ETH zürich

Introduction to Relational Event Models

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REM-Workshop

Today:

- Introduction to relational event models
- Basic idea and lab sessions in `R`

Tomorrow:

- Broader discussion of when REMs are useful (and when not)
- Linking REMs to ABMs
- Research design discussion

Resources

Slides and R-tutorial (script and data) can be found

1. on Github:

https://github.com/brandenberger/relational_event_model_tutorial.git

2. in Dropbox folder:

https://goo.gl/65gpnN

Content

Chapter 1

Introduction to Relational Event Models (REM)

- what are REMs?
- when can we use them?
- what can they tell us about social networks?

Basic idea behind REMs (1/2)

- Who does what and when?

How do actors react to changes in their immediate network surroundings?

World War 1, declarations of war	July 26, 1914	Austria-Hungary $\rightarrow$ Serbia
	August 1, 1914	German Empire $\rightarrow$ Russian Empire
	August 6, 1914	Austria-Hungary $\rightarrow$ Russian Empire
	August 7, 1914	Serbia $\rightarrow$??

Basic idea behind REMs (2/2)

- Who does what and when?

How do actors react to changes in their immediate network surroundings?

World War 1, declarations of war	July 26, 1914	Austria-Hungary $\rightarrow$ Serbia
	August 1, 1914	German Empire $\rightarrow$ Russian Empire
	August 6, 1914	Austria-Hungary $\rightarrow$ Russian Empire
	August 7, 1914	Serbia $\rightarrow$ German Empire

- Why did some node tie to another at this point in time and not previously?
- Combination of event history analysis and network analysis
- First introduced by Butts (2008)

Longitudinal network analysis: ERGMs - TERGMs - REMs (1/4)

- The choice of network inference model depends on how time is recorded
- 3 main network inference models:

1. Exponential Random Graph Models (or latent space models)
2. Temporal Exponential Random Graph Models (or SAOMs)
3. Relational Event Models

- For an overview over cross-sectional models, read: Cranmer et al. (2017)

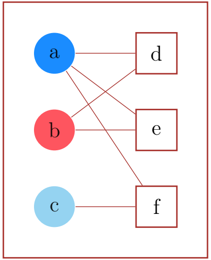
Longitudinal network analysis: ERGMs - TERGMs - REMs (2/4)

- If you have 1 snapshot of your network $\rightarrow$ run an ERGM
- ERGM = exponential random graph model

Research question

Which factors affect the structure of the network?

snapshot



$\mathbf{t = 1}$

Figure 1: Network snapshot

Longitudinal network analysis: ERGMs - TERGMs - REMs (3/4)

- If you have multiple snapshots of your network $\rightarrow$ run an tERGM
- tERGM = temporal exponential random graph model

Research question

Which factors affect the structure of the networks and how do networks change over time?

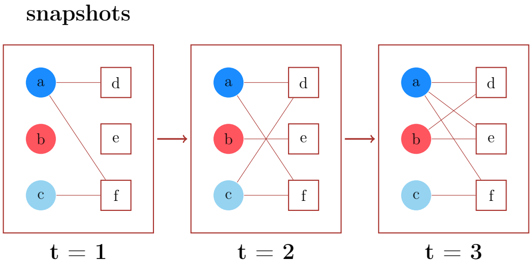


Figure 2: Multiple network snapshots

Longitudinal network analysis: ERGMs - TERGMs - REMs (4/4)

- If you know the time/order each tie is created in a network → run a REM
- Data: micro-steps of the network ..
- .. recorded in exact time or ordered

Research question

Which factors affect the probability of an edge forming at time point *t*?

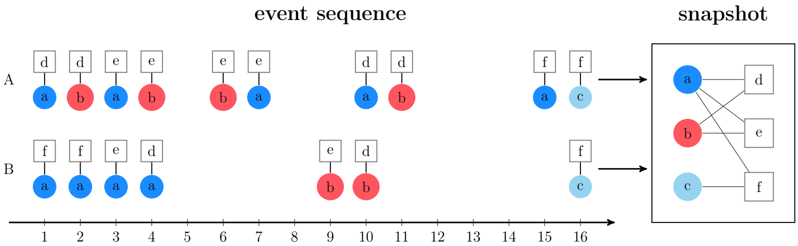


Figure 3: Different event sequences form the same network snapshot

REMs: Make use of additional information of timing of edges

- .. to improve accuracy
- .. Example: Examine four-cycle (a, d), (a, e), (b, d), (b, e)

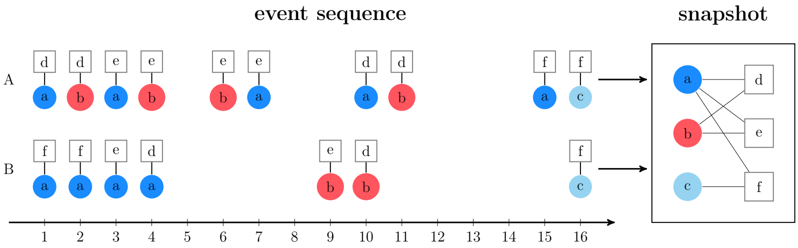


Figure 4: Different event sequences form the same network snapshot

Chapter 2

Empirical examples

- patient transfers among hospitals
- parliamentary vetoing dynamics
- international relations and social balance
- favor trading in congress
- food-sharing habits among birds
- coalition building in policy debates

