CAPES
Brazil

Analyzing the Evolution of Web Usage Data

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Outline

- Introduction
- Motivations for this work
- Our proposition
- Clustering approach based on time sub-periods
- The benchmark website analyzed
- Results analysis
- Final conclusion
- Future works

Introduction

- **The WWW:**
  - one of the most relevant examples of voluminous and dynamic data sources
- **Web access patterns have a dynamic nature, due to:**
  - the dynamism of the website's content and structure
    or
  - the change of user's interest
- **Access patterns may depend on:**
  - time of day, day of the week
  - recurrent factors (summer/winter vacations, national holidays, seasonality)
  - non-recurrent global events (epidemics, wars, the World Cup)
  - etc.

Motivations for this work

- The majority of methods in the Web Usage Mining (WUM) domain take into account the **whole period** of usage traces.
  - Consequence:
    - the results are those predominant in the entire period of analysis
  - Negative side effects:
    - behaviour patterns occurring in short periods of time are not detected by traditional methods

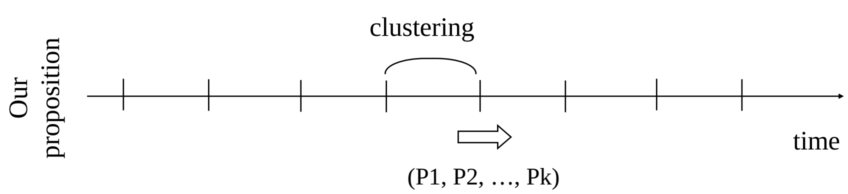
Our proposition

- To carry out an analysis on significant time **sub-periods**, in order to:
  - identify the change of user's interest
  - follow the evolution of user's profiles over time

using

Summaries to represent user profiles

Our proposition



The website analyzed

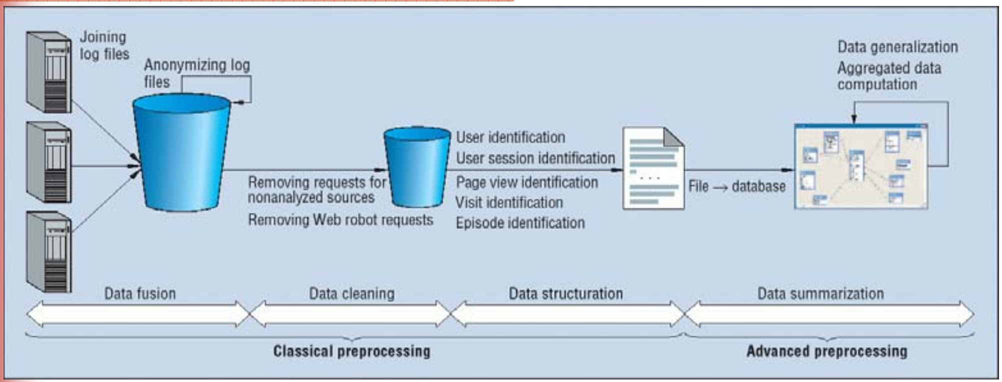
- Recife’s (Brazil) Information Technology Centre website (http://www.cin.ufpe.br/):
  - static pages (personal web pages, lessons pages, etc.)
  - 91 dynamic pages (maintained by *Java* servlets in a semantic structure)
- We retrieved the traces of usage:
  - 1 July 2002 – 31 May 2003 (roughly 2Go of raw data)

Common Log Format (CLF)

[remotehost] [name] [login] [date] [url] [status] [size] [referrer] [agent]

- remotehost ***remote identification (hostname or IP address)***
- name/login ***the remote login name of the user***
- date ***date and time of the request***
- URL ***requested page in the site (www.<...>)***
- status ***returned code (Indicates whether or not the file was successfully retrieved)***
- size ***the number of bytes transferred***
- referrer ***the url the client was on before requesting the current url***
- agent ***the software the client is using***

Data Pre-processing



Tanasa & Trousse (Advanced Data Preprocessing for Intersites Web Usage Mining, IEEE Intelligent Systems, vol. 19, n° 2, pp. 56-65, April 2004)

Tanasa's Thesis (2005)

