Event sequence analysis

Network analysis of sequences of events

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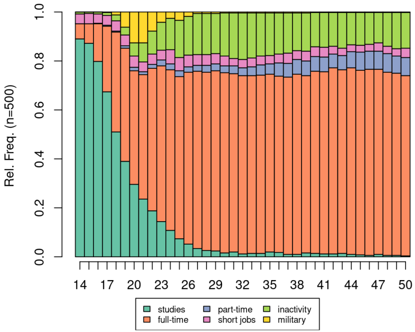
IMFM, FDV, UP IAM, Oštro

1343+1344. sredin seminar

Ljubljana, March 6, 2024

Outline



Vladimir Batagelj: vladimir.batagelj@fmf.uni-lj.si

Current version of slides (March 13, 2024 at 15 : 36): slides PDF

https://github.com/bavla/TQ/tree/master/trajectories/Feb24

Oštro

Last year in mid-November, Nuša was contacted by the Center for Investigative Journalism Oštro, asking if she could advise them on the analysis of data on members of the current Slovenian government and parliamentarians. Nuša agreed to the meeting, which I also attended. It turned out that Oštro collected the CVs of all the mentioned politicians. We found the data interesting. So we agreed to see how we could tackle them.

Person X's CV

$$CV_X = (e_1, e_2, \ldots, e_{k_X})$$

consists of a sequence of events e_i. For an event e_i

$$e_i = (s_i, f_i, r_i, q_i, \ldots)$$

we at least know its start date s_i, its end (finish) date f_i, the type r_i of the event, the location q_i of the event, and maybe something else.

Sequence analysis

Event sequence data encode sequences of events over time. I became aware of this kind of data years ago because for their analysis [1–4] results from my article on the generalized Ward criterion function [5] were used.

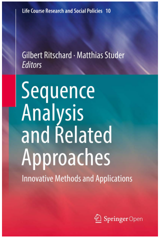
This subfield of longitudinal data analysis is closely related to time series analysis but the emphasis is on **categorical** values represented as states.

It is described by several tags: sequence analysis, life course, trajectory, career path, event history, multichannel sequence, discrepancy analysis, etc.

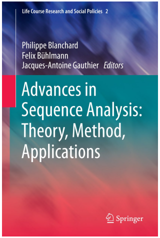
There is The Sequence Analysis Association (SAA).

Sequence analysis

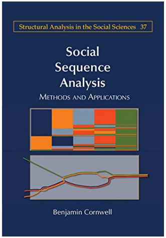
Books



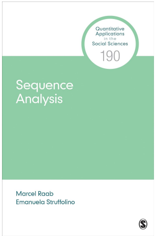
2018



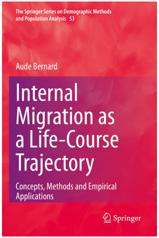
2014



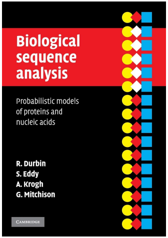
2015



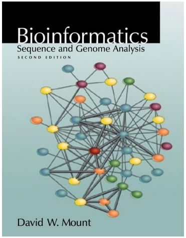
2022



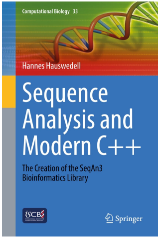
2022



1998



2004



2022

Sequence analysis

Fields of application

Recent overviews [6–9].
Sequence analysis in social sciences.

Fields of application:

- IT processes logs,
- healthcare,
- social science: life course research, career paths, daily patterns, life (family, housing, employment, demographic, etc.) trajectories,
- bank transactions,
- social media,
- sports,
- music, text,
- bibliometrics,
- etc.

Example gene homologies / Pax6 gene

Mouse	GTATCCAACGGTTGTGTGAGTAAAATTCTGGGCAGGTATTACGAGACTGGCTCCATCAGA
Fly	GTATCAAATGGATGTGTGAGCAAAATCCTCGGGAGGTATTATGAAACAGGAACCATACGA
Shark	GTGTCCAACGGTTGTGTCAGTAAAATCCTGGGCAGATACTATGAAACAGGATCCATCAGA
Squid	GTCTCCAACGGCTGCGTTAGCAAGATTCTCGGCAGGTACTATGAGACGGGCTCCATAAGA
Worm	GTGTCTAATGGTTGTGTTAGTAAAATACTTTGCCGATATTATGGAACAGGTTCTATTAAA

video

Sequence analysis

Example music [10]

Silvio Hein, "Maria Cahill's Arab Love Song"

Joseph E. Howard, "I Think I Hear a Woodpecker"

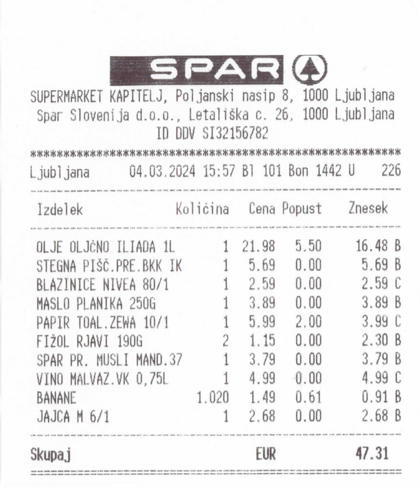
Sequence analysis

Example KEDS, Cameo


```
...
910625  YUG     YUGCRO  198     (WITHDRAW FROM) DECLARED INDEPENDENCE
910625  YUG     SLO     198     (WITHDRAW FROM) DECLARED INDEPENDENCE
910625  YUGCRO  YUG     081     (MAKE AGREEMENT)        IS PLANS
910625  YUGCRO  YUG     198     (WITHDRAW FROM) DECLARE INDEPENDENCE
910625  USA     YUG     102     (URGE)  REITERATED
910625  GER     YUG     031     (MEET)  TELEPHONED
910625  YUG     GER     031     (MEET)  TELEPHONED
910625  ITA     YUG     031     (MEET)  TELEPHONED
910625  YUG     ITA     031     (MEET)  TELEPHONED
910625  FRN     SLO     121     (CRITICIZE)     DISAPPROVED
910625  FRN     YUGCRO  121     (CRITICIZE)     DISAPPROVED
910626  SLO     YUG     043     (RALLY) CELEBRATED
910626  YUGCRO  SERMIL  223     (MIL ENGAGEMENT)        KILLED
910626  USR     YUGCRO  042     (ENDORSE)       SOVIET SUPPORT FOR CROATIA
910626  USR     SLO     042     (ENDORSE)       SOVIET SUPPORT FOR CROATIA
910626  YUG     SLO     182     (MILITARY DEMO) PUT ON ALERT
910626  YUG     YUGCRO  223     (MIL ENGAGEMENT)        KILLED
910626  SERMIL  SLO     199     ()      COMBAT
910626  YUGGOV  SLO     197     (CENSOR)        OUTLAWED
910626  YUGGOV  YUGCRO  197     (CENSOR)        OUTLAWED
910626  YUGGOV  SLO     210     (SEIZE) SEIZE
910626  AUL     YUGCRO  022     (PESSIMIST COMMENT)     SAID NOT
910626  USAGOV  YUG     022     (PESSIMIST COMMENT)     SAID NOT
910626  USA     YUG     112     (REFUSE)        OPPOSED
910626  USA     EUR     160     (WARN)  WARNED
910626  UNK     YUG     094     (CALL FOR)      CALLED ON
910626  NTH     EEC     022     (PESSIMIST COMMENT)     SAID NOT
910626  GERGOV  YUG     102     (URGE)  URGED
910627  SLO     SERMIL  223     (MIL ENGAGEMENT)        FIGHTING ERUPTED
910627  SLO     SERMIL  223     (MIL ENGAGEMENT)        SHOT
910627  SERMIL  SLO     031     (MEET)  SENT
910627  SLO     SERMIL  121     (CRITICIZE)     SLOVENIA SAID YUGOSLAV SOLDIER KILLED
...
```

Sequence analysis

Example purchase



SPAR

SUPERMARKET KAPITELJ, Poljanski nasip 8, 1000 Ljubljana
Spar Slovenija d.o.o., Letališka c. 26, 1000 Ljubljana
ID DDV SI32156782

