The Multiple Flavours of Multilevel Issues for Networks

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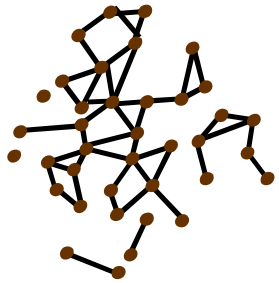
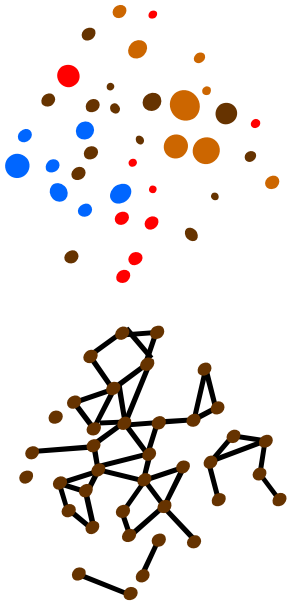
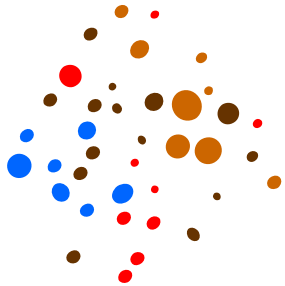
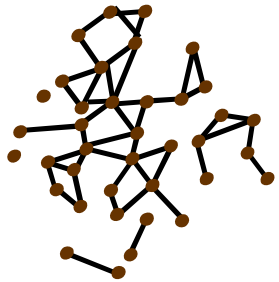
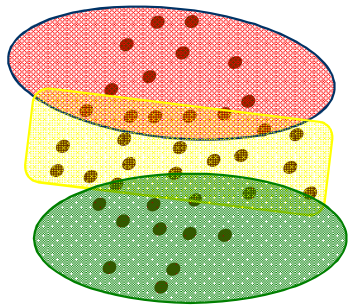
This variety further multiplies
when you think of network analysis.

