**Summaries of reviews, modeling papers, or empirical analyses about the effects of social mixing in networks or assortative mixing by risk level, age, sex on disease prevalence overall or sex-specific prevalence**

(Newman 2002):

What are the properties of networks assorted by degrees? This is a short paper describing basic findings of Newman 2003 for assortativity based on degree. One interesting finding is that assortative networks (high degree with high degree) are redundant (i.e., removing one highly connected node doesn’t do much to overall network connectivity because they are so clustered with other highly connected nodes).

(Newman 2003)**:**

How can you assemble models of discrete assortative networks? Analytical methods using MGF’s are given in part b, but I’m struggling to follow the full derivations. Simulation methods are given in part c, which are still complicated. (1) Choose number of edges, M. Generate M edges, each one identified by the types of vertices that it connects, in some manner such that the fraction of edges between males and females tends to as M becomes large. “In practice, a simple transformation method works well (Newman 1999)”. (2) Count number of ends of edges of each type i, to give sums of the degrees of vertices of each class. Calculate expected number of vertices of each type from rounded to nearest integer and is desired mean degree of type i. (3) Draw vertices from desired degree distribution for vertices of type i, . (4) pair up ends of edges with vertices generated, so that each vertex has the # of attached edges corresponding to its chosen degree. (5) repeat step (3) for each vertex type. What’s important to remember from this paper about assortatively mixed networks? Assortatively mixed networks might percolate at lower edge densities and are more robust to edge removal than random or disassorative networks.

(Bansal, Grenfell, and Meyers 2007)**:**

Are realistic contact patterns similar to scale-free or exponential? All found to be more similar to exponential. How good can homogenous mixing models approximate more realistic contact patterns? For highly connected exponential networks, the homogeneous-mixing compartmental models offer reasonable approximation to epidemic size. As the tail of the degree distribution gets fatter, what happens to the predictions from homogeneous mixing models? Predicted disease dynamics from fat tails differ from homogeneous mixing models. What can I return to this paper for? For a good review of earlier ways to model heterogeneity in contact patterns using networks. In addition to questions answered in summary above and a source for network definitions of vocabulary, they also give some analytical expressions for solving epidemics on network models.

(EAMES 2007)**:**

Argue that contact-tracing is a powerful public health tool that could in some cases be made more powerful. This modeling paper asks how useful contact tracing is when networks are random-mixing or (dis)assortative? They also investigate targeted interventions by asking, how much better can contact tracing be if we target it towards individuals at higher risk? They use a “pair-wise” SI model that considers pairs of individuals as the basic variable (see vocab). They show you can reduce the overall prevalence some by doing single-step tracing (see vocab), especially when r is close to 1 but for eradication, the space is limited. In contrast, equilibrium prevalence can be greatly reduced by iterative tracing which is introduced into their model as a “hyper-infection” which spreads through the population into “tracing class” [T]. They remain in tracing class for units. With this model, they investigate how disease is concentrated into different sub-groups of the population, finding that as equilibrium prevalence increases, the more spread out the infection is across the population. The lower prevalence is, the more disease is situated in certain parts of the network (i.e., individuals with lots of infected contacts?). They show how iterative tracing, not single-step, can greatly reduce the prevalence, especially among sub-groups, i.e., the ability of core-group to sustain infection is greatly reduced. Next, they study mixing between high and low risk groups. Super important: R0 is maximized with high assortativity because transmission is intense and spreadable among condensed high-risk individuals but PREVALENCE is maximized at intermediate assortativity because enough transmission in high risk but also enough transmission to low risk. Then he proceeds to see if tracing is better in assortative or disassortative mixed populations. Contact tracing requires lower relative effort in assortative networks to eradicate infection. In disassortative mixing patterns, there is a relatively even distribution of infection meaning that targeting is of little worth. The main thing is to figure out where are the core groups.

(Perkins, Ferrari, and Hudson 2008)**:**

Used a natural wild rodent – parasite system where there is no sex-bias in prevalence but a strong sex-bias in transmission has been observed (Ferrari 2004). In this study, asked to what extent is the observed overall prevalence and prevalence by sex in this system due to observed sex-assortativity? Also, asked what strength of male-biased transmission predicts empirical patterns of macroparasite prevalence and sex ratio of infected hosts? Found disassortative mixing by sex (-0.13) which was somewhat surprising given the breeding biology of mice. With these disassortative networks, they simulated outbreaks with chain binomial model where I is infected neighbors in the network and is the sex-specific shedding rates. *Note: I wonder how difficult this is in larger networks*. They determined by and and so by increasing c, you increase . They found that without male-bias in shedding, the overall prevalence and prevalence by sex in this system does not match up with field results. But when you increase c all the way up to 10, then simulation results match with field results… Thus, they conclude that heterogeneity at the individual level (differences in shedding) not mixing-patterns at the population-level for macroparasite dynamics analyzed here. They say future work entails figuring out whether network characteristics (I assume centrality) are associated with parasite burden, which could have implications for their findings.