Data selection

- We selected navigations with two shared constraints:
  - long
    - *number of requests >= 10*
    - *total duration >= 60 seconds*
  - those of human origin
    - *total duration / number of requests >= 4* (15 requests/ min)
- After filtering and eliminating the outliers:
  - 138,536 navigations

Statistical attributes for navigations' description

N°	Field	Meaning
1	**IDNavigation**	Navigation code
2	**NbRequests_OK**	Number of successful requests (status = 200) in the navigation
3	**NbRequests_bad**	Number of failed requests (status < > 200) in the navigation
4	**MRequests_OK**	Percentage of successful requests (= NbRequests_OK/ NbRequests)
5	**NbRepetitions**	Number of repeated requests in the navigation
6	**MRepetitions**	Percentage of repeated requests (= NbRepetitions / NbRequests)
7	**TotalDuration**	Total duration of the navigation (in secondes)
8	**ADuration**	Average of request duration (= TotalDuration / NbRequests)
9	**ADuration_OK**	Average of duration among successful requests (= TotalDuration _OK / NbRequests_OK)
10	**NbRequests_Sem**	Number of requests for the (91) dynamic pages concerning the site's semantic structure
11	**MRequests_Sem**	Percentage of semantic requests (=NbRequests_Sem/ NbRequests) in the navigation
12	**TotalSize**	Total bytes transferred in a navigation
13	**ASize**	Average of transferred bytes among requests (= TotalSize / NbRequests_OK)
14	**MaxDuration_OK**	Maximum request duration among successful requests

Clustering approach based on time sub-periods

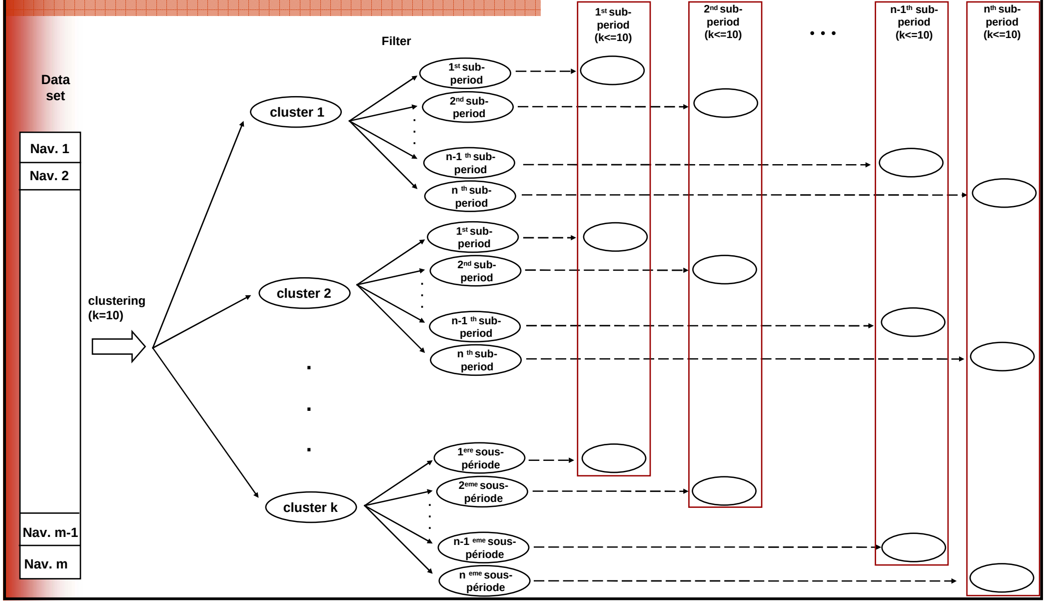
- To split the analyzed period into more significant time sub-periods: *months of the year*
- The clustering is carried out by an adapted version of the dynamic clustering algorithm (Celeux et al. (1989)):
  1. Assignment of new individuals to a previous clustering
  2. Initialization of the algorithm with the results of another clustering carried out by itself