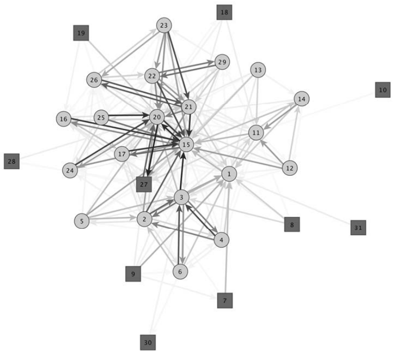
Example I: Patient transfers among hospitals

- Article by Kitts et al. (2016)

Research question

Does reciprocity guide patient transfers among hospitals?

- Patient transfers in complementary setting (where hospitals have different expertise) and in competitive setting (where hospitals have the same expertise)
- Data set: patient transfers among 31 hospitals in Abruzzo, Italy between 2003-2007



Public hospitals are light grey circles and private hospitals are dark grey squares. The shade of arcs represents the number of patients transferred between the two hospitals over a period of five years.

Figure 5: Patient transfer network

Example I: Patient transfers among hospitals - Results

Short-Term		
Embedding Inertia	0.034** (0.012)	0.031* (0.012)
Embedding Reciprocity	0.032* (0.012)	
Dependence Reciprocity		0.031** (0.009)

Figure 6: Reciprocity between hospitals with different specialities

Short-Term		
Embedding Inertia	0.000 (0.022)	0.01 (0.021)
Embedding Reciprocity	0.013 (0.027)	
Dependence Reciprocity		-0.008 (0.019)

Figure 7: Reciprocity between hospitals with the same speciality

Example II: Parliamentary vetoing dynamics

- Article by Malang et al. (2018)

Research question

Do similar parliamentary chambers influence each other to veto the same proposals?

- Early warning system of the EU: if vetoing quorum is reached, EU-commission has to re-evaluate the proposal
- Homophily on different attributes: party familiy, EU-accession round, neighboring states

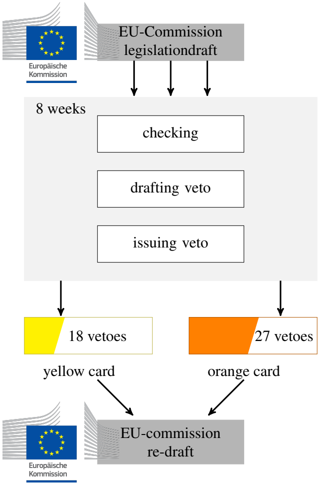


Figure 8: Early-warning system procedure

Example II: Parliamentary vetoing dynamics - empirical evidence

- Early warning system introduced more power for individual parliaments
- After its introduction, chambers met regularly (Cooper 2015)
- They built an online platform to exchange information (IPEX)
- Open question: network dynamics?

Example II: Parliamentary vetoing dynamics - homophily effect

Homophily principle

"Birds of a feather flock together"
Nodes with the same/similar attributes tend to cluster together

- Chambers with similar attribute tend to veto the same proposals
- Which attributes?
  - parliament ruled by the same party family
  - neighboring countries
  - same EU-accession round

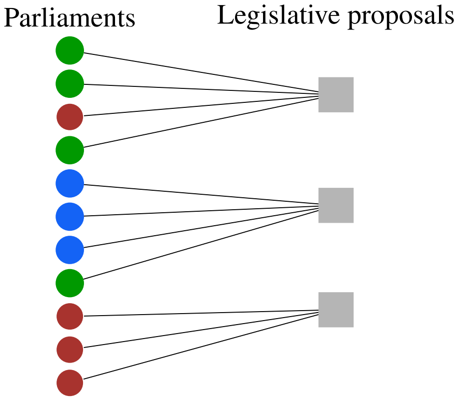


Figure 9: Homophily between EU parliaments

Example II: Parliamentary vetoing dynamics - Data

- Data set: hand-coded vetoes from the IPEX-data base
- 120+ legislative proposals
- over 300 vetoes

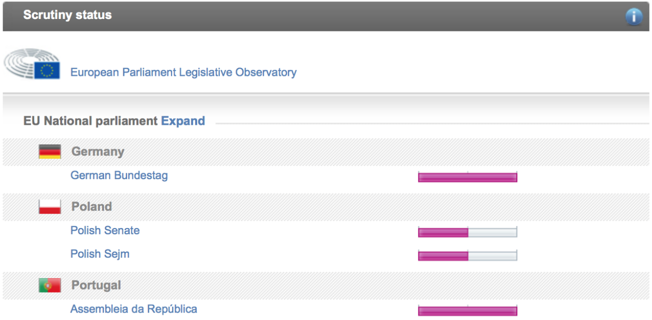


Figure 10: IPEX-Webpage

Example II: Parliamentary vetoing dynamics - Result

	Relational event model		
	Coefficient	SE	P-value
Independent variables			
H1: Ideological homophily	10.688	3.0243	0.0004
H2: EU accession homophily	4.7879	3.532	0.1752
H3: EU location homophily	4.8067	4.0555	0.2359
H4: Institutional homophily	8.2675	1.9455	0.0000
Control variables	*yes*	*yes*	*yes*

The coefficients in the first column are reported as log odds.

