Mining Life Event Sequences

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Society For Longitudinal and Life Course Studies International Conference
Amsterdam, September 23-25, 2013

Objectives

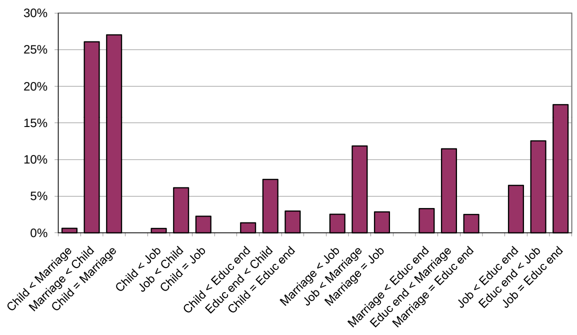
- Data-mining-based methods (pattern mining)
  - Discovering interesting information from sequences of life events, i.e., on how people sequence important life events
    - What is the most typical succession of family or professional life events?
    - Are there standard ways of sequencing those events?
    - What are the most typical events that occur after a given subsequence such as after leaving home and ending education?
    - How is the sequencing of events related to covariates?
    - Which event sequencings do best discriminate groups such as men and women?
  - Mining of frequent (Agrawal and Srikant, 1995; Mannila et al., 1995; Bettini et al., 1996; Mannila et al., 1997; Zaki, 2001) and discriminant event subsequences

Objectives (continued)

- Demonstrate the kind of results that can be obtained by mining event subsequences
- Search for
  - most frequent subsequences
  - subsequences that best discriminate groups (provided covariate)
- New concept of frequent maximal subsequence for more interesting results

What's new

- Previous attempts with event sequences in social sciences (e.g. Billari et al., 2006; Ritschard et al., 2007) mainly consisted in counting predefined subsequences.



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

Event sequences versus state sequences

- State sequence: states last a whole interval period

age	20	21	22	23	24	25	26
state	2P	2P	A	A	UC	UC	UC

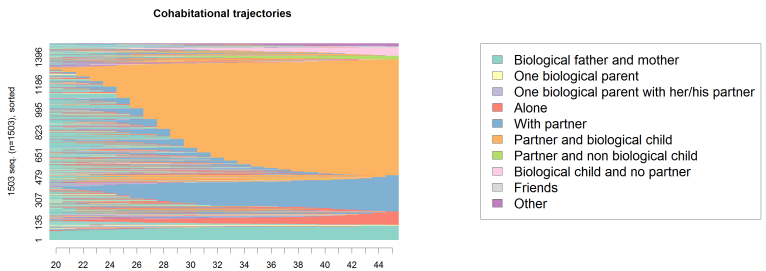
- Event sequence: events occur at a given (time) position
  - Interest in their order, in their sequencing
  - Can be time stamped (TSE)

id	Timestamp	Event
101	22	Leaving Home
101	24	Start living with partner
101	24	Childbirth

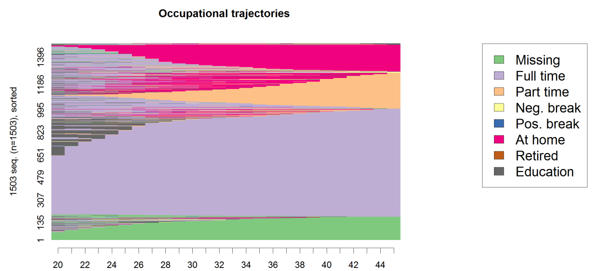
The Biographical SHP Data

- Sequences derived from the biographical survey conducted in 2002 by the Swiss Household Panel `www.swisspanel.ch`
- Retain the 1503 cases studied in Widmer and Ritschard (2009) with techniques for state sequences
- Two channels: Cohabitational and occupational
- Only individuals aged 45 or more at survey time
- Focus on life trajectory between 20 and 45 years
- Granularity is yearly level

