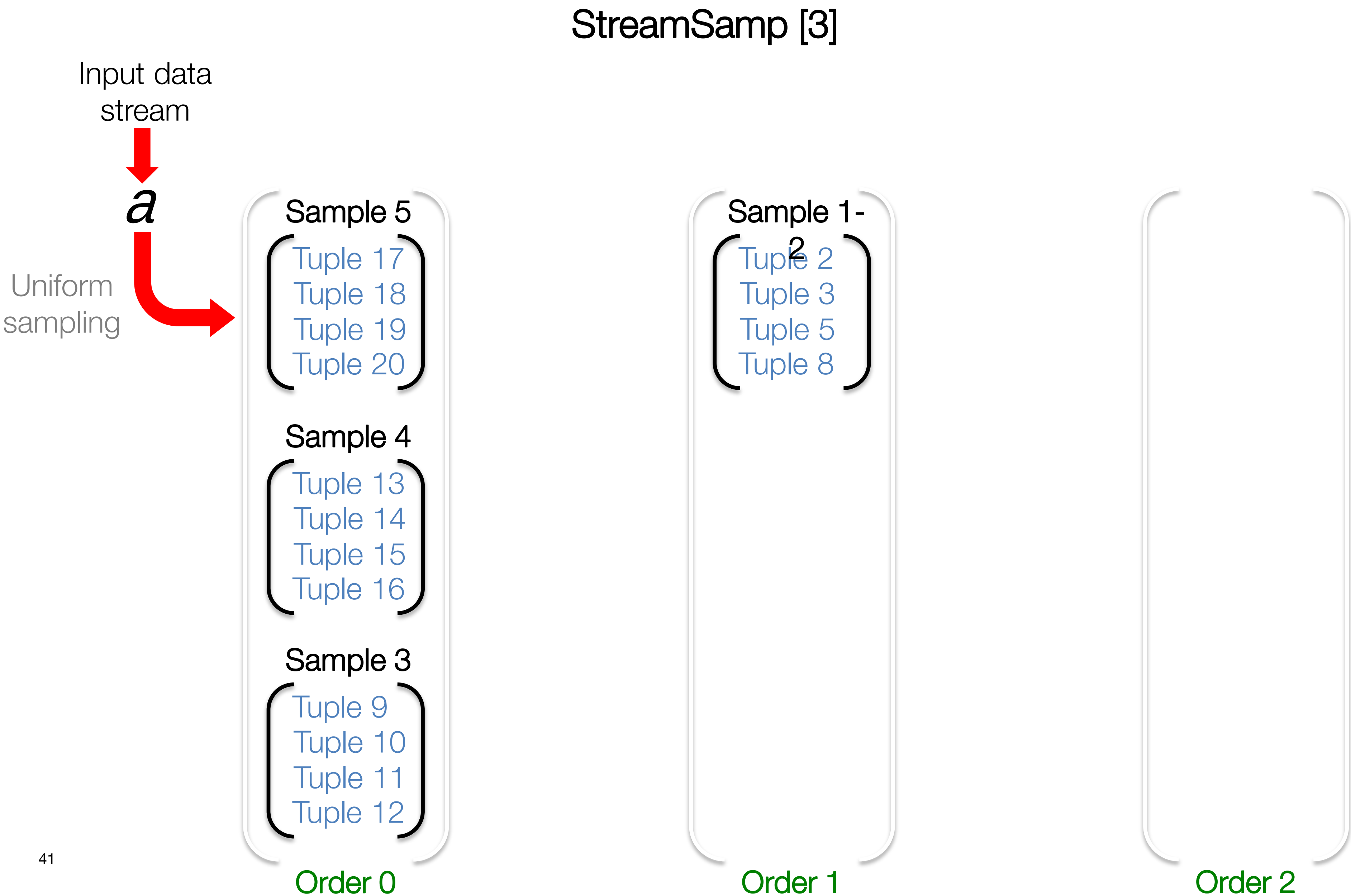
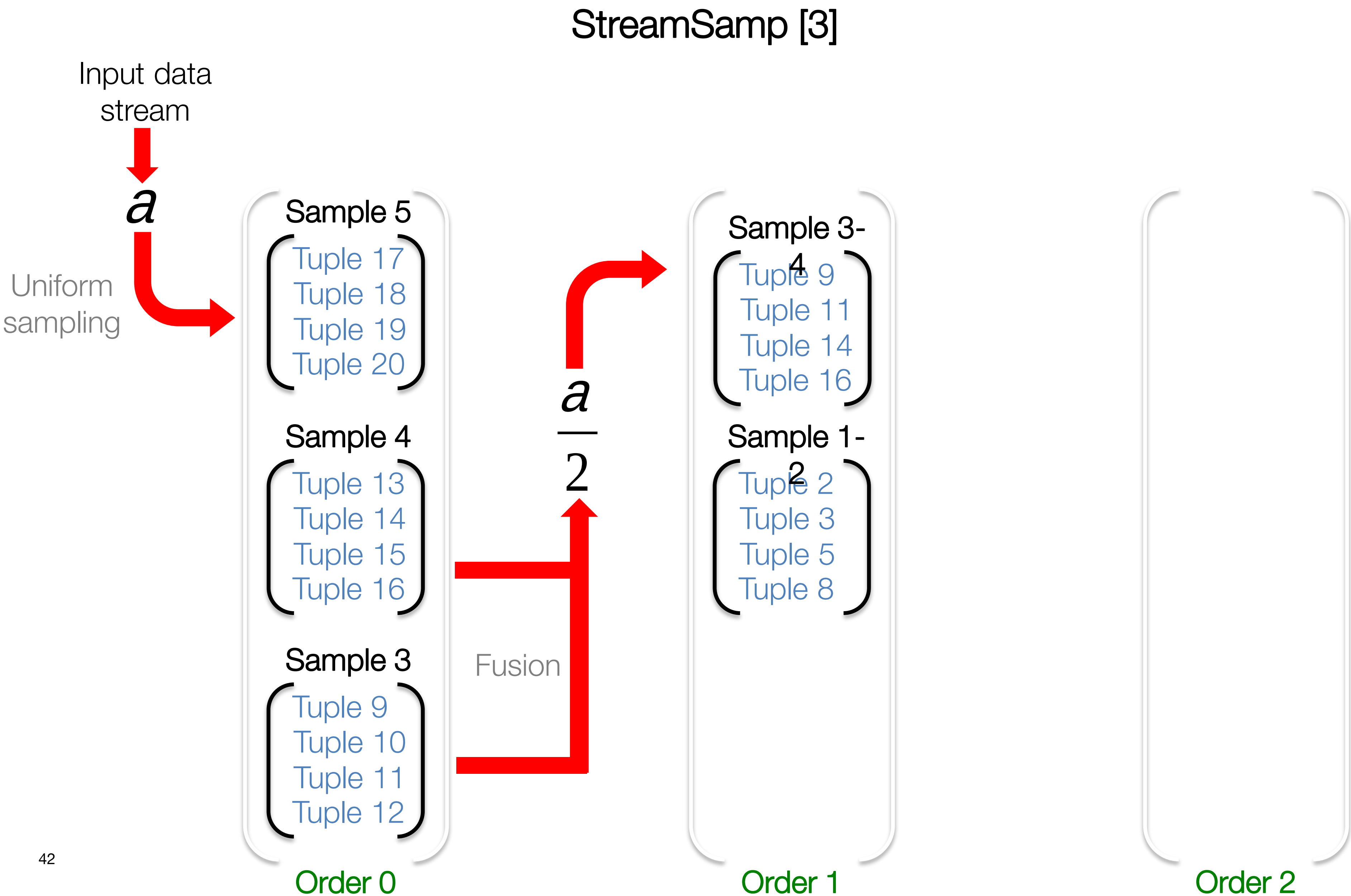
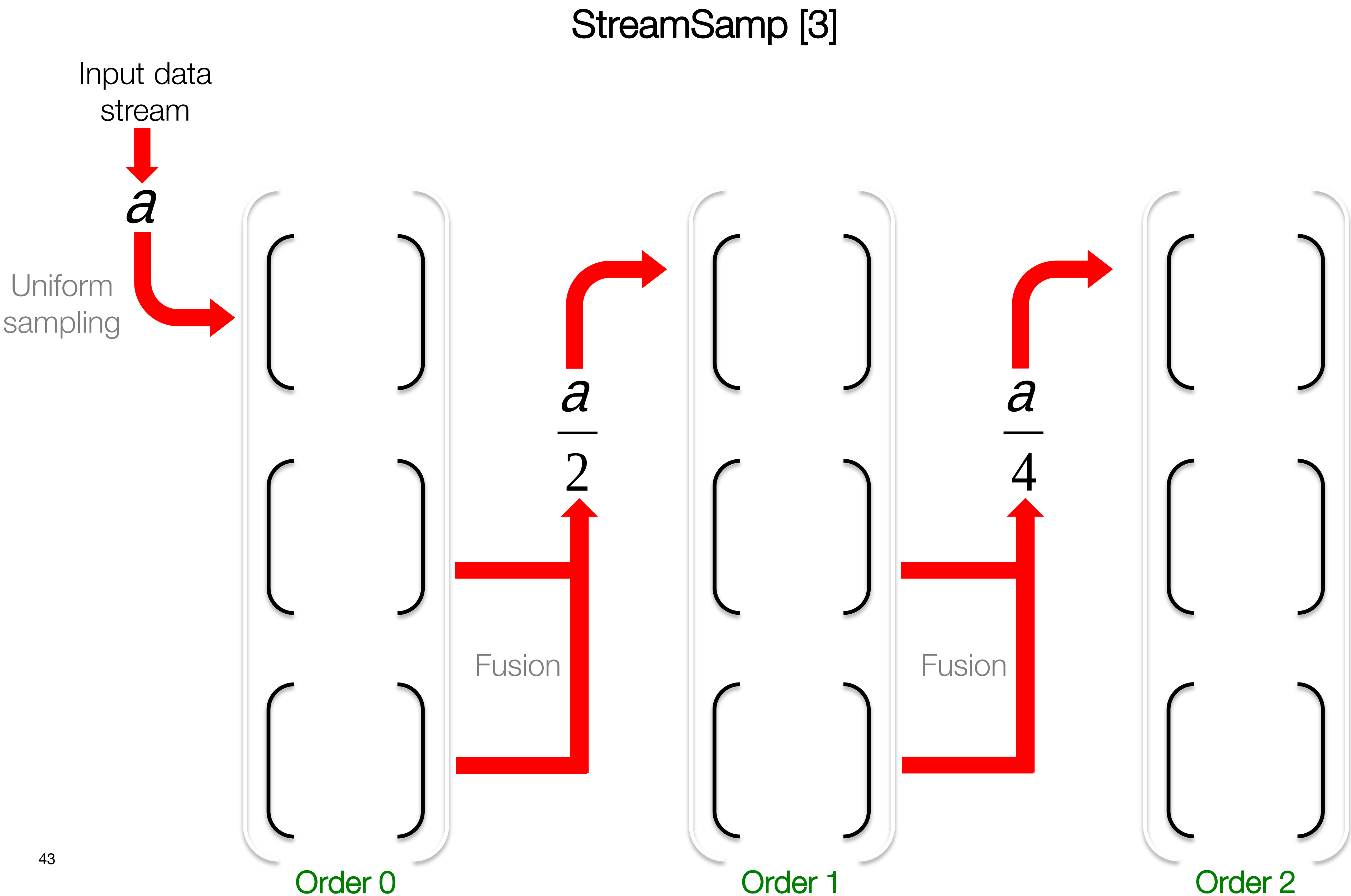


Sampling based summaries

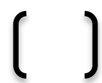


Sampling based summaries

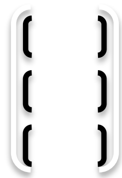


Sampling based summaries

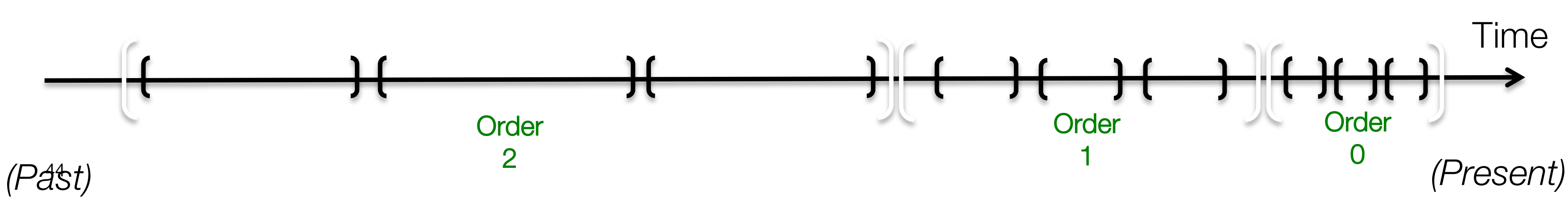
StreamSamp [3]



- A **sample** gathers ***k*** uniformly drawn tuples



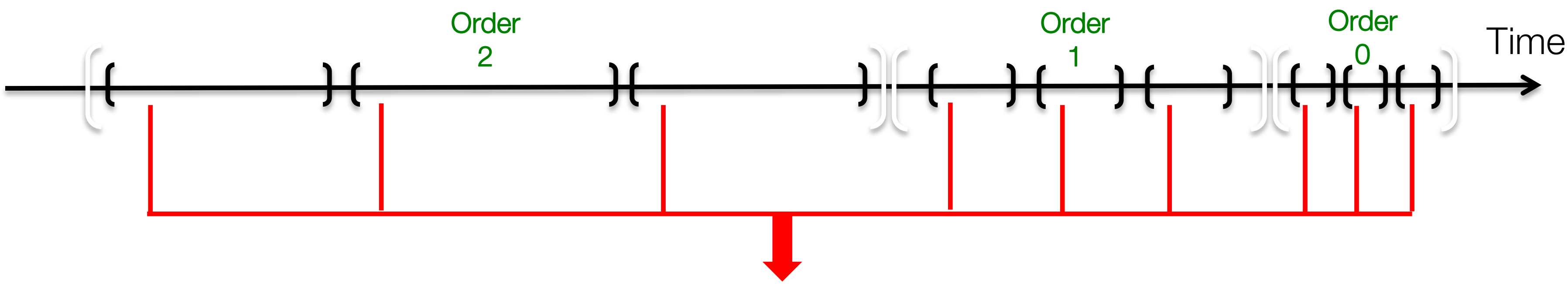
- A **collection of samples** gathers ***h*** samples
- Each **collection** has an order ***o***
- The **sampling rate** of samples is equal to $\dfrac{a}{2^o}$



Sampling based summaries

StreamSamp [3]

How to exploit this summary offline ?



Fusion of all samples

Weighting of tuples to keep
their representativeness

$$W_{tuple} = \frac{2^o}{a}$$

Use of any *Datamining* approach able to
process a weighted training set

Two types of summary

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Micro-clustering based summaries

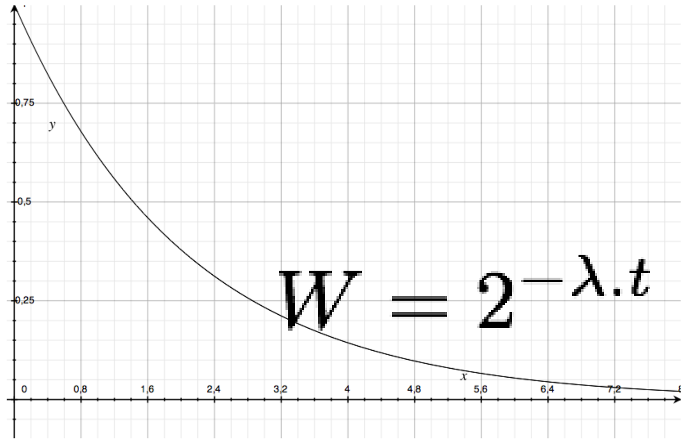
What is a micro-clustering ?

- Micro-clusters *(MC)* are **small groups** of tuples,
- MC are represented by **features** which locally describe the **density of tuples**,
- DenStream : Micro-clustering approache handle **evolving data**,
- MC are maintained **in RAM memory** within a bounded memory space
- MC summarize the **density** of the input data stream, while giving **more importance** to the **recent past**.

Micro-clustering based summaries

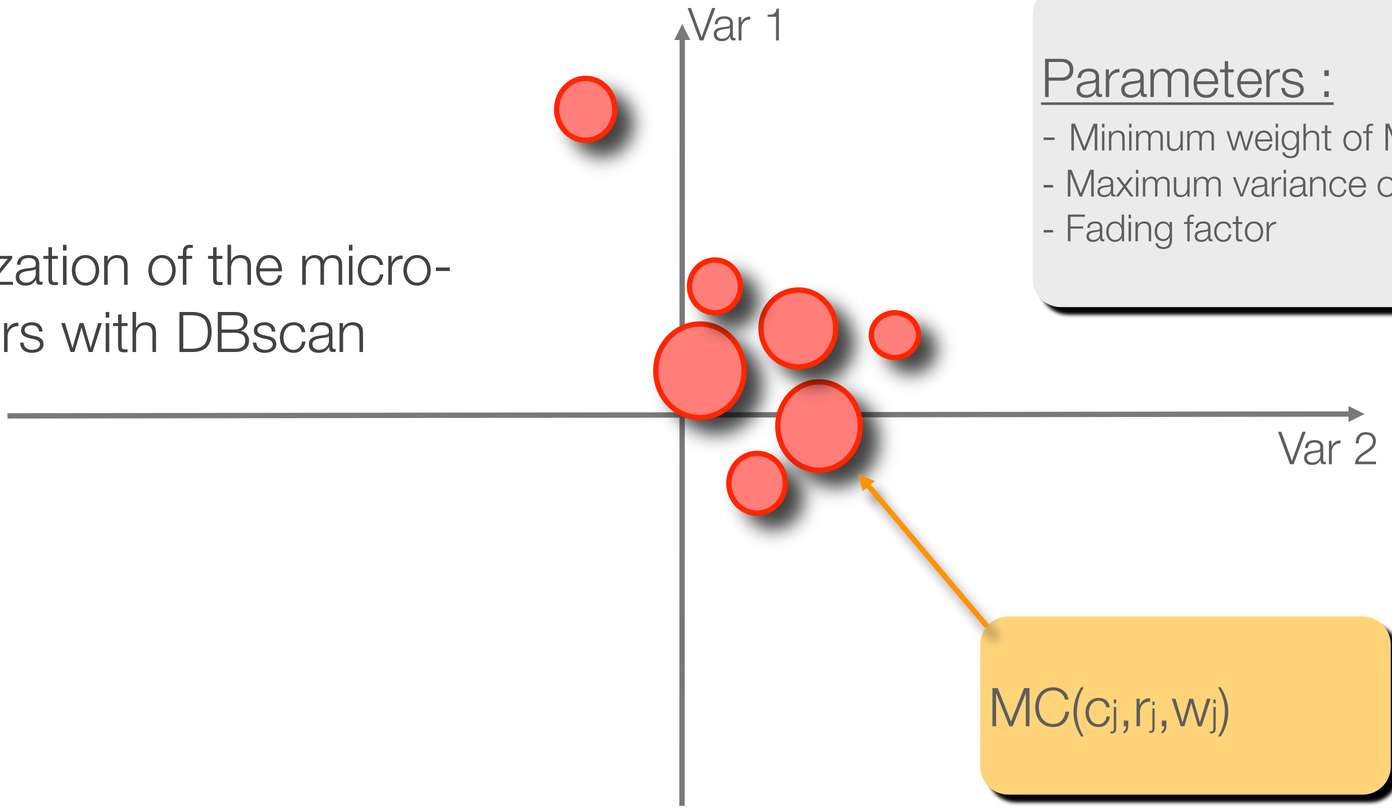
DenStream [4]

- **Density** based **micro-clustering**
- **Weighting** of the tuples over time



Micro-clustering based summaries

DenStream [4]

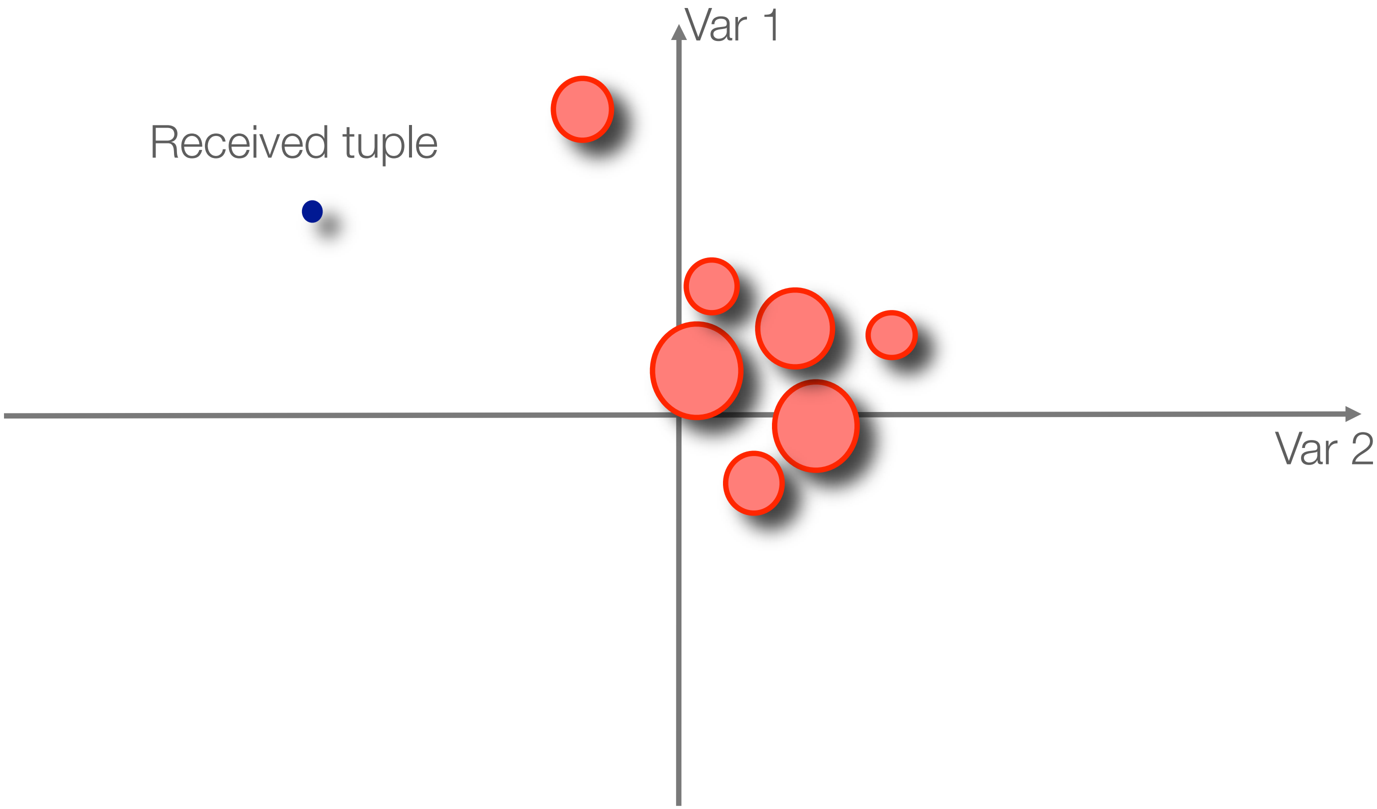


Parameters :
- Minimum weight of Mc
- Maximum variance of Mc
- Fading factor

Initialization of the micro-clusters with DBscan

Micro-clustering based summaries

DenStream [4]



Micro-clustering based summaries

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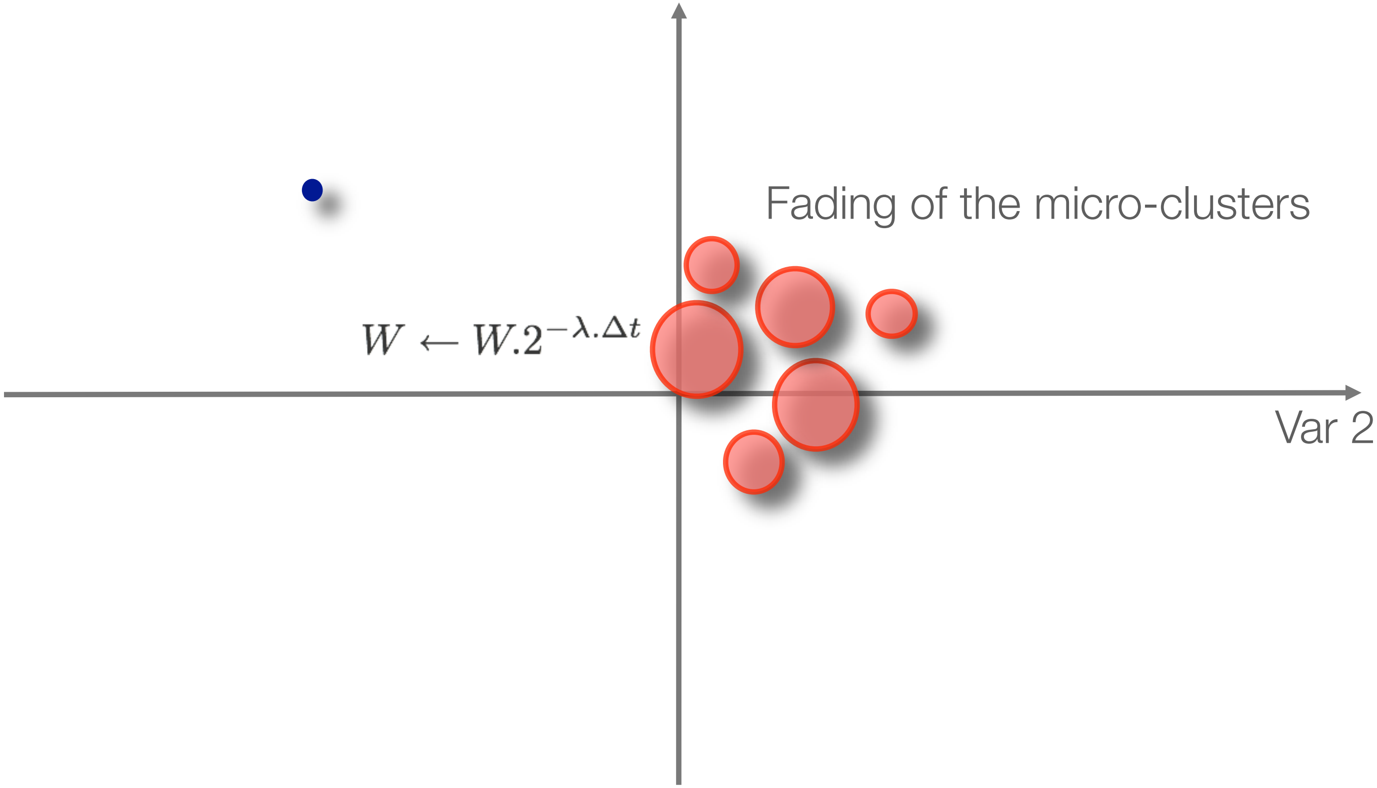

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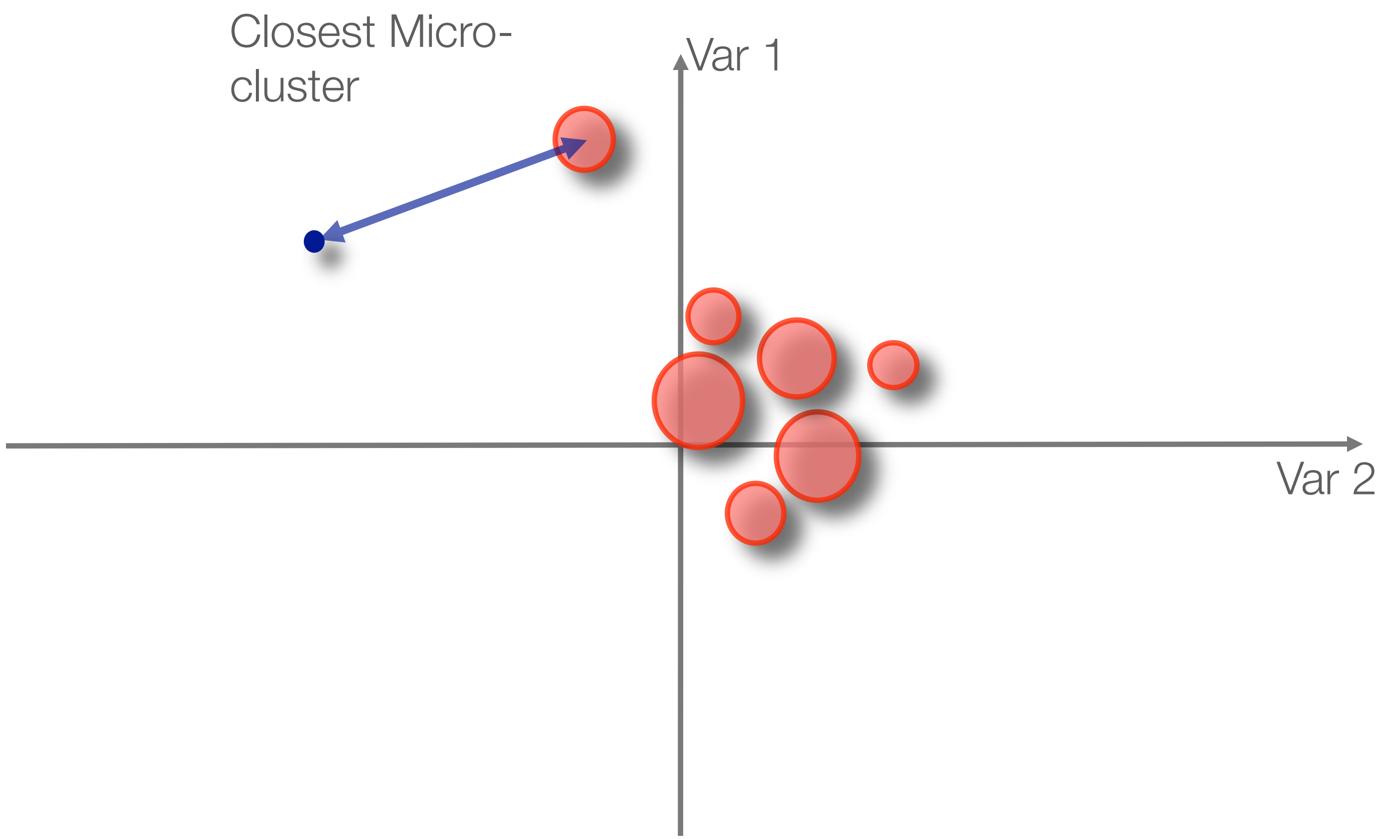

