

SUPPLEMENTARY INFORMATION

A network analysis of female sexual function: comparing symptom networks in women with decreased, increased, and stable sexual desire

Annika Gunst, Marlene Werner, Lourens J. Waldorp, Ellen T. M. Laan, Marianne Källström,
Patrick Jern

Data

Data can be made available upon request to the corresponding author, Annika Gunst (annika.gunst@utu.fi).

Measures

Sexual Desire Groups

A short form of the revised Sexual Desire Inventory¹ (SDI-2) was used for creating a grouping variable assessing change in sexual desire over time. The short form included six items (3, 5, 9, 11, 13, and 14) from the original SDI-2, summed together to form a composite variable. In the present study, the short-form SDI-2 demonstrated acceptable internal consistency at T1 ($\alpha = .79$) and good internal consistency at T2 ($\alpha = .84$).

Measures Included in the Networks

Female sexual function. The Female Sexual Function Index² (FSFI) was used to assess sexual function. The FSFI includes 19 Likert-type items, assessing six subdomains of sexual

function over the past four weeks: *sexual desire*, (subjective) *sexual arousal*, *lubrication*, *orgasm function*, *sexual satisfaction*, and *sex-related pain*. Item scores range from 1 to 5 or 0 to 5 (0 representing the supplementary option "no sexual activity / did not attempt intercourse") with lower scores indicating worse sexual function. We added the response option "no partnered activity" to items 14 and 15, which analogous to the response options of other items, was given the value of 0. We calculated domain-scores according to the guidelines².

The FSFI has repeatedly demonstrated good validity and reliability in different settings^{2,3}, including the Genetics of Sex and Aggression data collection from 2006⁴. In the present study, the FSFI demonstrated acceptable to excellent internal consistency for all six domains at both time points (Cronbach's α 's ranging from .77 to .98). Due to a technical error in the data collection phase, one item was omitted from the T2 data collection (item 18: '*Over the past 4 weeks, how often did you experience discomfort or pain following vaginal penetration?*'). Thus, the composite variable for *sex-related pain* included two items instead of three items the present study, both at T1 and T2. Nevertheless, the composite variable demonstrated excellent internal consistency at both time points ($\alpha_{T1} = .97$, $\alpha_{T2} = .98$).

Sexual distress. A short form of the Female Sexual Distress Scale⁵ (FSDS) was used to assess sexual distress. The short form included seven Likert-type items from the original scale (1, 3, 5, 8, 9, 10, and 11), with a sum score ranging from 0 to 28. Higher scores indicate higher sexual distress. The FSDS has previously demonstrated good discriminant validity and test-retest reliability⁶. In the present study, the questionnaire demonstrated good internal consistency at T1 ($\alpha = .89$) and excellent internal consistency at T2 ($\alpha = .92$).

Psychological distress. Two subscales from the Brief Symptom Inventory-18⁷ (BSI-18) were used to assess symptoms of anxiety and depression. Both subscales include six Likert-type

items, summed together to form composite variables ranging from 6 to 30 with higher scores indicating higher psychological distress. The BSI-18 has previously demonstrated good psychometric properties in various clinical population-based samples⁸. In the present study, both the *anxiety* subscale (α_{T1} and $\alpha_{T2} = .85$) and the *depression* subscale ($\alpha_{T1} = .84$, $\alpha_{T2} = .85$) demonstrated good internal consistency at both time points.

Body dissatisfaction. The body image subscale of the Derogatis Sexual Function Inventory⁹ (DSFI) was used to assess body dissatisfaction. Eleven gender-neutral Likert-type items were summed together to form a composite variable ranging from 11 to 55 with higher scores indicating higher body dissatisfaction. The DSFI has previously demonstrated sound psychometric properties in various settings measuring sexual function¹⁰. In the present study, the *body dissatisfaction* composite variable demonstrated acceptable internal consistency at both time points ($\alpha_{T1} = .70$, $\alpha_{T2} = .75$).

Alcohol use. The Alcohol Use Disorders Identification Test¹¹ (AUDIT) was used to assess (hazardous) alcohol use. The AUDIT consists of ten Likert-type items, summed together to form a composite variable ranging from 0 to 40 with higher scores indicating more frequent and hazardous alcohol use. The AUDIT is one of the most frequently used screening measures of alcohol use and related problems, and has previously demonstrated sound psychometric properties¹². In the present study, the AUDIT demonstrated good internal consistency at both time points (α_{T1} and $\alpha_{T2} = .81$).

Discrepancy in desired and actual sexual activity. The Desired and Actual Sexual Activity Scale¹³, a modified version of the drive subscale of the DSFI⁹, was used to assess discrepancy in desired and actual frequency of sexual behaviors. The DASA consists of 12 nine-point Likert-type items; 6 items inquiring about how frequently the respondent engages in

specific sexual behaviors (e.g., masturbation and oral sex) and 6 items inquiring about how frequently the respondent desires the specific sexual behaviors. Two discrepancy variables were created in the present study. First, the actual sexual activity items were subtracted from the desired sexual activity items, resulting in a discrepancy variable with a score range between -54 (indicating that the respondent had engaged in more sexual activity than she desired) and 54 (indicating that the respondent had engaged in less sexual activity than she desired). This variable was further divided into two variables: one ranging from -54 to 0 (i.e., positive values were replaced with 0) representing a variable of *too much sexual activity*, and another ranging from 0 to 54 (i.e., negative values were replaced with 0) representing a variable of *too little sexual activity*. For clarity, the absolute values were used for the *too much sexual activity* variable, meaning that higher scores indicated a bigger discrepancy between desired and actual behavior for both the *too much sexual activity* and the *too little sexual activity* variable.

Sociosexual orientation. The Sociosexual Orientation Inventory¹⁴ (SOI) was used to assess sociosexual orientation. Sociosexual orientation refers to an individual's attitudes towards and tendency to engage in casual and uncommitted sexual relations. The SOI includes four nine-point Likert-type items measuring attitudes and three open ended numerical items measuring behaviors. The items were summed together according to the original formula¹⁴ to form a composite variable with higher scores indicating a more liberal sexual orientation.

References

1. Spector, I. P., Carey, M. P. & Steinberg, L. The sexual desire inventory: development, factor structure, and evidence of reliability. *J. Sex Marital Ther.* **22**, 175-190 (1996).
2. Rosen, R. *et al.* The Female Sexual Function Index (FSFI): a multidimensional self-report

- instrument for the assessment of female sexual function. *J. Sex Marital Ther.* **26**, 191-208 (2000).
3. Wiegel, M., Meston, C. & Rosen, R. The Female Sexual Function Index (FSFI): cross-validation and development of clinical cutoff scores. *J. Sex Marital Ther.* **31**, 1-20 (2005).
 4. Witting, K. *et al.* Evaluation of the Female Sexual Function Index in a population based sample from Finland. *Arch. Sex. Behav.* **37**, 912-924 (2008).
 5. Derogatis, L. R. *et al.* The Female Sexual Distress Scale (FSDS): initial validation of a standardized scale for assessment of sexually related personal distress in women. *J. Sex Marital Ther.* **28**, 317-330 (2002).
 6. Derogatis, L., Clayton, A., Lewis-D'Agostino, D., Wunderlich, G. & Fu, Y. Validation of the female sexual distress scale-revised for assessing distress in women with hypoactive sexual desire disorder. *J. Sex. Med.* **5**, 357-364 (2008).
 7. Derogatis, L. R. *Brief Symptom Inventory (BSI)-18. Administration, Scoring and Procedures Manual* (Pearson, 2001).
 8. Derogatis, L. R. & Savitz, K. L. The SCL-90-R and Brief Symptom Inventory (BSI) in primary care in *Handbook of Psychological Assessment in Primary Care Settings* (ed. M. E. Maruish) 297-334 (Lawrence Erlbaum Associates, 2000).
 9. Derogatis, L. R. & Melisarotos, N. The DSFI: a multidimensional measure of sexual functioning. *J. Sex Marital Ther.* **5**, 244-281 (1979).
 10. Daker-White, G. Reliable and valid self-report outcome measures in sexual (dys)function: a systematic review. *Arch. Sex. Behav.* **31**, 197-209 (2002).
 11. Babor, T. F., Higgins-Biddle, J. C., Saunders, J. B. & Monteiro, M. G. *The Alcohol Use Disorders Identification Test Guidelines for Use in Primary Care. Second Edition* (World Health Organization, Department of Mental Health and Substance Dependence, 2001).

12. Allen, J. P., Litten, R. Z., Fertig, J. B., Babor, T. A review of research on the Alcohol Use Disorders Identification Test (AUDIT). *Alcohol. Clin. Exp. Res.* **21**, 613-619 (1997).
13. Santtila, P. *et al.* Discrepancies between sexual desire and sexual activity: gender differences and associations with relationship satisfaction. *J. Sex Marital Ther.* **34**, 31-44 (2007).
14. Simpson, J. A. & Gangestad, S. W. Individual differences in sociosexuality: evidence for convergent and discriminant validity. *J. Pers. Soc. Psychol* **60**, 870-883 (1991).

Statistical Analyses

Table of Contents

1. Data Import
2. Data Preparation
3. Data Descriptives
4. Network Estimation (incl. hormonal contraception)
5. Network Visualization (incl. hormonal contraception)
6. Network Estimation (excl. hormonal contraception)
7. Network Visualization (excl. hormonal contraception)
8. Network Stability
9. Network Comparison
10. Network Communities
11. Replication - Data Import and Preparation
12. Replication - Network Estimation (incl. hormonal contraception)
13. Replication - Network Estimation (excl. hormonal contraception)
14. Replication - Network Visualization (excl. hormonal contraception)
15. Replication - Network Stability
16. Replication - Network Comparison
17. Replication - Network Communities

1. Data Import

```
#####  
# 1. Data Import First Timepoint#  
#####  
setwd("C:/Users/Lene/Desktop/FSFI Collaboration/Datasets/Supplementary Material")  
library(haven)  
FSFI_Gunstetal_Imputed_NegTo0 <- read_sav("C:/Users/Lene/Desktop/FSFI Collaboration/Datasets/FSFI_Gunstetal_Imputed_NegTo0.sav")
```

2. Data Preparation

```
#####  
# 2. Data preparation #  
#####
```

```
DataNetwork <- FSFI_Gunstetal_Imputed_NegTo0[,3:22]  
DataNetwork[,21] <- FSFI_Gunstetal_Imputed_NegTo0$SDI_groups  
DataNetwork[,22] <- FSFI_Gunstetal_Imputed_NegTo0$SDI_change
```

```
colnames(DataNetwork)[21] <- "SDI_groups"  
colnames(DataNetwork)[22] <- "SDI_change"
```

3. Data Descriptive Statistics

```
# check whether there are any variables with missing values left
```

```
apply(apply(DataNetwork, 2, is.na), 2, sum) # no NA
```

```
##          age_OLD      height_OLD      weight_OLD      hc_OLD  
##           0           0           0           0  
##    biolchild_OLD    FSFIides_OLD    FSFIaro_OLD    FSFIilub_OLD  
##           0           0           0           0  
##    FSFIorg_OLD    FSFIisat_OLD    FSFIpain_OLD    SDS_OLD  
##           0           0           0           0  
##    BSIdep_OLD    BSIanx_OLD    BI_OLD    AUDIT_OLD  
##           0           0           0           0  
## DSFItoolittle_OLD    DSFItoomuch_OLD    SOI_OLD    haspartner_OLD  
##           0           0           0           0  
##    SDI_groups    SDI_change  
##           0           0
```

```
cor(DataNetwork)
```

```
##          age_OLD      height_OLD      weight_OLD      hc_OLD  
## age_OLD      1.000000000 0.026286749 0.169905620 -0.129566839  
## height_OLD    0.026286749 1.000000000 0.344403818 0.013777569  
## weight_OLD    0.169905620 0.344403818 1.000000000 -0.041399265  
## hc_OLD        -0.129566839 0.013777569 -0.041399265 1.000000000  
## biolchild_OLD 0.553024853 -0.015544891 0.122468948 -0.114682329  
## FSFIides_OLD  -0.158600184 -0.011732344 -0.004808011 0.051986124  
## FSFIaro_OLD    0.066602656 0.011364167 0.007128246 0.105847045  
## FSFIilub_OLD   0.069994684 0.017092991 0.017119480 0.116073879  
## FSFIorg_OLD    0.139823381 0.015797078 0.047068992 0.028293057  
## FSFIisat_OLD   0.046719679 -0.016479377 -0.038709108 0.211418912  
## FSFIpain_OLD   0.135371696 0.055805252 0.037091493 0.205547420  
## SDS_OLD        0.036611918 -0.037451549 0.044780692 -0.048357103  
## BSIdep_OLD     -0.109035675 -0.030893066 0.029177358 -0.036115628  
## BSIanx_OLD     -0.125321488 -0.031507516 -0.034318398 -0.008353472  
## BI_OLD         -0.036467471 -0.116201100 0.282914633 -0.082925802  
## AUDIT_OLD      -0.171922696 -0.013499062 0.032441472 0.065568794  
## DSFItoolittle_OLD -0.065208434 -0.002056568 0.062283886 -0.117266029  
## DSFItoomuch_OLD 0.037159678 -0.034300268 -0.036211889 -0.021652321  
## SOI_OLD        0.075946510 0.017580255 0.084583548 0.024438576  
## haspartner_OLD 0.191395727 -0.014633106 0.001151473 0.188922760  
## SDI_groups     -0.007982908 0.005344832 0.009586199 0.019841234  
## SDI_change     -0.006013512 0.016108854 0.007035689 0.022717709  
##    biolchild_OLD    FSFIides_OLD    FSFIaro_OLD    FSFIilub_OLD  
##    age_OLD      0.553024853 -0.158600184 0.066602656 0.069994684  
##    height_OLD    -0.015544891 -0.011732344 0.011364167 0.017092991  
##    weight_OLD    0.122468948 -0.004808011 0.007128246 0.017119480  
##    hc_OLD        -0.114682329 0.051986124 0.105847045 0.116073879  
##    biolchild_OLD 1.000000000 -0.088111575 0.085649735 0.086861428  
##    FSFIides_OLD  -0.088111575 1.000000000 0.441855986 0.334567339
```

##	FSFIaro_OLD	0.085649735	0.441855986	1.000000000	0.899402740
##	FSFIilub_OLD	0.086861428	0.334567339	0.899402740	1.000000000
##	FSFIorg_OLD	0.153792430	0.243985692	0.746921907	0.703853945
##	FSFIisat_OLD	0.119966743	0.299865876	0.678226212	0.647558766
##	FSFIpain_OLD	0.188080729	0.215881099	0.603903882	0.643406041
##	SDS_OLD	-0.015576057	-0.242072473	-0.241864866	-0.145039989
##	BSIdep_OLD	-0.083599516	0.021111699	-0.159799617	-0.137973383
##	BSIanx_OLD	-0.060763923	0.072267129	-0.098326574	-0.075064116
##	BI_OLD	-0.002154330	-0.108127152	-0.183241501	-0.134036418
##	AUDIT_OLD	-0.205861974	0.207832652	0.104553534	0.108883719
##	DSFItoolittle_OLD	-0.140972947	0.075255684	-0.245232790	-0.279415900
##	DSFItoomuch_OLD	0.049212237	-0.060309219	-0.033565309	-0.008889944
##	SOI_OLD	0.007744323	0.154122379	0.109679984	0.097243532
##	haspartner_OLD	0.216884564	0.081102801	0.399819735	0.427587487
##	SDI_groups	0.031060566	-0.154437586	-0.090639955	-0.075902013
##	SDI_change	0.035612623	-0.201990379	-0.105756365	-0.082546771
##	FSFIorg_OLD	FSFIisat_OLD	FSFIpain_OLD	SDS_OLD	
##	age_OLD	0.139823381	0.046719679	0.135371696	0.03661192
##	height_OLD	0.015797078	-0.016479377	0.055805252	-0.03745155
##	weight_OLD	0.047068992	-0.038709108	0.037091493	0.04478069
##	hc_OLD	0.028293057	0.211418912	0.205547420	-0.04835710
##	biolchild_OLD	0.153792430	0.119966743	0.188080729	-0.01557606
##	FSFIides_OLD	0.243985692	0.299865876	0.215881099	-0.24207247
##	FSFIaro_OLD	0.746921907	0.678226212	0.603903882	-0.24186487
##	FSFIilub_OLD	0.703853945	0.647558766	0.643406041	-0.14503999
##	FSFIorg_OLD	1.000000000	0.505977015	0.433936468	-0.22411195
##	FSFIisat_OLD	0.505977015	1.000000000	0.755847134	-0.35936046
##	FSFIpain_OLD	0.433936468	0.755847134	1.000000000	-0.17629530
##	SDS_OLD	-0.224111949	-0.359360457	-0.176295298	1.000000000
##	BSIdep_OLD	-0.157038229	-0.251549353	-0.159838540	0.37395858
##	BSIanx_OLD	-0.123474750	-0.116658825	-0.076692419	0.32713673
##	BI_OLD	-0.156999934	-0.208781570	-0.146122660	0.34253970
##	AUDIT_OLD	-0.001343699	0.006748583	0.059143282	0.12698738
##	DSFItoolittle_OLD	-0.221013112	-0.538806064	-0.434677671	0.19581689
##	DSFItoomuch_OLD	-0.009370435	0.039744947	0.047522034	0.02803851
##	SOI_OLD	0.015379267	0.028864166	0.110870841	0.02748733
##	haspartner_OLD	0.314389620	0.643055966	0.632449098	-0.04810504
##	SDI_groups	-0.055456791	-0.006424257	-0.012644879	0.01425262
##	SDI_change	-0.057887062	-0.005970852	-0.003337505	0.01698209
##	BSIdep_OLD	BSIanx_OLD	BI_OLD	AUDIT_OLD	
##	age_OLD	-0.10903567	-0.125321488	-0.03646747	-0.171922696
##	height_OLD	-0.03089307	-0.031507516	-0.11620110	-0.013499062
##	weight_OLD	0.02917736	-0.034318398	0.28291463	0.032441472
##	hc_OLD	-0.03611563	-0.008353472	-0.08292580	0.065568794
##	biolchild_OLD	-0.08359952	-0.060763923	-0.00215433	-0.205861974
##	FSFIides_OLD	0.021111170	0.072267129	-0.10812715	0.207832652
##	FSFIaro_OLD	-0.15979962	-0.098326574	-0.18324150	0.104553534
##	FSFIilub_OLD	-0.13797338	-0.075064116	-0.13403642	0.108883719
##	FSFIorg_OLD	-0.15703823	-0.123474750	-0.15699993	-0.001343699
##	FSFIisat_OLD	-0.25154935	-0.116658825	-0.20878157	0.006748583
##	FSFIpain_OLD	-0.15983854	-0.076692419	-0.14612266	0.059143282
##	SDS_OLD	0.37395858	0.327136728	0.34253970	0.126987381
##	BSIdep_OLD	1.000000000	0.699078928	0.38785277	0.225342801
##	BSIanx_OLD	0.69907893	1.000000000	0.25878846	0.249435233
##	BI_OLD	0.38785277	0.258788462	1.000000000	0.103043308
##	AUDIT_OLD	0.22534280	0.249435233	0.10304331	1.000000000
##	DSFItoolittle_OLD	0.25233862	0.112831588	0.14471601	0.127408954
##	DSFItoomuch_OLD	0.02370179	0.043392691	0.04673992	-0.006716973
##	SOI_OLD	0.11283699	0.079464057	0.01633989	0.341677274
##	haspartner_OLD	-0.16614574	-0.042841563	-0.12790931	-0.083739426
##	SDI_groups	0.02578302	0.033911659	0.03508038	-0.085544567
##	SDI_change	0.01362354	0.024294324	0.03100555	-0.104291038
##	DSFItoolittle_OLD	DSFItoomuch_OLD	SOI_OLD		

```

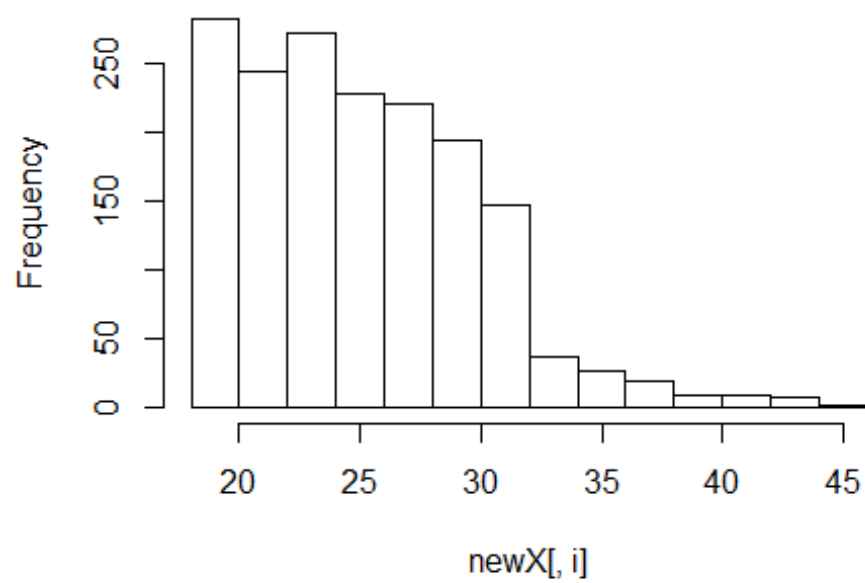
## age_OLD -0.065208434 0.037159678 0.075946510
## height_OLD -0.002056568 -0.034300268 0.017580255
## weight_OLD 0.062283886 -0.036211889 0.084583548
## hc_OLD -0.117266029 -0.021652321 0.024438576
## biolchild_OLD -0.140972947 0.049212237 0.007744323
## FSFIdes_OLD 0.075255684 -0.060309219 0.154122379
## FSFIaro_OLD -0.245232790 -0.033565309 0.109679984
## FSFIilub_OLD -0.279415900 -0.008889944 0.097243532
## FSFIorg_OLD -0.221013112 -0.009370435 0.015379267
## FSFIisat_OLD -0.538806064 0.039744947 0.028864166
## FSFIpain_OLD -0.434677671 0.047522034 0.110870841
## SDS_OLD 0.195816890 0.028038505 0.027487326
## BSIddep_OLD 0.252338622 0.023701790 0.112836993
## BSIanx_OLD 0.112831588 0.043392691 0.079464057
## BI_OLD 0.144716008 0.046739918 0.016339895
## AUDIT_OLD 0.127408954 -0.006716973 0.341677274
## DSFItoolittle_OLD 1.000000000 -0.204318304 0.127275481
## DSFItoomuch_OLD -0.204318304 1.000000000 0.029169988
## SOI_OLD 0.127275481 0.029169988 1.000000000
## haspartner_OLD -0.589114197 0.064522766 -0.019818780
## SDI_groups -0.068915731 0.034473712 -0.073218732
## SDI_change -0.107234469 0.059502478 -0.091306208
## haspartner_OLD SDI_groups SDI_change
## age_OLD 0.191395727 -0.007982908 -0.006013512
## height_OLD -0.014633106 0.005344832 0.016108854
## weight_OLD 0.001151473 0.009586199 0.007035689
## hc_OLD 0.188922760 0.019841234 0.022717709
## biolchild_OLD 0.216884564 0.031060566 0.035612623
## FSFIdes_OLD 0.081102801 -0.154437586 -0.201990379
## FSFIaro_OLD 0.399819735 -0.090639955 -0.105756365
## FSFIilub_OLD 0.427587487 -0.075902013 -0.082546771
## FSFIorg_OLD 0.314389620 -0.055456791 -0.057887062
## FSFIisat_OLD 0.643055966 -0.006424257 -0.005970852
## FSFIpain_OLD 0.632449098 -0.012644879 -0.003337505
## SDS_OLD -0.048105036 0.014252621 0.016982085
## BSIddep_OLD -0.166145743 0.025783020 0.013623544
## BSIanx_OLD -0.042841563 0.033911659 0.024294324
## BI_OLD -0.127909305 0.035080384 0.031005546
## AUDIT_OLD -0.083739426 -0.085544567 -0.104291038
## DSFItoolittle_OLD -0.589114197 -0.068915731 -0.107234469
## DSFItoomuch_OLD 0.064522766 0.034473712 0.059502478
## SOI_OLD -0.019818780 -0.073218732 -0.091306208
## haspartner_OLD 1.000000000 0.035148707 0.044823579
## SDI_groups 0.035148707 1.000000000 0.885106810
## SDI_change 0.044823579 0.885106810 1.000000000
# SDI group variable is not too strongly correlated with other variables
# this would be a problem because we might otherwise condition on a latent effect!

#####
# Histograms of all variables to check distributions#
#####
colnames(DataNetwork) # to use with histograms
## [1] "age_OLD" "height_OLD" "weight_OLD"
## [4] "hc_OLD" "biolchild_OLD" "FSFIdes_OLD"
## [7] "FSFIaro_OLD" "FSFIilub_OLD" "FSFIorg_OLD"
## [10] "FSFIisat_OLD" "FSFIpain_OLD" "SDS_OLD"
## [13] "BSIddep_OLD" "BSIanx_OLD" "BI_OLD"
## [16] "AUDIT_OLD" "DSFItoolittle_OLD" "DSFItoomuch_OLD"
## [19] "SOI_OLD" "haspartner_OLD" "SDI_groups"
## [22] "SDI_change"

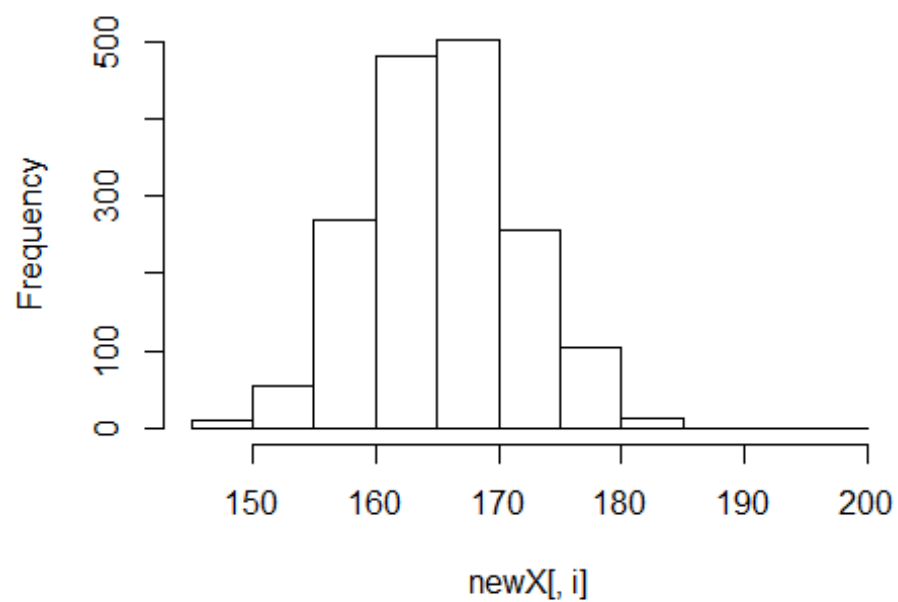
apply(DataNetwork, 2, hist)

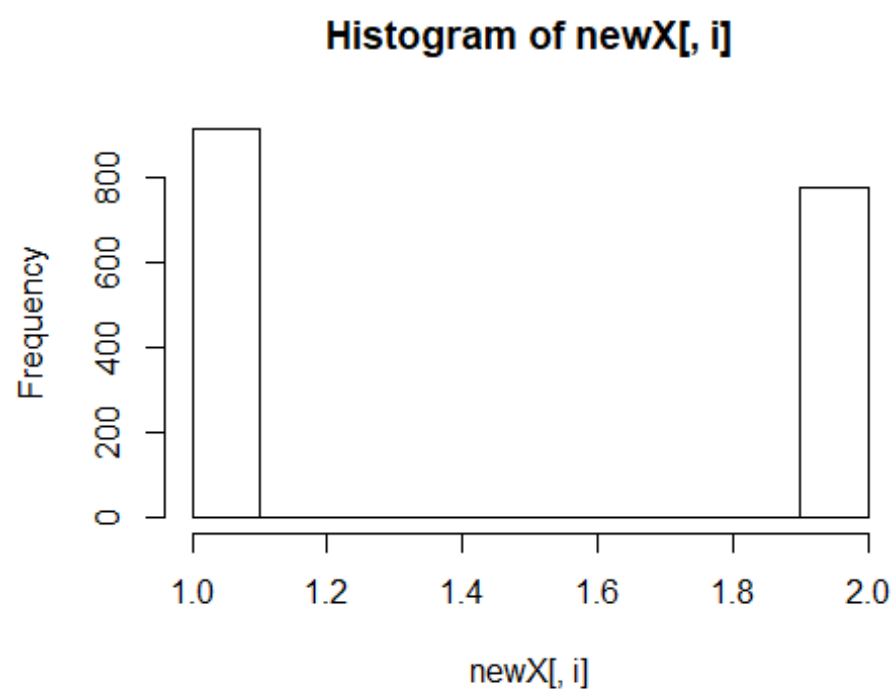
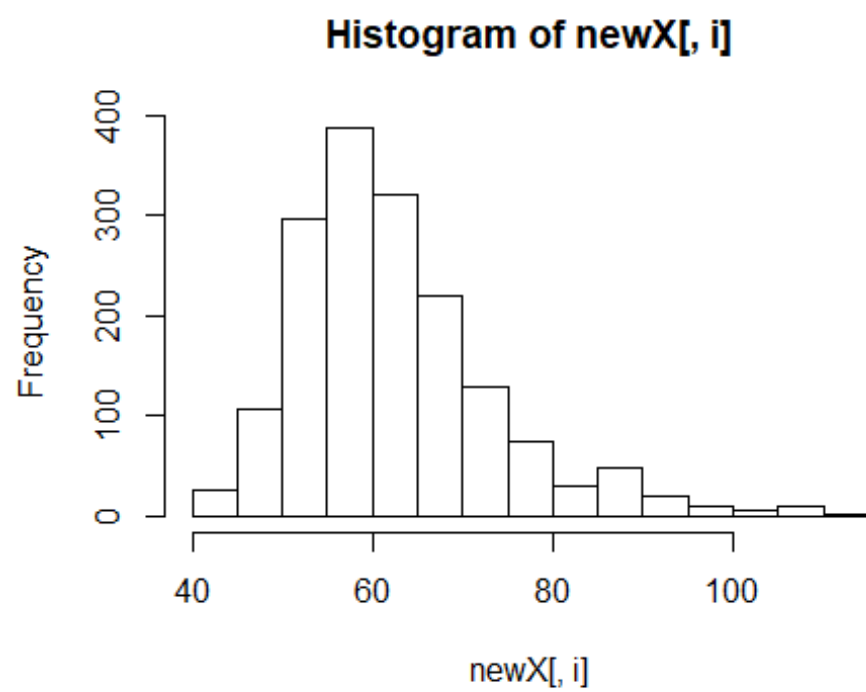
```

Histogram of newX[, i]

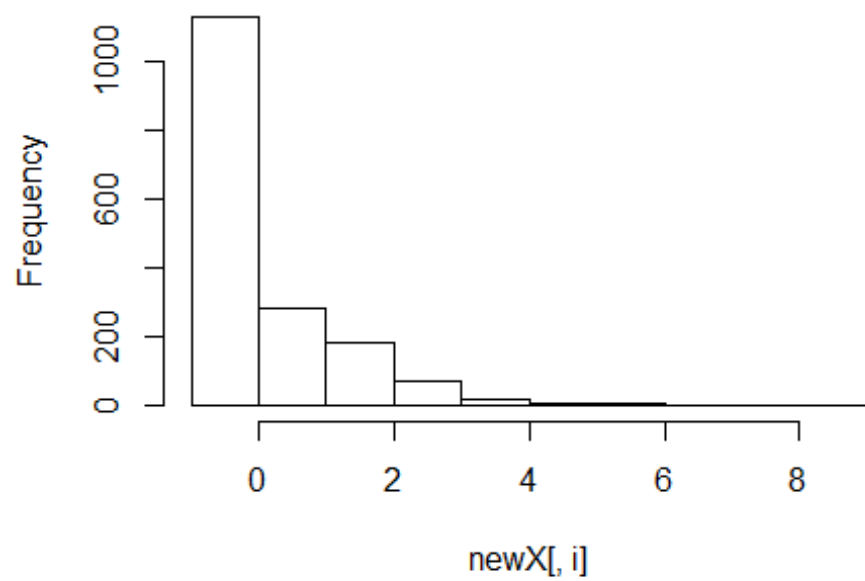


Histogram of newX[, i]

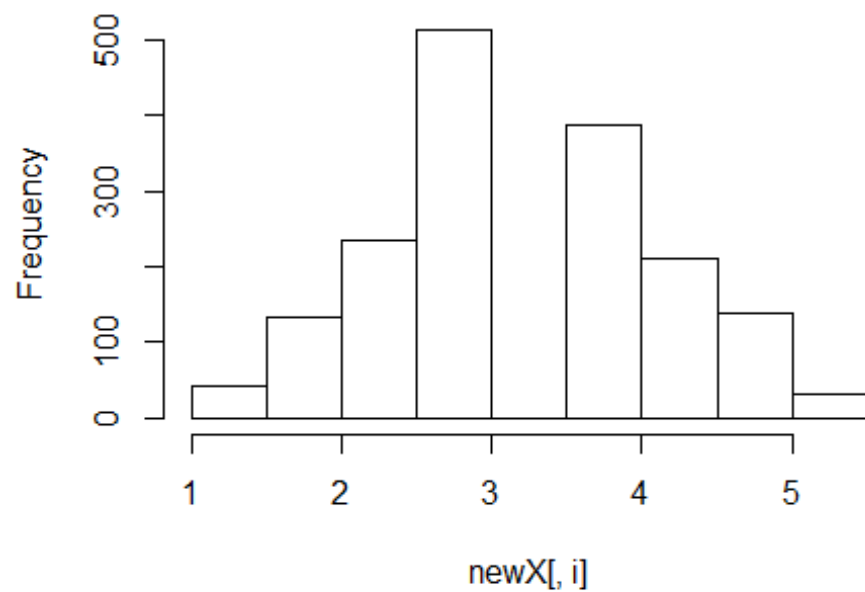


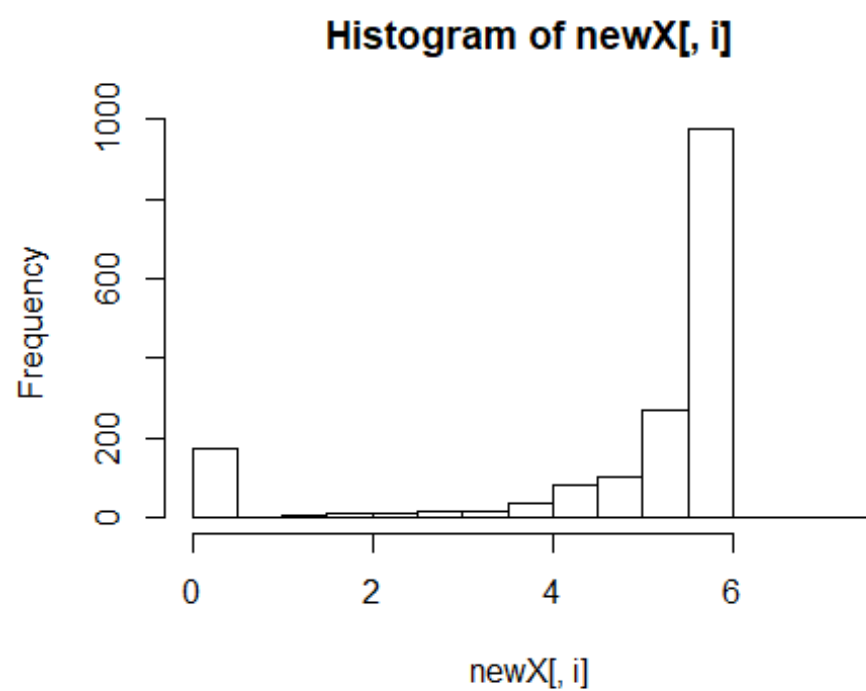
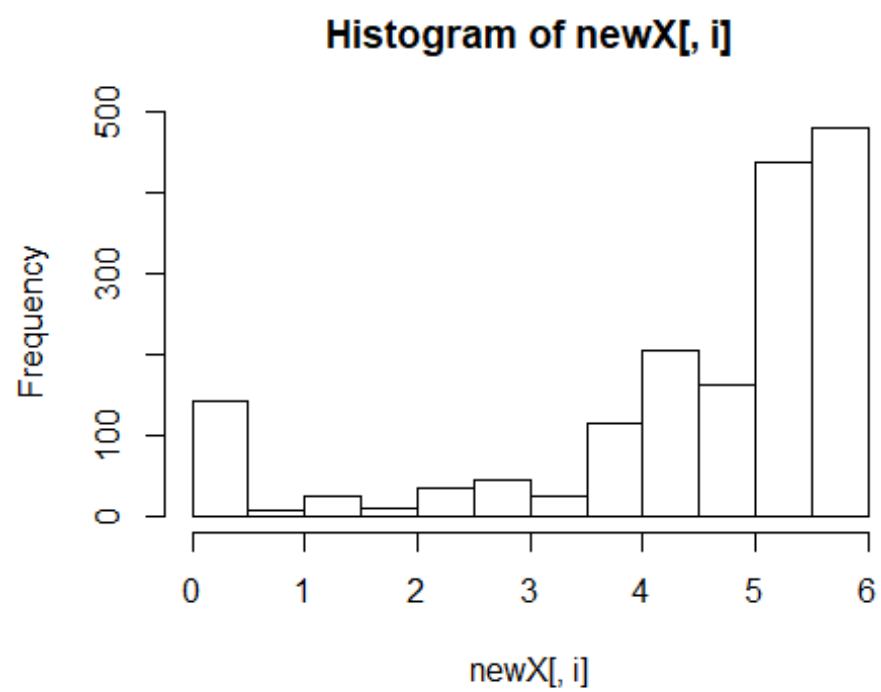


