Mining Event or State Sequences: A Social Science Perspective

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- My talk is about life courses,
- Example of scientific life course
- to help you understand what a social scientist does at IIS

date	event
1970-1979	Studies in econometrics
1980-1992	Mathematical Economics
1985-...	Work with Social scientists (Family studies)
	Interest in Statistics for social sciences
1990-1995	Interest in Neural Networks
2000-...	KDD and data mining (Clustering, supervised learning)
2003-...	Work with historians, demographers, psychologists
	(longitudinal data)
2005-...	KDD and Data mining approaches
	for analysing life course data

Outline

Motivation

- Individual life course paradigm.
  - Following macro quantities (e.g. #divorces, fertility rate, mean education level, ...) over time
    insufficient for understanding social behavior.
  - Need to follow individual life courses.
- Data availability
  - Large panel surveys in many countries
    (SHP, CHER, SILC, GGP, ...)
  - Biographical retrospective surveys (FFS, ...).
  - Statistical matching of censuses, population registers and other administrative data.

Motivation

- Need for suited methods for discovering interesting knowledge from these individual longitudinal data.
- Social scientists use
  - Essentially Survival analysis (Event History Analysis)
  - More rarely sequential data analysis (Optimal Matching, Markov Chain Models)
- Could social scientists benefit from data-mining approaches?
  - Which methods?
  - Are there specific issues with those methods for social scientists?

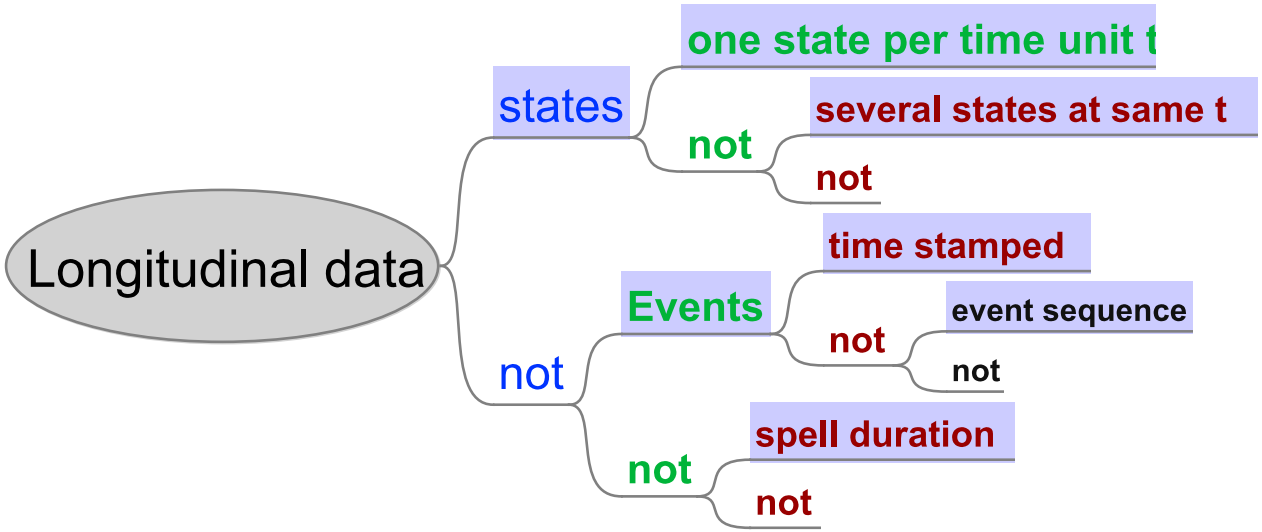
Motivation: KD in Social sciences

- In KDD and data mining, focus on prediction and classification.
- Improve prediction and classification errors.

- In Social science, aim is understanding/explaining (social) behaviors.
- Hence focus is on process rather than output.

What kind of data

- What kind of data are we dealing with?
- Mainly categorical longitudinal data describing life courses
- An ontology of longitudinal data (Aristotelean tree).



Alternative views of Individual Longitudinal Data

Table: Time stamped events, record for Sandra

ending secondary school in 1970	first job in 1971	marriage in 1973

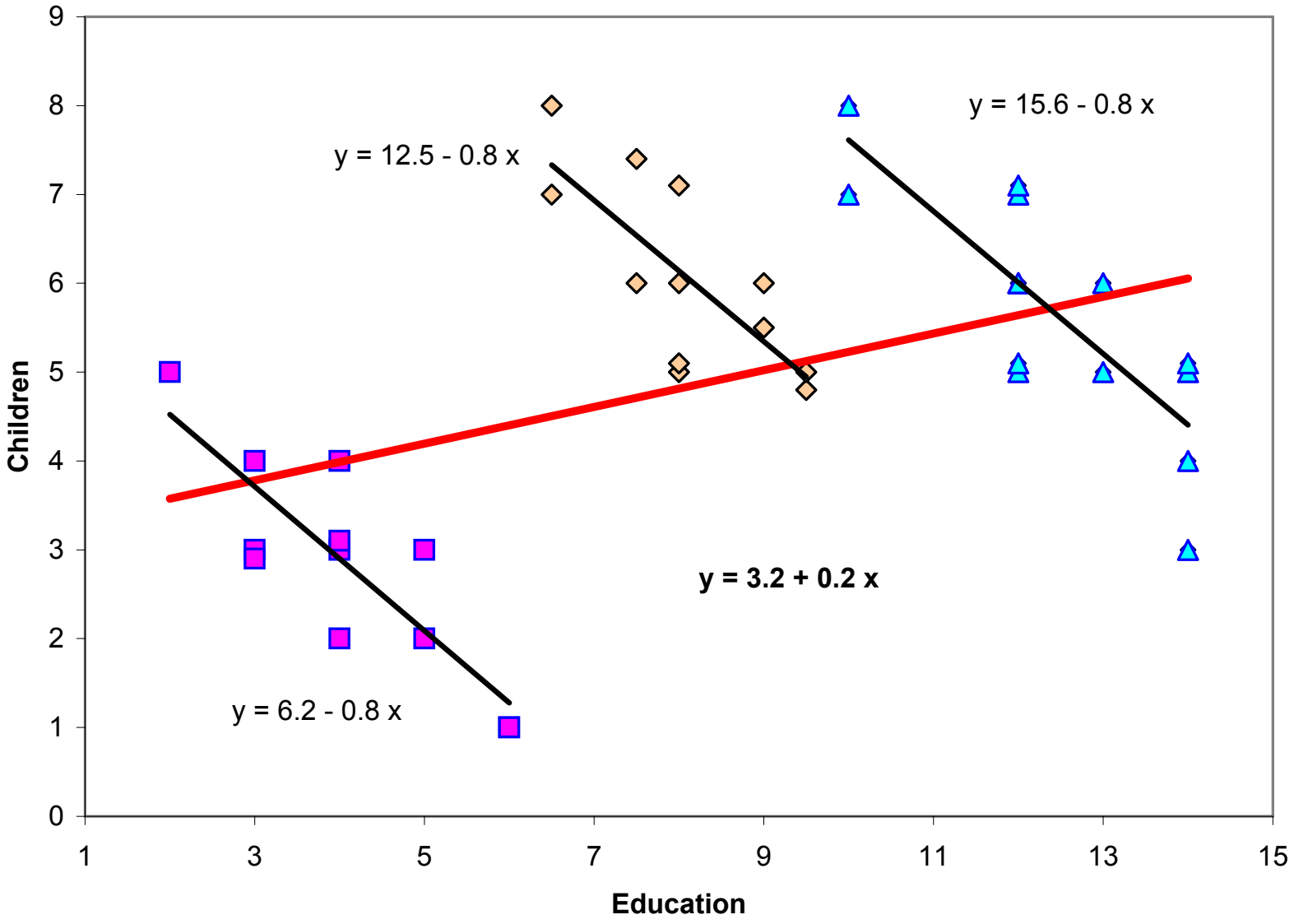
Table: State sequence view, Sandra

year	1969	1970	1971	1972	1973
civil status	single	single	single	single	married
education level	primary	secondary	secondary	secondary	secondary
job	no	no	first	first	first

Issues with life course data

- Incomplete sequences
  - Censored and truncated data:
    Cases falling out of observation before experiencing an event of interest.
  - Sequences of varying length.
- Time varying predictors.
  - Example: When analysing time to divorce, presence of children is a time varying predictor.
- Data collected by clusters
  - Example: Household panel surveys.
  - Multi-level analysis to account for unobserved shared characteristics of members of a same cluster.

Multi-level: Simple linear regression example



Classical statistical approaches

Survival Approaches

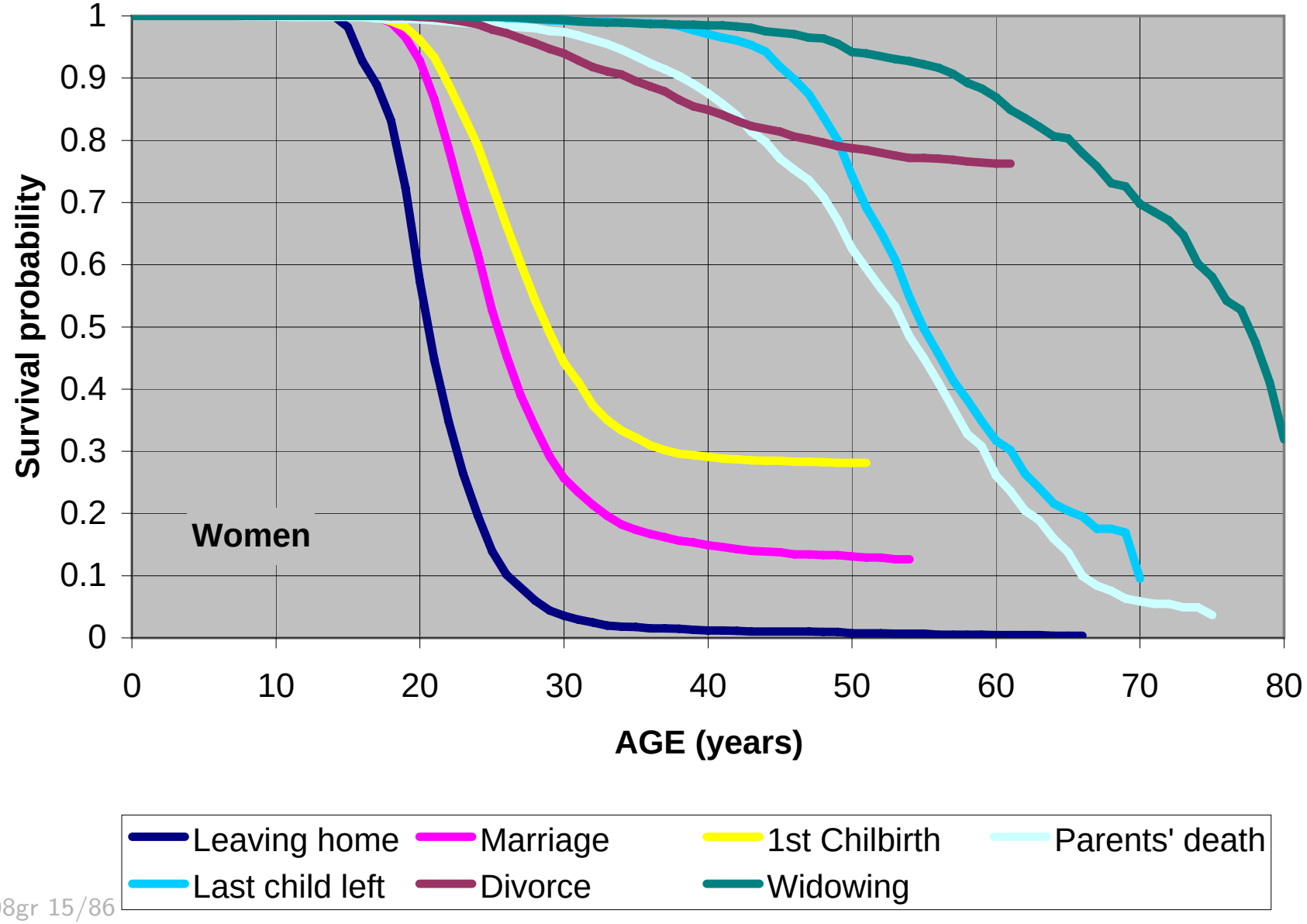
- Survival or Event history analysis (Blossfeld and Rohwer, 2002)
  - Focuses on one event.
  - Concerned with duration until event occurs or with hazard of experiencing event.
- Survival curves: Distribution of duration until event occurs

$$S(t) = p(T \geq t) \ .$$

- Hazard models: Regression like models for $S(t, \mathbf{x})$ or hazard $h(t) = p(T = t \mid T \geq t)$

$$h(t, \mathbf{x}) = g\Big(t, \beta_0 + \beta_1 x_1 + \beta_2 x_2(t) + \cdots\Big) \ .$$

Survival curves (Switzerland, SHP 2002 biographical survey)



Analysis of sequences

- Frequencies of given subsequences
  - Essentially event sequences.
  - Subsequences considered as categories ⇒ Methods for categorical data apply (Frequencies, cross tables, log-linear models, logistic regression, ...).
- Markov chain models
  - State sequences.
  - Focuses on transition rates between states.
    Does the rate also depend on previous states?
    How many previous states are significant?
- Optimal Matching (Abbott and Forrest, 1986) .
  - State sequences.
  - Edit distance (Levenshtein, 1966; Needleman and Wunsch, 1970) between pairs of sequences.
  - Clustering of sequences.

