plos_manuscript.R

mghancean

2021-03-13

```
# Plos One manuscript #####
# Hancean, M.-G., Lubbers, M.J., Molina, J.L.
# 0. Load packages ####
library(easypackages)
libraries("statnet", "igraph", "intergraph", "ergmito", "texreg", "dplyr", "ggpubr")
```

```
## Loading required package: statnet

## Loading required package: tergm

## Loading required package: ergm

## Loading required package: network

## network: Classes for Relational Data
## Version 1.16.1 created on 2020-10-06.
## copyright (c) 2005, Carter T. Butts, University of California-Irvine
##                     Mark S. Handcock, University of California -- Los Angeles
##                     David R. Hunter, Penn State University
##                     Martina Morris, University of Washington
##                     Skye Bender-deMoll, University of Washington
##  For citation information, type citation("network").
##  Type help("network-package") to get started.

##
## ergm: version 3.11.0, created on 2020-10-14
## Copyright (c) 2020, Mark S. Handcock, University of California -- Los Angeles
##                     David R. Hunter, Penn State University
##                     Carter T. Butts, University of California -- Irvine
##                     Steven M. Goodreau, University of Washington
##                     Pavel N. Krivitsky, UNSW Sydney
##                     Martina Morris, University of Washington
##                     with contributions from
##                     Li Wang
##                     Kirk Li, University of Washington
##                     Skye Bender-deMoll, University of Washington
##                     Chad Klumb
##                     Michal Bojanowski, Kozminski University
##                     Ben Bolker
## Based on "statnet" project software (statnet.org).
## For license and citation information see statnet.org/attribution
## or type citation("ergm").
```

```
## NOTE: Versions before 3.6.1 had a bug in the implementation of the bd()
## constraint which distorted the sampled distribution somewhat. In
## addition, Sampson's Monks datasets had mislabeled vertices. See the
## NEWS and the documentation for more details.

## NOTE: Some common term arguments pertaining to vertex attribute and
## level selection have changed in 3.10.0. See terms help for more
## details. Use 'options(ergm.term=list(version="3.9.4"))' to use old
## behavior.

## Loading required package: networkDynamic

##
## networkDynamic: version 0.10.1, created on 2020-01-16
## Copyright (c) 2020, Carter T. Butts, University of California -- Irvine
##                     Ayn Leslie-Cook, University of Washington
##                     Pavel N. Krivitsky, University of Wollongong
##                     Skye Bender-deMoll, University of Washington
##                     with contributions from
##                     Zack Almquist, University of California -- Irvine
##                     David R. Hunter, Penn State University
##                     Li Wang
##                     Kirk Li, University of Washington
##                     Steven M. Goodreau, University of Washington
##                     Jeffrey Horner
##                     Martina Morris, University of Washington
## Based on "statnet" project software (statnet.org).
## For license and citation information see statnet.org/attribution
## or type citation("networkDynamic").

##
## tergm: version 3.7.0, created on 2020-10-15
## Copyright (c) 2020, Pavel N. Krivitsky, UNSW Sydney
##                     Mark S. Handcock, University of California -- Los Angeles
##                     with contributions from
##                     David R. Hunter, Penn State University
##                     Steven M. Goodreau, University of Washington
##                     Martina Morris, University of Washington
##                     Nicole Bohme Carnegie, New York University
##                     Carter T. Butts, University of California -- Irvine
##                     Ayn Leslie-Cook, University of Washington
##                     Skye Bender-deMoll
##                     Li Wang
##                     Kirk Li, University of Washington
##                     Chad Klumb
## Based on "statnet" project software (statnet.org).
## For license and citation information see statnet.org/attribution
## or type citation("tergm").

## Loading required package: ergm.count

##
```

```
## ergm.count: version 3.4.0, created on 2019-05-15
## Copyright (c) 2019, Pavel N. Krivitsky, University of Wollongong
##                     with contributions from
##                     Mark S. Handcock, University of California -- Los Angeles
##                     David R. Hunter, Penn State University
## Based on "statnet" project software (statnet.org).
## For license and citation information see statnet.org/attribution
## or type citation("ergm.count").

## NOTE: The form of the term 'CMP' has been changed in version 3.2 of
## 'ergm.count'. See the news or help('CMP') for more information.

## Loading required package: sna

## Loading required package: statnet.common

##
## Attaching package: 'statnet.common'

## The following object is masked from 'package:base':
##
##     order

## sna: Tools for Social Network Analysis
## Version 2.6 created on 2020-10-5.
## copyright (c) 2005, Carter T. Butts, University of California-Irvine
##  For citation information, type citation("sna").
##  Type help(package="sna") to get started.

## Loading required package: tsna

##
## statnet: version 2019.6, created on 2019-06-13
## Copyright (c) 2019, Mark S. Handcock, University of California -- Los Angeles
##                     David R. Hunter, Penn State University
##                     Carter T. Butts, University of California -- Irvine
##                     Steven M. Goodreau, University of Washington
##                     Pavel N. Krivitsky, University of Wollongong
##                     Skye Bender-deMoll
##                     Martina Morris, University of Washington
## Based on "statnet" project software (statnet.org).
## For license and citation information see statnet.org/attribution
## or type citation("statnet").

## unable to reach CRAN

## Loading required package: igraph

##
## Attaching package: 'igraph'
```

```
## The following objects are masked from 'package:sna':
##
##     betweenness, bonpow, closeness, components, degree, dyad.census,
##     evcent, hierarchy, is.connected, neighborhood, triad.census

## The following objects are masked from 'package:network':
##
##     %c%, %s%, add.edges, add.vertices, delete.edges, delete.vertices,
##     get.edge.attribute, get.edges, get.vertex.attribute, is.bipartite,
##     is.directed, list.edge.attributes, list.vertex.attributes,
##     set.edge.attribute, set.vertex.attribute

## The following objects are masked from 'package:stats':
##
##     decompose, spectrum

## The following object is masked from 'package:base':
##
##     union

## Loading required package: intergraph

## Loading required package: ergmito

##
## Attaching package: 'ergmito'

## The following object is masked from 'package:igraph':
##
##     is_directed

## Loading required package: texreg

## Version:  1.37.5
## Date:     2020-06-17
## Author:   Philip Leifeld (University of Essex)
##
## Consider submitting praise using the praise or praise_interactive functions.
## Please cite the JSS article in your publications -- see citation("texreg").

## Loading required package: dplyr

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:igraph':