Table 1: Results of the conditional logit regression on reasoned opinion

Example III: International relations and social balance

- Article by Lerner et al. (2013)

Research question

Can nations' bonding tactics explain war/war-like events?

- Structural balance theory: friend of my enemy is my enemy..
- Data set: Correlates Of War (COW)

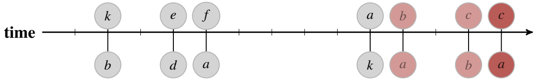


Figure 11: Triadic closure in event networks

The following excerpt is an (incomplete) list of events that happened on August 10th, 1990 in the Gulf region.

900810	ARB	IRQ	012	RETREAT
900810	IRQ	USA	122	DENIGRATE
900810	IRQ	ARB	094	CALL FOR
900810	USA	IRQ	160	WARN
900810	USA	IRQ	051	PROMISE POLICY
900810	USA	IRQ	223	MIL ENGAGEME

Figure 12: Triadic closure in event networks

Example III: International relations and social balance - Results

Table 3 *Event rate parameters and standard errors*

statistic	event network model	covariate model	combined model
inertia	-0.114 (0.002)	·	$-1.9E^{-4}$ (0.002)
reciprocity	-0.090 (0.003)	·	0.042 (0.003)
triangle	0.506 (0.002)	·	0.348 (0.003)
activitySource	0.202 (0.001)	·	0.161 (0.001)
activityTarget	0.168 (0.001)	·	0.118 (0.001)
popularitySource	0.094 (0.001)	·	0.073 (0.001)
popularityTarget	0.131 (0.001)	·	0.119 (0.001)
lnCapRatio	·	-0.289 (0.002)	-0.225 (0.002)
allies	·	0.064 (0.006)	-0.223 (0.006)
polityWeakLink	·	-0.137 (0.001)	-0.122 (0.001)
minorPowers	·	-2.726 (0.007)	-1.970 (0.007)
lnTrade	·	0.062 (0.001)	0.142 (0.001)
contiguity	·	1.362 (0.006)	1.310 (0.007)
lnDistance	·	-0.287 (0.002)	-0.343 (0.002)
lnJointIGO	·	1.344 (0.005)	1.313 (0.005)
constant	-6.774 (0.002)	-6.964 (0.017)	-7.530 (0.016)
#events	217, 479	200, 886	200, 886
log-likelihood	-1 302 411	-1 271 416	-1 029 255
ll-ratio to M_0	326 687	357 682	599 843
#params	8	9	16
BIC	2 604 920	2 542 941	2 058 705
AIC	2 604 838	2 542 850	2 058 542

Figure 13: Results from Lerner et al. 2013

- positive significant effect of triangle
- = evidence of bonding or alliance formation over time
- Formal interpretation: the more two nations *a* and *c* interacted with common other actors *b*, the more likely is an event with *a* and *c*

Example IV: Favor trading in congress

- Article by Brandenberger (2018)

Research question

Do members of Congress cosponsor bills in order to repay a favor?

- Content vs. connections
- Collective action theory: Reciprocity can overcome a waiting game
- Data set: Cosponsorship signature in 113th U.S. Congress

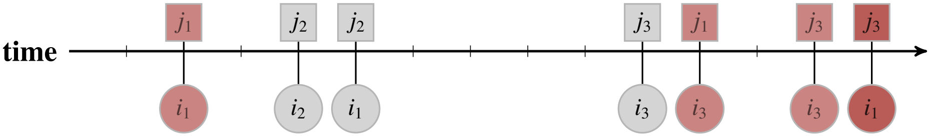


Figure 14: Reciprocity in event networks

Example IV: Favor trading in congress - Results

Table 2: Results of the logistic regression on active cosponsorship with interaction effect on party membership

	(1) REM 20	(2) REM 20	(3) REM 50	(4) REM 100
Reciprocity: received cosponsor support	-0.01	-0.18^{**}	-0.23^{**}	-0.09
	0.03	(0.06)	(0.09)	(0.08)
Reciprocity X party (Republican $=$ 1)	–	0.26^{***}	0.45^{***}	0.27^{**}
	–	(0.06)	(0.10)	(0.08)
Other network statistics	yes	yes	yes	yes
Homophily/heterophily variables	yes	yes	yes	yes
Additional controls	yes	yes	yes	yes
Party (Republican $=$ 1)	–	$0.32^{\cdot}$	0.14	0.19
	–	(0.18)	(0.19)	(0.21)
BIC	250261.94	258319.23	254747.27	254310.79
McFadden *pseudo* $- R^2$	.09	0.10	0.10	0.10

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$; cluster-robust standard errors reported in parenthesis. All control variables do not change drastically with the inclusion of the interaction effect.

Example V: Food-sharing habits among birds

- Article by Tranmer et al. (2015)

Research question

is food-sharing more likely among birds who shared the same nest box (= are more familiar with each other)?

