No Paradoxes

Interpreting Within- and Between-subject Network Structures

Sacha Epskamp

EAPP / EAPA Expert Meeting

- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components

- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components
  - Cramer, A. O., et al. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26(4)*, 414-431.

- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components
  - Cramer, A. O., et al. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26(4)*, 414-431.
- From this idea new exploratory data analysis tools (network psychometrics) have been developed which visualize variation in a dataset as networks

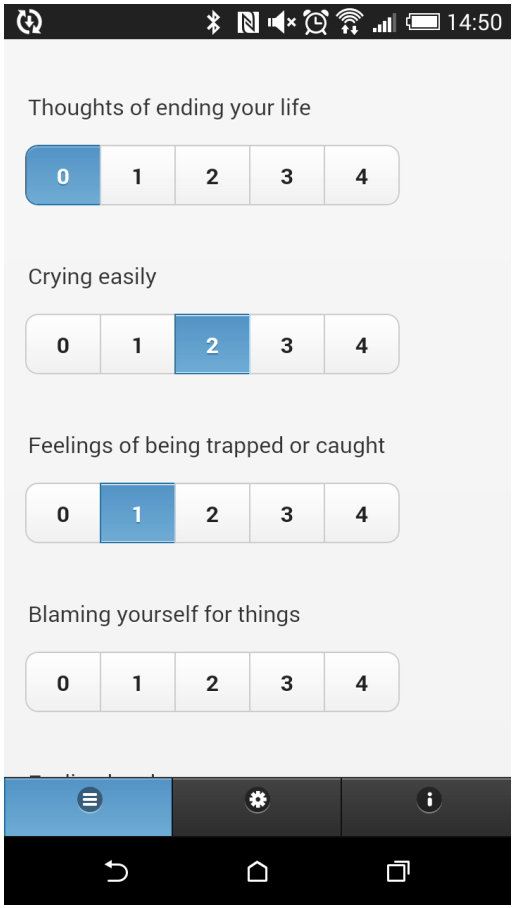
- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components
  - Cramer, A. O., et al. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26(4)*, 414-431.
- From this idea new exploratory data analysis tools (network psychometrics) have been developed which visualize variation in a dataset as networks
  - Costantini, G., et al. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality, 54*, 13-29.

- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components
  - Cramer, A. O., et al. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26(4)*, 414-431.
- From this idea new exploratory data analysis tools (network psychometrics) have been developed which visualize variation in a dataset as networks
  - Costantini, G., et al. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality, 54*, 13-29.
  - Epskamp, S., et al. (2018). The Gaussian Graphical Model in Cross-sectional and Time-series Data. *Multivariate Behavioral Research*

- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components
  - Cramer, A. O., et al. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26(4)*, 414-431.
- From this idea new exploratory data analysis tools (network psychometrics) have been developed which visualize variation in a dataset as networks
  - Costantini, G., et al. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality, 54*, 13-29.
  - Epskamp, S., et al. (2018). The Gaussian Graphical Model in Cross-sectional and Time-series Data. *Multivariate Behavioral Research*
- A prominent topic of discussion in network psychometrics is what the source of data should be (cross-sectional vs time-series analysis)

- The network approach has been proposed to re-conceptualize personality traits as clusters in a network of interacting components
  - Cramer, A. O., et al. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26(4)*, 414-431.
- From this idea new exploratory data analysis tools (network psychometrics) have been developed which visualize variation in a dataset as networks
  - Costantini, G., et al. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality, 54*, 13-29.
  - Epskamp, S., et al. (2018). The Gaussian Graphical Model in Cross-sectional and Time-series Data. *Multivariate Behavioral Research*
- A prominent topic of discussion in network psychometrics is what the source of data should be (cross-sectional vs time-series analysis)
- This talk will discuss apparent paradoxes that may arise as well as empirical investigations to the overlap between within- and between-subject network structures

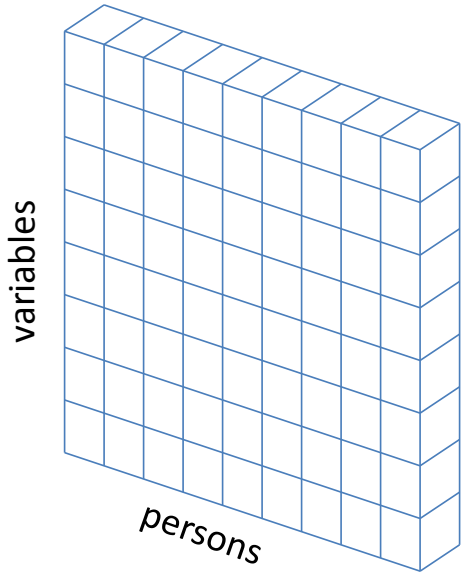
Cross-sectional Analysis



Subject	Time	Item 1	Item 2	Item 3
Subject 1	Time 1	2	2	4
Subject 2	Time 1	4	1	2
Subject 3	Time 1	1	3	0

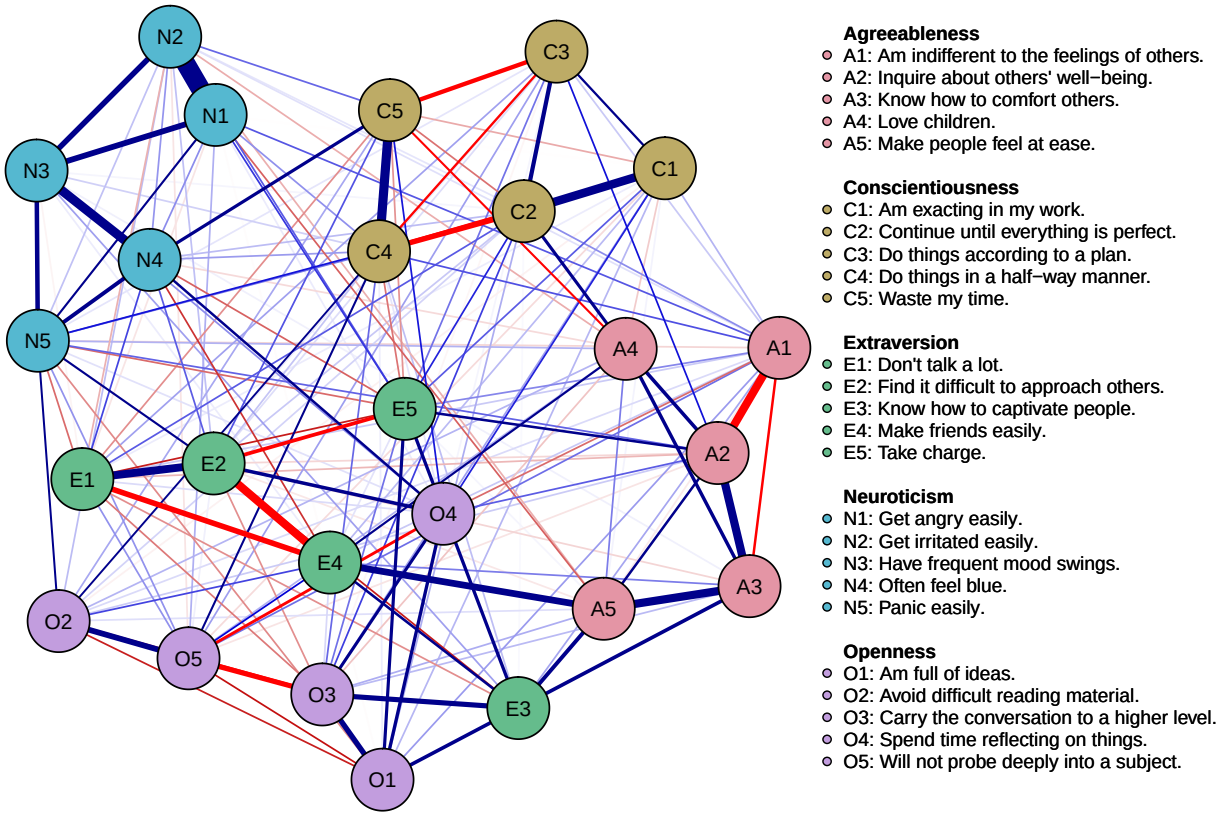
- Multiple people measured once: *cross-sectional analysis*

Cross-sectional research: A single snapshot



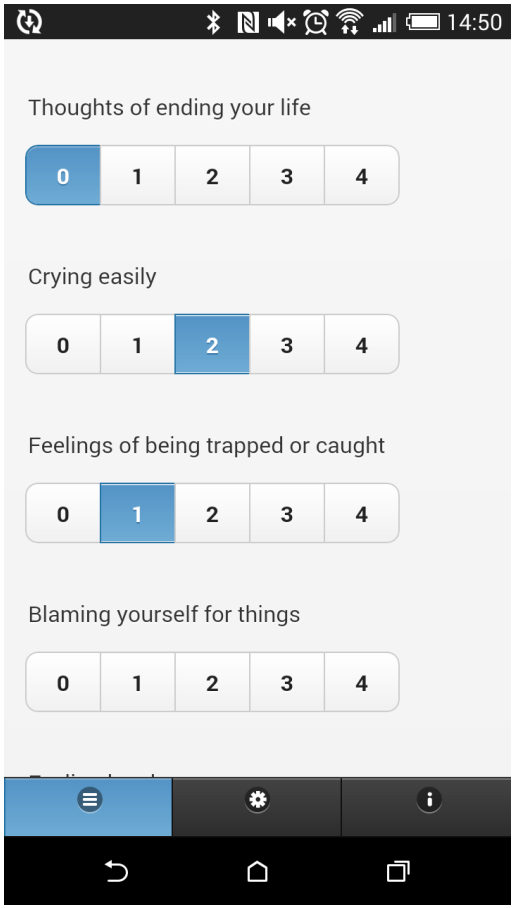
Slide by Ellen Hamaker

Cross-sectional Analysis



- Concentration network: conditional association between two variables

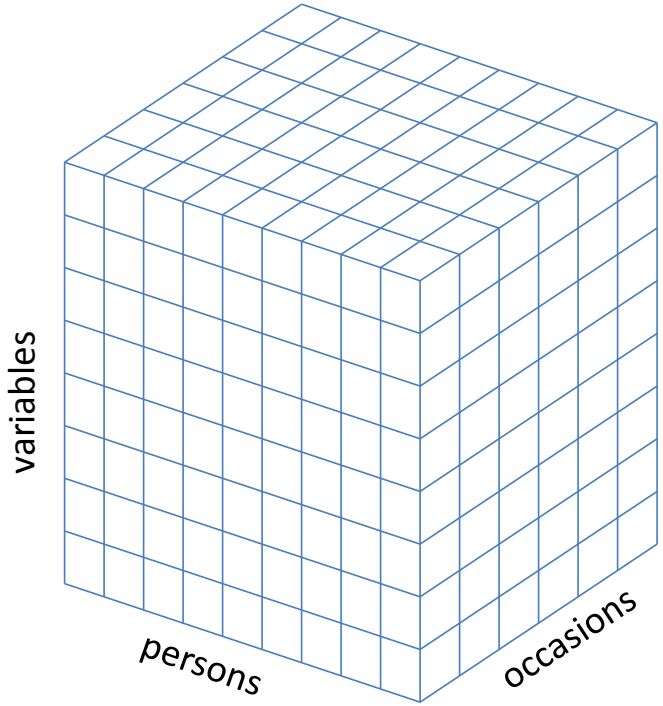
Time-series data



Subject	Time	Item 1	Item 2	Item 3
Subject 1	Time 1	2	2	4
Subject 1	Time 2	2	4	4
Subject 1	Time 3	1	4	3
Subject 2	Time 1	4	1	2
Subject 2	Time 2	3	1	2
Subject 2	Time 3	3	2	1
Subject 3	Time 1	1	3	0
Subject 3	Time 2	4	0	1
Subject 3	Time 3	0	3	3