Histogram of newX[, i]

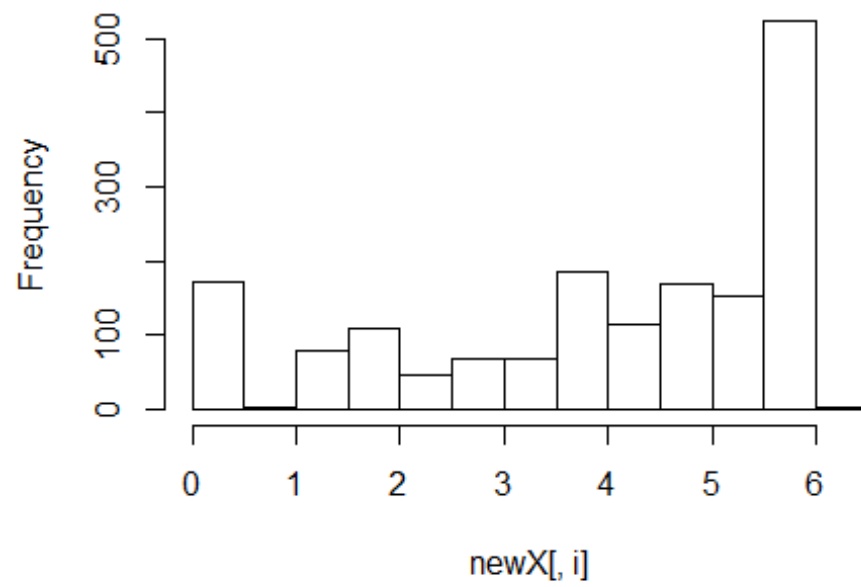


Histogram of newX[, i]

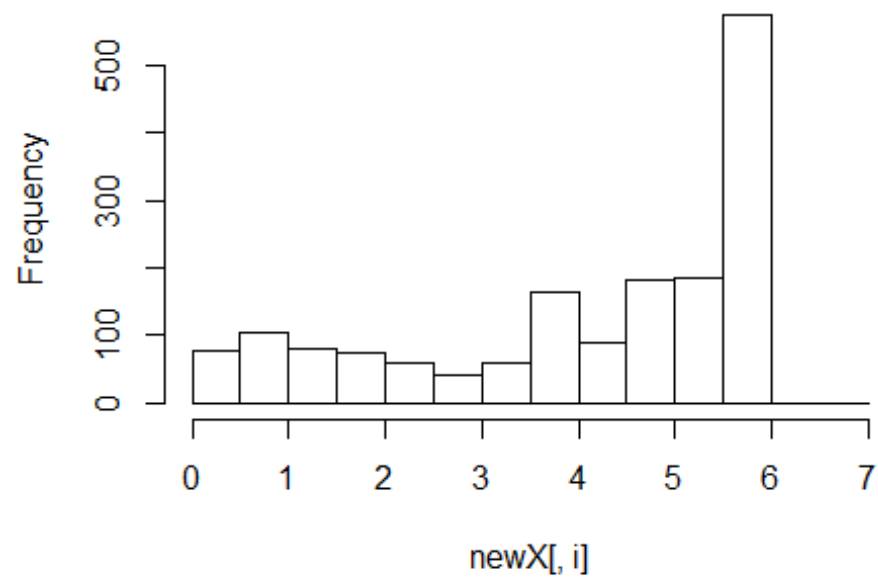




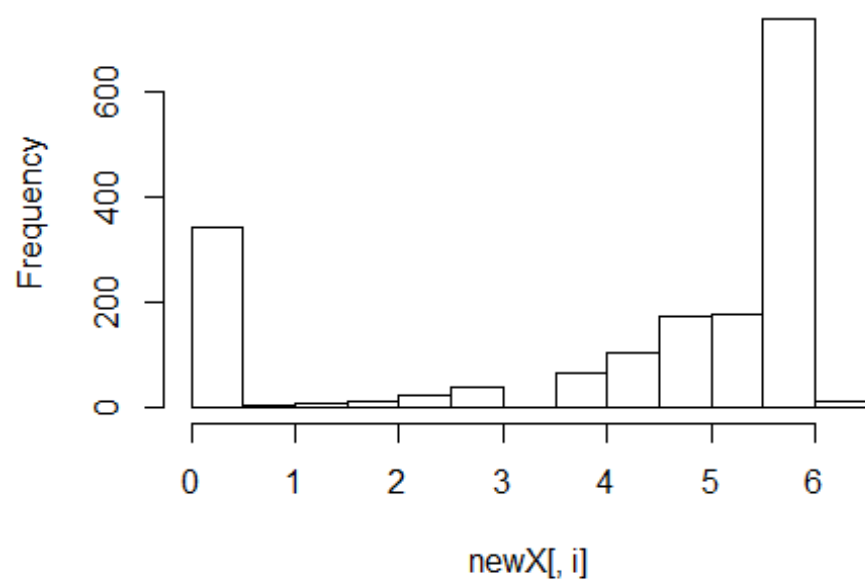
Histogram of newX[, i]



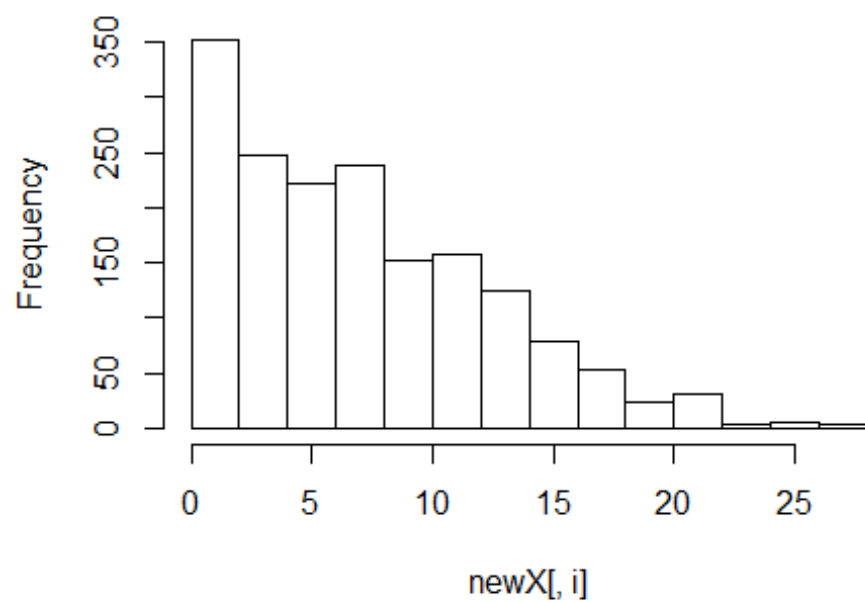
Histogram of newX[, i]



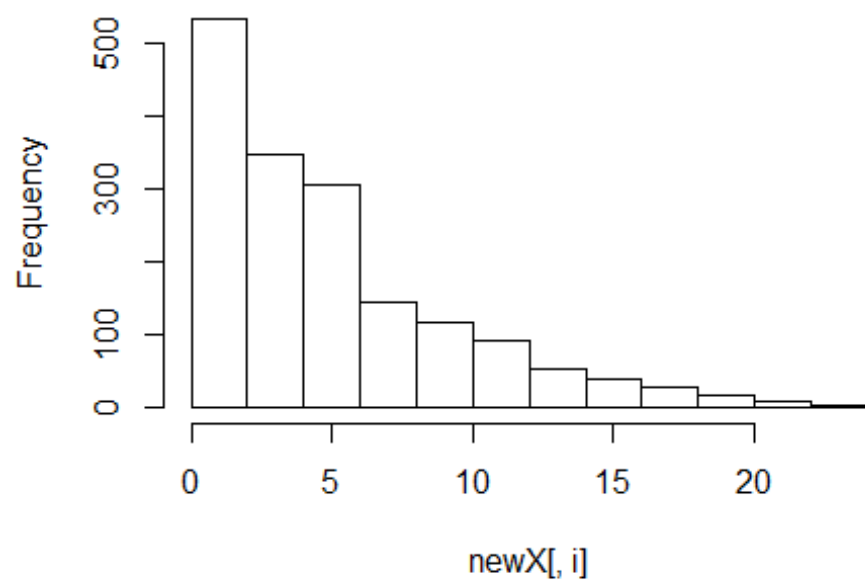
Histogram of newX[, i]



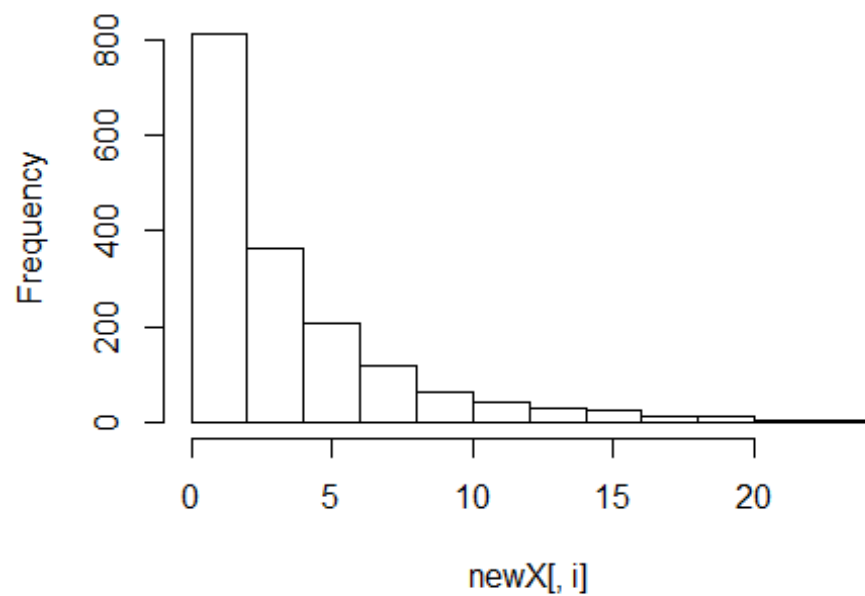
Histogram of newX[, i]



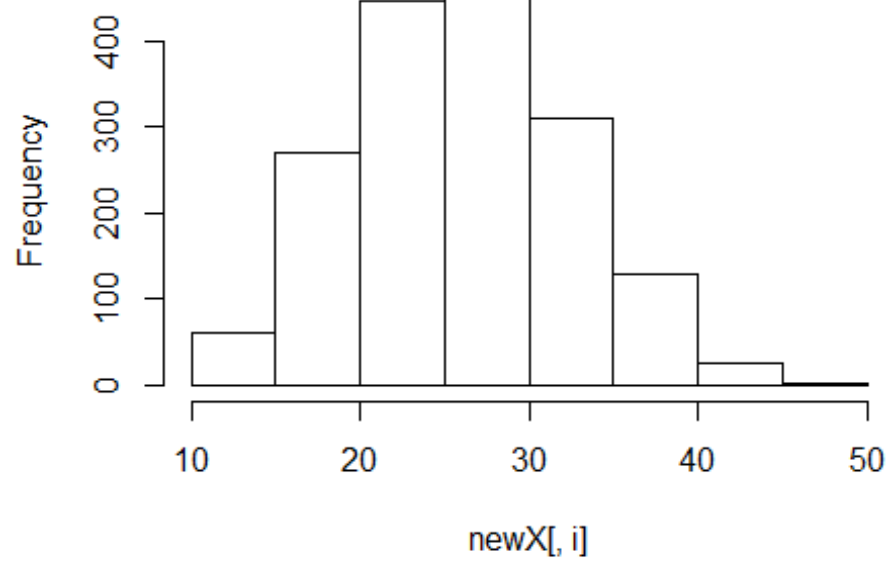
Histogram of newX[, i]



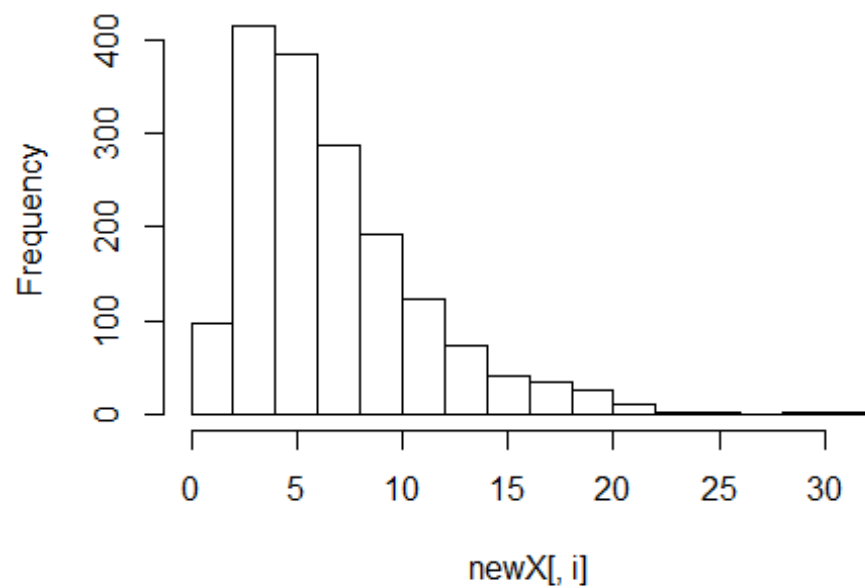
Histogram of newX[, i]



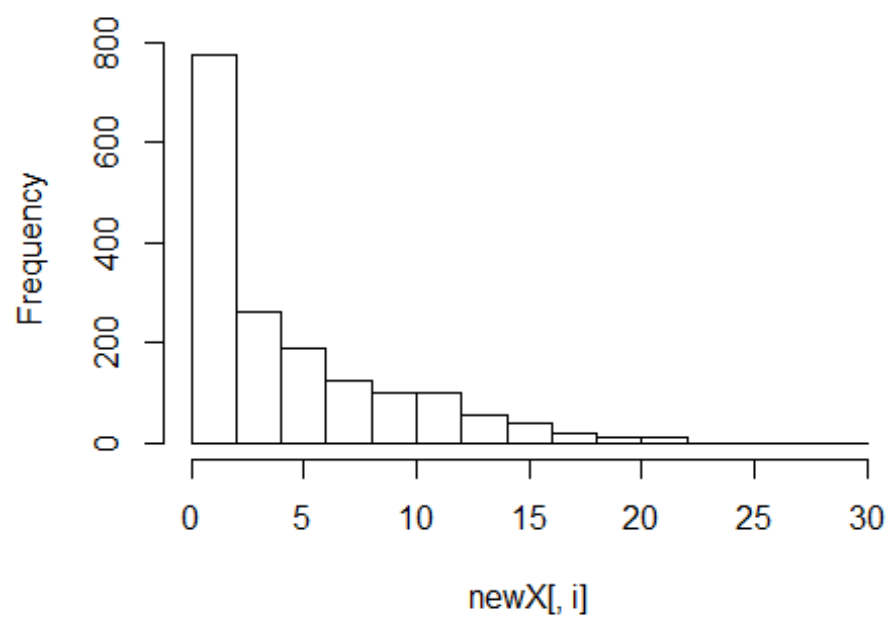
Histogram of newX[, i]



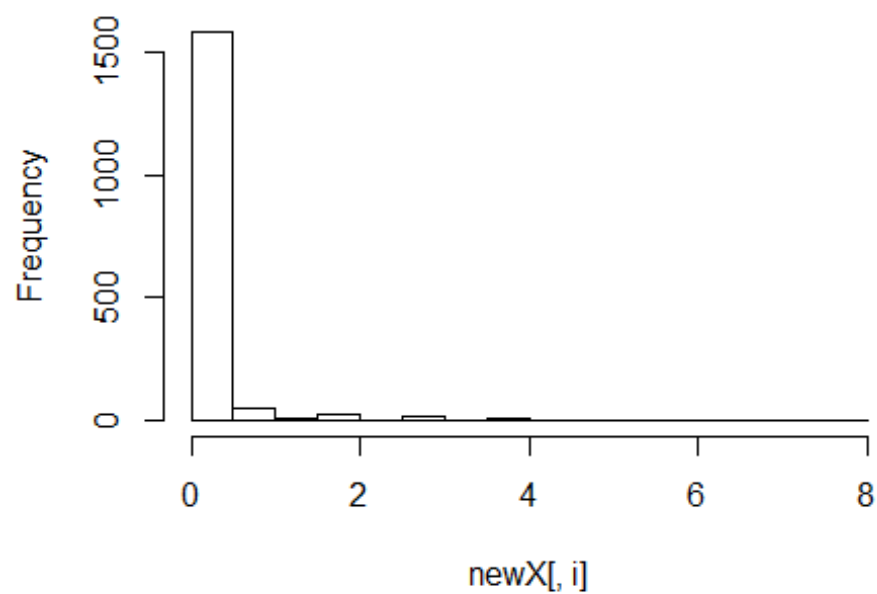
Histogram of newX[, i]



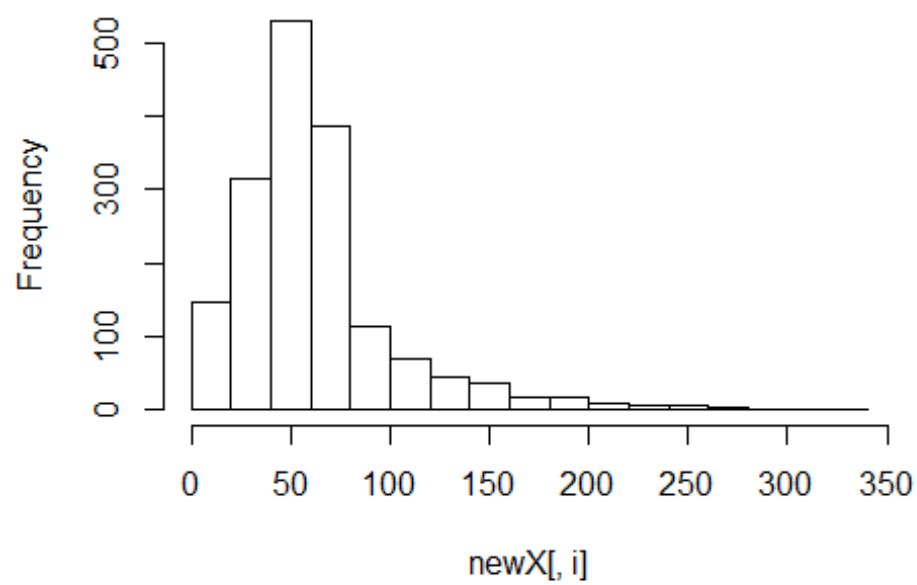
Histogram of newX[, i]



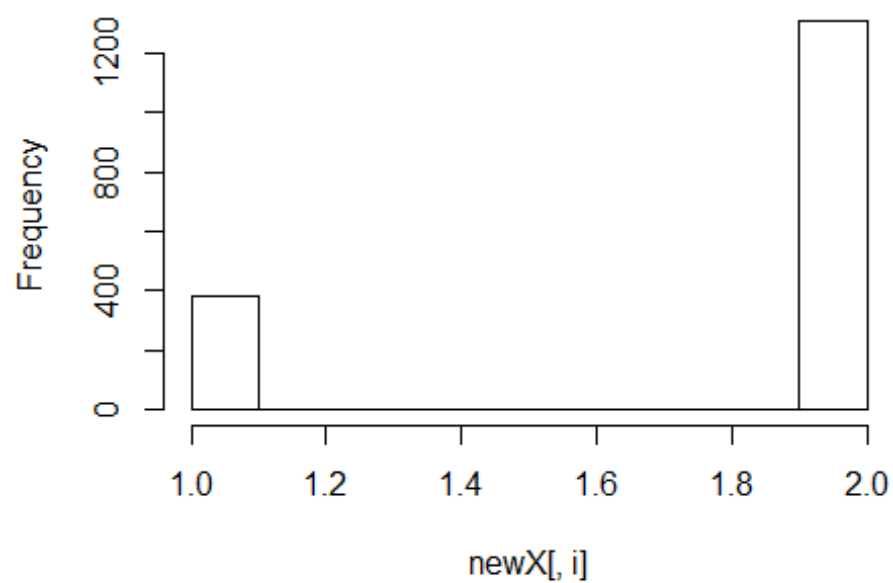
Histogram of newX[, i]

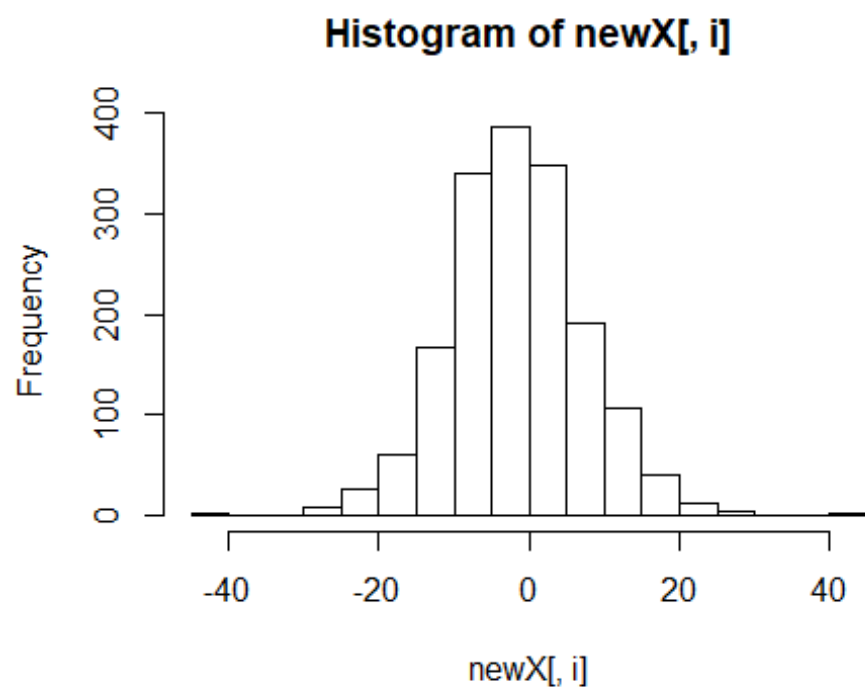
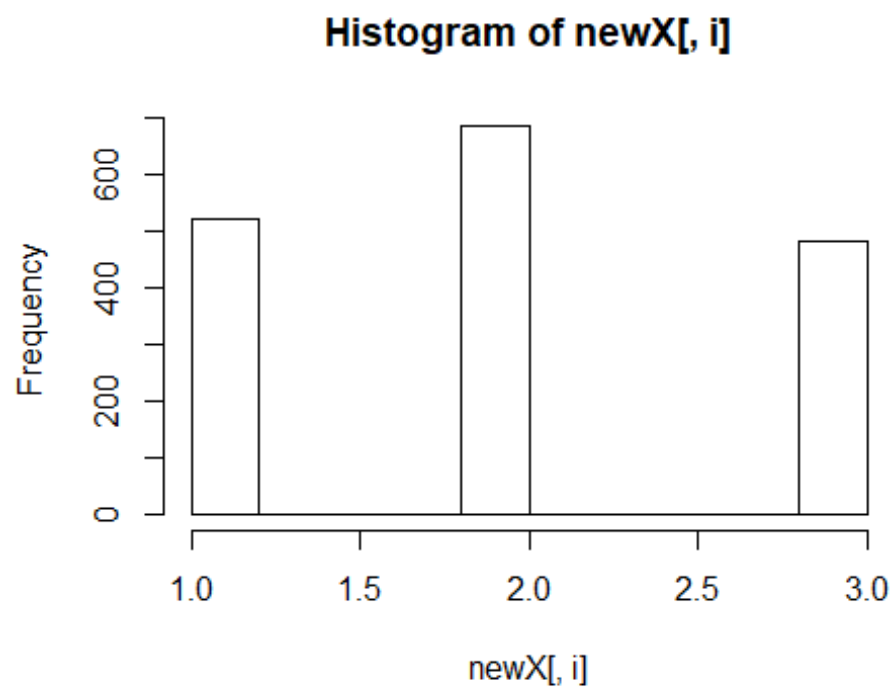


Histogram of newX[, i]



Histogram of newX[, i]





```
# round the children variable (count variable instead of continuous)
DataNetwork[,5] <- round(DataNetwork[,5])
```

```
summary(DataNetwork) # old dataset
##   age_OLD   height_OLD   weight_OLD   hc_OLD
##   Min.   :18.00   Min.   :145.0   Min.   : 41.00   Min.   :1.000
##   1st Qu.:22.00   1st Qu.:162.0   1st Qu.: 55.00   1st Qu.:1.000
```

```

## Median :25.00   Median :166.0   Median : 61.00   Median :1.000
## Mean :25.47    Mean :166.1   Mean : 63.45    Mean :1.459
## 3rd Qu.:29.00   3rd Qu.:170.0   3rd Qu.: 68.09   3rd Qu.:2.000
## Max. :45.00     Max. :196.2    Max. :115.00     Max. :2.000
## biolchild_OLD   FSFIdes_OLD     FSFIaro_OLD     FSFIub_OLD
## Min. :0.0000    Min. :1.200    Min. :0.000    Min. :0.000
## 1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:4.200   1st Qu.:4.800
## Median :0.0000   Median :3.000   Median :5.100   Median :5.700
## Mean :0.5296    Mean :3.256    Mean :4.482    Mean :4.927
## 3rd Qu.:1.0000   3rd Qu.:3.600   3rd Qu.:5.700   3rd Qu.:6.000
## Max. :9.0000     Max. :5.400    Max. :6.000    Max. :7.438
## FSFIorg_OLD     FSFIisat_OLD    FSFIpain_OLD    SDS_OLD
## Min. :0.000     Min. :0.281    Min. :0.000    Min. : 0.000
## 1st Qu.:2.800    1st Qu.:2.800   1st Qu.:3.600   1st Qu.: 3.000
## Median :4.788    Median :4.800   Median :5.400   Median : 7.000
## Mean :3.964     Mean :4.149    Mean :4.229    Mean : 7.502
## 3rd Qu.:5.600    3rd Qu.:5.600   3rd Qu.:6.000   3rd Qu.:11.000
## Max. :6.306     Max. :6.840    Max. :6.412    Max. :28.000
## BSIdp_OLD       BSIdanx_OLD     BI_OLD          AUDIT_OLD
## Min. : 0.000    Min. : 0.000    Min. :11.00     Min. : 0.7428
## 1st Qu.: 2.000   1st Qu.: 1.000   1st Qu.:22.00    1st Qu.: 4.0000
## Median : 4.000   Median : 3.000   Median :26.00    Median : 6.0000
## Mean : 5.375    Mean : 3.884    Mean :26.42     Mean : 7.1840
## 3rd Qu.: 8.000   3rd Qu.: 5.000   3rd Qu.:31.00    3rd Qu.: 9.0000
## Max. :24.000    Max. :23.000    Max. :45.06     Max. :31.0000
## DSFItoolittle_OLD DSFItoomuch_OLD SOI_OLD         haspartner_OLD
## Min. : 0.00     Min. :0.0000    Min. : 6.00     Min. :1.000
## 1st Qu.: 1.00    1st Qu.:0.0000   1st Qu.: 38.01    1st Qu.:2.000
## Median : 3.00     Median :0.0000   Median : 56.00    Median :2.000
## Mean : 4.58       Mean :0.1224    Mean : 62.36     Mean :1.774
## 3rd Qu.: 7.00     3rd Qu.:0.0000   3rd Qu.: 73.00    3rd Qu.:2.000
## Max. :29.00       Max. :7.6294    Max. :335.68     Max. :2.000
## SDI_groups       SDI_change
## Min. :1.000     Min. : -40.025
## 1st Qu.:1.000    1st Qu.: -7.000
## Median :2.000    Median : -1.000
## Mean :1.977     Mean : -1.092
## 3rd Qu.:3.000    3rd Qu.: 4.000
## Max. :3.000     Max. : 41.000

```

```
describe(DataNetwork) # old dataset
```

```

##          vars    n  mean    sd median trimmed  mad   min
## age_OLD          1 1692 25.47  4.87  25.00   25.16  5.19 18.00
## height_OLD       2 1692 166.07  6.22 166.00  165.98  5.93 145.00
## weight_OLD       3 1692 63.45 11.46  61.00   62.14  8.90 41.00
## hc_OLD           4 1692  1.46  0.50  1.00    1.45  0.00  1.00
## biolchild_OLD    5 1692  0.53  0.98  0.00    0.31  0.00  0.00
## FSFIdes_OLD      6 1692  3.26  0.91  3.00    3.25  0.89  1.20
## FSFIaro_OLD      7 1692  4.48  1.70  5.10    4.83  0.89  0.00
## FSFIub_OLD       8 1692  4.93  1.83  5.70    5.41  0.44  0.00
## FSFIorg_OLD      9 1692  3.96  1.94  4.79    4.20  1.80  0.00
## FSFIisat_OLD     10 1692  4.15  1.83  4.80    4.36  1.78  0.28
## FSFIpain_OLD     11 1692  4.23  2.31  5.40    4.54  0.89  0.00
## SDS_OLD          12 1692  7.50  5.52  7.00    7.03  5.93  0.00
## BSIdp_OLD        13 1692  5.38  4.55  4.00    4.77  2.97  0.00
## BSIdanx_OLD      14 1692  3.88  4.00  3.00    3.19  2.97  0.00
## BI_OLD           15 1692 26.42  6.53 26.00   26.30  7.41 11.00
## AUDIT_OLD        16 1692  7.18  4.26  6.00    6.61  2.97  0.74
## DSFItoolittle_OLD 17 1692  4.58  4.83  3.00    3.83  4.45  0.00
## DSFItoomuch_OLD   18 1692  0.12  0.57  0.00    0.00  0.00  0.00
## SOI_OLD           19 1692 62.36 39.13 56.00   56.80 25.20  6.00
## haspartner_OLD    20 1692  1.77  0.42  2.00    1.84  0.00  1.00
## SDI_groups       21 1692  1.98  0.77  2.00    1.97  1.48  1.00