- Nestbox homophily
- Data set: 12 jackdows, living in a large aviary with researcher observing their feeding behavior

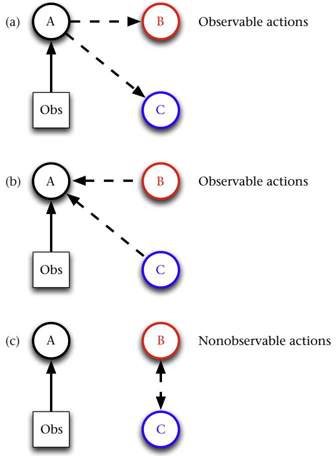


Figure 1. (a) Animal A directs its actions to animals B or C; the observer (Obs) records these actions as animal A sending behaviour. (b) Animals B or C direct their actions to animal A; the observer records these actions as animal A receiving behaviour. (c) Animals B and C interact; the observer is focusing on animal A, and hence does not observe or record the actions of animals B and C.

Example V: Food-sharing habits among birds - Results

Table 1
Relational event model results for jackdaw food sharing

Estimate	M1			M2			M3		
	B	SD	SL	B	SD	SL	B	SD	SL
B1	−4.128	0.161	***	−4.340	0.166	***	−6.799	0.236	***
B2	−4.976	0.243	***	−5.205	0.247	***	−6.529	0.313	***
B3	−3.854	0.141	***	−4.061	0.146	***	−5.501	0.262	***
B4	−4.460	0.190	***	−4.893	0.201	***	−6.822	0.286	***
B5	−5.393	0.302	***	−5.680	0.306	***	−7.391	0.360	***
B6	−4.567	0.201	***	−4.850	0.206	***	−6.693	0.275	***
B7	−3.983	0.150	***	−4.268	0.158	***	−5.857	0.252	***
B8	−5.637	0.334	***	−5.957	0.338	***	−7.463	0.364	***
B9	−3.817	0.139	***	−4.247	0.155	***	−4.832	0.400	***
B10	−5.304	0.289	***	−5.738	0.297	***	−7.135	0.323	***
B11	−5.062	0.259	***	−5.485	0.267	***	−7.519	0.380	***
B12	−3.764	0.135	***	−4.195	0.150	***	−7.323	0.349	***
floor	−3.523	0.115	***	−3.523	0.115	***	−6.540	0.217	***
hom				0.861	0.109	***	0.228	0.156	
PoA							2.261	0.121	***
recip							−0.397	0.239	
recenXrecip							0.003	<0.001	***

Figure 16: Results from Lerner et al. 2013

Example VI: Coalition building in policy debates

- Article by Leifeld and Brandenberger (2019)

Research question

Do political actors pick up policy beliefs from each other in a debate?

- Coalition formation through social learning
- Data set: hand-coded statements with policy beliefs from newspaper articles on the German pension reform

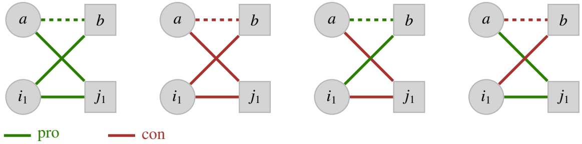


Figure 17: Policy learning through bonding

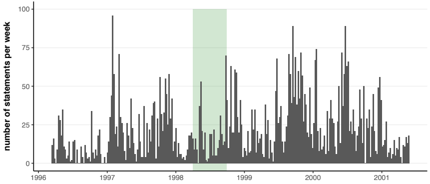


Figure 18: Number of statements during the policy debate on the German pension reform

Example VI: Coalition building in policy debates - Results

	(1)	(2)
Main hypotheses		
Positive reciprocity	0.39 (0.03)***	0.31 (0.01)***
Positive reciprocity × government org.	−0.12 (0.03)***	
Innovation learning	0.20 (0.03)***	0.11 (0.01)***
Innovation learning × government org.	−0.10 (0.03)***	
Negative reciprocity	0.17 (0.02)***	0.18 (0.01)***
Negative reciprocity × government org.	−0.01 (0.03)	
Control		
Inertia	0.13 (0.01)***	0.12 (0.01)***
Actor activity	−0.01 (0.02)	−0.02 (0.02)
Belief concept popularity	0.11 (0.01)***	0.12 (0.01)***
Monday (dummy)	0.07 (0.04)	0.08 (0.04)*
Government (dummy)	0.70 (0.04)***	0.47 (0.04)***
AIC	54032.32	54113.86
McFadden pseudo-R^2	0.14	0.13
Num. events	6044	6044
Num. obs.	883855	883855

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$; Coefficients are reported as log-odds.

Table 3: Results of the conditional logistic regression on the event rate.

Chapter 3

Data structure

- Relational events
- Event sequence
- REM data structure

Relational events

- Unit of analysis of REMs: events
- Events consist of
  - a sender node (e.g., person, organization)
  - a target node (e.g., person or event)
  - a time stamp (or ordinal time)
  - a weight (mostly 1, but can be anything)
- Events can have attributes
  - of the sender node (e.g., size of organization)
  - of the target node (e.g., event type)
  - of time (exogenous events, e.g., Fukushima)

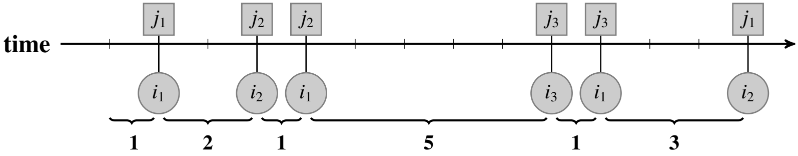
Multiple events form an *event sequence*

The following excerpt is an (incomplete) list of events that happened
August 10th, 1990 in the Gulf region.

