

Exploring Life Trajectories

From their visualization to the identification of typical sequences

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<http://mephisto.unige.ch/traminer>

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Outline

- 1 Sequences and sequence analysis
- 2 Some views of Swiss occupational trajectories
- 3 About TraMineR
- 4 Conclusion

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Section outline

- 1 Sequences and sequence analysis
 - About sequence data
 - What is sequence analysis (SA)?

Sequence data

Sequence data

- Multiple cases (n cases)
- For each case a sorted list of (categorical) values

- Example:

1: *a a d d c*

2: *a b b c c d*

3: *b c c*

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- Life trajectories described as chronological sequence data
 - Time order of the elements
 - Categorical longitudinal data

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Successive transversal data vs longitudinal data

- Successive **transversal** observations (same units)

id	t_1	t_2	t_3	...
1	B	B	D	...
2	A	B	C	...
3	B	B	A	...

- **Longitudinal** observations

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Repeated independent cross sectional observations

- Successive independent **transversal** observations

id	t_1	t_2	t_3	...
11	B
12	A
13	B
.
21	.	B
22	.	B
23	.	B
.
24	.	.	D	...
25	.	.	C	...
26	.	.	A	...
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- This is **not longitudinal** ...
- but ... sequences of transversal (aggregated) characteristics.

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Longitudinal data: Where do they come from?

- **Individual follow-ups**: Each important event is recorded as soon as it occurs (medical card, cellular phone, weblogs, ...).
- **Panels**: Periodic observation of same units
- **Retrospective data** (biography): Depends on interviewees' memory
- **(Statistical) match of data from different sources** (successive censuses, tax data, social security, population registers, acts of marriages, acts of deaths, ...)

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State sequences: an example

- Occupational state sequences, ages 20 to 45 (from SHP)

FT = Full Time, PT = Part Time, AH = At Home, ED = Education, ...

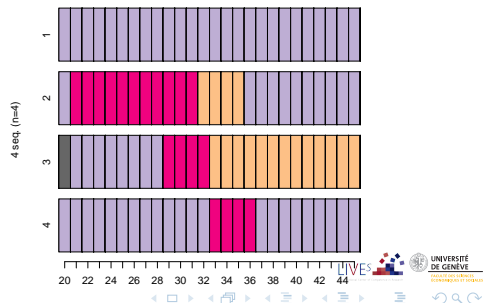
Sequence

- FT-FT
- FT-AH-AH-AH-AH-AH-AH-AH-AH-AH-AH-PT-PT-PT-PT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT
- ED-FT-FT-FT-FT-FT-FT-FT-FT-AH-AH-AH-AH-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT-PT
- FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-AH-AH-AH-AH-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT

- Compact representation

Sequence

- (FT, 26)
- (FT, 1) - (AH, 11) - (PT, 4) - (FT, 10)
- (ED, 1) - (FT, 8) - (AH, 4) - (PT, 13)
- (FT, 13) - (AH, 4) - (FT, 9)



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- FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-AH-AH-AH-AH-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT-FT

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- [1] (FT, 26)
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State versus event sequences

- Life course trajectories described by chronological sequences
- An important distinction for chronological sequences is between **state sequences** and **event sequences**
 - A **state**, such as 'living with a partner' or 'being unemployed', lasts the whole unit of time
 - An **event**, such as 'moving in with a partner' or 'ending education', does not last but provokes a state change, possibly in conjunction with other events.

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State versus event sequences: examples

Time stamped events

Sandra	Ending education in 1980	Start working in 1980
Jack	Ending education in 1981	Start working in 1982

- There can be simultaneous events (see Sandra)
- Elements at same position do not occur at same time

State sequence view

year	1979	1980	1981	1982	1983
Sandra	Education	Education	Employed	Employed	Employed
Jack	Education	Education	Education	Unemployed	Employed

- Only one state at each observed time
- Position conveys time information: All states at position 2 are states in 1980.

