ClusPath: a Temporal-driven Clustering to Infer Typical Evolution Paths

M.A. Rizoiu, J. Velcin, S. Bonnevay & S. Lallich Australian National University & University Lumière Lyon





1 The problem

- Detect typical evolution paths of individuals through time.
- "Slow changing world" hypothesis: changes in the population are gradual and smooth, detect of long term trends.
- Allow the relations between phases to emerge from the data.

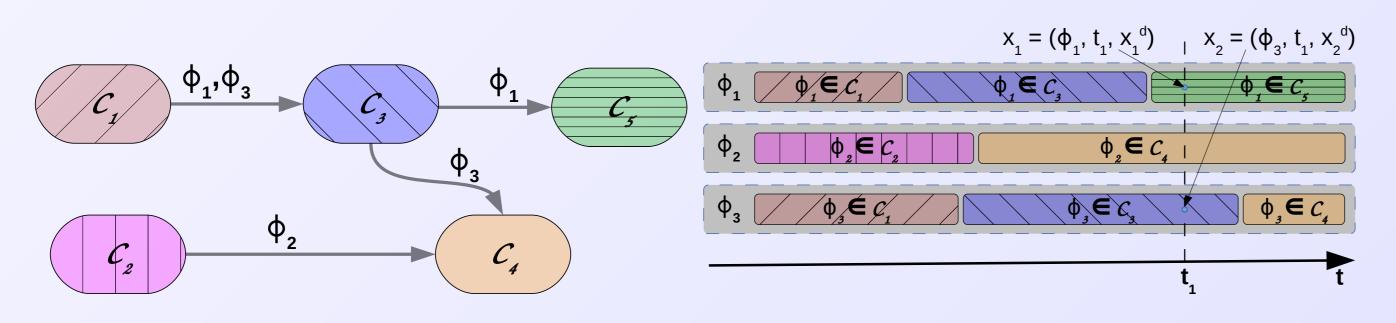


Figure 1: An example of a desired output, in which the evolutions of 3 entities (ϕ_1, ϕ_2) and ϕ_3 are described using 5 phases $(C_i, i = 1, ..., 5)$. For example, the evolution path of ϕ_3 is $C_1 \to C_3 \to C_3$. **Left:** The graph structure of the evolution phases. The arcs between two phases (C_i, C_j) are labeled with the entities presenting the transition $C_i \to C_j$. **Right:** The observations of the 3 entities are partitioned contiguously into the 5 phases.

2 A temporal clustering solution

- A temporal-aware constrained clustering algorithm, for which the resulted clusters serve as evolution phases.
- The relations between the evolution phases are inferred simultaneously with the partition.

3 objectives

Obj. 1 Construct clusters that are coherent in the temporal and in the descriptive space, using a temporal aware dissimilarity measure:

$$||x_i - x_j||_{TA} = 1 - \left(1 - \gamma_d \frac{||x_i^d - x_j^d||^2}{\Delta d_{max}^2}\right) \left(1 - \gamma_t \frac{||x_i^t - x_j^t||^2}{\Delta t_{max}^2}\right)$$

Obj. 2 Segment, as contiguously as possible, the series of observations for each entity, using temporally-oriented soft must-link pair-wise constraints. Inflict the penalty $w(x_i, x_k)$ when the constraint between x_i and x_k is violated.

Figure 2: Example of forward-oriented must-link constraints violated by the given segmentation.

Obj. 3 Present smooth passages between phases on evolution paths, i.e., changes should come in small increments.

- The evolution phases are structured as an oriented graph: $a_{p,q}$ strength of link between C_p and C_q .
- The strength of the link from C_p to C_q is proportional to the similarity of their prototypes μ_p and μ_q :

$$T_2 = \sum_{\substack{\mu_p \in \mathcal{M} \\ p \neq q}} \sum_{\substack{\mu_q \in \mathcal{M} \\ p \neq q}} a_{p,q}^2 ||\mu_p - \mu_q||_{TA}$$

• The strength of the link from C_p to C_q is proportional to the number of entities that present a transition from C_p to C_q :

$$inter_{\phi}(\mathcal{C}_{p}, \mathcal{C}_{q}) = 1 - \frac{|\{\phi_{l} \in \Phi | \mathcal{C}_{p} \xrightarrow{\phi_{l}} \mathcal{C}_{q}\}|}{|\Phi|}$$

$$T_{3} = \sum_{\substack{\mu_{p} \in \mathcal{M} \\ p \neq q}} \sum_{\substack{\mu_{q} \in \mathcal{M} \\ p \neq q}} a_{p,q}^{2} inter_{\phi}^{2}(\mathcal{C}_{p}, \mathcal{C}_{q})$$