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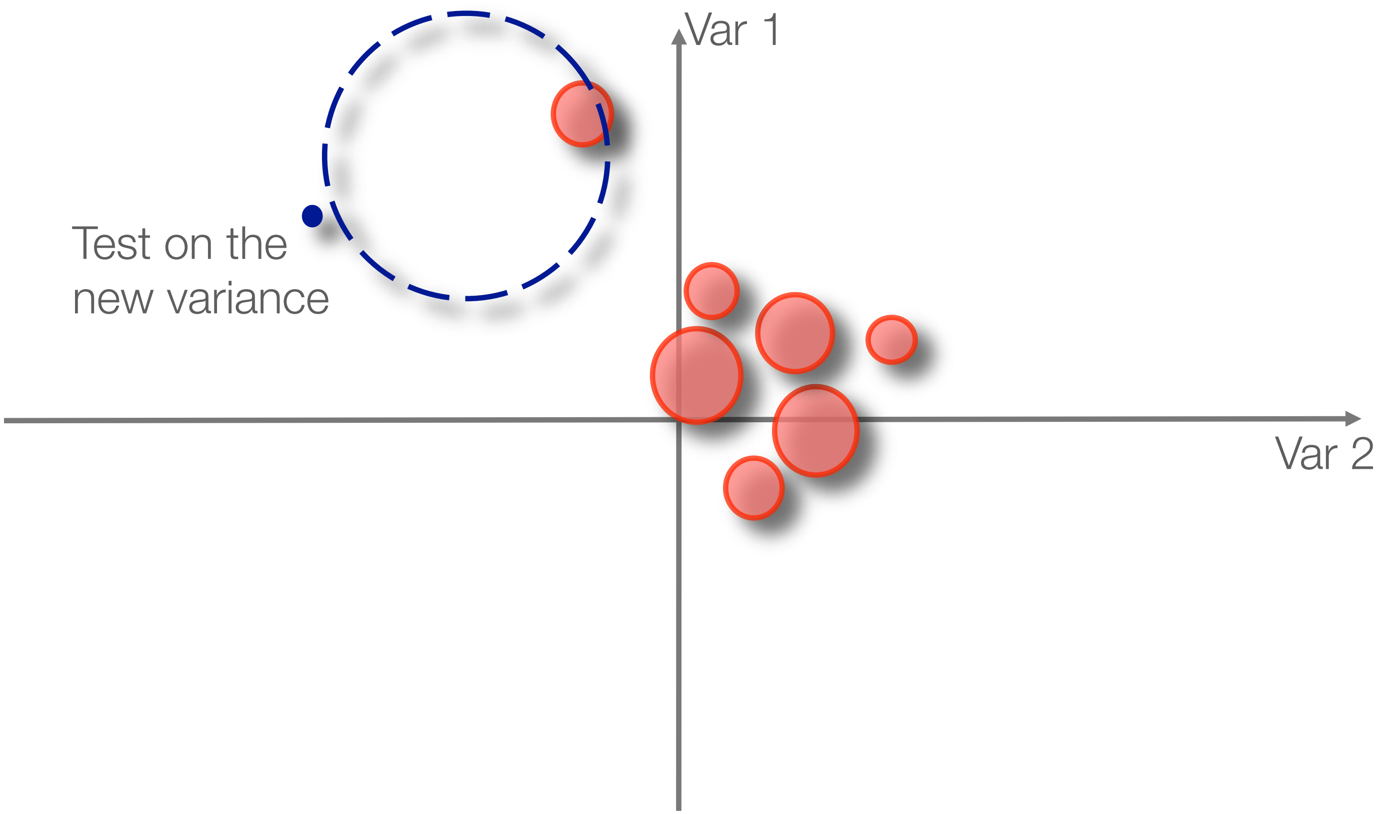
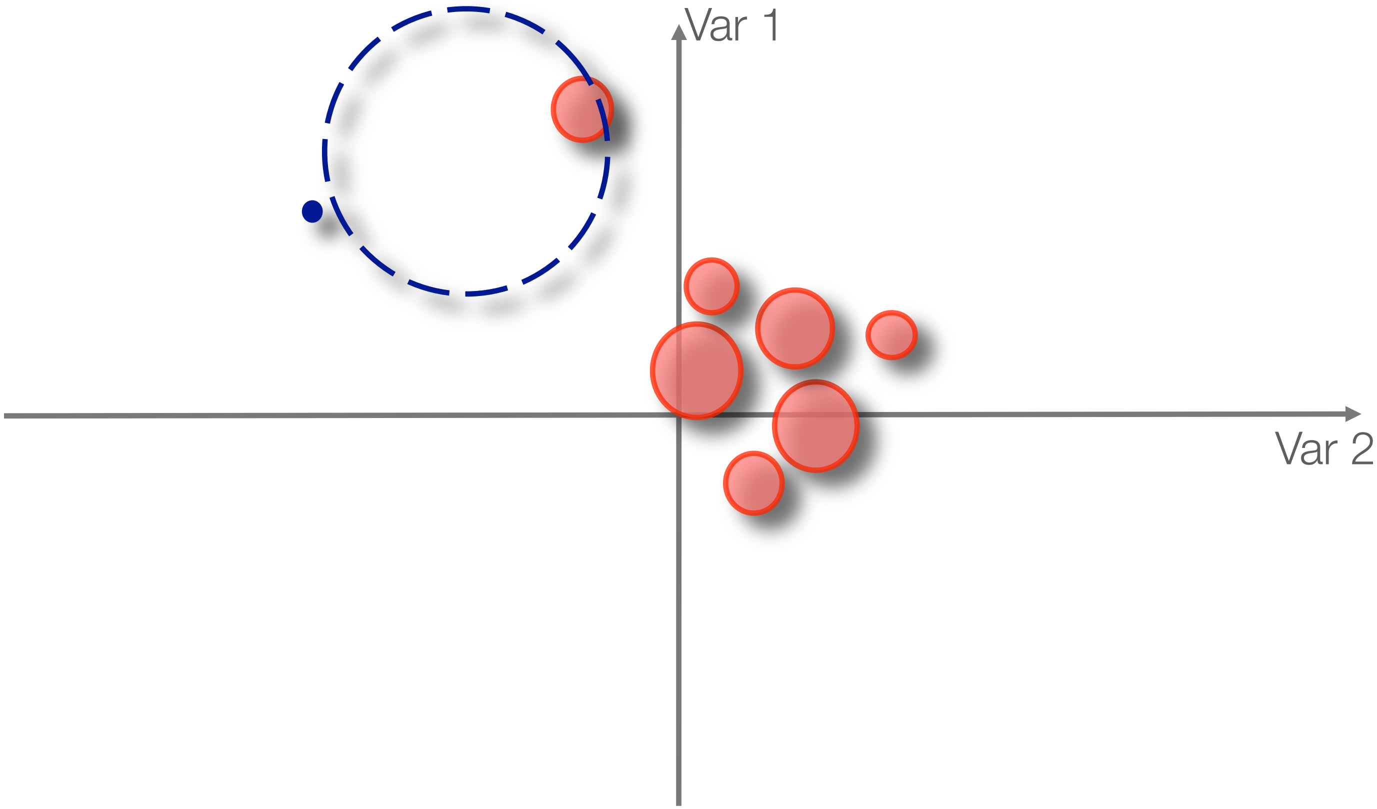


Micro-clustering based summaries

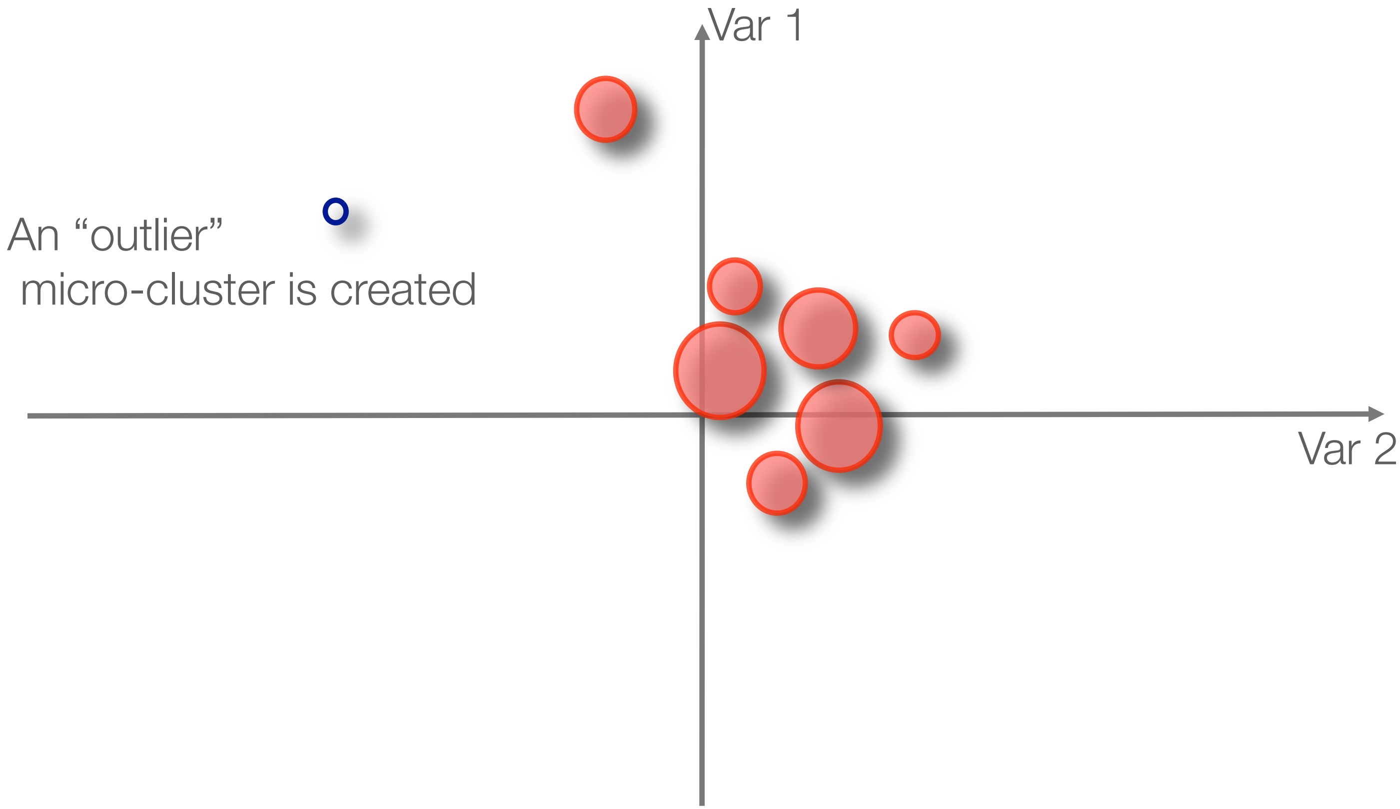
DenStream [4]

Here, the new variance is greater
than the maximum variance



Micro-clustering based summaries

DenStream [4]



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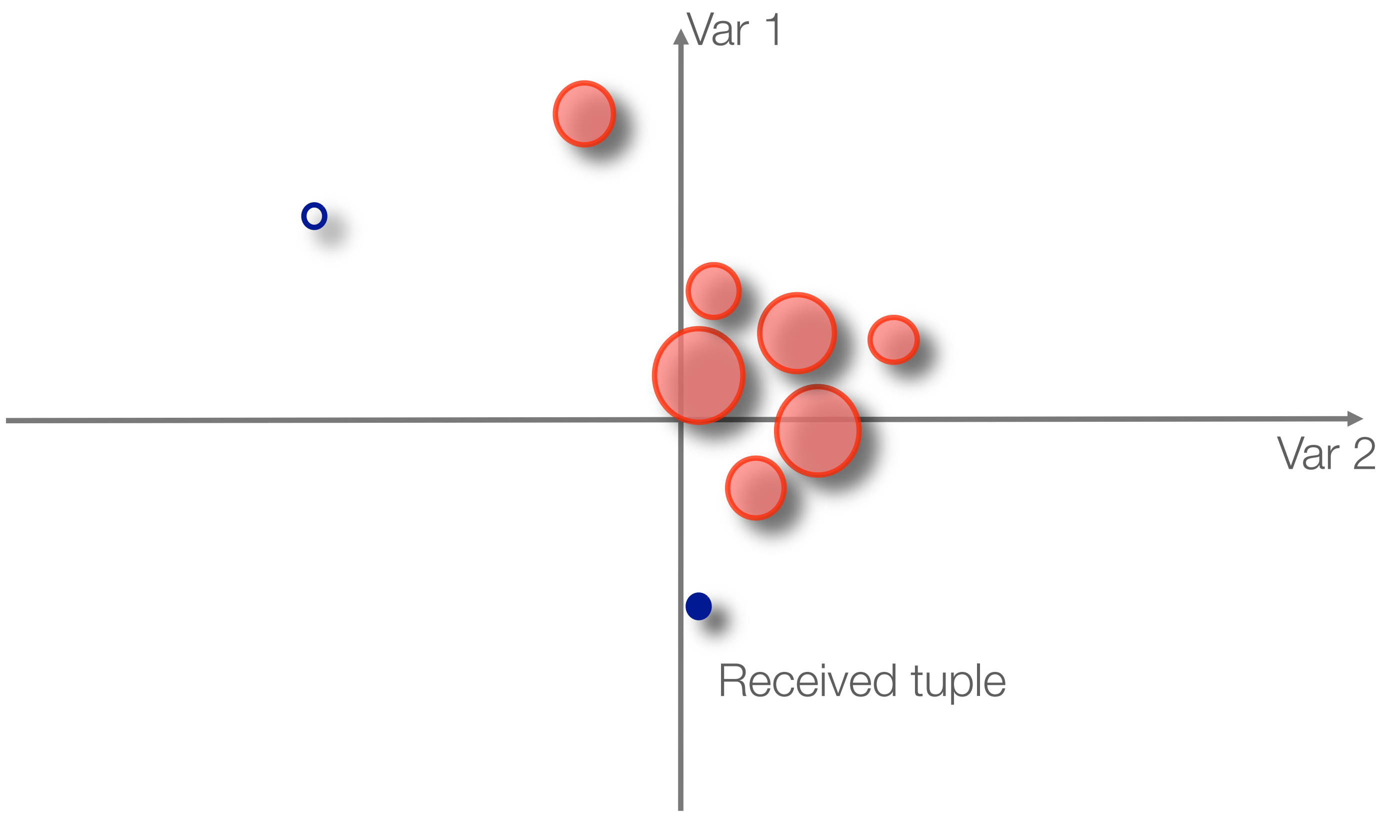

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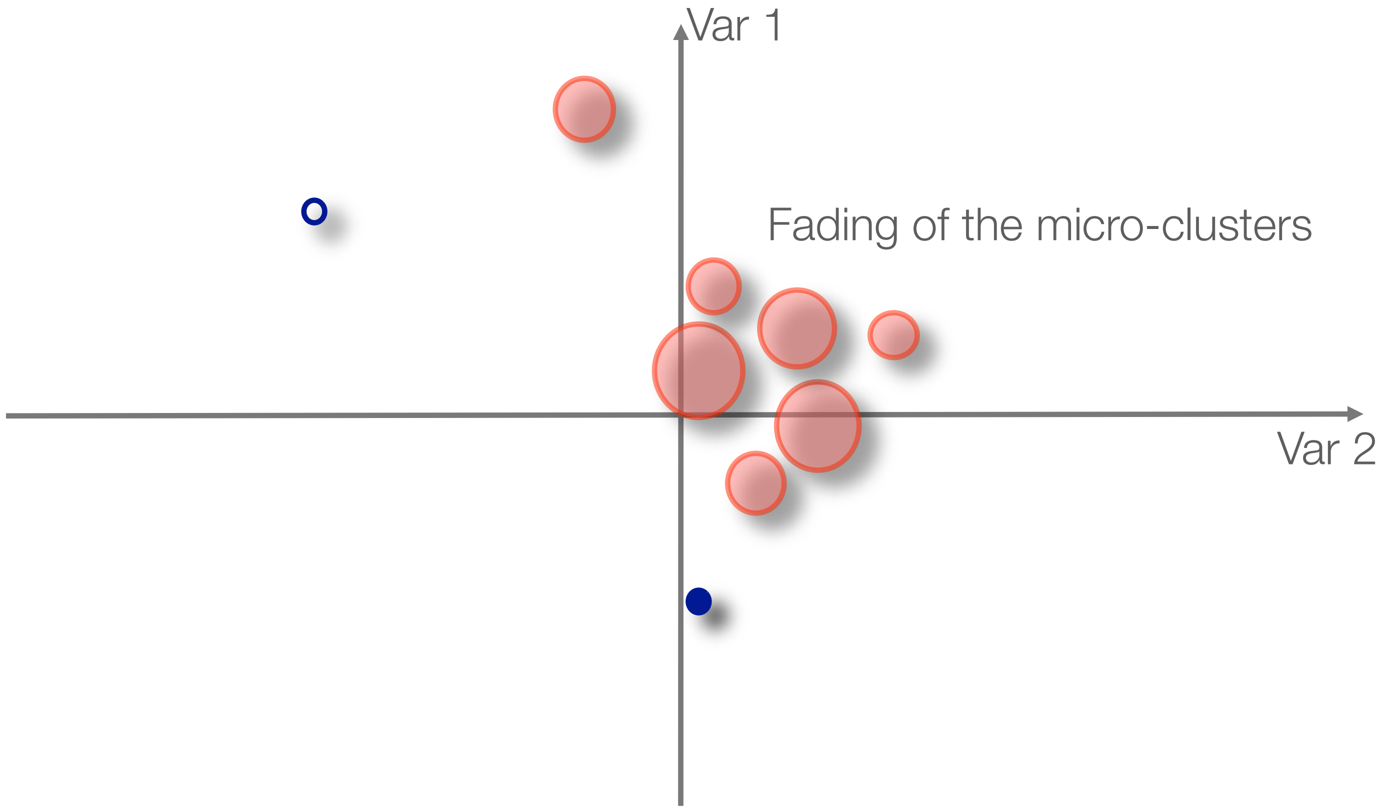

Micro-clustering based summaries

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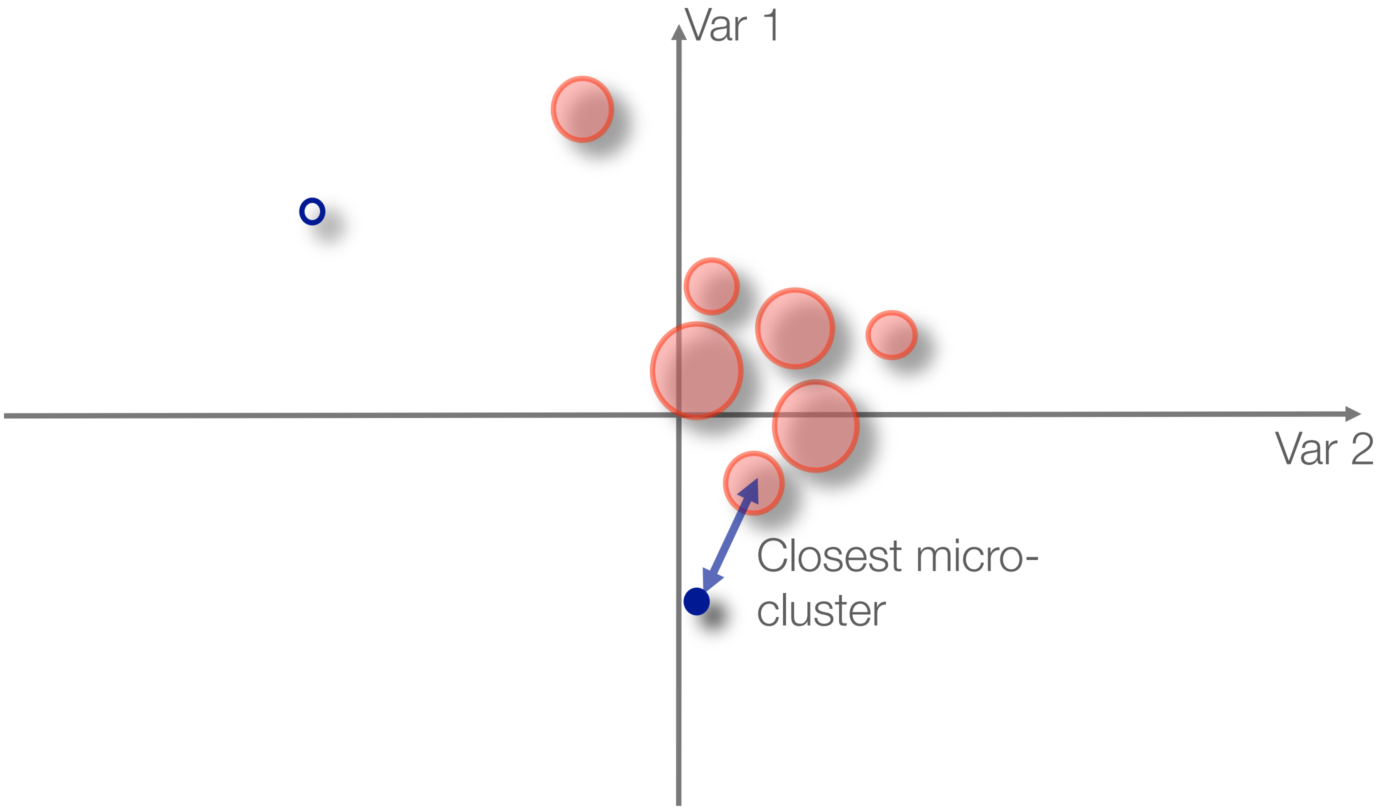
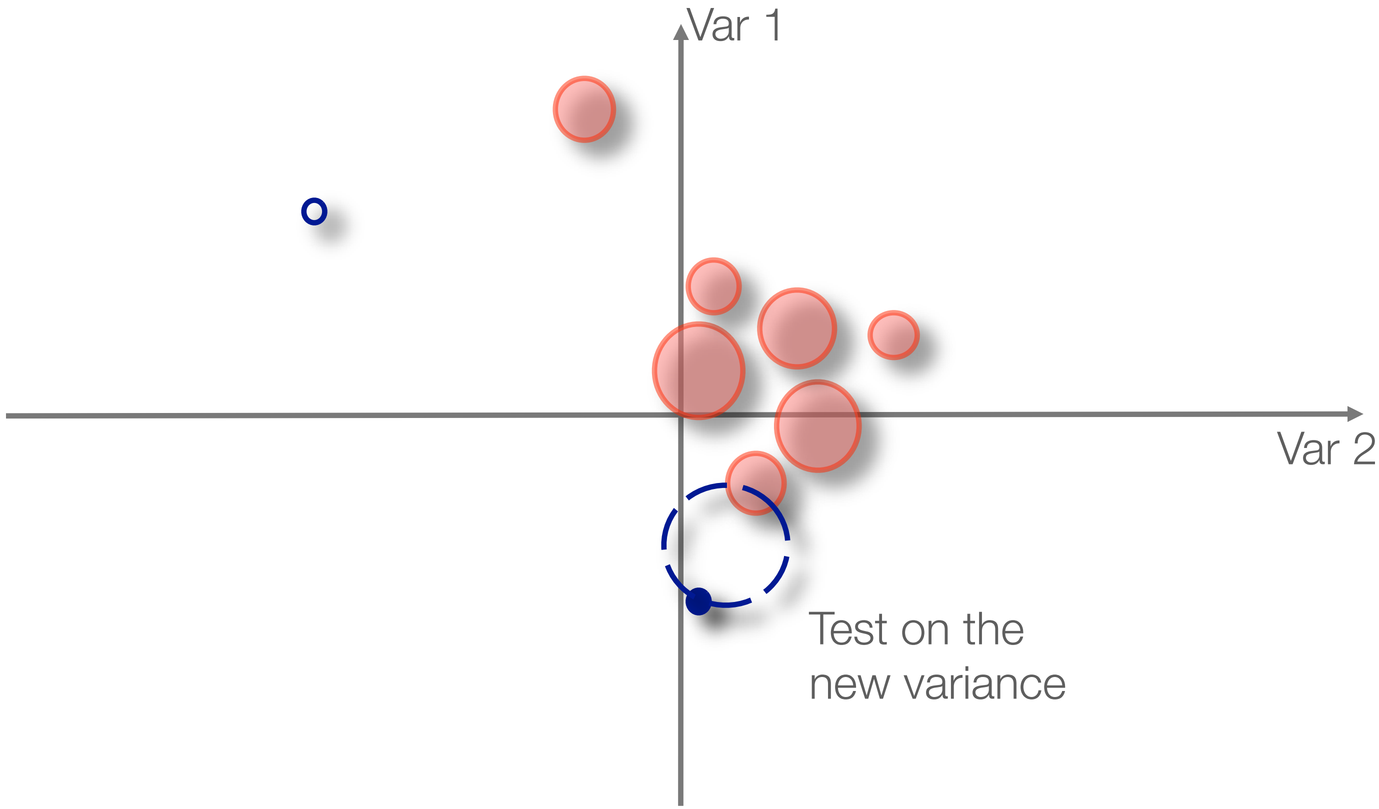


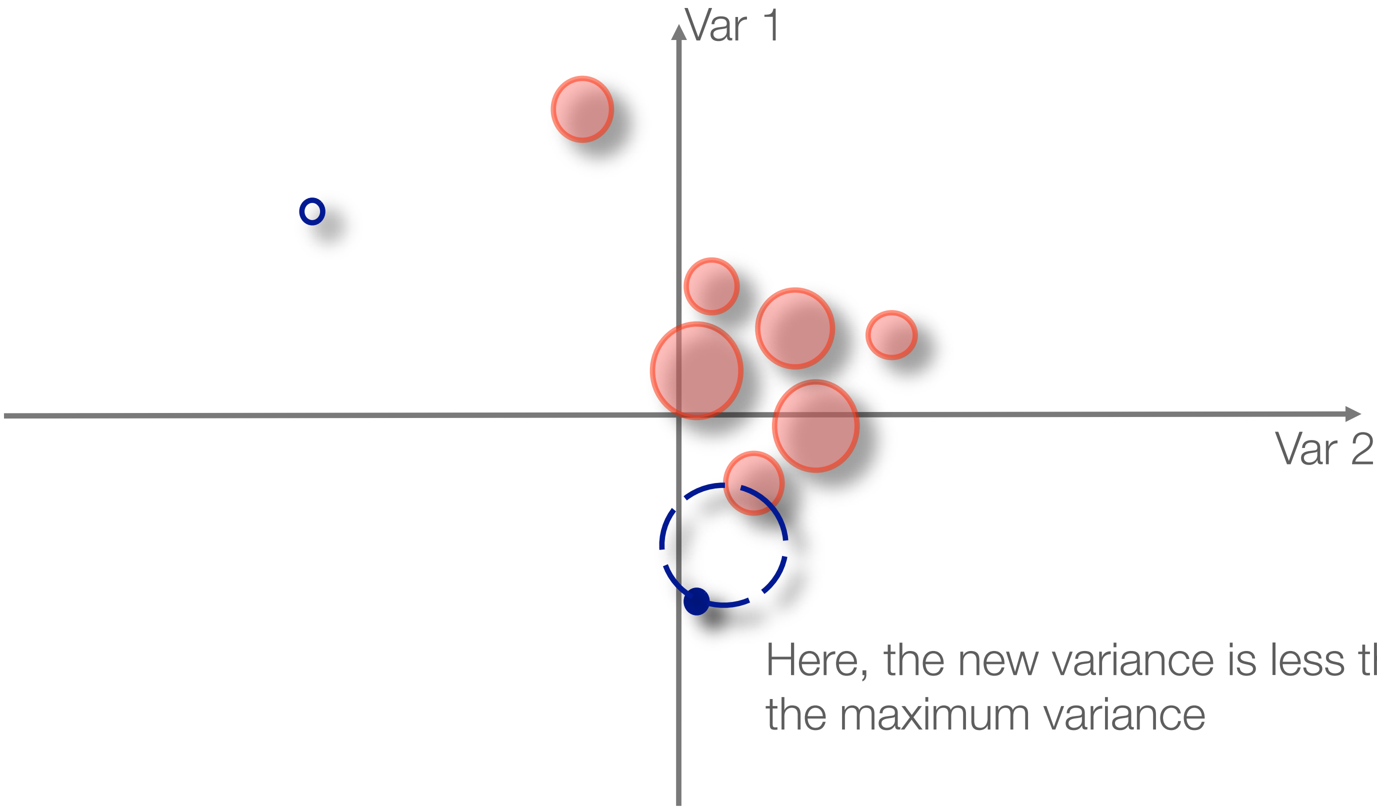
Micro-clustering based summaries

DenStream [4]



Micro-clustering based summaries

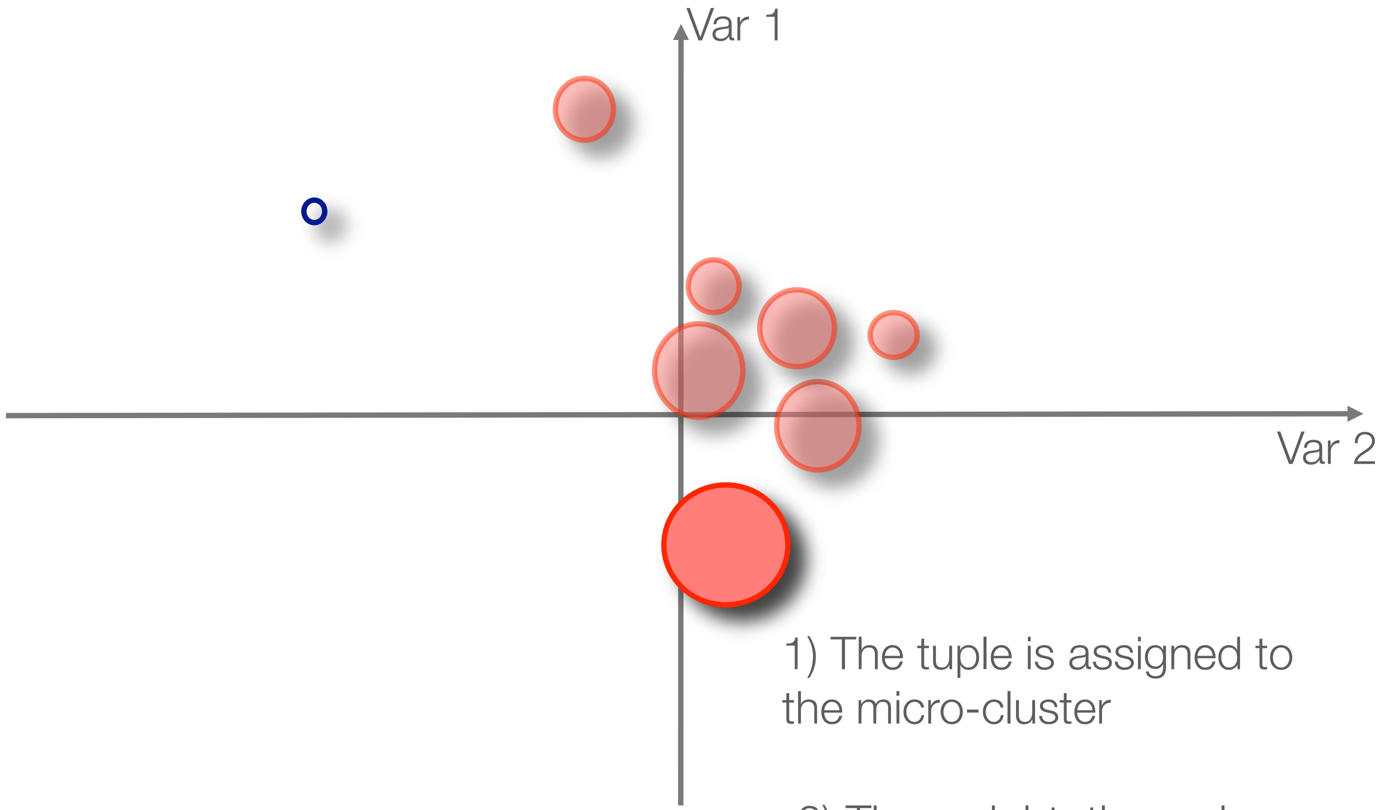
DenStream [4]



Here, the new variance is less than the maximum variance

Micro-clustering based summaries

DenStream [4]

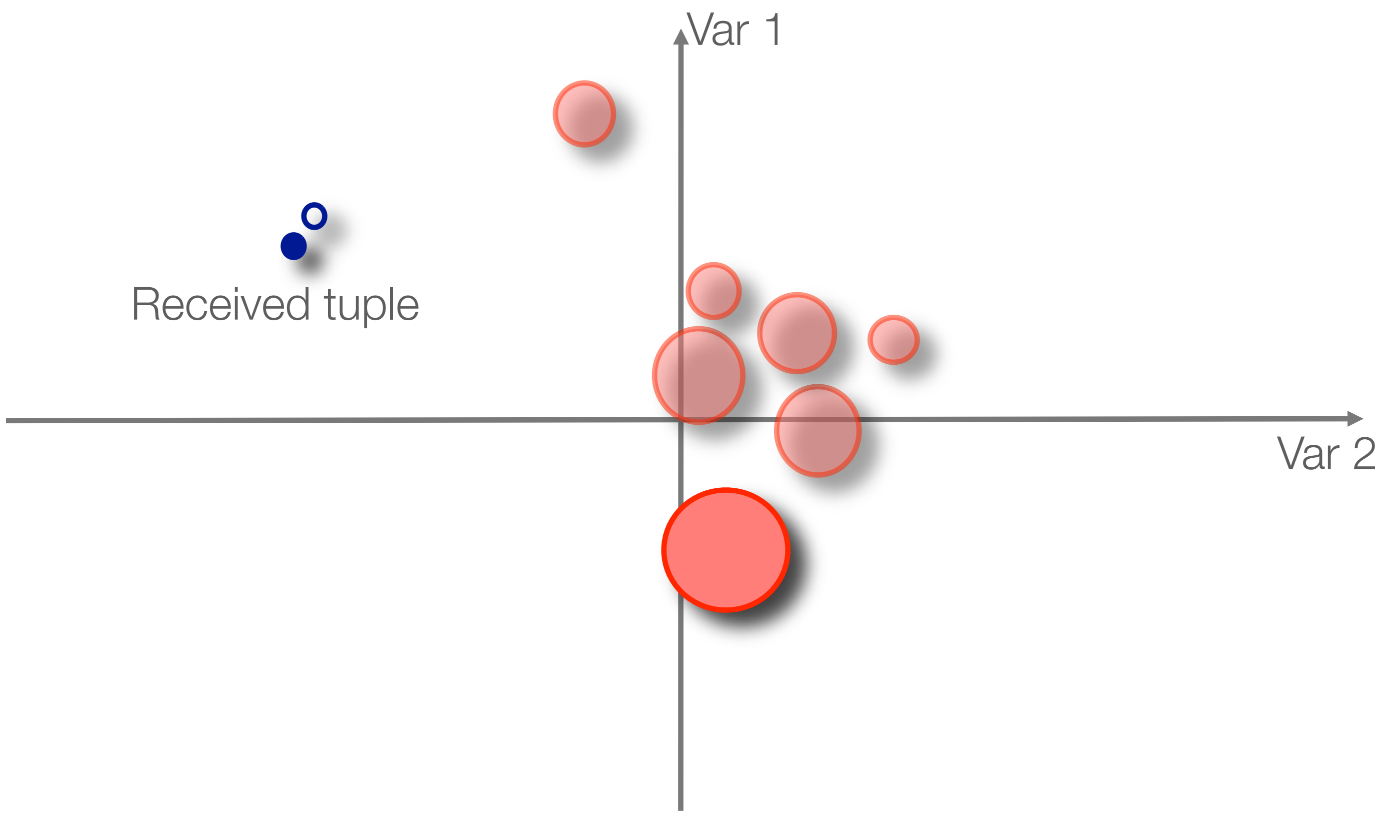


1) The tuple is assigned to the micro-cluster

2) The weight, the variance and the mean are updated

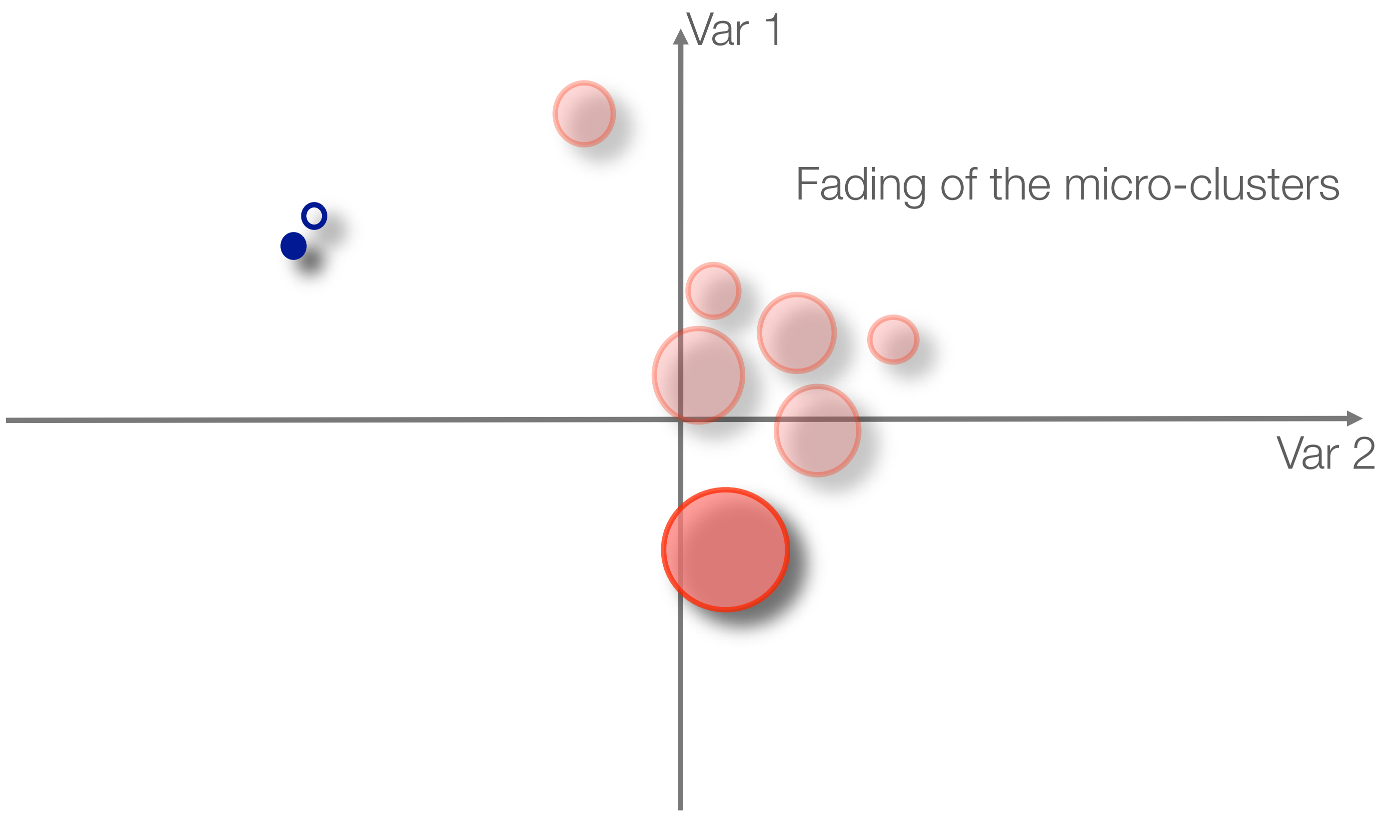
Micro-clustering based summaries

DenStream [4]