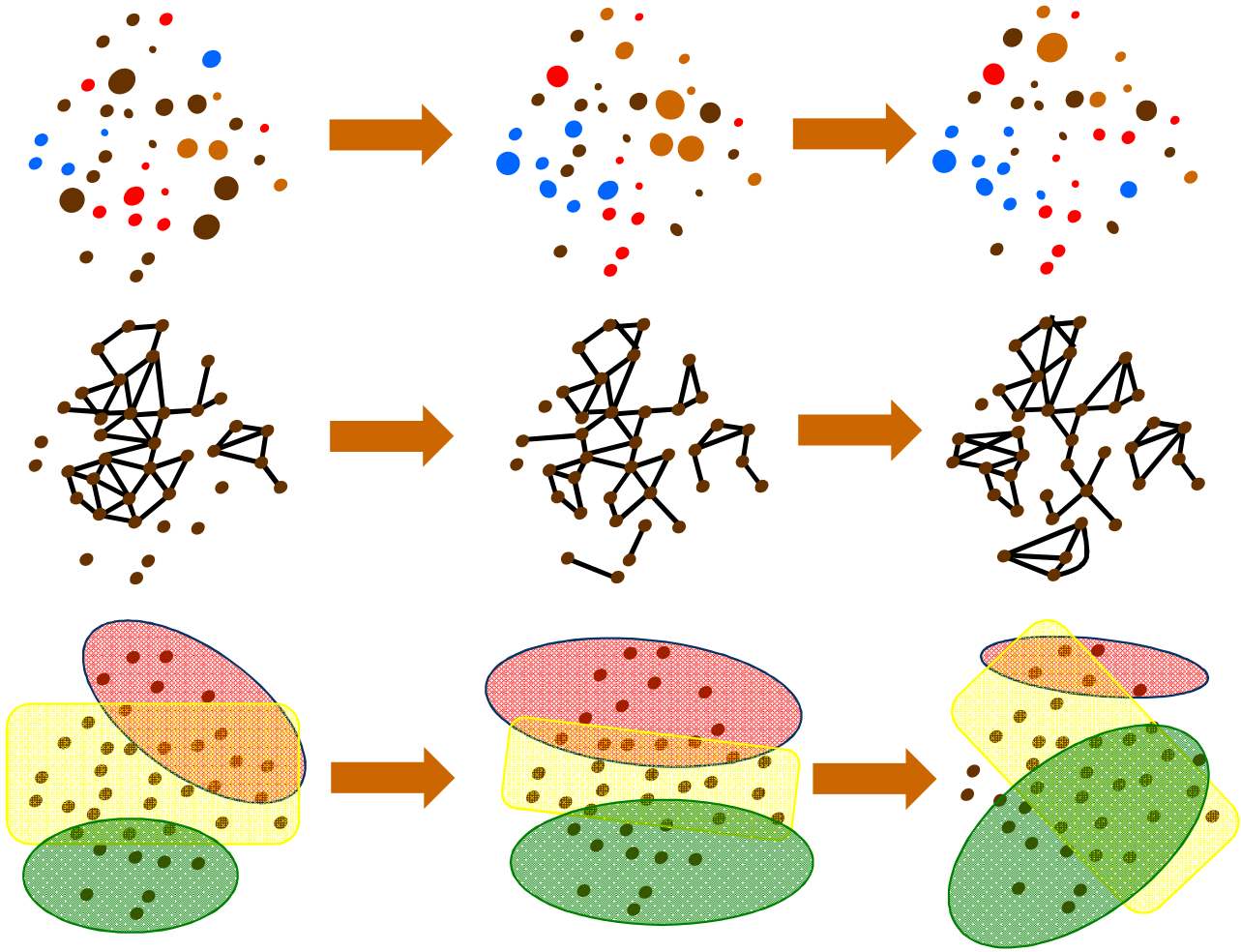


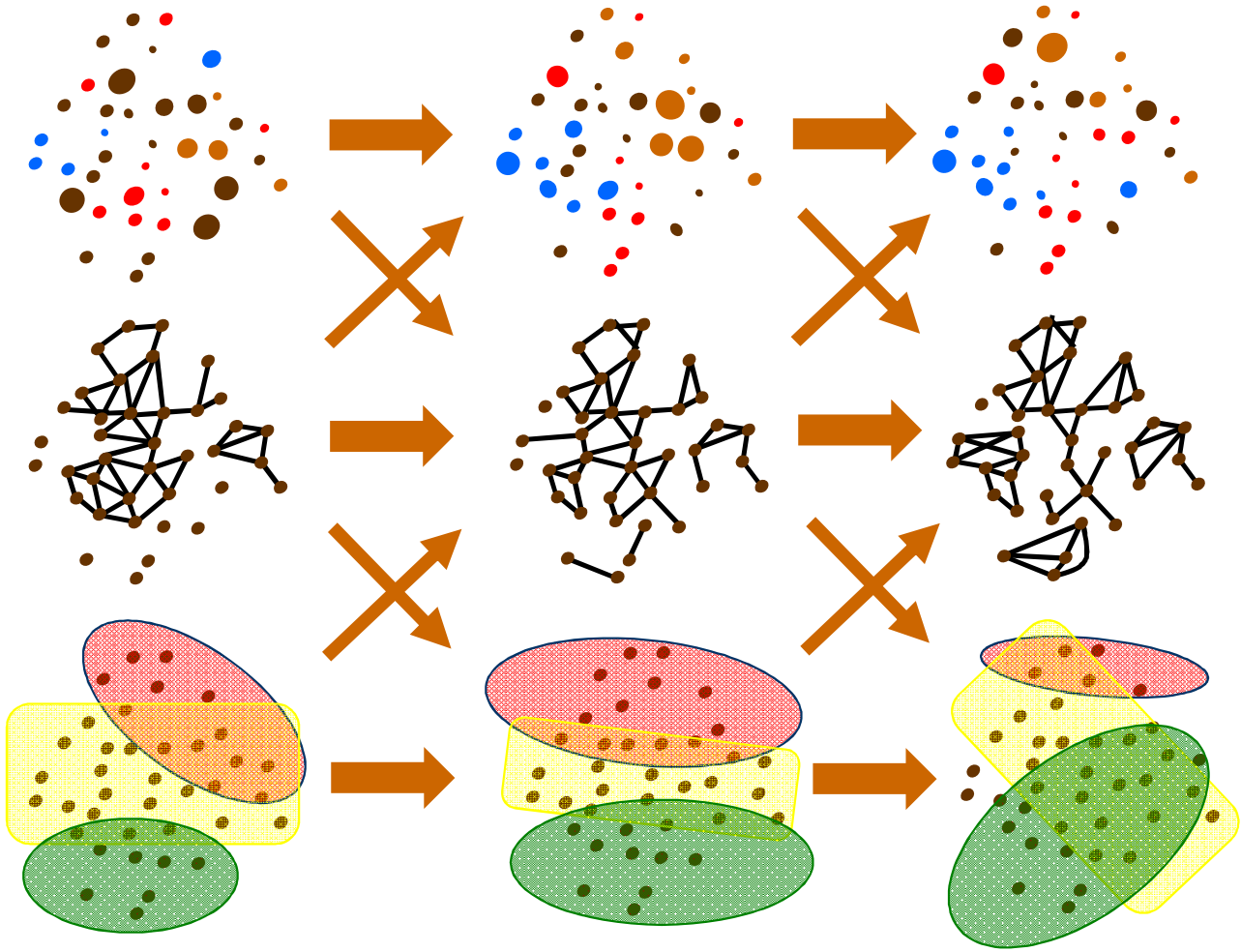












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differences may have to do with nesting;

random/unexplained variability associated with each 'level'.

1. levels in one network
2. multiple parallel networks:
   replication, populations of networks
3. multiple actor sets
   and multiple types of relation
4. actor sets with nested structure
5. large networks

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1
One Network, Multiple Levels

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Level 2	Dyads / Ties
Level 3	Triads
Higher	Larger subgroups ~ hypergraph models
Level 0	*Network*