900810	ARB	IRQ	012	RETREAT
900810	IRQ	USA	122	DENIGRATE
900810	IRQ	ARB	094	CALL FOR
900810	USA	IRQ	160	WARN
900810	USA	IRQ	051	PROMISE POLICY
900810	USA	IRQ	223	MIL ENGAGEME

Figure 19: Excerpt from the COW data

Event sequence



- Event sequence translated into a data frame:

```
##   time sender target
## 1    1     i1     j1
## 2    3     i2     j2
## 3    4     i1     j2
## 4    9     i3     j3
## 5   10     i1     j3
## 6   13     i2     j1
```

REM data structure

- REMs are estimated using event history models (or survival models)

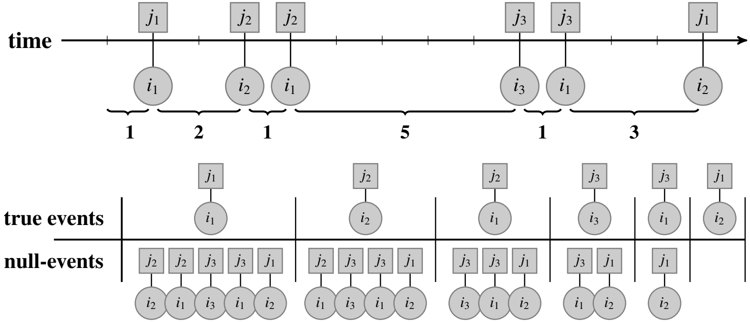
Conting process formulation

Every time an event takes place, you add null-events that could have taken place, but did not

- developed by Andersen and Gill (1982)

Counting process formulation (1/2)

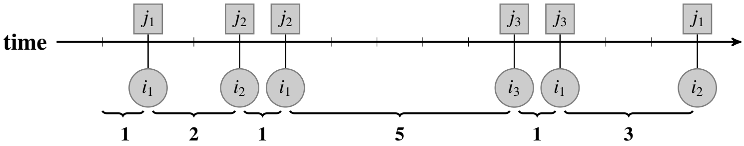
- Counting process formulation (Andersen and Gill, 1982) = adding null-events
- Every time a event took place you add in null-events that could have taken place, but did not



Counting process formulation (2/2)

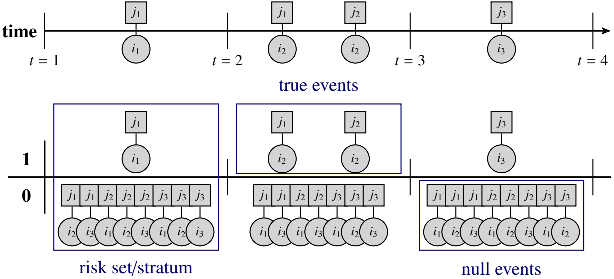
eventID	sender	target	eventTime	eventDummy	eventAtRiskFrom	eventAtRiskUntil
eventID1	i1	j1	1	1	0	1
eventID2	i2	j2	1	0	0	3
eventID2	i2	j2	3	1	0	3
eventID3	i1	j2	1	0	0	4
eventID3	i1	j2	3	0	0	4
eventID3	i1	j2	4	1	0	4
eventID4	i3	j3	1	0	0	9
eventID4	i3	j3	3	0	0	9
eventID4	i3	j3	4	0	0	9
eventID4	i3	j3	9	1	0	9
eventID5	i1	j3	1	0	0	10
eventID5	i1	j3	3	0	0	10
eventID5	i1	j3	4	0	0	10
eventID5	i1	j3	9	0	0	10
eventID5	i1	j3	10	1	0	10
eventID6	i2	j1	1	0	0	13
eventID6	i2	j1	3	0	0	13
eventID6	i2	j1	4	0	0	13
eventID6	i2	j1	9	0	0	13
eventID6	i2	j1	10	0	0	13
eventID6	i2	j1	13	1	0	13

Counting process formulation (2/2) - DETAILED



eventID	sender	target	eventTime	eventDummy	atRiskFrom	atRiskUntil
eventID6	i2	j1	1	0	0	13
eventID6	i2	j1	3	0	0	13
eventID6	i2	j1	4	0	0	13
eventID6	i2	j1	9	0	0	13
eventID6	i2	j1	10	0	0	13
eventID6	i2	j1	13	1	0	13

REM data terminology



risk set

Also called *stratum*; all events that have or could have occurred at one point in time

true event

Events that occurred at time t; observed events

null events

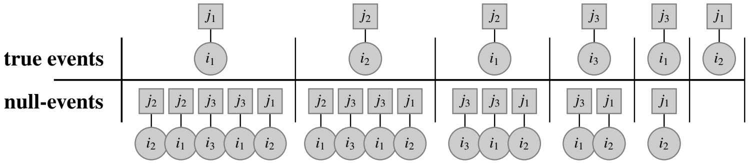
Events that did not occur at time t but could have occurred (events were possible, but did not happen)