Ljubljana 04.03.2024 15:57 B1 101 Bon 1442 U 226

Izdelek	Količina	Cena	Popust	Znesek	
OLJE OLJČNO ILIADA 1L	1	21.98	5.50	16.48	B
STEGNA PIŠČ.PRE.BKK IK	1	5.69	0.00	5.69	B
BLAZINICE NIVEA 80/1	1	2.59	0.00	2.59	C
MASLO PLANIKA 250G	1	3.89	0.00	3.89	B
PAPIR TOAL.ZEWA 10/1	1	5.99	2.00	3.99	C
FIŽOL RJAVI 190G	2	1.15	0.00	2.30	B
SPAR PR. MUSLI MAND.37	1	3.79	0.00	3.79	B
VINO MALVAZ.VK 0,75L	1	4.99	0.00	4.99	C
BANANE	1.020	1.49	0.61	0.91	B
JAJCA M 6/1	1	2.68	0.00	2.68	B

Skupaj EUR **47.31**

Sequence analysis

Example Ris

```
TY  - JOUR
AU  - Sun, F.
AU  - Chen, W.
AU  - Lin, T.
TI  - Improved Voting Algorithm Based on K-truss for Influence Maximization Problem
PY  - 2022
T2  - Jisuanji Gongcheng/Computer Engineering
VL  - 48
IS  - 11
SP  - 291
EP  - 298
DO  - 10.19678/j.issn.1000-3428.0063033
UR  - https://www.scopus.com/inward/record.uri?eid=2-s2.0-85143346303&doi=10.19678%2fj.issn.1000
AD  - School of Computer Science, South China Normal University, Guangzhou, 510631, China
AB  - In the Influence Maximization(IM) problem of social networks, approximation algorithms are
KW  - IC model
KW  - Influence Maximization(IM)
KW  - K-truss decomposition
KW  - SIR model
KW  - Social network
KW  - voting algorithm
PB  - Editorial Office of Computer Engineering
SN  - 10003428 (ISSN)
LA  - Chinese
J2  - Jisuanji Gongcheng
M3  - Article
DB  - Scopus
N1  - Export Date: 15 November 2023; Cited By: 0; Correspondence Address: F. Sun; School of Comp
ER  -
```

Event sequences

Example hospital

A — Event enumeration (OCEL)

22.10.2014 12:13	ER Registration	John Smith
22.10.2014 22:31	ER Registration	William Brown
23.10.2014 08:23	ER Sepsis Triage	John Smith
24.10.2014 08:11	CRP	John Smith
24.10.2014 09:19	ER Sepsis Triage	William Brown
25.10.2014 11:47	Leucocytes	William Brown
26.10.2014 11:48	IV Antibiotic	William Brown
26.10.2014 17:50	Release A	John Smith
28.10.2014 15:01	Release A	William Brown

B — Case-event enumeration (XES)

John Smith

22.10.2014 12:13	ER Registration
23.10.2014 08:23	ER Sepsis Triage
24.10.2014 08:11	CRP
26.10.2014 17:50	Release A

William Brown

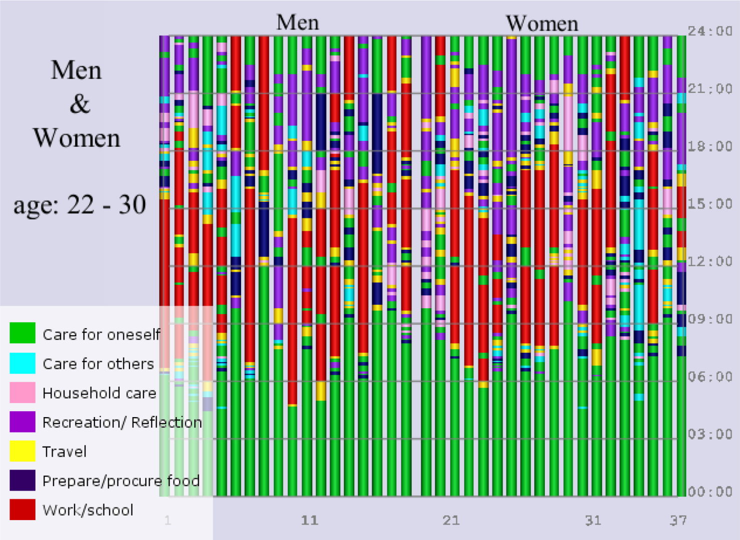
22.10.2014 22:31	ER Registration
24.10.2014 09:19	ER Sepsis Triage
25.10.2014 11:47	Leucocytes
26.10.2014 11:48	IV Antibiotic
28.10.2014 15:01	Release A

Object-Centric Event Log (OCEL)

1849-2023 - IEEE Standard for eXtensible Event Stream (XES)

Event sequences

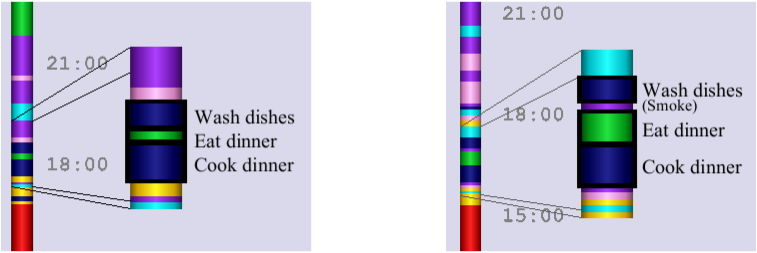
Diaries – A weekday of a group of individuals aged 22-30 [11]



Event sequences

Diaries – A weekday of a group of individuals aged 22-30 [11]

Examples of the activity sequence (*tuple*) "cook dinner→ eat dinner→ wash dishes" integrated in different ways in two individuals' diaries



a) a zero gap match

b) a gap = 1 match

Sequence analysis

basic notions

A *raw event sequence* S is a list of events

$$S = (e_1, e_2, \ldots, e_n)$$

n is the *length* of the sequence S. Each event is a list of *named attributes*

$$e_i = (ind = i, t = t_i, a_1 = a_{1i}, a_2 = a_{2i}, \ldots, a_m = a_{mi})$$

where ind is the event's *index*, t is the event's *temporal* information, and a_is are *data attributes* describing different event characteristics. Their values can be structured objects.

In an event, some attributes can be missing. Each event has at least one data attribute defined (has value). An attribute a_i is called *general* if it is defined for all events in the sequence S. The attribute ind and usually also the time t are general attributes.

An alternative is to list for each event all its attributes with "missing" attributes having value *undefined* □.

Sequence analysis

time

The temporal information can be described in different ways

- implicitly – the time is determined by the event's index. It expresses the ordering of events,
- $t_i \in \mathbb{N}$ – it expresses the ordering of events or starts of events on a discrete timeline (hours, days, years, etc.),
- $t_i = (s_i, f_i)$ – it specifies the time interval of event e_i; s_i is the start and f_i is the finish time of the event; $s_i \leq f_i$,
- $t_i = (s_i, d_i)$ – it specifies the time interval of event e_i; s_i is the start and d_i is the duration time of the event; $d_i \geq 0$.

Quantities s_i and f_i are expressed as numbers or as date-time stamps. In some applications, an event's time can be of different types: *interval* (both values are defined) and *instantaneous* (the second value is undefined).
The time can be measured on a *common* timeline or on a *relative* timeline (for example from a birthday of each person).

Sequence analysis

In the dataset that includes events in the careers of 40 professors, we have both: point events (e.g., time they received their bachelor's or master's degrees, published a journal or conference paper) and interval events (e.g., appointments as an assistant or associate professor).

We denote

- e_i – event with $ind = i$,
- $e_i.a$ – value of the attribute a in the event e_i.

Often in our analyses, we do not need all the available data attributes and some attributes need to be recoded – we transform the raw event sequence S into a work event sequence S'.

Usually, we also have some additional data about the (values of) attributes used in the event description. For example: address, age, gender, etc. of persons.

Let π be a *partition* of $1:n$ into k classes. A sublist of S

$$S_j^\pi = (e_i : (e_i \in S) \wedge (\pi(i) = j))$$

is the *event sequence* of the class j. The order of events in a list S_j has to be compatible with the time t: $p < q \Rightarrow s_p \leq s_q$. We get a *set of event sequences* $E^\pi = \{S_j^\pi : j \in 1:k\}$.

Usually, for a categorical general attribute a with a range C , the partition π_a is defined by

$$\pi_a(i) = \mathrm{ind}(a_i)$$

where the function ind returns the position (index) of the value a_i in the list C.

Note that in a general event sequence, some events can be active in parallel.