Typology of methods for life course data

	Issues	
Questions	duration/hazard	state/event sequencing
descriptive	• Survival curves: Parametric (Weibull, Gompertz, ...) and non parametric (Kaplan-Meier, Nelson-Aalen) estimators.	• Optimal matching clustering • Frequencies of given patterns • Discovering typical episodes
causality	• Hazard regression models (Cox, ...) • Survival trees	• Markov models • Mobility trees • Association rules among episodes

SHP biographical retrospective survey

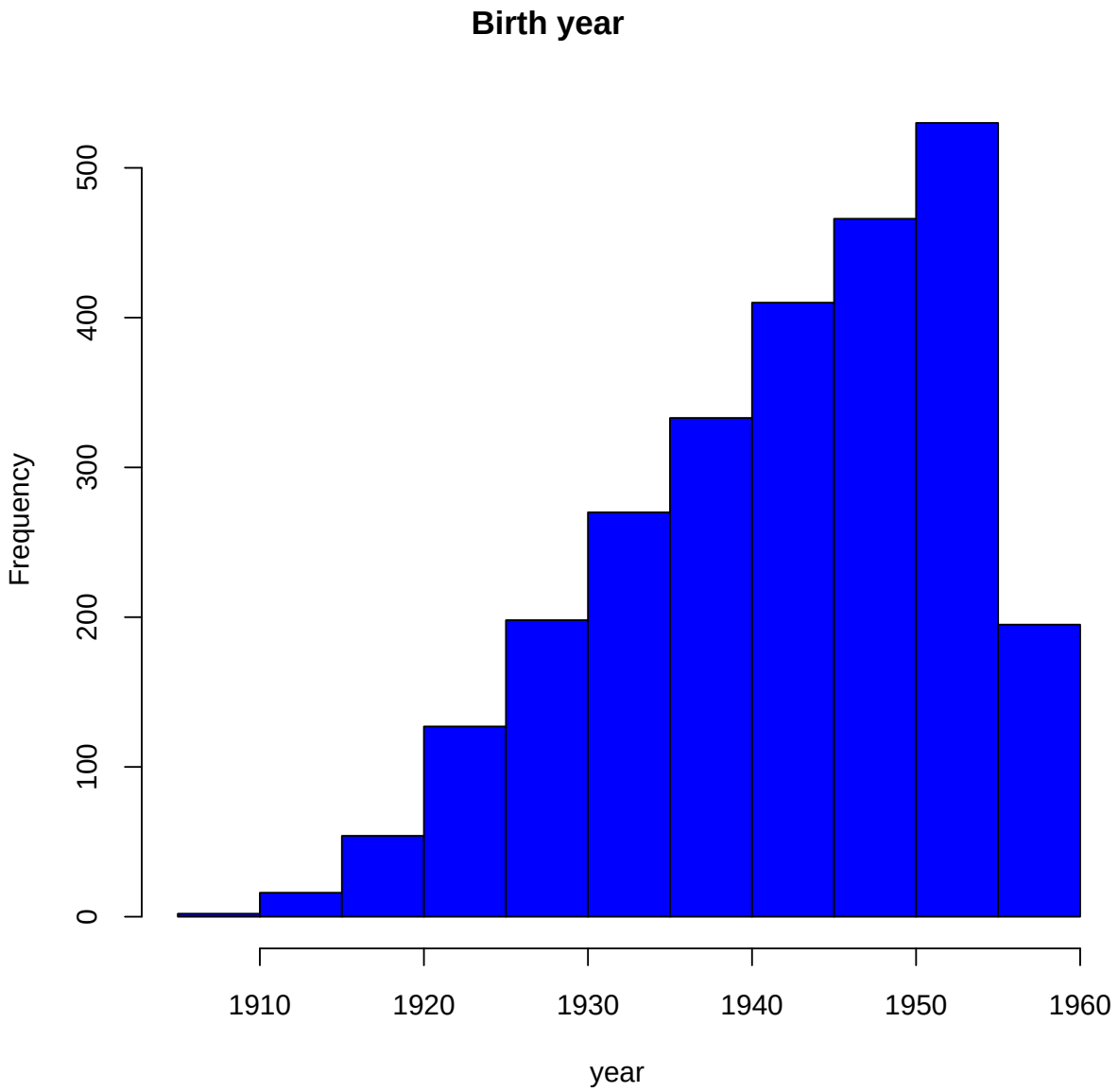
http://www.swisspanel.ch

- SHP retrospective survey: 2001 (860) and 2002 (4700 cases).
- We consider only data collected in 2002.
- Data completed with variables from 2002 wave (language).

Characteristics of retained data for divorce
(individuals who get married at least once)

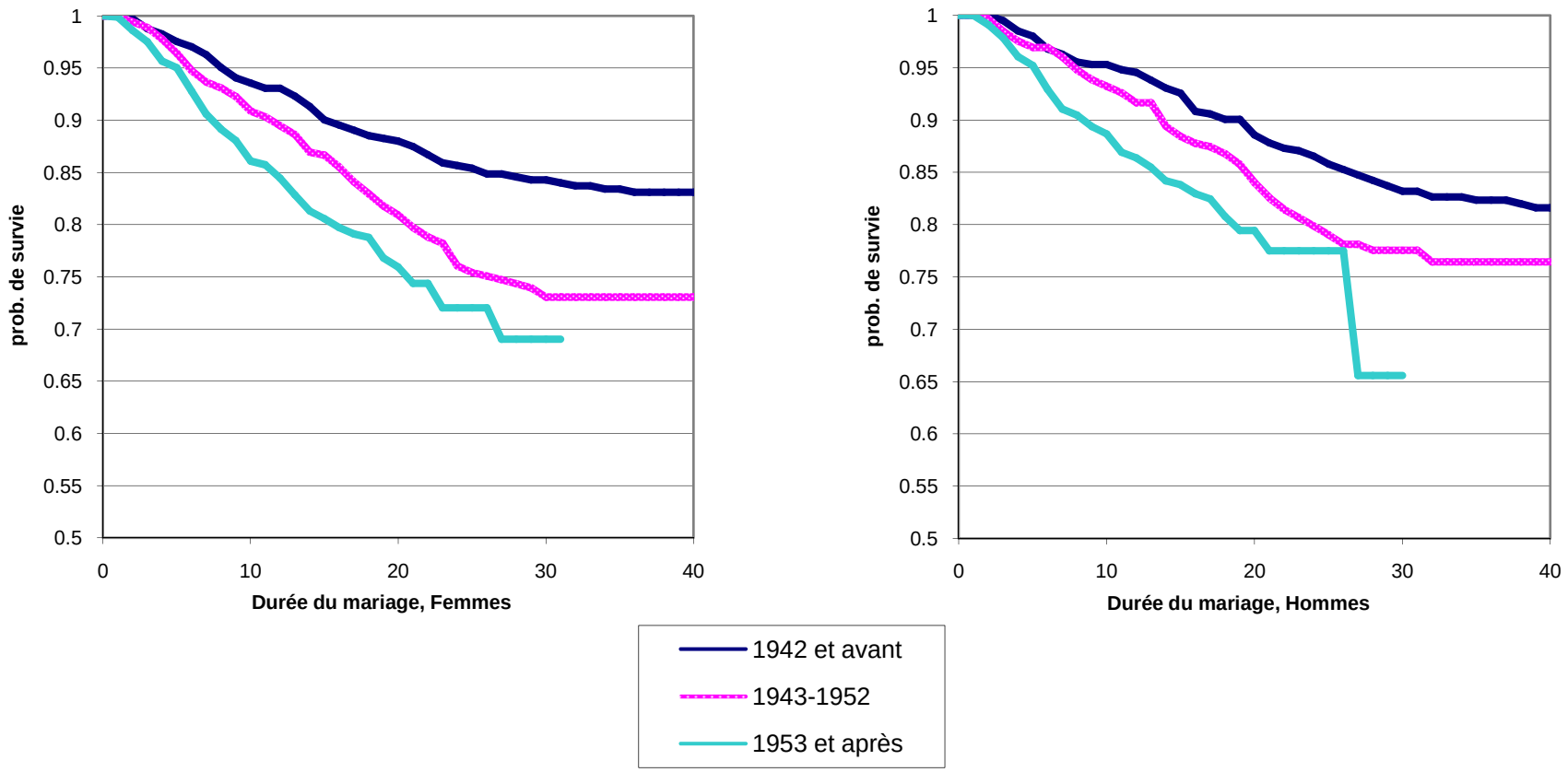
	men	women	Total
Total	1414	1656	3070
1st marriage dissolution	231	308	539
	16.3%	18.6%	17.6%

Distribution by birth cohort



Marriage duration until divorce

Survival curves



Marriage duration until divorce

Hazard model

- Discrete time model (logistic regression on person-year data)
- $\exp(B)$ gives the Odds Ratio, i.e. change in the odd $h/(1-h)$ when covariate increased by 1 unit.

		exp(B)	Sig.
birthyr		1.0088	0.002
university		1.22	0.043
child		0.73	0.000
language	unknwn	1.47	0.000
	French	1.26	0.007
	German	1	ref
	Italian	0.89	0.537
Constant		0.0000000004	0.000

Survival trees: Principle

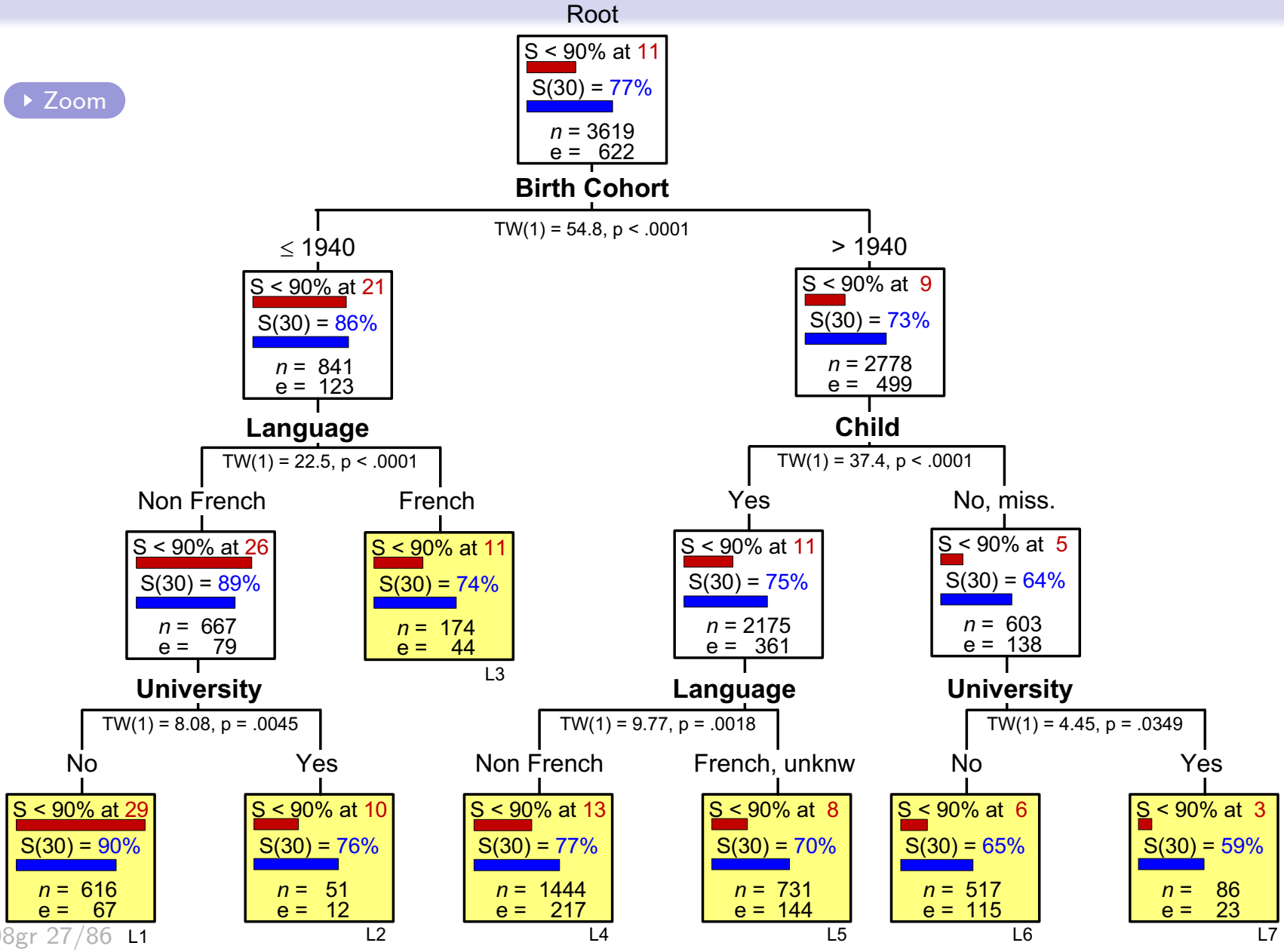
- Target is survival curve or some other survival characteristic.
- Aim: Partition data set into groups that
- differ as much as possible (max between class variability)
  - Example: Segal (1988) maximizes difference in KM survival curves by selecting split with smallest p-value of Tarone-Ware Chi-square statistics

$$TW = \sum_i \frac{w_i \Big(d_{i1} - \mathrm{E}(D_i) \Big)}{\Big(w_i^2 \, \mathrm{var}(D_i) \Big)^{1/2}}$$

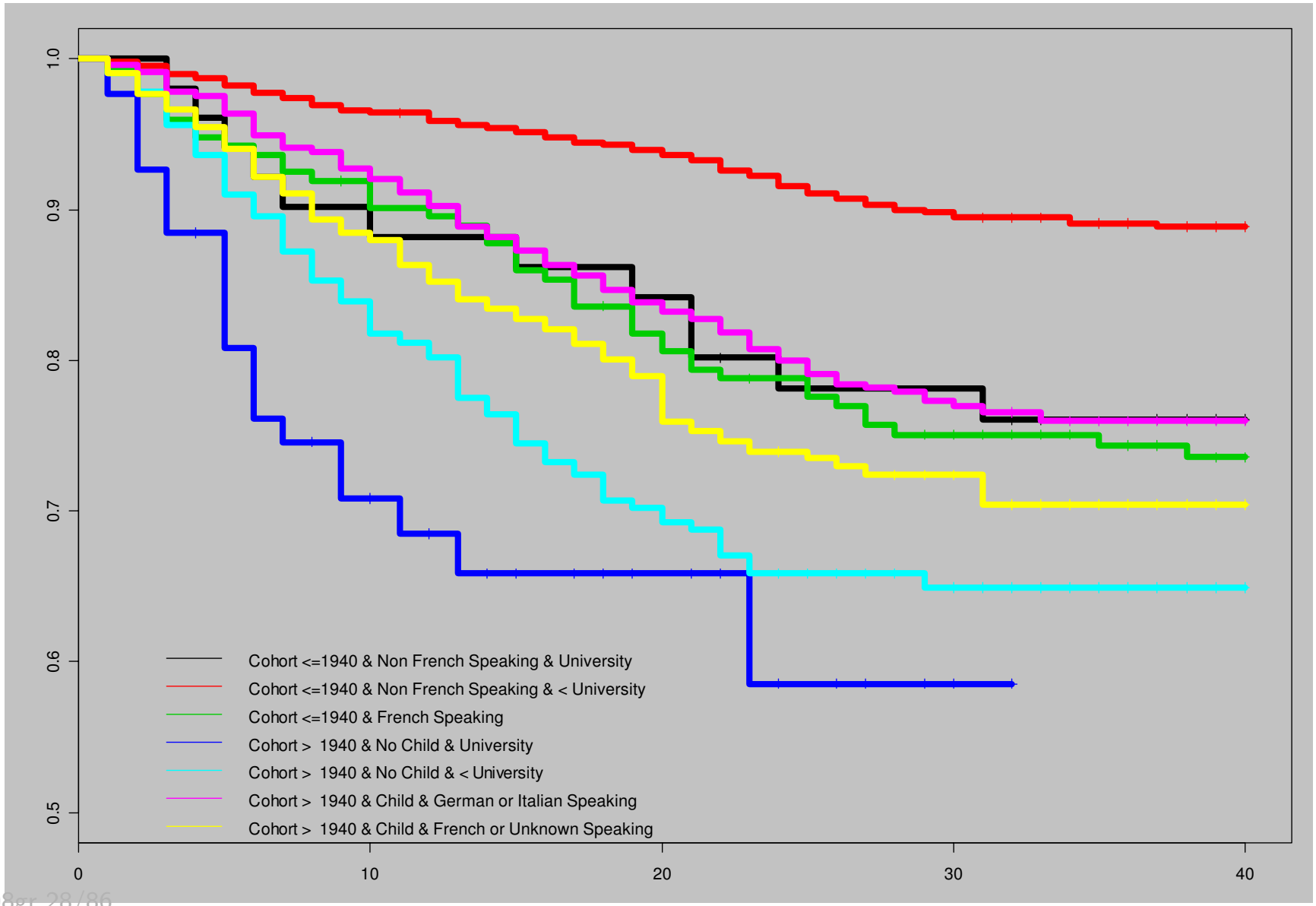
- are as homogeneous as possible (min within class variability)
  - Example: Leblanc and Crowley (1992) maximize gain in deviance (-log-likelihood) of relative risk estimates.