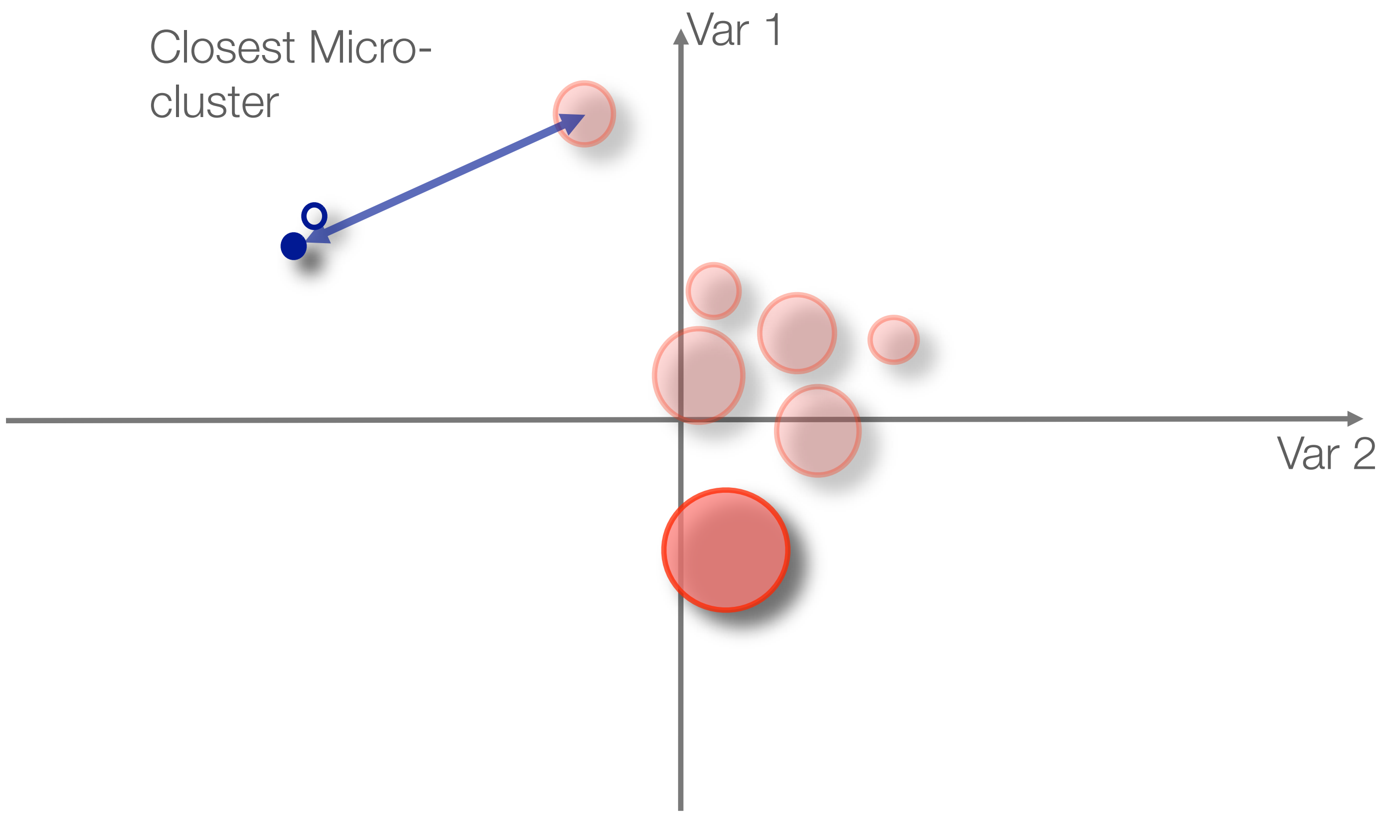
Micro-clustering based summaries

DenStream [4]



Micro-clustering based summaries

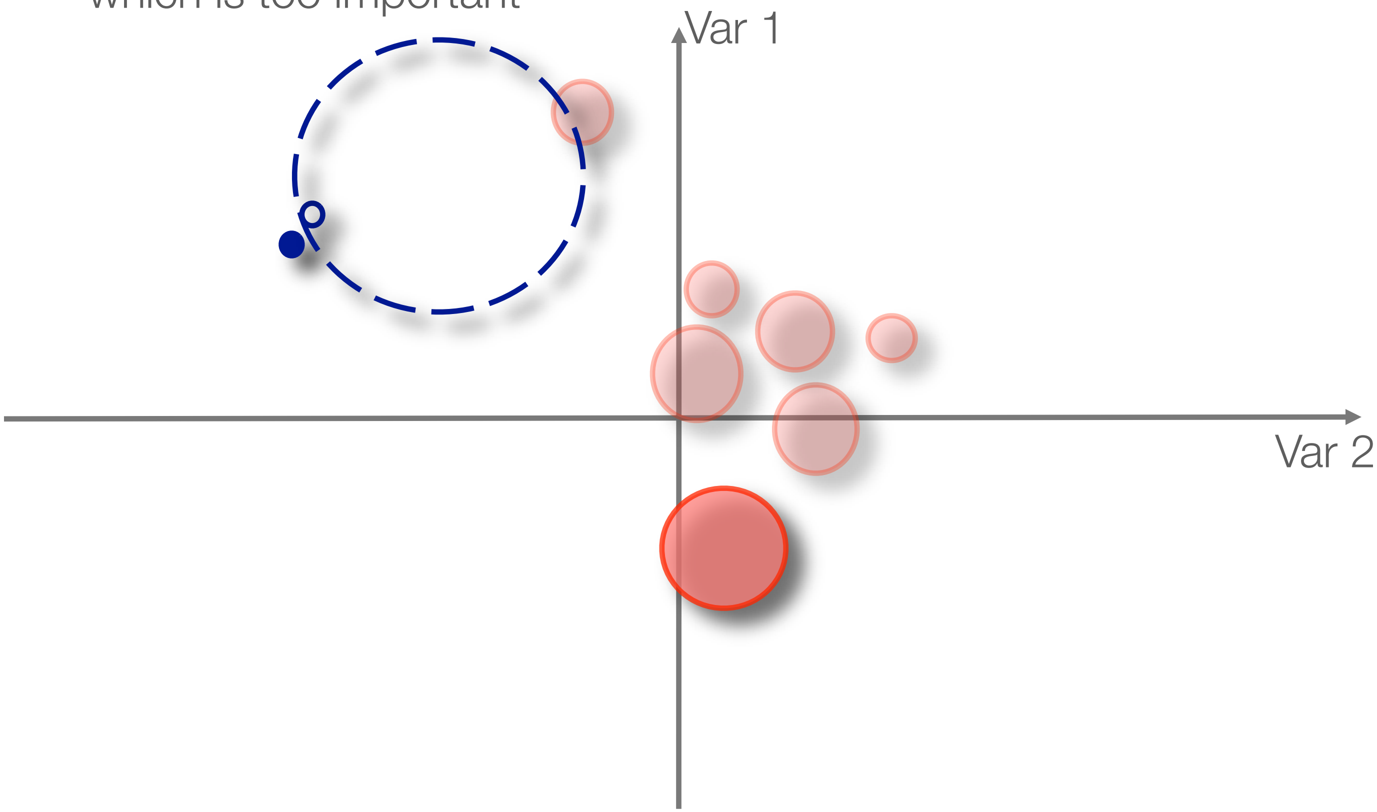
DenStream [4]



Micro-clustering based summaries

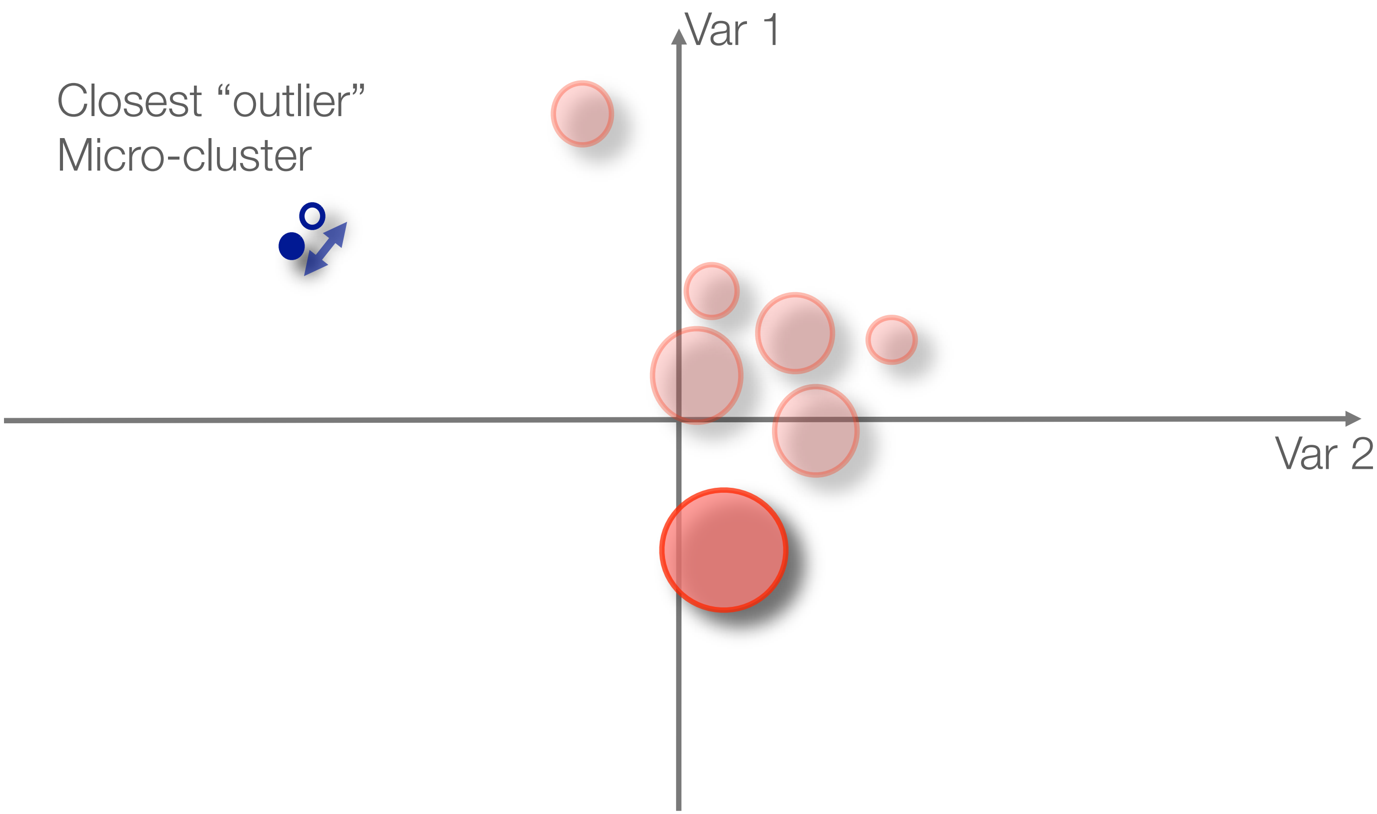
DenStream [4]

Test on the new variance,
which is too important



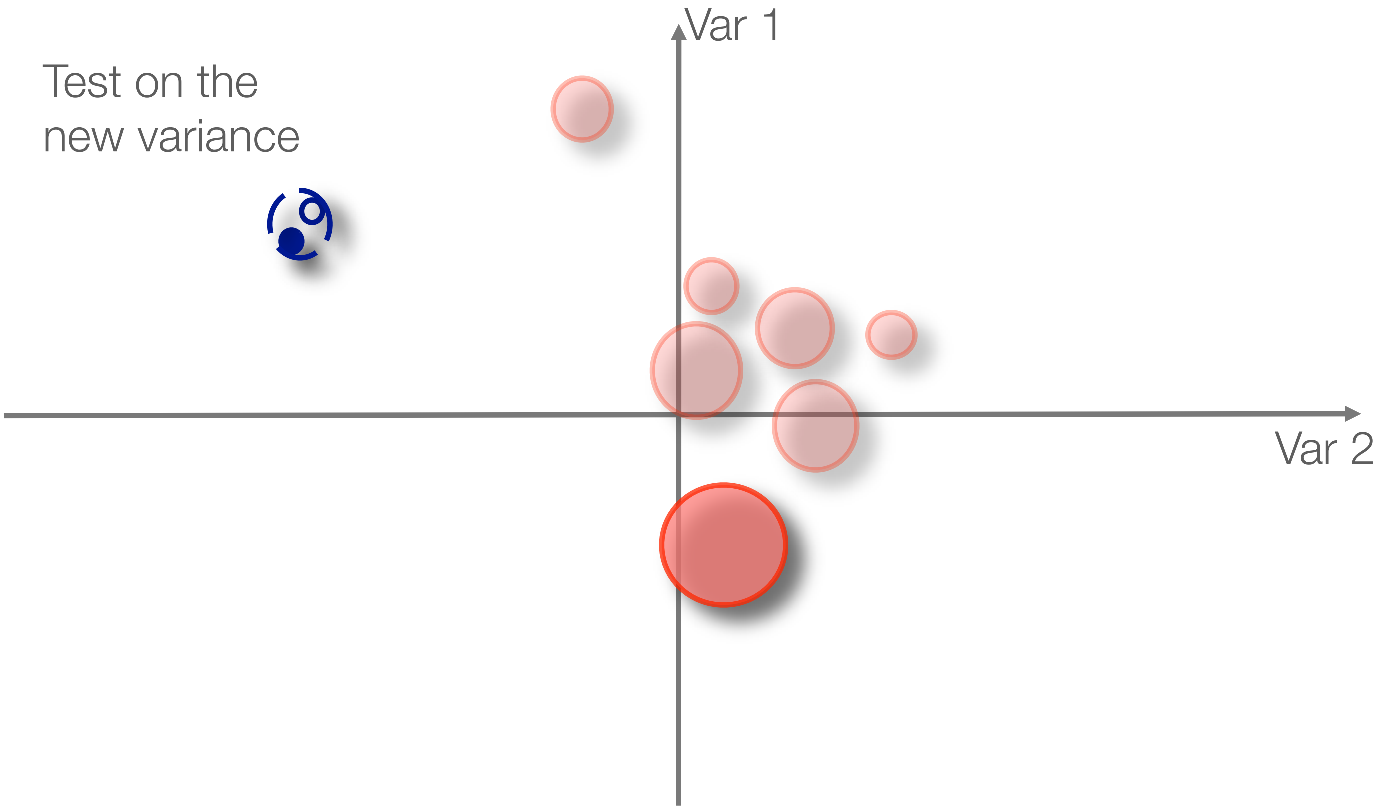
Micro-clustering based summaries

DenStream [4]



Micro-clustering based summaries

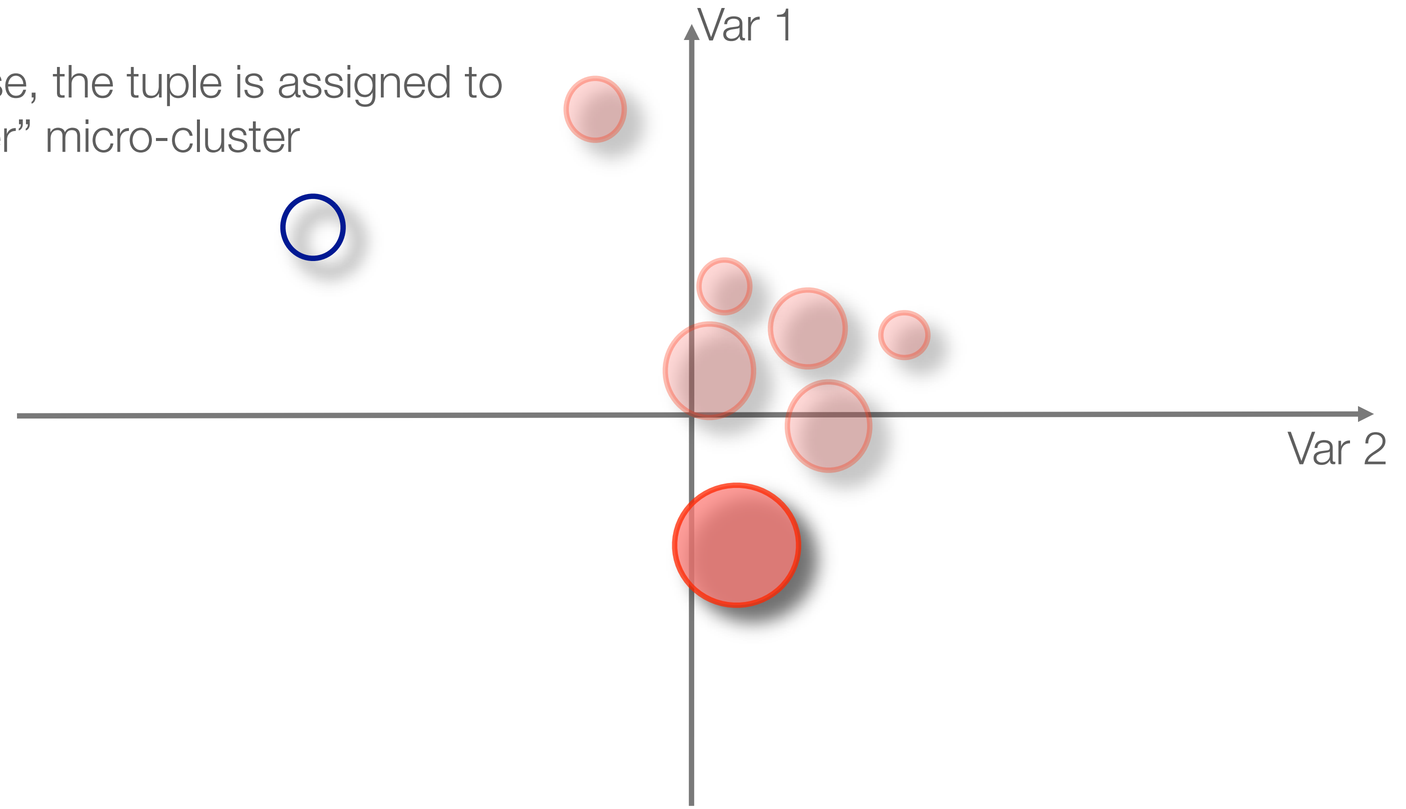
DenStream [4]



Micro-clustering based summaries

DenStream [4]

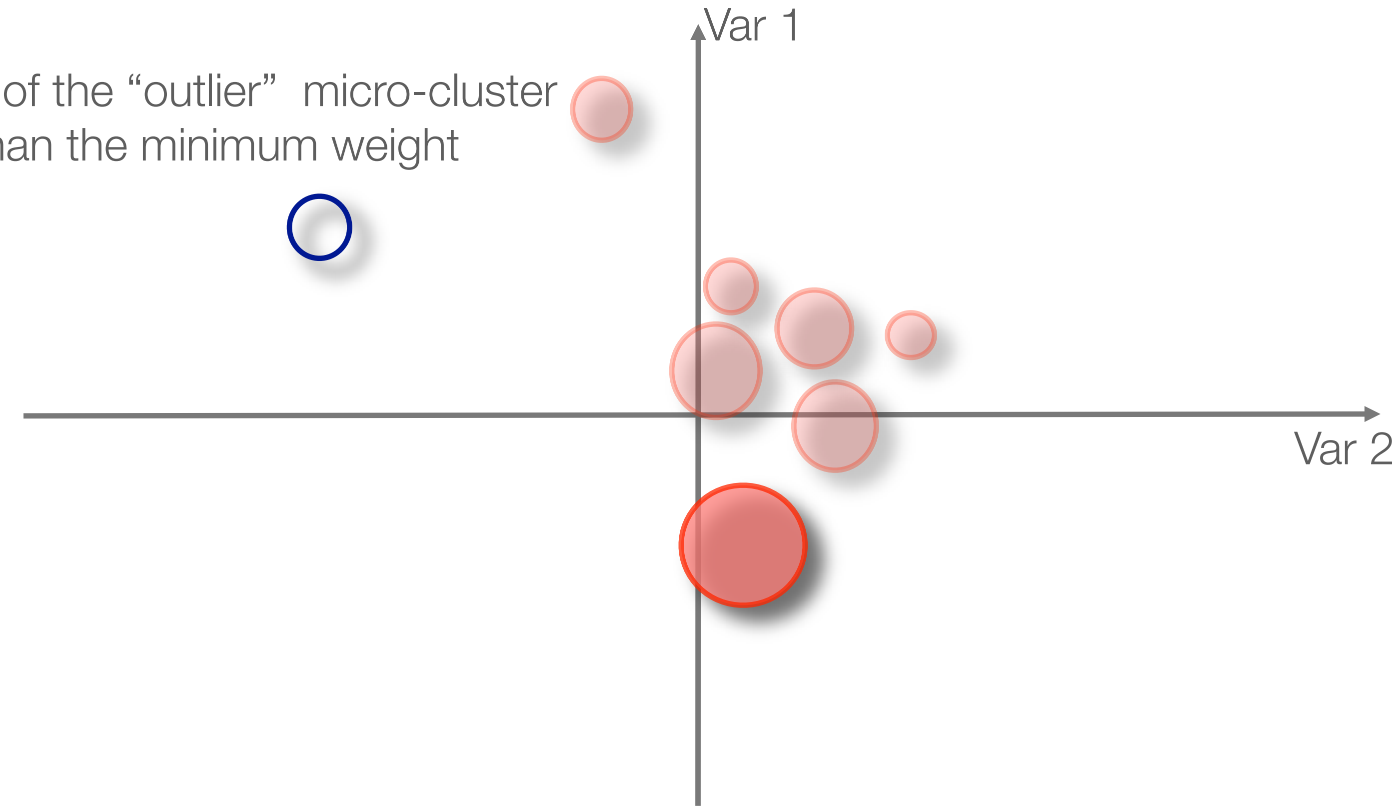
In this case, the tuple is assigned to the “outlier” micro-cluster



Micro-clustering based summaries

DenStream [4]

The weight of the "outlier" micro-cluster is greater than the minimum weight



Micro-clustering based summaries

DenStream [4]

The "outlier" micro-cluster becomes a regular micro-cluster

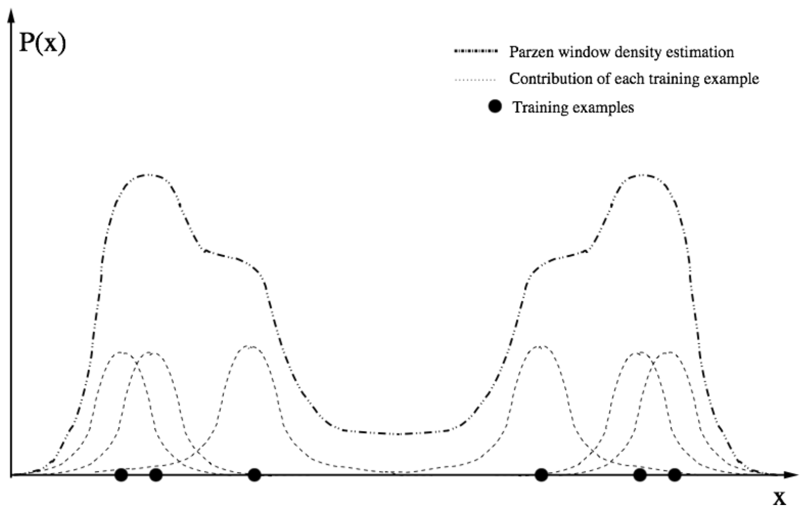
Micro-clustering based summaries

DenStream [4]

How to exploit this summary to estimate the density of the data stream ?

… the example of the Parzen widows estimator [5] *…*

$$\hat{P}(x) = \frac{1}{N}\sum_{i=1}^{N} K(x - x_i) \qquad K(x - x_i) = \frac{1}{\left(\sigma\sqrt{2\pi}\right)^k} \exp^{-\frac{d(x,x_i)^2}{2.\sigma^2}}$$

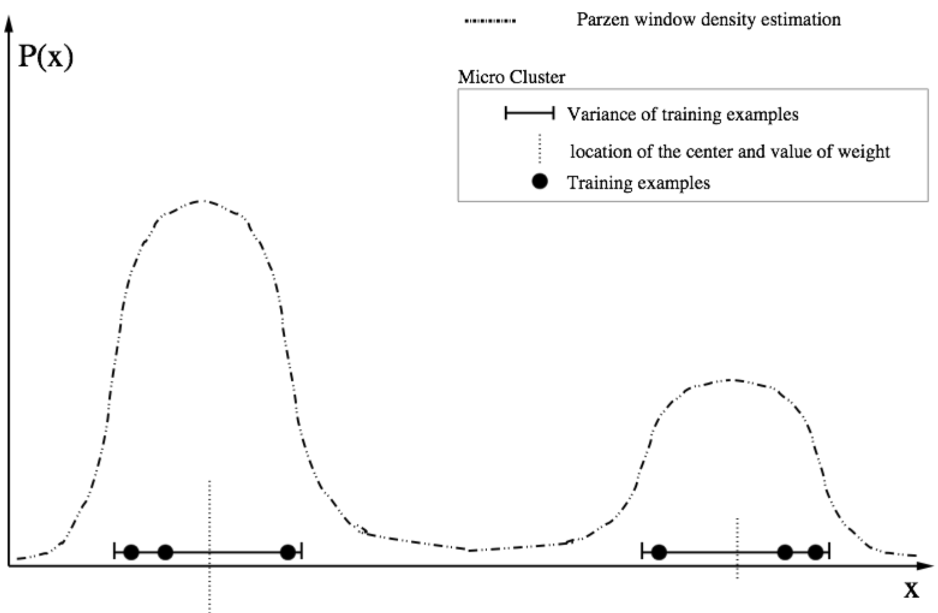


Micro-clustering based summaries

DenStream [4]

Adapted Parzen window [5] :

$$\hat{P}^*(x) = \frac{1}{C.W}\sum_{j=1}^{C}\frac{\omega_j}{\sqrt{2\pi\left(\delta^2+r_j^2\right)}^{k}}\exp^{-\frac{d(x,c_j)^2}{2\left(\delta^2+r_j^2\right)}}$$



- W : total weight of the data stream
- C : number of micro-clusters
- wj : weight of the *j-th* micro-cluster
- rj : standard deviation of the *j-th* micro-cluster
- d : smoothing parameter

Hypothesis : each tuple represents a set of none-observed tuples, with a fixed effective and a standard deviation d equal to

➡Law of total variance

Conclusion

Main ideas to retain :

- **Summaries** allow to process data streams with very **high emission rate**,
- By using **limited hardware resources** *(CPU, RAM).*
- In most cases, a trade off must be reached between the **accuracy** and the available **memory.**
- There are **two types of summary** *(specific and generic)*
- Limitation : most of generic summaries involves user **parameters.**

References

[1] Flajolet, P. et G. Martin (1985). Probabilistic counting algorithms for data base applications. *Journal of Computer and System Sciences 31*(2), 182–209

[2] J. S. Vitter. Random sampling with a reservoir. *ACM Trans. Math. Softw.*, 11(1) :37– 57, 1985.

[3] B. Csernel, F. Clerot, and G. Hébrail. Streamsamp : Datastream clustering over tilted windows through sampling. In *ECML PKDD 2006 Workshop on Knowledge Discovery from Data Streams*, 2006.

[4] Feng Cao, F., M. Ester, W. Qian, and A. Zhou (2006). Density-based clustering over an evolving data stream with noise. In *SIAM Conference on Data Mining*, pp. 328–339.

[5] A. Bondu, B. Grossin, M.L. Picard. Density estimation on data streams : an application to Change Detection.

In EGC (Extraction et Gestion de la connaissance) 2010.

Related documents :

Thesis of Gasbi, N. Extension et interrogation des résumés de flux de données, 2011

Outline

- Introduction on data-streams
- Part 1 : Querying
- Part 2 : Unsupervised Learning
- Part 3 : Supervised Learning
- Conclusion

Outline

1. From Batch mode to Online Learning
2. Implementation of on-line classifiers
3. Evaluation of on-line classifiers
4. Taxonomy of classifier for data stream
5. Two examples
6. Concept drift
7. Make at simplest

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From Batch mode to Online Learning

What is supervised learning ?

- <u>Output</u> : prediction of a **target variable** for new observations
- <u>Data</u> : a supervised model is **learned** from **labeled examples**
- <u>Objective</u> : learn **regularities** from the training set and **generalize** it *(with parsimony)*

Several types of supervised models :

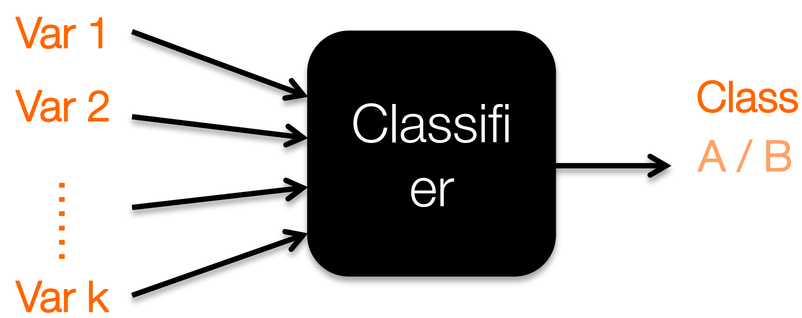
In this talk .

- Categorical target variable -> **Classifier**
- Numeric target variable -> **Regression**
- Time series -> **Forecasting**

From Batch mode to Online Learning

Training set

Var 1	Var 2	…	Clas s
O	12	…	A
Y	98	…	B
Y	4	…	A



A learning algorithm exploits the training set to automatically adjust the classifier

From Batch mode to Online Learning

Batch mode learning :

- An entire **dataset is available**
- The examples can be processed **several times**
- **Weak constrain** on the computing time
- The **distribution** of data does **not change**

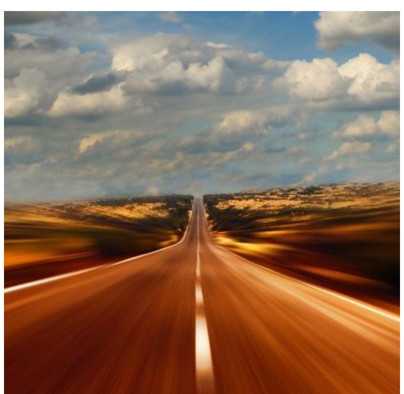
Any time learning algorithm :

- Can be **interrupted** before its end
- Returns a **valid classifier** at any time
- Is expected to find **better and better** classifier
- Relevant for **time-critical** application

From Batch mode to Online Learning

Incremental learning algorithm :

- Only a **single pass** on the training examples is required.
- The classifier is **updated** at each **example.**
- **Avoid** the **exhaustive storage** of the examples in the **RAM.**
- Relevant for **time-critical** applications and for **progressively recorded** data.



Online learning algorithm :

- The training set is substituted by an **input data stream**
- The classifier is **continually updated** over time,
- By exploiting the **current** tuple,
- ➡ With a very **low latency.**
- ➡ The **distribution** of data **can change** over time *(concept drif*

From Batch mode to Online Learning

Machine Learning: What are the pros and cons of offline vs. online learning?

Try to find answers to:
(which is which)

- Computationally much faster and more space efficient
- Usually easier to implement
- A more general framework.
- More difficult to maintain in production.
- More difficult to evaluate online
- Usually more difficult to get "right".
- More difficult to evaluate in an offline setting, too.
- Faster and cheaper
- …

From Batch mode to Online Learning

Focus today - Supervised classifier

- Try to find answers to:
  - Can the examples be stored in memory?
  - Which is the availability of the examples: any presents? In stream ? Visible only once?
  - Is the concept stationary?
  - Does the algorithm have to be anytime? (time critical)
  - What is the available time to update the model?
  - …

- The answers to these questions will give indications to select the algorithms adapted to the situation and to know if one need an incremental algorithm, even a specific algorithm for data stream.

