Networks and geographies of global social policy diffusion.

Culture, economy and colonial legacies.

Workshop on event history network diffusion models and `netdiffuseR`

Bremen, Sept. 11, 2020

Outline

1. What does "diffusion" mean?
2. How does diffusion look like?

3. Bring the network in!

4. Moran's I   Spatial dependence of y
5. Graph, show diffusion via network "slices"

6. Discrete time event-history analysis
7. Core explanatory variable: exposure
8. Discrete time event-history analysis: time dependence

9. Classification of adopters

10. References

What does “diffusion” mean?

Strand (1991) Gilardi (2016)
Rogers (2003) Valente (1995)

“… any process where prior adoption of a trait or practice in a population alters the probability of adoption for the remaining non-adopters” (Strand 1991: 325).

- Problem: the „any process“ is often unspecified in the definition of diffusion.
- Not easy to distinguish *policy diffusion*, *transfer*, *convergence*, and different mechanisms at work at the micro-level (Holzinger, Jörgens, Knill 2007; Obinger, Schmitt, Starke, 2013)

What does “diffusion” mean?

Strand (1991) Gilardi (2016)
Rogers (2003) Valente (1995)

“… any process where prior adoption of a trait or practice in a population alters the probability of adoption for the remaining non-adopters” (Strand 1991: 325).

- micro-level mechanisms of how adoption takes place are not our issue today.
- but they are crucial to any meaningful explanation of diffusion. To be done in each project!

What does "diffusion" mean?

Strand (1991) Gilardi (2016)
Rogers (2003) Valente (1995)

- Today, we are happy with an abstract concept, let's say "**contagion**" (Crane 1991, Valente 1995: 11-12)

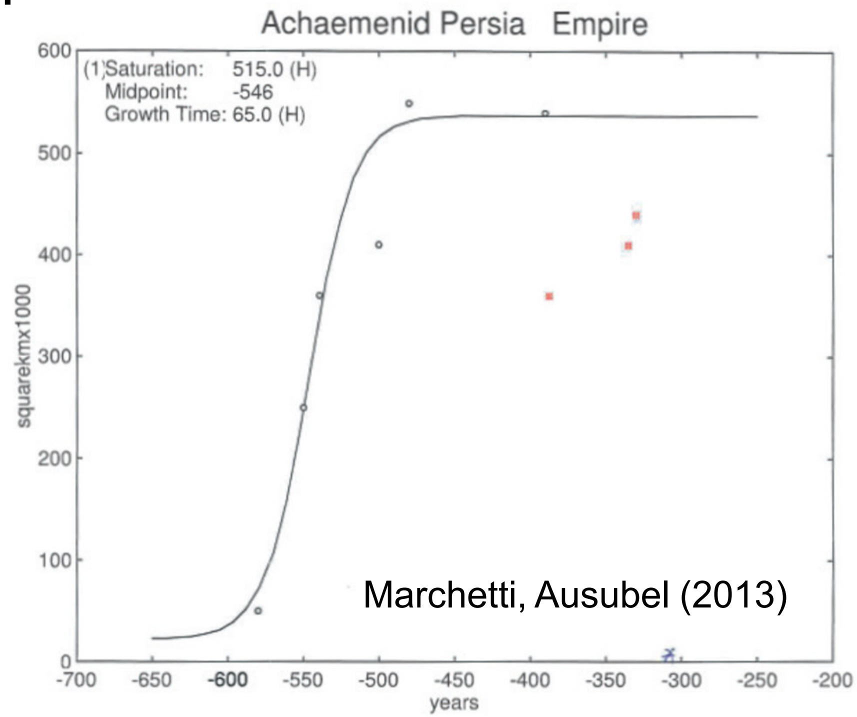
- But even **contagion** is based **interaction** or **contact** among units of observation!

- Th. Valente (1995) systematically introduced the **dynamics of social networks** into the concept and analysis of **diffusion**.

- A result is the R package `netdiffuseR`.

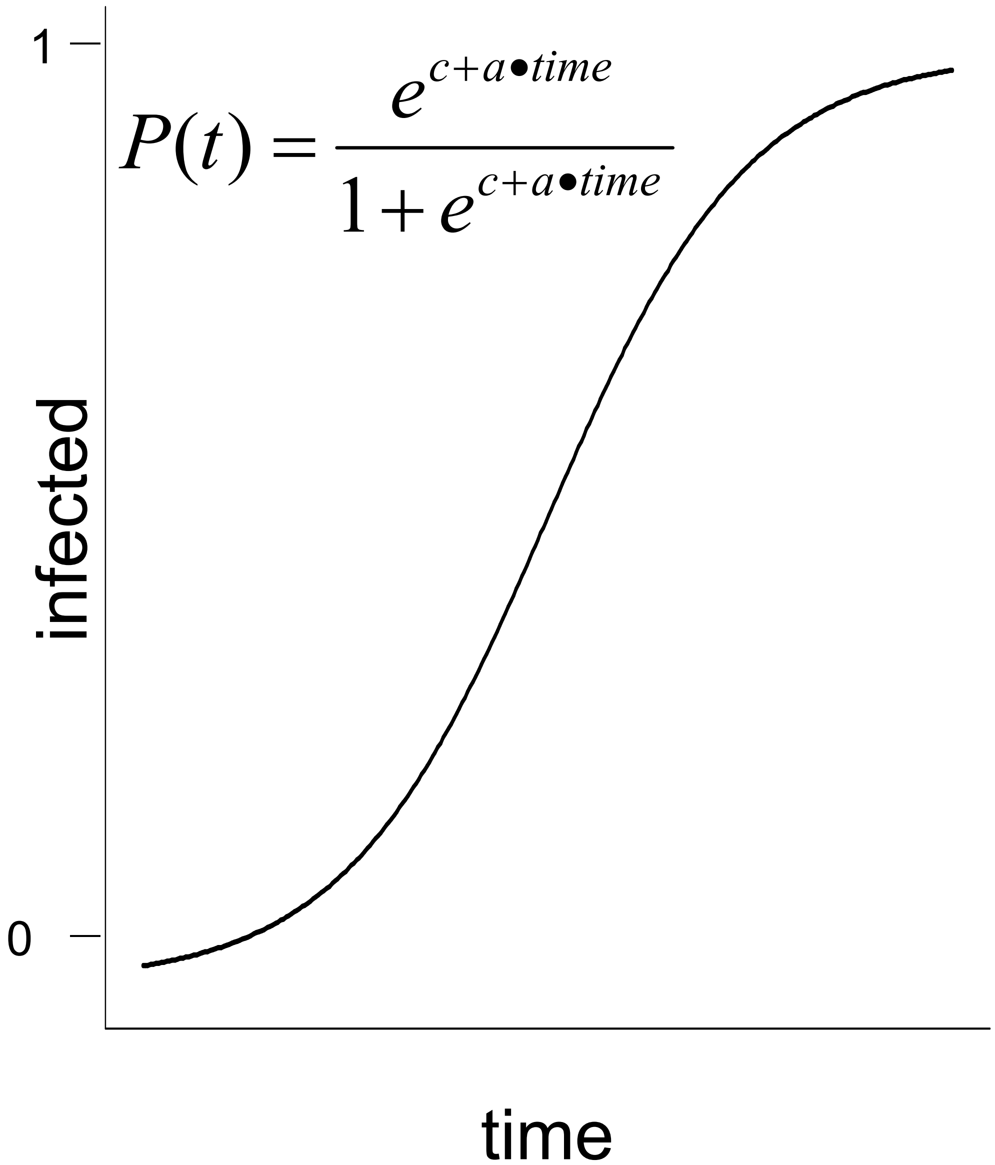
How does diffusion look like? Some examples …

- growth to limit, the Persian Empire 550–330 BC



- over time, more and more spatial units became “infected” by “being part of the empire”. But this growth had a kind of “natural limitation”.