Sequence analysis deals with questions about the set of event sequences E

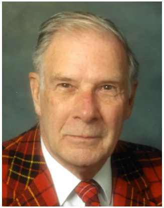
- structure of the set E (statistics, clustering, visualization)
- models that generate sequences from the set E (transition matrices, Petri nets, Markov chains)
- frequent patterns – motifs (subsequences) in sequences from E
- networks derived from E
- etc

Sequence analysis

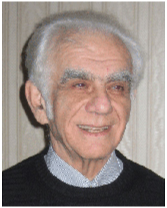
History

Event sequences were studied already in the first half of the 20th century in Engineering and Operation research (tasks scheduling, CPM, Pert, transportation) and Computer and Communication sciences (signal processing, coding, language and automata theory [12, 13]). In the second half of the 20th century, they found an application in Biology in studying DNA [14].

Sequence Analysis (SA) was introduced in the field of social sciences in 1983 by Andrew Abbott [15] and by Abbott and Forrest [16] (1986). It has become a very popular tool for studying trajectories.



Hamming

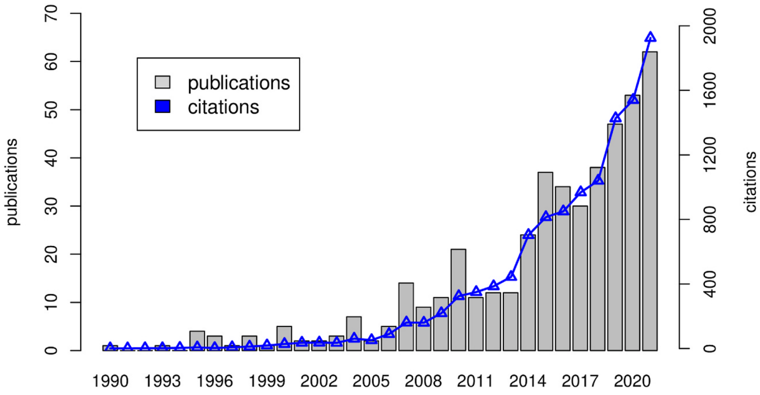


Levenshtein

Abbott

Sequence analysis

Journal publication and citation trends [6]



Sequence analysis

A typical application of SA, according to Abbott and Tsay [17], involves three steps: coding narratives or processes as sequences, measuring pairwise dissimilarities between sequences, and some form of data reduction such as cluster analysis, and post-analysis of the obtained results.

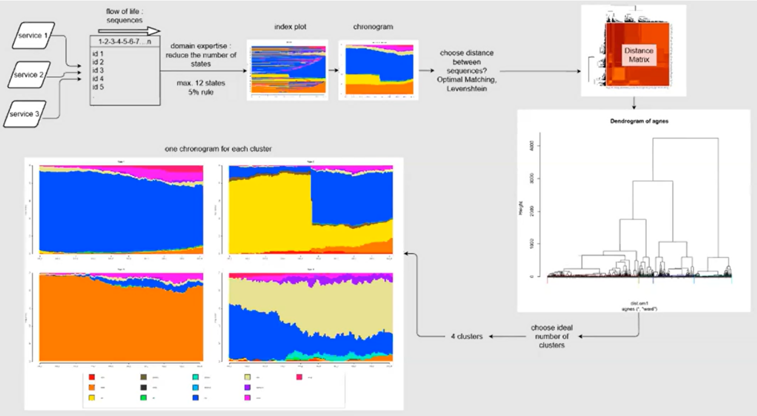
Often in the data-cleaning phase, we need to reduce the number of states – alphabet reduction: state $< 2\% \rightarrow$ "other". Also in the case of multiple states at the same time point are replaced by the dominant state.

For details see:

Fasang, A, Struffolino, E (2022) Sequence Analysis for Social Science [18]

Robette, N (2023) Tutorial on sequence analysis [19]

Basic steps video



Sequence analysis

Sequence (dis)similarity measures [20]

- Hamming distance (Hamming, 1950) and dynamic HD (Lesnard, 2010)
- Optimal matching (OM) distance based on state editing (substitution, insertion, deletion; Abbott & Forrest, 1986 [16]) – essentially the Levenshtein distance (Levenshtein, 1965 [13])
- Elzinga's combinatorial measures (Elzinga, 2003, 2005, 2007)
- TWED – Time warp edit distance (Marteau, 2009)
- DTW – Dynamic time warping distance (Rabiner & Juang, 1993)
- LCS – Longest common subsequence (Wagner & Fischer, 1974)

Sequence analysis

Datasets

- Sample Datasets
- UC Irvine Machine Learning Repository
- IEEE Task Force Event Log repository
- International Event Data Sets; books
- Kaggle / event sequence

The Sequence Analysis Association / software

- TraMineR/CRAN,
- EventFlow, EventAction,
- Stata: SADI, SQ,
- Gantt Chart, LiveGantt,
- Flow, LifeFlow, OutFlow, DecisionFlow,
- StoryLines, Narrative, StoryFlow,
- MatrixFlow, MatrixWave,
- Episogram, CarePathway, Frequence, Peekquence, Logan, TreatmentExplorer,
- EventThread, PatternFinder, Similan2,
- VISUAL-TimePAcTS,

Event sequences

Clusters, state proportion plots, modal plots [6]

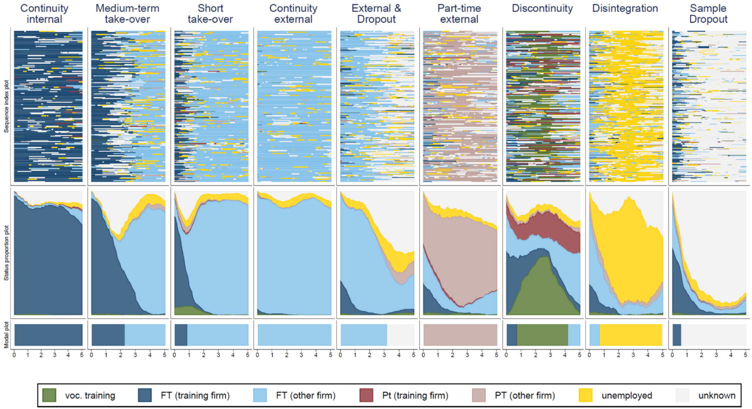
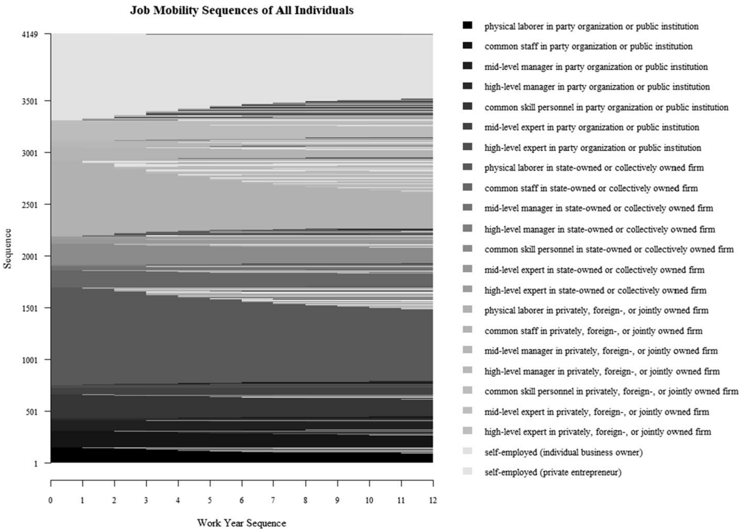


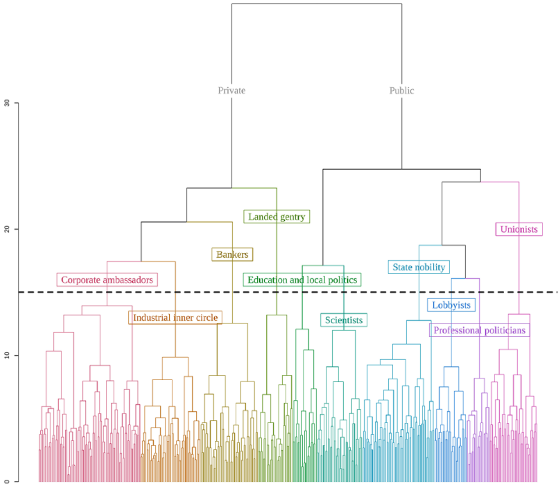
Fig. 3. Example of combination of sequence index plots, state proportion plots and modal plots; taken from Brzinsky-Fay et al. (2016).