FROM BATCH MODE TO ONLINE LEARNING

→ STREAM MINING IS REQUIRED… SOMETIMES

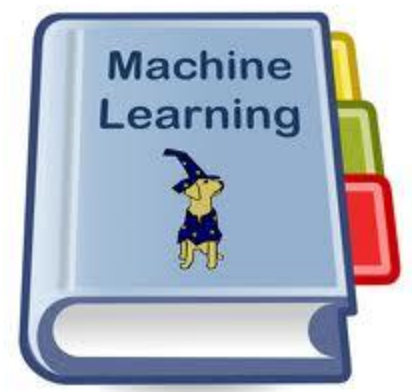
From Batch mode to Online Learning

but...

Do not make the confusion!

Between Online Learning

and Online Deployment



A lot of advantages and drawback for both – but offline learning used 99% of the time

From Batch mode to Online Learning

"Incremental / online learning": a new topic?

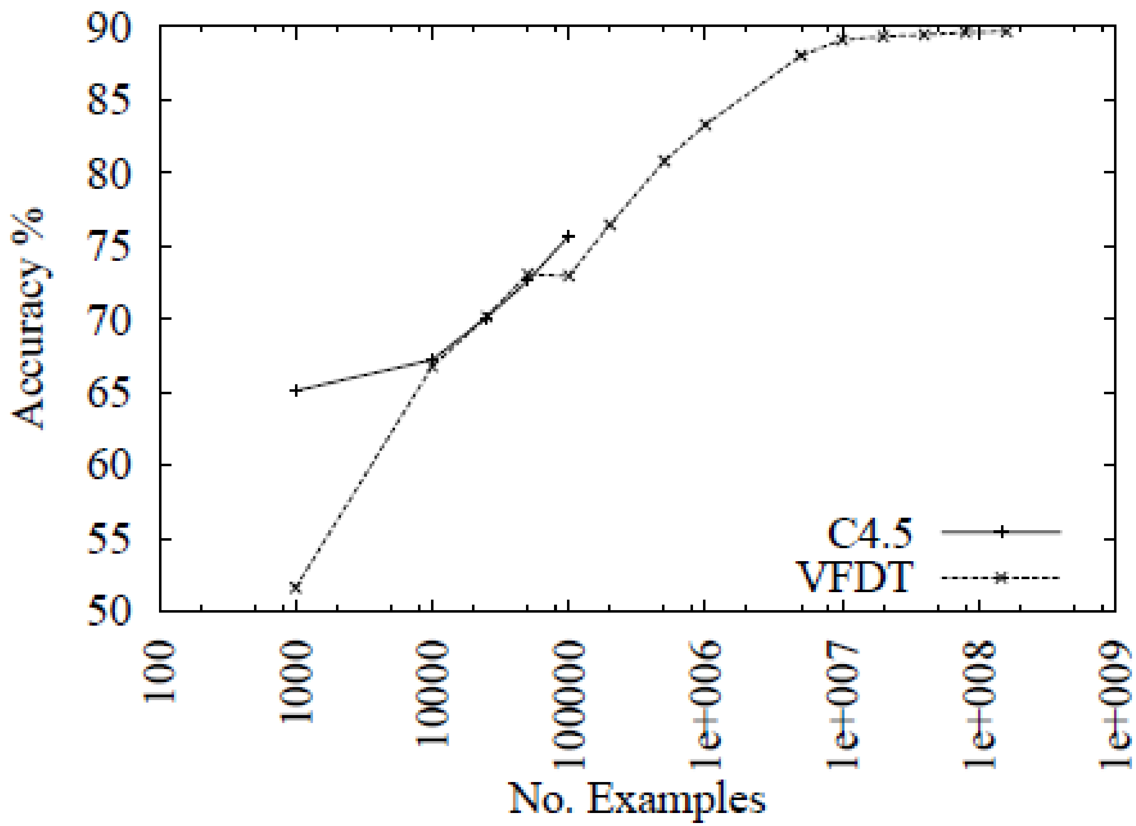
The first learning algorithms were all incremental:

- Perceptron [Rosenblatt, 1957-1962]
- CHECKER [Samuel, 1959]
- ARCH [Winston, 1970]
- Version Space [Mitchell, 1978, 1982], ...

However, **most existing learning algorithms are not!**

From Batch mode to Online Learning

Why not use the classic algorithms?



Classic decision tree learners assume all training data can be simultaneously stored in main memory

Domingos, P., & Hulten, G. (2000). Mining high-speed data streams. *SIGKDD*

From Batch mode to Online Learning

Stream - supervised classification: what changes?

- Properties
  - Receives examples one-by-one
  - discards the example after processing it.
  - Produce a hypothesis after each example is processed
    - i.e. produces a series of hypotheses
  - No distinct phases for learning and operation
    - i.e. produced hypotheses can be used in classification
  - Allowed to store other parameters than model parameters (e.g. learning rate)
  - Is a real time system
    - Constraints: time, memory, …
    - What is affected: hypotheses prediction accuracy
  - Can never stop
  - No i. i. d

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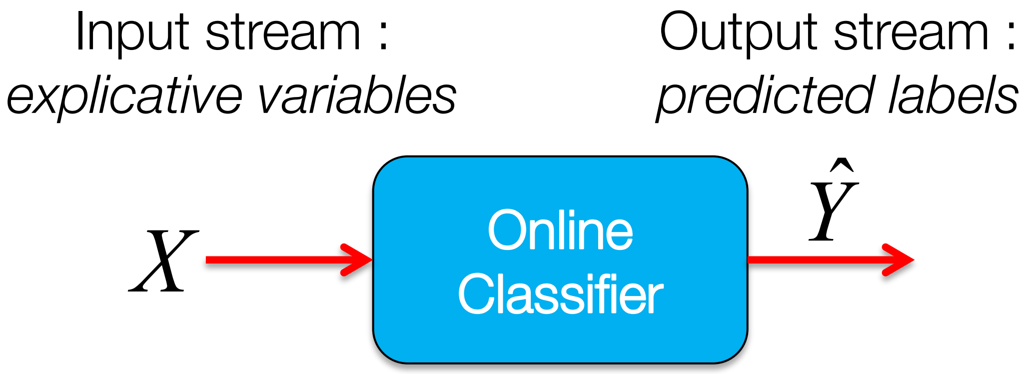
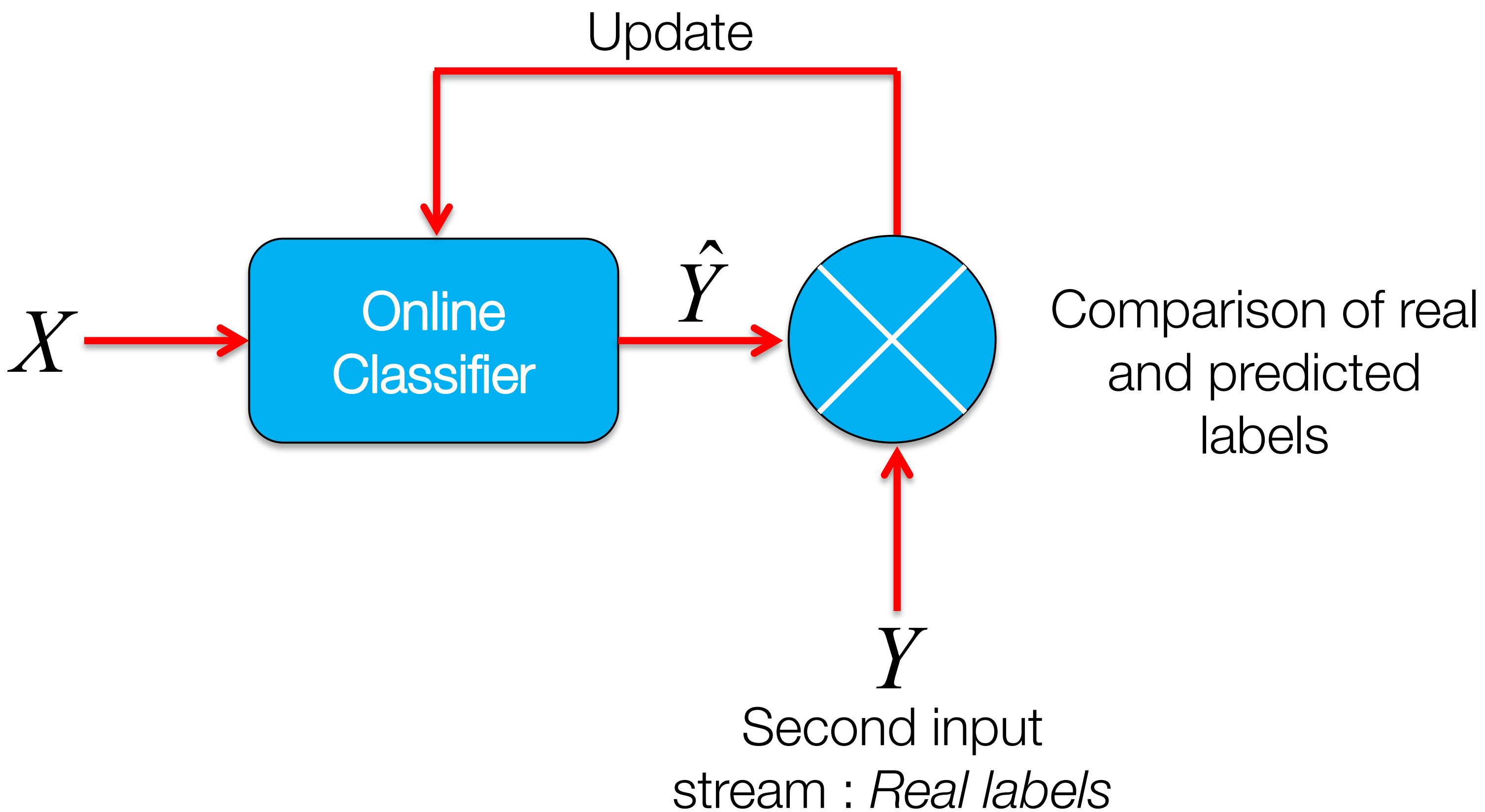
Implementation of on-line classifiers



Implementation of on-line classifiers



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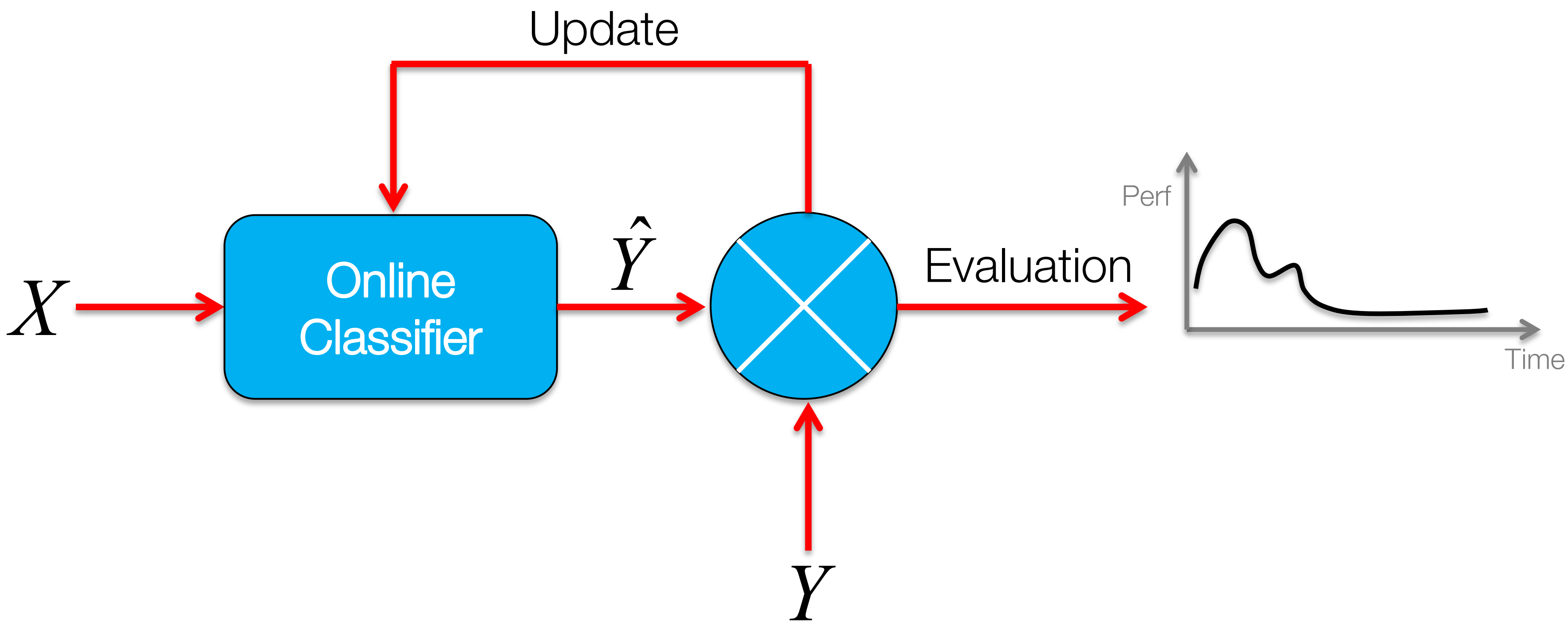
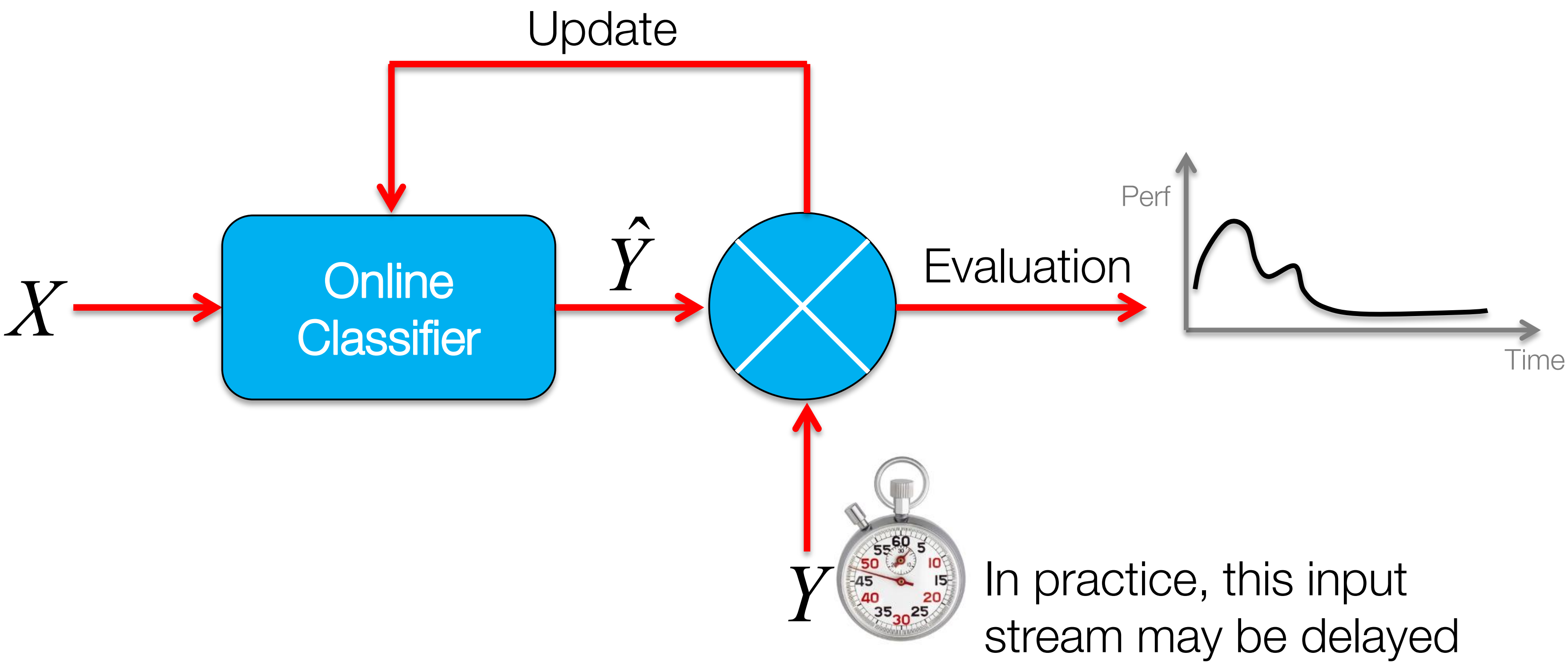


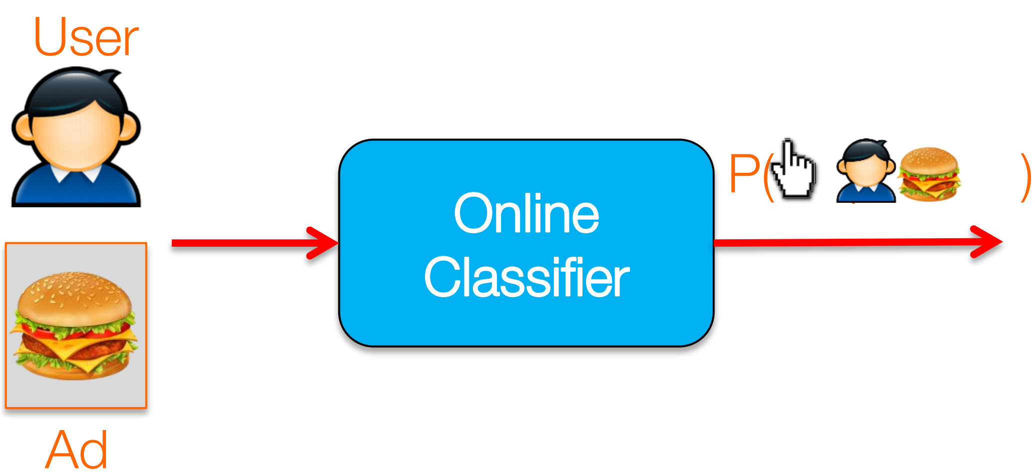
Implementation of on-line classifiers



A on-line classifier predicts the class label of tuples **before** receiving the true label …

Implementation of on-line classifiers

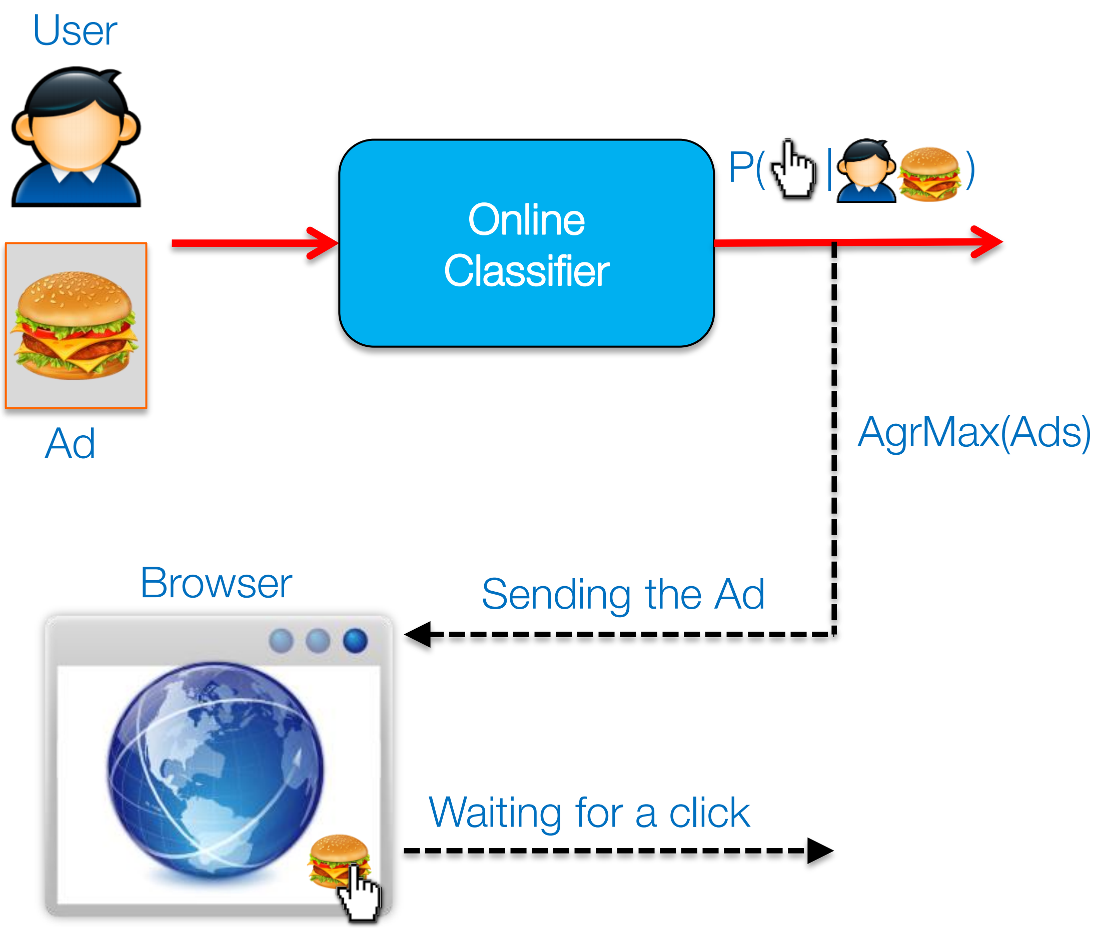
<u>Example</u> : online advertising targeting



- <u>Input tuples</u> : couples *“User – Ad”*
- <u>Out tuples</u> : estimated probability that a *User* clicks on an *Ad*

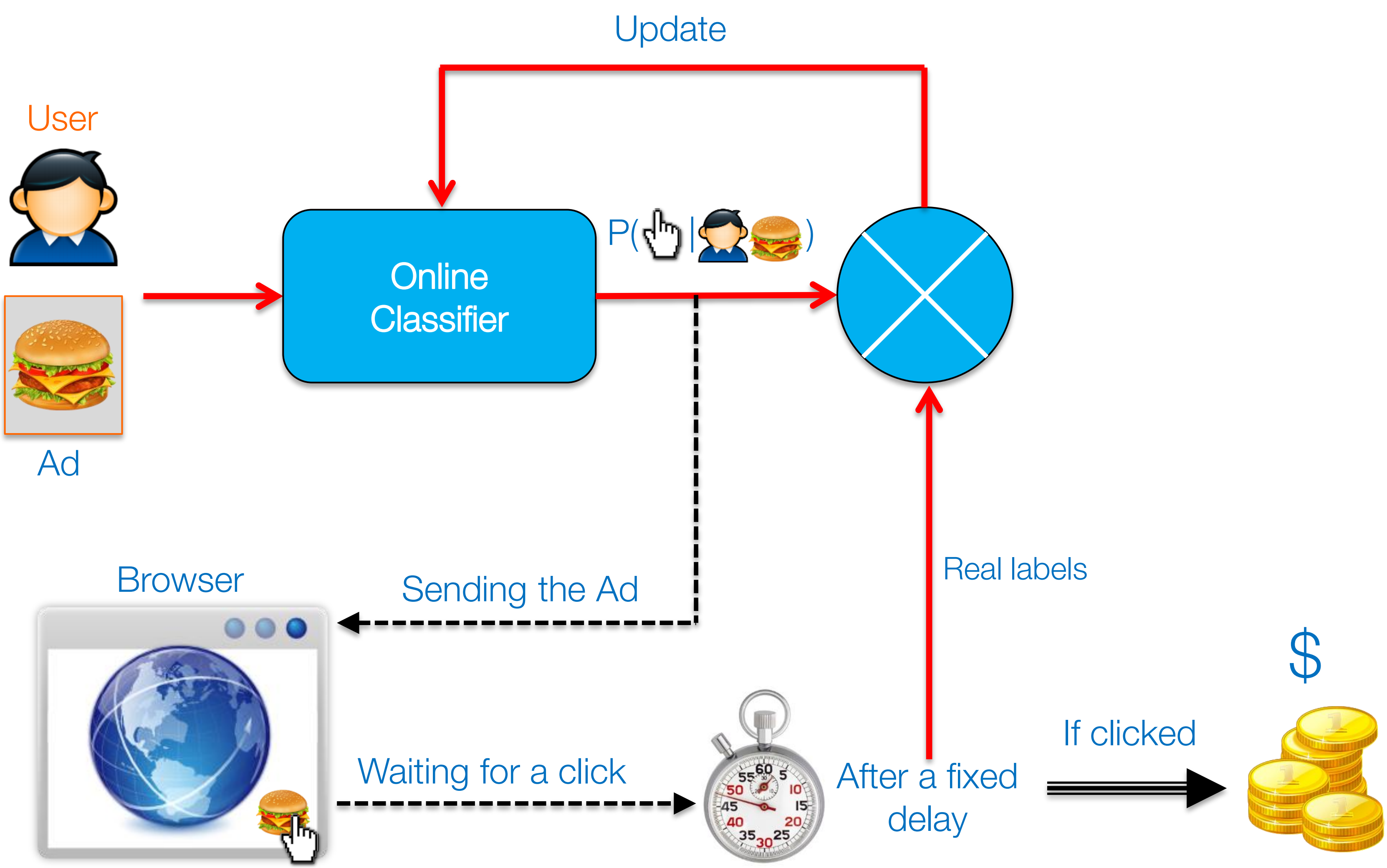
Implementation of on-line classifiers

<u>Example</u> : online advertising targeting



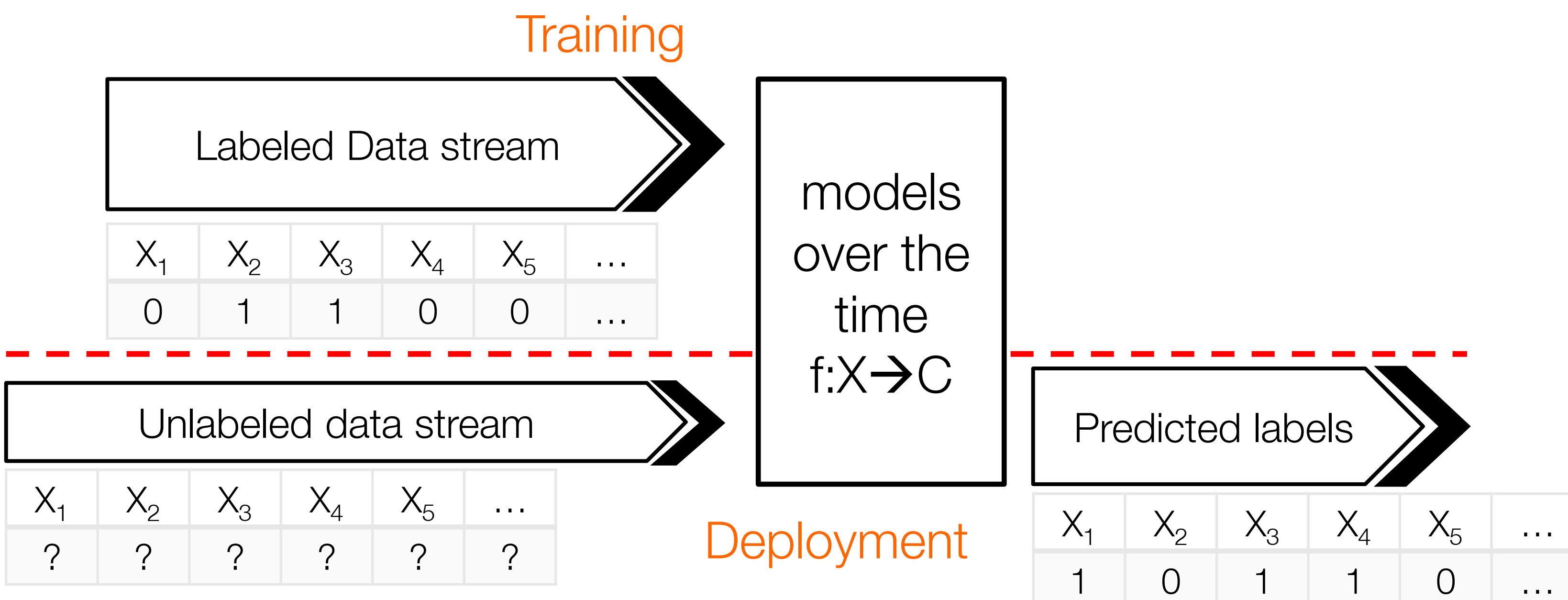
Implementation of on-line classifiers

Example : online advertising targeting



Implementation of on-line classifiers

- Two streams exist
- Two drift detection have to be managed



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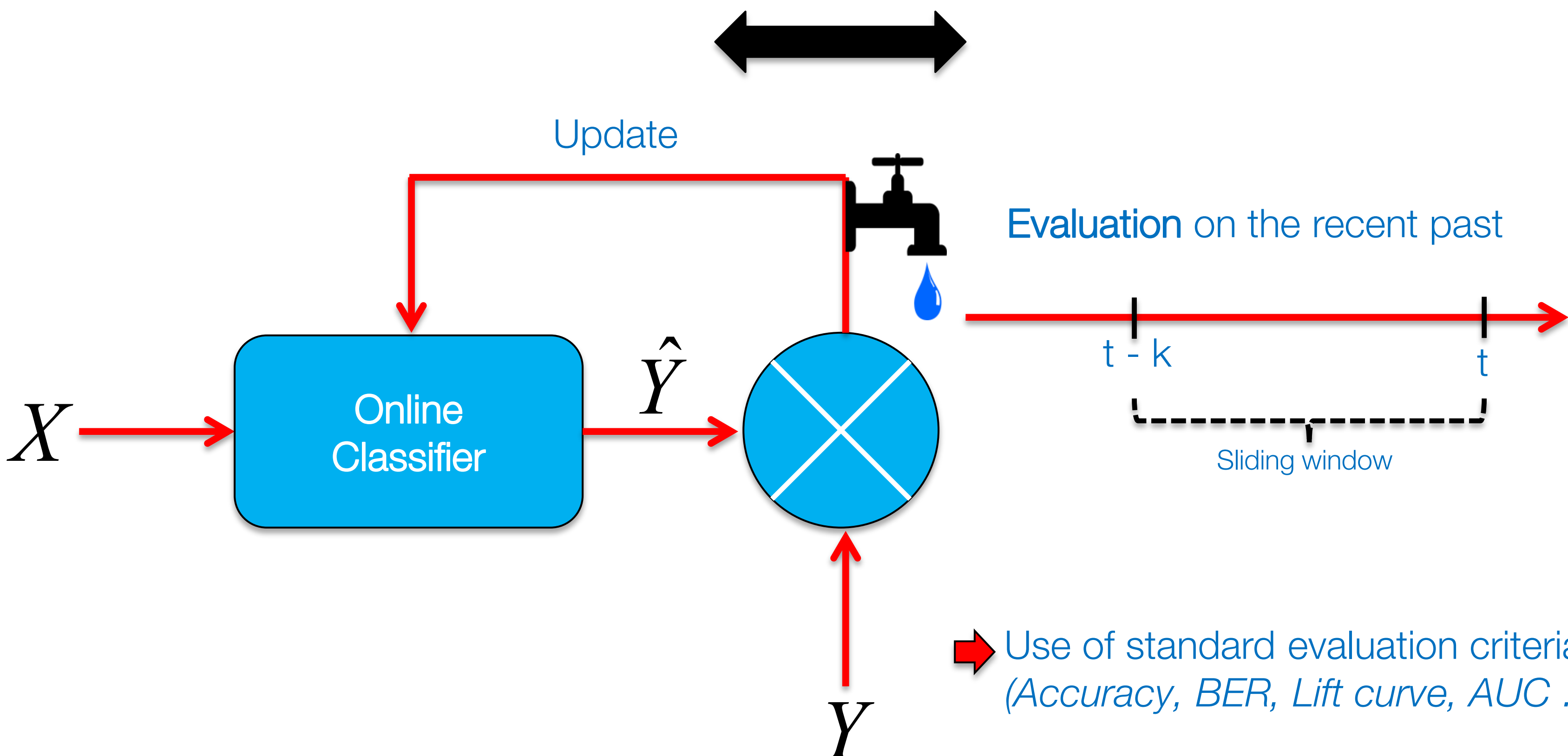
Evaluation of on-line classifiers

A – Holdout Evaluation

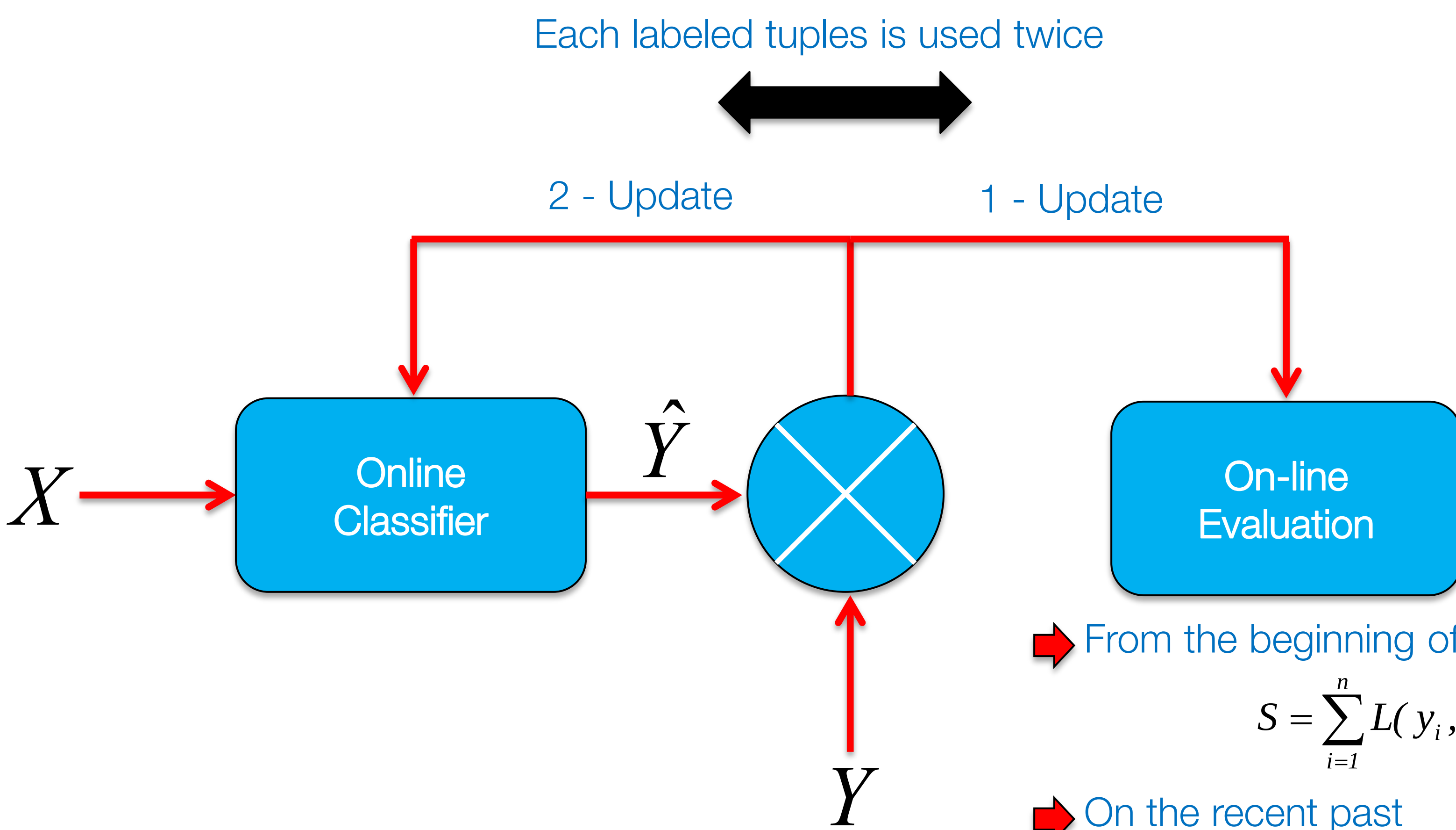
The stream of labeled tuples is split



- Use of standard evaluation criteria *(Accuracy, BER, Lift curve, AUC … etc.)*
- Unbiased evaluation

Evaluation of on-line classifiers

B – Prequential Evaluation



- From the beginning of the stream

$$S = \sum_{i=1}^{n} L(y_i, \hat{y}_i)$$

- On the recent past *(buffer on a sliding window)*

Evaluation of on-line classifiers

C – Kappa Statistic

- **p0:** prequential accuracy of the classifier
- **pc:** probability that a random classifier makes a correct prediction.

$$\mathbf{K} = (p0 - pc)/(1 - pc)$$

- K = 1 if the classifier is always correct
- K = 0 if the predictions coincide with the correct ones as often as those of the random classifier

Evaluation of on-line classifiers

RAM Hours

A server RAM hour is the amount of RAM allocated to a server multiplied by the number of hours the server has been deployed.