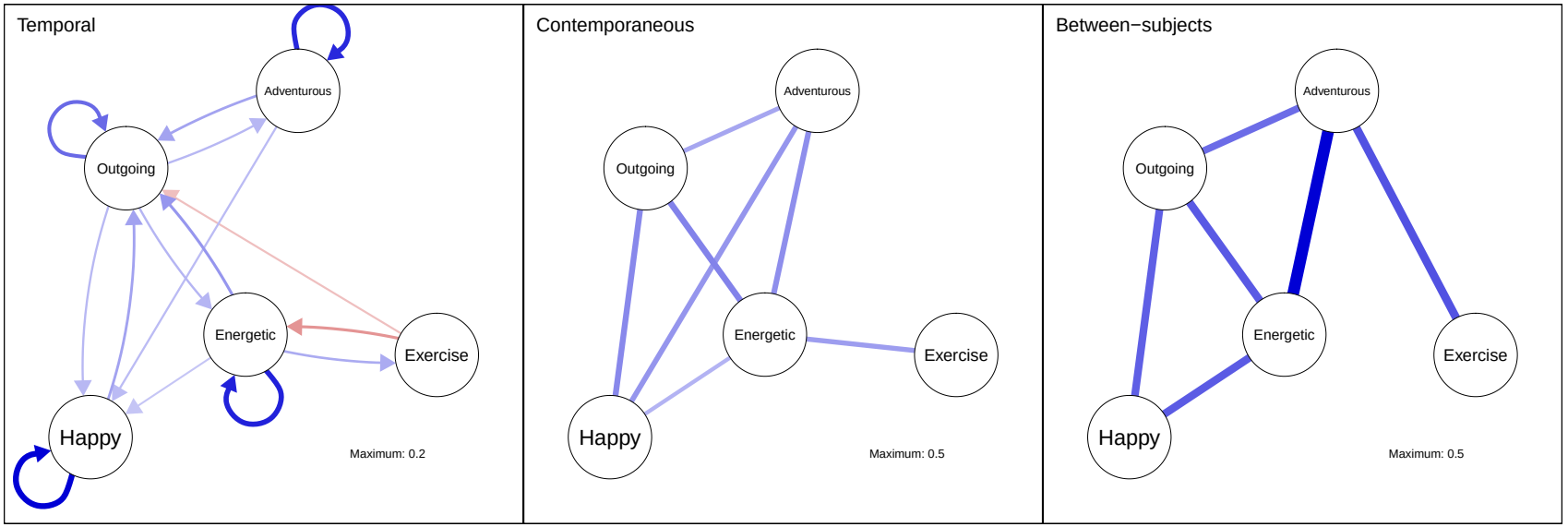
- Multiple people measured once: *cross-sectional analysis*
- One person measured multiple times: $N = 1$ *time-series*
- Multiple people measured multiple times: $N > 1$ *time-series*

Cattell's data box

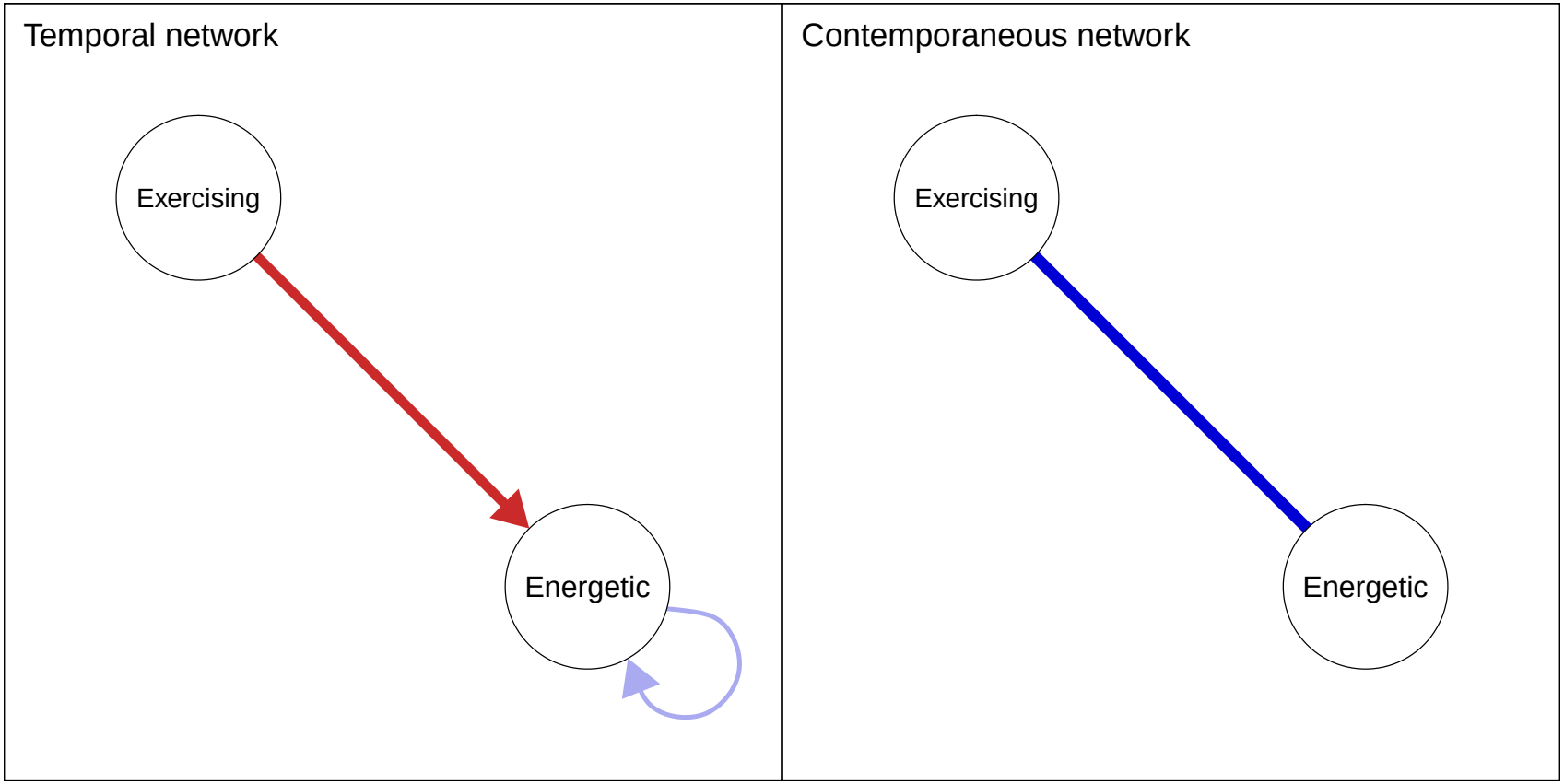


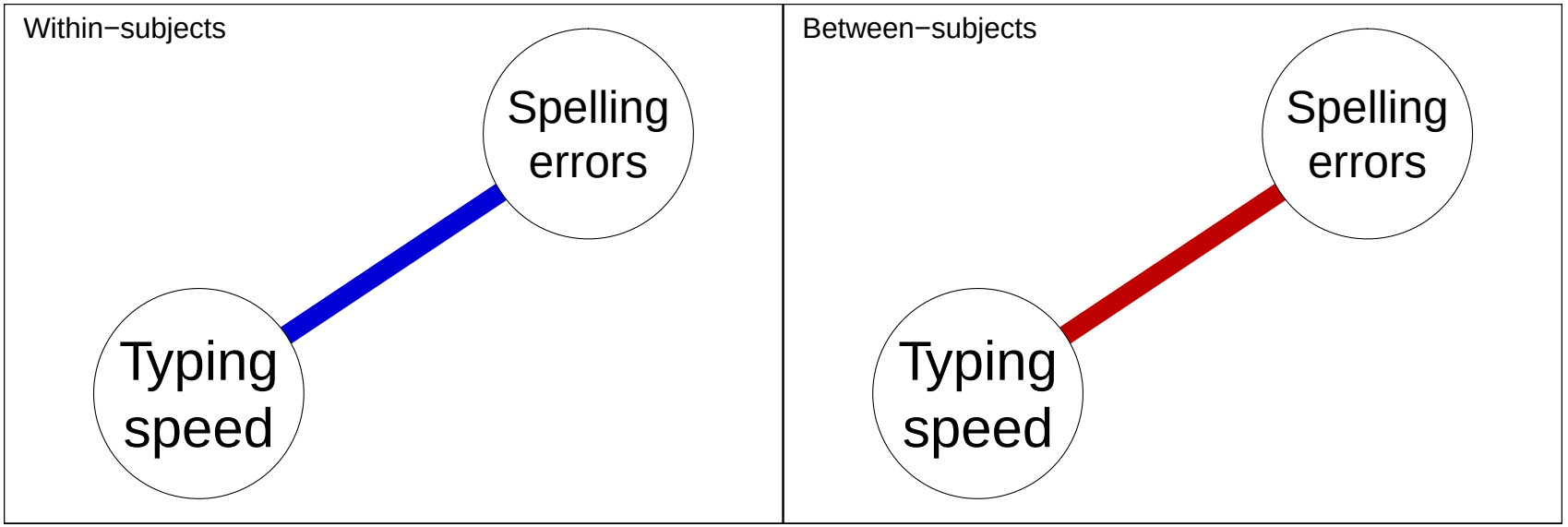
Slide by Ellen Hamaker

Time-series Analysis

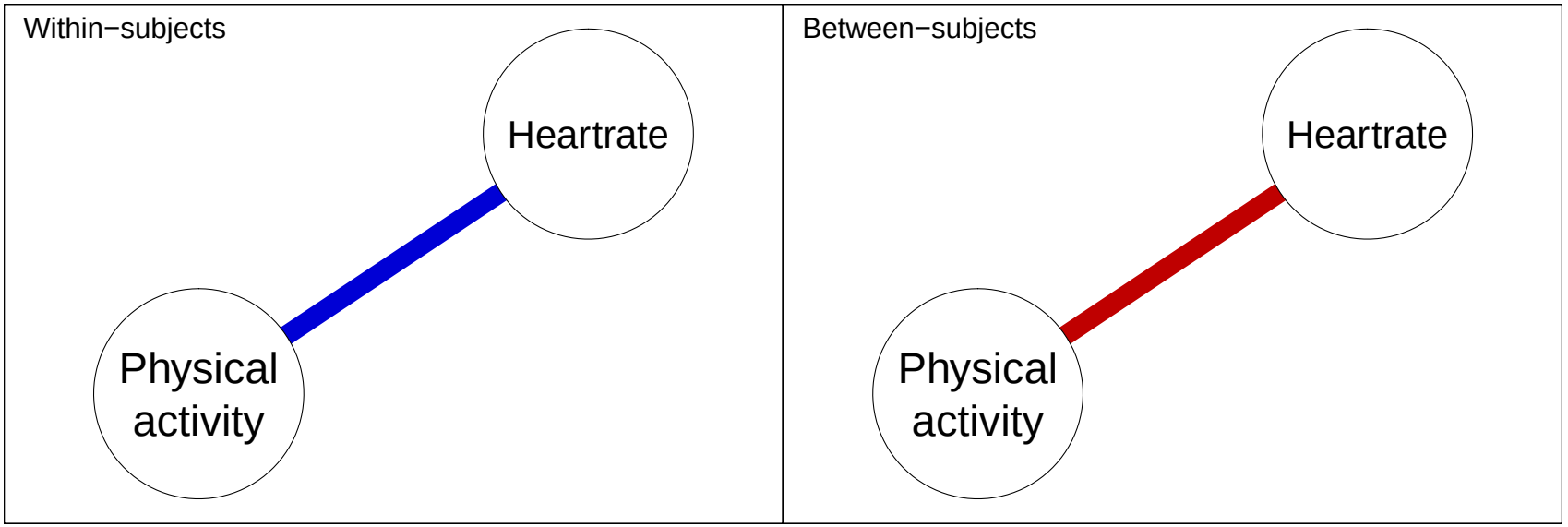


- Per subject (and fixed effects): temporal and contempraneous networks
  - Relationships between deviations from the means
- Between-subjects network: concentration network between stationary means
  - Relationships between the means


Temporal network
Exercising
Energetic
Contemporaneous network
Exercising
Energetic



Example based on Hamaker, E. L. (2012). Why Researchers Should Think 'Within-Person': A Paradigmatic Rationale. *Handbook of Research Methods for Studying Daily Life*. The Guilford Press New York, NY, 43–61.



Example kindly provided by Ellen Hamaker and based on Hoffman, L. (2015). *Longitudinal analysis: Modeling within-person fluctuation and change*. New York, NY, USA: Routledge.