Event sequences

Job mobility sequences ordered by start level [22]

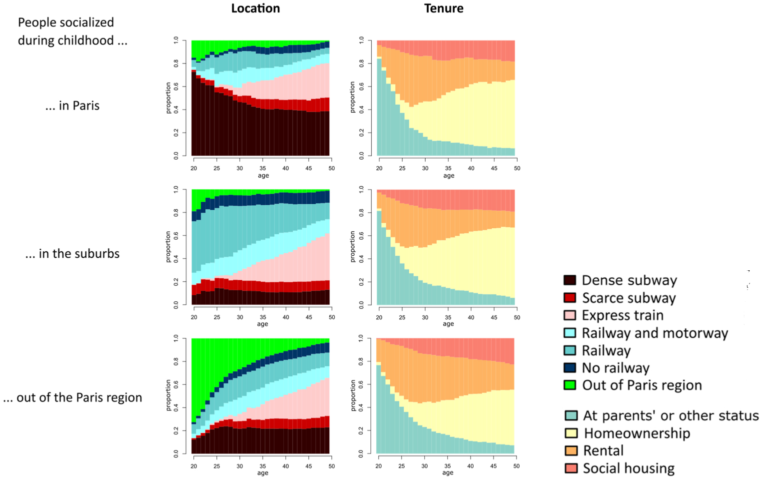


Interpreted dendrogram, Ellersgaard (2019)



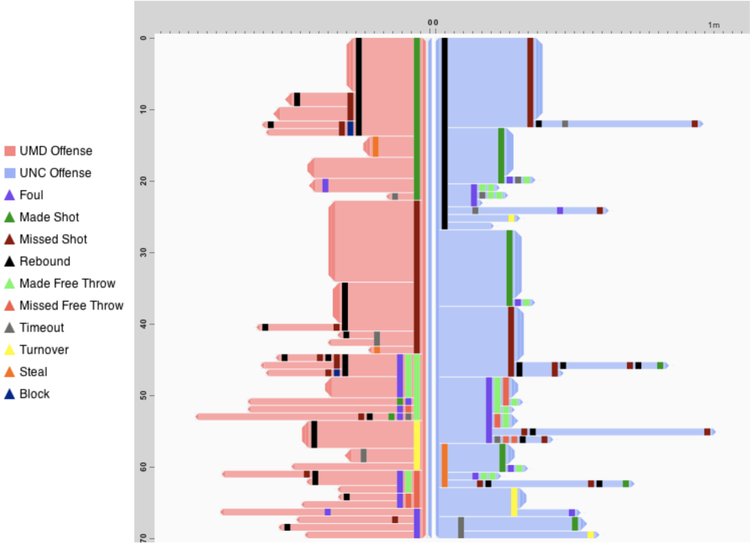
Event sequences

Partition based on selected attribute [2]

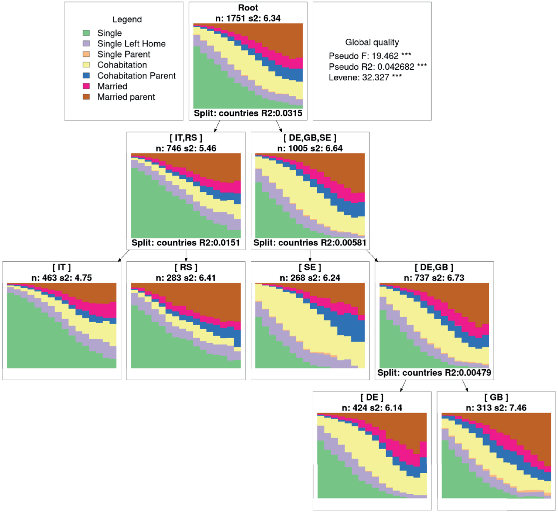


Event sequences

Basketball Play-by-play Analysis, Monroe (2013, slides)

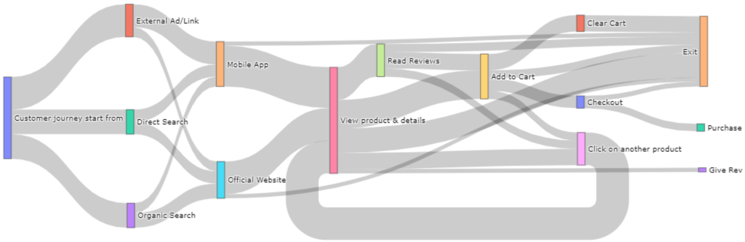


Hierarchical plot, Stanojevic (2021)



Event sequences

Sankey Diagram for Customer Journey, Warudkar (2020, page)



Oštro

Problem

Oštro, Center for Investigative Journalism in the Adriatic Region compiled data on the career paths of all current public officials (prime minister, ministers, secretaries, and deputies in the National Assembly) from their CVs and then verified and supplemented it with the help of registers, specialized databases, media archives, independent investigative work, etc.

1. who [person name] is related to whom [person name]? The longer the common time period [start_day/start_month_start_year - end_day/end_month_end_year] in the common institution [institution_si], the stronger the connection
2. how many different institutions [institution_si] connect two individuals [name]
3. how much time [start_day/start_month_strat_year - end_day/end_month_end_year] individuals [name] spent in political positions [affiliation type = politician]
4. number of management positions before and after political office [affiliation type = manager in a public company], [affiliation type = manager in a company], [position = state secretary], [position = minister], [position = Prime Minister]

Oštro

Problem

5. the number of advisory positions [part of CV = advisory and supervisory functions etc.] before and after the political function [affiliation type = politician]
6. what is the last position [position_si] before starting the political office [affiliation type = politician] and what is the first position [position_si] after the end of the political office
7. party power - how "profitable" is an individual party [PERSONS_LIVE tab: party_si], in terms of what positions [position_si] the functionaries move to after the end of the political function [affiliation type = politician]
8. the highest level of education achieved [part of CV = education] - is there a difference between MPs, secretaries and ministers [PERSONS LIVE: position tab]
9. gender [PERSONS LIVE tab: gender]
10. newbies [PERSONS LIVE tab: IS_FIRST_TIME_IN_OFFICE]

We will try to analyze the data following the research question: Do the former connections in different areas affect political connections among the current political office holders? What is the structure of the current set of Slovenian public officials?

Oštro

Raw data

The raw **Zvezoskop** data table was prepared in Excel for “human inspection”. It contains 3157 events. It had to be normalized for “computer processing”

- uppercase and lowercase initials
- extra spaces at the end of strings
- masculine/feminine form of words (poslanec / poslanka, etc.)
- mixed date format (dd/mm/yyyy / mm/dd/yyyy)
- incomplete dates (month and year only or year only)

Oštro event sequences dataset has some specifics: real-time events, parallel events in the same sequence, and different types of events.

Oštro

Raw data

```
,person_id,person_name,part_of_cv,show_in_network,start_day,start_month,
start_year,institution_si,institution_standardized_si,institution_department_si,
affiliation_type_si,position_si,end_day,end_month,end_year,notes_institution_si,notes_position_s
...
2241,112,Matej Tonin,izobraževanje,True,,9,1998,gimnazija in srednja šola rudolfa maistra kamnik
2242,112,Matej Tonin,izobraževanje,True,,10,2002,ul fakulteta za družbene vede,,,dodiplomski št
2243,112,Matej Tonin,izobraževanje,True,,10,2007,ul fakulteta za družbene vede,,,magistrski štu
2244,112,Matej Tonin,delovne izkušnje,True,16/4/2007,,2007,državni zbor,,poslanska skupina NSi,j
2245,112,Matej Tonin,strankarska pozicija,True,,,2006,nsi,,občinski odbor Kamnik,,predsednik,,,2
2246,112,Matej Tonin,strankarska pozicija,True,10/9/2010,,2010,nsi,,,,kanididat za župana v obči
2247,112,Matej Tonin,delovne izkušnje,True,29/11/2006,,2006,občina kamnik,,,politik,občinski sve
2248,112,Matej Tonin,strankarska pozicija,True,,,2007,nsi,,Mlada Slovenija,,podpredsednik,,,2009
2249,112,Matej Tonin,delovne izkušnje,True,3/11/2008,,2008,vizija agencija za komuniciranje mate
2250,112,Matej Tonin,strankarska pozicija,True,,,2010,nsi,,,,podpredsednik,,,2012,,
2251,112,Matej Tonin,delovne izkušnje,False,21/12/2011,,2011,državni zbor,,,politik,poslanec,13/
2253,112,Matej Tonin,delovne izkušnje,True,22/6/2018,,2018,državni zbor,,,politik,predsednik,23/
2254,112,Matej Tonin,delovne izkušnje,False,13/5/2022,,2022,državni zbor,,,politik,poslanec,,,21
2255,112,Matej Tonin,strankarska pozicija,True,22/8/2008,,2008,nsi,,,,kandidat za poslanca,21/9/
2256,112,Matej Tonin,delovne izkušnje,True,13/3/2020,,2020,ministrstvo za obrambo,,,politik,mini
2257,112,Matej Tonin,delovne izkušnje,True,13/3/2020,,2020,vlada,,,politik,podpredsednik,1/6/202
2258,112,Matej Tonin,strankarska pozicija,True,1/2/2018,,2018,nsi,,,,v d predsednika ,20/4/2018,
2259,112,Matej Tonin,strankarska pozicija,False,21/4/2018,,2018,nsi,,,,predsednik,,,2100,,
2260,112,Matej Tonin,svetovalne in nadzorne funkcije etc.,True,,,2015,inštitut dr janeza evangel
2261,112,Matej Tonin,prostočasne aktivnosti,True,27/11/2006,,2006,športno društvo tuhinj,,,,pred
2262,112,Matej Tonin,strankarska pozicija,False,,12,2001,nsi,,,,član,,,2100,,
2263,112,Matej Tonin,strankarska pozicija,False,1/2/2018,,2018,nsi,,izvršilni odbor,,predsednik,
...
```

Oštro

Reduced data

The cleaned data table was first reduced to variables considered in the analysis.