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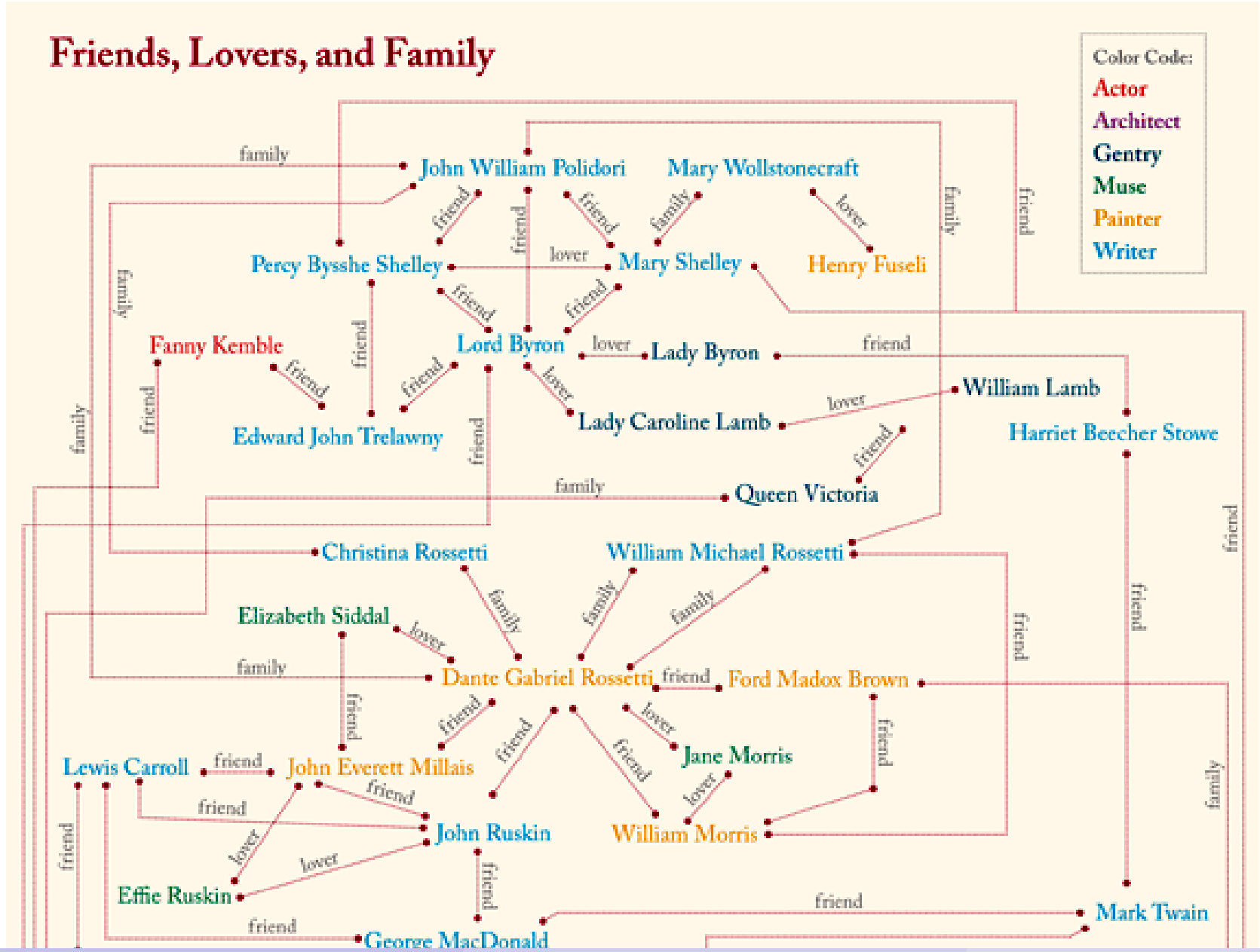
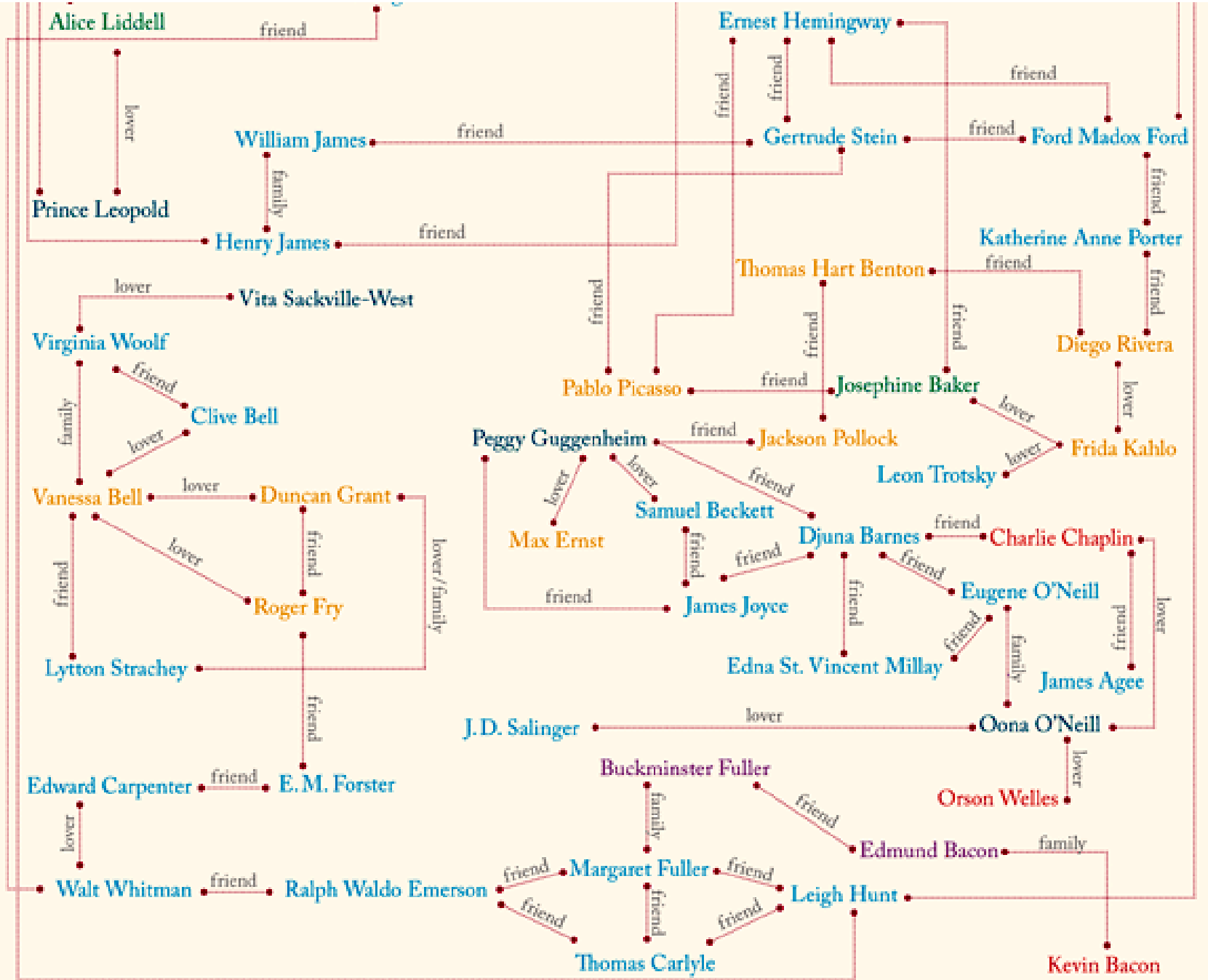
activities occurring in groups and
emails with multiple recipients.

Theoretical interest for the distinction
between the actor and dyad levels
becomes even more interesting with multivariate networks.

Lapham's Quarterly literary magazine published
in June 2010 a network
showing friends, lovers and family relations
and running from Mary Wollstonecraft to,
amongst many others,
William Morris and Leon Trotsky.


Friends, Lovers, and Family
Color Code:
Actor
Architect
Gentry
Muse
Painter
Writer
John William Polidori
Mary Wollstonecraft
Percy Bysshe Shelley
Mary Shelley
Henry Fuseli
Fanny Kemble
Lord Byron
Lady Byron
William Lamb
Edward John Trelawny
Lady Caroline Lamb
Harriet Beecher Stowe
Queen Victoria
Christina Rossetti
William Michael Rossetti
Elizabeth Siddal
Dante Gabriel Rossetti
Ford Madox Brown
Lewis Carroll
John Everett Millais
Jane Morris
John Ruskin
William Morris
Effie Ruskin
Mark Twain
George MacDonald
family
friend
lover