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 - holistic: interest is in the whole sequence, not just one element in the sequence (unlike survival analysis for example)
- Aim is
 - Characterizing sets of sequences
 - Identifying typical (sequence) patterns
 - Studying relationship with individual characteristics and environment
- Popularized in social sciences by Abbott (Abbott and Forrest, 1986)
- Some other important names: Elzinga (2003, 2010), Halpin (2010), Piccarreta and Billari (2007), Grelet (2002), Rousset et al. (2011) and the TraMineR team (Gabadinho, Studer, Bürigin, ...). SA in social sciences inspired from bioinformatics and other fields (Sankoff and Kruskal, 1983).

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What kind of questions may SA answer to?

- Are there standard sequences, types of sequences?
- How are those standards linked to covariates such as sex, birth cohort, ... ?
- How does some target variable (e.g., social status) depend on the followed sequence (lived trajectory)?
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 - **Sequencing:** Order in which the different elements occur.
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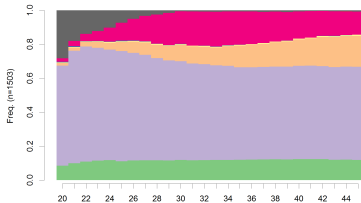
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 - Rendering transversal and longitudinal characteristics
 - Dissimilarity-based analysis
 - Methods for event sequences

Rendering sequences

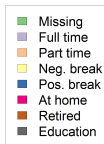
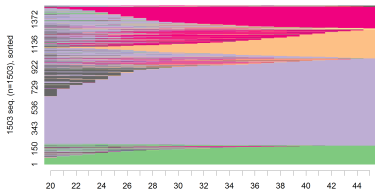
d-plot, Occupational Trajectories



f-plot, Occupational Trajectories

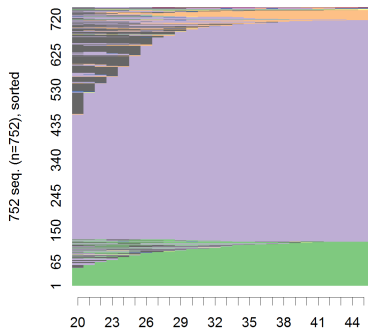


i-plot, Occupational Trajectories

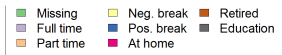
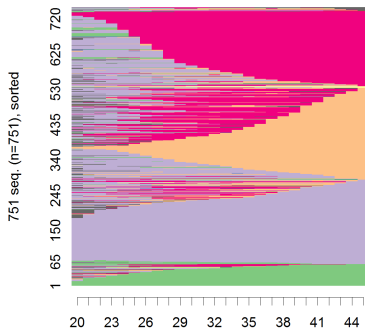


Rendering sequences by group (sex)

I-plot, Occupational Trajectories - man



I-plot, Occupational Trajectories - woman



Characterizing set of sequences

- Sequence of **transversal** measures (modal state, between entropy, ...)

id	t_1	t_2	t_3	...
1	B	B	D	...
2	A	B	C	...
3	B	B	A	...

- Summary of **longitudinal** measures (within entropy, transition rates, mean duration ...)

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- Other global characteristics: sequence medoid, diversity of sequences, ...

Characterizing set of sequences

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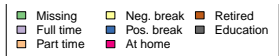
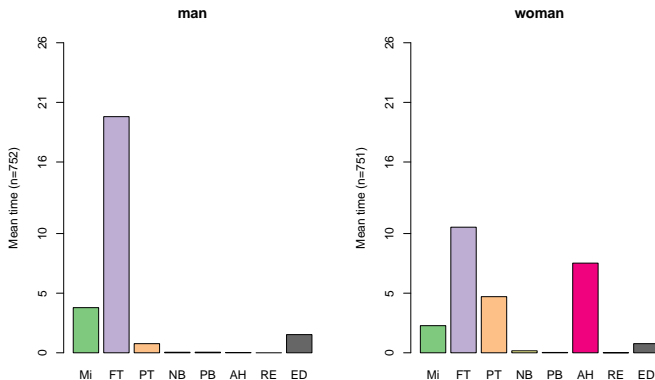
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Mean time in each state

```
seqmplot(seqs.occ, group = seqs$sex)
```