- R – row (event) number (index)
- ID – `person_name`: person's name
- s – `start_day|month|year`: start date
- f – `end_day|month|year`: finish date
- S – `part_of_cv`: type of activity
- T – `institution_si`: location (institution, party, organization, etc.)

Oštro

data

```
raw2events <- function(D,Tday="",CSV="events.csv"){
  if(Tday=="") Tday <- format(Sys.time(),"%d/%m/%Y")
  csv <- file(CSV,"w",encoding="UTF-8")
  cat("R  ID  s  f  S  T\n",file=csv)
  n <- nrow(D); OK <- TRUE; k <- 0; td <- datum(Tday,0,0)
  for(i in 1:n){add <- TRUE
    ID <- trimws(D$person_name[i]); rel <- trimws(tolower(D$part_of_cv[i]))
    test <- trimws(tolower(D$institution_si[i]))
    ds <- D$start_day[i]; ms <- D$start_month[i]; ys <- D$start_year[i]
    sd <- datum(ds,ms,ys)
    if(sd>=td) add <- FALSE
    if(!OK) {cat(i,":",ID,ds,ms,ys,rel,'*** wrong date\n')
      flush.console(); OK <- TRUE; add <- FALSE}
    de <- D$end_day[i]; me <- D$end_month[i]; ye <- D$end_year[i]
    ed <- if(ye==2100) datum(Tday,NA,0) else datum(de,me,ye)
    ed <- min(ed,td)
    if(!OK) {cat(i,":",ID,de,me,ye,rel,'*** wrong date\n')
      flush.console(); OK <- TRUE; add <- FALSE}
    if(add) cat(i,' "',ID,'" ',sd,' ',ed,' "',rel,'" "',test,'"\n',sep='',file=csv) else
      k <- k+1
  }
  close(csv)
  if(k>0) {cat(k," events skipped\n"); flush.console()}
}
```

Oštro

Data – co-presence

R	ID	s	f	S	T
64	Igor Papič	1973-09-01	1981-08-01	education	oš v kočevju
1116	Robert Golob	1979-09-01	1983-08-01	education	gim nova gorica
65	Igor Papič	1981-09-01	1985-06-01	education	vegova ljubljana
1068	Robert Golob	1983-10-01	1989-09-29	education	ul fe
66	Igor Papič	1986-10-01	1992-01-01	education	ul fe
1070	Robert Golob	1989-11-15	1994-11-14	work	ul fe
1069	Robert Golob	1992-10-01	1994-10-17	education	ul fe
67	Igor Papič	1992-10-01	1995-01-01	education	ul fe
1115	Robert Golob	1994-01-01	1994-01-01	education	tu georgia atlanta us
70	Igor Papič	1994-01-01	1996-01-01	work	siemens de
1071	Robert Golob	1994-11-15	1995-10-31	work	ul fe
69	Igor Papič	1993-03-01	1996-01-01	work	ul fe
68	Igor Papič	1995-10-01	1998-01-01	education	ul fe
1072	Robert Golob	1995-11-01	1997-09-30	work	ul fe
1073	Robert Golob	1997-10-01	2001-06-30	work	ul fe
1078	Robert Golob	1998-11-01	1999-08-31	work	min za gospodarstvo
71	Igor Papič	1999-01-01	2007-01-01	work	ul fe
96	Igor Papič	2000-01-01	2002-06-30	work	ul fe
94	Igor Papič	2001-01-01	2002-12-31	work	ul fe

...

	u	v	s	f	rel	d	Ru	Rv
1	Robert Golob	Igor Papič	1986-10-01	1989-09-29	education	1094	1068	66
2	Robert Golob	Igor Papič	1993-03-01	1994-11-14	work	623	1070	69
3	Robert Golob	Igor Papič	1992-10-01	1994-10-17	education	746	1069	67
4	Igor Papič	Robert Golob	1994-11-15	1995-10-31	work	350	69	1071
5	Igor Papič	Robert Golob	1995-11-01	1996-01-01	work	61	69	1072
7	Robert Golob	Igor Papič	1999-01-01	2001-06-30	work	911	1073	71
10	Robert Golob	Igor Papič	2000-01-01	2001-06-30	work	546	1073	96
12	Robert Golob	Igor Papič	2001-01-01	2001-06-30	work	180	1073	94

...

GitHub

Oštro

Co-presence network

We decided to base our analysis on the corresponding *co-presence network* – a weighted multi-relational temporal network $\mathcal{N} = (V, L, w, t)$.

The set of nodes V consists of persons from the data table.

There is a link (edge) $\ell = (u : v; S)$ of type (relation) S between persons $u, v \in V$ iff there exist events
$e_u = (ID = u, s = s_u, f = f_u, S = S_u, T = T_u)$ and
$e_v = (ID = v, s = s_v, f = f_v, S = S_v, T = T_v)$ such that
$S_u = S_v = S$ and $T_u = T_v$ and $[s, f] = [s_u, f_u] \cap [s_v, f_v] \neq \emptyset$.
The weight of the link $\ell \in L$ is $w(\ell) = f - s$, that is the length (in days) of the corresponding time interval $[s, f]$.

Oštro

Co-presence network: Mestna občina Nova Gorica

Oštro

Co-presence network

In preliminary experiments, we found that parallel events of the same kind can greatly increase the similarity between persons. One way to reduce this influence is to count parallel events of the same type between two persons only once.

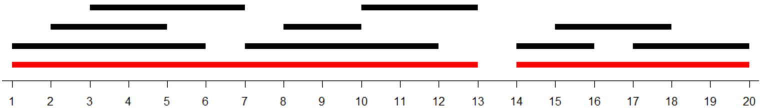
We can do this by creating an associated set of time intervals for each quadruple (u, v, S, T) and computing its union, which we use to determine links. An efficient procedure is obtained if the data is ordered according to (u, v, S, T, s, f).

Oštro

Co-presence network

The weight of a link (similarity of a pair of persons) is based on

- only pairs with different names are considered - the network has no loops
- in the results, the pairs are ordered ($u < v$)
- parallel connections of the same type are counted only once



All time intervals $\{[s_i, f_i] : i \in 1 : k\}$ of edges between nodes u and v of kind S we replace with a single edge with weight

$$w(u, v; S) = |\bigcup_{i=1}^{k} [s_i, f_i]|$$

Oštro

Co-presence network

```
intUnion <- function(N){
  k <- nrow(N); z <- rep(0,k); L <- data.frame(s=z,f=z)
  i <- 1; r <- 0; s <- N$s[i]; f <- N$f[i]
  while(i<k){i <- i+1
    if(N$s[i]<=(f+1)){ if(N$f[i]>f) f <- N$f[i]
    } else { r <- r+1; L[r,] <- list(s=s,f=f); s <- N$s[i]; f <- N$f[i] }
  }
  r <- r+1; L[r,] <- list(s=s,f=f)
  return(L[1:r,])
}

traj2Pajek <- function(E,kMax,Net){
  I <- order(E$s,E$f)
  n <- length(I); k <- 0; r <- 0; sent <- "?????"
  cn <- rep(0,kMax); cs <- rep("",kMax)
  N <- data.frame(u=cs,v=cs,s=cn,f=cn,rel=cs,test=cs)
  cat("% traj2Pajek",date(),"\nevents",n,"\n")
  for(p in 1:(n-1)){i <- I[p]; tm <- E$f[i]
    cat("."); if(p%%50==0) {cat(p,k,date(),"\n")}; flush.console()
    for(q in (p+1):n){j <- I[q]; r <- r+1
      if(E$s[j]>tm) break
      uID <- E$ID[i]; vID <- E$ID[j]
      if(uID!=vID) {
        if(uID > vID) {vID <- E$ID[i]; uID <- E$ID[j]}
        if(E$S[i]==E$S[j]) if(E$T[i]==E$T[j]) {
          fm <- min(E$f[i],E$f[j]); sM <- max(E$s[i],E$s[j]); T <- fm-sM+1
          if(T>0){k <- k+1; if(k>kMax) stop("kMax too small")
            N[k,] <- list(u=uID,v=vID,s=sM,f=fm,rel=E$S[i],test=E$T[i])}
        }
      }
    }
  }
  cat("\n",date(),"\ndensity R =",2*r/n/(n-1),"  tests =",r,
    "\ndensity E =",2*k/n/(n-1),"  edges =",k,"\n"); flush.console()
```