Cross-sectional Data

Cross-sectional Data

- Only under unrealistic assumptions do cross-sectional results align with time-series results (see Molenaar, 2004)

Cross-sectional Data

- Only under unrealistic assumptions do cross-sectional results align with time-series results (see Molenaar, 2004)
- A lot of critisism towards cross-sectional network analysis because of this

Cross-sectional Data

- Only under unrealistic assumptions do cross-sectional results align with time-series results (see Molenaar, 2004)
- A lot of critisism towards cross-sectional network analysis because of this
  - *"[T]he utility of cross-sectional psychopathology networks fundamentally relies on the assumption of ergodicity: that the between-person structure at one time is the same as the within-person structure over time (Molenaar, 2004)"* — Forbes et al. (in press)

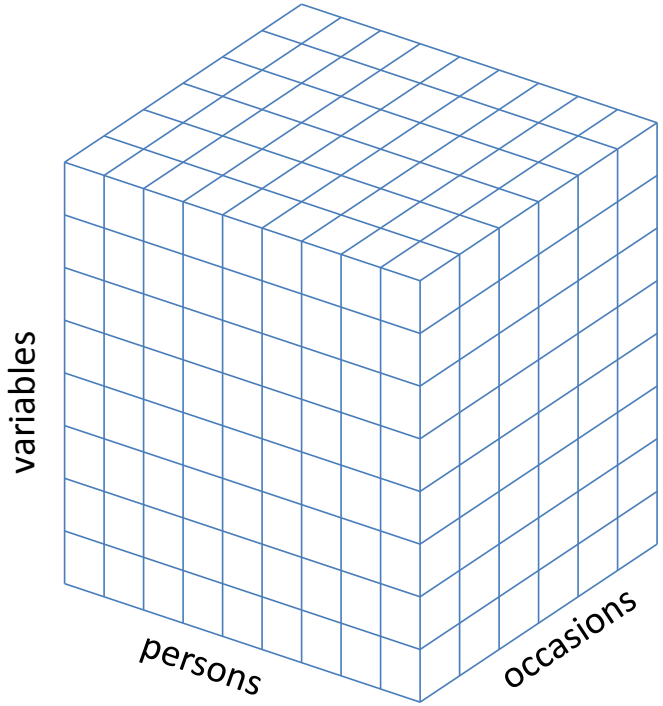
Cross-sectional Data

- Only under unrealistic assumptions do cross-sectional results align with time-series results (see Molenaar, 2004)
- A lot of critisism towards cross-sectional network analysis because of this
  - *"[T]he utility of cross-sectional psychopathology networks fundamentally relies on the assumption of ergodicity: that the between-person structure at one time is the same as the within-person structure over time (Molenaar, 2004)"* — Forbes et al. (in press)
  - *"We think it is time to investigate networks at the proper level of investigation (ie, at the intraindividual level). As long as we keep investigating cross-sectional group-level networks, the results will remain compatible with a traditional disease model, will not be informative of symptom interactions within individuals, and will obscure scientific reasoning"* — Bos & Wanders (2016)

Cross-sectional Data

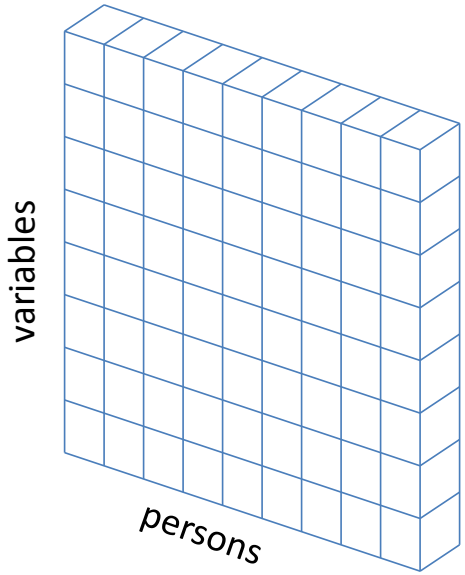
- Only under unrealistic assumptions do cross-sectional results align with time-series results (see Molenaar, 2004)
- A lot of critisism towards cross-sectional network analysis because of this
  - *"[T]he utility of cross-sectional psychopathology networks fundamentally relies on the assumption of ergodicity: that the between-person structure at one time is the same as the within-person structure over time (Molenaar, 2004)"* — Forbes et al. (in press)
  - *"We think it is time to investigate networks at the proper level of investigation (ie, at the intraindividual level). As long as we keep investigating cross-sectional group-level networks, the results will remain compatible with a traditional disease model, will not be informative of symptom interactions within individuals, and will obscure scientific reasoning"* — Bos & Wanders (2016)
  - *"If both [cross-sectional GGM and temporal VAR] result in similar conclusions, this would greatly facilitate future research and clinical applications (...). If not, then cross-sectional symptom networks are unlikely to reflect causal symptom dynamics, as postulated by this network theory."* — Bos et al. (2017)

Cattell's data box



Slide by Ellen Hamaker

Cross-sectional research: A single snapshot



Slide by Ellen Hamaker

But what is a cross-sectional network really?

But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis

But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews

But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews
  - E.g., questions such as "Are you a person that likes to..." and clinician rated scores over a period of time

But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews
  - E.g., questions such as "Are you a person that likes to..." and clinician rated scores over a period of time
- Thus, often cross-sectional analyses *can* be interpreted as between-subjects analyses

But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews
  - E.g., questions such as "Are you a person that likes to..." and clinician rated scores over a period of time
- Thus, often cross-sectional analyses *can* be interpreted as between-subjects analyses
- No reason to expect these to align with time-series results

But what is a cross-sectional network really?

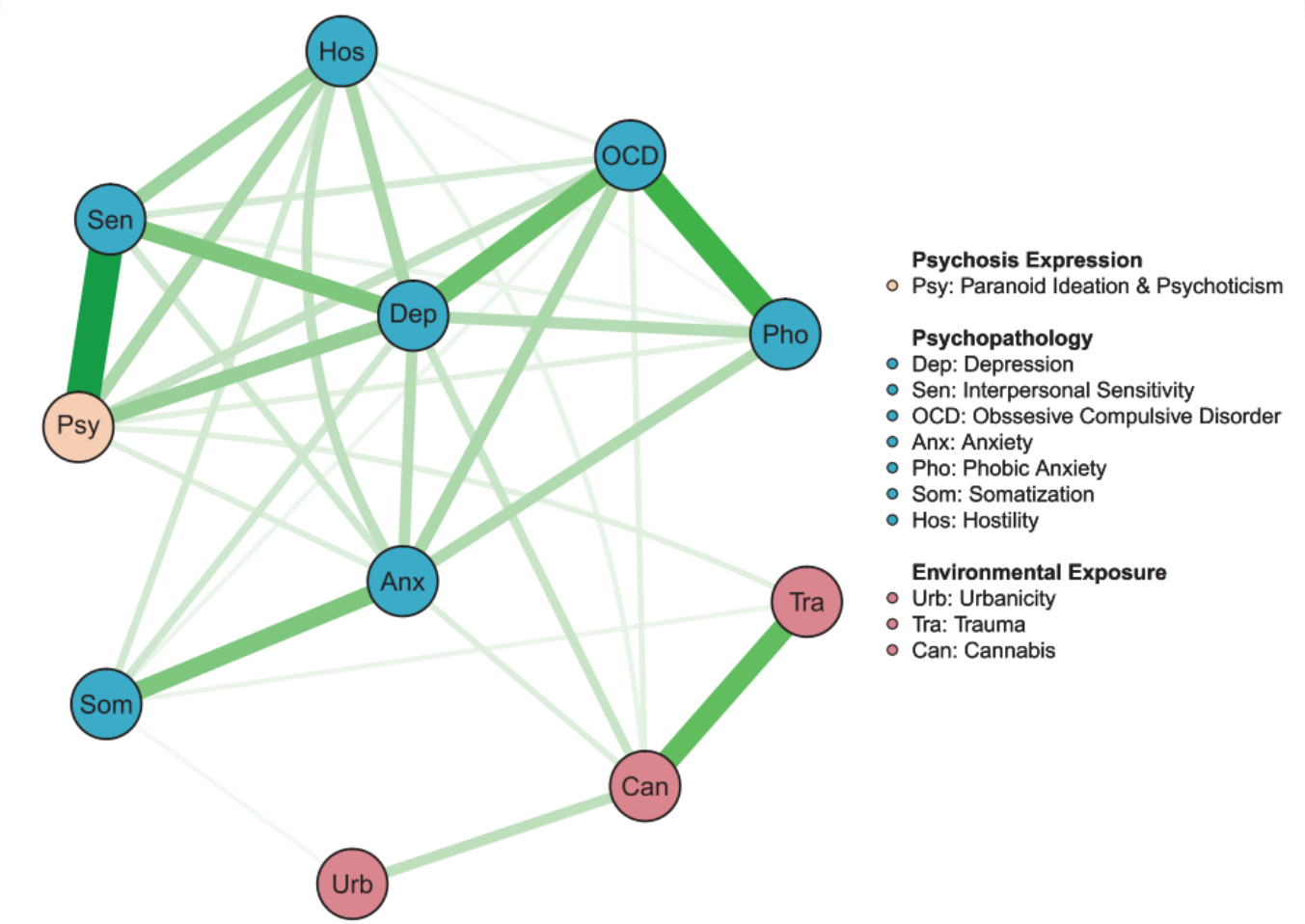
- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews
  - E.g., questions such as "Are you a person that likes to..." and clinician rated scores over a period of time
- Thus, often cross-sectional analyses *can* be interpreted as between-subjects analyses
- No reason to expect these to align with time-series results
  - Also not problematic!

But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews
  - E.g., questions such as "Are you a person that likes to..." and clinician rated scores over a period of time
- Thus, often cross-sectional analyses *can* be interpreted as between-subjects analyses
- No reason to expect these to align with time-series results
  - Also not problematic!
- *Only* investigating time-series data leads to losing rich sources of data

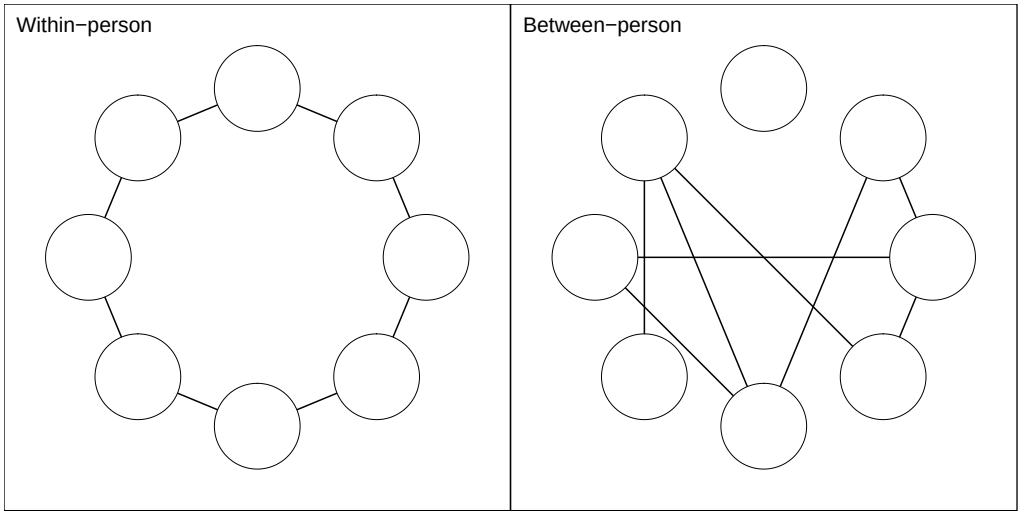
But what is a cross-sectional network really?