##
##     as_data_frame, groups, union

## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

## Loading required package: ggpubr

## Loading required package: ggplot2

## All packages loaded successfully
```

```
# 1. Read the data ####
my_net <- read.csv("linktracing_network_parti.csv", header = TRUE, as.is = TRUE)
my_net <- my_net[,c(2,3)]
my_net
```

```
##           from         to
## 1   ELEBAR0888 ADISER3882
## 2   MILVUS7129 ADISER3882
## 3   RODMAR1610 ADISER3882
## 4   FLOLAM0770 ADRAND8482
## 5   TUDMAG4968 ADRBOT3464
## 6   MARBUG0557 ADRCIO9071
## 7   OANENA0111 ADRIVA2842
## 8   ALIBAN1184 ADRLEU7410
## 9   CATCIR4723 ADRMUN4738
## 10  PATSTA7106 ADRPRE0365
## 11  MARVIN7133 ADRSLA0666
## 12  OANSIM9507 ADRSLA0666
## 13  SINNIC2893 ADRVLA3930
## 14  BOVALE5350 ALBENA5796
## 15  ADRMUN4738 ALCSAF2565
## 16  ADRPRE0365 ALEDOB4417
## 17  PATSTA7106 ALEDOB4417
## 18  BIAUDR6009 ALEGHI7329
## 19  RALALE1024 ALEMAT6371
## 20  LUBION3700 ALEMIH6840
## 21  ADRIVA2842 ALEMLA2259
## 22  IULSEC4156 ALESEC0164
## 23  VALRIS4042 ALESER4777
## 24  DACMIH1609 ALESOI6040
## 25  ELVPLE1000 ALGLEP8844
## 26  IULARZ4792 ALIBAN1184
## 27  ALEMIH6840 ALIBIT4626
## 28  DACMIH1609 ALIDRA6546
## 29  ANDCON2353 ALIIVA5725
## 30  GHEIVA5822 ALIIVA5725
## 31  LAUSEN7409 ALIIVA5725
## 32  ANGCAT5731 ALIMIN4996
## 33  NELMIN9830 ALIMIN4996
## 34  ADRPRE0365 ALINIT4931
## 35  ALESER4777 ALSSER6008
## 36  CONSER9980 ALSSER6008
## 37  IOACAR6440 AMCTRE1196
```

```
## 38  ELESTA0468 ANCSTA8141
## 39  LAROLA1045 ANDBUF7502
## 40  MIHVOI6906 ANDBUF7502
## 41  OANENA0111 ANDBUR9472
## 42  LAUSEN7409 ANDCON2353
## 43  CLACAT1858 ANDMAN6033
## 44  BIAUDR6009 ANDMIH4668
## 45  VLCCHI3795 ANDPOP5828
## 46  COASUT1963 ANDPRE2503
## 47  CRITOM7446 ANEMIH2014
## 48  MIHBAZ7530 ANGCAT5731
## 49  SILGRI7274 ANGCAT5731
## 50  CRMCER8270 ANGTOM3746
## 51  IONDUM5180 ANMMAR4216
## 52  SILPET0456 ANMMAR4216
## 53  NICPAR9193 ANMPAR7339
## 54  IONILI6099 ANRGHE2145
## 55  BOAVAS1800 ANRVAS6941
## 56  STESAV3834 ANVDRA5974
## 57  GAOVIN1446 AURALE8981
## 58  ELEPAD8471 AURMAT4393
## 59  ALEGHI7329 AURMEG8297
## 60  LUMGHE9639 AURMEG8297
## 61  CONIOR9255 AURPET4354
## 62  STEGRI0788 AURPET4354
## 63  DANCOR3745 BEAPOP2738
## 64  MANPOP4820 BEAPOP2738
## 65  THEMIL3513 BEAPOP2738
## 66  IONHER0420 BENGHE9525
## 67  GABDIN8210 BETANC4019
## 68  MAPMIH2031 BIAPOP5123
## 69  ADRMUN4738 BIASAF2334
## 70  ALCSAF2565 BIASAF2334
## 71  CATCIR4723 BIAUDR6009
## 72  REMDOB0532 BOAVAS1800
## 73  SILCRA2707 BOGTOB9747
## 74  BIAPOP5123 BOVALE5350
## 75  COARAD5222 CAFMIT4837
## 76  MARDIN0602 CAFMIT4837
## 77  ROMMIT5030 CAFMIT4837
## 78  SEGTUD0780 CAFMIT4837
## 79  MAGTUD6627 CAGTUD2149
## 80  NIDTUD0285 CAGTUD2149
## 81  ANMMAR4216 CARMAR9000
## 82  CLVSIM2624 CATCIR4723
## 83  DRADUM5007 CATTUD9936
## 84  IONDUM5180 CLACAT1858
## 85  ADRSLA0666 CLAMAR8627
## 86  LEOCOS8783 CLMAND6388
## 87  DRADUM5007 CLMSER5044
## 88  ALIDRA6546 CLVSIM2624
## 89  MARDIN0602 COARAD5222
## 90  ALIBIT4626 COASUT1963
## 91  SINNIC2893 COCTAL6560
```

```
## 92  ELESTA7038 CONIOR9255
## 93  MIHCON7927 CONMUS0105
## 94  ELEPAD8471 CONMUS3016
## 95  ALESER4777 CONSER9980
## 96  LAUSEN7409 CONSER9980
## 97  SILCRA2707 COPPIR4066
## 98  COASUT1963 CORERE4381
## 99  ALEDOB4417 COSGAN8568
## 100 ALIBAN1184 COSGAN8568
## 101 LARMAR6523 COSSAN5803
## 102 DANCUC1198 CRGMAR4677
## 103 IOAATI7055 CRIATI2144
## 104 RAMHAR1356 CRIHAR4135
## 105 RAPPAV4473 CRIPAR4497
## 106 IOAATI7055 CRIPOP2464
## 107 MOMAVA8566 CRIPOP2464
## 108 ELCSTO7017 CRIRAD2879
## 109 ADRSLA0666 CRISLA6039
## 110 COSSAN5803 CRITOM7446
## 111 DIAVAS1818 CRMCER8270
## 112 LAAMOL7425 CRSMOL2560
## 113 MICHAR5046 CRSMOL2560
## 114 DANSER3377 DACMIH1609
## 115 BOGTOB9747 DAFMAR0608
## 116 MARPOP1848 DANCOR3745
## 117 OANGOL3414 DANCUC1198
## 118 GABDOB4563 DANFLO7479
## 119 LILSER3330 DANFLO7479
## 120 MARLIN8867 DANPOP7046
## 121 MOMAVA8566 DANPOP7046
## 122 NELMIN9830 DANPOP7046
## 123 CLAMAR8627 DANSAN0751
## 124 ANVDRA5974 DANSER3377
## 125 EMIIEF0491 DANTAN5700
## 126 MABDUT2054 DEEDIN7226
## 127 MIHDIN1519 DEEDIN7226
## 128 IOACAR6440 DIAVAS1818
## 129 MOTMAN5742 DIMMAN6485
## 130 ANGCAT5731 DORCAT7658
## 131 ALIBAN1184 DORPER2487
## 132 MAROLA5643 DORPER2487
## 133 LAFVIN1569 DRADUM5007
## 134 ROAMAR5931 DUMMAN4411
## 135 ALIIVA5725 DUMTOF3509
## 136 ANMMAR4216 ELCSTO7017
## 137 CARMAR9000 ELCSTO7017
## 138 RODCIS3502 ELEBAR0888
## 139 DANCUC1198 ELECHI1338
## 140 LUAVLA0198 ELECHI2472
## 141 COCTAL6560 ELEDOG4991
## 142 SINNIC2893 ELEDOG4991
## 143 FESTUD9863 ELEGHI3110
## 144 FLOLAM0770 ELELAM8896
## 145 TUDMAG4968 ELEMAN5255
```

```
## 146 CLAMAR8627 ELEMAR1401
## 147 CRISLA6039 ELEMAR1401
## 148 MARMAR0624 ELEMAR1401
## 149 ELEMAR1401 ELEPAD8471
## 150 IONDUM5180 ELESTA0468
## 151 DIAVAS1818 ELESTA7038
## 152 ANRVAS6941 ELIFRA9338
## 153 VALPIR9591 ELRNEA4613
## 154 REMDOB0532 ELVPLE1000
## 155 CRIATI2144 EMIIEF0491
## 156 DANTAN5700 EMIIEF0491
## 157 GHEIVA5822 EMIIEF0491
## 158 SILPET0456 EMILUN8780
## 159 ANMMAR4216 EMIMAR9445
## 160 IULFUR8867 EUGBOC3688
## 161 DANSAN0751 EUGCIU5866
## 162 EVEIVA3317 EUGNEG9666
## 163 HOIOLA8773 EUGNEG9666
## 164 HOIOLA8773 EVEIVA3317
## 165 MAGTUD6627 FESTUD9863
## 166 NIDTUD0285 FESTUD9863
## 167 FLOAND2205 FLGCOC6662
## 168 ANDBUR9472 FLOAND2205
## 169 ELECHI1338 FLOAND2205
## 170 CONMUS3016 FLOBOL9085
## 171 IONBOC1639 FLOCIO6499
## 172 MARVIN7133 FLOLAM0770
## 173 NELMIN9830 FLOMIN1738
## 174 ELECHI1338 FLOTOB5871
## 175 HORMAN2884 GABBEN6103
## 176 IONBOC1639 GABCIO2580
## 177 ANRGHE2145 GABDIN8210
## 178 DANFLO7479 GABDOB4563
## 179 EUGBOC3688 GABFUR1783
## 180 ILEAPO6677 GABTUR5757
## 181 SEFMAR7405 GAEBAD2789
## 182 ALGLEP8844 GAOVIN1446
## 183 EUGNEG9666 GEOBOH7300
## 184 ILEFLO6720 GEOBUN1297
## 185 DANSAN0751 GEOCIU0789
## 186 LIDVIN1655 GEODIA1252
## 187 EUGBOC3688 GEODUM6066
## 188 MIHION7998 GEOION7998
## 189 EUGNEG9666 GEOIVA2682
## 190 EVEIVA3317 GEOIVA2682
## 191 IONBOC1639 GEOSPI5782
## 192 BOVALE5350 GEOSTE6501
## 193 ALBENA5796 GEOTUD9284
## 194 ALCSAF2565 GEOVOI7108
## 195 ALESER4777 GHEIVA5822
## 196 ANDCON2353 GHEIVA5822
## 197 DUMTOF3509 GHEIVA5822
## 198 MOTMAN5742 GHEMAN6674
## 199 MARDIN0602 GHERAD7837
```

```
## 200 ANDBUF7502 HOIOLA8773
## 201 LAROLA1045 HOIOLA8773
## 202 OVIMIT2914 HORMAN2884
## 203 CORERE4381 ILEAPO6677
## 204 EUGNEG9666 ILEFLO6720
## 205 RAMHAR1356 ILIHAR4135
## 206 CRIATI2144 IOAATI7055
## 207 CRIPOP2464 IOAATI7055
## 208 NELDUM4387 IOAATI7055
## 209 ALIIVA5725 IOACAR6440
## 210 GEOSPI5782 IOAPAR1019
## 211 DUMTOF3509 IOATOF5422
## 212 LORSAN2950 IOAZEG2449
## 213 IONVAS9540 IODMIT4383
## 214 IONILI6099 IOIBUT8969
## 215 IULFUR8867 IONBOC1639
## 216 ROMMIT5030 IONDUM5180
## 217 GABFUR1783 IONFUR4001
## 218 IULFUR8867 IONFUR4001
## 219 GEODUM6066 IONMIH0732
## 220 IONVAS9540 IONRUS6824
## 221 LAUSAV5240 IONSAV3659
## 222 IOIBUT8969 IONVAS9540
## 223 LUBION3700 IONVAS9540
## 224 IOATOF5422 IOVCOM7913
## 225 IULARZ4792 IRIBAD1618
## 226 COSGAN8568 IULARZ4792
## 227 DORPER2487 IULARZ4792
## 228 MAROLA5643 IULARZ4792
## 229 LAUSEN7409 IULFUR8867
## 230 DANCUC1198 IULSEC4156
## 231 MARMAR0624 LAAMOL7425
## 232 MARVIN7133 LAFVIN1569
## 233 GABCIO2580 LAIBUC6919
## 234 CRISLA6039 LARMAR6523
## 235 EUGNEG9666 LAROLA1045
## 236 EVEIVA3317 LAROLA1045
## 237 HOIOLA8773 LAROLA1045
## 238 CORERE4381 LARVAD8858
## 239 SIDCOM3865 LAUSAV5240
## 240 ALESER4777 LAUSEN7409
## 241 ALIIVA5725 LAUSEN7409
## 242 MIFMAM4698 LEOCOS8783
## 243 VALPIR9591 LEOCOS8783
## 244 LAFVIN1569 LIDVIN1655
## 245 OANGOL3414 LILGEO1798
## 246 GEOION7998 LILGHE9391
## 247 MIHION7998 LILGHE9391
## 248 CONSER9980 LILSER3330
## 249 RAMSAN5041 LORSAN2950
## 250 IOATOF5422 LUAVLA0198
## 251 VASCHI2472 LUAVLA0198
## 252 IOIBUT8969 LUBION3700
## 253 IONILI6099 LUBION3700
```