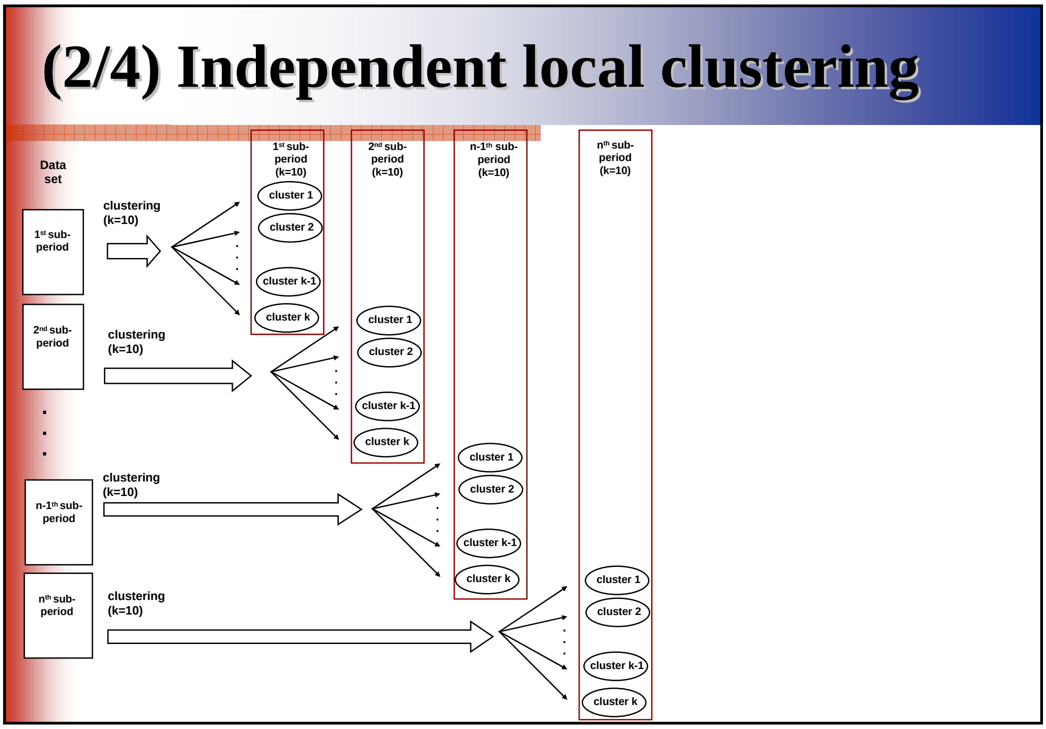
Clustering approach based on time sub-periods

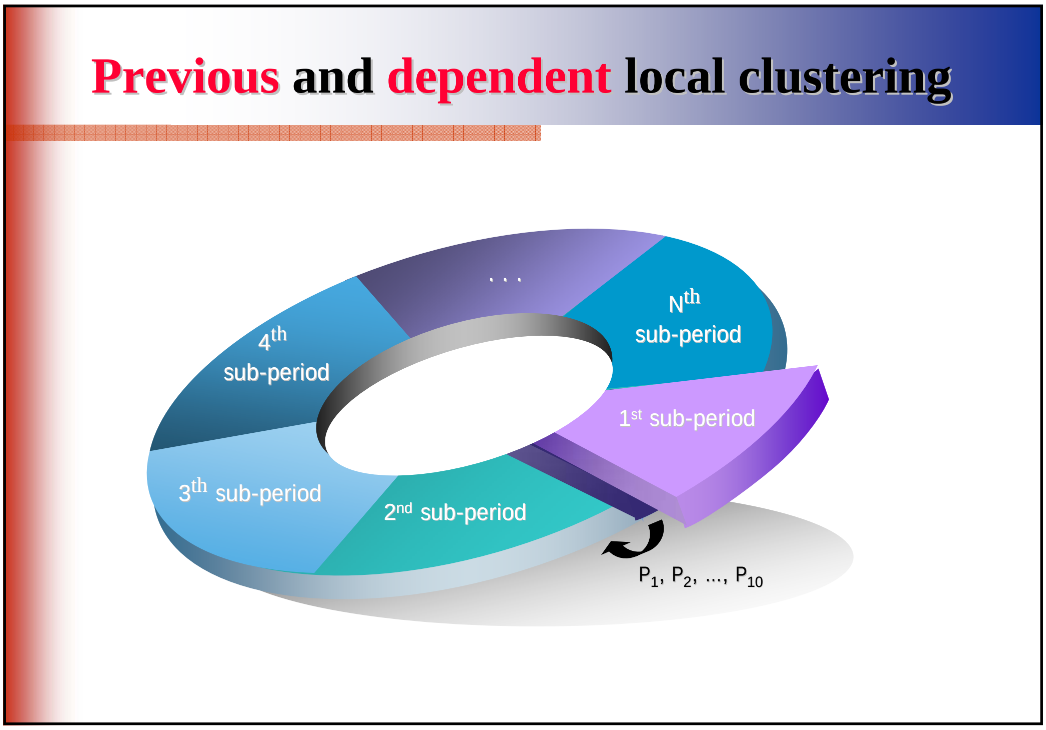
- Algorithm parameters :
  - Number of clusters = 10
  - Number of repetitions = 100