- Mathematically, a mixture of within- and between-subject networks if the cross-sectional dataset is equal to a snapshot in time-series analysis
- However, many cross-sectional datasets come from very different types of questionaires / interviews
  - E.g., questions such as "Are you a person that likes to..." and clinician rated scores over a period of time
- Thus, often cross-sectional analyses *can* be interpreted as between-subjects analyses
- No reason to expect these to align with time-series results
  - Also not problematic!
- *Only* investigating time-series data leads to losing rich sources of data
  - "Don't throw the baby out with the bathwater" — Angelique Cramer (APS 2018)

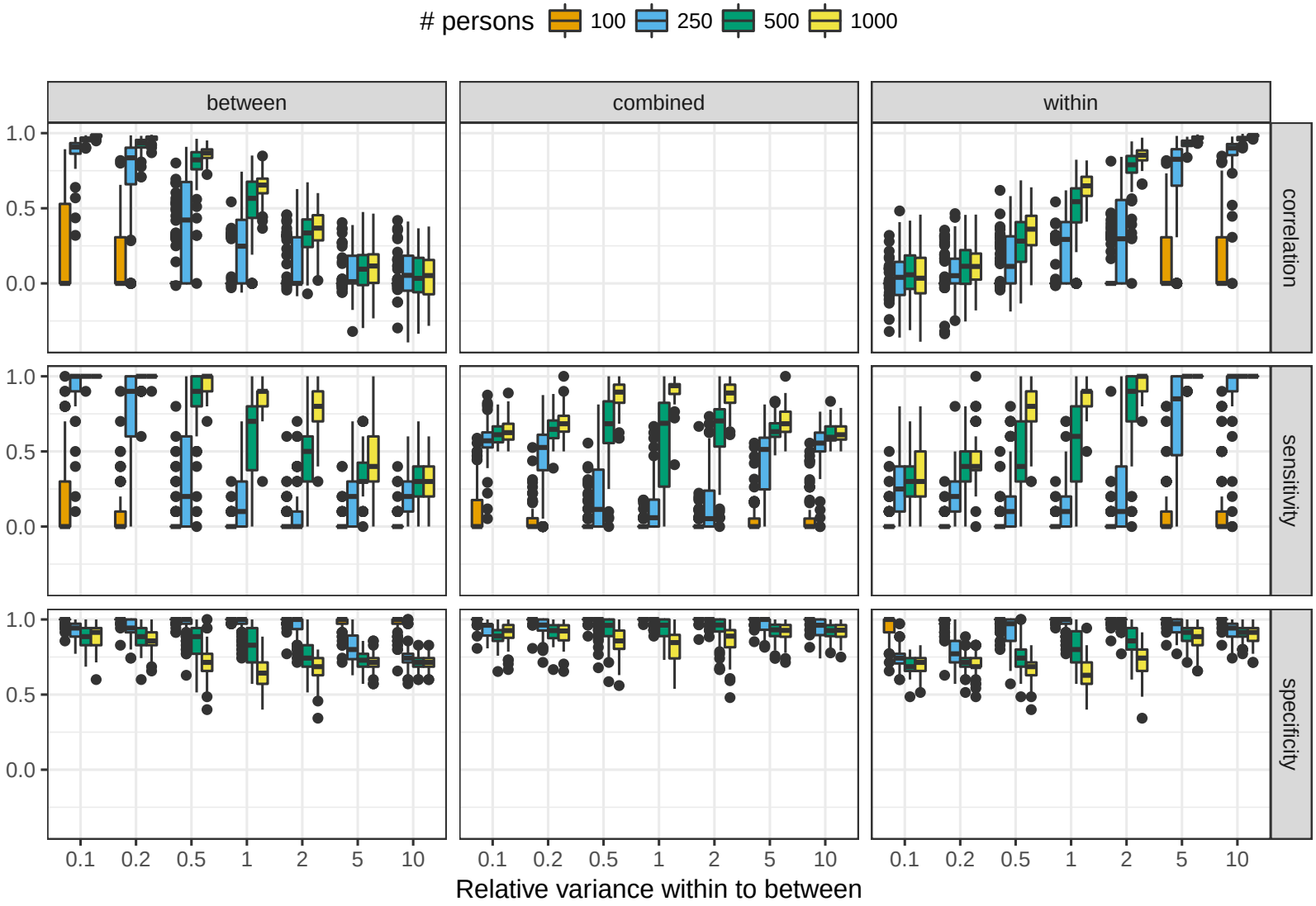


Isvoranu, A. M., Borsboom, D., van Os, J. & Guloksuz, S. (2016). A Network Approach to Environmental Impact in Psychotic Disorder: Brief Theoretical Framework. Schizophrenia Bulletin, 42(4), 870-873.

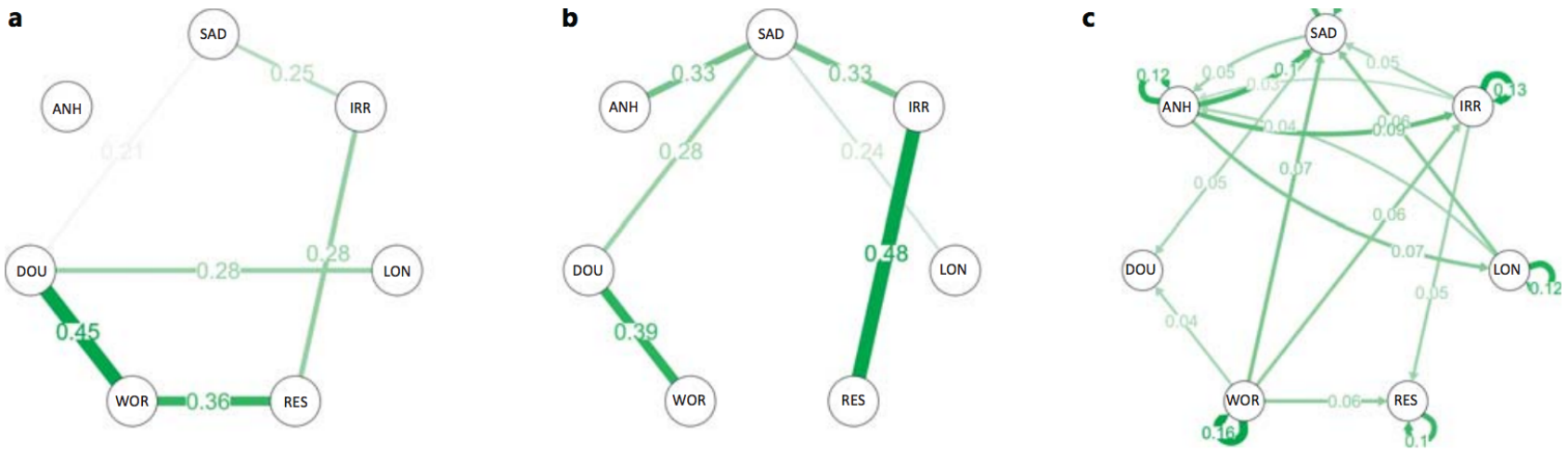
Simulation Study



- Generated data under chain graph within-person network and random graph between-person network
  - Edges set to 0.25 and made negative with 50% probability
- Relative within-person SD to between-person SD 0.1, 0.2, 0.5, 1, 2, 5 or 10
- Simulate cross-sectional dataset (within + between), and estimate network model using *ggmModSelect*


persons
100
250
500
1000
between
combined
within
correlation
sensitivity
specificity
1.0
0.5
0.0
0.1
0.2
0.5
1
2
5
10
Relative variance within to between

Empirical studies to cross-sectional data



a: first observation network ($n = 104$); person-mean network ($n = 104$); c: the dynamic network ($n = 104 \times 50$)

- Bos, F. M., Snippe, E., de Vos, S., Hartmann, J. A., Simons, C. J., van der Krieke, L., De Jonge, P. & Wichers, M. (2017). Can We Jump from Cross-Sectional to Dynamic Interpretations of Networks? Implications for the Network Perspective in Psychiatry. *Psychotherapy and Psychosomatics, 86(3)*, 175-177.

- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:

- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:
  - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one, 8(4)*, e60188. (data from Geschwind et al. 2011; $N = 130$ / 14,300)

- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:
  - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one, 8(4)*, e60188. (data from Geschwind et al. 2011; $N = 130$ / 14,300)
  - Wright, A. G., Gates, K., Arizmendi, C., Lane, S., Woods, W., & Edershile, E. A. (2018). Focusing Personality Assessment on the Person: Modeling General, Shared, and Person Specific Processes in Personality and Psychopathology. *PsyArXiv pre-print*. `http://doi.org/10.17605/OSF.IO/NF5ME` ($N = 94$ / 8,599)

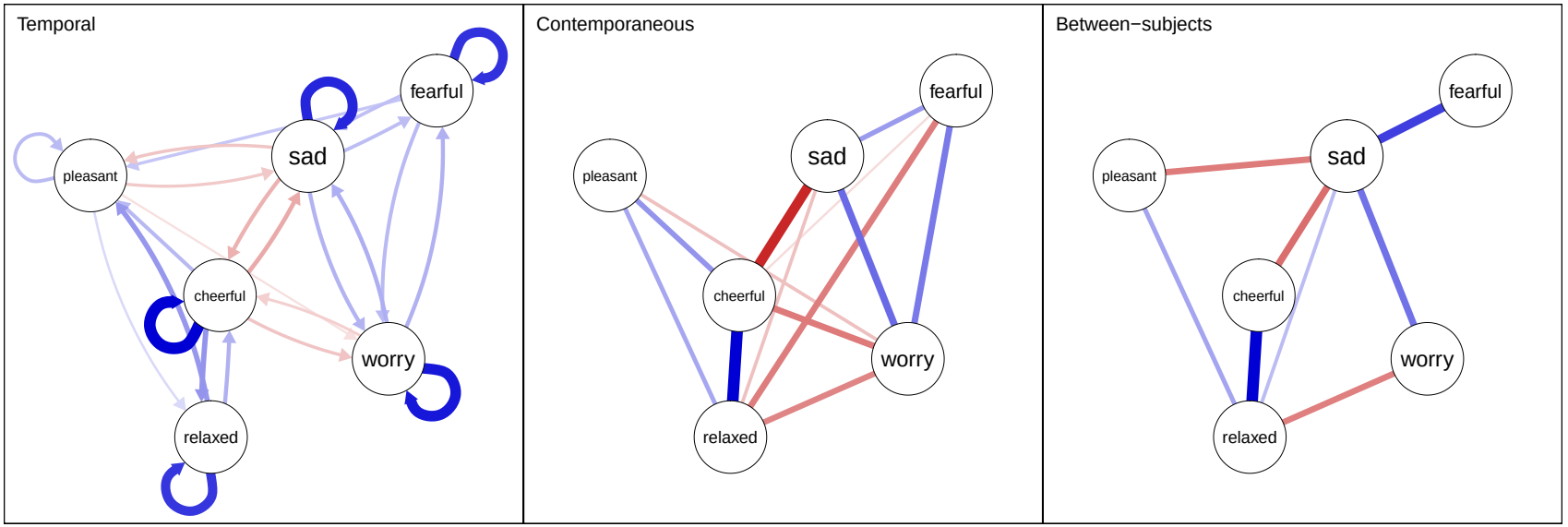
- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:
  - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one, 8(4)*, e60188. (data from Geschwind et al. 2011; $N = 130$ / 14,300)
  - Wright, A. G., Gates, K., Arizmendi, C., Lane, S., Woods, W., & Edershile, E. A. (2018). Focusing Personality Assessment on the Person: Modeling General, Shared, and Person Specific Processes in Personality and Psychopathology. *PsyArXiv pre-print*. `http://doi.org/10.17605/OSF.IO/NF5ME` ($N = 94$ / 8,599)
  - Mõttus, R., Epskamp, S., & Francis, A. (2017). Within-and between individual variability of personality characteristics and physical exercise. *Journal of Research in Personality, 69*, 139-148. ($N = 88$ / 3,516)

- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:
  - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one, 8(4)*, e60188. (data from Geschwind et al. 2011; $N = 130$ / 14,300)
  - Wright, A. G., Gates, K., Arizmendi, C., Lane, S., Woods, W., & Edershile, E. A. (2018). Focusing Personality Assessment on the Person: Modeling General, Shared, and Person Specific Processes in Personality and Psychopathology. *PsyArXiv pre-print*. `http://doi.org/10.17605/OSF.IO/NF5ME` ($N = 94$ / 8,599)
  - Mõttus, R., Epskamp, S., & Francis, A. (2017). Within-and between individual variability of personality characteristics and physical exercise. *Journal of Research in Personality, 69*, 139-148. ($N = 88$ / 3,516)
- Models estimated using *mlVAR* and compared on correlation between edge parameters (after rescaling reverse coded items) and shared edges / missing edges