```

```
## SDI_change      22 1692 -1.09  8.74 -1.00  -1.21  8.90 -40.02
##               max range skew kurtosis  se
## age_OLD        45.00 27.00 0.70    0.54 0.12
## height_OLD     196.20 51.20 0.17    0.46 0.15
## weight_OLD     115.00 74.00 1.25    2.16 0.28
## hc_OLD         2.00  1.00 0.17    -1.97 0.01
## biolchild_OLD  9.00  9.00 2.33    7.28 0.02
## FSFIde_OLD     5.40  4.20 0.07    -0.23 0.02
## FSFIaro_OLD    6.00  6.00 -1.59    1.56 0.04
## FSFIilub_OLD   7.44  7.44 -1.98    2.55 0.04
## FSFIorg_OLD    6.31  6.31 -0.79    -0.59 0.05
## FSFIisat_OLD   6.84  6.56 -0.80    -0.74 0.04
## FSFIpain_OLD   6.41  6.41 -1.05    -0.56 0.06
## SDS_OLD        28.00 28.00 0.71    0.01 0.13
## BSIddep_OLD    24.00 24.00 1.22    1.26 0.11
## BSIanx_OLD     23.00 23.00 1.85    3.95 0.10
## BI_OLD         45.06 34.06 0.16    -0.49 0.16
## AUDIT_OLD      31.00 30.26 1.33    2.14 0.10
## DSFItoolittle_OLD 29.00 29.00 1.26    1.22 0.12
## DSFItoomuch_OLD 7.63  7.63 6.37    50.41 0.01
## SOI_OLD        335.68 329.68 1.95    5.79 0.95
## haspartner_OLD 2.00  1.00 -1.31    -0.29 0.01
## SDI_groups     3.00  2.00 0.04    -1.32 0.02
## SDI_change     41.00 81.02 0.13    0.55 0.21
```

```
#####
```

```
# Subset Data into Groups#
```

```
#####
```

```
# double checked that 1 = decrease 2 = stable 3 = increase
```

```
Decrease <- subset(DataNetwork, SDI_groups==1, select=age_OLD:haspartner_OLD)
```

```
Stable <- subset(DataNetwork, SDI_groups==2, select=age_OLD:haspartner_OLD)
```

```
Increase <- subset(DataNetwork, SDI_groups==3, select=age_OLD:haspartner_OLD)
```

```
nrow(Decrease) + nrow(Stable) + nrow(Increase) # check whether everyone has been assigned
```

```
## [1] 1692
```

```
# descriptives per group
```

```
describe(Decrease)
```

```
##          vars    n   mean    sd median trimmed   mad    min    max
## age_OLD      1 522  25.63  4.86  25.00   25.31  4.45  18.00  43.00
## height_OLD   2 522 166.09  6.51 166.00  166.00  5.93 145.00 196.20
## weight_OLD   3 522  63.51 11.46  61.00   62.20 10.38  41.00 110.00
## hc_OLD       4 522   1.44  0.50   1.00   1.42  0.00   1.00   2.00
## biolchild_OLD 5 522   0.51  0.95   0.00   0.29  0.00   0.00   6.00
## FSFIde_OLD   6 522   3.46  0.88   3.60   3.46  0.89   1.20   5.40
## FSFIaro_OLD  7 522   4.72  1.56   5.40   5.07  0.89   0.00   6.00
## FSFIilub_OLD  8 522   5.15  1.63   6.00   5.60  0.00   0.00   6.00
## FSFIorg_OLD  9 522   4.15  1.85   4.80   4.40  1.78   0.00   6.00
## FSFIisat_OLD 10 522   4.20  1.81   4.80   4.43  1.78   0.28   6.84
## FSFIpain_OLD 11 522   4.34  2.29   5.40   4.67  0.89   0.00   6.05
## SDS_OLD     12 522   7.40  5.38   7.00   6.98  5.93   0.00  26.00
## BSIddep_OLD 13 522   5.34  4.59   4.00   4.68  2.97   0.00  23.00
## BSIanx_OLD  14 522   3.73  3.79   2.14   3.05  2.75   0.00  22.00
## BI_OLD      15 522  26.08  6.52  26.00  25.93  7.41  11.00  44.00
## AUDIT_OLD   16 522   7.76  4.46   7.00   7.16  4.45   1.02  26.00
## DSFItoolittle_OLD 17 522   4.99  4.88   4.00   4.34  4.45   0.00  26.00
## DSFItoomuch_OLD 18 522   0.10  0.48   0.00   0.00  0.00   0.00   4.00
## SOI_OLD     19 522  67.96 41.51  59.00  62.06 25.57   7.00 277.86
## haspartner_OLD 20 522   1.77  0.42   2.00   1.83  0.00   1.00   2.00
##          range skew kurtosis  se
## age_OLD    25.00  0.68    0.36 0.21
## height_OLD  51.20  0.17    0.55 0.28
```

```
## weight_OLD      69.00  1.23    2.05 0.50
## hc_OLD          1.00  0.25   -1.94 0.02
## biolchild_OLD   6.00  2.32    6.45 0.04
## FSFIides_OLD    4.20 -0.04   -0.18 0.04
## FSFIaro_OLD     6.00 -1.90    2.98 0.07
## FSFIilub_OLD    6.00 -2.46    4.93 0.07
## FSFIorg_OLD     6.00 -0.92   -0.27 0.08
## FSFIisat_OLD    6.56 -0.85   -0.60 0.08
## FSFIpain_OLD    6.05 -1.15   -0.35 0.10
## SDS_OLD         26.00  0.63   -0.26 0.24
## BSIddep_OLD     23.00  1.33    1.54 0.20
## BSIanx_OLD      22.00  1.76    3.32 0.17
## BI_OLD          33.00  0.18   -0.49 0.29
## AUDIT_OLD       24.98  1.25    1.58 0.20
## DSFItoolittle_OLD 26.00  1.08    0.75 0.21
## DSFItoomuch_OLD  4.00  5.48   32.58 0.02
## SOI_OLD         270.86  1.71    3.94 1.82
## haspartner_OLD  1.00 -1.25   -0.43 0.02
```

```
describe(Stable)
```

```
##          vars    n  mean    sd median trimmed  mad   min   max
## age_OLD      1 687 25.30  4.82  25.0   24.97  4.45 18.00 45.00
## height_OLD   2 687 165.99  6.03 166.0  165.85  5.93 145.00 195.00
## weight_OLD   3 687 63.16 11.24  61.0   61.91  8.90 42.00 113.00
## hc_OLD       4 687  1.47  0.50   1.0    1.46  0.00   1.00   2.00
## biolchild_OLD 5 687  0.52  0.95   0.0    0.31  0.00   0.00   6.00
## FSFIides_OLD  6 687  3.21  0.89   3.0    3.20  0.89   1.20   5.40
## FSFIaro_OLD   7 687  4.41  1.70   5.1    4.73  0.89   0.00   6.00
## FSFIilub_OLD  8 687  4.85  1.86   5.7    5.31  0.44   0.00   6.13
## FSFIorg_OLD   9 687  3.89  1.92   4.4    4.11  1.78   0.00   6.00
## FSFIisat_OLD 10 687  4.09  1.84   4.8    4.28  1.78   0.40   6.00
## FSFIpain_OLD 11 687  4.12  2.34   5.4    4.40  0.89   0.00   6.41
## SDS_OLD      12 687  7.51  5.45   7.0    7.04  5.93   0.00  28.00
## BSIddep_OLD  13 687  5.21  4.32   4.0    4.66  2.97   0.00  22.00
## BSIanx_OLD   14 687  3.87  3.98   3.0    3.19  2.97   0.00  23.00
## BI_OLD       15 687 26.49  6.29  26.0   26.35  7.01 11.00 45.00
## AUDIT_OLD    16 687  7.00  4.09   6.0    6.49  3.67  0.93 29.00
## DSFItoolittle_OLD 17 687  4.59  5.02   3.0    3.77  4.45  0.00 22.00
## DSFItoomuch_OLD 18 687  0.11  0.51   0.0    0.00  0.00  0.00  6.00
## SOI_OLD      19 687 59.28 36.79  56.0   54.44 23.72  7.00 335.68
## haspartner_OLD 20 687  1.76  0.43   2.0    1.82  0.00   1.00   2.00
##          range  skew kurtosis   se
## age_OLD      27.00  0.76    0.78 0.18
## height_OLD   50.00  0.23    0.57 0.23
## weight_OLD   71.00  1.20    2.00 0.43
## hc_OLD        1.00  0.12   -1.99 0.02
## biolchild_OLD  6.00  2.08    4.64 0.04
## FSFIides_OLD  4.20  0.13   -0.22 0.03
## FSFIaro_OLD   6.00 -1.54    1.39 0.06
## FSFIilub_OLD  6.13 -1.88    2.15 0.07
## FSFIorg_OLD   6.00 -0.75   -0.60 0.07
## FSFIisat_OLD  5.60 -0.76   -0.81 0.07
## FSFIpain_OLD  6.41 -0.96   -0.73 0.09
## SDS_OLD      28.00  0.75    0.18 0.21
## BSIddep_OLD  22.00  1.18    1.25 0.16
## BSIanx_OLD   23.00  1.92    4.42 0.15
## BI_OLD       34.00  0.22   -0.49 0.24
## AUDIT_OLD    28.07  1.21    1.77 0.16
## DSFItoolittle_OLD 22.00  1.24    0.73 0.19
## DSFItoomuch_OLD  6.00  6.12   45.88 0.02
## SOI_OLD     328.68  2.39    9.66 1.40
## haspartner_OLD  1.00 -1.20   -0.57 0.02
```

```
describe(Increase)
##          vars    n  mean    sd median trimmed   mad   min   max
## age_OLD      1 483  25.54  4.94  25.00  25.25  5.93 18.00 44.00
## height_OLD   2 483 166.18  6.18 166.00 166.13  5.93 146.00 186.00
## weight_OLD   3 483  63.81 11.77  62.00  62.41  8.90  42.00 115.00
## hc_OLD       4 483   1.46  0.50   1.00   1.45  0.00   1.00   2.00
## biolchild_OLD 5 483   0.57  1.05   0.00   0.33  0.00   0.00   9.00
## FSFIides_OLD  6 483   3.10  0.92   3.00   3.08  0.89   1.20   5.40
## FSFIaro_OLD   7 483   4.33  1.82   5.10   4.66  0.89   0.00   6.00
## FSFIilub_OLD  8 483   4.79  1.98   5.70   5.23  0.44   0.00   7.44
## FSFIorg_OLD   9 483   3.87  2.04   4.80   4.09  1.78   0.00   6.31
## FSFIisat_OLD 10 483   4.18  1.85   4.80   4.38  1.78   0.40   6.00
## FSFIpain_OLD 11 483   4.27  2.31   5.40   4.58  0.89   0.00   6.21
## SDS_OLD      12 483   7.60  5.79   7.00   7.10  5.93   0.00  27.00
## BSIddep_OLD  13 483   5.65  4.83   4.00   5.03  4.45   0.00  24.00
## BSIanx_OLD   14 483   4.08  4.24   3.00   3.34  2.97   0.00  23.00
## BI_OLD       15 483  26.67  6.85  27.00  26.62  7.41  11.00  45.06
## AUDIT_OLD    16 483   6.82  4.24   6.00   6.20  2.97   0.74  31.00
## DSFItoolittle_OLD 17 483   4.12  4.47   3.00   3.41  4.45   0.00  29.00
## DSFItoomuch_OLD 18 483   0.16  0.72   0.00   0.00  0.00   0.00   7.63
## SOI_OLD      19 483  60.69 39.16  55.75  55.08 27.80   6.00 249.00
## haspartner_OLD 20 483   1.81  0.40   2.00   1.88  0.00   1.00   2.00
##          range  skew kurtosis   se
## age_OLD      26.00  0.65    0.38 0.22
## height_OLD   40.00  0.08    0.12 0.28
## weight_OLD   73.00  1.32    2.38 0.54
## hc_OLD       1.00  0.14   -1.98 0.02
## biolchild_OLD 9.00  2.54    9.95 0.05
## FSFIides_OLD 4.20  0.16   -0.20 0.04
## FSFIaro_OLD  6.00 -1.37    0.72 0.08
## FSFIilub_OLD 7.44 -1.72    1.43 0.09
## FSFIorg_OLD  6.31 -0.70   -0.88 0.09
## FSFIisat_OLD 5.60 -0.80   -0.81 0.08
## FSFIpain_OLD 6.21 -1.06   -0.53 0.11
## SDS_OLD     27.00  0.72   -0.03 0.26
## BSIddep_OLD 24.00  1.12    0.85 0.22
## BSIanx_OLD  23.00  1.80    3.60 0.19
## BI_OLD      34.06  0.07   -0.53 0.31
## AUDIT_OLD   30.26  1.58    3.27 0.19
## DSFItoolittle_OLD 29.00  1.52    2.96 0.20
## DSFItoomuch_OLD  7.63  6.15   44.68 0.03
## SOI_OLD     243.00  1.70    3.92 1.78
## haspartner_OLD 1.00 -1.54    0.37 0.02
```

```
#####
# Random Subsamples of same size #
#####
```

```
set.seed(17) # to make sure we always get the same random sample
```

```
nrow(Decrease)
```

```
## [1] 522
```

```
nrow(Stable)
```

```
## [1] 687
```

```
nrow(Increase) # 483
```

```
## [1] 483
```

```
randomSample = function(df,n) {
  return (df[sample(nrow(df), n),])
}
```

```
DecreaseRS <- randomSample(Decrease, n = 483)
```

```
StableRS <- randomSample(Stable, n = 483)
```

```
IncreaseRS <- Increase
```

```
describe(DecreaseRS)
```

```
##          vars    n  mean    sd median trimmed  mad   min   max
## age_OLD      1 483  25.67  4.84   25.0   25.35  4.45  18.00  43.00
## height_OLD   2 483 166.20  6.44  166.0  166.10  5.93 147.00 196.20
## weight_OLD   3 483  63.58 11.33   62.0   62.29 10.38  41.00 110.00
## hc_OLD       4 483   1.43  0.50    1.0    1.42  0.00   1.00   2.00
## biolchild_OLD 5 483   0.50  0.96    0.0    0.29  0.00   0.00   6.00
## FSFIdeas_OLD  6 483   3.45  0.87    3.6    3.45  0.89   1.20   5.40
## FSFIaro_OLD   7 483   4.74  1.56    5.4    5.09  0.89   0.00   6.00
## FSFIilub_OLD  8 483   5.16  1.63    6.0    5.62  0.00   0.00   6.00
## FSFIorg_OLD   9 483   4.18  1.84    4.8    4.45  1.78   0.00   6.00
## FSFIisat_OLD 10 483   4.20  1.81    4.8    4.43  1.78   0.28   6.84
## FSFIpain_OLD 11 483   4.32  2.29    5.4    4.65  0.89   0.00   6.05
## SDS_OLD      12 483   7.34  5.30    7.0    6.92  5.93   0.00  26.00
## BSIddep_OLD  13 483   5.35  4.59    4.0    4.69  2.97   0.00  23.00
## BSIanx_OLD   14 483   3.67  3.71    2.0    3.02  2.97   0.00  22.00
## BI_OLD       15 483  26.04  6.48   26.0   25.88  7.41  11.00  44.00
## AUDIT_OLD    16 483   7.74  4.45    7.0    7.15  4.45   1.02  26.00
## DSFItoolittle_OLD 17 483   5.07  4.91    4.0    4.42  4.45   0.00  26.00
## DSFItoomuch_OLD 18 483   0.10  0.47    0.0    0.00  0.00   0.00   4.00
## SOI_OLD      19 483  68.38 42.17   59.0   62.36 26.69   7.00 277.86
## haspartner_OLD 20 483   1.76  0.43    2.0    1.83  0.00   1.00   2.00
##
##          range  skew kurtosis  se
## age_OLD      25.00  0.67    0.34 0.22
## height_OLD   49.20  0.23    0.57 0.29
## weight_OLD   69.00  1.25    2.19 0.52
## hc_OLD       1.00  0.26   -1.94 0.02
## biolchild_OLD 6.00  2.38    6.81 0.04
## FSFIdeas_OLD 4.20  0.00   -0.23 0.04
## FSFIaro_OLD  6.00 -1.94    3.14 0.07
## FSFIilub_OLD 6.00 -2.46    4.93 0.07
## FSFIorg_OLD  6.00 -0.97   -0.16 0.08
## FSFIisat_OLD 6.56 -0.85   -0.61 0.08
## FSFIpain_OLD 6.05 -1.13   -0.40 0.10
## SDS_OLD     26.00  0.66   -0.15 0.24
## BSIddep_OLD 23.00  1.35    1.69 0.21
## BSIanx_OLD  22.00  1.77    3.42 0.17
## BI_OLD      33.00  0.20   -0.41 0.30
## AUDIT_OLD   24.98  1.29    1.72 0.20
## DSFItoolittle_OLD 26.00  1.07    0.73 0.22
## DSFItoomuch_OLD  4.00  5.50   33.08 0.02
## SOI_OLD     270.86  1.69    3.81 1.92
## haspartner_OLD 1.00 -1.23   -0.50 0.02
```

```
describe(StableRS)
```

```
##          vars    n  mean    sd median trimmed  mad   min   max
## age_OLD      1 483  25.18  4.73  25.00   24.89  4.45  18.00  43.00
## height_OLD   2 483 165.93  6.13 165.02  165.69  5.96 149.00 195.00
## weight_OLD   3 483  63.21 11.11  61.00   61.92  8.90  44.00 113.00
## hc_OLD       4 483   1.47  0.50    1.00   1.46  0.00   1.00   2.00
## biolchild_OLD 5 483   0.52  0.96    0.00   0.31  0.00   0.00   6.00
## FSFIdeas_OLD  6 483   3.25  0.92    3.00   3.24  0.89   1.20   5.40
## FSFIaro_OLD   7 483   4.39  1.74    5.10   4.73  0.89   0.00   6.00
## FSFIilub_OLD  8 483   4.84  1.88    5.70   5.29  0.44   0.00   6.13
## FSFIorg_OLD   9 483   3.85  1.93    4.40   4.06  1.78   0.00   6.00
## FSFIisat_OLD 10 483   4.10  1.84    4.80   4.29  1.78   0.40   6.00
## FSFIpain_OLD 11 483   4.14  2.32    5.40   4.42  0.89   0.00   6.41
## SDS_OLD      12 483   7.44  5.48    7.00   6.95  5.93   0.00  28.00
## BSIddep_OLD  13 483   5.29  4.45    4.00   4.74  4.45   0.00  22.00
## BSIanx_OLD   14 483   3.98  4.15    3.00   3.27  2.97   0.00  23.00
## BI_OLD       15 483  26.50  6.24   26.00   26.36  5.93  11.00  44.00
## AUDIT_OLD    16 483   7.16  4.12    6.00   6.65  3.61   0.93  22.00
## DSFItoolittle_OLD 17 483   4.60  5.03    3.00   3.76  4.45   0.00  22.00
```

```
## DSFItoomuch_OLD      18 483    0.09  0.46  0.00    0.00  0.00  0.00  4.00
## SOI_OLD               19 483   60.81 37.68 56.00   55.68 23.72  7.00 335.68
## haspartner_OLD       20 483    1.76  0.43  2.00    1.82  0.00  1.00  2.00
##
## range skew kurtosis se
## age_OLD              25.00  0.63    0.41 0.22
## height_OLD           46.00  0.42    0.65 0.28
## weight_OLD           69.00  1.29    2.34 0.51
## hc_OLD               1.00  0.12   -1.99 0.02
## biolchild_OLD        6.00  2.17    5.33 0.04
## FSFIde_OLD           4.20  0.10   -0.31 0.04
## FSFIaro_OLD          6.00 -1.51    1.18 0.08
## FSFIilub_OLD         6.13 -1.85    1.99 0.09
## FSFIorg_OLD          6.00 -0.73   -0.63 0.09
## FSFIisat_OLD         5.60 -0.76   -0.78 0.08
## FSFIpain_OLD         6.41 -0.98   -0.69 0.11
## SDS_OLD              28.00  0.83    0.49 0.25
## BSIdep_OLD           22.00  1.14    1.06 0.20
## BSIanx_OLD           23.00  1.90    4.25 0.19
## BI_OLD               33.00  0.22   -0.45 0.28
## AUDIT_OLD            21.07  1.02    0.61 0.19
## DSFItoolittle_OLD    22.00  1.25    0.75 0.23
## DSFItoomuch_OLD      4.00  6.04   40.15 0.02
## SOI_OLD              328.68  2.36    9.52 1.71
## haspartner_OLD       1.00 -1.20   -0.56 0.02
```

```
describe(IncreaseRS)
```

```
## vars n mean sd median trimmed mad min max
## age_OLD      1 483 25.54 4.94 25.00 25.25 5.93 18.00 44.00
## height_OLD   2 483 166.18 6.18 166.00 166.13 5.93 146.00 186.00
## weight_OLD   3 483 63.81 11.77 62.00 62.41 8.90 42.00 115.00
## hc_OLD       4 483 1.46 0.50 1.00 1.45 0.00 1.00 2.00
## biolchild_OLD 5 483 0.57 1.05 0.00 0.33 0.00 0.00 9.00
## FSFIde_OLD   6 483 3.10 0.92 3.00 3.08 0.89 1.20 5.40
## FSFIaro_OLD  7 483 4.33 1.82 5.10 4.66 0.89 0.00 6.00
## FSFIilub_OLD 8 483 4.79 1.98 5.70 5.23 0.44 0.00 7.44
## FSFIorg_OLD  9 483 3.87 2.04 4.80 4.09 1.78 0.00 6.31
## FSFIisat_OLD 10 483 4.18 1.85 4.80 4.38 1.78 0.40 6.00
## FSFIpain_OLD 11 483 4.27 2.31 5.40 4.58 0.89 0.00 6.21
## SDS_OLD      12 483 7.60 5.79 7.00 7.10 5.93 0.00 27.00
## BSIdep_OLD   13 483 5.65 4.83 4.00 5.03 4.45 0.00 24.00
## BSIanx_OLD   14 483 4.08 4.24 3.00 3.34 2.97 0.00 23.00
## BI_OLD       15 483 26.67 6.85 27.00 26.62 7.41 11.00 45.06
## AUDIT_OLD    16 483 6.82 4.24 6.00 6.20 2.97 0.74 31.00
## DSFItoolittle_OLD 17 483 4.12 4.47 3.00 3.41 4.45 0.00 29.00
## DSFItoomuch_OLD 18 483 0.16 0.72 0.00 0.00 0.00 0.00 7.63
## SOI_OLD      19 483 60.69 39.16 55.75 55.08 27.80 6.00 249.00
## haspartner_OLD 20 483 1.81 0.40 2.00 1.88 0.00 1.00 2.00
##
## range skew kurtosis se
## age_OLD      26.00  0.65    0.38 0.22
## height_OLD    40.00  0.08    0.12 0.28
## weight_OLD    73.00  1.32    2.38 0.54
## hc_OLD        1.00  0.14   -1.98 0.02
## biolchild_OLD 9.00  2.54    9.95 0.05
## FSFIde_OLD    4.20  0.16   -0.20 0.04
## FSFIaro_OLD   6.00 -1.37    0.72 0.08
## FSFIilub_OLD  7.44 -1.72    1.43 0.09
## FSFIorg_OLD   6.31 -0.70   -0.88 0.09
## FSFIisat_OLD  5.60 -0.80   -0.81 0.08
## FSFIpain_OLD  6.21 -1.06   -0.53 0.11
## SDS_OLD       27.00  0.72   -0.03 0.26
## BSIdep_OLD    24.00  1.12    0.85 0.22
## BSIanx_OLD    23.00  1.80    3.60 0.19
## BI_OLD        34.06  0.07   -0.53 0.31
```

```
## AUDIT_OLD      30.26  1.58      3.27 0.19
## DSFItoolittle_OLD 29.00  1.52      2.96 0.20
## DSFItoomuch_OLD  7.63  6.15     44.68 0.03
## SOI_OLD        243.00  1.70      3.92 1.78
## haspartner_OLD  1.00 -1.54      0.37 0.02

table(DecreaseRS[,20])
##
##      1      2
## 115 368
table(DecreaseRS[,20])[1]/483
##      1
## 0.2380952
table(DecreaseRS[,20])[2]/483
##      2
## 0.7619048

table(StableRS[,20])
##
##      1      2
## 117 366
table(StableRS[,20])[1]/483
##      1
## 0.242236
table(StableRS[,20])[2]/483
##      2
## 0.757764

table(IncreaseRS[,20])
##
##      1      2
##  94 389
table(IncreaseRS[,20])[1]/483
##      1
## 0.194617
table(IncreaseRS[,20])[2]/483
##      2
## 0.805383
```

4. Network Estimation including Hormonal Contraception

```
#####
# 4. Network estimation #
#####
colnames(DataNetwork)
## [1] "age_OLD"      "height_OLD"    "weight_OLD"
## [4] "hc_OLD"       "biolchild_OLD" "FSFIdes_OLD"
## [7] "FSFIaro_OLD"  "FSFIlub_OLD"   "FSFIorg_OLD"
## [10] "FSFIisat_OLD" "FSFIpain_OLD"  "SDS_OLD"
## [13] "BSIdep_OLD"   "BSIanx_OLD"    "BI_OLD"
## [16] "AUDIT_OLD"    "DSFItoolittle_OLD" "DSFItoomuch_OLD"
## [19] "SOI_OLD"      "haspartner_OLD" "SDI_groups"
## [22] "SDI_change"

VarDomain <- c("g", "g", "g", "c",
               "p", "g", "g",
               "g", "g", "g",
               "g", "g", "g",
               "g", "g", "g",
               "g", "g", "g",
               "c")
```

```

VarLevel <- c(1,1,1,2,
             1,1,1,
             1,1,1,
             1,1,1,
             1,1,1,
             1,1,1,
             2)

library(mgm)

fit_Decrease <- mgm(data = as.matrix(DecreaseRS),
                   type = VarDomain,
                   level = VarLevel,
                   k = 2,
                   lambdaSel = 'EBIC',
                   lambdaGam = 0.5) # hyper parameter

fit_Stable <- mgm(data = as.matrix(StableRS),
                  type = VarDomain,
                  level = VarLevel,
                  k = 2,
                  lambdaSel = 'EBIC',
                  lambdaGam = 0.5) # hyper parameter

fit_Increase <- mgm(data = as.matrix(IncreaseRS),
                    type = VarDomain,
                    level = VarLevel,
                    k = 2,
                    lambdaSel = 'EBIC',
                    lambdaGam = 0.5) # hyper parameter

#####
# Predictive Strength #
#####

pred_Decrease <- predict(fit_Decrease,
                        DecreaseRS,
                        errorCon = 'R2') #save R2 into an object (varExpl = cont var)

pred_Stable <- predict(fit_Stable,
                      StableRS,
                      errorCon = 'R2') #save R2 into an object (varExpl = cont var)

pred_Increase <- predict(fit_Increase,
                        IncreaseRS,
                        errorCon = 'R2') #save R2 into an object (varExpl = cont var)

predR_Decrease <- pred_Decrease$errors$error.R2
predR_Decrease <- as.numeric(as.character(predR_Decrease))

predR_Stable <- pred_Stable$errors$error.R2
predR_Stable <- as.numeric(as.character(predR_Stable))

predR_Increase <- pred_Increase$errors$error.R2
predR_Increase <- as.numeric(as.character(predR_Increase))

# set 'predictability' of categorical variables

predR_Decrease[4] <- pred_Decrease$errors$error.CC[4]
predR_Stable[4] <- pred_Stable$errors$error.CC[4]
predR_Increase[4] <- pred_Increase$errors$error.CC[4]
predR_Decrease[20] <- pred_Decrease$errors$error.CC[20]
predR_Stable[20] <- pred_Stable$errors$error.CC[20]

```

```

predR_Increase[20] <- pred_Increase$errors$error.CC[20]

mean(predR_Decrease, na.rm = TRUE) # mean variance explained across all nodes
## [1] 0.4168
sd(predR_Decrease, na.rm = TRUE)
## [1] 0.2517671

pred_Decrease$errors
##           Variable Error.R2 Error.CC Error.nCC CCmarg
## 1         age_OLD   0.255      NA      NA      NA
## 2        height_OLD   0.100      NA      NA      NA
## 3        weight_OLD   0.241      NA      NA      NA
## 4           hc_OLD     NA    0.631    0.152  0.565
## 5    biolchild_OLD   0.256      NA      NA      NA
## 6      FSFIde_OLD   0.208      NA      NA      NA
## 7      FSFIaro_OLD   0.828      NA      NA      NA
## 8      FSFIub_OLD   0.774      NA      NA      NA
## 9      FSFIorg_OLD   0.505      NA      NA      NA
## 10     FSFIst_OLD   0.666      NA      NA      NA
## 11     FSFIpain_OLD   0.599      NA      NA      NA
## 12         SDS_OLD   0.286      NA      NA      NA
## 13     BSIdp_OLD   0.541      NA      NA      NA
## 14     BSIanx_OLD   0.449      NA      NA      NA
## 15         BI_OLD   0.326      NA      NA      NA
## 16     AUDIT_OLD   0.198      NA      NA      NA
## 17 DSFItoolittle_OLD   0.452      NA      NA      NA
## 18 DSFItoomuch_OLD   0.040      NA      NA      NA
## 19         SOI_OLD   0.111      NA      NA      NA
## 20    haspartner_OLD     NA    0.870    0.452  0.763

mean(predR_Stable, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.43065
sd(predR_Stable, na.rm = TRUE)
## [1] 0.2675724

pred_Stable$errors
##           Variable Error.R2 Error.CC Error.nCC CCmarg
## 1         age_OLD   0.300      NA      NA      NA
## 2        height_OLD   0.138      NA      NA      NA
## 3        weight_OLD   0.171      NA      NA      NA
## 4           hc_OLD     NA    0.530    0.000  0.530
## 5    biolchild_OLD   0.299      NA      NA      NA
## 6      FSFIde_OLD   0.299      NA      NA      NA
## 7      FSFIaro_OLD   0.870      NA      NA      NA
## 8      FSFIub_OLD   0.814      NA      NA      NA
## 9      FSFIorg_OLD   0.526      NA      NA      NA
## 10     FSFIst_OLD   0.768      NA      NA      NA
## 11     FSFIpain_OLD   0.660      NA      NA      NA
## 12         SDS_OLD   0.261      NA      NA      NA
## 13     BSIdp_OLD   0.535      NA      NA      NA
## 14     BSIanx_OLD   0.420      NA      NA      NA
## 15         BI_OLD   0.163      NA      NA      NA
## 16     AUDIT_OLD   0.214      NA      NA      NA
## 17 DSFItoolittle_OLD   0.547      NA      NA      NA
## 18 DSFItoomuch_OLD   0.026      NA      NA      NA
## 19         SOI_OLD   0.167      NA      NA      NA
## 20    haspartner_OLD     NA    0.905    0.607  0.758

mean(predR_Increase, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4575
sd(predR_Increase, na.rm = TRUE)
## [1] 0.267907

```

```

pred_Increase$errors
##          Variable Error.R2 Error.CC Error.nCC CCmarg
## 1         age_OLD   0.283      NA      NA      NA
## 2        height_OLD 0.166      NA      NA      NA
## 3        weight_OLD 0.208      NA      NA      NA
## 4          hc_OLD    NA    0.536    0.000 0.536 # nCC is the relative improvement
## 5    biolchild_OLD 0.315      NA      NA      NA
## 6      FSFIde_OLD 0.336      NA      NA      NA
## 7      FSFIaro_OLD 0.880      NA      NA      NA
## 8      FSFIub_OLD 0.850      NA      NA      NA
## 9      FSFIorg_OLD 0.595      NA      NA      NA
## 10     FSFIisat_OLD 0.779      NA      NA      NA
## 11     FSFIpain_OLD 0.657      NA      NA      NA
## 12      SDS_OLD    0.393      NA      NA      NA
## 13     BSIdep_OLD 0.587      NA      NA      NA
## 14     BSIanx_OLD 0.541      NA      NA      NA
## 15       BI_OLD    0.316      NA      NA      NA
## 16     AUDIT_OLD 0.201      NA      NA      NA
## 17 DSFItoolittle_OLD 0.426      NA      NA      NA
## 18 DSFItoomuch_OLD 0.031      NA      NA      NA
## 19       SOI_OLD    0.110      NA      NA      NA
## 20   haspartner_OLD    NA    0.940    0.691 0.806 # first is total last is intercept m
odel

```

5. Network Visualization including Hormonal Contraception

```

#####
# Network Layout Specifics #
#####

colNames <- c("Age", "Height", "Weight", "HC", "Child", "Des", "Aro",
             "Lub", "Org", "Sat", "Pain", "Distr", "Dep", "Anx",
             "Body", "Alc", "Little", "Much", "SO", "Rel")

nodeDescr <- c("", "", "", "", "Number of children", "Desire",
               "Arousal", "Lubrication", "Orgasm", "Satisfaction", "Pain",
               "Sexually related personal distress", "Depression", "Anxiety",
               "Body image and dissatisfaction", "(Hazardous) Alcohol use",
               "Too little sexual scitivity", "Too much sexual activity",
               "Tendency/attitudes to(wards) uncommitted sexual relationships",
               "Relationship status (partnered or single)")

groupsNoHc <- list(Demographics = c(1:5, 20),
                  Female_Sexual_Function_Index = c(6:11),
                  Sexual_Distress_Scale = c(12),
                  Brief_Symptom_Inventory = c(13:14),
                  Derogatis_Sexual_Function_Inventory = c(15),
                  Alcohol_Use_Disorders_Identification_Test = c(16),
                  Desired_and_Actual_Sexual_Activity_Scale = c(17:18),
                  Sociosexual_Orientation_Inventory = c(19))

nodeLabelColors <- c("white", "white", "white", "white", "white",
                    "white", "white", "white", "white", "white", "white",
                    "white",
                    "white", "white",
                    "black", "black", "black", "black", "black",
                    "white")

#Plot Networks including hormonal contraception

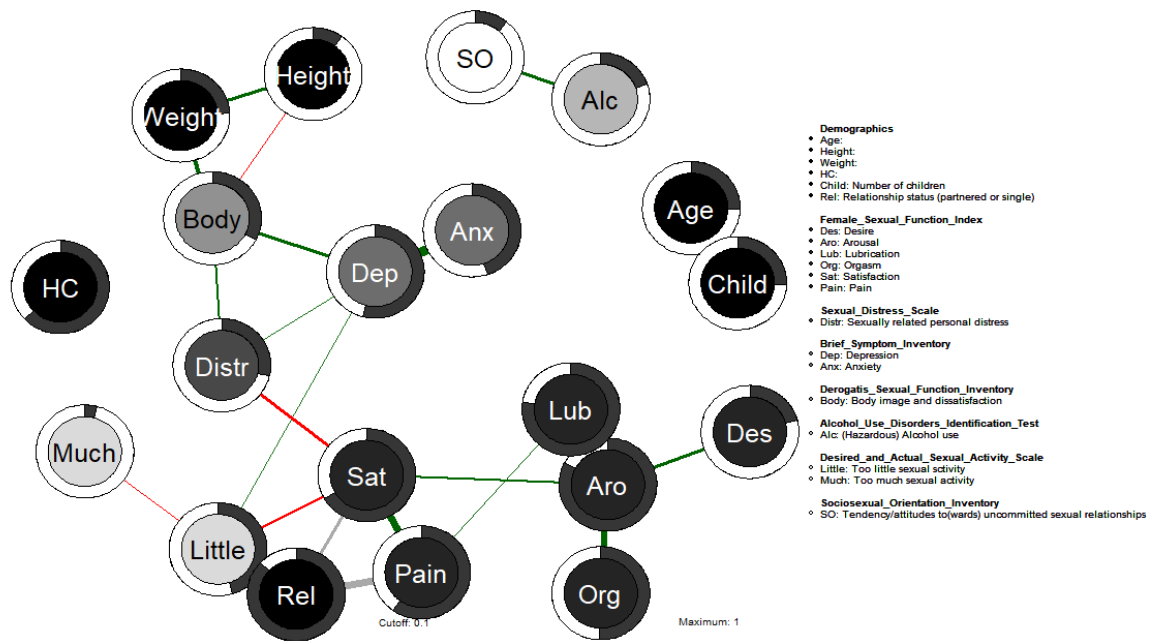
library(qgraph)
qgraph(fit_Decrease$pairwise$wadj,

```

```

edge.color = fit_Decrease$pairwise$edgecolor,
layout = 'spring',
labels = colNames,
maximum = 1,
minimum = 0,
cut = 0.1,
details = TRUE,
vsize = 9,
label.cex = 1.2,
label.scale.equal = TRUE,
pie = predR_Decrease,
pieColor = "gray21",
pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,
legend.mode = "style1",
legend.cex = 0.3,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



```

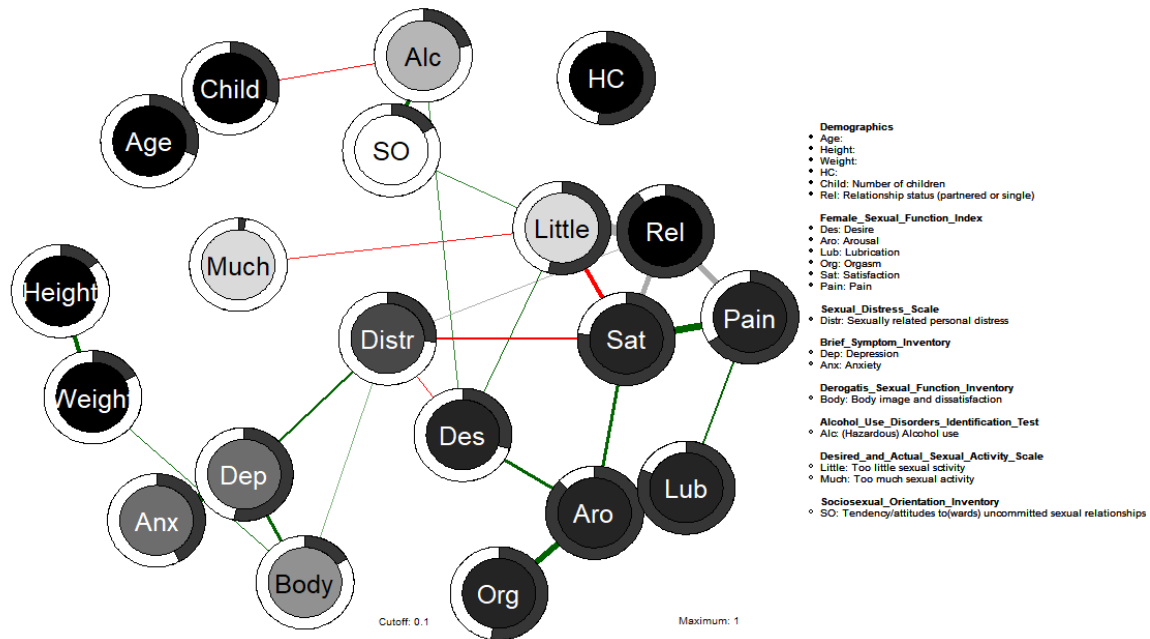
qgraph(fit_Stable$pairwise$wadj,
edge.color = fit_Stable$pairwise$edgecolor,
layout = 'spring',
labels = colNames,
maximum = 1,
minimum = 0,
cut = 0.1,
details = TRUE,
vsize = 9,
label.cex = 1.2,
label.scale.equal = TRUE,
pie = predR_Stable,
pieColor = "gray21",
pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,

```

```

legend.mode = "style1",
legend.cex = 0.3,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

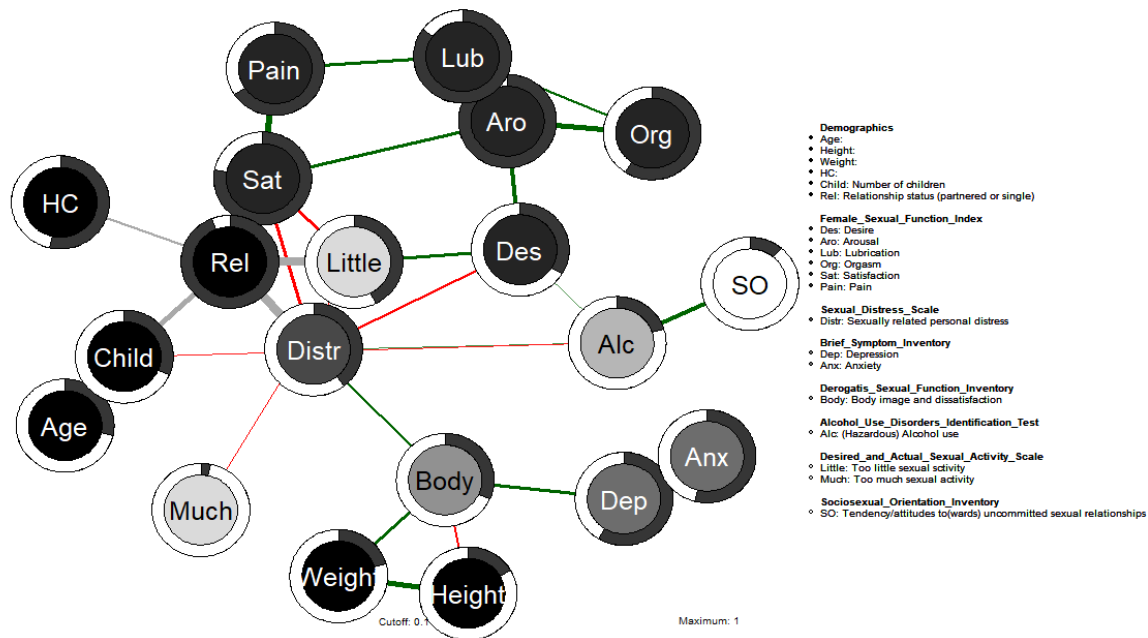
```



```

qgraph(fit_Increase$pairwise$wadj,
edge.color = fit_Increase$pairwise$edgecolor,
layout = 'spring',
labels = colNames,
maximum = 1,
minimum = 0,
cut = 0.1,
details = TRUE,
vsize = 9,
label.cex = 1.2,
label.scale.equal = TRUE,
pie = predR_Increase,
pieColor = "gray21",
pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,
legend.mode = "style1",
legend.cex = 0.3,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