```
## 254 VICFUD6927 LUMGHE1776
## 255 BENGHE9525 LUMGHE9639
## 256 MARBUG0557 LUMION0233
## 257 MIHDIN1519 MABDUT2054
## 258 PAUZDR6556 MACZDR8078
## 259 ALESER4777 MAGTUD6627
## 260 GABDIN8210 MALDIN1944
## 261 BEAPOP0757 MANPOP4820
## 262 STEGRI0788 MANPOP4820
## 263 THEMIL3513 MANPOP4820
## 264 OANENA0111 MAPMIH2031
## 265 ADRCIO9071 MARBUG0557
## 266 ELEPAD8471 MARBUG0557
## 267 EUGNEG9666 MARCAR7518
## 268 IOATOF5422 MARCAZ2759
## 269 ROMMIT5030 MARDIN0602
## 270 GEOCIU0789 MARDRA5854
## 271 CONMUS0105 MARDUM1746
## 272 MOMAVA8566 MARLIN8867
## 273 MOTMAN5742 MARMAN8387
## 274 ELEMAR1401 MARMAR0624
## 275 RODMAR6128 MARMAR0624
## 276 DORCAT7658 MARNEA9263
## 277 ROXNIC5372 MARNIC9806
## 278 ADISER3882 MAROLA5643
## 279 DORPER2487 MAROLA5643
## 280 LAROLA1045 MAROLA5643
## 281 COCTAL6560 MARPOP1848
## 282 MAROLA5643 MARPUI7579
## 283 DRADUM5007 MARVIN7133
## 284 MARDIN0602 MIATUD3087
## 285 OANGOL3414 MIATUD3087
## 286 LAAMOL7425 MICHAR5046
## 287 DUMMAN4411 MIDAND8778
## 288 RAMMAR9120 MIDAND8778
## 289 ALEMLA2259 MIFMAM4698
## 290 VALMIL4370 MIGMIH6001
## 291 ANGCAT5731 MIHBAZ7530
## 292 NELMIN9830 MIHBAZ7530
## 293 DRADUM5007 MIHCON7927
## 294 ADISER3882 MIHDIA6232
## 295 DEEDIN7226 MIHDIN1519
## 296 GABDIN8210 MIHDIN1519
## 297 MABDUT2054 MIHDIN1519
## 298 GEOION7998 MIHION7998
## 299 LUAVLA0198 MIHION7998
## 300 LUMION0233 MIHVOI6906
## 301 ADISER3882 MILVUS7129
## 302 ADRVLA3930 MILVUS7129
## 303 ANGTOM3746 MIRFLO2046
## 304 ADRBOT3464 MOMAVA8566
## 305 ANGCAT5731 MOMAVA8566
## 306 GABBEN6103 MOTMAN5742
## 307 ALEMIH6840 NAJALC3490
```

```
## 308 IONRUS6824 NAJALC3490
## 309 DORCAT7658 NELDUM4387
## 310 ALIMIN4996 NELMIN9830
## 311 FLOMIN1738 NELMIN9830
## 312 MIHBAZ7530 NELMIN9830
## 313 LILSER3330 NICPAR9193
## 314 ALIDRA6546 NICPET2678
## 315 ALESER4777 NIDTUD0285
## 316 GEOBOH7300 NINRAD0374
## 317 CORERE4381 OANENA0111
## 318 CLAMAR8627 OANSIM9507
## 319 FLOCIO6499 OLGCIR3349
## 320 DRADUM5007 OVIMIT2914
## 321 LAFVIN1569 PAINEC0501
## 322 MARVIN7133 PAINEC0501
## 323 ALIBAN1184 PATSTA7106
## 324 MIHCON7927 PAUOPR0885
## 325 VASOPR5822 PAUOPR0885
## 326 GHERAD7837 PAUZDR6556
## 327 HOIOLA8773 RADMAT4747
## 328 LAROLA1045 RADMAT4747
## 329 RADMAT4747 RALALE1024
## 330 AURMAT4393 RAMDIN6295
## 331 MARDIN0602 RAMHAR1356
## 332 ROAMAR5931 RAMMAR9120
## 333 MARCAZ2759 RAMSAN5041
## 334 ADRIVA2842 RAPPAV4473
## 335 DACMIH1609 REMDOB0532
## 336 VALPIR9591 ROAMAR5931
## 337 MIGMIH6001 ROBDEM4959
## 338 ANDMAN6033 RODCIS3502
## 339 MARDUM5924 RODMAR1610
## 340 SINNIC2893 RODMAR1610
## 341 CRISLA6039 RODMAR6128
## 342 ELEMAR1401 RODMAR6128
## 343 AMCTRE1196 RODONC8848
## 344 MARDIN0602 ROMMIT5030
## 345 LUMGHE9639 ROXNIC5372
## 346 MARNIC9806 ROXNIC5372
## 347 GHEMAN6674 SAMPAC3071
## 348 ELVPLE1000 SARDOG0560
## 349 RAPPAV4473 SEFMAR7405
## 350 THEMIL3513 SEFMAR7405
## 351 ROMMIT5030 SEGTUD0780
## 352 CAFMIT4837 SIDCOM3865
## 353 MAROLA5643 SIDCOM3865
## 354 ANEMIH2014 SILCRA2707
## 355 IOAZEG2449 SILGRI7274
## 356 MIHBAZ7530 SILGRI7274
## 357 COSSAN5803 SILPET0456
## 358 IOACAR6440 SINNIC2893
## 359 MILVUS7129 SINNIC2893
## 360 RODMAR1610 SINNIC2893
## 361 LUMGHE9639 STEGRI0788
```

```
## 362 ALEMIH6840 STESAV3834
## 363 NAJALC3490 STESAV3834
## 364 CRIPAR4497 THEMIL3513
## 365 RAPPAV4473 THEMIL3513
## 366 ELEMAN5255 TUDMAG4968
## 367 FLOTOB5871 VALJUR9551
## 368 ANVDRA5974 VALMIL4370
## 369 MIFMAM4698 VALPIR9591
## 370 LIDVIN1655 VALPUR3900
## 371 DRADUM5007 VALRIS4042
## 372 LUAVLA0198 VASCHI2472
## 373 IOVCOM7913 VASCOM1984
## 374 CONMUS0105 VASDIA9074
## 375 VICBRA6781 VASOPR5822
## 376 AURMEG8297 VASSTA6830
## 377 PAUOPR0885 VICBRA6781
## 378 VALDRA9888 VICFUD6927
## 379 LARVAD8858 VLCCHI3795
## 380 RAMMAR9120 VLSNEA7572
## 381 MANPOP4820 BEAPOP0757
## 382 RODMAR1610 MARDUM5924
```

```
# #
my_attr <- read.csv("linktracing_network_parti_attr.csv", header = TRUE, as.is = TRUE)
# 2. Create objects ####
my_net_igraph <- graph_from_data_frame(
  d = my_net,
  vertices = my_attr,
  directed = TRUE)

my_network <- asNetwork(my_net_igraph)
my_network
```

```
##  Network attributes:
##   vertices = 301
##   directed = TRUE
##   hyper = FALSE
##   loops = FALSE
##   multiple = FALSE
##   bipartite = FALSE
##   total edges= 382
##     missing edges= 0
##     non-missing edges= 382
##
##  Vertex attribute names:
##     age E_COUNTRY education education_cat NUMBER residence RESP_TYPE sex sex_cat vertex.names
##
## No edge attributes
```

```
# 3. Models ####
# Descriptives
summary(my_network ~ gwodegree(0:10))
```

```
##  gwodegree#1  gwodegree#2  gwodegree#3  gwodegree#4  gwodegree#5  gwodegree#6
```

```
##          114           56           31           10            1            3
##  gwodegree#7  gwodegree#8  gwodegree#9 gwodegree#10 gwodegree#11 gwodegree#12
##            0            0            0            0            0            0
## gwodegree#13 gwodegree#14 gwodegree#15 gwodegree#16 gwodegree#17 gwodegree#18
##            0            0            0            0            0            0
## gwodegree#19 gwodegree#20 gwodegree#21 gwodegree#22 gwodegree#23 gwodegree#24
##            0            0            0            0            0            0
## gwodegree#25 gwodegree#26 gwodegree#27 gwodegree#28 gwodegree#29 gwodegree#30
##            0            0            0            0            0            0
```

```
summary(my_network ~ gwidegree(0:10))
```

```
##  gwidegree#1  gwidegree#2  gwidegree#3  gwidegree#4  gwidegree#5  gwidegree#6
##          229           52           15            1            0            0
##  gwidegree#7  gwidegree#8  gwidegree#9 gwidegree#10 gwidegree#11 gwidegree#12
##            0            0            0            0            0            0
## gwidegree#13 gwidegree#14 gwidegree#15 gwidegree#16 gwidegree#17 gwidegree#18
##            0            0            0            0            0            0
## gwidegree#19 gwidegree#20 gwidegree#21 gwidegree#22 gwidegree#23 gwidegree#24
##            0            0            0            0            0            0
## gwidegree#25 gwidegree#26 gwidegree#27 gwidegree#28 gwidegree#29 gwidegree#30
##            0            0            0            0            0            0
```

```
summary(my_network ~ nodematch ("sex", diff= TRUE))
```

```
## nodematch.sex.1 nodematch.sex.2
##              94             168
```

```
summary(my_network ~ nodematch ("E_COUNTRY", diff= TRUE))
```

```
## nodematch.E_COUNTRY.ROMANIA   nodematch.E_COUNTRY.SPAIN
##                         150                         175
```

```
summary(my_network ~ esp (0:10))
```

```
##  esp0  esp1  esp2  esp3  esp4  esp5  esp6  esp7  esp8  esp9 esp10
##   345    34     3     0     0     0     0     0     0     0     0
```

```
summary(my_network ~ dsp (0:10))
```

```
##  dsp0  dsp1  dsp2  dsp3  dsp4  dsp5  dsp6  dsp7  dsp8  dsp9 dsp10
## 89839   447    14     0     0     0     0     0     0     0     0
```

```
# Fitted models
model_1 <- ergm(my_network ~ edges
                + nodematch ("sex", diff = TRUE)
                + nodematch ("E_COUNTRY", diff = TRUE))
```

```
## Starting maximum pseudolikelihood estimation (MPLE):
```