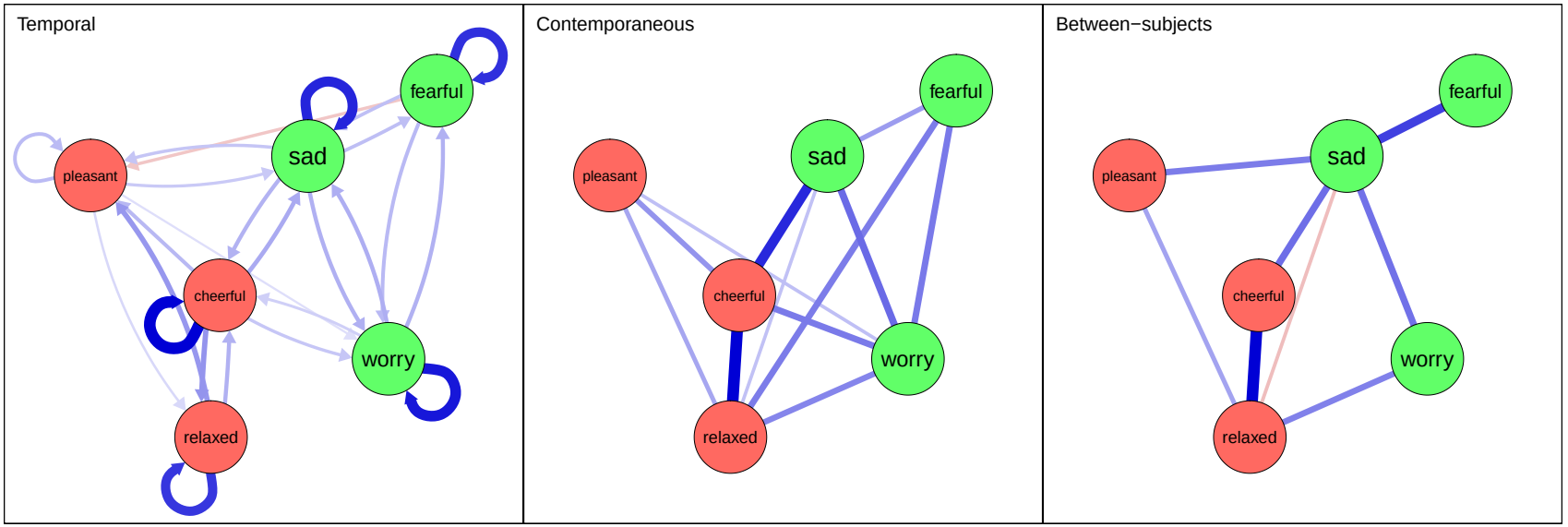
- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:
  - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one, 8(4)*, e60188. (data from Geschwind et al. 2011; $N = 130$ / 14,300)
  - Wright, A. G., Gates, K., Arizmendi, C., Lane, S., Woods, W., & Edershile, E. A. (2018). Focusing Personality Assessment on the Person: Modeling General, Shared, and Person Specific Processes in Personality and Psychopathology. *PsyArXiv pre-print*. `http://doi.org/10.17605/OSF.IO/NF5ME` ($N = 94$ / 8,599)
  - Mõttus, R., Epskamp, S., & Francis, A. (2017). Within-and between individual variability of personality characteristics and physical exercise. *Journal of Research in Personality, 69*, 139-148. ($N = 88$ / 3,516)
- Models estimated using *mlVAR* and compared on correlation between edge parameters (after rescaling reverse coded items) and shared edges / missing edges
- For each dataset, 1000 generated *cross-sectional* datasets by taking one measurement at random for each subject

- Based on the work of Bos et al. (2017), my student *Alex Alverez Perez* investigated empirical overlap between within- and between-subject effects in three datasets:
  - Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A network approach to psychopathology: new insights into clinical longitudinal data. *PloS one, 8(4)*, e60188. (data from Geschwind et al. 2011; $N = 130$ / 14,300)
  - Wright, A. G., Gates, K., Arizmendi, C., Lane, S., Woods, W., & Edershile, E. A. (2018). Focusing Personality Assessment on the Person: Modeling General, Shared, and Person Specific Processes in Personality and Psychopathology. *PsyArXiv pre-print*. `http://doi.org/10.17605/OSF.IO/NF5ME` ($N = 94$ / 8,599)
  - Mõttus, R., Epskamp, S., & Francis, A. (2017). Within-and between individual variability of personality characteristics and physical exercise. *Journal of Research in Personality, 69*, 139-148. ($N = 88$ / 3,516)
- Models estimated using *mlVAR* and compared on correlation between edge parameters (after rescaling reverse coded items) and shared edges / missing edges
- For each dataset, 1000 generated *cross-sectional* datasets by taking one measurement at random for each subject
  - Analyzed using *ggmModSelect* from qgraph

Bringmann et al. data

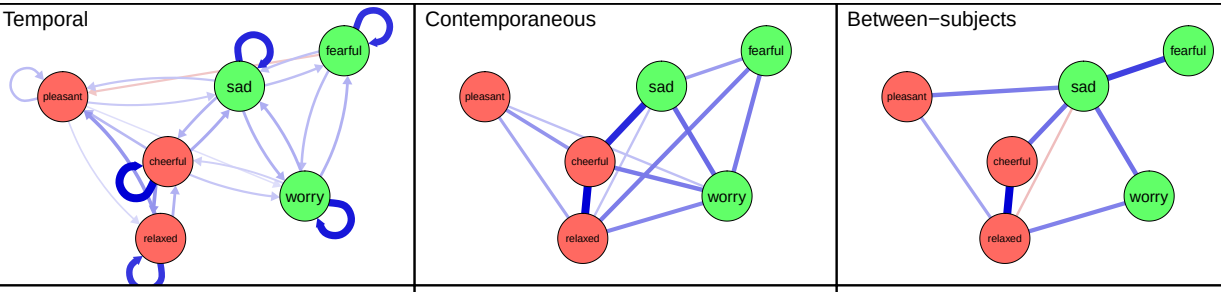


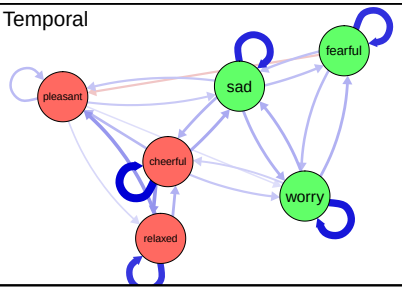
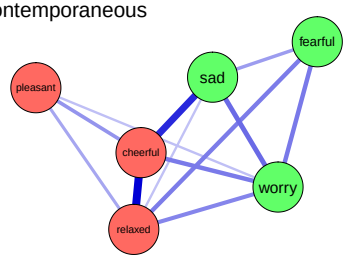
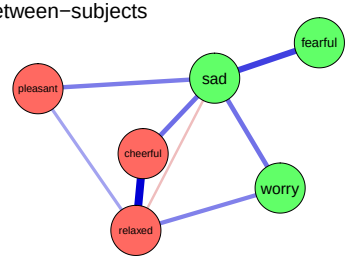
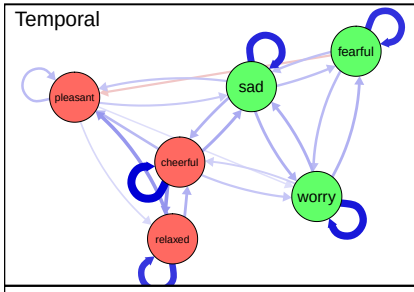
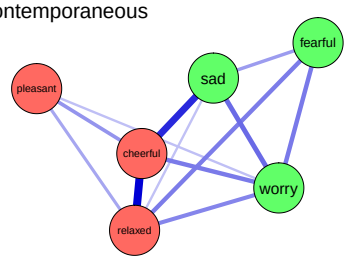
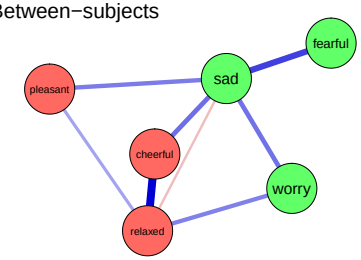
Bringmann et al. data



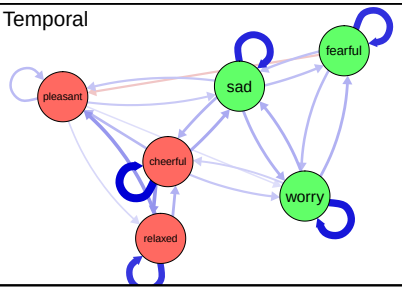
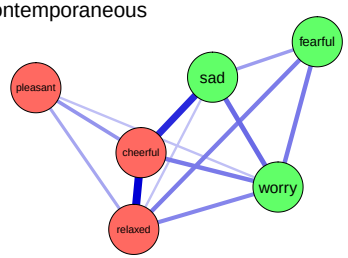
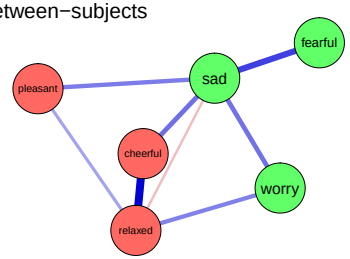
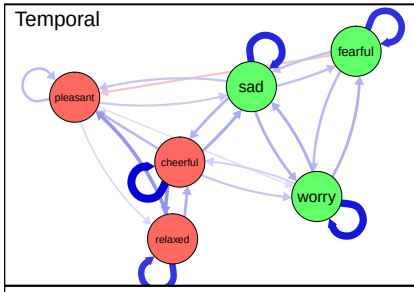
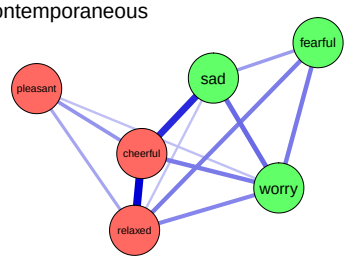
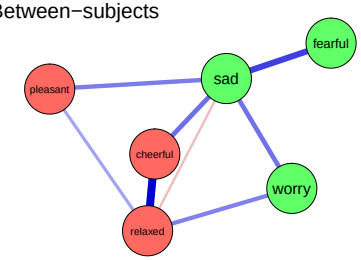
Bringmann et al.
Edge correlation

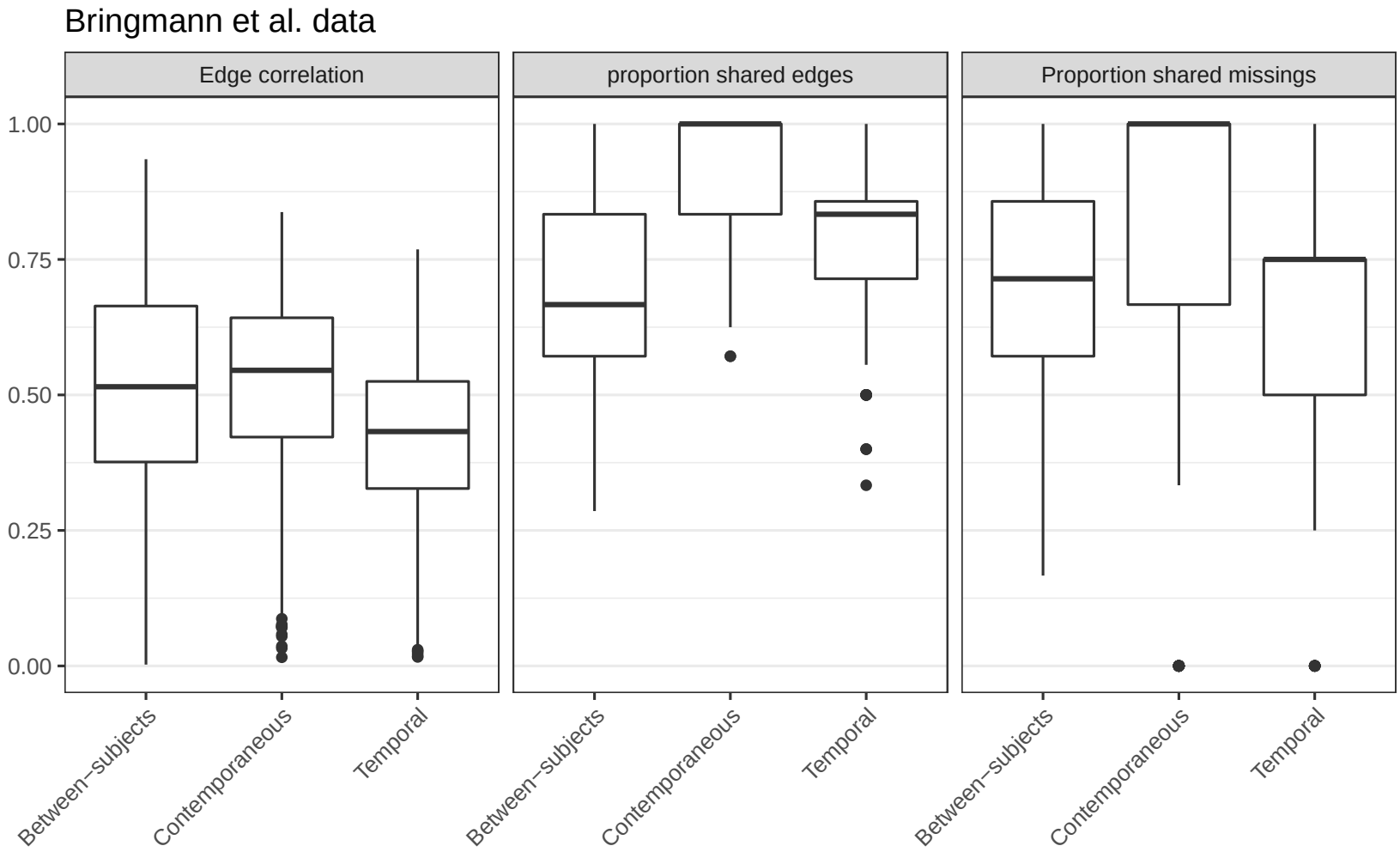
	Temporal	Contemporaneous	Between−subjects
Temporal	1	0.59	0.6
Contemporaneous	0.59	1	0.53
Between−subjects	0.6	0.53	1