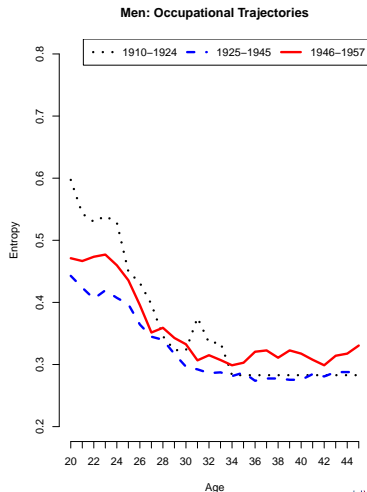
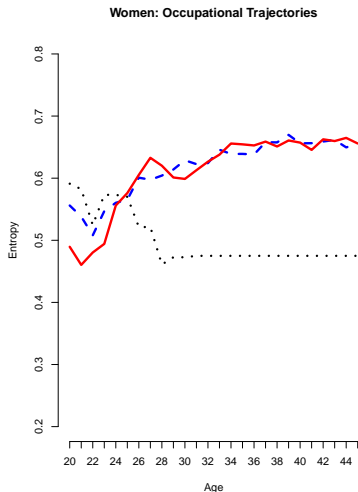


Transition rates

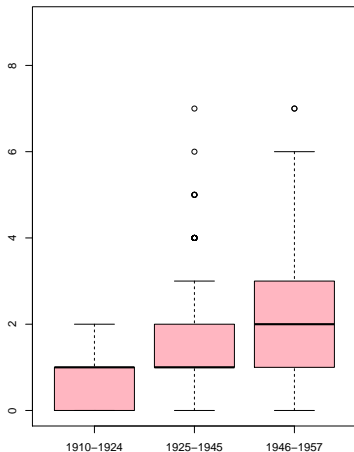
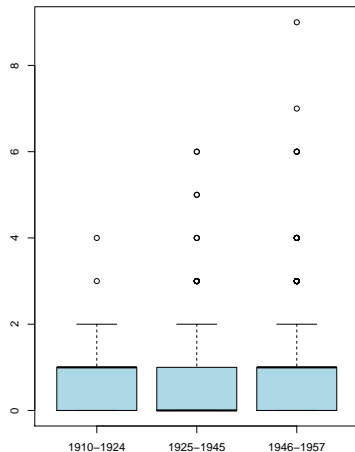
	[-> Mi]	[-> FT]	[-> PT]	[-> NB]	[-> PB]	[-> AH]	[-> RE]	[-> ED]
[Mi ->]	0.969	0.005	0.004	0.001	0.001	0.011	0.000	0.008
[FT ->]	0.003	0.971	0.009	0.001	0.001	0.013	0.000	0.003
[PT ->]	0.005	0.026	0.939	0.001	0.001	0.018	0.000	0.010
[NB ->]	0.040	0.047	0.027	0.880	0.000	0.007	0.000	0.000
[PB ->]	0.105	0.316	0.105	0.000	0.404	0.018	0.000	0.053
[AH ->]	0.003	0.007	0.032	0.000	0.000	0.956	0.000	0.002
[RE ->]	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
[ED ->]	0.044	0.236	0.045	0.001	0.002	0.006	0.000	0.664

Heterogeneity: Sequence of transversal entropies

Occupational, Women vs Men (example from Widmer and Ritschard 2009)



Number of state transitions (longitudinal)

Women: Occupational Trajectories**Men: Occupational Trajectories**

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Pairwise dissimilarities between sequences

- Distance between sequences
 - Different metrics (LCP, LCS, OM, HAM, DHD)
- Once we have pairwise dissimilarities, we can
 - Partition a set of sequences into homogeneous clusters
 - Identify representative sequences (medoid, densest neighborhood)
 - Measure the discrepancy between sequences
 - Run self-organizing maps (SOM) on sequences
 - MDS scatterplot representation of sequences
 - Discrepancy analysis of a set of sequences (ANOVA)
 - Grow regression trees for explaining the sequence discrepancy