6. Network Estimation excluding Hormonal Contraception

```
#####
# get rid of HC ####
#####
# We decided to exclude hormonal contraception from the main analysis since it only related to
# relationship status in the increase group - such an unconnected node can lead to problems
# with the centrality computation

DataNetwork <- DataNetwork[,-4]

colnames(DataNetwork)
## [1] "age_OLD" "height_OLD" "weight_OLD"
## [4] "biolchild_OLD" "FSFIdes_OLD" "FSFIaro_OLD"
## [7] "FSFILub_OLD" "FSFIorg_OLD" "FSFIsat_OLD"
## [10] "FSFIpain_OLD" "SDS_OLD" "BSIdep_OLD"
## [13] "BSIanx_OLD" "BI_OLD" "AUDIT_OLD"
## [16] "DSFIttoolittle_OLD" "DSFIttoomuch_OLD" "SOI_OLD"
## [19] "haspartner_OLD" "SDI_groups" "SDI_change"

#####
# Subset Data into Groups#
#####
# double checked that 1 = decrease 2 = stable 3 = increase
Decrease <- subset(DataNetwork, SDI_groups==1, select=age_OLD:haspartner_OLD)
Stable <- subset(DataNetwork, SDI_groups==2, select=age_OLD:haspartner_OLD)
Increase <- subset(DataNetwork, SDI_groups==3, select=age_OLD:haspartner_OLD)

nrow(Decrease) + nrow(Stable) + nrow(Increase) # check whether everyone has been assigned
## [1] 1692

#####
# Random Subsamples of same size #
#####

set.seed(17) # to make sure we always get the same sample...
nrow(Decrease)
```

```
## [1] 522
nrow(Stable)
## [1] 687
nrow(Increase) # 483
## [1] 483

randomSample = function(df,n) {
  return (df[sample(nrow(df), n),])
}

DecreaseRS <- randomSample(Decrease, n = 483)
StableRS <- randomSample(Stable, n = 483)
IncreaseRS <- Increase

describe(DecreaseRS)
##          vars    n  mean    sd median trimmed   mad   min   max
## age_OLD          1 483  25.67  4.84   25.0   25.35  4.45  18.00  43.00
## height_OLD        2 483 166.20  6.44  166.0  166.10  5.93 147.00 196.20
## weight_OLD         3 483  63.58 11.33   62.0   62.29 10.38  41.00 110.00
## biolchild_OLD      4 483   0.50  0.96   0.0    0.29  0.00   0.00   6.00
## FSFIde_OLD         5 483   3.45  0.87   3.6    3.45  0.89   1.20   5.40
## FSFIaro_OLD        6 483   4.74  1.56   5.4    5.09  0.89   0.00   6.00
## FSFIub_OLD         7 483   5.16  1.63   6.0    5.62  0.00   0.00   6.00
## FSFIorg_OLD         8 483   4.18  1.84   4.8    4.45  1.78   0.00   6.00
## FSFIst_OLD         9 483   4.20  1.81   4.8    4.43  1.78   0.28   6.84
## FSFIpain_OLD       10 483   4.32  2.29   5.4    4.65  0.89   0.00   6.05
## SDS_OLD           11 483   7.34  5.30   7.0    6.92  5.93   0.00  26.00
## BSIdep_OLD        12 483   5.35  4.59   4.0    4.69  2.97   0.00  23.00
## BSIanx_OLD        13 483   3.67  3.71   2.0    3.02  2.97   0.00  22.00
## BI_OLD            14 483  26.04  6.48  26.0   25.88  7.41  11.00  44.00
## AUDIT_OLD         15 483   7.74  4.45   7.0    7.15  4.45   1.02  26.00
## DSFItoolittle_OLD  16 483   5.07  4.91   4.0    4.42  4.45   0.00  26.00
## DSFItoomuch_OLD   17 483   0.10  0.47   0.0    0.00  0.00   0.00   4.00
## SOI_OLD           18 483  68.38 42.17  59.0   62.36 26.69   7.00 277.86
## haspartner_OLD    19 483   1.76  0.43   2.0    1.83  0.00   1.00   2.00
##          range  skew kurtosis    se
## age_OLD      25.00  0.67    0.34 0.22
## height_OLD   49.20  0.23    0.57 0.29
## weight_OLD   69.00  1.25    2.19 0.52
## biolchild_OLD 6.00  2.38    6.81 0.04
## FSFIde_OLD   4.20  0.00   -0.23 0.04
## FSFIaro_OLD  6.00 -1.94    3.14 0.07
## FSFIub_OLD   6.00 -2.46    4.93 0.07
## FSFIorg_OLD  6.00 -0.97   -0.16 0.08
## FSFIst_OLD   6.56 -0.85   -0.61 0.08
## FSFIpain_OLD 6.05 -1.13   -0.40 0.10
## SDS_OLD     26.00  0.66   -0.15 0.24
## BSIdep_OLD   23.00  1.35    1.69 0.21
## BSIanx_OLD   22.00  1.77    3.42 0.17
## BI_OLD      33.00  0.20   -0.41 0.30
## AUDIT_OLD    24.98  1.29    1.72 0.20
## DSFItoolittle_OLD 26.00  1.07    0.73 0.22
## DSFItoomuch_OLD  4.00  5.50   33.08 0.02
## SOI_OLD     270.86  1.69    3.81 1.92
## haspartner_OLD 1.00 -1.23   -0.50 0.02

describe(StableRS)
##          vars    n  mean    sd median trimmed   mad   min   max
## age_OLD          1 483  25.18  4.73  25.00   24.89  4.45  18.00  43.00
## height_OLD        2 483 165.93  6.13 165.02  165.69  5.96 149.00 195.00
## weight_OLD         3 483  63.21 11.11  61.00   61.92  8.90  44.00 113.00
## biolchild_OLD      4 483   0.52  0.96   0.00   0.31  0.00   0.00   6.00
## FSFIde_OLD         5 483   3.25  0.92   3.00   3.24  0.89   1.20   5.40
```

```
## FSFIaro_OLD      6 483  4.39  1.74  5.10  4.73  0.89  0.00  6.00
## FSFIilub_OLD     7 483  4.84  1.88  5.70  5.29  0.44  0.00  6.13
## FSFIorg_OLD      8 483  3.85  1.93  4.40  4.06  1.78  0.00  6.00
## FSFIisat_OLD     9 483  4.10  1.84  4.80  4.29  1.78  0.40  6.00
## FSFIpain_OLD    10 483  4.14  2.32  5.40  4.42  0.89  0.00  6.41
## SDS_OLD         11 483  7.44  5.48  7.00  6.95  5.93  0.00 28.00
## BSIdep_OLD      12 483  5.29  4.45  4.00  4.74  4.45  0.00 22.00
## BSIanx_OLD      13 483  3.98  4.15  3.00  3.27  2.97  0.00 23.00
## BI_OLD          14 483 26.50  6.24 26.00 26.36  5.93 11.00 44.00
## AUDIT_OLD       15 483  7.16  4.12  6.00  6.65  3.61  0.93 22.00
## DSFItoolittle_OLD 16 483  4.60  5.03  3.00  3.76  4.45  0.00 22.00
## DSFItoomuch_OLD 17 483  0.09  0.46  0.00  0.00  0.00  0.00  4.00
## SOI_OLD         18 483 60.81 37.68 56.00 55.68 23.72  7.00 335.68
## haspartner_OLD  19 483  1.76  0.43  2.00  1.82  0.00  1.00  2.00
##
##                range  skew kurtosis  se
## age_OLD          25.00  0.63    0.41 0.22
## height_OLD       46.00  0.42    0.65 0.28
## weight_OLD       69.00  1.29    2.34 0.51
## biolchild_OLD    6.00  2.17    5.33 0.04
## FSFIides_OLD     4.20  0.10   -0.31 0.04
## FSFIaro_OLD      6.00 -1.51    1.18 0.08
## FSFIilub_OLD     6.13 -1.85    1.99 0.09
## FSFIorg_OLD      6.00 -0.73   -0.63 0.09
## FSFIisat_OLD     5.60 -0.76   -0.78 0.08
## FSFIpain_OLD     6.41 -0.98   -0.69 0.11
## SDS_OLD          28.00  0.83    0.49 0.25
## BSIdep_OLD       22.00  1.14    1.06 0.20
## BSIanx_OLD       23.00  1.90    4.25 0.19
## BI_OLD           33.00  0.22   -0.45 0.28
## AUDIT_OLD        21.07  1.02    0.61 0.19
## DSFItoolittle_OLD 22.00  1.25    0.75 0.23
## DSFItoomuch_OLD  4.00  6.04   40.15 0.02
## SOI_OLD          328.68  2.36    9.52 1.71
## haspartner_OLD   1.00 -1.20   -0.56 0.02
```

```
describe(IncreaseRS)
```

```
##                vars    n  mean    sd median trimmed  mad    min    max
## age_OLD          1 483  25.54  4.94  25.00  25.25  5.93  18.00  44.00
## height_OLD       2 483 166.18  6.18 166.00 166.13  5.93 146.00 186.00
## weight_OLD       3 483  63.81 11.77  62.00  62.41  8.90  42.00 115.00
## biolchild_OLD    4 483   0.57  1.05   0.00   0.33  0.00   0.00   9.00
## FSFIides_OLD     5 483   3.10  0.92   3.00   3.08  0.89   1.20  5.40
## FSFIaro_OLD      6 483   4.33  1.82   5.10   4.66  0.89   0.00  6.00
## FSFIilub_OLD     7 483   4.79  1.98   5.70   5.23  0.44   0.00  7.44
## FSFIorg_OLD      8 483   3.87  2.04   4.80   4.09  1.78   0.00  6.31
## FSFIisat_OLD     9 483   4.18  1.85   4.80   4.38  1.78   0.40  6.00
## FSFIpain_OLD    10 483   4.27  2.31   5.40   4.58  0.89   0.00  6.21
## SDS_OLD         11 483   7.60  5.79   7.00   7.10  5.93   0.00 27.00
## BSIdep_OLD      12 483   5.65  4.83   4.00   5.03  4.45   0.00 24.00
## BSIanx_OLD      13 483   4.08  4.24   3.00   3.34  2.97   0.00 23.00
## BI_OLD          14 483  26.67  6.85  27.00  26.62  7.41  11.00 45.06
## AUDIT_OLD       15 483   6.82  4.24   6.00   6.20  2.97   0.74 31.00
## DSFItoolittle_OLD 16 483   4.12  4.47   3.00   3.41  4.45   0.00 29.00
## DSFItoomuch_OLD 17 483   0.16  0.72   0.00   0.00  0.00   0.00  7.63
## SOI_OLD         18 483  60.69 39.16  55.75  55.08 27.80   6.00 249.00
## haspartner_OLD  19 483   1.81  0.40   2.00   1.88  0.00   1.00  2.00
##
##                range  skew kurtosis  se
## age_OLD          26.00  0.65    0.38 0.22
## height_OLD       40.00  0.08    0.12 0.28
## weight_OLD       73.00  1.32    2.38 0.54
## biolchild_OLD    9.00  2.54    9.95 0.05
## FSFIides_OLD     4.20  0.16   -0.20 0.04
## FSFIaro_OLD      6.00 -1.37    0.72 0.08
```

```

## FSFIlub_OLD      7.44 -1.72      1.43 0.09
## FSFIorg_OLD      6.31 -0.70     -0.88 0.09
## FSFIisat_OLD     5.60 -0.80     -0.81 0.08
## FSFIpain_OLD     6.21 -1.06     -0.53 0.11
## SDS_OLD          27.00  0.72     -0.03 0.26
## BSIdiep_OLD      24.00  1.12      0.85 0.22
## BSIanx_OLD       23.00  1.80      3.60 0.19
## BI_OLD           34.06  0.07     -0.53 0.31
## AUDIT_OLD        30.26  1.58      3.27 0.19
## DSFItoolittle_OLD 29.00  1.52      2.96 0.20
## DSFItoomuch_OLD  7.63  6.15     44.68 0.03
## SOI_OLD          243.00  1.70      3.92 1.78
## haspartner_OLD   1.00 -1.54      0.37 0.02

table(DecreaseRS[,19]) # same random sample!
##
##      1      2
## 115 368
table(DecreaseRS[,19])[1]/483
##      1
## 0.2380952
table(DecreaseRS[,19])[2]/483
##      2
## 0.7619048

table(StableRS[,19])
##
##      1      2
## 117 366
table(StableRS[,19])[1]/483
##      1
## 0.242236
table(StableRS[,19])[2]/483
##      2
## 0.757764

table(IncreaseRS[,19])
##
##      1      2
##  94 389
table(IncreaseRS[,19])[1]/483
##      1
## 0.194617
table(IncreaseRS[,19])[2]/483
##      2
## 0.805383

#####
# Network estimation #
#####

colnames(DataNetwork)
## [1] "age_OLD"      "height_OLD"    "weight_OLD"
## [4] "biolchild_OLD" "FSFIides_OLD"  "FSFIaro_OLD"
## [7] "FSFIlub_OLD"  "FSFIorg_OLD"   "FSFIisat_OLD"
## [10] "FSFIpain_OLD" "SDS_OLD"       "BSIdiep_OLD"
## [13] "BSIanx_OLD"   "BI_OLD"        "AUDIT_OLD"
## [16] "DSFItoolittle_OLD" "DSFItoomuch_OLD" "SOI_OLD"
## [19] "haspartner_OLD" "SDI_groups"    "SDI_change"

VarDomain <- c("g", "g", "g",
               "p", "g", "g",
               "g", "g", "g",

```

```

      "g", "g", "g",
      "g", "g", "g",
      "g", "g", "g",
      "c")

VarLevel <- c(1,1,1,
             1,1,1,
             1,1,1,
             1,1,1,
             1,1,1,
             1,1,1,
             2)

library(mgm)

fit_Decrease <- mgm(data = as.matrix(DecreaseRS),
                   type = VarDomain,
                   level = VarLevel,
                   k = 2,
                   lambdaSel = 'EBIC',
                   lambdaGam = 0.5) # hyper parameter

fit_Stable <- mgm(data = as.matrix(StableRS),
                  type = VarDomain,
                  level = VarLevel,
                  k = 2,
                  lambdaSel = 'EBIC',
                  lambdaGam = 0.5) # hyper parameter

fit_Increase <- mgm(data = as.matrix(IncreaseRS),
                    type = VarDomain,
                    level = VarLevel,
                    k = 2,
                    lambdaSel = 'EBIC',
                    lambdaGam = 0.5) # hyper parameter

#####
# Predictive Strength ##
#####

pred_Decrease <- predict(fit_Decrease,
                        DecreaseRS,
                        errorCon = 'R2') #save R2 into an object (varExpl = cont var)

pred_Stable <- predict(fit_Stable,
                      StableRS,
                      errorCon = 'R2') #save R2 into an object (varExpl = cont var)

pred_Increase <- predict(fit_Increase,
                        IncreaseRS,
                        errorCon = 'R2') #save R2 into an object (varExpl = cont var)

predR_Decrease <- pred_Decrease$errors$error.R2
predR_Decrease <- as.numeric(as.character(predR_Decrease))

predR_Stable <- pred_Stable$errors$error.R2
predR_Stable <- as.numeric(as.character(predR_Stable))

predR_Increase <- pred_Increase$errors$error.R2
predR_Increase <- as.numeric(as.character(predR_Increase))

# set 'predictability' of categorical variable
predR_Decrease[19] <- pred_Decrease$errors$error.CC[19]

```

```

predR_Stable[19] <- pred_Stable$errors$error.CC[19]
predR_Increase[19] <- pred_Increase$errors$error.CC[19]

mean(predR_Decrease, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4055263
sd(predR_Decrease, na.rm = TRUE)
## [1] 0.2534266

pred_Decrease$errors
##      Variable Error.R2 Error.CC Error.nCC CCmarg
## 1      age_OLD   0.255      NA      NA      NA
## 2     height_OLD   0.100      NA      NA      NA
## 3     weight_OLD   0.241      NA      NA      NA
## 4  biolchild_OLD   0.256      NA      NA      NA
## 5   FSFides_OLD   0.208      NA      NA      NA
## 6   FSFIaro_OLD   0.828      NA      NA      NA
## 7   FSFIlub_OLD   0.774      NA      NA      NA
## 8   FSFIorg_OLD   0.505      NA      NA      NA
## 9   FSFisat_OLD   0.666      NA      NA      NA
## 10  FSFIpain_OLD   0.599      NA      NA      NA
## 11    SDS_OLD     0.286      NA      NA      NA
## 12   BSIdcp_OLD   0.541      NA      NA      NA
## 13   BSIanx_OLD   0.449      NA      NA      NA
## 14    BI_OLD      0.326      NA      NA      NA
## 15   AUDIT_OLD    0.198      NA      NA      NA
## 16 DSFItoolittle_OLD 0.452      NA      NA      NA
## 17 DSFItoomuch_OLD   0.040      NA      NA      NA
## 18    SOI_OLD      0.111      NA      NA      NA
## 19  haspartner_OLD    NA      0.87    0.452 0.763

mean(predR_Stable, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4295789
sd(predR_Stable, na.rm = TRUE)
## [1] 0.2742941

pred_Stable$errors
##      Variable Error.R2 Error.CC Error.nCC CCmarg
## 1      age_OLD   0.300      NA      NA      NA
## 2     height_OLD   0.138      NA      NA      NA
## 3     weight_OLD   0.171      NA      NA      NA
## 4  biolchild_OLD   0.299      NA      NA      NA
## 5   FSFides_OLD   0.306      NA      NA      NA
## 6   FSFIaro_OLD   0.870      NA      NA      NA
## 7   FSFIlub_OLD   0.814      NA      NA      NA
## 8   FSFIorg_OLD   0.526      NA      NA      NA
## 9   FSFisat_OLD   0.768      NA      NA      NA
## 10  FSFIpain_OLD   0.680      NA      NA      NA
## 11    SDS_OLD     0.271      NA      NA      NA
## 12   BSIdcp_OLD   0.535      NA      NA      NA
## 13   BSIanx_OLD   0.420      NA      NA      NA
## 14    BI_OLD      0.163      NA      NA      NA
## 15   AUDIT_OLD    0.239      NA      NA      NA
## 16 DSFItoolittle_OLD 0.549      NA      NA      NA
## 17 DSFItoomuch_OLD   0.029      NA      NA      NA
## 18    SOI_OLD      0.167      NA      NA      NA
## 19  haspartner_OLD    NA    0.917    0.658 0.757

mean(predR_Increase, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4515263
sd(predR_Increase, na.rm = TRUE)
## [1] 0.2759063

pred_Increase$errors

```

##	Variable	Error.R2	Error.CC	Error.nCC	CCmarg
## 1	age_OLD	0.283	NA	NA	NA
## 2	height_OLD	0.166	NA	NA	NA
## 3	weight_OLD	0.208	NA	NA	NA
## 4	biolchild_OLD	0.286	NA	NA	NA
## 5	FSFIdes_OLD	0.336	NA	NA	NA
## 6	FSFIaro_OLD	0.880	NA	NA	NA
## 7	FSFIlub_OLD	0.850	NA	NA	NA
## 8	FSFIorg_OLD	0.595	NA	NA	NA
## 9	FSFIsat_OLD	0.779	NA	NA	NA
## 10	FSFIpain_OLD	0.657	NA	NA	NA
## 11	SDS_OLD	0.393	NA	NA	NA
## 12	BSIdep_OLD	0.587	NA	NA	NA
## 13	BSIanx_OLD	0.541	NA	NA	NA
## 14	BI_OLD	0.308	NA	NA	NA
## 15	AUDIT_OLD	0.201	NA	NA	NA
## 16	DSFItoolittle_OLD	0.426	NA	NA	NA
## 17	DSFItoomuch_OLD	0.031	NA	NA	NA
## 18	SOI_OLD	0.110	NA	NA	NA
## 19	haspartner_OLD	NA	0.942	0.702	0.805

7. Network Visualization excluding Hormonal Contraception

```
#####
# Network Layout Specifics #
#####

colNames <- c("Age", "Height", "Weight", "Child", "Des", "Aro",
              "Lub", "Org", "Sat", "Pain", "Distr", "Dep", "Anx",
              "Body", "Alc", "Little", "Much", "SO", "Rel")

nodeDescr <- c("", "", "", "Number of children", "Desire",
               "Arousal", "Lubrication", "Orgasm", "Satisfaction", "Pain",
               "Sexually related personal distress", "Depression", "Anxiety",
               "Body image and dissatisfaction", "(Hazardous) Alcohol use",
               "Too little sexual activity", "Too much sexual activity",
               "Tendency/attitudes to(wards) uncommitted sexual relationships",
               "Relationship status (partnered or single)")

groupsNoHc <- list(Demographics = c(1:4,19),
                   Female_Sexual_Function_Index = c(5:10),
                   Sexual_Distress_Scale = c(11),
                   Brief_Symptom_Inventory = c(12:13),
                   Derogatis_Sexual_Function_Inventory = c(14),
                   Alcohol_Use_Disorders_Identification_Test = c(15),
                   Desired_and_Actual_Sexual_Activity_Scale = c(16:17),
                   Sociosexual_Orientation_Inventory = c(18))

nodeLabelColors <- c("white", "white", "white", "white",
                    "white", "white", "white", "white", "white", "white",
                    "white",
                    "white", "white",
                    "black", "black", "black", "black", "black",
                    "white")

#Plot Networks
# We adjusted the visualization so that the edges are also in gray-scale and so that negative
# edges are visualized as dashed edges

library(qgraph)
```

```

fit_Decrease$pairwise$edgecolor[which(fit_Decrease$pairwise$edgecolor=="red")]<- "gray50"
fit_Decrease$pairwise$edgecolor[which(fit_Decrease$pairwise$edgecolor=="darkgreen")]<- "gray70"
fit_Decrease$pairwise$edgecolor[which(fit_Decrease$pairwise$edgecolor=="darkgrey")]<- "black"
fit_Decrease$pairwise$edgecolor[c(16),19] <- "gray50" # categ relationship
fit_Decrease$pairwise$edgecolor[c(19),16] <- "gray50"
fit_Decrease$pairwise$edgecolor[c(9,10),19] <- "gray70"
fit_Decrease$pairwise$edgecolor[19,c(9,10)] <- "gray70"
fit_Decrease$pairwise$wadj[which(fit_Decrease$pairwise$edgecolor=="gray50")] <- fit_Decrease$pairwise$wadj[which(fit_Decrease$pairwise$edgecolor=="gray50")]*-1

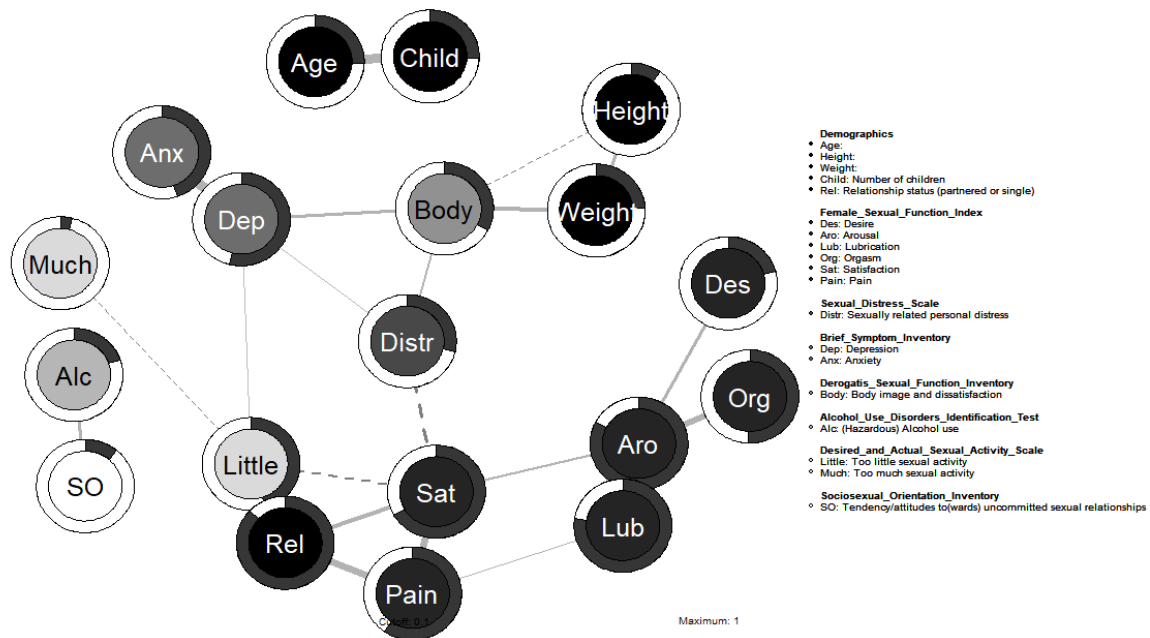
fit_Decrease$pairwise$wadj[which(fit_Decrease$pairwise$edgecolor=="gray50")]
## [1] -0.1200629 -0.1844332 -0.1624988 -0.1844332 -0.1200629 -0.1624988
## [7] -0.1121987 -0.7201683 -0.1121987 -0.7201683

fit_Decrease$pairwise$wadj[c(16),19]
## [1] -0.7201683

fit_Decrease$pairwise$wadj[19, 16]
## [1] -0.7201683

qDecrease <- qgraph(fit_Decrease$pairwise$wadj,
  edge.color = fit_Decrease$pairwise$edgecolor,
  layout = 'spring',
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 9,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_Decrease,
  pieColor = "gray21",
  pieBorder = 0.25,
  groups = groupsNoHc,
  nodeNames = nodeDescr,
  legend = TRUE,
  legend.mode = "style1",
  legend.cex = 0.5,
  palette = "gray",
  negDashed = TRUE,
  label.color = nodeLabelColors)

```



```

fit_Stable$pairwise$edgecolor[which(fit_Stable$pairwise$edgecolor=="red")]<- "gray50"
fit_Stable$pairwise$edgecolor[which(fit_Stable$pairwise$edgecolor=="darkgreen")]<- "gray70"
fit_Stable$pairwise$edgecolor[which(fit_Stable$pairwise$edgecolor=="darkgrey")]<- "black"
fit_Stable$pairwise$edgecolor[c(16),19] <- "gray50" # categ relationship
fit_Stable$pairwise$edgecolor[c(19),16] <- "gray50"
fit_Stable$pairwise$edgecolor[c(9,10,4,11),19] <- "gray70"
fit_Stable$pairwise$edgecolor[19,c(9,10,4,11)] <- "gray70"
fit_Stable$pairwise$wadj[which(fit_Stable$pairwise$edgecolor=="gray50")] <- fit_Stable$pairwise
$wadj[which(fit_Stable$pairwise$edgecolor=="gray50")]*-1

fit_Stable$pairwise$wadj[which(fit_Stable$pairwise$edgecolor=="gray50")]
## [1] -0.1315370 -0.1247692 -0.1668837 -0.2775090 -0.1247692 -0.1668837
## [7] -0.1315370 -0.2775090 -0.1068109 -0.6522733 -0.1068109 -0.6522733

fit_Stable$pairwise$wadj[c(9,10,4,11),19]
## [1] 0.4016786 0.4042179 0.2631987 0.2038407

fit_Stable$pairwise$wadj[c(16),19]
## [1] -0.6522733

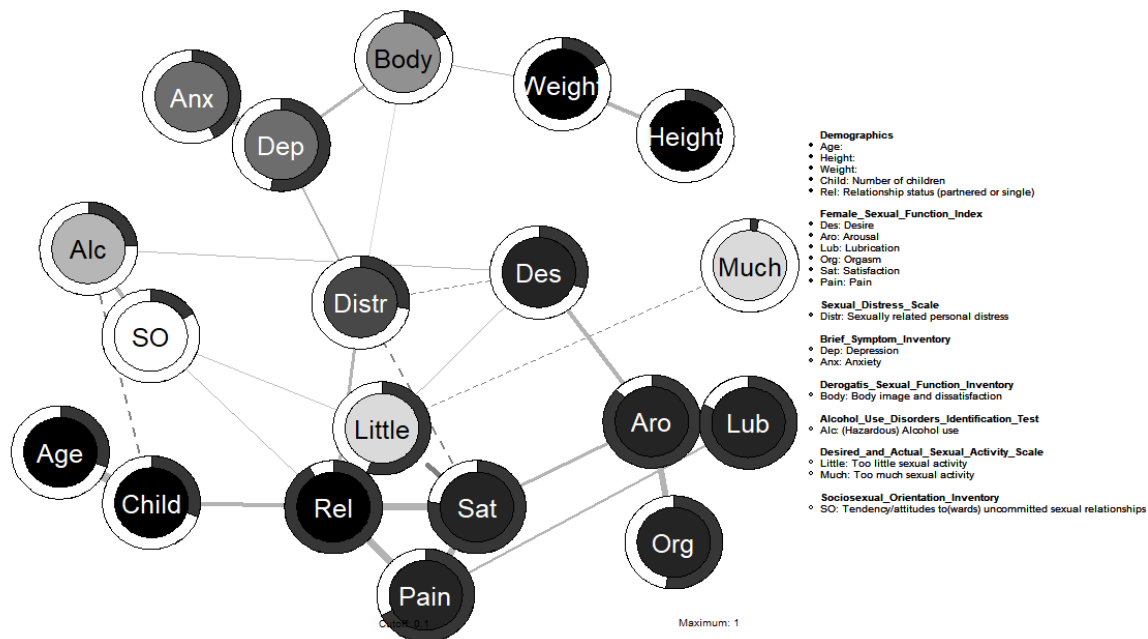
qStable <- qgraph(fit_Stable$pairwise$wadj,
  edge.color = fit_Stable$pairwise$edgecolor,
  layout = 'spring',
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 9,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_Stable,
  pieColor = "gray21",
  pieBorder = 0.25,
  groups = groupsNoHc,
  nodeNames = nodeDescr,
  legend = TRUE,
  legend.mode = "style1",

```

```

legend.cex = 0.5,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



```

fit_Increase$pairwise$edgecolor[which(fit_Increase$pairwise$edgecolor=="red")]<- "gray50"
fit_Increase$pairwise$edgecolor[which(fit_Increase$pairwise$edgecolor=="darkgreen")]<- "gray70"
fit_Increase$pairwise$edgecolor[which(fit_Increase$pairwise$edgecolor=="darkgrey")]<- "black"
fit_Increase$pairwise$edgecolor[c(16),19] <- "gray50" # categ relationship
fit_Increase$pairwise$edgecolor[c(19),16] <- "gray50"
fit_Increase$pairwise$edgecolor[c(9,4,11),19] <- "gray70"
fit_Increase$pairwise$edgecolor[19,c(9,4,11)] <- "gray70"
fit_Increase$pairwise$wadj[which(fit_Increase$pairwise$edgecolor=="gray50")] <- fit_Increase$pa
irwise$wadj[which(fit_Increase$pairwise$edgecolor=="gray50")]*-1

fit_Increase$pairwise$wadj[which(fit_Increase$pairwise$edgecolor=="gray50")]
## [1] -0.1529757 -0.1063900 -0.1759594 -0.2062433 -0.2153194 -0.1759594
## [7] -0.2062433 -0.1529757 -0.1063900 -0.2153194 -0.1191332 -0.4778137
## [13] -0.1191332 -0.4778137

fit_Increase$pairwise$wadj[c(19),16]
## [1] -0.4778137

fit_Increase$pairwise$wadj[16, 19]
## [1] -0.4778137

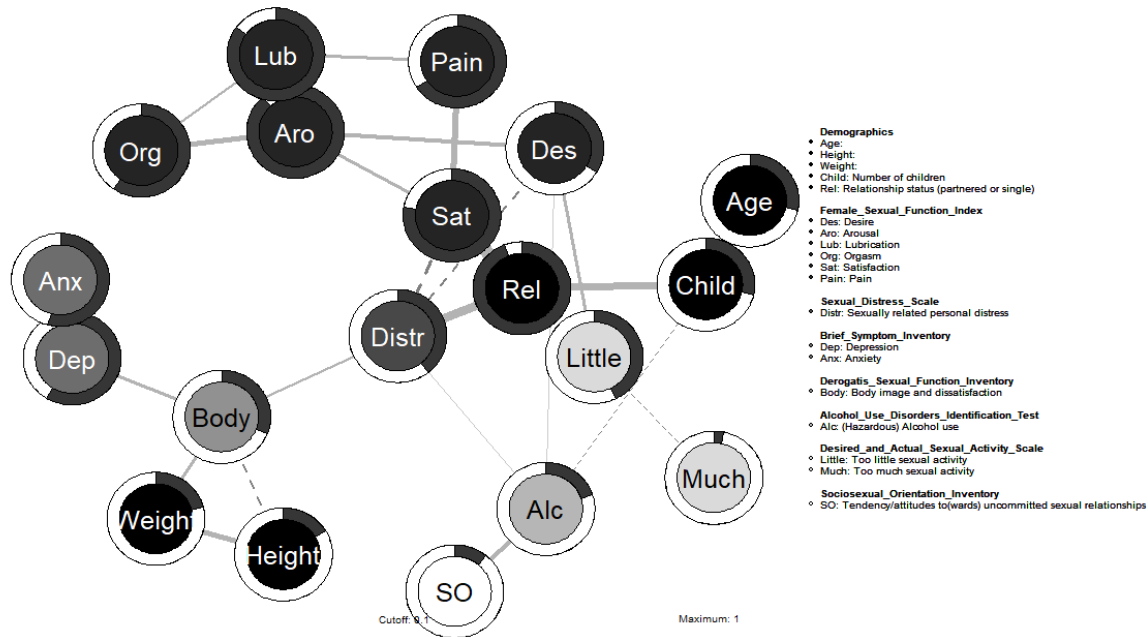
qIncrease <- qgraph(fit_Increase$pairwise$wadj,
  edge.color = fit_Increase$pairwise$edgecolor,
  layout = 'spring',
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 9,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_Increase,
  pieColor = "gray21",

```

```

pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,
legend.mode = "style1",
legend.cex = 0.5,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



```

length(qDecrease$Edgelist$weight)
## [1] 22
length(qStable$Edgelist$weight)
## [1] 28
length(qIncrease$Edgelist$weight)
## [1] 27

LayoutAverage <- averageLayout(qDecrease, qStable, qIncrease)
LayoutAverage
##           [,1]           [,2]
## [1,] -0.11530750 -1.000000000
## [2,] -1.00000000 0.0322473495
## [3,] -0.85772120 0.3954204609
## [4,] 0.10621364 -0.782882333
## [5,] 0.06047028 0.4589610011
## [6,] 0.47985819 0.7147809183
## [7,] 0.75187419 0.6374354693
## [8,] 0.18336058 1.0000000000
## [9,] 0.67935638 0.0586519881
## [10,] 1.00000000 -0.0006634476
## [11,] 0.05954809 -0.3086100067
## [12,] -0.54064749 -0.5866338083
## [13,] -0.81726660 -0.5840684455
## [14,] -0.54255762 -0.0567517604
## [15,] -0.42461600 0.5310292915
## [16,] 0.37896893 -0.1213227140
## [17,] 0.65704109 -0.8224269149
## [18,] -0.41163631 0.9333091298
## [19,] 0.59209635 -0.3196238530

```

```
LayoutAverage[16,1] <- LayoutAverage[16,1]-0.15 # Move the "little" node to make edges visible
LayoutAverage[16,2] <- -0.0006634476
```

```
LayoutAverage
##           [,1]           [,2]
## [1,] -0.11530750 -1.0000000000
## [2,] -1.00000000  0.0322473495
## [3,] -0.85772120  0.3954204609
## [4,]  0.10621364 -0.7828882333
## [5,]  0.06047028  0.4589610011
## [6,]  0.47985819  0.7147809183
## [7,]  0.75187419  0.6374354693
## [8,]  0.18336058  1.0000000000
## [9,]  0.67935638  0.0586519881
## [10,] 1.00000000 -0.0006634476
## [11,]  0.05954809 -0.3086100067
## [12,] -0.54064749 -0.5866338083
## [13,] -0.81726660 -0.5840684455
## [14,] -0.54255762 -0.0567517604
## [15,] -0.42461600  0.5310292915
## [16,]  0.22896893 -0.0006634476
## [17,]  0.65704109 -0.8224269149
## [18,] -0.41163631  0.9333091298
## [19,]  0.59209635 -0.3196238530
```

```
pdf('FSFINetworkWithPrednoHCGrayScale.pdf', width = 55, height = 15)
par(mfrow = c(1,3))
```

```
qDecrease2 <- qgraph(fit_Decrease$pairwise$wadj,
  edge.color = fit_Decrease$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 10,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_Decrease,
  pieColor = "gray21",
  pieBorder = 0.25,
  groups = groupsNoHc,
  nodeNames = nodeDescr,
  legend = TRUE,
  legend.mode = "style1",
  legend.cex = 0.5,
  palette = "gray",
  negDashed = TRUE,
  label.color = nodeLabelColors,
  repulsion = 2)
```

```
qStable2 <- qgraph(fit_Stable$pairwise$wadj,
  edge.color = fit_Stable$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 10,
  label.cex = 1.2,
  label.scale.equal = TRUE,
```

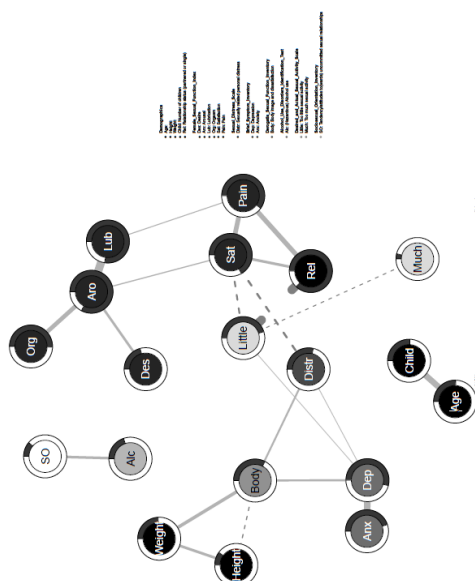
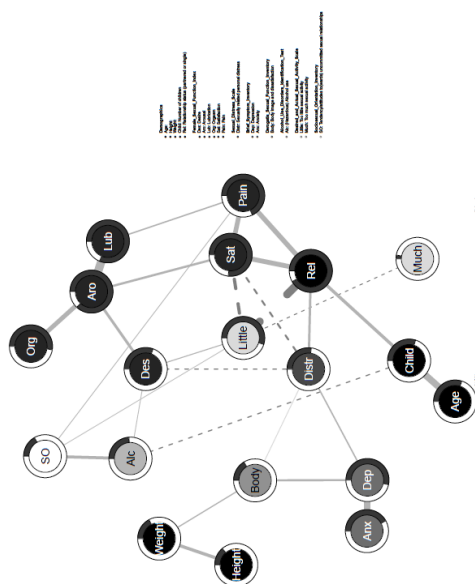
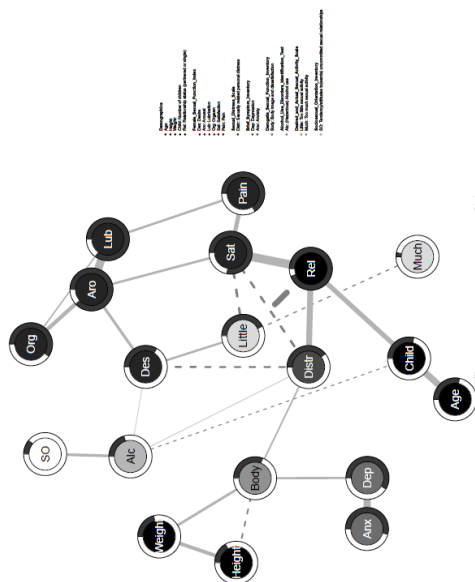
```

        pie = predR_Stable,
        pieColor = "gray21",
        pieBorder = 0.25,
        groups = groupsNoHc,
        nodeNames = nodeDescr,
        legend = TRUE,
        legend.mode = "style1",
        legend.cex = 0.5,
        palette = "gray",
        negDashed = TRUE,
        label.color = nodeLabelColors,
        repulsion = 2)

qIncrease2 <- qgraph(fit_Increase$pairwise$wadj,
                     edge.color = fit_Increase$pairwise$edgecolor,
                     layout = LayoutAverage,
                     labels = colNames,
                     maximum = 1,
                     minimum = 0,
                     cut = 0.1,
                     details = TRUE,
                     vsize = 10,
                     label.cex = 1.2,
                     label.scale.equal = TRUE,
                     pie = predR_Increase,
                     pieColor = "gray21",
                     pieBorder = 0.25,
                     groups = groupsNoHc,
                     nodeNames = nodeDescr,
                     legend = TRUE,
                     legend.mode = "style1",
                     legend.cex = 0.5,
                     palette = "gray",
                     negDashed = TRUE,
                     label.color = nodeLabelColors,
                     repulsion = 2)

dev.off()
## png
## 2