Chapter 4

Data preparation and estimation

- Conditional logistic regression
- Data preparation using the `rem`-package

Conditional logistic regression



Conditional independence of relational events

events are considered conditionally independent of each other - IF you include all endogenous (and exogenous) covariates (Lerner et al. 2013, Butts 2008)

So estimation can be done using survival models:

- stratified Cox with time-varying covariates
- simplified estimation procedure: conditional logistic regression

The `rem`-Package

- prepare your data
- calculate endogenous network statistics
- estimate models using the `survival`-package
- examine goodness of fit (coming soon)
- sampling for large event sequences (coming soon)

rem-Package: Step 1 - preparing the event sequence

```
dt <- eventSequence(dt$date, '%Y-%m-%d', data = dt,
                    excludeTypeOfDay = 'Sonntag',
                    byTime = "daily",
                    type = "ordinal"
                    returnData = TRUE,
                    sortData = TRUE)
```

rem-Package: Step 2 - creating counting process data

- adding null events to the data set
- most conservative way: conditional logit = an event is at risk only until it occurs

```
remdt <- createRemDataset(
  dt, sender = dt$actor,
  target = dt$belief,
  dt$event.seq.ord,
  eventAttribute = dt$stance,
  start = NULL, end = NULL,
  atEventTimesOnly = TRUE,
  untilEventOccurrs = TRUE,
  returnInputData = TRUE)
```

Lab 1: data preparation

Chapter 5

Endogenous network statistics

- Endogenous network statistics
- Network of past events
- Time weighting and memory decay
- REM statistics (or model terms)
  - Inertia
  - Sender activity
  - Target popularity
  - Four-cycles

Endogenous network statistics

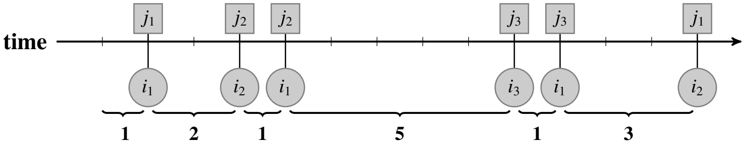
- Network model terms = endogenous network statistics
- Ide: what happened before affects what happens next

Main idea of REMs

Find patterns in past events that predict/forshadow next events

- Patterns can be anything! They can test the wildest hypotheses! Go crazy!

Network of past events



- Idea: a edge forms at time t because of previous network activity (+ exogenous variables)
- The network of past events is defined as:

$$G_t = G_t(E) = (A; B; w_t) \tag{1}$$

G_t = Network of past events E = Event sequence A = nodes from the first mode B = nodes from the second mode w_t = a time-weighting function

Time weighting of past events

- All past events can be weighted
- Idea: memeory deteriorates; forgetting
- I use an exponential decay: event that occurred in the very recent past are weighted more than events that occurred long ago

$$w_t(i,j) = \sum_{\substack{e: a_e = i, b_e = j, \\ t_e < t}} |w_e| \cdot e^{-(t - t_e) \cdot \left(\frac{ln(2)}{T_{1/2}}\right)} \cdot \frac{ln(2)}{T_{1/2}} \tag{2}$$

- $w_t(i,j)$ = weight function for a specific dyad (i, j) in G_t
  - w_e = weight of the event (usually 1)
  - $T_{1/2}$ = halflife parameter

REM statistics (= model terms)

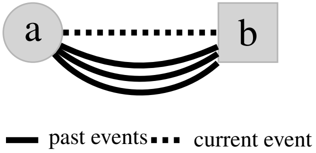
- with the weight-function you can calculate network statistics
- simple ones: inertia, activity, popularity
- more complex ones: triads, four-cycles, six-cycles
- homophily, heterophily, absolute difference
- Again: can be any sequence of events that you hypothesize

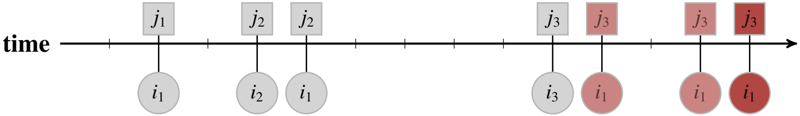
REM statistics: Inertia

Inertia statistic

$inertia(G_t; a, b) = w_t(a, b)$

In words: an event with a and b occurrs next/faster, if events with the same sender a and target b occurred in the (recent) past



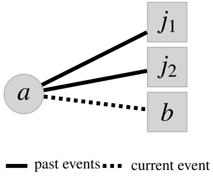


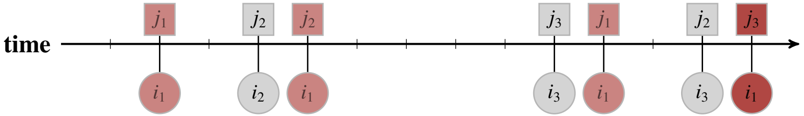
REM statistics: Sender activity

Sender activity statistic

$\texttt{activitySender}(G_t; a, b) = \sum_{j \in B} w_t(a, j)$

In words: an event with a and b occurs next, if events with the same sender a (and different targets j) occurred in the (recent) past