Pairwise dissimilarities between sequences

- Distance between sequences
 - Different metrics (LCP, LCS, OM, HAM, DHD)
- Once we have pairwise dissimilarities, we can
 - Partition a set of sequences into homogeneous clusters
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Dissimilarity matrix

```
print(seqs.occ[1:4, ], format = "SPS")
```

Sequence

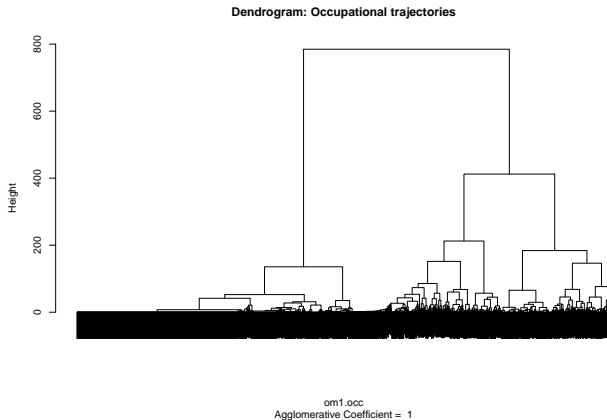
```
[1] (FT,26)
[2] (FT,26)
[3] (Mi,6)-(ED,3)-(Mi,17)
[4] (ED,1)-(Mi,3)-(PT,4)-(FT,18)
```

```
dm <- seqdist(seqs.occ[1:4, ], method = "LCS")
dm[1:4, 1:4]
```

	[,1]	[,2]	[,3]	[,4]
[1,]	0	0	52	16
[2,]	0	0	52	16
[3,]	52	52	0	44
[4,]	16	16	44	0

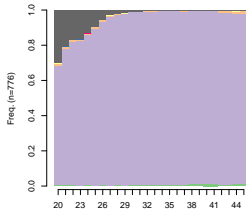
Cluster analysis: determining typologies

Example from Widmer and Ritschard (2009)

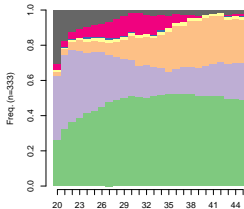


Rendering clusters: d-plots

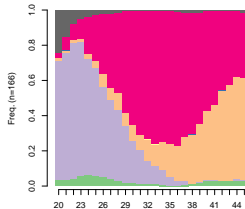
Type 1: Full Time Trajectories (52 %)



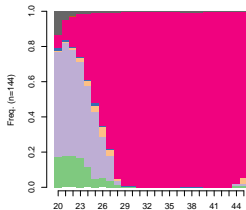
Type 2: Mixed Occupational Trajectories (22 %)



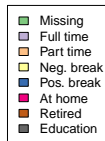
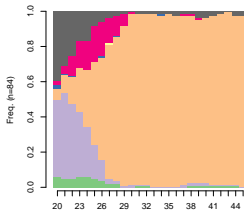
Type 3: Return Trajectories (11 %)



Type 4: At Home Trajectories (9.5 %)

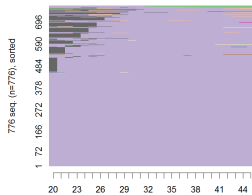


Type 5: Part Time Trajectories (5.5 %)

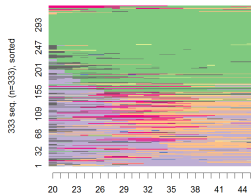


Rendering clusters: i-plots (sorted by 1st MDS factor)

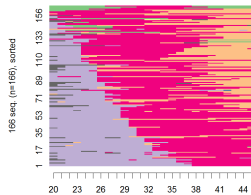
Type 1: Full Time Trajectories (52 %)



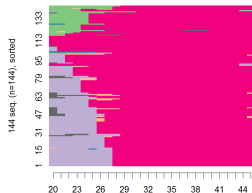
Type 2: Mixed Occupational Trajectories (22 %)



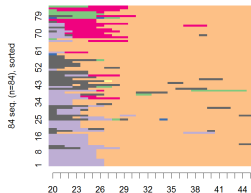
Type 3: Return Trajectories (11 %)