```



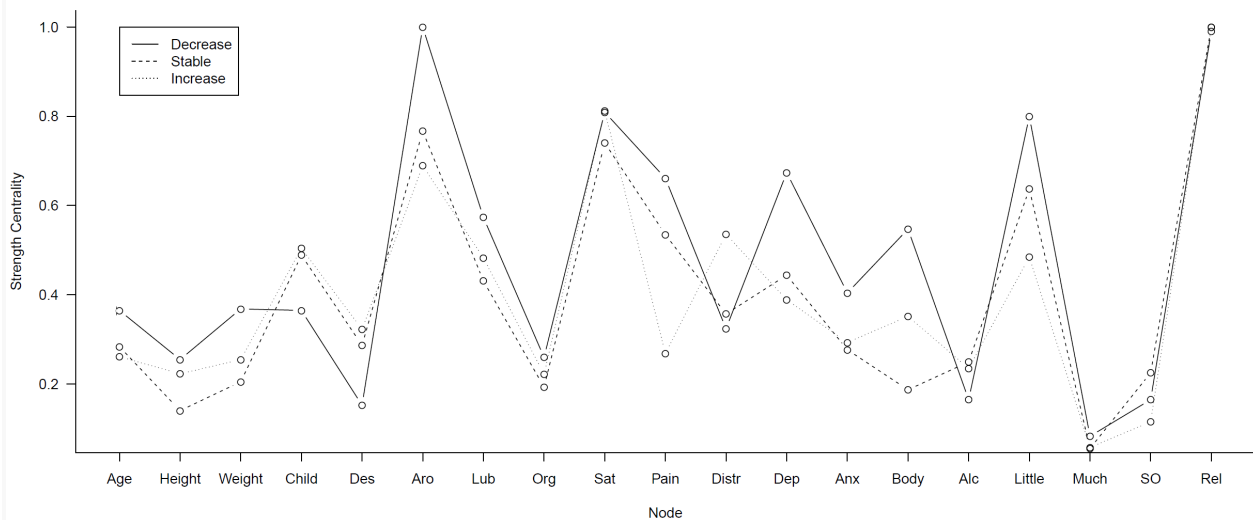
```

par(mfrow = c(1,1))

# CUSTOM MADE CENTRALITY PLOT
cenDecrease <- centralityTable(qDecrease2, standardized = FALSE, relative = TRUE)
cenIncrease <- centralityTable(qIncrease2, standardized = FALSE, relative = TRUE)
cenStable <- centralityTable(qStable2, standardized = FALSE, relative = TRUE)

pdf("CustomCentralityFSFINetwork.pdf", width = 15, height = 7)
plot(cenDecrease$value[39:57],
     type = "b",
     bty = "n",
     family = "sans",
     las = 1,
     lwd = 1,
     xaxt="n",
     xlab = "Node",
     ylab = "Strength Centrality")
axis(side = 1, labels = colNames, at = c(1:19))
lines(cenIncrease$value[39:57], type = "b", lty = "dotted")
lines(cenStable$value[39:57], type = "b", lty = "dashed")
legend(x = 1, legend=c("Decrease", "Stable", "Increase"),
      lty=c("solid", "dashed", "dotted"))
dev.off()
## png
## 2

```



```

#####
# RETRIEVE EDGE WEIGHTS CATERGORICAL (Relationship Status)
# Decrease Network
fit_Decrease$rawfactor$indicator[[1]][13,] # 9 and 19 satisfaction
## [1] 9 19
fit_Decrease$rawfactor$indicator[[1]][14,] # 10 and 19 pain
## [1] 10 19
fit_Decrease$rawfactor$indicator[[1]][22,] # 16 and 19 too little
## [1] 16 19
fit_Decrease$rawfactor$weights[[1]][13]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.2 0.2562422
##

```

```

## [[1]][[2]]
## [1] -0.1982032  0.1982032
fit_Decrease$rawfactor$weights[[1]][14]
## [[1]]
## [[1]][[1]]
##          [,1]
## V19.2 0.4611961
##
## [[1]][[2]]
## [1] -0.3254598  0.3254598
fit_Decrease$rawfactor$weights[[1]][22]
## [[1]]
## [[1]][[1]]
##          [,1]
## V19.2 -0.9094696
##
## [[1]][[2]]
## [1]  0.530867 -0.530867

# Stable Network
fit_Stable$rawfactor$indicator[[1]][5,] # 4 child
## [1]  4 19
fit_Stable$rawfactor$indicator[[1]][17,] # 9 satisfaction
## [1]  9 19
fit_Stable$rawfactor$indicator[[1]][19,] # 10 pain
## [1] 10 19
fit_Stable$rawfactor$indicator[[1]][22,] # 11 distress
## [1] 11 19
fit_Stable$rawfactor$indicator[[1]][28,] # 16 too little
## [1] 16 19
fit_Stable$rawfactor$weights[[1]][5]
## [[1]]
## [[1]][[1]]
##          [,1]
## V19.2 0.4400181
##
## [[1]][[2]]
## [1] -0.08637923  0.08637923
fit_Stable$rawfactor$weights[[1]][17]
## [[1]]
## [[1]][[1]]
##          [,1]
## V19.2 0.2881257
##
## [[1]][[2]]
## [1] -0.5152314  0.5152314
fit_Stable$rawfactor$weights[[1]][19]
## [[1]]
## [[1]][[1]]
##          [,1]
## V19.2 0.4640637
##
## [[1]][[2]]
## [1] -0.3443721  0.3443721
fit_Stable$rawfactor$weights[[1]][22]
## [[1]]
## [[1]][[1]]
##          [,1]
## V19.2 0.1816205
##
## [[1]][[2]]
## [1] -0.226061  0.226061
fit_Stable$rawfactor$weights[[1]][28]

```

```
## [[1]]
## [[1]][[1]]
##           [,1]
## V19.2 -0.8035653
##
## [[1]][[2]]
## [1] 0.5009813 -0.5009813

# Increase Network
fit_Increase$rawfactor$indicator[[1]][6,] # 4 child
## [1] 4 19
fit_Increase$rawfactor$indicator[[1]][19,] # 10 pain
## [1] 9 19
fit_Increase$rawfactor$indicator[[1]][22,] # 11 distress
## [1] 11 19
fit_Increase$rawfactor$indicator[[1]][27,] # 16 too little
## [1] 16 19
fit_Increase$rawfactor$weights[[1]][6]
## [[1]]
## [[1]][[1]]
##           [,1]
## V19.2 0.4287313
##
## [[1]][[2]]
## [1] -0.3607776 0.3607776
fit_Increase$rawfactor$weights[[1]][19]
## [[1]]
## [[1]][[1]]
##           [,1]
## V19.2 0.5852141
##
## [[1]][[2]]
## [1] -0.8122344 0.8122344
fit_Increase$rawfactor$weights[[1]][22]
## [[1]]
## [[1]][[1]]
##           [,1]
## V19.2 0.6671867
##
## [[1]][[2]]
## [1] -0.3205457 0.3205457
fit_Increase$rawfactor$weights[[1]][27]
## [[1]]
## [[1]][[1]]
##           [,1]
## V19.2 -0.6792773
##
## [[1]][[2]]
## [1] 0.2763501 -0.2763501
```

8. Network Stability

```
#####
# BOOTNET
library(bootnet)
fit_DecreaseBoot <- estimateNetwork(as.matrix(DecreaseRS),
                                   default = "mgm",
                                   type = VarDomain,
                                   lev = VarLevel,
                                   degree = 2,
                                   criterion = "EBIC",
                                   tuning = 0.5)
```

```

fit_StableBoot <- estimateNetwork(as.matrix(StableRS),
                                default = "mgm",
                                type = VarDomain,
                                lev = VarLevel,
                                degree = 2,
                                criterion = "EBIC",
                                tuning = 0.5)

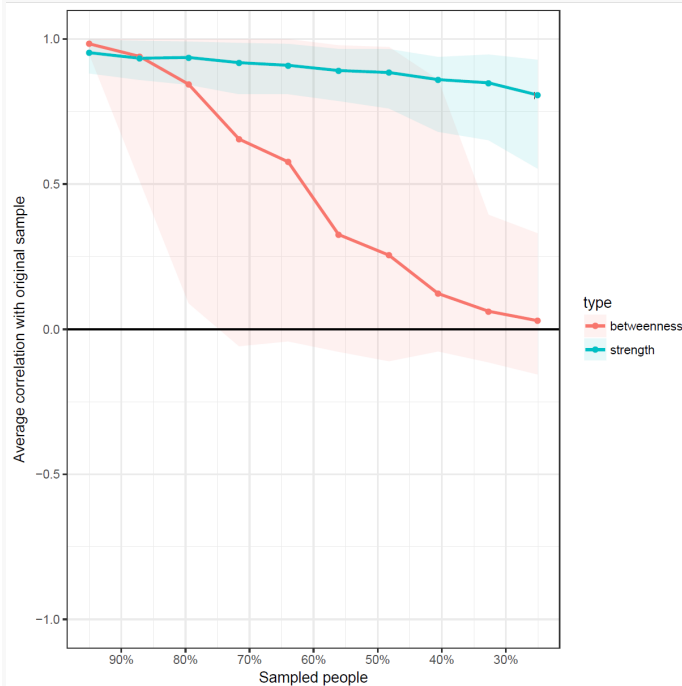
fit_IncreaseBoot <- estimateNetwork(as.matrix(IncreaseRS),
                                    default = "mgm",
                                    type = VarDomain,
                                    lev = VarLevel,
                                    degree = 2,
                                    criterion = "EBIC",
                                    tuning = 0.5)

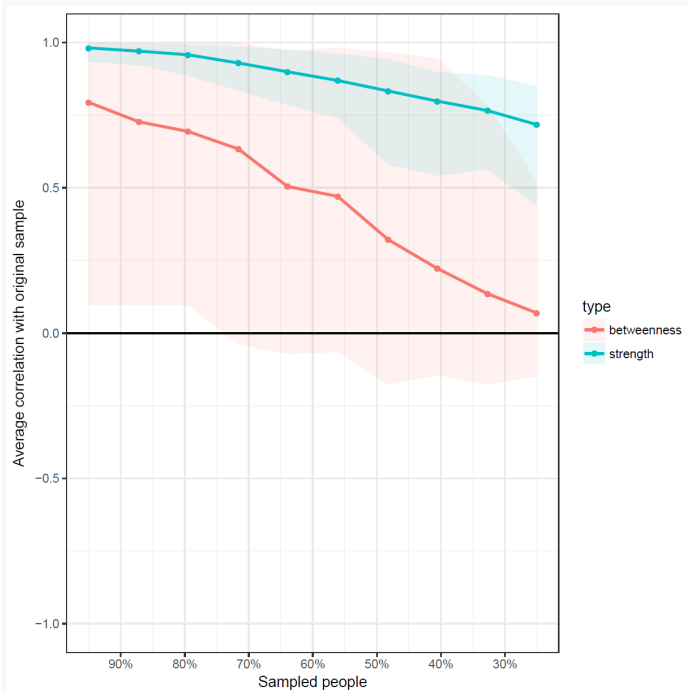
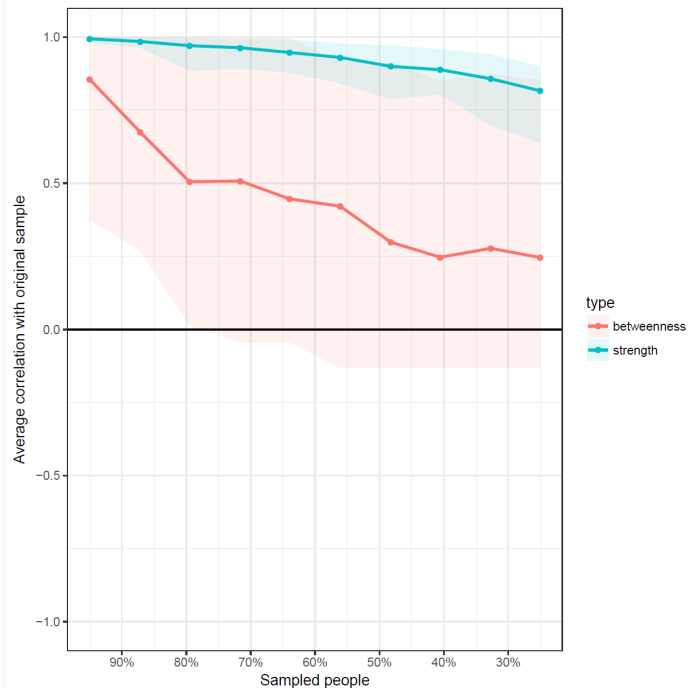
fit_DecreaseBoot1 <- bootnet(fit_DecreaseBoot, nBoots = 1000, nCores = 8, type = "case")

fit_StableBoot1 <- bootnet(fit_StableBoot, nBoots = 1000, nCores = 8, type = "case")

fit_IncreaseBoot1 <- bootnet(fit_IncreaseBoot, nBoots = 1000, nCores = 8, type = "case")
pdf("CentralityStability.pdf")
plot(fit_DecreaseBoot1)
## Warning in plot.bootnet(fit_DecreaseBoot1): Statistic closeness does not
## contain any variance and is therefore not shown.
plot(fit_StableBoot1)
## Warning in plot.bootnet(fit_StableBoot1): Statistic closeness does not
## contain any variance and is therefore not shown.
plot(fit_IncreaseBoot1)
## Warning in plot.bootnet(fit_IncreaseBoot1): Statistic closeness does not
## contain any variance and is therefore not shown.
dev.off()
## png
## 2

```





```
corStability(fit_DecreaseBoot1)
## == Correlation Stability Analysis ==
##
## Sampling levels tested:
##   nPerson Drop%   n
## 1      121  74.9  96
## 2      158  67.3  84
## 3      196  59.4 109
## 4      233  51.8 127
## 5      271  43.9 114
## 6      309  36.0 102
## 7      346  28.4  93
```

```

## 8      384  20.5  99
## 9      421  12.8  93
## 10     459   5.0  83
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:
##
## betweenness: 0.05
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.128)
##
## closeness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## strength: 0.673
##   - For more accuracy, run bootnet(..., caseMin = 0.594, caseMax = 0.749)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.

corStability(fit_StableBoot1)
## === Correlation Stability Analysis ===
##
## Sampling levels tested:
##   nPerson Drop%   n
## 1      121  74.9 113
## 2      158  67.3  97
## 3      196  59.4  99
## 4      233  51.8 104
## 5      271  43.9 116
## 6      309  36.0  97
## 7      346  28.4  99
## 8      384  20.5  87
## 9      421  12.8  93
## 10     459   5.0  95
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:
##
## betweenness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## closeness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## strength: 0.749
##   - For more accuracy, run bootnet(..., caseMin = 0.673, caseMax = 1)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.

corStability(fit_IncreaseBoot1)
## === Correlation Stability Analysis ===
##
## Sampling levels tested:
##   nPerson Drop%   n
## 1      121  74.9  85
## 2      158  67.3 100
## 3      196  59.4  96
## 4      233  51.8  97
## 5      271  43.9 100
## 6      309  36.0 111
## 7      346  28.4 105
## 8      384  20.5 100
## 9      421  12.8  99
## 10     459   5.0 107
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:

```

```

##
## betweenness: 0
## - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## closeness: 0
## - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## strength: 0.518
## - For more accuracy, run bootnet(..., caseMin = 0.439, caseMax = 0.594)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.

fit_DecreaseBoot2 <- bootnet(fit_DecreaseBoot, nBoots = 1000, nCores = 8)

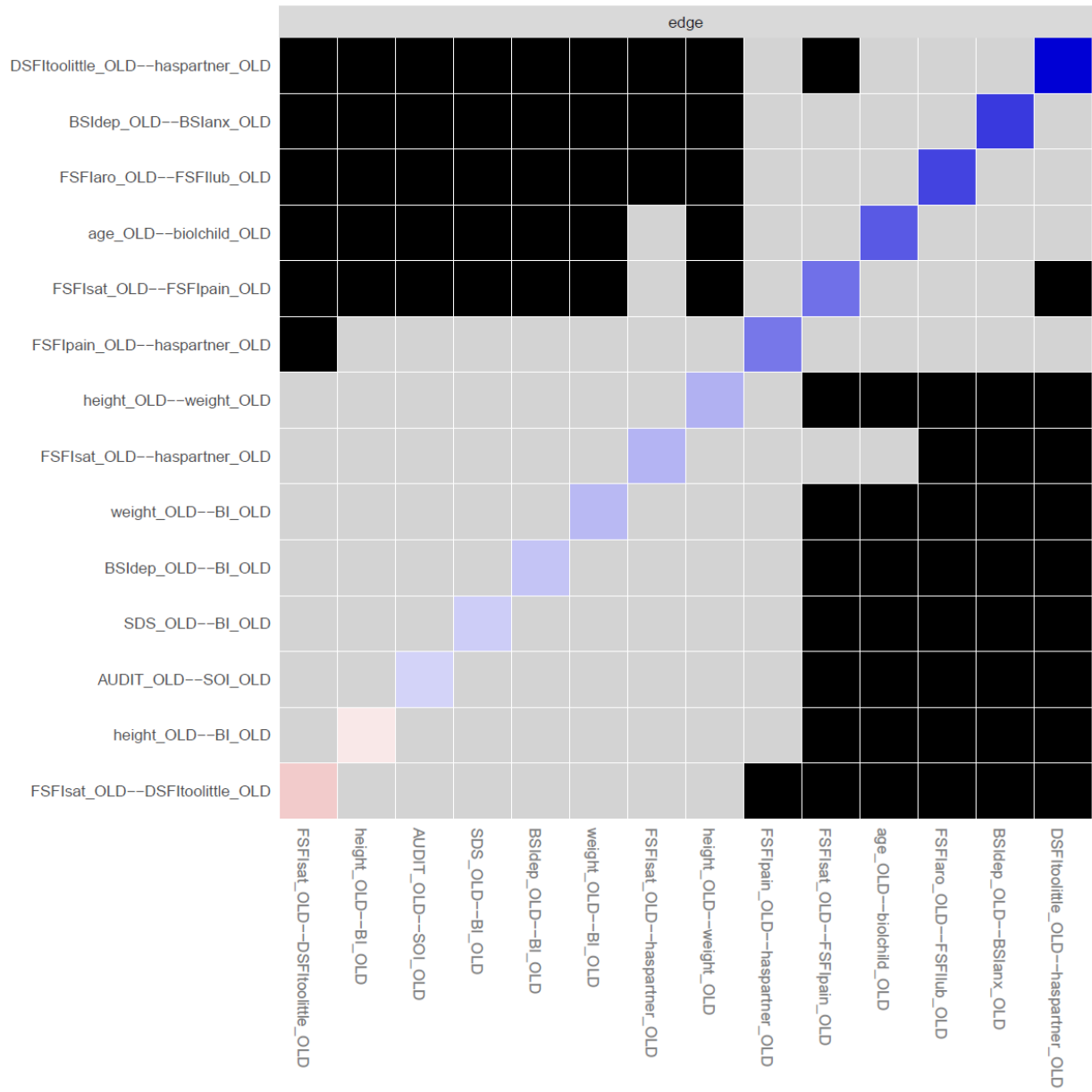
fit_StableBoot2 <- bootnet(fit_StableBoot, nBoots = 1000, nCores = 8)

fit_IncreaseBoot2 <- bootnet(fit_IncreaseBoot, nBoots = 1000, nCores = 8)

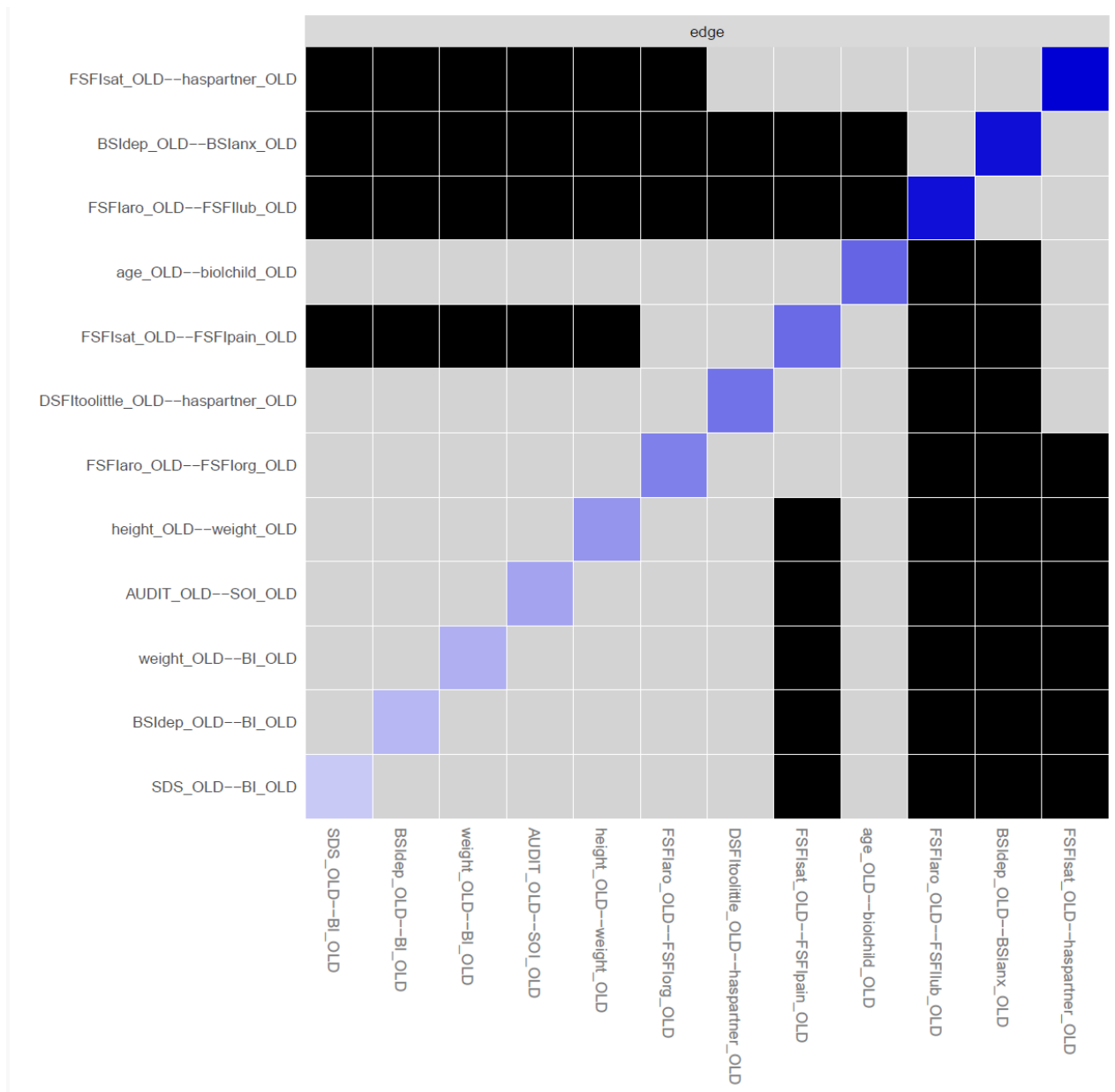
# See Pdf for edge stability
pdf("EdgeStability.pdf", height = 25)
plot(fit_DecreaseBoot2, labels = TRUE, order = "sample")
plot(fit_StableBoot2, labels = TRUE, order = "sample")
plot(fit_IncreaseBoot2, labels = TRUE, order = "sample")
dev.off()
## png
## 2

pdf("EdgeSignificance.pdf")
plot(fit_DecreaseBoot2, "edge", plot = "difference", onlyNonZero = TRUE, order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_StableBoot2, "edge", plot = "difference", onlyNonZero = TRUE, order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_IncreaseBoot2, "edge", plot = "difference", onlyNonZero = TRUE, order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
dev.off()
## png
## 2

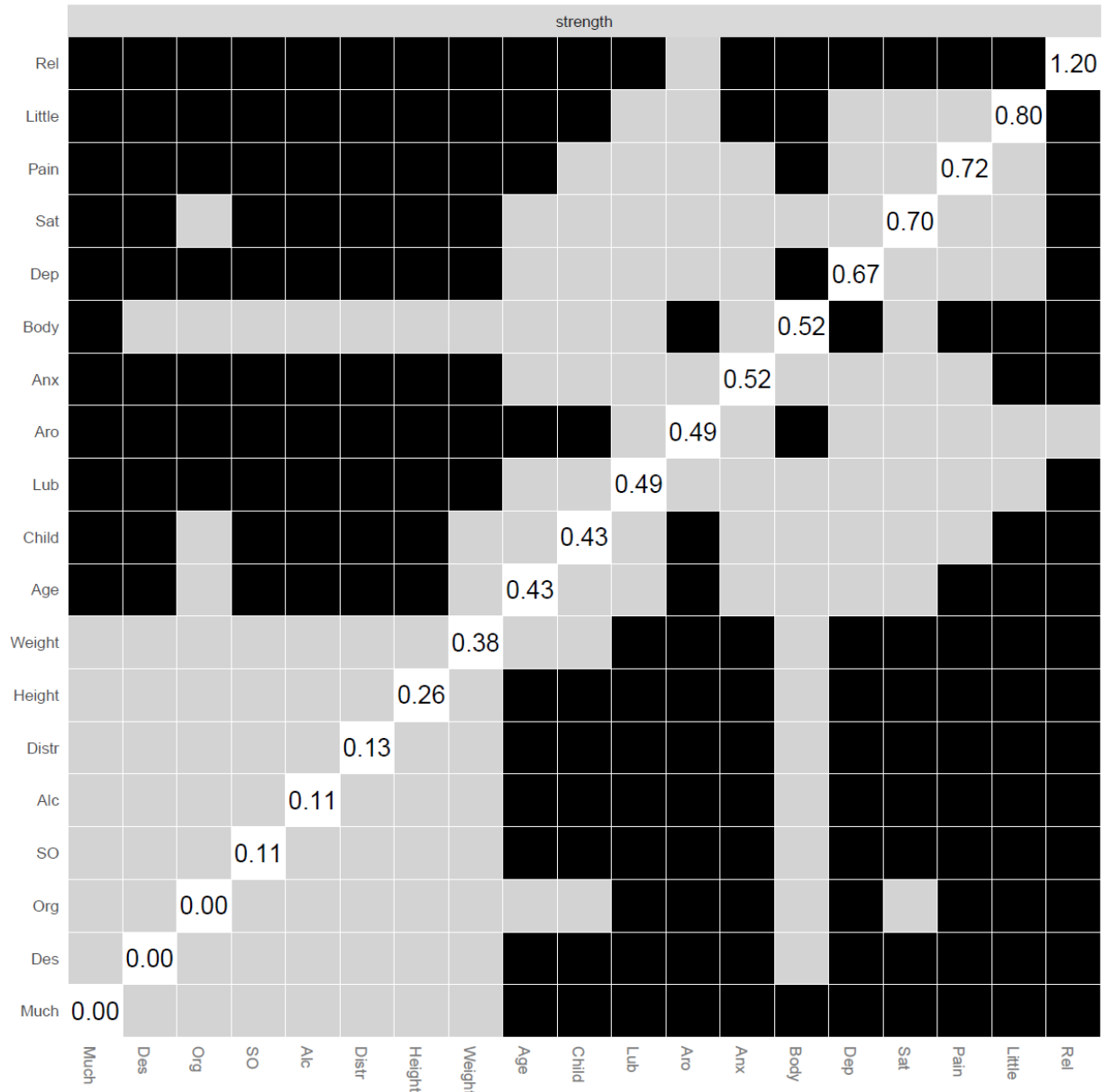
```

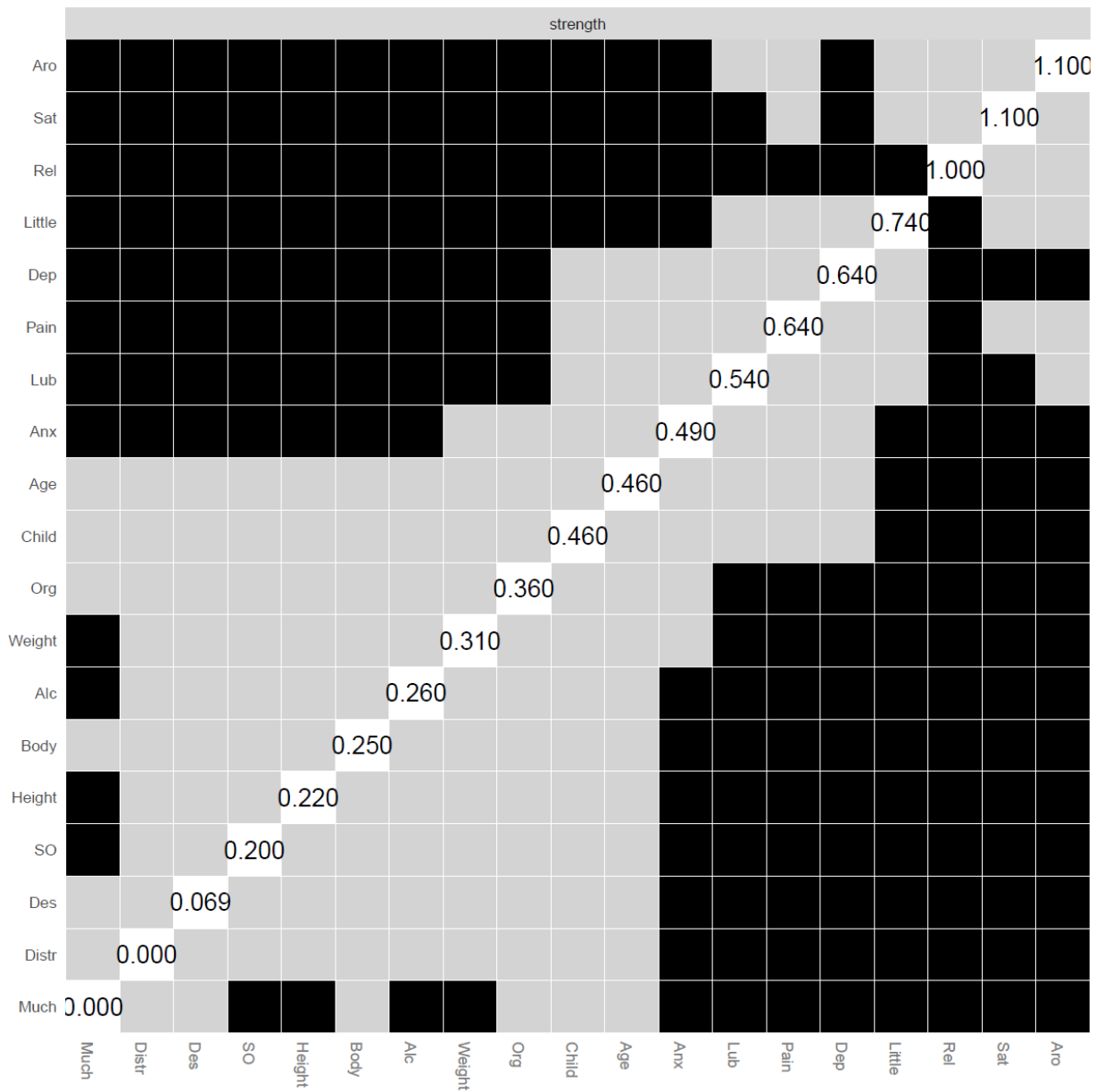


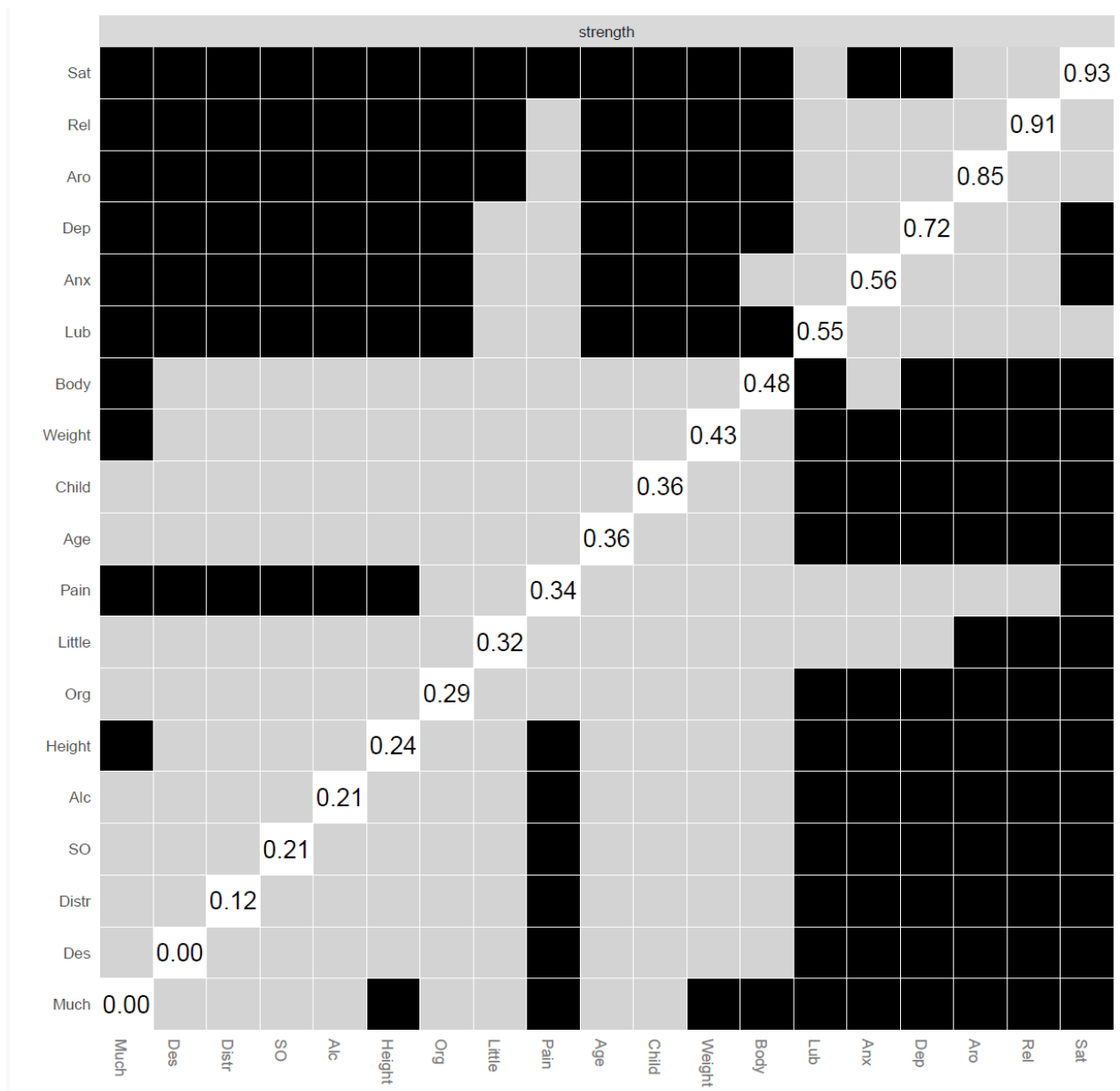
[illegible]



```
pdf("StrengthSignificance.pdf")
plot(fit_DecreaseBoot2, "strength", plot = "difference", order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_StableBoot2, "strength", plot = "difference", order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_IncreaseBoot2, "strength", plot = "difference", order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
dev.off()
## png
## 2
```







9. Network Comparison Test

```
#####
# NCT
library(NetworkComparisonTest)
NCTDecStab <- NCT(DecreaseRS, StableRS, gamma = 0.5, it = 1000, binary.data=FALSE,
paired=FALSE, weighted=TRUE, progressBar=TRUE)
NCTDecStab$nwinv.pval
## [1] 0.56

NCTDecStab$glstrinv.real
## [1] 1.426189
NCTDecStab$glstrinv.pval
## [1] 0.071

NCTIncStab <- NCT(StableRS, IncreaseRS, gamma = 0.5, it = 1000, binary.data=FALSE,
paired=FALSE, weighted=TRUE, progressBar=TRUE)
NCTIncStab$nwinv.pval
```

```
## [1] 0.603

NCTIncStab$glstrinv.real
## [1] 0.0696736
NCTIncStab$glstrinv.pval
## [1] 0.938

NCTDecInc <- NCT(DecreaseRS, IncreaseRS, gamma = 0.5, it = 1000, binary.data=FALSE,
paired=FALSE, weighted=TRUE, progressbar=TRUE)
NCTDecInc$nwinv.pval
## [1] 0.245

NCTDecInc$glstrinv.real
## [1] 1.356516
NCTDecInc$glstrinv.pval
## [1] 0.081
# no significant differences, but presumably because of power

#####
mean(as.matrix(clustcoef_auto(qDecrease2)))
## [1] 0.07866428
mean(as.matrix(clustcoef_auto(qStable2)))
## [1] 0.0504125
mean(as.matrix(clustcoef_auto(qIncrease2)))
## [1] 0.09442654
#####
```