The Cohabitational State Sequences



The Occupational State Sequences



Short and long state labels

Cohabitational		Occupational	
2P	Biological father and mother	Mi	Missing
1P	One biological parent	FT	Full time
PP	One biological parent with her/his partner	PT	Part time
A	Alone	NB	Neg. break
U	With partner	PB	Pos. break
UC	Partner and biological child	AH	At home
UN	Partner and non biological child	RE	Retired
C	Biological child and no partner	ED	Education
F	Friends		
O	Other		

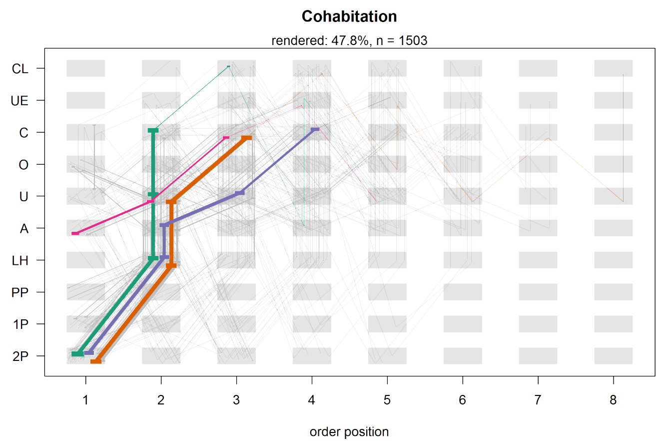
Events associated to cohabitational state transitions

- For cohabitational trajectories, we convert states to events by defining the events associated to the state transitions

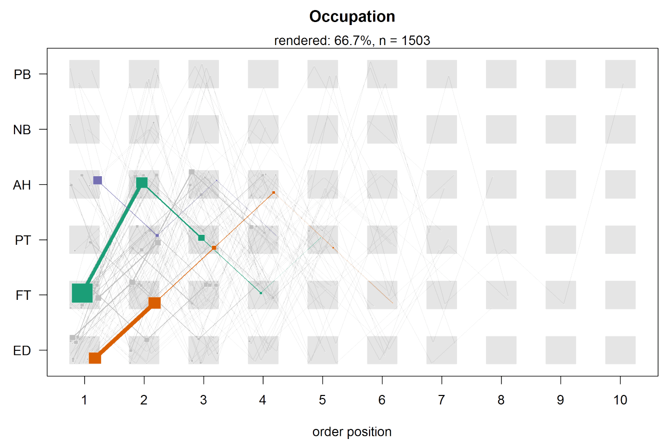
	2P	1P	PP	A	U	UC	UN	C	F	O
2P	"2P"	"1P"	"PP"	"LH,A"	"LH,U"	"LH,U,C"	"LH,U,C"	"LH,C"	"LH,A"	"LH,O"
1P	"2P"	"1P"	"PP"	"LH,A"	"LH,U"	"LH,U,C"	"LH,U,C"	"LH,C"	"LH,A"	"LH,O"
PP	"2P"	"1P"	"PP"	"LH,A"	"LH,U"	"LH,U,C"	"LH,U,C"	"LH,C"	"LH,A"	"LH,O"
A	"2P"	"1P"	"PP"	"A"	"U"	"U,C"	"U,C"	"C"	""	"O"
U	"2P"	"1P"	"PP"	"UE,A"	"U"	"C"	"C"	"C"	"UE,A"	"UE,O"
UC	"2P"	"1P"	"PP"	"UE,CL,A"	"CL"	"U,C"	"CL,C"	"UE"	"UE,CL,A"	"UE,CL,O"
UN	"2P"	"1P"	"PP"	"UE,CL,A"	"CL"	"C"	"U,C"	"UE,C"	"UE,CL,A"	"UE,CL,O"
C	"2P"	"1P"	"PP"	"CL,A"	"CL,U"	"U"	"CL,C"	"C"	"CL,A"	"CL,O"
F	"2P"	"1P"	"PP"	""	"U"	"U,C"	"U,C"	"C"	"A"	"O"
O	"2P"	"1P"	"PP"	"A"	"U"	"U,C"	"U,C"	"C"	"A"	"O"

- For occupational trajectories, we assign an event to the start of each spell in a state.