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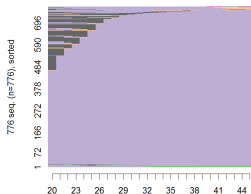


Type 5: Part Time Trajectories (5.5 %)

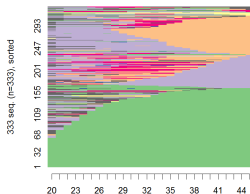


Rendering clusters: i-plots (sorted from end)

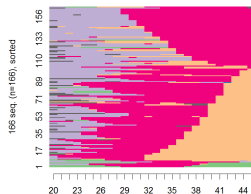
Type 1: Full Time Trajectories (52 %)



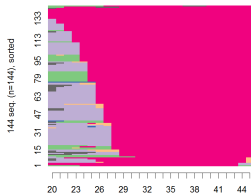
Type 2: Mixed Occupational Trajectories (22 %)



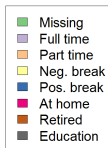
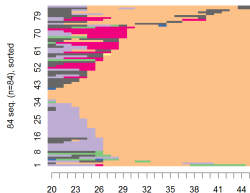
Type 3: Return Trajectories (11 %)



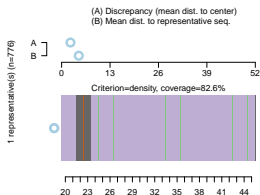
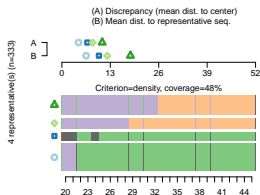
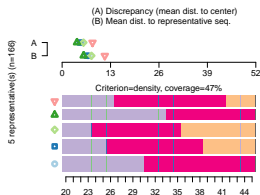
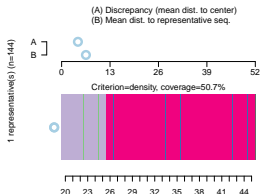
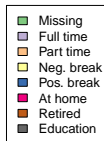
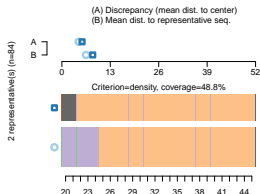
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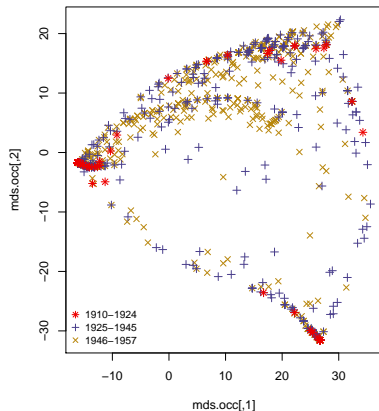
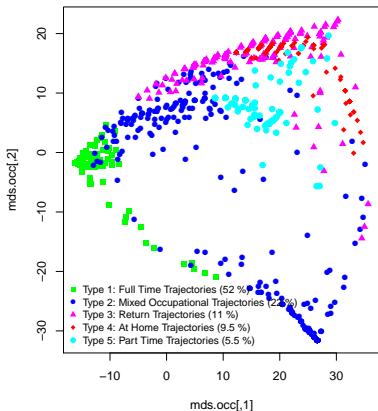
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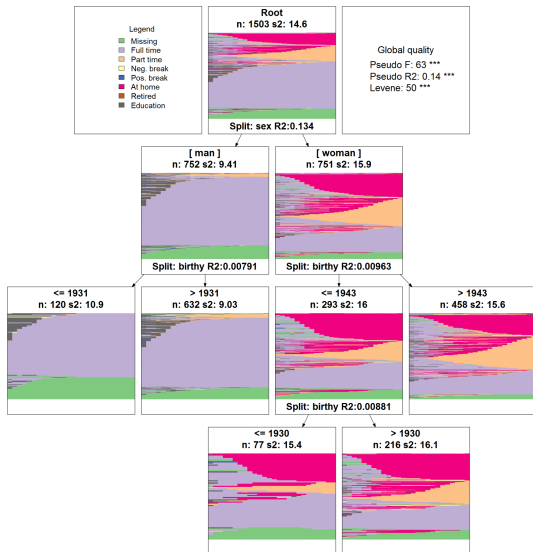
Representative sequences Gabadinho et al. (2011)