**Other relevant papers**

* Malloy & Reed (1995): configuration models
* Ferrari et al. (2004): wild rodent – parasite system apparently identifies sex-specific transmission rates
* (Read et al. 2012; Danon et al. 2012): review of contact patterns relevant to respiratory transmitted infection
* (Mossong et al. 2008): age-structured contacts
* (Dodd et al. 2016): age-sex prevalence in TB and finding that males drive transmission
* Felipe et al (2005): deterministic age-sex-structured model with differences in transmission rates
* Newman 1999: “Monte Carlo Methods in Statistical Physics”
* Bansal (2007): how much do real populations depart from homogenous mixing assumptions
* Garnett & Anderson (1996): STDs and sexual behavior: insights from math models, assortativity results?
* Barlow et al. (1997): assortative mixing, a limiting factor in HIV spread
* Edumunds WJ, OCallaghan, and Nokes 1997: Who mixes with whom? A method to determine the contact patterns of adults that may lead to the spread of airborne infections
* Garnett GP et al. (1996): Sexual mixing patterns of patients attending sexually transmitted disease clinics
* Boguna, Pastor-Satorras, Vespignani (2003): Epidemic spreading in complex networks with degree correlations.
* Hethcote & York 1984: modeled STI in male/female/high/low risk groups

**Definitions**

**Contact network model:** explicitly represents host interactions that mediate disease spread (Bansal et al. 2007)

**Degree-based differential equations:** Models track numbers of individuals in each disease state for each degree class (there are 3k differential equations for a SIR model). See Pastor-Satorras & Vespignani (2002) for details on this model.

**Iterative tracing**: when infected partners of any diagnosed cases being sought for treatment and further tracing (e.g., HIV today).

**Pair-wise (pair-counting) model**: Count the number of pairs of individuals in each disease class. More simple than full stochastic simulation on networks and because of this cannot capture large-scale dynamics (e.g., giant component?) but can capture local network structure. For example can capture networks with clustering or spatial networks. Assume underlying mixing remains fixed. Infection parameter and denote as the number of connections between S and I where new infections can occur. Evolution of new infections then is but changes over time as well . But triples can change over time as well.. so they introduce a moment closure approximation. Single-step contact tracing introduced as and similarly, for [I] where fraction f of contacts of an index case receive treatment at the same time as the index patient. Seems to have been developed in Keeling (1999) but also used in Eames 2007.

**Percolation-theory methods:** Based on generating functions and only require degree distribution of the network, average transmissibility T of the pathogen. These methods are very general and very tractable. They provide excellent final-state predictions but do not predict the dynamics of an outbreak. Examples are Newman 2002; Meyers et al. 2003, 2005, 2006

**Probability generating function model:** Tracks global epidemiological dynamics in complex random networks (Volz, referenced in Bansal 2007).

**Single-step tracing**: a proportion of the partners of index cases is treated concurrently with the index patient, thus resulting in the recovery of pairs of individuals; this is an appropriate model for certain STD situations when patients and their partners attend a clinic together

**Full citations**

Bansal, Shweta, Bryan T Grenfell, and Lauren Ancel Meyers. 2007. “When Individual Behaviour Matters: Homogeneous and Network Models in Epidemiology.” *Journal of the Royal Society Interface* 4 (16). The Royal SocietyLondon: 879–91. doi:10.1098/rsif.2007.1100.

Danon, Leon, Thomas A House, Jonathan M Read, and Matt J Keeling. 2012. “Social Encounter Networks: Collective Properties and Disease Transmission.” *Journal of the Royal Society Interface* 9 (76). The Royal Society: 2826–33. doi:10.1098/rsif.2012.0357.

Dodd, Peter J, Clare Looker, Ian D Plumb, Virginia Bond, Ab Schaap, Kwame Shanaube, Monde Muyoyeta, et al. 2016. “Age- and Sex-Specific Social Contact Patterns and Incidence of Mycobacterium Tuberculosis Infection.” *American Journal of Epidemiology* 183 (2): 156–66. doi:10.1093/aje/kwv160.

EAMES, K T D. 2007. “Contact Tracing Strategies in Heterogeneous Populations.” *Epidemiology and Infection* 135 (3): 443–54. doi:10.1017/S0950268806006923.

Mossong, Joël, Niel Hens, Mark Jit, Philippe Beutels, Kari Auranen, Rafael Mikolajczyk, Marco Massari, et al. 2008. “Social Contacts and Mixing Patterns Relevant to the Spread of Infectious Diseases..” Edited by Steven Riley. *PLoS Med* 5 (3). Public Library of Science: e74. doi:10.1371/journal.pmed.0050074.

Newman, M E J. 2002. “Assortative Mixing in Networks.” *Phys. Rev. Lett.* 89 (20). American Physical Society: 208701. doi:10.1103/PhysRevLett.89.208701.

Newman, MEJ. 2003. “Mixing Patterns in Networks.” *Physical Review E* 67 (2). American Physical Society. doi:10.1103/PhysRevE.67.026126.

Perkins, S E, M F Ferrari, and P J Hudson. 2008. “The Effects of Social Structure and Sex-Biased Transmission on Macroparasite Infection.” *Parasitology* 135 (13): 1561–69. doi:10.1017/S0031182008000449.

Read, J M, W J Edmunds, S Riley, J Lessler, and D A T Cummings. 2012. “Close Encounters of the Infectious Kind: Methods to Measure Social Mixing Behaviour.” *Epidemiology and Infection* 140 (12). Cambridge University Press: 2117–30. doi:10.1017/S0950268812000842.