The ClusPath algorithm

- K-Means inspired, iterates three update phases: a) recompute prototypes, b) assign observations to clusters and c) recompute adjacency matrix between phases.
- Evaluate resulted partition using four measures: **MDvar**, **Tvar** (descriptive and temporal variance), **ShaP** (contiguous segmentation) and **SPass** (smooth passage)

ShaP =
$$\frac{1}{|\Phi|} \sum_{\phi \in \Phi} \sum_{i=1}^{k} \left[-p_{\phi}(\mathcal{C}_i) \log_2(p_{\phi}(\mathcal{C}_i)) \right] \left(1 + \frac{n_{ch} - n_{min}}{N-1} \right), \quad p_{\phi}(\mathcal{C}_i) = \sum_{x_j \in \mathcal{C}_i} \frac{1}{N}$$

$$x_j^{\phi} = \phi$$

 $\mathbf{SPass} = \sum_{\phi \in \Phi} \sum_{\substack{c_i \to c_j \\ \mathcal{C}_i \to \mathcal{C}_j}}^{i,j \in 1, \dots, k} \frac{||\mu_i - \mu_j||_{TA}}{n_{ch}}$

3 Two datasets

Comparative Political Dataset I

- 23 countries
- 60 years
- 207 political, social and economic variables

European Companies

- 836 companies
- 5 years
- 7 economic variables

Automatically setting parameters using an evolutionary technique

The six parameters of ClusPath (α , β , δ , λ_1 , λ_2 , λ_3) can be automatically tunned using an evolutionary technique, that approximates the Pareto front in the four-dimensional space of the measures. We chose the parameters that produce a balanced solution (closest to the ideal point (0,0,0,0)).

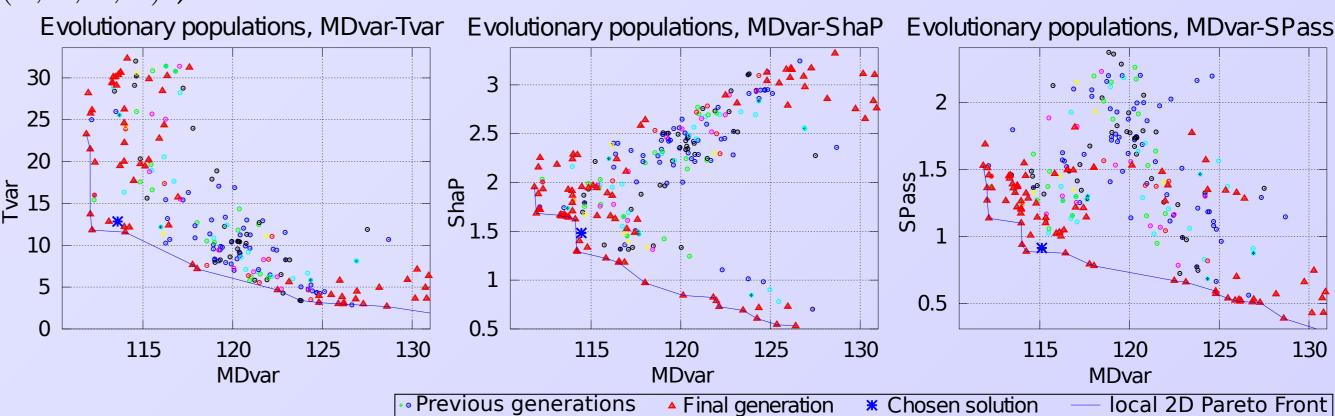


Figure 3: Typical example of execution of the evolutionary algorithm on CPDS1. The obtained 4-dimensional Pareto front is projected onto the (*MDvar*, *Tvar*) space (left), (*MDvar*, *ShaP*) space (middle) and (*MDvar*, *SPass*) space (right).

4 Detecting political systems

Typical evolution paths are taken by most entities (e.g. $C_7 \longrightarrow C_{11} \longrightarrow C_{15}$). Their meaning emerges by studying the entities following them: $C_5 \longrightarrow C_{11}$ (Spain, Portugal and Greece) coincides with non-democratic regimes and $C_4 (\longrightarrow C_7) \longrightarrow C_{11}$ (Denmark, Finland, Iceland, Norway and Sweden) maps onto the "Swedish Social and Economical Model".