Oštro

Co-presence network

```
    N <- N[1:k,]; I <- order(N$u,N$v,N$rel,N$test,N$s,N$f); N <- N[I,]
    N[k+1,] <- list(u=sent,v=sent,s=0,f=0,rel="",test="")
    cn <- rep(0,k); cs <- rep("",k); r <- 0; q <- 0; k <- k+1
    M <- data.frame(u=cs,v=cs,s=cn,f=cn,rel=cs,test=cs)
    Q <- data.frame(s=cn,f=cn); i <- 1; H <- N[i,c("u","v","rel","test")]
    for(p in 1:k){
      G <- N[p,c("u","v","rel","test")]
      if(all(H==G)) {q <- q+1; Q[q,] <- list(s=N$s[p],f=N$f[p])} else {
        L <- intUnion(Q[1:q,])
        for(h in 1:nrow(L)){ r <- r+1
          M[r,] <- list(u=H$u,v=H$v,s=L$s[h],f=L$f[h],rel=H$rel,test=H$test)
        }
        if(p==k) break
        H <- G; i <- p; q <- 0
      }
    }
    M <- M[1:r,]; sf <- as.matrix(M[,c("s","f")])
    cat("density E' =",2*r/n/(n-1),"  edges' =",r,"\n"); flush.console()
    uvrwt2net(M$u,M$v,w=M$f-M$s+1,r=M$rel,t=sf,directed=FALSE,Net=Net)
    cat("% finished",date(),"\n")
}

> D <- read.csv("./ostro_podatki.csv",sep=",",head=TRUE)
> raw2events(D,Tday="",CSV="Slo4all.csv")
> raw2events(D,Tday="24/4/2022",CSV="Slo4apr22.csv")
> Ea <- read.csv("Slo4all.csv",sep="")
> traj2Pajek(Ea,500000,"./Slo4all.net")
> Ee <- read.csv("Slo4apr22.csv",sep="")
> traj2Pajek(Ee,500000,"./Slo4apr22.net")
```

R library trajector.R

```
> source("https://raw.githubusercontent.com/bavla/TQ/master/trajectories/trajector4.R")
> E <- read.csv("Slo4.csv",sep="")
> p1 <- "Mojca Šetinc Pašek"; p2 <- "Tanja Fajon"
> (X <- explain(E,p1,p2))
                   u           v          s          f    d       rel     test
1 Mojca Šetinc Pašek Tanja Fajon 1996-11-18 2001-09-03 1751      work  rtv slo
2 Mojca Šetinc Pašek Tanja Fajon 2001-10-01 2009-07-13 2843      work  rtv slo
3 Mojca Šetinc Pašek Tanja Fajon 1996-11-18 1998-05-03  532 education   ul fdv
> p1 <- "Igor Papič"; p2 <- "Robert Golob"
> (X <- explain(E,p1,p2))
          u            v          s          f    d       rel  test
1 Igor Papič Robert Golob 1993-03-01 1996-01-01 1037      work  ul fe
2 Igor Papič Robert Golob 1999-01-01 2021-01-01 8037      work  ul fe
3 Igor Papič Robert Golob 1992-10-01 1994-10-17  747 education  ul fe
```

Oštro

data

Two co-presence networks were constructed: before the elections on April 24, 2022, and till February 1, 2024.

	relation	apr22	feb24
1	work	1767	5925
2	education	470	470
3	leisure activities	6	8
4	party	1086	2714
5	counseling & supervision	10	10
	total	3339	9127
	nodes	154	160

The link values in the network February 2024 are in the interval $[1, 14344]$. Applying the square root we transform them into the interval $[1, 120]$. Another application of the square root gives the interval $[1, 11]$.

Monotonicity?!

Oštro

Analyzing a co-presence network in Pajek

We first combine all Pajek files related to a co-presence network into a Pajek project file. We also replace full names of persons with corresponding short names.

```
read network Slo4all.net
network Info button
Network/Multiple relations network/Info
Network/Create new network/Transform/Add/vertex labels/default [Yes]
Network/Create new network/Transform/Add/vertex labels/from file(s) [ostro_short.nam]
select network 1 Slo4all.net
File/Network/Dispose
select network 2 default
File/Network/Dispose
read clustering gender.clu
read clustering party.clu
read clustering position.clu
File/Network/Save [Slo4allShort.paj]
```

Procedures for automatically determining the network layout produce node placements that make sense, but are rather unreadable. The layout of the total co-presence network till April 2022 displayed on the next slide is created using the VOS Mapping procedure.

VOS april 2022

Oštro

Partitions

In the data on persons, I chose three partitions that describe the characteristics of an individual person: party (party membership), position (role in the country), and gender. We determine their use in Pajek by selecting them as current partitions:

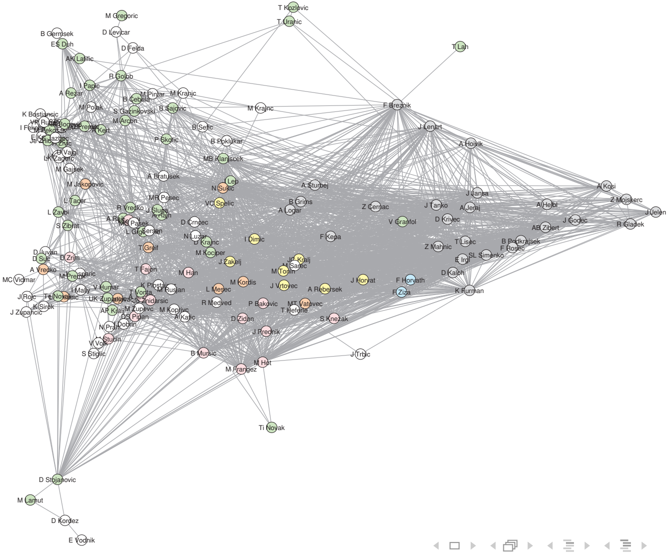
1. Partition: party
2. Partition: position
3. Partition: gender

We request the display of the network with `Draw/Network+First Partition`. Initially, only party affiliation will be displayed as the node color. I chose the following bright colors

1: Undefined ; 2: Freedom (Svoboda) Movement; 3: Left; 4: NSi; 5: IT+HU; 6: SD; 7: SDS.

Oštro

Co-presence network on April 2022 by VOS Mapping



Oštro

Cutout at a given threshold

Link cutout (pruning) at a threshold level t in a given network preserves only the strongest links whose weight is at least t. It also removes any isolated nodes. In Pajek, we get it like this:

```
Network/Create new network/Transform/Remove/Multiple lines/Sum values [No]
Network/Create new network/Transform/Remove/Lines with Value/lower than [t, OK]
Network/Create Partition/Degree/All
Operations/Network+Partition/Extract/Subnetwork ... [1-*, OK]
```

If we want to show some of the partitions in the picture, we have to adjust it to the obtained cutout

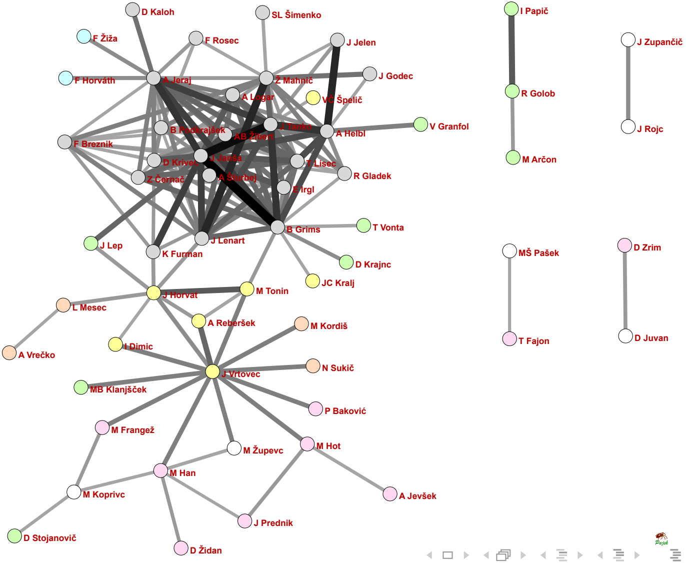
```
select the selected partition as the First partition
select Degree All partition as the Second partition
Partitions/Extract Subpartition
```

Cutout at level 5000 on whole April 2022 network

Cutout at level 3000 on work April 2022 network

Oštro

Cutout at level 5000 on whole April 2022 network



For a quick inspection of the structure of weighted networks, we use various skeletons, in which less important elements (nodes, links) are discarded. An example of a skeleton is a *k-neighbors* network, in which we keep only the k most important neighbors (highest weights) in each node.