```
## Evaluating the predictor and response matrix.

## Maximizing the pseudolikelihood.

## Finished MPLE.

## Stopping at the initial estimate.

## Evaluating log-likelihood at the estimate.
```

```
summary(model_1)
```

```
## Call:
## ergm(formula = my_network ~ edges + nodematch("sex", diff = TRUE) +
##     nodematch("E_COUNTRY", diff = TRUE))
##
## Iterations:  8 out of 20
##
## Monte Carlo MLE Results:
##                             Estimate Std. Error MCMC % z value Pr(>|z|)
## edges                        -7.0122     0.1500      0 -46.764   <1e-04 ***
## nodematch.sex.1               0.7864     0.1409      0   5.581   <1e-04 ***
## nodematch.sex.2               0.5135     0.1229      0   4.177   <1e-04 ***
## nodematch.E_COUNTRY.ROMANIA   1.5429     0.1579      0   9.772   <1e-04 ***
## nodematch.E_COUNTRY.SPAIN     1.8730     0.1546      0  12.119   <1e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##      Null Deviance: 125182  on 90300  degrees of freedom
##  Residual Deviance:   4685  on 90295  degrees of freedom
##
## AIC: 4695    BIC: 4742    (Smaller is better.)
```

```
#
model_2 <- ergm (my_network ~ edges
                 + nodematch ("sex", diff = TRUE)
                 + nodematch ("E_COUNTRY", diff = TRUE)
                 + nodecov ("age"))
```

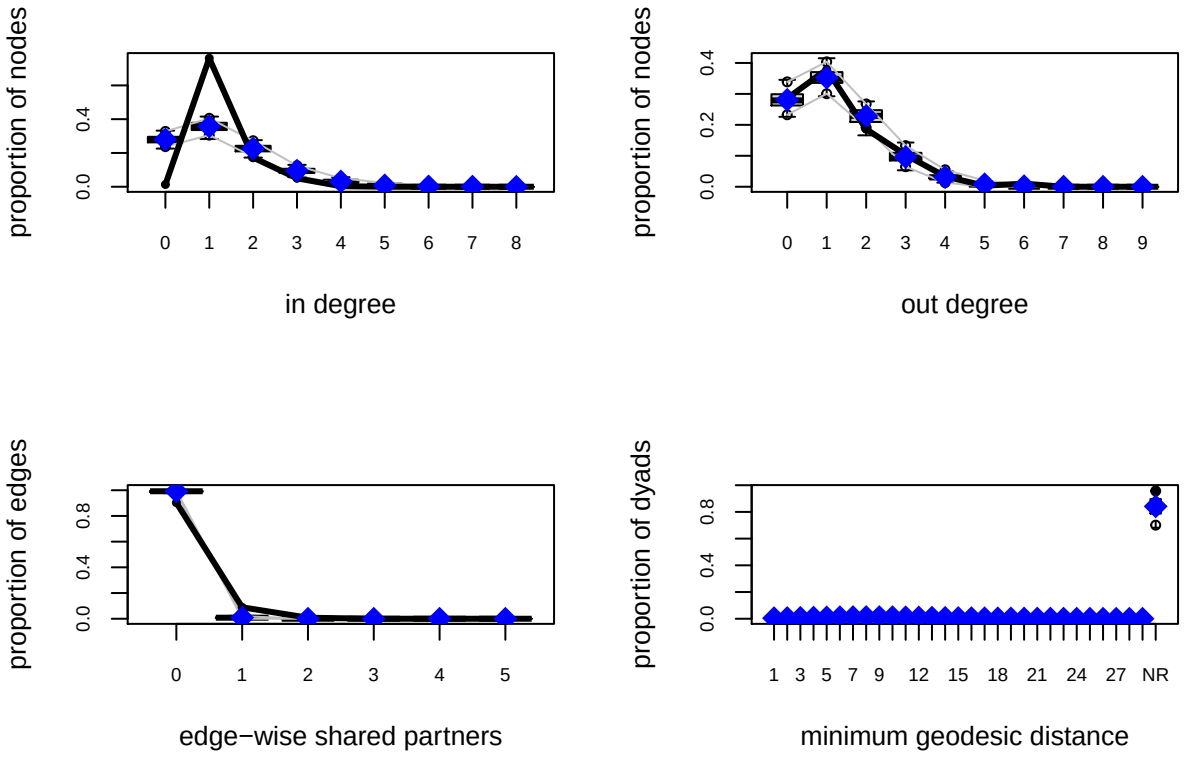
```
## Starting maximum pseudolikelihood estimation (MPLE):
## Evaluating the predictor and response matrix.
## Maximizing the pseudolikelihood.
## Finished MPLE.
## Stopping at the initial estimate.
## Evaluating log-likelihood at the estimate.
```

```
summary(model_2)
```

```
## Call:
## ergm(formula = my_network ~ edges + nodematch("sex", diff = TRUE) +
##     nodematch("E_COUNTRY", diff = TRUE) + nodecov("age"))
```

```
##
## Iterations:  8 out of 20
##
## Monte Carlo MLE Results:
##                               Estimate Std. Error MCMC % z value Pr(>|z|)
## edges                      -6.9605872  0.1562046      0 -44.561   <1e-04 ***
## nodematch.sex.1             0.7802112  0.1409738      0   5.534   <1e-04 ***
## nodematch.sex.2             0.5210445  0.1230254      0   4.235   <1e-04 ***
## nodematch.E_COUNTRY.ROMANIA 1.5363890  0.1579340      0   9.728   <1e-04 ***
## nodematch.E_COUNTRY.SPAIN   1.8801431  0.1546103      0  12.161   <1e-04 ***
## nodecov.age                -0.0006060  0.0005295      0  -1.145    0.252
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##      Null Deviance: 125182  on 90300  degrees of freedom
##  Residual Deviance:   4683  on 90294  degrees of freedom
##
## AIC: 4695    BIC: 4752    (Smaller is better.)
```

```
par(mfrow=c(2,2))
plot(gof(model_2))
```




```
dev.off()
```

```
## null device
##           1
```

```
#
model_3 <- ergm (my_network ~ edges
                 + nodematch ("sex", diff = TRUE)
                 + nodematch ("E_COUNTRY", diff = TRUE)
                 + ostar (2, attr = NULL, levels = NULL)
                 + istar (2, attr = NULL, levels = NULL)
                 )
```

```
## Starting maximum pseudolikelihood estimation (MPLE):
## Evaluating the predictor and response matrix.
## Maximizing the pseudolikelihood.
## Finished MPLE.
## Starting Monte Carlo maximum likelihood estimation (MCMLE):
## Iteration 1 of at most 20:
## Optimizing with step length 0.232865014889234.
## The log-likelihood improved by 3.276.
## Iteration 2 of at most 20:
## Optimizing with step length 0.586390295870738.
## The log-likelihood improved by 4.59.
## Iteration 3 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 1.727.
## Step length converged once. Increasing MCMC sample size.
## Iteration 4 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 0.03958.
## Step length converged twice. Stopping.
## Finished MCMLE.
## Evaluating log-likelihood at the estimate. Using 20 bridges: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 1
## This model was fit using MCMC.  To examine model diagnostics and check
## for degeneracy, use the mcmc.diagnostics() function.
```

```
summary(model_3)
```

```
## Call:
## ergm(formula = my_network ~ edges + nodematch("sex", diff = TRUE) +
##     nodematch("E_COUNTRY", diff = TRUE) + ostar(2, attr = NULL,
##     levels = NULL) + istar(2, attr = NULL, levels = NULL))
##
## Iterations:  4 out of 20
##
## Monte Carlo MLE Results:
##                             Estimate Std. Error MCMC % z value Pr(>|z|)
## edges                       -5.00730    0.27776      0 -18.027  < 1e-04 ***
## nodematch.sex.1              0.82962    0.15535      0   5.340  < 1e-04 ***
## nodematch.sex.2              0.49926    0.13489      0   3.701 0.000215 ***
## nodematch.E_COUNTRY.ROMANIA  1.37438    0.16593      0   8.283  < 1e-04 ***
## nodematch.E_COUNTRY.SPAIN    2.08958    0.17570      0  11.893  < 1e-04 ***
## ostar2                       0.06394    0.05649      0   1.132 0.257653
## istar2                      -2.35734    0.24279      0  -9.709  < 1e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