Bringmann et al. Shared edges	Temporal 	Contemporaneous 	Between−subjects 
Temporal 	25 (100%) Total: 25 & 25	9 (81.82%) Total: 11 & 12	6 (75%) Total: 11 & 8
Contemporaneous 	9 (81.82%) Total: 12 & 11	12 (100%) Total: 12 & 12	7 (87.5%) Total: 12 & 8
Between−subjects 	6 (75%) Total: 8 & 11	7 (87.5%) Total: 8 & 12	8 (100%) Total: 8 & 8

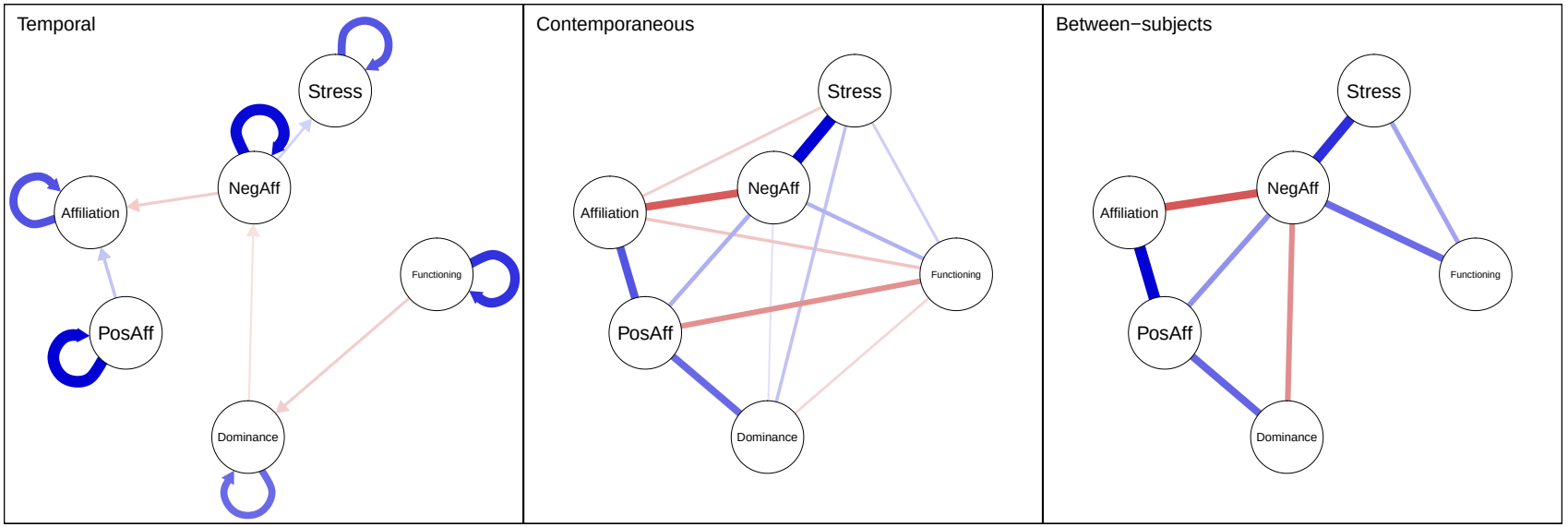
Bringmann et al.
Shared zeroes

	Temporal 	Contemporaneous 	Between−subjects 
Temporal 	11 (100%) Total: 11 & 11	1 (33.33%) Total: 4 & 3	2 (50%) Total: 4 & 7
Contemporaneous 	1 (33.33%) Total: 3 & 4	3 (100%) Total: 3 & 3	2 (66.67%) Total: 3 & 7
Between−subjects 	2 (50%) Total: 7 & 4	2 (66.67%) Total: 7 & 3	7 (100%) Total: 7 & 7

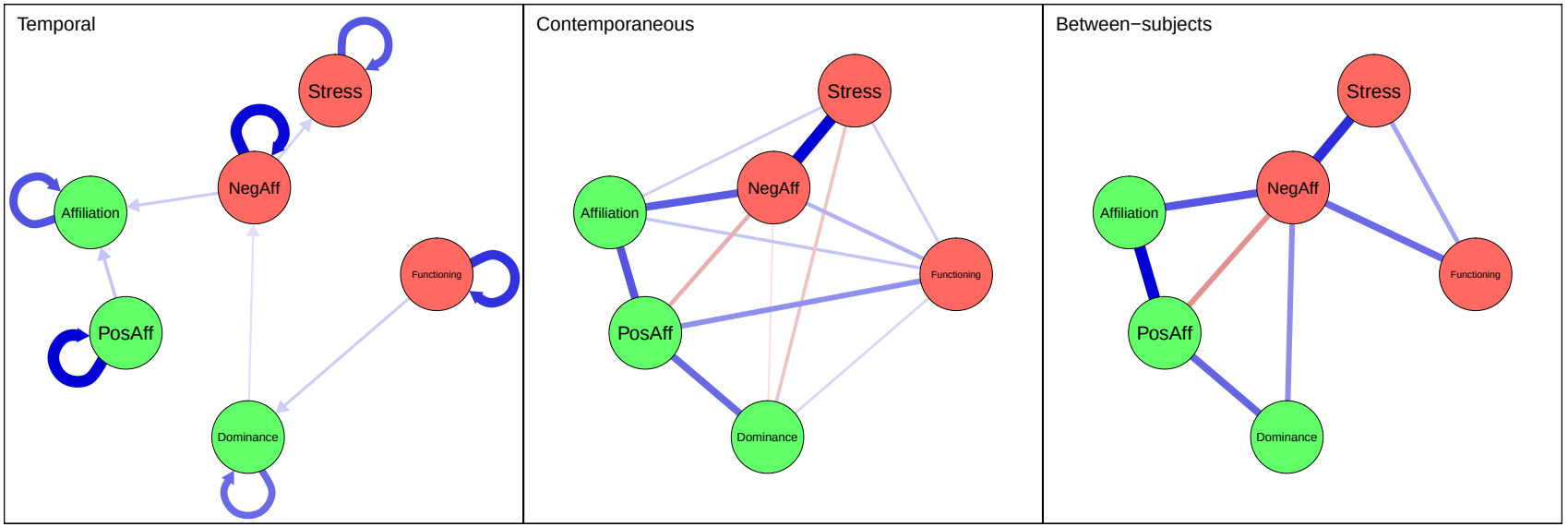


“Cross-sectional” results

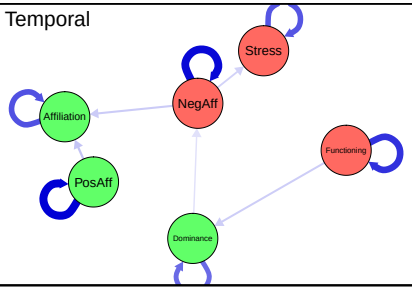
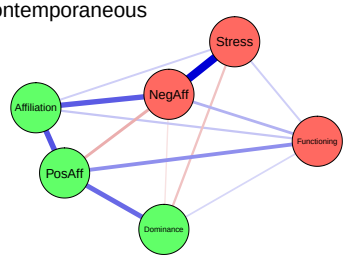
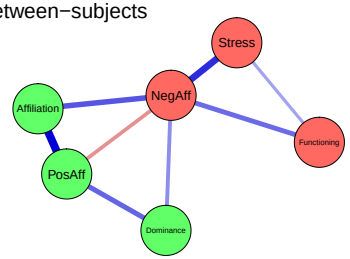
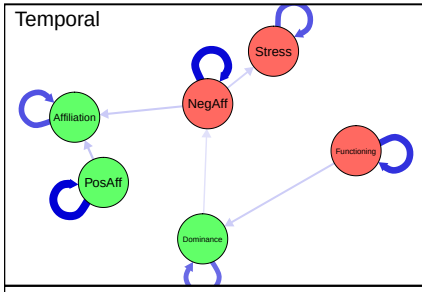
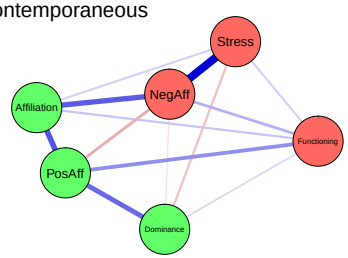
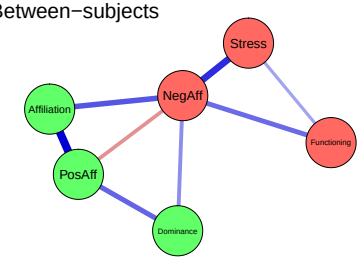
Wright et al. data

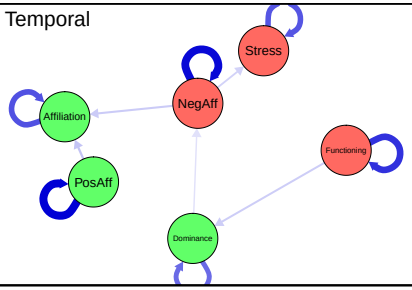
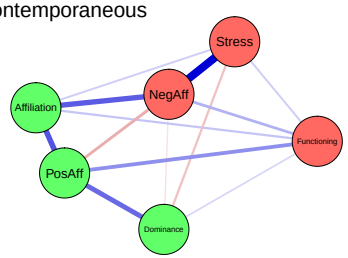
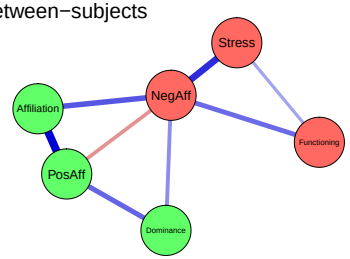
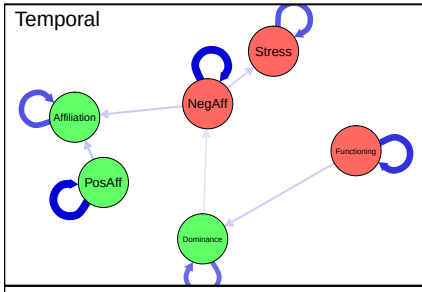
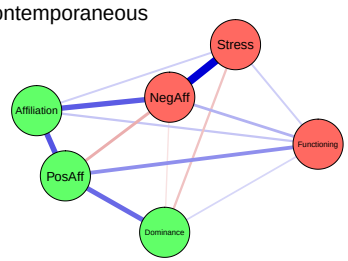
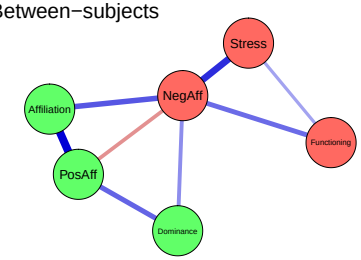