First, we create a simple temporal network from the basic multi-relational temporal network: if we keep all/selected relations, we use

```
Network/Multiple relations network/Change Relation Number-Label [1-*,1,All together,OK][Yes]
```

but if we only want the r-th relation, we can use

```
Network/Multiple relations network/Extract Relation(s) into Separate Network(s) [r,OK][Yes]
```

The k-neighbors procedure goes like this in Pajek:

```
Network/Create new network/Transform/Remove/Multiple lines/Sum values [No]
Network/Create new network/Transform/Line values/Abs+sqrt
File/Network/Change label [Sqrt]
Network/Create new network/Transform/Edges -> arcs [yes]
File/Network/Change label [Sqrt directed]
Network/Create new network/Transform/Remove/all arcs ... except/k with highest ...[k]
Network/Create partition/Components/Weak [2]
```

Finally, we draw the network and export the layout to the selected format

```
Draw/Network+First partition
Layout/Energy/Kamada-Kawai/Separate components
manually improve the picture
set Options and Export/Options
Export/2D/SVG/General [sosedi.svg]
```

1-neighbors for party links February 2024

Whole network for party links February 2024 on the 1-neighbors nodes layout

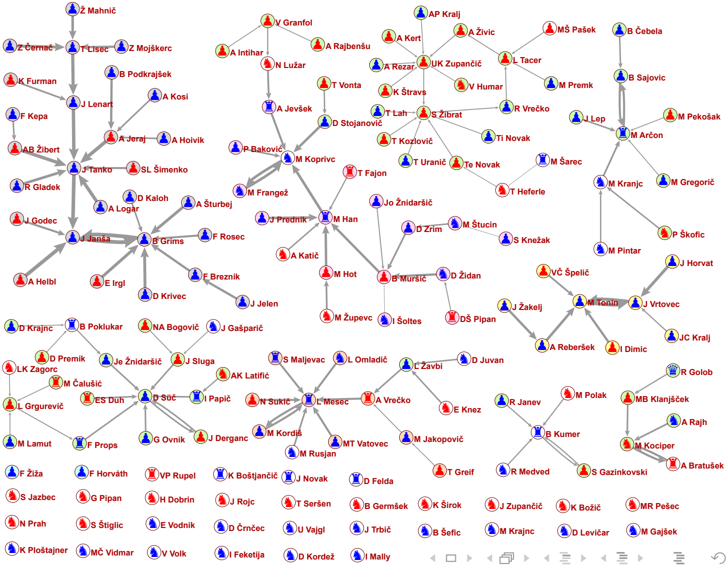
We display the second partition with the selected symbols with `Options/Mark vertices using/Cluster symbols of second partition`. The selected symbols are defined with `Options/Symbols for partition clusters/Change`. I chose the following symbols

- ♟ : Member of Parliament
- ♞ : Secretary
- ♜ : Minister
- ♛ : Prime Minister

The third partition will be represented with the color of the symbol. We enable its display with `Options/Colors/Use third partition for symbol color`. I chose (`Options/Colors/Partition colors/for Symbols`) the usual colors - red: female, blue: male.

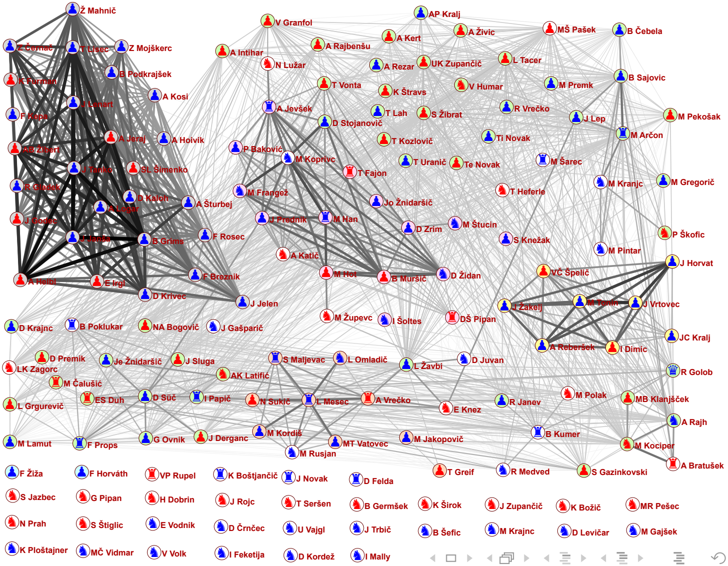
Oštro

1-neighbors / Parties February 2024 – relation Party



Oštro

Parties February 2024 – relation Party



Oštro

Network matrix display

In larger (more than 10 nodes) dense (higher average degree) networks, its display with a graph is very unreadable. For networks of size up to some thousands, a matrix display is a more suitable solution. In a matrix display, the order of the nodes is very important – a good order will create patterns in the display that reveal the structure of the network.

Let the current network be a simplified network (a simple network without parallel links). Then we can determine an ordering of the nodes by clustering them. Since the range of weight values is very large, we reduce it using a monotonic mapping (eg $\ln(w)$ or $\sqrt{\sqrt{w}}$). In our case, we will use double square rooting

```
Network/Create new network/Transform/Line values/Abs + Sqrt
Network/Create new network/Transform/Line values/Abs + Sqrt
Cluster/Create complete cluster [160][OK]
Operations/Network+Cluster/Dissimilarity*/Network based/d5-Corrected Euclidean [1][OK]
select network Sqrt(Sqrt)
File/Network/Export as Matrix to/EPS/using permutation
```

Oštro

Network matrix display

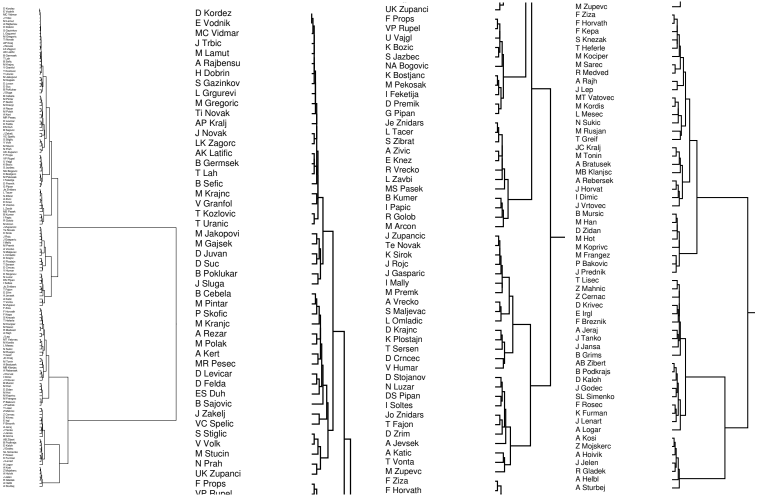
We open the resulting files `dendro.eps` and `matrix.eps` in Acrobat reader and save them in PDF format. We then open the matrix display in Inkscape and save it in SVG format.

In Pajek, individual clusters can be rearranged (change the order of individual branches in the tree) and get an improved display. We can also specify clusters and get the corresponding partition.