Example: One 2 GB server deployed for 1 hour = 2 server RAM hours.

	Accuracy	Time	Memory
Classifier A	70%	100	20
Classifier B	80%	20	40

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Taxonomy of classifier for data stream

full example memory Store *all* examples

- allows for efficient restructuring
- good accuracy
- huge storage needed

Examples: ID5, ID5R, ITI

no example memory Only store statistical information in the nodes

- loss of accuracy (depending on the information stored or again huge storage needed)
- relatively low storage space

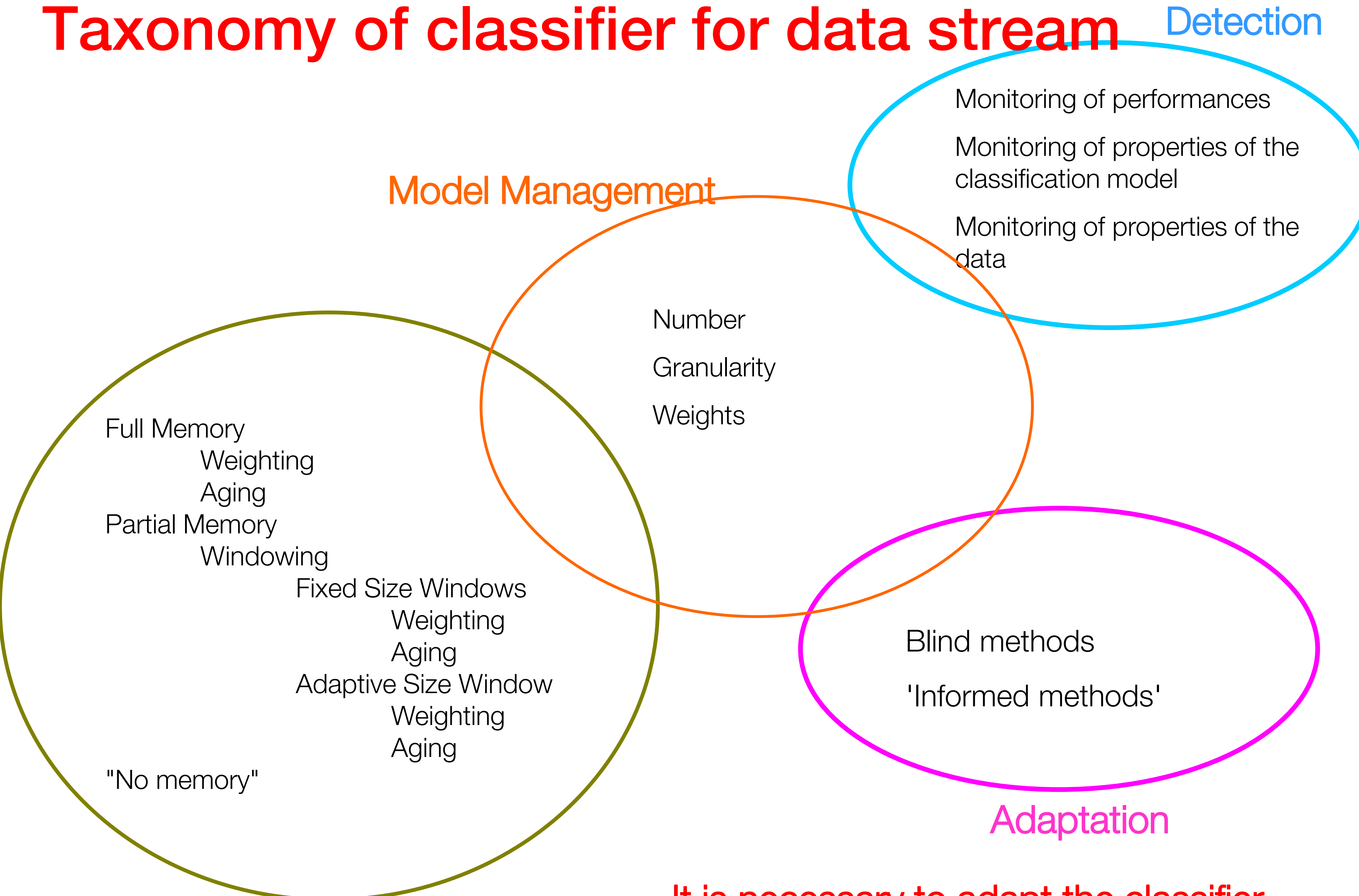
Examples: ID4

partial example memory Only store *selected* examples

- trade of between storage space and accuracy

Examples: FLORA, AQ-PM

Taxonomy of classifier for data stream



Data Management

It is necessary to adapt the classifier to the application context

Taxonomy of classifier for data stream

Incremental Algorithm (no stream)

- Decision Tree
  - ID4 (Schlimmer - ML'86)
  - ID5/ITI (Utgoff – ML'97)
  - SPRINT (Shaffer - VLDB'96)
  - …
- Naive Bayes
  - Incremental (for the standard NB)
  - Learn fastly with a low variance (Domingos – ML'97)
  - Can be combined with decision tree: NBTree (Kohavi – KDD'96)

Taxonomy of classifier for data stream

Incremental Algorithm (no stream)

- Neural Networks
  - IOLIN (Cohen - TDM’04)
  - learn++ (Polikar - IJCNN’02),…
- Support Vector Machine
  - TSVM (Transductive SVM – Klinkenberg IJCAI’01),
  - PSVM (Proximal SVM – Mangasarian KDD’01),…
  - LASVM (Bordes 2005)
- Rules based systems
  - AQ15 (Michalski - AAAI’86), AQ-PM (Maloof/Michalski - ML’00)
  - STAGGER (Schlimmer - ML’86)
  - FLORA (Widmer - ML’96)

Taxonomy of classifier for data stream

Incremental Algorithm (for stream)

- Rules
  - FACIL (Ferrer-Troyano – SAC'04,05,06)
- Ensemble
  - SEA (Street - KDD'01) based on C4.5
- K-nn
  - ANNCAD (Law – LNCS'05).
  - IBLS-Stream (Shaker et al – Evolving Systems" journal 2012)
- SVM
  - CVM (Tsang – JMLR'06)

Taxonomy of classifier for data stream

Incremental Algorithm (for stream)

- Decision Tree – the only ones used ?
  - Domingos : VFDT (KDD’00), CVFDT (KDD’01)
  - Gama : VFDTc (KDD’03), UFFT (SAC’04)
  - Kirkby : Ensemble d’Hoeffding Trees (KDD’09)
  - del Campo-Avila : IADEM (LNCS’06)

Taxonomy of classifier for data stream

Properties of a efficient algorithm

- low and constant duration to learn from the examples;
- read only once the examples in their order of arrival;
- use of a quantity of memory fixed “a priori;”
- production of a model close to the “offline model”
- (anytime)
- concept drift management

(0) Domingos, P. et G. Hulten (2001). Catching up with the data : Research issues in mining data streams. In Workshop on Research Issues in Data Mining and Knowledge Discovery.
(1) Fayyad, U. M., G. Piatetsky-Shapiro, P. Smyth, et R. Uthurusamy (1996). Advances in Knowledge Discovery and Data Mining. Menlo Park, CA, USA : American Association for Artificial Intelligence
(2) Hulten, G., L. Spencer, et P. Domingos (2001). Mining time-changing data streams. In Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 97–106. ACM New York, NY, USA.
(3) Stonebraker, M., U. Çetintemel, et S. Zdonik (2005). The 8 requirements of real-time stream processing. ACM SIGMOD Record 34(4), 42–47.

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4. Taxonomy of classifier for data stream
5. Two examples
6. Concept drift
7. Make at simplest

Incremental Decision Tree

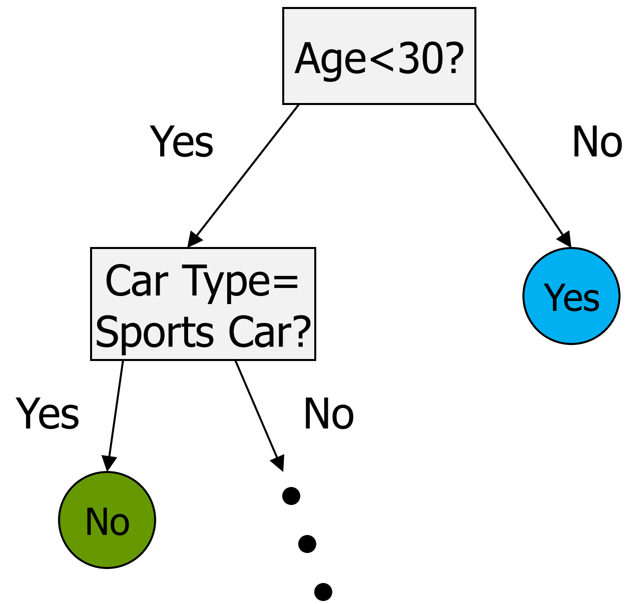
Definitions

- A classification problem is defined as:
  - <u>N</u> is a set of training examples of the form <u>(x, y)</u>
  - <u>x</u> is a vector of d attributes
  - <u>y</u> is a discrete class label
- Goal: To produce from the examples a model y=f(x) that predict the classes y for future examples x with high accuracy

Incremental Decision Tree

Decision Tree Learning

- One of the most effective and widely-used classification methods
- Induce models in the form of decision trees
  - Each node contains a test on the attribute
  - Each branch from a node corresponds to a possible outcome of the test
  - Each leaf contains a class prediction
  - A decision tree is learned by recursively replacing leaves by test nodes, starting at the root



Incremental Decision Tree

The example of the **Hoeffding Trees** [D]

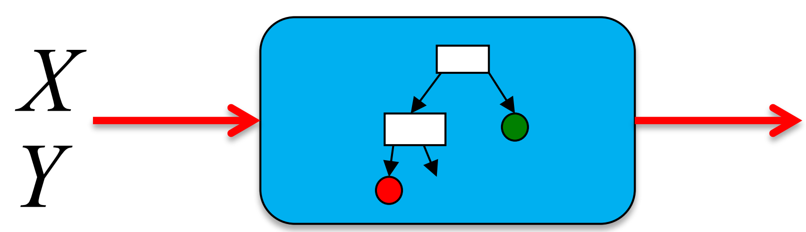
<u>How an incremental decision trees is learned ?</u>

- **Single pass** algorithm,
- With a **low latency**,
- Which **avoids** the **exhaustive storage** of training examples in the **RAM.**
- The drift is not managed

Training examples are processed one by one

Var 1	Var 2	…	Clas s
O	12	…	A
Y	98	…	B
Y	4	…	A

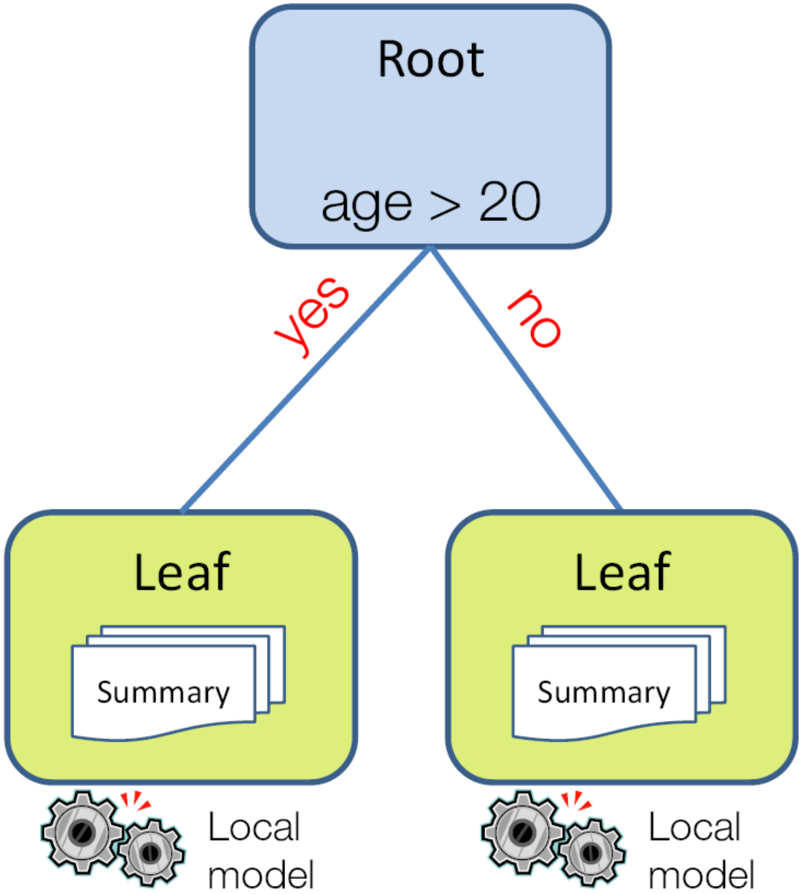
Input stream : labeled examples



Incremental Decision Tree

The 4 elements of an online tree

- Online decision tree:
  - a bound…
  - a split criterion
  - summaries in the leaves
  - a local model



Incremental Decision Tree

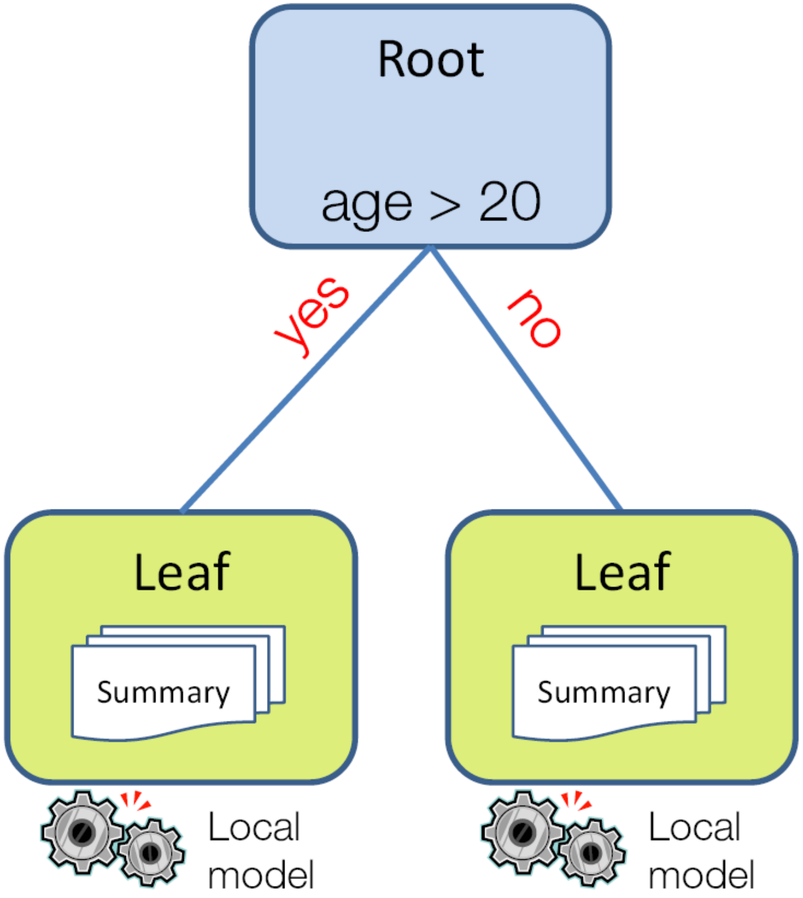
The 4 elements of an online tree

- Online decision tree:
  - a bound: *How many examples before cutting an attribute ?*
  - a split criterion: *Which attribute and which cut point ?*
  - summaries in the leaves; *How to manage high speed data streams ?*
  - a local model: *How to improve the classifier ?*

Incremental Decision Tree

The 4 elements of an online tree

- Online decision tree:
  - a bound…
  - a split criterion
  - summaries in the leaves
  - a local model



Incremental Decision Tree

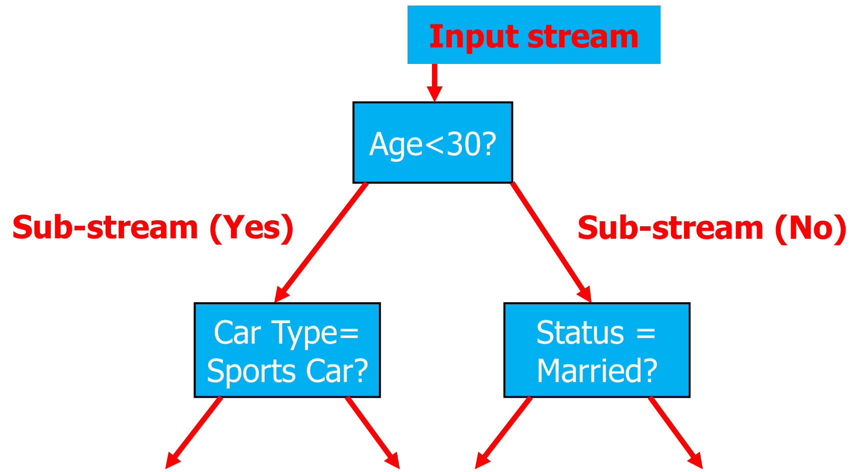
The example of the **Hoeffding Trees** [D]

<u>Key ideas :</u>

The **best attribute** at a node is found by exploiting **a small subset** of the labeled examples that pass through that node :

- The **first examples** are exploited to choose the **root attribute**
- Then, the other examples are passed down to the **corresponding leaves**
- The attributes to be split are **recursively chosen** …

✓ The **Hoeffding bound** answers the question : *How many examples are required to split an attribute ?*



Hoeffding Bound

- Consider a random variable a whose range is R
- Suppose we have n observations of a
- Mean: $\bar{a}$
- Hoeffding bound states:

With probability 1- δ, the true mean of a is at least $\bar{a} - \varepsilon$

where

$$\varepsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}}$$

Incremental Decision Tree

How many examples are enough?

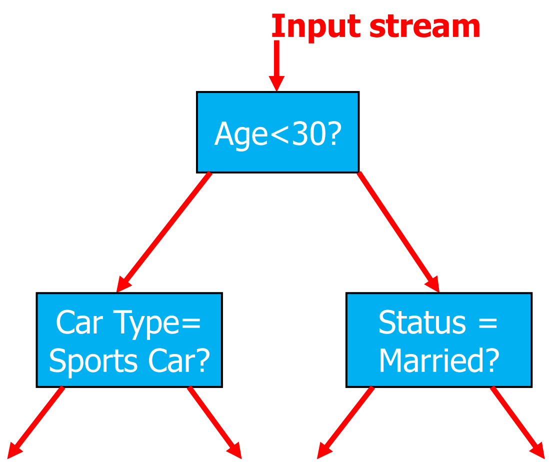
- Let G(X_i) be the heuristic measure used to choose test attributes (e.g. Information Gain, Gini Index)
- X_a : the attribute with the highest attribute evaluation value after seeing n examples.
- X_b : the attribute with the second highest split evaluation function value after seeing n examples.
- Given a desired δ, if $\Delta\overline{G} = \overline{G}(X_a) - \overline{G}(X_b) > \varepsilon$ after seeing n examples at a node,
  - Hoeffding bound guarantees the true $\Delta G >= \Delta\overline{G} - \varepsilon > 0$, with probability $1\text{-}\delta$.
  - This node can be split using X_a, the succeeding examples will be passed to the new leaves.

$$\varepsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}}$$

Incremental Decision Tree

The example of the **Hoeffding Trees** [D]

The algorithm



If not satisfied

- Find the two best attributes
- Check the condition $DG > e$

If satisfied

- Create a new test at the current node
- Split the stream of examples
- Create 2 new leaves
- Recursively run the algorithm on new leaves

➡ This algorithm has been adapted in order to manage concept drift [E]

- ✓ By maintaining an incremental tree on a sliding windows
- ✓ Which allows to forget the old tuples
- ✓ A collection of alternative sub-trees is maintained in memory and used in case of drift

Incremental Decision Tree

An example of Hoeffding Tree : VFDT (Very Fast Decision Tree)

- A decision-tree learning system based on the Hoeffding tree algorithm
- Split on the current best attribute (δ), if the difference is less than a user-specified threshold (T)
  - Wasteful to decide between identical attributes
- Compute G and check for split periodically (n_{min})
- Memory management
  - Memory dominated by sufficient statistics

“Mining High-Speed Data Streams”, KDD 2000.
Pedro Domingos, Geoff Hulten

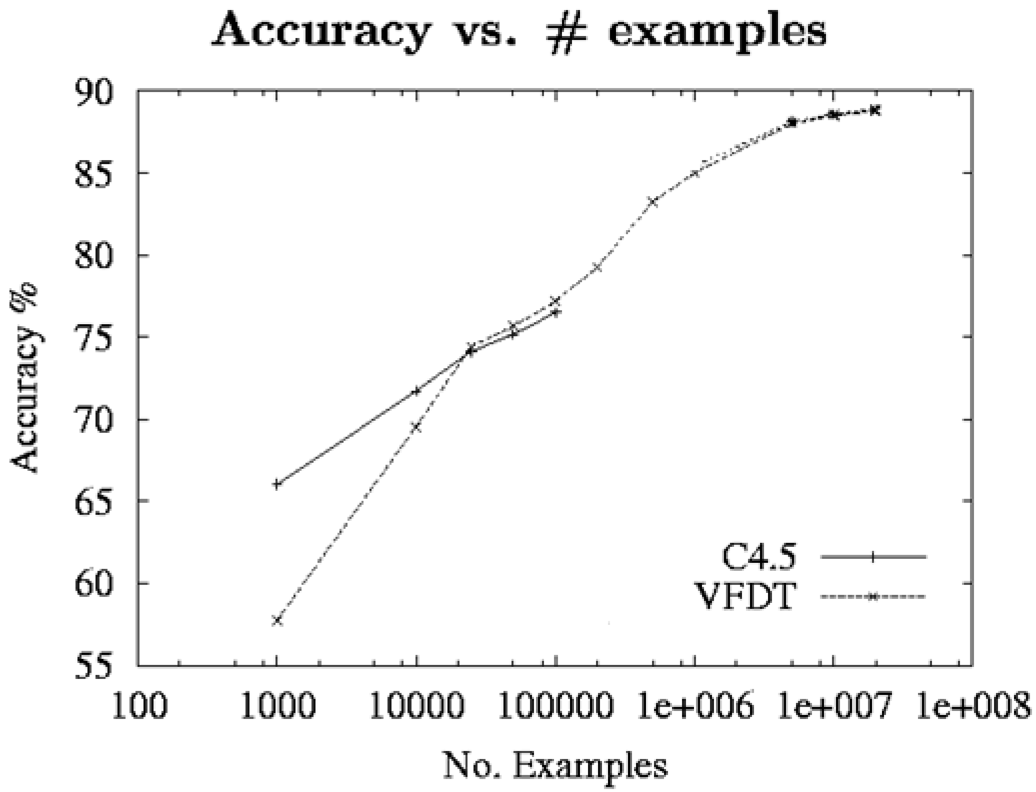
Incremental Decision Tree

Experiment Results (VFDT vs. C4.5)

- Compared VFDT and C4.5 (Quinlan, 1993)
- Same memory limit for both (40 MB)
  - 100k examples for C4.5
- VFDT settings: $\delta = 10^{-7}$, T=5%, $n_{min}=200$
- Domains: 2 classes, 100 binary attributes
- Fifteen synthetic trees 2.2k – 500k leaves
- Noise from 0% to 30%

Incremental Decision Tree

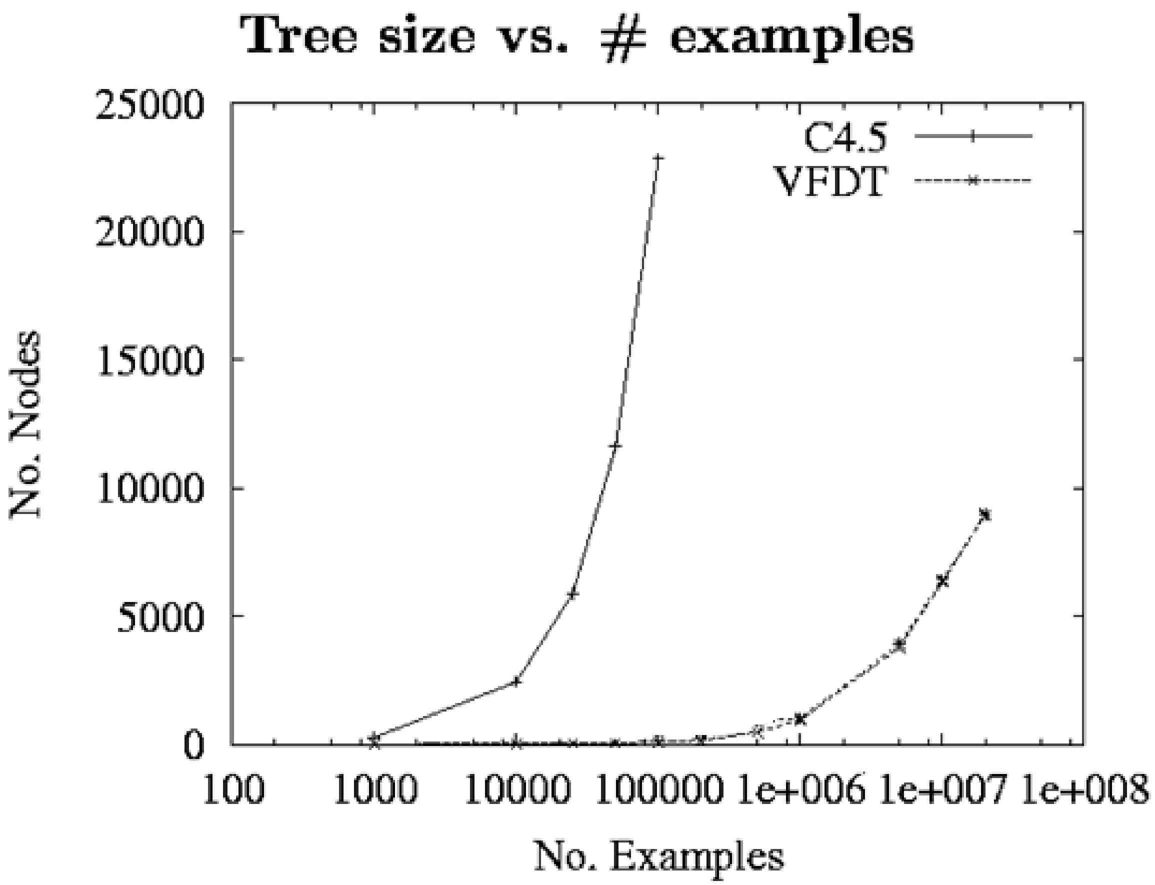
Experiment Results



Accuracy as a function of the number of training examples

Incremental Decision Tree

Experiment Results



Tree size as a function of number of training examples

Incremental Decision Tree

An example of Hoeffding Tree in case of concept drift : CVFDT

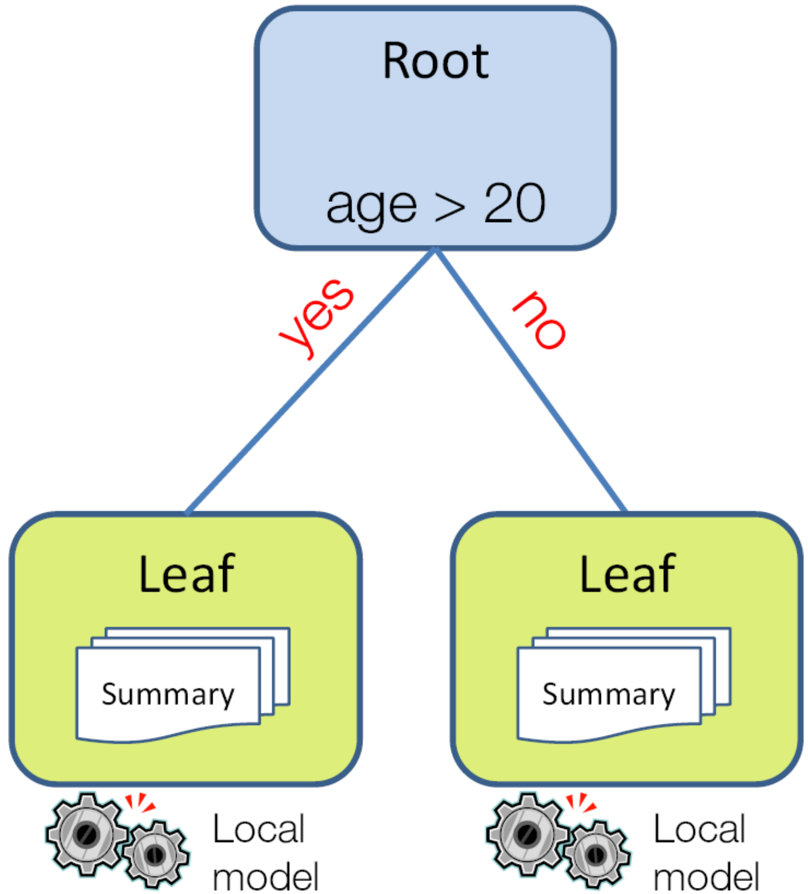
- CVFDT (Concept-adapting Very Fast Decision Tree learner)
  - Extend VFDT
  - Maintain VFDT's speed and accuracy
  - Detect and respond to changes in the example-generating process

- See the Part "Concept Drift" of this talk

Incremental Decision Tree

The 4 elements of an online tree

- Online decision tree:
  - a bound…
  - a split criterion
  - summaries in the leaves
  - a local model



Incremental Decision Tree

Differents Split Criterion

- Used to transform a leaf into a node
  - determine at the same time on
    - which attribute to cut and
    - on which value (cut point).