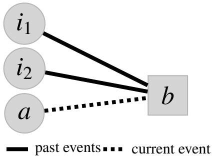


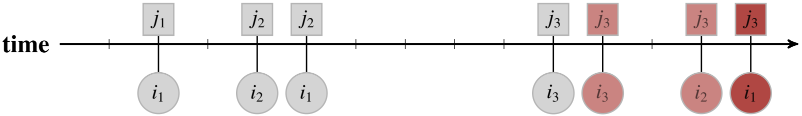
REM statistics: Target popularity

Target popularity statistic

$\texttt{popularityTarget}(G_t; a, b) = \sum_{i \in A} w_t(i, b)$

In words: an event with a and b occurrs next, if events with the same target b (and different sender i) occurred in the (recent) past



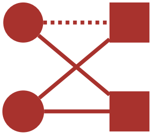


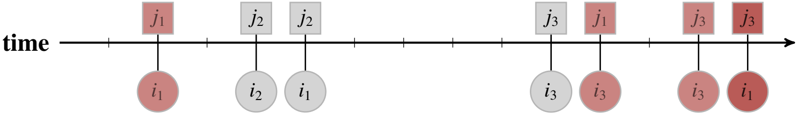
REM statistics: Four-cycles

Four-cycle statistic

$$\texttt{closingFourCycle}(G_t; a, b) = \sqrt[3]{\sum_{\substack{i \in A,\\ j \in B}} w_t(a,j) \cdot w_t(i,b) \cdot w_t(i,j)}$$

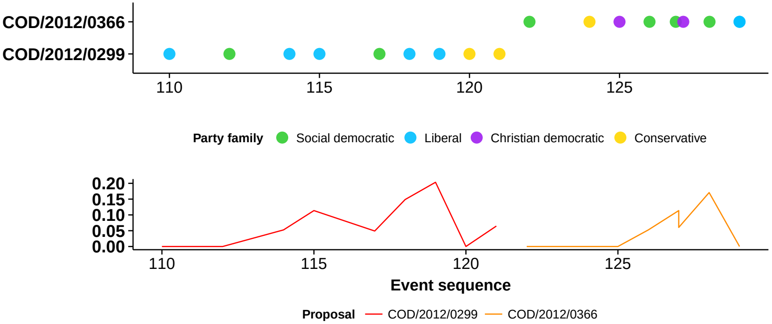
In words: an event with a and b occurs next, if 3 other events $[(a - j), (i - j), (i - b)]$ occurred in the (recent) past





REM statistics: using event attributes

- Every event can have attributes
- These attributes can be used in the network statistics
- e.g., target popularity can be filtered for past actors with a specific attribute → homophily



Chapter 6

Fitting REMs and coefficient interpretation

- Fitting REMs
- coefficient interpretation

Fitting REMs

- usually done using a conditional logistic regression
- eventDummy: which variables explain the 1 over the 0?

eventID	sender	target	eventTime	eventDummy	eventAtRiskFrom	eventAtRiskUntil
eventID1	i1	j1	1	1	0	1
eventID2	i2	j2	1	0	0	3
eventID2	i2	j2	3	1	0	3
eventID3	i1	j2	1	0	0	4
eventID3	i1	j2	3	0	0	4
eventID3	i1	j2	4	1	0	4
eventID4	i3	j3	1	0	0	9
eventID4	i3	j3	3	0	0	9
eventID4	i3	j3	4	0	0	9
eventID4	i3	j3	9	1	0	9
eventID5	i1	j3	1	0	0	10
eventID5	i1	j3	3	0	0	10
eventID5	i1	j3	4	0	0	10
eventID5	i1	j3	9	0	0	10
eventID5	i1	j3	10	1	0	10
eventID6	i2	j1	1	0	0	13
eventID6	i2	j1	3	0	0	13
eventID6	i2	j1	4	0	0	13
eventID6	i2	j1	9	0	0	13
eventID6	i2	j1	10	0	0	13
eventID6	i2	j1	13	1	0	13

Coefficient interpretation

- If you use exponential decay in your endogenous network statistics, interpretation of coefficients gets complicated
- What can be done: rescale the statistics to something that can be interpreted
- Rescale = divide by unit that you can interpret
- Example: Brandenberger (2018):

Variable	One unit	+1 unit
Reciprocity: received cosponsor support	0.0036	sponsored a bill 60 days ago and received cosponsor support from average other cosponsor 5 days after *a* submitted bill. Unit increase varies for different half-life specifications: $T_{1/2} = 20 = +0.0036$, $T_{1/2} = 50 = +0.0051$, $T_{1/2} = 100 = +0.0038$, $T_{1/2} = 200 = +0.0024$
Inertia: previously sponsored together	0.0043	sponsored together 60 days ago
Member activity - active cosponsoring	0.0245	having sponsored 2 bills, 30 days ago

Table 4: Rescaling of regression coefficients: Network scenarios show which network events are necessary to increase an endogenous statistic by one unit for an event involving member *a* and bill *b*.