##      Null Deviance: 125182  on 90300  degrees of freedom
##  Residual Deviance:   4485  on 90293  degrees of freedom
##
## AIC: 4499    BIC: 4565    (Smaller is better.)
```

```
mcmc.diagnostics(model_3)
```

```
## Sample statistics summary:
##
## Iterations = 16384:4209664
## Thinning interval = 1024
## Number of chains = 1
## Sample size per chain = 4096
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                               Mean     SD Naive SE Time-series SE
## edges                       0.5078 10.202   0.1594         0.1823
## nodematch.sex.1            -1.2126  7.170   0.1120         0.2128
## nodematch.sex.2            -0.1804  8.990   0.1405         0.2583
## nodematch.E_COUNTRY.ROMANIA -0.4314  7.994   0.1249         0.2060
## nodematch.E_COUNTRY.SPAIN   0.1838  7.928   0.1239         0.2066
## ostar2                      0.8257 22.894   0.3577         0.5444
## istar2                      1.0232  9.465   0.1479         0.1603
##
## 2. Quantiles for each variable:
##
##                             2.5% 25% 50%   75% 97.5%
## edges                        -20  -6   1  7.00    20
## nodematch.sex.1              -15  -6  -1  4.00    13
## nodematch.sex.2              -17  -7   0  6.00    18
## nodematch.E_COUNTRY.ROMANIA  -17  -6   0  5.00    15
## nodematch.E_COUNTRY.SPAIN    -16  -5   0  5.25    16
## ostar2                       -41 -16   1 16.00    47
## istar2                       -17  -5   1  7.00    20
##
##
## Sample statistics cross-correlations:
##                                edges nodematch.sex.1 nodematch.sex.2
## edges                      1.0000000      0.32807098      0.49225547
## nodematch.sex.1            0.3280710      1.00000000     -0.04776279
## nodematch.sex.2            0.4922555     -0.04776279      1.00000000
## nodematch.E_COUNTRY.ROMANIA 0.5004145      0.33096927      0.09111337
## nodematch.E_COUNTRY.SPAIN  0.5723755      0.04006654      0.43093635
## ostar2                     0.6204449      0.19624212      0.31269616
## istar2                     0.8976002      0.28133745      0.44801817
##                            nodematch.E_COUNTRY.ROMANIA
## edges                                       0.50041452
## nodematch.sex.1                             0.33096927
## nodematch.sex.2                             0.09111337
## nodematch.E_COUNTRY.ROMANIA                 1.00000000
## nodematch.E_COUNTRY.SPAIN                  -0.03427398
## ostar2                                      0.21128873
```

```
## istar2                                        0.39700629
##                              nodematch.E_COUNTRY.SPAIN    ostar2    istar2
## edges                                        0.57237549 0.6204449 0.8976002
## nodematch.sex.1                              0.04006654 0.1962421 0.2813374
## nodematch.sex.2                              0.43093635 0.3126962 0.4480182
## nodematch.E_COUNTRY.ROMANIA                 -0.03427398 0.2112887 0.3970063
## nodematch.E_COUNTRY.SPAIN                    1.00000000 0.4363656 0.5608549
## ostar2                                       0.43636556 1.0000000 0.5637354
## istar2                                       0.56085495 0.5637354 1.0000000
##
## Sample statistics auto-correlation:
## Chain 1
##                edges nodematch.sex.1 nodematch.sex.2
## Lag 0    1.000000000      1.00000000      1.00000000
## Lag 1024 0.133379182      0.50786570      0.45621256
## Lag 2048 0.035644508      0.29569337      0.25874113
## Lag 3072 0.017120703      0.19090243      0.15611939
## Lag 4096 0.015588712      0.12933721      0.11490377
## Lag 5120 0.005854016      0.09069119      0.08319807
##          nodematch.E_COUNTRY.ROMANIA nodematch.E_COUNTRY.SPAIN     ostar2
## Lag 0                    1.00000000                1.00000000 1.00000000
## Lag 1024                 0.37735794                0.38415143 0.34340020
## Lag 2048                 0.18717371                0.19294686 0.17226977
## Lag 3072                 0.10537394                0.10310645 0.08654888
## Lag 4096                 0.07887258                0.08470943 0.06115445
## Lag 5120                 0.05103514                0.03979036 0.02144506
##                istar2
## Lag 0     1.000000000
## Lag 1024  0.080041259
## Lag 2048  0.020748317
## Lag 3072 -0.005095602
## Lag 4096  0.003823039
## Lag 5120  0.007228543
##
## Sample statistics burn-in diagnostic (Geweke):
## Chain 1
##
## Fraction in 1st window = 0.1
## Fraction in 2nd window = 0.5
##
##                       edges             nodematch.sex.1
##                      0.4345                      1.9530
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                     -1.6533                      0.8363
##   nodematch.E_COUNTRY.SPAIN                     ostar2
##                      0.2172                      1.1189
##                      istar2
##                      0.3067
##
## Individual P-values (lower = worse):
##                       edges             nodematch.sex.1
##                  0.66395138                  0.05081737
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                  0.09827211                  0.40295809
```

```
##   nodematch.E_COUNTRY.SPAIN                     ostar2
##                  0.82806261                 0.26319187
##                      istar2
##                  0.75906267
## Joint P-value (lower = worse):  0.3697783 .

##
## MCMC diagnostics shown here are from the last round of simulation, prior to computation of final para
```

```
par(mfrow=c(2,2))
plot(gof(model_3))
dev.off()
```

```
## null device
##           1
```

```
#
model_4 <- ergm (my_network ~ edges
                 + nodematch ("sex", diff = TRUE)
                 + nodematch ("E_COUNTRY", diff = TRUE)
                 + gwodegree(0.25, fixed = TRUE) #activity spread
                 + gwidegree(0.25, fixed = TRUE) #popularity spread
)
```

```
## Starting maximum pseudolikelihood estimation (MPLE):
## Evaluating the predictor and response matrix.
## Maximizing the pseudolikelihood.
## Finished MPLE.
## Starting Monte Carlo maximum likelihood estimation (MCMLE):
## Iteration 1 of at most 20:
## Optimizing with step length 0.273813462056175.
## The log-likelihood improved by 4.354.
## Iteration 2 of at most 20:
## Optimizing with step length 0.420802019084523.
## The log-likelihood improved by 3.803.
## Iteration 3 of at most 20:
## Optimizing with step length 0.673921888853858.
## The log-likelihood improved by 3.511.
## Iteration 4 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 1.012.
## Step length converged once. Increasing MCMC sample size.
## Iteration 5 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 0.01212.
## Step length converged twice. Stopping.
## Finished MCMLE.
## Evaluating log-likelihood at the estimate. Using 20 bridges: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 1
## This model was fit using MCMC.  To examine model diagnostics and check
## for degeneracy, use the mcmc.diagnostics() function.
```

```r
summary(model_4)
```

```
## Call:
## ergm(formula = my_network ~ edges + nodematch("sex", diff = TRUE) +
##     nodematch("E_COUNTRY", diff = TRUE) + gwodegree(0.25, fixed = TRUE) +
##     gwidegree(0.25, fixed = TRUE))
##
## Iterations:  5 out of 20
##
## Monte Carlo MLE Results:
##                             Estimate Std. Error MCMC % z value Pr(>|z|)
## edges                      -8.83497    0.24082      0 -36.686  < 1e-04 ***
## nodematch.sex.1             0.84024    0.15662      0   5.365  < 1e-04 ***
## nodematch.sex.2             0.48486    0.14195      0   3.416 0.000636 ***
## nodematch.E_COUNTRY.ROMANIA 1.33332    0.16797      0   7.938  < 1e-04 ***
## nodematch.E_COUNTRY.SPAIN   2.13798    0.18814      0  11.364  < 1e-04 ***
## gwodeg.fixed.0.25          -0.06671    0.19348      0  -0.345 0.730239
## gwideg.fixed.0.25           5.25084    0.53039      0   9.900  < 1e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##      Null Deviance: 125182  on 90300  degrees of freedom