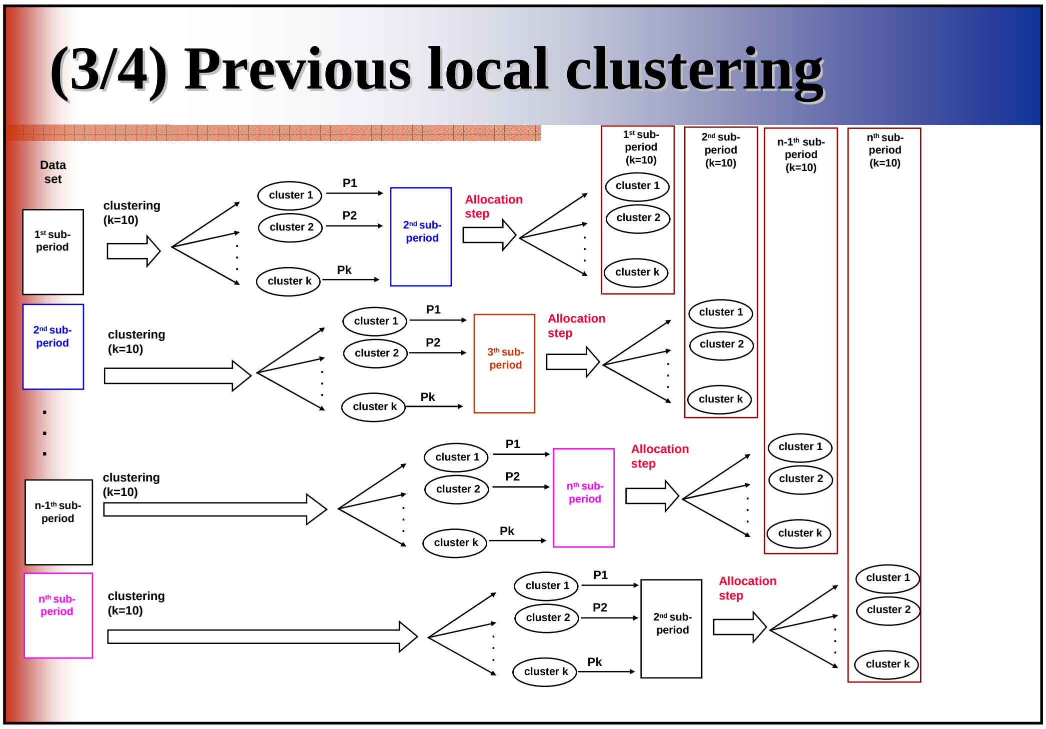
- To carry out four types of clustering :
  1. Global clustering
  2. Independent local clustering
  3. Previous local clustering
  4. Dependent local clustering