Divorce, Switzerland, Differences in KM Survival Curves I

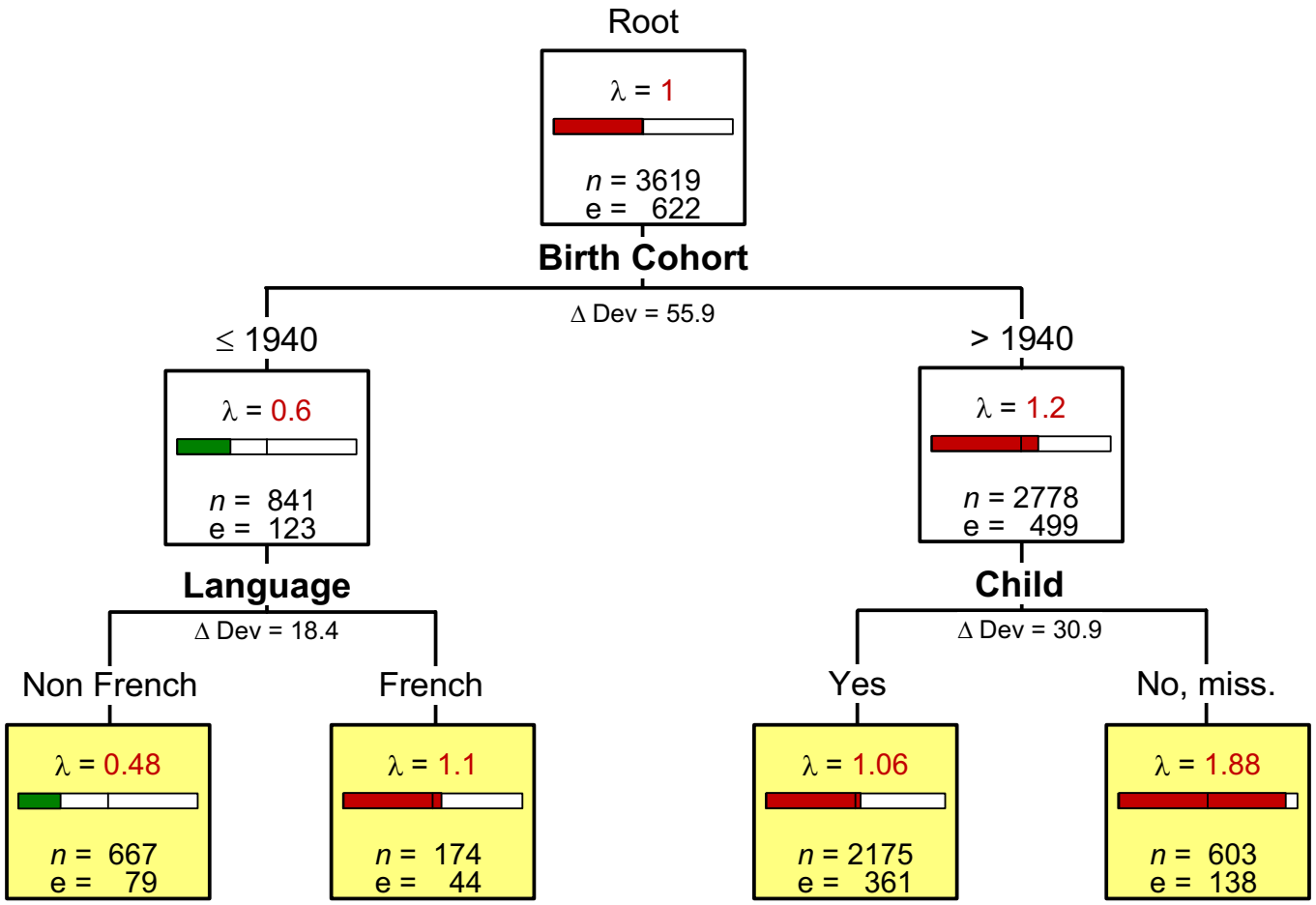
Zoom



Divorce, Switzerland, Differences in KM Survival Curves II



Divorce, Switzerland, Relative risk



Hazard model with interaction

- Adding interaction effects detected with the tree approach
- improves significantly the fit (sig $\Delta\chi^2 = 0.004$)

		exp(B)	Sig.
born after 1940		1.78	0.000
university		1.22	0.049
child		0.94	0.619
language	unknwn	1.50	0.000
	French	1.12	0.282
	German	1	ref
	Italian	0.92	0.677
b_before_40*French		1.46	0.028
b_after_40*child		0.68	0.010
Constant		0.008	0.000

Issues with survival trees in social sciences

1. Dealing with time varying predictors
   - Segal (1992) discusses few possibilities, none being really satisfactory.
   - Huang et al. (1998) propose a piecewise constant approach suitable for discrete variables and limited number of changes.
   - Room for development ...
2. Multi-level analysis
   - How can we account for multi-level effects in survival trees, and more generally in trees?
   - Conjecture: Should be possible to include unobserved shared effect in deviance-based splitting criteria.

Sequence analysis

- Survival approaches not useful in a unitary (holistic) perspective of the whole life course.
- Sequence analysis of whole collection of life events better suited for such holistic approach (Billari, 2005).

Rendering sequences

- **Colorize your life courses**

- Results from the analysis of the retrospective Swiss Household Panel (SHP) survey.
- Focus on visualization of life course data.

Evolution tendencies in familial life course trajectories

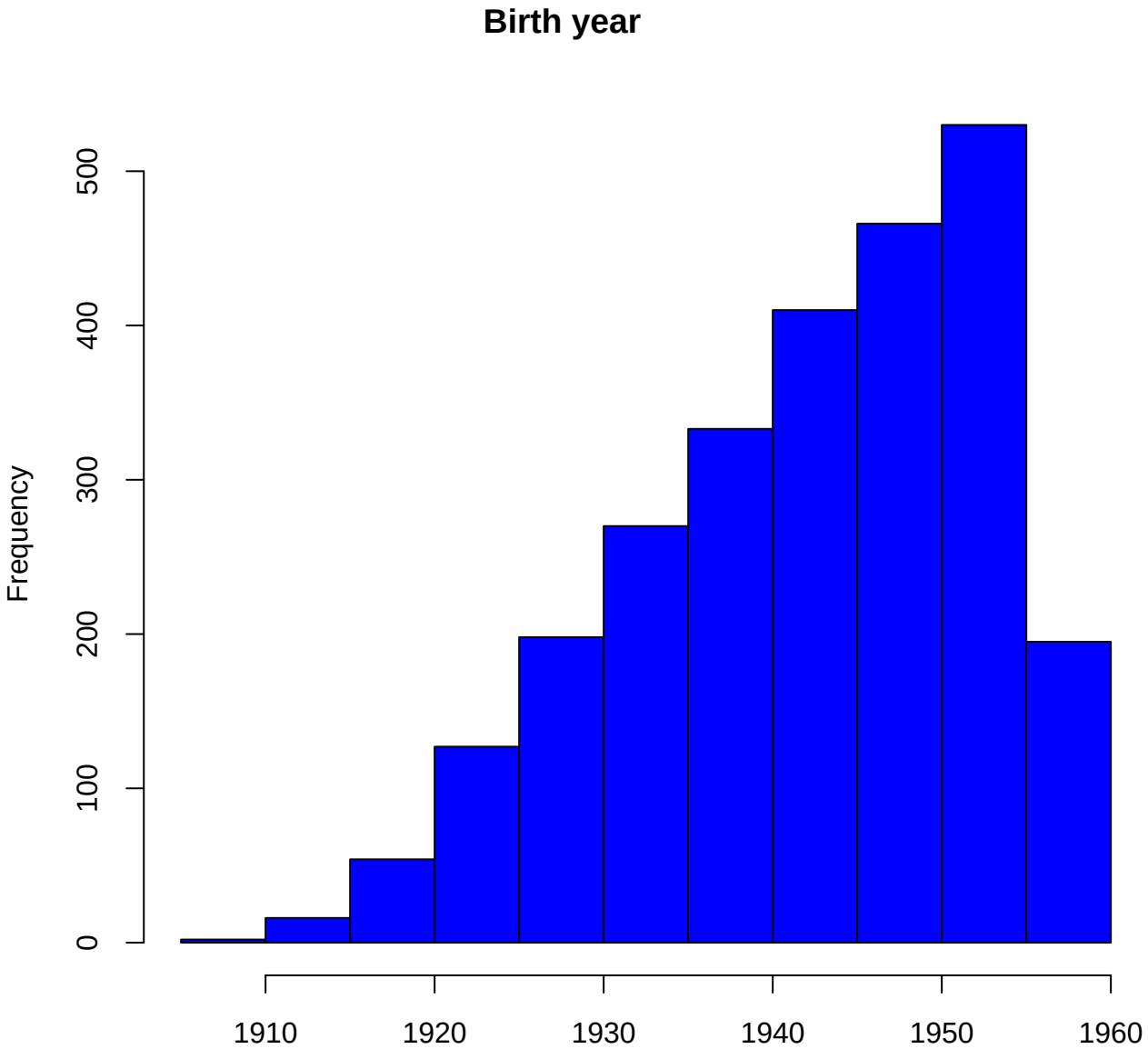
Sequence analysis techniques permit to test hypotheses about evolution in these familial life trajectories. (Elzinga and Liefbroer, 2007):

- De-standardization: Some states and events of familial life are shared by decreasing proportions of the population, occur at more dispersed ages and their duration is also more scattered.
- De-institutionalization: Social and temporal organization of life courses becomes less driven by normative, legal or institutional rules.
- Differentiation: Number of distinct steps lived by individual increases.

Presentation of the "BioFam" data

- Data from the retrospective survey conducted in 2002 by the Swiss Household Panel (SHP)
- (with support of Federal Statistical Office, Swiss National Fund for Scientific Research, University of Neuchatel.)
- Retrospective survey: 5560 individuals
- Retained familial life events: Leaving Home, First childbirth, First marriage and First divorce.
- Age 15 to 45 $\rightarrow$ 2601 remaining individuals, born between 1909 et 1957.

Distribution by birth cohort



Creating state sequences

- Example of time stamped data:

individual	LHome	marriage	childbirth	divorce
1	1989	1990	1992	NA

Deriving the states

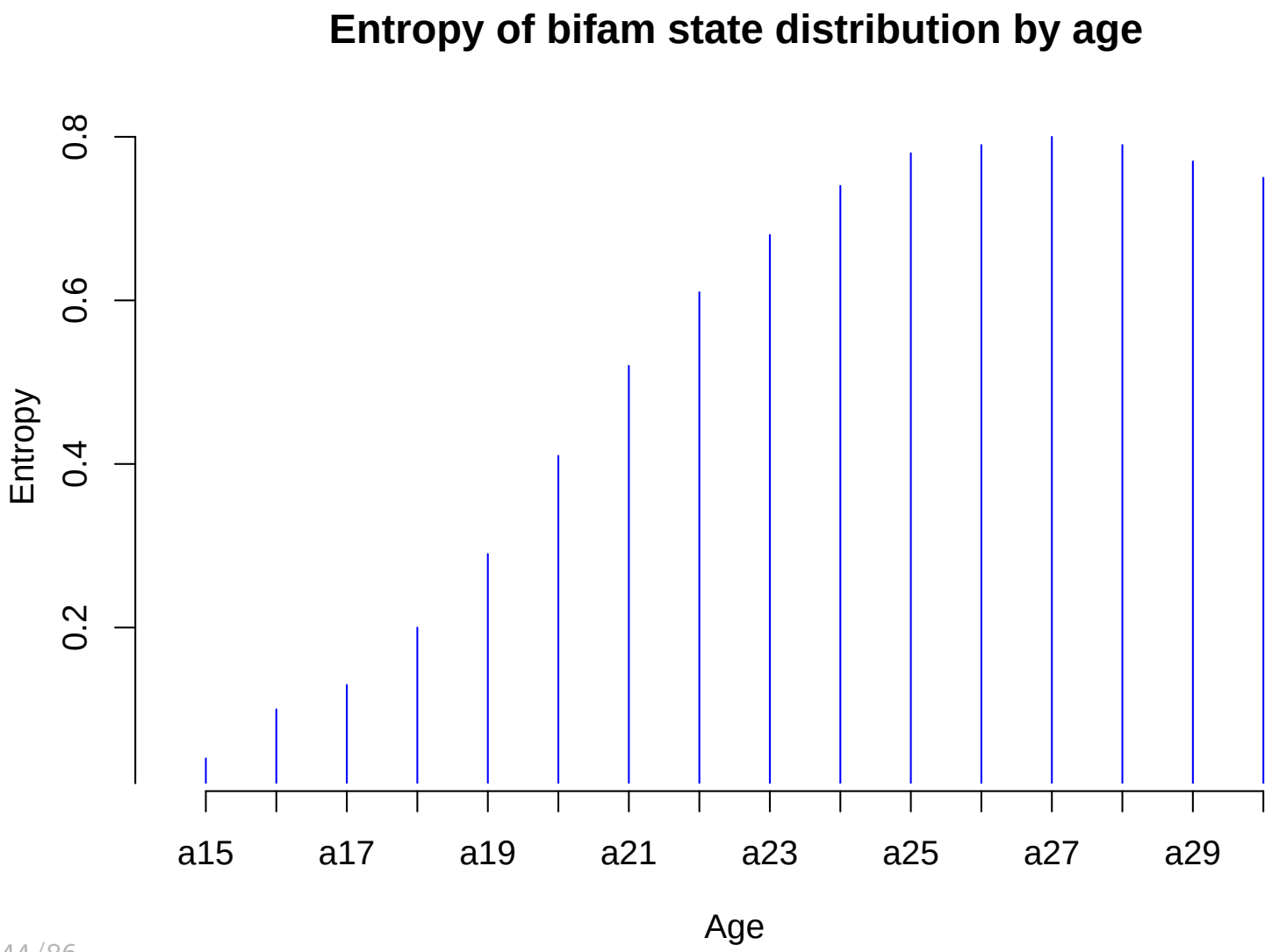
Need one state for each combination of events:

	LHome	marriage	childbirth	divorce
0	no	no	no	no
1	yes	no	no	no
2	no	yes	yes/no	no
3	yes	yes	no	no
4	no	no	yes	no
5	yes	no	yes	no
6	yes	yes	yes	no
7	yes/no	yes	yes/no	yes

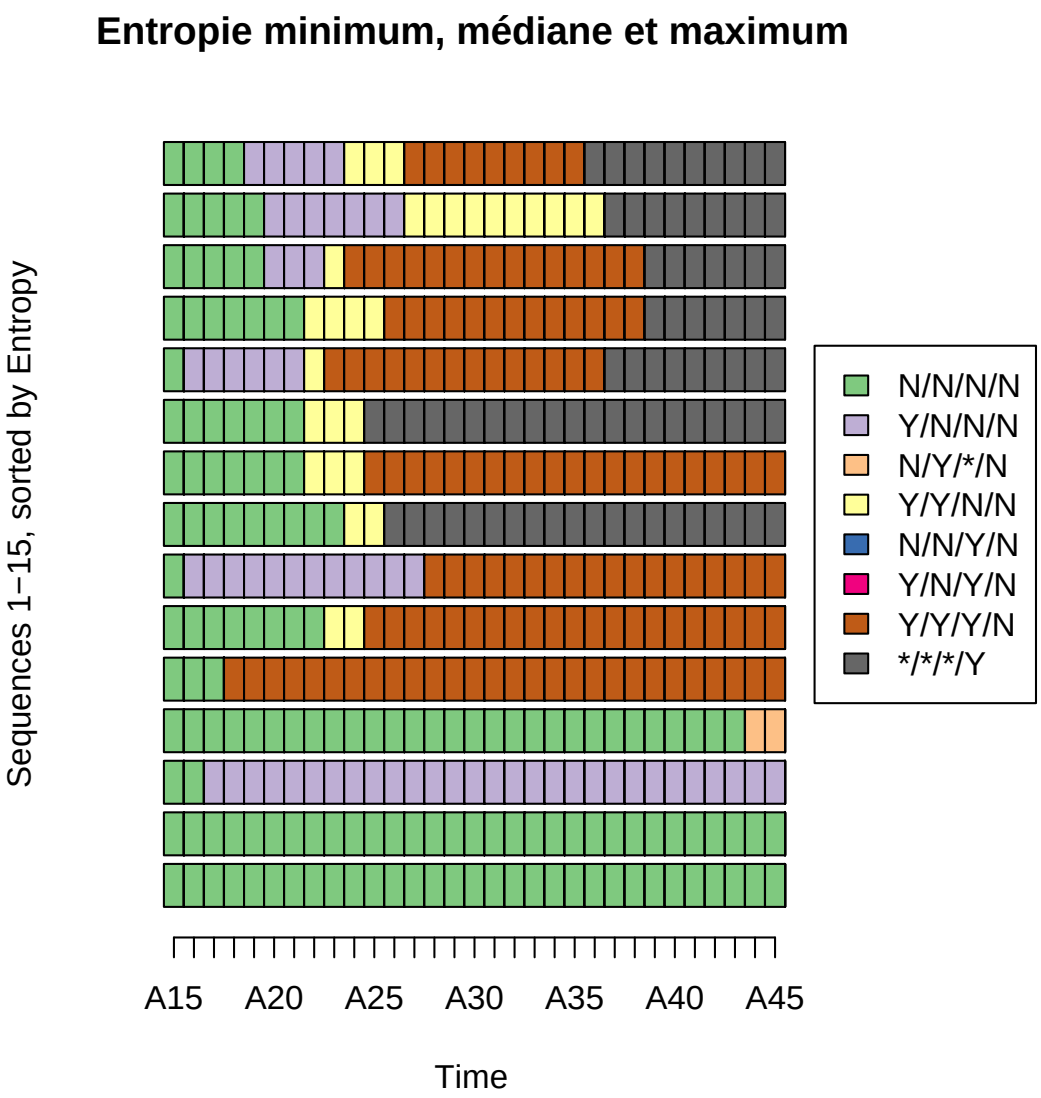
Definition

- Entropy: measure of uncertainty regarding sequence predictability.
  - p_i, proportion of cases (or time points) in state i.
  - Shannon $h(p) = \sum_i -p_i \log_2(p_i)$
  - Other type of entropies: Quadratic (Gini), Daroczy, ...
- Two ways of using entropies.
  - Entropy of the state at each time (age) point: Entropy increases with diversity of states observed at each time point (age).
  - Entropy of each individual sequences: Entropy increases with diversity of states during the observed life course and varies with the time spend in each state.

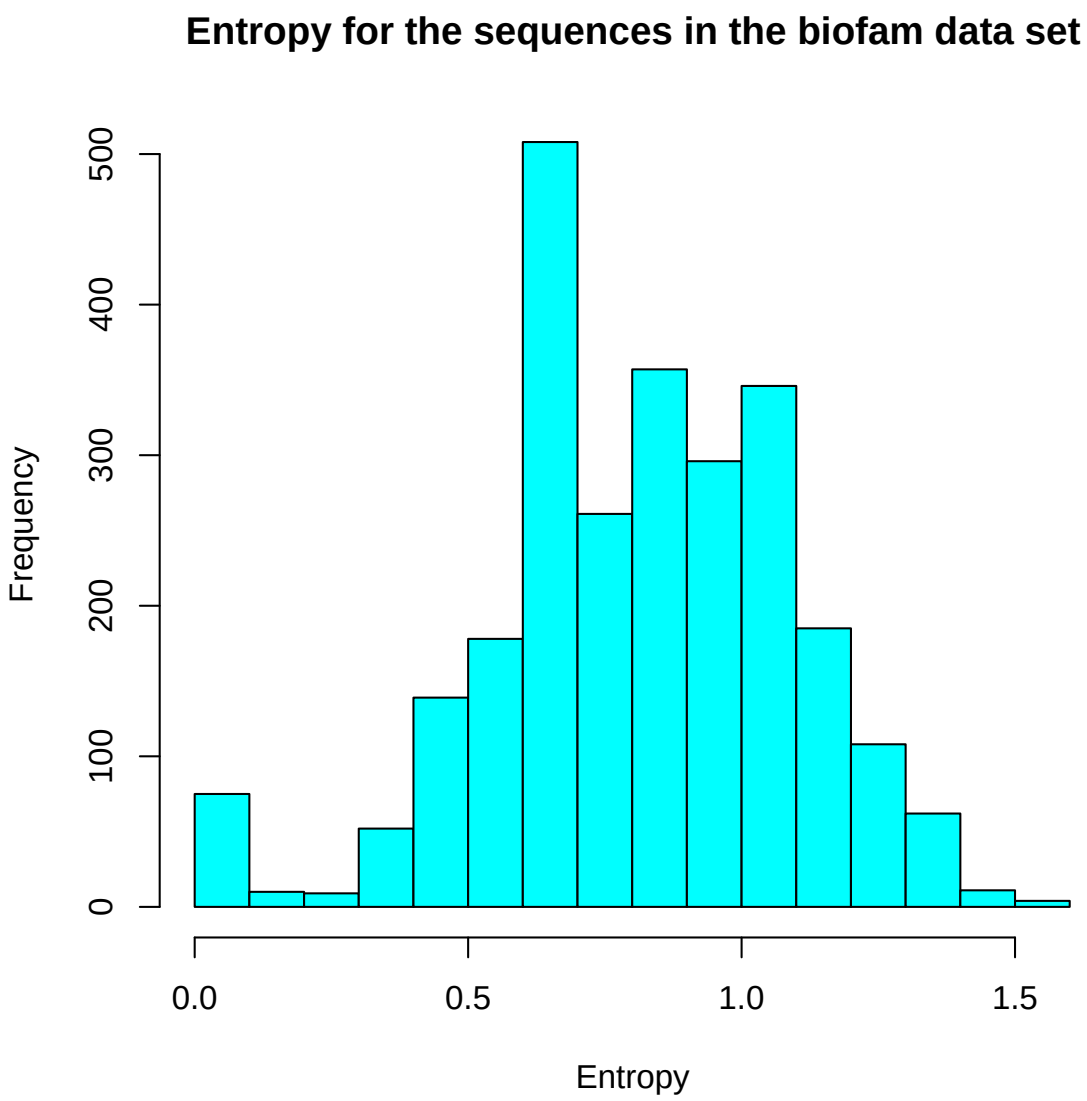
Entropy of the state at each time (age) point



Entropy: Minimum/maximum



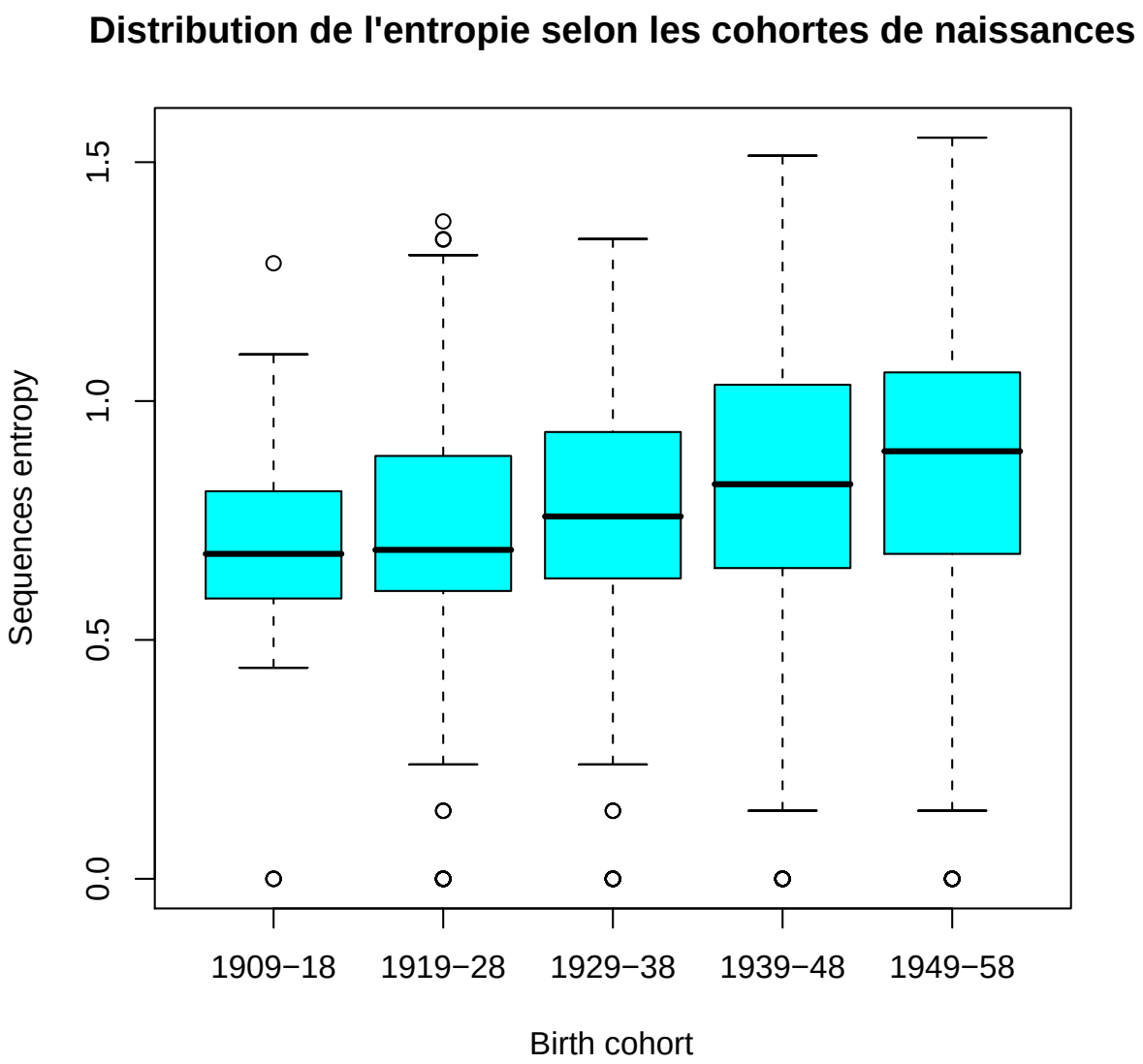
Entropy - histogram



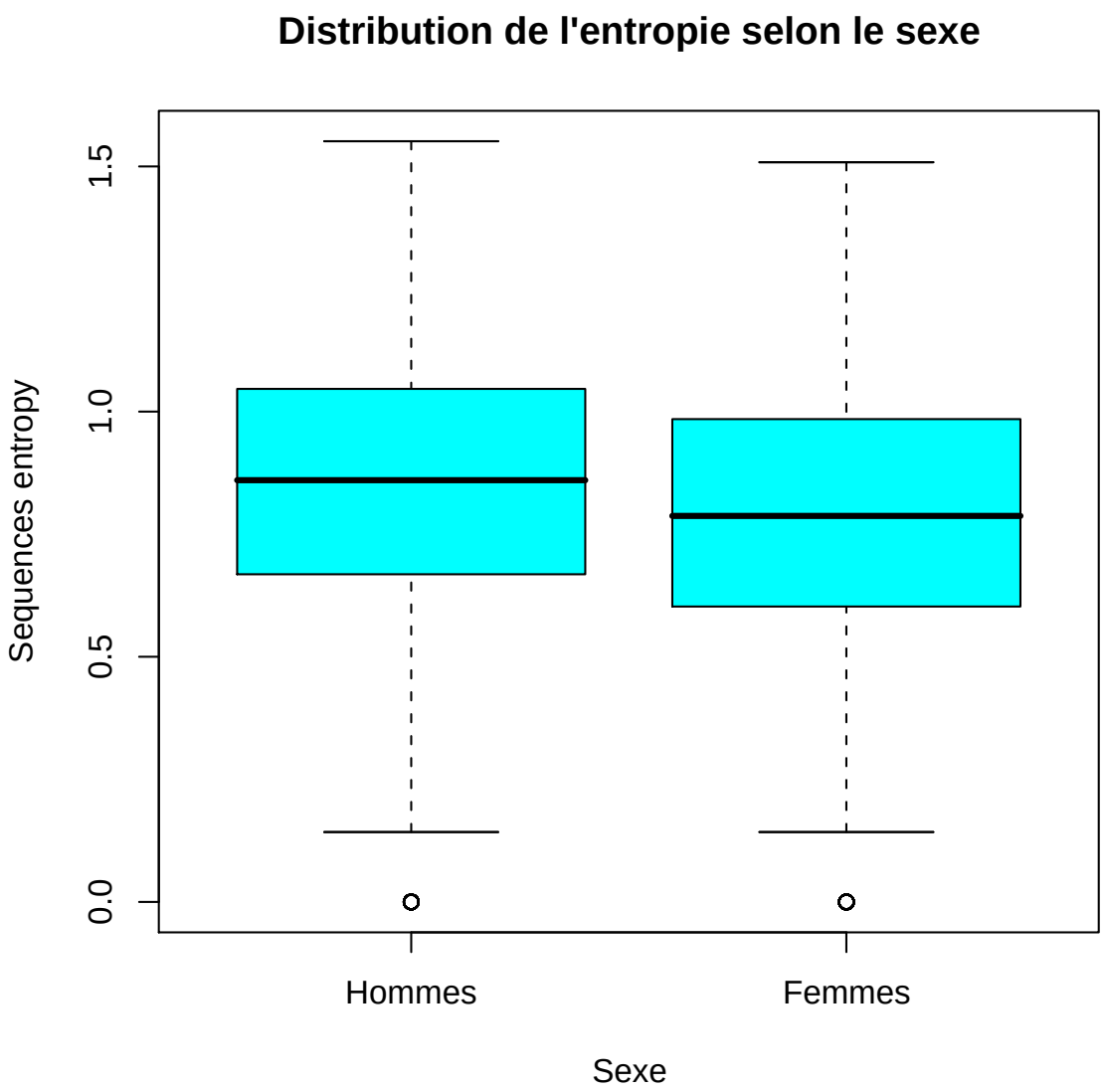
Hypothesis

- Evolutions of familial life trajectories gives rise to an increase in the entropy of individual sequences,
- because they become less predictable and more diversified.