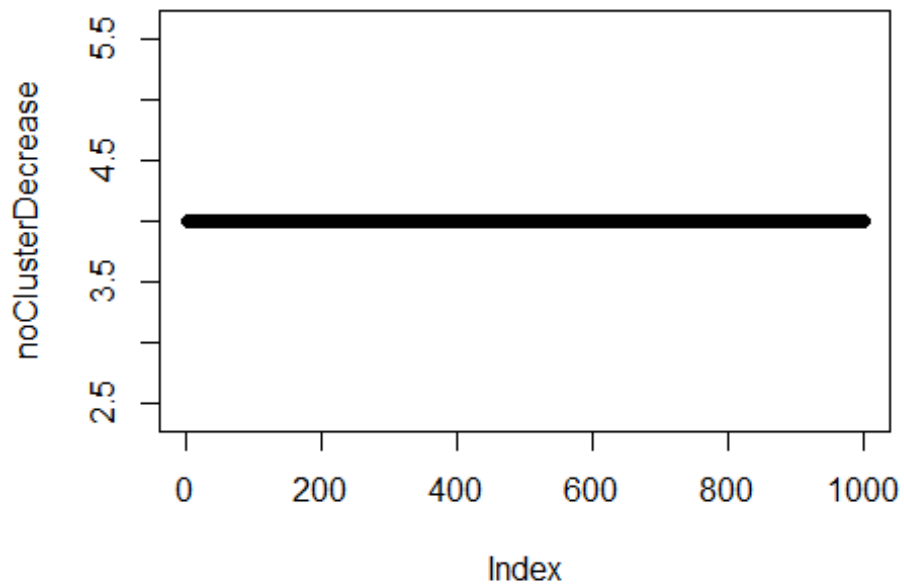
10. Network Communities

CLUSTER ANALYSIS

```
#### DECREASE
library(igraph)
NetworkDecreaseIgraph <- as.igraph(qDecrease2)

noClusterDecrease <- 0
for (i in 1:1000){
  communityWTDecrease <- cluster_walktrap(NetworkDecreaseIgraph,
                                           weights = E(NetworkDecreaseIgraph)$weight,
                                           steps = i,
                                           merges = TRUE,
                                           modularity = TRUE,
                                           membership = TRUE)
  noClusterDecrease[i] <- length(communityWTDecrease)
}

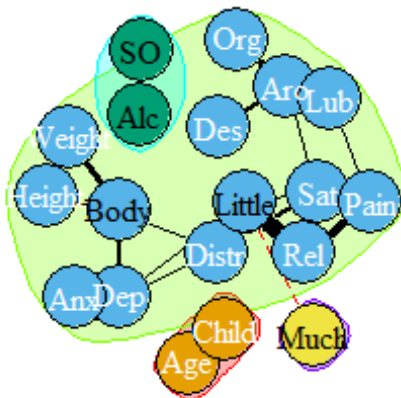
plot(noClusterDecrease)
```



```
median(noClusterDecrease)
## [1] 4
mean(noClusterDecrease)
## [1] 4

communityWPlotDecrease <- cluster_walktrap(NetworkDecreaseIgraph,
  weights = E(NetworkDecreaseIgraph)$weight,
  steps = 200,
  merges = TRUE,
  modularity = TRUE,
  membership = TRUE)

plot(communitWPlotDecrease, NetworkDecreaseIgraph, layout = qDecrease2$layout)
```



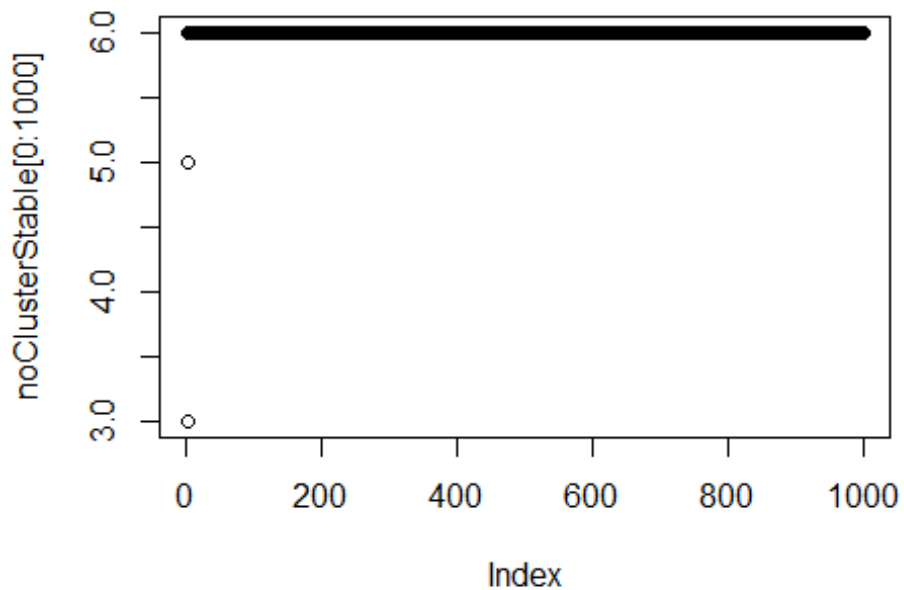
```
# STABLE
NetworkStableIgraph <- as.igraph(qStable2)

noClusterStable <- 0
for (i in 1:1000){
  communityWTStable <- cluster_walktrap(NetworkStableIgraph,
```

```

        weights = E(NetworkStableIgraph)$weight,
        steps = i,
        merges = TRUE,
        modularity = TRUE,
        membership = TRUE)
noClusterStable[i] <- length(communityWTStable)
}
plot(noClusterStable[0:1000])

```



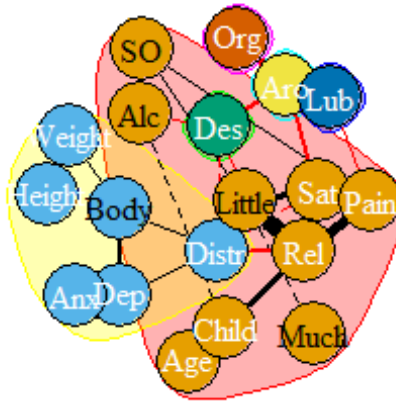
```

median(noClusterStable[0:1000])
## [1] 6
mean(noClusterStable[0:1000])
## [1] 5.996

communityWTPlotStable <- cluster_walktrap(NetworkStableIgraph,
        weights = E(NetworkStableIgraph)$weight,
        steps = 200,
        merges = TRUE,
        modularity = TRUE,
        membership = TRUE)

plot(communityWTPlotStable, NetworkStableIgraph, layout = qStable2$layout)

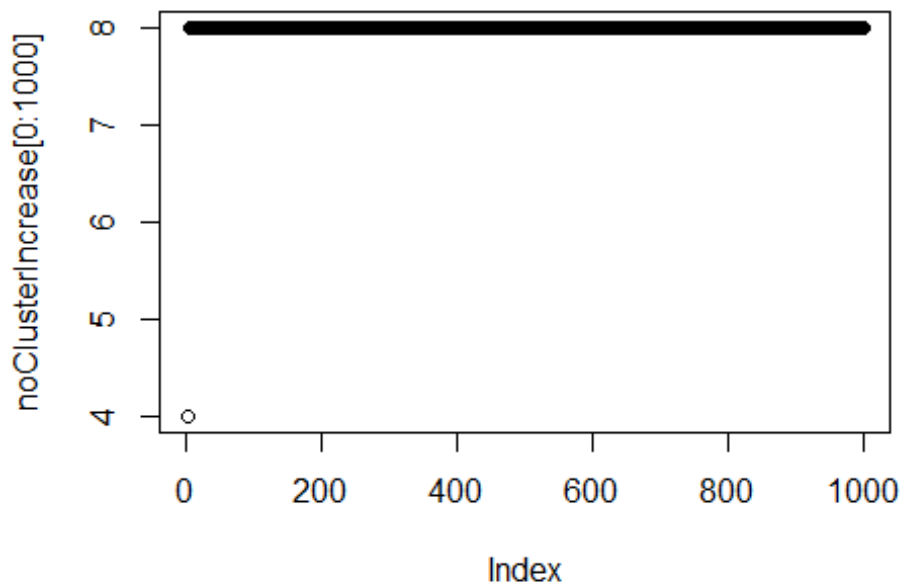
```



```
#### Increase
NetworkIncreaseIgraph <- as.igraph(qIncrease2)

noClusterIncrease <- 0
for (i in 1:1000){
  communityWTIncrease <- cluster_walktrap(NetworkIncreaseIgraph,
    weights = E(NetworkIncreaseIgraph)$weight,
    steps = i,
    merges = TRUE,
    modularity = TRUE,
    membership = TRUE)
  noClusterIncrease[i] <- length(communityWTIncrease)
}

plot(noClusterIncrease[0:1000])
```



```
median(noClusterIncrease[0:1000])
## [1] 8
mean(noClusterIncrease[0:1000])
## [1] 7.988
```

```
communityWPlotIncrease <- cluster_walktrap(NetworkIncreaseIgraph,
  weights = E(NetworkIncreaseIgraph)$weight,
  steps = 200,
  merges = TRUE,
  modularity = TRUE,
  membership = TRUE)

plot(communitWPlotIncrease, NetworkIncreaseIgraph, layout = qIncrease2$layout)
```



```
pdf("WalktrapCluster.pdf")
plot(communitWPlotDecrease, NetworkDecreaseIgraph, layout = qDecrease2$layout)
plot(communitWPlotStable, NetworkStableIgraph, layout = qStable2$layout)
plot(communitWPlotIncrease, NetworkIncreaseIgraph, layout = qIncrease2$layout)
dev.off()
## png
## 2
```

11. Replication – Data Importation

```
#####
# NEW DATASET #
#####

DataNetworkNEW <- FSFI_Gunstetal_Imputed_NegTo0[,23:42]
colnames(DataNetworkNEW)
## [1] "age_NEW" "height_NEW" "weight_NEW"
## [4] "hc_NEW" "biolchild_NEW" "FSFIides_NEW"
## [7] "FSFIaro_NEW" "FSFIilub_NEW" "FSFIorg_NEW"
## [10] "FSFIisat_NEW" "FSFIipain2_NEW" "SDS_NEW"
## [13] "BSIidep_NEW" "BSIianx_NEW" "BI_NEW"
## [16] "AUDIT_NEW" "DSFItoomuch_NEW" "DSFItoolittle_NEW"
## [19] "SOI_NEW" "haspartner_NEW"
colnames(DataNetwork)
## [1] "age_OLD" "height_OLD" "weight_OLD"
## [4] "biolchild_OLD" "FSFIides_OLD" "FSFIaro_OLD"
## [7] "FSFIilub_OLD" "FSFIorg_OLD" "FSFIisat_OLD"
## [10] "FSFIipain_OLD" "SDS_OLD" "BSIidep_OLD"
## [13] "BSIianx_OLD" "BI_OLD" "AUDIT_OLD"
## [16] "DSFItoolittle_OLD" "DSFItoomuch_OLD" "SOI_OLD"
## [19] "haspartner_OLD" "SDI_groups" "SDI_change"
DSFItoolittle_NEW <- c()
DSFItoolittle_NEW <- DataNetworkNEW[,18]
DataNetworkNEW[,18] <- DataNetworkNEW[,17]
DataNetworkNEW[,17] <- DSFItoolittle_NEW
rm(DSFItoolittle_NEW)

colnames(DataNetworkNEW)[17] <- "DSFItoolittle_NEW"
```

```

colnames(DataNetworkNEW)[18] <- "DSFItoomuch_NEW"
colnames(DataNetworkNEW)
## [1] "age_NEW"          "height_NEW"       "weight_NEW"
## [4] "hc_NEW"           "biolchild_NEW"    "FSFIides_NEW"
## [7] "FSFIaro_NEW"       "FSFIilub_NEW"     "FSFIorg_NEW"
## [10] "FSFIisat_NEW"      "FSFIpain2_NEW"    "SDS_NEW"
## [13] "BSIdep_NEW"        "BSIanx_NEW"       "BI_NEW"
## [16] "AUDIT_NEW"         "DSFItoolittle_NEW" "DSFItoomuch_NEW"
## [19] "SOI_NEW"           "haspartner_NEW"
DataNetworkNEW[,21] <- FSFI_Gunstetal_Imputed_NegTo0$SDI_groups
colnames(DataNetworkNEW)[21] <- "SDI_groups"

DataNetworkNEW[,5] <- round(DataNetworkNEW[,5]) # adjust children to count variable

apply(apply(DataNetworkNEW, 2, is.na), 2, sum) # no NA
##      age_NEW      height_NEW      weight_NEW      hc_NEW
##           0             0             0             0
##      biolchild_NEW      FSFIides_NEW      FSFIaro_NEW      FSFIilub_NEW
##           0             0             0             0
##      FSFIorg_NEW      FSFIisat_NEW      FSFIpain2_NEW      SDS_NEW
##           0             0             0             0
##      BSIdep_NEW      BSIanx_NEW      BI_NEW      AUDIT_NEW
##           0             0             0             0
## DSFItoolittle_NEW DSFItoomuch_NEW      SOI_NEW      haspartner_NEW
##           0             0             0             0
##      SDI_groups
##           0

DecreaseNEW <- subset(DataNetworkNEW, SDI_groups==1, select=age_NEW:haspartner_NEW)
StableNEW <- subset(DataNetworkNEW, SDI_groups==2, select=age_NEW:haspartner_NEW)
IncreaseNEW <- subset(DataNetworkNEW, SDI_groups==3, select=age_NEW:haspartner_NEW)
nrow(DecreaseNEW) + nrow(StableNEW) + nrow(IncreaseNEW)
## [1] 1692
library(psych)

describe(DecreaseNEW)
##      vars      n      mean      sd      median      trimmed      mad      min      max
## age_NEW      1 522  33.21  4.85   33.0    32.90  5.93  25.0  51.0
## height_NEW    2 522 166.03  6.45  166.0   166.01  5.93 145.0 182.0
## weight_NEW     3 522  68.38 15.57  65.0    66.36 11.86  44.0 164.0
## hc_NEW         4 522   0.40  0.49   0.0     0.37  0.00   0.0   1.0
## biolchild_NEW  5 522   1.15  1.27   1.0     0.98  1.48   0.0   9.0
## FSFIides_NEW   6 522   2.67  0.95   2.4     2.63  0.89   1.2   5.4
## FSFIaro_NEW    7 522   3.92  1.88   4.5     4.15  1.33   0.0   6.0
## FSFIilub_NEW   8 522   4.62  2.04   5.7     5.02  0.44   0.0   6.0
## FSFIorg_NEW    9 522   4.00  2.09   4.8     4.24  1.78   0.0   6.0
## FSFIisat_NEW  10 522   4.12  1.84   4.8     4.33  1.78   0.4   6.0
## FSFIpain2_NEW 11 522   4.33  2.25   5.4     4.66  0.89   0.0   6.0
## SDS_NEW       12 522   8.75  6.38   8.0     8.36  7.41   0.0  28.0
## BSIdep_NEW    13 522   4.50  4.74   3.0     3.69  2.97   0.0  23.0
## BSIanx_NEW    14 522   3.22  3.74   2.0     2.51  2.97   0.0  21.0
## BI_NEW        15 522  26.80  6.77  27.0    26.67  7.41  11.0  48.0
## AUDIT_NEW     16 522   5.08  3.87   4.0     4.58  2.97   0.0  23.0
## DSFItoolittle_NEW 17 522   3.44  3.97   2.0     2.71  2.97   0.0  25.0
## DSFItoomuch_NEW 18 522   0.18  0.69   0.0     0.00  0.00   0.0   8.0
## SOI_NEW       19 522  71.81 34.06  64.0    65.81 17.79  20.0 211.0
## haspartner_NEW 20 522   0.91  0.29   1.0     1.00  0.00   0.0   1.0
##
##      range      skew      kurtosis      se
## age_NEW      26.0  0.67      0.38 0.21
## height_NEW    37.0 -0.03     -0.06 0.28
## weight_NEW   120.0  2.15      8.15 0.68
## hc_NEW        1.0  0.42     -1.83 0.02
## biolchild_NEW  9.0  1.32      3.26 0.06
## FSFIides_NEW  4.2  0.34     -0.11 0.04

```

```
## FSFIaro_NEW      6.0 -1.03    -0.16 0.08
## FSFIilub_NEW     6.0 -1.49     0.70 0.09
## FSFIorg_NEW      6.0 -0.83    -0.72 0.09
## FSFIisat_NEW     5.6 -0.77    -0.79 0.08
## FSFIpain2_NEW    6.0 -1.12    -0.35 0.10
## SDS_NEW          28.0  0.44    -0.69 0.28
## BSIddep_NEW      23.0  1.45     1.83 0.21
## BSIanx_NEW       21.0  1.84     3.64 0.16
## BI_NEW           37.0  0.17    -0.33 0.30
## AUDIT_NEW        23.0  1.32     1.98 0.17
## DSFItoolittle_NEW 25.0  1.66     2.99 0.17
## DSFItoomuch_NEW  8.0  5.64    42.70 0.03
## SOI_NEW          191.0 1.85     3.49 1.49
## haspartner_NEW   1.0 -2.82     5.94 0.01
```

describe(StableNEW)

```
##          vars    n   mean    sd median trimmed   mad   min max
## age_NEW          1 687 32.92  4.89   33.0   32.57  4.45 25.0  53
## height_NEW       2 687 165.99  6.06  166.0  165.87  5.93 143.0 186
## weight_NEW       3 687  66.46 13.70   64.0   64.71 10.38  38.5 175
## hc_NEW           4 687  0.39  0.49    0.0    0.37  0.00   0.0   1
## biolchild_NEW    5 687  1.08  1.29    1.0    0.89  1.48   0.0   9
## FSFIides_NEW     6 687  2.94  0.97    3.0    2.91  0.89   1.2   6
## FSFIaro_NEW      7 687  4.12  1.83    4.8    4.41  0.89   0.0   6
## FSFIilub_NEW     8 687  4.71  2.00    5.7    5.13  0.44   0.0   6
## FSFIorg_NEW      9 687  4.16  2.02    4.8    4.44  1.78   0.0   6
## FSFIisat_NEW    10 687  4.16  1.84    4.8    4.38  1.78   0.4   6
## FSFIpain2_NEW   11 687  4.48  2.21    6.0    4.85  0.00   0.0   6
## SDS_NEW         12 687  8.56  5.87    8.0    8.14  5.93   0.0  28
## BSIddep_NEW     13 687  4.67  4.48    3.0    4.00  2.97   0.0  23
## BSIanx_NEW      14 687  3.40  3.90    2.0    2.68  2.97   0.0  24
## BI_NEW          15 687 26.14  6.75   26.0   25.99  7.41  12.0  44
## AUDIT_NEW       16 687  5.18  4.01    4.0    4.67  2.97   0.0  30
## DSFItoolittle_NEW 17 687  4.00  4.57    3.0    3.19  4.45   0.0  28
## DSFItoomuch_NEW 18 687  0.20  0.80    0.0    0.00  0.00   0.0   8
## SOI_NEW         19 687 72.82 38.20   62.0   65.12 17.79  24.0 261
## haspartner_NEW  20 687  0.84  0.37    1.0    0.92  0.00   0.0   1
##          range  skew kurtosis   se
## age_NEW        28.0  0.80    0.93 0.19
## height_NEW     43.0  0.11    0.13 0.23
## weight_NEW    136.5  1.89    7.44 0.52
## hc_NEW         1.0  0.44   -1.81 0.02
## biolchild_NEW  9.0  1.41    3.37 0.05
## FSFIides_NEW   4.8  0.33   -0.05 0.04
## FSFIaro_NEW    6.0 -1.25    0.37 0.07
## FSFIilub_NEW   6.0 -1.60    1.04 0.08
## FSFIorg_NEW    6.0 -0.99   -0.37 0.08
## FSFIisat_NEW   5.6 -0.84   -0.65 0.07
## FSFIpain2_NEW  6.0 -1.28    0.01 0.08
## SDS_NEW       28.0  0.59   -0.17 0.22
## BSIddep_NEW   23.0  1.31    1.47 0.17
## BSIanx_NEW    24.0  1.81    3.74 0.15
## BI_NEW        32.0  0.18   -0.67 0.26
## AUDIT_NEW     30.0  1.73    4.96 0.15
## DSFItoolittle_NEW 28.0  1.49    2.02 0.17
## DSFItoomuch_NEW 8.0  5.22   31.59 0.03
## SOI_NEW      237.0  2.12    4.50 1.46
## haspartner_NEW 1.0 -1.83    1.37 0.01
```

describe(IncreaseNEW)

```
##          vars    n   mean    sd median trimmed   mad   min max
## age_NEW          1 483 33.13  4.94   32.0   32.84  5.93 25.00  52.0
## height_NEW       2 483 166.42  6.27  166.5  166.38  5.39 150.00 186.0
```



```

fit_StableNEW <- mgm(data = as.matrix(StableNEW),
  type = VarDomain,
  level = VarLevel,
  k = 2,
  lambdaSel = 'EBIC',
  lambdaGam = 0.5) # hyper parameter

fit_IncreaseNEW <- mgm(data = as.matrix(IncreaseNEW),
  type = VarDomain,
  level = VarLevel,
  k = 2,
  lambdaSel = 'EBIC',
  lambdaGam = 0.5) # hyper parameter

fit_DecreaseNEW$pairwise$wadj[,4]
## [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
fit_StableNEW$pairwise$wadj[,4]
## [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
fit_IncreaseNEW$pairwise$wadj[,4] # HC has no edge with anything again
## [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

```

13. Replication – Network Estimation (excl. hormonal contraception)

```

#####
# No HC #
#####
DataNetworkNEW <- DataNetworkNEW[,-4] # get rid off HC
colnames(DataNetworkNEW)
## [1] "age_NEW" "height_NEW" "weight_NEW"
## [4] "biolchild_NEW" "FSFIdes_NEW" "FSFIaro_NEW"
## [7] "FSFIilub_NEW" "FSFIorg_NEW" "FSFIisat_NEW"
## [10] "FSFIpain2_NEW" "SDS_NEW" "BSIdep_NEW"
## [13] "BSIanx_NEW" "BI_NEW" "AUDIT_NEW"
## [16] "DSFItoolittle_NEW" "DSFItoomuch_NEW" "SOI_NEW"
## [19] "haspartner_NEW" "SDI_groups"
DecreaseNEW <- subset(DataNetworkNEW, SDI_groups==1, select=age_NEW:haspartner_NEW)
StableNEW <- subset(DataNetworkNEW, SDI_groups==2, select=age_NEW:haspartner_NEW)
IncreaseNEW <- subset(DataNetworkNEW, SDI_groups==3, select=age_NEW:haspartner_NEW)
nrow(DecreaseNEW) + nrow(StableNEW) + nrow(IncreaseNEW)
## [1] 1692

#####
# Random Subsamples of same size #
#####
set.seed(17)
nrow(DecreaseNEW)
## [1] 522
nrow(StableNEW)
## [1] 687
nrow(IncreaseNEW) # 483
## [1] 483
randomSample = function(df,n) {
  return (df[sample(nrow(df), n),])
}

DecreaseNEWRS <- randomSample(DecreaseNEW, n = 483)
StableNEWRS <- randomSample(StableNEW, n = 483)
IncreaseNEWRS <- IncreaseNEW

library(psych)
describe(DecreaseNEWRS)

```

```
##          vars    n  mean    sd median trimmed  mad   min   max
## age_NEW      1 483 33.25  4.84   33.0   32.95  5.93 25.0  51.0
## height_NEW   2 483 166.13  6.39  166.0  166.07  5.93 145.0 182.0
## weight_NEW   3 483  68.38 15.13   65.0   66.47 10.38  44.0 164.0
## biolchild_NEW 4 483  1.14  1.27    1.0    0.96  1.48   0.0   9.0
## FSFIdeS_NEW  5 483  2.67  0.95    2.4    2.63  0.89   1.2   5.4
## FSFIaro_NEW  6 483  3.94  1.88    4.5    4.18  1.33   0.0   6.0
## FSFIilub_NEW 7 483  4.63  2.03    5.7    5.03  0.44   0.0   6.0
## FSFIorg_NEW  8 483  4.02  2.08    4.8    4.27  1.78   0.0   6.0
## FSFIisat_NEW 9 483  4.15  1.83    4.8    4.36  1.78   0.4   6.0
## FSFIpain2_NEW 10 483  4.35  2.24    5.4    4.68  0.89   0.0   6.0
## SDS_NEW     11 483  8.61  6.41    8.0    8.17  7.41   0.0  28.0
## BSIdép_NEW  12 483  4.54  4.80    3.0    3.71  2.97   0.0  23.0
## BSIanx_NEW  13 483  3.20  3.77    2.0    2.46  2.97   0.0  21.0
## BI_NEW      14 483 26.76  6.72   27.0   26.63  7.41  11.0  48.0
## AUDIT_NEW   15 483  5.10  3.91    4.0    4.59  2.97   0.0  23.0
## DSFItoolittle_NEW 16 483  3.37  3.91    2.0    2.65  2.97   0.0  25.0
## DSFItoomuch_NEW 17 483  0.18  0.68    0.0    0.00  0.00   0.0   8.0
## SOI_NEW     18 483 72.47 34.68   64.0   66.28 17.79  20.0 211.0
## haspartner_NEW 19 483  0.91  0.29    1.0    1.00  0.00   0.0   1.0
##
##          range  skew kurtosis  se
## age_NEW      26.0  0.66    0.37 0.22
## height_NEW   37.0  0.02   -0.14 0.29
## weight_NEW  120.0  2.14    8.36 0.69
## biolchild_NEW  9.0  1.40    3.62 0.06
## FSFIdeS_NEW  4.2  0.33   -0.10 0.04
## FSFIaro_NEW  6.0 -1.06   -0.11 0.09
## FSFIilub_NEW  6.0 -1.50    0.74 0.09
## FSFIorg_NEW  6.0 -0.85   -0.68 0.09
## FSFIisat_NEW  5.6 -0.78   -0.77 0.08
## FSFIpain2_NEW  6.0 -1.13   -0.32 0.10
## SDS_NEW     28.0  0.49   -0.64 0.29
## BSIdép_NEW  23.0  1.47    1.82 0.22
## BSIanx_NEW  21.0  1.90    3.80 0.17
## BI_NEW      37.0  0.18   -0.28 0.31
## AUDIT_NEW   23.0  1.34    1.98 0.18
## DSFItoolittle_NEW 25.0  1.65    3.05 0.18
## DSFItoomuch_NEW  8.0  5.89   47.12 0.03
## SOI_NEW     191.0  1.83    3.31 1.58
## haspartner_NEW  1.0 -2.83    6.04 0.01
```

```
describe(StableNEWSRS)
```

```
##          vars    n  mean    sd median trimmed  mad   min   max
## age_NEW      1 483 32.78  4.75   33.0   32.48  4.45 25.0  51.0
## height_NEW   2 483 165.97  6.09  165.0  165.77  5.93 149.0 186.0
## weight_NEW   3 483  66.60 14.00   64.0   64.68 10.38  38.5 175.0
## biolchild_NEW 4 483  1.09  1.32    1.0    0.90  1.48   0.0   9.0
## FSFIdeS_NEW  5 483  2.95  0.99    3.0    2.93  0.89   1.2   5.4
## FSFIaro_NEW  6 483  4.09  1.88    4.8    4.36  0.89   0.0   6.0
## FSFIilub_NEW 7 483  4.66  2.03    5.7    5.07  0.44   0.0   6.0
## FSFIorg_NEW  8 483  4.11  2.06    4.8    4.39  1.78   0.0   6.0
## FSFIisat_NEW 9 483  4.11  1.86    4.8    4.31  1.78   0.4   6.0
## FSFIpain2_NEW 10 483  4.42  2.25    6.0    4.77  0.00   0.0   6.0
## SDS_NEW     11 483  8.63  5.95    8.0    8.22  5.93   0.0  28.0
## BSIdép_NEW  12 483  4.75  4.54    3.0    4.06  2.97   0.0  23.0
## BSIanx_NEW  13 483  3.59  4.17    2.0    2.79  2.97   0.0  24.0
## BI_NEW      14 483 26.36  6.75   26.0   26.24  7.41  12.0  44.0
## AUDIT_NEW   15 483  5.32  4.20    4.0    4.76  2.97   0.0  30.0
## DSFItoolittle_NEW 16 483  4.11  4.70    3.0    3.27  4.45   0.0  28.0
## DSFItoomuch_NEW 17 483  0.20  0.78    0.0    0.00  0.00   0.0   8.0
## SOI_NEW     18 483 74.09 39.17   63.0   66.42 19.27  24.0 261.0
## haspartner_NEW 19 483  0.85  0.36    1.0    0.93  0.00   0.0   1.0
##
##          range  skew kurtosis  se
```

```
## age_NEW      26.0  0.66    0.53 0.22
## height_NEW   37.0  0.26    0.03 0.28
## weight_NEW   136.5 2.16    9.23 0.64
## biolchild_NEW 9.0  1.55    4.18 0.06
## FSFIdeS_NEW  4.2  0.26   -0.23 0.04
## FSFIaro_NEW  6.0 -1.19    0.15 0.09
## FSFIilub_NEW 6.0 -1.54    0.83 0.09
## FSFIorg_NEW  6.0 -0.94   -0.51 0.09
## FSFIisat_NEW 5.6 -0.77   -0.81 0.08
## FSFIpain2_NEW 6.0 -1.20   -0.18 0.10
## SDS_NEW      28.0  0.55   -0.23 0.27
## BSIdép_NEW   23.0  1.32    1.56 0.21
## BSIanx_NEW   24.0  1.80    3.47 0.19
## BI_NEW       32.0  0.15   -0.74 0.31
## AUDIT_NEW    30.0  1.83    5.37 0.19
## DSFItoolittle_NEW 28.0 1.51    2.22 0.21
## DSFItoomuch_NEW 8.0  5.42   35.47 0.04
## SOI_NEW      237.0 2.00    3.92 1.78
## haspartner_NEW 1.0 -1.92    1.69 0.02
```

```
describe(IncreaseNEWRS)
```

```
##          vars    n  mean    sd median trimmed  mad   min  max
## age_NEW      1 483 33.13  4.94  32.0   32.84  5.93 25.00 52.0
## height_NEW   2 483 166.42  6.27 166.5  166.38  5.39 150.00 186.0
## weight_NEW   3 483  67.74 15.00  65.0   65.68 10.38  42.00 166.0
## biolchild_NEW 4 483   1.12  1.39   1.0    0.93  1.48   0.00  12.0
## FSFIdeS_NEW  5 483   3.40  1.02   3.6    3.40  0.89   1.20   5.4
## FSFIaro_NEW  6 483   4.52  1.69   5.1    4.87  0.89   0.00   6.0
## FSFIilub_NEW 7 483   5.08  1.73   6.0    5.56  0.00   0.00   6.0
## FSFIorg_NEW  8 483   4.46  1.90   5.2    4.81  1.19   0.00   6.0
## FSFIisat_NEW 9 483   4.23  1.88   4.8    4.47  1.78   0.40   6.0
## FSFIpain2_NEW 10 483  4.64  2.23   6.0    5.05  0.00   0.00   6.0
## SDS_NEW      11 483   7.90  5.95   8.0    7.40  5.93   0.00  28.0
## BSIdép_NEW   12 483   4.77  4.42   4.0    4.14  4.45   0.00  22.0
## BSIanx_NEW   13 483   3.33  3.86   2.0    2.61  2.97   0.00  22.0
## BI_NEW       14 483  25.34  7.26  25.0   25.07  7.41  11.00  47.0
## AUDIT_NEW    15 483   5.62  4.22   5.0    5.05  2.97   0.00  30.0
## DSFItoolittle_NEW 16 483  5.24  5.05   4.0    4.55  4.45   0.00  27.0
## DSFItoomuch_NEW 17 483  0.06  0.34   0.0    0.00  0.00   0.00   4.0
## SOI_NEW      18 483  78.76 44.42  65.0   70.58 23.72  15.04 252.0
## haspartner_NEW 19 483  0.77  0.42   1.0    0.84  0.00   0.00   1.0
##          range  skew kurtosis  se
## age_NEW      27.00  0.65    0.40 0.22
## height_NEW   36.00  0.07   -0.01 0.29
## weight_NEW   124.00  1.91    6.03 0.68
## biolchild_NEW 12.00  1.82    7.66 0.06
## FSFIdeS_NEW  4.20  0.09   -0.43 0.05
## FSFIaro_NEW  6.00 -1.62    1.74 0.08
## FSFIilub_NEW 6.00 -2.21    3.61 0.08
## FSFIorg_NEW  6.00 -1.24    0.30 0.09
## FSFIisat_NEW 5.60 -0.89   -0.63 0.09
## FSFIpain2_NEW 6.00 -1.42    0.32 0.10
## SDS_NEW      28.00  0.70    0.19 0.27
## BSIdép_NEW   22.00  1.18    1.04 0.20
## BSIanx_NEW   22.00  1.88    4.06 0.18
## BI_NEW       36.00  0.34   -0.29 0.33
## AUDIT_NEW    30.00  1.51    3.14 0.19
## DSFItoolittle_NEW 27.00  1.19    1.13 0.23
## DSFItoomuch_NEW 4.00  7.24   61.45 0.02
## SOI_NEW      236.96  1.71    2.40 2.02
## haspartner_NEW 1.00 -1.29   -0.33 0.02
```

```
table(DecreaseNEWRS[,19])
```



```

fit_IncreaseNEW <- mgm(data = as.matrix(IncreaseNEWRS),
  type = VarDomain,
  level = VarLevel,
  k = 2,
  lambdaSel = 'EBIC',
  lambdaGam = 0.5) # hyper parameter

#####
# Predictive Strength ##
#####

pred_DecreaseNEW <- predict(fit_DecreaseNEW,
  DecreaseNEWRS,
  errorCon = 'R2') #save R2 into an object (varExpl = cont var)

pred_StableNEW <- predict(fit_StableNEW,
  StableNEWRS,
  errorCon = 'R2') #save R2 into an object (varExpl = cont var)

pred_IncreaseNEW <- predict(fit_IncreaseNEW,
  IncreaseNEWRS,
  errorCon = 'R2') #save R2 into an object (varExpl = cont var)

predR_DecreaseNEW <- pred_DecreaseNEW$errors$error.R2
predR_DecreaseNEW <- as.numeric(as.character(predR_DecreaseNEW))

predR_StableNEW <- pred_StableNEW$errors$error.R2
predR_StableNEW <- as.numeric(as.character(predR_StableNEW))

predR_IncreaseNEW <- pred_IncreaseNEW$errors$error.R2
predR_IncreaseNEW <- as.numeric(as.character(predR_IncreaseNEW))

# set 'predictability' of categorical variable

predR_DecreaseNEW[19] <- pred_DecreaseNEW$errors$error.CC[19]
predR_StableNEW[19] <- pred_StableNEW$errors$error.CC[19]
predR_IncreaseNEW[19] <- pred_IncreaseNEW$errors$error.CC[19]

mean(predR_DecreaseNEW, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4255789
sd(predR_DecreaseNEW, na.rm = TRUE)
## [1] 0.3061924

pred_DecreaseNEW$errors
##
##      Variable Error.R2 Error.CC Error.nCC CCmarg
## 1      age_NEW  0.140      NA      NA      NA
## 2    height_NEW  0.056      NA      NA      NA
## 3    weight_NEW  0.125      NA      NA      NA
## 4  biolchild_NEW  0.175      NA      NA      NA
## 5   FSFides_NEW  0.391      NA      NA      NA
## 6   FSFIaro_NEW  0.894      NA      NA      NA
## 7   FSFIlub_NEW  0.816      NA      NA      NA
## 8   FSFIorg_NEW  0.747      NA      NA      NA
## 9   FSFisat_NEW  0.804      NA      NA      NA
## 10  FSFIpain2_NEW 0.603      NA      NA      NA
## 11      SDS_NEW  0.417      NA      NA      NA
## 12   BSIdes_NEW  0.576      NA      NA      NA
## 13   BSIanx_NEW  0.539      NA      NA      NA
## 14      BI_NEW  0.212      NA      NA      NA
## 15   AUDIT_NEW  0.146      NA      NA      NA
## 16 DSFItoolittle_NEW 0.366      NA      NA      NA
## 17 DSFItoomuch_NEW 0.101      NA      NA      NA

```

```
## 18      SOI_NEW      0.048      NA      NA      NA
## 19    haspartner_NEW      NA      0.93      0.227      0.909

mean(predR_StableNEW, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4344211
sd(predR_StableNEW, na.rm = TRUE)
## [1] 0.2920332

pred_StableNEW$errors
##      Variable Error.R2 Error.CC Error.nCC CCmarg
## 1      age_NEW      0.204      NA      NA      NA
## 2     height_NEW      0.136      NA      NA      NA
## 3     weight_NEW      0.258      NA      NA      NA
## 4   biolchild_NEW      0.274      NA      NA      NA
## 5   FSFides_NEW      0.188      NA      NA      NA
## 6   FSFIaro_NEW      0.883      NA      NA      NA
## 7   FSFIlub_NEW      0.856      NA      NA      NA
## 8   FSFIorg_NEW      0.726      NA      NA      NA
## 9   FSFisat_NEW      0.768      NA      NA      NA
## 10  FSFIpain2_NEW      0.655      NA      NA      NA
## 11    SDS_NEW      0.313      NA      NA      NA
## 12   BSIdcp_NEW      0.591      NA      NA      NA
## 13   BSIanx_NEW      0.519      NA      NA      NA
## 14    BI_NEW      0.264      NA      NA      NA
## 15   AUDIT_NEW      0.203      NA      NA      NA
## 16 DSFItoolittle_NEW      0.474      NA      NA      NA
## 17 DSFItoomuch_NEW      0.021      NA      NA      NA
## 18      SOI_NEW      0.043      NA      NA      NA
## 19    haspartner_NEW      NA      0.878      0.203      0.847

mean(predR_IncreaseNEW, na.rm = TRUE) #mean variance explained across all nodes
## [1] 0.4360526
sd(predR_IncreaseNEW, na.rm = TRUE)
## [1] 0.2661239

pred_IncreaseNEW$errors
##      Variable Error.R2 Error.CC Error.nCC CCmarg
## 1      age_NEW      0.170      NA      NA      NA
## 2     height_NEW      0.142      NA      NA      NA
## 3     weight_NEW      0.235      NA      NA      NA
## 4   biolchild_NEW      0.250      NA      NA      NA
## 5   FSFides_NEW      0.250      NA      NA      NA
## 6   FSFIaro_NEW      0.877      NA      NA      NA
## 7   FSFIlub_NEW      0.836      NA      NA      NA
## 8   FSFIorg_NEW      0.632      NA      NA      NA
## 9   FSFisat_NEW      0.695      NA      NA      NA
## 10  FSFIpain2_NEW      0.608      NA      NA      NA
## 11    SDS_NEW      0.374      NA      NA      NA
## 12   BSIdcp_NEW      0.594      NA      NA      NA
## 13   BSIanx_NEW      0.515      NA      NA      NA
## 14    BI_NEW      0.336      NA      NA      NA
## 15   AUDIT_NEW      0.227      NA      NA      NA
## 16 DSFItoolittle_NEW      0.558      NA      NA      NA
## 17 DSFItoomuch_NEW      0.023      NA      NA      NA
## 18      SOI_NEW      0.135      NA      NA      NA
## 19    haspartner_NEW      NA      0.828      0.245      0.772
```