Alice Liddell
friend
lover
Prince Leopold
William James
friend
family
Henry James
friend
Ernest Hemingway
friend
friend
friend
Gertrude Stein
friend
Ford Madox Ford
friend
Katherine Anne Porter
friend
Diego Rivera
lover
Frida Kahlo
lover
Leon Trotsky
friend
Thomas Hart Benton
friend
friend
friend
Pablo Picasso
friend
Josephine Baker
lover
lover
Vita Sackville-West
Virginia Woolf
friend
Clive Bell
family
lover
Vanessa Bell
lover
Duncan Grant
friend
lover
Roger Fry
friend
lover/family
Lytton Strachey
friend
Edward Carpenter
friend
E.M. Forster
lover
Walt Whitman
friend
Ralph Waldo Emerson
Peggy Guggenheim
friend
Jackson Pollock
friend
lover
lover
Max Ernst
Samuel Beckett
friend
Djuna Barnes
friend
Charlie Chaplin
friend
friend
friend
James Joyce
friend
Eugene O'Neill
friend
friend
Edna St. Vincent Millay
family
James Agee
friend
lover
J.D. Salinger
lover
Oona O'Neill
lover
Orson Welles
Buckminster Fuller
family
friend
Edmund Bacon
family
Kevin Bacon
friend
Margaret Fuller
friend
friend
friend
friend
Leigh Hunt
friend
friend
Thomas Carlyle

Multilevel issues in multivariate networks

... on the variety of how relations can affect relations ...

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(cf. also the algebraic approach;
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Here the various levels are not nested:

ties, dyads, actors, triads, subgroups, ...,

Different relations can impinge on one another in many different ways.

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Dyad level

direct association (within tie) entrainment

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(within tie)

entrainment

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Dyad level

direct association (within tie) entrainment

mixed reciprocity

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Dyad level

direct association (within tie) entrainment

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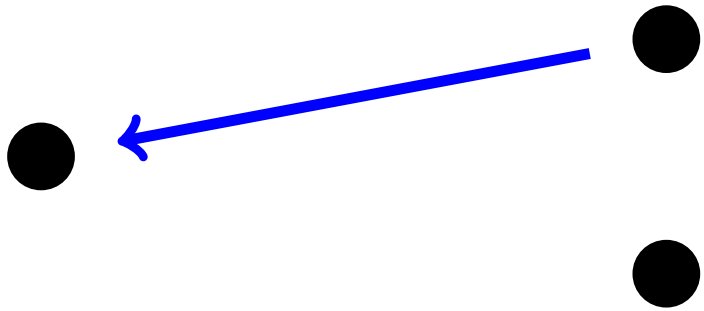
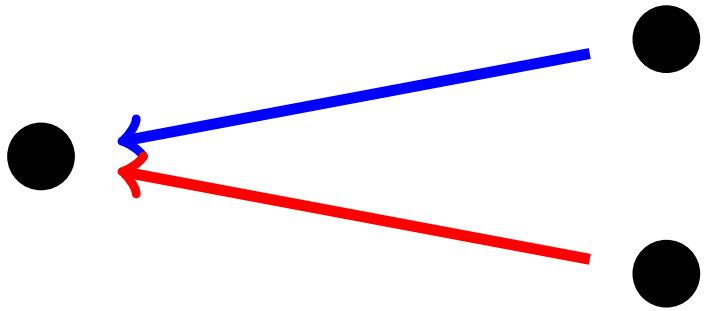
Actor level

mixed popularity



Actor level

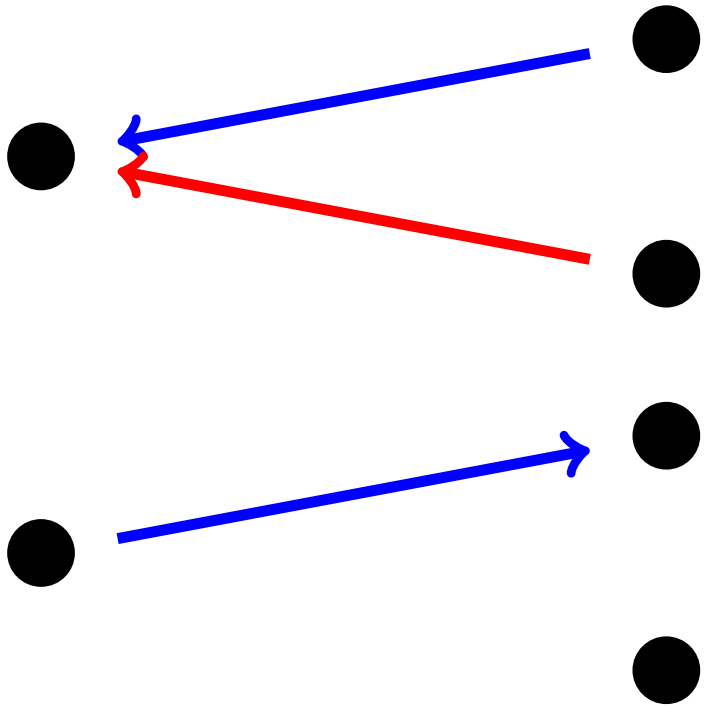
mixed popularity



Actor level

mixed popularity

mixed activity



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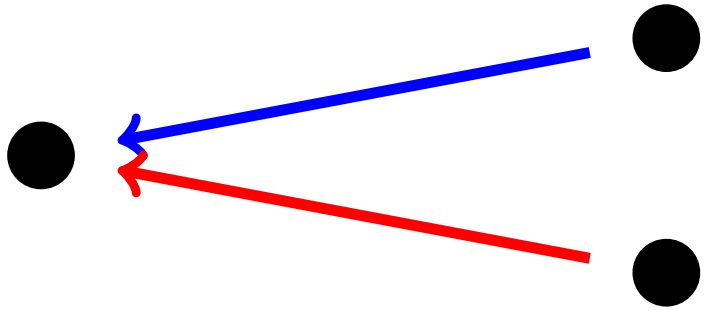