Entropy by birth cohorts



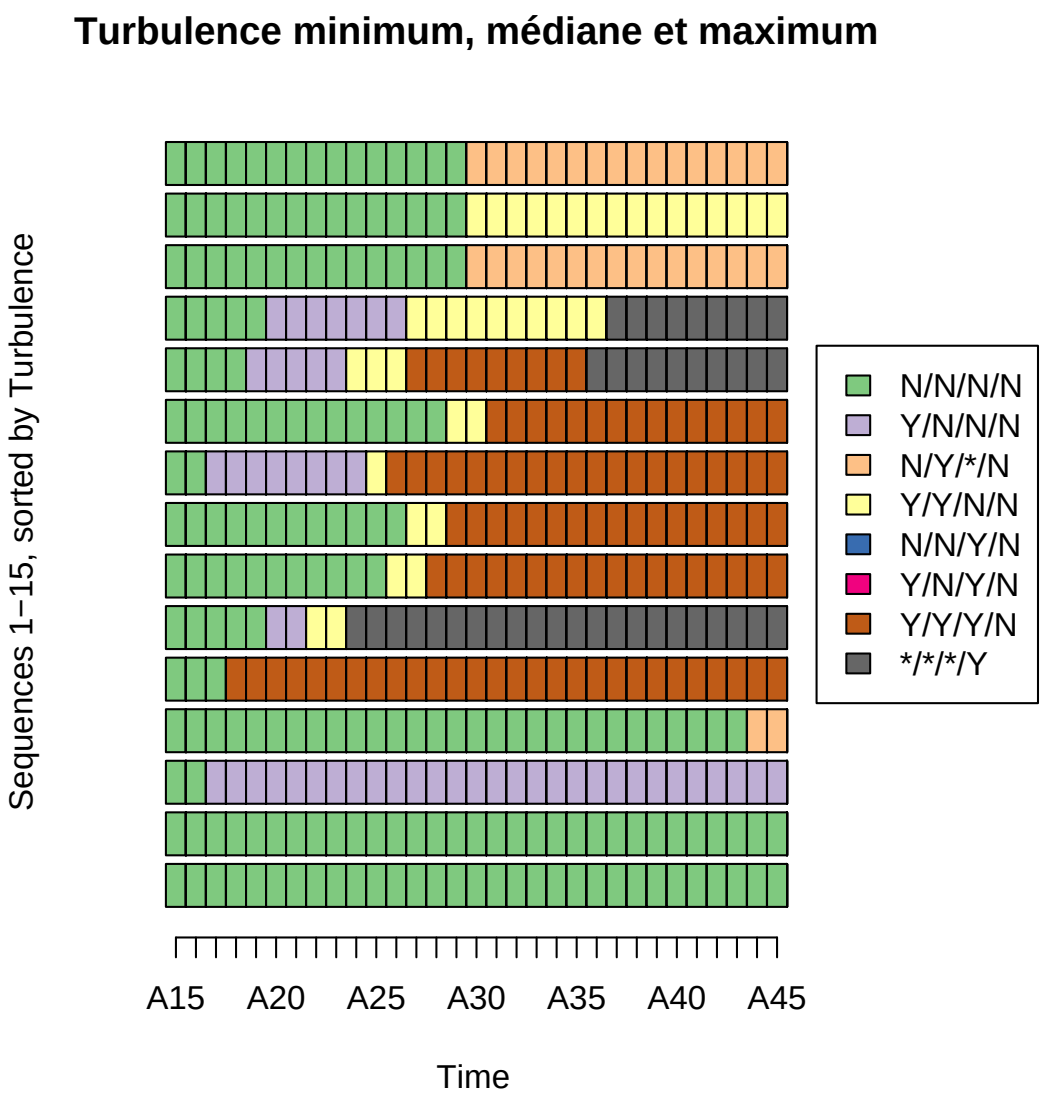
Entropy by sex



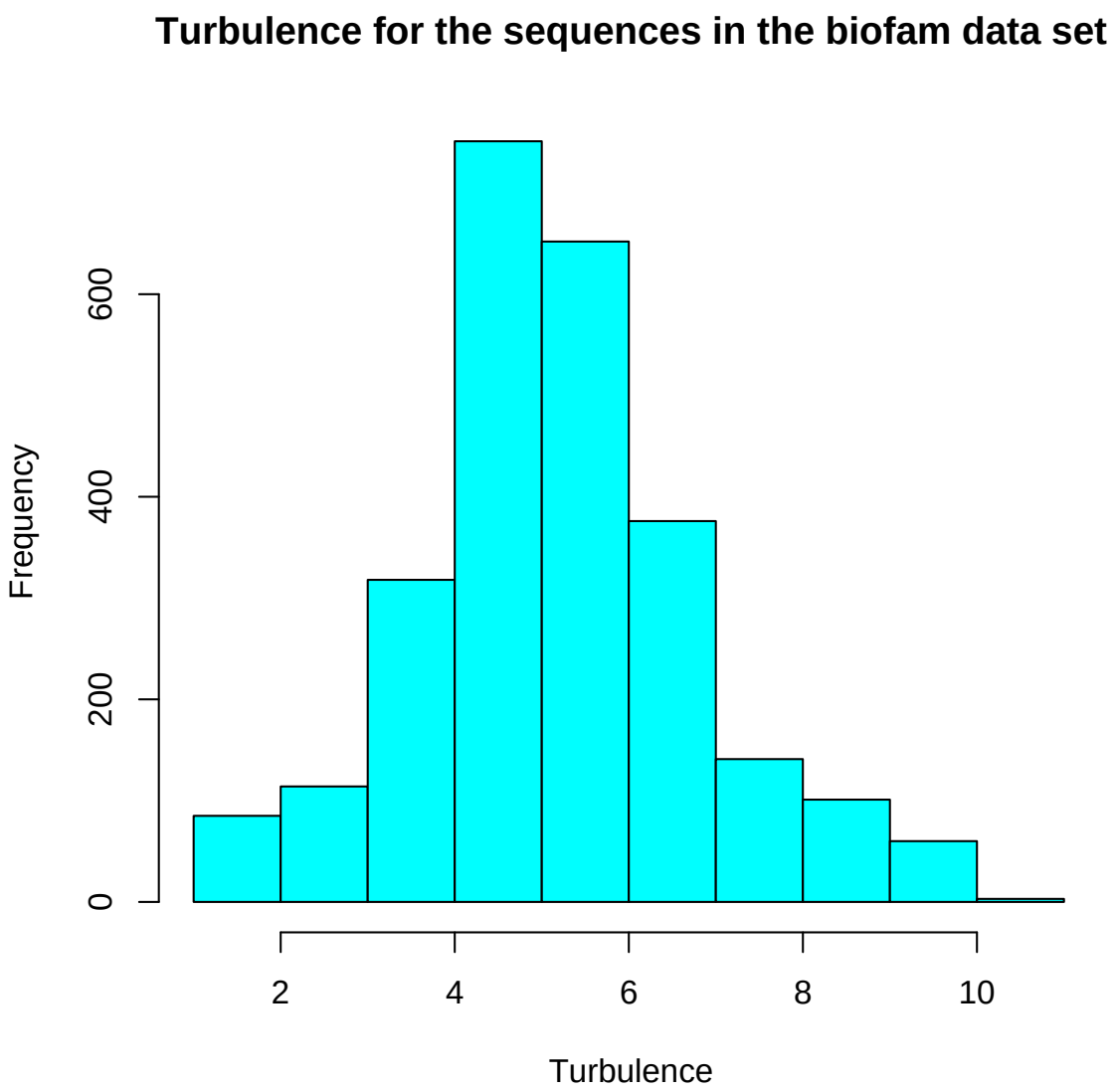
Definition

- Turbulence (Elzinga and Liefbroer, 2007): Somewhat similar to entropy.
- Turbulence accounts for state sequencing (which is not the case of the entropy).
- Turbulence accounts of the following two elements:
  - number of subsequences:
    x=S,U,M,MC - 16 subsequences more turbulent than
    y=S,U,S,C - 15 subsequences
  - variance of duration in each state:
    S/10 U/2 M/132 is less turbulent than
    S/48 U/48 M/48

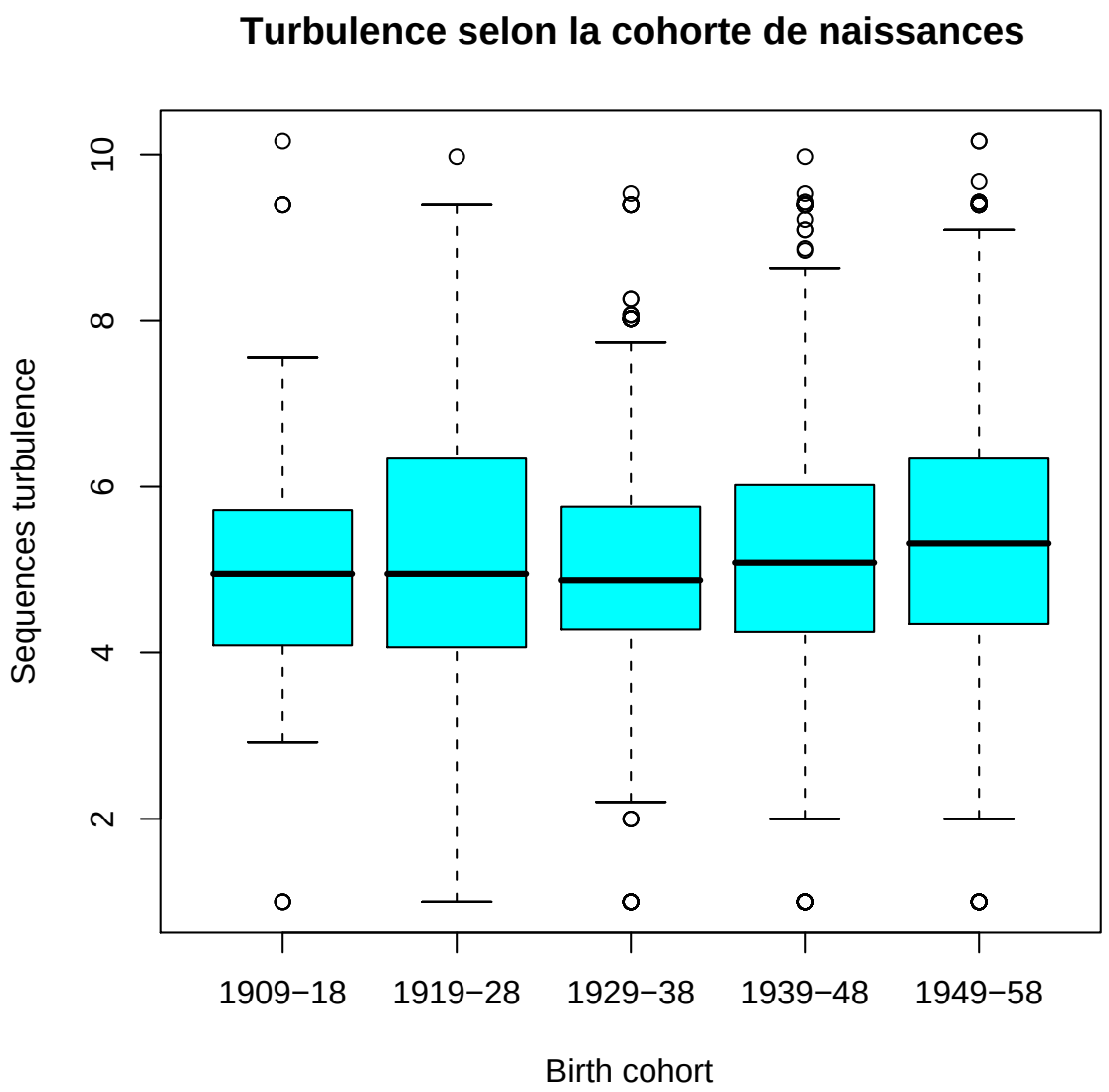
Turbulence - Minimum/maximum



Turbulence - histogram



Turbulence by cohorts



Clustering, Multidimensional scaling and more

- Once you are able to compute 2 by 2 distances between sequences you can among others:
- Cluster sequences
- Make scatter plot representation of sets of sequences using multidimensional scaling.

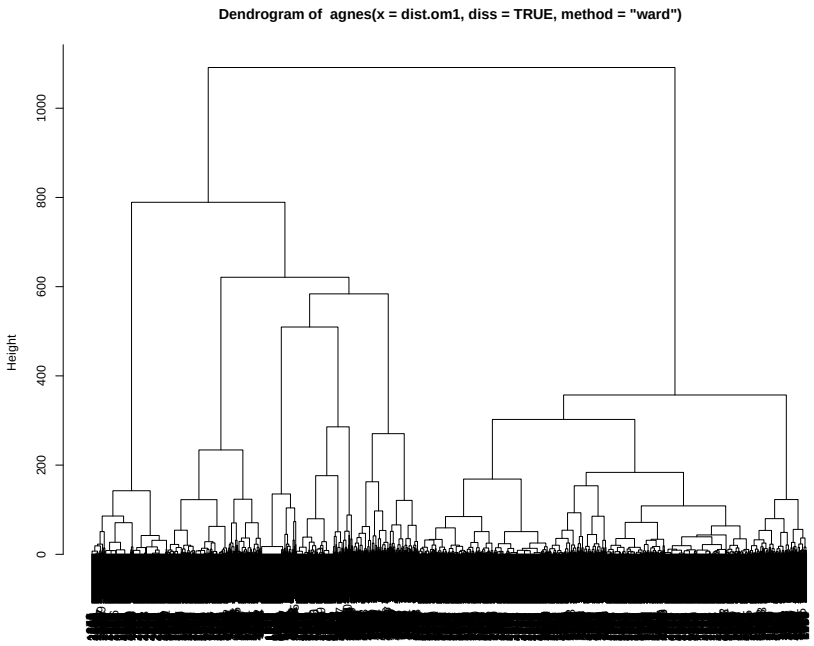
Distances between sequences

- Edit distance (known as Optimal matching in Social sciences) (Levenshtein, 1966; Needleman and Wunsch, 1970; Abbott and Forrest, 1986)
  - $d(x, y)$ Total cost of insert, deletion and substitution changes required to transform sequence x into y.
  - Different solutions depending on indel and substitution costs.
- Other metrics proposed by (Elzinga, 2008)
  - LCP: Longest common prefix (also longest common postfix)
  - LCS: Longest common subsequence (same as OM with indel cost $= 1$, and substitution cost $= 2$).
  - NMS: Number of matching subsequences
  - ...