Matrix display whole April 2022 network/$\sqrt{w}$; Dendro PDF; Matrix PDF

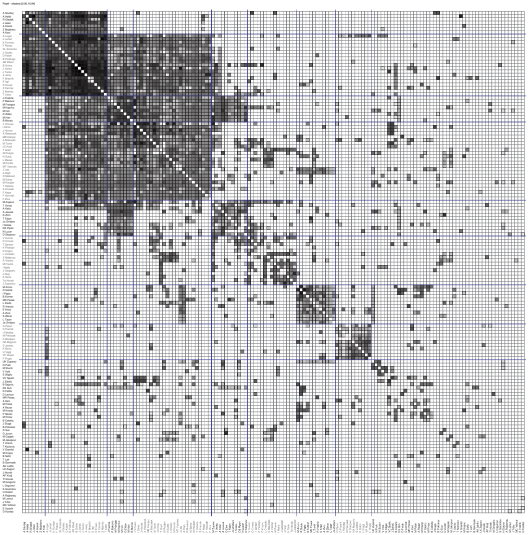
Matrix display whole February 2024 network/$\sqrt{w}$; Dendro PDF; Matrix PDF

Zvezoskop analysis

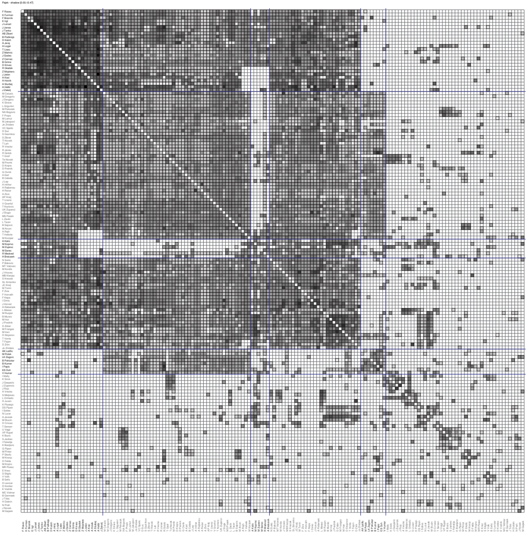


D Kordez
E Vodnik
MC Vidmar
J Trbic
M Lamut
A Rajbensu
H Dobrin
S Gazinkov
L Grgurevi
M Gregoric
Ti Novak
AP Kralj
J Novak
LK Zagorc
AK Latific
B Germsek
T Lah
B Sefic
M Krajnc
V Granfol
T Kozlovic
T Uranic
M Jakopovi
M Gajsek
D Juvan
D Suc
B Poklukar
J Sluga
B Cebela
M Pintar
P Skofic
M Kranjc
A Rezar
M Polak
A Kert
MR Pesec
D Levicar
D Felda
ES Duh
B Sajovic
J Zakelj
VC Spelic
S Stiglic
V Volk
M Stucin
N Prah
UK Zupanci
F Props
UK Zupanci
F Props
VP Rupel
U Vajgl
K Bozic
S Jazbec
NA Bogovic
K Bostjanc
M Pekosak
I Feketija
D Premik
G Pipan
Je Znidars
L Tacer
S Zibrat
A Zivic
E Knez
R Vrecko
L Zavbi
MS Pasek
B Kumer
I Papic
R Golob
M Arcon
J Zupancic
Te Novak
K Sirok
J Rojc
J Gasparic
I Mally
M Premk
A Vrecko
S Maljevac
L Omladic
D Krajnc
K Plostajn
T Sersen
D Crncec
V Humar
D Stojanov
N Luzar
DS Pipan
I Soltes
Jo Znidars
T Fajon
D Zrim
A Jevsek
A Katic
T Vonta
M Zupevc
F Ziza
F Horvath
M Zupevc
F Ziza
F Horvath
F Kepa
S Knezak
T Heferle
M Kociper
M Sarec
R Medved
A Rajh
J Lep
MT Vatovec
M Kordis
L Mesec
N Sukic
M Rusjan
T Greif
JC Kralj
M Tonin
A Bratusek
MB Klanjsc
A Rebersek
J Horvat
I Dimic
J Vrtovec
B Mursic
M Han
D Zidan
M Hot
M Koprivc
M Frangez
P Bakovic
J Prednik
T Lisec
Z Mahnic
Z Cernac
D Krivec
E Irgl
F Breznik
A Jeraj
J Tanko
J Jansa
B Grims
AB Zibert
B Podkrajs
D Kaloh
J Godec
SL Simenko
F Rosec
K Furman
J Lenart
A Logar
A Kosi
Z Mojskerc
A Hoivik
J Jelen
R Gladek
A Helbl
A Sturbej

Network matrix display April 2022 / $\sqrt{w}$



Network matrix display February 2024 / $\sqrt{w}$



Event sequence analysis
V. Batagelj &
Introduction
Sequence analysis
Oštro
Conclusions
References
References

For a given clustering (partition), we can obtain the corresponding partition contraction matrix [23]

```
select SUM network as the First network
select the clustering partition as the First partition
Operations/Network+Partition/Shrink network
select the clustering partition as the First partition
Partition/Count
```

For the April 2022 network we get (click on the relevant register) the matrix

	size	1	2	3	4	5	6	7	8	9	Label
1.	47	51934	23424	72685	14499	36016	45941	13235	9347	9787	#AK Latifić
2.	11	23424	34047	36714	0	42487	10418	26731	106358	1442	#A Jevšek
3.	24	72685	36714	334267	5562	522702	34194	58636	192011	5373	#A Reberšek
4.	7	14499	0	5562	43790	348917	0	5593	458	0	#A Helbl
5.	19	36016	42487	522702	348917	927203	6737	22678	121872	7797	#A Jeraj
6.	12	45941	10418	34194	0	6737	55999	4821	31	8993	#A Živic
7.	15	13235	26731	58636	5593	22678	4821	59184	4508	828	#A Vrečko
8.	8	9347	106358	192011	458	121872	31	4508	94293	1494	#B Muršič
9.	11	9787	1442	5373	0	7797	8993	828	1494	36673	#D Premik

Oštro

Blockmodel

In a text editor we put the obtained data into a table and read it into R.

We still need to normalize the values in the matrix M. For $i \neq j$ the normalized weight is $Q[i,j] = \frac{M[i,j]}{n[i] \cdot n[j]}$ and for $i = j$ it is $Q[i,i] = \frac{M[i,j]}{n[i].(n[j]-1)}$ (for a directed network; or its double for an undirected network).

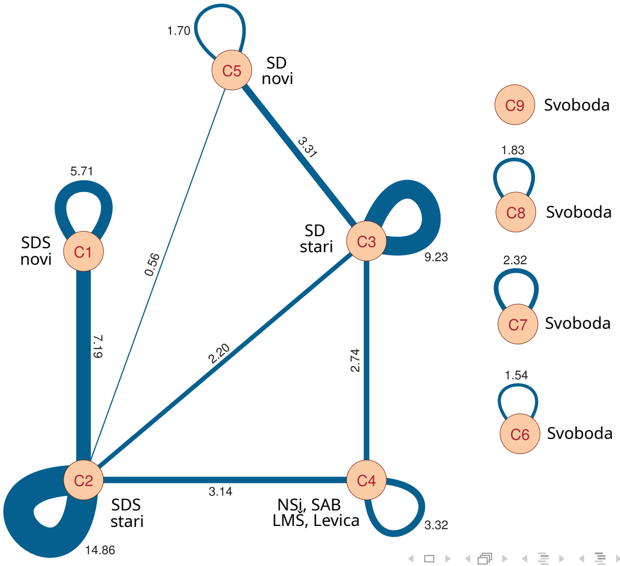
```
S <- read.table("./pics/shrink22.csv",head=TRUE)
M <- as.matrix(S[,1:9])
B <- matrix(0,nrow=9,ncol=9)
for(i and 1:9) for(j and 1:9) B[i,j] <- M[i,j] / S$n[i] / (S$n[j]-(i== j))
diag(B) <- 2*diag(B)
matrix2net(B,Net="BM22.net")
```

The resulting normalized matrix is exported as a Pajek network and displayed in Pajek.

PS1. During normalization, we could also divide by the number of links in the block – we get them by first setting all weights to 1 in the network and then shrinking them.
PS2. Full normalization can be done in Pajek (my *Introduction to Network Analysis* slides).

Oštro

Blockmodel April 2022 (weights in years)



Conclusions

1. Apply traditional sequence analysis to Zvezoskop data.
   Extend the dataset at least to public officials from the previous government. Kinship!? Additional personal attributes. Homophily $uE_a v \equiv a(u) = a(v)$.
2. Networks and sequence analysis [24], [25], [26], [27], [28].
   Traditional SA concentrate attention mainly to the states. Our network approach deals primary with units.
3. Find interesting and well documented datasets.
4. The Sequence Analysis Association (SAA).

Acknowledgments

The computational work reported in this paper was performed using a collection of R functions `trajectoR` and the program Pajek for analysis of large networks. The code and data are available at Github/Bavla/trajectories.

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YouTube/Oštro: video 1, video 2.

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