##  Residual Deviance:   4423  on 90293  degrees of freedom
##
## AIC: 4437    BIC: 4503    (Smaller is better.)
```

```r
mcmc.diagnostics(model_4)
```

```
## Sample statistics summary:
##
## Iterations = 16384:4209664
## Thinning interval = 1024
## Number of chains = 1
## Sample size per chain = 4096
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                                Mean    SD Naive SE Time-series SE
## edges                      0.125488 9.290  0.14515        0.16121
## nodematch.sex.1            0.012451 6.985  0.10913        0.22953
## nodematch.sex.2            0.780273 8.408  0.13138        0.24250
## nodematch.E_COUNTRY.ROMANIA 0.579834 7.257  0.11340        0.20580
## nodematch.E_COUNTRY.SPAIN  0.269531 7.545  0.11789        0.17984
## gwodeg.fixed.0.25          0.250638 6.157  0.09620        0.13360
## gwideg.fixed.0.25          0.005037 3.048  0.04763        0.05563
##
## 2. Quantiles for each variable:
##
##                              2.5%    25%     50%   75%  97.5%
## edges                      -18.000 -6.000 0.00000 6.000 19.000
## nodematch.sex.1            -13.000 -5.000 0.00000 5.000 14.000
```

```
## nodematch.sex.2             -16.000 -5.000 1.00000 6.000 18.000
## nodematch.E_COUNTRY.ROMANIA -14.000 -4.000 1.00000 5.000 15.000
## nodematch.E_COUNTRY.SPAIN   -14.000 -5.000 0.00000 5.000 16.000
## gwodeg.fixed.0.25           -12.020 -3.899 0.15534 4.389 12.474
## gwideg.fixed.0.25            -6.105 -2.007 0.09721 2.030  5.855
##
##
## Sample statistics cross-correlations:
##                                edges nodematch.sex.1 nodematch.sex.2
## edges                      1.0000000      0.32267316      0.49092240
## nodematch.sex.1            0.3226732      1.00000000     -0.01766734
## nodematch.sex.2            0.4909224     -0.01766734      1.00000000
## nodematch.E_COUNTRY.ROMANIA 0.4323431      0.27313394      0.09042991
## nodematch.E_COUNTRY.SPAIN  0.6308138      0.09818034      0.42664014
## gwodeg.fixed.0.25          0.5333174      0.16467158      0.28433221
## gwideg.fixed.0.25          0.7786903      0.26209959      0.37275202
##                            nodematch.E_COUNTRY.ROMANIA
## edges                                     0.432343081
## nodematch.sex.1                           0.273133938
## nodematch.sex.2                           0.090429910
## nodematch.E_COUNTRY.ROMANIA               1.000000000
## nodematch.E_COUNTRY.SPAIN                 0.006573032
## gwodeg.fixed.0.25                         0.310127390
## gwideg.fixed.0.25                         0.402870737
##                            nodematch.E_COUNTRY.SPAIN gwodeg.fixed.0.25
## edges                                     0.630813756         0.5333174
## nodematch.sex.1                           0.098180345         0.1646716
## nodematch.sex.2                           0.426640144         0.2843322
## nodematch.E_COUNTRY.ROMANIA               0.006573032         0.3101274
## nodematch.E_COUNTRY.SPAIN                 1.000000000         0.2946455
## gwodeg.fixed.0.25                         0.294645475         1.0000000
## gwideg.fixed.0.25                         0.416538997         0.4203691
##                            gwideg.fixed.0.25
## edges                              0.7786903
## nodematch.sex.1                    0.2620996
## nodematch.sex.2                    0.3727520
## nodematch.E_COUNTRY.ROMANIA        0.4028707
## nodematch.E_COUNTRY.SPAIN          0.4165390
## gwodeg.fixed.0.25                  0.4203691
## gwideg.fixed.0.25                  1.0000000
##
## Sample statistics auto-correlation:
## Chain 1
##                 edges nodematch.sex.1 nodematch.sex.2
## Lag 0     1.000000000       1.0000000      1.00000000
## Lag 1024  0.104383009       0.5442117      0.43797127
## Lag 2048  0.021977032       0.3672276      0.27024996
## Lag 3072 -0.006181741       0.2566845      0.18576540
## Lag 4096 -0.013072526       0.1828746      0.10557949
## Lag 5120 -0.025504023       0.1122880      0.07072594
##          nodematch.E_COUNTRY.ROMANIA nodematch.E_COUNTRY.SPAIN
## Lag 0                    1.00000000                1.00000000
## Lag 1024                 0.41803571                0.26897825
## Lag 2048                 0.26090152                0.12583033
```

```
## Lag 3072                  0.17848720                0.08709648
## Lag 4096                  0.12055123                0.08117483
## Lag 5120                  0.07210777                0.05506915
##          gwodeg.fixed.0.25 gwideg.fixed.0.25
## Lag 0          1.000000000      1.0000000000
## Lag 1024       0.285908186      0.1539287611
## Lag 2048       0.112995105      0.0252578807
## Lag 3072       0.024578322     -0.0044012352
## Lag 4096       0.004596061     -0.0087063802
## Lag 5120      -0.014720383     -0.0007300733
##
## Sample statistics burn-in diagnostic (Geweke):
## Chain 1
##
## Fraction in 1st window = 0.1
## Fraction in 2nd window = 0.5
##
##                       edges             nodematch.sex.1
##                     -0.4376                     -0.1370
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                     -0.3988                      0.9213
##   nodematch.E_COUNTRY.SPAIN           gwodeg.fixed.0.25
##                      0.4756                      1.7883
##           gwideg.fixed.0.25
##                     -1.1756
##
## Individual P-values (lower = worse):
##                       edges             nodematch.sex.1
##                  0.66167226                  0.89105091
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                  0.69001195                  0.35687440
##   nodematch.E_COUNTRY.SPAIN           gwodeg.fixed.0.25
##                  0.63435271                  0.07372395
##           gwideg.fixed.0.25
##                  0.23974640
## Joint P-value (lower = worse):  0.3161828 .

##
## MCMC diagnostics shown here are from the last round of simulation, prior to computation of final para
```

```
par(mfrow=c(2,2))
plot(gof(model_4))
dev.off()
```

```
## null device
##           1
```

```
#
model_5 <- ergm (my_network ~ edges
                 + nodematch ("sex", diff = TRUE)
                 + nodematch ("E_COUNTRY", diff = TRUE)
                 + gwesp(0.25, fixed = TRUE)
                 + gwdsp(0.25, fixed = TRUE)
)
```

```
## Starting maximum pseudolikelihood estimation (MPLE):
## Evaluating the predictor and response matrix.
## Maximizing the pseudolikelihood.
## Finished MPLE.
## Starting Monte Carlo maximum likelihood estimation (MCMLE):
## Iteration 1 of at most 20:
## Optimizing with step length 0.771263498907164.
## The log-likelihood improved by 4.122.
## Iteration 2 of at most 20:
## Optimizing with step length 0.93398956538055.
## The log-likelihood improved by 2.745.
## Iteration 3 of at most 20:
## Optimizing with step length 0.21902519552557.
## The log-likelihood improved by 3.992.
## Iteration 4 of at most 20:
## Optimizing with step length 0.0276079012959569.
## The log-likelihood improved by 2.488.
## Iteration 5 of at most 20:
## Optimizing with step length 0.0102646262425269.
## The log-likelihood improved by 1.67.
## Iteration 6 of at most 20:
## Optimizing with step length 0.0113074398324567.
## The log-likelihood improved by 2.626.
## Iteration 7 of at most 20:
## Optimizing with step length 0.0120942335445166.
## The log-likelihood improved by 2.728.
## Iteration 8 of at most 20:
## Optimizing with step length 0.0356181575256569.
## The log-likelihood improved by 1.839.
## Iteration 9 of at most 20:
## Optimizing with step length 0.0530786919521101.
## The log-likelihood improved by 3.087.
## Iteration 10 of at most 20:
## Optimizing with step length 0.189679781096796.
## The log-likelihood improved by 2.675.
## Iteration 11 of at most 20:
## Optimizing with step length 0.248030817286503.
## The log-likelihood improved by 3.116.
## Iteration 12 of at most 20:
## Optimizing with step length 0.387711727565943.
## The log-likelihood improved by 3.323.
## Iteration 13 of at most 20:
## Optimizing with step length 0.462260825050001.
## The log-likelihood improved by 3.478.
## Iteration 14 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 2.396.
## Step length converged once. Increasing MCMC sample size.
## Iteration 15 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 0.5291.
## Step length converged twice. Stopping.
## Finished MCMLE.
## Evaluating log-likelihood at the estimate. Using 20 bridges: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 1
```

```
## This model was fit using MCMC.  To examine model diagnostics and check
## for degeneracy, use the mcmc.diagnostics() function.
```

```
summary(model_5)
```

```
## Call:
## ergm(formula = my_network ~ edges + nodematch("sex", diff = TRUE) +
##     nodematch("E_COUNTRY", diff = TRUE) + gwesp(0.25, fixed = TRUE) +
##     gwdsp(0.25, fixed = TRUE))
##
## Iterations:  15 out of 20
##
## Monte Carlo MLE Results:
##                             Estimate Std. Error MCMC % z value Pr(>|z|)
## edges                      -6.78064    0.16851      0 -40.238  < 1e-04 ***
## nodematch.sex.1             0.75123    0.14301      0   5.253  < 1e-04 ***
## nodematch.sex.2             0.46275    0.11577      0   3.997  < 1e-04 ***
## nodematch.E_COUNTRY.ROMANIA 1.41588    0.14990      0   9.446  < 1e-04 ***
## nodematch.E_COUNTRY.SPAIN   1.69494    0.14742      0  11.497  < 1e-04 ***
## gwesp.fixed.0.25            2.26077    0.12723      0  17.770  < 1e-04 ***
## gwdsp.fixed.0.25           -0.11597    0.04125      0  -2.812  0.00493 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##      Null Deviance: 125182  on 90300  degrees of freedom