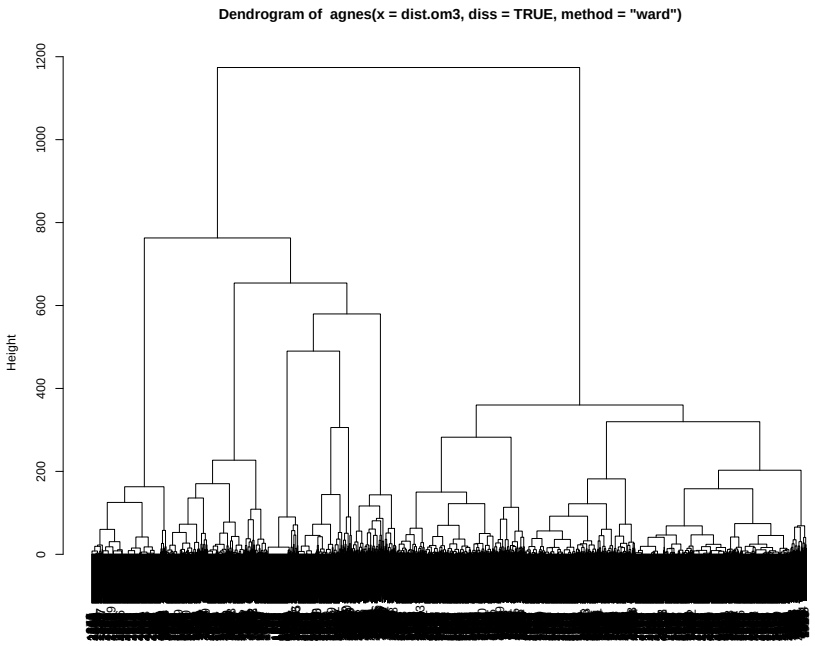
  Elzinga (2008) proposes a nice formalization of these metrics.

Dendrogram, OM1 versus OM3

different indel costs (1 vs 3)

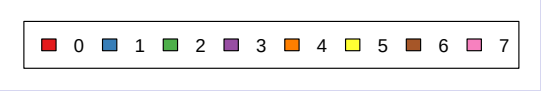


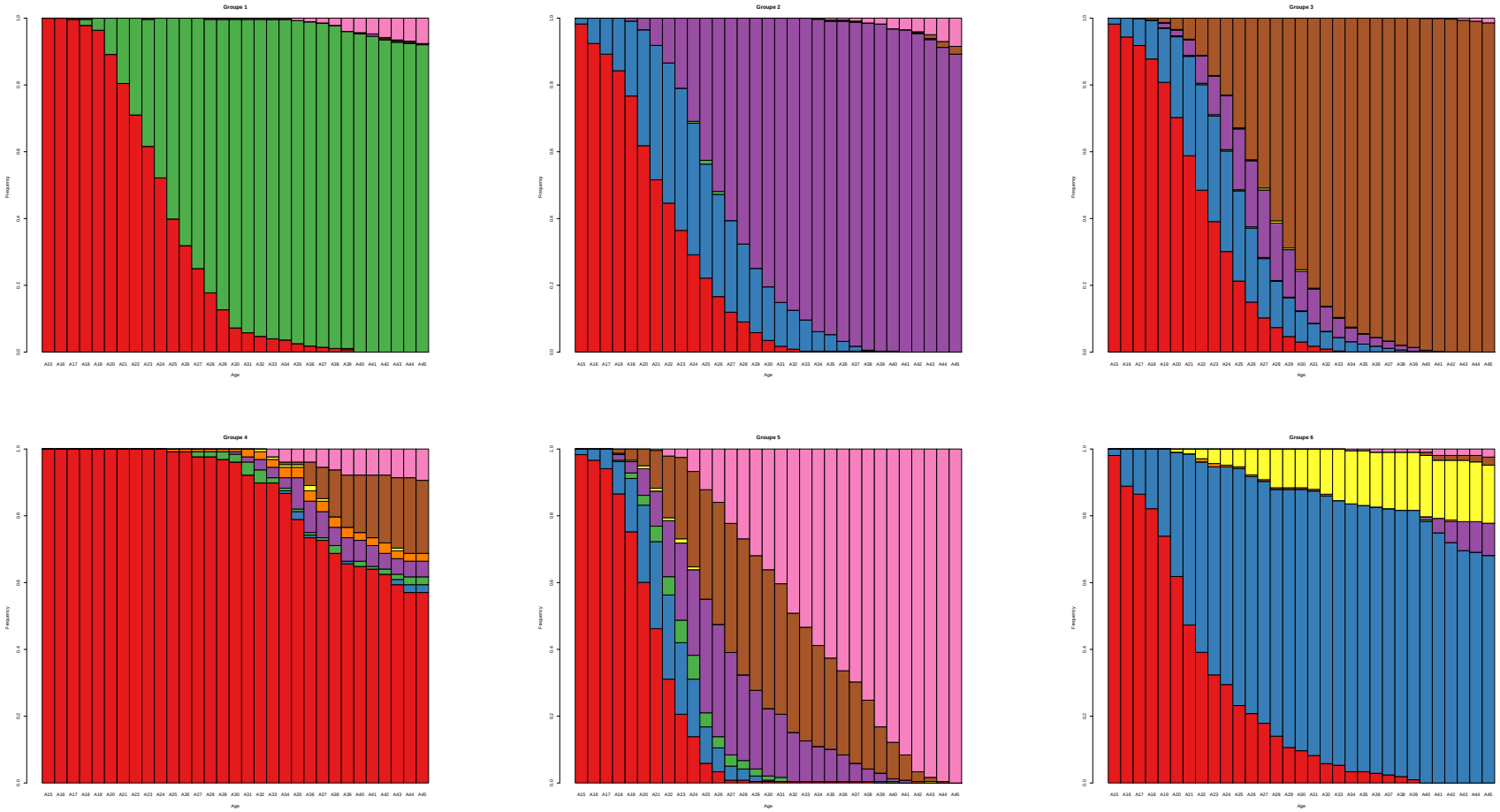
OM1



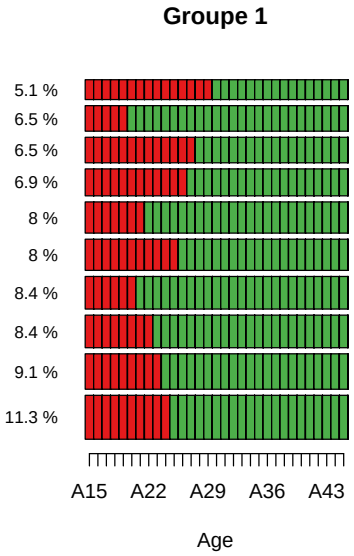
OM3

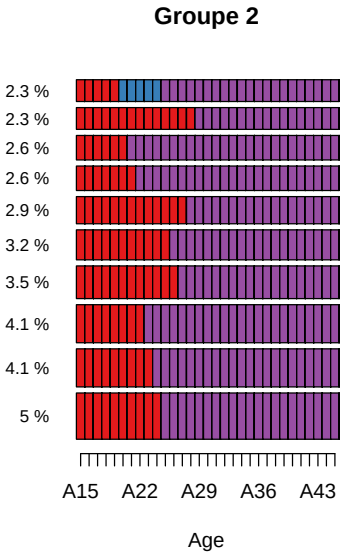
State distribution by age, within cluster