How does diffusion look like? Some examples …



Simulation of criminal contagion in Australian suburbs

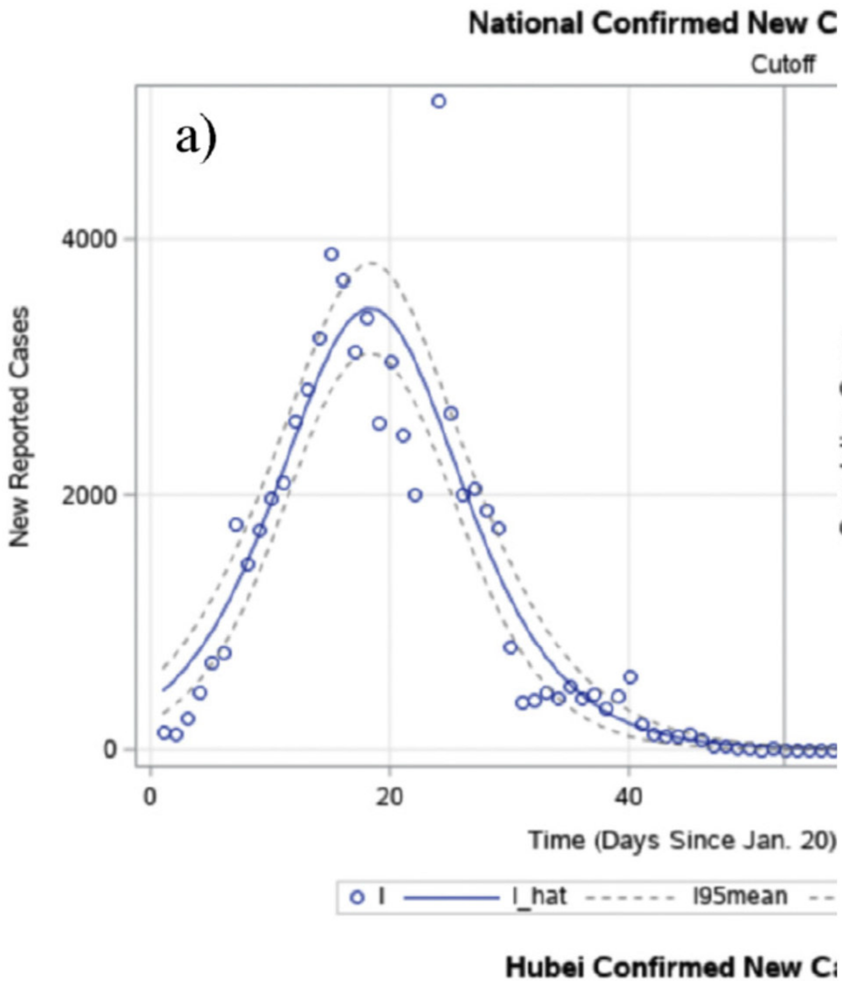
Weatherburn & Lind (1997)

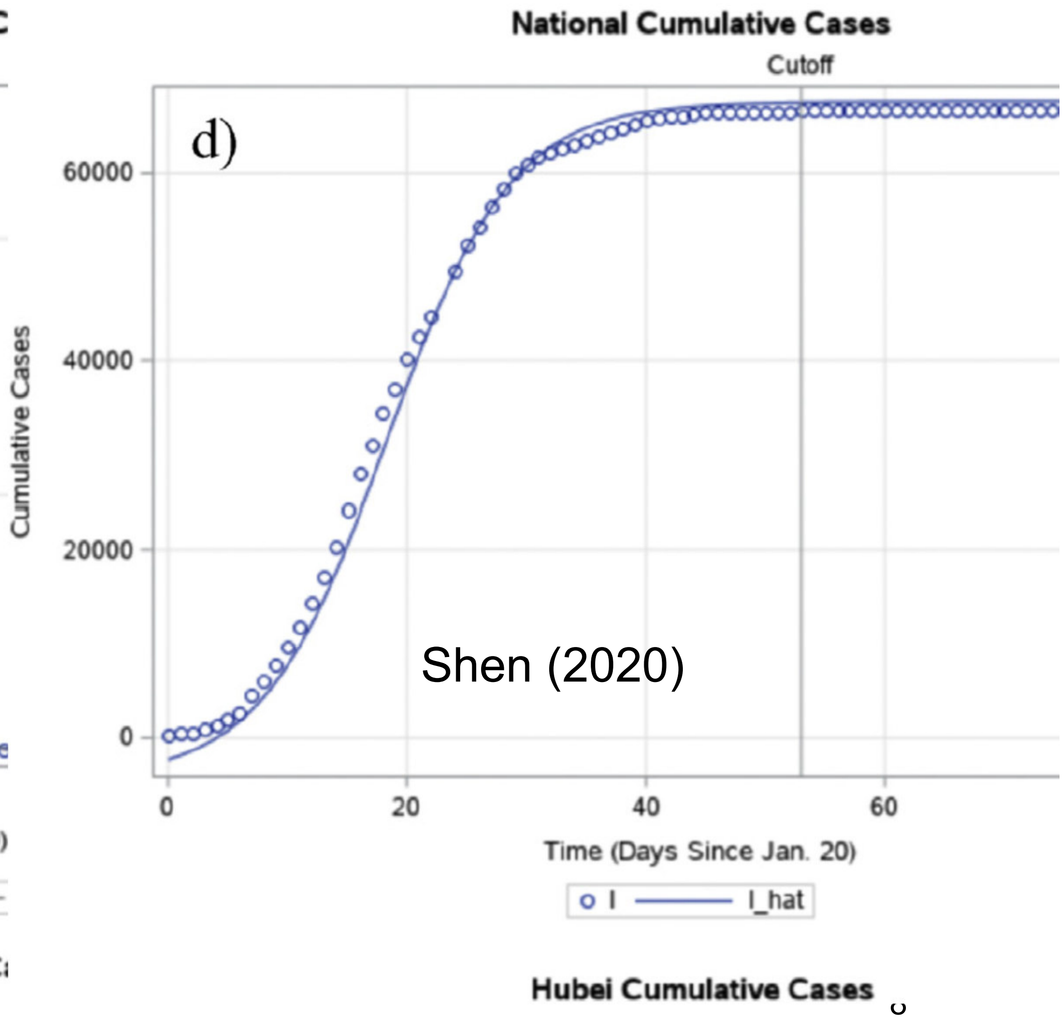
Crime epidemic starts if share of susceptible persons in neighborhood is above a threshold

After crime epidemic started, crime consolidates at high levels

How does diffusion look like? Some examples …

- COVID-19 epidemic in China, since January 2020

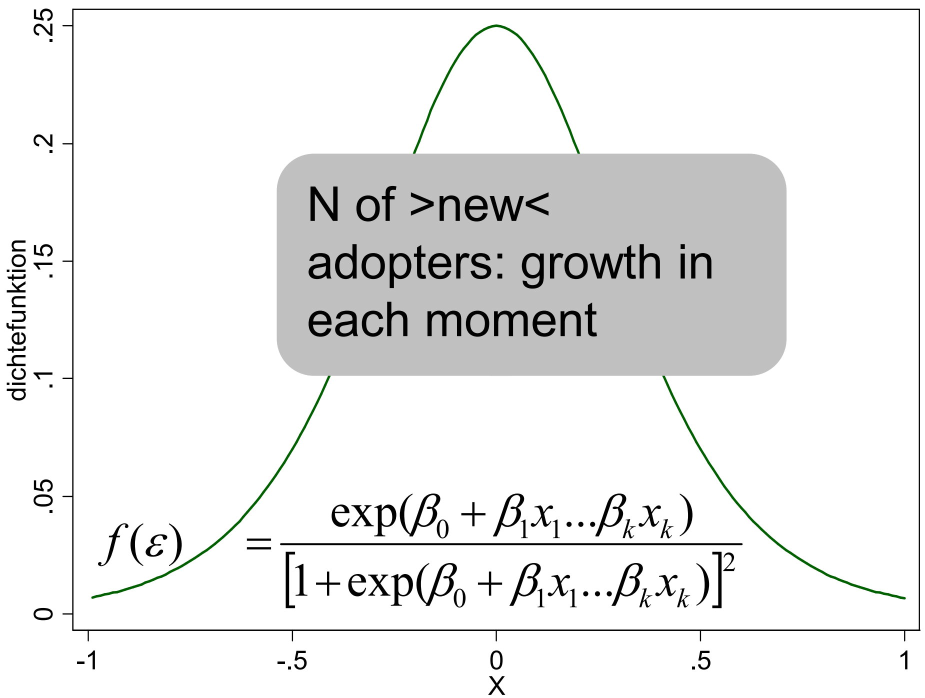


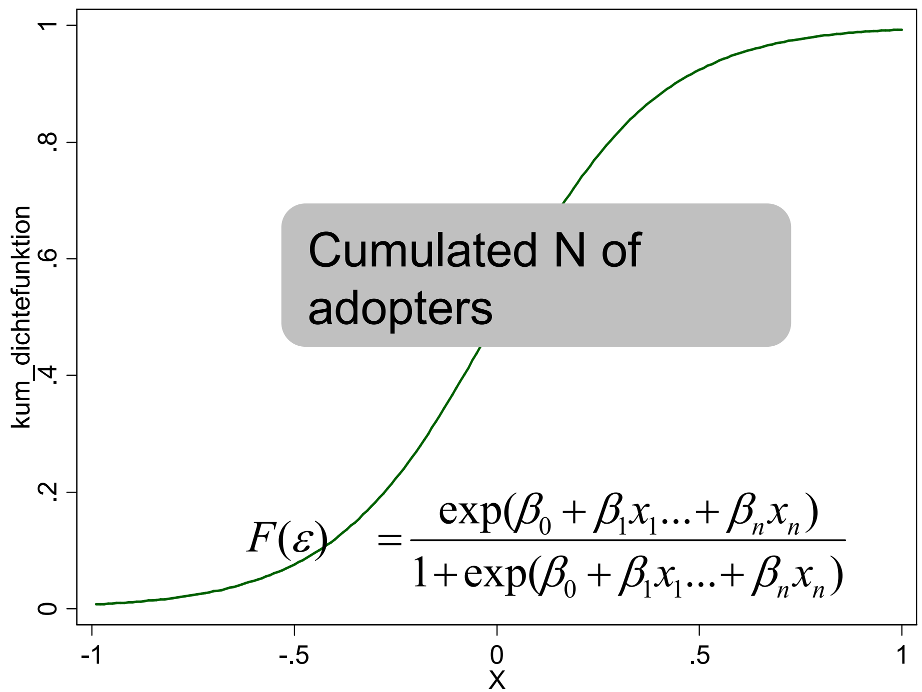


Shen (2020)