Type 1: Full Time Trajectories (52 %)

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Type 3: Return Trajectories (11 %)

Type 4: At Home Trajectories (9.5 %)

Type 5: Part Time Trajectories (5.5 %)


MDS: Scatterplot view of sequences



Regression tree (Studer et al., 2011)



Section outline

- 2 Some views of Swiss occupational trajectories
 - Rendering transversal and longitudinal characteristics
 - Dissimilarity-based analysis
 - Methods for event sequences

Event sequences

- Instead of the successive states, we may consider the **transitions** between states and more specifically the—possibly simultaneous—**events** that provoke the transitions.
- Event sequences are more difficult to render because they have no duration!
- Event sequences are of interest for studying the sequencing
 - What are the typical sequencing of life events?
 - Which event sequencing distinguishes men and women?
younger and older cohorts?

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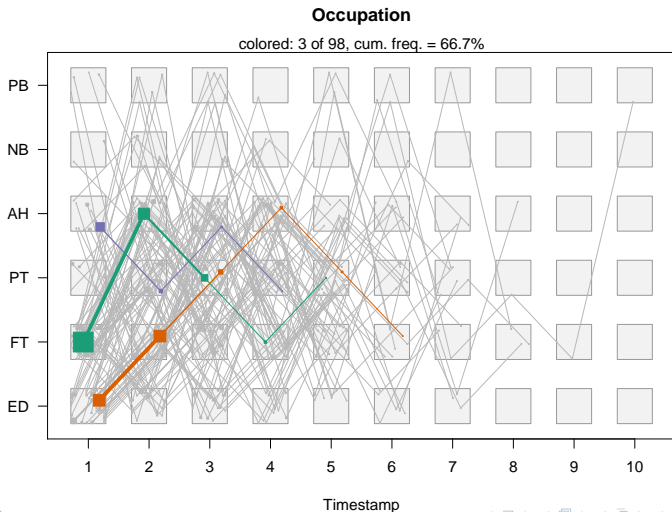
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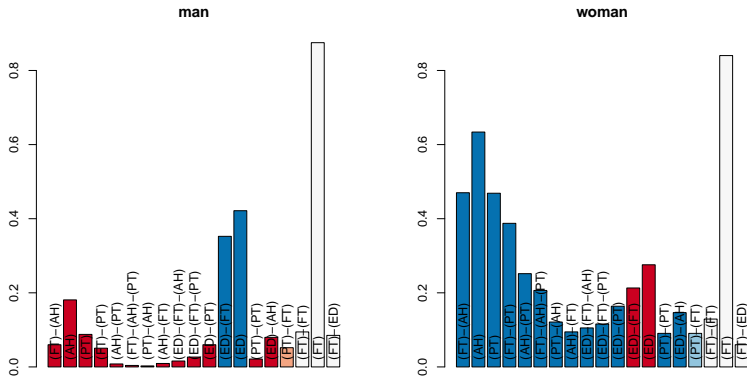
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Rendering event sequences

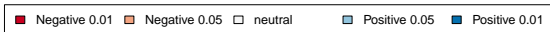
Parallel coordinate plot (Bürgin and Ritschard, 2012)



Event sequences: discriminating sub-sequences



Color by sign and significance of Pearson's residual



Outline

- 1 Sequences and sequence analysis
- 2 Some views of Swiss occupational trajectories
- 3 About TraMineR**
- 4 Conclusion

TraMineR: What is it?

TraMineR

- **Trajectory Miner in R**: a toolbox for exploring, rendering and analyzing categorical sequence data
- Developed within the SNF (Swiss National Fund for Scientific Research) project **Mining event histories** 1/2007-1/2011
- ... development goes on within IP 14 methodological module of the **NCCR LIVES: Overcoming vulnerability: Life course perspectives** (<http://www.lives-nccr.ch>) .