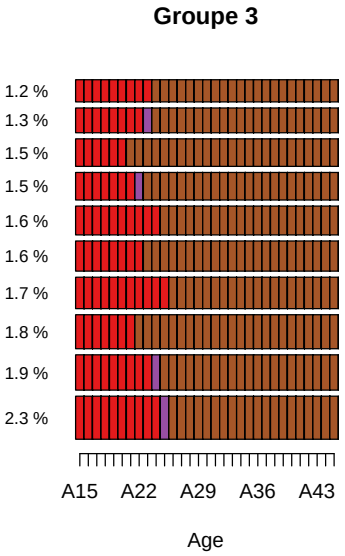


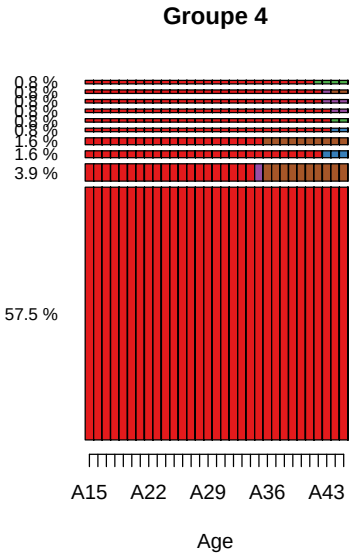


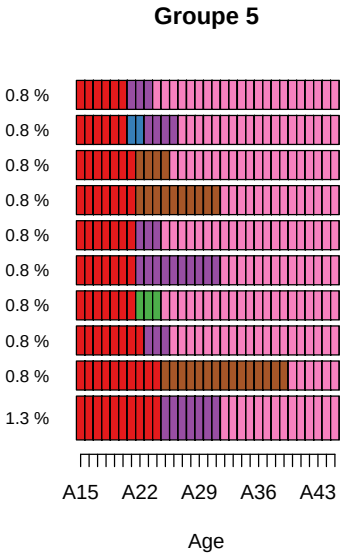
Most frequent sequences by cluster

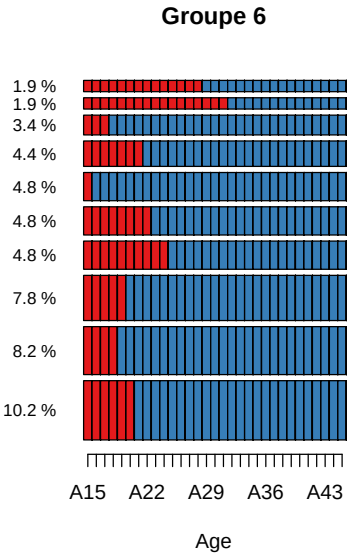




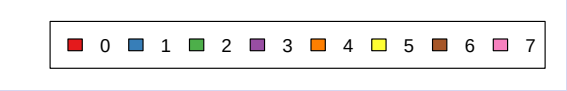


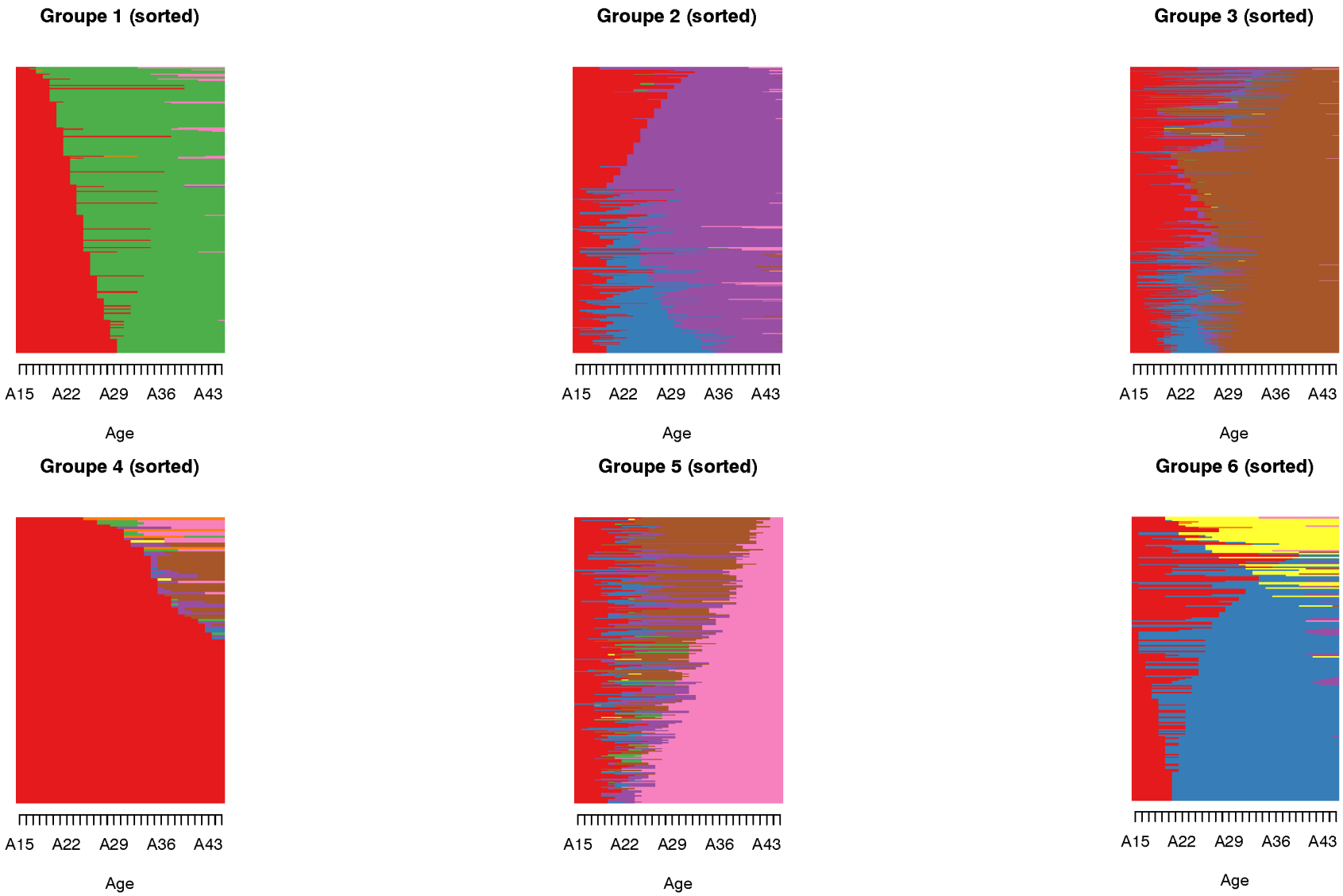




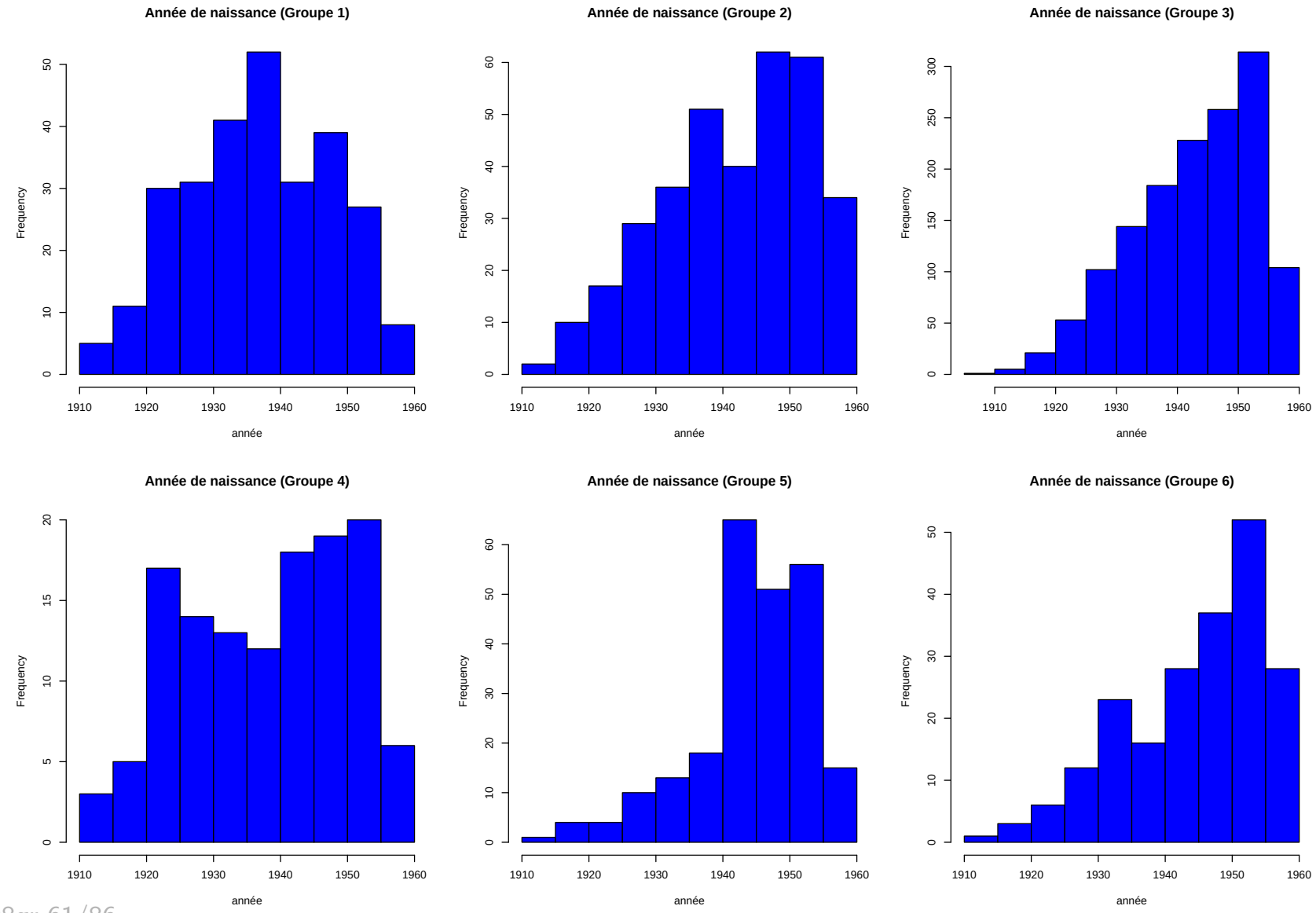


I-plot by cluster





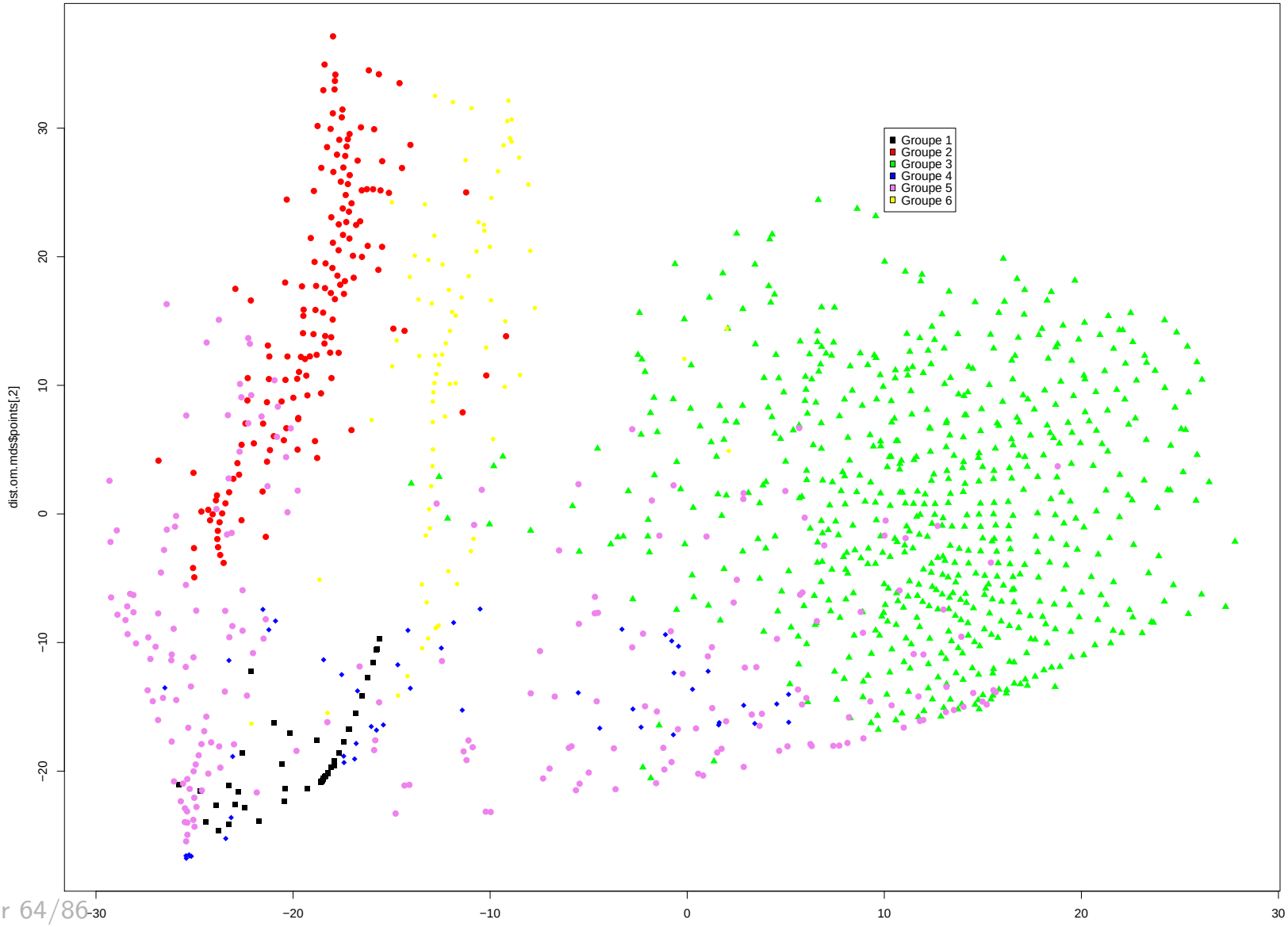
Distribution by birth cohort within each cluster



Multidimensional Scaling: Principle

- Let D be a distance matrix between sequences.
- D computed using OM, LPS, LCS, ... metrics.
- Multidimensional Scaling consists in
  - Finding a set of real valued variables (f_1, f_2) such that the $\delta_{ij} = \sqrt{(f_i1 - f_j1)^2 + (f_i2 - f_j2)^2}$ best approximate the distances d_{ij}. between sequences.
  - Plotting the points in the (f_1, f_2) space.

Multidimensional Scaling



Mining Frequent Episodes

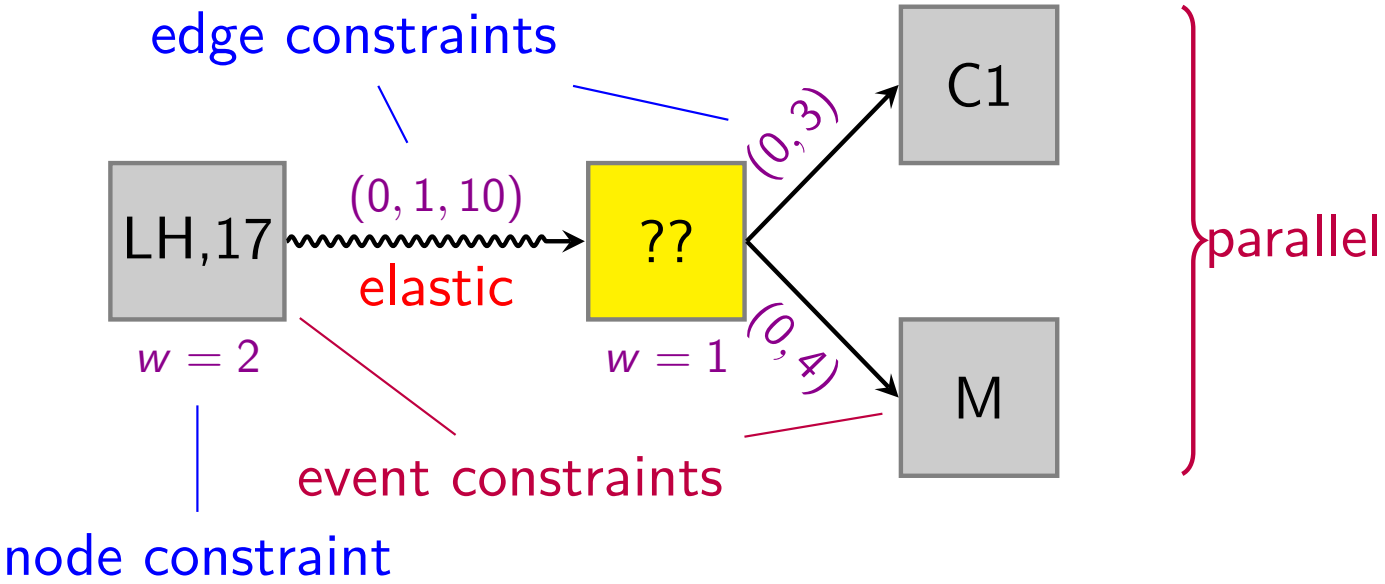
- What can we expect from frequent episodes mining?
  - GSP (Srikant and Agrawal, 1996)
  - MINEPI, WINEPI (Mannila et al., 1997)
  - TCG, TAG (Bettini et al., 1996)
  - SPADE (Zaki, 2001)
- Are there specific issues when applying these methods in social sciences?

Frequent episodes. What is it?

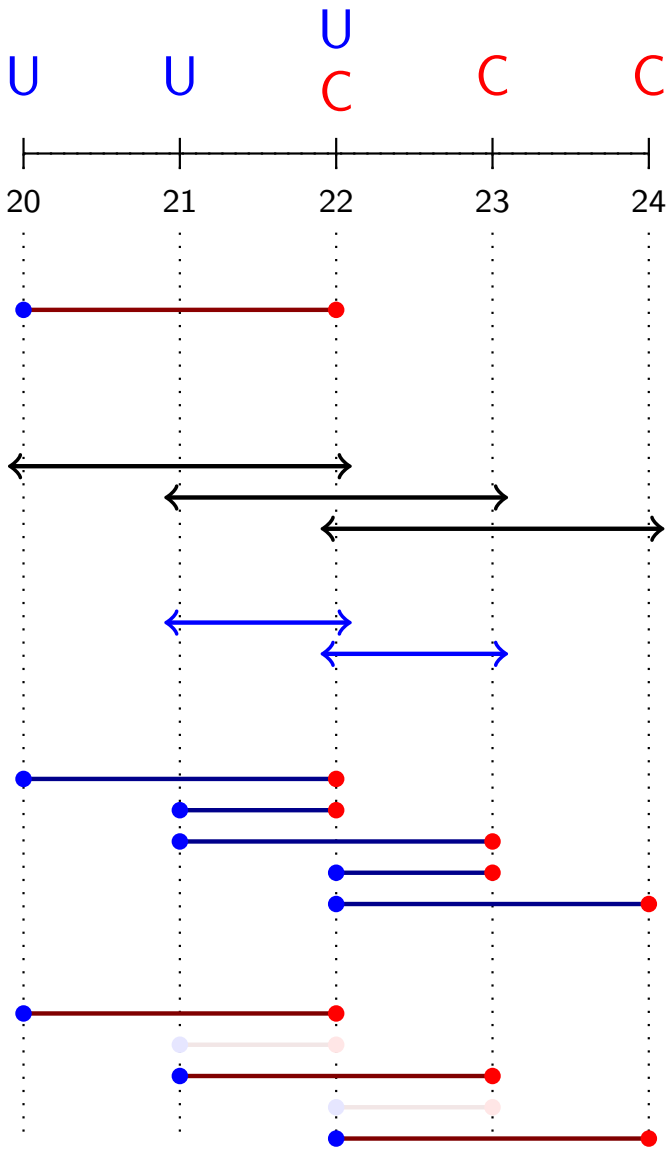
- Episode: Collection of events occurring frequently together.
- Mining typical episodes:
  - Specialized case of mining frequent itemsets.
  - Time dimension $\Rightarrow$ Partially ordered events.
- More complex than unordered itemsets: User must
  - specify time constraints (and episode structure constraints).
  - select a counting method.

Episode structure constraints

For people who leave home within 2 years from their 17, what are typical events occurring until they get married and have a first child?