How does diffusion look like? Some examples …

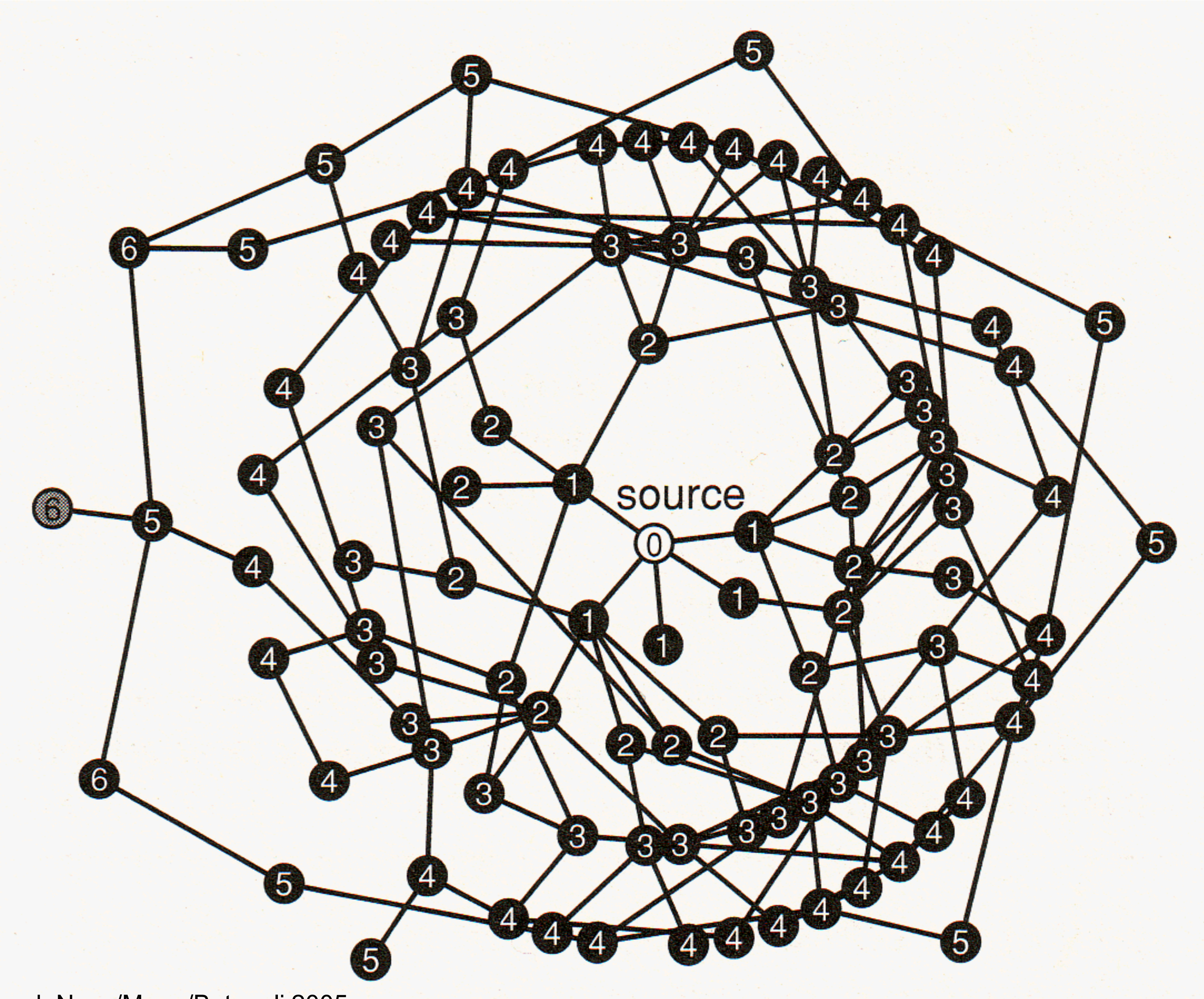
```
clear
set obs 200
gen x = _n - 100
gen X= x / 100
        ** logistic density function ***
gen density_function = exp(X*5) / ( 1 + exp(X*5) )^2
        ** logistic cumulative density function
gen cum_density_function = exp(X*5) / ( 1 + exp(X*5) )
graph twoway line density_function X
graph twoway line cum_density_function X
```



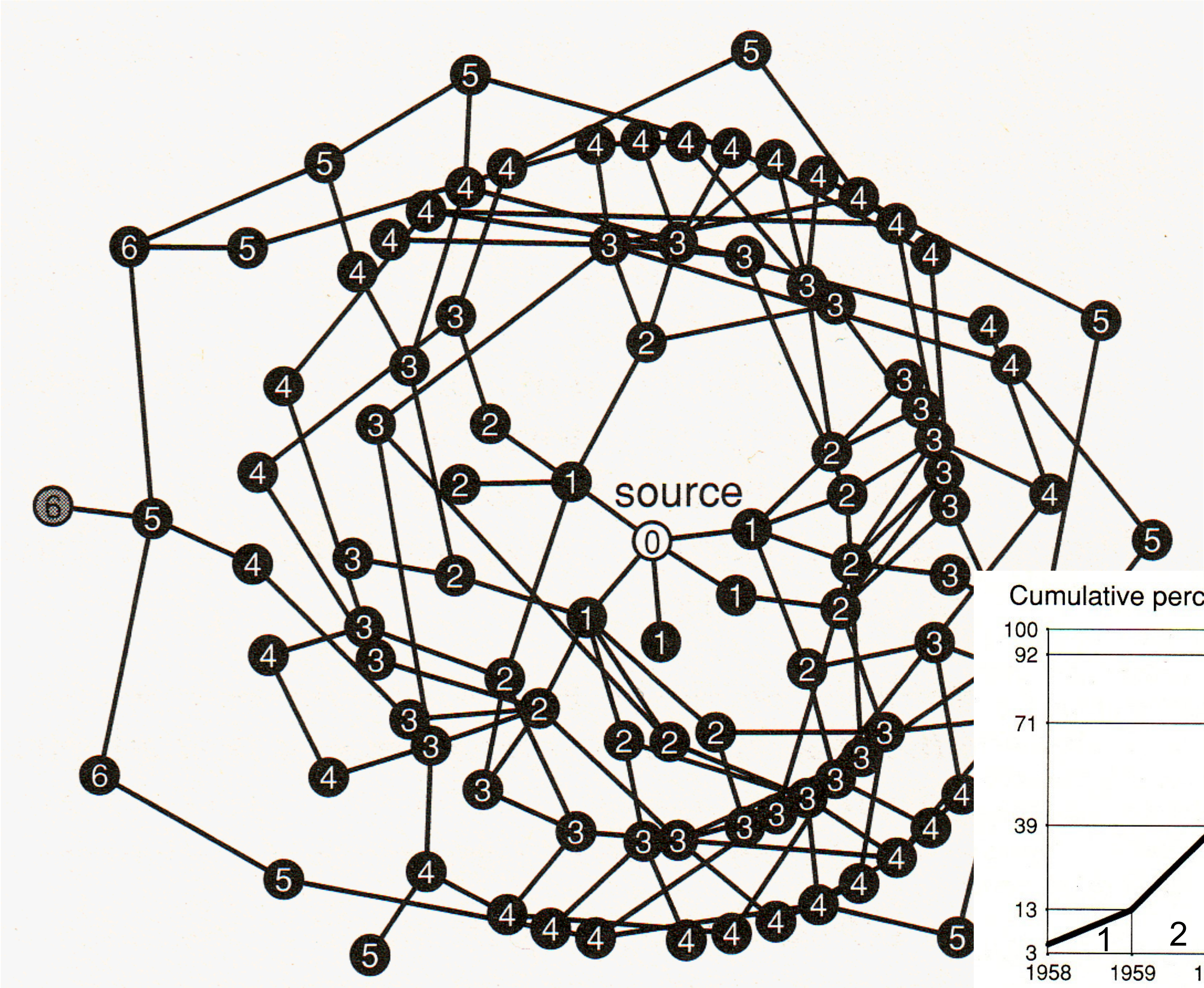


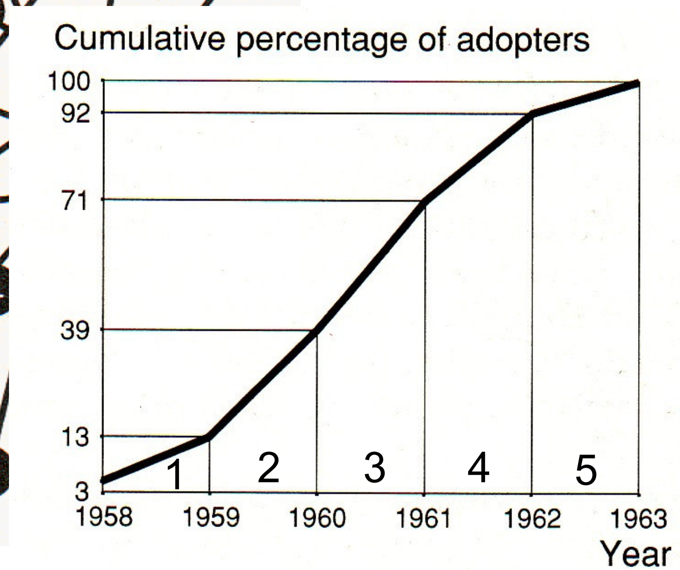
Bring the network in!