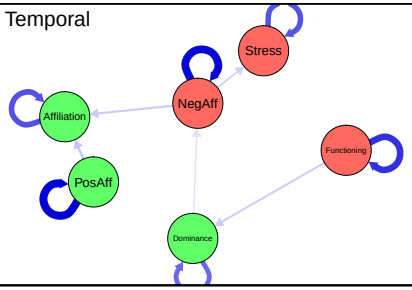
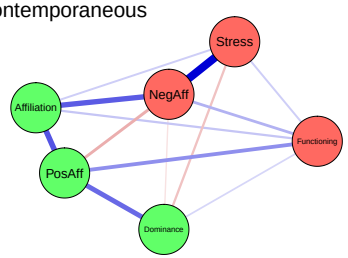
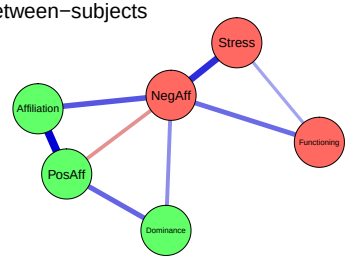
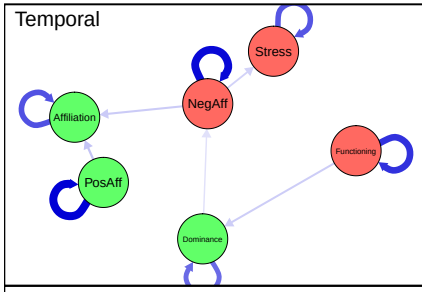
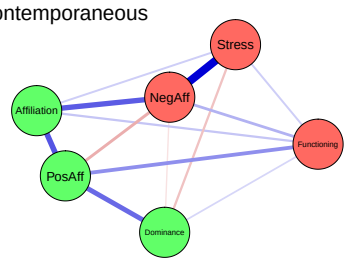
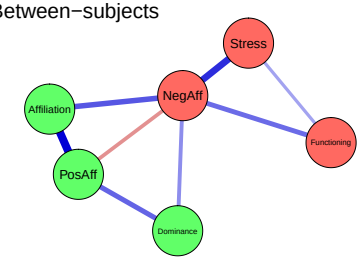
Wright et al. data

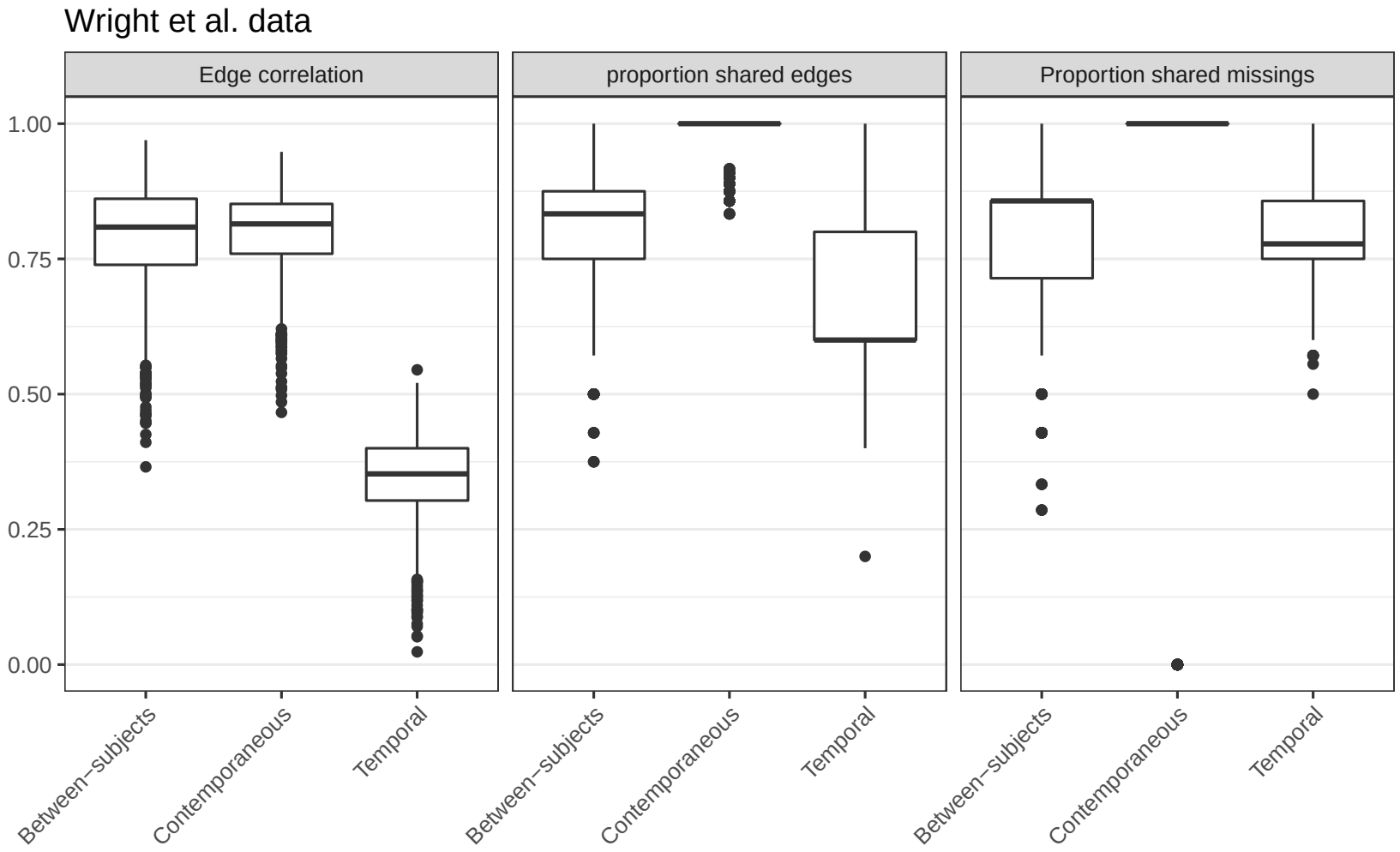


Wright et al.
Edge correlation

	Temporal 	Contemporaneous 	Between−subjects 
Temporal 	1	0.33	0.38
Contemporaneous 	0.33	1	0.78
Between−subjects 	0.38	0.78	1

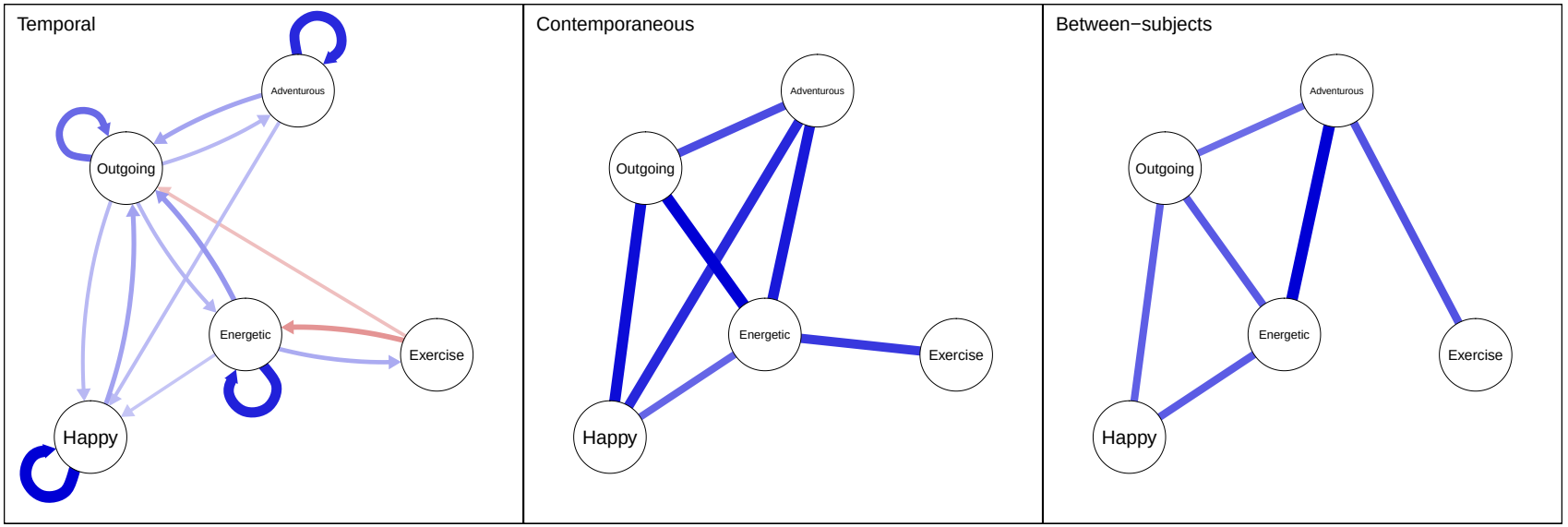
Wright et al. Shared edges			
	11 (100%) Total: 11 & 11	5 (100%) Total: 5 & 14	4 (80%) Total: 5 & 8
	5 (100%) Total: 14 & 5	14 (100%) Total: 14 & 14	8 (100%) Total: 14 & 8
	4 (80%) Total: 8 & 5	8 (100%) Total: 8 & 14	8 (100%) Total: 8 & 8

Wright et al. Shared zeroes			
	25 (100%) Total: 25 & 25	1 (100%) Total: 10 & 1	6 (85.71%) Total: 10 & 7
	1 (100%) Total: 1 & 10	1 (100%) Total: 1 & 1	1 (100%) Total: 1 & 7
	6 (85.71%) Total: 7 & 10	1 (100%) Total: 7 & 1	7 (100%) Total: 7 & 7

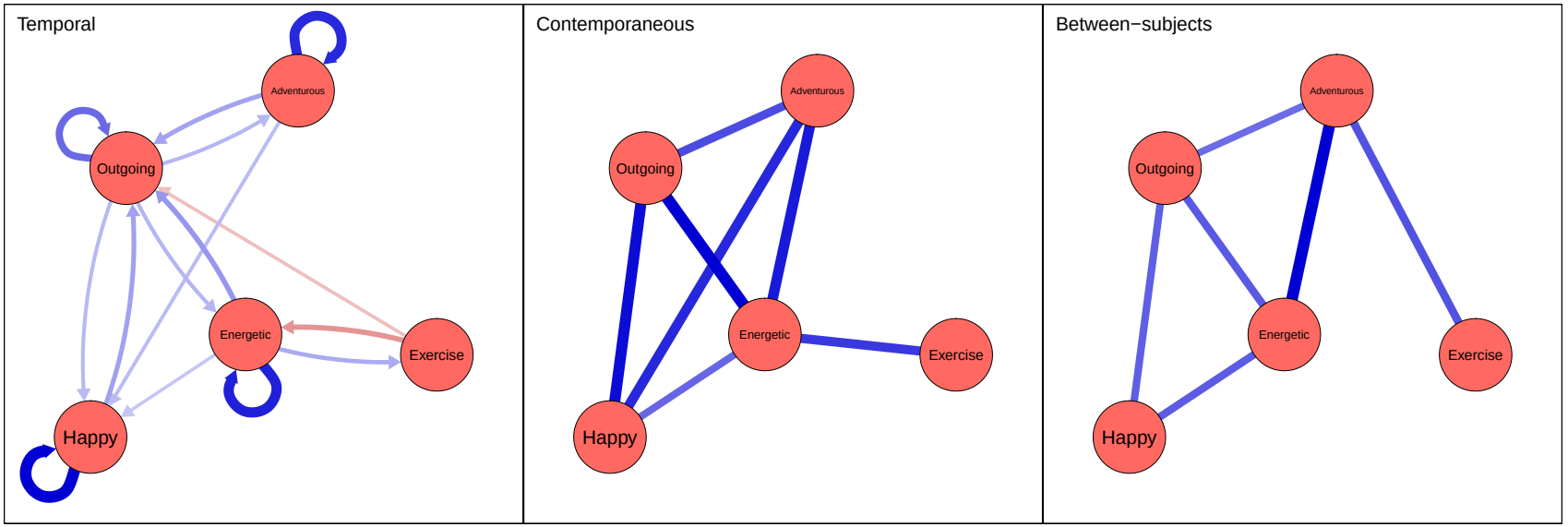


“Cross-sectional” results

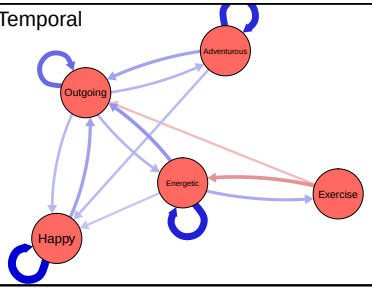
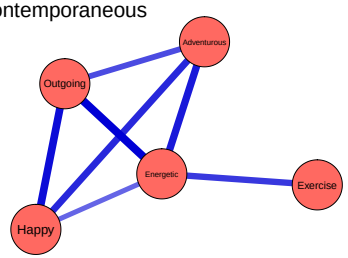
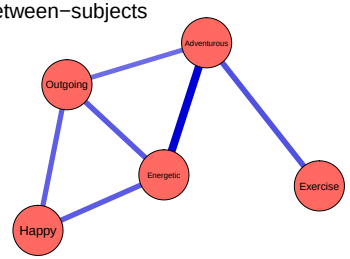
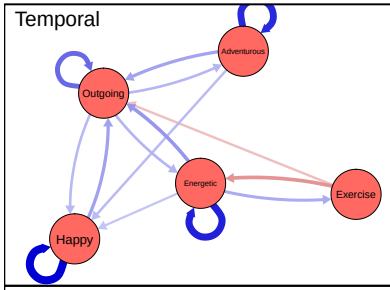
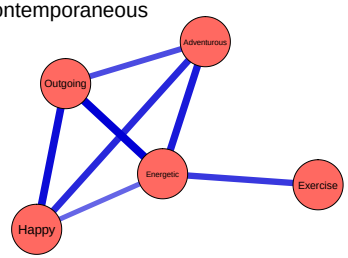
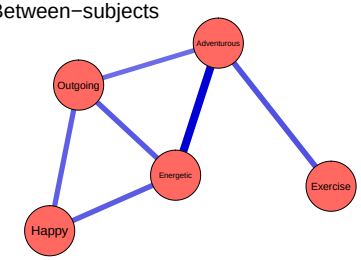
Mottus et al. data