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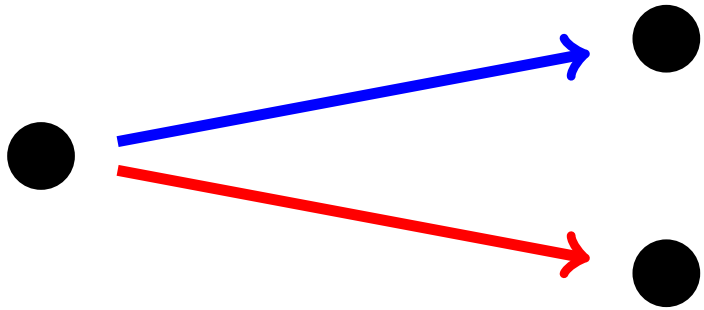
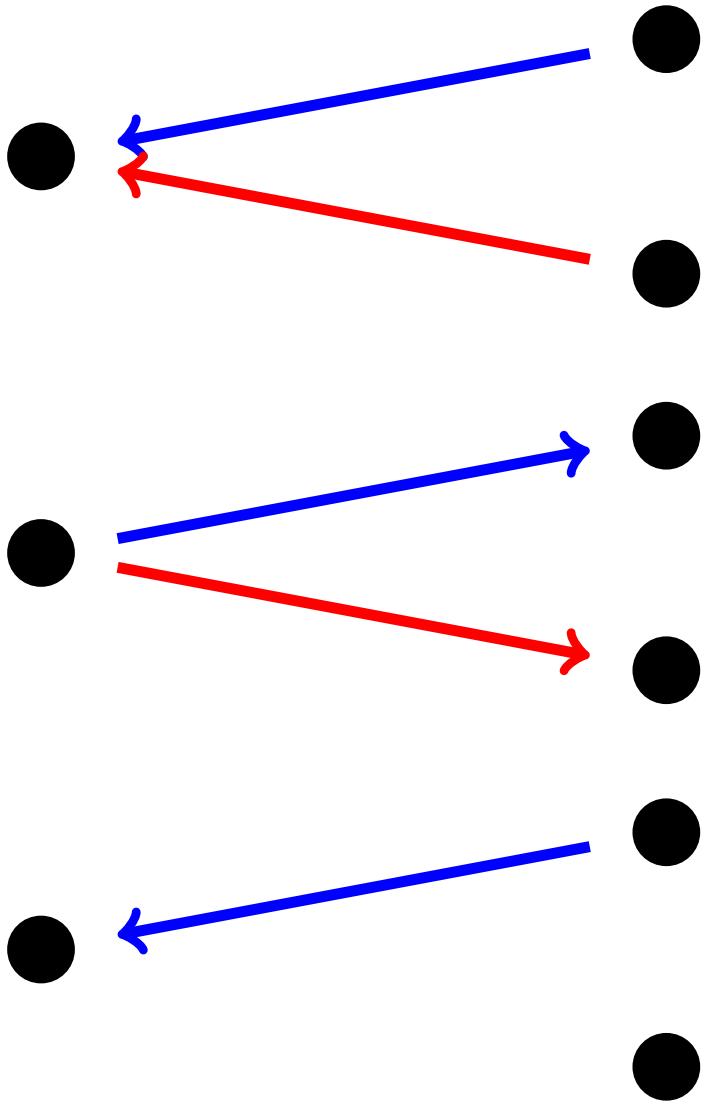


Actor level

mixed popularity

mixed activity

mixed twopathity



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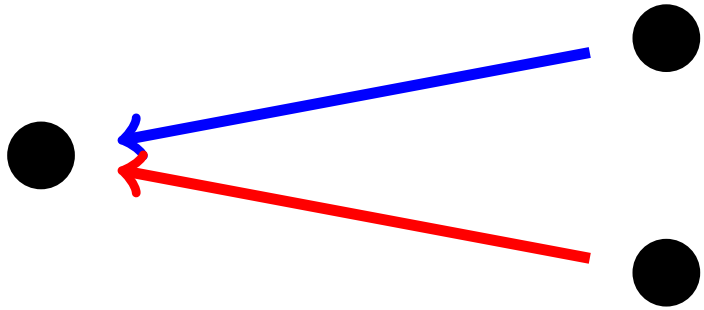
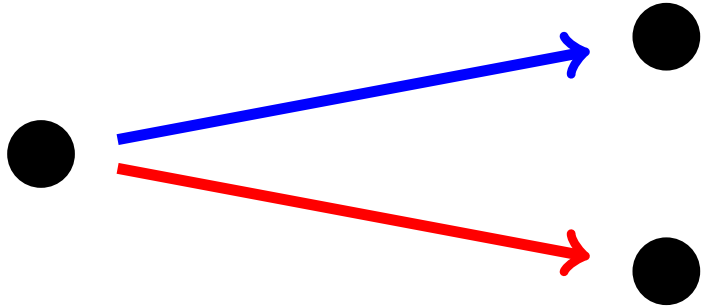
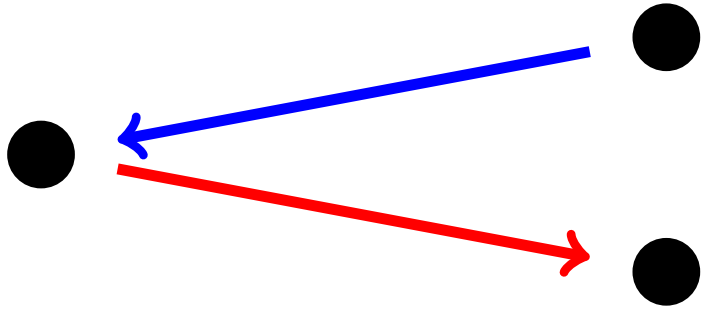


mixed activity



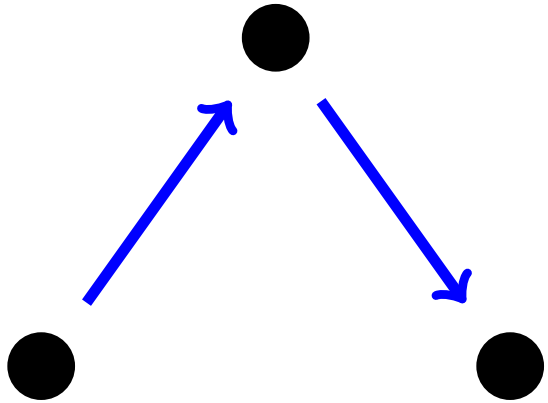
mixed twopathity



Triad level

mixed

transitive closure



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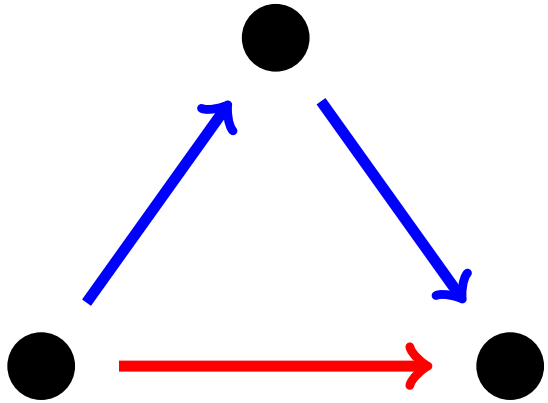