- is contagion just logistic growth?
- description of growth process is interesting, but …
- … the minimum requirement for **contagion** (and diffusion in our sense) is **contact among units**
- Bring the **network** in! (Valente 1995)
- we don't discuss the causality issue here (Windzio 2020)

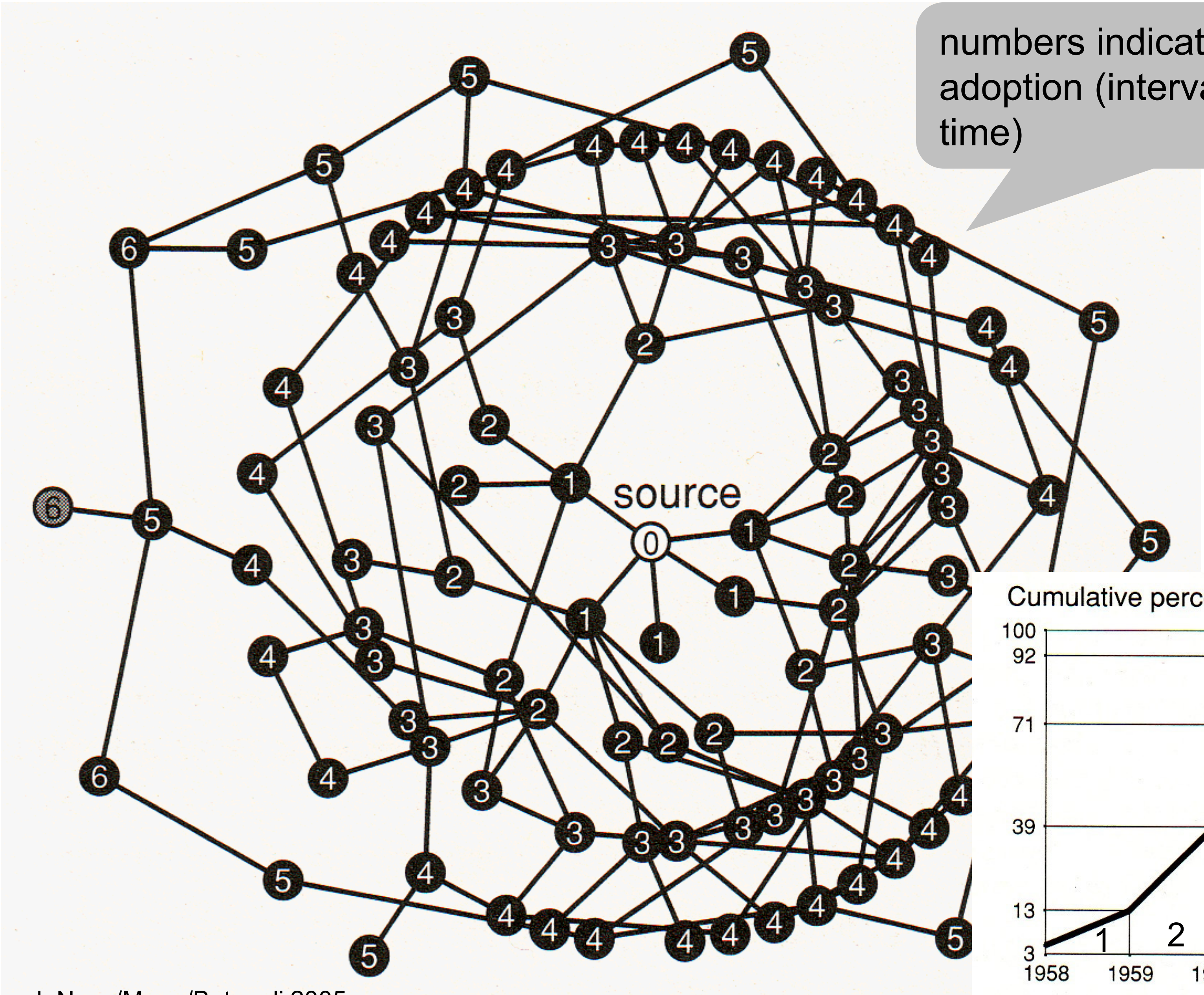


deNooy/Mrvar/Batageli 2005

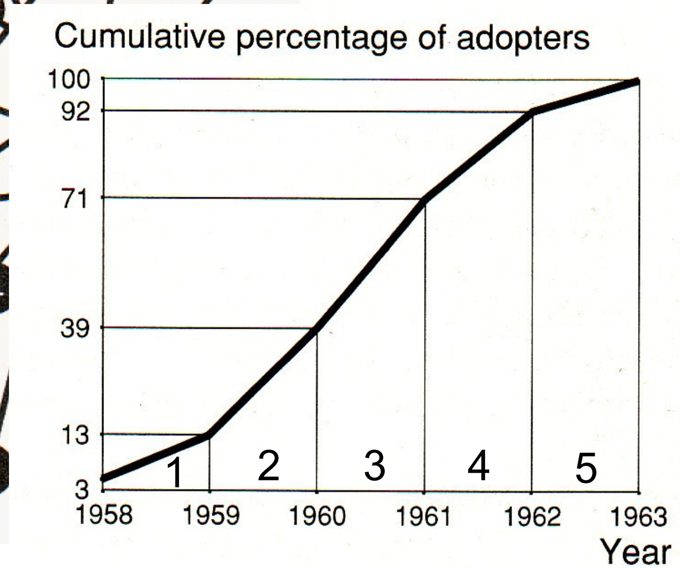




deNooy/Mrvar/Batageli 2005



numbers indicate time of adoption (intervals in process time)



deNooy/Mrvar/Batageli 2005

Moran's I Spatial dependence of *y*

- in spatial models, neighborhood or proximity (e.g. 1/dist.) between units is arranged in a matrix
- *Moran's I* estimates the spatial autocorrelation of a unit's characteristic y (e.g. how being infected (0/1) is correlated with proximity)
- The proximity matrix is a *graph*, and so it is a **network**

In our case, Moran's I indicates whether ***y*** (e.g. social insurance systems) correlates with a tie, or the strength of a tie in the **network**, i.e. with "**neighborhood**" **in the network**

Moran's I Spatial dependence of *y*

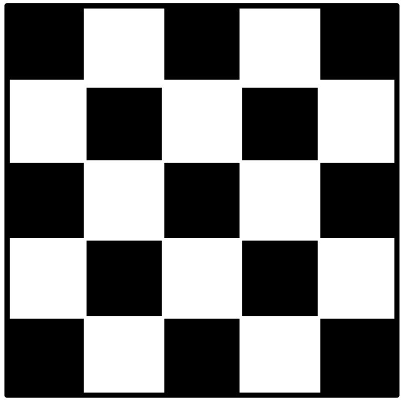
- Take a case *i*. Compute the ***degree of co-deviation*** of y_i and y_j from *the overall mean* $\bar{y}$.
- This is standardized by
  - … the sq. degree of y_i's deviation from $\bar{y}$
  - … ratio of no. of units N and the sum of all weights (weighted edges) W
- The *weight* of each edge in the graph is w_{ij}
- If w_{ij} is zero *i* and *j* are not neighbors, no contribution

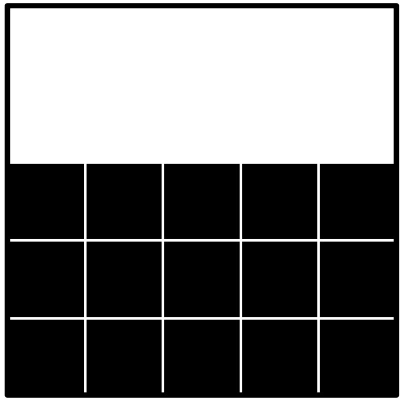
$$I = \frac{N}{W} \bullet \frac{\Sigma_i \Sigma_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\Sigma_i (y_i - \bar{y})^2}$$

Moran's I Spatial dependence of *y*

not infected

infected





Moran's I = **-1**
perfectly negative association between neighborhood and infection

Moran's I ~ **+1**
perfectly positive association between neighborhood and infection

$$I = \frac{N}{W} \bullet \frac{\Sigma_i \Sigma_j w_{ij} (y_i - \overline{y})(y_j - \overline{y})}{\Sigma_i (y_i - \overline{y})^2}$$