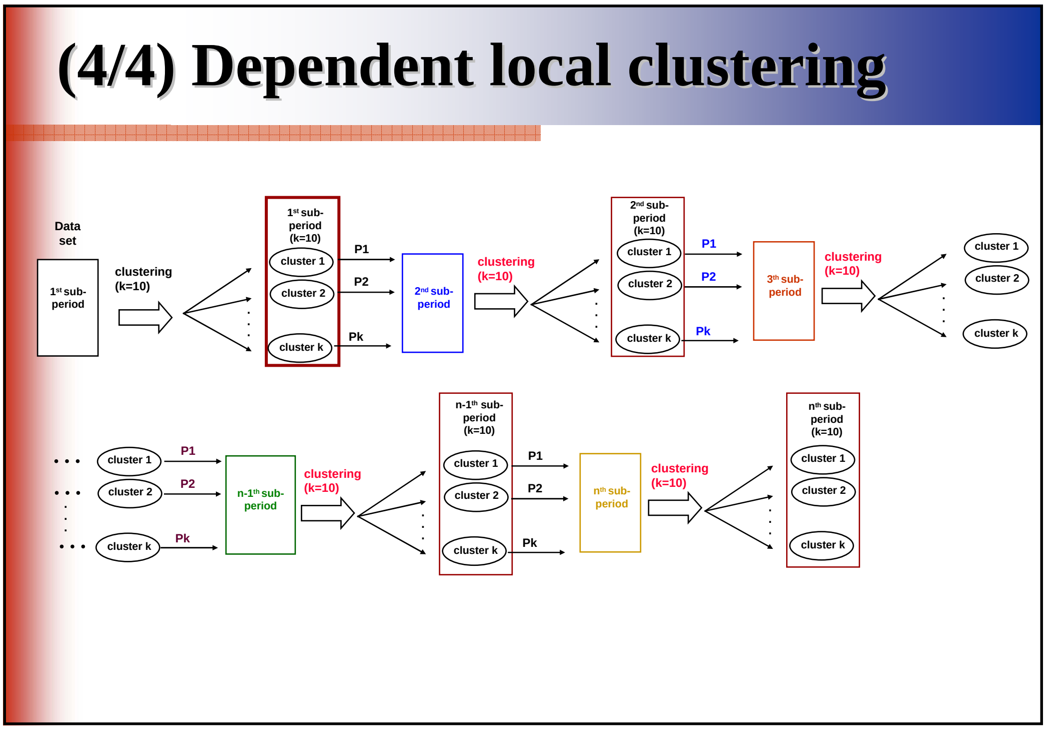
(1/4) Global clustering




(2/4) Independent local clustering
Data set
1st sub-period
2nd sub-period
n-1th sub-period
nth sub-period
clustering (k=10)
1st sub-period (k=10)
2nd sub-period (k=10)
n-1th sub-period (k=10)
nth sub-period (k=10)
cluster 1
cluster 2
cluster k-1
cluster k


Previous and dependent local clustering
. . .
Nth sub-period
4th sub-period
1st sub-period
3th sub-period
2nd sub-period
P1, P2, ..., P10


(3/4) Previous local clustering
Data set
1st sub-period
2nd sub-period
n-1th sub-period
nth sub-period
clustering (k=10)
cluster 1
cluster 2
cluster k
P1
P2
Pk
2nd sub-period
3th sub-period
nth sub-period
Allocation step
1st sub-period (k=10)
2nd sub-period (k=10)
n-1th sub-period (k=10)
nth sub-period (k=10)


(4/4) Dependent local clustering
Data set
1st sub-period
clustering (k=10)
1st sub-period (k=10)
cluster 1
cluster 2
cluster k
P1
P2
Pk
2nd sub-period
2nd sub-period (k=10)
3th sub-period
n-1th sub-period
n-1th sub-period (k=10)
nth sub-period
nth sub-period (k=10)

Results analysis

- Evaluation criteria :
  - For a cluster-by-cluster analysis
    - F-measure (van Rijsbergen (1979))
  - For a global analysis between two partitions
    - Corrected Rand index (Hubert et Arabie (1985))

Follow-up of cluster prototypes

- To better understand the cluster evolution over time sub-periods, we planned to:
  - Follow the evolution of cluster prototypes (month by month) for the local clustering: *independent* and *dependent*
  - Project these prototypes on the factorial plan computed over the total population