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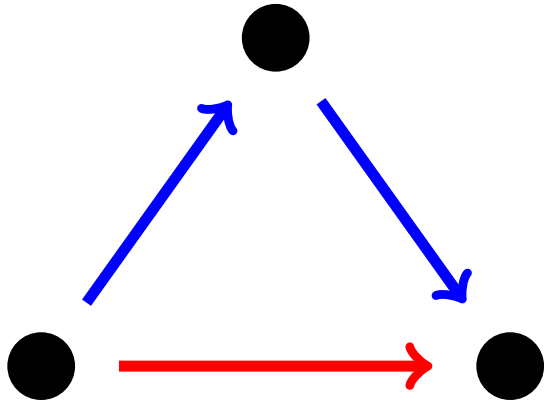
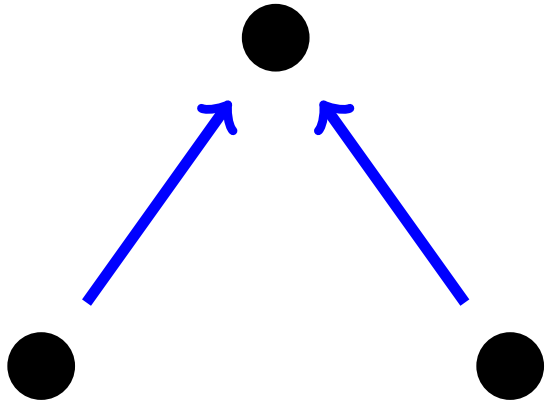


agreement ⇒

red tie



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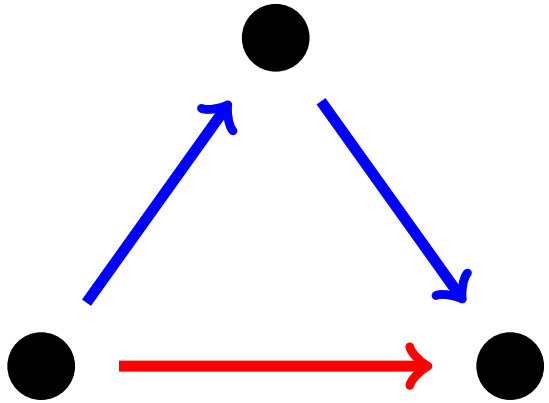

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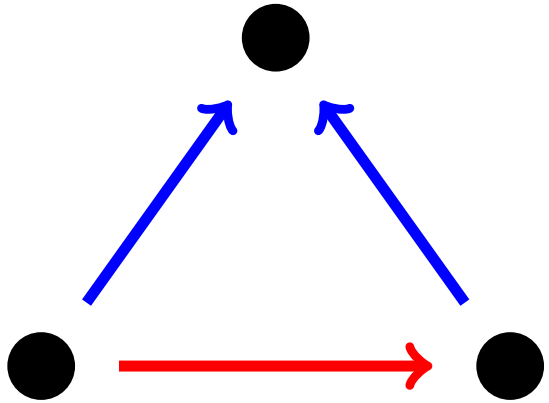

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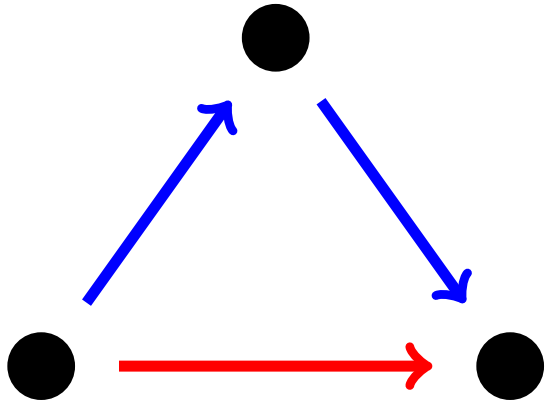
transitive closure



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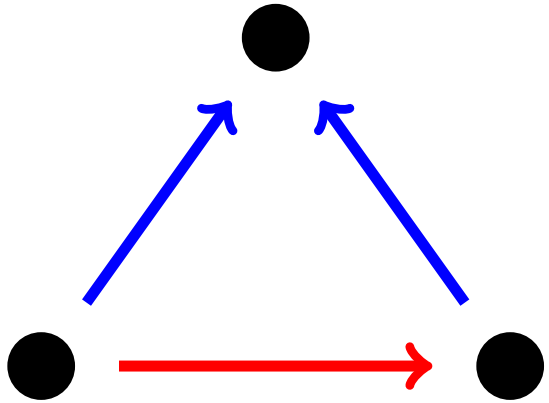

. . . and other tie orientations . . .

Multivariate Stochastic Actor-Oriented Models

This shows that in multivariate networks
the researcher is confronted almost automatically
by multilevel issues.

The co-evolution of multivariate networks
(i.e., multiple interdependent networks on one node set)
can be studied by Stochastic Actor-oriented Models using RSiena;
see Snijders, Lomi, and Torló (*Social Networks*, 2013).

Dynamics of multivariate networks can be represented by stochastic actor-oriented models as a direct extension of such models for single networks.

Multivariate dynamics modeled as continuous-time Markov chain, with state = the multivariate network, where tie variables change one by one.

Note that in Markov process modeling, extending the state space means relaxing the Markov assumption: the current state then provides more information.

2
Multiple Parallel Networks

Multilevel network analysis in the sense of analyzing multiple similar networks, mutually independent, permits research to transcend the level of network as case studies, and to *generalize to a population of networks*.

This was proposed by Snijders & Baerveldt (*J. Math. Soc. 2003*).

Also see Entwisle, Faust, Rindfuss, & Kaneda (*AJS*, 2007).