Rendering cohabitational event sequences
(Bürgin and Ritschard, 2012)



Rendering occupational event sequences
(Bürgin and Ritschard, 2012)



Frequent subsequences versus Frequent itemsets - 1

- Mining of frequent itemsets and association rules has been popularized in the 90's with the work of Agrawal and Srikant (1994); Agrawal et al. (1995) and their Apriori algorithm.
  - Find out items that customers often buy together
  - Symptoms that often occur together before a failure

Frequent subsequences versus Frequent itemsets - 2

- Interest on sequences for accounting for the time order of the buys or symptoms
- Mining typical event sequences is a specialized case of the mining of frequent itemsets
  - More complicated however
  - Must specify a counting method: How should we count multiple occurrences of a subsequence in a same sequence?
  - Which time span should be covered? Maximal gap between two events? ...
- Best known algorithms by Bettini et al. (1996), Srikant and Agrawal (1996), Mannila et al. (1997) and Zaki (2001).
- Algorithm in TraMineR is adaptation of the tree search described in Masseglia (2002).

Events and transitions

- Event sequence: ordered list of transitions.
- Transition: a set of non ordered events.

Example

(LHome, Union) → (Marriage) → (Childbirth)

- (LHome, Union) and (Marriage) are transitions.
- "LHome", "Union" et "Marriage" are events.

Subsequence

- A subsequence B of a sequence A is an event sequence such that
  - each event of B is an event of A,
  - events of B are in same order as in A.

Example

A (LHome, Union) → (Marriage) → (Childbirth).
B (LHome, Marriage) → (Childbirth).
C (LHome) → (Childbirth).

- C is a subsequence of A and B, since order of events is respected.
- B is not a subsequence of A, since we don't know in B whether "LHome" occurs before "Marriage".

Frequent and discriminant subsequences

- Support of a subsequence: number of sequences that contain the subsequence.
  - Frequent subsequence: sequence with support greater than a minimal support.
  - A subsequence is discriminant between groups when its support varies significantly across groups.

Frequent cohabitational subsequences

10 most frequent subsequences, min support = 50

- With at least 2 events

  Remember that we assigned the state at age 20 as start event

	Subsequence	Support	Count	#Transitions	#Events
1	(2P) → (LH)	0.621	934	2	2
2	(2P) → (U)	0.582	874	2	2
3	(2P) → (C)	0.477	717	2	2
4	(LH,U)	0.454	682	1	2
5	(U) → (C)	0.429	645	2	2
6	(2P) → (LH,U)	0.392	589	2	3
7	(LH) → (C)	0.382	574	2	2
8	(A) → (U)	0.376	565	2	2
9	(2P) → (LH) → (C)	0.325	489	3	3
10	(C,U)	0.291	437	1	2

Frequent occupational subsequences

Most frequent subsequences, min support = 50

- With at least 2 events

  Remember that we assigned the state at age 20 as start event

	Subsequence	Support	Count	#Transitions	#Events
1	(ED) → (FT)	0.283	425	2	2
2	(FT) → (AH)	0.265	398	2	2
3	(FT) → (PT)	0.219	329	2	2
4	(AH) → (PT)	0.130	195	2	2
5	(ED) → (AH)	0.113	170	2	2
6	(ED) → (PT)	0.112	168	2	2
7	(FT) → (FT)	0.112	168	2	2
8	(FT) → (AH) → (PT)	0.105	158	3	3
9	(FT) → (ED)	0.073	109	2	2
10	(ED) → (FT) → (PT)	0.071	107	3	3

Frequent subsequences easily extends to multichannel

- Here we have cohabitational and occupational trajectories
- Merging the two series of time stamped events
  - we get mixed cohabitational/occupational event sequences

