Diachronic’Explorer : keep track of your clusters !

Nicolas Dugué, Jean-Charles Lamirel
LORIA-Synalp
Vandoeuvre lès Nancy, France.
e-mail : first.last@loria.fr

Pascal Cuxac
CNRS-INIST
Vandoeuvre lès Nancy, France.
e-mail: pascal.cuxac@inist.fr

Abstract—We introduce Diachronic’Explorer, a toolbox to produce and visualize diachronic results, which is based on a new complete theoretic framework for diachrony that we detail. This toolbox, which is dedicated to run diachronic algorithms from clustering results, allows also to explore complex diachronic results at all the granularity levels through a web application.

I. INTRODUCTION

The ISTEX project compiles and provides access to scientific publications to French research. ISTEX-R project aims to highlight evolution of research topics using the ISTEX database. To that aim, we designed a new theoretical framework to track scientific fields changes and similarities across time : appearing and disappearing topics, splitting and merging topics. This framework is based on diachronic analysis, which aims to compare data or results from two distinct periods. Furthermore, this framework was implemented as a toolbox called Diachronic’Explorer that integrates all diachronic analysis steps and provides efficient visualizations.

In the context of our framework, we basically consider time periods, containing documents split into separate sets according to these time periods and described by a set of features \( F \) (words or expressions) : \( D = \bigcup_{0 \leq i \leq tp} D_i \). For each time period, clustering algorithms detect cluster sets such as \( CS = \bigcup_{0 \leq i \leq tp} C_i \). Each set of clusters \( C_i = \{c_1, \ldots, c_{n_i}\} \) is constituted of \( n_i \) clusters describing data \( D_i \). Clusters gather similar documents and thus represent topics. Consequently, to monitor topic changes, our framework aims to track cluster changes and similarities across time periods.

The first step of our new framework consists in labeling clusters of every cluster sets. These labels will then be used to track cluster changes and similarities. Our labeling step consists in extracting prevalent features sets \( S_{c_j} \) for each cluster \( c_j \in C_i \) of all the cluster sets \( C_i \in CS \) using a feature selection method. We implement the feature maximization method proposed by Lamirel et al. [3] that has proven to be efficient for both supervised and unsupervised learning.

The second step processes diachronic analysis between time periods using cluster labels. Basically, using \( S_{c_j} \), the prevalent features sets of each cluster, we apply a diachronic algorithm based on MVDA, an unsupervised Bayesian process operating between views (here periods) for diachronic mining [4].

II. FEATURE SELECTION FOR CLUSTER LABELING

The first step of our framework consists in labeling clusters using a feature selection method. The one we implement is non-parametric, only weakly influenced by feature scaling, and it allows to label clusters with ordered weighted features [3]. We apply it independently to each period. Thus, for each cluster set \( C_i, 0 \leq i \leq tp \), two ratios are processed over each cluster \( c_j \in C_i, 0 \leq j \leq n_i \) to give a weight to features of \( F \) for the cluster considered. On the first hand, Feature Predominance (Equation 1) aims to evaluate if a feature \( f \in F \) allows to discriminate \( c_j \) from other clusters of \( C_i \). On the other hand, Feature Recall (Equation 2) aims to evaluate whether \( f \) allows to faithfully describe data in \( c_j \).

*\[
FP_{c_j}(f) = \frac{W_{f_j}^c}{W_{f_j}^c + W_{f_j}^d} \quad (1) \quad FR_{c_j}(f) = \frac{W_{f_j}^c}{W_{f_j}^c + W_{f_j}^d} \quad (2)
\]*

with \( W_{f_j}^c = \sum_{d \in c_j} W_{f_j}^d \) the weighted sum of \( f \) across cluster \( c_j \), \( W_{f_j}^c = \sum_{d \in C_i} W_{f_j}^d \) the weighted sum of \( f \) across the data of the time period considered, \( W_{c_j} = \sum_{f \in F} W_{f_j}^c \) the weighted sum of all features across cluster \( c_j \). The Feature F-Measure \( FF_{c_j}(f) \) is the harmonic mean of these two values.

The Feature F-Measure is thus used to select features that are discriminant and representative for each cluster \( c_j \) using Equation 3.

*\[
S_{c_j} = \{f \in F | FF_{c_j}(f) > FF_{C_i}(f), FF_{c_j}(f) > FF_{C_i} \}\quad (3)
\]*

with \( FF(f) \) the mean F-Measure value of \( f \) across clusters of \( C_i \) where \( f \) is non-null, and \( FF_{C_i} \) the mean F-Measure across all features and all data of the considered period. Figure 1 shows how features selected for a cluster with Diachronic’Explorer are used as labels to describe the cluster in the visualization module.

III. DIACHRONY WITH MVDA

Once the representative labels of each cluster extracted, our second step consists in applying MVDA diachronic analysis between each time periods pairs. MVDA was firstly experimented as a fully unsupervised approach by Lamirel [4],...
but here, we use cluster labels instead of indexer keywords. This process is theoretically based on Bayesian reasoning [4] whose operating mode can be summarized as this in our context: the diachronic analysis is processed by computing matching probabilities between clusters of distinct sets (thus time periods) using the selected labels they share or not. The matching probability of a cluster \( s \) from a set \( C_{src} \) and a cluster \( t \) from a set \( C_{tgt} \) is computed as shown in Equation 4.

\[
P(t|s) = \frac{\sum_{f \in S \cap T} FF_t(f)}{\sum_{f \in S} FF_t(f)}
\]

The matching probability between \( t \) and \( s \) is processed symmetrically. Finally, an asymmetric match from \( s \) to \( t \) is detected if the matching probability \( P(t|s) \) is greater than the average matching probability of \( s \) with the clusters of \( C_{tgt} \). A symmetric match exists if both asymmetric match from \( s \) to \( t \), and from \( t \) to \( s \) are detected. In such a case, the set of features describing this match is called the matching kernel (Figure 2).

These different kind of match detected by Diachronic'Explorer allow us to track and describe changes and similarities between cluster sets of distinct periods.

**IV. EXPERIMENTAL RESULTS AND VISUALIZATIONS**

Experiments and visualizations shown in these papers were conducted on a corpus constituted of bibliographic data from the ISTEX project [6]. The ISTEX database is queried to extract papers related to research in medical care between years 1996 and 2010. This results in a dataset of 9779 papers. Because the goal is to observe evolution of this field across time, a community detection algorithm [5] exploiting the relationship between documents indexes and the publication time, a community detection algorithm [5] exploiting the relationship between documents indexes and the publication time, is launched several times on the data of each meta-period. Obtained meta-periods are 1996-2000, 2000-2005, 2006-2010 [1]. GNG clustering [2] is launched several times on the data of each meta-period to extract an optimal number of clusters with the help of ad-hoc quality indexes [4]. Then, using Diachronic'Explorer\(^1\), we produce and then visually explore the diachronic results with powerful dynamic visualizations using advanced Javascript\(^2\). Visualization tool of Diachronic'Explorer makes possible to navigate easily from one granularity level to another: cluster and their labels (Figure 1), match between two periods (Figure 2), overall dataset evolution (Figure 3).

**V. CONCLUSION**

Integrating a new framework using powerful labeling method and unsupervised Bayesian reasoning among clusters sets, Diachronic'Explorer allows to produce diachronic results and provides a web application to visualize these results, navigating easily from one granularity level to another.

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**References**


\(^1\)Demo - Choose "2iers1tiers" experiment - http://107.170.67.36:3000/

\(^2\)https://d3js.org/