##  Residual Deviance:   4566  on 90293  degrees of freedom
##
## AIC: 4580    BIC: 4646    (Smaller is better.)
```

```
mcmc.diagnostics(model_5)
```

```
## Sample statistics summary:
##
## Iterations = 16384:4209664
## Thinning interval = 1024
## Number of chains = 1
## Sample size per chain = 4096
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                               Mean     SD Naive SE Time-series SE
## edges                       0.6418 21.713   0.3393         1.2773
## nodematch.sex.1            -6.9521  9.579   0.1497         0.3898
## nodematch.sex.2             7.3203 16.296   0.2546         1.4641
## nodematch.E_COUNTRY.ROMANIA -2.4224 12.948   0.2023         0.5160
## nodematch.E_COUNTRY.SPAIN    1.8477 16.612   0.2596         1.3809
## gwesp.fixed.0.25            -2.8760 12.595   0.1968         2.1929
## gwdsp.fixed.0.25             2.3614 65.973   1.0308         6.2300
##
## 2. Quantiles for each variable:
##
##                               2.5%    25%    50%    75%  97.5%
```

```
## edges                          -41.00 -14.00  0.000 16.000  43.00
## nodematch.sex.1                -25.00 -13.00 -7.000 -1.000  12.00
## nodematch.sex.2                -22.62  -4.00  6.000 18.000  41.00
## nodematch.E_COUNTRY.ROMANIA    -27.00 -11.00 -3.000  6.000  23.00
## nodematch.E_COUNTRY.SPAIN      -28.00 -10.00  1.000 13.000  36.00
## gwesp.fixed.0.25               -22.66 -11.66 -4.664  4.336  25.57
## gwdsp.fixed.0.25              -112.86 -44.77 -1.221 44.329 143.82
##
##
## Sample statistics cross-correlations:
##                                   edges nodematch.sex.1 nodematch.sex.2
## edges                          1.0000000      0.44123162      0.72523468
## nodematch.sex.1                0.4412316      1.00000000     -0.01497712
## nodematch.sex.2                0.7252347     -0.01497712      1.00000000
## nodematch.E_COUNTRY.ROMANIA    0.5664262      0.55521830      0.16274074
## nodematch.E_COUNTRY.SPAIN      0.7248520      0.06556262      0.75680190
## gwesp.fixed.0.25               0.6229513      0.16047722      0.63169071
## gwdsp.fixed.0.25               0.8953264      0.31602247      0.73766603
##                                nodematch.E_COUNTRY.ROMANIA
## edges                                        0.56642619
## nodematch.sex.1                              0.55521830
## nodematch.sex.2                              0.16274074
## nodematch.E_COUNTRY.ROMANIA                  1.00000000
## nodematch.E_COUNTRY.SPAIN                   -0.02537031
## gwesp.fixed.0.25                             0.20186594
## gwdsp.fixed.0.25                             0.40239952
##                                nodematch.E_COUNTRY.SPAIN gwesp.fixed.0.25
## edges                                       0.72485200        0.6229513
## nodematch.sex.1                             0.06556262        0.1604772
## nodematch.sex.2                             0.75680190        0.6316907
## nodematch.E_COUNTRY.ROMANIA                -0.02537031        0.2018659
## nodematch.E_COUNTRY.SPAIN                   1.00000000        0.6563858
## gwesp.fixed.0.25                            0.65638585        1.0000000
## gwdsp.fixed.0.25                            0.75587701        0.7441663
##                                gwdsp.fixed.0.25
## edges                                 0.8953264
## nodematch.sex.1                       0.3160225
## nodematch.sex.2                       0.7376660
## nodematch.E_COUNTRY.ROMANIA           0.4023995
## nodematch.E_COUNTRY.SPAIN             0.7558770
## gwesp.fixed.0.25                      0.7441663
## gwdsp.fixed.0.25                      1.0000000
##
## Sample statistics auto-correlation:
## Chain 1
##              edges nodematch.sex.1 nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
## Lag 0    1.0000000       1.0000000       1.0000000                   1.0000000
## Lag 1024 0.6024386       0.5684047       0.7038995                   0.5413230
## Lag 2048 0.4657488       0.3963137       0.5854257                   0.3583050
## Lag 3072 0.3938328       0.2944552       0.5222538                   0.2876594
## Lag 4096 0.3631322       0.2440848       0.4828526                   0.2666247
## Lag 5120 0.3187514       0.1955003       0.4440252                   0.2448316
##          nodematch.E_COUNTRY.SPAIN gwesp.fixed.0.25 gwdsp.fixed.0.25
## Lag 0                    1.0000000        1.0000000        1.0000000
```

```
## Lag 1024                  0.7356113        0.9569155        0.6622372
## Lag 2048                  0.6268139        0.9235993        0.5650250
## Lag 3072                  0.5599466        0.8953110        0.5127872
## Lag 4096                  0.5167634        0.8717181        0.4835322
## Lag 5120                  0.4728272        0.8506299        0.4579912
##
## Sample statistics burn-in diagnostic (Geweke):
## Chain 1
##
## Fraction in 1st window = 0.1
## Fraction in 2nd window = 0.5
##
##                        edges             nodematch.sex.1
##                      1.43725                    -0.62975
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                      1.95599                    -1.30933
##   nodematch.E_COUNTRY.SPAIN            gwesp.fixed.0.25
##                      2.08953                     0.05517
##            gwdsp.fixed.0.25
##                      0.87450
##
## Individual P-values (lower = worse):
##                        edges             nodematch.sex.1
##                   0.15064640                   0.52886003
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                   0.05046635                   0.19042183
##   nodematch.E_COUNTRY.SPAIN            gwesp.fixed.0.25
##                   0.03665971                   0.95600111
##            gwdsp.fixed.0.25
##                   0.38184699
## Joint P-value (lower = worse):  0.04127645 .

##
## MCMC diagnostics shown here are from the last round of simulation, prior to computation of final para
```

```
par(mfrow=c(2,2))
plot(gof(model_5))
dev.off()
```

```
## null device
##           1
```

```
#
model_6 <- ergm (my_network ~ edges
                 + nodematch ("sex", diff = TRUE)
                 + nodematch ("E_COUNTRY", diff = TRUE)
                 + nodecov ("age")
                 + gwesp(0.25, fixed = TRUE)
                 + gwdsp(0.25, fixed = TRUE)
                 + gwodegree(0.25, fixed = TRUE) #activity spread
                 + gwidegree(0.25, fixed = TRUE) #popularity spread
)
```

```
## Starting maximum pseudolikelihood estimation (MPLE):
## Evaluating the predictor and response matrix.
## Maximizing the pseudolikelihood.
## Finished MPLE.
## Starting Monte Carlo maximum likelihood estimation (MCMLE):
## Iteration 1 of at most 20:
## Optimizing with step length 0.192059558541711.
## The log-likelihood improved by 2.66.
## Iteration 2 of at most 20:
## Optimizing with step length 0.257522644179324.
## The log-likelihood improved by 2.814.
## Iteration 3 of at most 20:
## Optimizing with step length 0.308785069993936.
## The log-likelihood improved by 2.321.
## Iteration 4 of at most 20:
## Optimizing with step length 0.409842340306608.
## The log-likelihood improved by 3.387.
## Iteration 5 of at most 20:
## Optimizing with step length 0.6450151131003.
## The log-likelihood improved by 2.314.
## Iteration 6 of at most 20:
## Optimizing with step length 0.898011514978562.
## The log-likelihood improved by 2.002.
## Iteration 7 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 1.329.
## Step length converged once. Increasing MCMC sample size.
## Iteration 8 of at most 20:
## Optimizing with step length 1.
## The log-likelihood improved by 4.252.
## Step length converged twice. Stopping.
## Finished MCMLE.
## Evaluating log-likelihood at the estimate. Using 20 bridges: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 1
## This model was fit using MCMC.  To examine model diagnostics and check
## for degeneracy, use the mcmc.diagnostics() function.
```

```
summary(model_6)
```

```
## Call:
## ergm(formula = my_network ~ edges + nodematch("sex", diff = TRUE) +
##     nodematch("E_COUNTRY", diff = TRUE) + nodecov("age") + gwesp(0.25,
##     fixed = TRUE) + gwdsp(0.25, fixed = TRUE) + gwodegree(0.25,
##     fixed = TRUE) + gwidegree(0.25, fixed = TRUE))
##
## Iterations:  8 out of 20
##
## Monte Carlo MLE Results:
##                               Estimate Std. Error MCMC % z value Pr(>|z|)
## edges                       -8.7062680  0.3348258      0 -26.002  < 1e-04 ***
## nodematch.sex.1              0.8213234  0.1613789      0   5.089  < 1e-04 ***
## nodematch.sex.2              0.4069631  0.1424368      0   2.857  0.00427 **
## nodematch.E_COUNTRY.ROMANIA  1.2606490  0.1714089      0   7.355  < 1e-04 ***
## nodematch.E_COUNTRY.SPAIN    1.9550989  0.1804243      0  10.836  < 1e-04 ***
## nodecov.age                 -0.0014655  0.0009352      0  -1.567  0.11709
```

```
## gwesp.fixed.0.25             3.2660557  0.1769533      0  18.457  < 1e-04 ***
## gwdsp.fixed.0.25            -0.2338467  0.0980051      0  -2.386  0.01703 *
## gwodeg.fixed.0.25            0.3051823  0.2017378      0   1.513  0.13034
## gwideg.fixed.0.25            5.8124758  0.5458449      0  10.649  < 1e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##      Null Deviance: 125182  on 90300  degrees of freedom