Merged cohabitational and occupational sequences

12 most frequent subsequences, min support 150

	Subsequence	Support	Count	#Transitions	#Events
1	(FT) → (U)	0.695	1045	2	2
2	(2P) → (LH)	0.621	934	2	2
3	(FT) → (C)	0.583	876	2	2
4	(2P) → (U)	0.582	874	2	2
5	(FT) → (LH)	0.555	834	2	2
6	(2P) → (C)	0.477	717	2	2
7	(LH,U)	0.454	682	1	2
8	(U) → (C)	0.429	645	2	2
9	(2P) → (LH,U)	0.392	589	2	3
10	(LH) → (C)	0.382	574	2	2
11	(2P,FT)	0.378	568	1	2
12	(A) → (U)	0.376	565	2	2

Interesting frequent subsequences

- To get interesting knowledge we need to compare
  - most frequent subsequences
  - with longer less frequent subsequences in which they are included.
- For example,

	Subsequence	Support	Count	#Transitions	#Events
2	(2P) → (LH)	0.621	934	2	2
4	(2P) → (U)	0.582	874	2	2
9	(2P) → (LH,U)	0.392	589	2	3

- Here, we know that
  - among the 62.1% who left home (LH) after living with both parents (2P) when 20 years old
  - $39.2/62.1 = 63\%$ left home to start a union the same year

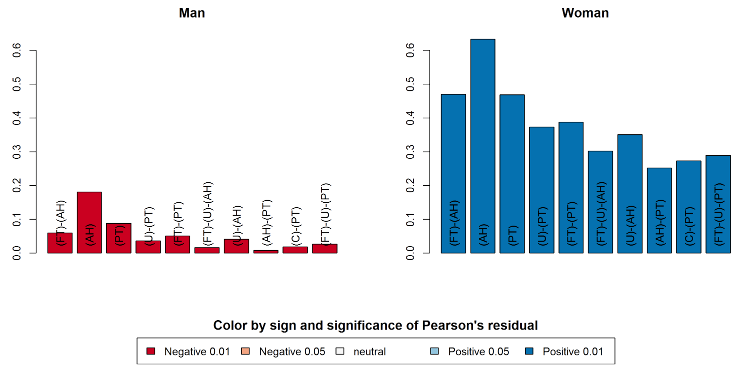
Mixed events: Subsequences that best discriminate sex

	Subsequence	Chi-2	Support	Freq. Men	Freq. Women	Diff
1	(FT) → (AH)	322.7	0.26	0.060	0.470	-0.410
2	(AH)	317.5	0.41	0.181	0.634	-0.453
3	(PT)	269.7	0.28	0.088	0.469	-0.381
4	(U) → (PT)	260.4	0.20	0.036	0.373	-0.337
5	(FT) → (PT)	247.5	0.22	0.051	0.387	-0.337
6	(FT) → (U) → (AH)	228.2	0.16	0.016	0.302	-0.286
7	(U) → (AH)	226.0	0.20	0.041	0.350	-0.309
8	(AH) → (PT)	195.5	0.13	0.008	0.252	-0.244
9	(C) → (PT)	193.3	0.15	0.019	0.273	-0.254
10	(FT) → (U) → (PT)	192.7	0.16	0.027	0.289	-0.262

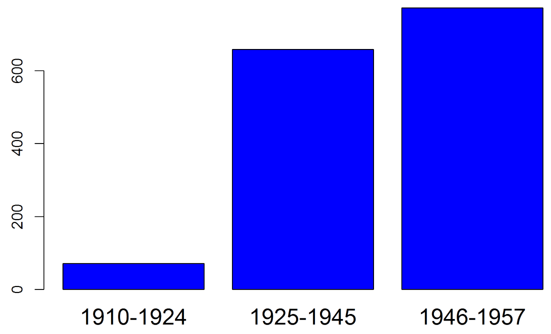
- Mainly occupational events (FT, PT and AH)
- In conjunction with a few cohabitational ones (U and C)