- Uses the information contained in the summaries:
  - not on all data
  - a definitive action

- Batch algorithm used:
  - Gain ratio using entropie (C4.5)
  - Gini (CART)
  - MODL Level

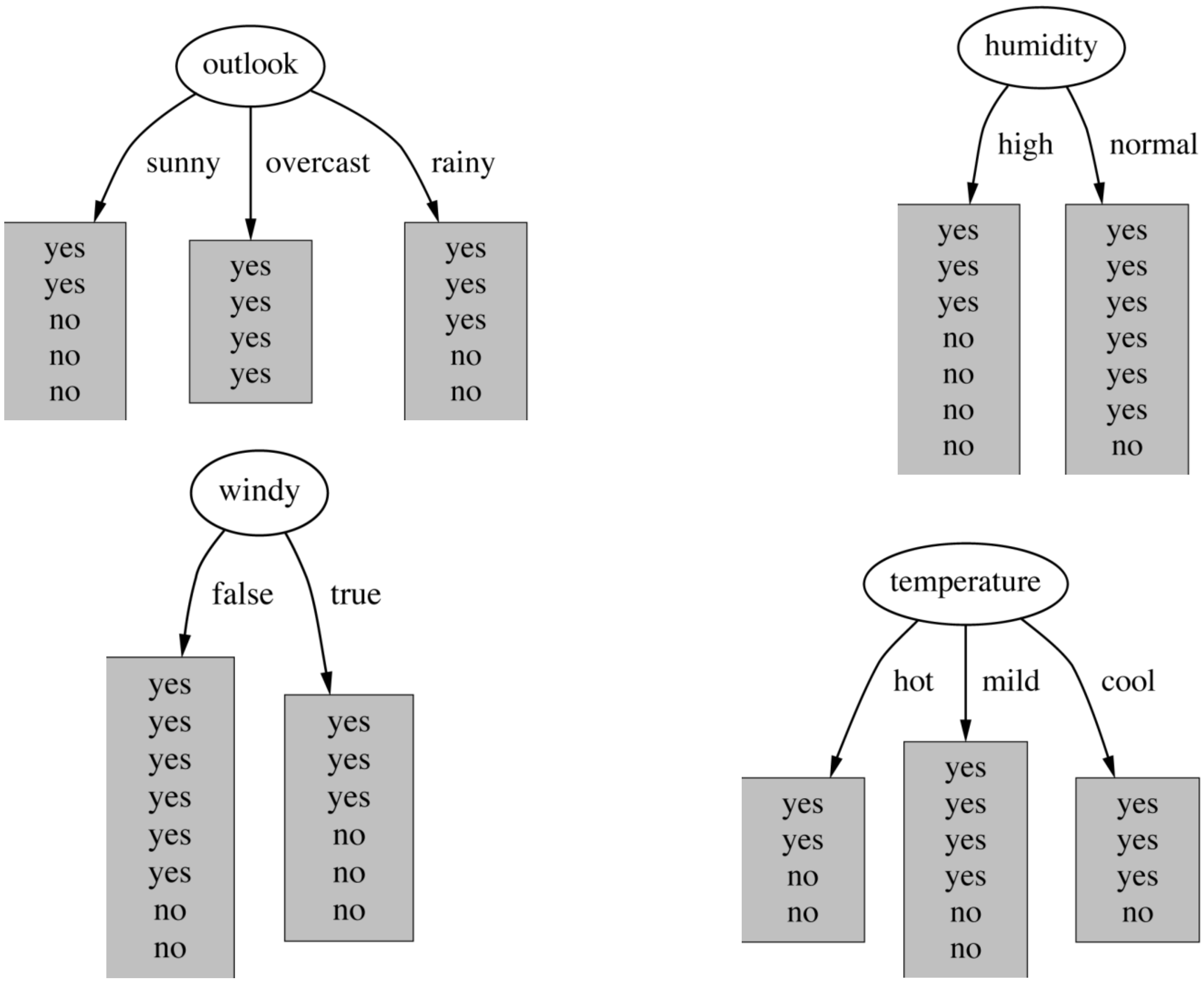
Incremental Decision Tree

A criterion for attribute selection

- Which is the best attribute?
  - The one which will result in the smallest tree
  - Heuristic: choose the attribute that produces the "purest" nodes
- Popular *impurity criterion*: *information gain*
  - Information gain increases with the average purity of the subsets that an attribute produces
  - Information gain uses entropy H(*p*)
- Strategy: choose attribute that results in greatest information gain

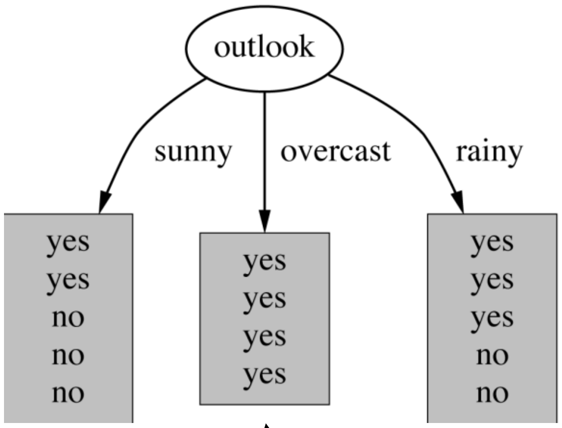
Incremental Decision Tree

Which attribute to select?



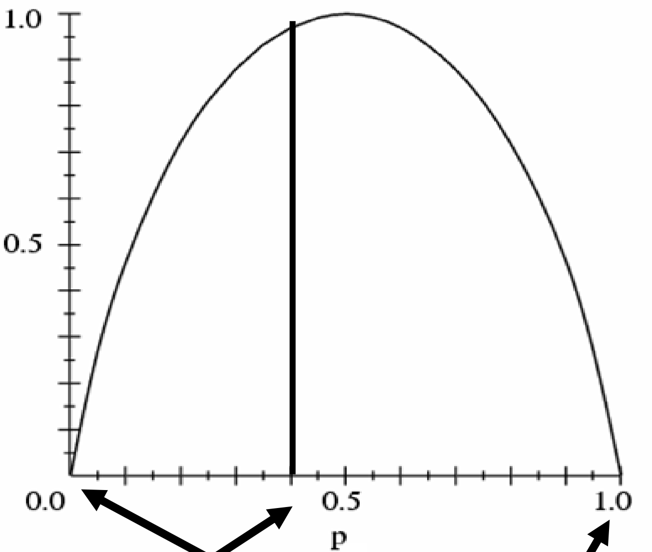
Incremental Decision Tree

Consider entropy H(*p*)



pure, 100% yes

not pure at all, 40% yes



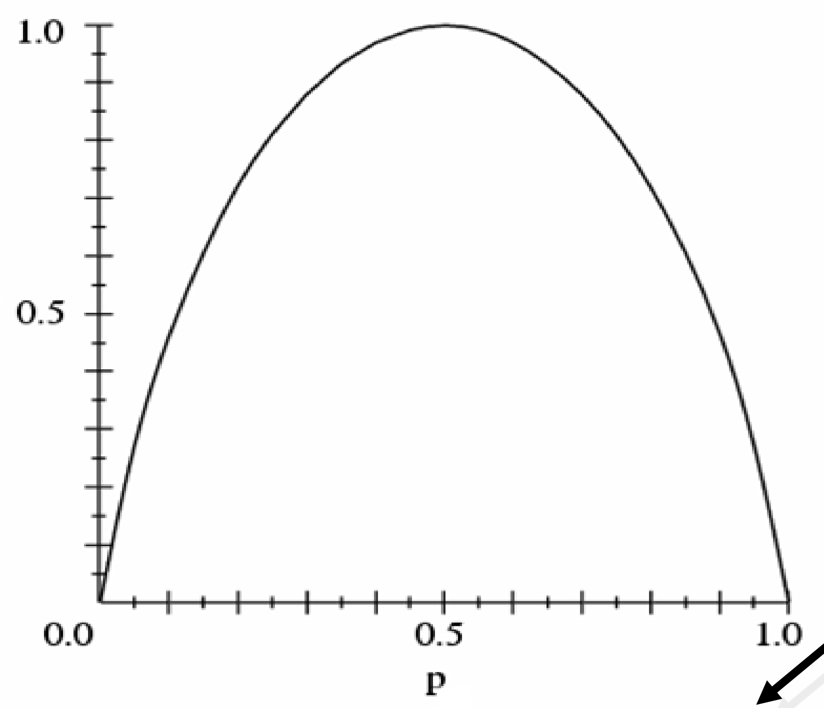
pure, 100% yes

not pure at all, 40% yes

allmost 1 bit of information required
to distinguish yes and no

Incremental Decision Tree

Entropy



$\log(p)$ is the 2-log of p

Entropy: $H(p) = -p\log(p) - (1-p)\log(1-p)$

$H(0) = 0$	pure node, distribution is skewed
$H(1) = 0$	pure node, distribution is skewed
$H(0.5) = 1$	mixed node, equal distribution

$$\text{entropy}(p_1, p_2, \ldots, p_n) = -p_1 \log p_1 - p_2 \log p_2 \ldots - p_n \log p_n$$

Incremental Decision Tree

Example: attribute "Outlook"

- "Outlook" = "Sunny":

$$\text{info}([2,3]) = \text{entropy}(2/5,3/5) = -2/5\log(2/\ \ldots\ .971\ \text{bits}$$

Note: log(0) is not defined, but we evaluate 0*log(0) as zero

- "Outlook" = "Overcast":

$$\text{info}([4,0]) = \text{entropy}(1,0) = -1\log(1) - 0\log(0) = 0\ \text{bits}$$

- "Outlook" = "Rainy":

$$\text{info}([3,2]) = \text{entropy}(3/5,2/5) = -3/5\log(3/5) - 2/5\log(2/5) = 0.971\ \text{bits}$$

- Expected information for "Outlook":

$$\text{info}([3,2],[4,0],[3,2]) = (5/14)\times 0.971 + (4/14)\times 0 + (5/14)\times 0.971$$
$$= 0.693\ \text{bits}$$

Incremental Decision Tree

Computing the information gain

- Information gain:

(information before split) – (information after split)

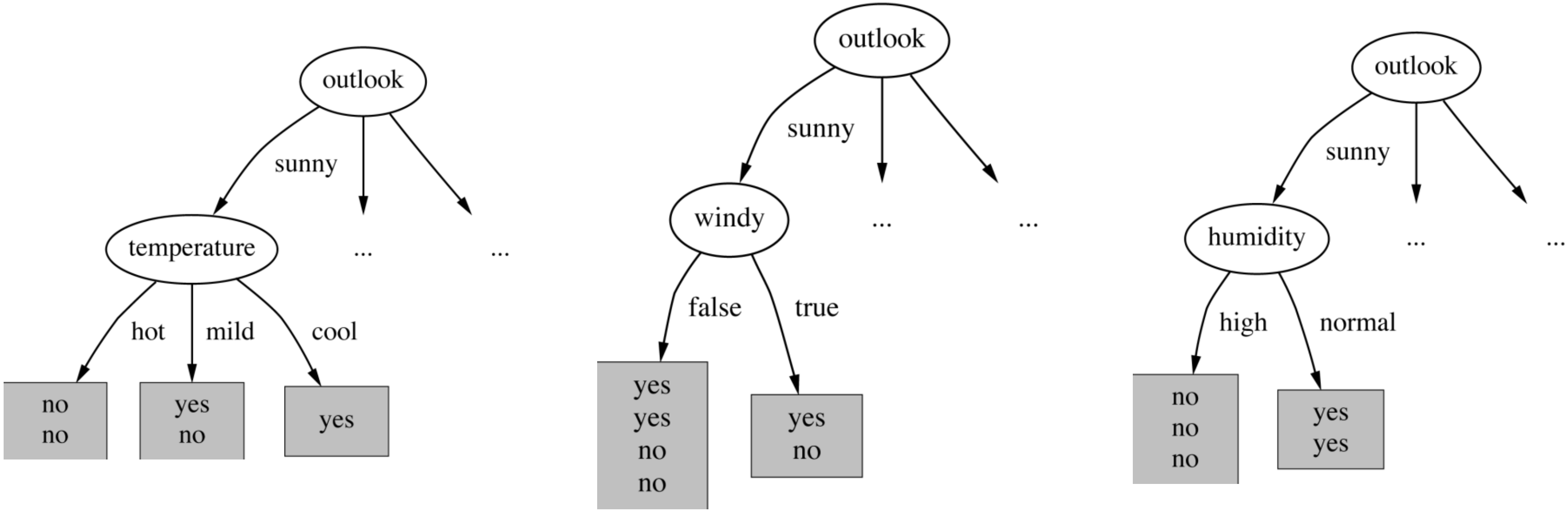
$$\text{gain}(\text{"Outlook"}) = \text{info}([9,5]) - \text{info}([2,3],[4,0],[3,2]) = 0.940 - 0.693$$
$$= 0.247 \text{ bits}$$

- Information gain for attributes from weather data:

$$\boxed{\text{gain}(\text{"Outlook"}) = 0.247 \text{ bits}}$$
$$\text{gain}(\text{"Temperature"}) = 0.029 \text{ bits}$$
$$\text{gain}(\text{"Humidity"}) = 0.152 \text{ bits}$$
$$\text{gain}(\text{"Windy"}) = 0.048 \text{ bits}$$

Incremental Decision Tree

Continuing to split



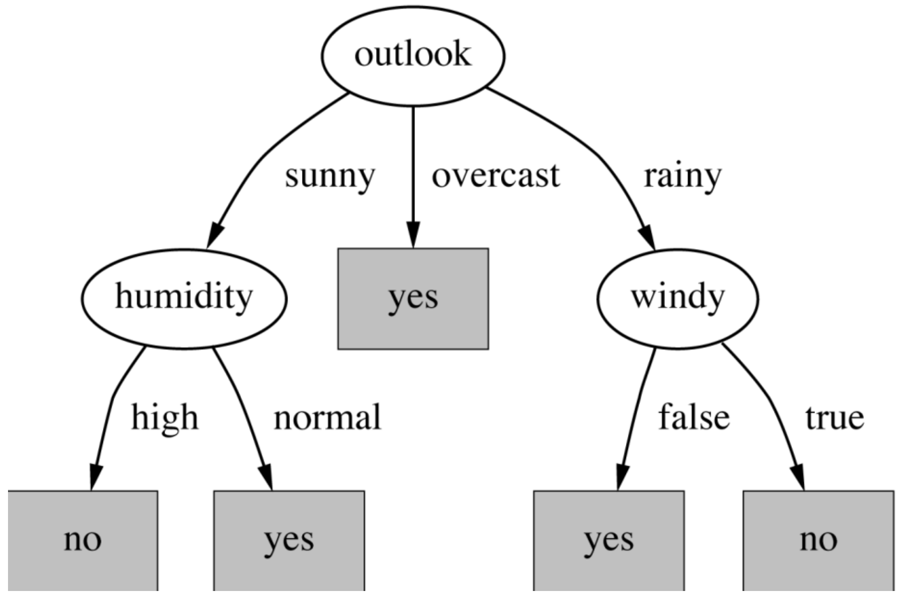
$$\text{gain}(\text{"Temperature"}) = 0.571 \text{ bits}$$

$$\text{gain}(\text{"Windy"}) = 0.020 \text{ bits}$$

$$\boxed{\text{gain}(\text{"Humidity"}) = 0.971 \text{ bits}}$$

Incremental Decision Tree

The final decision tree



- Note: not all leaves need to be pure; sometimes identical instances have different classes

  ⇒ Splitting stops when data can't be split any further

Incremental Decision Tree

Highly-branching attributes

- Problematic: attributes with a large number of values (extreme case: customer ID)
- Subsets are more likely to be pure if there is a large number of values
  - Information gain is biased towards choosing attributes with a large number of values
  - This may result in *overfitting* (selection of an attribute that is non-optimal for prediction)

Incremental Decision Tree

Gain ratio

- *Gain ratio*: a modification of the information gain that reduces its bias on high-branch attributes
- Gain ratio should be
  - Large when data is evenly spread
  - Small when all data belong to one branch
- Gain ratio takes number and size of branches into account when choosing an attribute
  - It corrects the information gain by taking the *intrinsic information* of a split into account (i.e. how much info do we need to tell which branch an instance belongs to)

Incremental Decision Tree

The 4 elements of an online tree

- Online decision tree:
  - a bound…
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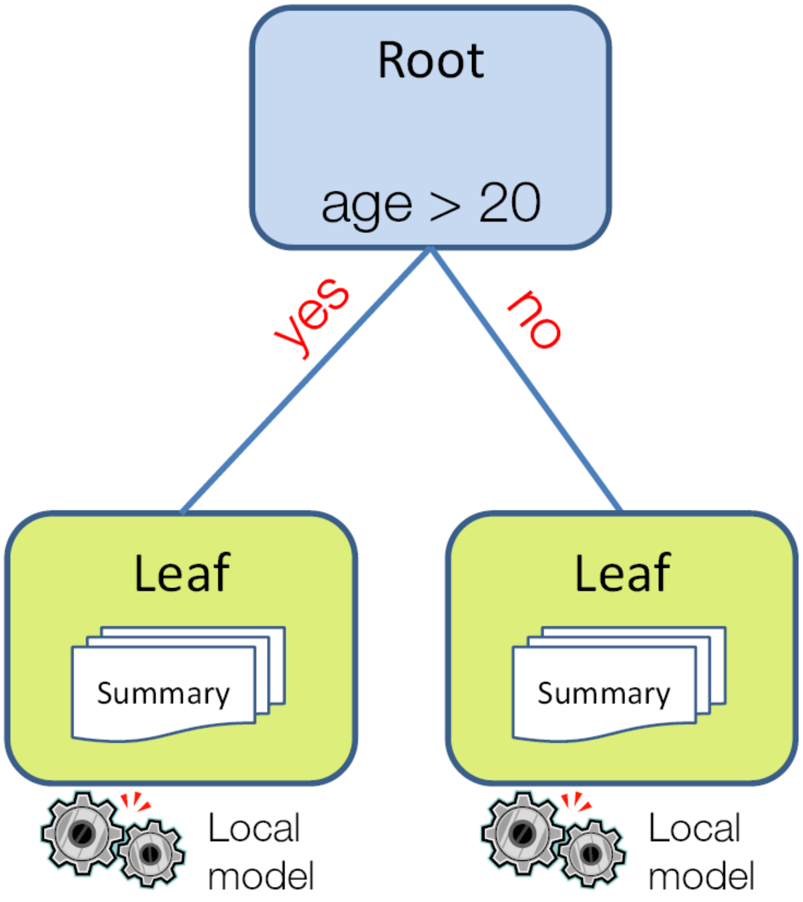
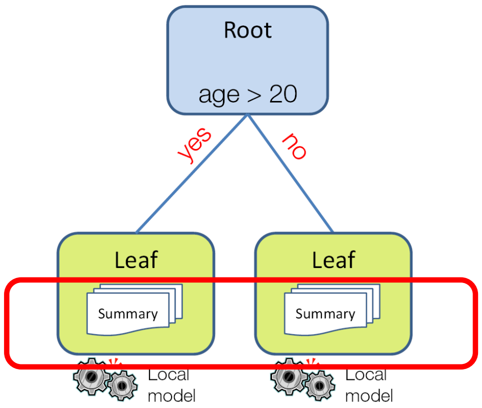


Incremental Decision Tree

Summaries in the leaves



- Numerical attributes
  - Exhaustive counts [Gama2003]
  - Partition Incremental Discretization [Gama2006]
  - VFML: intervals defined by first values and used as cut points [Domingos]
  - Gaussian approximation [Pfahringer2008]
  - Quantiles based summary [GK2001]

- Categorical attributes
  - for each categorical variable and for each value the number of occurrences is stored (but CMS could be used)

Incremental Decision Tree

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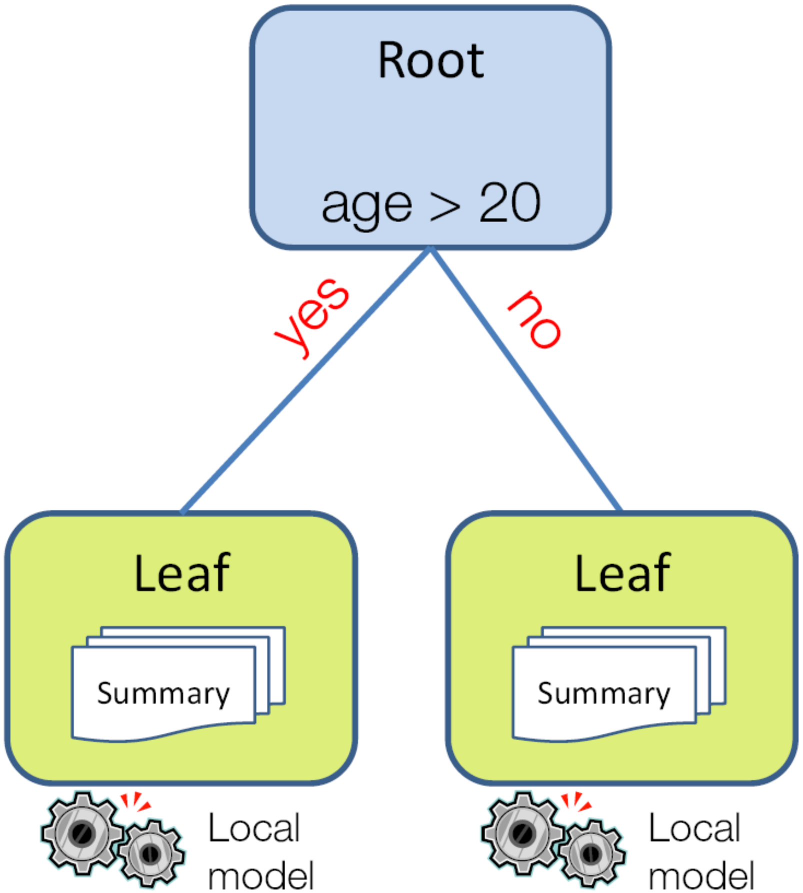
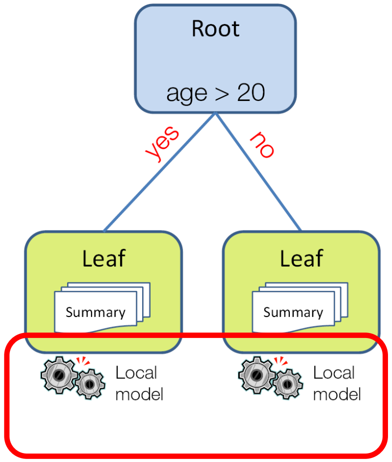


Incremental Decision Tree

Local model



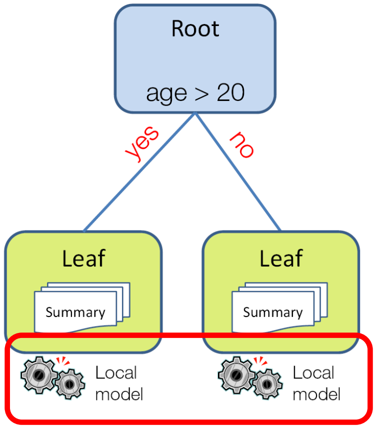
- Purpose: improve the quality of the tree (especially at the beginning of training)
- A good local model for online decision trees has to:
  - consume a small amount of memory
  - be fast to build
  - be fast to return a prediction
- A study on the speed (in number of examples) of different classifiers show that

  ➔ naive Bayes classifier has these properties

VFDT -> VFDTc

Incremental Decision Tree

Local model: naive Bayes classifier

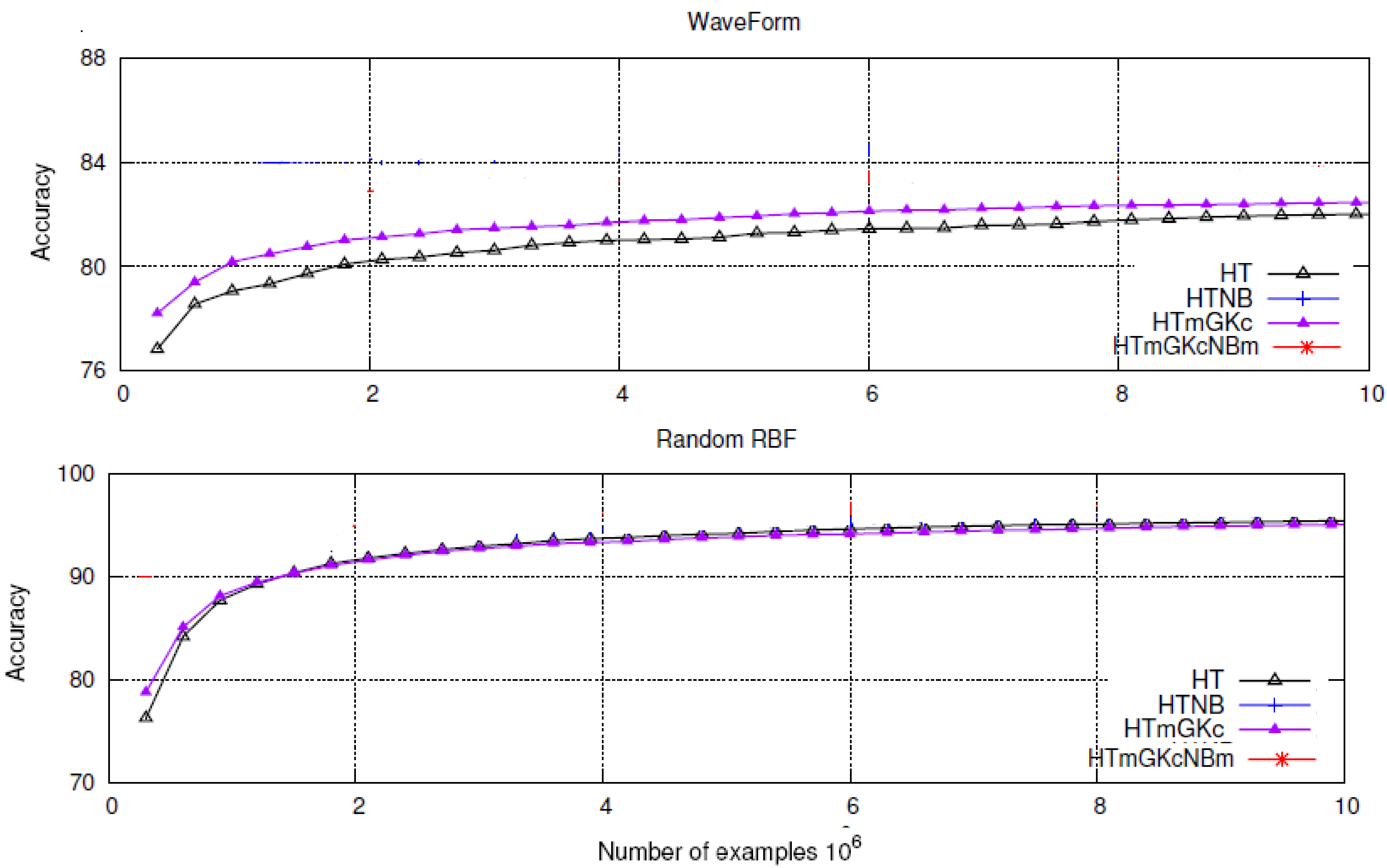


- to predict the class it requires an estimation of the class conditional density, for every attribute j, $P(V_j|C)$:

$$P(C_z|x_k) = \frac{P(C_z)\prod_{j=1}^{J} P(V_j = x_{jk}|C_z)}{\sum_{t=1}^{C}\left[P(C_t)\prod_{j=1}^{J} P(V_j = x_{jk}|C_t)\right]}$$

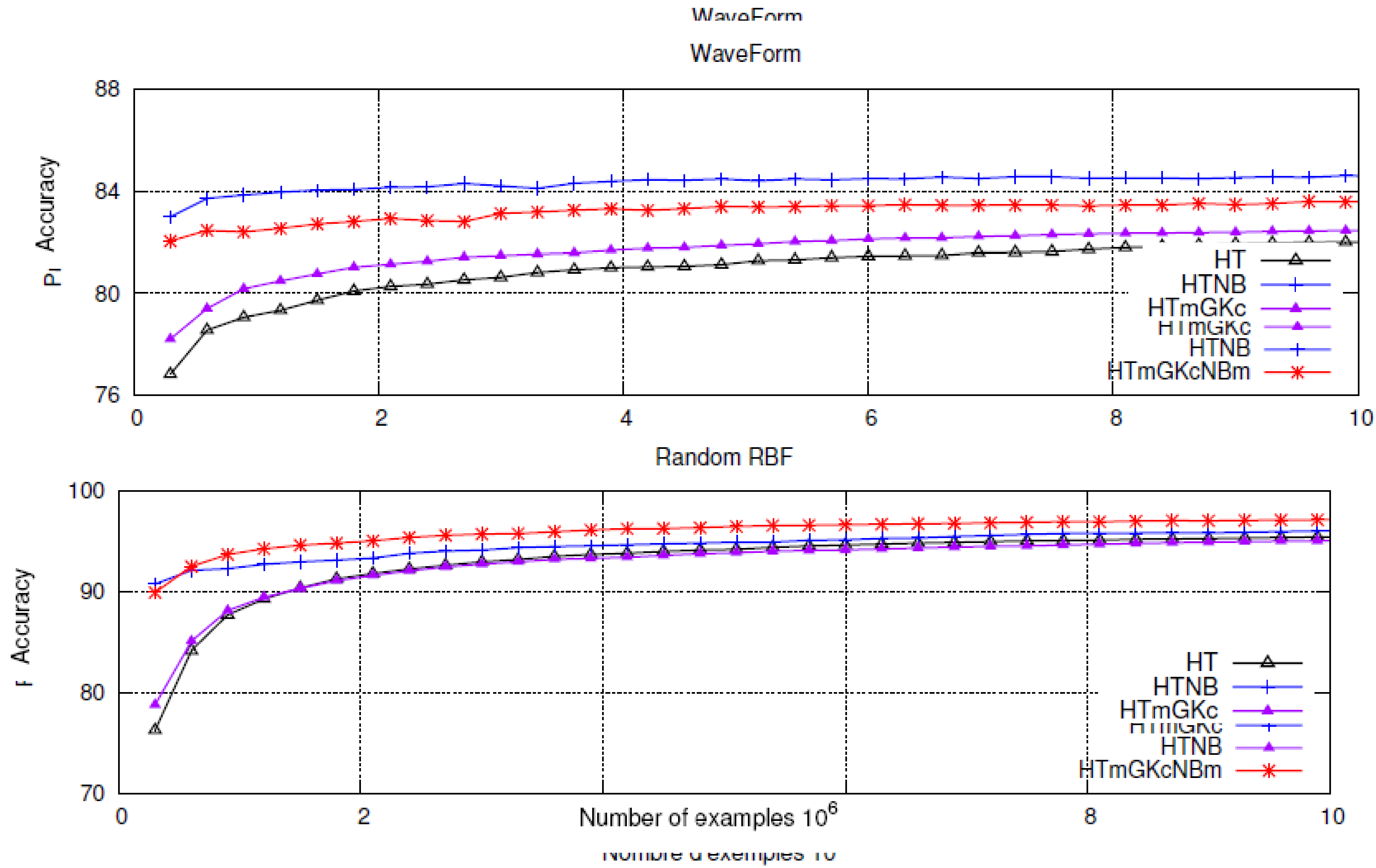
Incremental Decision Tree

Experimentations: Influence of the local model



Incremental Decision Tree

Experimentations: Influence of the local model



Incremental Decision Tree

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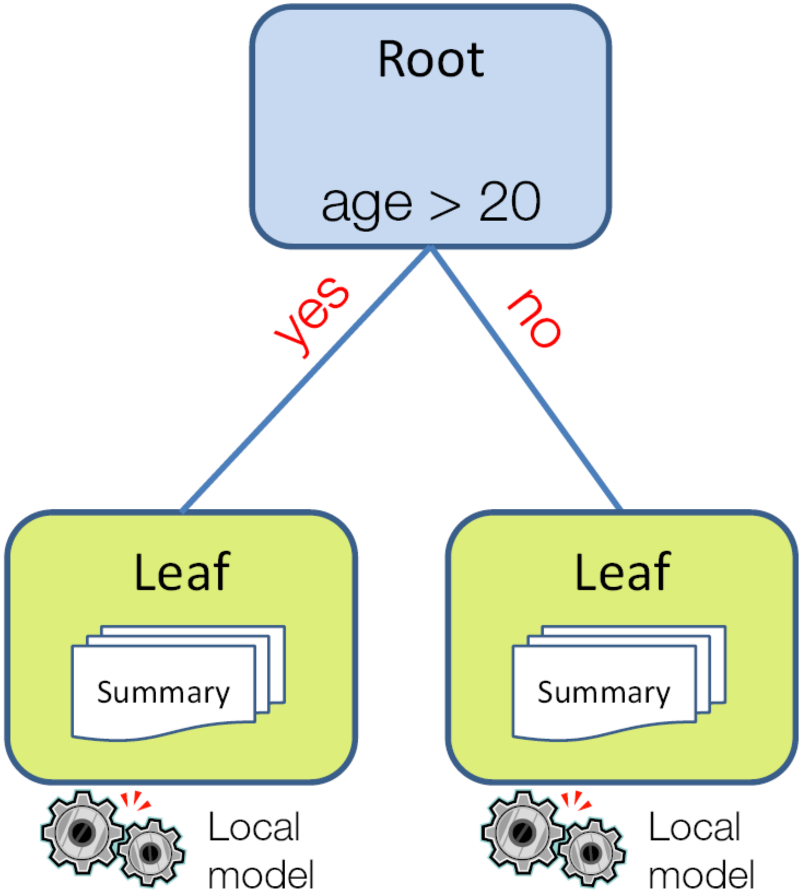


Note : Summaries are used by the split criterion and the local model.

Idea : Try to have these 3 'coherent'

2 EXAMPLES

HOEFFDING TREE, NAÏVE BAYES

Incremental Naïve Bayes

Bayes' Rule

$$P(C, X) = P(C \mid X)P(X) = P(X \mid C)P(C)$$

$$\boxed{P(C \mid X) = \frac{P(X \mid C)P(C)}{P(X)}}$$

Incremental Naïve Bayes

Naive Bayes Classifiers

Task: Classify a new instance D based on a tuple of attribute values $D = \langle x_1, x_2, \ldots, x_n \rangle$ into one of the classes $c_j \in C$

$$c_{MAP} = \underset{c_j \in C}{\operatorname{argmax}}\ P(c_j \mid x_1, x_2, \ldots, x_n)$$

$$= \underset{c_j \in C}{\operatorname{argmax}}\ \frac{P(x_1, x_2, \ldots, x_n \mid c_j) P(c_j)}{P(x_1, x_2, \ldots, x_n)}$$

$$= \underset{c_j \in C}{\operatorname{argmax}}\ P(x_1, x_2, \ldots, x_n \mid c_j) P(c_j)$$

Incremental Naïve Bayes

Naïve Bayes Classifier:
Naïve Bayes Assumption

- $P(c_j)$
  - Can be estimated from the frequency of classes in the training examples.

Naïve Bayes Conditional Independence Assumption:

- Assume that the probability of observing the conjunction of attributes is equal to the product of the individual probabilities $P(x_i|c_j)$.