14. Replication – Network Visualization

```
#####
# Network Layout Specifics #
#####
```

```

colNames <- c("Age", "Height", "Weight", "Child", "Des", "Aro",
             "Lub", "Org", "Sat", "Pain", "Distr", "Dep", "Anx",
             "Body", "Alc", "Little", "Much", "SO", "Rel")

nodeDescr <- c("", "", "", "Number of children", "Desire",
              "Arousal", "Lubrication", "Orgasm", "Satisfaction", "Pain",
              "Sexually-related personal distress", "Depression", "Anxiety",
              "Body image and dissatisfaction", "(Hazardous) Alcohol use",
              "Too little sexual activity", "Too much sexual activity",
              "Tendency/attitudes to(wards) uncommitted sexual relationships",
              "Relationship status (partnered or single)")

groupsNoHc <- list(Demographics = c(1:4,19),
                  Female_Sexual_Function_Index = c(5:10),
                  Sexual_Distress_Scale = c(11),
                  Brief_Symptom_Inventory = c(12:13),
                  Derogatis_Sexual_Function_Inventory = c(14),
                  Alcohol_Use_Disorders_Identification_Test = c(15),
                  Desired_and_Actual_Sexual_Activity_Scale = c(16:17),
                  Sociosexual_Orientation_Inventory = c(18))

nodeLabelColors <- c("white", "white", "white", "white",
                    "white", "white", "white", "white", "white", "white",
                    "white",
                    "white", "white",
                    "black", "black", "black", "black", "black",
                    "white")

#Plot Networks
library(qgraph)

fit_DecreaseNEW$pairwise$edgecolor[which(fit_DecreaseNEW$pairwise$edgecolor=="red")]<- "gray50"
fit_DecreaseNEW$pairwise$edgecolor[which(fit_DecreaseNEW$pairwise$edgecolor=="darkgreen")] <- "
gray70"
fit_DecreaseNEW$pairwise$edgecolor[which(fit_DecreaseNEW$pairwise$edgecolor=="darkgrey")] <- "b
lack"
fit_DecreaseNEW$pairwise$edgecolor[c(16),19] <- "gray50" # categ relationship
fit_DecreaseNEW$pairwise$edgecolor[c(19),16] <- "gray50"
fit_DecreaseNEW$pairwise$edgecolor[c(4,11),19] <- "gray70"
fit_DecreaseNEW$pairwise$edgecolor[19,c(4,11)] <- "gray70"
fit_DecreaseNEW$pairwise$wadj[which(fit_DecreaseNEW$pairwise$edgecolor=="gray50")] <- fit_Decre
aseNEW$pairwise$wadj[which(fit_DecreaseNEW$pairwise$edgecolor=="gray50")]*-1

fit_DecreaseNEW$pairwise$wadj[which(fit_DecreaseNEW$pairwise$edgecolor=="gray50")]
## [1] -0.0734519 -0.1072308 -0.1290201 -0.2589329 -0.2615573 -0.1290201
## [7] -0.2589329 -0.0734519 -0.1072308 -0.2615573 -0.1343503 -0.5925076
## [13] -0.1343503 -0.5925076

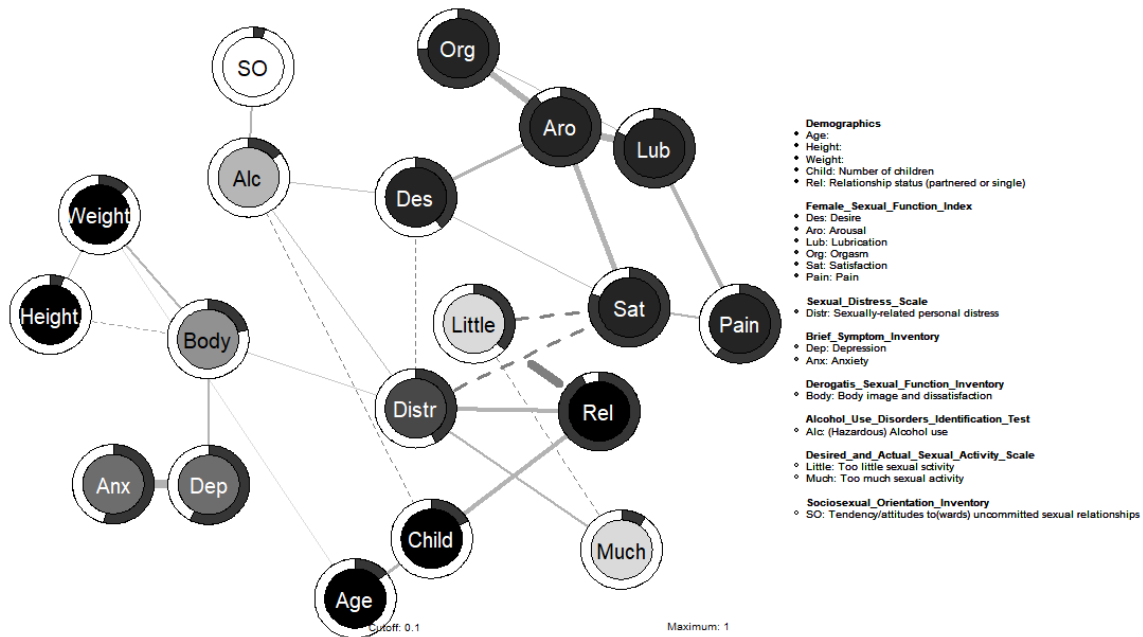
qDecreaseNEW <- qgraph(fit_DecreaseNEW$pairwise$wadj,
                      edge.color = fit_DecreaseNEW$pairwise$edgecolor,
                      layout = LayoutAverage,
                      labels = colNames,
                      maximum = 1,
                      minimum = 0,
                      cut = 0.1,
                      details = TRUE,
                      vsize = 7.5,
                      esize = 10,
                      label.cex = 1.2,
                      label.scale.equal = TRUE,
                      pie = predR_DecreaseNEW,
                      pieColor = "gray21",

```

```

pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,
legend.mode = "style1",
legend.cex = 0.5,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



```

fit_StableNEW$pairwise$edgecolor[which(fit_StableNEW$pairwise$edgecolor=="red")] <- "gray50"
fit_StableNEW$pairwise$edgecolor[which(fit_StableNEW$pairwise$edgecolor=="darkgreen")] <- "gray70"
fit_StableNEW$pairwise$edgecolor[which(fit_StableNEW$pairwise$edgecolor=="darkgrey")] <- "black"

fit_StableNEW$pairwise$edgecolor[c(16),19] <- "gray50" # categ relationship
fit_StableNEW$pairwise$edgecolor[c(19),16] <- "gray50"
fit_StableNEW$pairwise$edgecolor[c(4,10),19] <- "gray70"
fit_StableNEW$pairwise$edgecolor[19,c(4,10)] <- "gray70"
fit_StableNEW$pairwise$wadj[which(fit_StableNEW$pairwise$edgecolor=="gray50")] <- fit_StableNEW$pairwise$wadj[which(fit_StableNEW$pairwise$edgecolor=="gray50")]*-1

fit_StableNEW$pairwise$wadj[which(fit_StableNEW$pairwise$edgecolor=="gray50")]
## [1] -0.12336030 -0.17160096 -0.18511236 -0.24273522 -0.18511236
## [6] -0.12336030 -0.17160096 -0.24273522 -0.09988514 -0.73386154
## [11] -0.09988514 -0.73386154

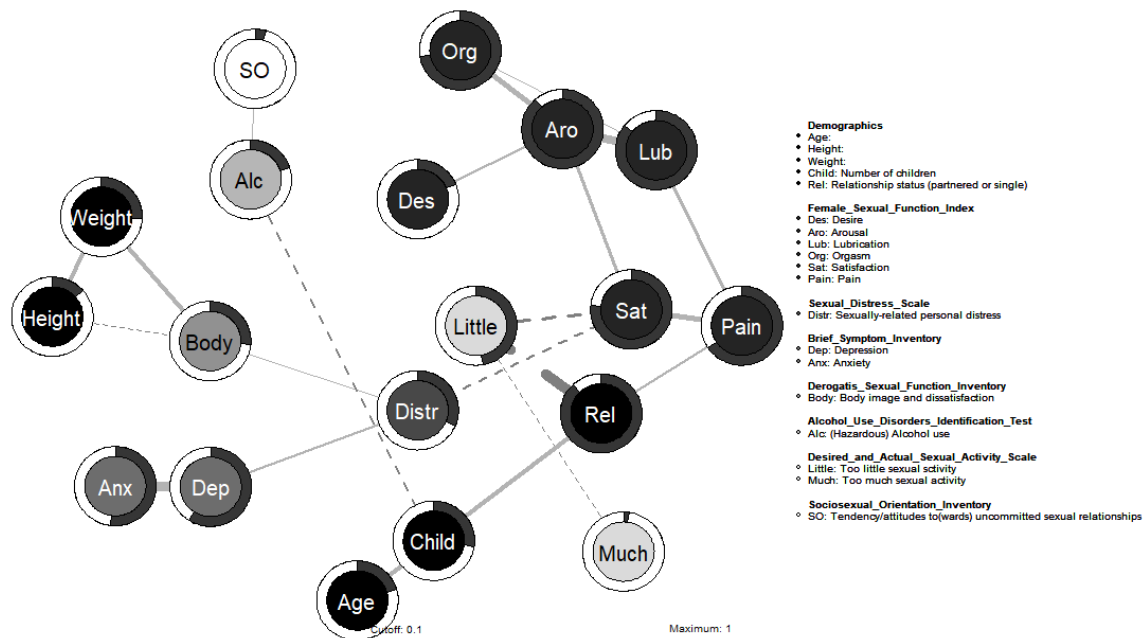
qStableNEW <- qgraph(fit_StableNEW$pairwise$wadj,
  edge.color = fit_StableNEW$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 7.5,
  esize = 10,
  label.cex = 1.2,

```

```

label.scale.equal = TRUE,
pie = predR_StableNEW,
pieColor = "gray21",
pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,
legend.mode = "style1",
legend.cex = 0.5,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



```

fit_IncreaseNEW$pairwise$edgecolor[which(fit_IncreaseNEW$pairwise$edgecolor=="red")] <- "gray50"
fit_IncreaseNEW$pairwise$edgecolor[which(fit_IncreaseNEW$pairwise$edgecolor=="darkgreen")] <- "gray70"
fit_IncreaseNEW$pairwise$edgecolor[which(fit_IncreaseNEW$pairwise$edgecolor=="darkgrey")] <- "black"
fit_IncreaseNEW$pairwise$edgecolor[c(16),19] <- "gray50" # categ relationship
fit_IncreaseNEW$pairwise$edgecolor[c(19),16] <- "gray50"
fit_IncreaseNEW$pairwise$edgecolor[c(10),19] <- "gray70"
fit_IncreaseNEW$pairwise$edgecolor[19,c(10)] <- "gray70"
fit_IncreaseNEW$pairwise$wadj[which(fit_IncreaseNEW$pairwise$edgecolor=="gray50")] <- fit_IncreaseNEW$pairwise$wadj[which(fit_IncreaseNEW$pairwise$edgecolor=="gray50")]*-1

fit_IncreaseNEW$pairwise$wadj[which(fit_IncreaseNEW$pairwise$edgecolor=="gray50")]
## [1] -0.12932642 -0.07260171 -0.13256000 -0.24693582 -0.13256000
## [6] -0.12932642 -0.07260171 -0.24693582 -0.09528064 -0.68644211
## [11] -0.09528064 -0.68644211

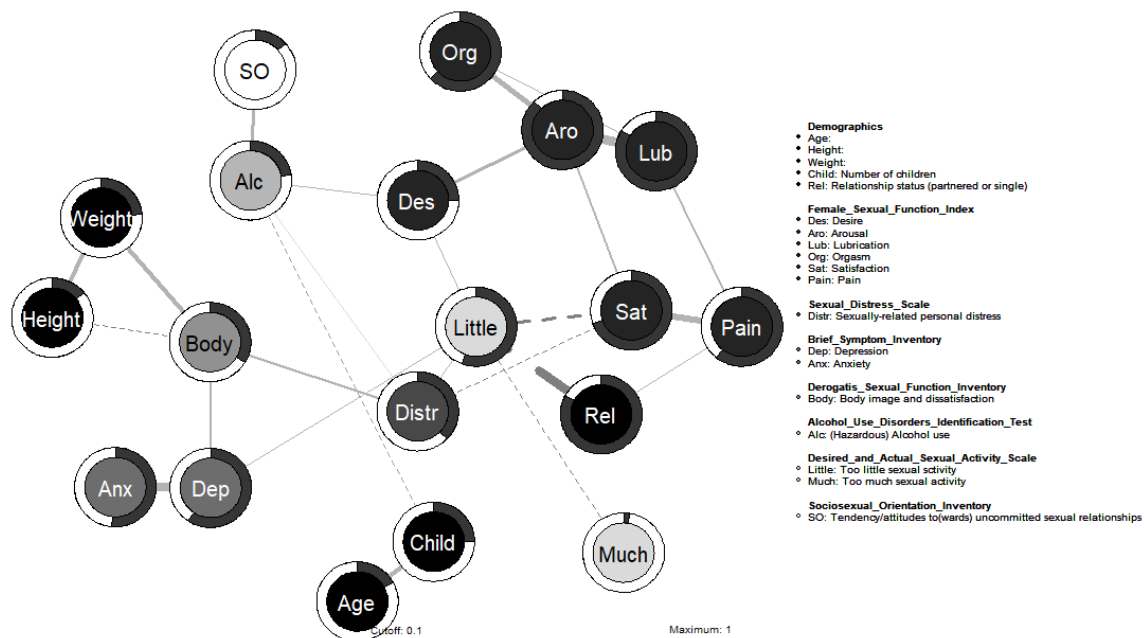
qIncreaseNEW <- qgraph(fit_IncreaseNEW$pairwise$wadj,
  edge.color = fit_IncreaseNEW$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,

```

```

minimum = 0,
cut = 0.1,
details = TRUE,
vsize = 7.5,
esize = 10,
label.cex = 1.2,
label.scale.equal = TRUE,
pie = predR_IncreaseNEW,
pieColor = "gray21",
pieBorder = 0.25,
groups = groupsNoHc,
nodeNames = nodeDescr,
legend = TRUE,
legend.mode = "style1",
legend.cex = 0.5,
palette = "gray",
negDashed = TRUE,
label.color = nodeLabelColors)

```



```

pdf('FSFINetworkWithPrednoHCGrayScaleReplication.pdf', width = 55, height = 15)
par(mfrow = c(1,3))
qDecreaseNEW <- qgraph(fit_DecreaseNEW$pairwise$wadj,
  edge.color = fit_DecreaseNEW$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 10,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_DecreaseNEW,
  pieColor = "gray21",
  pieBorder = 0.25,
  groups = groupsNoHc,
  nodeNames = nodeDescr,
  legend = TRUE,

```

```

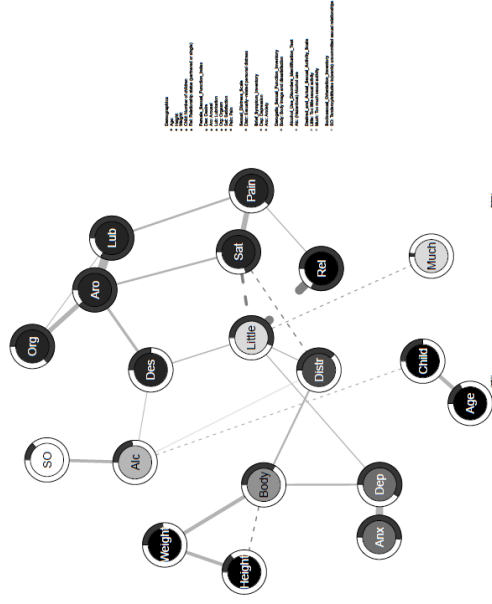
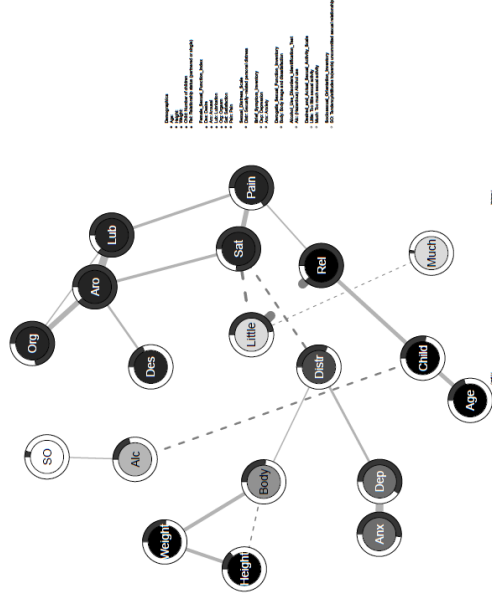
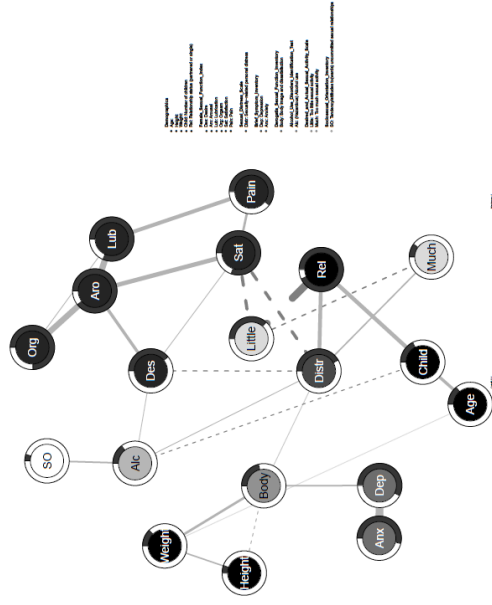
        legend.mode = "style1",
        legend.cex = 0.5,
        palette = "gray",
        negDashed = TRUE,
        label.color = nodeLabelColors,
        repulsion = 2)

qStableNEW <- qgraph(fit_StableNEW$pairwise$wadj,
  edge.color = fit_StableNEW$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 10,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_StableNEW,
  pieColor = "gray21",
  pieBorder = 0.25,
  groups = groupsNoHc,
  nodeNames = nodeDescr,
  legend = TRUE,
  legend.mode = "style1",
  legend.cex = 0.5,
  palette = "gray",
  negDashed = TRUE,
  label.color = nodeLabelColors,
  repulsion = 2)

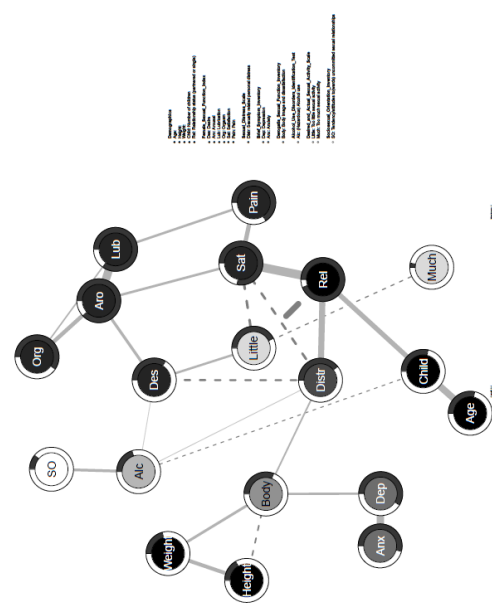
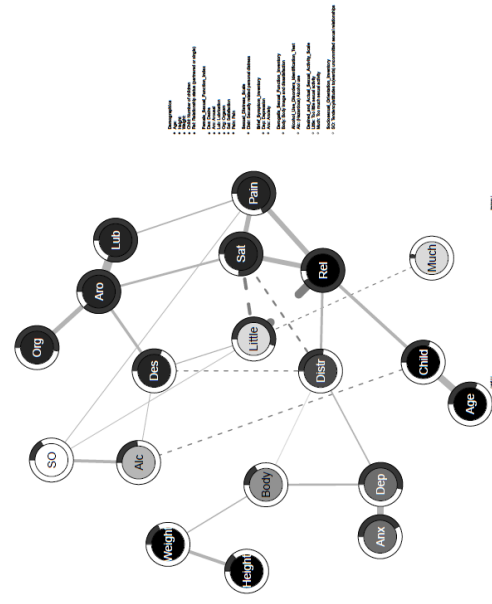
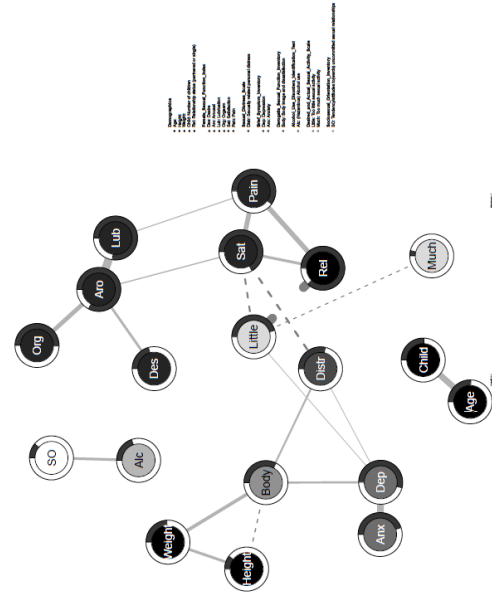
qIncreaseNEW <- qgraph(fit_IncreaseNEW$pairwise$wadj,
  edge.color = fit_IncreaseNEW$pairwise$edgecolor,
  layout = LayoutAverage,
  labels = colNames,
  maximum = 1,
  minimum = 0,
  cut = 0.1,
  details = TRUE,
  vsize = 10,
  label.cex = 1.2,
  label.scale.equal = TRUE,
  pie = predR_IncreaseNEW,
  pieColor = "gray21",
  pieBorder = 0.25,
  groups = groupsNoHc,
  nodeNames = nodeDescr,
  legend = TRUE,
  legend.mode = "style1",
  legend.cex = 0.5,
  palette = "gray",
  negDashed = TRUE,
  label.color = nodeLabelColors,
  repulsion = 2)

dev.off()
## png
## 2

```



For comparison's sake we copied the first graph here below:

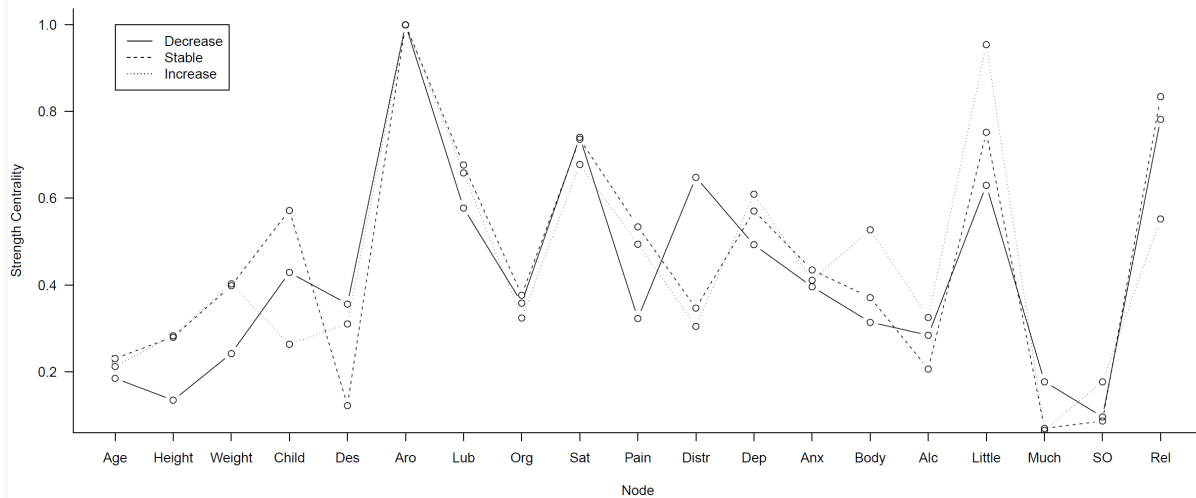


```

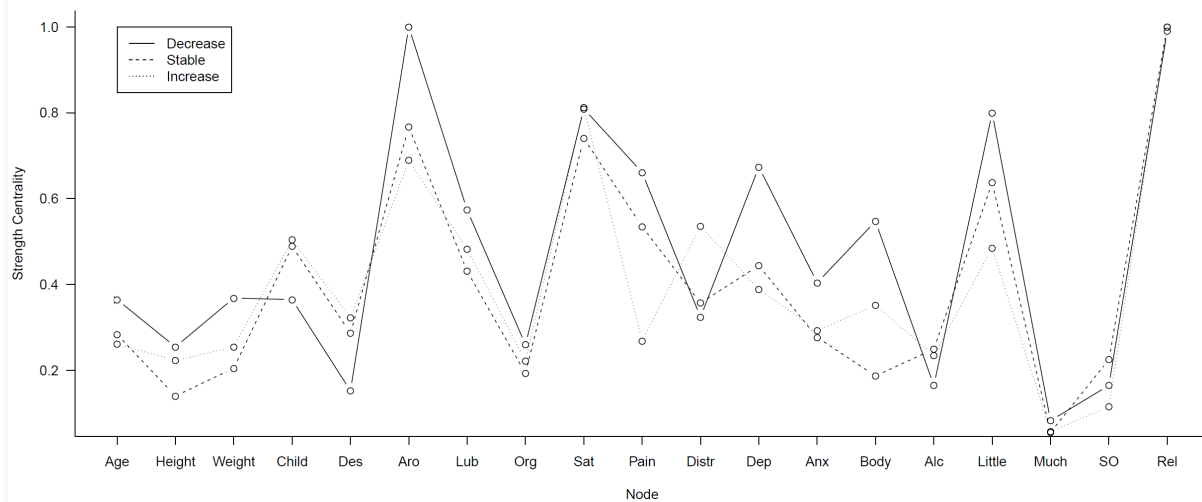
length(qDecreaseNEW$Edgelist$weight)
## [1] 28
length(qStableNEW$Edgelist$weight)
## [1] 22
length(qIncreaseNEW$Edgelist$weight)
## [1] 26

# CUSTOM MADE CENTRALITY PLOT
cenDecreaseNEW <- centralityTable(qDecreaseNEW, standardized = FALSE, relative = TRUE)
cenIncreaseNEW <- centralityTable(qIncreaseNEW, standardized = FALSE, relative = TRUE)
cenStableNEW <- centralityTable(qStableNEW, standardized = FALSE, relative = TRUE)
pdf("CustomCentralityFSFINetworkReplication.pdf", width = 15, height = 7)
plot(cenDecreaseNEW$value[39:57],
     type = "b",
     bty = "n",
     family = "sans",
     las = 1,
     lwd = 1,
     xaxt="n",
     xlab = "Node",
     ylab = "Strength Centrality")
axis(side = 1, labels = colNames, at = c(1:19))
lines(cenIncreaseNEW$value[39:57], type = "b", lty = "dotted")
lines(cenStableNEW$value[39:57], type = "b", lty = "dashed")
legend(x = 1, legend=c("Decrease", "Stable", "Increase"),
      lty=c("solid", "dashed", "dotted"))
dev.off()

```



For comparison's sake we copied the first graph here below:



#####

EDGE COEFFICIENTS

```
fit_DecreaseNEW$rawfactor$indicator[[1]][7,] # 4 child
## [1] 4 19
fit_DecreaseNEW$rawfactor$indicator[[1]][23,] # 11 distress
## [1] 11 19
fit_DecreaseNEW$rawfactor$indicator[[1]][28,] # 16 too little
## [1] 16 19
fit_DecreaseNEW$rawfactor$weights[[1]][7]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 0.4850364
##
## [[1]][[2]]
## [1] -0.1563666 0.1563666
fit_DecreaseNEW$rawfactor$weights[[1]][23]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 0.5823611
##
## [[1]][[2]]
## [1] -0.04556507 0.04556507
fit_DecreaseNEW$rawfactor$weights[[1]][28]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 -0.793869
##
## [[1]][[2]]
## [1] 0.3911461 -0.3911461
fit_StableNEW$rawfactor$indicator[[1]][6,] # 4 child
## [1] 4 19
fit_StableNEW$rawfactor$indicator[[1]][16,] # 10 pain
## [1] 10 19
fit_StableNEW$rawfactor$indicator[[1]][22,] # 16 too little
## [1] 16 19
fit_StableNEW$rawfactor$weights[[1]][6]
## [[1]]
## [[1]][[1]]
##      [,1]
```

```

## V19.1 0.5694836
##
## [[1]][[2]]
## [1] -0.06555586 0.06555586
fit_StableNEW$rawfactor$weights[[1]][16]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 0.160404
##
## [[1]][[2]]
## [1] -0.1257695 0.1257695
fit_StableNEW$rawfactor$weights[[1]][22]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 -1.03362
##
## [[1]][[2]]
## [1] 0.4341031 -0.4341031

fit_IncreaseNEW$rawfactor$indicator[[1]][17,] # 10 pain
## [1] 10 19
fit_IncreaseNEW$rawfactor$indicator[[1]][26,] # 16 too little
## [1] 16 19
fit_IncreaseNEW$rawfactor$weights[[1]][17]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 0.1343324
##
## [[1]][[2]]
## [1] -0.08722788 0.08722788
fit_IncreaseNEW$rawfactor$weights[[1]][26]
## [[1]]
## [[1]][[1]]
##      [,1]
## V19.1 -0.8716168
##
## [[1]][[2]]
## [1] 0.5012674 -0.5012674

```

15. Replication – Network Stability

```
#####
```

```
# BOOTNET
```

```
library(bootnet)
```

```

fit_DecreaseBootNEW <- estimateNetwork(as.matrix(DecreaseNEWRS),
                                     default = "mgm",
                                     type = VarDomain,
                                     lev = VarLevel,
                                     degree = 2,
                                     criterion = "EBIC",
                                     tuning = 0.5)

```

```

fit_StableBootNEW <- estimateNetwork(as.matrix(StableNEWRS),
                                    default = "mgm",
                                    type = VarDomain,
                                    lev = VarLevel,
                                    degree = 2,

```

```

criterion = "EBIC",
tuning = 0.5)

fit_IncreaseBootNEW <- estimateNetwork(as.matrix(IncreaseNEWRS),
                                     default = "mgm",
                                     type = VarDomain,
                                     lev = VarLevel,
                                     degree = 2,
                                     criterion = "EBIC",
                                     tuning = 0.5)

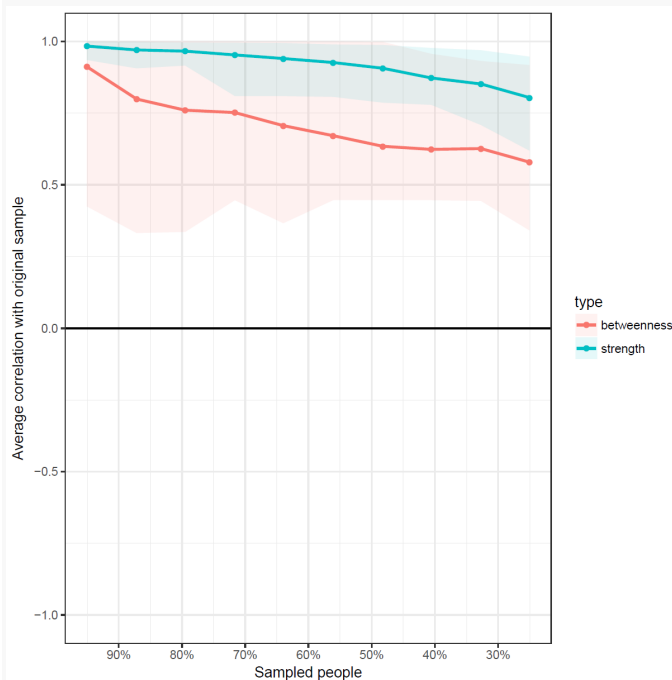
fit_DecreaseBootNEW1 <- bootnet(fit_DecreaseBootNEW, nBoots = 1000, nCores = 8,type = "case")

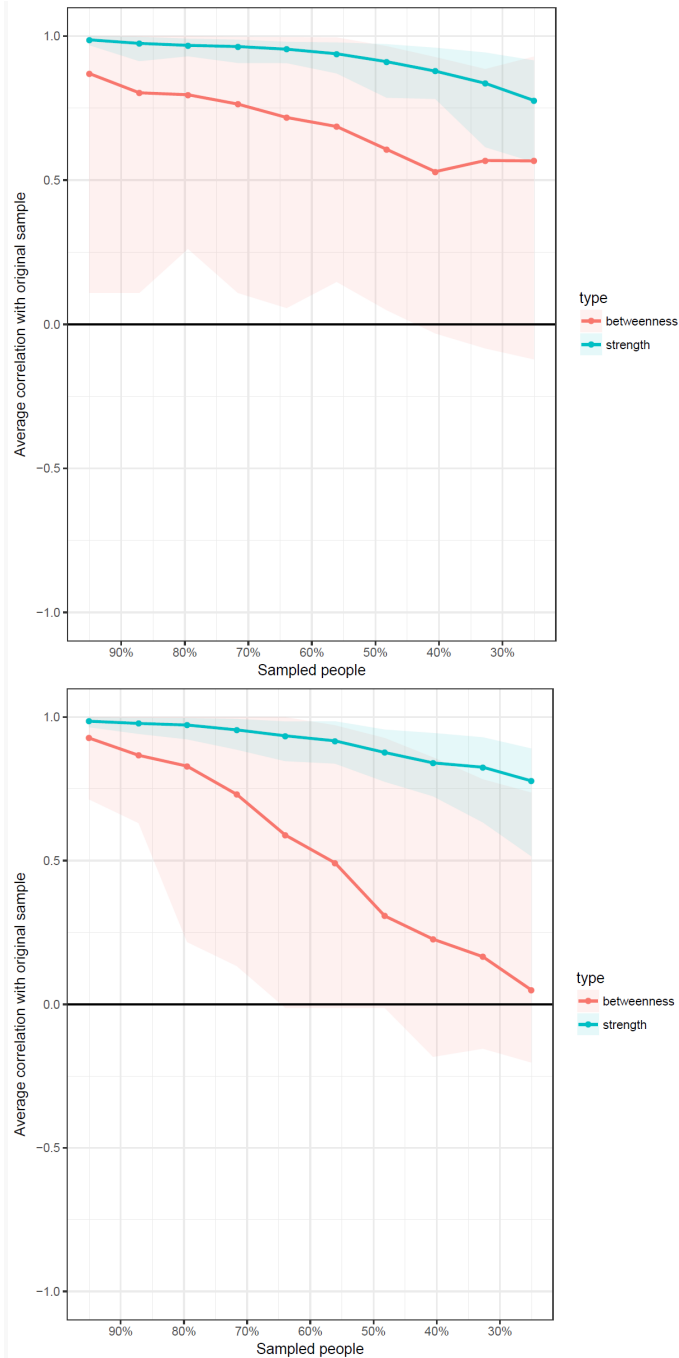
fit_StableBootNEW1 <- bootnet(fit_StableBootNEW, nBoots = 1000, nCores = 8,type = "case")

fit_IncreaseBootNEW1 <- bootnet(fit_IncreaseBootNEW, nBoots = 1000, nCores = 8,type = "case")

pdf("CentralityStabilityReplication.pdf")
plot(fit_DecreaseBootNEW1)
## Warning in plot.bootnet(fit_DecreaseBootNEW1): Statistic closeness does not
## contain any variance and is therefore not shown.
plot(fit_StableBootNEW1)
## Warning in plot.bootnet(fit_StableBootNEW1): Statistic closeness does not
## contain any variance and is therefore not shown.
plot(fit_IncreaseBootNEW1)
## Warning in plot.bootnet(fit_IncreaseBootNEW1): Statistic closeness does not
## contain any variance and is therefore not shown.
dev.off()
## png
## 2

```





```
corStability(fit_DecreaseBootNEW1)
## === Correlation Stability Analysis ===
##
## Sampling levels tested:
##   nPerson Drop%  n
## 1      121  74.9  93
## 2      158  67.3 119
## 3      196  59.4 109
## 4      233  51.8  99
## 5      271  43.9 100
## 6      309  36.0  90
## 7      346  28.4 112
## 8      384  20.5  85
```

```

## 9      421  12.8  93
## 10     459   5.0 100
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:
##
## betweenness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## closeness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## strength: 0.673
##   - For more accuracy, run bootnet(..., caseMin = 0.594, caseMax = 0.749)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.

corStability(fit_StableBootNEW1)
## === Correlation Stability Analysis ===
##
## Sampling levels tested:
##      nPerson Drop%   n
## 1      121   74.9   95
## 2      158   67.3  113
## 3      196   59.4   96
## 4      233   51.8  106
## 5      271   43.9  107
## 6      309   36.0   91
## 7      346   28.4   88
## 8      384   20.5  101
## 9      421   12.8  113
## 10     459    5.0   90
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:
##
## betweenness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## closeness: 0
##   - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## strength: 0.594
##   - For more accuracy, run bootnet(..., caseMin = 0.518, caseMax = 0.673)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.

corStability(fit_IncreaseBootNEW1)
## === Correlation Stability Analysis ===
##
## Sampling levels tested:
##      nPerson Drop%   n
## 1      121   74.9   96
## 2      158   67.3   94
## 3      196   59.4  105
## 4      233   51.8   87
## 5      271   43.9  108
## 6      309   36.0  111
## 7      346   28.4  103
## 8      384   20.5  108
## 9      421   12.8   92
## 10     459    5.0   96
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:
##