Mixed events: Subsequences that best discriminate sex

at the 0.1% level



Birth cohort distribution

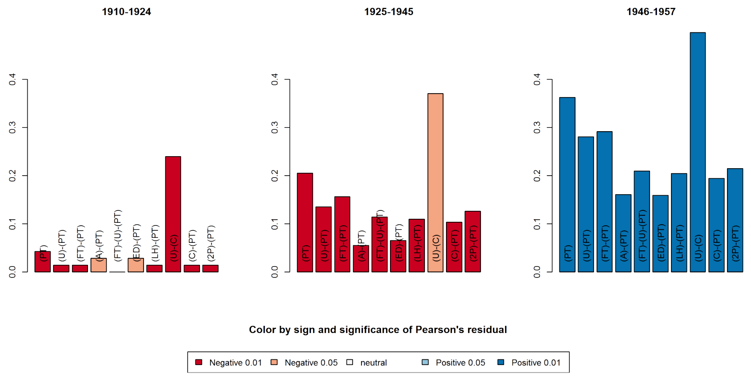


Mixed events: Subsequences that best discriminate birth cohorts

	Subsequence	Chi-2	Support	1910-25	1926-45	1946-57
1	(PT)	64.5	0.28	0.042	0.205	0.362
2	(U) → (PT)	63.0	0.20	0.014	0.135	0.281
3	(FT) → (PT)	56.1	0.22	0.014	0.156	0.291
4	(A) → (PT)	46.3	0.11	0.028	0.055	0.160
5	(FT) → (U) → (PT)	38.5	0.16	0.000	0.114	0.210
6	(ED) → (PT)	36.8	0.11	0.028	0.065	0.159
7	(LH) → (PT)	35.9	0.15	0.014	0.109	0.204
8	(U) → (C)	34.2	0.43	0.239	0.370	0.497
9	(C) → (PT)	34.0	0.15	0.014	0.103	0.194
10	(2P) → (PT)	32.7	0.17	0.014	0.126	0.215

- Mainly emergence of Part-time (PT)

Mixed events: Subsequences that best discriminate birth cohorts



Too many frequent subsequences

- There are often too many frequent subsequences!
- How can we structure those subsequences?
  - Eliminate redundant subsequences: When you experience one subsequence you also experiment all its subsequences.
    - Count only maximal subsequences
    - If subsequence (FT) → (AH) → (PT) is observed,
    - we would not count the occurrence of (FT) → (AH), (FT) → (PT) or (AH) → (PT)

Frequent maximal subsequence: Definition

- Frequent maximal subsequence: In each sequence, we count only those subsequences which are not themselves a subsequence of another frequent subsequence present in the same sequence.
  - Example: The subsequence (2P) → (LH) will be considered a maximal subsequence of sequences which do not also have a frequent supersequence such as (2P) → (LH,U).

Maximal frequent sequence in pattern mining

- Our definition of a frequent maximal subsequence differs from the notion of maximal frequent sequence used in pattern mining, where a frequent sequence is said maximal if none of its supersequence is frequent.
- In pattern mining, if *s* is a maximal frequent sequence, then none of its subsequences is a maximal frequent subsequence, even if it occurs frequently in sequences which do not include *s*.
- This is not very useful for life trajectories where we may be interested to know that
  - It is frequent to start a union (U) without having a child afterwards (U)→(C)

Frequent maximal subsequences: algorithm

1. Find frequent subsequences for the selected support
2. Starting from the longest obtained frequent subsequence
   - Adjust the count of each of its subsequence (by reducing their counts by the number of occurrences of the considered frequent sequence).
   - Delete from the list subsequences with counts falling below the support threshold.
3. Iterate on frequent subsequences ordered in decreasing order of length (using their already adjusted counts)

Max subsequences, cohabitational-occupational events

12 most frequent maximal subsequences, min support 150

	Subsequence	Support	Count	#Transitions	#Events
1	(2P) → (C,LH,U)	0.160	241	2	4
2	(FT) → (U) → (AH)	0.159	239	3	3
3	(FT) → (U) → (PT)	0.158	237	3	3
4	(FT) → (A,LH) → (U)	0.152	228	3	4
5	(2P,ED) → (FT) → (U)	0.140	210	3	4
6	(FT) → (C,LH,U)	0.140	210	2	4
7	(AH) → (C)	0.137	206	2	2
8	(2P) → (LH) → (AH)	0.133	200	3	3
9	(AH) → (U)	0.130	195	2	2
10	(2P,FT) → (LH,U)	0.129	194	2	4
11	(2P) → (LH) → (PT)	0.128	193	3	3
12	(2P,FT) → (AH)	0.126	190	2	3