Follow-up of cluster prototypes

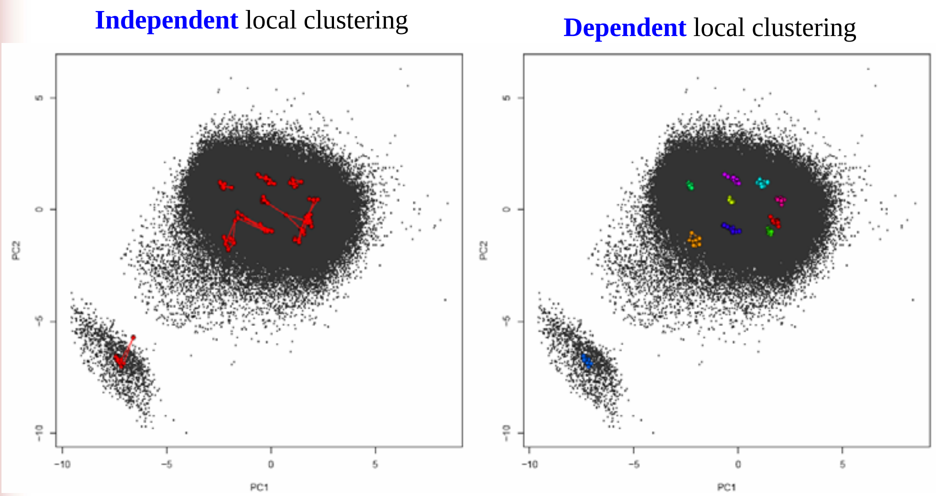


Fig.1 *Projection and follow-up of cluster prototypes for local clustering.*

Intra-cluster variance

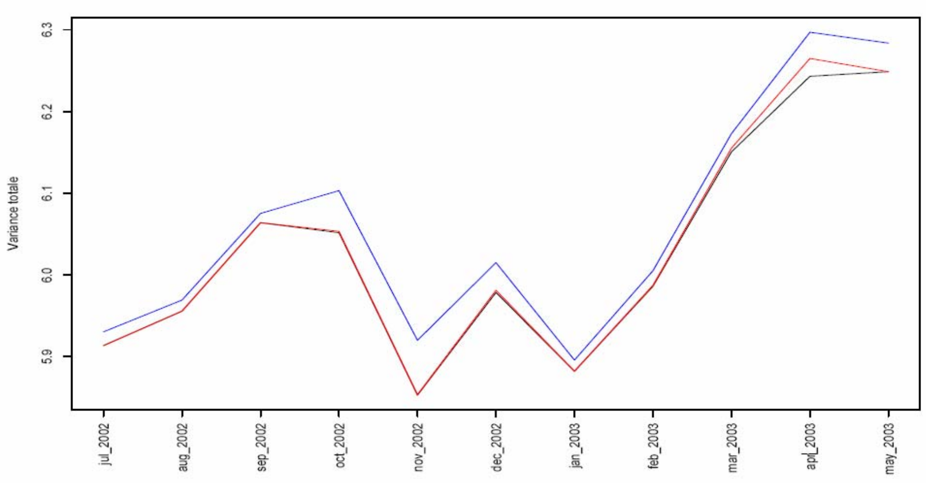


Fig.3 *Intra-cluster variance for clustering : independent (**black** line), dependent (**red** line) and global (**blue** line).*