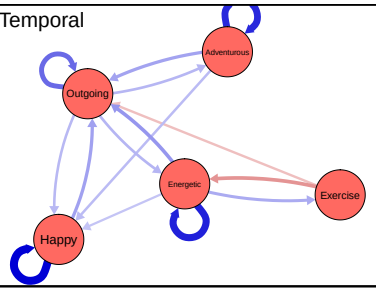
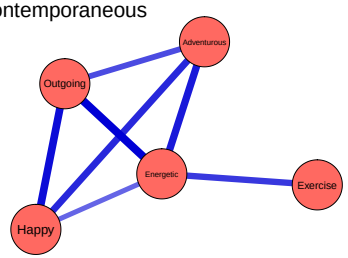
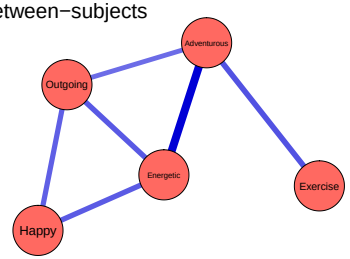
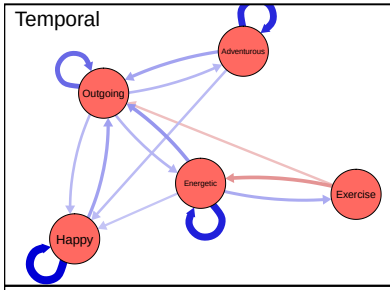
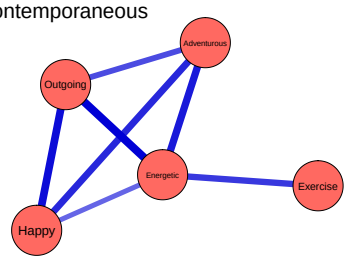
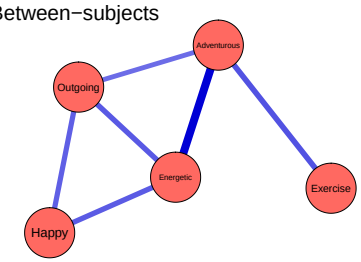


Mottus et al. data

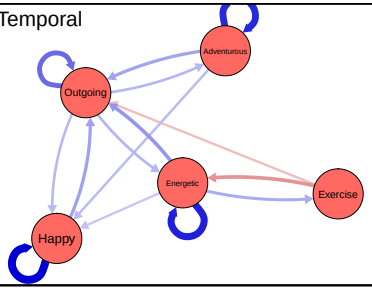
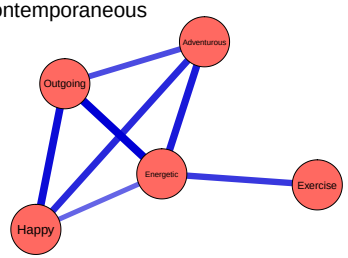
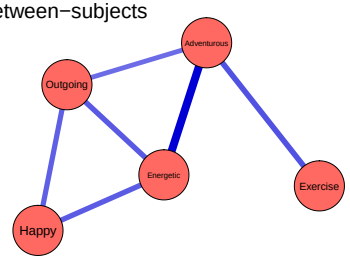
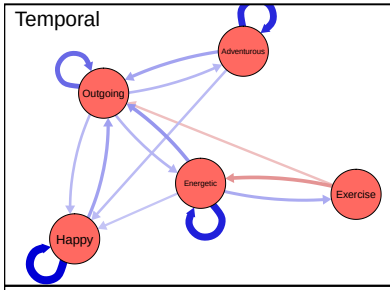
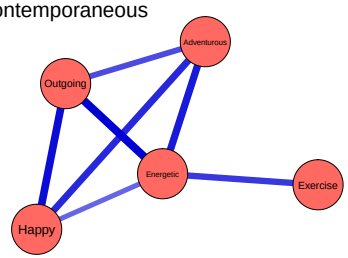
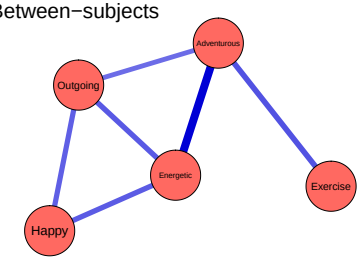


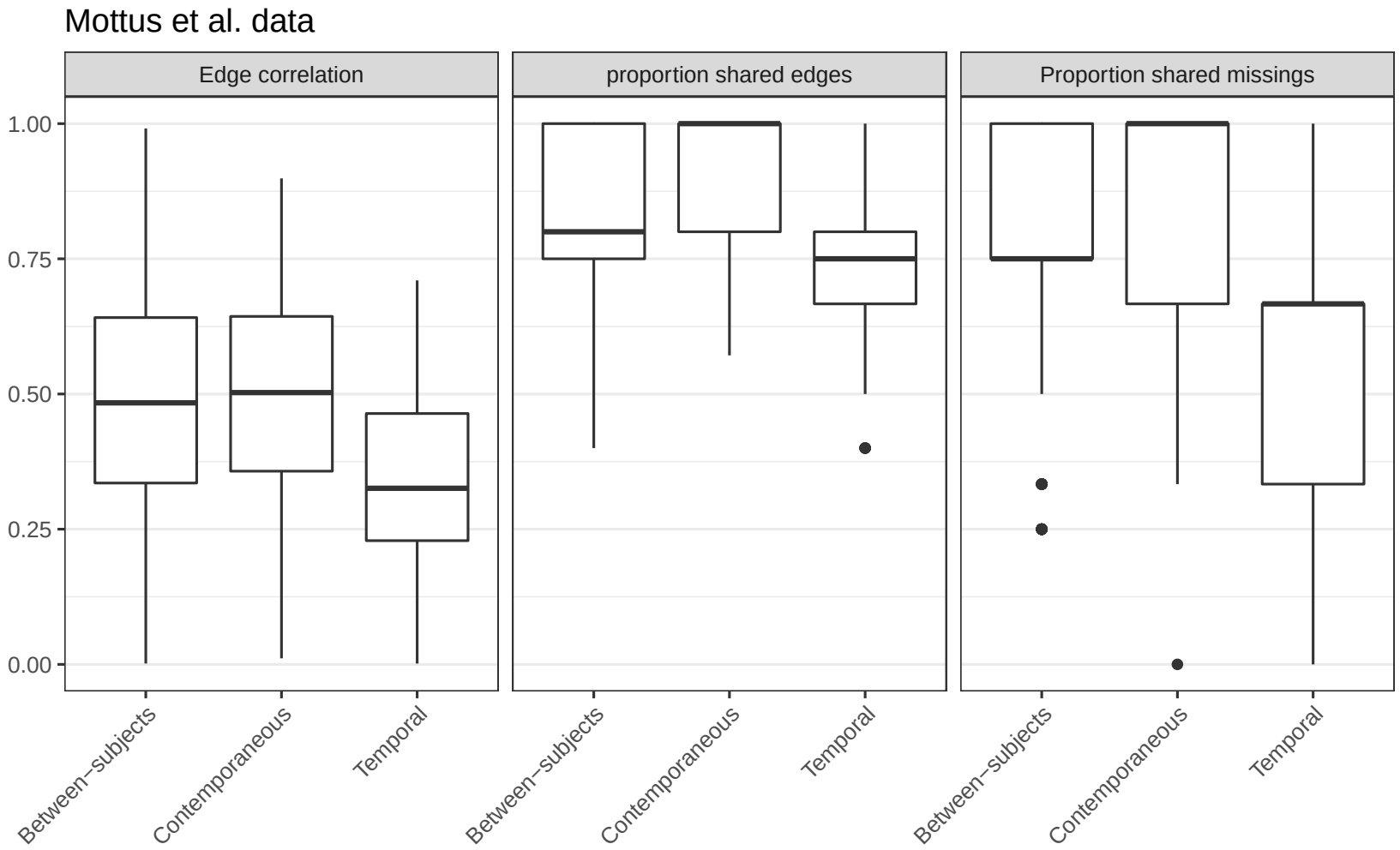
Mottus et al.
Edge correlation

	Temporal 	Contemporaneous 	Between−subjects 
Temporal 	1	0.49	0.32
Contemporaneous 	0.49	1	0.37
Between−subjects 	0.32	0.37	1

Mottus et al. Shared edges			
	15 (100%) Total: 15 & 15	6 (85.71%) Total: 7 & 7	4 (66.67%) Total: 7 & 6
	6 (85.71%) Total: 7 & 7	7 (100%) Total: 7 & 7	5 (83.33%) Total: 7 & 6
	4 (66.67%) Total: 6 & 7	5 (83.33%) Total: 6 & 7	6 (100%) Total: 6 & 6

Mottus et al.
Shared zeroes

	Temporal 	Contemporaneous 	Between−subjects 
Temporal 	10 (100%) Total: 10 & 10	2 (66.67%) Total: 3 & 3	1 (33.33%) Total: 3 & 4
Contemporaneous 	2 (66.67%) Total: 3 & 3	3 (100%) Total: 3 & 3	2 (66.67%) Total: 3 & 4
Between−subjects 	1 (33.33%) Total: 4 & 3	2 (66.67%) Total: 4 & 3	4 (100%) Total: 4 & 4



“Cross-sectional” results

Conclusion

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects
  - All three can give valuable insight and may even lead to generate hypothesis to expected effects under interventions

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects
  - All three can give valuable insight and may even lead to generate hypothesis to expected effects under interventions
  - Seemingly paradoxical results can usually be explained with interpretation of different sources of variation

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects
  - All three can give valuable insight and may even lead to generate hypothesis to expected effects under interventions
  - Seemingly paradoxical results can usually be explained with interpretation of different sources of variation
- Take method of data gathering into account when interpreting cross-sectional results

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects
  - All three can give valuable insight and may even lead to generate hypothesis to expected effects under interventions
  - Seemingly paradoxical results can usually be explained with interpretation of different sources of variation
- Take method of data gathering into account when interpreting cross-sectional results
  - May often allow for between-subjects interpretation

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects
  - All three can give valuable insight and may even lead to generate hypothesis to expected effects under interventions
  - Seemingly paradoxical results can usually be explained with interpretation of different sources of variation
- Take method of data gathering into account when interpreting cross-sectional results
  - May often allow for between-subjects interpretation
- No theoretical reason to expect overlap between within- and between-subject results

Conclusion

- Network analysis can be used to gain exploratory insight in *temporal*, *contemporaneous*, and *between-subject* effects
  - All three can give valuable insight and may even lead to generate hypothesis to expected effects under interventions
  - Seemingly paradoxical results can usually be explained with interpretation of different sources of variation
- Take method of data gathering into account when interpreting cross-sectional results
  - May often allow for between-subjects interpretation
- No theoretical reason to expect overlap between within- and between-subject results
- But empirical studies do show sizeable overlap between within- and between-subject results

Thank you for your attention!

- Website: `sachaepskamp.com`
  - Slides at: `sachaepskamp.com/presentations`
  - Dissertation at: `sachaepskamp.com/dissertation`
- Twitter: `twitter.com/SachaEpskamp`
- Join our Facebook group!
  - `facebook.com/groups/PsychologicalDynamics`

University of Amsterdam
Institute for Advanced Study