##  Residual Deviance:   4228  on 90290  degrees of freedom
##
## AIC: 4248    BIC: 4342    (Smaller is better.)
```

```
mcmc.diagnostics(model_6)
```

```
## Sample statistics summary:
##
## Iterations = 16384:4209664
## Thinning interval = 1024
## Number of chains = 1
## Sample size per chain = 4096
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##                                 Mean       SD Naive SE Time-series SE
## edges                         -6.7808    9.318  0.14560        0.44963
## nodematch.sex.1               -9.6597    6.598  0.10310        0.25789
## nodematch.sex.2               -0.5933    8.937  0.13964        0.45138
## nodematch.E_COUNTRY.ROMANIA   -0.9688    6.987  0.10917        0.24546
## nodematch.E_COUNTRY.SPAIN     -7.5010    8.327  0.13011        0.43207
## nodecov.age                 -362.5630 1337.112 20.89238       40.88065
## gwesp.fixed.0.25             -17.1442    7.482  0.11690        1.33066
## gwdsp.fixed.0.25             -16.1739   24.083  0.37630        1.58850
## gwodeg.fixed.0.25              1.2599    5.862  0.09160        0.14298
## gwideg.fixed.0.25             -1.4163    3.018  0.04716        0.09072
##
## 2. Quantiles for each variable:
##
##                                 2.5%       25%      50%      75%    97.5%
## edges                         -25.00   -13.000   -7.000  -1.0000   12.000
## nodematch.sex.1               -23.00   -14.000  -10.000  -5.0000    3.000
## nodematch.sex.2               -18.00    -7.000   -1.000   6.0000   17.000
## nodematch.E_COUNTRY.ROMANIA   -15.00    -6.000   -1.000   4.0000   13.000
## nodematch.E_COUNTRY.SPAIN     -24.00   -13.000   -7.000  -2.0000    9.000
## nodecov.age                 -3126.75 -1138.250 -339.000 425.0000 2393.625
## gwesp.fixed.0.25              -29.66   -22.664  -17.664 -11.6636   -1.664
## gwdsp.fixed.0.25              -60.95   -33.097  -16.876   0.1244   32.788
## gwodeg.fixed.0.25             -10.43    -2.676    1.311   5.2964   12.505
## gwideg.fixed.0.25              -7.55    -3.396   -1.345   0.7292    4.160
##
##
## Sample statistics cross-correlations:
##                                 edges nodematch.sex.1 nodematch.sex.2
## edges                       1.0000000      0.28261879      0.56207248
```

```
## nodematch.sex.1             0.2826188      1.00000000      0.07040837
## nodematch.sex.2             0.5620725      0.07040837      1.00000000
## nodematch.E_COUNTRY.ROMANIA 0.4149246      0.25150643      0.08829696
## nodematch.E_COUNTRY.SPAIN   0.6663696      0.08410105      0.51913660
## nodecov.age                 0.5824224      0.12059761      0.40803984
## gwesp.fixed.0.25            0.5552914      0.09508568      0.43741359
## gwdsp.fixed.0.25            0.9004987      0.24590888      0.52523324
## gwodeg.fixed.0.25           0.4461708      0.15379072      0.18640993
## gwideg.fixed.0.25           0.7819931      0.23934833      0.41396401
##                             nodematch.E_COUNTRY.ROMANIA
## edges                                        0.41492455
## nodematch.sex.1                              0.25150643
## nodematch.sex.2                              0.08829696
## nodematch.E_COUNTRY.ROMANIA                  1.00000000
## nodematch.E_COUNTRY.SPAIN                    0.04911008
## nodecov.age                                  0.19477333
## gwesp.fixed.0.25                             0.09534830
## gwdsp.fixed.0.25                             0.31437278
## gwodeg.fixed.0.25                            0.27526792
## gwideg.fixed.0.25                            0.36949908
##                             nodematch.E_COUNTRY.SPAIN nodecov.age
## edges                                      0.66636956   0.5824224
## nodematch.sex.1                            0.08410105   0.1205976
## nodematch.sex.2                            0.51913660   0.4080398
## nodematch.E_COUNTRY.ROMANIA                0.04911008   0.1947733
## nodematch.E_COUNTRY.SPAIN                  1.00000000   0.4279353
## nodecov.age                                0.42793533   1.0000000
## gwesp.fixed.0.25                           0.53976427   0.3294588
## gwdsp.fixed.0.25                           0.64162808   0.5181787
## gwodeg.fixed.0.25                          0.19784205   0.2886342
## gwideg.fixed.0.25                          0.45947975   0.4940428
##                             gwesp.fixed.0.25 gwdsp.fixed.0.25 gwodeg.fixed.0.25
## edges                            0.55529143        0.9004987        0.44617076
## nodematch.sex.1                  0.09508568        0.2459089        0.15379072
## nodematch.sex.2                  0.43741359        0.5252332        0.18640993
## nodematch.E_COUNTRY.ROMANIA      0.09534830        0.3143728        0.27526792
## nodematch.E_COUNTRY.SPAIN        0.53976427        0.6416281        0.19784205
## nodecov.age                      0.32945876        0.5181787        0.28863419
## gwesp.fixed.0.25                 1.00000000        0.5102601        0.02961169
## gwdsp.fixed.0.25                 0.51026013        1.0000000        0.43067337
## gwodeg.fixed.0.25                0.02961169        0.4306734        1.00000000
## gwideg.fixed.0.25                0.35225986        0.7221353        0.36642549
##                             gwideg.fixed.0.25
## edges                               0.7819931
## nodematch.sex.1                     0.2393483
## nodematch.sex.2                     0.4139640
## nodematch.E_COUNTRY.ROMANIA         0.3694991
## nodematch.E_COUNTRY.SPAIN           0.4594797
## nodecov.age                         0.4940428
## gwesp.fixed.0.25                    0.3522599
## gwdsp.fixed.0.25                    0.7221353
## gwodeg.fixed.0.25                   0.3664255
## gwideg.fixed.0.25                   1.0000000
##
```

```
## Sample statistics auto-correlation:
## Chain 1
##              edges nodematch.sex.1 nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
## Lag 0    1.0000000       1.0000000       1.0000000                   1.0000000
## Lag 1024 0.3342418       0.5984103       0.6043715                   0.4840846
## Lag 2048 0.2496710       0.4490045       0.4689758                   0.3296705
## Lag 3072 0.2494278       0.3518132       0.3930940                   0.2567898
## Lag 4096 0.2150082       0.2784816       0.3301166                   0.2037435
## Lag 5120 0.2039083       0.2097734       0.2859108                   0.1710801
##          nodematch.E_COUNTRY.SPAIN nodecov.age gwesp.fixed.0.25
## Lag 0                    1.0000000   1.0000000        1.0000000
## Lag 1024                 0.5753057   0.3409125        0.9198888
## Lag 2048                 0.4602872   0.2037403        0.8730398
## Lag 3072                 0.3926402   0.1594154        0.8355094
## Lag 4096                 0.3393825   0.1278081        0.8054801
## Lag 5120                 0.3171733   0.1121904        0.7850123
##          gwdsp.fixed.0.25 gwodeg.fixed.0.25 gwideg.fixed.0.25
## Lag 0           1.0000000        1.00000000        1.00000000
## Lag 1024        0.3471911        0.32781150        0.23700755
## Lag 2048        0.2465981        0.16509705        0.15134795
## Lag 3072        0.2322027        0.10722595        0.10483295
## Lag 4096        0.2005786        0.06536405        0.09104764
## Lag 5120        0.1930903        0.02952149        0.07985009
##
## Sample statistics burn-in diagnostic (Geweke):
## Chain 1
##
## Fraction in 1st window = 0.1
## Fraction in 2nd window = 0.5
##
##                      edges             nodematch.sex.1
##                    -4.1367                     -1.5836
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                    -4.2471                     -0.4751
##   nodematch.E_COUNTRY.SPAIN                 nodecov.age
##                    -3.9797                     -3.8594
##            gwesp.fixed.0.25            gwdsp.fixed.0.25
##                    -3.2762                     -2.5693
##           gwodeg.fixed.0.25           gwideg.fixed.0.25
##                     2.3801                     -3.1665
##
## Individual P-values (lower = worse):
##                       edges             nodematch.sex.1
##               3.523041e-05                1.132887e-01
##             nodematch.sex.2 nodematch.E_COUNTRY.ROMANIA
##                2.165626e-05                6.347200e-01
##   nodematch.E_COUNTRY.SPAIN                 nodecov.age
##                6.901183e-05                1.136833e-04
##            gwesp.fixed.0.25            gwdsp.fixed.0.25
##                1.052140e-03                1.019144e-02
##           gwodeg.fixed.0.25           gwideg.fixed.0.25
##                1.730920e-02                1.542765e-03
## Joint P-value (lower = worse):  0.001525925 .
```

```
##
## MCMC diagnostics shown here are from the last round of simulation, prior to computation of final para
```

```
par(mfrow=c(2,2))
plot(gof(model_6))
dev.off()
```

```
## null device
##           1
```

```
# 4. Print of all models ####
screenreg(list(model_1, model_2, model_3, model_4, model_5, model_6))
```

```
##
## ============================================================================================
##                               Model 1       Model 2       Model 3       Model 4       Model 5       M
## --------------------------------------------------------------------------------------------
## edges                          -7.01 ***     -6.96 ***     -5.01 ***     -8.83 ***     -6.78 ***
##                                (0.15)        (0.16)        (0.28)        (0.24)        (0.17)
## nodematch.sex.1                 0.79 ***      0.78 ***      0.83 ***      0.84 ***      0.75 ***
##                                (0.14)        (0.14)        (0.16)        (0.16)        (0.14)
## nodematch.sex.2                 0.51 ***      0.52 ***      0.50 ***      0.48 ***      0.46 ***
##                                (0.12)        (0.12)        (0.13)        (0.14)        (0.12)
## nodematch.E_COUNTRY.ROMANIA     1.54 ***      1.54 ***      1.37 ***      1.33 ***      1.42 ***
##                                (0.16)        (0.16)        (0.17)        (0.17)        (0.15)
## nodematch.E_COUNTRY.SPAIN       1.87 ***      1.88 ***      2.09 ***      2.14 ***      1.69 ***
##                                (0.15)        (0.15)        (0.18)        (0.19)        (0.15)
## nodecov.age                                  -0.00
##                                              (0.00)
## ostar2                                        0.06
##                                              (0.06)
## istar2                                       -2.36 ***
##                                              (0.24)
## gwodeg.fixed.0.25                                          -0.07
##                                                            (0.19)
## gwideg.fixed.0.25                                           5.25 ***
##                                                            (0.53)
## gwesp.fixed.0.25                                                          2.26 ***
##                                                                          (0.13)
## gwdsp.fixed.0.25                                                         -0.12 **
##                                                                          (0.04)
## --------------------------------------------------------------------------------------------
## AIC                             4695.24       4695.25       4498.94       4436.95       4579.95
## BIC                             4742.29       4751.72       4564.82       4502.82       4645.82
## Log Likelihood                 -2342.62      -2341.63      -2242.47      -2211.47      -2282.97
## ============================================================================================
## *** p < 0.001; ** p < 0.01; * p < 0.05
```

```
texreg::wordreg(list(model_1, model_2, model_3, model_4,
                     model_5, model_6), file = "structural_models.doc")
```

```
##
##
## processing file: file436021fb3ab9.Rmd
```

```
##   |                                                                                 |
## label: unnamed-chunk-2 (with options)
## List of 1
##  $ echo: logi FALSE

## output file: file436021fb3ab9.knit.md

## "C:/Program Files/RStudio/bin/pandoc/pandoc" +RTS -K512m -RTS file436021fb3ab9.utf8.md --to html4 --

##
## Output created: structural_models.doc
```