Corrected Rand index results

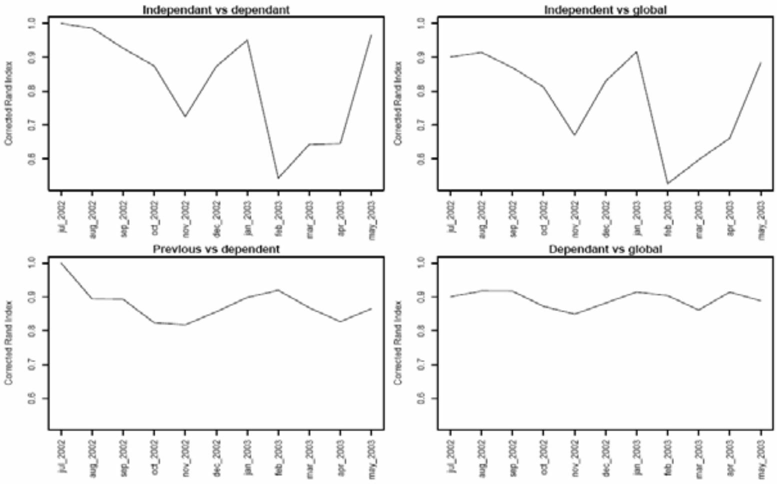


Fig.4 *Cluster-by-cluster corrected Rand index.*

F-measure results

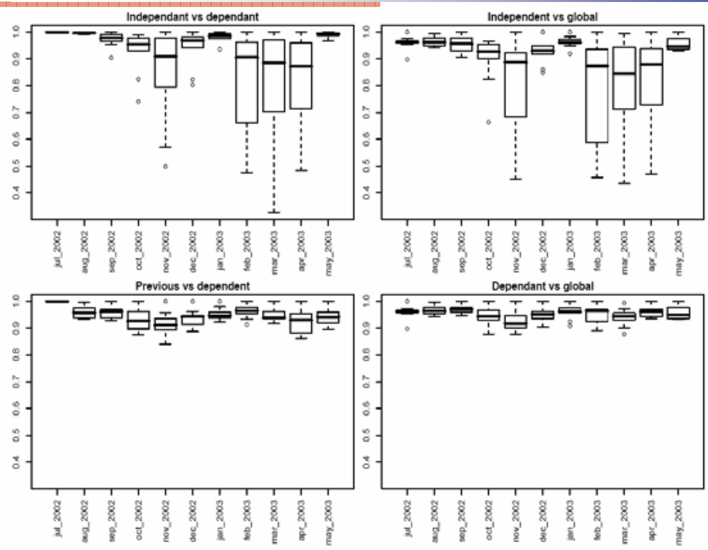


Fig.5 *Boxplots corresponding to cluster-by-cluster F-measures.*

Conclusion

- The methods of ***global*** and ***dependent local*** clustering show that the obtained partition do not change over time or change only a bit
- The method of **independent local clustering** is more sensitive to changes occurring between two sub-periods
- The analysis of dynamic data by means of time sub-periods offers advantages:
  - makes the method more effective in terms of cluster discovery
  - allows to overcome difficulties related to physical limitations (memory size, processor speed, etc.)

Future works

- Implementation of other clustering methods
- Application of techniques allowing the automatic discovery of the cluster number
- Identification of merge and split between clusters over time

Thanks for your attention!

Questions

Intra-cluster variation

$$V(Q) = \sum_{j=1}^{k} \sum_{x \in C_j} d(x, P_j)$$

F-measure

The F-mesure combines the concepts of precision and recall between two U_i and C_k of two partitions.

The recall is defined as R(i,k) = n_{ki} / $n_{k.}$
It computes the percentage of elements from class a priori k founded in class i obtained by the classification method.
The recall also decreases when the number of classes in the partition obtained by the classification decreases.

The precision is defined as P(i,k) = n_{ki} / $n_{.i}$
It computes the percentage of elements from class i founded in the a priori class k.
The precision increases when the number of classes in the partition obtained by the classification decreases.

F-measure

The F-measure between the *a priori* partition U in K classes and the partition P obtained by the classification method is defined as:

$$F = \sum_{k=1}^{K} (n_{.k}, n) \max_{j} (2.R(k, j).P(k, j)/(R(k, j) + P(k, j)))$$

F-measure for the *a priori* class k :

$$F(k) = \max_{j} (2.R(k, j).P(k, j)/(R(k, j) + P(k, j)))$$

Corrected Rand index

$$
\begin{array}{c|cccc|c}
 & v_1 & v_2 & \cdots & v_c & \\
\hline
u_1 & n_{11} & n_{12} & \cdots & n_{1C} & n_{1.} \\
u_2 & n_{21} & n_{22} & \cdots & n_{2C} & n_{2.} \\
\vdots & \vdots & \vdots & & \vdots & \vdots \\
u_R & n_{R1} & n_{R2} & \cdots & n_{RC} & n_{R.} \\
\hline
 & n_{.1} & n_{.2} & & n_{.C} & n_{..} = n
\end{array}
$$

$$
CR = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}\binom{n_{ij}}{2} - \binom{n}{2}^{-1}\sum_{i=1}^{R}\binom{n_{i.}}{2}\sum_{j=1}^{C}\binom{n_{.j}}{2}}{\frac{1}{2}\left[\sum_{j=1}^{C}\binom{n_{.j}}{2} + \sum_{i=1}^{R}\binom{n_{i.}}{2} + \right] - \binom{n}{2}^{-1}\sum_{i=1}^{R}\binom{n_{i.}}{2}\sum_{j=1}^{C}\binom{n_{.j}}{2}}
$$

Key statistics

- **After the pre-processing and data selection:**
  - – 138,536 navigations
  - – 184,275 pages (where 91 dynamics)
  - – 56,314 users
  - – Average duration of page visualization:
    - 1.19 minutes

Web Usage Mining: Sequential Pattern Extraction with a Very Low Support. Masseglia et al. In Advanced Web Technologies and Applications, APWeb 2004, Hangzhou, China. Vol. 3007, pages 513-522 of LNCS, 2004.