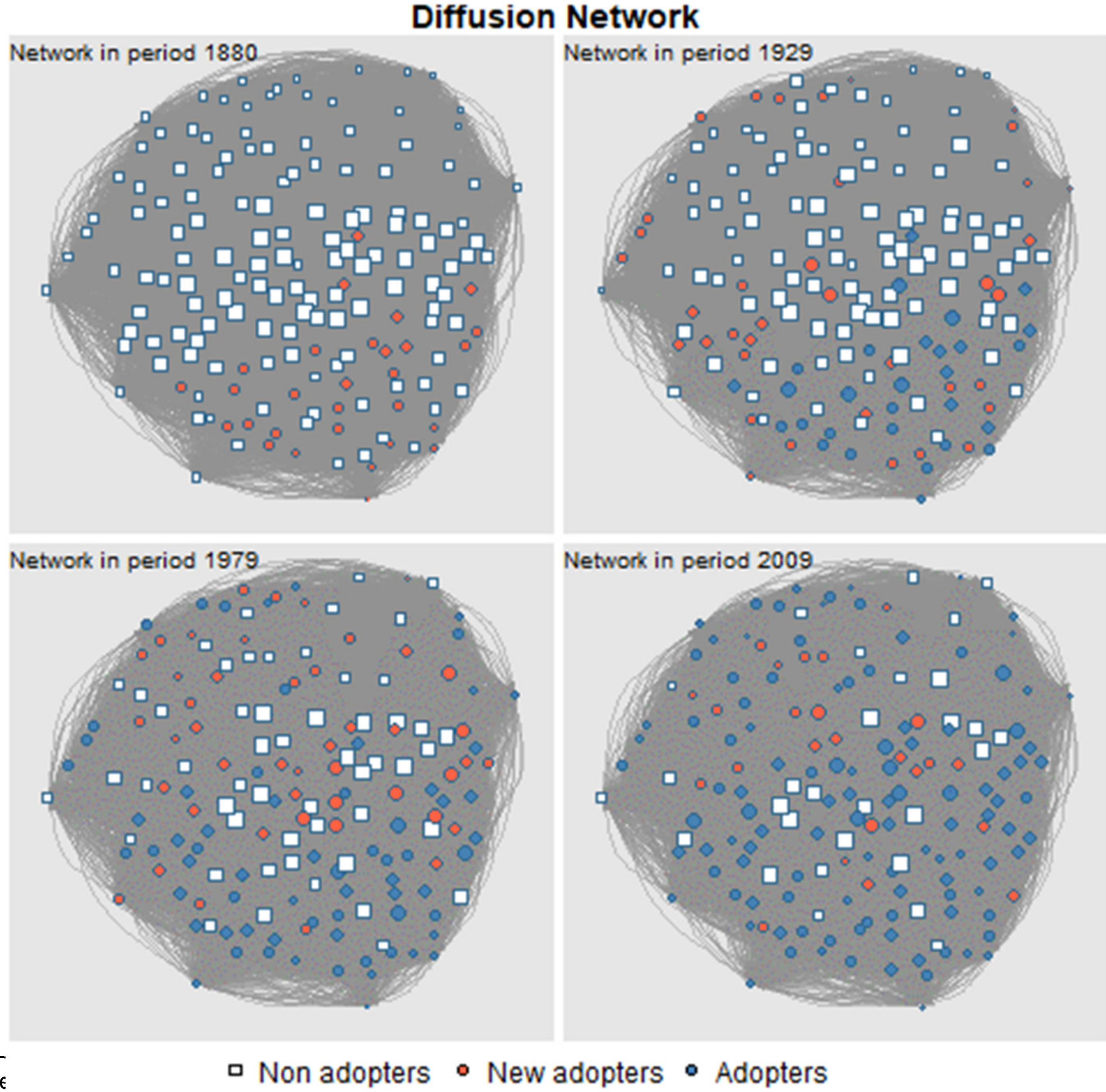
Moran's I Spatial dependence of *y*

Period	Adopters	Cum Adopt. (%)	Hazard Rate	Density	Moran's I (sd)
1880	29	29 (0.18)	-	0.77	0.02 (0.00) ***
1881	0	29 (0.18)	0.00	0.77	0.02 (0.00) ***
1882	3	32 (0.20)	0.02	0.77	0.03 (0.00) ***
1883	0	32 (0.20)	0.00	0.76	0.03 (0.00) ***
1884	1	33 (0.20)	0.01	0.76	0.03 (0.00) ***
1885	0	33 (0.20)	0.00	0.76	0.03 (0.00) ***
1886	0	33 (0.20)	0.00	0.76	0.03 (0.00) ***
1887	0	33 (0.20)	0.00	0.76	0.03 (0.00) ***
1888	0	33 (0.20)	0.00	0.76	0.03 (0.00) ***
1889	0	33 (0.20)	0.00	0.77	0.03 (0.00) ***
…					
2009	0	135 (0.82)	0.00	0.79	-0.01 (0.00) *
2010	1	136 (0.83)	0.03	0.80	-0.01 (0.00) *

- Check in which period Moran's I is significant and positive
- If neighborhood-dependence doesn't matter at all, diffusion might be weak or non-existent – at least via this particular network

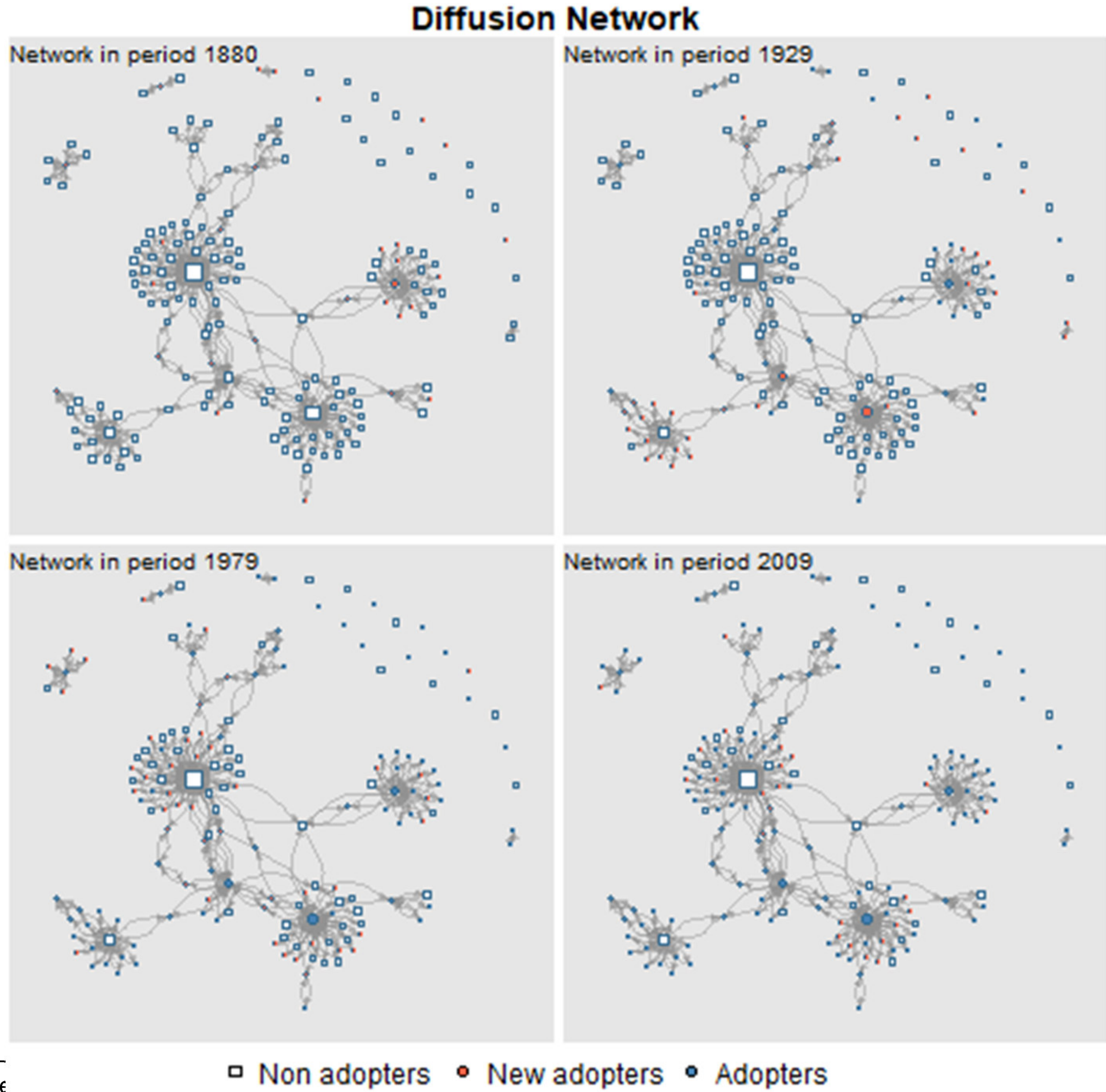
Graph, show diffusion via network "slices"

compulsory education and cultural spheres network



Graph, show diffusion via network “slices”

compulsory education and colony network



Discrete time event-history analysis

- recall the concept of "**odds ratios**" from **logistic regression**

Do countries get a VISA waiver for the Schengen area?
N= 140 non-Schengen countries

	rich	poor
VISA waiver (=1)	40 **66.6%**	10 **12.5%**
Schengen VISA required	20 **33.3%**	70 **87.5%**

$$P(waiver = yes \mid rich) = 40/60 = .666$$
$$P(waiver = no \mid rich) = 20/60 = .333$$
$$P(waiver = yes \mid poor) = 10/80 = .125$$
$$P(waiver = no \mid poor) = 70/80 = .875$$

Odds = P / (1 - P)