Counting methods (Joshi et al., 2001)



Searching (U,C)

min gap= 1, max gap= 2, win size= 2

indiv. with episode — COBJ = 1

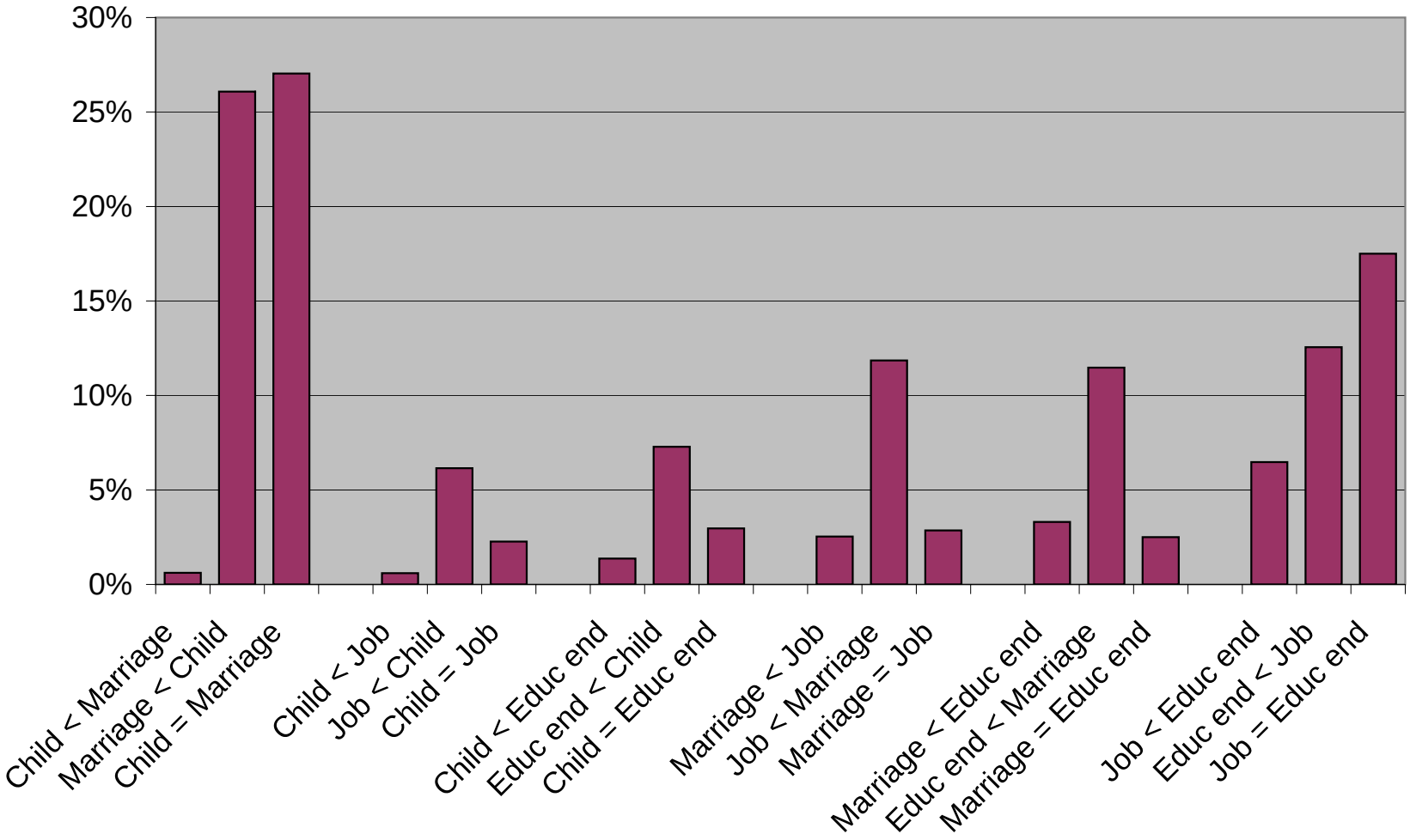
windows with episode — CWIN = 3

min win. with episode — CminWIN = 2

distinct occurrences — CDIS_o = 5

dist. occ. without overlap — CDIS = 3

Example: Counting alternate structures (COBJ, no max gap)



Switzerland, SHP 2002 biographical survey ($n = 5560$).

Rules between episodes

- Social scientists like causal explanations.
- Empirically assessed rules are valuable material in that respect.
- Little attention paid to this aspect in the literature on frequent subsequences.
  - Mined episodes are already structured: if (U,C) is a frequent episode, then we know that C often follows U.
  - Deriving association rules from frequent ordered patterns is similar to what is done with unordered itemsets.
- Rule relevance criteria: confidence, surprisingness, implication strength, ...
- Their value depends on the selected counting method.

Issues with episode rules in social sciences

- Parallel life courses:
  - Family events and professional life course.
  - Life courses of each partner of a couple.
- Mining associations between frequent episodes of a sequence with those of its parallel sequence.
  - Frequent episodes from mix of the 2 sequences, and then restrict search of rules among candidates with premise and consequence belonging to a different sequence.
  - Frequent episodes from each sequence, and then search rules among candidates obtained by combining frequent episodes from each sequence.
- Accounting for multi-level effects when validating rules.
  - Is rule relevant among groups, or within groups?

Summary

- Data mining approaches (survival trees, clustering sequences, frequent episodes) have promising future in life course analysis.
  - Complement classical statistical outcomes with new insights.
- Their use within social sciences raises specific issues:
  - Accounting for multi-level effects when growing survival tree or mining association rules.
  - Handling time varying predictors in survival trees.
  - Selecting relevant counting methods (event dependent)?
  - Suitable criteria for measuring association strength between frequent episodes.
  - ...

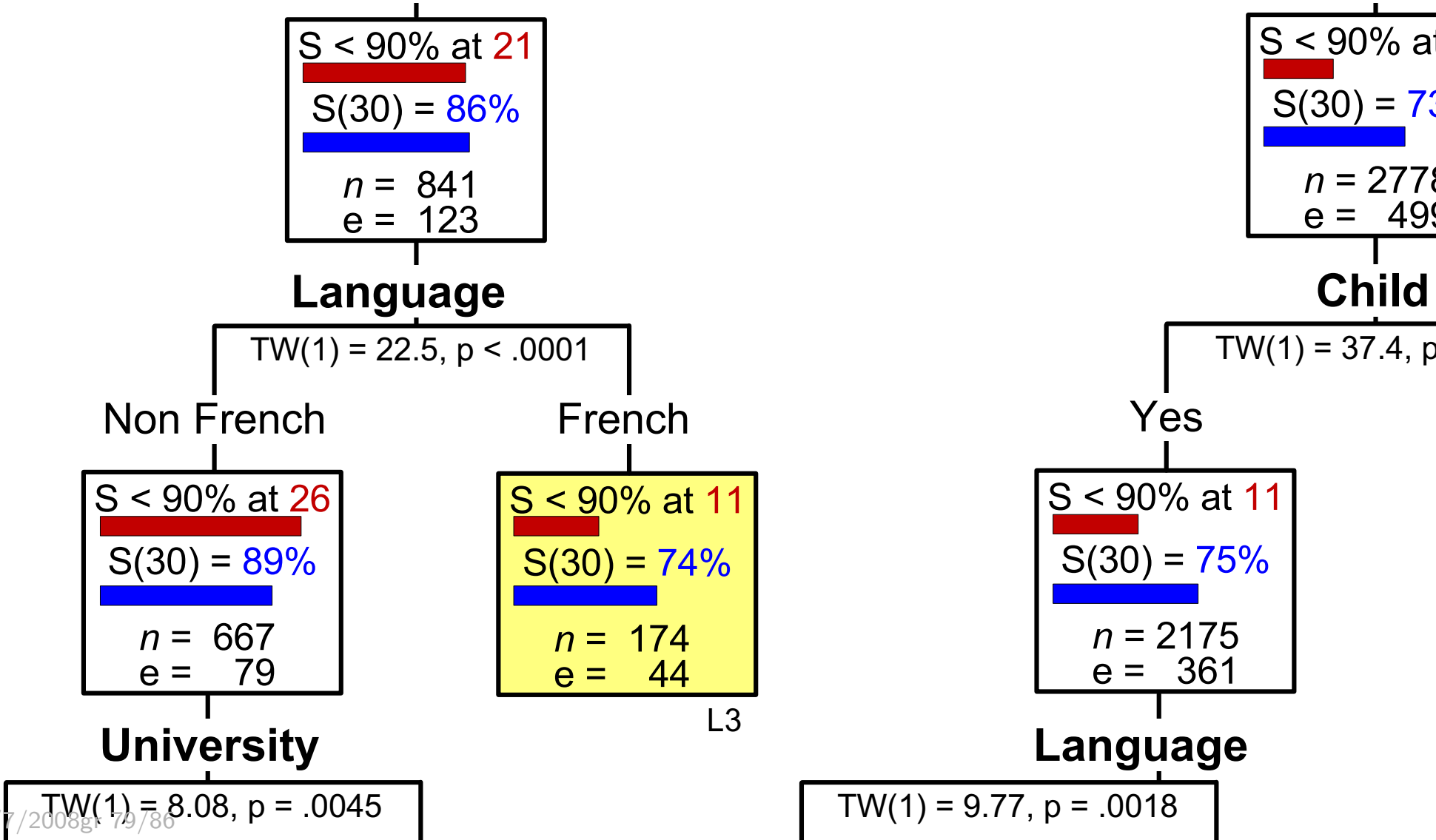
Our TraMineR R-package

- Let me finish with an Add ...

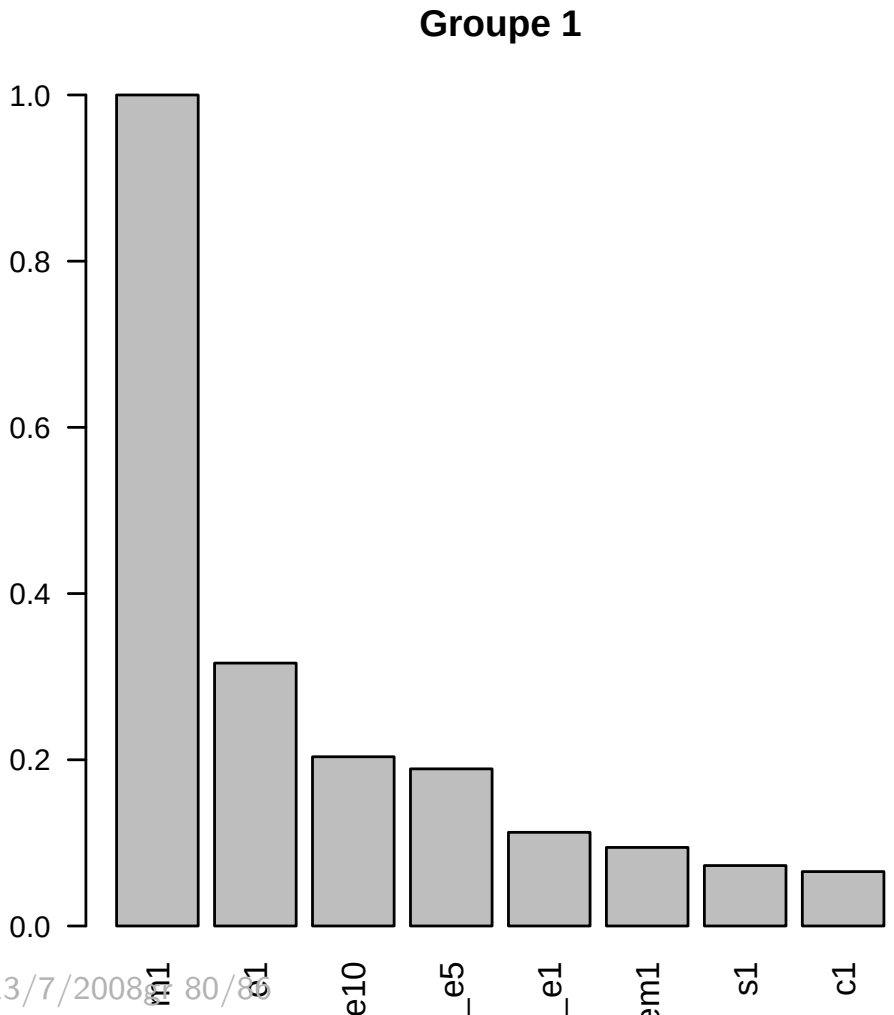
- TraMineR, a free life trajectory mining tool
- for the free open source R statistical environment.
- downloadable from http://mephisto.unige.ch/biomining
- and soon from the CRAN

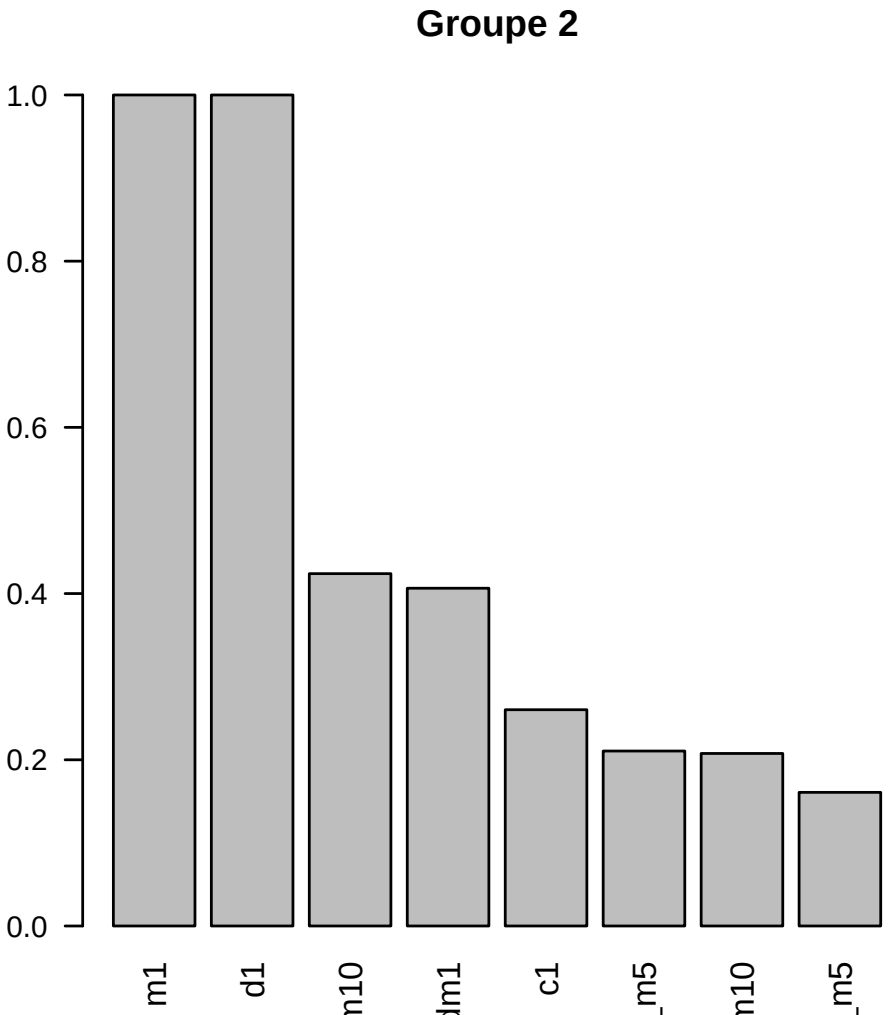
Thank You!

Divorce, Switzerland, Differences in KM Survival Curves I



Clusters and subsequences





Biofam data: Legend

- no event
- left home
- married with/without child
- left home, married
- with child
- left home, with child
- left home, married, child
- divorced

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