Incremental Naïve Bayes

$$P_{NB}(Y=C \mid X=x^n) = \frac{\boxed{P(Y=C)}\prod_{k=1}^{K}\boxed{p(x_k^n \mid C)}}{\sum_{j=1}^{J}\boxed{P(C_j)}\prod_{k=1}^{K}\boxed{p(x_k^n \mid C_j)}}$$

Principe : hypothèse d'indépendance conditionnelle des variables explicatives entre elles

Point fort : prédicteur très simple à calculer à partir des estimations univariées et des probabilités a priori des modalités cible

Limites :

- dégradation des performances lorsque les variables sont redondantes
- peu interprétable pour un grand nombre de variables

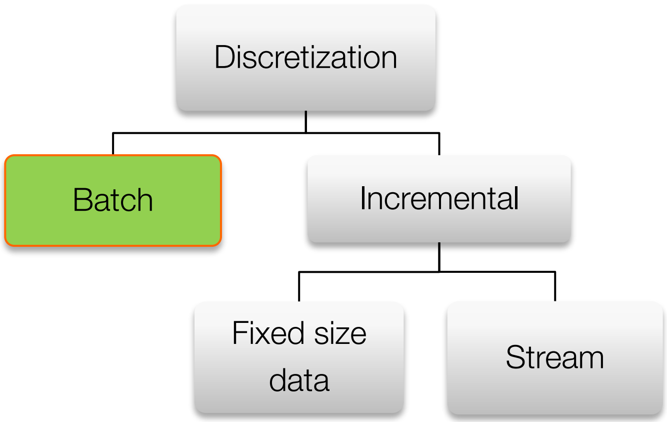
Incremental Naïve Bayes

$$P_{NB}(Y = C \mid X = x^n) = \frac{\boxed{P(Y = C)} \prod_{k=1}^{K} \boxed{p(x_k^n \mid C)}}{\sum_{j=1}^{J} \boxed{P(C_j)} \prod_{k=1}^{K} \boxed{p(x_k^n \mid C_j)}}$$

- Each instance, x_k, is a vector of values (numerical or categorical)
- However, when the Xi are continuous we must choose some other way to represent the distributions P(Xi | Y).
    - discretization / grouping respectively for numerical / categorical variables
    - using a discretization method and a grouping method.

Incremental Naïve Bayes

Well performing methods for supervised discretization

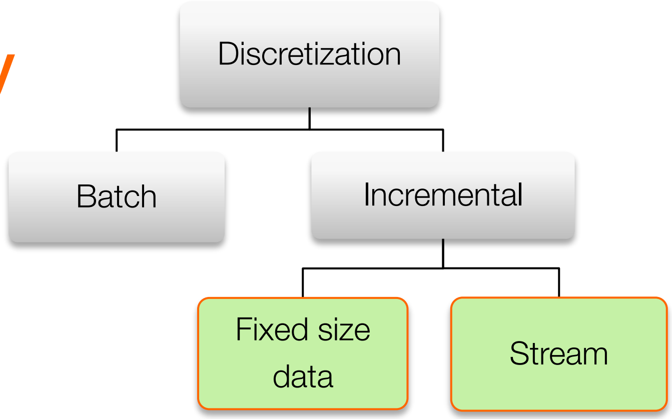


- MDLP: find the best intervals based on the entropy. The best number of interval is found using a MDL approach.
  Fayyad U, Irani K. *Multi-interval discretization of continuous-valued attributes for classification learning*. Proceedings of the International Joint Conference on Uncertainty in AI. 1993

- MODL: based on Bayesian formalism and MDL principle. This method aims to find the best discretization parameters (intervals number, intervals boundaries, classes distribution within an interval) in a Bayesian way.
  Boullé M. *MODL: A Bayes optimal discretization method for continuous attributes*. Machine Learning. 2006.

Incremental Naïve Bayes

Related works – DBMS community
Online statistics

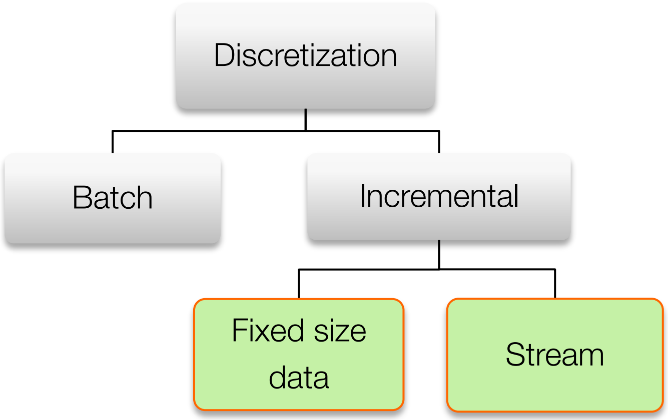


Goal: find the best execution plan

- **Reservoir** (kind of « reservoir sampling ») + « EqualFrequency **histogram** »
  Gibbons P, Matias Y, Poosala V. *Fast incremental maintenance of approximate histograms.* ACM Transactions on Database. 2002
- **Quantiles**: many quantiles lists are maintained. If memory become full some lists are merged to recover it.
  Manku GS, Rajagopalan S, Lindsay BG. *Approximate medians and other quantiles in one pass and with limited memory*. SIGMOD'98
- **Quantiles**: a data structure is used to maintain online ranks and errors. This method has strong error garantee on the quantiles
  Greenwald M, Khanna S. *Space-efficient online computation of quantile summaries.* SIGMOD'01

Incremental Naïve Bayes

Related works – Data mining
Incremental discretization



- **IFFD** : Incremental Flexible Frequency Discretization. Keep all the data and adapt interval sizes between a minimum and a maximum
  Lu J, Yang Y, Webb G. *Incremental discretization for naive-bayes classifier*. Advanced Data Mining and Applications. 2006
- **PID**: two levels discretization
  level 1: mix between "EqualFreq" and "EqualWidth"
  level 2: all batch methods
  Gama J, Pinto C. *Discretization from data streams: applications to histograms and data mining.* Proceedings of the 2006 ACM symposium on Applied Computing. 2006.
- **Gaussian approximation**: approximate the data distribution with a Gaussian per class: μ and σ parameters are kept online. Very low memory footprint.
  Pfahringer B, Holmes G, Kirkby R. *Handling numeric attributes in hoeffding trees*. Advances in Knowledge Discovery and Data Mining. 2008.

Incremental Naïve Bayes

Methods comparison

Method	Global / local	Multi variate	Parametric	Supervised	Online / stream
Equal Width	Global	No	Yes	No	No
Equal Freq	Global	No	Yes	No	No
Greenwald Khanna	Global	No	Yes	No	Yes
K-means clustering	Global and local	Yes	Yes	No	Yes / No
PID (Layer 1)	Global	No	Yes	No	Yes
MDLP / MODL	Global and local	No	No	Yes	No
IFFD	Global	No	Yes	No	Yes / No
Gaussian	Global	No	Yes	No	Yes

3 criteria were proposed by: Dougherty J, Kohavi R, Sahami M. *Supervised and unsupervised discretization of continuous features*. ML1995.

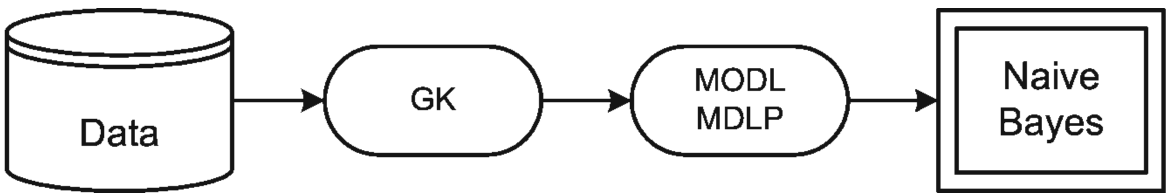
Incremental Naïve Bayes

Online Discretization: Gaussian approximation

- Gaussian Approximation (GAUSS)
  - Assume values conform to Normal Distribution
  - Maintain five numbers (eg mean, variance, weight, max, min)
  - Note: not sensitive to data order
  - Incrementally updateable
  - Using the max, min information per class – split the range into N equal parts

Incremental Naïve Bayes

Online Discretization: A two levels discretization



- Level 1: Greenwald et Khanna - GK (or another method adapted to streams) based on a quantile summary

  global / not supervised / parametric / **online**

- Level 2: MODL or MDLP
  methods based on the entropy for intervals quality and on MDL principle to stop finding new intervals

  global / **supervised** / without parameters

➔ Both levels are based on order statistics

Incremental Naïve Bayes

Averaging of Naïve Bayes Classifier

$$P(C_z|x_k) = \frac{P(C_z)\prod_{j=1}^{J} P(V_j = x_{jk}|C_z)}{\sum_{t=1}^{C}\left[P(C_t)\prod_{j=1}^{J} P(V_j = x_{jk}|C_t)\right]}$$

$$P(C_z|x_k) = \frac{P(C_z)\prod_{j=1}^{J} P(V_j = x_{jk}|C_z)^{W_j}}{\sum_{t=1}^{C}\left[P(C_t)\prod_{j=1}^{J} P(V_j = x_{jk}|C_t)^{W_j}\right]}$$

[KS96] Daphne Koller and Mehran Sahami. Toward Optimal Feature Selection. *International Conference on Machine Learning*, 1996(May) :284–292, 1996.

[HMR99] JA Hoeting, David Madigan, and AE Raftery. Bayesian model averaging : a tutorial. *Statistical science*, 14(4) :382–417, 1999.

[LS94] Pat Langley and S Sage. Induction of Selective Bayesian Classifiers. In R Lopez De Mantras Poole and D, editors, *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, pages 399–406. Morgan Kaufmann, 1994.

[Bou06b] Marc Boullé. Regularization and Averaging of the Selective Naive Bayes classifier. *The 2006 IEEE International Joint Conference on Neural Network Proceedings*, pages 1680–1688, 2006.

Incremental Naïve Bayes

Averaging of Naïve Bayes Classifier

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Littérature : les poids sont obtenus suite à un moyennage de modèles qui correspondent à des sélections de variables différentes (Hoeting et al., 1999) (Boullé, 2007)

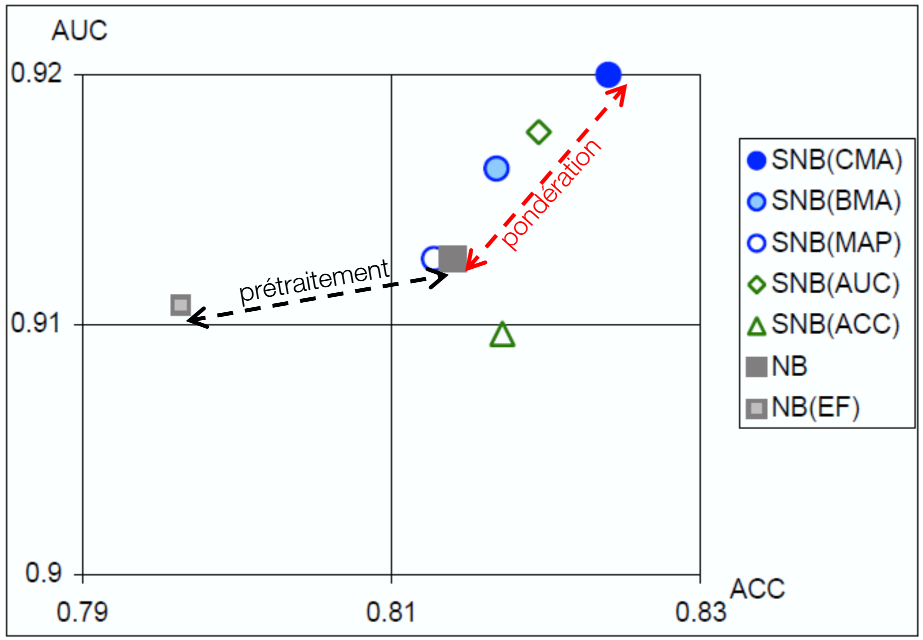
Incremental Naïve Bayes

Wj? Intuition

on paper board

Incremental Naïve Bayes

Benefits of Averaging of Naïve Bayes Classifier



Methods to compute the weights

No weights

Mean of the ACC, AUC evaluation criteria on the 30 UCI data sets.

Same results conclusion on the large scale learning challenge

[Bou06b] Marc Boullé. Regularization and Averaging of the Selective Naive Bayes classifier. *The 2006 IEEE International Joint Conference on Neural Network Proceedings*, pages 1680–1688, 2006.

Incremental Naïve Bayes

Requirements of 'Online' Averaging of Naïve Bayes Classifier

The "classic" averaging of naïve Bayes classifier
requires the storage of all the data
(a data table allowing the link between the instances and their labels)

Incremental Naïve Bayes

Cost function

$$ll(w, D_N) = -\sum_{n=1}^{N}\left(\log P(Y = y^n) + \sum_{k=1}^{K}\log p(x_k^n|y^n)^{w_k} - \log\left(\sum_{j=1}^{J}P(C_j)\prod_{k=1}^{K}p(x_k^n|C_j)^{w_k}\right)\right)$$

$$CR^{D_N}(w) = \underbrace{-\sum_{n=1}^{N}\log(P^{w}_{SNB}(y_n|x_n))}_{\text{log-vraisemblance négative}} + \underbrace{\lambda\, f(w)}_{\text{régularisation}}$$

poids de la régularisation

On cherchera la pondération w qui minimise la log-vraisemblance régularisée

Incremental Naïve Bayes

Régularisation de la log-vraisemblance :

$$f(w) = \sum_{k=1}^{K} \boxed{w_k^p}$$

parcimonie

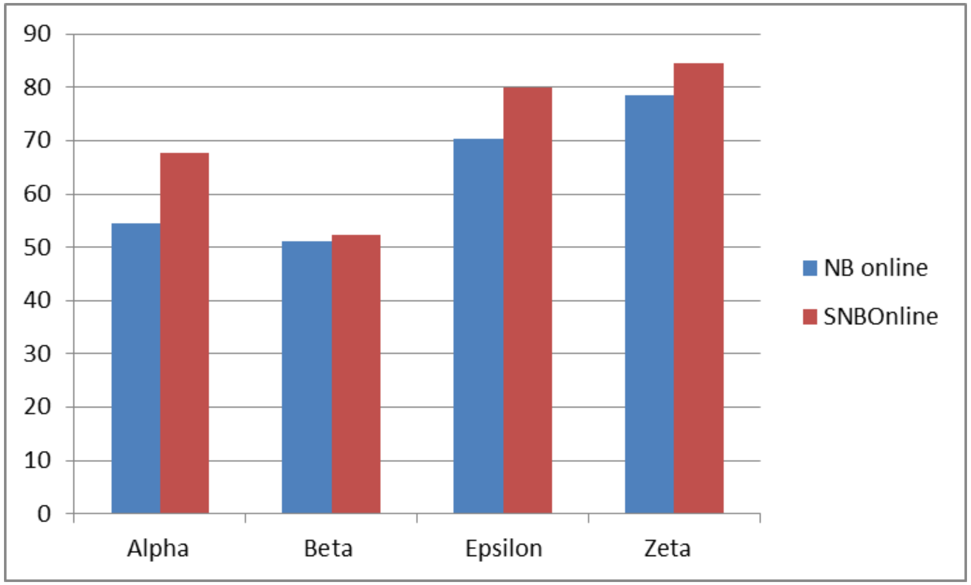
- p > 1 : convexe mais non parcimonieux
- p <= 1 : non convexe mais parcimonieux

Exemple : X_1, X_2 deux variables identiques

	$w_1 = w_2 = 0.5$	$w_1 = 0; w_2 = 1$
$w_1^2 + w_2^2$	0.5 Non parcimonieux	1
$\sqrt{w_1} + \sqrt{w_2}$	1.41	1 parcimonieux

Incremental Naïve Bayes

Averaging of Naïve Bayes Classifier – Performances



Outline

1. From Batch mode to Online Learning
2. Implementation of on-line classifiers
3. Evaluation of on-line classifiers
4. Taxonomy of classifier for data stream
5. Two examples
6. Concept drift
7. Make at simplest

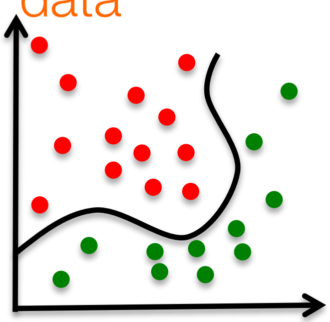
Concept drift

What does it means ?

- The input stream is **not stationary**
- The **distribution** of data **changes** over time
- Two strategies : **adaptive learning** or **drift detection**
- Several types of concept drift :

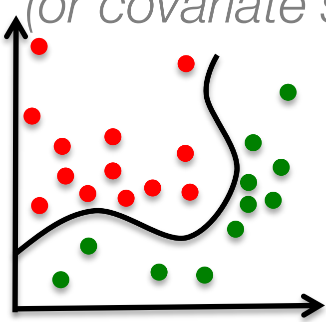
$$P(x,y) = P(x) \, . \, P(y|x)$$

Original data

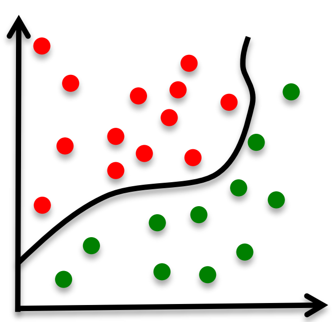


Virtual drift [B]

(or covariate shift)



Concept drift [A]



Concept drift

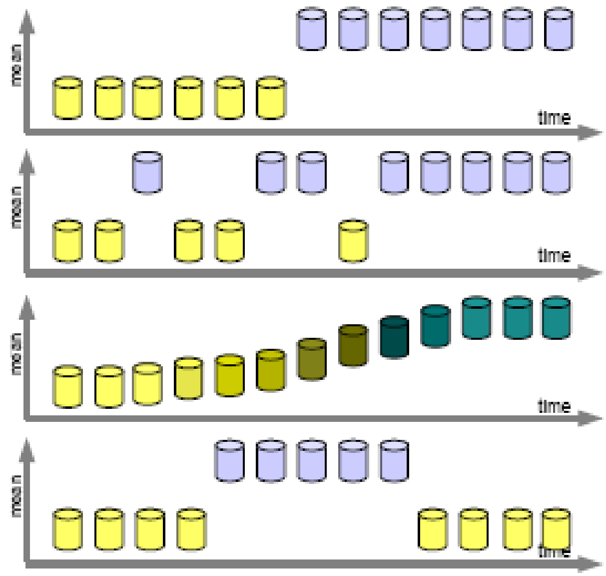
What kinds of drift can be expected [C]?

Abrupt

Gradual

Incremental

Reoccuring



Drift detection

On-line adaptive learning

Drift detection & models management

Learning under Concept Drift: an Overview

Indrė Žliobaitė
Faculty of Mathematics and Informatics
Vilnius University, Lithuania zliobaite@gmail.com

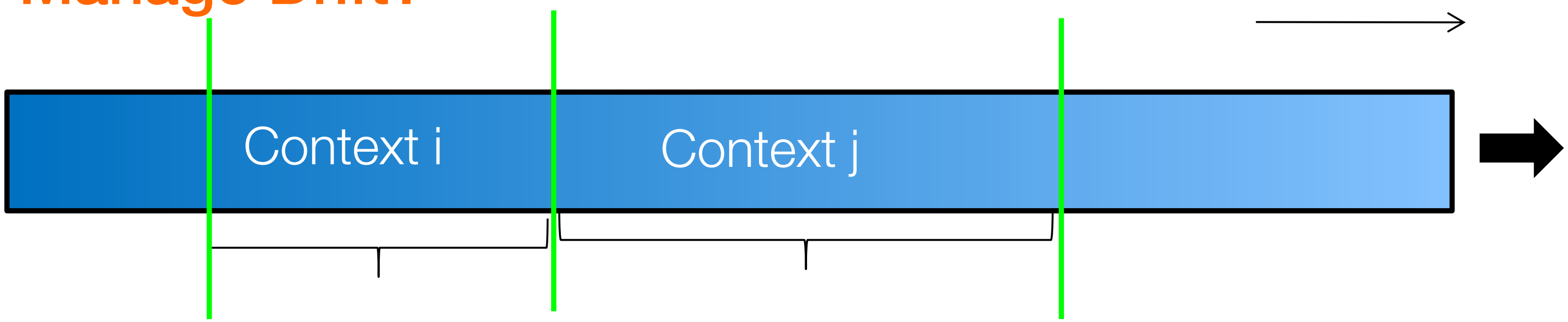
Concept drift

Some specific constrains to manage :

- Adapt to concept drift asap
- Distinguish noise from changes *(Robust to noise, Adaptive to changes)*
- Recognizing and reacting to reoccurring contexts
- Adapting with limited hardware resources *(CPU, RAM, I/O)*

Concept drift

Manage Drift?



- Either detect and :
  1) Retrain the model
  2) Adapt the current model
  3) Adapt statistics (summaries) on which the model is based
  4) Work with a sequence of
     - models
     - summaries
- or detect anything but train (learn) fastly
  - a single models
  - an ensemble of models)

Concept drift

Desired Properties of a System To Handle Concept Drift

- Adapt to concept drift asap

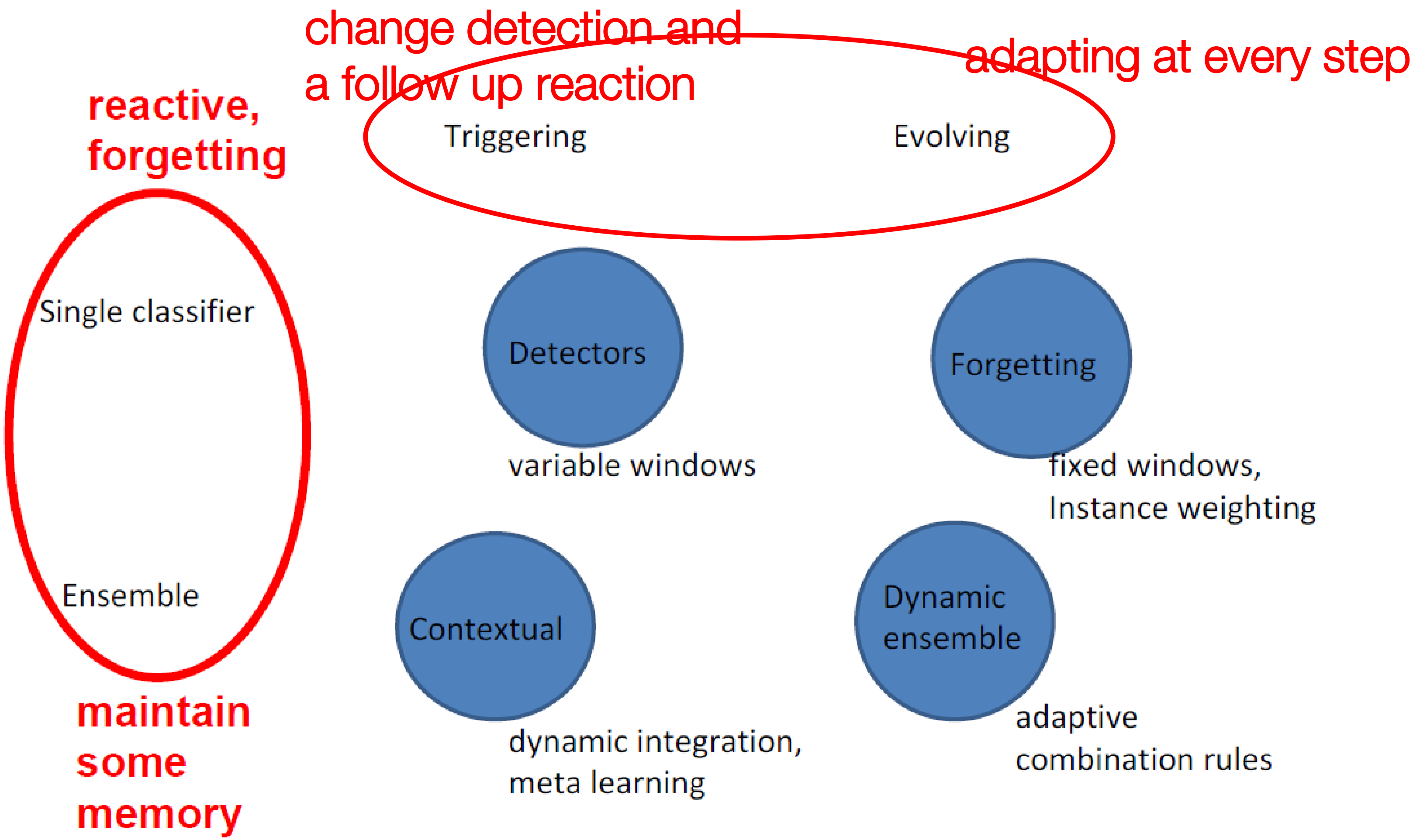
- Distinguish noise from changes
  – robust to noise, but adaptive to changes

- Recognizing and reacting to reoccurring contexts

- Adapting with limited resources
  – time and memory

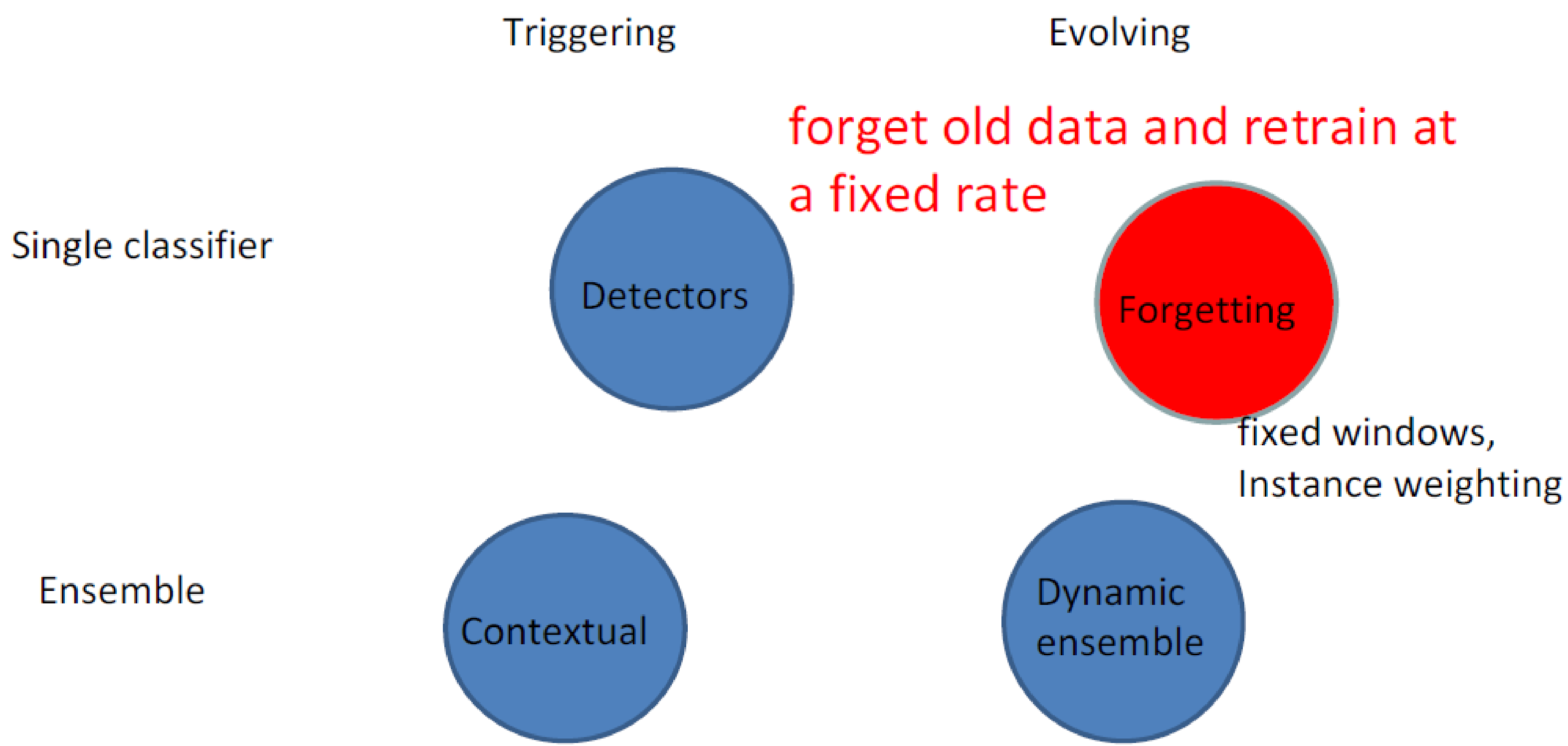
Concept drift

Adaptive learning strategies

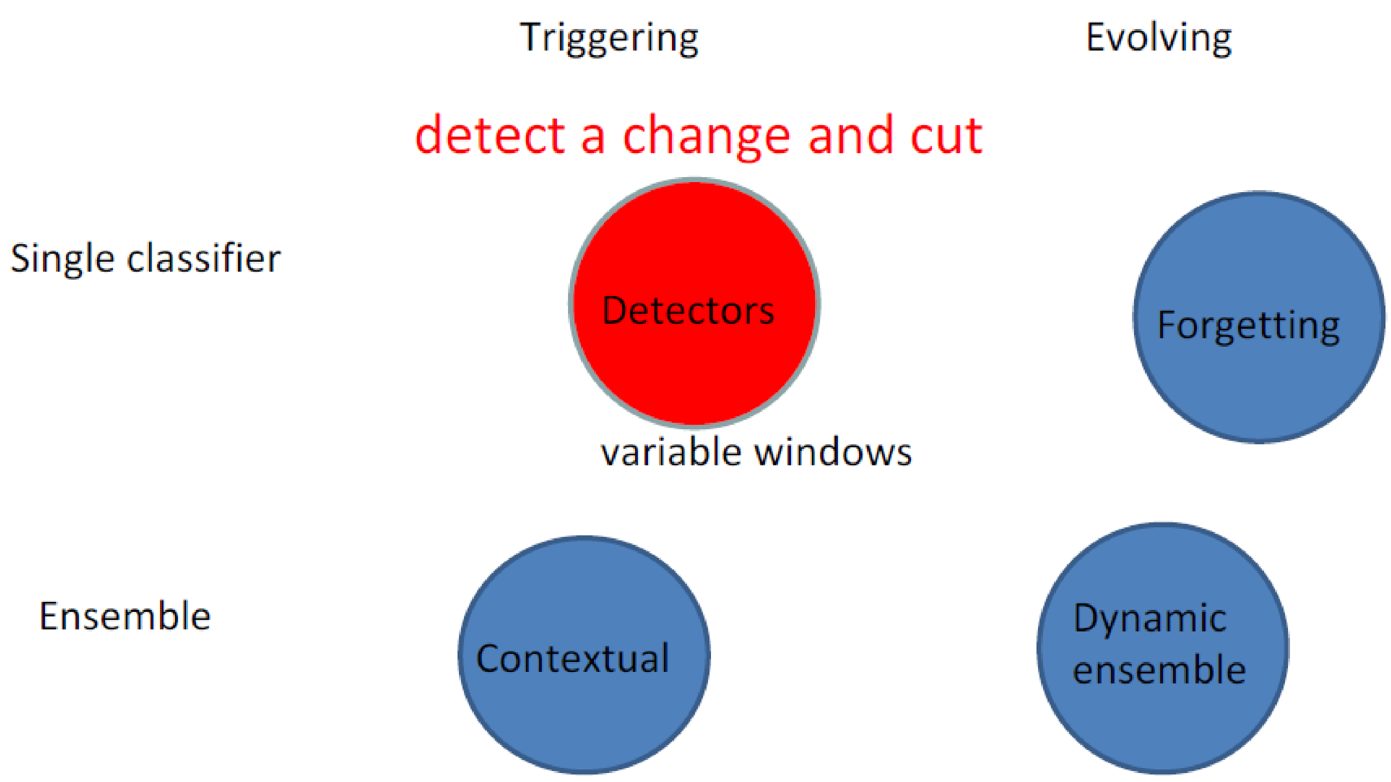


Concept drift

Adaptive learning strategies

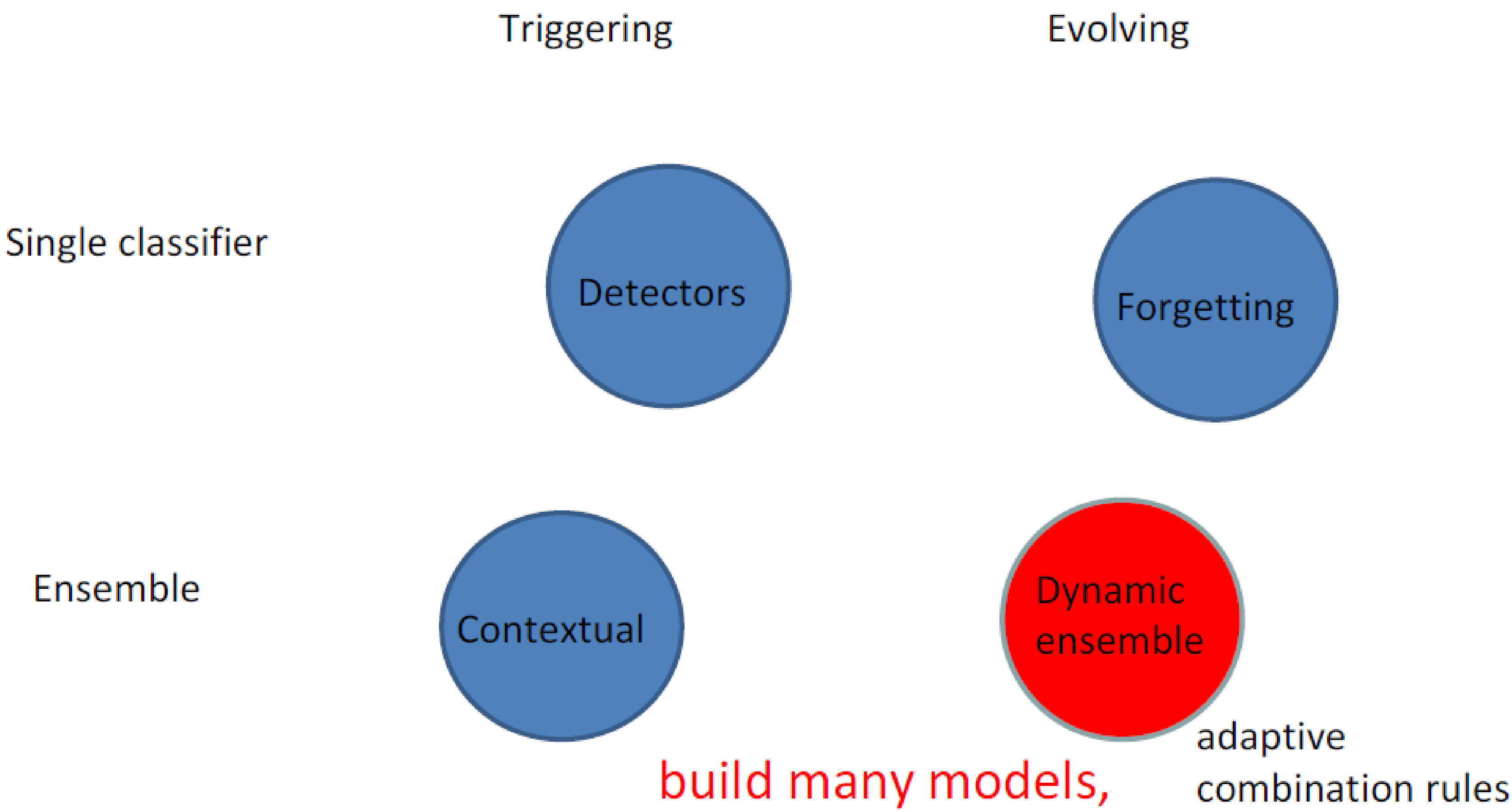


Concept drift
Adaptive learning strategies



Concept drift

Adaptive learning strategies



build many models, dynamically combine

Concept drift

Adaptive learning strategies

	Triggering	Evolving
Single classifier	Detectors	Forgetting
Ensemble	Contextual	Dynamic ensemble