Odds Ratio = Odds_{rich} / Odds_{poor}

$$Odds(waiver = yes \mid rich) = 0.666/(1-0.666) = 1.994$$
$$Odds(waiver = yes \mid poor) = 0.333/(1-0.333) = .499$$

$\boxed{\text{Odds Ratio} = \text{Odds}_{rich} / \text{Odds}_{poor}}$ = 1.994 / 0.499

= 4

Discrete time event-history analysis

- Time: waiting time since **1985** to max. **2020**

When do countries get a VISA waiver for the Schengen area?
N= 140 non-Schengen countries, **time since 1985**

	rich	poor
VISA waiver=1	40*10years	10*20years
VISA waiver=0	20*35years	70*35years

$\mapsto$ right censored, not a waiver until 2020 $\rightarrow$ 35years

hazard rate
$r(t) = \Sigma$ events / Σ time-at-risk

also censored cases are part of the risk set

$$\text{rate} \mid \text{rich} = 40 / (\underbrace{40*10+20*35}) = .03636$$

$$\text{rate} \mid \text{poor} = 10 / (10*20+70*35) = .00377$$

$$\boxed{\text{Hazard Ratio} = \text{rate}_{\text{rich}} / \text{rate}_{\text{poor}}} = 0.03636 / 0.00377$$
$$= 9.6$$

Discrete time event-history analysis

```
clear
input id dur des female
1 83 0 0
2 23 1 0
3 80 1 0
4 11 0 0
5 47 1 0
6 148 1 1
7 68 1 1
8 34 0 1
9 42 1 1
10 140 1 1
end
list, clean
```

men: Σ time-at-risk = 244, events = 3

```
stset dur, failure(des==1) /*defines episodes*/
streg, dist(exp) nohr /*estimates model*/
gen rate = exp(_b[_cons]) /*antilog*/
sum rate /*overall rate in pop.: 7/676= .01035 */
```

women: Σ time-at-risk = 432, events = 4

```
*** hazard ratio of "female" ***
bysort female : egen sum_dur=total(dur) /*sum time*/
bysort female : egen sum_des=total(des) /*sum events*/
gen r=sum_des / sum_dur /*rate=event/time-at-risk*/
sum r /*one rate per group*/
```

disp (4/432) / (3/244)=**0.7530**

```
*** compute hazard ratio
gen hr= r(min) / r(max) /*hazard ratio*/
sum hr

stset dur, failure(des==1) id(id)
streg female,  dist(exp) // 0.7530
```

Windzio 2013: 125

Core explanatory variable: exposure

Valente (1995: 44, 72)

"The basic model is exposure to adoption by immediate neighbors (…) at the time period prior to ego's adoption" (manual p. 55)

simple form, exposure of case *i* at time t:

to whom ego has a tie at t …

… multiplied by whether alter j already belongs to cumulative adopters

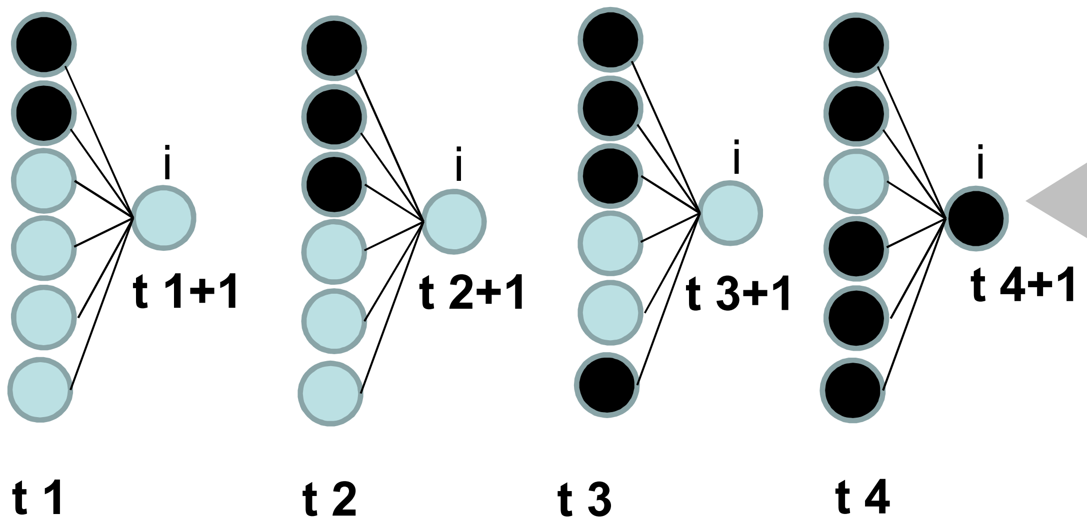
$$E_i(t) = \frac{(\sum_{j \neq i} x_{ij} \bullet a_j)_t}{(\sum_{j \neq i} x_{ij})_t}$$

to whom ego has a tie at t …

= share of alteri to whom ego is tied (neighbors) who are already infected → "exposure to contagion"

Core explanatory variable: exposure

Valente (1995: 44, 72)



Now ego joined the cumulative adopters and can infect subjects in the risk set

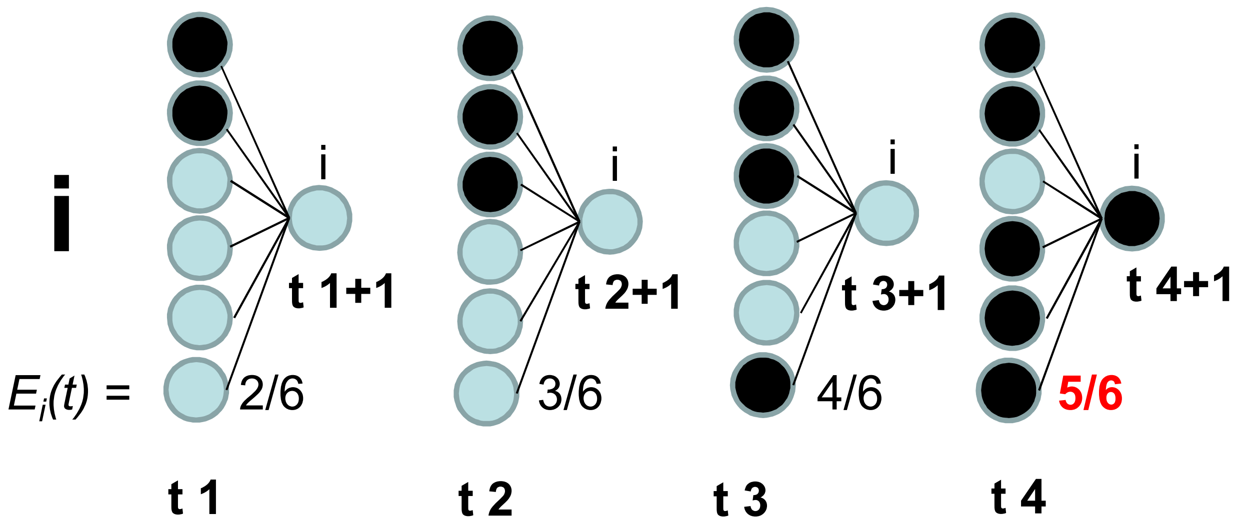
$E_i(t)$ = 2/6 3/6 4/6 5/6

$$E_i(t) = \frac{\left(\sum_{j \neq i} x_{ij} \bullet a_j\right)_t}{\left(\sum_{j \neq i} x_{ij}\right)_t}$$

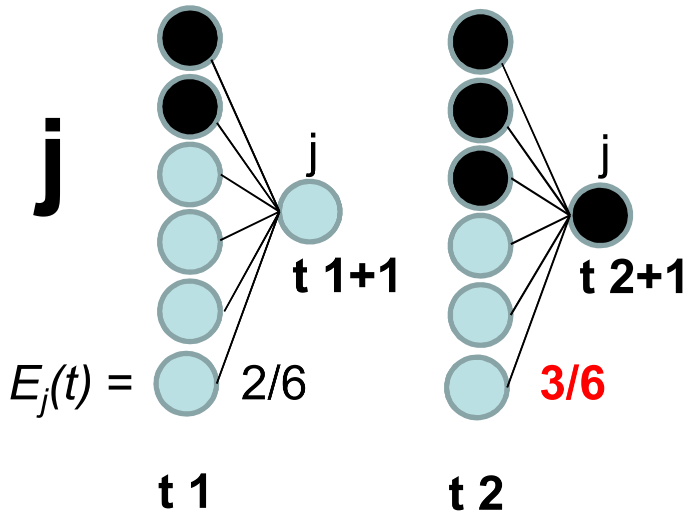
- i's **threshold** is thus **5/6**. If 5 out of 6 neighbors are infected, he/she adopts the infection
- of course, different subjects can have different thresholds (important for classification, see below, e.g. **5/6** and **3/6**)
- ties can be *weighted*, which they are in some of our nets.