```

```

## betweenness: 0.128
## - For more accuracy, run bootnet(..., caseMin = 0.05, caseMax = 0.205)
##
## closeness: 0
## - For more accuracy, run bootnet(..., caseMin = 0, caseMax = 0.05)
##
## strength: 0.673
## - For more accuracy, run bootnet(..., caseMin = 0.594, caseMax = 0.749)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.
fit_DecreaseBootNEW2 <- bootnet(fit_DecreaseBootNEW, nBoots = 1000, nCores = 8)

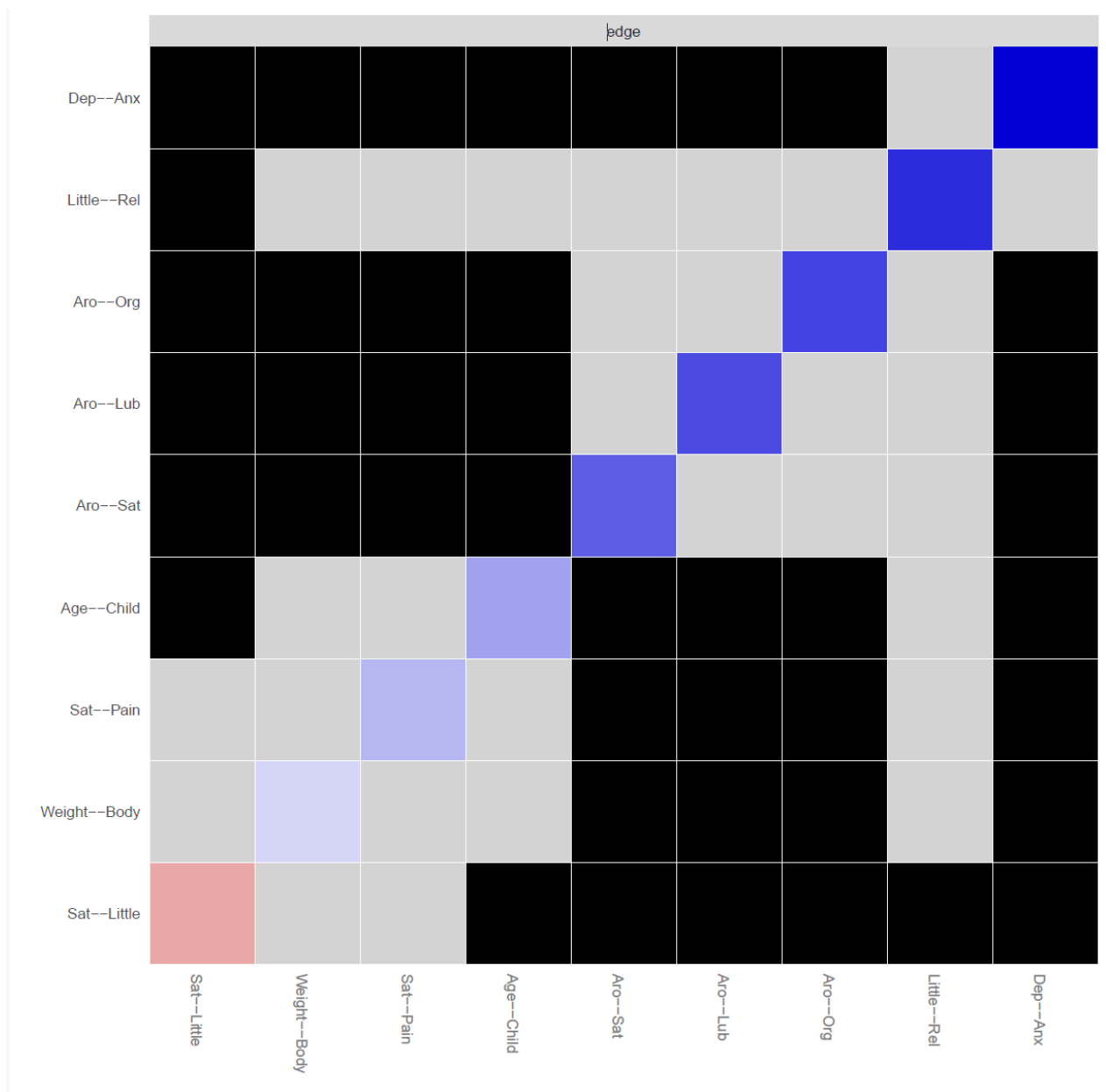
fit_StableBootNEW2 <- bootnet(fit_StableBootNEW, nBoots = 1000, nCores = 8)

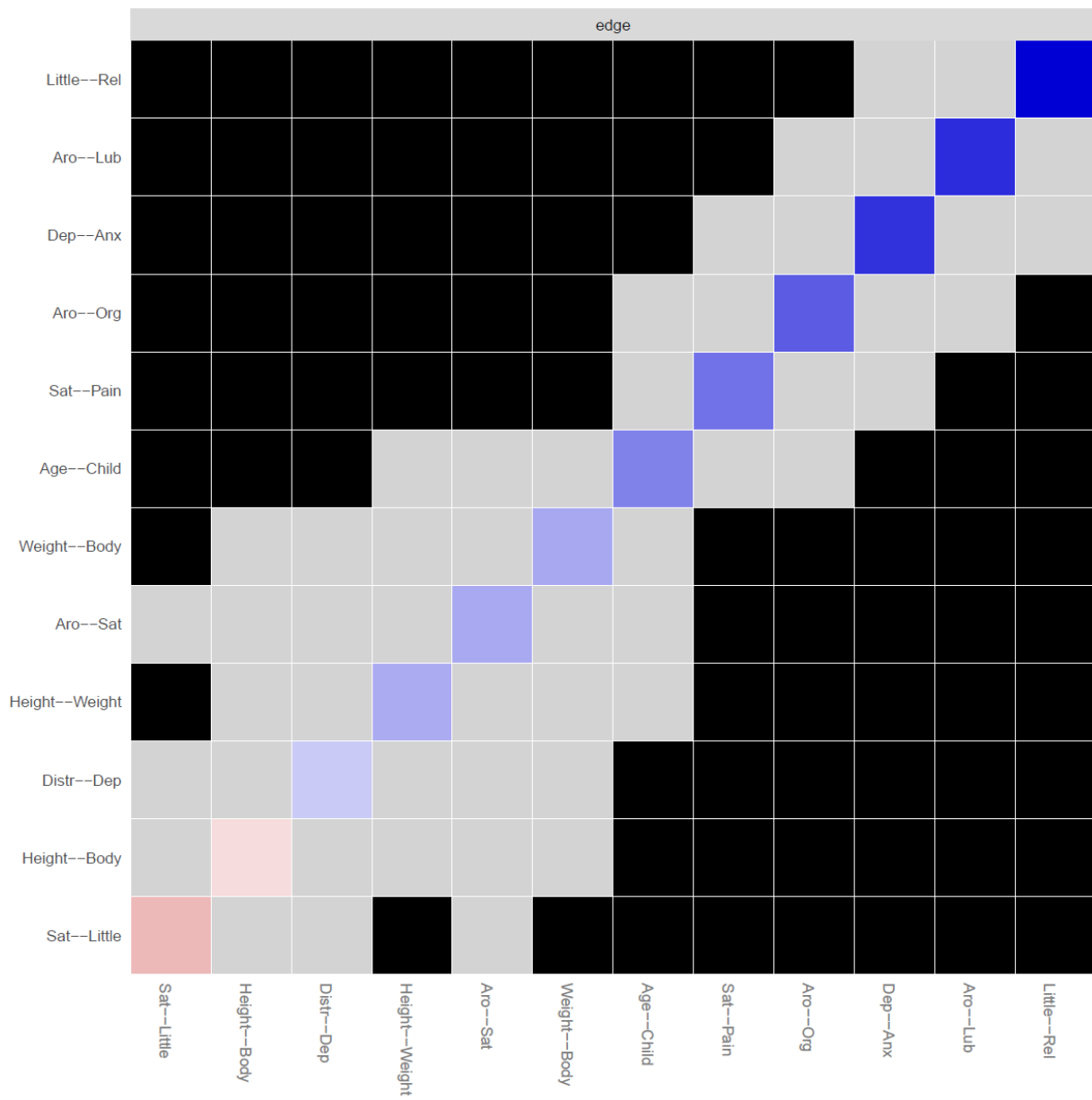
fit_IncreaseBootNEW2 <- bootnet(fit_IncreaseBootNEW, nBoots = 1000, nCores = 8)

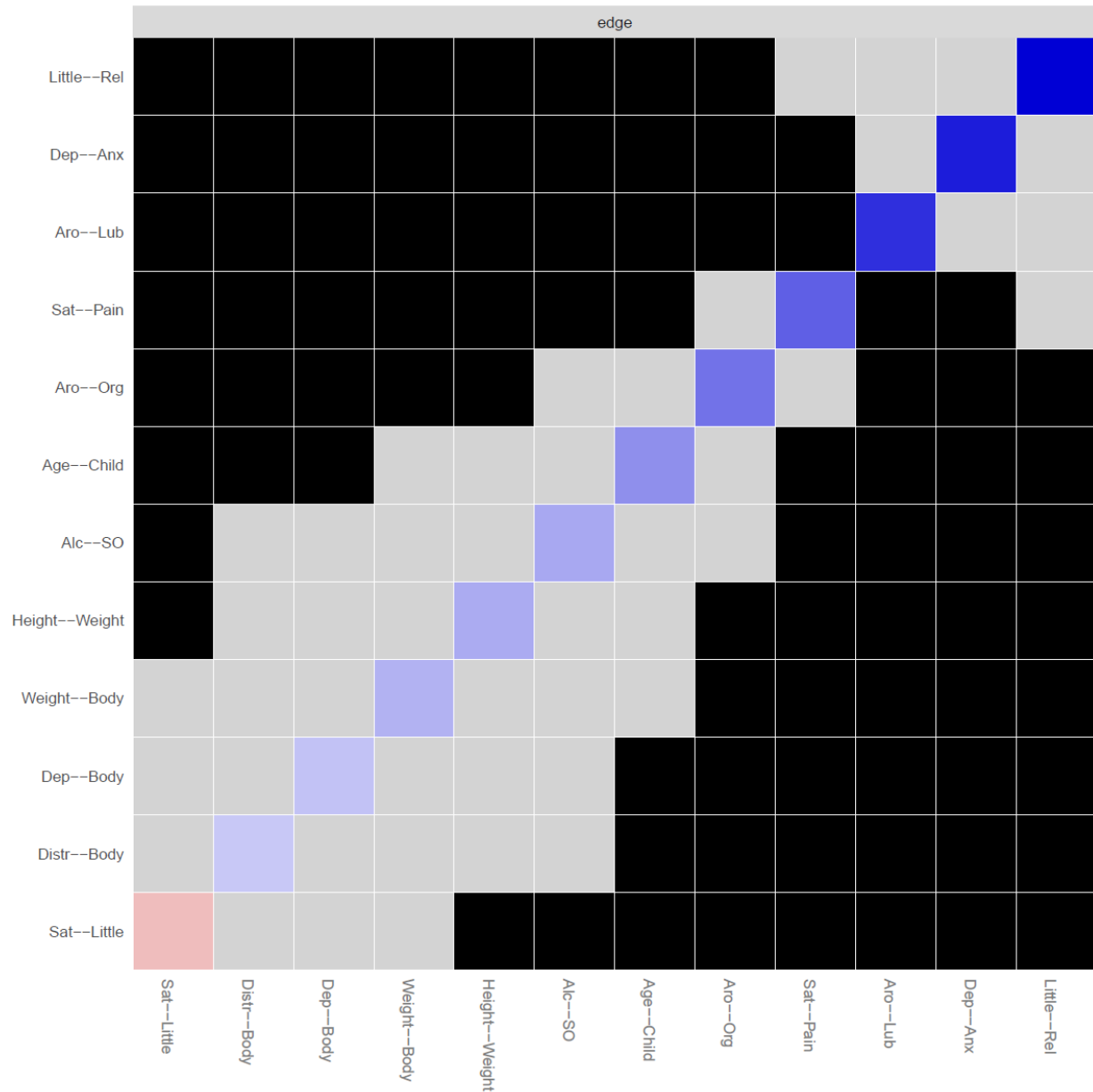
# See pdf for edge stability plots
pdf("EdgeStabilityReplication.pdf", height = 25)
plot(fit_DecreaseBootNEW2, labels = TRUE, order = "sample")
plot(fit_StableBootNEW2, labels = TRUE, order = "sample")
plot(fit_IncreaseBootNEW2, labels = TRUE, order = "sample")
dev.off()
## png
## 2

pdf("EdgeSignificanceReplication.pdf")
plot(fit_DecreaseBootNEW2, "edge", plot = "difference", onlyNonZero = TRUE,
     order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_StableBootNEW2, "edge", plot = "difference", onlyNonZero = TRUE,
     order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_IncreaseBootNEW2, "edge", plot = "difference", onlyNonZero = TRUE,
     order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
dev.off()
## png
## 2

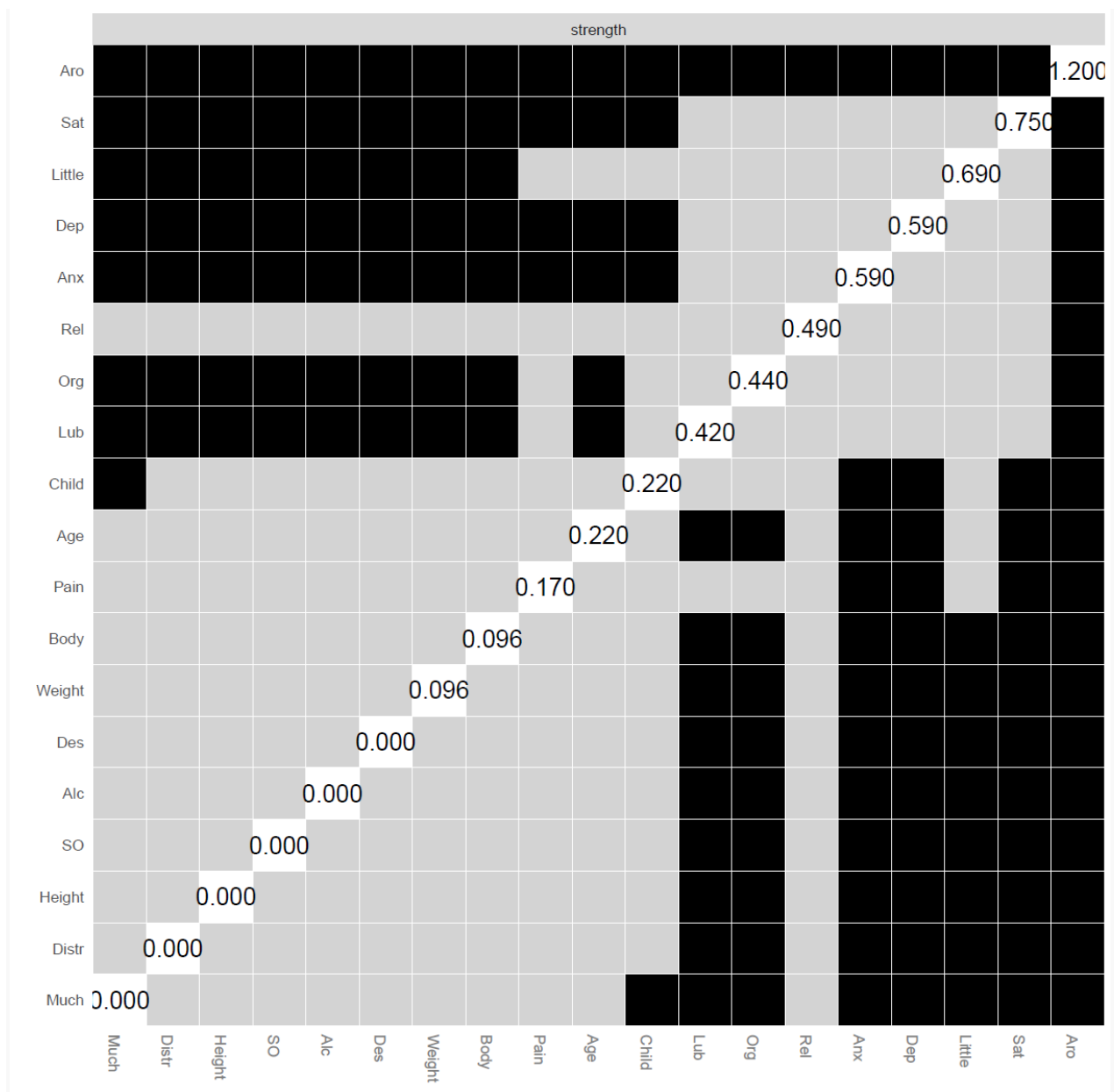
```

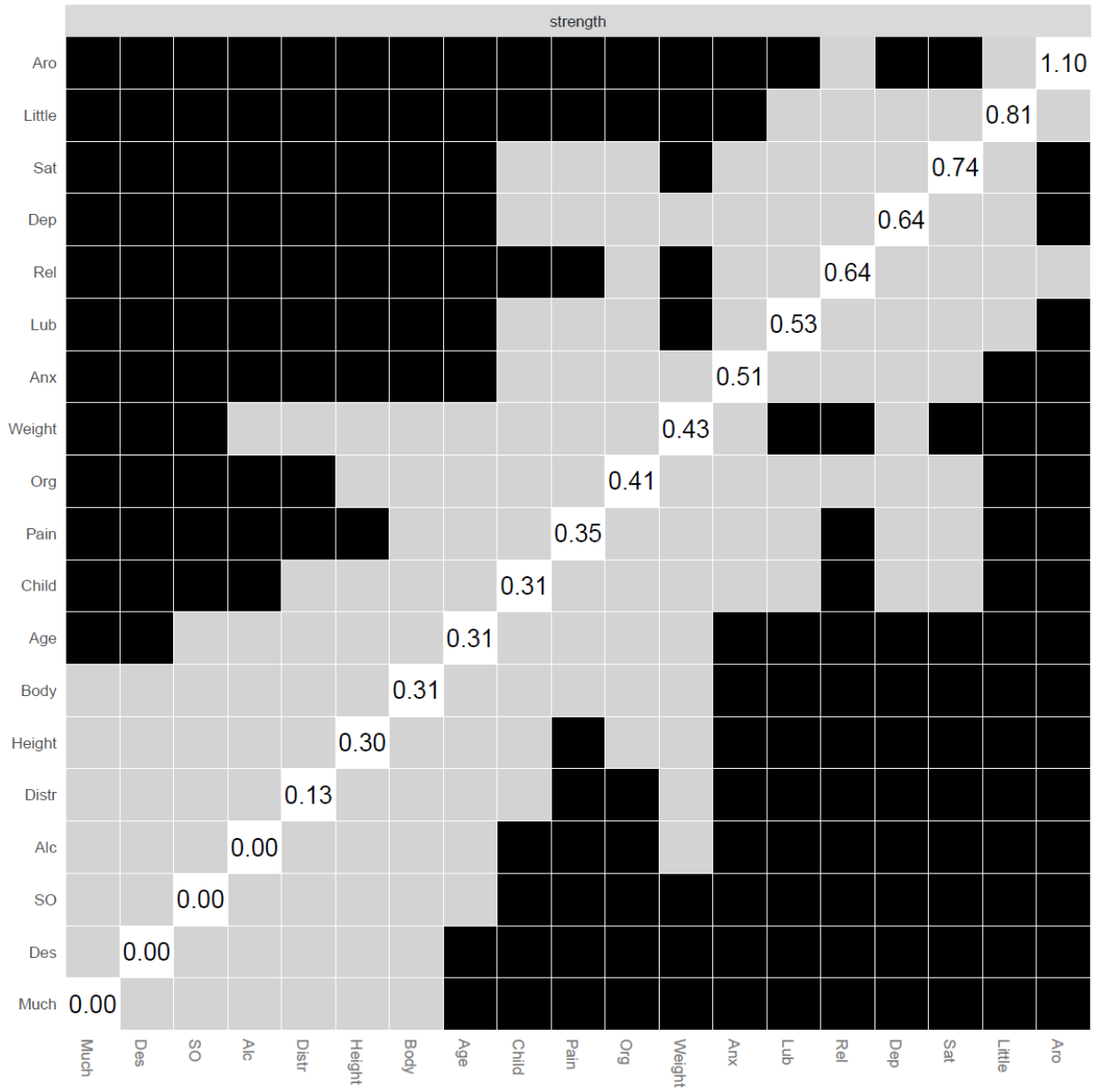


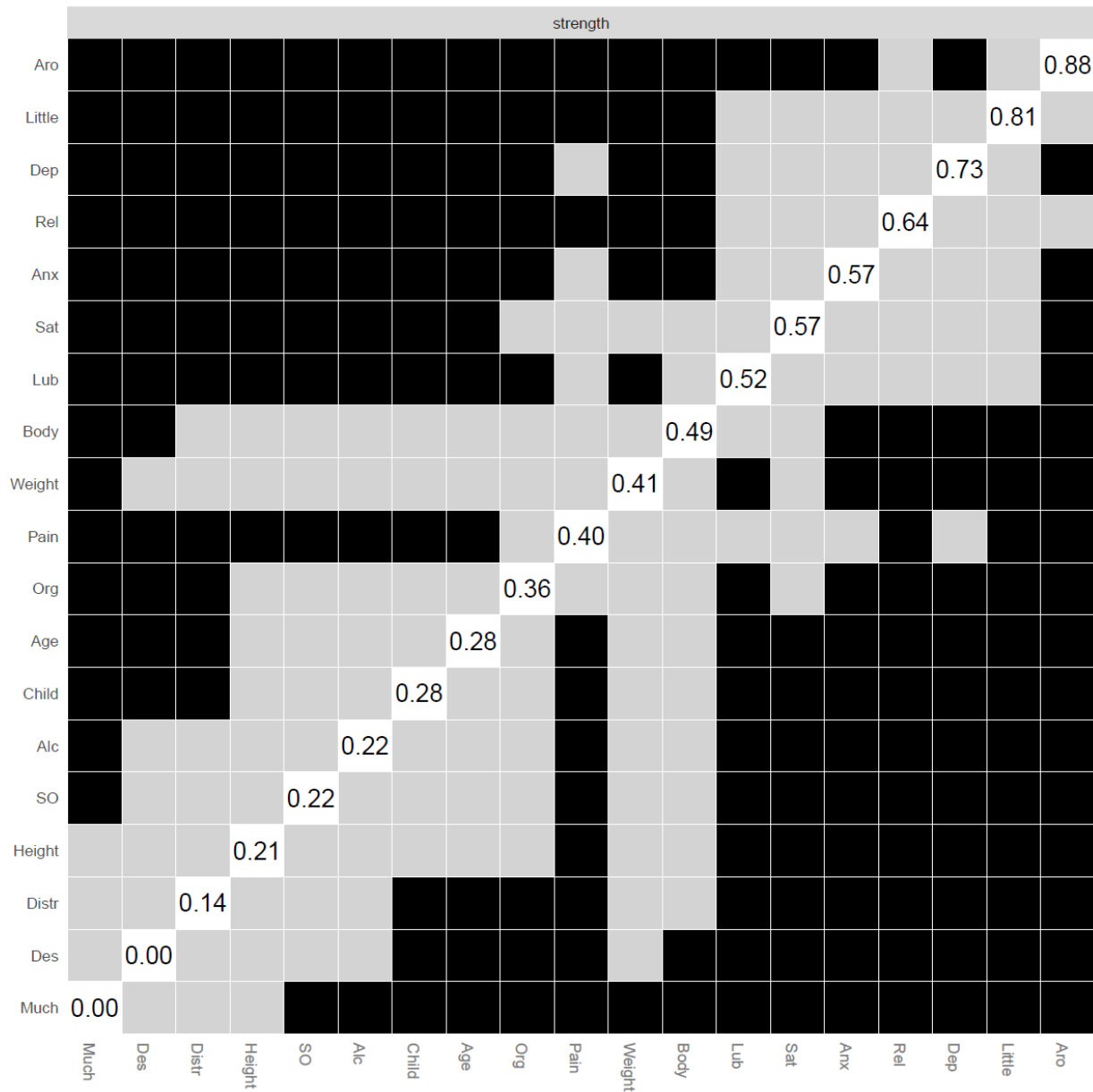




```
pdf("StrengthSignificanceReplication.pdf")
plot(fit_DecreaseBootNEW2, "strength", plot = "difference", order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_StableBootNEW2, "strength", plot = "difference", order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
plot(fit_IncreaseBootNEW2, "strength", plot = "difference", order = "sample")
## Expected significance level given number of bootstrap samples is approximately: 0.05
dev.off()
## png
## 2
```







16. Replication – Network Comparison

```
#####
# NCT

library(NetworkComparisonTest)

NCTDecStabNEW <- NCT(DecreaseNEWRS, StableNEWRS, gamma = 0.5, it = 1000, binary.data=FALSE, pai
red=FALSE, weighted=TRUE, progressbar=TRUE)

NCTDecStabNEW$nwinv.pval
## [1] 0.128

NCTDecStabNEW$glstrinv.real
## [1] 0.419842
NCTDecStabNEW$glstrinv.pval
## [1] 0.577
```

```

NCTIncStabNEW <- NCT(StableNEWRS, IncreaseNEWRS, gamma = 0.5, it = 1000, binary.data=FALSE, paired=FALSE, weighted=TRUE, progressbar=TRUE)

NCTIncStabNEW$nwinv.pval
## [1] 0.55

NCTIncStabNEW$glstrinv.real
## [1] 0.4022591
NCTIncStabNEW$glstrinv.pval
## [1] 0.556

NCTDecIncNEW <- NCT(DecreaseNEWRS, IncreaseNEWRS, gamma = 0.5, it = 1000, binary.data=FALSE, paired=FALSE, weighted=TRUE, progressbar=TRUE)

NCTDecIncNEW$nwinv.pval
## [1] 0.003

NCTDecIncNEW$glstrinv.real
## [1] 0.01758292
NCTDecIncNEW$glstrinv.pval
## [1] 0.974
# no significant differences, but presumably because of power
#####
mean(as.matrix(clustcoef_auto(qDecreaseNEW)))
## [1] 0.08534148
mean(as.matrix(clustcoef_auto(qStableNEW)))
## [1] 0.07164526
mean(as.matrix(clustcoef_auto(qIncreaseNEW)))
## [1] 0.08100884
#####

```

17. Replication – Network Communities

```

# CLUSTER ANALYSIS
#### DECREASE

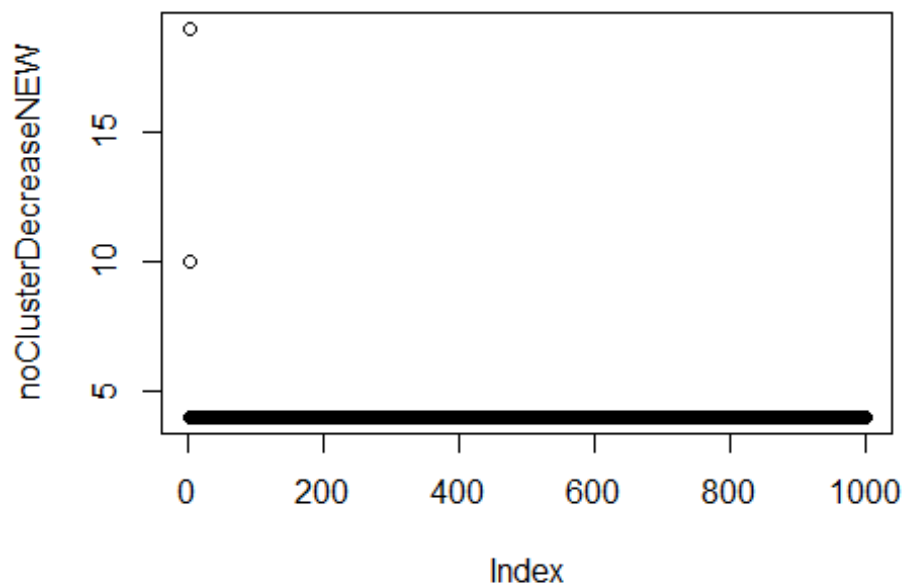
library(igraph)

NetworkDecreaseIgraphNEW <- as.igraph(qDecreaseNEW)

noClusterDecreaseNEW <- 0
for (i in 1:1000){
  communityWTDecreaseNEW <- cluster_walktrap(NetworkDecreaseIgraphNEW,
                                              weights = E(NetworkDecreaseIgraphNEW)$weight,
                                              steps = i,
                                              merges = TRUE,
                                              modularity = TRUE,
                                              membership = TRUE)
  noClusterDecreaseNEW[i] <- length(communityWTDecreaseNEW)
}

plot(noClusterDecreaseNEW)

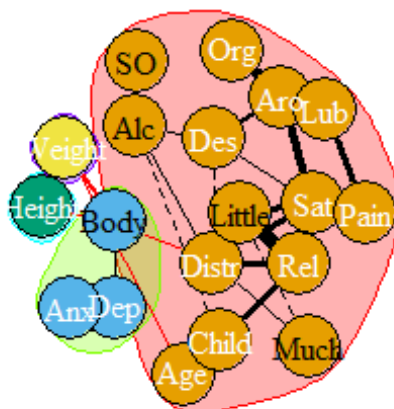
```



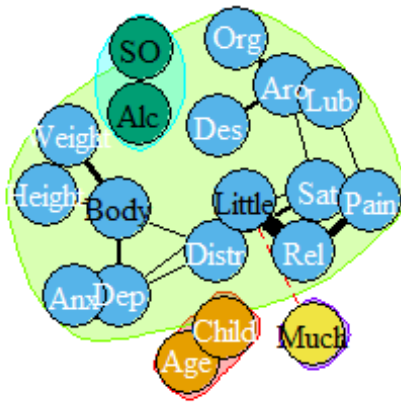
```
median(noClusterDecreaseNEW)
## [1] 4
mean(noClusterDecreaseNEW)
## [1] 4.021

communityWPlotDecreaseNEW <- cluster_walktrap(NetworkDecreaseIgraphNEW,
                                              weights = E(NetworkDecreaseIgraphNEW)$weight,
                                              steps = 200,
                                              merges = TRUE,
                                              modularity = TRUE,
                                              membership = TRUE)

plot(communitWPlotDecreaseNEW, NetworkDecreaseIgraphNEW, layout = qDecreaseNEW$layout)
```



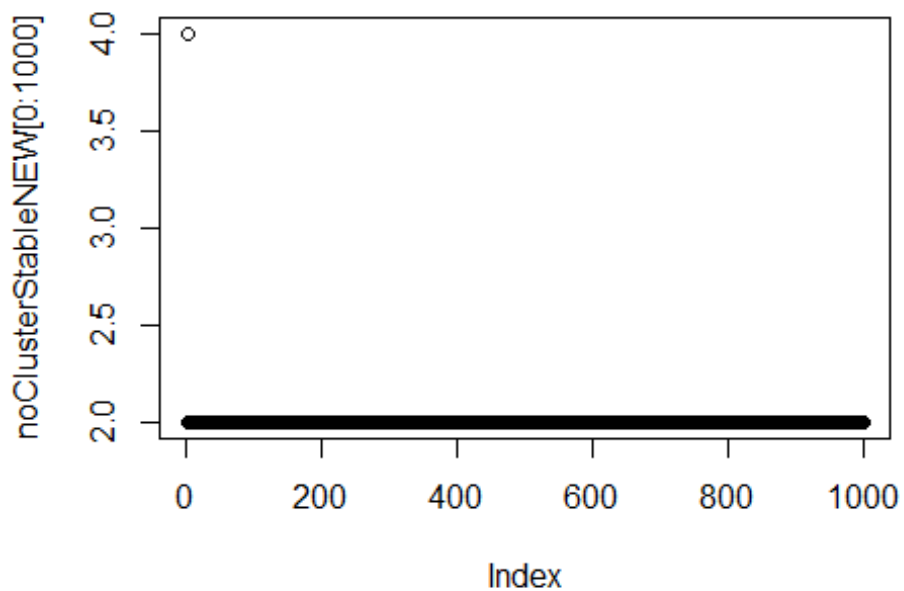
For comparison's sake we copied the first graph here below:



```
# STABLE
NetworkStableIgraphNEW <- as.igraph(qStableNEW)

noClusterStableNEW <- 0
for (i in 1:1000){
  communityWTStableNEW <- cluster_walktrap(NetworkStableIgraphNEW,
                                           weights = E(NetworkStableIgraphNEW)$weight,
                                           steps = i,
                                           merges = TRUE,
                                           modularity = TRUE,
                                           membership = TRUE)
  noClusterStableNEW[i] <- length(communityWTStableNEW)
}

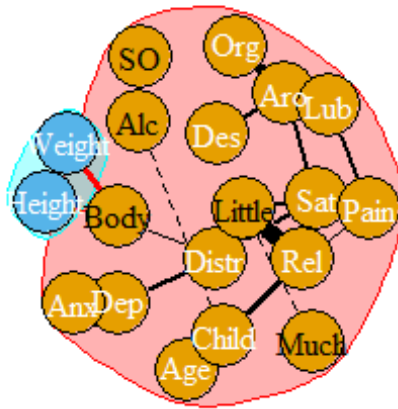
plot(noClusterStableNEW[0:1000])
```



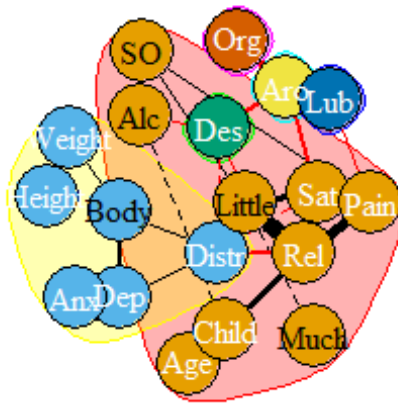
```
median(noClusterStableNEW[0:1000])
## [1] 2
mean(noClusterStableNEW[0:1000])
```

```
## [1] 2.002
```

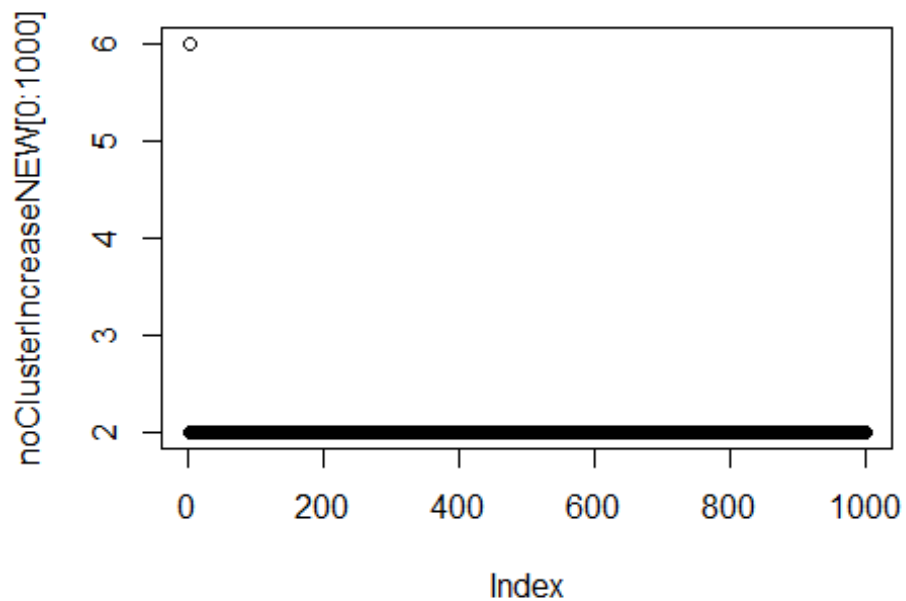
```
communityWPlotStableNEW <- cluster_walktrap(NetworkStableIgraphNEW,  
  weights = E(NetworkStableIgraphNEW)$weight,  
  steps = 200,  
  merges = TRUE,  
  modularity = TRUE,  
  membership = TRUE)  
  
plot(communitWPlotStableNEW, NetworkStableIgraphNEW, layout = qStableNEW$layout)
```



For comparison's sake we copied the first graph here below:



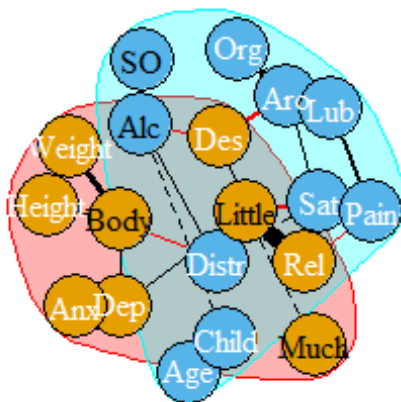
```
#### Increase  
NetworkIncreaseIgraphNEW <- as.igraph(qIncreaseNEW)  
  
noClusterIncreaseNEW <- 0  
for (i in 1:1000){  
  communityWTIncreaseNEW <- cluster_walktrap(NetworkIncreaseIgraphNEW,  
    weights = E(NetworkIncreaseIgraphNEW)$weight,  
    steps = i,  
    merges = TRUE,  
    modularity = TRUE,  
    membership = TRUE)  
  noClusterIncreaseNEW[i] <- length(communitWIncreaseNEW)  
}  
  
plot(noClusterIncreaseNEW[0:1000])
```



```
median(noClusterIncreaseNEW[0:1000])
## [1] 2
mean(noClusterIncreaseNEW[0:1000])
## [1] 2.004

communityWPlotIncreaseNEW <- cluster_walktrap(NetworkIncreaseIgraphNEW,
                                              weights = E(NetworkIncreaseIgraphNEW)$weight,
                                              steps = 200,
                                              merges = TRUE,
                                              modularity = TRUE,
                                              membership = TRUE)

plot(communitWPlotIncreaseNEW, NetworkIncreaseIgraphNEW, layout = qIncreaseNEW$layout)
```



For comparison's sake we copied the first graph here below:



```
pdf("WalktrapClusterReplication.pdf")
plot(communitWTPlotDecreaseNEW, NetworkDecreaseIgraphNEW, layout = qDecreaseNEW$layout)
plot(communitWTPlotStableNEW, NetworkStableIgraphNEW, layout = qStableNEW$layout)
plot(communitWTPlotIncreaseNEW, NetworkIncreaseIgraphNEW, layout = qIncreaseNEW$layout)
dev.off()
## png
## 2
```