- The authors propose a method of recursive division for discovering sequential patterns of weak support (until 0.006%):
  - hacking activities
  - minority users' behaviours

- The split is based on a classification over the whole log and on time

The dynamic clustering method

Let E be a set of n objects $\{s_1,\ldots,s_n\}$ described by p variables, Λ be a set of prototypes and ψ be a distance function on $D_x \times \Lambda$.

Each object s of E is described by a vector $\mathbf{x}_s$ of D_x (the representation space of elements in E).

The problem is to find simultaneously:

- one partition $P = (C_1,\ldots,C_K)$ of E in not empty K classes
- the prototypes $L = (L_1,\ldots,L_K)$ of Λ which optimise the criteria $\Delta(P,L)$:

$$\boxed{\Delta(P,L) = \sum_{k=1}^{K} \sum_{s \in C_i} \psi(\mathbf{x}_s, L_k) \quad C_k \in P, L_k \in \Lambda}$$

The dynamic clustering algorithm
Diday (1971)

(a) Initialization

Choose K distinct prototypes $L_1,\ldots,L_K$ in Λ

(b) Allocation

For each objet s_i of E compute the index l of the affectation class which verifies $l = \arg\min_{k=1,\ldots,K} \psi(\mathbf{x}_i, L_k)$

(c) Representation

For each class k find the prototype L_k in Λ which minimizes $w(C_k, L) = \sum_{s \in C_k} \psi(\mathbf{x}_s, L)$

Repeat (b) and (c) until the convergence

The original *k-means* algorithm

Suppose we have a sample of infinite size.

With the $\mathbf{x}_t$ implementation, we only have information regarding the sample of size t .

Initialization Choose K points in $\Re^p$ $L_0 = (L_0^1, \ldots, L_0^K)$

At the t step We associate the $\mathbf{x}_t$ implementation to the class k which has the nearest prototype $k = \arg\min_{l=1,\ldots,K} \psi\left(L_t^l, x_t\right)$

We modify the prototype of the class k by $L_{t+1}^k = \frac{n_k L_t^k + x_t}{n_k + 1}$

where n_k is the number of implementation already put into the class k.

Stopping criterion we must have $\psi\left(L_{t+1}, L_t\right) \leq \varepsilon$

Projection of cluster prototypes

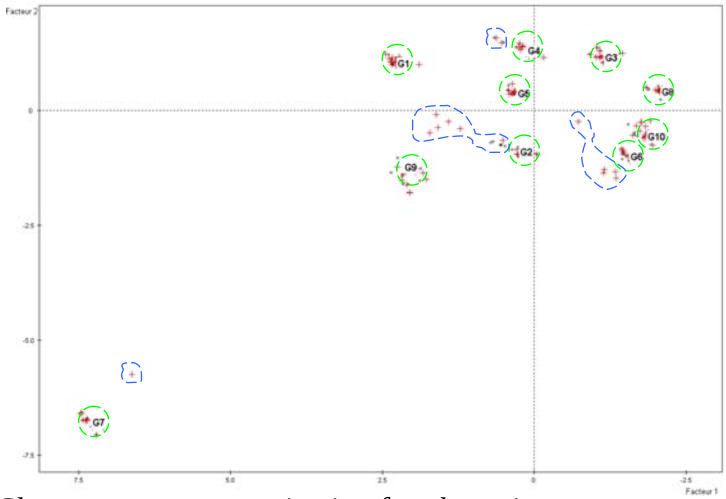


Fig.2 *Cluster prototypes projection for clustering : global (G1, G2, ...,G10), dependent local (o) and independent local (+).*