TraMineR, Who?

- Under supervision of a scientific committee:
 - Gilbert Ritschard (Statistics for social sciences)
 - Alexis Gabadinho (Demography)
 - Nicolas S. Müller (Sociology, Computer science)
 - Matthias Studer (Economics, Sociology)
 - Additional members of the development team:
 - Reto Bürgin (Statistics)
 - Emmanuel Rousseaux (KDD and Computer science)
- both PhD students within NCCR LIVES IP-14

TraMineR: Where and why in R?

- Package for the free open source R statistical environment
 - freely available on the CRAN (Comprehensive R Archive Network) <http://cran.r-project.org>
R> install.packages("TraMineR", dependencies=TRUE)
- TraMineR runs in R, it can straightforwardly be combined with other R commands and libraries. For example:
 - dissimilarities obtained with TraMineR can be inputted to already optimized processes for clustering, MDS, self-organizing maps, ...
 - TraMineR 's plots can be used to render clustering results;
 - complexity indexes can be used as dependent or explanatory variables in linear and non-linear regression, ...

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TraMineR's features

- Handling of longitudinal data and **conversion between various sequence formats**
- **Plotting sequences** (distribution plot, frequency plot, index plot and more)
- Individual **longitudinal characteristics** of sequences (length, time in each state, longitudinal entropy, turbulence, complexity and more)
- Sequence of **transversal characteristics** by position (transversal state distribution, transversal entropy, modal state)
- Other **aggregated characteristics** (transition rates, average duration in each state, sequence frequency)
- **Dissimilarities between pairs of sequences** (Optimal matching, Longest common subsequence, Hamming, Dynamic Hamming, Multichannel and more)
- **Representative sequences** and **discrepancy measure** of a set of sequences
- **ANOVA-like analysis** and **regression tree** of sequences
- Rendering and highlighting frequent event sequences
- Extracting **frequent event subsequences**
- Identifying **most discriminating event subsequences**
- **Association rules** between subsequences

Outline

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Conclusion: Limits of sequence analysis

- By focusing on complete trajectories until 45 years
=> we **ignore recent generations**
- Most recent birth year is **1957** (2002 – 45)
- Other issues:
 - **Granularity**: year, month, day, ...
 - **State definition**: should we distinguish {separated, divorced, widowed} or consider a single state? works by Raffaella Piccaretta

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SA Scalability

- SA main bottleneck is dimension of dissimilarity matrix.
 - Dimension depends on **number of cases** (should not exceed about 10000).
 - Solution: work on a representative sample of the sequences
- Other limitations are
 - **Size of alphabet** (should be less than 20), especially for graphical rendering, but also computation time.
 - Solution: aggregate elements of alphabet.
 - **Sequence length** (< 200), affects computation time.
 - Solution: change time granularity.

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Work in progress? ...

- SA is mainly static analysis of sequences
- Analysis of **generating processes** (Alexis Gabadinho's thesis)
 - Markov-Chain (MC) models
 - Variable length MC or probabilistic suffix trees (PST)
 - Model of the generating process
 - Likelihood of each sequence for a given model
 - Likelihood-based mining of typical and rare sequences
 - Testing divergence between groups with nested stratified models
- Modeling time evolution of tendencies in sequences (mixed effect model trees of longitudinal ordinal data) (Reto Bürgin's thesis)

Thank you!

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Other programs for sequence analysis

- **Optimize** (Abbott, 1997)
 - Computes optimal matching distances
 - No longer supported
- **TDA** (Rohwer and Pötter, 2002)
 - free statistical software, computes optimal matching distances
- **Stata**, SQ-Ados (Brzinsky-Fay et al., 2006)
 - free, but licence required for Stata
 - optimal matching distances, visualization and a few more
 - See also the add-ons by Brendan Halpin
<http://teaching.sociology.ul.ie/seqanal/>
- **CHESA** free program by Elzinga (2007)
 - Various metrics, including original ones based on non-aligning methods
 - Turbulence