Max subsequences, cohabitational-occupational events

12 most frequent maximal subsequences, min support 200

	Subsequence	Support	Count	#Transitions	#Events
1	(2P,FT) → (LH,U)	0.229	344	2	4
2	(A) → (U) → (C)	0.194	291	3	3
3	(2P,ED) → (LH)	0.189	284	2	3
4	(ED) → (FT) → (C)	0.189	284	3	3
5	(2P) → (A,LH) → (U)	0.181	272	3	4
6	(2P,FT) → (LH) → (C)	0.178	268	3	4
7	(2P) → (LH,U) → (C)	0.168	253	3	4
8	(2P) → (PT)	0.166	250	2	2
9	(FT) → (LH,U) → (C)	0.166	250	3	4
10	(2P) → (C,LH,U)	0.160	241	2	4
11	(FT) → (U) → (AH)	0.159	239	3	3
12	(FT) → (U) → (PT)	0.158	237	3	3

Solutions change with chosen support

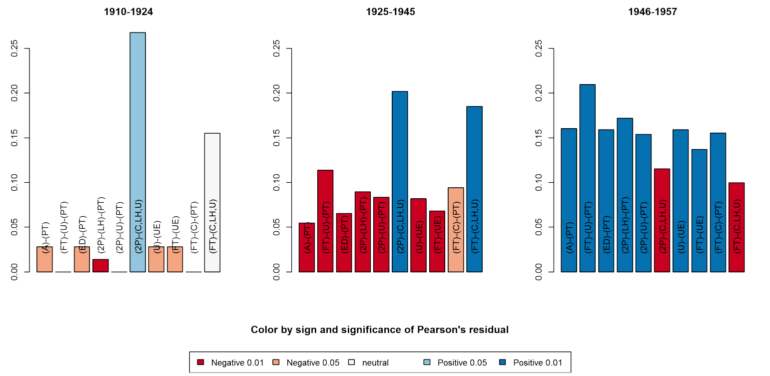
- As seen, solutions vary with chosen minsupport
- For minsupport $= 0$, we get the set of complete event sequences.
- We are working on criteria to select an optimal minsupport
  - to minimize the number of subsequences with no representative
  - maximize the average number of representatives
  - ...

Frequent max-subsequences discriminating birth cohorts

Minsupport=150

	Subsequence	Chi-2	Support	1910-25	1926-45	1946-57
1	(A) → (PT)	46.3	0.11	0.028	0.055	0.160
2	(FT) → (U) → (PT)	38.5	0.16	0.000	0.114	0.210
3	(ED) → (PT)	36.8	0.11	0.028	0.065	0.159
4	(2P) → (LH) → (PT)	30.4	0.13	0.014	0.090	0.172
5	(2P) → (U) → (PT)	27.0	0.12	0.000	0.083	0.154
6	(2P) → (C,LH,U)	26.2	0.16	0.268	0.202	0.115
7	(U) → (UE)	26.1	0.12	0.028	0.082	0.159
8	(FT) → (UE)	22.9	0.10	0.028	0.068	0.137
9	(FT) → (C) → (PT)	22.8	0.12	0.000	0.094	0.155
10	(FT) → (C,LH,U)	21.8	0.14	0.155	0.185	0.100

Frequent max-subsequences discriminating between cohorts



Conclusion

- Three approaches for event sequences
  - frequent episodes
  - discriminant episodes
  - cluster analysis (not addressed in this presentation)
- Complementary insights
  - most common characteristics
  - salient distinctions between groups
  - identify types of trajectories
- Easy to extend to other types of analyses (representative sequences, discrepancy analyses, ...)

Conclusion

- Looking at frequent max-subsequences produces more directly interpretable results
- Issue: Solutions vary with the minsupport threshold

Thank You!

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