Core explanatory variable: exposure

Valente (1995: 44, 72)



id	t	d (ad.)	expo.	fem.
i	1	0	-	1
i	2	0	2/6	1
i	3	0	3/6	1
i	4	0	4/6	1
i	5	1	**5/6**	1
j	1	0	-	0
j	2	0	2/6	0
j	3	1	**3/6**	0



$$r_{i=male} = 1/5$$

$$r_{j=male} = 1/3$$

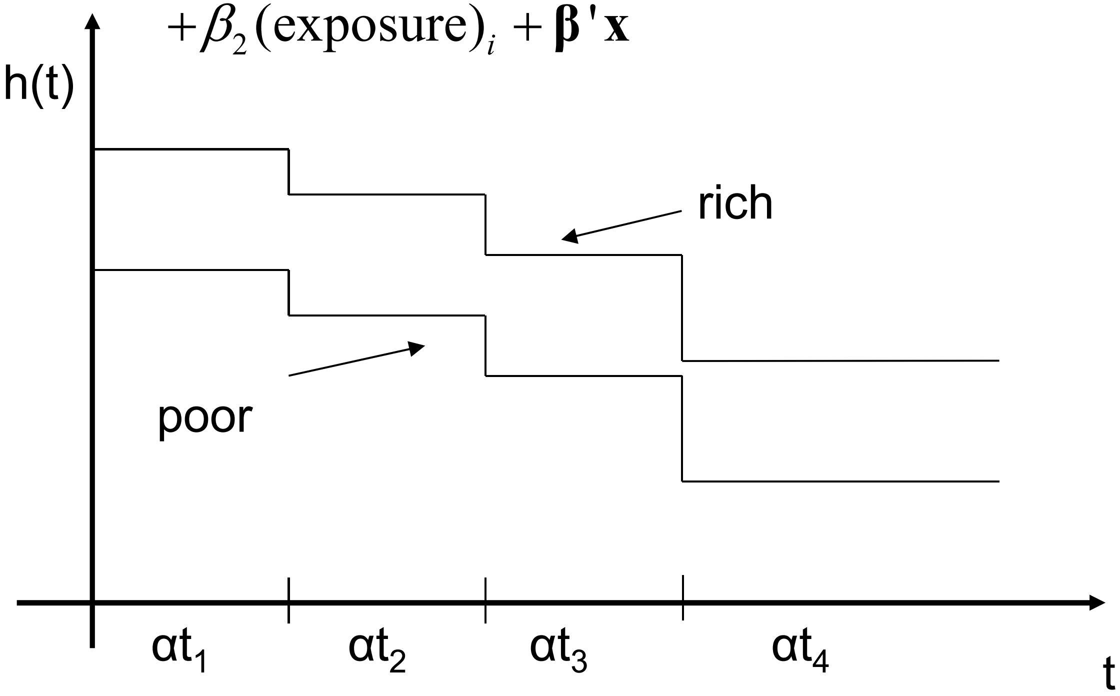
$$hr_{\text{male vs. female}} = (1/5)/(1/3) = 0.6$$

Now: estimate *exposure* effect on adoption rate!

Discrete time event-history analysis: time dependence

„multiple intercepts" αt_j: „t" are dummies (0/1) for the respective time-period. Assumption of proportional hazards: ratio of hazards remains constant over time.
Piecewise constant rate model

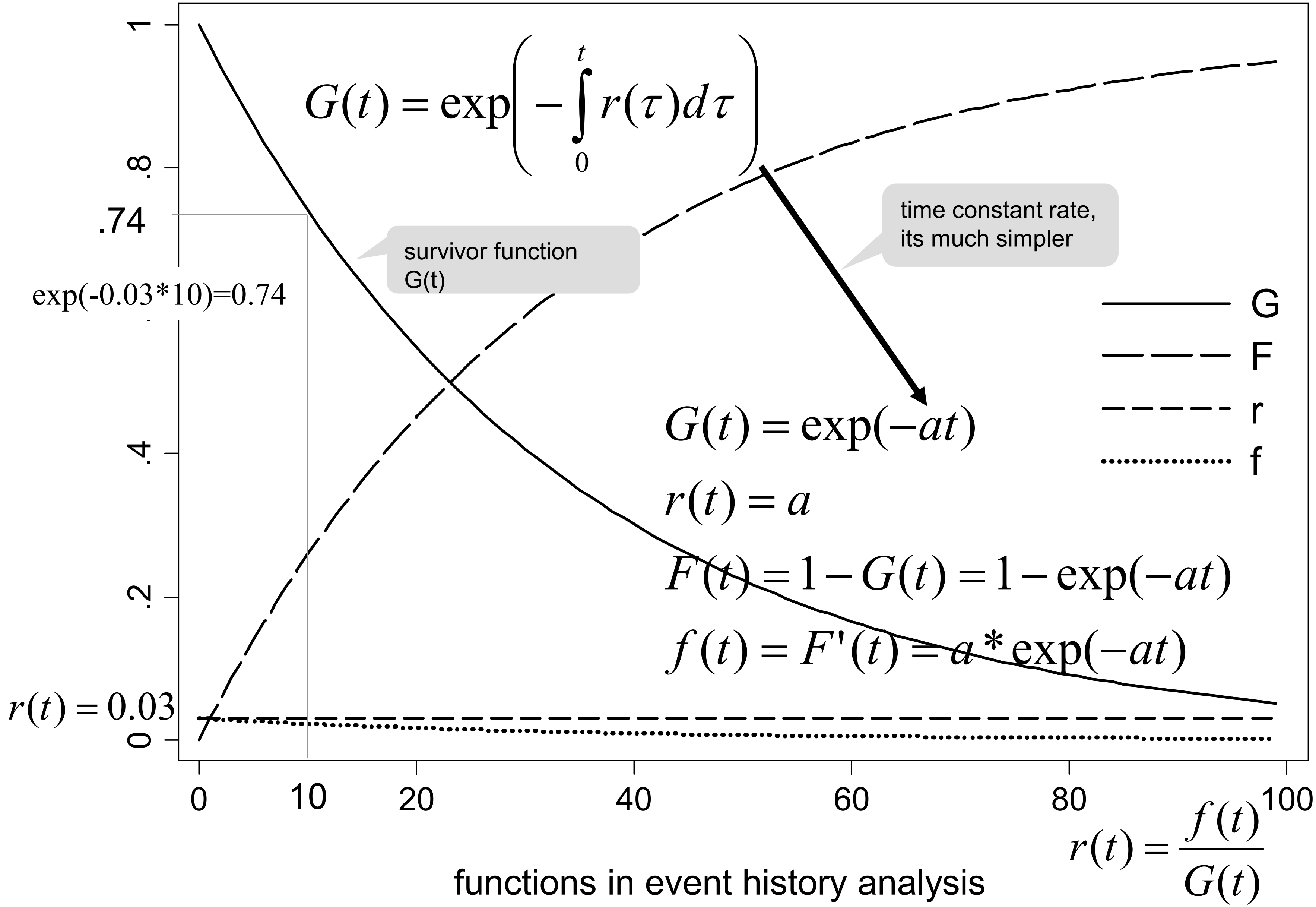
$$\text{logit } h(t_j) = [\alpha t_1 + \alpha t_2 + .. + \alpha t_j] + \beta_1 (rich)_i + \beta_2 (\text{exposure})_i + \boldsymbol{\beta}'\mathbf{x}$$