Lab 2: calculating statistics and estimating REMs

Chapter 7

Goodness-of-fit assessment

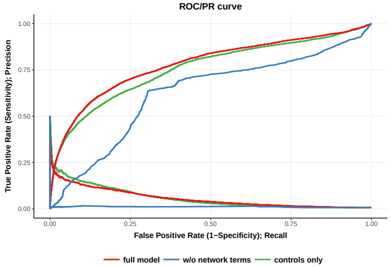
- why we should care about goodness-of-fit
- how to assess goodness-of-fit for a dynamic network model

Why Goodness-of-fit matters

- REMs only produce unbiased results if you include all endogenous network statistics/patterns that affect the event sequence
- Butts 2008, page 168

Where conventional GOF tools (often) fail for dynamic network models

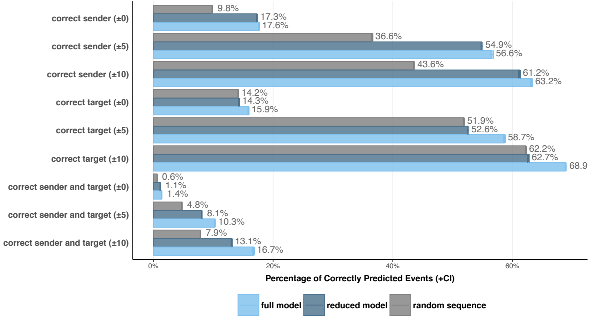
- Precision-Recall: good but too narrow
- AIC/BIC: goood for model selection but not specification
- No tools to measure if you captured all endogenous dynamics



Assess GOF via simulated sequences

- Idea: predict the next event, then use it to predict the next next event
- Simulate entire sequences and compare them to the original sequence
- within sample prediction (or out-of sample)
- Assess:

1. if the prediction is right? (with some temporal tolerance!)



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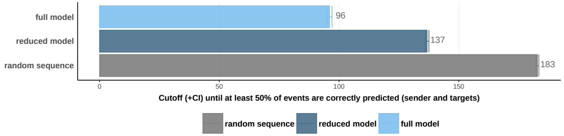
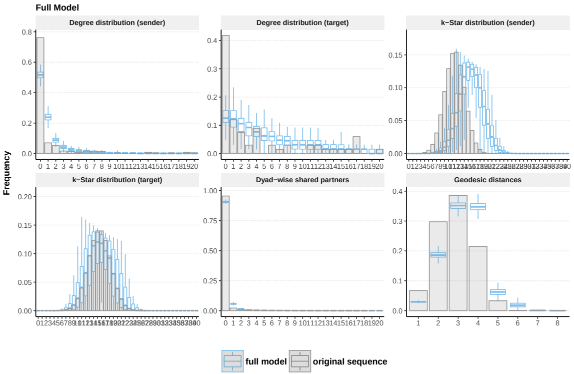
2. which model performs best?



Assess GOF via simulated sequences

- Idea: predict the next event, then use it to predict the next next event
- Simulate entire sequences and compare them to the original sequence
- within sample prediction (or out-of sample)
- Assess:

1. if the prediction is right? (with some temporal tolerance!)
2. which model performs best?
3. if other network effects should be included?



Details, see Brandenberger (Forthcoming)

Literature

Andersen, Per Kragh, and Richard D Gill. 1982. "Cox's Regression Model for Counting Processes: A Large Sample Study." The Annals of Statistics 10 (4). JSTOR: 1100–1120.

Brandenberger, Laurence. 2018. "Trading Favors – Examining the Temporal Dynamics of Reciprocity in Congressional Collaborations Using Relational Event Models." Social Networks 54: 238–53. doi:https://doi.org/10.1016/j.socnet.2018.02.001.

Brandenberger, Laurence. Forthcoming. "Predicting Network Events to Assess Goodness of Fit of Relational Event Models." Political Analysis Conditional Acceptance.

Butts, Carter T. 2008. "A Relational Event Framework for Social Action." Sociological Methodology 38 (1). Wiley Online Library: 155–200.

Cranmer, Skyler J, Philip Leifeld, Scott D McClurg, and Meredith Rolfe. 2017. "Navigating the Range of Statistical Tools for Inferential Network Analysis." American Journal of Political Science 61 (1). Wiley Online Library: 237–51.

Kitts, James A, Alessandro Lomi, Daniele Mascia, Francesca Pallotti, Eric Quintane et al. 2016. "Investigating the temporal dynamics of inter-organizational exchange: Patient transfers among Italian hospitals." American Journal of Sociology .

Leifeld, Philip, Laurence Brandenberger. 2019. Endogenous coalition formation in policy debates. Working paper.

Lerner, Jürgen, Margit Bussmann, Tom AB Snijders and Ulrik Brandes. 2013. "Modeling frequency and type of interaction in event networks." Corvinus Journal of Sociology and Social Policy (1):3–32.

Malang, Thomas, Laurence Brandenberger and Philip Leifeld. 2017. "Networks and Social Influence in European Legislative Politics.".

Tranmer, Mark, Christopher Steven Marcum, F Blake Morton, Darren P Croft and Selvino R de Kort. 2015. "Using the relational event model (REM) to investigate the temporal dynamics of animal social networks." Animal behaviour 101:99–105.