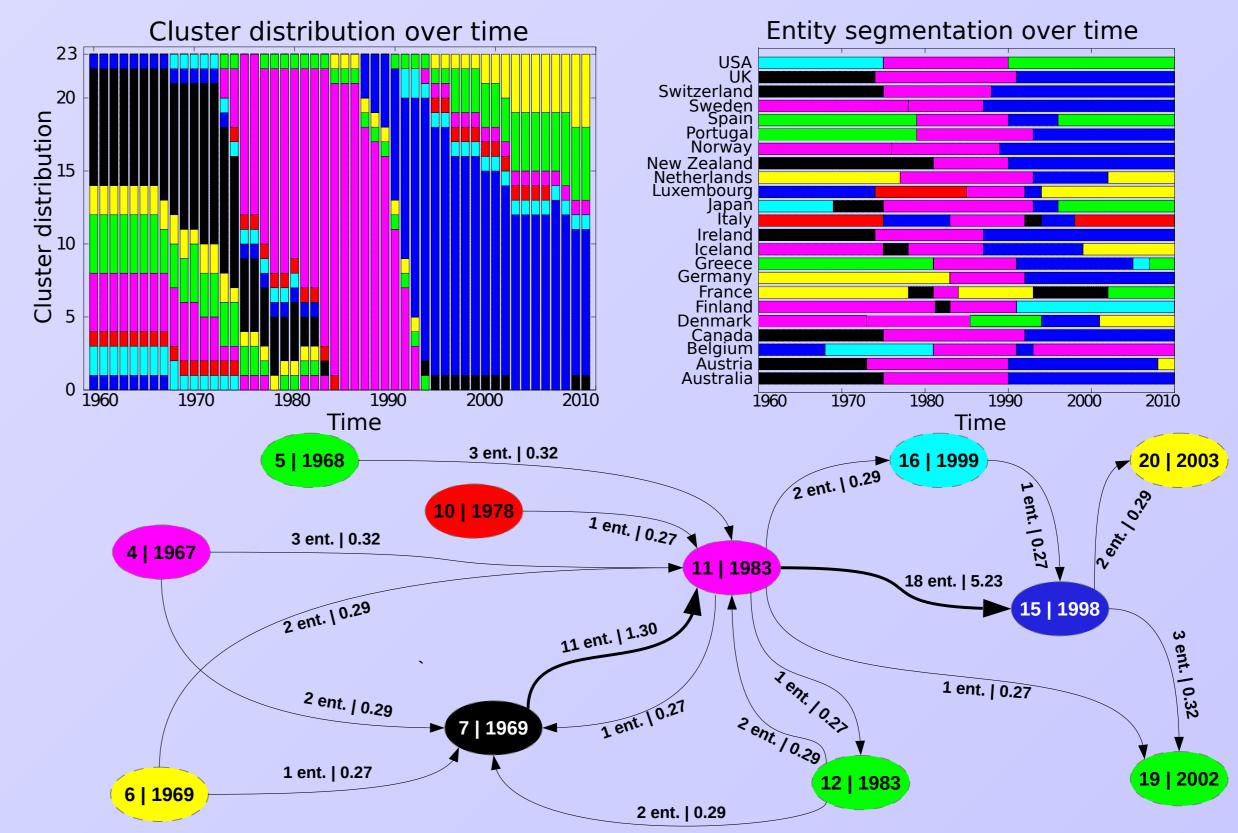


Figure 4: Typical evolution phases constructed by ClusPath on CPDS1, with 20 clusters. Number of entities in each phase per year (a), segmentation of entities over phases (b) and the phase evolution graph (c)

5 Detecting fiscal optimization

"Tax optimization" undertook by most companies in the EC dataset: most companies arrive to decrease significantly their tax rate, while increasing the net income.

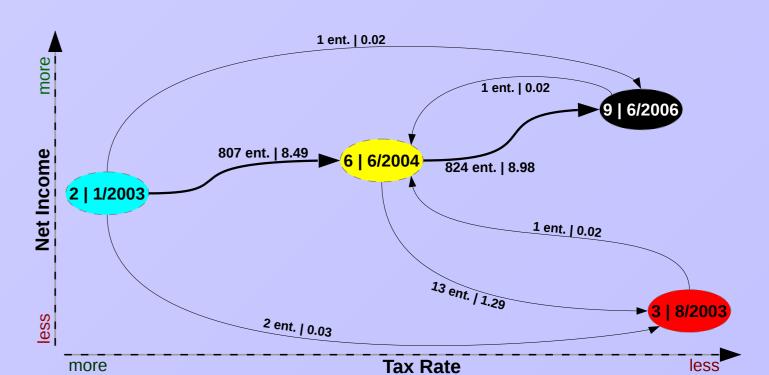


Figure 5: Typical evolution phases constructed by ClusPath on EC, with 10 clusters. The evolution graph is projected in the space *NetIncome/TaxRate*.