Sample from Population of Networks

Suppose we have a sample indexed by $j = 1, \ldots, N$
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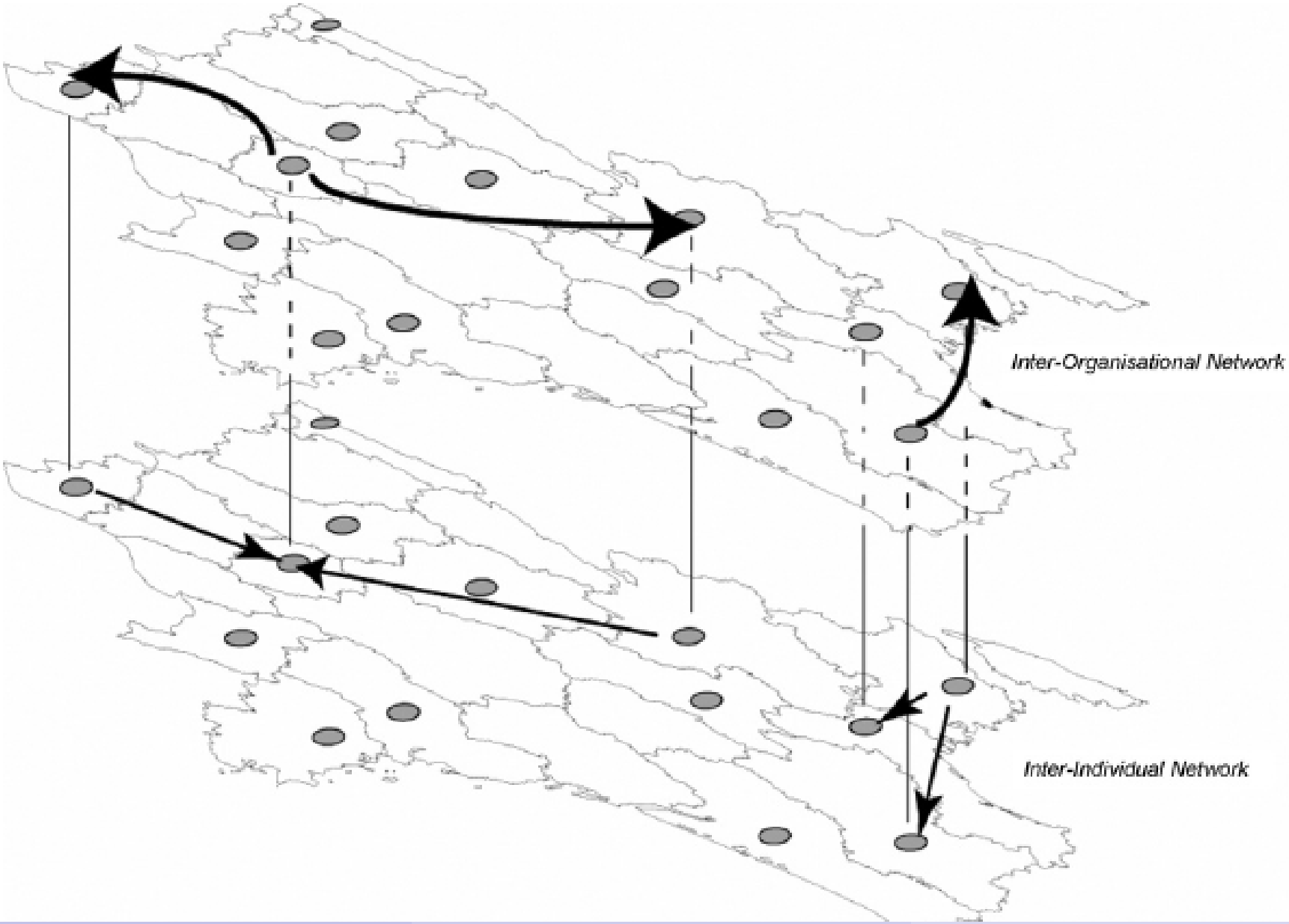
stochastic replicates of each other;
they all are regarded as realizations of
processes obeying the same model,
but having different parameters $\theta_1, \ldots, \theta_j, \ldots, \theta_N$.

This can be studied in RSienaTest
using the function `sienaBayes`.

3
Multiple Actor Sets and Multiple Relations

E. Lazega et al./ Social Networks 30 (2008) 159–176



Multilevel network analysis with multiple actor types
was pioneered by Breiger (*Social Forces*, 1974),
Hedstrøm, Sandell & Stern (*AJS*, 2000) and
Lazega, Jourda, Mounier & Stofer (*Social Networks*, 2008).

In 2013 an important paper appeared in *Social Networks*
by Peng Wang, Garry Robins, Pip Pattison, and Emmanuel Lazega
defining a multilevel network
as a network with nodes of several types,
distinguishing between types of ties
according to types of nodes they connect.

Longitudinal data of linked networks with multiple actor types
also can be analyzed using *RSiena*,
thanks to the flexible design by Krists Boitmanis and Ruth Ripley.