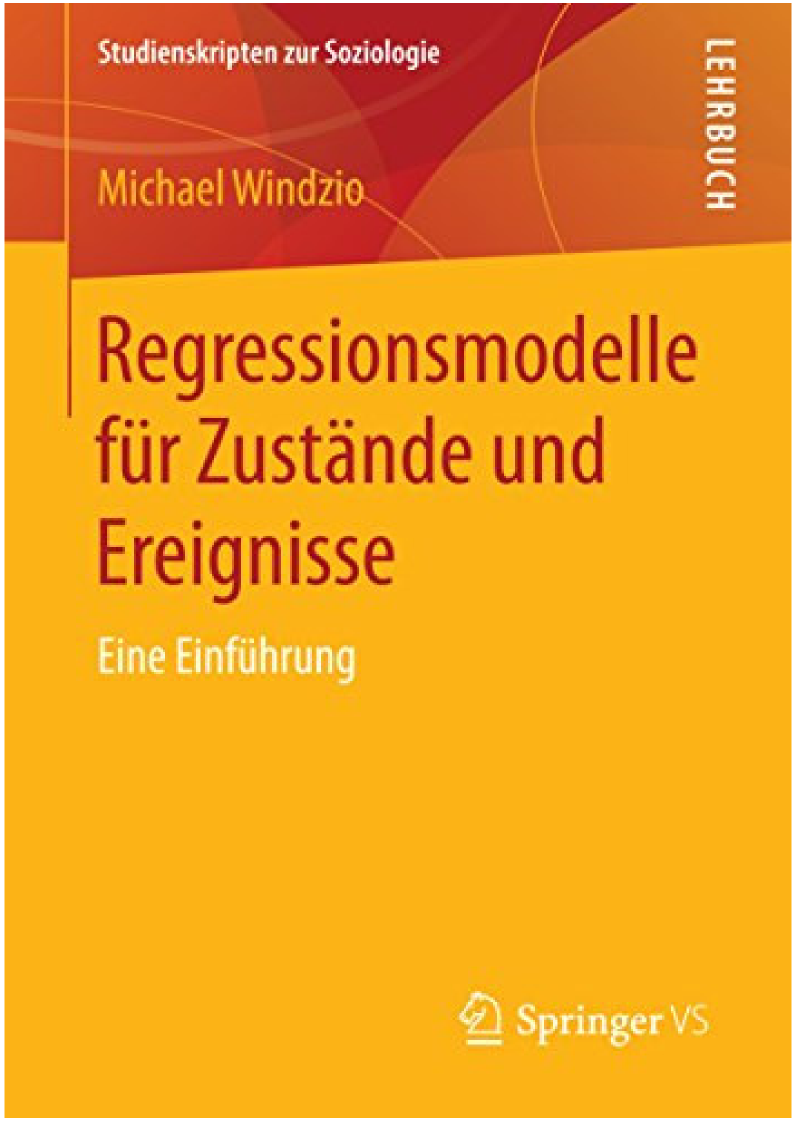


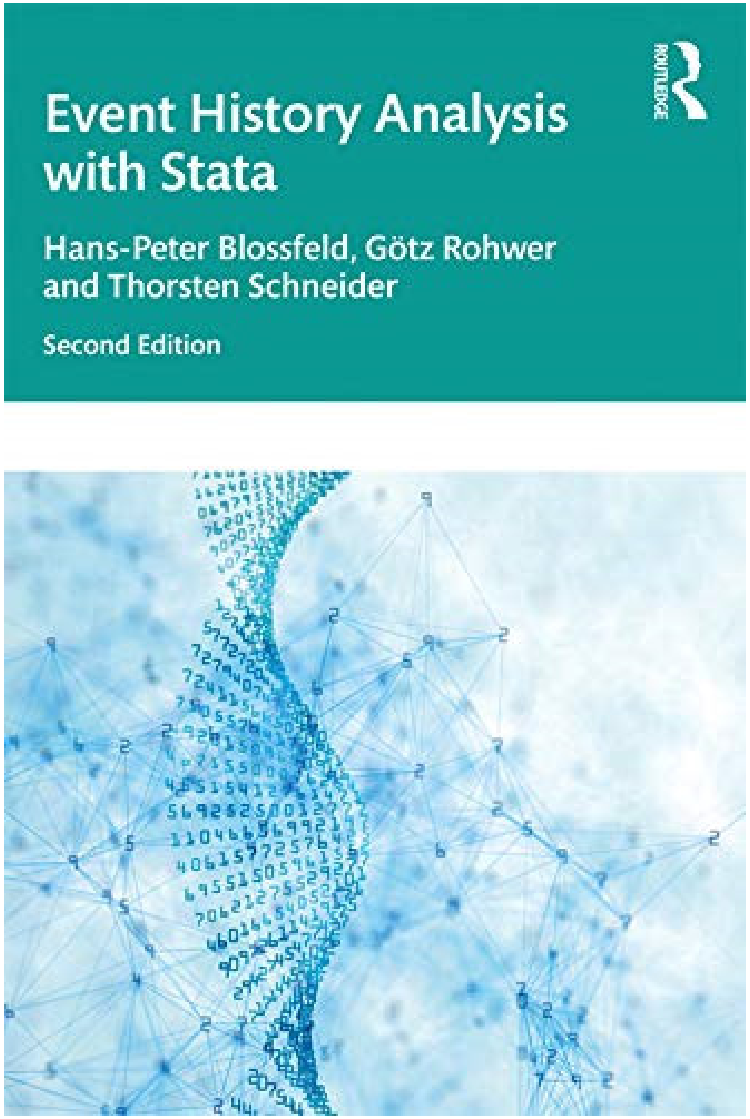
id	p 1	p 2	t	d (ad.)	expo.	rich
i	1	0	1	0	-	1
i	1	0	2	0	2/6	1
i	0	1	3	0	3/6	1
i	0	1	4	0	4/6	1
i	0	1	5	1	5/6	1
j	1	0	1	0	-	0
j	1	0	2	0	2/6	0
j	0	1	3	1	3/6	0

cf. Windzio 2013: 112

exponential model, time-constant rate assumed




Studienskripten zur Soziologie
LEHRBUCH
Michael Windzio
Regressionsmodelle für Zustände und Ereignisse
Eine Einführung
Springer VS


Event History Analysis with Stata
Hans-Peter Blossfeld, Götz Rohwer and Thorsten Schneider
Second Edition
ROUTLEDGE

Diffusion of Compulsory Education - Cultural Spheres Network, discrete-time logistic hazard model of network diffusion

	Introduction of Compulsory Schooling (1)
Weighted Exposure (complete network)	4.450***
Year	0.184
Year^2	-0.00005
Log of GDP per capita	0.054
Lower Middle Income	0.393
Upper Middle Income	1.099***
High Income	0.629*
Constant	-188.752
	(123.589)
N (Country years)	20,354
N (countries)	165
N (events)	145
Log Likelihood	-709.731
Akaike Inf. Crit.	1,435.462

Source: CRC 1342, project A05, standard errors in parentheses

Classification of adopters

Valente (1995)

Classification of adopters is done depending on the
- distance from the mean of **Time-of-Adoption** and **Threshold**.
- distance is measured in terms of standard deviations

`netdiffuseR` manual refers to Valente (1995: 95), who only focused on

„**average time of adoption**" (the **median** because of right censored cases? But there is no standard deviation for median, so censored cases might be ignored in this classification). See also Rogers (2003: 281)

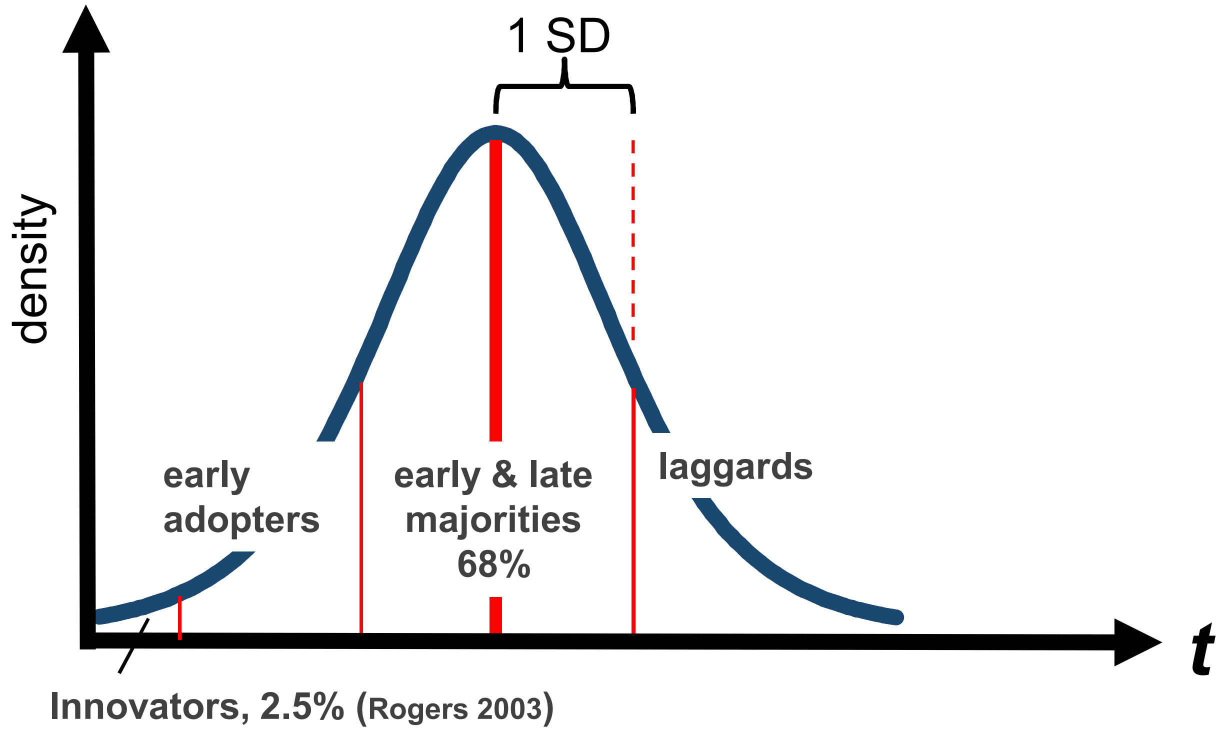
- distance from the mean of **Time-of-Adoption** measured in standard deviations

early adopters:	units whose ***t*** is more than one SD earlier than the average
early and late majorities:	***t*** is bounded by one SD earlier and later than the average
laggards:	***t*** is later than one SD from the average

Classification of adopters

Valente (1995: 95)
Rogers (2003: 281)

early adopters:	units whose ***t*** is more than one SD earlier than the average
early and late majorities:	***t*** is bounded by one SD earlier and later than the average
laggards:	***t*** is later than one SD from the average



Classification of adopters

Valente (1995)

```
out <- classify_adopters(diffnet_culture)
out
```

```
                              thr    diffnet_culture$toa ids
Early Majority     Low Thresh.                     1931 AFG
Late Majority Very High Thresh.                    1975 AGO
Early Majority     Low Thresh.                     1913 ALB
Late Majority      High Thresh.                    1971 ARE
Early Adopters     Low Thresh.                     1884 ARG
Early Majority     Low Thresh.                     1920 ARM
```

- Who is early adopter or laggard?
- explain category by `mlogit` (`ologit`?) by time-constant variables, or deal with backward causality. Be careful, but it might make sense in some cases.

Thanks for listening!

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