build many models,
switch models according
to the observed incoming data

dynamic integration,
meta learning

Concept drift

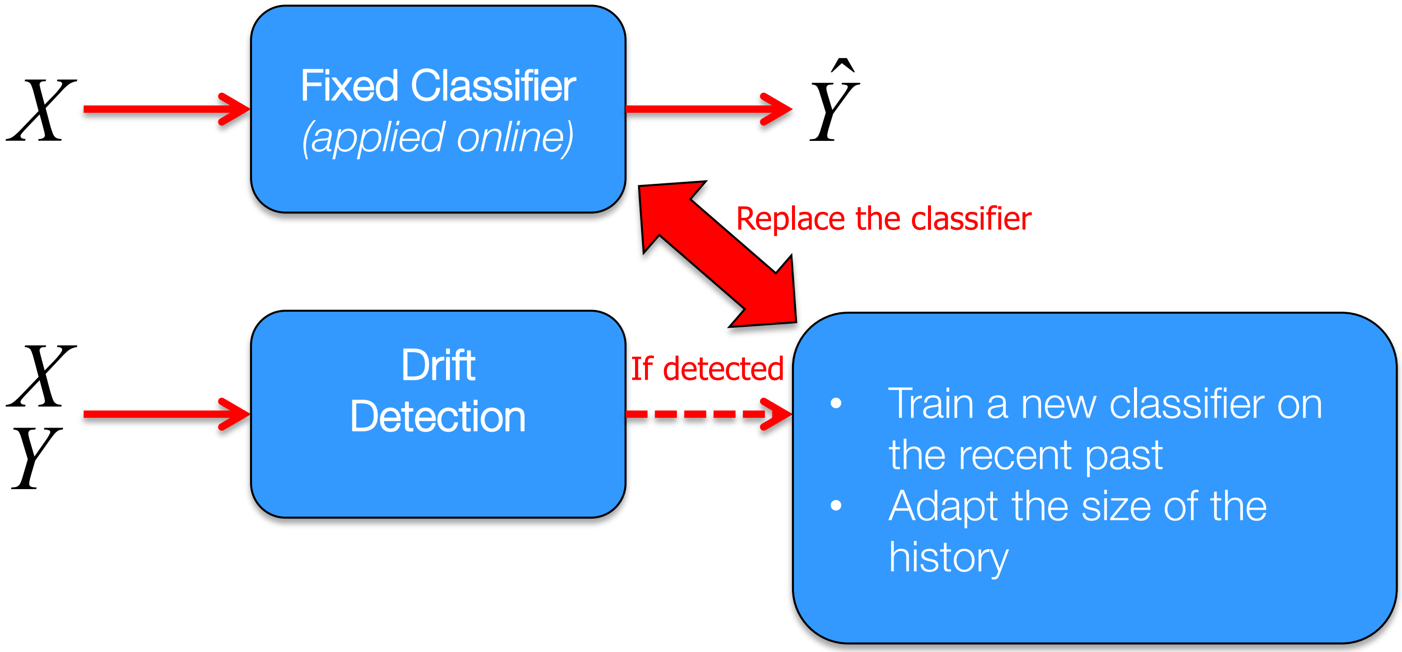
Which approach to use?

- changes occur over time
- we need models that evolve over time
- choice of technique depends on
  - what type of change is expected
  - user goals/ applications

Concept drift

Drift detection

General schema :



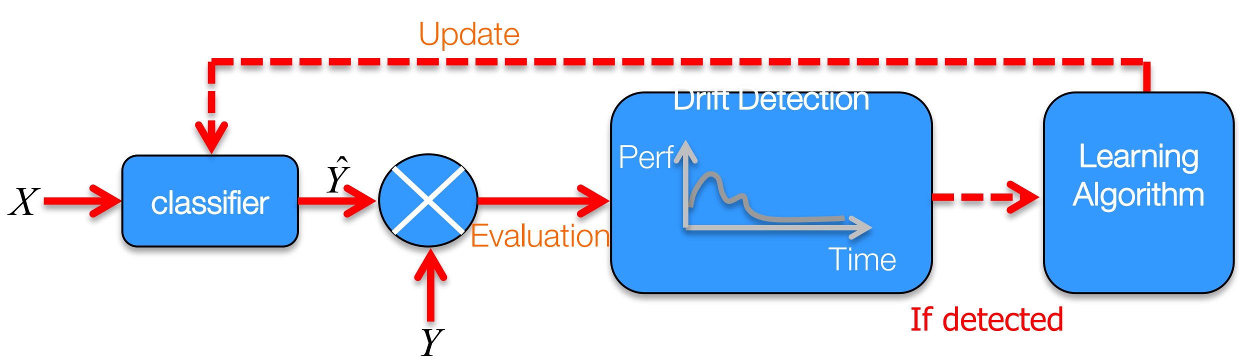
Concept drift

Drift detection

<u>How to detect the drift ?</u>

Based on the online evaluation :

- <u>Main idea</u> : if the performance of the classifier changes, that means a drift is occurring ...
- <u>For instance</u> : if the error rate increases, the size of the sliding windows decreases and the classifier is retrained [F].
- <u>Limitation</u> : the user has to define a threshold



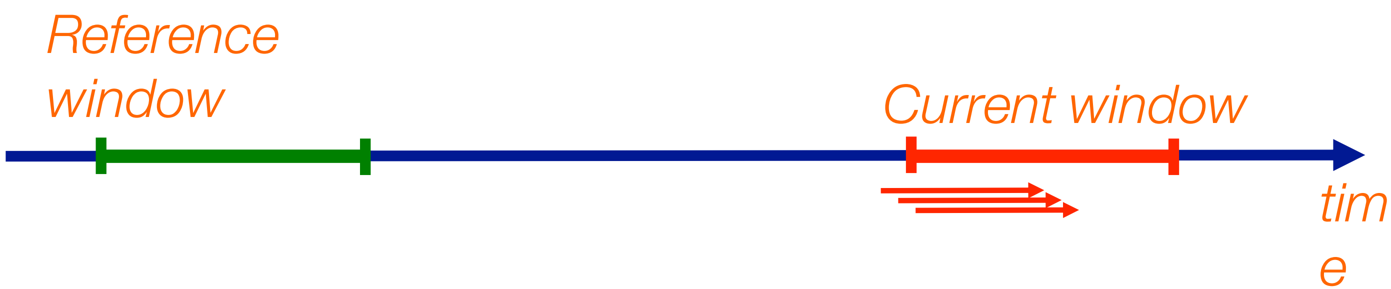
Concept drift

Drift detection

<u>How to detect the drift ?</u>

Based on the distribution of tuples :

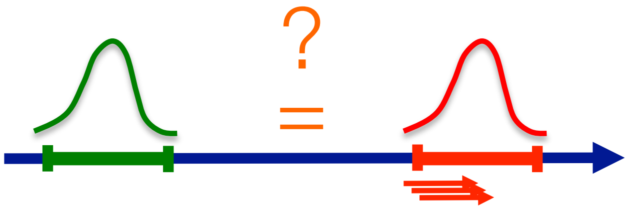
- <u>Main idea</u> : if the distributions of the "*current window*" and the "*reference window*" are significantly different, that means a drift is occurring ….



Concept drift

Drift detection

<u>How to detect the drift ?</u>



Based on the distribution of tuples :

Detection of covariate shift : P(X)

- In [G] the author uses **statistical tests** in order to compare the both distributions
  - Welch test – *Mean values are the same ?*
  - Kolmogorov Smirnov test – *Both samples of tuples come from the same distribution ?*
- A **classifier** can be exploited to **discriminate** tuples belonging to **both windows** [H]
  - If the quality of the classifier is good, that means a drift is occurring …
  - Explicative variables : X
  - Target variable : W *(the window)*

Detection of concept shift : P(Y|X)

- In [I] a classifier is exploited, the **class value** is considered as an **additional input variable**
  - Explicative variables : X **and Y**
  - Target variable : W *(the window)*

More details … see

Handling Concept Drift:
Importance, Challenges & Solutions

A. Bifet, J. Gama, M. Pechenizkiy, I. Žliobaitė

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BU Bournemouth University

PAKDD-2011 Tutorial
May 27, Shenzhen, China

http://www.cs.waikato.ac.nz/~abifet/PAKDD2011/

Concept drift

Parameters – The devil inside

Concept drift

No drift assumption?

Do not use online learning !

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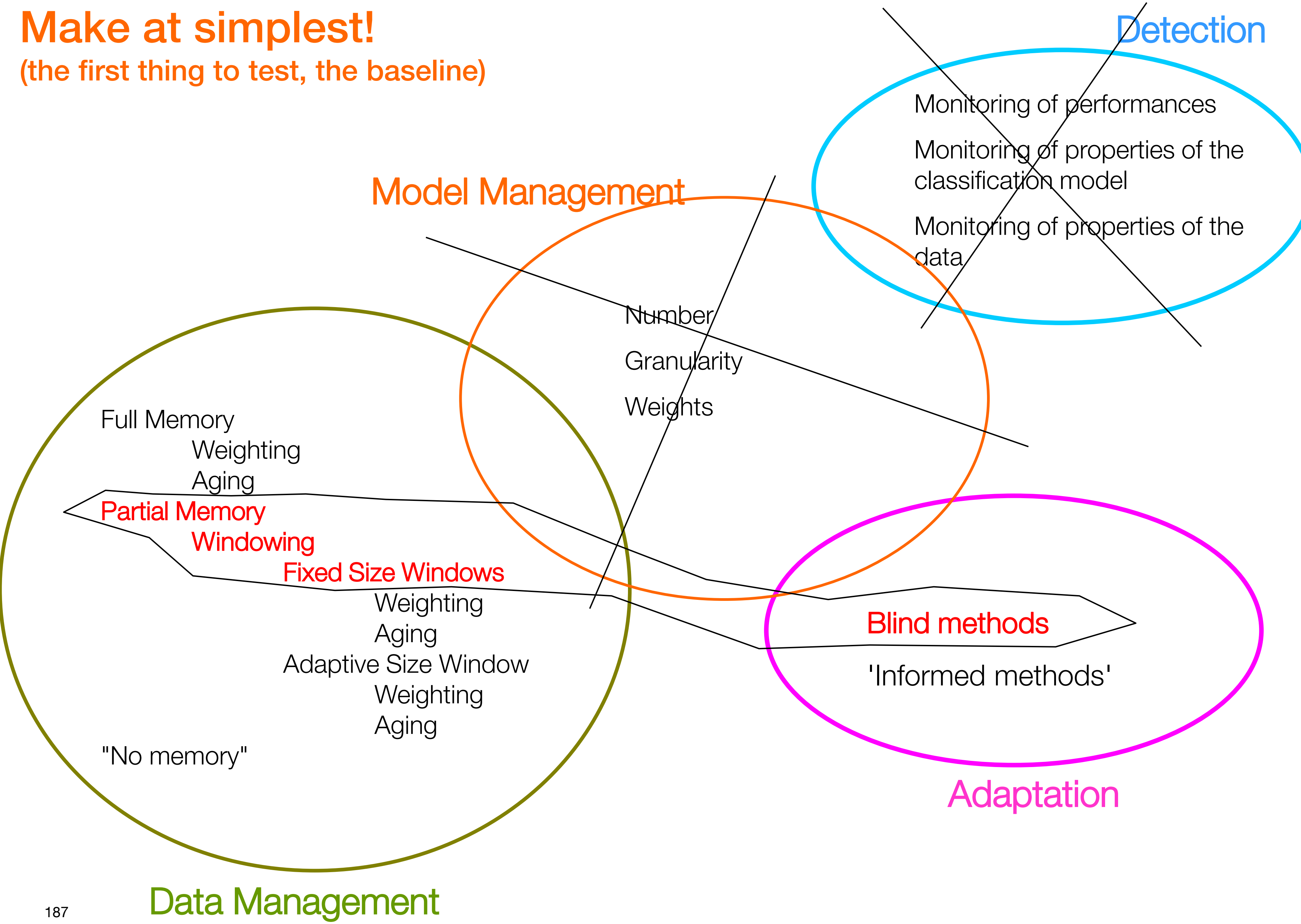
Make at simplest!

(the first thing to test, the baseline)



Make at simplest

A classifier trained with few examples but often!

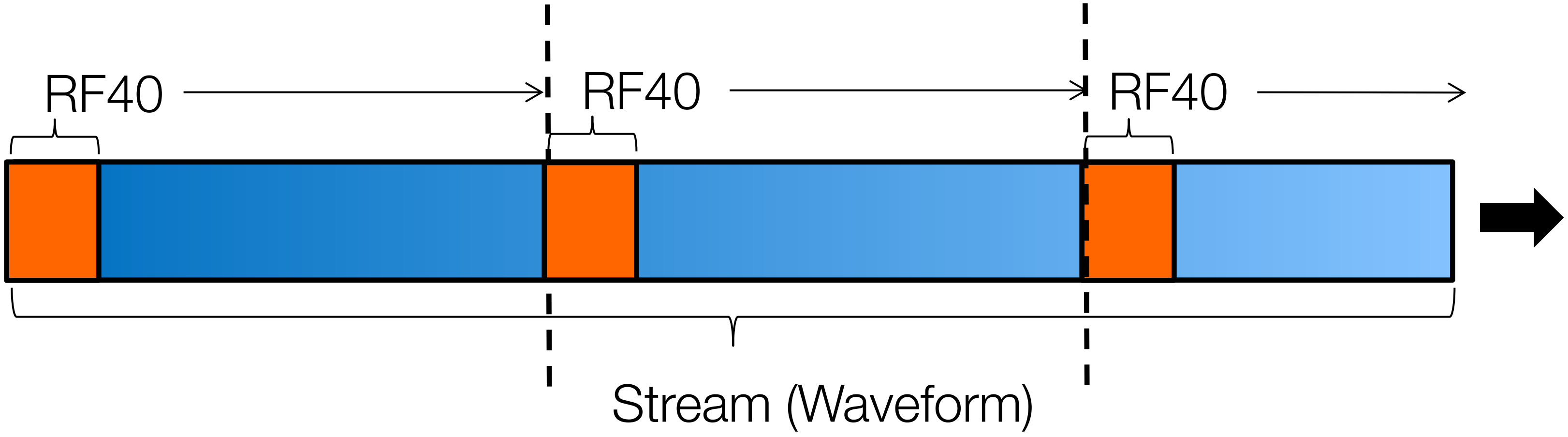
- Which classifier ?

  - Generative classifiers are better than discriminant classifiers when the number of examples is low and there is only one classifier (Bouchard 2004)
  - Ensemble of classifiers are very good (Bauer 1999)
  - Bagging of discriminative classifiers supplants a single generative classifier (and with a low variance) (Breiman 1996)
  - Methods "very" regularized "are very (too) strong (Cucker 2008)

Make at simplest

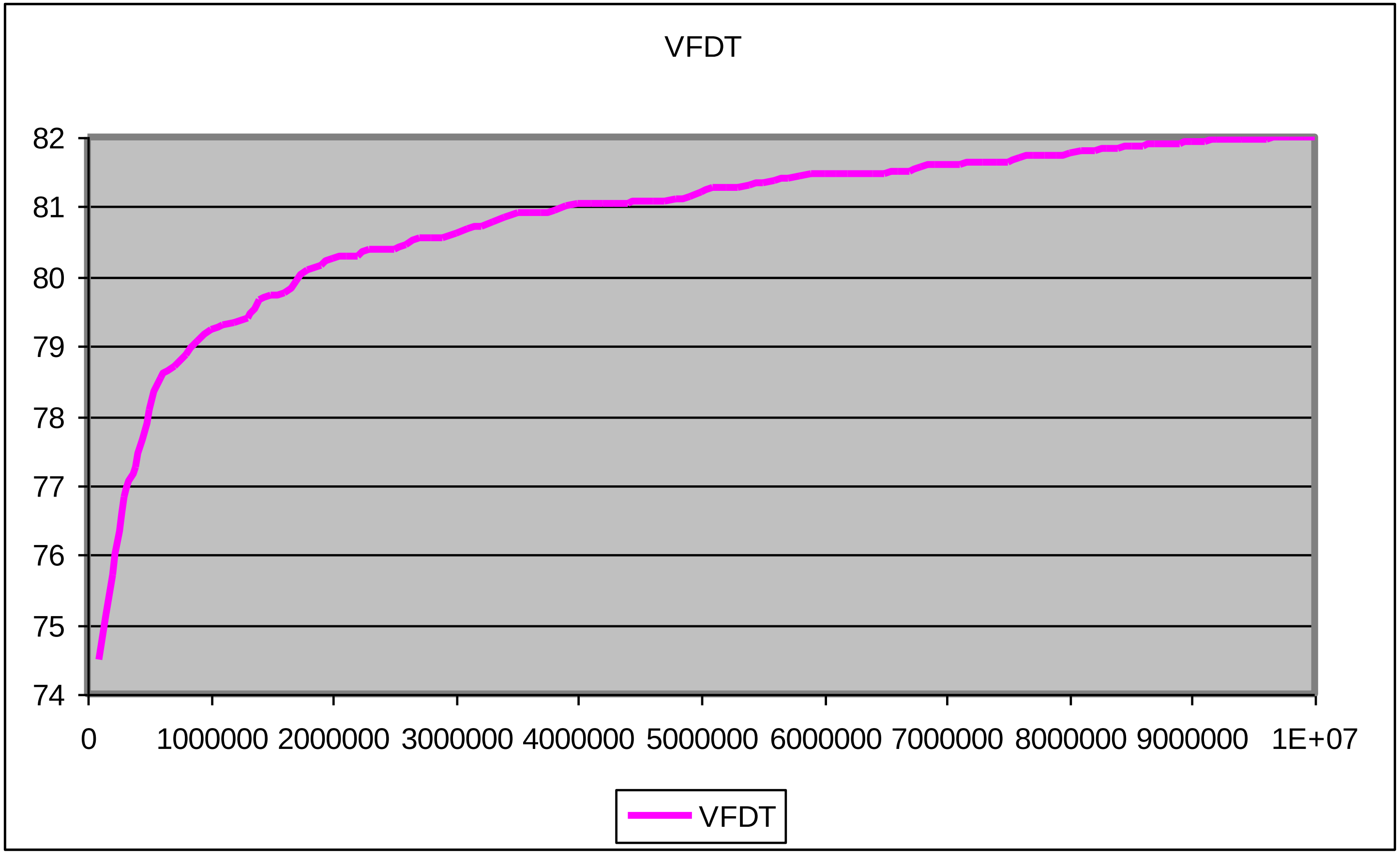
A classifier trained with few examples but often!

- Which classifier ?
  - a random forest (based on « "Learning with few examples: an empirical study on leading classifiers ", Christophe Salperwyck and Vincent Lemaire, in International Joint Conference on Neural Networks (IJCNN July 2011)»)
  - using 4096 examples



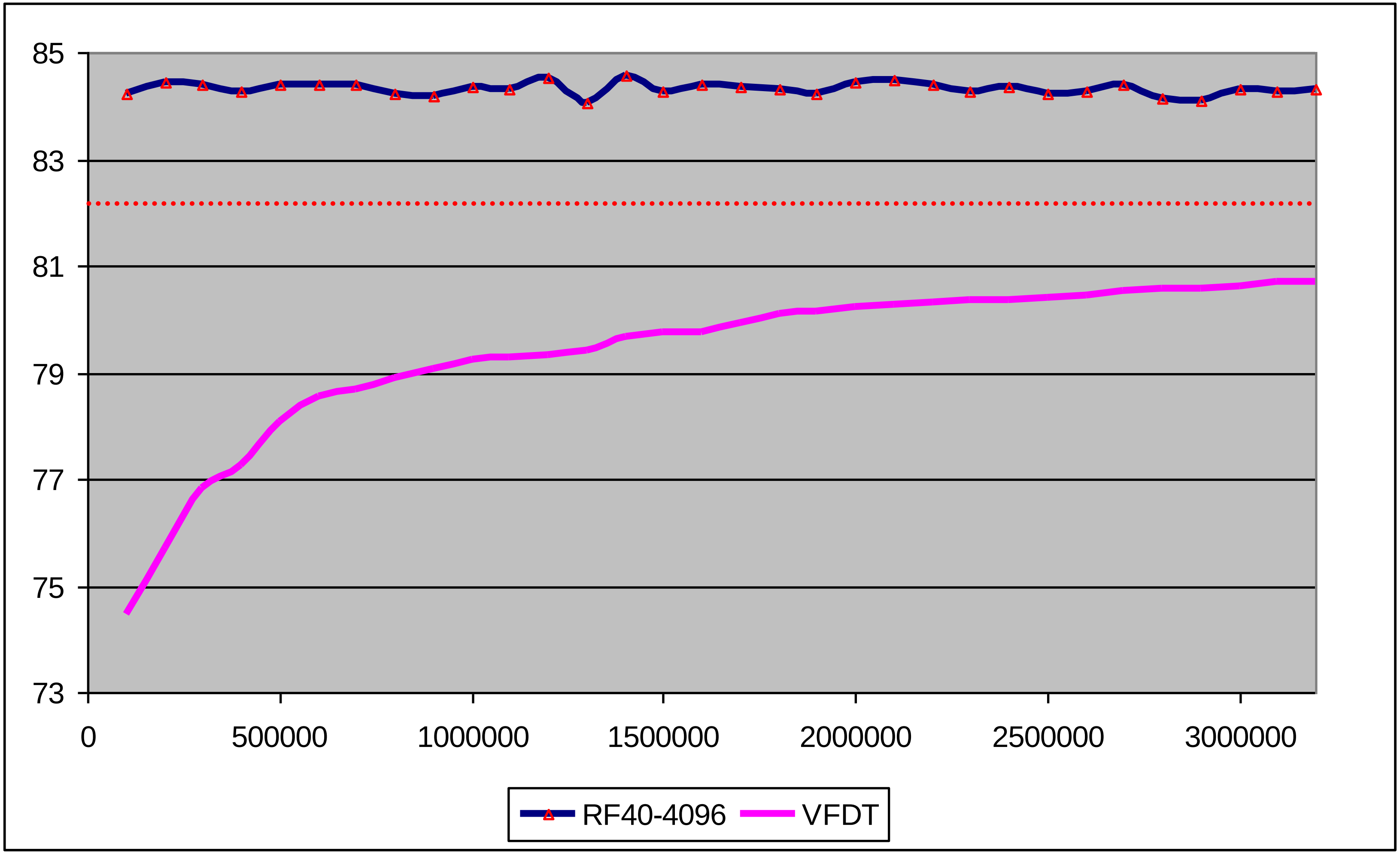
Make at simplest

Waveform



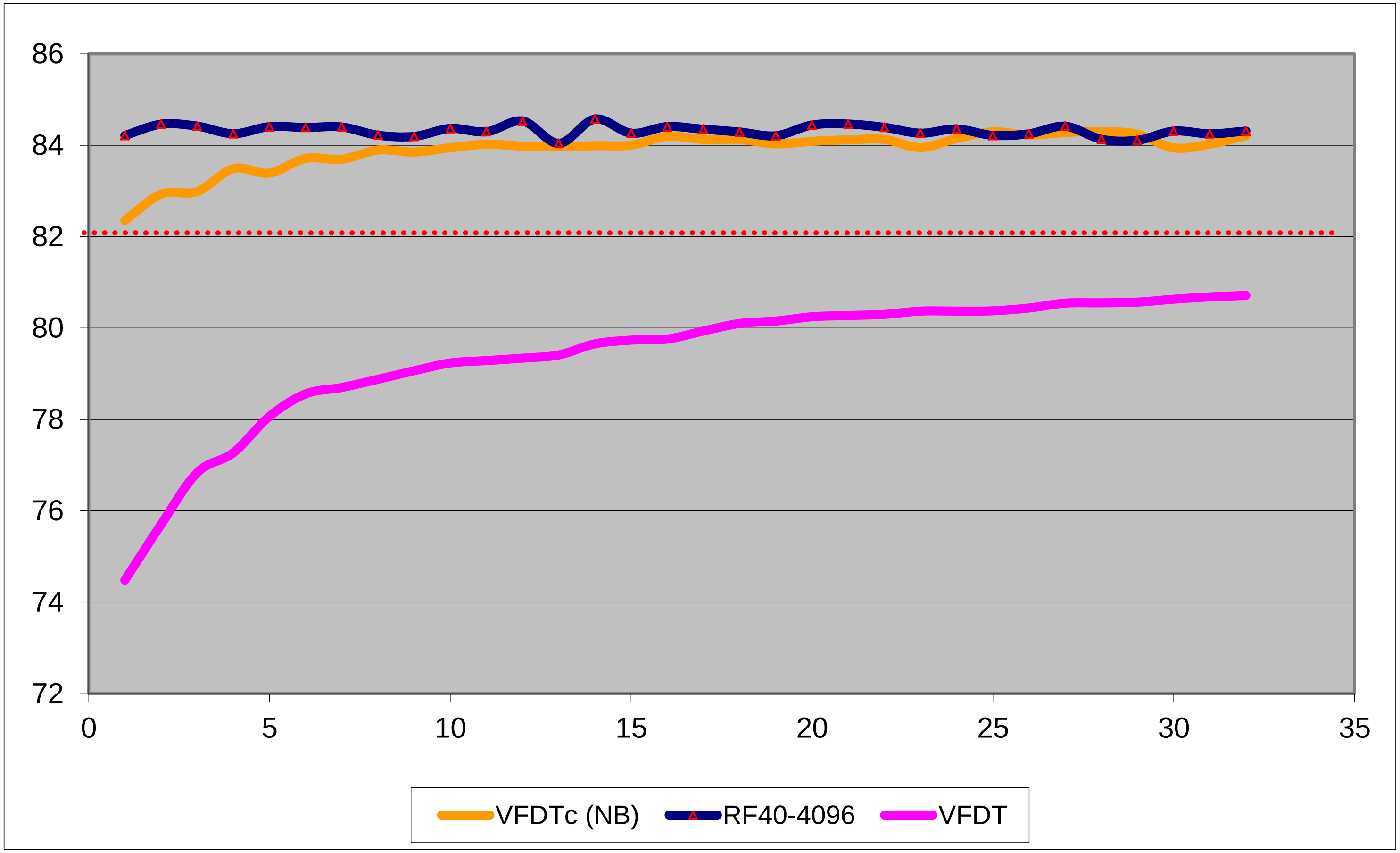
Make at simplest

Waveform



Make at simplest

Waveform



Make at simplest

Alternative problem settings

Make at simplest

Alternative problem settings

Multi-armed bandits explore and exploit online set of decisions, while minimizing the cumulated regret between the chosen decisions and the optimal decision.

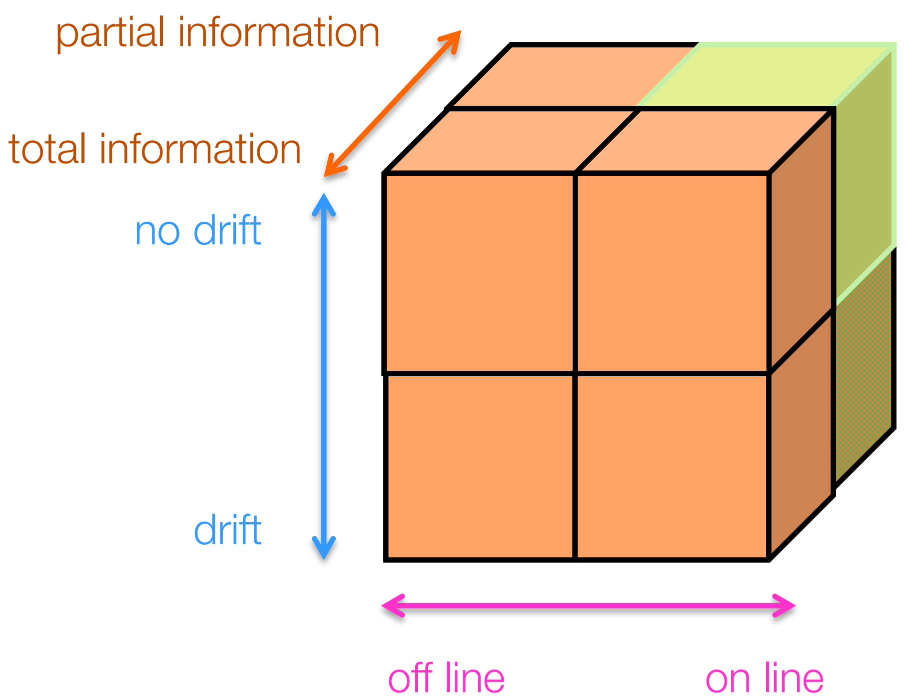
Originally, Multi-armed bandits have been used in pharmacology to choose the best drug while minimizing the number of tests.

Today, they tend to replace A/B testing for web site optimization (Google analytics), they are used for ad-serving optimization.

Make at simplest

When ?

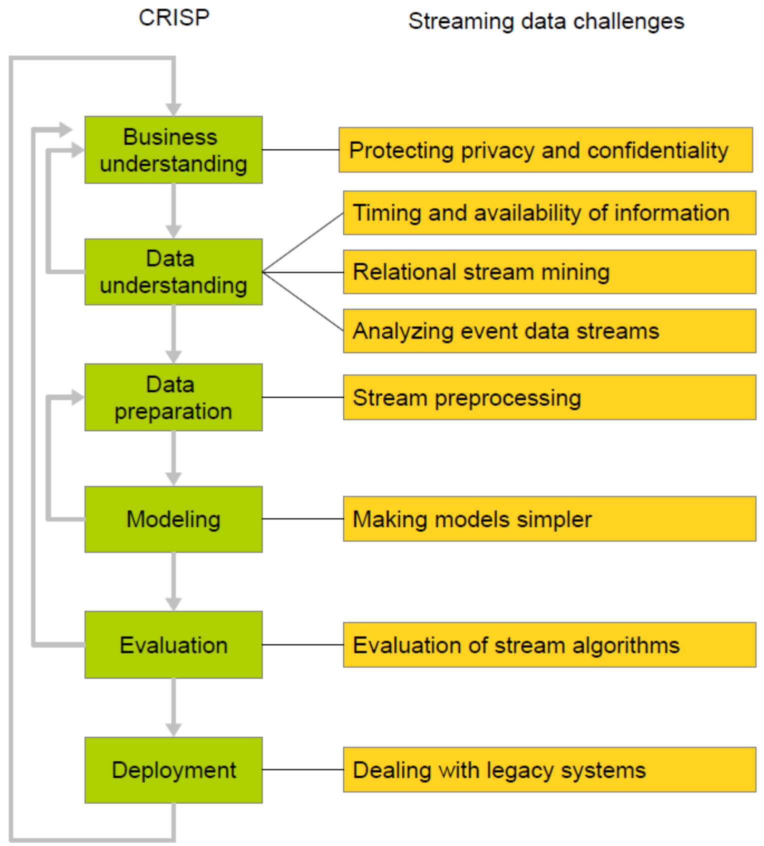
Partial information (multi classes problem)



just before the end

More Real-World Challenges for Data Stream Mining

Data stream research challenges positioned in the CRISP cycle.



"Open Challenges for Data Stream Mining Research", - submited to SIGKDD Explorations (Special Issue on Big Data)

Conclusion

<u>Main ideas to retain :</u>

- Online learning **algorithm** are designed in accordance with **specific constrains**
  - One pass
  - Low latency
  - Adaptive … etc

- In practice the **true labels** are **delayed** : *an online classifier predicts the labels before observe it*
- The **evaluation** of the classifiers **is specific** to data streams processing
- The **distribution** of the tuples may **change over time** :
  - Some approaches **detect** the drifts, and then **update** the classifier ***(abrupt drift)***
  - Other approaches **progressively adapt** the classifier ***(incremental drift)***

- In practice, the type of **expected drift must be known** in order to choose an appropriate approach
- The distinction between **noise** and **drifts** can be viewed as a **plasticity / stability** dilemma