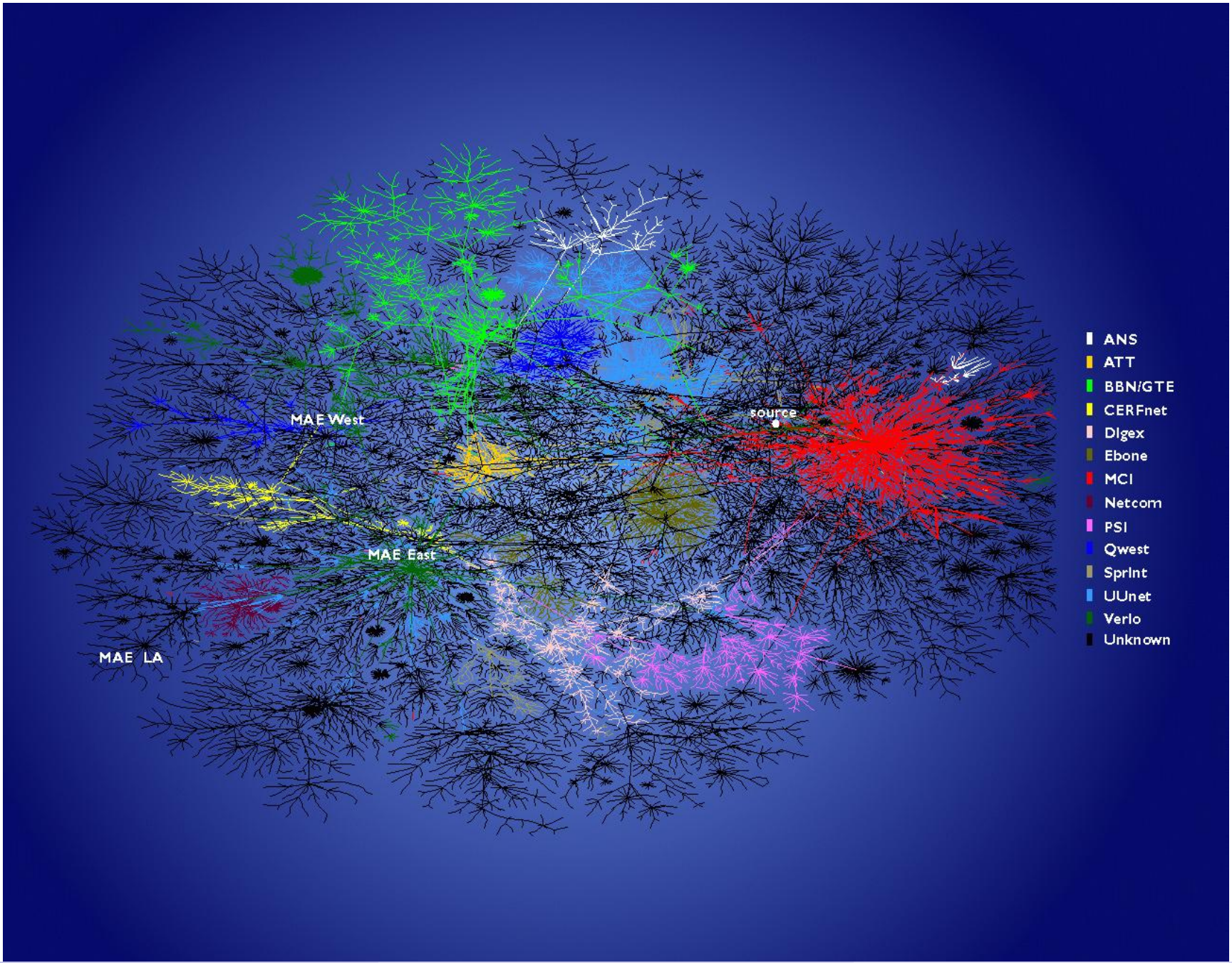
4
Networks with Nested Node Sets

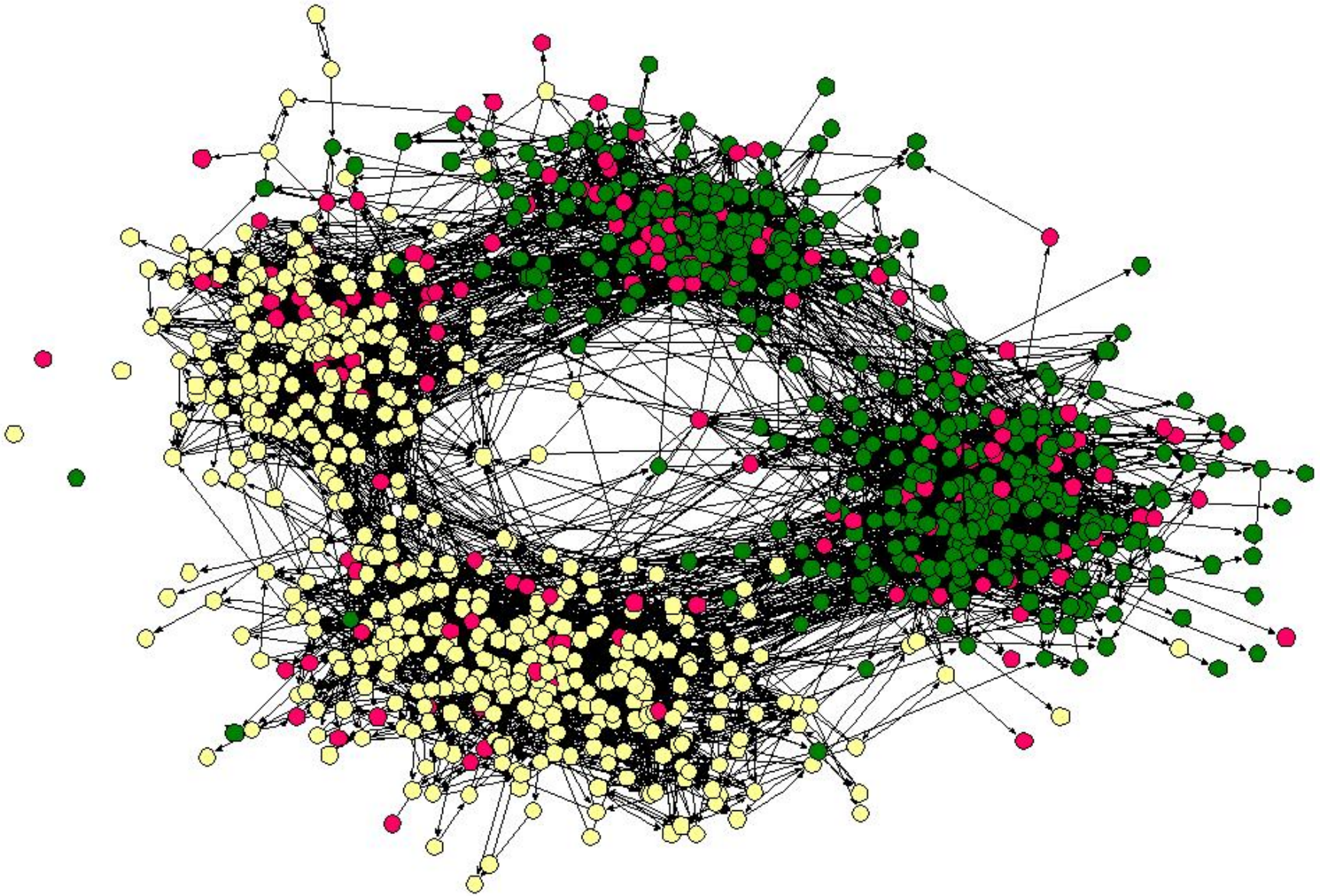
Networks with Nested Node Sets

Networks with nested node sets
lead to special considerations.

An example will be given where this is handled
by a multivariate network: Within and Between.

5
Large Networks


MAE West
source
MAE East
MAE LA
ANS
ATT
BBN/GTE
CERFnet
Digex
Ebone
MCI
Netcom
PSI
Qwest
Sprint
UUnet
Verio
Unknown



A collection of many groups ~ many ‘parallel’ networks
is really a case of a large network
where between-group ties are ignored.

The applicability of our usual network models to large groups
(hundreds of actors and more) seems limited by the fact
that we still do not know a lot about how
the large-scale structure of networks differs from the
small-scale and medium-scale structures;

and large networks must be full of heterogeneity
where, e.g., ERGM parameters will not be constant
in all ‘regions’ of the network
– but how to define such ‘regions’?

This is not treated in this course...